Heterogeneous preferences toward landscape externalities of wind turbines – combining choices and attitudes in a hybrid model

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Abstract

Expanding the share of renewable energy sources might substantially increase externalities as, for example, wind turbines may disturb the landscape and negatively affect biodiversity. This paper investigates the public's sensitivities towards these externalities by using discrete choice experiments and shows how preferences differ across inhabitants of our study region. As a further insight into the sources for these variations, a hybrid choice model is employed in order to incorporate individuals' latent attitudes in the estimated model. Our latent class structure allocates individuals to classes according to underlying latent attitudes that also influence the answers to attitudinal questions. We show that these underlying attitudes are a function of a number of socio-demographic characteristics, with young people, men with low income and those living closer to turbines having a stronger pro-wind power generation attitude. The inclusion of the attitudes in the class allocation component of the latent class model leads to a richer picture of people's valuations, revealing, for example, antagonistic preferences of two distinct groups of respondents, i.e. advocates and opponents of wind power generation.

Keywords: discrete choice, hybrid latent class model, wind power externalities

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1. Introduction

Expanding the share of renewable energy sources is a central element of the climate and energy policy of the Federal German Government (BMU, 2007). The stated target is to produce 30% of the electricity from renewable sources. This goal was reiterated after the accident at the nuclear power plant of Fukushima in 2011 resulting in a strategy that aims at transforming the whole energy system. This transition, called *Energiewende in Germany,* pursues the aims of lowering greenhouse gas emissions by 80 to 95% by 2050 and of fully phasing out the use of nuclear power by 2022. In order to achieve this objective it is planned to constantly increase the share of renewable energy sources and growing energy efficiency (BMWi 2014a).

Among the sources of renewable energy available in Germany, onshore wind power is of great importance. In 2013, an additional capacity of 2,997 MW was installed onshore. This is, as in previous years, a renewed increase of the capacity growth of onshore wind power (BMWi 2014b). In total, the installed capacity in 2013 was 33,757 MW for onshore wind power (offshore: 903 MW), with wind producing 34.4% of the electricity supply from renewable energy resources in 2013; renewables provided altogether 152.6 billion kilowatt hours. This underlines the important role wind power is playing as part of the transformation process of the energy system in Germany. On the other hand, particularly wind turbines are said to cause so called landscape externalities, among them negative impacts on the landscape by disturbing scenic views or negatively affecting biodiversity (e.g, Molnarova et al., 2012; Aravena et al., 2012; Strazzerra et al., 2012). Therefore, an increasing share of onshore wind power in future is also likely to result in increasing externalities. Additionally, increasing electricity production from renewables both on- and offshore requires new transmission lines, also causing new externalities (e.g., Navrud et al., 2008; McNair et al., 2011). Thus, land use conflicts are likely to increase, especially in densely populated countries such as Germany and knowledge of the extent of the externalities can help to mitigate or even solve these conflicts. In a recent study in Sweden, Ek and Persson (2014) discuss how results from discrete choice experiments can be used to support decision making concerning the question of where and how to place turbines in order to minimize externalities at the societal level.

The objective of this paper is, therefore, to similarly investigate the externalities of wind turbines using a discrete choice experiment, but to employ a still rarely used hybrid choice model combining preferences and attitudes. This is based on our hypothesis that attitudes are a key factor in driving people's sensitivities. The basic choice model methodology, now frequently applied in environmental valuation, involves the generation and analysis of choice data through constructing a hypothetical market via surveys. The data from these hypothetical choice scenarios (stated choice) are usually analysed by models based on the classical Random Utility Theory in which an individual is assumed to maximise his/her utility. The utility of an alternative is generally a function of attributes of the alternative and observable characteristics of the individual such as socio-demographics. A big effort has been made in the literature to model differences across individuals in taste parameters, i.e. the sensitivities of an individual to changes in the attributes, either in a deterministic or a random way (e.g., Swait, 2007; Train, 2009). Recently, additional information coming from responses to attitudinal questions has been used to shed light on taste differences in a hybrid choice modelling framework set out by Ben-Akiva et al. (1999) and Ben-Akiva et al. (2002). Incorporating underlying attitudes potentially plays a substantial role in explaining choices in discrete choice experiments as they further inform models about differences among individuals and their valuations (Hess and Beharry-Borg, 2012; Kløjgaard and Hess, 2014).

We follow this stream of literature based on the recognition that individuals' preferences are not only driven by attributes and observable characteristics but are also related to individuals' attitudes and perceptions. A suitable and widely used way to collect data on attitudes or perceptions is to show a number of attitudinal statements asking respondents to indicate their degree of agreement (Eagly and Chaiken, 1993; Eagly and

Chaiken, 2005). An example for incorporating attitudes into the analysis of discrete choice data was recently presented by Yoo and Ready (2014). They used a series of 23 questions to measure respondents' attitudes toward renewable energy and renewable energy policy. Their motivation for using attitudinal data was that they are a potentially important source of preference heterogeneity. Thus, they use principle component analysis to identify a limited set of dimensions, three components in the end, and incorporate them subsequently in their choice models. However, authors in favour of the hybrid model (e.g., Ben-Akiva et al., 1999; Ben-Akiva et al., 2002) question whether responses to attitudinal questions should be included directly as error free explanatory variables in a model. They argue that it is crucial to account for the latent nature of attitudes as answers are merely an indicator of true underlying attitudes and adding the responses directly could potentially lead to an endogeneity bias. Hence, this article not only aims at determining the landscape externalities of wind turbines but also aims at additionally incorporating individuals' attitudes toward wind power generation in a hybrid choice model. These models have seen only very limited exposure in the fields of environmental and resource economics, with Hess and Beharry-Borg (2012) potentially giving the first application.

The present study adds to the literature a novel approach by specifying a latent class (LC) model that captures taste heterogeneity and simultaneously allocates individuals to classes according to underlying attitudes that also influence the answers to a number of attitudinal questions. To the best of our knowledge this modelling approach, a Hybrid Latent Class (HLC) model, has not been used in environmental valuation before. Breffle et al. (2011) presented a joint latent class model combining attitudinal data with choice data, and their model is also motivated by the assumption that using attitudinal data in addition to choice data provides an opportunity to enhance the understanding of preference heterogeneity. However, their approach to link choices and attitudes differs significantly from the HLC model presented here and fails to create the full linkage allowed for in our model, as explained towards the end of our paper. The paper is organised as follows. Section 2 presents a literature review on hybrid choice models, Section 3 describes the case study and Section 4 defines the model to be used. Section 5 contains the main results and, finally, Section 6 draws some conclusions on the hybrid choice model application.

2. Hybrid choice models

The first studies making use of responses to statements aimed at capturing environmental attitudes directly incorporated these responses as explanatory variables in the utility specification (among others, Milon and Scrogin, 2006; Ojea and Loureiro, 2007). These responses are, however, indicators of underlying attitudes rather than a direct measure of attitudes. Therefore, they are likely to suffer from measurement error, which is amplified by the widespread use of categorical formats such as Likert scale. Additionally, these responses may be correlated with other unobserved factors, causing correlation between the modelled and random components of utility, potentially leading to endogeneity bias (Ben-Akiva et al., 1999; Ben-Akiva et al., 2002; Bolduc et al., 2005). As a response to this situation, hybrid choice models have been developed over the last fifteen years, with key developments by Ben-Akiva et al. (1999); Ben-Akiva et al. (2002); Bolduc et al. (2005).

These models specify latent variables to explain unobserved attitudes and other psychological constructs. In the resulting Integrated Choice and Latent Variable (ICLV) models, the latent variables, which are functions of socio-demographics and an error term, are used both in the choice model and in a separate measurement model used to explain answers to follow up questions. These models have seen a gradual uptake in applications across various fields in the last few years. As an example, in a transport application, Abou-Zeid et al. (2010) use the model to incorporate individuals' attitudes towards travel into a choice model using data on two car alternatives which differed in terms of travel times, travel costs, and number of speed cameras. The starting idea was that a traveller with the perception that public transport is uncomfortable (car-lover) is likely to be more sensitive to the time and cost changes associated with public transport trips. The value of time associated with public transport is therefore expected to be different for this traveller in comparison to another traveller who has a positive perception of public transport.

In an application from environmental valuation, Hess and Beharry-Borg (2012) analyse the non-market values for improvements to coastal water quality in Tobago. Their model includes ten attributes of which nine are interacted with the latent variable representing respondents' attitudes towards coastal water quality protection. Similar to the previous study, the authors conclude that the latent attitude can be used to explain both the stated choices and the responses to the attitudinal questions. As a result, they find differences in willingness to pay for attributes associated with higher environmental quality such as the amount of coral cover that can be viewed when snorkelling or the abundance of fish species.

The paper by Daly et al. (2012) addresses a number of theoretical issues not treated before. One of its important contributions is the proof of equivalence of two different normalisations discussed in the literature. Noteworthy is also that this application recognises the repeated choice nature of the data, i.e., that each respondent has responded to a couple of choice sets, and that the application makes use of an ordered logit model to explain the answers to Likert scale questions, replacing the commonly used continuous treatment. Their study examines rail travellers' willingness to trade privacy or liberty against security improvements. Respondents answer a series of questions about their attitudes towards privacy for two latent attitudinal variables used in three interaction terms included in the final ICLV model which includes seven attributes.

Glerum et al. (2014) is another application from transport research focused on the impact of perceptions on mode choice. An interesting point of this paper is the use of adjectives describing a series of transport modes, freely reported by respondents, as indicators of travellers' perception of comfort in public transports. These adjectives are coded similar to responses to a five-point Likert scale.

Hess et al. (2013) is another transport study analysing how the willingness to reduce greenhouse gas emissions and accept longer travel time depends on underlying attitudes towards the environment. Their approach is novel in that a LC model is used which allocates respondents to classes according to underlying attitudes that also influence the responses to environmental attitudinal questions, that is, the same approach (HLC model) adopted in our study. The estimation of the model leads to the simulated relative sensitivities to CO_2 reduction expressed in percentage of reduction in travel time, which are then linked through the underlying environmental attitudes to the socio-demographic characteristics.

Generally, not many socio-demographic variables are found to be significant in the hybrid models described above. This is an undesirable situation as the relatively complicated hybrid model in comparison to an LC or MXL model should shed some light on unobserved heterogeneity among respondents using the answers to attitudinal questions related through the attitudinal variables to the socio-demographic variables. Nevertheless, the models still have a key advantage in making use of additional data to better represent heterogeneity.

In the approach applied in our paper, the attitudes are considered as latent variables, which, in line with Hess et al. (2013), are used in the class allocation function of a classical LC model. The aim of this approach is to capture adequately individual taste heterogeneity through attitudinal indicators. Some of the heterogeneity can be related to socio-demographic characteristics of respondents but non-observed attitudes may in fact be the main cause of heterogeneity (Small et al., 2005; Small et al., 2006). That is why we jointly estimate attitudinal and choice models using a case study on valuation of landscape externalities of wind power generation in Germany, analysing the role of latent attitudes in an environmental context. We take into account the repeated choice nature of the data, in line with Hess & Beharry-Borg (2012) and Daly et al. (2012), while the ordinal nature of the indicators is also taken into account by using an ordered logit structure for their incorporation in the model, in line with Daly et al. (2012).

3. Case study

The expansion of renewable energy is a central element of the climate and energy policy of the German Federal Government, whose target for 2020 is to produce 30% of electricity from renewable sources. A crucial part of this target would be the expansion of wind power generation. However, building new onshore wind turbines and replacing old ones with modern turbines (so called ‘repowering’) is not universally accepted. This controversy is also found for other renewable energy investments and analysed in the literature (Ku and Yoo, 2010). Thus, the objective of the survey used in this study was to analyse the preferences of German citizens regarding wind power generation, in order to quantify the externalities provoked by building new and replacing old turbines.

Respondents were presented with a choice set including three generic alternatives, which showed how wind power generation might look in 2020 in their region. The alternatives were described by five attributes including a cost attribute. The first four attributes are the size of wind farms (three levels: large, 16 to 18 mills; medium, 10 to 12 mills; small, 4 to 6 mills), maximum height of windmills (three levels: 110 m; 150 m; 200 m), effect on the red kite population in the region (three levels: 5%, 10%, or 15% reduction in red kite population by 2020), and the minimum distance windmills have to be from towns and villages (three levels: 750 m; 1,100 m; 1,500 m). Especially the height of the turbines and the minimum distance from towns and villages are highly debated aspects of wind power generation in Germany. Both strongly influence the opportunities for building new turbines and replacing old ones, that is, substituting old turbines with newer ones with a higher production capacity. New turbines are, in general, larger than old ones and, owing to current federal state legislation, have to be built further away from towns and villages. In a country as densely populated as Germany, this raises the problem that enough space for building new turbines might not be available. The monetary attribute was defined as a surcharge on monthly energy bills (four levels: €1, €2.5, €4, or €6 per month). Figure 1 presents an example of a choice task.

Figure 1: Example of a choice task

	Program A	Program B	Program C
Size of the wind farms	large farms	small farms	large farms
Height of the turbines	200 m	110 m	110 m
Effect on red kite population	10 %	5 %	10 %
Minimum distance from village	750 m	1,100 m	1,500 m
Surcharge on energy bill per month	€ 0	€ 6	€ 1
I would choose:	□	□	□

Among the alternatives presented, Program A describes what wind power generation would look like in the year 2020, so that this would be the reference or status quo for the valuation exercise. Respondents were informed that the base levels of the first four attributes would allow electricity production from wind power at relatively low cost. Choosing this alternative would not require a surcharge on the monthly energy bill. Program A always has the same attribute levels. The other two alternatives, Program B and Program C, have attribute levels that restrict the use of wind power compared to Program A. For example, in Program B or Program C, the maximum height of turbines can be restricted to 110 or 150 m. People were informed that the implementation of these two programs would require a surcharge on their energy bills because the costs of electricity production would rise. For example, building turbines further away from villages would lead to higher infrastructure costs. The amount of electricity production by wind power was set to be constant, in order to avoid confounding landscape externalities with the reduction of carbon dioxide emissions. A D-optimal fractional factorial design consisting of 40 choice sets was generated using the SAS-macro provided by

Kuhfeld (2005), and the sets were divided into eight blocks. The attributes and their levels are reported in Table 1.

Table 1: Attribute levels

Attribute	Programme A (future "status quo")	Programmes B and C (constrained development)	Variable
Size of wind farms	large farms (16 - 18 turbines)	medium farms (10 - 12 turbines)	$Size_{medium}$
		small farms (4 - 6 turbines)	$Size_{small}$
Maximum height of turbines	200 metres	110 metres	$High_{low}$
		150 metres	$High_{medium}$
Effect on red kite population	10% decline	15% decline	Red_{high}
		5% decline	Red_{low}
Minimum distance to residential areas	750 metres	1100 metres	Min_{medium}
		1500 metres	Min_{large}
Monthly surcharge to energy bill	€0	€1, €2.5, €4, €6	$Cost$

Table 2 reports the attitudinal statements used in the HLC model. The statements were chosen in order to cover a wide set of aspects of wind power generation, e.g., the effect of turbines on housing prices or their usefulness to combat climate change. Some attitudinal statements were taken from other surveys such as the report of environmental awareness in Germany (BMU, 2004; BMU, 2006) while others were newly developed. The response scale ranged from "completely disagree (1)" to "completely agree (5)". The last column of Table 2 shows the expected tendency of responses advocates of wind power generation. A positive sign indicates that they would be expected to be more likely to choose higher values on the response scale. For example, respondents who are in favour of wind power generation should, on average, agree more with the statement that living within the sight of turbines would not disturb them (*att1*) and should disagree more with the statement that electricity from wind power does not contribute much to climate protection (*att3*).

Table 2. Attitudinal statements toward wind power generation

	Item	
att1	Living within sight of wind turbines would not disturb me	+
att2	Through wind power we become less dependent on energy supplies from abroad.	+
att3	Electricity from wind power does not contribute much to climate protection	-
att4	Wind turbines make the landscape more interesting	+
att5	As the wind does not blow all the time wind power is an unreliable source of power.	-
att6	In the neighbourhood of turbines real estate loses values	-
att7	Along freeways, railroads or power lines turbines do not bother me.	+
att8	Wind power is the best source for renewable energy in Germany.	+

Note: response scale ranges from “completely disagree (1)” to “completely agree (5)”

Table 3 provides the descriptive statistics for the socio-demographic variables and for the attitudinal statements from Table 2. The mean age is 47.76 years, half of the respondents are female and the average net household income is 1,950 Euro per month. Around 38% of respondents live in the biggest city of the study region, Leipzig. Furthermore, among them, 24% have donated to nature conservation projects during the 12 months prior to the interview (*donation*) but only 6% are a member of an environmental organization (*natver*). The average number of years a respondent has lived at her or his place of residence is 25.33 years. Two variables describe respondents’ exposure to turbines in the study region. The first, *turdis*, gives the distance between the respondent’s household and the closest turbine in the landscape. The second, *den5km*, reports how many turbines are present within 5 kilometres of a respondent’s place of residence. Both were measured using a Geographic Information System (GIS). The variables show that on average, the closest turbine is 5.521 kilometres from a respondent's place of residence and that the surrounding contains on average 2.63 turbines. However, both measures vary strongly. Some respondents live just a few hundred metres away from a turbine while others are more than 22 kilometres away from the closest one. The density also varies strongly, ranging from zero to 48 turbines within a 5km radius. Finally, the table reports the responses to the attitudinal statements.

Table 3. Summary statistics of the socio-demographic and attitudinal variables

Variable	Description		Mean	Std. Dev.	Min.	Max.
age	Age of the respondent in years		47.76	16.10	18.00	81.00
edu	Education level		4.18	1.56	0.00	6.00
gender	Gender (1 = female)		0.50	0.50	0.00	1.00
income	Net household income in Euro		1,951.00	1,071.22	500	4,500.00
wohort	Years living a current place of residence		25.33	20.15	0.00	78.00
donation	Donated to nature conservation project with last 12 months		0.24	0.43	0.00	1.00
natver	Member of an environmental group (1 = yes)		0.06	0.24	0.00	1.00
turdistance	Distance to closest turbine in km		5,521.00	2,708.75	255	22,240.00
dens5km	Density of turbines with 5km surrounding		2.63	5.67	0.00	48.00
urban	Urban dweller (1 = yes)		0.38	0.48	0.00	1.00
				Responses		
		1	2	3	4	5
att1	attitudinal statement 1	11.49%	11.14%	21.25%	30.66%	25.43%
att2	attitudinal statement 2	4.52%	11.84%	17.42%	26.48%	39.72%
att3	attitudinal statement 3	41.81%	31.35%	14.63%	8.01%	4.18%
att4	attitudinal statement 4	29.61%	29.26%	29.61%	8.71%	2.78%
att5	attitudinal statement 5	8.71%	35.54%	32.05%	14.28%	9.4%
att6	attitudinal statement 6	5.22%	19.16%	27.87%	28.22%	19.51%
att7	attitudinal statement 7	3.13%	2.43%	4.18%	17.07%	73.17%
att8	attitudinal statement 8	3.83%	14.63%	39.02%	22.99%	19.51%

Note: response scale for attitudinal statements ranges from "completely disagree (1)" to "completely agree (5)"

The variable *donation* collects information on whether respondents had donated to nature conservation and environmental projects within the last twelve months prior to the interview. This is arguably also a function of environmental attitudes, and a decision was thus taken to not include it as an explanatory variable but to use it as an additional ninth indicator in the hybrid structure.

4. Model specification

In the present paper, we adopt the approach presented by Hess et al. (2013), using a LC model within the hybrid modelling framework (Ben-Akiva et al., 1999; Ashok et al., 2002; Ben-Akiva et al., 2002; Bolduc et al., 2005). The hybrid model framework describes how attitudes affect choices through class allocation probabilities and treats answers provided by respondents to the attitudinal questions as dependent rather than as explanatory variables.

The model is composed of a group of structural equations and a group of measurement relationships. The structural equations explain, firstly, the latent variables in terms of observable exogenous variables, and, secondly, typical utility functions in terms of observable attributes. The measurement equations link latent variables to the indicators, generally responses to attitudinal questions. In the specific context of the HLC model, we also have the additional class allocation model, which itself has structural equations describing the *utility* of the different classes.

The first structural equation is therefore based on the random utility theory (McFadden, 1974) linking the deterministic model to a statistical model of human behaviour. The utility of alternative i for respondent n in the choice occasion t is given by

$$U_{int} = V_{int} + \varepsilon_{int}, \tag{1}$$

where the term V_{int} depends on observable explanatory variables, which are usually attributes (x_{int}) and vector of estimated attribute parameters β and ε_{int} is a random variable following an extreme value distribution with location parameter 0 and scale parameter 1. In addition, we include alternative specific constants for all but one of the alternatives. LC models are based on the assumption that individuals can be sorted into a set of C classes, each of which is characterised by unique class-specific utility parameters β_C. Given membership to class c_s, the probability of respondent n's sequence of choices is given by

$$P_n = \Pr(y_n^t | c_s, x_n) = \prod_{t=1}^{T_n} \frac{\exp(ASC_i + \beta'_{c_s} x_{int})}{\sum_{j=1}^{J} \exp(ASC_i + \beta'_{c_s} x_{jnt})}, \tag{2}$$

where y_n^t is the sequence of choices over the T_n choice occasions for respondent n and ASC_i is an alternative specific constant for alternative i normalised to zero for one of J alternatives. Equation (2) is a product of MNL probabilities. The LC framework recognises that the actual membership to a class is not observed. If the probability of membership to a latent class c_s of respondent n is defined as π_{n,c_s}, the unconditional probability of a sequence of choices can be derived by taking the expectation over all C classes, that is

$$P_n = \Pr(y_n^t|x_n) = \sum_{s=1}^{C} \pi_{n,c_s} \prod_{t=1}^{T_n} \frac{\exp(ASC_i + \beta'_{c_s} x_{int})}{\sum_{j=1}^{J} \exp(ASC_i + \beta'_{c_s} x_{jnt})}. \quad (3)$$

The class allocation probabilities are usually modelled using a logit structure, where the *utility* of a class is a function of the socio-demographics of the respondent (z_n) and estimated parameters (λ_s), in addition to an estimated constant, say $\mu_{0,s}$ for class s, where for normalisation, this constant is fixed to zero for one of the classes.

$$\pi_{n,c_s} = \frac{\exp(\mu_{0,s} + \lambda'_s z_n)}{\sum_{s=1}^{C} \exp(\mu_{0,s} + \lambda'_s z_n)}, \quad (4)$$

If the class allocation probabilities are not linked to any variable and are therefore generic across respondents, only the $\mu_{0,s}$ are estimated. One of the main appeals of LC models is that the respondents are sorted into homogenous subgroups based on their preferences and it provides policy makers with very useful information on which they can tailor policies to specific subgroups of the population. In our case the term V_{int} is defined as

$$\begin{aligned} V_{int} = {} & ASC_i + \beta_{Size_{small}} Size_{small_{int}} + \beta_{Size_{medium}} Size_{medium_{int}} + \\ & \beta_{High_{low}} High_{low_{int}} + \beta_{High_{medium}} High_{medium_{int}} + \beta_{Red_{low}} Red_{low_{int}} + \\ & \beta_{Red_{high}} Red_{high_{int}} + \beta_{Min_{medium}} Min_{medium_{int}} + \beta_{Min_{large}} Min_{large_{int}} + \\ & \beta_{Cost} Cost_{int}, \end{aligned} \quad (5)$$

where ASC_i is an alternative specific constant for alternative i (normalised to zero for one alternative), and where $Size$, $High$, Red, Min, and $Cost$ are the choice attributes described in Table 1. Variable $Size\_small_{int}$ represents the value (either 0 or 1) of the $Size$ attribute corresponding to the level small for alternative i in choice situation t for respondent n. The remaining attributes are coded similarly and thus the parameters show the relative valuation with respect to the base scenario that is large for the attribute $Size$, high for $High$, medium for Red and small for Min.

The above model corresponds to a standard LC specification which forms the basis of the developments in this paper. As a next step, we now wish to make use of the answers to attitudinal statements provided by respondents to the eight statements reported in Table 2. It is recognised that these answers are together with respondents' actual choices driven by underlying respondent's attitudes but are not their direct measures. The attitudes are thus treated as latent variables and the eight responses are used as indicators in the models. Similarly, as mentioned earlier, the attribute relating to donations to nature conservation projects is not treated as an exogenous explanatory variable in the structural equation (7) as it is likely to depend on the underlying environmental attitudes of the respondent. It is consequently included as a ninth indicator in our model.

In the present model only one latent variable representing respondent's underlying attitude toward wind power generation is included. The structural equation for the latent variable is, therefore, given by

$$LV_n = h(Z_n, \gamma) + \omega_n, \tag{6}$$

where $h(Z_n, \gamma)$ represents the determinist part of LV_n, where the specification $h()$ is in our case linear with Z_n being a vector of socio-demographic variables of respondent n, and γ being a vector of estimated parameters. Additionally, ω_n is a random disturbance which is assumed to be normally distributed with a zero mean and standard deviation σ_ω. Therefore, in our case, we have that:

$$LV_n = \gamma_1 Z_{1n} + \gamma_2 Z_{2n} + \cdots + \gamma_m Z_{mn} + \omega_n, \tag{7}$$

where $Z_{1n}, Z_{2n}, \dots, Z_{mn}$ are specific socio-demographic variables.

The measurement equations use the values of the attitudinal indicators as dependent variables. Therefore, the ℓ^{th} indicator (of total L indicators) for respondent n is defined as

$$I_{\ell n} = m(LV_n, \zeta) + v_n, \tag{8}$$

where the indicator $\boldsymbol{I_{\ell n}}$ is a function of latent variable $\boldsymbol{LV_n}$ and a vector of parameters $\boldsymbol{\zeta}$. The specification of $\boldsymbol{v_n}$ determines the behaviour of the measurement model and is dependent on the nature of the indicator.

The responses to the attitudinal statements, the first eight indicators in the present model, are collected using a Likert type response scale. The measurement equations are therefore given by threshold functions. For a discrete indicator with $\boldsymbol{K}$ levels $\boldsymbol{i_1}, \boldsymbol{i_2}, \dots, \boldsymbol{i_K}$ such that $\boldsymbol{i_1} < \boldsymbol{i_2} < \cdots < \boldsymbol{i_K}$, the measurement equation for individual $\boldsymbol{n}$ is modelled as an ordered logit model for the latent variable, where $\boldsymbol{\tau_1}, \boldsymbol{\tau_2}, \dots, \boldsymbol{\tau_{K-1}}$ are thresholds that need to be estimated:

$$I_{\ell n} = \begin{cases} i_1 & if \quad -\infty < LV_n \leq \tau_{\ell,1} \\ i_2 & if \quad \tau_{\ell,1} < LV_n \leq \tau_{\ell,2} \\ & \vdots \\ i_K & if \quad \tau_{\ell,(K-1)} < LV_n < \infty \end{cases}. \tag{9}$$

The likelihood of specific observed value of $I_{\ell n}$ ($\ell = 1,2, \dots, 8$) is then given by

$$L_{\boldsymbol{I}_{\ell n}} = I_{(I_{\ell n}=i_1)} \left[\frac{\exp(\tau_{\ell,i_1} - \zeta_\ell LV_n)}{1+\exp(\tau_{\ell,i_1} - \zeta_\ell LV_n)}\right] +$$

$$\sum_{k=2}^{K-1} I_{(I_{\ell n}=i_k)} \left[\frac{\exp(\tau_{\ell,k} - \zeta_\ell LV_n)}{1+\exp(\tau_{\ell,k} - \zeta_\ell LV_n)} - \frac{\exp(\tau_{\ell,(k-1)} - \zeta_\ell LV_n)}{1+\exp(\tau_{\ell(k-1)} - \zeta_\ell LV_n)}\right] +$$

$$I_{(I_{\ell n}=i_K)} \left[1 - \frac{\exp(\tau_{\ell,(K-1)} - \zeta_\ell LV_n)}{1+\exp(\tau_{\ell,(K-1)} - \zeta_\ell LV_n)}\right], \tag{10}$$

where $\boldsymbol{\zeta_\ell}$ measures the impact of the latent variable $\boldsymbol{LV_n}$ on indicator $\boldsymbol{I_{\ell n}}$ and $\boldsymbol{\tau_{\ell,1}}, \boldsymbol{\tau_{\ell,2}}, \dots, \boldsymbol{\tau_{\ell,K-1}}$ are a set of estimated threshold parameters. In practice, each $\boldsymbol{\tau_{\ell,1}}, \boldsymbol{\tau_{\ell,2}}, \dots, \boldsymbol{\tau_{\ell,K-1}}$ are estimated using a set of auxiliary parameters $\boldsymbol{\delta_{\ell,1}}, \boldsymbol{\delta_{\ell,2}}, \dots, \boldsymbol{\delta_{\ell,(K-2)}}$ such that

$$\begin{gathered}\boldsymbol{\tau_{\ell,2}} = \boldsymbol{\tau_{\ell,1}} + \boldsymbol{\delta_{\ell,1}} \\ \boldsymbol{\tau_{\ell,3}} = \boldsymbol{\tau_{\ell,2}} + \boldsymbol{\delta_{\ell,2}} \\ \boldsymbol{\tau_{\ell,4}} = \boldsymbol{\tau_{\ell,3}} + \boldsymbol{\delta_{\ell,3}} \\ \vdots\end{gathered}$$

where $\delta_{\ell,k} \geq 0, \forall\, k$. The definition of the auxiliary parameters assures that $\tau_{\ell,1} < \tau_{\ell,2} < \cdots < \tau_{\ell,(K-1)}$.

For the ninth indicator $\boldsymbol{I_{9n}}$, i.e. the donations response, the value was treated as a binary response, and modelled using a binary logit model. There is therefore only one threshold that need to be estimated as:

$$I_{9n} = \begin{cases} 0 & if \quad -\infty < LV_n \leq \tau_{9,1} \\ 1 & if \quad \tau_{9,1} < LV_n \leq \infty \end{cases}. \tag{11}$$

The likelihood of specific observed value of I_{9n} is then given by

$$L_{I_{9n}} = I_{(I_{9n}=1)} \left[\frac{\exp(\tau_{9,1} - \zeta_9 LV_n)}{1+\exp(\tau_{9,1} - \zeta_9 LV_n)}\right] + I_{(I_{9n}=0)} \left[1 - \frac{\exp(\tau_{9,1} - \zeta_9 LV_n)}{1+\exp(\tau_{9,1} - \zeta_9 LV_n)}\right]. \tag{12}$$

The latent variable LV_n is linked to the remaining part of the model through the class allocation probabilities defined in (4), which are respondent specific by being a function of the latent variable:

$$\pi_{n,c_s} = \frac{\exp(\mu_{0,s} + \mu_{1,s} LV_n)}{\sum_{s=1}^{C} \exp(\mu_{0,s} + \mu_{1,s} LV_n)}, \tag{13}$$

where $\mu_{0,s}$, $\mu_{1,s}$ are parameters to be estimated. The sign of $\mu_{1,s}$ determines whether increases in the value of the latent variable lead to an increased or decreased probability for a specific taste class. In our application, an extensive specification testing for the class allocation model revealed no significant socio-demographic interactions other than those captured through the latent variable defined in (7), explaining the absence of λ terms in (13) in contrast with (4).

The model is finally estimated by maximum likelihood. The estimation involves maximising the joint likelihood of the observed sequence of choices and the observed answers to the attitudinal questions. The two components are conditional on the given realisation of the latent variable LV_n. Accordingly, the log-likelihood function of the model is given by integration over ω_n:

$$LL(\beta,\mu,\gamma,\mu,\zeta,\tau) = \sum_{n=1}^{N} ln \int_{\omega} (P_n \prod_{\ell=1}^{9} L_{I_{\ell n}})\, g(\omega) d\omega, \quad (14)$$

where P_n is defined in (3), but with class allocation probabilities π_{n,c_s} as in (13) rather than (3), $L_{I_{\ell n}}$ is defined in (10) for $\ell = 1,2,\ldots,8$ and in (12) for $\ell = 9$. The joint likelihood function (14) depends on parameters of the utility functions defined in (3) which in our case are

$\beta = (ASC_1,\ ASC_2, \beta_{Size_{small}}, \beta_{Size_{medium}}, \beta_{High_{low}}, \beta_{High_{medium}}, \beta_{Red_{low}}, \beta_{Red_{high}}, \beta_{Min_{medium}}, \beta_{Min_{large}}, \beta_{Cost})$,

parameters $\mu = (\mu_{0,s}, \mu_{1,s})$ containing the parameters used in the allocation probabilities defined in (13), $\gamma = (\gamma_0, \gamma_{1,}\gamma_{2,\ldots,}\gamma_m)$ containing the parameters for the socio-demographic interactions in the latent variable specification defined in (7), and $\zeta = (\zeta_1, \zeta_2, \ldots, \zeta_9)$ and $\tau = (\tau_{1,1}, \tau_{1,2}, \ldots, \tau_{1,K-1}, \ldots, \tau_{8,1}, \tau_{8,2}, \ldots, \tau_{8,K-1}, \tau_{9,1})$ containing the parameters defined in (10) and (12). There are different possibilities of identification called usually Ben-Akiva and Bolduc normalisations described in detail in Daly et al. (2012). We follow the Bolduc normalisation by setting $\sigma_{\omega} = 1$. All model components were estimated simultaneously using PythonBiogeme (Bierlaire, 2003; Bierlaire, 2009).

5. Results and discussion

Similarly to a standard LC model, the first task is to determine the number of classes. Usually, the goodness of fit indicators BIC and AIC are used to make this determination (Swait, 2007). Table 4 reports their value together with the number of parameters and the log-likelihood value for HLC models with two to four classes. The log-likelihood increases as expected with an increasing number of classes and the remaining statistics offer mixed results. BIC indicates a solution with three classes while the AIC favours models with four classes. As it is evident from the literature that the AIC tends to overestimate the number of classes and there is a consensus that parsimony is preferable in modelling, especially in this complicated hybrid framework, the preferred LC model discussed below has three classes.

Table 4: Goodness of fit criteria for models with different number of classes

	2 Classes	*3 Classes*	*4 Classes*
Log likelihood	-4165.35	-4117.03	-4089.53
Number of parameters	70	83	95
N	1435	1435	1435
AIC	8470.69	8400.06	**8369.06**
BIC	8839.52	**8837.39**	8869.61

Table 5 and 6 presents, therefore, estimations of two three-classes models. The first model is a latent class model and the second is the HLC model described in the previous section. The socio-demographic variables presented in Table 3 have not been included in the allocation probabilities functions (4) and (13), as the inclusion led to their non-significance or non-convergence of the estimation procedure for models with four and more classes in the two (LC and HLC) models. Focusing firstly on the LC model, we can say that consistent with economic theory, the cost coefficient is negative and statistically significant in all classes, implying that respondent utility decreases when the cost of the programme increases. The existing taste heterogeneity of respondents is, however, evident by coefficients comparison among the three classes.

Table 5: LC and HLC model estimation results – choice models

	LC model									**HLC model**								
Observations	1,435									1,435								
Respondents	287									287								
Parameters	35									83								
Log-L	-1034.2									-4165.4								
	Class 1			Class 2			Class 3			Class 1			Class 2			Class 3		
Class prob.	0.24			0.37			0.39											
	Est.		rob. t-rat.	Est.		rob. t-rat.	Est.		rob. t-rat.	Est.		rob. t-rat.	Est.		rob. t-rat.	Est.		rob. t-rat.
$\beta_{Size_{small}}$	-0.47	***	-2.61	0.26		0.45	0.32	**	2.50	-0.44	***	-2.58	0.25		0.39	0.31	**	2.50

$\beta_{Size_{medium}}$	-0.09		-0.54	-0.68		-0.82	0.15		1.27	-0.09		-0.52	-0.69		-0.73	0.15		1.24
$\beta_{High_{small}}$	0.17		0.9	0.25		0.25	0.09		0.71	0.16		0.88	0.35		0.32	0.10		0.76
$\beta_{High_{medium}}$	0.03		0.18	-1.53		-1.41	0.14		1.27	0.02		0.12	-1.72		-1.12	0.15		1.34
$\beta_{Red_{low}}$	1.17	***	4.63	2.02	***	3.21	0.28	**	2.10	1.17	***	5.03	2.05	***	2.82	0.28	**	2.04
$\beta_{Red_{high}}$	-1.36	***	-4.46	-1.60		-1.36	-0.36	**	-2.32	-1.38	***	-4.52	-1.51		-0.98	-0.36	**	-2.29
$\beta_{Min_{medium}}$	0.19		1.15	-0.03		-0.06	0.46	***	4.19	0.20		1.18	-0.06		-0.11	0.46	***	4.29
$\beta_{Min_{high}}$	0.11		0.42	0.89		1.52	0.48	***	3.62	0.07		0.25	0.97		1.13	0.49	***	3.73
β_{Cost}	-0.42	***	-2.95	-1.25	***	-3.28	-0.17	**	-2.36	-0.40	***	-3.02	-1.31	**	-2.26	-0.17	**	-2.41
ASC SQ	-0.52		-1.08	1.89		1.40	-0.74	*	-1.79	-0.48		-1.05	1.92		1.29	-0.77	**	-1.96
ASB B	0.61	**	2.53	-0.24		-0.23	0.57	***	5.03	0.64	***	2.60	-0.23		-0.17	0.55	***	4.98
Class allocation functions																		
$\mu_{0,2}$	0.49	**	2.08							0.89	**	2.43						
$\mu_{1,2}$										-0.46	*	-1.75						
$\mu_{0,3}$	0.45	*	1.71							-0.37		-0.81						
$\mu_{1,3}$										0.60	***	2.77						

The height of turbines does not have a statistically significant effect in any class. The attribute was chosen during the design process because at that time there was a widespread debate within Germany about the relation of the heights of turbines and their minimum distance to residential areas. Several federal states, which are responsible in Germany for these regulations, wanted to link the minimum distance to the height of a turbine by a factor of 10. For example, a turbine that would have a height of 100 metres would have to be at least 1000 metres away from residential areas[1]. Our results thus suggest that the effect of height seems to be less strong in the general population than among administrations and decision makers.

Table 6: HLC model estimation results - structural and measurement equations

Structural equation parameters				*Measurement equation parameters (effects of LV)*			
γ_{age}	0.008	*	1.73	ζ_1	-1.540	***	-6.36
γ_{female}	0.327	**	2.27	ζ_2	-1.110	***	-5.48

[1] To investigate the relationship between turbine height and minimum distance an interaction effect between both was incorporated in the experimental design. This effect was not significant in any model specification.

γ_{income}	0.138	**	1.98	ζ_3	1.020	***	5.70
$\gamma_{\text{turdistance}}$	0.059	**	2.29	ζ_4	-1.380	***	-6.65
				ζ_5	0.633	***	4.06
				ζ_6	1.150	***	5.94
Class allocation model parameters				ζ_7	-1.340	***	-5.47
$\mu_{0,2}$	0.885	**	2.43	ζ_8	-1.410	***	-6.42
$\mu_{1,2}$	-0.456	*	-1.75	ζ_9	-0.402	**	-2.40
$\mu_{0,3}$	-0.365		-0.81				
$\mu_{1,3}$	0.595	***	2.77				
Measurement equation parameters (thresholds and constants)							
$\tau_{1,1}$	-4.610	***	-6.63	$\tau_{5,1}$	-1.780	***	-5.84
$\delta_{1,1}$	1.170	***	5.72	$\delta_{5,1}$	2.240	***	10.57
$\delta_{1,2}$	1.400	***	7.75	$\delta_{5,2}$	1.520	***	10.49
$\delta_{1,3}$	1.830	***	9.15	$\delta_{5,3}$	1.170	***	6.73
$\tau_{2,1}$	-4.950	***	-9.32	$\tau_{6,1}$	-2.150	***	-4.97
$\delta_{2,1}$	1.700	***	5.86	$\delta_{6,1}$	2.040	***	7.91
$\delta_{2,2}$	1.200	***	7.26	$\delta_{6,2}$	1.510	***	9.21
$\delta_{2,3}$	1.340	***	8.87	$\delta_{6,3}$	1.680	***	9.12
$\tau_{3,1}$	0.748	**	2.24	$\tau_{7,1}$	-5.960	***	-7.7
$\delta_{3,1}$	1.650	***	9.60	$\delta_{7,1}$	0.724	**	2.53
$\delta_{3,2}$	1.190	***	6.63	$\delta_{7,2}$	0.787	***	3.61
$\delta_{3,3}$	1.290	***	4.58	$\delta_{7,3}$	1.620	***	7.11
$\tau_{4,1}$	-2.690	***	-5.13	$\tau_{8,1}$	5.830	***	-9.59
$\delta_{4,1}$	1.680	***	9.22	$\delta_{8,1}$	2.300	***	6.86
$\delta_{4,2}$	2.120	***	9.38	$\delta_{8,2}$	2.400	***	10.73
$\delta_{4,3}$	1.720	***	4.92	$\delta_{8,3}$	1.410	***	8.44
				$\tau_{9,1}$	0.719	***	2.93

As a next step, WTP measures were computed from the LC model estimates, giving the implied monetary valuation of different changes in attribute levels. A positive WTP in our presentation of results shows how much the respondents would be willing to pay for a change of the given attribute from its base level whereas negative WTP suggests the amount willing to pay to prevent this change. Table 7 presents WTP measures corresponding to significant attributes in the three classes of the LC model. In the biggest class 3, for example, the WTP estimates per month for moving turbines 1100 metres or 1500 metres away from residential areas are 2.7 € and 2.8 € , respectively.

Table 7: WTP measures of the LC model

	Class 1	Class 2	Class 3
Size small	-1.12	n.s.	1.88
Size medium	n.s.	n.s.	n.s.
High small	n.s.	n.s.	n.s.
High medium	n.s.	n.s.	n.s.
Red low	2.81	1.62	1.66
Red high	-3.26	n.s.	-2.14
Min medium	n.s.	n.s.	2.72
Min high	n.s.	n.s.	2.85

All three classes agree on protecting the red kite population, where, in the second class, the WTP for lowering the impact on the Red Kite population is the only relevant attribute. This group can thus be labelled *advocates* of wind power as they only experience minor externalities from the zero-price option (programme A). The other big class, class 3, is in favour of the most radical changes compared to programme A, and is therefore labelled *opponents*. Respondents who are likely to be members of this class prefer small wind farms located at longer distances from their home. Finally, respondents with a higher probability of being in class 1 prefer, apart from protecting the Red Kite population, bigger wind farms. Consequently, this class is between the other two classes indicating that members would experience modest externalities.

We next turn to the HLC model. The fit of this structure cannot be directly compared to the LC model log-likelihood as we are now looking at the joint estimation of the choice model and measurement model. The coefficients estimations in the LC and HLC models are very similar and the expected increase in the precision given the use of additional information (attitudinal questions) which should make the *t*-statistics higher (in absolute value), can be observed only in some of the significant coefficients.

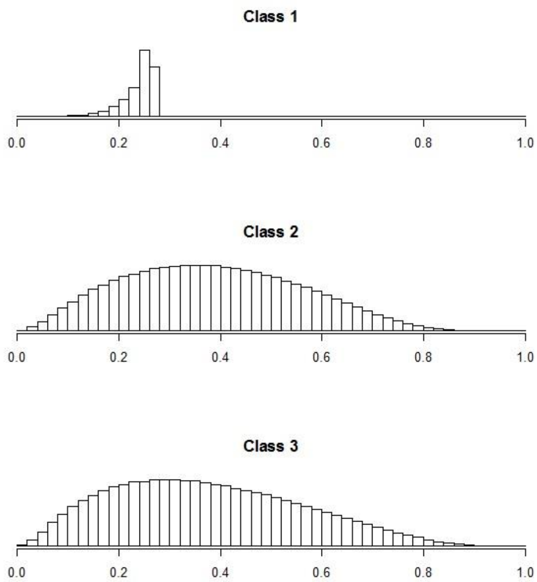
Nevertheless, the significant coefficients in Table 6 confirm that the underlying environmental attitudes influence the class allocation probabilities of the respondents collected by the survey. All coefficients are significant at 10% except for the non-relevant constant term $\mu_{0,3}$ in the probability allocation function.

As can be seen in Table 6, the impact of the latent variable was significant on all nine attitudinal indicators (ζ) and from all socio-demographic variables presented in Table 2 only four are significant (γ). The significant variables include traditional characteristics such as age, gender (*female*), monthly net household income (*income*) together with the distance to the turbine that is located at the shortest distance to the respondents' place of residence (*turdist*). The socio-demographic variables can be helpful in the description of the two groups of advocates and opponents to wind power generation. The coefficients signs indicate that older people, female respondents, people who have higher incomes, and those who live at a greater distance to turbines have a more positive value for the latent variable. The signs of the ζ parameters presented in Table 6 suggest that a higher latent variable identifies someone as an opponent to wind farms. Indeed, for the attitudinal questions from Table 2, advocates are expected to give high values in attitudinal question number 1, 2, 4, 7 and 8 and low values in the remaining questions, and with the signs in Table 6 being opposite to this, it becomes clear that a higher latent variable means greater opposition. The sign of the parameter ζ_9 corresponding to the variable *donation* indicates that advocates of wind power are characterized by donation to nature conservation projects in the year before the survey, or the opposite for opponents.

Finally, turning to the class allocation model, we see that respondents with a more positive latent variable, which we now know equates to greater opposition to wind farms, are more likely to fall into class 3 and least likely to fall into class 2. These results are in line with having earlier identified class 3 as being characterised by strong opposition to wind farms.

The incorporation of the responses to the attitudinal statements has also a significant influence on class probabilities as we will see now. The class allocation probabilities defined in (13) are respondent specific and are a function of the latent variable LV_n which at the same time depends on the random error term, meaning that the allocation probabilities themselves follow a random distribution. We simulated the class allocation probabilities according to (13) using 10,000 draws for the latent variable of each respondent according to (7), combining the estimated parameters γ with corresponding values of socio-demographic variables and adding generated random errors ω. The resulting values are presented in Figure 2 through the use of histograms.

Figure 2: Simulated allocation probabilities



As can be easily seen from Figure 2, the probabilities of belonging to classes 2 and 3 vary more than the probability of belonging to class 1 but their median indicates that these classes are bigger than class 1.

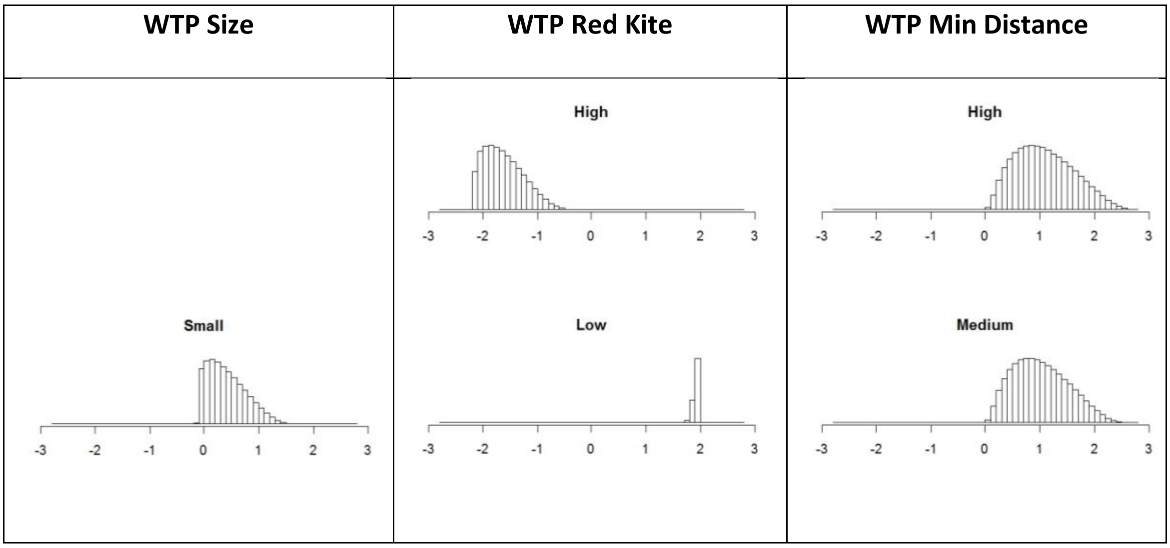
Next, we simulate the WTP values for the sample population of respondents computed as weighted mean of the WTP values in each class. That is, for example, for attribute *Size* and level *small*, the corresponding value for respondent n is

$$WTP_n = \pi_{n,c_1} \frac{\beta^{c1}_{Size_{small}}}{\beta^{c1}_{Cost}} + \pi_{n,c_2} \frac{\beta^{c2}_{Size_{small}}}{\beta^{c2}_{Cost}} + \pi_{n,c_3} \frac{\beta^{c3}_{Size_{small}}}{\beta^{c3}_{Cost}}. \tag{15}$$

The simulated allocation probabilities π_{n,c_s} presented in Figure 2 are therefore used in (15) and combined across respondents to obtain sample level distributions which are presented for the relevant attributes from Table 7 in Figure 3.

The simulated WTP values display that the effect of turbines on the Red kite is the largest of the externalities experienced by respondents. Allocating turbines across the region in a way that would harm the red kite would cause disutility among respondents while an allocation that would avoid conflicts would be clearly beneficial. Therefore, locations far away from aeries would minimise landscape externalities from turbines. Second, distance of turbines to residential areas matters and on average respondents would prefer larger distances than those defined in programme A. The lowest of the externalities, apart from turbine heights, is associated with the size of wind farms. Reducing the number of turbines compared to the number associated with the zero-prize option would result in rather small benefits.

Figure 3: Simulated WTP values



As the latent variable LV_n depends on various socio demographic variables, the WTP values can be also simulated for specific subgroups of respondents. Figure 4 presents the simulated allocation probabilities for two antagonistic groups which can be labelled *young advocates* and *old opponents*. Both are characterised by the values of the socio demographic variables defined in Table 8. Values in the first column of Table 8 define *young advocates* as being below the 25th percentiles of the corresponding variables age, income and turbine distance, and being male. Similarly, the second column uses the 75th percentiles of these variables to define *old opponents*, who are also female. The *young advocates* are therefore young males with low income living close to wind turbines and the *old opponents* present opposite characteristics.

Table 8: Definition of two antagonistic groups

	Advocates	Opponents
Age	< 34	> 61
Gender	Male	Female
Income	< 1 250	> 2 750
Turbine distance	< 3 691	> 6 959

Figure 4 presents simulated allocation probabilities for the two antagonistic groups. They confirm the interpretation of classes 2 and 3 mentioned above based on the WTP measures presented in Table 7. The median of simulated probabilities to belong to classes 2 and 3 for *young advocates* are 0.49 and 0.27 respectively, while, for *old opponents*, these probabilities are 0.29 and 0.49, showing the opposite pattern.

Figure 4: Simulated allocation probabilities for two groups of respondents

Advocates	**Oponents**

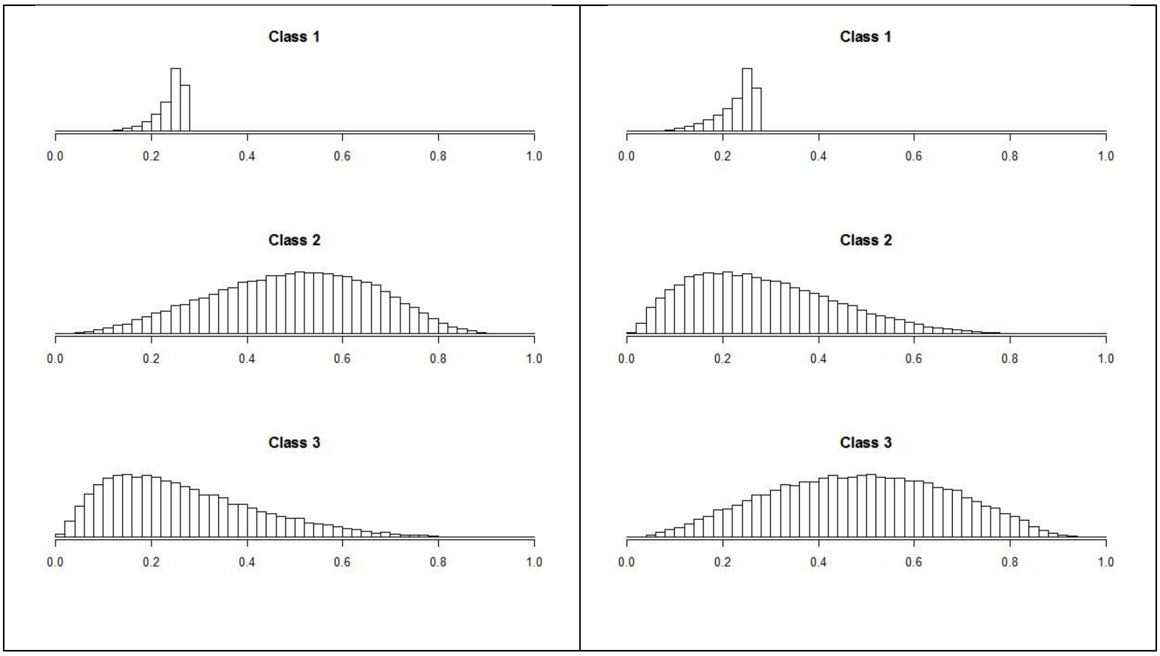


Table 9 presents median values, lower and upper quartile of the overall simulated WTP values and values for the two antagonistic groups based on the simulated allocation probabilities from Figure 4. The first column in Table 9 therefore shows the values presented graphically in Figure 3 and the second and third column show how these values change according to different socio-demographic characteristics. The simulated WTP values again display that regardless of whether respondents are advocates or opponents of wind power generation, both are in favour of reducing the impact of turbines on red kites. This reflects public opinion in Germany toward turbines. In contrast, the valuation of wind farm size and distance to turbines differs strongly between both groups. Here, the opponents would experience much larger externalities, particularly when turbines are located too close to residential areas.

Table 9: Simulated WTP values for two groups of respondents

	Overall	Young Advocates	Old Opponents
Size small	0.36	0.15	0.62
	(0.13,0.64)	(0.01, 0.37)	(0.34,0.90)
Red low	1.92	1.92	1.91

	(1.89,1.93)	(1.88,1.94)	(1.88,1.94)
Red high	-1.67	-1.41	-1.89
	(-1.91,-1.38)	(-1.68,-1.11)	(-2.05, -1.65)
Min medium	0.97	0.65	1.32
	(0.62,1.37)	(0.39, 0.98)	(0.95, 1.69)
Min high	1.03	0.69	1.42
	(0.66,1.46)	(0.41,1.05)	(1.01,1.80)

6. Discussion and conclusions

The results from the discrete choice experiment show that wind turbines cause externalities and that the valuation of these externalities differs among inhabitants of our study region. One group of respondents are clearly concerned about the effects turbines have on red kites and about the minimum distance the turbines are located from residential areas. Respondents in the group of labelled opponents would pay a surcharge to their monthly energy bill in order to move them further away from residential areas. On the other hand, one group of respondents is solely concerned about the negative effects turbines might have on red kites. Therefore, they were labelled advocates. Using a hybrid choice model enabled us to investigate the role that underlying environmental attitudes may play in explaining people's preferences towards different schemes of wind power generation. The results show that individuals' latent attitudes are significantly related to variables in the structural equation, with a number of key socio-demographic influences relating to age, gender and income. It is especially noteworthy that the latent variable is significantly related to the variable measuring the distance from each respondent's place of residence to the closest turbines in the landscape. The latent variable gives a strong explanation of the answers respondents give to a number of attitudinal questions. In terms of the role of the latent attitude in the choice model, people who are more in favour of wind power generation are more likely to choose an alternative that restricts the location of turbines in a landscape less than respondents who hold more negative attitudes towards wind power generation. Our results therefore confirm findings from other studies indicating that respondents' choices are, apart from the attributes of the alternatives, related to their attitudes.

Our approach to incorporate responses to attitudinal statements into a LC model differs from the one presented by Breffle et al. (2011). The essential difference is that a latent variable is used which explains attitudes at the person level. This latent attitude is a function of socio-demographics and a random component. It is used to explain both the answers to the follow-up questions, and the probability of being allocated to a given class. This has a number of key advantages. First, it breaks the absolute relationship between a given class in terms of taste coefficients and answers to the follow-up questions. Second, it allows for measurement error in the follow-up questions. Third, the structural equation at the latent variable level means that we can allow for socio-demographic interactions that explain the underlying attitudes while separate interactions can be used in the class allocation formulae.

The hybrid choice model approach captures more closely choice processes by incorporating latent characteristics of decision makers because it makes use of additional information related to choices and it leads generally to reduced standard errors for parameters estimated jointly on the choice data and attitudinal data. Apart from that virtue, hybrid choice model allows for decomposition of the preference heterogeneity into a purely random part and a part related to attitudes (Vij and Walker, 2012). It allows a deeper understanding of the role of socio-demographics, and, subsequently, better policy recommendations. Another benefit of this approach is that the observed indicators of the latent characteristics are treated as endogenous and not used to make choice predictions avoiding any possibility of endogeneity problem.

Our results have revealed that the sample is characterized by strongly antagonistic preferences among respondents, i.e., people who are advocates or opponents of wind power generation. The HLC model provides valuable insights into individuals' decision processes, where the latent variables significantly influence the allocation of respondents to classes, and hence explain the heterogeneity of preferences articulated in the choices among the alternatives on the choice sets, as well as explaining the answers to attitudinal questions. As a consequence, fewer non-price attributes of the wind power programs seem to significantly influence individuals' choices, and, also importantly, lower the marginal WTP estimates for moving turbines further away from residential areas. Assuming that the HLC model as the more informed model results in less biased estimates, it is obvious that this has strong policy implications.

The HLC model allows, therefore, deeper analysis of the existing preference heterogeneity than a plain LC model trough the linking of allocation probabilities to socio-demographic variables by the use of underlying attitudes. It is important to highlight that that link was not found in the plain LC model. The estimation cost of the HLC models is high due to the high number of estimated parameters involved, but as shown by our application, this complexity allows richer interpretation. Whether the application of a hybrid choice model will always result in richer insights into determinants of taste heterogeneity is an empirically question and we would thus encourage other researchers to investigate to what extent these models provide richer interpretations. Therefore, using a hybrid choice model could be advantageous when policy makers aim at minimizing the externalities of renewable energy resources such as turbines, and thus could help to increase the future share of renewable energy sources. Whether these findings apply to other data sets as well remains a question for further research.

A main implication for energy policy from this survey is that people do care strongly about the environmental impacts of turbines. This is reflected by the willingness to pay people stated regardless of whether they are classified as advocates or opponents. Thus, in order to increase acceptance of wind power, it is essential to minimize the conflict between wind power generation and nature protection. Eichhorn et al. (2012) have shown that the location of the turbines is crucial and that choosing installation sites accordingly can significantly lower this conflict. The policy implications of the other main finding, the preferences concerning the minimum distance, are not as obvious. As people differ significantly with respect to their valuation of the minimum distance turbines should be located, placing turbines at different distances would be optimal from an economic point of view. However, people who prefer to move turbines further away (“Old-Opponents”) might live next to people who do not care as much about the minimum distance (“Young-Advocates”). Additionally, how far turbines can be moved away from residential areas depends on the respective landscape and its opportunities to harvest wind power as well as the target set by energy policy. Further analysis would have to show how far turbines have to be placed away from residential areas to achieve certain energy target and how big the externalities are that will remain.

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