Spatial relationships: preferences for offshore wind power

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Abstract

A vast number of economic valuation studies jointly verify that the benefits of environmental quality changes are spatially correlated in several dimensions. As the first paper, we test and find similar spatial relations in preferences for the location of offshore wind farms. Using data from a Choice Experiment aimed at eliciting preference for the location of 3600 MW of offshore wind farms in Denmark, we find that both a linear travel time and a discrete (percentile) travel time model is significant. The results point towards that the further, the respondents live from a potential offshore wind power site, the lower is the WTP for locating offshore wind farms at 12 km, 18 km or 50 km relative to 8 km from the coast.

1. Introduction

While the existing environmental valuation literature varies regarding the way in which the choice scenarios are presented, the majority of recent studies have reached similar conclusions in that preferences are spatially heterogeneous. Spatial aspects have been found to significantly affect the heterogeneity in WTP across disciplines and geographical scales for improvements in environmental quality or services. Statistically significant findings regarding spatially heterogeneous preferences have been found included initiatives for watershed protection or water quality improvement (Bateman et al. 2011; Brouwer et al., 2010; Meyerhoff et al., 2014; Tait et al., 2012); provision of recreation services (Abildtrup et al., 2013; Ezebilo et al., 2013; Jones et al., 2010; Termansen et al., 2013) or ecosystem services (Broch et al., 2013; De Valck et al., 2014; van Berkel and Verberg, 2014) through creating or improving natural areas and forests; and traditional, fossil fuel energy development (Popkin et al., 2013). Because the non-market services that ecosystem provide are often disparately and unevenly distributed across the landscape, failure to include various spatial effects has severely biased, both over or underestimated, aggregated welfare gains from improvements in environmental goods (Brouwer et al., 2010; Tait et al., 2010; Meyerhoff et al., 2014) while not accounting for effects form substitute sites over and underestimated WTP values up to 40% (Schaafsma et al., 2013). Accounting therefore of these spatial effects has potential to substantively elevate reliability in WTP estimates and better inform future policy decisions.

These studies have accounted for the effects of distance decay and substitute availability on WTP through variables that measure respondents' distance or travel time to: the proposed improvement site in question, alternative existing substitute sites in question, and existing substitute sites not presented in the choice scenarios. In some cases, dummy variables have been included to capture regional proximity or similar as an indirect (discrete) measure of proximity. As several of these spatial variables were tested in the current analysis, relevant results from some of the aforementioned studies are discussed in turn below.

In the present paper we test for similar preference relations with regard to the location of offshore wind farm. Interestingly, we find that the preferences are significantly spatial dependent. The paper is structured as follows. First we give a review of the spatial preference literature and present the few examples from the wind power literature. This is followed by a short presentation of the study, the results and a conclusion.

2. Literature review

2.1. Distance decay of WTP for future offshore wind farms: distance effects considering ***proposed*** development

A number of studies have found a significant relationship between stated preferences for a change in environmental quality (or disamenity) and the respondent's distance to that proposed site in question, known as distance decay. The seminal paper by Sutherland and Walsh (Sutherland and Walsh, 1985) was one of the first economic valuation studies that addressed spatial issues in relation to the demand for river water quality in the US. The study indicated that the further the respondents lived from the river, the lower the likelihood that the respondent had visited the river at least once during the previous year. Because visit rate significantly influenced demand, Sutherland and Walsh established a single dimensional "distance decay" spatial model. It has since become increasingly common to include measures of distance in economic models and thereby explore the spatial dimensions on preferences (Meyerhoff et al.; Yao et al., 2014), though not necessarily significant (Barton et al., 2010; Bulte et al., 2005; Hanley et al., 2003; Payne et al., 2000).

Since then, the distance models have substantially advanced. Moore et al. (2011) include a measure of the quality at the nearest point from a respondent's residence in the their distance model. Their results suggest that the distance decay function alone might be a simplification of the spatial heterogeneity in preferences. The variable controlling for the (inverse) water clarity at the nearest point to the respondents residences is significant and positive, suggesting respondents living relatively close to murky waters have a higher WTP compared to respondents who live at the same distance to more clear water, all else equal. Similar spatial effects have been found regarding forest recreation values and nature development; Abildtrup et al. (Abildtrup et al., 2013) and Liekens et al. (2013) find preferences for nearer forest/nature sights relative to more distant ones. Finally, it should be noted that with the introduction of the attribute based economic valuation methods such as Choice experiments (Adamowicz et al., 1994) and Contingent Ranking (Georgiou et al., 2000), the (internal) spatial dimension in preferences has been analyzed by including the distance to the good in focus as an attribute in the choice sets. One recent energy development example explicitly tested respondent's distance to potential drilling sites as an attribute for preferences to have natural gas from those sites be a part of their electricity generation fuel in New York state, USA (Popkin et al., 2013). Results strongly suggest higher welfare costs would be incurred the closer the residents lived to the proposed sites. That is, respondents living farthest outside shale counties (i.e., outside those counties with proposed fracturing sites, approximately 250 miles away) would incur a -$21.84 welfare loss per month compared to those respondents living inside shale counties (i.e., inside those counties closest to the proposed fracturing sites, approximately 1 mile away) that would incur a -$47.63 welfare loss per month, on average.

2.1.1. Wind power studies

The majority of the wind power valuation studies to date have largely included discrete measures that estimate distance decay effects, if at all. While not always explicitly tested, some of the existing studies give insight into possible distance decay relationships influencing WTP. Krueger et al. (2011) include a variable for respondents for their "in-land" strata (who, on average, live furthest from the coast) in an analysis of preferences to reduce the perceived visual disamenities for proposed offshore wind farms in Delaware (USA). The results suggest that relative to the coastal strata (i.e., Ocean and Bay samples), the inland respondents have the weakest preferences to move the project farther from shore. Using a different approach but a somewhat similar discrete measure of respondent distance to the proposed offshore wind development site, these results are somewhat supported by Westerberg et al. (2013). In the analysis of visual disamenity reduction from offshore wind farms among tourists recreational demand in southern France, the respondents in Segment 2 (based on a Latent class model), hold relatively weaker preferences for visual impact reductions compared to the respondents in Segment 3. The member class function, point towards that Segment 2 has a significantly higher number of respondents living in Northern Europe and thus living far from the coastline of interest in France. Additionally, Boulatoff and Boyer (2009) estimated the preferences for the location of an onshore wind farm and find people perceive the wind farm as gain and consequently are willing to pay a positive amount for location the wind farm in a specific area. They find a positive relation between the distance to the proposed wind farm site and the place the respondents live. Accordingly, the WTP increases with the distance to the site, suggesting that vicinity to the wind turbines could be associated with a perceived externality.

Testing internally for a spatial effect by integrating the distance to the proposed project as an explicit attribute within wind power development choice scenario, several studies find significant effects for both offshore (Ladenburg and Dubgaard, 2007; Vecchiato, 2014) and onshore (Meyerhoff, 2013; Boatwright, 2013 *unpublished*; Vecchiato, 2014) wind farms. Jointly the studies suggest that people have preferences for locating wind farms farther from the coast (offshore) or residential areas (both onshore and offshore), though heterogeneity is present (Meyerhoff, 2013; Westerberg et al., 2013). Most recently, Vecchiato included an explicit 'distance from turbines' attribute in a choice experiment for wind power development in Italy in addition to a location attribute (onshore or offshore) and found an increasing, yet declining marginal, utility for respondents with increased distance from the proposed wind project (Vecchiato, 2014). Relative to a minimum distance of 100 meters from house/coast, respondents were willing to pay 47€ and 78€ to move the proposed wind site to 250 or 1,000 meters (1 km) away. Interestingly, the 1 km minimum distance from the respondents' house/coast was the second most important attribute behind and offshore location, both suggesting that distance was a critical attribute in preferences. While distance was not internally tested as an attribute in the present study, it is accounted for as the distance from the postal area (based on zip code) to the nearest proposed offshore wind farm in the spatial analysis to estimate any distance decay effects.

2.2. Distance decay of WTP for future offshore wind farms: distance effects considering *existing* development

Similar to the previous section, several studies suggest preferences for an amenity are influenced by a respondent's distance to existing amenities (i.e., substitutes), or disamenities. The distance to existing amenities/disamenities represents more than just having access to an amenity or being close to a disamenity. In the case of offshore wind farms, which are subject to specific geographical siting constraints, it can be argued that the distance to an amenity/disamenity also captures the propensity to have experience with offshore wind turbines. Differences in preferences between respondents living close to an offshore wind farm compared to those living relatively far from an offshore wind farm can thus be an expression of both the level of nuisances from offshore wind turbines, having experience with an offshore wind farm, and a combination of both.

Pate and Loomis (1997) was one of the first papers (if not the first) to estimate a demand model which combined a distance decay measure with the level/quantity of substitutes resources (on a stated level) in a CVM study. The WTP for three programs was estimated: 1) WTP for the protection and expansion of wetlands; 2) WTP for a reduction in wild life contamination in the San Joaquin Valley (USA); and 3) WTP for improvement of salmon stocks in San Joaquin River. They find a significant distance decay (log distance) effect for the first two programs concerning wetland and contamination control improvement. Furthermore, the availability of substitutes, measured as the number of acres of wetlands in the sampling area (California, Oregon, Washington and Nevada), influenced demand significantly. Accounting for substitute water bodies, Jørgensen et al. (2013) find that the preferences for improving the water quality in Odense River (Denmark) is positively influenced by the lack of substitute rivers/stream and ocean water bodies among both users and non-users of the Odense River. The study finds that the longer distance to a substitute site, the higher WTP. Though they do not account for substitute water bodies,

Schaafsma (2012) also finds that non-users hold preferences that are characterised by a stronger distance decay relation compared to users. Not done in previous analyses, Schaafsma et al. (2012) find that including the directional dummy variables for the location of the residence relative to the lakes improves the model. After a step-wise exclusion of insignificant directional dummy variables, seven variables were found to be significant. The final model indicates that the distance decay effects are also conditional on the location of the residence relative to the lakes subjected to valuation. Depending on the respondents' area of residence, the upward (weaker) and downward (stronger) shifts in the distance decay function is related with with having fewer or more substitutes nearby. Finally, Termansen et al (2008) and Schaafsma et al. (2013) find substitution effects in the demand for recreational forest visits and improvements in water quality changes for recreation-related, ecosystem services, respectively, although the latter comments that further research is required to estimate the effect on WTP from substitute recreation sites of both significant cultural interest and outside the study area.

2.2.1. Wind power studies

In the wind power literature, even fewer examples exist that capture distance decay relations of existing wind power projects on the preferences for future (onshore or offshore) wind power development. These emerging findings, however, suggest that proximity to existing wind farms negatively influence preferences for marginal development. One of the few is Meyerhoff (2013). Focusing on preferences for onshore wind power development in Germany, Meyerhoff (2013) finds using a MNL model that the further people live from the nearest wind turbine, the weaker the preferences for the wind alternative compared to the status quo. This wind development scenario includes large wind farms, taller wind turbines, greater impacts on the red kite population and a distance to the nearest town of 750 m. This finding suggests that the further people live from a wind turbine, the stronger preferences they have for constraining wind power development and minimizing ensuing impacts. In other words, increased proximity to the wind turbines increases the likelihood of being a wind power opponent, i.e. decreases the likelihood of being a wind power proponent. These results are backed up by a latent class model. Using a more discrete measure of distance, Ladenburg and Dubgaard (2007) find a negative effect on preferences for the location of offshore wind farms among respondents who can currently see an offshore wind farm from their residence/summer house. Respondents with an offshore wind farm in their view shed thus have a WTP for locating a wind farm at 12, 18 or 50 km (relative to 8 km) from the coast, which is between 212 and 365% higher than respondents who do not have a view of offshore wind turbine(s). The study did not include an opt-out alternative.

2.3. Cumulative effects

While the previously discussed distance decay has potential to measure spatial relationship on WTP through the measure of distance to existing wind projects, capturing spatial effects in a single dimension is perhaps not robust enough to capture all the spatially heterogeneous effects, such as been found with accounting only for distance to nearest possible substitute sites (Scaafsma et al., 2013). Holding constant each respondent’s proximity to the nearest wind project, there might exist a cumulative exposure effect for people that encounter wind turbines multiple times on a daily basis because there are more projects near their daily routine or more turbines in the those projects. These aspects suggest the impact on preferences might also be multidimensional in a multiplicable function of the number of turbine encounters or the number of turbines in a given distance from the residence. Any cumulative effects on preferences might be sensitive to and depend upon the numbers of amenities/disamenities within a relevant area.

In this multidimensional relationship, recently the role of spatial direction of the respondent in relation to the proposed/substitute site(s) been identified to significantly affect WTP for users and non-users. Using the spatial expansion method to test directional, user vs. non-user, and substitution effects, Schaafsma et al. (2013) find significant directional effects for 2 of the 3 sites that occur in addition to the effects on WTP from travel distance to the site in question and substitutes. Related to relative experience to these areas, whether or not respondents frequent or utilize these areas in question has shown varying significant effects on preferences. For one site in the study, the (linear) distance decay function was only significant for users. Whereas at another site, while both users and non-users showed a logarithmic distance decay, the nonusers' WTP decayed more quickly, suggesting previous experiences positively influenced the users' preferences for water quality improvements of this site in question.

Finally, Popkin et al. (2013) find that, on average, respondents living in a county in New York (USA) with a significant amount of proposed hydraulic fracturing (HF) drilling sites exhibited a larger disutility for the development compared to respondents living outside the HF county. While the significant in- HF county result was only briefly interpreted and discussed in the original analysis, this relationship suggests a possible (discrete) measure of how perceived, future development negatively affects WTP for those respondents inside the region where energy development is expected to cumulatively, and spatially, proliferate. It is worth noting that this effect was significant in addition to the highly significant distance decay measure (estimated measuring respondent distance to the nearest proposed drilling site). This finding is somewhat supported somewhat in the opposite way for an improvement in an environmental good; recently de Valck et al. (2014) found that *perceived* density of nearby (within 5 km) substitute sites for forest recreation negatively affected WTP to improve nature sites close to the respondents' homes in the choice scenario.

2.3.1. Wind power studies

Meyerhoff (2013), discussed previously, includes a measure to estimate any effect of 'respondent's exposure' on preferences using self-reported numbers of turbines and wind farms within a 5 km radius of each respondent's residence. Assuming the number of turbines impacts preferences linearly, the estimated models do not suggest a cumulative effect in that the number of turbines within a 5 km radius did not exhibit a statistically significant effect on latent membership in any of the identified classes (classes are wind 'Advocates', 'Moderates', or Opponents').

However, in two wind power acceptance studies, Ladenburg and Dahlgaard (2012) and Ladenburg et al. (2013) test the effect of the stated number of turbines seen on a daily basis on the acceptance on the existing onshore wind turbines, more onshore wind turbines and repowering (replacement of smaller turbines with fewer larger ones) of onshore wind turbines. Ladenburg and Dahlgaard (2012) find significant effects related to the acceptance of existing onshore wind turbines. Ladenburg et al. (2013) find similar effects in acceptance for more onshore wind turbines, though the effect is only significant among respondents that have onshore wind turbines in the viewshed from their residence.

In the present study, the stated number of daily turbine encounters is used to measure cumulative effects from wind turbines on preferences. As argued in Meyerhoff (2013), this approach is advantageous in that it takes into account wind turbine encounters as function of daily travelling patterns of the respondents. Compared to the two GIS-based distance decay measures, the stated number of turbines is naturally a more subjective measure and therefore is dependent upon the individual's ability to recall the amount of turbines seen daily. If people who dislike offshore wind farms are also better at recalling the number of turbines and to a higher extent can mentally register daily encounters with turbines, the stated number of turbines would be a function of offshore wind power acceptance, biasing the results. That said, these properties are tested in the results section but do not suggest to be problematic for the analysis.

3. Study Design

The analysis of preferences for the location for offshore wind farms and the test of spatial relations survey are based on Cheap Talk sample reported in Ladenburg et al. (2011). The data origins from a survey in 2006 using a nationwide internet panel consisting of approximately 17,000 people. Initially, the desired sample size was set to 350 respondents. To obtain the sample size 619 respondents were emailed a questionnaire. Of these 355 completed the questionnaire. Removing protest answers (see the end of this section for a description of the definition of protest answers), the effective sample size was 338 respondents. This gave an effective response rate of 54.6 percent.

In the beginning of the survey the respondents were asked about their attitude a perception of wind power. After those questions, the respondents were introduced to the Choice Experiments and were told to assume that one-third of electricity in Denmark by 2030 will be generated using wind turbines. Therefore, they were told the purpose of the following choice questions was to (a) inquire about how they think offshore wind development in Denmark should be implemented and (b) where that development would be appropriate.

To elicit the preferences for location, each respondent was given six choice sets, which were represented by a status quo alternative (offshore wind farms located at 8 km with no extra costs to the household) and two hypothetical wind farm locations. In the hypothetical alternatives, the offshore wind farms could be located at 12, 18 and 50 km, representing reduction in the visual impacts compared to 8 km, where a wind farm located at 50 km would not be visible from the coast. As a payment vehicle, an annual fixed increase in the household electricity bill was used. The choice of payment vehicle was based on a focus group interview in which the respondents stressed that they found it difficult to remember their annual electricity consumption. In order to minimise biases in WTP associated with uncertainty regarding the annual electricity consumption, applying a marginal increase in the electricity price as a payment vehicle was abandoned. The annual increase could take the values

13.33, 53.33, 93.33 and 186.67 € per household per year[1]. The attributes are presented in Table 1 below.

Table 1: Attributes in the choice experiment

Attribute	Levels
Distance to the Coast (km)	12, 18, and 50 (relative to 8)
Increase in costs (€/household/year)	13.33, 53.33, 93.33 and 186.67 (relative to 0)

With three hypothetical distances and four prices, a total of 12 (3×4) alternatives were constructed (full factorial design). Following Kuhfeld (2004)the alternatives were arranged into choice sets so that there would be a minimum overlap and minimum correlation in attributes within each choice set. Given the full factorial design, level balance in which each attribute level is represented an equal number of times (Huber and Zwerina, 1996) was also obtained. Each respondent stated their preference six times. As the example choice set presented below illustrates, each location of the wind farms were visualised for each alternative[2].

[1] In the survey the payment levels were presented in Danish Kroner (DKK). The equivalent levels are 100, 400, 700 and 1,400 DKK/household/year

[2] In the original survey the visualizations were larger to give the respondents a better feeling of the visual impacts. Each choice set thus covered an area on the computer screen equivalent to an entire A4 page.

Alternative 1 Distance to the Coast. 8 km Increase in costs 0 DKK

Alternative 2 Distance to the Coast. 12 km Increase in costs 400 DKK.

Alternative 3 Distance to the Coast. 50 km Increase in costs 1400 DKK

I prefer	Alternative 1 ( )	Alternative 2 ( )	Alternative 3 ( )

Figure 1. Example of a choice set.

Prior to the choice sets, respondents were shown a map of Denmark (Figure 2) that denoted proposed wind projects (in yellow) that would total 3600 MW if built, plus the existing offshore wind farm sites (shaded in black and yellow). Respondents were also informed of the tradeoff for locating the wind turbines further from the coast because of increased capital costs.

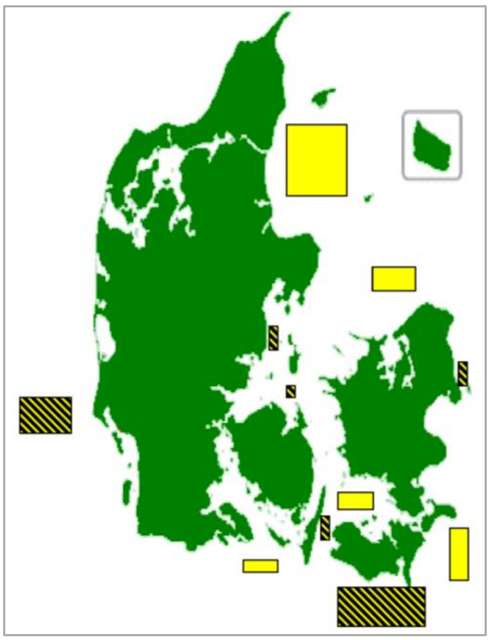

Figure 2: Study area map shown to respondents with the preamble preceding the CE. Yellow and black shaded areas represent existing offshore wind power sites. Yellow blocks represent proposed or hypothetical project sites totaling 3600 MW potential power capacity.

All respondents who chose the status quo alternative were given a follow-up question in order to get a deeper understanding of the preferences governing the serial choice of the status quo alternative (i.e. no preferences for reducing the visual disamenities). Respondents answering that their primary reason was that they prefer the wind turbines to be located at a larger distance but did not want to pay a higher electricity bill were classified as protest zero bidders, as were those respondents stating that they could not relate to paying a higher electricity bill. The reason for classifying these respondents as protesters is that their primary reason for choosing the status quo alternative was due to the setup of the survey and not their preferences as such. To reduce protest bias in the stated preferences, the 19 protest respondents were excluded from the analysis. For a more detailed presentation of protest zero bidding see Meyerhoff and Liebe (2008)or Bonnichsen and Ladenburg (2009). (2009)

3.1. Modelling transport time to the nearest potential offshore wind farm site.[3]

The study uses a geographical information system (GIS) and network analysis to link the proposed offshore wind farm sites to the geostatistical entities of the survey participants. As the study uses postal districts to geographically locate survey participants, the centroids of a postal district theme were used. A road network database with a simplified road network structure including road segment length and average car speed was used to link wind farm locations and postal district centroids. It was hereby assumed that the link from the wind farm to the road network happened through the road segment nearest to the coast, using a straight line distance.

The variables used to analyse proximity are road distance, which is the distance travelled via the road network, as well as travel time, which is the accumulated time spent on travelling along the road distance at speeds recorded for every road segment. Distances from all wind farms to all postal district centroids were calculated using the ArcGIS version 9.2 including Network Analyst. Inaccuracies and uncertainties in the applied method appear in several places. First of all, the concept of road distance and travel time is only an approximation of proximity. While better than Euclidean distance, it still excludes personal preferences, cognitive aspects of nearness, and the general image of the coastal areas and their accessibility. Further inaccuracies appear in using the postal district and wind farm centroids rather than the exact location of residence and the wind farm boundaries. The errors in distance and travel time are, however, assessed to be less than 4% and often as little as 1% for the majority of the population. As the road network database is an older version available to the researchers, some new roads and motorways are not included, resulting in overestimated distances and travel times. Finally, uncertainty prevails in the calculated travel times like function of distance and speed, which leaves out road congestion and stops at traffic lights, and neglects personal preferences in travel patterns.

4. Choice and Econometric Framework

4.1. Random Utility Model

Assuming utility-maximising behaviour of the individual, the choices made are analysed using the Random Utility Model (RUM) (McFadden, 1974). The RUM states that the true but ultimately unobservable utility U for individual n conditional on choice i can be broken down into two components, an observable systematic component V and the unobservable random component, the error term ε:

[3] The author would like Associate Professor Bernd Möller, University of Aalborg, Denmark for estimating the relevant transport times matrices.

$$U_{ni} = V_{ni}(x_{ni}, S_n, \beta) + \varepsilon_{ni},$$

where the observable component V_{ni} is a function of the attributes of the alternatives x_{ni}, characteristics of the individuals S_n and a set of unknown preference parameters β. The observable component V_{ni} is assumed to be a linear function:

$$V_{ni} = \alpha ASC_{ni} + \beta x_{ni},$$

where α and β denote vectors of preference parameters associated with the specific alternatives ASC_{ni}, and the attributes of the alternatives x_{ni} respectively. The characteristics of the individuals are left out for simplicity. In the present application the alternative specific constant (ASC) is labelled ASC23. The variable thus represents the joint utility of moving offshore to larger distances than 8 km, all else being equal (i.e. the joint utility of alternative 2 and 3). Assuming a specific parametric distribution of the error term allows a probabilistic analysis of individual choice behaviour:

$$P_{ni} = Prob\left(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}\right) \forall i, j \in C, j \neq i,$$

where P_{ni} is the probability that individual n's utility is maximised by choosing alternative i from choice set C. The researcher chooses the distribution of the error term and different distributions result in models with different properties(Ben-Akiva and S.R., 1985).

4.2. Deriving Estimates of Willingness to Pay

The focus of attention is the WTP and hoe WTP is spatially distributed in the sample population. When a respondent chooses an alternative they are making a trade-off between the distance to the coast of the offshore wind farms and an annual fixed increase in the household electricity bill and thus the respondent's preferences are implicitly revealed. By including a monetary attribute it is possible to estimate WTP for the non-monetary attributes, i.e. the distance of the offshore wind farm to the coast. This is done by scaling the coefficient of interest with the coefficient representing the marginal utility of price and multiplying with –1(Louviere et al., 2000):

$$WTP_x = -\frac{\beta_x}{\beta_{price}},$$

where β_x is the coefficient of the attribute of interest and β_{price} is the price coefficient.

4.3. Econometric Specifications

The parametric analysis applies Random Parameter Error Component Logit (RPECL) models. The models rely on McFadden's RUM (McFadden 1974) described earlier.

Conditional Logit

If the error terms are assumed to be independently and identically Gumbel distributed, then this results in a Conditional Logit (CL) specification for the probability of individual *n* choosing alternative *i*:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in C} e^{V_{nj}}},$$

where the scale parameter is normalised to 1, and omitted. The CL model imposes several restrictive assumptions in that it does not allow for random taste variation, for unrestricted substitution patterns and for correlation in unobserved factors over time (Train, 2003). The model also suffers from having to adhere to the restrictive independence of irrelevant alternatives (IIA) property.

Error Component Logit

In the Error Component Logit (ECL) model, an additional error component is incorporated in the CL model to capture any remaining alternative specific effects in the stochastic part of utility (Scarpa et al., 2005). The additional error component has zero-mean and is a normally distributed random parameter assigned only to alternatives two and three. Following Meyerhoff and Liebe (2009), the utility function of the ECL specification can be written as:

$$U_{ni} = V_{ni} + E_{ni} + \varepsilon_{ni},$$

where V_{ni} is the systematic component of utility, E_{ni} are the error components and ε_{ni} is the same Gumbel distributed error term from the CL. When the error components are associated with alternative two and three, the utility functions can be written as:

$$U_{SQ} = \beta x_{SQ} + \varepsilon_{SQ},$$
$$U_2 = \alpha ASC_{23} + \beta x_2 + E_{23} + \varepsilon_2,$$
$$U_3 = \alpha ASC_{23} + \beta x_3 + E_{23} + \varepsilon_3,$$

where subscripts *2* and *3* indicate alternatives two and three and the subscript *SQ* indicates the status quo. By including the additional error components E_{23}, the IIA restriction is eliminated and any remaining systematic effect of choosing a non status quo alternative relative to the status quo is captured by the ASC23 (Scarpa et al. 2005).

Random Parameter Error Component Logit

To further extend the ECL model, the RPECL specification is applied. The RPECL specification allows for taste heterogeneity in preferences by specifying some or all attribute coefficients as random reflecting the heterogeneity of individuals' preferences. The model also does not exhibit the restrictive IIA property and it allows for correlation in unobserved utility over alternatives and time (Train 2003). The specification can be generalised to allow for the panel structure (repeated choices by the same respondent) of Choice Experiment (CE) data. In other words, the RPECL model allows for the utility coefficients to vary over respondents, but remain constant over choice occasions for each respondent (Train 2003). Here individual n's true utility for the ith alternative in choice situation t can be written as:

$$U_{ni} = V'_{ni}(ASC23_{ni}, \alpha, x_{ni}, \beta, \beta_n) + E_{ni} + \varepsilon_{ni},$$

where β_n denotes individual specific random parameters while α and β denote the fixed parameters of the ASC23 and the attributes of the alternative. Again, the characteristics of the individuals are left out for simplicity. The model is specified with the ASC23 and the price coefficient being fixed and all other coefficients being normally distributed[4]. Assuming that the error term is still Gumbel distributed, the probability of individual n choosing alternative i can be written:

$$P_{ni} = \int \left(\frac{e^{V'_{ni} + E_{ni}}}{\sum_{j \in C} e^{V'_{nj} + E_{nj}}} \right) \phi(\beta | b, W) d\beta,$$

where $\phi(\beta | b, W)$ is the normal density with mean b and covariance W. This probability can be described as an integral of the standard CL function evaluated at different values of β with the density function as a mixing distribution (Train 2003).

With the assumption that the unobserved heterogeneity in preferences follows a normal distribution, several models have been tested with regard to identifying the potential level of correlation in the unobserved heterogeneity in the preference for reducing the visual impacts from offshore wind farms.

[4] Other distributions, such as a uniform, triangular and lognormal distribution have also been tested, but the choice of distribution does not improve the model or change the conclusions of the paper.

In the main model, a model allowing for full correlation was initially estimated, but the estimated mean parameters were insignificant and had reversed the sign. As a consequence, only the variables controlling for wind farms located 18 and 50 km from the coast (Distance 18 km and Distance 50 km) were allowed to correlate. However, when interacting the attribute variables with the socio-economic demographics of the respondents and the spatial variables, models allowing for correlation in the unobserved utility of wind farms located at 18 and 50 km from the coast could not be identified. Accordingly, it was decided restrict the variance-covariance to diagonal elements only. Additionally, several definitions of the error component have also been tested, but all models indicated that only correlation patterns in the variance between the two non-status quo alternatives were significant in a fully specified model with interactions. (Meyerhoff and Liebe 2009; Bonnichsen and Ladenburg 2010). However, as highlighted in Ladenburg (2014) other correlation patterns are significant when estimating a main effect model.

5. Results

The preferences for reducing the visual disamenities are presented in the table below. Three models are shown. A main effect model and two spatial models with only the significant variables are shown. The first spatial model is a percentile travel time model. In that model, the travel time to the nearest potential offshore wind development site is divided in two five 20 percentiles. It is subsequently tested if preferences differ between the five percentiles. In the second model, a simple linear spatial travel time relations is tested.

Table 2: Random Parameter Error Component Logit models

	Main effect Model	Percentile spatial model	Linear spatial model
Mean			
Costs	-0.00301^{***}	-0.00300^{***}	-0.00193^{***}
	[0.000200]	[0.000310]	[0.000367]
Distance 12 km (ASC23)[a]	0.433	0.0396	0.0434
	[0.336]	[0.537]	[0.537]
Distance 18 km[b]	0.210	0.139	0.137
	[0.161]	[0.174]	[0.174]
Distance 50 km[b]	0.703^{***}	0.467^{*}	0.472^{**}
	[0.120]	[0.183]	[0.183]

Costs*Female		-0.00167***	-0.00164***
		[0.000328]	[0.000327]
Household Income 66,667-120,000 €/year* Distance 12 km		1.098^{c}	1.084^{c}
		[0.727]	[0.726]
Household Income >120,000 €/year* Costs		0.00112*	0.00116*
		[0.000535]	[0.000535]
Household Income >120,000 €/year*Distance 12 km		2.779$^{+,c}$	2.739$^{+,c}$
		[1.532]	[1.526]
Household Income >120,000 €/year*Distance 18 km		1.168^{+}	1.155^{+}
		[0.608]	[0.607]
Visit the beach at least 1/second month*Distance 50 km		0.416^{+}	0.406^{+}
		[0.230]	[0.229]
Travel time 10-66 minutes to nearest protential offshore wind farms site(0-60th percentile) * Costs		0.000807*	-
		[0.000318]	
Travel time (linear)		-	-0.00000829^{+}
			[0.00000438]
Standard deviation			
d18	1.608***	1.554***	1.562***
	[0.213]	[0.218]	[0.219]
d50	0.546^{+}	0.637*	-0.633*
	[0.294]	[0.283]	[0.284]
Error component parameters	5.318***	5.322***	5.310***
σ_{23}	[0.452]	[0.456]	[0.454]
No. choices		2028	
No. respondents		338	
AIC	2516.6	2488.5	2491.5
LL(0)		-2228.0	
LL(β)	-1251.3	-1222.3	-1223.8
Mcfadden R2	0.438	0.451	0.451

Notes: [a] 8 km is the reference, [b] 12 km is the reference. [c] Jointly significant on a 90% level of confidence Standard errors in brackets
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.1. Main effects

The average main effect respondent models point towards that the respondents hold significant preferences for reducing the visual disamenities from offshore wind farms. The Distance 12 km (ASC23), Distance 18 km and Distance 50 km estimated preferences parameters are all positive, though $\beta_{\text{Distance 12 km}}$ and $\beta_{\text{Distance 18 km}}$ are not significantly different from 0. Furthermore, $\beta_{\text{Distance 50 km}}$ is significantly larger than $\beta_{\text{Distance 18 km}}$. Respondents thus prefer wind farms to be located at 50 km from the coast relative to 18 km. However, remember that the WTP for location the wind farms at 18 and 50 km are estimated by $(\beta_{\text{Distance 12 km}} + \beta_{\text{Distance 18 km}})/\beta_{\text{Costs}}$ and $(\beta_{\text{Distance 12 km}} + \beta_{\text{Distance 50 km}})/\beta_{\text{Costs}}$. In this perspective the WTPs for location the offshore wind farms at 12, 18 or 50 km from the coast are 19, $28^{+}$and 50^{**} €/household/year. The WTP of 28 € for locating the wind farms at 18 km from the coast is thus significant on 90 level of confidence. Marginally, this equals to that the respondents are willing to pay 2.25 euros/km in the distance interval 8-12 km, 1.5 euros/km in the distance interval 12-18km and 0.69 euros/km in the distance interval 18-50. Thus clearly marginally disminishing WTP to locate the offshore wind farms an additional km from the coast and in line with the review by Ladenburg and Lutzeyer (2012).

5.2. Socio-demographic results

If we move on to the socio-demographic interaction model, the preferences relations suggest that female respondents are more sensitive towards an increase in costs and therefore also have lower WTP for reducing the visual disamenities ($\beta\text{Costs}_{\text{Female}}>0$). This equal a difference in WTP between male and females of 36%.

Respondents with a household income level above 119,999 Euros/year are less sensitive towards an increase in the cost and therefore also have a higher WTP ($\beta\text{Costs}_{\text{HH. Income}\geq 120{,}000€/\text{year}}>0$). In addition, the same respondents also associate a location at 12 km (relative to 8 km) and 18 km (relative to 12 km) from the coast with higher utility ($\beta\text{Distance 12km}_{\text{HH. Income}\geq 120{,}000€/\text{year}}>0$ and $\beta\text{Distance 18km}_{\text{HH. Income}\geq 120{,}000€/\text{year}}>0$). However, the former is only significant on a 90 level of confidence. Respondents with a household income between 66,667 and 119,999€ (both included) also have significant stronger preferences for location offshore wind farms at 12 km relative to 8 km ($\beta\text{ASC23}_{\text{HH. Income}>66.666 \text{ and } <120{,}000€/\text{year}}>0$). The parameter estimate is though only significant on a 90 % level of confidences. The results are in line with Ladenburg & Dubgaard (2007). The Income WTP relations are shown in Figure 3 below.

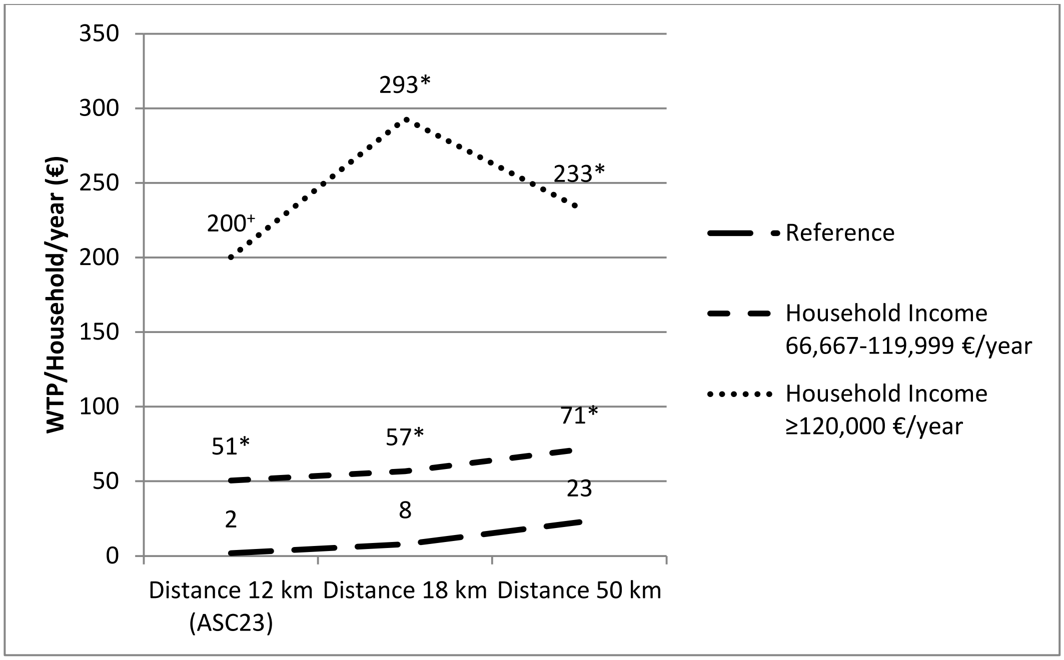

Figure 3: Household income and WTP relations. * $p < 0.05$

As the figure illustrates, respondents from high income households (>120,000 €/year) have markedly higher level of WTP compared to respondents from the references group, where the respondents have a household income below 66.667 €/year. The WTPs are 10-100 times higher than the reference group.

Viewshed effects

Ladenburg and Dubgaard (2007) finds that the view shed to offshore wind farms influence WTP significantly. We have used a similar approach and tested whether respondents who have an offshore wind farm in the view shed from the residence or summer house have different preferences. That was not the case. Though an interaction between having a viewshed to an offshore wind farm and the Costs varaiable was significant, subsequent test suggested that it was merely a scale effect. The test was carried out using a heteroscedastic conditional logit model. Similarly, we have also tested, whether view shed to onshore wind farms influence preference and WTP with the same results – no significant effects.

Visits to the beach

As found in Ladenburg and Dubgaard (2009) , respondents who visit the beach at least once per month have a higher WTP, compare to respondents who visit the beach less frequently. The preferences for reducing the visual disamenitiesin our analysis seem to be in line with Ladenburg and Dubgaard (2009). More specifically, the preferences for locating the wind farms at 50 km from the coast seems to be significantly higher among respondents who visit the beach at least once every second month. The references group is respondents visiting the beach less frequently. The estimated parameter is though only significant on a 90 level of confidence. In WTP terms the WTP for location the wind farms at 50 km is app. 89% higher for the respondents visiting the beach at least once/second month.

5.3. Spatial preferences

Cumulative effects

The cumulative effects are estimated with three dummy variables, which represent respondents seeing 6-10, 11-20 and more than 20 turbines daily. The references level is respondents who see less than 6 turbines daily. The cumulative dummy variables have been interacted with all attributes (Distance 12 km (ASC23), Distance 18 km Distance 50 km and Costs. In addition variables controlling for the respondents who do not know the number of turbines seen daily (No. Turbines miss), are included. Off all the tested variables, no one turned out to be significant. In this perspective, the results point towards that the preferences for location offshore wind farms at large distance from the coast are insensitive towards the number of turbines seen daily.

Distance to the nearest potential offshore wind farm

As presented, in the data we have the travel time by road from the center of each individual zip code area and to the beach where each of the potential locations for offshore wind farms can be located. Several models have been estimated, such as a linear, loglinear, quadratic and squared distance function. However, only the linear model seems to be worth investigating further. As shown in the table, the further respondents live from the nearest potential offshore wind power site, the more sensitive they are toward the cost attribute ($\beta Costs_{Travel\ time} < 0$), though only significant on a 90% level of confidence. Naturally, this suggests a lower WTP for reducing the visual disamenities from offshore wind farms, the further respondents live from nearest potential offshore wind power site. The travelling time to the nearest potential wind farm does not influence the distance variables (Distance 12 km (ASC23), Distance 18 km and Distance 50 km). However, we decided to take a closer look on this otherwise significant slope relation. Accordingly, we divided the travelling time data into five 20 percentiles and defined four percentiles dummy: Travel time 11-45 minutes, Travel time 46-55 minutes, Travel time 56-66 minutes and Travel time 67-107 minutes. The reference percentile is the respondents living more than 107 minutes from the nearest potential offshore wind power site. The percentile dummies were interacted with all attributes (Distance 12 km (ASC23), Distance 18 km Distance 50 km and Costs). As is can be seen, the spatial preferences might not be linear related to the travel time to the nearest potential offshore wind farm site. $\beta Costs_{Travel\ time\ 10\_66} > 0$. Accordingly, the respondent living within 66 minutes of travel time from the nearest offshore wind power site are significantly less sensitive towards paying more for locating offshore wind farms at larger distances than 8 km.

In terms of WTP, the two distance decay functions are presented in figure 4 below. In the models, the WTP is estimated for the average sample respondent with regards to gender and income.

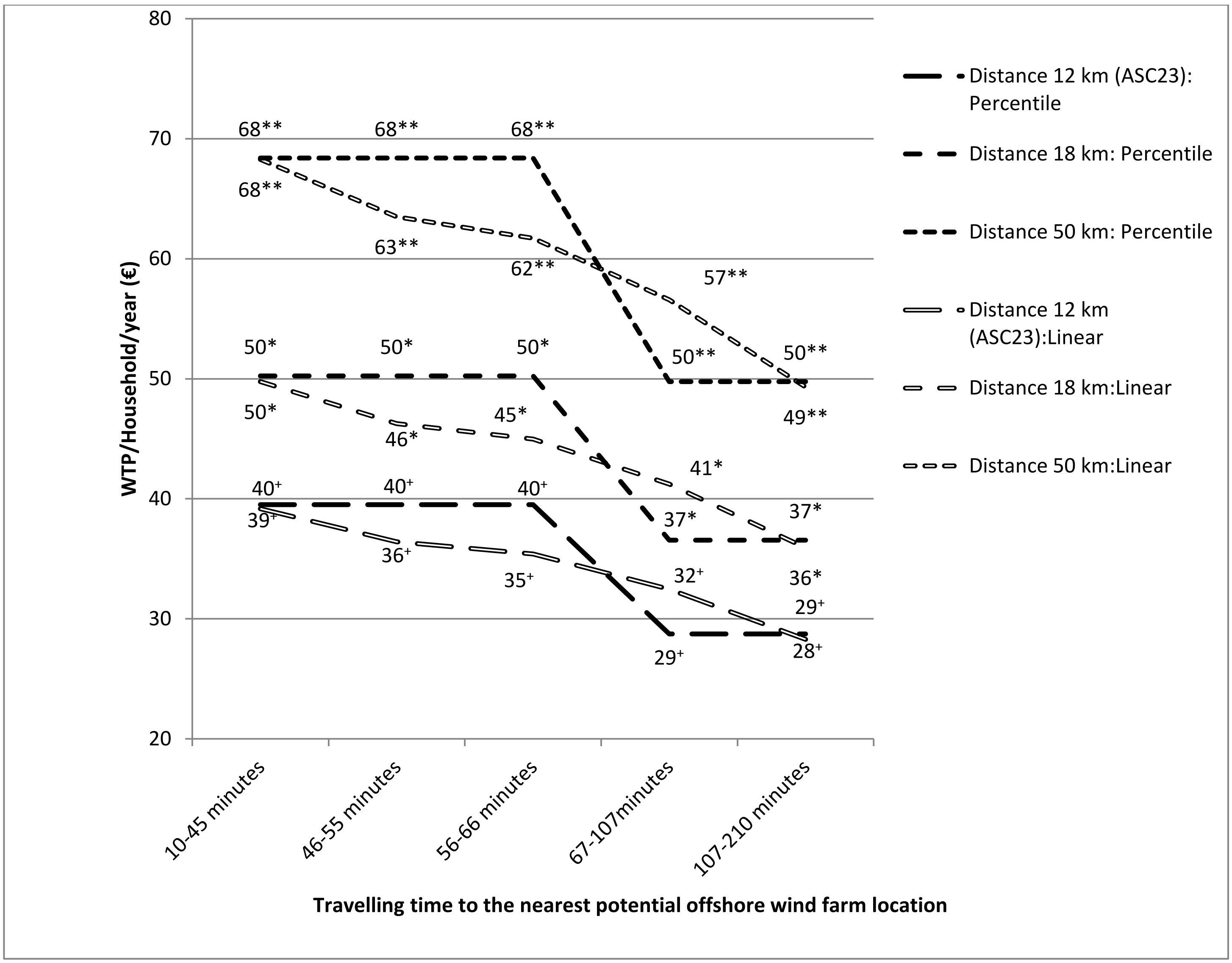

Figure 4: Travel time to the nearest potential offshore wind farm site and WTP for the average sample

respondents. Based on percentile and linear spatial models^{+} $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

The relation between the travel time to the nearest potential offshore wind farm site from the residence (centre of the zip code area) and WTP for reducing visual disamenities from offshore wind farms demonstrate that WTP is reduced with the travel time. Thus, longer travel time the respondents have to the nearest potential site, the lower WTP do they have. As spatial preference heterogeneity only is expressed as a WTP leveler through the Cost attribute, the travel time induced spatial preferences relations are the same for the location of the wind farms at 12, 18 and 50 km. If we start with the percentile model results, the $WTP_{\text{Distance 50 km}}$ goes from 68 €/household/year for the respondents, who lives within 66 minutes of travelling from the nearest site to 50 €/household/year for the respondents who more than 66 minutes from the nearest site, respectively. In the linear model, the WTP graduately is reduced from 68 50 €/household/year to 49 €/household/year. Similar relations are evident in with regard to the WTP for location wind farms at 12 and 18 km from the coast.

6. Conclusions

In the present paper we have tested whether preference for the location of offshore wind farms are spatially related to the distance from the residence of the respondents and the travel time to the nearest potential site for offshore wind power development. Based on Choice Experiment used to elicit preference for the location of 3600 MW of offshore wind farms in Denmark we find that both a linear travel time and a discrete (percentile) travel time model is significant. The results point towards that the further, the respondents live from a potential offshore wind power site, the lower is the WTP for locating offshore wind farms at 12 km, 18 km or 50 km relative to 8 km from the coast. To the authors knowledge this is the first study to establish such a relation in the increasing literature that deals with preferences for offshore wind power locations.

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