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Impact of beliefs about negative effects of wind turbines on preference heterogeneity regarding renewable energy development in Poland

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A R T I C L E I N F O

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A B S T R A C T

In this study we investigate people's preferences for renewable energy development in Poland. Our main objective is to examine whether preferences renewable energy development near individuals' place of residence are influenced by personal beliefs about the negative effects of wind turbine activity. The study focuses on beliefs about wind power because it has had the most dynamic development among all renewable energy investments in Poland. To elicit values on avoiding renewable energy externalities, we apply a choice experiment method. The data are analysed using the hybrid mixed logit model. The obtained results indicate that individuals' beliefs about wind turbines' negative impacts on environment, landscape, human health and wellbeing have distinct effects on people's preferences concerning renewable energy development. Additionally, the results denote that people who generally hold an opinion about wind turbines' negative effects, regardless of whether they believe or deny that such effects exist, would like to have an input on renewable energy development in their neighbourhood, in contrast to people who do not hold any opinion about the effects. Holding beliefs that wind power is not harmful enhanced individuals' preferences for implementing wind energy projects and had a significant impact on willingness to pay for increasing the distance from renewable energy production sites to residential areas.

1. Introduction

Generating electricity from renewable sources is seen as a crucial measure to reduce carbon dioxide emissions and combat climate change. A recent special report on global warming by the IPCC (2018) strongly underlined the importance of renewables. In pathways that would limit global warming to 1.5 °C with no or limited overshoot, the report projects that renewables will supply 70 to 80% of electricity worldwide in 2050. Reaching this objective would require a rapid and far-reaching transition of the energy system, including a massive expansion of renewables compared with today. Renewable electricity production sites (REPs), such as wind farms or large solar fields in the open landscape, allow for carbon dioxide–free generation of electricity; however, they simultaneously have negative effects, for example, due to noise or visual disturbance.

With the expansion of renewables, it is notable that the negative effects tend to occur locally, while the benefits of carbon-free electricity generation are a global public good. The negative effects may prompt members of local communities to strongly oppose the development of electricity production from renewable energy sources. Opposition can be based not only on well-reasoned judgements but also on beliefs without scientific bases, such as wind power generation having adverse impacts on human health.

Consequently, a better understanding of how people view the local negative effects of REPs can help to find locations that are optimal with respect to both energy harvest and minimising negative effects. Different approaches exist in the literature to investigate peoples' acceptance of and objection to nearby REPs. These approaches range from qualitative interviews (see e.g. Zoellner et al., 2008) or interviews using standardised questionnaires, comprising, for example, sets of attitudinal items (see e.g. Musall and Kuik, 2011), to economic approaches that try to capture the negative local effects of renewables in monetary terms. The advantage of the latter is that once the negative effects have been measured in monetary terms, cost-benefit comparisons can be conducted and optimisation techniques can be used to identify optimal locations for placing REPs (see e.g. Drechsler et al., 2011, 2017). In this sense, economic valuation techniques are valuable as a policy decision-making tool to pursue renewable energy development in more effective and socially acceptable ways.

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Economic valuation techniques utilise the Random Utility Theory which assumes that individuals have preferences among the available choice alternatives. The underlying assumption in this approach is that individuals make choices (express their preferences) which enhance their welfare. Individuals' preferences can be elicited using either revealed or stated preference non-market valuation methods. These methods allow for measuring individuals' preferences and quantifying the monetary valuation for a good in question.

Non-market valuation studies have often been used to estimate the value of renewable energy construction characteristics (e.g., Koundouri et al., 2009; Dimitropoulos and Kontolen, 2009; van Rijnsoever et al., 2015) or to investigate preferences about locating renewable energy production sites (see e.g., Bergmann et al., 2006; Ladenburg and Dubgaard, 2007; Ek and Persson, 2014). Most of this analysis pertains to wind power, which is the second most important source of renewable energy generation worldwide and is expected to increase substantially in the near future.

Wind power development may result in a variety of negative effects, including landscape disruption (Azjen, 1991), noise pollution, and adverse impacts on wildlife, particularly birds. According to a meta-analysis of more than 30 non-market valuation studies on wind power production impacts (Mattmann et al., 2016), most of the research attention so far has been devoted to investigating the visual aspects of wind farms. Most of these studies focused on both positive impacts of wind turbine activity (i.e., the decrease level of air pollution) and negative effects. Only a few of the studies included in the meta-analysis evaluated noise impacts or assessed the economic consequences of wind power effects on fauna and bird life.

In this study, we investigated individuals' preferences for renewable energy development in Poland. Our main objective was to examine whether personal beliefs about the negative effects of wind turbines influence preferences for avoiding externalities from renewable energy development in the vicinity of respondents' place of residence. Individuals' preferences depend on certain characteristics of the good in question, but they can also be endogenously determined. In our study we follow the stream of literature which is based on the recognition that individuals' preferences are not only driven by the good's attributes and people's socio-economic characteristics, but they are also related to people's beliefs and attitudes. Beliefs or attitudes are broadly defined as affective evaluations with regard to a particular good or policy, and they can have an impact on people's choices (expressed preferences) (Azjen and Fishbein, 1977). There are many theoretical frameworks which explain the impact of beliefs and attitudes on individuals' behaviour with the most prominent being the Theory of Reasoned Action (Fishbein and Azjen, 1977) and the Theory of Planned Behaviour (Azjen, 1991). According to these theories, before performing a specific behaviour an individual first considers their beliefs about negative and positive consequences of the behaviour in question. Next, these beliefs form an individual's attitude, which then leads to the behaviour itself. Empirical findings show that incorporating individuals' perceptions about positive or negative effects of the good in question can play a substantial role in explaining peoples' choices, preference heterogeneity, and differences in their valuation (see e.g. Hess and Beharry-Borg, 2012; Mariel et al., 2015; Amaris et al., 2021).

We focused on beliefs about wind power because it has had the most dynamic development among all renewable energy investments in Poland (almost 70-fold increase) in the last decade (PWEA, 2016). Wind power has also drawn some of the fiercest opposition. Although protests were numerous, they did not involve many people; therefore, it is hard to assess from protests alone whether the arguments have widespread support in society. By identifying what drives opposition to the development of REPs, it may be possible to preemptively address concerns. For example, decision makers could pursue an appropriately targeted information policy and/or spatial planning that accounts for the externalities of REPs that are the most important to society. We have assumed that beliefs about negative effects connected with one type of REPs can cause a spillover effect on attitudes towards other renewable energy sources. Empirical findings from studies such as Akin et al. (2019) show that people may use their experiences and beliefs about familiar technologies as a basis for evaluating the technologies about which they know less. Of all renewable energy sources, Poles are most familiar with wind turbines, whereas electricity generation from solar farms constitutes the lowest share of familiarity.

Our study contributes to the literature in two ways. To the best of our knowledge, we are the first to analyse the impact of beliefs about negative effects of wind turbines on preference heterogeneity regarding renewable energy development. Previous similar studies, such as Mariel et al. (2015) and Liebe and Dobers (2019), focused on the impact of general attitudes towards renewable energy development, rather than on concerns about negative externalities, such as negative impacts of windmills on human health, the quality of life in a neighbourhood, visual aspects, and the environment. In addition, in this study we examined the impact of concerns related to the construction and operation of windmills on preferences towards not only the wind power extension but also towards the development of REPs generating electricity from alternative renewable energy sources such as biomass and the sun. This study design allowed examining whether people tend to view alternative energy sources holistically or separately.

To elicit values on avoiding renewable energy externalities, we used a choice experiment (CE) approach. The CE is a non-market valuation method based on the Consumer Theory of Lancaster (1966) and the Random Utility Theory of McFadden (1974). The Consumer Theory posits that any good can be described in terms of its attributes. When people make choices between different bundles of attributes associated with a good, they express their preferences about that particular good. The observed choices subsequently enable making inferences about which attributes significantly influenced decisions and then deriving a marginal rate of substitution between those attributes. If one of the attributes is a price or a cost, then the marginal rate of substitution between a nonmonetary and a monetary attribute provides a marginal willingness to pay (WTP) for the nonmonetary attribute. The Random Utility Theory provides the theoretical foundations for an analysis of CE data. This theory posits that people make rational choices and the utility a person derives from a choice depends on its observable characteristics and on stochastic (unobservable) factors. Both of these theories are standard economic theories used in microeconomic analyses.

To carry out our analysis, we applied a theoretically robust econometric approach, the hybrid mixed logit (HMXL) model (Ben-Akiva et al., 2002), which allows the inclusion of psychological factors into the utility functions of the alternative being considered. An HMXL model is a structural model that incorporates a choice component from a CE and a non-choice component that provides measurement of latent variables. Attitudes and beliefs, which are often directly measured in studies, are actually unobservable and can only be approximated through various indicators. The HMXL approach avoids the problem of measurement error, which may occur when stated measures are directly included in the choice model as explanatory variables as reported, for example, by Thomson and Kempton (2018). Recently, this approach was used inter alia by Grilli and Notaro (2019) to investigate the influence of an extended theory of planned behaviour on preferences and WTP for participatory natural resources management, and by Amaris et al. (2021) to examine the impact of attitudes on residential greywater reuse preferences. In the current study, latent variables were based on self-reported beliefs about different negative effects of wind turbine activities.

From the methodological point of view we propose a new approach how to incorporate "*I don't know*" answers into attitudinal statements in hybrid choice models (HCMs). We asked respondents to indicate the strength of their beliefs about the negative effects on a Likert scale, but they also had the opportunity to indicate a lack of opinion about the issue (this option was presented outside the scale). In this study we propose a model with measurement equations that are modelled as a two-part process. This approach allowed us to separately investigate a willingness to reveal/having opinions about the negative effects of wind turbines and believing

Table 1
Renewable energy installation in Poland at the end of 2015.

Type of installation	Quantity	Power (MW)
Wind power stations	1003	4254
Biomass power stations	36	1033
Photovoltaic power stations	225	51

Source: Energy Regulatory Office (as of December 2015).

in them. As far as we know, the "I don't know" answers in HCMs have so far been either treated as a part of the Likert scale and modelled as a one-part process, or simply excluded from further analysis as observations for which people did not reveal opinions.

The rest of the article is structured as follows. Section 2 briefly describes energy production in Poland. In Section 3, the applied methodology is described. Section 4 elaborates the survey structure, the design, and data collection, while Section 5 reports the results. Section 6 discusses the results and offers some recommendations for energy policy.

2. Background information

According to Energy-Climate Package, the development of renewable energy is a key component in the energy strategy of moving towards a low-carbon economy. In 2016 renewable energy accounted for 86% of all new European Union (EU) power installations, with 21.1 GW of total capacity and 24.5 GW of new power capacity (Wind Europe, 2018). Among renewable energies, the most important source in EU countries was wood and other solid biofuels as well as renewable wastes, which together accounted for 44.7% of primary renewable energy conversion. Hydropower was the second most important contributor to the renewable energy mix, followed by wind power (12.4%) and solar power (6.3%) (EC, 2018). Particularly the latter two have seen a fast expansion in recent years. In 2016, for example, installation of wind power has outweighed installation of any other form of power generation in Europe (Wind Europe, 2018).

The Polish energy sector is traditionally based on fossil fuels – hard and brown coal. In Poland about 80% of electricity is generated by burning coal, whereas the average figure for the EU is just around 25% (EC, 2016). In 2016, renewable resources accounted for only 14% of Polish electricity production. Among these renewable energy sources, the most important was wind. Wind turbines accounted for 48% of renewable energy production in Poland at the end of 2015 (GUS, 2017). In terms of wind capacity installed, Poland was in seventh place among EU countries. In the analysed period of time, in terms of the dynamics of wind energy development, with a total of 1145 MW in new onshore capacity installed, Poland was second in Europe after Germany (PWEA, 2016). In comparison, energy production from biomass amounted to 40% of renewable energy production, and its share has been decreasing in recent years. Compared with the previously mentioned energy sources, solar energy production in Poland was negligible. At the end of 2015, it accounted for only 0.3% of energy production from REPs. Compared with other European countries such as Germany, Poland started promoting the expansion of renewable energies relatively late – it was only 2005 when Poland implemented its system to support renewable energy using certificates. In 2016 (after the current study took place), the Polish government implemented a very restrictive policy on wind power that dramatically slowed investments in this sector. In Poland renewables still continue to play a marginal role in the power sector. Table 1

3. Survey

3.1. Survey structure and data collection

The survey used in the current study had five main parts. The first part provided respondents with general information about wind, solar, and biomass energy and collected data on respondents' exposure to REPs and their general attitude towards them. Pictures and graphical illustrations supported the text. Part 2 presented the choice tasks. For each task, respondents were asked to choose their preferred option from among several alternatives regarding the development of REPs within 10 km of their place of residence. The choice sets, which were presented in a randomised order, contained both increases and decreases in the household's monthly energy bill, according to the experimental design. In part 3, individuals' financial risk preferences were elicited.[1] Part 4 contained attitudinal statements, including those concerning respondents' beliefs about the negative effects of wind turbines and general preferences towards the renewable energy development in Poland. Socio-demographic information was requested in the last section.

Table 2
Descriptive statistics of the sample characteristics.

	Share/median in sample	Share/median in Polish population
Women	53%	52%
Education		
Primary	37%	43%
Secondary	35%	34%
High	28%	23%
Age		
18–35	27%	31%
35–65	52%	51%
Over 65	21%	18%
Net monthly household income in zł	2500	3300

Note: * Number of respondents, $N = 744$; 13% of those respondents did not reveal their income. At the time of the study, 1 PLN ≈ 0.25 EUR ≈ 0.33 USD.

The survey took place in January 2016. The sample was representative of the Polish population in terms of age, gender, community size, and geographical location. In total, 800 face-to-face interviews were conducted by a professional polling agency using a computer-assisted personal interviewing system. The response rate was 78%. The questionnaire was tested for understandability with students from the Faculty of Economic Sciences at the University of Warsaw and people from the general public. Additionally, the discrete choice part of the survey was tested earlier in a survey in Germany (see Oehlmann and Meyerhoff, 2017). The pilot study was conducted with about 100 respondents. The final sample used for analysis consisted of 744 respondents, after exclusion of respondents who chose the same column in all presented choice tasks both in the CE and in the risk preferences elicitation part. Table 2 reports the socio-demographic characteristics of the sample analysed and the Polish population as a whole. In terms of education, people with a higher level of education were slightly overrepresented in the final sample and people with primary education underrepresented. Additionally, in the analysed sample we had a slight overrepresentation of people over 65 years old and an underrepresentation of people younger than 36 years.

3.2. Attributes and experimental design

The CE was introduced as follows:

"Renewable energies as well as the electricity grid will be expanded in Poland. In the following choice sets, you can choose among different alternatives for renewable energy development. Please think of REPs being built within 10 km of your place of residence. If you live in a large city, please consider the surrounding area of your city. You can choose among the following alternatives:

- Electricity from wind energy (wind farms),

[1] The influence of risk preferences on respondents' WTP for the renewable energy development in Poland is the subject of a different study (see Bartczak et al., 2017).

Table 3
Renewable energy: definitions and pictograms.

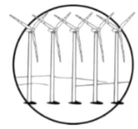
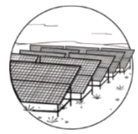
Type	Definition	Pictogram
Wind energy	Electricity generation with single wind turbines and wind farms exclusively onshore	
Solar energy	Electricity generation with photovoltaic system in the open landscape	
Biomass	Electricity generation with biogas and biomass from the cultivation of, for example, corn	

Table 4
CE attributes and levels.

Attribute	Attribute label	Attribute level
Minimum distance to residential areas	Distance	300 m, 600 m, 900 m (FSQ), 1600 m, 2500 m
Size of renewable energy production sites	REPs size	Small, medium (FSQ), large*
Number of renewable energy production sites	REPs number	1, 2, 3 (FSQ), 4, 5
Share of landscape not used for renewable energy expansion	Landscape	10%, 20%, 30% (FSQ), 40%, 50%
High-voltage transmission lines	HVTL	Overhead (FSQ), underground
Monthly surcharge or rebate to energy bill (annually) in EUR	Cost	−10 (−120), −5 (−60), 0 (FSQ), +2 (24), +7 (84), +14 (168), +23 (276)

* For the wind energy alternative, small was defined as 5–10 turbines, medium as 18–25 turbines, and large as 35–50 turbines. In the case of the solar energy alternative, 0.5–5 hectares, 20–40 hectares, and 60–100 hectares indicated small, medium, and large, respectively. For the biomass energy alternative, small meant 1–3 fermentation tanks; medium, 5–8 fermentation tanks; and large, 15–25 fermentation tanks.

- Electricity from solar energy (solar fields),
- Electricity from biomass (biogas power stations),
- It does not matter to me (you do not have any opinion on the type of renewable energy

which will be developed within 10 km of your place of residence)".

Each choice set comprised four labelled alternatives. The first three referred to the development of wind, solar, and biomass energy sites within 10 km of a respondent's place of residence while the last alternative, labelled *"It does not matter to me"*, represented a general plan for renewable energy development without a specific focus on extending the use of one of the three types of renewable energy sources (business-as-usual). We refer to the last alternative as the future status quo (FSQ). The definitions and pictograms used to describe renewable energy sources are presented in Table 3.

In the CE we used five attributes related to renewable energy externalities and a monetary attribute. Nonmonetary attributes were related to the minimum distance of REPs to the edge of a respondent's town/place of residence and the size and number of REPs. These attributes were alternative specific (i.e., wind energy, solar energy, or biogas energy). The next attribute "Share of landscape not used for renewable energy expansion" pertained to the share of the landscape in the surrounding 10 km that would not be used for any renewable energy development in the future. Additionally, one attribute was related to transition lines (whether the new lines should be built overhead or underground). The monetary attribute took the form of a surcharge or a rebate on respondents' current energy bills. As Aravena et al. (2014) reported, the effect on the electricity price paid by consumers due to the introduction of new sources of energy generation or the reduction in the probability of future power outages is often uncertain. In the CE, we used both increases and decreases in the electricity bills to depict the uncertainty about the effect of new sources of energy generation on the current price level. The FSQ option was associated with no change in the electricity bill. The CE design was adopted from the EnergyEFFAR project.[2] Table 4 shows the full list of attributes and their levels used in the experimental design.

The choice sets were created using a Bayesian efficient design applying the C-error optimisation criterion (Scarpa and Rose, 2008). The final design comprised 24 choice tasks that were grouped into four blocks of six choice tasks, and respondents were randomly assigned to one of the blocks. To control for the ordering effects, we randomised both the order of choice tasks and the order of the first three labelled alternatives across respondents. We ensured that each choice set and each alternative were presented in every position a comparable number of times. In each choice set, respondents were asked to choose which alternative they would prefer within a 10-km radius of their place of residence. Fig. 1 shows an example choice set.

3.3. Beliefs about negative effects of wind turbines

We collected respondents' beliefs about the negative effects of wind turbine activity in follow-up questions. We asked them to express their level of agreement or disagreement with four statements on potential negative effects of wind turbine activity:

- "Wind turbine activity is harmful to human health",
- "Wind turbine activity is troublesome for local residents",
- "Wind turbines destroy the landscape",
- "Wind turbine activity is harmful to animals and/or cultivation".

These statements were chosen based on results from in-depth interviews with a selected number of people. In the main survey, respondents were asked to assess each statement on a 4-point Likert scale based on the following responses: *"I definitely disagree", "I disagree", "I agree",* and *"I definitely agree"*. Responses were coded from 1 to 4, with higher numbers corresponding to greater agreement with the statement.[3] Respondents could declare that they did not have an opinion, but this option was not shown in the answer scale and responses were coded separately. According to Willis et al. (1994) and Kroh (2006), for

[2] The "Efficient and Fair Allocation of Renewable Energy Production at the National Level" project was funded by the Federal Ministry of Education and Research in Germany.

[3] The impact of various response formats of Likert scales on data collection and interpretation has been a topic of discussion in many social sciences (e.g., Baka et al., 2012; Nadler et al., 2015; Chyung et al., 2017). In this manuscript we have followed arguments for using 4 point Likert scale with the addition of "I don't know" answers outside the scale presented *inter alia* by Johns (2005) and Nadler et al. (2015). These arguments are twofold. First, the presence of a neutral midpoint in the Likert scale opens possibility for central tendency bias and social desirability bias. Second, and what is more important in our opinion, the meaning attached to the midpoint by respondents is not fully understood. The qualitative studies by Baka et al. (2012) and Nadler et al. (2015) show that respondents apply a variety of meanings to the "neither, nor" option. For example, in the case of Nadler et al. (2015) study, respondents' interpretations of the midpoint varied wildly, with the most common responses such as "no opinion", "I don't care", "unsure", or "neutral". This poses a problem for proper data encoding and further analysis. Since these findings indicate that respondents may interpret the midpoint in ways not intended by researcher, we think that it is desirable to omit a midpoint on the Likert scale and offer instead an "I don't know" option.

	Electricity from wind	Electricity from biomass	Electricity from solar	“It does not matter to me”
Minimum distance to residential areas	600 m	2500 m	300 m	900 m
Size of renewable energy production sites	large (35–50 turbines)	large (15–25 fermentation tanks)	small (0.5–5 hectares)	medium
Number of renewable energy production sites	4	5	5	3
Share of landscape not used for renewable energy expansion	20%	50%	10%	30%
High-voltage transmission lines	underground	underground	overhead	overhead
Monthly surcharge or rebate to energy bill (annually)	+14 EUR (+168 EUR)	−5 EUR (−60 EUR)	+14 EUR (+ 168 EUR)	0 EUR
I prefer	□	□	□	□

Fig. 1. Example of a choice set.

example, an answer of *“I don’t know”* provides valid information about respondents’ indecision. Respondents who give this answer more frequently might be less informed or aware of the object under study (Faulkenberry and Mason, 1978; Dolnicar and Rossiter, 2009) or less interested in the topic (Krosnick, 2002). Additionally, as Manisera and Zuccolotto (2014) pointed out, *“I don’t know”* choices can reflect item difficulty/complexity.

4. Methodology

To analyse our data, we employed an HMXL model in order to incorporate individuals’ attitudes regarding wind power external effects into a random utility framework. HMXL models are a type of HCMs, which are very flexible tools that provide a link between behavioural sciences (e.g., psychology) and fields based on estimation, such as engineering and economics (Ben-Akiva et al., 2002). This specification uses latent variables to simultaneously explain individuals’ choices and individuals’ answers to attitudinal questions, which are usually measured on a Likert scale. Applications of HCMs in the environmental literature include valuation of water quality improvements (Hess and Beharry-Borg, 2012) and analyses of preferences for flood risk policies (Dekker et al., 2013) and land management (Mariel et al., 2015).

In the current setting, the HMXL approach enabled decomposing preference heterogeneity for renewable energy development. Specifically, we were interested in the extent to which preferences are driven by individuals’ beliefs about external effects generated by wind energy. We use only wind energy as we consider it to be the most familiar renewable energy type in Poland, and individuals are therefore more likely to have well-formed attitudes towards it.

This topic would be difficult to investigate without the HCM framework because the alternative would be to directly incorporate answers to the attitudinal questions into the model. That approach would likely cause a measurement bias issue as such answers are functions of real attitudes and not direct measures of them. The issue is avoided in an HMXL approach through direct incorporation of measurement error into the model (Budziński and Czajkowski, 2018). In addition, in many cases numerous indicators may describe a single psychological factor, which can lead to a large number of estimable parameters in the model, collinearity, and difficulty in interpreting the results; an HCM avoids these issues. The HMXL model used in this study contained two parts: a discrete choice model and measurement equations.[4]

4.1. Discrete choice model

In a discrete choice model, the dependant variable is a choice that an individual makes in a given choice task. Specifically, .. is equal to 1 if individual i chooses alternative j in choice task t, and 0 otherwise.[5] In accordance with Random Utility Theory, we assumed that individuals’ choices are a function of their utility, namely alternative j is chosen only if it renders the highest utility of all available alternatives. Furthermore, we assumed that the utility a person derives depends on observed characteristics and unobserved idiosyncrasies, represented by a stochastic component (McFadden, 1974). As a result, individual i’s utility resulting from choosing alternative j in choice set t can be expressed as

$$V_{ijt} = \beta_i \boldsymbol{X}_{ijt} + \varepsilon_{ijt}, \quad (1)$$

where $\boldsymbol{X}_{ijt}$ is a vector of monetary and nonmonetary attributes (Table 4), β_i is a vector of individual-specific parameters, and ε_{ijt} is a stochastic component allowing for factors not observed to affect individuals’ utility and choices.

We assumed that heterogeneity of preferences, described by the distribution of individual-specific parameters, $\boldsymbol{\beta}_i$, depends on latent variables, which correspond to individuals’ attitudes. The functional form of this dependence may vary due to the distributional assumptions. If an individual’s parameter for the kth attribute is assumed to be normally distributed, it will be specified as follows:

$$\beta_{ik} = \alpha_{1k} LV_{1i} + \alpha_{2k} LV_{2i} + \beta^*_{ik}, \quad (2)$$

whereas if it is assumed to be log-normally distributed, it would be

[4] Most HCMs have a third part, structural equations, in which latent variables are explained by socio-demographic characteristics. We did not include it here as most variables were not highly significant, and its inclusion did not change the obtained results and inference.

[5] In our case $i \in \{1, \ldots, 744\}$, $j \in \{1, 2, 3, 4\}$, and $t \in \{1, \ldots, 6\}$

$$\beta_{ik} = \exp\left(\alpha_{1k}LV_{1i} + \alpha_{2k}LV_{2i} + \beta^{*}_{ik}\right). \tag{3}$$

In both cases β^{*}_{ik} denotes the unexplained part of heterogeneity distributed normally with mean and standard deviation to be estimated, and $LV_{1i}$and LV_{2i} denote two separate latent variables which are assumed to follow normal distribution with zero mean and unit standard deviation.[6] Furthermore, given the usual assumption of the independent Gumbel distribution for the error terms, ε_{ijt}, then the conditional probability of individual i's choices, $\mathbf{y}_i$, will be given by the multinomial logit formula:

$$P\left(\mathbf{y}_i|\beta^{*}_i, LV_{1i}, LV_{2i}\right) = \prod_{t=1}^{T}\sum_{j} y_{ijt}\frac{\exp\left(\beta_i \boldsymbol{X}_{ijt}\right)}{\sum_{l}\exp\left(\beta_i \boldsymbol{X}_{ilt}\right)}. \tag{4}$$

4.2. Measurement equations

One of the key purposes for including latent variables in a choice model is that they describe various psychological factors. These factors usually cannot be measured in a direct way, unlike other individual characteristics, such as age and gender. Instead, a researcher must use various attitudinal questions in a survey, with the expectation that the responses are determined by the latent variables.

The model choice for the measurement equations depends on the particular application. In this study, we included responses to four questions regarding the potential negative effects of wind turbines, which were measured on a 4-point Likert scale. Respondents also had the opportunity to state *"I don't know"*, if they did not want to answer a particular question. Therefore, each measurement equation was modelled as a two-part process. Consider lth measurement equation and denote by K_{il} a variable equal to 1 if an individual chooses the *"I don't know"* option, and 0 otherwise. We model it with a binary probit model:

$$\begin{aligned}P(K_{il}|LV_{1i}, LV_{2i}) = {} & K_{il}\Phi(\lambda_{1l} + \lambda_{2l}LV_{1i} + \lambda_{3l}LV_{2i}) \\ & + (1-K_{il})(1-\Phi(\lambda_{1l} + \lambda_{2l}LV_{1i} + \lambda_{3l}LV_{2i})),\end{aligned} \tag{5}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of a normal distribution. Then, if $K_{il} = 0$(individual did not choose *"I don't know"*), we denote an individual's answer to the lth attitudinal question as I_{il}, which we then model by using ordered probit:

$$\begin{aligned}P(I_{il}|LV_{1i}, LV_{2i}) = {} & \sum_{k=1}^{4}\mathbf{1}\{I_{il} = k\}(\Phi(\delta_{kl} - \gamma_{1l}LV_{1i} - \gamma_{2l}LV_{2i}) \\ & - \Phi(\delta_{k-1l} - \gamma_{1l}LV_{1i} - \gamma_{2l}LV_{2i})),\end{aligned} \tag{6}$$

where $\delta_{1l} < \delta_{2l} < \ldots < \delta_{4l}$ are thresholds to be estimated[7] and $\mathbf{1}\{\cdot\}$denotes an indicator function that is equal to 1 if the condition in parentheses is fulfilled, and 0 otherwise. The probability of an answer that an individual provides for the lth attitudinal question is then given by:

$$\begin{aligned}P(I_{il}, K_{il}|LV_{1i}, LV_{2i}) = {} & (1-K_{il})P(I_{il}|LV_{1i}, LV_{2i})P(K_{il}|LV_{1i}, LV_{2i}) \\ & + K_{il}P(K_{il}|LV_{1i}, LV_{2i}).\end{aligned} \tag{7}$$

Finally, after combining Eqs. (4) and (7) we obtain the full-information likelihood function for the HMXL model:

$$\begin{aligned}L_i = \int & P\left(\mathbf{y}_i|\beta^{*}_i, LV_{1i}, LV_{2i}\right)\left[\prod_{l} P(I_{il}, K_{il}|LV_{1i}, LV_{2i})\right]\times \\ & \times f\left(\beta^{*}_i, LV_{1i}, LV_{2i}\right)d\left(\beta^{*}_i, LV_{1i}, LV_{2i}\right).\end{aligned} \tag{8}$$

As random disturbances $\boldsymbol{\beta}^{*}_i$, as well as latent variables, are not directly observed, they must be integrated out of the conditional likelihood, with $f(\boldsymbol{\beta}^{*}_i, LV_{1i}, LV_{2i})$ being their density function. This multidimensional integral can be approximated using a simulated maximum likelihood approach – we used 2000 Sobol draws with random linear scramble and random digital shift to make approximation more precise (Czajkowski and Budziński, 2015). As can be seen, we used one-step estimation. This approach has two main advantages over the two-step method; first, it is more efficient and, second, it allows for identification of more flexible specifications as it has more degrees of freedom.

[6] Standard deviation is normalized for the identification (Raveau et al., 2012).

[7] It is assumed that:$\delta_{0l} = -\infty$, $\delta_{4l} = \infty$

Table 5
Statistics of beliefs about negative effects of wind turbines.

Statements	Mean	St. dev.	Median
Wind turbine activity is harmful to human health	2.29	0.91	2
Wind turbine activity is troublesome for local residents	2.70	0.93	3
Wind turbines destroy the landscape	2.06	0.90	2
Wind turbine activity is harmful to animals and/or cultivation	2.41	0.94	2

Note: We use a Likert scale, where 1 indicates strong disagreement, and 4, strong agreement with the statement.

5. Results

5.1. Descriptive statistics

The results show that the majority (88%) of respondents supported the development of renewable energy in Poland, while a notable minority advocated for conventional energy.[8] Collected information regarding respondents' experience with REPs indicates that 91% had encountered wind turbines, whereas 33% had wind energy sites within 10 km of their place of residence.

In general, beliefs about the negative effects of wind turbine activity were not deeply rooted among the respondents. The majority of respondents did not agree with statements that wind turbine activity is harmful to human health, destroys the landscape, or can negatively affect the environment (see Table 5 and Fig. 2). For the analysed sample, the biggest disadvantage of wind turbine activity was that windmills can be a nuisance (e.g., can generate noise or a moving blade shadow) for local residents.

The results also suggest that the lack of opinion about wind turbine externalities decreased with familiarity of the effect (see Fig. 2). The lowest number of *"I don't know"* answers occurred when respondents were asked about the effect of wind turbines on the landscape, and the highest occurred when they were asked to assess the impact on animals and/or cultivation. In other words, respondents were cautious in judging the most complex issues.

5.2. Estimation results

The HMXL model consisted of two parts: a discrete choice component and measurement equations. To ensure that we were employing a proper specification of the model, we estimated multiple specifications that differed across several dimensions, such as (i) treatment of "*I don't know*" answers in measurement equations (either separately or as a middle value on the Likert scale), (ii) adding socio-demographic covariates to choice model and structural equations, (iii) using one or two latent factors, (iv) accounting for correlations between random parameters and latent variables, and (v) using discrete form of preference heterogeneity (latent class model). To guide our choice of specification, we examined the share of preference heterogeneity explained by latent variables and compared goodness-of-fit measures such as information

[8] Similar findings are reported, for example, by CBOS (2016) and Mroczek and Kurpas (2014) in studies on the representative samples of Poles.

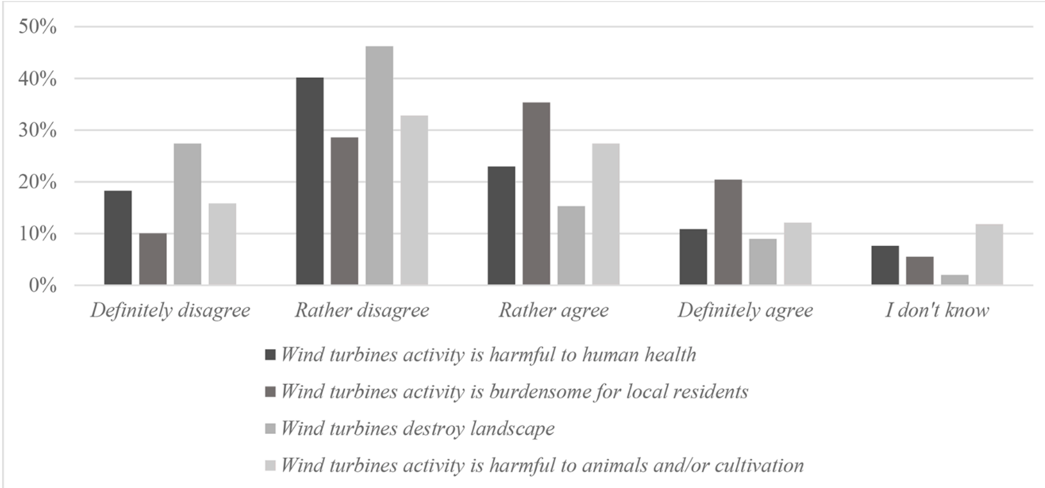


Fig. 2. Distribution of the responses to wind turbine negative effects statements.

Table 6
Comparison of information criteria for different specifications of HCMs.

	HMXL(2 step, 2 LV)	HMXL(2 step, 1 LV)	HMXL(1 step, 2 LV)	HMXL(1 step, 1 LV)	HLC(2 LV, 3 classes)	HLC(2 LV, 4 classes)
AIC/n	3.341	3.373	3.373	3.375	3.526	3.442
BIC/n	3.509	3.515	3.529	3.511	3.624	3.558

Note: HLC refers to hybrid latent class model, whereas 1 step and 2 step refers to whether the "*I don't know*" answers were treated as a middle value of the Likert scale (1 step) or separately as a two-step process (2 step).

criteria. In Table 6 we present information criteria for several specifications of HCMs. The chosen specification (HMXL, 2 step, 2 latent variables (LV)) had the lowest AIC and BIC measures. Furthermore, we provide estimates of a regular mixed logit model for reference in Table A1 in the Appendix.

Results from the chosen model are presented in Table 7 (the discrete choice component) and Tables 8 and 9 (results from the measurement components).[9] Overall, the signs of the parameters for attributes were generally as expected (see Table 7).[10] The results indicate that on average, respondents wanted to have input on renewable energy extension in their neighbourhood. The significance and signs of alternative-specific constants (ASCs) indicate that, all else held constant, the respondents preferred solar power over wind power and wind power over electricity from biogas in their neighbourhood.

The results also suggest that people generally wanted REPs to be further from their place of residence as opposed to nearby. This finding aligns with what many other studies on externalities have found, especially for wind power (e.g., Knapp and Ladenburg, 2015). The probability of choosing an alternative was significantly and positively influenced by the size of area in respondents' neighbourhood not used for renewable energy expansion and by building new high-voltage transmission lines underground. Similar evidence was provided by Des Rosiers (2002) and Navrud et al. (2008). A coefficient for the cost attribute was also highly significant. By assuming lognormal distribution of the cost parameters in our model, we imposed positive utility of money (income). The other attributes (i.e., the size and the number of REPs) did not seem to influence the average respondent's choices. Relatively large and significant standard deviations indicated the presence of substantial unobserved preference heterogeneity in the model, which justified the use of the random parameters specification.

With regard to the main objectives of our study, the measurement equations show that latent variables captured intrinsic beliefs regarding the negative impacts of wind turbines activity. Following the specification described in Section 4.2, we included both latent variables in both parts for all indicator variables.[11] We used this approach because we did not want to impose any particular structure of relationship between indicator variables and latent variables, but rather recover this relationship from the data. The one-step approach employed here allowed for more degrees of freedom, and the model could therefore be properly identified. In what follows, we label latent variables and interpret them based on the significance and direction of their effect on the indicator variables. We acknowledge that, as is usual in these cases, the labelling of latent variables is subjective and up for discussion.

We found that only the second latent variable was related to having opinions on wind turbines' external effects, with an exception for environmental externality, for which the first latent variable is weakly significant (see Table 8). Higher values for these variables were associated with an increased probability of giving an assessment on the potential effects of wind turbines. The effect of the second latent variable effect was the lowest in the case of landscape externality – an assessment which was probably the least troublesome for respondents, and the highest for disturbance externality.

Apart from that, the first latent variable could be associated with a belief that wind energy generation is not harmful, whereas the second latent variable did not affect respondents' stated beliefs (see Table 9). We therefore labelled the first latent variable as *"WT (wind turbines) not harmful"* as its high values were related to stronger stated beliefs that wind turbine activity does not cause the negative effects. This effect was the weakest in the case of landscape externalities, probably because the visual effect was the most known from among all wind turbine external effects. The vast majority of respondents stated that they encountered wind turbines in Poland. As the second latent variable only affected whether respondents reported *"I don't know"* answers to the attitudinal questions, we labelled it as *"Having opinion"*.

The influence of unobserved beliefs about the negative impacts of wind turbines activity on stated preferences in the CE component was revealed by interactions of the latent variables with the attributes (see

[9] All analyzed model can be provided by the authors on request.

[10] Note, that *Mean* and *Standard Deviation* in Table 6 refer to estimated means and standard deviation of random parameters, β_i^*, whereas *interaction with*, refers to αcoefficients, as per Eq. (2).

[11] The specification with one latent variable was also tested, but led to inferior fit to the data, as indicated by higher values of information criteria such as AIC and BIC (consult Table 6).

Table 7
Discrete choice component.

Discrete choice component			***interaction with***			
	Coefficient	st. error	$LV_{WT\_not\ harmful}$ Coefficient	st. error	$LV_{having\ opinion}$ coefficient	st. error
Mean						
ASC_wind energy	1.8756***	0.3479	0.8500***	0.2882	1.4324***	0.3566
ASC_solar energy	3.8481***	0.3518	−0.425	0.2894	1.5075***	0.3329
ASC_biomass energy	0.7567**	0.3638	−0.2284	0.2705	1.2577***	0.3585
Distance	0.3658***	0.0566	−0.1116**	0.0564	−0.0396	0.082
REPs size_medium	0.0621	0.132	−0.0083	0.1151	0.0479	0.164
REPs size_large	−0.1393	0.1545	−0.0077	0.1332	0.0813	0.197
REPs number	0.0126	0.0441	−0.0051	0.0396	0.0014	0.06
Landscape	0.8235**	0.3232	−0.1608	0.3149	−0.6503	0.4226
HVTL	0.2213**	0.0947	0.2122**	0.0939	−0.1575	0.1308
Cost	−3.1223***	0.0949	0.2721***	0.0696	−0.2577***	0.087
Standard deviation						
ASC_wind energy	4.8405***	0.3813				
ASC_solar energy	5.0300***	0.3852				
ASC_biomass energy	4.2925***	0.3993				
Distance	0.5060***	0.0824				
REPs size_medium	0.7119***	0.1718				
REPs size_large	0.8134***	0.1842				
REPs number	0.2500***	0.064				
Landscape	2.5319***	0.5075				
HV transmission lines	0.7623***	0.1716				
Cost	1.3228***	0.0894				

Note: ***, **, * indicate 1%, 5%, and 10% significance level, respectively.

Table 8
Measurement component – the first step: Opinions vs. lack of opinions about potential wind turbine external effects (binary probit: 1 = "*I don't know*"; 0 = otherwise).

measurement equation dependant variable:	1 health externality coeff.	st. err.	2 disturbance externality coeff.	st. err.	3 landscape externality coeff.	st. err.	4 environmental externality coeff.	st. err.
$LV_{WT\_not\ harmful}$	−0.3328	0.2804	−0.2955	0.3365	−0.3432	0.2144	−0.4052*	0.2253
$LV_{having\ opinion}$	−1.4880***	0.3374	−1.8118***	0.5615	−0.8189***	0.2322	−1.2530***	0.2506
Cutoff 1	2.6107***	0.4112	3.3509***	0.7878	2.7507***	0.3266	1.9617***	0.2446

Note: ***, **, * indicate 1%, 5% and 10% significance level, respectively.

Table 9
Measurement component – the second step: Attitudinal statements about potential wind turbine external effects (ordered probit: 1 = strong disagreement and 4 = strong agreement with the statement).

measurement equation dependant variable:	5 health externality coeff.	st. err.	6 disturbance externality coeff.	st. err.	7 landscape externality coeff.	st. err.	8 environmental externality coeff.	st. err.
$LV_{WT\_not\ harmful}$	−1.4319***	0.1175	−1.6947***	0.1669	−0.6735***	0.0616	−1.4473***	0.1205
$LV_{having\ opinion}$	−0.0607	0.2595	−0.2876	0.3219	0.0318	0.1395	−0.126	0.2886
Cutoff 1	−1.4861***	0.1113	−2.4944***	0.1996	−0.7004***	0.0605	−1.6751***	0.1253
Cutoff 2	0.5226*	0.2715	−0.4938	0.426	0.7955***	0.1785	0.1134	0.3071
Cutoff 3	2.0114***	0.7163	1.4549**	0.6855	1.5864***	0.2015	1.8150***	0.3298

Note: ***, **, * indicate 1%, 5% and 10% significance level, respectively.

Table 6). Identifying these effects was a main reason for employing the HMXL approach in this study; finding their magnitudes and decomposing attitudes into two dimensions of *"WT not harmful"* and *"Having opinion"* would not be possible otherwise. Therefore, based on the framework proposed by Vij and Walker (2016), the use of the HMXL model was justified, as the obtained insights can be used to inform the policy, and they could not be derived from a simpler model such as mixed logit. We found that effects of latent variables on respondents' preferences were highly significant and explained a significant portion of the preference heterogeneity as presented in Table 10.

The significant and positive coefficient of interaction of $LV_{WT\_not\ harmful}$ with ASC for wind energy indicates that respondents with weaker belief about the negative effects of wind turbine activity were more in favour of wind power development in Poland over the FSQ. Additionally, we observed that respondents who were less convinced about wind turbine external effects did not mind having REPs closer to their place of residence and were more in favour of HV transmission lines. Regarding the cost attribute, its interaction with $LV_{WT\_not\ harmful}$ is significant and positive, indicating that respondents who did not believe in the negative effects of wind turbine activity were more sensitive to cost.[12] The effect of $LV_{WT\_not\ harmful}$ on the WTP is therefore a combination of increased sensitivity to cost and change in preferences for a given attribute (if a given interaction in Table 7 is significant).

The significant and positive coefficients of the interaction of $LV_{having\ opinion}$ with ASCs for wind, solar, and biomass energy development suggest that respondents who generally had an opinion about potential

[12] The cost parameter is log-normally distributed. The effect of this attribute is calculated as a value of natural exponential function.

Table 10
Percentage of variance of preference heterogeneity explained by latent variables.

Labels and attributes	Percentage of explained variance
ASC_wind energy	10.59%
ASC_solar energy	8.84%
ASC_biomass energy	8.15%
Distance	5.19%
HV transmission lines	10.73%
Cost	7.43%

Note: We report the results only for the attributes for which an interaction with at least one latent variable is significant.

Table 11
Median WTP estimates in zł per month per household.

	Median	St. error
ASC_wind energy	24.44***	5.77
ASC_solar energy	56.45***	7.36
ASC_biomass energy	9.65**	4.75
Distance (in km)	5.66***	1.22
REPs size_medium	0.93	1.55
REPs size_large	−1.89	2.03
REPs number	0.09	0.48
Landscape (in shares)	9.15**	3.89
HV transmission lines	2.64**	1.23

Note: ***, **, * indicate 1%, 5% and 10% significance level, respectively. Nominal exchange rate in January 2016: 1 Euro = 4.36 zł.

wind turbine effects (i.e., they either agreed or disagreed that such effects exist) would like to have input on the renewable energy development in their neighbourhood. They were more interested in the subject and/or more informed about it.

We also calculated a median WTP which gives the implied monetary valuation of changes in attributes.[13] In the case of continuous attributes (*Distance, REPs number*, and *Landscape*), a positive median WTP indicates how much respondents would be willing to pay for a unit change of the given attribute; whereas, in the case of discrete attributes, it indicates how much the respondents would be willing to pay for a change from its base level. As shown in Table 11, the respondents displayed a positive WTP for development of wind and solar power compared with FSQ, and they were willing to pay to have energy production sites farther away from their place of residence and to protect the landscape in their neighbourhood from those investments. The respondents also revealed a positive WTP for building new transmission lines underground. In Table A2 in the Appendix we provide median WTP estimates from a regular mixed logit model for comparison. These estimates are not significantly different from the ones reported in Table 11.

To illustrate the differences in preferences between respondents with different levels of beliefs about wind turbine negative effects, we simulated the median WTP and its 90% confidence interval associated with our choice attributes for respondents with different levels of $LV_{WT\_not\ harmful}$.[14] The results for significant WTPs are provided in Fig. 3. For the electricity generated from the sun and biomass, as well for the attributes *Distance* and *Landscape*, we obtained a decreasing relationship, which stemmed from a negative sign of interaction of a given attribute with $LV_{WT\_not\ harmful}$ and/or the increased sensitivity to cost (Table 7). For the wind energy and *HV transmission lines*, we observed a positive relationship due to a positive sign of a given interaction, even though cost sensitivity was also higher.

6. Conclusions and discussion

Similarly to other European countries, Poland faces significant challenges related to changes in energy policy. As an EU member state, Poland is required to adjust its energy strategies to meet the European energy and climate targets. The Polish energy sector is traditionally based on fossil fuels – hard and brown coal – Poland is consequently a major emitter of greenhouse gases. With regard to CO_2 from fuel combustion in the energy sector, Poland is Europe's second highest emitter, after Germany. According to Energy-Climate Package, the development of renewable energy is a key component of the energy strategy in moving towards a low-carbon economy.

Renewable energy production in Poland is relatively new, and its development has led to controversies within the country. For example, the expansion of wind farms in recent years prompted numerous protests by local populations, leading to the creation of associations that oppose the development of wind energy in Poland. It should be emphasised, however, that the protests did not attract a lot of people. However, locally anticipated negative effects of REPs may lead to not building them at all in certain locations or building them in locations with suboptimal conditions, such as low levels of wind or insulation, for example. The local opposition may contribute to changes in the law concerning renewable energy development and slow investments in this sector (see e.g. Cass and Walker, 2009 or Sokołowski, 2017). The way in which beliefs about the negative effects are taken into account therefore has a critical influence on the expansion of renewables.

This study adds to the growing body of literature focusing on the non-market valuation of renewable energy externalities. We examined individuals' preferences for different REPs and for different spatial regulations regarding, for example, the distance of renewable electricity production sites to residential areas or the number of REPs in the vicinity of respondents' place of residence. Our results indicate that, on average, respondents preferred electricity from solar energy over wind energy, and electricity from wind energy over electricity from biogas within 10 km of their residence. Similar evidence is provided inter alia by Oehlmann and Meyerhoff (2016) and Borchers et al. (2007). Solar energy might be preferred because the solar power plants are noiseless during operation and they have relatively low impact on wildlife. In terms of spatial regulations we found out that the distance to REPs seems to be the most important attribute for respondents. This finding aligns with what some other studies on externalities have found, especially for wind power (e.g., Knapp and Ladenburg, 2015). These results can be used to support decision making concerning the question of what kind of renewable energy develop and where and how to place REPs in order to minimise externalities at the societal level.

In this article, we shed light on whether heterogeneity in the preferences on renewable energy extension in Poland might be explained by the beliefs about negative effects of wind turbines, which are the

[13] The median WTP was simulated in a two-step procedure. In the first step, model parameters are drawn from normal distribution, with a mean equal to their estimated values and covariance matrix equal to inverse of hessian. In the second step, conditional on the draw from the first step, random parameters and latent variables are drawn from their assumed distributions. Then, WTP is calculated as a ratio of parameter for given attribute and the cost (as per Eqs. (2) and (3)). In the first step we generate 20,000 draws and for each of them we generate 10,000 draws in the second step. The median is then calculated over 10,000 draws, and 20,000 draws from the first step are used to obtain confidence intervals.

[14] The mean of the $LV_{WT\_not\ harmful}$ is normalized to zero. The increased uncertainty for higher values of latent variable in Fig. 3 (depicted by wider confidence intervals) is due to the fact that coefficients for interactions between latent variable and attributes are multiplied by the value of latent variable. As there is some uncertainty in estimates of these coefficients, upon multiplication by some higher value uncertainty increases.

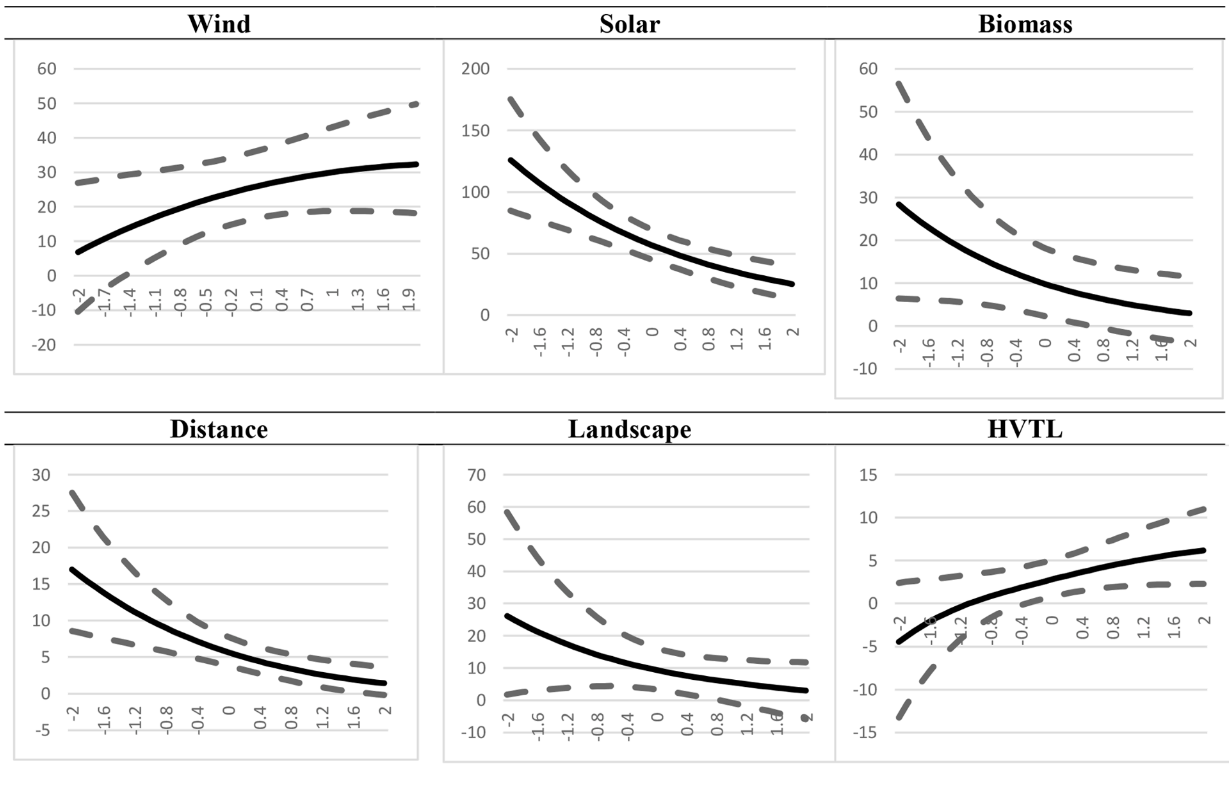


Fig. 3. Median WTP (zł) of respondents with varying strength of the latent beliefs that wind energy does not cause negative effects.

predominant source of renewable energy generation in the country. Although protests against wind turbine expansion in Poland have used the argument that wind energy is harmful to human health or destroys the landscape, our survey revealed that the public does not broadly hold the opinion that wind turbine activity generates negative effects. The obtained results indicate that the visual impacts of windmills was perceived by respondents as the least onerous factor, which contradicts the results of some previous studies (e.g., Mattmann et al., 2016; Betakova et al., 2015; Wolsink, 2007). This finding might be explained by the relatively low density of wind turbines in Poland compared with some other European countries.

For the main objectives of our analysis, we found distinctive effects of beliefs about the negative effects of wind turbines on respondents' preferences concerning renewable energy development. Our results indicate that latent beliefs that wind power is not harmful enhanced respondents' preferences for implementing wind energy projects. Apart from that, our findings add to the literature in which opposition to development of renewable energy is typically characterised by the "not in my back yard" concept (Devine-Wright, 2005; Van der Horst, 2007). We found that respondents who were less convinced about wind turbine negative effects did not mind having renewable energy sites closer to their place of residence in general. This intrinsic belief appeared to be significantly correlated with respondents' marginal utility of money. Not believing in the negative effects of wind turbine activity increased sensitivity to cost and simultaneously lowered respondents' WTP to avoid renewable energy externalities.

The results obtained with HCMs can be potentially useful for policymakers. Knowing that beliefs influence behaviour, it would seem rational to influence behaviour via promotional or informational campaigns targeted at people's most important concerns, rather than changing their behaviour directly via processes such as regulations or pricing policies (Kroesen et al., 2017). For example, the significant effect of the latent variable on individuals' WTP for the increased distance to residential areas means that an educational campaign targeted at changing individuals' beliefs about the harmfulness of wind turbines could actually affect residents choices.

The methodological novelty of this study arises from the treatment of *"I don't know"* responses to the attitudinal statements. We employed a two-part model for attitudinal statements which allowed us to separately analyse the effect of having any opinions about wind turbine external effects and the effect of holding beliefs that wind energy generation is harmful. This approach allowed us to avoid strong assumptions regarding the treatment of *"I don't know"* answers, such as assuming that they are equivalent to the middle value on the Likert scale.

Our results suggest that respondents who held opinions about wind turbines' negative effects, regardless of whether they believed or denied that such effects exist, wanted to have input on renewable energy development in their neighbourhood. Having an opinion about wind turbine externalities enhanced respondents' preferences for implementing a specific renewable energy project (wind turbines, solar energy, or energy from biomass), rather than sticking with the business-as-usual option represented by a general plan for renewable energy development without a specific focus on one of the three types of renewable energy sources. The relationship of *"I don't know"* answers to the attitudinal statements with the choice of status quo option in the CE may imply not only respondents' indecision suggested by, for example, Kroh (2006) and Iannario et al. (2017), but also indicate a lower commitment to making decisions about common issues.

More research is needed to investigate the generalizability of our results. It would be interesting to see if a similar pattern of behaviour exists in countries where renewable energy is more developed. Additionally, a better understanding of the socio-demographic profile of respondents with differing latent traits would help in designing renewable energy policy in a way that minimises social opposition. Finally, deeper insights into people's personality characteristics might help to explain better public support or rejection for specific renewable energy generated from the different sources.

CRediT authorship contribution statement

Anna Bartczak: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing. **Wiktor Budziński:** Methodology, Formal analysis, Investigation, Writing – original draft. **Bernadeta Gołębiowska:** Investigation, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Anna Bartczak, Wiktor Budziński, Bernadeta Gołębiowska

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2021.105530.

Appendix

Table A1

Table A1
Results of MXL.

Discrete choice component	*Mean* coefficient	st. error	*St. dev.* Coefficient	st. error
ASC_wind energy	1.8747***	0.3294	5.0523***	0.39
ASC_solar energy	3.8438***	0.3312	5.1279***	0.389
ASC_biomass energy	0.7964**	0.3489	4.3317***	0.3973
Distance	0.3660***	0.0563	0.5173***	0.0834
REPs size_medium	0.082	0.1307	0.7117***	0.1714
REPs size_large	−0.1262	0.1507	0.8056***	0.1948
REPs number	0.0092	0.0434	0.2984***	0.097
Landscape	0.7794**	0.3161	3.1173***	0.9127
HVTL	0.2358**	0.0936	0.9473***	0.2735
Cost	−3.1246***	0.0927	1.3542***	0.0911

Table A2
Comparison of median WTP estimates (in zł per month per household) from the HMXL and the MXL.

	Median WTP HMXL	Median WTP (MXL)
ASC_wind energy	24.44***	23.31***
ASC_solar energy	56.45***	55.82***
ASC_biomass energy	9.65**	9.07**
Distance (in km)	5.66***	5.54***
REPs size_medium	0.93	0.93
REPs size_large	−1.89	−1.83
REPs number	0.09	0.09
Landscape (in%)	9.15**	8.14**
HV transmission lines	2.64**	2.67**

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