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PARTICIPATORY DEMOCRACY IN QUESTION: THE CASE OF “THE SEA IN DEBATE”

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Participatory democracy in question: The case of "The Sea in Debate"

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Abstract: While participatory democracy invites all citizens to take part directly in the decision-making process, the selection of participants in public debates is a critical issue for the legitimacy of the resulting public choices. This paper examines this question in the context of the national public debate on offshore wind energy held in France in the first quarter of 2024. We study an original survey measuring spatial preferences for offshore wind energy in which both participants in the public debate and respondents from the general population were simultaneously surveyed. We find large differences between the two groups of respondents in terms of gender, age, and education, as well as in their spatial preferences for wind farm locations. Using an entropy balancing approach, we reject the hypothesis that these differences in spatial preferences are due to composition effects. These findings underscore the need for policymakers to exercise caution when interpreting the outcomes of public debates.

Keywords: participatory democracy; spatial preferences; offshore wind energy; discrete choice experiment; entropy balancing

JEL Classification: D7, Q51

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1. Introduction

In many democratic societies, direct citizen involvement in public decision-making has increasingly been viewed as a core component of democratic governance. This broad set of practices, commonly discussed under the heading of participatory democracy, includes referendums, public consultations, citizens' assemblies, and other mechanisms intended to engage people beyond representative channels (Smith, 2009; Towfigh et al., 2016). Proponents argue that such instruments can increase the legitimacy of public decisions by widening the range of voices heard and improving transparency (Aragonès and Sánchez-Pagés, 2009; Fung, 2006). At the same time, participatory processes are increasingly used to inform spatially sensitive public choices, such as the development and siting of new infrastructure, where local opposition or support can determine whether projects proceed.

A well-documented, albeit under-examined, challenge within this broad agenda is the problem of selection and representation. When participation is voluntary and recruitment is non-random, who takes part matters. A growing body of literature highlights that participatory mechanisms often suffer from systematic biases, attracting participants who are not representative of the general public (Williamson, 2014; Griffin et al., 2015; Einstein et al., 2019). In particular, studies consistently find an over-representation of individuals with higher socio-economic status, stronger political interest, and more extreme views (Verba et al., 1995; Rolheiser and Saiz, 2020; Kübler and Rochat, 2024). Furthermore, as García-Espín and Lancha-Hernández (2025) argue, even formalized participatory institutions such as citizen advisory councils can exhibit class and cultural biases.

Such selection can yield samples whose socio-demographic composition and preferences systematically differ from those of the general population. If policy decisions rely on inputs from these participatory processes, they may reflect the views of the most mobilized or informed participants rather than those of the general population (OECD, 2020; Monnery and Wolff, 2023). Despite the practical importance of this issue, empirical work that directly compares the views of participants in real public consultations with those of a representative population remains scarce. A possible reason is that many large consultations omit basic socio-demographic information necessary to enable such comparisons (Lironi and Peta, 2017).

We study this selection issue in the policy-relevant context of offshore wind siting. Offshore wind siting offers an instructive case, as it raises multiple place-based concerns, including visual impacts, ecological effects, and local economic linkages. These features make offshore wind highly salient for local communities and policymakers. At the same time, the spatial character of the choices makes them particularly susceptible to selection. In particular, coastal residents, stakeholders in marine industries, or environmentally engaged individuals may be over-represented among participants and thereby influence consultation outcomes (Jami and Walsh, 2017).

Our empirical setting focuses on the national public debate on maritime planning and offshore wind energy held in France during the first quarter of 2024, specifically on one element of that debate consisting of an online public consultation[1]. We conducted a survey including a Discrete Choice Experiment (DCE) on two different samples. On the one hand, we deployed

[1] In what follows, we use public debate to refer to this online public consultation.

an online questionnaire measuring spatial preferences for large-scale offshore wind on the public debate website. On the other hand, the same questionnaire was administered to a quota-based representative sample of the French population by a polling company. This simultaneous, identical measurement on a self-selected public debate audience and a representative sample allows us to isolate selection patterns. Specifically, we assess whether observed differences in stated preferences for offshore wind farms are due to composition effects or to preference divergences tied to the institutional context of participation.

Our empirical strategy proceeds in two steps. First, we document how participants in the public debate differ from the general population in terms of the following observable characteristics: gender, age, education, coastal residence, and self-reported maritime knowledge. Second, we study whether composition effects can account for preference gaps by reweighting the debate sample using entropy balancing so that observable characteristics match those of the general population (Hainmueller, 2012). We rely on weighted versions of discrete choice models to examine differences between the two groups of respondents in their preferences for wind farm criteria. We further provide a simulation-based diagnostic that explores whether a wide range of plausible reweighted compositions could reconcile the two groups' choices.

This paper contributes to the literature in three main ways. First, it provides a detailed assessment of selection into a large-scale online public debate and documents how participants differ from the general population. Second, it evaluates whether preferences elicited inside a participatory institutional context diverge from those obtained in a representative survey and whether such differences persist after accounting for composition effects. Third, it introduces a methodological approach combining entropy balancing, DCE estimation, and simulation, offering a practical framework for interpreting consultation data.

Our analysis is also embedded within the literature on stated-preference DCEs. While numerous studies have primarily examined how administration modes influence responses (Determann et al., 2017), we test whether stated preferences vary depending on the institutional context in which the DCE is conducted, namely whether it is part of a public debate or administered as an independent population survey. Furthermore, unlike previous studies that either combine DCEs with attribute ranking tasks (Balcombe et al., 2014) or compare DCEs with alternative ranking tasks in which respondents rank full profiles (Caparrós et al., 2008), we assess whether ranking attributes and their levels yields similar results to those obtained through the DCE.

The findings have important implications for both policy design and participatory practice. If participatory exercises systematically over-represent particular groups or produce preference patterns that cannot be explained by composition effects, policymakers should be cautious about using raw consultation results as measures of general public sentiment. The remainder of the paper is organized as follows. Section 2 describes the institutional context, questionnaire design, and empirical strategy. Section 3 presents the main results from the ranking and DCE analyses, as well as the simulation exercise. Section 4 discusses implications for participatory practice and policy, and Section 5 concludes.

2. Methodology

2.1. Context

To meet ambitious greenhouse gas emission reduction targets, many developed countries have rapidly expanded renewable energy. In response to increasing demand, wind power has played a central role in this transition over the past decade in major economies, including China, the United States, Germany, and France. By the end of 2024, total global wind power capacity had exceeded 1,136 gigawatts (GW), including 83 GW of offshore capacity, according to the Global Wind Energy Council. Most new capacity installed in 2024 was onshore (106.9 GW out of 114.9 GW). Offshore wind is nonetheless increasingly seen as an important contributor to decarbonization goals (Díaz and Guedes Soares, 2020).

France provides a particularly informative case for studying public participation in maritime planning. First, the country has large, nationally stated ambitions for offshore wind, with an objective of roughly 50 offshore parks and 45 GW by 2050. Second, France already hosts several operational and planned projects that concentrate local economic and environmental stakes. There are currently four offshore wind farms in operation (Fécamp, Bay of Saint-Brieuc, Saint-Nazaire, and Faraman-Port-Saint-Louis-du-Rhône) and nineteen projects are underway. Third, France has an established, formal mechanism for nationwide public debate run by an independent body, the National Commission for Public Debate (*Commission Nationale du Débat Public,* CNDP). As a result, decisions about offshore wind in France combine national targets with local conflicts over coastal uses when deciding on the location choices for future wind farms. These features make France a relevant laboratory for comparing participatory outputs with representative public opinion.

At the request of the Ministry for Energy Transition, the General Secretariat for the Sea, and RTE (France's Transmission System Operator), the CNDP organized a public debate on maritime planning entitled The Sea in Debate (*La Mer en Débat*)[2]. The public debate ran from 20 November 2023 to 26 April 2024. It aimed to gather citizens' views on marine renewable energy and maritime space management. It combined hundreds of events and multiple participation modes, such as public meetings, online consultations, roundtables, and surveys. It was explicitly designed to feed into policy-making. The CNDP's role as an independent, formal forum for public participation gives the debate institutional weight, with contributions being collected and communicated to decision-makers.

This institutional setting created a unique empirical opportunity. The same questionnaire was published on the CNDP debate website (a presumably self-selected audience) and, simultaneously, administered by a polling institute to a quota-based representative sample of the national population. The identical, concurrent administration to both a participatory audience and a representative sample allows for a direct comparison between preferences expressed in a participatory venue and those from a representative sample. This comparison matters for policy. It shows whether and how the views produced by participatory processes

[2] For further information, see https://www.debatpublic.fr/la-mer-en-debat. Participants were invited to contribute through the following link: https://participer-la-mer-en-debat.cndp.fr/. An "Express your preferences" button was available during the public debate, but was removed once it ended.

differ from broader public opinion, and whether participatory democracy can effectively contribute to maritime policy decisions.

2.2. Description of the survey

Selection of attributes and levels

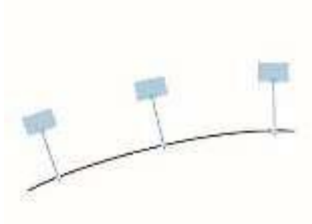
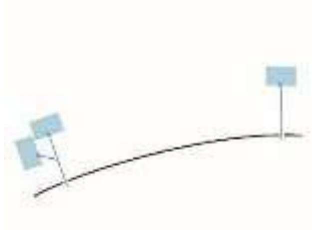
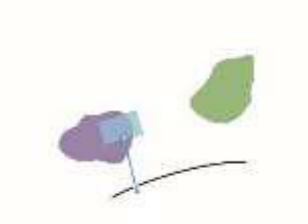
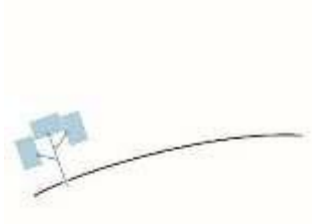
A team of economists and geographers (the authors of this paper) designed the questionnaire to reduce respondent burden by keeping it short, limiting the number of choice tasks and attributes, and adding pictograms to support comprehension. Four attributes were selected based on existing literature (Mattmann et al., 2016; Joalland and Mahieu, 2023), and discussions with experts: i) distance from the coast, ii) overlap with other issues (such as protected natural areas and fishing zones), iii) connection to the territory (for instance, location of wind turbine manufacturing), and iv) concentration or dispersion of wind farms along the coastline. The selection was guided by their expected influence on individual preferences and their potential to inform policy-makers in choosing wind farm locations. These attributes were reviewed by CNDP officials to confirm their relevance and assessed through semi-structured interviews with maritime stakeholders (mainly students, researchers, and members of civil society) to ensure their credibility. In addition, a pre-test was conducted to ensure that the questions were clear and meaningful.

In the literature, both meta-analyses and recent empirical studies show that preferences are highly sensitive to turbine visibility and perceived ecological impacts (Joalland and Mahieu, 2023; Cranmer et al., 2023). Accordingly, our first two attributes capture these effects. The inclusion of overlap with either protected natural areas or fishing zones introduces a novel dimension, as previous studies have rarely considered these simultaneously (Börger et al., 2015; Kim et al., 2019; Klain et al., 2020). The third attribute represents local economic linkages, such as the domestic manufacturing of turbines, and relates to the importance of local benefits for public acceptance. Socioeconomic payoffs are increasingly recognized as key determinants of support for offshore wind (Parton et al., 2024). Finally, the fourth attribute concerns the spatial concentration of wind farms along the coastline. This aspect has been largely ignored in previous DCEs or contingent valuation studies, which typically valued a single project, exceptions being Joalland and Mahieu (2023), Cranmer et al. (2023), Lee et al. (2023), and Ladenburg et al. (2024).

The questionnaire was administered exclusively online. To simplify visual comprehension and maintain neutrality across respondents, pictograms were used to represent each attribute level. These pictograms were then combined to generate the alternatives presented to respondents. Table 1 provides the complete set of pictograms used in the DCE, along with a brief description. Information on attributes and their levels was presented in a clear, factual, and easily understandable way, consistent with current knowledge.

The distance of wind farms from the coast (low, medium, high) affects both installation and connection costs, as well as visual impacts and electricity production. The overlap with existing uses (none, protected natural areas, fishing zones) may influence fishing activities and marine ecosystems, with potentially positive or negative effects. The territorial connection (local, national, international) captures where economic benefits, such as job creation during construction and maintenance, are expected to occur. Finally, the concentration of wind farms along the coastline (low, medium, high) reflects the spatial organization of projects, which may affect other maritime activities such as recreation and tourism. Table 1 presents the pictograms and the corresponding coding for each attribute and level.

Table 1. Description of pictograms and codification (in brackets)

Distance	Overlap	Territorial link	Concentration
			
The distance from the coast is low (*low*)	There is no overlap with fishing zones and protected natural areas (*none*)	The link with the territory is mostly local (*local*)	The concentration of parks along the coast is low (*low*)
			
The distance from the coast is intermediate (*medium*)	There is overlap with protected natural areas (*protected natural areas*)	The link with the territory is mostly national (*national*)	The concentration of parks along the coast is intermediate (*medium*)
			
The distance from the coast is high (*high*)	There is overlap with fishing zones (*fishing zones*)	The link with the territory is mostly international (*international*)	The concentration of parks along the coast is high (*high*)

Source: authors' representation.

Structure of the questionnaire

The questionnaire was divided into four sections. After explaining that the results of the survey would be communicated to public policymakers, the first section asked questions about gender, age, education level, and place of residence. A question on income was deliberately excluded, as it was deemed too intrusive. Its omission was intended to avoid discouraging some respondents from completing the survey. The second section provided general information on offshore wind farms, including the target of 50 wind farms and 45 GW of production by 2050. A description of the attributes and their levels was also included.

The third section aimed to measure respondents' preferences for the location of future wind farms using two approaches. On the one hand, a double-ranking exercise required respondents to rank the four attributes and then the three levels within each attribute. On the other hand, participants completed a DCE exercise, in which they were asked to choose one option from three, repeated over six choice tasks. In the fourth section, respondents reported their knowledge of wind farms and maritime issues, as well as their support for the installation of 50 wind farms along the French coasts by 2050.

Experimental design

In the DCE module, each respondent faced six choice sets, each containing three alternatives, yielding a total of 18 alternatives. These tasks were organized into two blocks of 18 scenarios, and respondents were randomly assigned to one of the blocks. The experimental design followed an efficient design approach using "non-informative priors" (Bliemer and Rose, 2024). Sign priors were imposed for all attributes, except for the concentration attribute, for which the priors were set to zero, as we had no a priori expectation on which level would be preferred. Compared to an orthogonal design, an efficient design avoids dominated alternatives and thus compels respondents to make substantive trade-offs, producing richer information on spatial preferences. The two blocks were identical for the CNDP sample and the general population survey. Full details of the attribute combinations are provided in Table A in the Appendix.

Following Bliemer and Rose (2024), we adopted an unlabeled design as our objective was to compare the relative importance of attributes rather than to forecast market shares or demand elasticities. We deliberately excluded a status quo (SQ) option, as such an option is mainly useful when respondents might diverge from a reference policy. In our case, the government's 45 GW target is non-negotiable, and the public debate explicitly assumed that new wind farms would be developed. Consequently, including a SQ option corresponding to no new wind farms would have lacked policy relevance and could have confused respondents, by introducing a hypothetical scenario inconsistent with the policy framework.

From a methodological perspective, omitting the SQ option has two main implications. First, it allows respondents to focus on the relative trade-offs among attribute levels rather than on the binary choice between action and inaction, thereby improving the precision of marginal estimates for each attribute and reducing cognitive burden. Second, since the DCE aimed to compare preferences between two samples under the same policy assumption, excluding the SQ option ensured identical framing and avoided potential heterogeneity in the interpretation of a baseline alternative. While including an SQ option is often useful for deriving welfare measures such as the willingness to pay for policy changes, this was not the purpose of the present study. Our design therefore prioritizes internal consistency and comparability between the public debate and the representative survey samples. Finally, avoiding the SQ option facilitates the comparison between the DCE task and the ranking task.

In the ranking exercise, each respondent completed two separate tasks. First, they ranked the four attributes from most to least preferred. Then, for each attribute, they ranked its three possible levels from most to least preferred, resulting in four additional rankings. To control for order effects due to fatigue, the ranking module and the DCE module were presented in random order across respondents. Additional details can be found in Wolff et al. (2024).

Survey administration

The questionnaire, developed in the fall of 2023 and formatted using the LimeSurvey platform, was posted online on the CNDP website in early 2024. Before its launch, we conducted semi-structured interviews and a pre-test with 30 individuals to ensure the questionnaire's relevance and comprehensibility. For nearly four months, visitors to the CNDP's public debate The Sea in Debate were able to participate in the survey by clicking on an "Express your preferences" button. Responses within this public debate were collected from January 10 to April 26, 2024.

In parallel, and in order to assess the selection of participants in The Sea in Debate website, the same questionnaire was administered online by the survey company Easypanel to a quota-based representative sample of the national population. Easypanel is a company specializing in online market research. It relies on a panel of more than 120,000 members across mainland France who have volunteered to take part in online surveys. Panel members are compensated for their participation when they respond to internet-based questionnaires. The survey used a quota sampling method with quotas defined only on gender and age (benchmarked to INSEE). Although representativity was enforced only on these two criteria, the large size and broad geographic coverage of the Easypanel panel also tend to improve coverage across other geographic and socio-economic dimensions. Nevertheless, deviations from the general population on other observables cannot be entirely excluded. Data collection took place from March 19 to March 28, 2024. In total, we obtained two samples of individuals who completed the same questionnaire about their spatial preferences for the location of wind farms: 966 participants in the public debate and 2,401 respondents from the general population.

Two exclusion criteria were applied to both samples. First, individuals who did not identify as male or female were excluded to maintain comparability with official demographic data from INSEE, which defines gender in binary categories for statistical representativeness (16 observations in the public debate and 3 in the national survey). Second, respondents under the age of 18 or over the age of 76 were removed (14 in the public debate and 8 in the national survey). These exclusions reduced the public debate sample from 966 to 936 and the general population sample from 2,401 to 2,390. While these restrictions slightly narrow the population scope, they enhance the internal consistency and comparability of both samples. Moreover, their impact on overall representativeness is expected to be negligible, given the very small number of excluded cases.

2.3. Empirical strategy

Entropy balancing

Spatial preferences between respondents to the public debate and those from the general population may differ for two non-mutually exclusive reasons. Individuals may vary in their observable characteristics, but they may also have different preferences even when endowed with the same characteristics. To understand the extent to which differences in characteristics influence spatial preferences, we rely on entropy balancing, which is a multivariate reweighting method (Hainmueller, 2012; Hainmueller and Xu, 2013; Jann, 2021). Given two distinct groups, this approach allows us to make them perfectly identical based on selected moments (mean, variance, …) of a set of explanatory variables used for the comparison.

We opted for entropy balancing rather than alternative reweighting or matching approaches, such as propensity score matching, coarsened exact matching, or inverse probability weighting (see Hainmueller, 2012). This choice is motivated by several advantages. First, entropy balancing ensures an exact balance of selected covariates by directly matching specified moments across groups. The balance constraints are taken into account directly in the reweighting process. Second, unlike traditional matching methods, it avoids the loss of observations by adjusting weights smoothly rather than discarding units. Third, it is flexible and compatible with all econometric models that can be estimated in a weighted version. This reduces model dependency, which is helpful in our setting where we estimate weighted discrete choice models. Fourth, it is computationally efficient due to the convex nature of its optimization problem and doubly robust (Zhao and Percival, 2017).

Let $\mathcal{D}$ denote the sample of respondents from the public debate website, $\mathcal{P}$ the sample of participants from the general population survey, and $\mathcal{PD} = \mathcal{P} \cap \mathcal{D}$ the combined data set. Let d_i be a binary variable such that $d_i = 1$ if individual i belongs to sample $\mathcal{D}$ and $d_i = 0$ otherwise, with $i = \{1, \dots, N\}$. Sample $\mathcal{D}$ includes $N_{\mathcal{D}}$ observations and sample $\mathcal{P}$ includes $N_{\mathcal{P}}$ observations. Let $w_i = 1$ represent the initial weight of each respondent in both samples, so that $\sum_{i \in \mathcal{D}} w_i = N_{\mathcal{D}}$ and $\sum_{i \in \mathcal{P}} w_i = N_{\mathcal{P}}$. Let X_i be a vector of observable individual characteristics. The objective of entropy balancing is to adjust the sample $\mathcal{D}$ so that the reweighted moments of X_i match those in sample $\mathcal{P}$. Let $\hat{\mu} = \frac{1}{N_{\mathcal{P}}} \sum_{i \in \mathcal{P}} X_i$ denote the empirical moments of X_i in sample $\mathcal{P}$. The task is then to compute new weights $\widehat{\omega}_i$ for individuals in sample $\mathcal{D}$. Entropy balancing consists of estimating α and β such that:

$$\begin{cases} \hat{\mu} = \frac{1}{N_{\mathcal{P}}} \sum_{i \in \mathcal{D}} \widehat{\omega}_i X_i \\ \sum_{i \in \mathcal{D}} \widehat{\omega}_i = N_{\mathcal{P}} \\ s.t. \widehat{\omega}_i = \exp(X_i{}'\hat{\beta} + \hat{\alpha}) \end{cases} \tag{1}$$

It is possible to account for higher-order moments by adding polynomial terms (such as a quadratic term for the variance) to the vector X_i. In its general form, entropy balancing can be expressed as a system of moment equations (Jann, 2021), so the parameters α and β can be estimated in two steps. First, the coefficients $\hat{\beta}$ are obtained by minimizing the loss function:

$$\mathcal{L} = \ln[\sum_{i \in \mathcal{D}} \exp((X_i - \mu)'\beta)] \tag{2}$$

using an iterative optimization algorithm such as Newton-Raphson. Second, once $\hat{\beta}$ is known, the constant $\hat{\alpha}$ can be computed as:

$$\hat{\alpha} = \ln(N_{\mathcal{P}}) - \ln(\sum_{i \in \mathcal{P}} \exp(X_i{}'\,\hat{\beta})) \tag{3}$$

In practice, we apply entropy balancing by reweighting the public debate sample so that its distribution of observable characteristics becomes identical to that of the general population sample.

Estimation of weighted discrete choice models

To examine how individual characteristics influence spatial preferences, we estimate discrete choice models. We considered four different model specifications to analyze respondents' choices in the DCE: the conditional Logit model (McFadden, 1974), the mixed Logit model with uncorrelated random parameters (McFadden and Train, 2000; Hole, 2007; Train, 2009), the mixed Logit model with correlated random parameters (Mariel and Meyerhoff, 2018), and the latent class Logit model (Hensher and Greene, 2003; Pacifico and Yoo, 2013). The external appendix outlines the advantages and limitations of each specification and presents the corresponding estimates. In the main analysis, we focus on the mixed Logit model with uncorrelated random parameters, which accounts for individual-level heterogeneity in preferences. The utility that individual i derives from alternative j is:

$$U_{ij} = Z_{ij}\theta_i + \varepsilon_{ij} \tag{4}$$

where Z_{ij} is a vector of observed levels associated with the four attributes for alternative j, θ_i is an individual-specific vector of parameters to be estimated, and ε_{ij} is an error term assumed to follow a type I extreme value distribution. The vector θ_i is treated as a random draw from a distribution (for instance normal), capturing unobserved heterogeneity in preferences. The choice probability that individual i selects alternative j from the choice set $\mathcal{C}_i$ is expressed as an integral over the distribution of θ:

$$p_{ij} = \int \exp(Z_{ij}\theta) \,/\, \sum_{k\in\mathcal{C}_i} \exp(Z_{ik}\theta)\, f(\theta|\Omega)d\theta \tag{5}$$

where $f(\theta|\Omega)$ is the density function of the random parameters defined by a set of parameters Ω. Unlike the conditional Logit model, the mixed Logit does not rely on the independence of irrelevant alternatives (IIA) assumption, and can flexibly account for repeated choices and correlation in unobserved utility components. To assess the extent to which preference differences persist after adjusting for composition effects, we estimate the model using the public debate sample, incorporating the entropy balancing weights $\widehat{\omega}_i$ computed in the previous step. Estimation is performed by maximizing the following weighted log-likelihood:

$$L(\theta) = \sum_i \widehat{\omega}_i \ln\big(p_i(\theta)\big) \tag{6}$$

where $p_i(\theta)$ is the probability of the observed choice made by individual i. Robust sandwich estimators are used to compute standard errors. The weights ensure that each respondent's contribution to the likelihood reflects their representativeness relative to the target population. The use of entropy balancing weights allows the estimated preferences to be interpreted as those of a counterfactual population, namely the public debate participants if they had the same observable characteristics as the general population.

Simulation-based assessment of compositional alignment

To quantify whether the observed preference differences between public debate participants and the general population can be reconciled by altering only the observable composition of the public debate sample, we implemented a large-scale simulation combined with entropy balancing and weighted inference. We proceed as follows.

First, we draw a set of target means for the observable characteristics X of participants in the public debate. Each vector $\hat{\mu}_{\mathcal{D}}$ contains 19 elements that correspond to the proportions for the categorical variables used in the regression analysis (gender, age, …). For each draw $\mathfrak{t}$ with $\mathfrak{t} = \{1; \dots; T\}$, each element of $\{\hat{\mu}_{\mathcal{D}}\}^{\mathfrak{t}}$ is generated independently from a uniform distribution $U(0,1)$ and then normalized by categorical group so that the proportions for each variable sum to one and the overall vectors represent feasible category shares. For computational feasibility, we set $T = 100{,}000$ [3].

Second, for each target vector $\{\hat{\mu}_{\mathcal{D}}\}^{\mathfrak{t}}$, we apply entropy balancing so that the average characteristics of the respondents in the public debate samples match perfectly those in $\{\hat{\mu}_{\mathcal{D}}\}^{\mathfrak{t}}$. This yields a system of weights $\{\widehat{\omega}_i\}^{\mathfrak{t}}$. In some cases, these weights do not exist: it is not always possible to find a reweighting scheme that makes the respondents comparable to the target averages $\{\hat{\mu}_{\mathcal{D}}\}^{\mathfrak{t}}$ for draw $\mathfrak{t}$. If the entropy balancing optimization does not find a feasible solution for a draw $\mathfrak{t}$, that draw is recorded as infeasible and omitted from subsequent steps.

Third, for each feasible draw, we estimate a weighted Logistic regression of the DCE choice indicator on the attribute levels Z_{iam}, where $a = \{1; 2; 3; 4\}$ indexes the four attributes and $m = \{1; 2\}$ the non-base levels. We also include interaction terms between each attribute level and the public-debate indicator d_i with $d_i = 1$ for public debate participants and $d_i = 0$ for respondents in the general population. The corresponding conditional model is:

$$\Pr(S_{ik} = 1) = \Lambda(\theta_i + \textstyle\sum_{a=1}^{4} \sum_{m=1}^{2} \gamma_{am} Z_{iam} + \sum_{a=1}^{4} \sum_{m=1}^{2} \lambda_{am} (Z_{iam} * d_i)) \qquad (7)$$

where $\Lambda(.)$ denotes the logistic function and θ_i represents an individual effect. For each feasible draw $\mathfrak{t}$, the weights are equal to 1 for respondents from the general population and to $\{\widehat{\omega}_i\}^{\mathfrak{t}}$ for participants in the public debate. We test the joint null hypothesis $H_0: \lambda_{11} = \lambda_{12} = \cdots = \lambda_{41} = \lambda_{42} = 0$ that all interaction coefficients are zero using a Wald test. If the null hypothesis is rejected, the implication is that even after reweighting the public debate sample to have the specified average characteristics $\{\hat{\mu}_{\mathcal{D}}\}^{\mathfrak{t}}$, the effects of attribute levels differ statistically between public debate participants and the general population.

Finally, it is possible to further identify which average individual characteristics increase the likelihood of alignment across the two groups. For each draw $\mathfrak{t}$, we construct a binary variable $\hbar_{\mathfrak{t}}$ such that $\hbar_{\mathfrak{t}} = 1$ when the null hypothesis $H_0: \lambda_{11} = \lambda_{12} = \cdots = \lambda_{41} = \lambda_{42} = 0$ is accepted at the 10 percent level, and $\hbar_{\mathfrak{t}} = 0$ otherwise (results are similar using a 5 percent

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[3] An exhaustive approach that enumerates all combinations of averages is not feasible. For example, even in a simplified scenario with only three variables (gender with two categories, age with four categories, education with five categories), there are about 3 million possible combinations if each average varies between 0 and 1 in increments of 0.1. This number exceeds 385 million with a step size of 0.05. Implementing such an approach would require estimating as many conditional regressions as there are combinations. For reference, estimating 5,000 weighted regressions combined with entropy balancing takes approximately 10 hours.

threshold). We then estimate a linear probability model to explain the probability $\Pr(\hbar_{\mathfrak{t}} = 1)$ with $\hbar_{\mathfrak{t}}$ as the dependent variable and the components of $\{\hat{\mu}_{\mathcal{D}}\}^{\mathfrak{t}}$ as explanatory variables.

3. Results

3.1. Selection of participants in the public debate survey

The first research question examines who participates in the public debate and how their characteristics compare with those of the general population. We begin by describing respondents to the online survey conducted via the public debate website. We consider the following characteristics: gender, age (four age groups), education (five categories), residence in a coastal department, and self-reported knowledge of offshore wind energy and maritime issues (three levels each). As shown in column 1 of Table 2, participants are predominantly male (69.2%). The average age is 42.2 years, with only 16.8% aged 60 and older. Their educational profile is highly skewed: 71.0% hold a degree above a bachelor's level, while only 8.3% report education equivalent to or below a high school diploma. Respondents also display a strong interest in maritime issues: 55.2% report good or very good knowledge of offshore wind farms, and 61.3% report good or very good knowledge of maritime issues.

Table 2. Description of samples

Variables (means)		(1) Public debate	(2) General population	(3) Difference
Gender	Male	0.692	0.488	0.204***
	Female	0.308	0.512	-0.204***
Age	18 – 29	0.246	0.172	0.074***
	30 – 44	0.365	0.264	0.101***
	45 – 59	0.221	0.290	-0.069***
	60 and over	0.168	0.274	-0.106***
Diploma	Less than high school	0.026	0.215	-0.189***
	High school	0.057	0.241	-0.184***
	Two-year college degree	0.098	0.219	-0.121***
	Three-year college degree	0.109	0.136	-0.027***
	More than three-year college degree	0.710	0.188	0.522***
Department	No seafront	0.423	0.621	-0.198***
	Seafront	0.577	0.379	0.198***
Knowledge about wind farms	Very poor	0.107	0.315	-0.208***
	Poor	0.341	0.529	-0.188***
	Good – very good	0.552	0.155	0.397***
Knowledge about maritime issues	Very poor	0.075	0.293	-0.218***
	Poor	0.312	0.505	-0.193***
	Good – very good	0.613	0.202	0.411***
Observations		936	2,390	

Source: DCE survey on wind energy, authors' calculations.
Note: column (3) reports the difference in means between the two groups. The comparisons are based on two-sample t-tests. Significance levels are 1% (***), 5% (**) and 10% (*).

A comparison with the general population (column 2 of Table 2) reveals strong selection effects. As shown in column 3, the average characteristics differ significantly between the two samples at the 1% level for all selected variables. Respondents in the general population are less likely to be male (+20.4 points) and are significantly older on average (47.5 years against 42.2 years). They are also less educated. The share of respondents with a degree beyond three years of college is 52.2 points lower in the general population (18.8% against 71.0%). Participants in the public debate more often live in a coastal department (+19.8 points) and report substantially greater self-reported knowledge of offshore wind farms (+39.7 points) and maritime issues (+41.1 points).

These results clearly indicate that participants in the public debate are not representative of the general population. This selection of respondents is likely to affect preferences for offshore wind energy. On the one hand, differences in spatial preferences for wind farms may simply reflect that the two groups do not share the same characteristics on average. For example, younger generations who are over-represented in the public debate sample may exhibit stronger environmental preferences. On the other hand, participants may differ in their preferences regardless of observable characteristics. The public debate may attract individuals who are more supportive of wind energy and less concerned about the proximity of offshore wind farms to the coast, as well as those who are less supportive and want to ensure their views are represented.

Table 3. Explanatory factors of entropy balancing

Variables		(1)
Gender	Woman	0.784***
(ref: man)		(0.183)
Age	30 – 44 years	0.029
(ref: 18 – 29 years)		(0.191)
	45 – 59 years	0.510**
		(0.222)
	60 years and older	0.494**
		(0.243)
Education	High school	0.097
(ref: less than high school)		(0.377)
	Two-year college degree	-0.487
		(0.327)
	Three-year college degree	-1.343***
		(0.337)
	More than three-year college degree	-2.631***
		(0.302)
Department	Seafront	-0.667***
(ref: no seafront)		(0.178)
Knowledge about	Poor	0.205
wind farms		(0.273)
(ref: very poor)	Good – very good	-0.634**
		(0.288)
Knowledge about	Poor	-0.209
maritime issues		(0.278)
(ref: very poor)	Good – very good	-1.346***
		(0.317)
Constant		2.855***
		(0.383)
Observations		3,326

Source: DCE survey on wind energy, authors' calculations.
Note: estimates of the explanatory factors for entropy balancing following Jann (2021). Standard errors are reported in parentheses. Significance levels are 1% (***), 5% (**) and 10% (*).

To make the two groups of participants perfectly similar in terms of the covariates listed in Table 2, we use the regression-based approach described by Jann (2021). The results are presented in Table 3. Consistent with Table 2, women are significantly under-represented in public debate respondents. The same pattern holds for individuals aged 45 and above, with no difference between the 45-59 and 60+ age groups. Respondents with higher education are proportionally more numerous in the public debate sample, especially those with more than three years of college education. Individuals with strong maritime connections (living near the coast or reporting high knowledge of maritime issues) are also over-represented. These findings are consistent with expectations. Individuals closer to the sea and more informed about related issues are more inclined to take part in such public debates.

Given the magnitude of these differences, some respondents in the public debate sample receive relatively high weights to align their characteristics with those of the general population. This is particularly true for under-represented participants such as women or individuals with a low level of education. The average weight is 2.55, with a standard deviation of 6.56. The highest weight is 84.39, and 12 out of 936 respondents (1.3%) have a weight above 30. Among them, 9 are women, 11 are aged over 40, all have at most a high school education, and none report strong knowledge of wind farms or maritime issues.

3.2. Comparison of participants' preferences

The second research question investigates whether participants in the public debate express different preferences for offshore wind attributes compared to the general population.

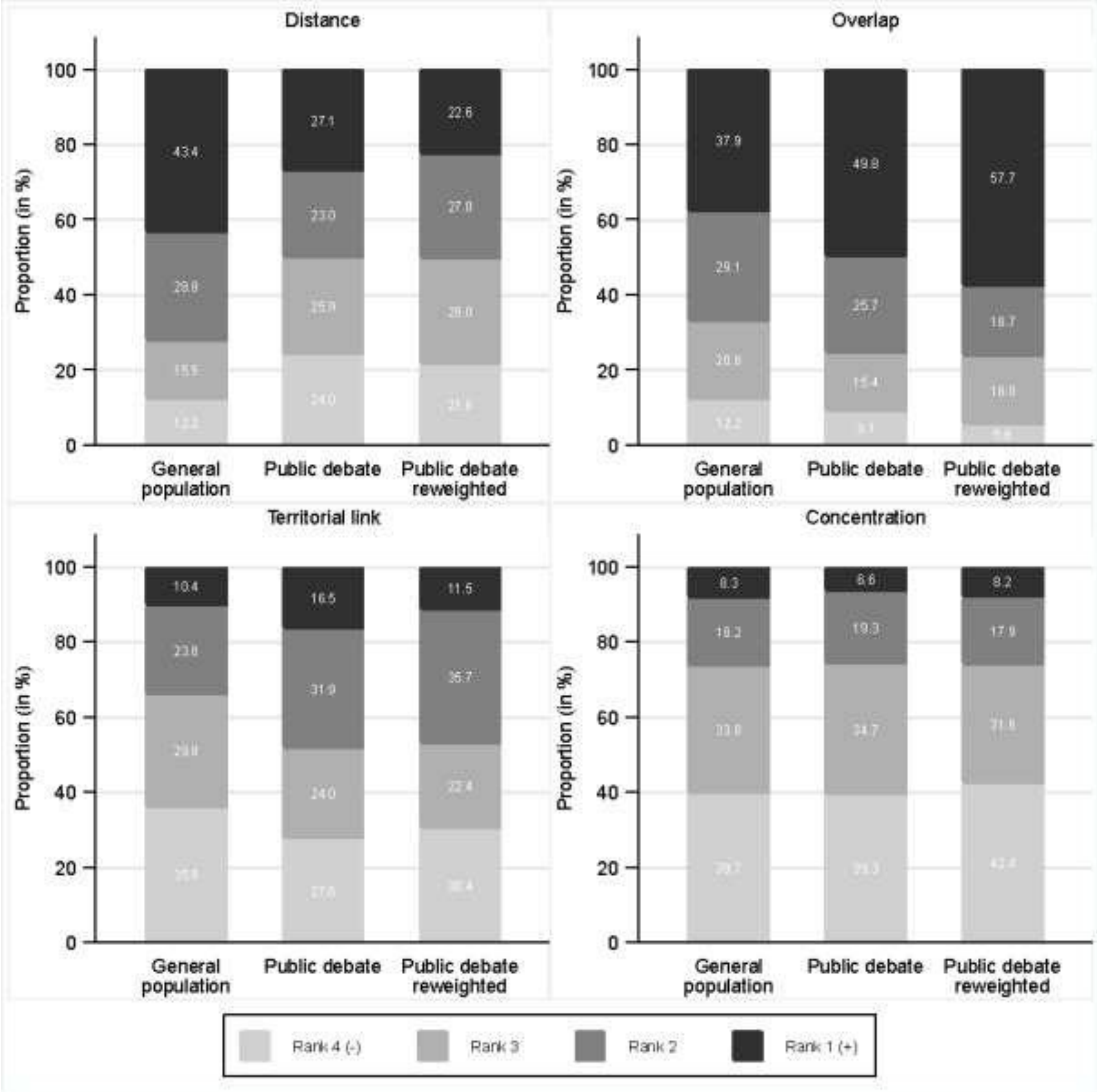
3.2.1. Ranking of attributes and levels

Respondents were asked to rank four attributes: distance from the coast, overlap with protected natural areas or fishing zones, territorial link, and spatial concentration of wind farms. Figure 1 presents the distribution of rankings across three samples: the general population, participants in the public debate, and the same public debate participants after reweighting.

For the general population, the most preferred attribute is distance (ranked first by 43.4% of respondents), followed by overlap with protected natural areas or fishing zones (37.9%), territorial link (10.4%), and concentration (8.3%). The ranking differs substantially among respondents in the public debate. Overlap is ranked first by nearly half of respondents (49.8%), followed by distance (27.1%). The territorial link attribute gains relative importance (16.5% compared to 10.4% in the general population), whereas concentration remains the least important. If policymakers were to rely solely on public debate participants, they would overestimate the importance of avoiding overlaps with protected natural areas or fishing zones relative to distance from the coast.

Reweighting public debate participants to match the characteristics of the general population does not fully align their preferences. For example, 27.1% of public debate respondents rank distance as their top preference, but this proportion drops to 22.6% after reweighting. Conversely, the share of respondents who rank overlap first increases after reweighting (57.7% compared to 49.8% unweighted). By contrast, the proportions of respondents who rank either territorial connection or concentration first become much closer to those in the general population once the sample is reweighted.

Figure 1. Ranking of attributes



Source: DCE survey on wind energy, authors' calculations.
Note: weights are obtained through entropy balancing.

To explain respondents' ranking of the different attributes, we estimate rank-ordered Logit models (Beggs et al., 1981; Allison and Christakis, 1994). The results are presented in Table 4. In the general population, the coefficients associated with overlap, territorial link, and concentration of parks are all negative and statistically significant (panel A). Respondents tend to rank distance highest, followed by overlap, while territorial link and concentration are ranked lower. In contrast, the preferences of participants in the public debate differ markedly (panel B). Overlap is strongly preferred to distance, while distance and territorial link are equally valued. Concentration is the least preferred attribute. The key finding is that these differences between the general population and public debate participants are not due to differences in observable characteristics between the two groups. After reweighting (panel C), participants in the public debate still assign higher ranks to overlap, which is clearly preferred over distance and territorial link. Concentration is significant and less preferred.

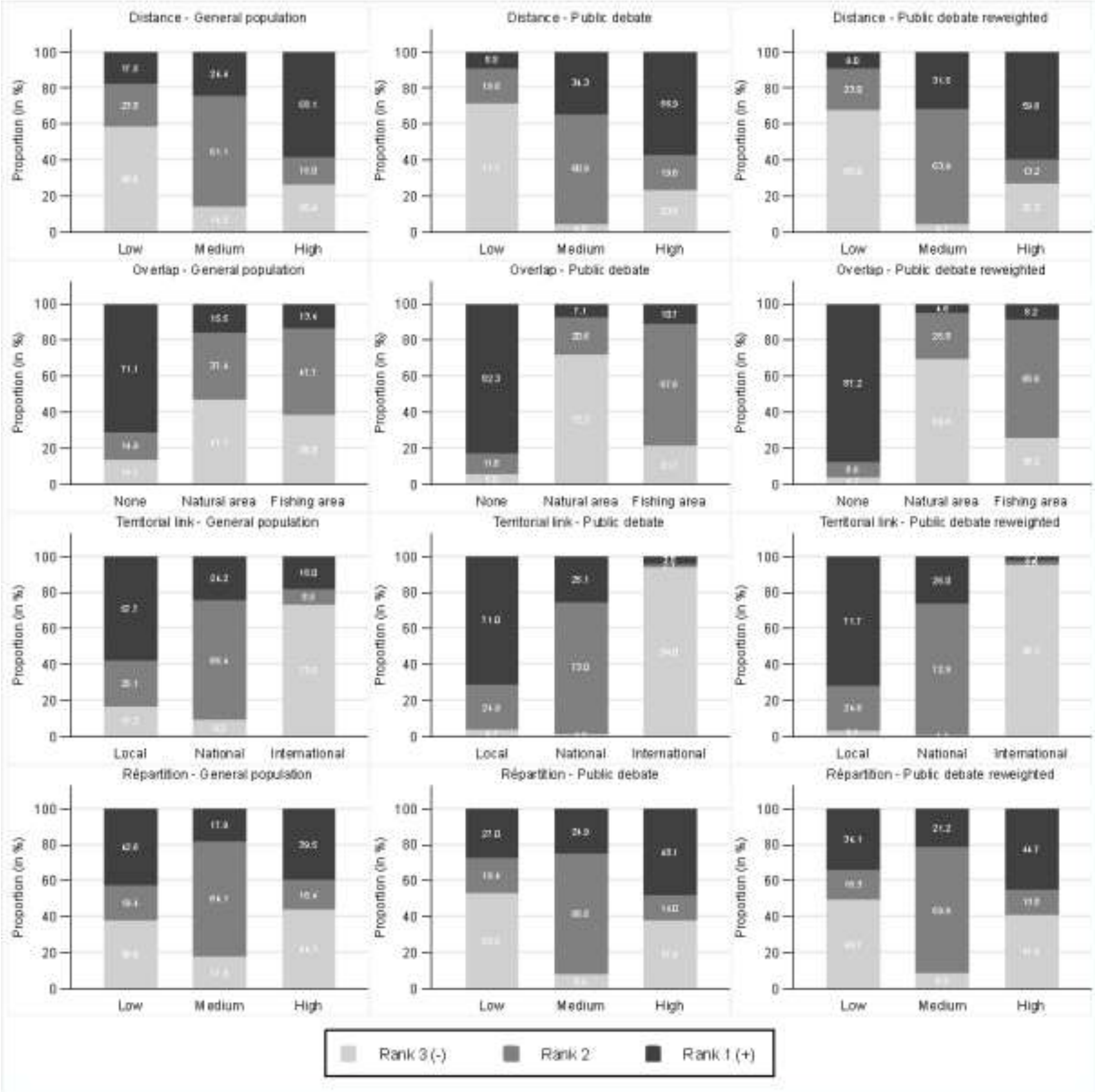
Table 4. Rank-ordered Logit models explaining the ranking of attributes

Variables	Attributes (ref: distance)		
	Overlap	Territorial link	Concentration
Panel A. General population			
Attribute	-0.112***	-0.973***	-1.074***
	(0.040)	(0.042)	(0.040)
Observations (respondents)		9,560 (2,390)	
Panel B. Public debate			
Attribute	0.727***	-0.096	-0.478***
	(0.070)	(0.065)	(0.054)
Observations (respondents)		3,744 (936)	
Panel C. Public debate reweighted			
Attribute	0.893***	-0.183	-0.537***
	(0.192)	(0.165)	(0.139)
Observations (respondents)		3,744 (936)	

Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating rank-ordered Logit models. Robust standard errors are reported in parentheses. Significance thresholds are 1% (***), 5% (**), and 10% (*). The weights used in panel C are obtained through entropy balancing.

We next examine how respondents rank the three levels within each attribute. As shown in Figure 2, across all samples, respondents prefer greater distance from the coast (58.1% in the general population and 56.9% in the public debate). The absence of overlap is the universally preferred level, but more strongly among public debate participants (82.3% against 71.1% in the general population). After reweighting, this proportion increases to 87.2%. Environmental concerns appear more prominent among public debate participants: 7 out of 10 respondents rank the overlap of wind farms with existing natural areas last, compared to less than 50% in the general population. Public debate participants also favor a local territorial link far more strongly than the general population (71.0% against 57.7%) and show greater aversion toward international projects. Preferences for spatial concentration are more mixed. While the general population tends to prefer lower concentration, debate participants exhibit a greater tolerance for higher concentration levels.

Figure 2. Ranking of attribute levels



Source: DCE survey on wind energy, authors' calculations.
Note: weights are obtained through entropy balancing.

Table 5 presents the estimates from rank-ordered Logit models explaining preferences for the levels of each attribute. For the distance attribute, respondents consistently prefer medium or high distances over low distances. In the general population, high distance is preferred over medium distance, but this pattern is not observed among public debate participants. Regarding overlap, the absence of overlap is the most preferred level in all cases. Although overlap with protected natural areas is the least preferred level across all groups, respondents in the public debate express stronger opposition than those in the general population. For the territorial link, the local dimension is most preferred, and the international level is the least favored, regardless of the sample. Finally, preferences are more mixed for the concentration attribute. Respondents from the general population tend to prefer a medium concentration over a low one, and a low concentration over a high one. In contrast, participants in the public debate prefer medium or high concentration to low concentration.

Table 5. Rank-ordered Logit models explaining the rankings of attribute levels

Variables	Distance attribute (ref: low)		Overlap attribute (ref: none)		Territorial link attribute (ref: local)		Concentration attribute (ref: low)	
Levels	Medium	High	Natural area	Fishing zone	National	Inter-national	Medium	High
Panel A. General population								
Levels	0.801***	0.999***	-1.319***	-1.180***	-0.325***	-1.630***	0.105***	-0.147***
	(0.032)	(0.053)	(0.051)	(0.047)	(0.036)	(0.060)	(0.033)	(0.051)
Obs. (respondents)	7,170 (2,390)		7,170 (2,390)		7,170 (2,390)		7,170 (2,390)	
Panel B. Public debate								
Levels	1.433***	1.425***	-2.629***	-1.578***	-0.842***	-3.730***	0.724***	0.488***
	(0.054)	(0.094)	(0.111)	(0.087)	(0.070)	(0.168)	(0.050)	(0.085)
Obs. (respondents)	2,808 (936)		2,808 (936)		2,808 (936)		2,808 (936)	
Panel C. Public debate – reweighted								
Levels	1.286***	1.275***	-2.896***	-2.001***	-0.851***	-3.957***	0.555***	0.258
	(0.108)	(0.280)	(0.258)	(0.276)	(0.197)	(0.381)	(0.151)	(0.229)
Obs. (respondents)	2,808 (936)		2,808 (936)		2,808 (936)		2,808 (936)	

Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating rank-ordered Logit models. Robust standard errors are reported in parentheses. Significance thresholds are 1% (***), 5% (**), and 10% (*). The weights used in panel C are obtained through entropy balancing.

3.2.2. DCE choices

For each set of three scenarios, respondents indicated only their preferred option, without ranking the other two scenarios. We estimate mixed Logit models with uncorrelated random parameters for the general population, the public debate sample, and the reweighted public debate sample. The coefficients are assumed to follow normal distributions. Results are presented in Table 6.

Across all samples, the results underline the need to account for heterogeneity in preferences: the standard deviations associated with the estimated parameters (shown in Table A2 in the external appendix) are statistically significant. In the general population (panel A), the probability of selecting a scenario is 1.53 times higher if it features a medium rather than a low distance from the coast, and 1.84 times higher if it includes a large rather than a low distance. Respondents are nearly twice as likely to reject scenarios overlapping with existing protected natural areas or fishing zones. Scenarios with a national link are chosen 9.9% less often, and those with an international link 40.9% less often. Compared to low concentration, scenarios with medium (-19.8%) or high (-15.0%) concentration are less frequently chosen. Overall, the DCE results are generally consistent with the ranking of attribute levels.

In contrast, the coefficients associated with the levels of the four attributes differ significantly for public debate participants (panel B). For three of the four attributes, the ranking remains consistent. Respondents in the public debate prefer medium and high distances to low distances, no overlapping with existing marine areas, and a local connection to the area rather than a national or international one. However, preferences diverge for the concentration of wind farms, with insignificant coefficients for the medium and high levels. Three main differences stand out compared to the general population. First, respondents in the public debate do not prefer high distances to medium distances. Second, there is a very strong aversion to scenarios overlapping with protected natural areas, substantially stronger than in the general population. Third, respondents show a pronounced aversion for scenarios with an international territorial link, more intense than in the general population.

Table 6. Mixed Logit models with uncorrelated random parameters explaining preferred scenarios (DCE)

Variables	Distance attribute (ref: low)		Overlap attribute (ref: none)		Territorial link attribute (ref: local)		Concentration attribute (ref: low)	
	Medium	High	Natural area	Fishing zone	National	Inter-national	Medium	High
Panel A. General population								
Mean of coefficients	0.424***	0.610***	-0.836***	-0.948***	-0.104**	-0.526***	-0.221***	-0.163***
	(0.046)	(0.073)	(0.054)	(0.076)	(0.040)	(0.068)	(0.037)	(0.060)
Observations = 43,020 ; respondents = 2,390								
Panel B. Public debate								
Mean of coefficients	0.734***	0.351*	-1.775***	-1.059***	-0.211**	-1.916***	0.112	-0.209
	(0.097)	(0.181)	(0.150)	(0.170)	(0.088)	(0.205)	(0.069)	(0.152)
Observations = 16,848 ; respondents = 936								
Panel C. Public debate – reweighted version								
Mean of coefficients	0.714***	-0.278	-2.540***	-1.300***	-0.377***	-2.076***	-0.078	-0.318
	(0.181)	(0.514)	(0.450)	(0.419)	(0.143)	(0.405)	(0.228)	(0.259)
Observations = 16,848 ; respondents = 936								

Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating mixed Logit models with uncorrelated random parameters. Robust standard errors are in parentheses below the coefficients. Significance thresholds are 1% (***), 5% (**), and 10% (*). The weights used in panel C are obtained through entropy balancing.

After reweighting, four results emerge (panel C). First, overlap with protected natural areas strongly decreases the probability of choosing a scenario, corresponding to a 74.7% reduction in odds. Overlap with fishing zones also significantly reduces the likelihood of selection, though the effect is less pronounced. Second, scenarios featuring an international territorial link are substantially less likely to be chosen (a 61.4% decrease in odds), confirming a strong aversion to international involvement. Third, respondents show little sensitivity to the concentration attribute: coefficients for both medium and high concentration are small and statistically insignificant. Fourth, regarding distance, only scenarios with a medium distance are more likely to be selected than those with a short distance, while the coefficient for high distance is not statistically different from zero. This suggests indifference between low and high distances, contrasting with the general population.

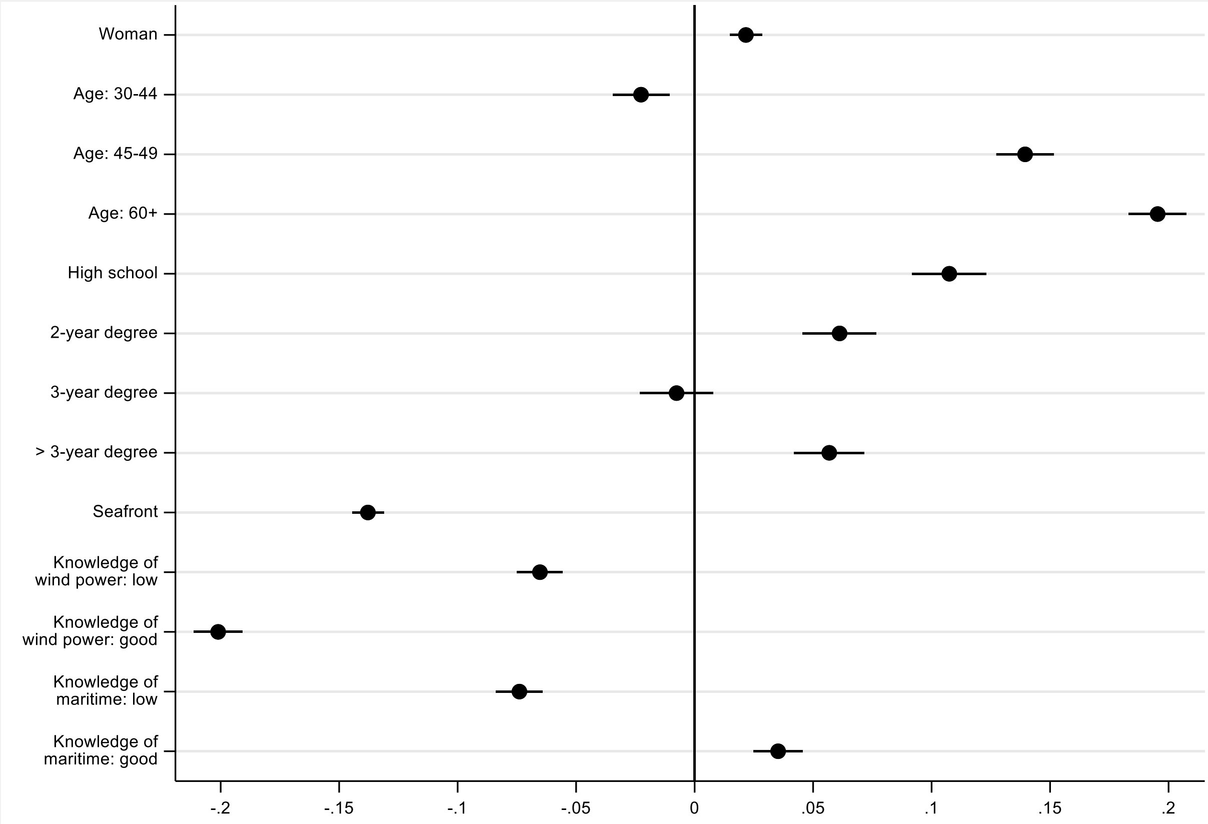
3.3. Reweighting and differences in preferences

The third research question evaluates whether reweighting the public debate sample using entropy balancing can correct for compositional biases and align preferences more closely with those of the general population. The simulation exercise yields three main results that bear directly on the limits of compositional adjustment and on the interpretation of participatory outputs.

First, entropy balancing fails to produce feasible reweighting in a substantial share of the simulated scenarios. Out of 100,000 randomly drawn target mean vectors, entropy balancing was infeasible in 26,853 draws. For more than one quarter of the hypothetical target compositions, it was not possible to find a set of weights that makes the debate sample match those averages. This finding highlights practical constraints on reweighting. Not all target compositions lie within the convex hull of the observed public debate sample, and some target profiles are therefore unreachable by reweighting alone.

Second, among draws for which reweighting is feasible, the hypothesis that the attribute-level effects are identical across the reweighted public debate sample and the general population is accepted only rarely. The joint null hypothesis for the estimated interaction coefficients $\hat{\lambda}_{am}$ is accepted in only 11.2% of cases at the 5 percent level and 7.5% of cases at the 10 percent level. The proportion of cases for which the null hypothesis H_0 is valid decreases with the selected significance level, because the most frequently observed scenarios are those in which the estimated coefficients $\hat{\lambda}_{am}$ are different from 0. In the overwhelming majority of cases, the estimated interactions between attribute levels and the public-debate indicator remain statistically different from zero even after reweighting. This indicates that changing the observable composition of public debate participants is generally insufficient to reproduce the preference structure observed in the general population survey.

Figure 3. Linear estimates explaining the probability $\mathbf{Pr}(\boldsymbol{\hbar}_{\mathfrak{t}} = \mathbf{1})$



Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating a linear probability model, where the dependent variable equals 1 if the effects of attribute levels do not differ significantly between public debate participants and the general population (at the 10 percent level). The sample includes 75,147 simulations (out of 100,000) for which entropy balancing was successfully performed, using means of individual characteristics randomly drawn from uniform distributions.

Third, where alignment is more likely, it is associated with definite patterns in the average composition of the reweighted public debate sample. The linear-probability analysis over successful simulations shows that the probability of alignment increases when the public debate sample is, on average, composed predominantly of women, older respondents (age

45 and above), respondents with lower formal education (a high-school diploma or a two-year college degree rather than a longer tertiary degree), non-residents in a maritime department, and respondents reporting lower self-assessed knowledge of offshore wind. Figure 3 reports the estimated coefficients and their confidence intervals from this exercise. These results suggest that certain demographic and knowledge profiles within the public debate sample produce choices that are closer to those of a representative population, but these profiles are not typical within the public debate sample that we observe empirically.

4. Discussion

4.1. Key findings

Public debates can serve many functions, such as increasing transparency, informing citizens, and creating opportunities for voices that are otherwise excluded from formal politics. While the public debate examined here combined several participation modes, including in-person events, roundtables, and an online consultation, this paper focuses specifically on the online consultation component of The Sea in Debate. In this consultation, participants were invited to express their preferences through an open internet survey.

We compare the responses of this online consultation with those from a representative survey of the national population. By situating the online consultation within the broader debate, we can assess whether and how the outputs from one participation channel reflect the broader public's preferences and whether they can be used, without adjustment, to inform policy. The wind farm survey offers a unique opportunity to document the selection of participants by contrasting the characteristics of respondents in the public debate with those of an identical survey conducted among the general population. The results of this comparison are clear. Participants in the public debate differ markedly from the general population. They are predominantly male, younger, more highly educated, and possess greater knowledge of wind farms and maritime issues. This lack of representativeness is likely to affect the measurement of preferences for wind farm siting.

Public debate participants display stronger preferences for avoiding overlaps with existing marine areas, particularly protected natural areas, and are less concerned about distance from the shore than the general population. The entropy balancing analysis shows that even when both groups are made similar in terms of observable characteristics (such as gender, age, and education), these differences persist. Participants in the public debate consistently value the overlap attribute more than distance, whereas the opposite holds true for the general population. Both groups are sensitive to the visual impact of offshore wind turbines on the landscape, but the spatial concentration of wind farms appears to be of limited concern.

4.2. Methodological contributions

Our study contributes to the existing literature in two main ways. First, we provide detailed documentation of the participant selection process in online public consultations. Our findings from the public debate organized by the CNDP align with analyses of the Yellow Vest movement and the Great Debate in France (Monnery and Wolff, 2023), which highlight the strong selection of participants based on political beliefs that differ from those of the general population. Consistent with the OECD's (2020) comparative study of 289 deliberative processes between 1986 and 2019, our results confirm that participant recruitment remains a recurring methodological challenge in participatory democracy initiatives.

Citizens' juries represent another participatory mechanism developed to involve lay citizens in deliberating on complex policy questions. In the UK, such juries have been convened since the 1990s to address issues ranging from healthcare priorities to environmental planning and biotechnology. They typically bring together a small, demographically diverse group of citizens who, after receiving balanced information and hearing from experts, deliberate to produce collective recommendations. These experiences illustrate how structured, informed deliberation can complement broader consultation tools, providing policymakers with nuanced insights grounded in public reasoning (Coote and Lenaghan, 1997; Smith and Wales, 2000; Davies et al., 2006). At the same time, open participation still raises concerns about representativeness and legitimacy. This may ultimately contribute to declining interest in the instrument.

Despite a growing body of research on renewable energy preferences, empirical applications of DCEs to offshore wind policy design remain limited. Existing studies have largely focused on specific sites or isolated project attributes, particularly distance from the shore, while the large-scale spatial organization of offshore wind development has received little attention (Joalland and Mahieu, 2023; Ladenburg et al., 2024). Moreover, few studies have examined how methodological tools such as entropy balancing can correct for compositional biases when comparing distinct respondent groups (Hynes et al., 2021a, 2021b; Vass et al., 2022). Our second contribution is to address these gaps by introducing a novel DCE attribute on spatial concentration, and showing that choices based on ranking of attributes and attribute levels lead to similar findings. Furthermore, we propose for the first time a simulation-based entropy balancing approach to test for systematic differences between public debate participants and the general population and study differences in preferences in the context of a nationwide public debate rather than a localized case study.

All our results remain conditional on the socio-demographic variables controlled for in our various econometric models. Inevitably, this raises the question of the role of unobservable characteristics such as individual values, worldviews, or environmental beliefs. It is plausible that selection into the public debate was driven not only by higher education or coastal residency, but also by a stronger pre-existing commitment to environmental considerations. This could explain why, even after reweighting for socio-demographic composition, significant differences in preferences exist. Participants involved in local initiatives may fundamentally prioritize ecological integrity over other considerations. It is difficult, on a priori grounds, to determine whether a reweighting that includes values could bridge the difference between participatory outputs and general population preferences. Nevertheless, the large gap in preferences for offshore wind observed when comparing the two samples suggests that unobservables would need to have a very large influence to overturn our main findings[4].

[4] Monnery and Wolff (2023) demonstrate how to account for both observable and unobservable factors (through simulations) when explaining the selection of participants in the French political Grand Débat. Their main finding is that introducing a confounder does not alter the pattern of self-selection unless the marginal effect of that confounder is very large.

4.3. Policy implications

A central limitation of public debates, including “The Sea in Debate”, is selective participation. Certain groups or particular interests may dominate the discussion, potentially marginalizing voices that are underrepresented in these exchanges (Guyot-Téphany et al., 2024; Tissière and Trouillet, 2022). Participation in public consultations and deliberative processes often skews toward individuals who are already civically engaged, typically those with higher levels of education, urban residence, or stronger environmental awareness (Dalton, 2008; Olsen et al., 2018; Smith et al., 2009). This pattern is clearly observed in “The Sea in Debate”, with notable overrepresentation of men, younger individuals, and those with advanced education and knowledge of maritime issues.

Ignoring such selection effects risks leading policymakers to base decisions on consultation outcomes that do not reflect majority preferences. This may inadvertently contradict the inclusion goals of participatory democracy and contribute to a growing disconnect between citizens and policymakers (Theodossiou and Zangelidis, 2020). More broadly, our results have two main implications for the design and use of public debates in policy-making. First, they highlight the need for improved recruitment strategies to ensure representativeness and inclusivity in participatory processes. Mechanisms such as civic lotteries, targeted outreach, or hybrid formats combining open and randomized participation could help engage underrepresented groups and strengthen the legitimacy of outcomes.

Second, from a substantive policy perspective, the findings suggest that citizens (both in the general population and within the debate) are particularly sensitive to the visual and spatial impacts of offshore wind farms. Policymakers should therefore prioritize minimizing overlaps with protected natural areas and mitigating the visual impact of wind turbines. Interestingly, the limited concern for spatial concentration implies that clustering wind farms in specific zones may be socially acceptable, which could inform efficient spatial planning and reduce environmental conflicts.

5. Conclusion

This study examined differences between respondents to the public debate “The Sea in Debate” and the general population regarding offshore wind energy. The analysis reveals clear contrasts in both socio-demographic characteristics and preference structures. Two main empirical findings emerge. First, within the general population, the most valued aspects of offshore wind development are distance from the coast and the absence of overlap with existing marine areas. Second, participants in the public debate express strong opposition to wind farms overlapping with protected natural areas and to an international territorial link. These findings indicate that while the general population prioritizes broad spatial and environmental criteria, public debate participants tend to emphasize ecological protection and territorial identity.

These findings are of direct relevance for policymakers designing participatory processes in environmental planning. They show that relying solely on public debate data can lead to biased interpretations of public opinion because participants differ systematically from the broader population. Policymakers should therefore interpret participatory outcomes cautiously and, when representativeness is essential, consider integrating deliberative mini-publics or complementary representative surveys. Yet, such mechanisms face persistent recruitment challenges: non-participation is often correlated with education, time availability, or political engagement, thus reintroducing selection bias (Jacquet, 2017). Future research could explore strategies to broaden participation, such as monetary incentives, personalized outreach, or behavioral nudges that could increase participation rates and help maintain the intended representativeness of these forums. Informing the wider population about ongoing public debates could also help boost participation. There is further merit in combining data from public consultations with representative samples of the general population.

More generally, our findings support recent analyses emphasizing the limitations of participatory democracy and its difficulty in correcting unequal access to decision-making (Loisel and Rio, 2024). Public debates, whether national or local, will only gain legitimacy if participation is both numerous and representative. Otherwise, participatory mechanisms risk amplifying the voices of the most mobilized groups (whether supportive or opposed), thereby distorting the perception of societal preferences. Finally, the generalizability of our results remains context-dependent. Participation dynamics and preference structures are shaped by institutional design, issue salience, and national context. Further comparative work is needed to assess whether similar patterns of participant selection and preference divergence emerge in other participatory settings and policy domains.

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Appendix

Table A. DCE scenarios

Option A				Option B				Option C				
Distance	Overlap	Territorial link	Concentration	Distance	Overlap	Territorial link	Concentration	Distance	Overlap	Territorial link	Concentration	Block
Medium	Fishing zone	International	High	Medium	Natural area	International	Low	Low	None	Local	Medium	1
Low	None	National	Medium	High	Fishing zone	Local	High	Medium	None	International	Low	1
Medium	Fishing zone	Local	High	High	Natural area	National	Low	Low	None	International	High	1
High	Fishing zone	National	Low	Low	None	International	High	Medium	Fishing zone	Local	Medium	1
High	Natural area	International	Medium	Low	None	National	High	Medium	Fishing zone	National	Low	1
Low	None	National	High	Medium	Natural area	Local	Medium	High	Fishing zone	International	Medium	1
Low	Natural area	Local	Medium	Medium	Fishing zone	National	Medium	High	None	International	Low	2
Low	Fishing zone	Local	Low	Low	Natural area	Local	High	High	None	National	Medium	2
High	Natural area	National	High	Medium	None	International	Medium	Low	Fishing zone	Local	Low	2
Medium	None	International	Low	Low	Fishing zone	National	Medium	Low	Natural area	National	High	2
Medium	None	National	High	High	Fishing zone	International	Medium	Low	Natural area	Local	Low	2
High	Fishing zone	International	Medium	Low	None	Local	Low	Medium	Natural area	National	High	2

Source: authors' elaboration.

Note: Each respondent completes 6 choices, with block 1 and block 2 being randomly assigned to respondents.

External appendix. Comparative analysis of DCE model specifications

We consider four different approaches to modeling respondents' choice behavior in our DCE. Each specification offers distinct advantages, but also presents limitations. We begin with the conditional Logit model, based on McFadden (1974). This estimator provides a simple and computationally efficient baseline specification. Its main strength lies in its ease of estimation and interpretation, making it a useful reference point for evaluating more complex models. However, this simplicity comes at a cost. The model assumes complete preference homogeneity across respondents. This assumption is frequently violated in empirical applications. This can lead to biased estimates when unobserved heterogeneity is present. A further limitation is the model's reliance on the independence of irrelevant alternatives (IIA) property, which imposes restrictive substitution patterns that may not accurately reflect real-world decision making. The corresponding estimates are in Table A1.

Table A1. Conditional Logit models explaining preferred scenarios (DCE)

Variables	Distance attribute (ref: low)		Overlap attribute (ref: none)		Territorial link attribute (ref: local)		Concentration attribute (ref: low)	
	Medium	High	Natural area	Fishing zone	National	Inter-national	Medium	High
Panel A. General population								
Levels	0.361***	0.560***	-0.606***	-0.638***	-0.115***	-0.339***	-0.148***	-0.114**
	(0.032)	(0.045)	(0.028)	(0.041)	(0.028)	(0.041)	(0.026)	(0.036)
Observations = 43,020 ; respondents = 2,390 ; log-likelihood = -15,457.8 ; AIC = 30,935.7 ; BIC = 31,011.4								
Panel B. Public debate								
Levels	0.549***	0.515***	-0.880***	-0.492***	-0.130***	-0.822***	0.093**	-0.036
	(0.052)	(0.074)	(0.047)	(0.064)	(0.045)	(0.071)	(0.043)	(0.060)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,905.7 ; AIC = 11,831.5 ; BIC = 11,898.8								
Panel C. Public debate – reweighted version								
Levels	0.625***	0.427***	-1.374***	-0.692***	-0.332***	-0.951***	0.030	-0.075
	(0.052)	(0.071)	(0.047)	(0.059)	(0.046)	(0.067)	(0.043)	(0.058)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,598.9 ; AIC = 11,217.8 ; BIC = 11,284.2								

Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating conditional Logit models. Robust standard errors are in parentheses below the coefficients. Significance thresholds are 1% (***), 5% (**), and 10% (*). The weights used in panel C are obtained through entropy balancing.

The mixed Logit model (Hole, 2007; Train, 2009) addresses the issue of preference heterogeneity by introducing random parameters for selected attributes. This specification offers greater flexibility in capturing variations in individual preferences and relaxes the restrictive IIA assumption. By estimating distributions of preferences rather than single point estimates, the model yields richer behavioral insights. Nevertheless, the standard mixed logit implementation assumes independence between random parameters, which may overlook meaningful correlations in preference structures. In addition, estimation requires greater computational resources and careful attention to convergence issues, especially when using simulation-based methods. The random coefficients are usually on explanatory variables that vary across alternatives, but they may also vary across individuals and choice sets. There are several possible distributions for the random coefficients. Here, we assume that the distribution is normal for the eight attribute levels. Table A2 reports the corresponding estimates, consistent with those presented in Table 6, and additionally provides the estimated standard deviations of the random parameters as well as model fit criteria (AIC and BIC).

Table A2. Mixed Logit models with uncorrelated random parameters explaining preferred scenarios (DCE)

Variables	Distance attribute (ref: low)		Overlap attribute (ref: none)		Territorial link attribute (ref: local)		Concentration attribute (ref: low)	
	Medium	High	Natural area	Fishing zone	National	Inter-national	Medium	High
Panel A. General population								
Mean of coefficients	0.424***	0.610***	-0.836***	-0.948***	-0.104**	-0.526***	-0.221***	-0.163***
	(0.046)	(0.073)	(0.054)	(0.076)	(0.040)	(0.068)	(0.037)	(0.060)
St. dev. of coefficients	0.713***	1.095***	1.284***	1.166***	0.745***	0.909***	0.606***	0.724***
	(0.066)	(0.097)	(0.063)	(0.079)	(0.057)	(0.088)	(0.060)	(0.096)
Observations = 43,020 ; respondents = 2,390 ; log-likelihood = -14,973.5 ; AIC = 29,983.0 ; BIC = 30,119.3								
Panel B. Public debate								
Mean of coefficients	0.734***	0.351*	-1.775***	-1.059***	-0.211**	-1.916***	0.112	-0.209
	(0.097)	(0.181)	(0.150)	(0.170)	(0.088)	(0.205)	(0.069)	(0.152)
St. dev. of coefficients	1.161***	2.239***	2.430***	1.789***	1.262***	2.088***	0.555***	1.415***
	(0.141)	(0.247)	(0.191)	(0.183)	(0.113)	(0.225)	(0.131)	(0.230)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,444.5 ; AIC = 10,925.0 ; BIC = 11,044.4								
Panel C. Public debate – reweighted version								
Mean of coefficients	0.714***	-0.278	-2.540***	-1.300***	-0.377***	-2.076***	-0.078	-0.318
	(0.181)	(0.514)	(0.450)	(0.419)	(0.143)	(0.405)	(0.228)	(0.259)
St. dev. of coefficients	0.721*	2.446***	2.520***	2.159***	0.899***	1.969***	1.075***	0.983***
	(0.382)	(0.595)	(0.441)	(0.426)	(0.194)	(0.462)	(0.263)	(0.316)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -13,017.4; AIC = 26,070.7 ; BIC = 26,190.1								

Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating mixed Logit models with uncorrelated random parameters. Robust standard errors are in parentheses below the coefficients. Significance thresholds are 1% (***), 5% (**), and 10% (*). The weights used in panel C are obtained through entropy balancing.

The correlated mixed Logit model, discussed by Mariel and Meyerhoff (2018), is a methodological advancement that allows for non-zero covariances between random parameters. Unlike the standard mixed Logit framework, which assumes independence across taste parameters, this specification captures potential interdependencies in individual preferences. These interrelations may arise when respondents evaluate certain attributes together. By estimating a full covariance matrix, the model can therefore provide a more behaviorally realistic representation of decision-making processes and often leads to improved model fit. However, these gains in flexibility and realism come at a cost. The number of parameters to be estimated increases substantially, as the number of covariance terms grows quadratically with the number of random coefficients. This complexity amplifies computational demands and raises concerns about parameter identification, especially in small samples. Moreover, overparameterization can result in convergence difficulties or unstable estimates. The results obtained from this specification are reported in Table A3. For conciseness, the table displays only the estimated means and standard deviations of the random parameters, along with the model fit statistics (log-likelihood, AIC, and BIC). The additional covariance parameters, which are numerous in the correlated specification, are not reported here.

Table A3. Mixed Logit models with correlated random parameters explaining preferred scenarios (DCE)

Variables	Distance attribute (ref: low)		Overlap attribute (ref: none)		Territorial link attribute (ref: local)		Concentration attribute (ref: low)	
	Medium	High	Natural area	Fishing zone	National	International	Medium	High
Panel A. General population								
Mean of coefficients	0.466***	0.577***	-0.879***	-0.860***	-0.002	-0.417***	-0.103**	0.006
	(0.053)	(0.081)	(0.074)	(0.091)	(0.045)	(0.074)	(0.044)	(0.060)
St. dev. of coefficients	0.307***	0.475	0.508***	1.205***	0.613***	1.215***	0.577***	0.904***
	(0.115)	(0.360)	(0.131)	(0.146)	(0.087)	(0.119)	(0.126)	(0.110)
Observations = 43,020 ; respondents = 2,390 ; log-likelihood = -14,798.6 ; AIC = 29,689.3 ; BIC = 30,037.5								
Panel B. Public debate								
Mean of coefficients	0.697***	0.740***	-1.596***	-0.269	-0.006	-1.787***	0.273***	0.069
	(0.109)	(0.195)	(0.170)	(0.199)	(0.101)	(0.242)	(0.079)	(0.171)
St. dev. of coefficients	0.727***	0.441**	1.685***	1.731***	0.164	2.667***	0.581***	1.820***
	(0.142)	(0.203)	(0.162)	(0.365)	(0.160)	(0.303)	(0.116)	(0.193)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,324.8 ; AIC = 10,741.5 ; BIC = 11,046.7								
Panel C. Public debate – reweighted version								
Mean of coefficients	0.834***	0.159	-2.748***	-0.953**	-0.215	-1.739***	0.193	0.007
	(0.271)	(0.466)	(0.532)	(0.478)	(0.168)	(0.390)	(0.261)	(0.289)
St. dev. of coefficients	0.082	0.451	0.692***	1.014***	0.630**	2.321***	0.679***	1.802***
	(0.268)	(0.298)	(0.174)	(0.362)	(0.293)	(0.539)	(0.202)	(0.349)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -12,551.6; AIC = 25,195.3 ; BIC = 25,500.4								

Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating mixed Logit models with correlated random parameters. Robust standard errors are in parentheses below the coefficients. Significance thresholds are 1% (***), 5% (**), and 10% (*). The weights used in panel C are obtained through entropy balancing.

Latent class Logit models (Hensher and Greene, 2003; Pacifico and Yoo, 2013) offer a distinct conceptual framework for capturing preference heterogeneity. These models partition the sample into a finite number of latent segments, each with its own set of homogeneous utility parameters. Rather than modeling heterogeneity as a continuous distribution (as in mixed Logit models), this discrete specification assumes that individuals within each class share the same preferences, while allowing for sharp differences across classes. This approach can be valuable when theory or empirical evidence suggests the existence of distinct behavioral types or market segments. A key strength of the latent class approach is its non-parametric treatment of heterogeneity, which avoids imposing specific distributional assumptions on taste parameters.

As a result, it can accommodate complex and potentially multimodal preference structures that continuous models may struggle to represent. However, this flexibility introduces its own set of challenges. The main issue is selecting the appropriate number of latent classes, which must balance statistical fit criteria (such as AIC or BIC) with theoretical plausibility and practical interpretability. Different criteria can lead to conflicting recommendations, and overfitting is a real concern if too many classes are specified. Additionally, reliable estimation and precise characterization of each class's preferences require sufficiently large sample sizes, particularly as the number of classes increases. The estimates derived from this approach are reported in Table A4.

Table A4. Latent class Logit models explaining preferred scenarios (DCE)

Variables	Distance attribute (ref: low)		Overlap attribute (ref: none)		Territorial link attribute (ref: local)		Concentration attribute (ref: low)	
	Medium	High	Natural area	Fishing zone	National	Inter-national	Medium	High
Panel A. General population								
2 latent classes								
Class 1 – levels	0.359**	1.023***	-2.970***	-2.577***	0.306**	-0.104	-0.347***	-0.400***
	(0.153)	(0.214)	(0.205)	(0.202)	(0.137)	(0.192)	(0.109)	(0.149)
Class 2 - levels	0.372***	0.541***	-0.133***	-0.134**	-0.150***	-0.421***	-0.121***	-0.071*
	(0.038)	(0.056)	(0.042)	(0.054)	(0.034)	(0.056)	(0.031)	(0.043)
Observations = 43,020 ; respondents = 2,390 ; log-likelihood = -15,065.9 ; AIC = 30,173.9 ; BIC = 30,332.8								
3 latent classes								
Class 1 – levels	0.324*	0.577**	-3.065***	-2.847***	0.491***	-0.097	-0.335**	-0.060
	(0.166)	(0.245)	(0.216)	(0.231)	(0.160)	(0.219)	(0.131)	(0.184)
Class 2 – levels	0.054	0.120	-0.177**	-0.046	-0.394***	-0.858***	-0.234***	-0.323***
	(0.066)	(0.088)	(0.077)	(0.090)	(0.067)	(0.128)	(0.057)	(0.075)
Class 3 – levels	1.130***	1.515***	-0.110	-0.295	0.472***	0.669***	0.071	0.302**
	(0.178)	(0.263)	(0.183)	(0.214)	(0.119)	(0.175)	(0.113)	(0.140)
Observations = 43,020 ; respondents = 2,390 ; log-likelihood = -14,920.7 ; AIC = 29,905. 3 ; BIC = 30,147.6								
Panel B. Public debate								
2 latent classes								
Class 1 – levels	0.926***	0.243*	-1.938***	-1.280***	0.168**	-1.024***	0.159**	-0.110
	(0.098)	(0.124)	(0.104)	(0.120)	(0.085)	(0.112)	(0.073)	(0.094)
Class 2 - levels	0.416***	1.486***	0.422***	0.828***	-0.716***	-0.446**	-0.056	0.601***
	(0.102)	(0.203)	(0.104)	(0.162)	(0.091)	(0.201)	(0.086)	(0.141)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,638.5 ; AIC = 11,318.9; BIC = 11,458.2								
3 latent classes								
Class 1 – levels	0.563***	0.106	-2.171***	-1.218***	-0.009	-1.167***	0.150	-0.335***
	(0.116)	(0.149)	(0.154)	(0.169)	(0.102)	(0.127)	(0.097)	(0.118)
Class 2 – levels	-0.060	0.079	0.537***	1.731***	-0.769***	-1.306***	-0.092	0.749***
	(0.109)	(0.265)	(0.153)	(0.213)	(0.133)	(0.249)	(0.097)	(0.210)
Class 3 – levels	2.658***	5.055***	-1.037***	-2.000***	0.643***	-0.027	0.075	1.862***
	(0.365)	(1.043)	(0.319)	(0.591)	(0.175)	(0.469)	(0.217)	(0.587)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,488.4 ; AIC = 11,040.8; BIC = 11,253.1								
Panel C. Public debate – reweighted version								
2 latent classes								
Class 1 – levels	0.480***	-0.531***	-3.671***	-1.630***	-0.325**	-1.464***	0.737***	0.567***
	(0.132)	(0.142)	(0.303)	(0.155)	(0.146)	(0.183)	(0.143)	(0.175)
Class 2 - levels	0.806***	1.579***	-0.543***	-0.027	-0.413***	-0.715***	-0.251***	-0.300**
	(0.071)	(0.151)	(0.071)	(0.107)	(0.063)	(0.132)	(0.065)	(0.124)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,279.6 ; AIC = 10,601.2; BIC = 10,740.5								
3 latent classes								
Class 1 – levels	1.418***	-1.462***	-19.412	-4.208***	-4.155***	-1.961***	-1.206*	-5.814***
	(0.411)	(0.475)	(34.884)	(0.637)	(0.971)	(0.474)	(0.716)	(1.596)
Class 2 – levels	0.627***	0.066	-1.231***	0.023	-0.225***	-1.912***	-0.126*	0.118
	(0.082)	(0.114)	(0.084)	(0.102)	(0.079)	(0.124)	(0.071)	(0.087)
Class 3 – levels	0.685***	3.166***	0.761***	0.599*	-0.576***	1.274***	0.237	0.063
	(0.184)	(0.393)	(0.151)	(0.335)	(0.153)	(0.329)	(0.210)	(0.321)
Observations = 16,848 ; respondents = 936 ; log-likelihood = -5,050.1; AIC = 10,164.2 ; BIC = 10,376.5								

Source: DCE survey on wind energy, authors' calculations.
Note: coefficients are obtained by estimating latent class Logit models. Standard errors (panels A, B and C) are in parentheses below the coefficients. Significance thresholds are 1% (***), 5% (**), and 10% (*). The weights used in panel C are obtained through entropy balancing.

Table A4 shows estimates from Logit models with two or three latent classes. For our data analysis, however, we considered a larger number of latent classes. Specifically, we estimated latent class models with a range of 2 to 10 classes. We encountered convergence problems with the latent class models when the sample included respondents from the public debate, especially with the reweighted version of this sample. In this case, we were unable to obtain estimates for 5, 8, 9, or 10 classes. Table A5 summarizes the values obtained for the three following information criteria: log-likelihood, Akaike information criterion (AIC), and Bayesian information criterion (BIC). For the general population, the 10-class model has the lowest AIC, while the 9-class model has the lowest BIC. For the unweighted sample of public debate participants, the AIC is minimized at 9 classes, and the BIC is minimized at 7 classes. Therefore, the 7-class model may be preferred. For panel C, the AIC is minimized at 7 classes, and the BIC at 6 classes.

Table A5. Latent class Logit models and number of classes

Latent	*A. General population*			*B. Public debate*			*C. Public debate reweighted*		
classes	Log-L	AIC	BIC	Log-L	AIC	BIC	Log-L	AIC	BIC
2	-15,065.9	30,173.9	30,332.8	-5,638.5	11,318.9	11,458.2	-5,279.6	10,601.2	10,740.5
3	-14,920.7	29,905.3	30,147.6	-5,488.4	11,040.8	11,253.1	-5,050.1	10,164.2	10,376.5
4	-14,835.8	29,757.5	30,083.1	-5,420.2	10,926.3	11,211.5	-4,945.8	9,977.5	10,262.7
5	-14,768.7	29,645.3	30,054.2	-5,322.9	10,753.9	11,112.1	fail		
6	-14,715.5	29,561.0	30,053.1	-5,259.1	10,648.3	11,079.5	-4,684.0	9,498.1	9,929.2
7	-14,719.0	29,590.0	30,165.4	-5,247.9	10,647.8	11,152.0	-4,637.6	9,427.2	9,931.3
8	-14,629.3	29,432.5	30,091.2	-5,212.5	10,599.0	11,176.1	fail		
9	-14,565.6	29,327.1	30,069.0	-5,198.5	10,593.0	11,243.1	fail		
10	-14,553.4	29,324.7	30,149.9	fail			fail		

Source: DCE survey on wind energy, authors' calculations.

However, despite its interest, there are a few arguments against using the latent class Logit model in our setting. In practice, such models often require large samples and substantial heterogeneity to support multiple latent classes. This is clearly observed in the public debate sample. The number of respondents (936) is likely too small to estimate a reliable multiple latent class model with up to 7 classes. On the one hand, we experienced convergence problems with the reweighted sample, which suggests some instability or over-parameterization with the data. On the other hand, even with a small number of classes, we obtain extreme values that are implausible or uninterpretable. For example, this occurs for the natural area attribute in panel C with the 3-class model, which yields a coefficient of -19.4. Moreover, the reweighted public debate sample exacerbates convergence problems. This suggests that the latent class framework may not be suitable for handling such weighted data. Therefore, estimating mixed Logit models seems more justified, as they already account for continuous preference heterogeneity and fit the data well.

A final issue concerns the comparison between mixed Logit models with uncorrelated and correlated random parameters. We argue that the uncorrelated model emerges as a more appropriate choice in our context, for three main reasons. First, the uncorrelated mixed Logit model only estimates the means and standard deviations of the random coefficients. In contrast, the correlated version estimates a full covariance matrix, implying a quadratic increase in the number of parameters as the number of attributes grows. This complexity can lead to unstable or imprecise estimates, especially in samples of moderate size, such as ours. While the uncorrelated model yields well-behaved estimates with consistent signs, the correlated model presents imprecise or non-significant standard deviations, particularly in panel C. This raises concerns about parameter identification and robustness. Second, we acknowledge that the correlated model offers a better empirical fit in each sample, as indicated by a lower AIC. However, these improvements appear relatively modest in light of the increase in complexity. Third, the uncorrelated model facilitates interpretation. The mean and standard deviation of each coefficient are straightforward: the former represents average preferences and the latter reflects the extent of heterogeneity. In contrast, the correlated model produces a complex covariance structure (not reported here), which complicates the interpretation of individual attribute effects. Understanding the interaction of preferences across attributes requires analyzing the full covariance matrix, which is more difficult to convey.

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- Le **Centre d'Economie et de Management de l'Océan Indien**, **CEMOI**, University of La Réunion ;
- Le **Laboratoire d'économie de Poitiers**, **LéP**, University of Poitiers ;
- L'UMR **Structures et marchés agricoles, ressources et territoires**, **SMART**, INRAE, Agro Rennes-Angers Institute ;
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