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Research Article

Testing the Correlation between Prior Knowledge of - and Visualisation Guided WTPs for Reducing the Visual Impacts Visual from Offshore Wind Farms

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Abstract

Visual external costs are significant elements in the cost-benefit analysis of wind farm locations. This has been demonstrated well in the literature. However, in the assessment of the visual costs, a large share of the earlier studies used no or only simplistic visualizations of the visual impacts at stake. The cost estimates thus rely on the respondents' ability to imagine the visual impacts associated with wind turbines of different sizes and at different locations. This has been argued to potentially reduce the validity of the visual cost estimates. The present paper analyzes whether respondents' prior perceptions of the visual impacts from offshore wind farms correlate with their stated preferences for reducing the same visual impacts from offshore wind farms, when presented with visualizations of the visual impacts. The results show that respondents who perceive offshore wind farms to have positive or neutral visual impacts express equally strong preferences and high positive willingness to pay for reducing visual impacts, compared to respondents who perceive the visual impacts to be negative. The information in the visualizations thus appears to have updated the prior perception of the visual impacts of offshore wind farms.

Keywords
Offshore wind farms; visual impacts; use of visualizations; update of prior perceptions; choice experiments

1. Introduction

The development of wind power, and particularly offshore wind power, has increased drastically in the fight against global warming [1]. However, with more turbines being built, more people are exposed to their impacts. These impacts are particularly visual impacts and noise disturbances, and they lead to external costs of wind power [2-6].

The external costs have increased the need for having them quantified. The economic values of the impacts can guide policy-makers in making the difficult trade-offs between the technical/generation advantages of different wind farm sites and the associated external costs. The increase in demand for quantification has motivated researchers around the world to carry out Stated Preference (SP) economic valuation studies for assessing the external costs of wind power. So far, more than 25 such studies have been published.

As highlighted by Hevia-Koch and Ladenburg [7], the use of visualizations and the quality of those visualizations might be imperative for the validity of the estimated acceptance costs. The authors argue that unless the respondents have well updated prior information regarding the visual impacts of wind farms, they rely heavily on the use of visualizations in surveys. The need for visualizations is even more important, if the SP studies wish to take into account the visual impacts related to shadow effects/flickering and nighttime illumination [8-10]. Following the recommendations of Arrow et al. [11], Bateman et al. [12], and Champ et al. [13], the designers of SP studies must assure that the respondents are provided with the best tools possible to state valid and trustworthy preferences. This includes a thorough description and presentation of the attributes of the goods under investigation. Accordingly, “descriptions may require a combination of textual information, photographs, drawings, maps, charts, and graphs” [12].

The use of visualizations is of particular importance if the respondents have little knowledge on the good being valued. For example, Hoehn and Randall [14] find that varying the information about the quality and level of the good in focus in an SP study has an influence on the stated preferences. Another example is the research done by Czajkowski et al. [15]. Their test is about the quantum of knowledge that the respondents have about the good in focus. Interestingly, according to their findings, only 2.2% of the respondents have a high level of prior information. However, they also find that 59.1% have a low level of information. Finally, Kataria and co-authors [16] asked respondents about their perceptions of the current water quality in a river. Only 66% of the respondents had the objectively correct perception of the ecological quality of the river.

In complex choice situations, the influence of pictures and diagrams on choices has been tested. In the field of cognitive and educational psychology, if the information given is conveyed with diagrams [17] then the performance is improved. Hoehn et al. [18] tested two scenario information formats (text only and text, including tabular data). The tabular format both reduced the use of choice heuristics as well as the variance of the estimated preference parameters. Just recently, Shr et al. [19] have found that a combination of both visual and textual representations increases willingness to pay (WTP) for visual attributes compared to texts or visuals alone. This suggests that visualizations matter and might update the prior information about visual attributes. Another study by Patterson et al. [20] also finds similar results. The study compares preferences among respondents, who were represented to text-alone or a virtual reality experiment. They conclude that the preferences based on text-alone depend upon the respondents' mental images. The preferences are based on the images displayed in the virtual reality experiment. In a study by Rid et al. [21], 2D still pictures are compared to 3D movie sequences in relation to preferences for housing development. The 2D images provide more significant parameters. Matthews et al. [22] also tested virtual reality relative to 2D images. The study found that virtual reality, relative to 2D pictures, reduced choice error, lessened left-right bias, and improved respondent engagement and retention. Past studies reveal that preferences and choices are sensitive to the type of visualizations. Particularly, the study by Patterson et al. [20] and their conclusions are much in line with the aim of the present paper.

This paper aims to test if initial (prior) perceptions of the visual impacts from offshore wind farms correlate with visualization-guided stated preferences for reducing the same visual impacts. The analyses denote that irrespective of whether respondents initially perceive the visual impacts from offshore to be positive, neutral, or negative, all three groups of respondents express equally high positive WTP for reducing those specific visual impacts. Accordingly, the respondents seem to have their prior knowledge of the visual impacts of offshore wind farms updated by the visualizations given when stating the preferences and WTP for reducing the visual impacts from offshore wind farms. In application, these results indicate the importance of policy-makers and energy researchers in paying attention to the level of prior information regarding wind power in the population, while choosing an appropriate tool to assess the visual costs of wind power.

The paper is structured as follows: first, the survey and the theoretical model are presented; this is followed by the results, discussion, and conclusion.

2. Materials and Methods

2.1 Survey

The comparison of perceptions of visual impacts from offshore wind farms and the visualization-guided preferences for reducing them is based on a sample consisting of 700 randomly selected individuals between the age of 20 and 65 [23, 24], drawn from the Danish Civil Registration System's database. Information on the perceptions and preferences for the visual impacts was collected by mail-delivered questionnaires. In May 2004, each respondent received a cover letter and an 11-page questionnaire. Two reminders that did not include a new questionnaire were mailed to the respondents who had failed to respond. In total, 353 usable questionnaires were returned, which is equal to an effective response rate of 51%.[1]

In the questionnaire, each respondent was presented with a series of questions regarding wind power, the perception of impacts from wind power, an economic valuation scenario, and questions relating to the socioeconomic characteristics of the respondents (in that order).[2] The interest of this paper is in the perception of the visual impacts from offshore wind farms and the

[1] Compared to [23], respondents, who have not answered all the three choice sets, are excluded.
[2] The applied questionnaire is available in Ladenburg et al. [24]

economic valuation scenario, which includes visualizations. These are presented in the next two sections.

2.1.1 Perceptions

The information on the individual perceptions of the visual impacts from offshore wind farms was obtained from a single question. The respondents were asked to state their perceptions of the visual impacts from offshore wind farms on a five-point Likert-like scale with an additional option of an “I do not know” answer. Besides this, the visual impact scale ranged from “very positive”, “mainly positive”, “neutral”, “mainly negative” and “very negative”. The perception question was asked before the preference elicitation part of the questionnaire. Respondents who answered, “I do not know” are not included in the analysis.

2.1.2 Preferences

The economic valuation method, Choice Experiment (CE), was applied to elicit preferences for reducing the visual impacts from offshore wind farms [25, 26]. In short, CE is an economic valuation technique that has been applied in the field of marketing since the early seventies. It has been used in more than ten published papers focusing on offshore costs of wind power, see [4, 7, 27] for specific reviews of SP wind power studies.

In a CE, respondents were presented with a set of hypothetical “packages” with different characteristics, also called attributes. These packages also referred to as alternatives, and they are alternative provisions of the good in focus. In the present case, good refers to different levels of visual impacts from offshore wind farms. Respondents may choose their preferred alternatives from three choice sets. The choices reflect the respondents’ trade-offs between different attributes. CE builds on the theory proposed by Lancaster [28] and Rosen [29], where the bundle of attributes that the good consist of, gives utility to the consumer. If a cost attribute is included, the WTP for the different attributes, such a reduction in visual impacts from offshore wind farms, can be estimated.

The Danish offshore wind power development plan of 1996 forms the basis of the policy scenario under evaluation in the CE. It stipulated that, by 2030, 35% of Danish electricity consumption should come from wind power [30]. Further, 4,000 MW of power was expected to be developed offshore. At the time of the survey, the offshore wind power capacity was ~400 MW. Accordingly, the scenario entailed an offshore expansion of 3,600 MW of power. Turbines of 5 MW (100 m high and 120 m wingspan) were used in the valuation scenario. Consequently, the scenario entails the installation of 720 (720 × 5 = 3,600 MW) turbines offshore.

In order to represent the visual impacts, the attributes chosen were the distance from the coast and the size of the wind farm. The choices of attribute levels were made on recommendations from focus groups’ interviews, the members of an Environmental Steering Group of the CE project, and offshore wind power developers. In short, distances of 8 km, 12 km, and 18 km from the shore were considered as being realistic distances where future offshore wind farms could be located at. The distance of 50 km is the technical distance from where a 5 MW wind turbine cannot be seen from the shore due to the curvature of the earth. The number of turbines (49, 100, and 144) represents the possible wind farm sizes. To reach the target of 3,600 MW offshore wind power capacity, the number of 5 MW turbines in the scenario must be ~720 turbines. Accordingly, the number of turbines per wind farm and the total number of farms correlate almost perfectly (14 wind farms × 49 wind turbines/wind farm = 686 turbines, 7 wind farms × 100 wind turbines/wind farm = 700 wind turbines, and 5 wind farms × 144 turbines/wind farm = 720 turbines). The visual impacts associated with the wind farms of different sizes at different distances were illustrated by generic [7] computer-based visualizations. These were created by a specialist consultancy company. An example of the visualizations and a choice set is presented in Figure 1.

Alternative A

Alternative B

Figure 1 Example of the choice set. Alternative A Distance: 8 km, No. Turbines:100, No. Wind farms: 7 and Cost: 40 euro/year. Alternative B Distance: 18 km, No. Turbines:100, No. Wind farms: 7 and Cost: 80 euro/year.

I Choose A ☐ B ☐

In order to facilitate the payment for reducing the visual impacts on the hypothetical market in the scenario description, a uniform annual surcharge (lump sum) on all the households' electricity bills was realized. To minimize hypothetical bias, the respondents were prompted to be absolutely sure that their household would be willing to pay the amount specified, and a relatively short version of a "Cheap Talk" reminder was included [31, 32][3]. The text given to the respondent is presented in the Appendix.

2.2 Theoretical Model of the Link between Prior Perceptions and Update Preferences

From the two previous sections, the two processes of elicitation of perception and preferences are distinct. The perception question is short, simple, and solely relies on the prior knowledge that the respondents have on the visual impacts of offshore wind farms. The preference question entails information given to the respondent, advice with regard to how to state a rational preference (budget reminders and cheap talk), and visualizations. In other terms, the perception statements are based on the respondents' perceived prior knowledge with regard to the visual impacts from offshore wind farms, whereas stated preferences are based on a combination of prior knowledge, visualizations, and written information. This framework strongly links to the paper by Blomquist and Whitehead [33], where the perception of the value of a good is a function of the prior information and information given to the individual at the time of a choice decision. Following Blomquist and Whitehead [33], for a representative agent, the perceived quality q of a good can be expressed in terms of the actual quality of the good θ and the information received during the survey regarding the good's quality I is:

$$q = \overbrace{\beta \cdot \theta} + \overbrace{\delta \cdot I} \tag{1}$$

Both the actual quality of the good and the information received during the survey depend upon the individual learning parameters β and δ, respectively. These learning parameters do not directly refer to how much information the respondent is provided with; they merely represent the capability of the respondent to absorb this information. The learning parameters may be a function of personal characteristics [34], how motivated the respondent is for processing the information [35], how relevant and available the information is [14, 36], differences in how much prior information the respondent has about the good in focus [37, 38], or the type/quality of the information medium chosen [14, 33, 34]. The total amount of prior information on the resource quality, the respondent has, is represented by $\beta \cdot \theta$. Likewise, the total impact information provided in the survey has on the respondents' perception of the good in focus is represented by $\delta \cdot I$. Blomquist and Whitehead [33] developed their model in relation to the standard SP method—Contingent Valuation Method (CVM) [37, 39] study framework. Accounting for the different attributes in a CE, the quality changes under evaluation become a function of the values of n attributes and, therefore, the terms of Eq. (1) can be expressed as vectors:

$$\begin{aligned} q &= \boldsymbol{\beta} \cdot \boldsymbol{\theta} + \boldsymbol{\delta} \cdot \boldsymbol{I} \\ &= [\beta_1, \dots, \beta_n] \cdot [\theta_1, \dots, \theta_n] + [\delta_1, \dots, \delta_n] \cdot [I_1, \dots, I_n] \end{aligned} \tag{2}$$

Where every term of the vector $\boldsymbol{\theta}$ represents the objective change in quality related to a specific attribute of the good. Likewise, $\boldsymbol{I}$ represents the information about a specific attribute of the good that the respondent receives in the CE. In our case, we have two visual attributes: the distance to the coast (D) and the number of turbines (N) in each wind farm. These changes (2) to (3)

[3] The CT is marked with bold letters in the preamble.

$$q = [\beta_N, \beta_D] \cdot [\theta_N, \theta_D] + [\delta_N, \delta_D] \cdot [I_N, I_D] \quad (3)$$

In the second component of the perception/preference model $\delta_N{\cdot}I_N$ and $\delta_D{\cdot}I_D$, I_N and I_D are kept fixed and only vary with regard to the type of visualization the respondents are presented to in the choice sets. In these, the wind farms can be located at four different distances: 8 km, 12 km, 18 km, and 50 km from the coast. Accordingly, I_D can take the values I_8, I_{12}, I_{18}, and I_{50}. In terms of visibility of the offshore wind farms, the wind farms at 8 km are more visible than the wind farms at 12 km, etc., i.e., $I_8 > I_{12} > I_{18} > I_{50}$. However, whether the respondents perceive the visibility of the wind farms at different distances from the shore as being negative, neutral, or positive, strongly depends on the learning parameter δ_i, the prior information $\beta_i{\cdot}\vartheta$, and the background characteristics X_i.

The focus of the present study is to explore how $\beta_D{\cdot}\vartheta_D$ and $\delta_D{\cdot}I_D$ are related. Especially, it aims to test if the visual information given to the respondents via the given visualizations changes the perception so that the stated WTP is interpreted as being in contrast to the previously stated perceptions of the visual impacts. To be more specific, this research question can be broken down into relations between perceptions and preferences, as discussed in the following paragraphs.

For respondents who have a positive perception $\beta_D{\cdot}\vartheta_D > 0$, the visualization can confirm $\delta_D{\cdot}I_D > 0$ (visualizations induce a positive perception of the visual impact) or weaken $\delta_D{\cdot}I_D < 0$ (visualizations induce a negative perception of the visual impact) this perception. If the visualizations induce a negative perception that is equal to $|\beta_D{\cdot}\vartheta_D| = |\delta_D{\cdot}I_D|$ or stronger $|\beta_D{\cdot}\vartheta_D| < |\delta_D{\cdot}I_D|$ than the initial perception, the respondents will state a zero or positive WTP for reducing the visual impacts from offshore wind farms, respectively.

For respondents with a neutral perception $\beta_D{\cdot}\vartheta_D = 0$, the visualizations can confirm $\delta_D{\cdot}I_D = 0$ (visualizations induce a neutral perception of the visual impact) or weaken $\delta_D{\cdot}I_D >< 0$ (visualizations induce a negative or positive perception of the visual impact) this perception. If $\delta_D{\cdot}I_D < 0$, then the WTP for reducing the visual impacts will be positive and not the expected 'zero WTP'. If $\delta_D{\cdot}I_D > 0$, then the WTP for reducing the visual impacts will be negative.

Finally, for the respondents with a negative perception $\beta_D{\cdot}\vartheta_D < 0$, the visualization can confirm $\delta_D{\cdot}I_D < 0$ (visualizations induce a negative perception of the visual impact) or weaken $\delta_D{\cdot}I_D > 0$ (visualizations induce a positive perception of the visual impact) this perception. If the visualizations induce a positive perception that is equal to $|\beta_D{\cdot}\vartheta_D| = |\delta_D{\cdot}I_D|$ or stronger $|\beta_D{\cdot}\vartheta_D| < |\delta_D{\cdot}I_D|$ than the initial perception, the respondents will state a zero or negative WTP for reducing the visual impacts from offshore wind farms, respectively.

The tests for identical perceptions and preferences were carried out on groups of respondents. More specifically, the sample was divided into three groups, which represent the three types of initial perceptions of the visual impacts. While one group perceives the visual impacts to be positive (Positive Perception), a second group perceives the impacts to be neutral (Neutral Perception), and the last group perceives the impacts to be negative (Negative Perception).[4] Based on this grouping, the following main ($H1_0$ and $H2_0$) and sub-hypotheses ($H1A_0$, $H1B_0$, and $H1C_0$), are put forward:

$H1_0$: Perception and preferences are equal:

[4] By dividing the respondents into these three distinct groups, we also eliminate the potential biases associated with respondents using scales differently with regards to "mainly" and "very" positive/negative impacts.

$H1A_0$: Positive Perception respondents have negative preferences for reducing visual impacts from offshore wind farms, i.e., $WTP_{Positive\ Perception} < 0$

$H1B_0$: Neutral Perception respondents have neutral preferences for reducing visual impacts from offshore wind farms, i.e., $WTP_{Neutral\ Perception} = 0$

$H1C_0$: Negative Perception respondents have positive preferences for reducing visual impacts from offshore wind farms, i.e., $WTP_{Negative\ Perception} > 0$

$H1_1$: Perception and preferences are *not* equal

Stated perceptions and preferences might not be expressed on the same scale. This could be a potential explanation for the rejection of H1. However, we would still expect the relative differences between perceptions and preferences to persist. Hence, it is expected that respondents who perceive the visual impacts to be positive have weaker preferences for reducing the visual impacts from offshore wind farms compared to respondents who perceive the impacts to be neutral or negative and so forth. An alternative hypothesis H2 is therefore defined as:

$H2_o$: $WTP_{Positive\ Perception} < WTP_{Neutral\ Perception} < WTP_{Negative\ Perception}$

$H2_1$: $WTP_{Positive\ Perception} >< WTP_{Neutral\ Perception} >< WTP_{Negative\ Perception}$

Rejection of H2 suggests that there is no relation between prior perception of the visual impacts from offshore wind farms and the visualization guided preferences for reducing the visual impacts. Accordingly, the perceptions of the visual impacts from offshore wind farms seem to be updated by the use of visualizations, as argued in Hevia-Koch and Ladenburg [7].

2.3 Parametric Analysis of the Link between Prior Perceptions and Updated Preferences

The Mixed Logit model (MXL) is applied in the parametric analysis. MXL relies on McFadden's Random Utility Model [40]. In the CE, each respondent is asked to choose between two alternative layouts of Danish offshore wind power development. Under the assumption that respondent, n, chooses the alternative, which yields the highest utility, the systematic utility (V) can be expressed as:

$$V_n = \beta_1 \times D1250_n + \beta_2 \times D18_n + \beta_3 \times D50_n + \beta_4 \times SM_n + \beta_5 \times SL_n + \beta_6 \times COST_n + \varepsilon_n (4)$$

Where D1250 is used as a dummy variable controlling for locating the wind farms at distances (12, 18, or 50 km) beyond 8 km from the shore; D18 and D50 are dummy variables for locating the offshore wind farms at 18 and 50 km, relative to 12 km from the shore; SM and SL are dummy variables representing medium (100 turbines) and large wind (144 turbines) farms relative to small wind farms (49 turbines); COST is the cost associated with an offshore location; and the β1 to β6 are the estimated utility/preference parameters.

As mentioned, the flexible MXL is used to estimate respondents' preferences for offshore wind farms. The MXL model imposes fewer restrictions than the conditional logit model (CL) by allowing random taste variation and substitution over alternatives [41]. Applying a more general but equivalent utility definition, the following MXL model is estimated:

$$U_{nit} = V_{nit}(x_{nit}) = \beta_n^{'} x_{nit} + \varepsilon_{nit} = (\beta + \varphi_n)^{'} \ x_{nit} + \varepsilon_{nit} \cdots \varepsilon_{nit} \sim IID\ extreme\ value \qquad (5)$$

Where Unit is the utility, Vnit is the general systematic utility, x_{nit} is a vector of the offshore wind farm attributes of alternative I, t is choice task number [1-3] for individual n, β is the mean attribute preference, while φ_n is respondent n's deviation from the mean, β. The MXL model permits correlation in the stochastic part of the utility over alternatives, attributes, and choices, $\varphi_n{'}\ x_{nit} + \varepsilon_{nit}$. Conditional on β_n, the choice probability of respondent n's choice of alternative i in choice set t is defined as

$$L_{nit}(\beta_n) = P(i|x_{nt}, \beta_n) = \frac{exp\left(\beta_n^{'}\ x_{nit}\right)}{\sum_{j=1}^{J} exp\left(\beta_n^{'}\ x_{nit}\right)} \tag{6}$$

However, allowing for examination of unobserved preference heterogeneity through φ_n implies that φ_n is unknown to the researcher. It is, therefore, necessary for model identification to assume a distribution of $f(\beta_n|\theta)$. The MXL unconditional choice probability is then the integral of the conditional probability over all possible values of β_n from the distribution of θ [41].

$$Q_{nit}(\theta^*) = \int L_{nit}(\beta_n) f(\beta_n|\theta^*) d\beta_n \tag{7}$$

The dummy variable (*D*1250) controlling for locating offshore wind farms at a distance beyond 8 km (12 km, 18 km, or 50 km) is set as a random parameter with a normal distribution in the MXL specification. This allows for the heterogeneity of preferences to be both positive and negative for the location of the wind farms. All other variables are kept fixed (nonrandom).

A MXL model is estimated for each group (Positive Perception, Neutral Perception, and Negative Perception). Using 1,000 Halton draws from the mixed distribution to simulate the log-likelihood function, maximum simulated likelihood estimation (MSLE) is used.

2.3.1 Deriving Estimates of Willingness to Pay

The focus of attention, when comparing perceptions and preferences, is on the potential difference in preferences/WTPs between respondents with different impact perceptions for reducing the visual impacts from offshore wind farms. Assuming utility maximization, the alternative is a trade-off between the attribute levels of each alternative, revealing the preferences of the respondents. If a monetary attribute is included in the CE, an estimate of WTP for the non-monetary attributes can be obtained by scaling the coefficient of interest with the coefficient representing the marginal utility of price and multiplying with –1 [42]:

$$WTP_x = -\frac{\beta_x}{\beta_{COST}} \tag{8}$$

Where βx is the coefficient of the attribute of interest (D1250, D18, and D50) and βCOST is the COST coefficient.

3. Results

The estimated preferences for each of the three perception groups are presented in Table 1. The associated WTPs are estimated for each visual perception group in Table 2. Twelve respondents out of the original 365 respondents in the survey, answered "Don't know" to the perception question. These are left out of the analyses, leaving a sample survey of a total of 353 respondents. Of these, 102, 164, and 87 respondents have a positive, neutral, or negative perception, respectively.

Table 1 Preferences for reducing visual impacts from offshore wind farms, MXL model.

	Positive Perception Estimated parameter	Neutral Perception Estimated parameter	Negative Perception Estimated parameter
Mean estimate			
COST	-0.0395*** [0.00600]	-0.0436*** [0.00537]	-0.0539*** [0.00969]
D1250 km	0.599* [0.290]	0.485* [0.231]	1.024* [0.498]
D18 km[a]	0.382 [0.242]	0.950*** [0.213]	0.980** [0.335]
D50 km[a]	0.586* [0.258]	1.225*** [0.246]	1.699*** [0.453]
SL	-0.165 [0.204]	-0.251 [0.162]	-0.167 [0.263]
SM	-0.0497 [0.212]	-0.111 [0.172]	0.211 [0.303]
SD			
D1250 km	1.028+ [0.607]	0.934+ [0.505]	2.299** [0.828]
N	102	164	87
LL(0)	-211.4	-340.3	-180.9
LL(β)	-171.2	-252.7	-130.9
McFadden R^2	0.190	0.257	0.276

Notes: a) Relative to D1250 km. Standard errors in brackets: + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Across the three models, the preferences for moving future offshore wind farms to locations farther than 8 km from the coast are significant. The joined variable for locating the wind farms at 12, 18, or 50 km from the shore is positive and significant on a 95% level of confidence in all three models ($\beta_{D1250} > 0$). Accordingly, $H1A_0$ and $H1B_0$ are rejected, but not $H1C_0$. Interestingly, the estimated McFadden R^2 seems to be lower among the respondents who have a positive perception of the visual impacts ($R^2 = 0.190$), than those with a neutral and negative perception ($R^2 = 0.257$ and 0.276). This indicates that there is more variation in their stated preferences among respondents with a positive perception. This will be elaborated upon in the Discussion section. The rejection of $H1A_0$ and $H1B_0$ becomes even more apparent, when the WTPs among the three samples are compared in Table 2. The WTP estimates also allow us to test $H2_0$. Only the WTPs for locating the wind farms at 12 km, 18 km, and 50 km from the shore are shown as the hypothesis relates to the distance from shore.

Table 2 Comparisons of WTPs between perception groups (€/household/year).

	Positive Perception	Neutral Perception	Negative Perception	Positive vs. Neutral Perception[d]	Positive vs. Negative Perception[d]	Neutral vs. Negative Perception[d]
$WTP_{Distance\ 12\ km}$[a]	50.60* [24.75]	37.17* [17.87]	63.34* [30.29]	13.43 (0.324)	-12.73 (0.375)	-26.17 (0.234)
$WTP_{Distance\ 18\ km}$[b]	82.89** [26.98]	110.0*** [20.62]	124.0*** [32.89]	-27.07 (0.218)	-41.11 (0.169)	-14.04 (0.361)
$WTP_{Distance\ 50\ km}$[c]	100.1*** [26.55]	131.0*** [20.83]	168.5*** [33.59]	-30.90 (0.184)	-68.32 (0.056)	-37.42 (0.174)

Notes: a) $WTP_{Distance\ 12\ km} = (\beta_{D1250})/-\ \beta_{COST}$, b) $WTP_{Distance\ 18\ km} = (\beta_{D1250} + \beta_{D18})/-\ \beta_{COST}$, c) $WTP_{Distance\ 50\ km} = (\beta_{D1250} + \beta_{D50})/-\ \beta_{COST}$). Difference in WTP is tested with the Poe test [39, 40]. Standard errors in brackets: $^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

The respondents hold significant and positive WTPs; $WTP_{Distance\ 12\ km}$, $WTP_{Distance\ 18\ km}$, and $WTP_{Distance\ 50\ km} > 0$. More specifically, independent of whether the respondents have stated a negative, neutral, or positive perception, the respondents have expressed positive and significant WTPs for reducing visual impacts from offshore wind farms by locating them at 12 km, 18 km, or 50 km from the shore, relative to a location at 8 km. Consequently, as mentioned before, $H1A_0$ and $H1B_0$ are rejected. A comparison of the levels of WTP for reduction of the visual impacts across the three perception groups tests $H2_0$. The comparison of WTP across the three perception groups strongly suggests that the WTPs for reducing the visual impacts from offshore wind farms are equal. We cannot reject equality in WTP using the Poe test [43, 44], except when comparing the WTP for locating the wind farms at 50 km. In that case, the respondents with a positive perception have a significantly lower level of WTP when compared to respondents with a negative perception, although it is only 0.056. Thus, $H2_0$ is also rejected.

4. Discussion

The results of the present paper suggest that initial perceptions about the visual impacts from offshore wind farms seem to be updated by the visualizations at different distances from the shore. As a result, independent of initial perceptions, all respondents have positive preferences and WTPs for reducing the visual impacts from offshore wind farms by locating them far from the shore.

However, the methodological and estimation approach in the present study does not rest on a randomized experiment. There are several examples of experiments on wind power SP literature. Lutzeyer et al. [8] used a randomized experiment to test the impact of night light on offshore wind farms on the WTP for offshore wind farm locations. In an experiment, Ladenburg et al. [32] tested the impact of economic incentive reminders on stated preferences for offshore wind farm locations. The study found that giving respondents a Cheap Talk, had little influence on preferences. Another study, also focusing on the visual presentation of wind farms in CE, is the one done by Hevia-Koch and Ladenburg [45]. They tested the influence of screen size on preferences for onshore wind power locations. They found that smaller screens are associated with lower WTPs. In our case, an ideal setup would be to compare preferences with and without the use of visual aids. This calls for further research.

That the model variance seems to be decreasing as a function of the respondents' prior perception is an interesting result. The more negative the perception (going from positive to neutral to negative), the lower is the model variance (McFadden R^2 higher). This points to the fact that though the respondents with a positive perception have been updated in their perception of the visual impacts from offshore wind farms by the visualizations, they are more ambiguous in their preferences. This suggests that the information in the visualizations influences the preferences of the respondents differently.

Information on the level of certainty in the choices the respondents have made is utilized [46, 47] to explore this further. After making the three choices, the respondents were asked to state their levels of certainty in the choices they made on a scale from 0 to 10. Zero represents very uncertain and 10 means very certain. Table 3 shows the distribution of certainty levels.

Table 3 Distribution of certainty in choice levels across perception groups.

Level of certainty	Positive Perception	Neutral Perception	Negative Perception
0–3	10%	12%	13%
4–5	14%	16%	15%
6	7%	7%	3%
7	17%	21%	17%
8	33%	20%	26%
9	10%	15%	15%
10	10%	9%	10%

The differences in the levels of certainty are not perfectly mirrored in the McFadden R^2. Only 20% of the Positive Perception respondents have stated certainty of 9 or 10, while this is 24% and 25%, respectively, for the Neutral and Negative Perception groups. On the other hand, 33% of the respondents in the Positive Perception group have a certainty level of 8, while this is 20% and 36%, respectively, in the two other groups. However, it would be interesting to explore if differences in preferences and WTPs can be found among the respondents who are most certain in their choices. Again, under the assumption that prior perception correlates with preferences/WTPs, it could be expected that the stated level of certainty strengthens this correlation. More specifically, we would expect that the most certain respondents in the Positive, Neutral, and Negative Perception groups have negative, zero, and positive WTPs for locating wind farms that are 12 km, 18 km, or 50 km from the shore, respectively. The estimated preferences, parameters, and WTPs among respondents with a certainty level of 8, 9, or 10 are shown in Table 4. As the number of observations within each perception group is approximately halved, the model is estimated with only the *D*1250 km distance variable—the two dummy variables for the size of the wind farms and the cost attribute.

Table 4 Preferences and WTPs for reducing visual impacts from offshore wind farms, MXL model, certain respondents.

	Positive Perception Estimated parameter	Neutral Perception Estimated parameter	Negative Perception Estimated parameter
Mean estimate			
COST	–0.0341*** [0.00774]	–0.0360*** [0.00674]	–0.0475*** [0.0106]
D1250 km	1.298** [0.482]	1.705*** [0.513]	2.126** [0.761]
SL	–0.140 [0.297]	–0.0786 [0.252]	–0.478 [0.406]
SM	–0.170 [0.295]	–0.437+ [0.235]	–0.656 [0.415]
SD			
D1250 km	1.020 [1.013]	0.516 [1.729]	1.728+ [1.048]
WTP D1250 [€]	127.03* [51.70]	157.90*** [48.63]	149.38*** [48.25]
N	53	73	45
LL(0)	–111.6	–151.8	–93.6
LL(β)	–89.6	–110.5	–68.7
McFadden R^2	0.197	0.272	0.275

Notes: Standard errors in brackets: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

As the results strongly point, H1 and H2 are rejected among the respondents who are very certain in their choices. The estimated WTPs for locating the offshore wind farms at 12 km, 18 km, or 50 km from the shore are between 127 and 158 €/household/year. The Poe tests of equality in WTPs are not significant. The results from the uncertain respondents are shown in Table 5. They show the same picture, though the estimated WTPs for locating the offshore wind farms at 12 km, 18 km, or 50 km from shore are generally lower and less significant. The Poe tests of equality in WTPs are not significant. H1 and H2 are thus also rejected among the respondents, who are very uncertain in their choices.

Table 5 Preferences and WTPs for reducing visual impacts from offshore wind farms, MXL model, uncertain respondents.

	Positive Perception Estimated parameter	Neutral Perception Estimated parameter	Negative Perception Estimated parameter
Mean estimate			
COST	-0.0409*** [0.00873]	-0.0384*** [0.00595]	-0.0334*** [0.00905]
D1250 km	0.433 [0.324]	0.578** [0.196]	0.793+ [0.471]
SL	-0.152 [0.289]	-0.352+ [0.193]	-0.205 [0.313]
SM	-0.0564 [0.302]	-0.255 [0.199]	0.105 [0.317]
SD			
D1250 km	0.798 [0.891]	0.00105 [0.521]	0.984 [1.046]
WTP D1250 (€)	35.33 [25.29]	50.27** [17.94]	79.18+ [46.37]
N	48	91	42
LL(0)	-99.8	-188.5	-87.3
LL(*β*)	-82.3	-154.6	-73.6
McFadden R^2	0.176	0.180	0.158

Notes: Standard errors in brackets + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Conclusion

Based on a national sample of 353 respondents, perception of visual impacts from offshore wind farms and visualization-guided preferences/WTP for reducing visual impacts, are compared. The comparison is carried out by first asking the respondents about the perception of the visual impacts from offshore wind farms; then, they are given visualizations of offshore wind farms at different distances from the shore and asked to state their preferences/WTP for locating the wind farms at those distances. The results denote that respondents who perceive the same visual impacts as positive, neutral, or negative, have equally high and positive WTPs for the location of offshore wind farms at 12 km, 18 km, or 50 km from the shore. More specifically, the WTPs across the three groups are between 37–63€, 83–124€, and 100–168€ for locating the offshore wind farms at 12 km, 18 km, and 50 km, respectively. For WTPs locating the wind farms at different distances, there are no significant differences across the three perception groups. However, there is an exception in comparing the WTP for locating the wind farms at 50 km. In that case, the respondents with a positive perception have a significantly lower WTP when compared to respondents with a negative perception, although it is only 0.056. These results suggest that the respondents with a positive or neutral prior perception of the visual impacts from offshore wind farms have had their prior knowledge of the visual impacts updated by the visualizations.

The results are robust even if we condition the analysis on whether the respondent has been certain or not in the choices of offshore wind farm location. These results are noteworthy, as they imply that policy decisions with regard to the level of reducing visual impacts from offshore wind farms could be very different and depend upon the type of information available.

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Author Contributions

Jacob Ladenburg has carried out all parts of the paper

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