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Protester or non-protester: a binary state? On the use (and non-use) of latent class models to analyse protesting in economic valuation*

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In the analysis of stated preferences studies, it is often assumed that protesting is a discretely measured item only occurring among those who are not willing to pay. However, various studies have recently shown that protest beliefs are as well held by respondents who state a positive willingness to pay (WTP). Using latent class (LC) models, we investigate the extent of heterogeneity with respect to protest beliefs among all respondents of two contingent valuation studies. The advantage of LC models is that classes of individuals are endogenously identified and no selection bias is introduced by ad hoc definitions of protesters. Further we investigate whether it is possible to identify a class of non-protesters. Finding a group of pure non-protesters could indicate how strongly stated WTP in the whole sample is affected by protest beliefs. For both samples, we find a class with strong protest beliefs but no pure non-protest class. Overall, our results suggest that LC models might not be the first choice to determine unbiased WTP measures, but they provide valuable insights into the degree of protesting expressed by different groups and corresponding determinants of group membership.

Key words: contingent valuation, forest biodiversity, latent class analysis, protest beliefs, willingness to pay.

1. Introduction

The treatment of protest responses in stated preference studies is still an unsettled issue. Generally, protesters are defined as those individuals who do not reveal their true preferences toward the value of the good in question. The reason for not expressing their true preferences is seen in not agreeing with some features of the hypothetical market presented in the stated preference survey, for example, the payment vehicle used. Respondents who are protesting against the valuation scenario or other aspects of the hypothetical

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market are seen as an exception in the majority of stated preference studies. However, in some stated preference studies, the number of identified protesters is quite large and can be as high as 60% of the sample as a meta-study by Meyerhoff and Liebe (2010) shows. Additionally, in the majority of valuation studies, protesters are solely identified as those who reject payment.

Various studies, in contrast, provide evidence that the prevailing approach may not be defensible. Jorgensen and Syme (2000) were the first to point out that not only those respondents who have so far been identified as protesters hold protest beliefs. They argue that protesting rather reflects an attitude toward paying for the good in question that can also be present among those who are willing to pay a positive amount. Rollins *et al.* (2010) reason that public goods could be inseparable from attributes such as policy implementation and payment vehicle for some individuals. If these attributes are correlated with protest beliefs, for example, because of distrust toward public bodies based on past experience, willingness to pay (WTP) estimates will be affected. Rollins *et al.* hypothesise that some of the respondents probably evaluate a composite good, for example, 'ecosystem managed by a public agency' instead of solely the ecosystem and, therefore, hold protest beliefs.

In this study, we determine protest beliefs by presenting attitudinal statements to all respondents and investigate the degree of heterogeneity among their response patterns. As a method, we apply latent class (LC) models. The advantage of LC models is that no prior definition of protest responses is required, and thus, no selection bias is exogenously introduced by ad hoc definitions. Furthermore, LC models give information about the size of classes with a similar response pattern and about the individual characteristics that influence the likelihood of class membership. Knowing both the size of a protest class and the determinants of class membership can provide valuable information for decision makers concerning the acceptance of policy measures. Thus, finding a class of pure non-protesters in a LC model and determining their WTP would indicate how strongly the WTP stated by respondents in other classes is affected by protest beliefs, given the influence of other variables is controlled by the model.

Application of LC models has become more popular in environmental economics for investigating revealed choices (e.g. Scarpa and Thiene 2005; Hynes *et al.* 2008) or stated choices (e.g. Boxall and Adamowicz 2002; Scarpa *et al.* 2004). Some authors suggest using LC models to identify a protest class or a class of respondents who reject the valuation scenario (Morey *et al.* 2008; Breffle *et al.* 2011). Recently, LC models have been applied to identify protesters in stated preference studies. One study presented LC models with three or four distinct classes (Meyerhoff *et al.* 2009), and two papers present a protester and a non-protester class (Cunha-e-Sá *et al.* 2010; Barrio and Loureiro 2010).

The data we use for our analyses are from two contingent valuation studies aiming at eliciting preferences for higher levels of forest biodiversity in two different regions in Lower Saxony, Germany. This paper is organised as follows: Section 2 presents different approaches used so far to identify and treat protest responses in stated preference surveys. Section 3 briefly describes LC models, while Section 4 introduces the survey and data. Results are shown in Section 5 before Section 6 concludes.

2. Identification and treatment of protesting

There are two fundamental concerns regarding protest responses. The first concern relates to the *identification* of protest responses and subsequently protesters. Generally, respondents who refuse to pay for a good in question are presented a set of debriefing questions. Based on their responses, it is then determined whether they are protesting or whether they state a true WTP of zero. The debriefing questions or attitudinal statements typically used address, among other things, scepticism toward the hypothetical scenario (e.g. distrust toward the agency providing the good or the proposed payment vehicle), fairness aspects (e.g. polluter should pay) or ethical concerns (e.g. nature as a marketed good). However, content and wording of the attitudinal statements can vary significantly between surveys, and the choice of aspects used to determine protest answers depends very much on the subjective assessment of the researcher (Jorgensen *et al.* 1999; Dzięgielewska and Mendelsohn 2007). A common set of protest statements comparable to, for example, the New Environmental Paradigm, that is broadly used for determining a general attitude toward the environment (Hawcroft and Milfont 2010), has not yet emerged. Alternatively, some authors suggest using open-ended questions to identify protesters among respondents who refuse to pay (e.g. Bateman *et al.* 2002), while others propose a comprehensive procedure based on a system of valuation questions containing both discrete choice and open-ended questions (e.g. Dzięgielewska and Mendelsohn 2007).

Jorgensen and Syme (2000; see also Meyerhoff and Liebe 2006) suggested that protesting represents an attitude toward paying for the good in question underpinned by a set of protest beliefs. They also stated that holding protest beliefs is not restricted to those who refuse to pay but that protest beliefs can also be held by respondents who state positive WTP values. Therefore, they argue that censoring some of these beliefs by dropping certain respondents who were identified as protesters by the researcher might be indefensible. They accordingly conclude that all respondents should be presented attitudinal questions concerning protest beliefs and that all respondents should remain in the sample. Rollins *et al.* (2010), following on from Jorgensen and Syme (2000), identify protesters also among all respondents. However, the authors treat protest beliefs and opposition to the proposed environmental programme as separate concepts; those respondents with a negative WTP are labelled opposers. In their paper, Rollins *et al.* analyse the determinants for being a protester or an opponent and assess the impacts on stated WTP. In the end, they identify two groups of protesters: protester-opposer and protester-non-opposer.

The other fundamental concern relates to the *treatment* of protesters. In the literature, a couple of different approaches have been applied. Often protesters are treated as outliers and are removed from the analysed data set (Mitchell and Carson 1989). This simple truncation can bias the sample representativeness and subsequently the welfare estimates (Messonnier *et al.* 2000). Others have suggested treating protest bids as legitimate zero bids or assigning to protesters the mean WTP of those who are identified as non-protesters. All treatments can have significant effects on the aggregated WTP values.

To address the problem of a selection bias that may arise when protesters are simply dropped from further analysis, various authors have suggested use of sample selection models (e.g. Strazzera *et al.* 2003; Cho *et al.* 2008; Brouwer and Martín-Ortega 2011). Sample selection models take into account that the decision to participate in the hypothetical market and the stated WTP might be correlated. In this case, protesters are still identified through answers to a set of debriefing questions but remain in the sample. Applying a selection model, Collins and Rosenberger (2007) found that some protesters do hold positive WTP values. As the correlation between the error terms of both the selection and outcome equations was positive, WTP of protesters is supposed to be lower than that of those who stated a positive WTP in the survey. They found that assigning protesters a zero WTP would have resulted in an underestimation of 10%. Adding to these findings, Brouwer and Martín-Ortega (2011), who also applied a selection model, found that the true WTP held by protesters is higher than the sample mean. They argue, therefore, that accounting for the selection bias results in a more reliable and defensible indicator of WTP.

LC models have recently been applied to identify types of protesters or, alternatively, groups of protesters and non-protesters. In the context of a contingent valuation, Meyerhoff *et al.* (2009) were among the first to employ LC models for this purpose. Using data from two surveys on forest biodiversity and surface water, they investigated whether heterogeneity with respect to protest beliefs exists among respondents and how this affects WTP. The analysis reveals strong heterogeneity for both sets of attitudinal statements. In one sample they found three distinct classes, and in the other sample they found four distinct classes. They thus conclude that protesting is a matter of degree, ranging from ‘marginal’ to ‘strong’ protesting. WTP values varied significantly across classes. A shortcoming was that the LC models were solely informed by attitudinal data as no socio-demographics were incorporated via a class-membership function.

Following this, Cunha-e-Sá *et al.* (2010) as well as Barrio and Loureiro (2010) applied LC models to analyse protesters in stated preference surveys. Cunha-e-Sá *et al.* (2010) employed a LC model simultaneously incorporating both responses to a contingent valuation and attitudinal data for identifying protest responses. Their study aimed to elicit the WTP for preserving a wine growing region as a cultural landscape. The statements they used to address protest beliefs were solely related to the potential lack of trust in the institution responsible for providing the public good; other aspects of protesting were not addressed. They opted for a two-class model with one class showing a stronger protest attitude and on average a lower WTP estimate. Barrio and Loureiro (2010) used LC analysis to identify protesters in the context of a choice experiment. Their survey investigated management options for a national park in Spain. In their model, the attitudinal statements concerning protesting are incorporated via the membership function, that is, responses to the attitudinal statements can influence respondent class assignment, uncovering sources of preference heterogeneity. The attitudinal statements they used mainly focus on fairness aspects of paying for the public good. Their analysis reveals two classes with heterogeneous preferences and class membership being significantly influenced by the majority of attitudinal statements. Similar to the results by Cunha-e-Sá *et al.* (2010), respondents belonging to the protest class stated lower WTP values.

The present study contributes to and extends the existing literature on protest responses by (i) employing a broad set of attitudinal items to measure protesting, (ii) presenting attitudinal items on protest beliefs to all respondents irrespective of whether they are willing to pay or not, (iii) applying a LC model on protest items where several individual characteristics are included in the class-membership function, and (iv) comparing WTP values that are derived from different approaches to deal with protest responses (based on LC modelling and answers to attitudinal items).

3. Latent class attitudinal model

The LC model assumes that a population consists of a number of different preference classes but that an individual's preference class is unobserved (latent) from the researchers' point of view. People belonging to different classes ('C') will respond differently to attitudinal statements as they express different preferences. To identify the unobserved classes, the responses to a set of attitudinal statements (the individual's response pattern to statements concerning aspects of protesting toward the payment for the good in question) and characteristics of the individuals are observed. The response patterns of individuals from the same preference class are more correlated with each other than with response patterns of individuals in other classes. Thus, LC models are based on the assumption that once class membership is controlled attitudinal responses are independent across classes (Thacher *et al.* 2005; Morey *et al.* 2008).

Based on the answers to a set of attitudinal questions, an LC model can determine the conditional probability (CP) that an individual belongs to a certain class c out of C classes. This is the probability that the individual belongs to a certain class as a function of covariates and answers to the set of attitudinal statements. Given the observed response pattern to the attitudinal statements, the estimation goal is to find the most likely response and unconditional class-membership probabilities (Thacher *et al.* 2005). In the present study, the unconditional class probability is the probability that a respondent who is a user of a forest, for example, belongs to a particular protest class. The conditional class-membership probabilities can subsequently be calculated based on the unconditional class probabilities. They inform about the probability of an individual belonging to a certain class given the individual characteristics and the specific responses to the attitudinal statements. The log-likelihood function for a C-class model for attitudinal data as in our surveys is

$$\ln L = \sum_{i=1}^{N} \ln \left[\sum_{c=1}^{C} \Pr(c : z_i) \prod_{q=1}^{Q} \prod_{s=1}^{S} (\pi_{qs|c})^{x_{iqs}} \right], \tag{1}$$

where N is the number of respondents, C the number of distinct protest classes, Q the number of attitudinal statements used to measure protest beliefs, S the number of response options (Morey and Thiene 2008). Moreover, $\pi_{qs|c}$ is the probability that individual i answers level s on question q, conditional on being a member of class c, and $\Pr(c : z_i)$ is the unconditional probability that an individual i belongs to class c as a function of observable covariates. As the number of classes is unknown a priori, the use of multiple information criteria such as the Bayesian Information Criterion (BIC), the Akaike Information Criterion 3 (AIC3) or the Consistent Akaike Information Criterion (CAIC) is recommended to make an informed choice about the appropriate number of classes (e.g. Vermunt and Magidson 2005a). These criteria assess the fit and the parsimony of a model; the lower their value, the better the model. The usual procedure is to estimate models with a varying number of classes (2, 3, 4, 5, …) and to compare the value of the information criteria among estimations. However, the information criteria may not indicate a unique solution. Selection of the number of classes thus often requires using additional information such as size and signs of parameters (Bacher and Vermunt 2010; Scarpa and Thiene 2011).

4. Study and measurement instrument

4.1. The contingent valuation studies

Both contingent valuation studies focus on changes in forest biodiversity on a regional level. They were carried out in face-to-face interviews in 2004 in the Lüneburger Heide (LH) and the Solling–Harz (SH) areas, both located in Lower Saxony, Germany. The objective was to elicit the benefits people would derive from increased levels of biodiversity because of a long-term forest development programme (LÖWE). The programme aims at extending broadleaved and mixed forests, and its implementation would cause changes in forest biodiversity. The changes expected were described to respondents by a combination of four attributes: habitats for protected and endangered plant and animal species, number of plant and animal species, forest stand structure and landscape diversity. An annual contribution to a fund managed by the Forest Planning Office of Lower Saxony was used as a payment vehicle. A payment ladder was employed to determine respondents' WTP (see Figure 1).

The sampling population was restricted to citizens aged 18 years and older living in private households in the study regions. In total, 305 interviews were collected in the LH area and 324 in the SH area. Because of missing data, 262 observations from the LH area and 288 from the SH area were used in the analysis. Table 1 reports basic socio-demographic statistics and information about the WTP. In the LH 27% of respondents are willing to pay for forest conversion measures, while in the SH sample slightly more respondents (33%) are in-principle willing to pay for forest conversion measures. The mean WTP per year and respondent, calculated based on the midpoints of the payment ladder intervals, is €5.51 in the former sample and €6.61 in the latter.

4.2. Attitudinal statements and estimation

We use five attitudinal statements to identify protest beliefs (Table 2). They aim at different aspects of an individual's attitude towards a contribution to the provision of the public good: whether people feel they have a right to have the good in question provided (right), excessive financial burden (I already pay enough for other things), fairness concerns (who should pay), trust in the agency that would implement the forest conversion programme (confidence in implementation) and ethical aspects (monetary valuation). Similar attitudinal statements can be found in many stated preference studies. However, the

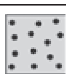
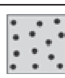
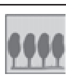
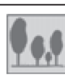
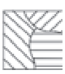
	Without forest conversion	**Programme A**	**Amount per year**	**WTP yes✓ unsure/no ×**
Broad-leaved trees	**30 per cent** 	**60 per cent** 	€0.50 €1.00 €2.00 €3.00 €5.00 €7.00 €10.00 €15.00 €20.00 €25.00 €30.00 €35.00 €50.00 €60.00 €75.00 €90.00 €100.00 €130.00 other amount	
Habitats for endangered/ protected species	**Medium** 	**High** 		
Species diversity	**Medium** 	**Medium** 		
Forest stand structure	**Low** 	**High** 		
Landscape diversity	**Low** 	**Medium** 		

Figure 1 Description of environmental good and payment ladder.

Table 1 Descriptive statistics

	Lüneburger Heide	Solling–Harz
	Mean (SD)	Mean (SD)
Variables		
Gender (1 = female, 0 = male)	0.62	0.53
Age of respondents (years)	49.88 (17.76)	47.57 (16.88)
Education (years)	9.65 (2.47)	9.73 (2.59)
Number of people per household	2.43 (1.11)	2.45 (1.34)
Net income per household (€ per month)	1960.95 (876.87)	1902.91 (925.55)
User of the forests (1 = yes, 0 = no)	0.71	0.59
WTP		
In-principle WTP (0 = no, 1 = yes)	0.27	0.33
Mean WTP for forest biodiversity (€ per year)	5.51 (15.46)	6.61 (18.87)
Sample size		
N	262	288

Note: WTP, willingness to pay.

Table 2 Items used to determine protest beliefs

Protest aspect	Attitudinal statements	Protesters tend to
Rights	It is my right to have a high level of forest biodiversity and not something I should have to pay extra for	Agree
Fairness	Above all those who enjoy biodiversity in forests should pay for the measures	Agree
Excessive financial burden	I already pay enough for other things	Agree
Trust towards scenario	Implementation of forest conversion by the Forest Planning Agency is not credible	Agree
Ethical beliefs	I refuse to assess nature in monetary terms	Agree

Note: Response scale: (1) Completely disagree, (2) Disagree, (3) Neither/nor, (4) Agree, (5) Completely agree.

present study differs from many others in presenting the attitudinal statements to all respondents, regardless of whether they were willing to pay or not. All interviewees were asked to indicate their disagreement or agreement on a five-point Likert scale (1 = completely disagree to 5 = completely agree).

Maximum likelihood estimations were conducted using Latent Gold 4.5. It combines the EM algorithm and the Newton–Raphson algorithm by starting with a number of EM iterations and switches to Newton–Raphson when close enough to the final solution (Vermunt and Magidson 2005b). To reduce the likelihood of local solutions, we used multiple sets of starting values (i.e. 30 values). Responses to the attitudinal statements were specified as ordinal in the model settings. To determine the number of classes, models with one to five LCs were estimated for each sample. Goodness of fit measures for all models are reported in Table 3. The membership function includes the socio-demographic variables gender, age, education, people per household, net household income and user status (forest visits yes/no).

5. Results

The information criteria indicate a different number of classes in each sample. The BIC and CAIC information criteria suggest a three-class model for the LH and a two-class model for the SH area. The AIC3 measure, in contrast, indicates a three-class model for the former and a five-class model for the latter (Table 3). Based on interpretability of the results and a preference for more parsimonious models, we opt for a three-class model in the LH and a two-class model in the SH sample.

Table 4 reports in the upper part (Class function) the mean CP. It reflects the average probability that respondents in a given class will choose one of the response categories to an attitudinal statement. In addition to the conditional probabilities, the mean values for each attitudinal statement per class are reported; they are the sum of products of the ordinal response category times the CP. In the lower part of Table 4 (Membership function), the parameters for the individual characteristics incorporated in the membership function are given. They show if and to what extent the individual characteristics influence the probabilities of being a member of a LC.

In Table 4, classes are sorted according to the degree of protesting in each sample. For both samples, the Wald statistics indicate that each attitudinal statement discriminates statistically significantly at the 5%-level between the classes. This means the null-hypothesis that the set of beta parameters associated with the attitudinal statement is equal to zero can be rejected.

Table 3 Goodness of fit criteria for latent classes

Classes	N_{par}†	LL‡	BIC§	AIC3¶	CAIC††
Lüneburger Heide					
1	20	−1929.92	3971.20	3919.83	3991.20
2	32	−1840.74	3859.67	3777.49	3891.68
3	44	−1799.50	**3844.01**	3731.01	**3888.02**
4	56	−1777.34	3866.51	**3722.68**	3922.51
5	68	−1750.44	3898.02	3723.37	3966.02
Solling–Harz					
1	20	−2108.13	4329.38	4276.26	4349.38
2	32	−2044.66	**4270.31**	4185.32	**4302.31**
3	44	−2018.60	4286.06	4169.20	4330.06
4	56	−1996.71	4310.16	4161.43	4366.16
5	68	−1975.92	4336.44	**4155.83**	4404.44

Note: †Number of parameters. ‡Log-Likelihood value. §BIC $= -2 \times \text{LL} + \ln(n) \times N_{\text{par}}$. ¶AIC3 $= -2 \times \text{LL} + 3 \times N_{\text{par}}$. ††CAIC $= -2 \times \text{LL} + [\ln(n) + 1] \times N_{\text{par}}$. BIC, Bayesian Information Criterion; CAIC, Consistent Akaike Information Criterion.

Table 4 Conditional probabilities

	Lüneburger Heide							Solling–Harz				
	Class 1 Low protest 22%†		Class 2 Partial protest 62%		Class 3 Strong protest 16%			Class 1 Low protest 58%		Class 2 Strong protest 42%		
	CP	SE	CP	SE	CP	SE	Wald	CP	SE	CP	SE	Wald
Class function												
Rights												
(1)	0.20	0.06	0.02	0.01	0.01	0.00	31.1	0.13	0.03	0.01	0.00	30.0
(2)	0.40	0.06	0.13	0.03	0.01	0.00		0.21	0.03	0.04	0.01	
(3)	0.29	0.04	0.32	0.04	0.02	0.02		0.38	0.03	0.21	0.04	
(4)	0.09	0.03	0.32	0.04	0.14	0.06		0.17	0.02	0.27	0.03	
(5)	0.02	0.01	0.20	0.04	0.84	0.08		0.10	0.03	0.47	0.05	
Ø	2.31		3.55		4.82			2.90		4.16		
Fairness												
(1)	0.57	0.08	0.40	0.04	0.07	0.05	13.8	0.36	0.04	0.21	0.04	8.9
(2)	0.21	0.03	0.22	0.03	0.09	0.04		0.26	0.03	0.22	0.03	
(3)	0.13	0.03	0.19	0.03	0.19	0.04		0.24	0.03	0.29	0.03	
(4)	0.07	0.03	0.13	0.02	0.32	0.06		0.10	0.02	0.18	0.03	
(5)	0.02	0.01	0.06	0.02	0.34	0.10		0.04	0.01	0.10	0.02	
Ø	1.76		2.23		3.78			2.20		2.73		
Excessive financial burden												
(1)	0.27	0.07	0.02	0.01	0.01	0.00	29.3	0.17	0.03	0.01	0.00	26.2
(2)	0.37	0.06	0.11	0.02	0.01	0.00		0.23	0.04	0.01	0.01	
(3)	0.24	0.04	0.23	0.03	0.03	0.03		0.35	0.04	0.10	0.04	
(4)	0.10	0.04	0.30	0.03	0.17	0.06		0.16	0.03	0.23	0.03	
(5)	0.03	0.02	0.34	0.04	0.79	0.09		0.09	0.03	0.66	0.06	
Ø	2.26		3.82		4.75			2.75		4.53		
Trust toward scenario												
(1)	0.01	0.00	0.04	0.01	0.01	0.00	20.4	0.01	0.00	0.02	0.01	8.3
(2)	0.01	0.01	0.11	0.03	0.01	0.00		0.03	0.01	0.08	0.02	
(3)	0.09	0.03	0.30	0.04	0.02	0.02		0.21	0.03	0.33	0.04	
(4)	0.35	0.05	0.37	0.03	0.21	0.08		0.36	0.03	0.34	0.03	
(5)	0.55	0.08	0.18	0.04	0.76	0.11		0.39	0.04	0.23	0.04	
Ø	4.44		3.55		4.74			4.12		3.69		
Ethical beliefs												
(1)	0.22	0.06	0.05	0.02	0.01	0.00	26.9	0.13	0.03	0.02	0.01	29.8
(2)	0.25	0.05	0.11	0.02	0.01	0.00		0.22	0.03	0.06	0.02	
(3)	0.32	0.04	0.31	0.03	0.01	0.01		0.32	0.03	0.20	0.03	
(4)	0.16	0.04	0.35	0.04	0.09	0.06		0.22	0.03	0.32	0.03	
(5)	0.04	0.02	0.18	0.04	0.90	0.07		0.12	0.02	0.40	0.05	
Ø	2.55		3.50		4.90			2.96		4.02		
Membership function												
Gender (female = 1)	0.34		−0.65*		0.32			0.28		−0.28		
Age (years)	0.01		0.02		−0.02*			−0.01		0.01		
Education (years)	0.25*		−0.04		−0.21*			0.05		−0.05		
People per household	−0.24		0.31*		−0.07			−0.09		0.09		
Income (€/month)	0.01*		−0.01		−0.01			0.01*		−0.01*		
User (user = 1)	0.04		−0.38		0.34			0.57*		−0.57*		
Observations (*n*)	169		53		40			164		122		

Note: *Significance at 5% level. Because of rounding the probabilities do not always sum to 100. Ordinal response scale: (1) Completely disagree, (2) Disagree, (3) Neither/nor (4), Agree, (5) Completely agree. †Class size. CP, conditional probability; SE, standard errors; Ø, mean value.

The standard errors for the conditional probabilities are reported in Table 4.

In the LH sample, class 1 reveals the lowest protesting. Respondents in this class are more likely to disagree that it is their right to have a high level of forest biodiversity, they strongly disagree with the statement that only those who enjoy the improvement should pay (mean of 2.3), do not as strongly object to the idea of monetary valuation (mean of 2.6) and do not feel that they already pay too much (mean of 2.3). However, respondents in this class oddly express strong distrust toward the institution responsible for implementing the forest programme (mean of 4.4). Class membership is significantly influenced by education and income. Respondents with higher education and income are more likely to be in this class. The class comprises 22% of this sample and is labelled 'low protest'.

In contrast, class 3 shows comparatively strong protest beliefs. It comprises 16% of the sample and is the smallest class. Class members strongly agree with the statement that it is their right to have high levels of forest biodiversity (mean of 4.8), believe they already pay enough (mean of 4.8), express the strongest distrust (mean of 4.7) and strongly reject monetary valuation (mean of 4.9). Class membership is statistically significantly influenced by age and education. On average, younger and less educated people are more likely to be in this class. Based on the response pattern, the class is labelled 'strong protest'.

Finally, respondents in class 2, with 62% the largest class in this sample, reveal a response pattern between low and strong protesting. Remarkably, members of this class express the highest trust toward the forest agency (mean of 3.6). Moreover, respondents in class 2 tend to believe that it is their right to have a high level of forest biodiversity (mean of 3.6), are rather unfavourable of using money for valuing nature (mean of 3.5) or tend to state that they already pay enough (mean of 3.8). Overall, on average, members of this class reveal a response pattern more similar to the 'strong' than to the 'low protest' class. This largest class is labelled 'partial protest'.

In the SH sample, a model with two classes reflects best the heterogeneity regarding protest beliefs. Class 1, comprising 58% of all respondents, exhibits a response pattern that indicates less protesting. That said, members of this class express a slightly stronger distrust toward the forest agency (mean of 4.1) than respondents in the other class (strong protest). A comparison of this response pattern to the 'low protest' class in the LH sample shows that it is neither similar to the low nor the partial protesters in that sample. This indicates that classes are not easily comparable across samples with respect to the pattern of protest beliefs. Class membership in the SH sample is significantly influenced by income and user status. People with higher income and people who are users of the forests are less likely to be in the class showing strong protest beliefs. In class 2, comprising 42% of the respondents, the response pattern indicates strong protest beliefs. Members tend to completely agree that it is their right to have high levels of forest biodiversity (mean of 4.2), that they already pay enough (mean of 4.5) and that they refuse to value nature with money (mean of 4.0). On the other hand, respondents in this class express higher trust in the forest agency than do respondents in class 1. However, with a mean value of 3.7, trust is still low (a value close to 1 would indicate high trust). Compared to the class with strong protest beliefs in the LH, protest beliefs are not as strong in the SH sample; most of the mean values are lower than in the strong protest class of the former sample. Table 5 reports the socio-demographics for each class.

Reflecting different treatments of protesters Table 6 presents four different WTP values for each sample. The first row reports the mean WTP when all respondents remain in the samples, that is, no protesters are identified and

Table 5 Socio-demographics per class (mean/standard deviation)

	Lüneburger Heide			Solling–Harz	
	Class 1	Class 2	Class 3	Class 1	Class 2
	Low protest	Partial protest	Strong protest	Low protest	Strong protest
Women (%)	70	57	72	55	48
Age (years)	48.30 (14.21)	51.36 (18.19)	45.73 (19.65)	46.51 (17.11)	50.86 (15.71)
Education (years)	11.66 (3.57)	9.18 (1.86)	8.97 (1.44)	9.87 (2.66)	9.28 (2.32)
People per household (*n*)	2.26 (0.96)	2.41 (1.17)	2.17 (1.08)	2.44 (1.32)	2.51 (1.40)
Net household income (€/month)	2499.43 (928.47)	1839.34 (737.34)	1761.30 (1074.90)	1969.28 (944.66)	1696.00 (825.65)
Users (%)	75	69	71	65	38

Table 6 Comparison of WTP values (in Euro) because of different protest treatments

Sample	Lüneburger Heide		Solling–Harz area	
	Mean (SD)	Respondents taken into account	Mean (SD)	Respondents taken into account
All respondents remain in the sample	5.51 (15.46)	262	6.61 (18.87)	288
Protesters are excluded based on the response ‘completely agree’ to attitudinal statements	7.25 (17.58)	193	7.78 (21.00)	214
Protesters excluded based on the responses ‘agree’ and ‘completely agree’ to attitudinal statements	28.3 (40.62)	10	6.66 (15.43)	18
Class ‘Low protest’	20.10 (28.50)	40	10.35 (5.75)	122

Note: WTP, willingness to pay.

dropped. This results in €5.51 per year per person for the LH and €6.61 per year per person for the SH for changes of forest biodiversity in these regions. Next, we define protesters by responses to the attitudinal statements. In the first case, those who have 'completely agreed' and in the other, those who have 'agreed' and 'completely agreed' to at least one of the five statements are defined as protesters and dropped from calculations. In the first case (completely agree), 69 respondents would be protesters. In the second case 74 respondents would be protesters. If those who 'agreed' or 'completely agreed' are defined as protesters, only a few respondents remain in the sample. Applying this approach, in the LH-sample only 10 respondents and in the SH-sample only 18 respondents do not express protest beliefs. The last row shows the values calculated based on the WTP values stated by those respondents who are members of the class that reveals the least protesting (low protest). The mean WTP of this class is, based on 40 respondents, €20.1 for the LH-sample and, based on 122 respondents, €10.4 for the SH-sample. However, the different treatments presented do not result in statistically significant WTP values.

6. Discussion and conclusions

Using a LC attitudinal model, we identify a class of respondents in each sample that expresses strong protest beliefs compared to the other class(es). This result seems to support the suggestion made by some researchers that LC models could be used to identify a group of protesters. However, a look at the other classes shows that the results are not so clear. Firstly, the response patterns of the other classes reveal protest beliefs also, especially in the case of the three-class model. Even in the two-class model, it can be seen that respondents in the class labelled 'low protest' hold strong protest beliefs when it comes to trust towards the agency responsible for implementing the proposed measures. It is, therefore, difficult to justify that the group labelled 'strong protest' comprises protestors, while the members of the other group(s) are considered non-protesters.

The individual characteristics do not reveal a consistent pattern across samples. However, income positively influences membership in the class labelled 'low protest' in both samples. Additionally, education in one and user status in the other sample have a positive influence on membership in the low protest class. This is similar to the results many contingent valuation studies show with respect to the determinants of WTP, indicating validity of class formation.

Secondly, when the LC models reveal more than two classes, it might be even more difficult to isolate a class of non-protesters. In our first sample, the three-class model clearly reflects better the heterogeneity present in the sample. The largest class in this model is expressing considerable protest beliefs, lower than those in the class labelled 'strong protest' but too obvious to ignore. Dropping just those who are in the group labelled 'strong protest' is thus not defensible. Both other applications using LC models to investigate protest beliefs (Cunha-e-Sá *et al.* 2010; Barrio and Loureiro 2010) have presented two-class models, but this could be sample specific and is not generalisable, as our results show.

Thirdly, comparisons across both samples reveal that the response patterns of those who are members of the class labelled ‘strong protest’ to the same attitudinal statements differ noticeably. The mean values for fairness and for trust toward the forest agency differ by one point, for example. The differences were tested using the non-parametric Mann–Whitney test; results show that for all protest beliefs, responses differ statistically significantly at the 5% level except for the item ‘Excessive financial burden’. Based on their response pattern, certain people might thus belong to the class of strong protesters in one sample while they would be assigned to another class in the other sample.

While the restrictive approach of defining all those as protesters who have at least ‘agreed’ or ‘completely agreed’ to one of the attitudinal statements results in a small number of respondents remaining in the ‘useable’ sample, the same can happen when LC models are applied. In one of our samples, the class of ‘low protest’ comprises only 40 respondents. Thus, if strong heterogeneity among respondents is present, LC models can result in rather small classes of respondents who do not protest or protest only to a small extent. Although no selection bias is present, censoring based on these small classes is, therefore, not advantageous compared to the current practise of dropping certain respondents based on ad hoc criteria. And even a two-class model can result in a very small class with low protesting. Using LC models thus may not be a generally usable approach to disclose the concealed true WTP.

Based on these findings, we argue that the main advantage of the LC model lies elsewhere. Rollins *et al.* (2010) point out that some public goods attributes, such as financing and delivery, may for some respondents be correlated with protest beliefs and may, therefore, not be separable from the good’s value. In many countries, certain environmental policies and programmes would necessarily be implemented by public agencies and the method of payment for these changes is restricted by regulatory requirements. For individuals who are aware that no alternatives for the policy or programme implementation exist and who are, based on their experience, sceptical toward current mechanisms, protest beliefs might be an integral part of the good. Subsequently, their WTP might always be lowered by scepticism. These respondents, as Rollins *et al.* (2010) suggest, define the good in question differently than other subgroups. Hence, the underlying preferences and distributions of WTP can differ among groups of respondents. The advantage of LC models is that they help to identify these different groups of respondents. If protest beliefs are an integral part of the good, identifying different groups can provide important information for policy makers, especially when class membership can be explained by socio-demographics or other individual characteristics such as 'distance' to the good in question, for example. Knowing how respondents define the good, that is, knowing which aspects of the hypothetical market are non-separable from the good in question for them, can provide valuable insights for researchers and decision makers.

Further studies will show whether our findings are solely specific to our data. One shortcoming of the present paper is that we did not use a compulsory payment vehicle. However, using a compulsory payment vehicle may affect results in either direction, that is, increasing protest rates (because respondents might feel forced to pay, for example) or lowering protest rates (because respondents think that other people cannot free ride, for example). Also, an open question is whether the attitudinal statements used indeed measure protest beliefs. In the present study, we have tried to cover various aspects of protesting by using five different attitudinal statements. Many other studies covered fewer aspects, sometimes only one, such as trust toward a public body. To clarify whether the content of the attitudinal statements reflects what motivates people to protest against the valuation scenario would require more empirical work using techniques such as think aloud protocols and in-depth interviews. Another drawback of attitudinal statements is that they might give respondents clues on how to justify their unwillingness to pay. The use of attitudinal statements can, therefore, lead to an overestimation of protesting. Research on this topic would help to clarify how ubiquitous protest beliefs are.

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