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Economic Valuation of the Externalities of Offshore and Onshore Wind farms in Denmark: Results from a Nationwide Choice Experiment Survey


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Foreword

This study uses a survey data from two projects:

1. Project 0602-00205B under the Danish Agency for Science, Technology and Innovation, and
2. Project 1305-00021B under the Danish Council for Strategic Research (Wind 2050).

The two projects were carried out with the aim of analyzing the minimum acceptance costs of wind power developments in Denmark. I have had access to this invaluable survey data from Jacob Ladenburg (Associate professor) who was involved in the projects.

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Abstract

For some years now, the trend in the wind power technology has been towards large offshore wind parks as a promising alternative energy source to solve the challenge of finding on-land sites. Nevertheless, there is a significant economic trade-off between offshore and onshore wind power development. Albeit offshore wind farm might entail lower external costs relative to onshore, it is more costly to produce than onshore. The present study revealed the choice between offshore and onshore wind farms each with location specific settings using an excellent choice experiment design. Everything being equal, the households are willing to pay 540 DKK/year/household to locate the future wind farms offshore as opposed to onshore.

When households choose the offshore wind farm, they are willing to pay 173 DKK/year/household to site the future offshore wind farms at 12 Km from the coast as opposed to 8 km. On the other hand, if households choose the onshore wind farm, they are willing to pay 198 and 317 DKK/year/household for having the 2X1.5 MW turbines and 1X3MW turbine, respectively as opposed to 4X750 KW turbines, if all placed at 500 M distance from residential areas. However, given the 1000 M distance, households are willing to pay 196 DKK/household/year for having 4X750 KW turbines in preference to 2X1.5 MW and 1X3 MW turbines. The preference for the onshore distance attribute given the sizes of turbines is mixed. Finally, we found a reasonable degree of preference heterogeneity with regard to socio-demographic and economic characteristics. However, we found limited preference heterogeneity with regard to prior experience to wind farms.

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1. Introduction

In the last two decades, where countries around the world have been striving to foster green growth for a sustainable development, the energy sector remained at the heart of the policymaking. A greater attention has been given to increase the share of renewable energy in the total energy mix of a substantial number of countries (Haas et al., 2011). This is because renewable energy production is considered as environmentally friendly (Juknys, 2010 and Dincer, 2000). To this end, a number of countries have been investing in renewable energy sources such as wind energy, biomass, solar energy, geothermal power, wave power, and tidal power (De Vries, van Vuuren, & Hoogwijk, 2007 and Resch et al., 2008). As a result, the share of renewable energy in the total energy mix of a substantial number of nations has registered a rapid growth. At the European Union (EU) level in particular, the renewable energy capacity share of the total installed power capacity has increased to 39.6 % in 2013 from 24.5 % in 2000 (EWEA, 2014).

Wind energy, as a renewable energy sources, has attracted the attention of many politicians and policy makers worldwide. At the global level, the cumulative installed wind capacity has reached 318,105 MW in 2013 from only 6,100 MW in 1996 (GWEC, 2014). Within the EU in particular, the wind energy share of total energy production and consumption has been growing rapidly over the last two decades (Meyer, 2007). Different energy strategies adopted at the EU level have contributed for this rapid wind power penetration in to the energy sector. One of these energy strategies is the "Energy strategy 2020". According to the European commission, the strategy was introduced with the aim of achieving a 20% renewable energy share in the total energy consumption by the year 2020, out of which wind power is expected to contribute 12% (European Commission, 2007). The commission also noted that offshore wind power developments are expected to provide one third of the total wind energy supply by the same year. According to the European wind energy association repot, wind power share of total installed power capacity in the EU has increased from 2.4 % in 2000 to 13 % in 2013. The agency also reported that at the end of 2013 the total installed power capacity was 117.3 GW out of which 6.6 GW is attributed to offshore installations (EWEA, 2014).

While the immediate priority is to implement fully the "Energy strategy 2020", the EU has already adopted a new "Energy Roadmap 2050". The strategy has two pillar objectives: cutting GHG emissions by at least 80% compared to 1990 levels by 2050 while maintaining or improving the energy security (Roadmap, 2011). According to this roadmap, by 2050, wind power is planned to provide more electricity than any other technology in the energy sector.

Turning to Denmark, the Danish energy policy has been a role model for how government support can led to a rapid penetration of wind energy in to the energy sector (Olivecrona, 1995). According to Danish Energy Agency, by the year 2012, 29.8 % of the Danish domestic electricity supply come from wind power as opposed to only 1.9 % in 1990 (DEA, 2014). The agency also reported that the onshore and offshore wind power capacity in the year 2012 was 3241 MW and 922 MW respectively as opposed to a total capacity of only 326 MW in the year 1990. Currently, the nation has already surpassed the “Energy strategy 2020” in terms of wind power share of total electricity consumption and adopted the “Energy Strategy 2050”. The aim of “Energy strategy 2050” is of becoming a fossil fuel independent economy by 2050 while increasing security of energy supply (Mathiesen et al., 2011, Danish Government, 2011). Currently, Denmark is striving to boost the share of renewable energy to 50% in 2030 and to 100% by the year 2050 and wind energy is expected to contribute the highest share (Lund & Mathiesen, 2009).

Despite its rapid development, wind power production does not come without external impacts. Relative to other sources of electricity, wind power has less negative environmental impact (Sundqvist, 2002). However, although there is no externality in the form of green house gas emissions from wind power generation, research has consistently shown that there are other forms of negative externalities. Previous studies have shown that wind farms pose landscape and/or seascape disamenities (Alvarez-Farizo & Hanley, 2002, Bergman et al., 2006, Krueger et al., 2011, Ladenburg & Dubgaard, 2007, Meyerhoff et al., 2010), have impacts on wild life (Kikuchi, 2008, Bergman et al., 2006), and noise effects (Schleisner & Nielsen, 1997, Ek, 2006). A recreational demand model studies have also shown that wind power developments hinder recreation (e.g. Landry et al., 2012 & Westerberg et al., 2013).

Therefore, there is a considerable challenge on where to install the future wind turbines due to their potential external impacts (Ek & Persson, 2014). According to Ladenburg (2009a), it is difficult to find sites for wind farms without reducing the welfare of the local population. Initially, these problems were associated with onshore wind power developments. As a result, for some years now, the trend has been towards large offshore wind farms as a promising alternative to solve onshore site challenges (Meyer, 2007). However, although offshore wind farms are less contested relative to onshore, they are found to be far from being conflict-free (Rudolph, 2014). Indeed, research has shown that offshore wind farms have external costs, in terms of utility reduction, on the society (e.g. Ladenburg & Dubgaard, 2007, Krueger et al., 2011, Bishop & Miller, 2007, Firestone & Kemptone, 2007 and Firestone et al., 2012). Ladenburg & Dubgaard (2009) indicated that coastal zone users are more resistant to offshore wind farms. However, Rudolph (2014) noted that offshore wind farms not only affect coastal zone users, but also adjacent communities. Moreover, offshore wind power production is very costly relative to onshore wind power production (Ladenburg, 2009a). Indeed, a Danish study assessed that onshore wind turbines have a long-term marginal production cost of about 320 DKK/MWh whereas the production costs of offshore wind power stands at just over 580 DKK/MWh (Energistyrelsen, 2014).

A large and growing body of a valuation literature has analyzed the impact of wind farms. These previous studies used both revealed and stated preference techniques. The hedonic pricing method (HPM) is the appropriate method of revealed preference techniques to quantify the effect of wind farms on property values. The majority of studies that applied the hedonic price method found no significant effect of wind farms on property value (e.g. Sims et al. 2008, Hoen 2010, Lang et al. 2014, and McCarthy & Balli, 2014). Interestingly, Heintzelman & Tuttle (2012) found a positive relationship between value diminution and the presence of wind turbines. Out of the stated preference techniques, the choice experiment (CE) method is the extensively used approach to value wind farm externalities. As a result, we review the CE studies in this section. Following Ladenburg (2009a) and Vecchiato (2014), the choice experiment studies that considered the preference for wind farm locations can be categorized in to three categories:

- *Offshore versus offshore* (e.g. Ladenburg & Dubgaard, 2007, 2009, Krueger et al., 2011,);
- *Onshore versus onshore* (e.g. Meyerhoff et al., 2010, Meyerhoff, 2013, Dimitropoulos & Kontoleon, 2009); and
- *Offshore versus onshore* (e.g. Ek, 2006, Ek & Persson, 2014, Aravena et.al., 2006, Vecchiato, 2014).

Studies in the "*offshore versus offshore*" category ask respondents to choose among different alternatives of offshore wind farms. For instance, Ladenburg & Dubgaard (2007) asked Danish respondents to choose between two hypothetical offshore wind farms with different settings. The authors considered a distance of 8 km, 12 km, 18 km and 50 km. Therefore, they found out that people are willing to pay more, though at a declining rate, to sit the wind farms further away from the coast. The offshore locations of the future wind farms in Ladenburg & Dubgaard were not site-specific. The present study is different from most of the previous studies because we have site-specific location of the future offshore wind farms. To the best of our knowledge, Krueger et al. (2011) is the first study that included site-specific locations.

Studies in the "*onshore versus onshore*" category require respondents to choose among different onshore wind farm settings. For instance, Meyerhoff et al. (2010) asked German respondents to choose among three different onshore wind farm settings. The authors considered a distance from residential areas of 750m, 1100m, and 1500m as one of their attributes and found out that respondents were willing to pay more to locate wind farms further away from their residential areas.

To the best of our knowledge, the present study is a breaking onshore study to control for "installed capacity demand effect". In terms of wind energy generation, large turbines have higher installed generating capacity than small turbines. Therefore, if the total installed generating capacity is not the same across choice sets, the respondents may always choose the onshore alternative with large turbines due to its high generating capacity even though they perceive larger turbines as more visually intrusive than small turbines. In such a case, wind energy production might be confounded with wind farm settings so that respondents might trade-off the visual intrusion with production capacity. When the two effects are confounded, it is impossible to disentangle the effect of visual intrusion from the installed capacity demand effect.

Therefore, the present study attempted to weed out the installed generating capacity demand effect by keeping the total installed generating capacity constant across choice sets while varying in terms of both number and size (MW) of the turbines. Accordingly, the respondents can choose between "few large" and "many small" wind turbines disregarding the installed capacity effect. The previous studies asked respondents to show their preferences for different sizes of a wind farm, in terms of the number of wind turbines per wind farm (Dimitropoulos & Kontoleon, 2009, Meyerhoff et al., 2010). However, in these studies, the size attribute does not help to identify whether households prefer large but fewer turbine or small but many turbines (Ladenburg & Dubgaard, 2007)

The "*offshore versus onshore*" studies asked respondents to value the location of wind farms in the broader sense of whether they are located offshore or onshore. Most of the studies found out that the offshore location was preferred to the onshore (e.g. Ek, 2006, Ek & Persson, 2014, Aravena et al., 2006). This indicates that, other things being equal, the environmental costs associated with offshore wind farms is less as compared to the onshore or mountains. Interestingly, McCartney

(2006) found out that respondents preferred onshore to offshore when the site of the future wind farm happens to be a marine park. However, it should be noted that McCartney applied the contingent valuation method (CVM).

The choice experiment in the present study was designed in a way that can bring the above-mentioned there categories of studies together in a single choice experiment. The respondents were asked to choose between offshore wind farm and onshore wind farm each with location specific settings. With this design, it is possible to see respondents' preferences for offshore vs. onshore location as well as the attributes of each alternative. Thus, the present choice experiment is novel in the sense that it combined offshore and onshore wind farm alternatives each with their location specific settings. The offshore alternative has two attributes: site-specific locations and the distance of the offshore wind farms from the coast. On the other hand, the onshore alternative contains three attributes: the size of the wind turbines (this attribute actually indicates both the number and the size of the turbines), the number of residents living in the locality, and the distance of the onshore wind farm from the residential areas. The cost/price attribute is common for both alternatives.

The main objective of this study is to examine Danish households' economic valuation of wind farm attributes, specifically, both onshore and offshore wind farms'. There was no an "opt-out" option in the present choice experiment. This is because the Danish government has planned to develop more of both offshore and onshore wind power production (DEA, 2014). Therefore, the policy-relevant question to ask is not whether wind power should develop. Rather, it is how the planned wind power expansion should be carried in order to minimize the potential external impacts. In such cases, it is reasonable not to include the status quo option (Hensher et al., 2005).

The study aims to address the following specific objectives:

- To measure the preference for and economic value of the attributes of offshore and onshore wind farms for Danish households;
- To assess preference heterogeneity among respondents with respect to socio-demographic and economic variables (age, gender, education, and income); and
- To examine preference variation among respondents with regard to prior experience to wind farms

This study has a vital importance for policymaking. Improved information on the relative importance of offshore wind farm and onshore wind farm locations is very important for choice of development strategy between them. Moreover, the study enables to find both onshore and offshore optimal wind farm settings. As noted in Bishop and Miller (2007), improved knowledge on the economic value of the attributes could help in site selection and impact assessments.

The present study mainly covers the attributes of both offshore and onshore wind farms. Besides, the study examined effects of socio-demographic & economic variables and prior experience to wind farms on the preference for wind farm settings. A number of variables measuring the attitude of respondents towards green energy in general and wind farms in particular were not included in our model because of endogeneity problems. It would have been interesting to see the effect of these attitudinal variables on the choice between onshore and offshore wind farms. Nevertheless, such variable demand applying more advanced models such as the hybrid choice model (Ben-Akiva et al., 2002). Finally, this study has not considered spatial variables such as respondents distance from their residential areas to current/ proposed wind farms.

2. Review of Related Literature

2.1. The general background of wind energy in Denmark

The Danish energy policy has been a role model for how government support can result in rapid promotion and penetration of wind energy in to the energy sector. According to Olivecrona (1995), the Danish government's policy to support the development of wind power projects at individual, cooperatives, or energy company level has shown a vital significance. The government has adopted various instruments such as investment subsidies, legislation, and fiscal incentives (i.e, tax-refund system) to encourage wind energy production (Olivecrona, 1995, Meyer, 2007). The government has also been effectively allocating research and development budget to encourage the wind power sector (Lewis and Weiser, 2007).

Initially, the Danish government started supporting the wind energy sector due to the outbreak of energy crisis in the early 70s, as part of the overall energy plan, to reduce Denmark's dependence on foreign energy supply (Olivecrona, 1995). However, since 1990, the issue of climate change also comes to the center of the energy policy and thus different energy action plans have been adopted since then with the twin objectives of ensuring energy security and fostering a green economy in an effort to negate climate change (Meyer and Koefoed, 2003, Olivecrona, 1995). Since then, the government adopted energy action plans "Energy 2000", "Energy 2020", and recently "Energy Roadmap 2050" to foster wind energy as alternative energy source.

According to Lund & Mathiesen (2009), Denmark is striving to raise the share of renewable energy to 50% in 2030 and to 100% by the year 2050 and wind power is expected to contribute the highest share. Accordingly, the government is working to raise the renewable energy share to 30% of final energy consumption and achieve an EU commitment of 30% reduction in greenhouse gas emissions by the year 2020 compared to 1991 level (DEA, 2014). While the immediate priority is to implement fully the "Energy strategy 2020", the government has already adopted the new "Energy Roadmap 2050". The strategy has two pillar objectives: cutting GHG emissions by at least 80% compared to 1990 levels by 2050 and maintaining or improving the energy security (Roadmap, 2011). The strategy outlines the energy policy instruments to transform Denmark into a green and sustainable society with stable energy supply (Mathiesen et al., 2011). According to this roadmap, by 2050, wind power is planned to provide more electricity than any other renewable energy technology.

According to Danish Energy Agency, by the year 2012, 29.8 % of the Danish domestic electricity supply come from wind power as opposed to only 1.9 % in 1990 (DEA, 2014). The agency also reported that the onshore and offshore wind power capacity in the year 2012 was 3241 MW and 922 MW respectively as opposed to a total capacity of only 326 MW in the year 1990. Recently, the trend has been toward fewer but larger turbines due to the higher generation capacity of larger turbines and many small turbines has been replaced with fewer large turbines (Ibid). According to the agency, offshore locations were chosen for such installations because they yield higher production relative to their capacity than onshore wind turbines.

However, specific wind power development programs have been facing local resistance due to its potential environmental problems. According to (McLaren Loring, 2007), establishment of wind power projects in many countries has been facing challenges due to land-use planning and there often is an objection by local community members because of noise pollution and visual disruptions. This is because the physical surrounding where wind power projects are located is said to be seriously affected (Nielsen, 1994). For some years now, the trend has been towards larger offshore wind parks. This is because, in countries like Denmark with shallow waters and long coastlines, offshore wind farms are seen as promising sites to solve the onshore site problems (Meyer, 2007). Nevertheless, many studies have shown that, although less contested than onshore location, offshore wind farms are found to be far from being conflict-free, hurting the interests of many stakeholders' (Ladenburg & Dubgaard, 2007, 2009, Bishop & Miller 2007, Firestone and Kemptone, 2007, Firsestone et al., 2012, Krueger et al., 2011). The sitting of offshore wind farms not only conflicts with coastal water users, but also conflicts with interests emanating from onshore areas due to their external effects so that the adjacent local communities may perceive offshore wind farms as more disruptive relative to onshore (Rudolph, 2014). This implies that there is an economic trade-off between offshore and onshore wind farms. Therefore, the relative cost of the offshore and onshore wind farms and their optimal setting can be evaluated using economic valuation methods which we will present them broadly in the subsequent sections.

2.2. Theoretical foundations of welfare measures

In the introduction of new policy reform of service, analysts are interested to evaluate the welfare impact of the policy reform on customers of the service. Before proceeding directly to the measures of welfare for improved services, it is imperative to start from the meaning and theoretical underpinnings of willingness to pay in order to have a clear understanding of the measures of welfare.

Willingness to pay (WTP) is the maximum amount of money an individual would be willing to give up in order to acquire the improvement in a service. The WTP definition can be used in environmental quality improvement. Hence, the theoretical explanation of willingness to pay which is taken from the Pearce *et al.* (2006) can be presented as follows.

Consider a household with initial state of well being U_o who gets incomeY_0, and environmental quality of E_0: $U_o(Y_0, E_0)$. Suppose that there is a proposal to improve the the environmental quality from E_0 to E_1. This improvement would increase household's wellbeing to U_1: $U_1(Y_0, E_1)$

To know by how much the well being of the household is increased due to the improvement in environmental quality $(U_1 - U_0)$, we look for indirect measure since utility can't be measured directly. Thus, willingness to pay is the indirect measure, the maximum amount of income the household would be willing to pay for the improvement. Household considers two combinations of income and environmental quality which both yield same level of well being,U_o. The combinations are; income reduced and environmental quality improved, and income and environmental quality not changed:

$U_o(Y_0 - WTP, E_1) = U_o(Y_0, E_0)$... (1)

The household adjusts WTP to the point at which these two combinations of income and environmental quality yield equal well being. At that point, WTP is defined as the monetary value of the change in the well being, $U_1 - U_o$ resulting from the improvement in environmental quality from E_0 to E_1.

Given that the objective of the policy reform is the improvement of the environmental quality, there are welfare measures[1] such as compensating variation, equivalent variation, compensating surplus, and equivalent surplus (Freeman;2003; Pearce *et al.*, 2006).

Compensating variation (CV) measures the households' maximum willingness to pay (WTP) for the quality improvement. CV is the amount that needs to be taken away from the household's

[1] According to Freeman (2003) and Pearce *et al*. (2006), there are various alternative measures of welfare such as compensating variation, equivalent variation, compensating surplus, equivalent surplus, consumer surplus. The first four of the measures (Compensating variation, Equivalent variation, Compensating surplus, Equivalent surplus) were developed by Hicks. The fifth measure is the Marshalian measure of consumer surplus. The details are available in Freeman (2003) and Pearce *et al*. (2006).

income at his new level E_1 such that he or she is as well off as he or she was at his or her initial level E_0 (before the change). Thus, it is measured relative to the initial level of wellbeing, U_o i.e. households have the right to status quo. The CV measure of this change is defined as in equation (2).

$U_o(Y_0 - CV, E_1) = U_o(Y_0, E_0)$……………………………………… (2)

Where, $CV = WTP$

If the quality of the service deteriorates, compensated variation is measured by WTA[2].

Equivalent variation (EV), considering the improvement in environmental quality, it measures household's minimum willingness to accept for not experiencing the improvement in environmental quality. EV is the amount that needs to be given to the household at his initial level E_0, to make him as well off as he would have been if the quality were to improve to E_1.In EV households have the right to change.

$U_1(Y_0 + EV, E_0) = U_1(Y_0, E_1)$……………………………………… (3)

Where, $EV = WTA$

If the quality of the environment deteriorates, equivalent variation is measured by WTP[3].

Mitchel & Carson (1989) recommended compensating surplus (CS) measures to value environmental quantity/quality changes. CS measures either the WTP for an environmental quality/quantity improvement or the WTA for the environmental quality /quantity deterioration (Pearce et al., 2006). However, Pearce, Atkinson & Mourato noted that the CS measures are based on the implicit assumption of right to the *initial* situation. Thus, the authors recommended the equivalent surplus (ES) measure when individual have some right to the "new" environmental good. ES measures households WTP for not experiencing the environmental quality deterioration or a WTA to forgo environmental quality/quantity improvement.

[2] According to Pearce *et al.* (2006), if the change in policy results in losses in wellbeing, CV is the amount of money the household would be willing to accept compensation to let the change occur but remain as well off as s/he was before the change. This can be represented as:

$U_o(Y_0 + WTA, E_1) = U_o(Y_0, E_0)$

[3] According to Pearce *et al.* (2006), if the change in policy results in losses in wellbeing, EV is the maximum amount of money the household would be willing to pay to avoid the change. This can be represented as: $U_1(Y_0 - WTP, E_0) = U_1(Y_0, E_1)$

2.3. Economic Valuation Methods

When applying cost benefit analysis for appraisal of various projects, policies and programs the computation should not only include the market price based costs and benefits, but also the external costs or benefits to the society who did not choose to incur that cost or benefit. As noted in Buchanan & Stubblebine (1962), the term externality is defined as the cost or benefit that incur to a party who did not choose to incur it. Nevertheless, the market often fails to capture such effects due to the untradeable nature of such goods and services. Bator (1958) defined market failure as follows:

"Typically, at least in allocation theory, we mean the failure of a more or less idealized system of price-market institutions to sustain "desirable" activities or to estop "undesirable" activities.' The desirability of an activity, in turn, is evaluated relative to the solution values of some explicit or implied maximum-welfare problem."

Therefore, when there is such a market failure, we can apply economic valuation techniques to estimate the value of the externalities and resort to other types of non-market resource-allocation mechanisms to bring efficiency to the specific program, policy or project. The failure of a competitive equilibrium and Pareto-efficiency is a sufficient condition for considering resort to non-market channels of resource allocation and the analysis of externalities should lead to criteria for such non-market allocation (Arrow, 1969). The wind energy market is no different to other types of markets and often fails to incorporate the social externalities posed by wind farms. The major externality posed by wind farm projects is a visual disamenity and in this study, we primarily focus on estimating Danish population's willingness to pay to reduce the externalities from onshore and offshore wind farm projects. Although economic valuation methods can be used to estimate the total value of a project or a program, in this study, we apply an economic valuation technique to only value the social externality posed by wind farms, not the total welfare effect of the wind farms.

Economic valuation is a method used for assigning monetary value to the outcomes of choices about policies, projects and programmes (Bateman et al., 2002). Freeman (2003) defined economic valuation as the task of assigning a monetary value to intangible goods and services. Economic valuation techniques are a range of approaches used to estimate the economic value of non-market or intangible impacts (Pearce et al., 2006). For instance, the costs and benefits associated with an environmental quality change can be estimated using economic valuation methods. As noted in Ladenburg et al., (2005), the economic valuation approaches can be seen in two broad categories:

Preference based methods (PBM) and Pricing methods (PM). As noted in Garrod and Wills (1999), the price-based methods are cost measures of value such as Effect on production approach; Opportunity cost measures; Human capital approach and Dose response functions; Replacement cost; and Preventative, mitigatory expenditure and averting behavior approaches. These approachs do not estimate economic behaviour relations and do not give any answers as to whether the costs associated with a specific project are larger than the benefits (they are not welfare maximizing) (Ladenburg et al., 2005). Since the focus of this study is on the welfare-based approaches, the cost measures of value will not be discussed further.

According to Bateman et al. (2002), there are two broad categories of preference based economic valuation techniques:

i. Revealed preference methods
ii. Stated preference methods

There is a third technique called Benefit transfer which relies on the estimates from stated preference and/or revealed preference studies to estimate the value of a new non-tradable goods and services. Benefit or value transfer involves taking economic values from one context and applying them to another (Pearce et al., 2006). Policy analysts frequently use benefit transfer studies because designing and implementing original studies are barely affordable. Due to the subjectivity and uncertainty of benefit transfer studies policy analysts should make a number of additional assumptions and judgments to those contained in the original studies (Pearce et al., 2006). In the present study, since we have designed and implemented our own choice experiment, there is no need for a benefit transfer and it will not be discussed further. The preferences based techniques including the benefit transfer method estimate economic behaviour relations and they are welfare maximizing. Therefore, we will present these techniques more broadly in the subsequent sections.

2.3.1. Revealed preference methods

Revealed preference methods rely on individual constrained utility maximization behavior for private goods to infer about public goods and services (Freeman, 2003). The influence of preference for the intangible good on the demand for the tradable good is the source of information to be exploited by revealed preference methods to estimate the value good or service that is being evaluated (Bateman et al., 2002). When non-tradable goods and services are implicitly traded with marketable goods and services, revealed preference methods are applied to unravel the value of non-market goods and services from the observed market price (Pearce et al., 2006). Revealed preference methods rely on the assumption that although intangible goods and services do not have an offering price, their quantity affects peoples' choice about tradable goods and services. Briefly, the implicit assumption is that an environmental service is either a substitute or complementary to a marketable good or service (Freeman, 2003). Therefore, models assuming some sort of relationship between the two goods and services are applied to infer the value of the environmental service. The travel cost method and Hedonic pricing method are the two distinguished market-based valuation methods identified in the literature which could be applied in studying the social externalities of wind farms and we will explore both in more detail in the next sub-sections.

2.3.1.1. The Travel Cost Method

The sole purpose of travel cost method is to elicit the amenity or recreational value of a specific geographical area or location (Ladenburg et al., 2005, Pearce et al., 2006). The underlying assumption in this method is that there is some sort of relationship, usually complements (weak), between the use of the site and costs incurred to the visitor. The travel cost method (TCM) infers the benefit a non-priced recreation site offers using the cost of traveling to the same site (Garrod and Wills, 1999). On site questionnaire survey are used to collect data on the visit frequency and cost of gaining access to the recreation site. Therefore, willingness to pay to visit the recreational site can be obtained by exploiting the information on the relationship between visit frequency and cost of gaining access. However, the travel cost method has its own caveats. For instance, multi-purpose trips to a recreational area could hinder to unravel the true value of the recreational site. According to Pearce et al. (2006), such problem could be solved by asking respondents the proportion of utility they derived from the site in question. For areas with wind farms, it is unlikely that people would see it as a recreational site and if they do, its attractiveness might continuously decline with the increment of wind farms.

2.3.1.2. The Hedonic Pricing Method

Hedonic pricing method drives from the assumption that peoples' market demand for a priced good is influenced by a confounding non-priced good. The method utilizes the assumption of substitutability or complementary relationship between a property value and an environmental quality considering environmental quality as one of the bundle of characteristics which affects the property price (Pearce et al., 2006). The value of the intangible good can be disentangled from the observed property price using statistical techniques when the intangible good is implicitly traded *via* the tradable property (Pearce et al., 2006, Freeman, 2003). The value of the amenity being analysed is the price differential between two identical properties except for the amenity in question. Property markets and labour markets are the two areas of application where the hedonic pricing method can be applied (Pearce et al., 2006). In the case of wind turbines, both substitutability and complementary relationship can be considered. If a site with wind turbines/parks is considered as a recreational site, there would be a complementary relationship between the presence of wind turbines and the property value. On the contrary, if wind turbines/parks are perceived as "Bads", there would be substitutability relationship between the two. Therefore, the effect of wind turbines on property values, especially house prices, could be investigated using the hedonic pricing method. As noted in Pearce et al. (2006), the hedonic pricing method cannot handle problems such as imperfect information about the property markets; and multicollinearity of property markets.

2.3.2. Stated Preference methods

Stated preference techniques are survey-based estimators of willingness to pay or willingness to accept for hypothetical changes in provision of non-market goods in a constructed market (Pearce et al., 2006). Unlike revealed preference methods, stated preference methods are applicable in *ex ante* and *ex post* valuations and are able to capture both use and non-use values of the non-market good (Ibid). In the literature, two well-distinguished stated preference techniques are identified: Contingent Valuation Method (CVM) and Choice Modeling Methods (CMM) (Pearce et al., 2006, Bateman et al., 2002). Stated preference methods offer a direct survey approach to estimate the economic value of changes in the provision of non-market good (Pearce et al., 2006).

2.3.2.1. Contingent Valuation Method (CVM)

In CVM, a hypothetical scenario of a change in non-market good or service is constructed so that respondents are asked to holistically value the change (Ladenburg et al., 2005, Bateman et al., 2002). As noted in Hanley et al. (2001), the contingent market defines the non-tradable good, the institutional setup, and mode of financing. By utilizing a questionnaire, CVM directly asks respondents to state their willingness to pay (accept) for a change in the level of provision of non-market good (Bateman et al., 2002). Albeit there remains concerns of validity and reliability of the method, recent research has sought to construct rigorous tests (Pearce et al., 2006).

In the case of wind turbines, respondents might be asked their aggregate willingness to pay to have onshore wind turbines positioned at a specific distance from their residential areas or from the coast in case of offshore wind parks. As CVM is an aggregate measure it is not possible to know which characteristics of the wind turbine is most valued by the respondents as the obtained willingness to pay is for the whole scenario in question. Therefore, if attribute level information is required, the choice modeling approach should be the appropriate one instead of CVM. In the present study, since the focus is on the value of the attributes of both onshore and offshore wind farms, the choice experiment method was the right choice to use in the survey.

2.3.2.2. Choice Modeling Methods (CMM)

Choice modeling method is a family of survey-based approaches useful to capture the multidimensional change in the provision of the non-market good or service (Bateman et al., 2002, Pearce et al., 2006, Hanley et al., 2001). The application of CMM in the area of environment started recently after the method has been extensively applied in the areas of market research and transport literature (Hanley et al., 2001). Unlike CVM, which measures the aggregate value of the change in the level of the provision of an environmental asset holistically, CMM gives rise to distinct valuation of each of the component attributes of a change in environmental asset affected by a proposed project or policy (Pearce et al., 2006). In CM, respondents are asked to choose their most preferred, to rank, or rate various alternatives presented to them with various description of the good, differentiated by their attributes and attribute levels (Hanley et al., 2001). The theoretical microeconomic framework behind all CMM approaches is Lancaster's theory characteristics of value (Lancaster, 1966), which assumes that the total utility that a consumer can drive from a good can be decomposed in to the bundles characteristics that make up the good. The willingness to pay estimate in CM approaches is the marginal rate of substitution between any attribute and the cost/price attribute. As in CVM, CMM are able to capture both use and non-use values of a proposed change. There are four well-distinguished approaches under the umbrella of choice modeling: Choice experiment (CE), Contingent ranking (CR), Contingent rating (CR), and Paired comparisons (PC). Table 1, which is adopted after Bateman et al. (2002), shows the task of these different approaches.

Table 1: Main choice modeling alternatives

Approach	Tasks
Choice Experiments	Choice between (usually) two alternatives versus the status quo
Contingent Ranking	Rank a series of alternatives
Contingent Rating	Score alternative scenarios on a scale of 1-10
Paired Comparisons	Score pairs of scenarios on similar scale

Source: Adopted after Bateman et al., (2002) p 250

2.3.2.2.1. Choice Experiments (CE)

In a choice experiment (CE) respondents are presented a choice set (or choice sets) with a series of alternatives of a good differentiated by attribute and attribute levels and are asked to choose the most preferred (Hanley et al., 2001, Bateman et al., 2006, Pearce et al., 2006). When the primary goal is to obtain welfare estimates, a baseline alternative which describes the current situation called the "*Status quo*" or "doing nothing" alternative is usually included in the choice set (Hanley et al., 2001). If the *Status quo* option is included in the choice set, CE is consistent with utility maximization and demand theory (Pearce et al., 2006, Bateman et al., 2002). However, since the focus of the present study is on how to carry out planned wind farms there is no an "opt-out" option in the choice set so that respondents were effectively being "forced" to choose one of the presented alternatives. Like the other CM approaches, CE is based on the theoretical framework that a utility not.

2.3.2.2.2. Contingent Ranking (CR)

In CRM, a respondent is presented with a set of options of a good differentiated by attributes and attribute levels, and is asked to rank the options in order of their preference (Bateman et al., 2002). For the results of contingent ranking to be interpreted in standard welfare economic terms, the *status quo* option should be included as one of the alternatives (Hanley et al., 2001). Albeit contingent ranking offers more information on consumers' preference structure than choice experiment (McFadden, 1986, Hanley et al., 2001), its cognitive burden on respondents is higher than choice experiment (Ben-Akiva et al., 1991). As noted in Louviere et al. (2000), the cognitive burden of the contingent ranking affects the reliability of the preference unless the ranking task is kept simple.

2.3.2.2.3. Contingent Rating (CRT)

In contingent rating experiment, respondents are presented with a choice set consisting a serious of scenarios and are asked to rate the scenarios on a predefined semantic or numeric scale (Hanley et al., 2001, Pearce et al., 2006, Bateman et al., 2002). Since the alternatives are rated independently from each other, this approach does not involve a direct comparison of the different options (Hanley et al., 2001). As this approach relies on the assumption of cardinality of the rating scale (Hanley et al., 2001, Pearce et al., 2006), there is no formal link between economic choices and the rating scale (Hanley et al., 2001). One way to solve the problem is to assume ordiniality about the rating scale (Pearce et al., 2006).

2.3.2.2.4. Paired Comparisons (PC)

In a paired comparison exercise, respondents are presented with a choice set consisting of a serious of alternative and they are asked to choose their most preferred and rate all alternatives on semantic or numeric scale so that they can reveal their preference strength for each alternative (Hanley et al., 2001, Bateman et al., 2002, Pearce et al., 2006)**.** This approach attempts to combine elements of choice experiment and contingent rating and therefore gather more information than each of the models separately does. However, the task becomes more complex by having a huge cognitive burden on the respondents (Pearce et al., 2006).

2.3.3. Choice of Methodology in this study

As discussed above, the hedonic pricing method is potentially applicable to measure the external effects of wind power projects given the wind farm projects have been in the specified site for long time. The long time presence of the wind farm is required to ensure enough exchange of the property being affected (Ladenburg et al., 2005). However, the HPM is not applicable to evaluate policy effects *ex ante.* Since the focus of the present study is on the potential impact of proposed wind power projects, the hedonic pricing method could not applied. Moving to stated preference approaches, since the CVM is an aggregate measure of peoples' willingness to pay for a given scenario holistically, it is difficult and costly to capture the effect of a multidimensional change of a proposed project. When changes are multidimensional, the CVM approach is not ideally suited to deal with the valuation (Hanley et al., 2001). The choice experiment is ideal when the change is multidimensional and trade-offs between attributes is of a particular interest (Hanley et al., 2001, Bateman et al., 2002, Pearce et al., 2006). Therefore, a choice experiment survey was used in the present study given the important characteristics of the approach compared to other choice modeling approaches.

2.4. Previous studies on the externalities of wind farms

Both revealed preference and stated preference valuation methods have been applied to investigate the externalities of wind power projects. We will review in more detail about the hedonic pricing method and choice experiments studies in the subsequent sections.

2.4.1. Hedonic pricing studies on the externalities of wind farms

Using 201 sales transactions of houses situated within half a mile of a 16-turbine wind farm in Cornwall, UK, Sims et al. (2008) examined the likely impact of wind farms on house prices. The authors found that both the number of wind turbines and the distance to the wind farms were not a significant determinants house price variation. However, they also found out that the specific location within the area was a significant factor affecting house price variation. Similarly, using 7,500 sales transactions located within 10 miles of 24 existing wind farms in the United States, Hoen (2010) found no apparent association between house value and the presence of wind turbines. Specifically, both the distance of the wind turbines from homes and the view of the wind farms were not significant determinants of house prices. Lang et al. (2014) also found out that the proximity to wind turbines, view shed and contrast are not statistically significant determinants of house price. The authors analysed a data collected from 48, 554 home sales transactions situated within 5 miles of the turbine site in Rhode Island, USA. In clear correspondence with the above findings, McCarthy and Balli (2014) also point out that there was no impact of wind turbines on house prices. The authors used 945 open market house sells situated within 8 km of the Tararua and Te Apiti wind farms in Austria and they found that the number of turbines visible from the property was not a significant factor affecting house sales price in both wind farms. Interestingly, using 11,331 property transactions, Heintzelman and Tuttle (2012) found a positive relationship between value diminution and the presence of wind turbines. Their study was conducted in three counties of the New York state, US: Clinton, Franklin and Lewis. While they found a positive and significant association between value diminution of houses and the proximity to wind turbines in the Clinton and Franklin counties the same variables for the Lewis County are either positive or not significant.

2.4.2. Choice experiment studies of the external effects of wind farms

Following Ladenburg (2009a) and Vecchiato (2014), in the context of choice experiment, the choice experiment studies can be categorized in to three:

i. offshore versus offshore

ii. Offshore versus offshore

iii. Offshore versus onshore

Due to their vital significance to the present study, we will review each category in more detail in the subsequent sections.

2.4.2.1. Offshore wind farms versus offshore wind farms

A growing body of literature has analyzed the impact of offshore wind farms on the seascape. In this kind of choice experiments, respondents are asked to choose between different bundles of attributes of offshore wind farms. The primary goal of this type of studies was to assess the visual disamenity from offshore wind farms. The studies estimated households' willingness to pay for moving the wind farms further away offshore from the shoreline. The implicit assumption in this kind of studies is that people see the presence of wind farms as negative externalities and, therefore, they are willing to pay more in order to move the wind turbines further offshore in order to minimize the externalities.

A study by Ladenburg & Dubgaard (2007) in Denmark is the first study to assess the visual impact of offshore wind farms. The authors asked Danish respondents to choose between two hypothetical wind farms. In addition to the "cost attribute" which is an annual surcharge in electricity bill, size of wind farms, the total number of wind farms to be developed, and the distance of the offshore wind farms from the shore were used to make up the alternatives. The "distance to the shore" attribute could take four levels: 8 km, 12 km, 18 km and 50 km. Their results show that the average respondent was willing to pay 47, 98 and 125 EUR/household/year to site the wind farms at 12, 18 and 50 km relative to 8 km baseline, respectively. The size of the wind farm was not a significant indicator of visual diamenity. However, in their study, it was not possible identify whether respondents prefer "many small" wind turbines to "few large" turbines. Moreover, the locations of the proposed offshore wind farms were not site-specific. With a similar setting, in the context of choice experiment, Ladenburg & Dubgaard (2009) estimated willingness to pay for sitting wind farms further away from the coast for different coastal zone user groups. The authors found out that anglers, boaters and people who can see offshore wind farms from their residence perceive wind farms more negatively compared to those respondents who do not use the coast for specific purposes. The willingness to pay estimates for the specific purpose users and frequent visitors of the coast was as twice as much as of those less frequent users.

The locations of the future offshore wind farms in Ladenburg & Dubgaard were not site-specific (Ladenburg 2009a, Krueger et al., 2011, Ladenburg & Lutzeyer, 2012). This might be a problem because respondents might reveal a different preference when they know the specific site. Krueger et al. (2011) is the first offshore study to include site-specific locations in the choice experiment. Krueger, Parsons, & Firestone estimated the demand for visual disamenty reduction for three different samples in the Delware shoreline, USA. The “Ocean sample” (households living living close to Atlantic ocean), the “Bay sample” (households living close to the Delawre Bay) and the “Inland sample” (other households in the state) were the three strata making up the whole sample. The authors used four attributes besides to the price attribute with “location of the wind farm” and “distance from the shore” as the two of the four attributes. In the choice experiment, the wind farm locations were site-specific and thus not generic. They used the Delware Bay, Rehoboth beach, and Frenwick Island as the specific geographical locations of the wind farms. However, the authors found no statistically different preferences for the three specific locations. The distance attribute could take 5 levels (in miles): 0.9, 3.6, 6, 9 and “too far to see”. Their results show that the average household in the Inland sample was willing to pay ($) 19, 9, 1, and 0 annually in monthly renewable energy surcharge to sit the wind farms at 0.9, 3.6, 6, and 9 miles offshore whereas the cost ($) for the Ocean sample was 80, 69, 35, and 27 for the same distance. The willingness to pay ($) of an average household in the Bay sample was 34, 11, 6, and 2 for the same distances.

There is also a growing body of literature analyzing the impact of offshore wind farms on recreational activities using a recreational demand model (e.g. Landry et al., 2012, Lilley et al., 2010, Westerberg et al., 2013). Using a choice experiment Landry et al. (2012) elicited the demand for reduction in visual disamenity form offshore wind farms in North Carolina, USA. In their choice experiment, they use four attributes: distance of the offshore wind farm from the coast, onsite parking, beach congestion levels, and travel distances. Offshore waters (Atlantic Ocean) and Sound waters (between the mainland and outer banks barrier islands) were the potential locations of the wind farms. The alternatives were not site-specific and thus were generic. About 118 respondents faced six choice sets with two hypothetical alternatives and a third *status quo* option (stay at home). For the distance attribute, the only significant compensating variation estimate was $55 ($102) for the weighted (raw) data model when an ocean view wind farm is located 1 mile further from the shore. The remaining ocean view distances and all sound view distances were not significant.

Another recreational demand model study by Westerberg et al. (2013) applied the latent class model to examine the effect offshore wind farms on coastal tourism in the region of Languedoc Roussillon, France. They use three segments in their model: segment one (most likely French origin, visitors and Loyal tourists), segment two (most likely European origin, Loyal tourists and culturally motivated), and segment three (most likely French origin, retired and non-loyal tourists). In their study, they considered distance of the wind farms from a shore with levels of "no wind farm", 5km, 8km, and 12km. The authors found out that the visual disamenity cost decreases as the wind farm is situated further away from the shore. The respondents in segment one demanded a reduction in accommodation price of 29.3 and 24 EUR/weekly/adult for having the wind turbines at 5 Km and 8 Km, respectively as opposed to no wind farms. They also found that at 12 Km the tourists do not demand any compensation. The tourists in segment two demanded a compensation of 38.9 and 20.3 EUR/week/adult for having wind turbines at 5km and 8km respectively as opposed to no wind turbines. However, the respondents were willing to pay 42.8 EUR/week/adult if the wind farm is placed at 12 km off the shore. Turning to segment three, respondents perceive visual intrusion from the wind turbines at all distances so that they demanded a compensation of 264.7, 143.1, and 39.1 EUR for having wind farms at 5km, 8km, and 12 km, respectively as opposed to no wind farms.

2.4.2.2. Onshore versus onshore wind farms

A large and accumulating body of literature has analyzed the impact of onshore wind turbines on the landscape (e.g. Meyerhoff et al., 2010 and Meyerhoff, 2013, Dimitropoulos & Kontoleon, 2009). In this type of studies, respondents were asked to choose between different onshore wind farm settings. The primary goal of this sort of studies is to measure the visual disamenity from onshore wind farms. Households' were willingness to pay more for moving the wind farms further away onshore. The implicit assumption in this kind of studies is that people see the presence of wind farms as negative externalities and, therefore, they are willing to pay more in order to move the wind turbines further onshore.

For instance, Meyerhoff et al. (2010) and Meyerhoff (2013) asked German respondents to choose among three onshore wind farm settings. In Meyerhoof et al. (2010), the survey was conducted in the Westachen and Nordhessen regions of Germany. The first alternative designated as "*Future status quo*" describes the current means of wind power development and its continuation up to the year of 2020 unless respondents choose otherwise. In their study, they use four attributes excluding the price attribute: size of the wind farms, maximum height of the turbines, effect on red kite population, and minimum distance of the wind farms to residential areas were the attributes used to explain the wind farm setting. The distance attribute could take three levels: 750m, 1100m, or 1500m. The conditional logit estimates show that an average household in the region of Westachen was willing to pay (Euro) 3.18 and 3.81/monthly to site the wind farms at 110 m and 1500 distance respectively. The same estimates for the Nordhessen region were EUR 3.87 and EUR 4.31. The same conclusion was also drawn from the three-segment latent class model for both regions: willingness to pay increases as the minimum distance of the wind farms from the residential area increases.

To the best of our Knowledge, the present study is a breaking study to control the “installed capacity demand effect” in the onshore versus onshore studies. In terms of wind energy generation, large turbines have high installed generating capacity than small turbines. Therefore, if the total installed generating capacity is not the same across choice sets, the respondents may always choose the onshore alternative with large turbines due to its high generating capacity even though they perceive the large turbines are more visually intrusive than the small turbines. This indicates that the wind farm settings may confound with generating capacity demand effects. In the literature, the size of a wind farm attribute (which only indicates the number of turbines per wind farm) was widely to explain onshore wind farm setting (e.g. Meyerhoof, 2010, Vecchiato, 2014). Therfore, in these studies, it was not possible to identify if households prefer large but fewer turbines or small but many turbines.

In the present choice experiment, we are able, in principle, to weed out the installed generating capacity demand effect by keeping the total installed generating capacity the same across choice sets while varying in terms of both number and size of the turbines. This ensures that the estimated effects would only show the effects of onshore wind farm settings. This implies that the external effect is not confounded with the installed capacity demand effect. Therefore, the preference would be between “few large” turbines and “many small” turbines. As noted in Ladenburg & Dubgaard (2007), some respondents may prefer many small wind turbines while others may like few large wind turbines.

2.4.2.3. Offshore versus onshore wind farms

The studies in this section are actually onshore studies. However, in the choice experiment, location was one of the attributes with offshore and onshore as its levels in the broader sense of whether the wind farm would be located offshore or onshore. The respondents do not know the location-specific characteristics of the wind farms. Most of the previous studies found out that the offshore wind farms were preferred to onshore wind farms (eg. Ek, 2006, Ek & Persson, 2014, Aravena et al., 2006, and Vecchiato, 2014).

For example, Vecchiato (2014) examined the external impact of wind farms using 386 Italian respondents facing eight choice sets. In addition to the price attribute; position of the wind farm (mountains/hills, plains, offshore), turbine height (50m, 120m, 200m), minimum distances from the houses/coast (100m, 200m, 1000m), and number of wind turbines per wind farm(4, 15, 50) were used to describe the alternatives in the choice experiment. The respondents had to choose between two hypothetical wind farms and one "opt-out" alternative. The author found out that an average household was willing to pay € 96/year to locate the wind farms offshore relative to plains. However, the turbine height of 200M compared to 50M and the numbers of turbines per wind farm attributes were not significant. For the minimum distance attribute, respondents, on average, were willing to pay 47.1 and 78.0 (€/year per household in terms of electricity bill surcharge) for wind farms located at 250M and 1000M respectively relative to 100M. The potential problem in this attribute is that the author used the same distance for the onshore and offshore wind turbines while in reality offshore wind farms are placed at higher distance from the coast compared to the distance of onshore wind farms from residential areas. The finding of the study signals that, other thing being equal, the environmental cost associated with offshore wind farm is low compared to plains.

However, the choice between an offshore versus onshore locations might likely depend on site-specific locations of the future wind farms. For instance, McCartney (2006) found out that respondents preferred onshore wind farm to offshore wind farm when the respondents know that the offshore wind farm would be located in a Marine park. In the present study, we have five site-specific locations of the offshore wind farms as one of the offshore attributes.

2.4.3. Observed Preference heterogeneity

A large and growing body of literature has found preference for wind farm settings to vary across groups in the sample. Thus, we review wind farm preference heterogeneity with regard to socio-demographic & economic characteristics and prior experience to wind farms/turbines in the subsequent sections.

2.4.3.1. Socio-demographic and economic characteristics

Specifically, age, gender, education, and income are the socio-demographic and economic characteristics that we cover in this section. Previous studies have reported varying preferences for wind power settings across age groups. For instance, Ladenburg & Dubgaard (2007), Krueger et al. (2011), and Bishop & Miller (2007) revealed that older age groups are more concerned about the visual disamenity than younger age groups. Likewise, Ladenburg (2008) found that older age group respondents have a more negative attitude towards onshore wind farms. Firestone & Kempton (2007), Westerberg et al. (2013), Lilley et al. (2010) also found a negative association between support for offshore wind power and age. However, Ladenburg (2009b) and Klick (2010) found mixed effects of age on the acceptance of wind turbines.

Preference is also found to vary with the sex of the respondents (Ek & Persson, 2014, Krueger et al., 2011, Ladenburg, 2010, Ladenburg, 2009b). Ek & Persson revealed that males have stronger preferences for offshore wind farms relative to females. On the contrary, Ladenburg (2009b) revealed that male respondents have weaker preference for offshore wind farm compared to females. Yet, Lilley et al. (2010) found no significant effect of gender on the likelihood of continuing to visit a specific beach if a wind farm is developed at a 10 Km off the shore.

The findings of preference variation with respect to education are mixed (e.g. Ladenburg, 2010). Firseton & kemptone, 2007, Krueger et al. (2011), Ladenburg (2009b) found a negative association between the education level of the respondents and visual intrusion perception/attitude. However, Ladenburg & Dubgaard (2007) and Lilley et al. (2010) found no significant effect of education on the preference for/attitude to wind farms.

In most of the previous studies, the level of households' incomes appears to be positively correlated with visual impact perception and negatively correlated with the attitude towards wind farms. For example, Ladenburg & Dubgaard(2007) revealed that the welfare loss interms of utility for middle and high income respondents from visual impact of offshore wind farms is higher than those of low income group. Likewise, the higher the respondents' income level, the higher is the visual impact perception and negative attitude towards wind farms (Firestone & Kemptone, 2007, Lilley et al., 2010, and Ladenburg, 2009b).

2.4.3.2. Exposure to wind turbines and preferences

In the literature, the preference for different wind farm settings varies with respondents' prior experience to onshore and/ or offshore wind farms (e.g. Ladenburg, 2010, Krueger et al., 2011, Ladenburg 2009b, Ladenburg & Dubgaard, 2007). Respondents with prior exposure to onshore wind farms show a positive inclination to offshore wind farms (Ladenburg, 2010 and Krueger et al., 2011). However, given an offshore wind farms, people who are familiar with the wind farms incur higher disutility compared to less familiar respondent (Ladenburg 2009b, Ladenburg & Dubgaard, 2007). Similarly, Ladenburg (2008) found that people who can see both onshore and offshore wind farms revealed a higher negative perception to wind farms in general. On the contrary, Ek (2006) found that respondents with prior exposure to wind farms are more positive towards more wind turbines than those who do not. Yet, Lilley et al. (2010) found out that prior experience with offshore and/or onshore wind turbine has no effect on the likelihood of continuing to visit a specific beach if a new wind farm is situated at 10 km off the coast. To end with, Ladenburg et al. (2013) examined the frequency of daily turbine encounter on the attitude of the respondents towards more onshore wind turbines. The authors found that those who can see many turbines on a daily basis perceive wind turbines more negatively than those respondents who can see fewer turbines. However, their results were conditional on having wind turbines in the viewshed. As a result, the authors revealed that for those respondents with no wind turbines in the viewshed, the frequency of turbines seen on a daily basis was not a significant determinant of attitude.

3. The survey and Econometric Model

3.1. Survey construction and Design issues

The survey was carried out using a choice experiment (CE) approach (Hensher, 1994, Louviere, 1991, Louviere & Hensher, 1982). This is because the CE allows trade-offs between attributes so that we can estimate the economic value (WTP) of the different attributes related to wind farms. In the present study, the attributes are the potential settings of both onshore and offshore wind farm projects that are envisaged in the near future. Within the choice experiment, respondents were asked to choose between an offshore and onshore wind power project alternatives each associated with different attributes and cost.

The choice scenario set up describes a planned development of 450 MW either in 150 different onshore locations or in one of five different offshore locations. The offshore wind power development entails the development of 450 MW using 5 MW turbines. For the onshore development, the municipalities have been asked to point out locations for 150 MW in addition to repowering scheme of a total of 350 MW – which gives a total of 500 MW. Based on data from late 2009, a net of approximately 50 MW had been put up onshore, leaving approximately 450 MW to be developed onshore. This number is naturally related with some uncertainty. Tage Duer (Person communication, political economics at Danish Energy Authority (DEA) at the time) was therefore consulted with regards to these matters and he confirmed that 450 MW was suitable. With an expected 3 MW turbines, this gives 150 locations. The locations are thus not defined as such, but are a function of the 450 MW, which subsequently were divided in to 150 locations.

3.1.1. Defining attributes and attributes levels

The primary and crucial task in a choice experiment is defining attributes and attributes levels (Bateman et al., 2002). First, the different attributes that make up the alternatives and choice sets in one-way or another should be very relevant for consumers and producers of wind energy. Second, the attributes and their levels should represent a real life scenario. This is because the inclusion of irrelevant attribute or an exclusion of a relevant attribute may affect responses negatively (Garrod and Wills, 1999). The choice of the attributes was based on the input of previous studies (e.g. Ladenburg & Dubgarrd, 2007, Ladenburg et al., 2011, Meyerhoff et al., 2010). The attributes for the offshore alternative, except the cost/price attribute, are different from the onshore attributes. This implies that the attributes are location-specific. The offshore wind farm setting is explained by three attributes: the *distance* of the wind turbines from residential areas, *the number of households* living in the locality, and the *size* of the wind turbines (which actually represents both the size and number of turbines). For the offshore alternative, the *distance* of the wind turbines from the coast and a *specific geographical site* of the wind farms were the attributes chosen to explain the wind farm settings. The attributes and their levels are given in table 2. All attributes except cost are dummy coded.

Table 2: Attributes, attributes levels and coding

Attribute	Levels & variables	Coding
Offshore attributes		
Distance (Km)	8	1 if located at 8 Km, 0 otherwise
	12	1 if located at 12 Km, 0 otherwise
	18	1 if located at 18 Km, 0 otherwise
	50	1 if located at 50 Km, 0 otherwise
Location	Bornholm	1 if placed at Bornholm site, 0 otherwise
	Moen	1 if placed at Moen site, 0 otherwise
	Anholt	1 if placed at Anholt site, 0 otherwise
	Vester	1 if placed at Vester site, 0 otherwise
	Jammer	1 if placed at Jammer site, 0 otherwise
Onshore attributes		
Distance (M)	500	1 if located at 500 M, 0 otherwise
	1000	1 if located at 1000 M, 0 otherwise
Size (KW,MW)	4X750 KW	1 if 4X750 KW turbines, 0 otherwise
	2X1.5 MW	1 if 2X1.5 MW turbines, 0 otherwise
	1X3 MW	1 if 1X3 MW turbines, 0 otherwise
No of residents	Below 10	1 if no of residents below 10, 0 otherwise
	Between 10 & 100	1 if no of residents between 10 & 100, 0 otherwise
	Above 100	1 if no of residents above 100, 0 otherwise
Common attribute		
Cost	Cost	The cost attribute could take 0, 50, 100, 300, 600, 1200 DKK./household/year

Km=Kilometer, M=Meter, KW=Kilowatt, MW=Megawatt

3.1.1.1. Attributes and attribute levels of the onshore alternative

1. **Distance of the wind turbines from residential areas**

Distance is one of the important attributes that can explain onshore wind power settings. Meyerhoff et al. (2010) and Meyerhoff (2013) used the distance attribute with different levels in their studies and found out that indeed distance highly has a significant role in the preference for onshore wind farm settings. The distances levels given in table 2 are the potential distances of future wind turbines from residential areas. The future wind turbines would be placed at either 500-meter (M) or 1000 meter from residential areas and it is based on present regulation that states that the minimum distance of onshore wind farms from residential areas should be at least four times the turbine height.

2. **Size of the wind turbines**

The size attribute in the present study actually represents the size (in terms of energy generating capacity) and number of turbines to be placed at a specific site. This means that the total energy generating capacity of the onshore wind farms is the same across choice sets. As we can see from table 2, the size attribute could take 4X750 KW turbines, 2X1.5 MW turbines, or 1X3 MW turbine. All the three size levels have identical energy generating capacity but they are different in the number of turbines. Therefore, if the total generating capacity is the same across choice sets, the choice would be between many but small turbines and few but large turbines.

This attribute is crucial to control the "installed capacity demand effect" of the respondents. In terms of wind energy generation, large turbines have high installed generating capacity than small turbines. Therefore, if the total installed generating capacity is not the same across choice sets, the respondents may always choose the onshore alternative with large turbines due to its high generating capacity even though they perceive the large turbines are more visually intrusive than the small turbines. This indicates that the externalities from wind turbines may confound with generating capacity demand effects. This creates a trade-off between wind power settings and wind power production demand. However, in the present choice experiment, we are able, in principle, to weed out the installed generating capacity demand effect by keeping the total installed generating capacity constant across choice sets while varying in terms of both number and size of the turbines. This ensures that the estimated effects would only show the externalities of onshore wind power projects and thus are not confounded with the installed capacity demand effect.

3. **The number of residents living in the locality**

The number of population living in the locality where the future wind farms would be installed is also another important attribute which could determine the acceptance of the onshore wind power projects. This attribute is assumed associated with total welfare loss due to the presence of wind turbines in the locality. Thus, it is assumed that the higher the number of population living in the locality the higher would be the welfare loss in terms of disutility from the wind turbines. As we can see from table 2, this attribute could take three values: *below 10, between 10 and 100,* and *above 100.*

3.1.1.2. Attributes and attributes levels of the offshore alternative

1. **Distance from the cost to the offshore wind farms**

This attribute is chosen to reflect the potential distance of future offshore wind farms. The same attribute has been used in Ladenburg & Dubgaard (2007, 2009) and Ladenburg et al. (2011). These previous studies have proven the very importance of this attribute. The attribute could take 8 Km, 12 Km, 18 Km, or 50 Km. As stated in Ladenburg & Dubgaard (2007), the minimum accepted offshore distance in Denmark is 8 Km from the shore line. For this reason, the 8 Km is the baseline distance in the choice experiment survey. A wind farm positioned at a 50 Km distance is technically invisible even for a wind turbines with a capacity of 5 MW (Ladenburg & Dubgaard, 2007, Ladenburg & Lutzeyer, 2012). Therefore, the 8 Km, 12 Km, and 18 Km distances are the realistic choices. However, the visibility of the offshore wind farm depends on a number of factors such as the type of the project, weather conditions and type of topography (Ladenburg & Dubgaard, 2007).

2. **Specific geographical locations of the offshore wind farms**

The location attribute identifies the specific geographical site of the future offshore wind farms. This attribute is important in the sense that knowledge of the specific geographical sites might affect their preference for onshore versus offshore locations as well as for the distance attribute. For instance, if the respondents know that the future offshore wind farm would be located in a very popular recreational area, they might either choose the onshore location or choose to place the offshore wind farm at a very distant location from the coast. A study carried out in Australia by McCartney (2006) revealed that respondents preferred the onshore location when the specific site of the offshore location happens to be a marine park. However, Krueger et al. (2011) did not find any significant difference in preference between three site-specific locations. In the present survey, respondents were told that the offshore wind farms would be located in one of five specific locations: the Bornholm site, Moen site, Anholt site, Vester site, and Jammer site. Besides, the respondents were shown a map showing the location of these five locations as presented in figure 1.

Figure 1: Locations of the five specific geographical sites

The payment Vehicle

The price/cost of externality reduction was a uniform lump sum payment on the households' electricity bills. As we can see from table 2, this attribute could take six levels ranging between 0 and 1,200 DKK/household/year. The households were reminded that their household would actually be willing to pay the amount specified in the chosen alternative. Besides, the respondents were reminded to make their choices depending on their income level and were given a "Cheap Talk" at the beginning of the choice experiment survey section to minimize bias in their hypothetical demand (Cummings & Taylor, 1999).

3.1.2. Survey development and data collection

The survey pretest was carried out in the start of December 2011 and developed through the use of focus groups. The pretest was very vital to ensure the relevance of the questions, correct wordiness, whether the questions are easily understandable. Moreover, a map significance and picture simulation of the wind farms was also tested. As a result, the test ensured that the attributes and attribute levels were quite relevant and the choice task was easily understandable and realistic. However, the participants expressed their concern that the questionnaire was quite demanding to complete.

The final version of the questionnaire contained three sections. The first part of the questionnaire covers attitudes on green energy in general and wind power in particular, demographics of the respondents. The second part contains the choice experiment and some follow-up questions. Finally, the third part collects information on the socio-economic characteristics of the respondents.

The survey was conducted between the end of December 2011 and January 2012. The sample was drawn based on quota sampling based on national sample on geography, gender, and education among members of user need internet panel with more than 150,000 members. A total sample of 26032 respondents were invited to participate in the survey. Accordingly, the respondent could not self-select into the survey. The survey mode was an internet survey. An email with a link to the questionnaire was sent to the respondents. Olsen (2009) found some evidence that internet survey performs better than mail survey. However, web-survey is associated with low response rate while it gives respondents enough time to contemplate on their answers and it is cost effective (Bateman et al., 2002). Arrow et al. (1993) recommended personal interviews over other approaches in the valuation of non-market goods. However, although personal interview could result in high response rates, it is costly compared to other modes (Bateman et al., 2002).

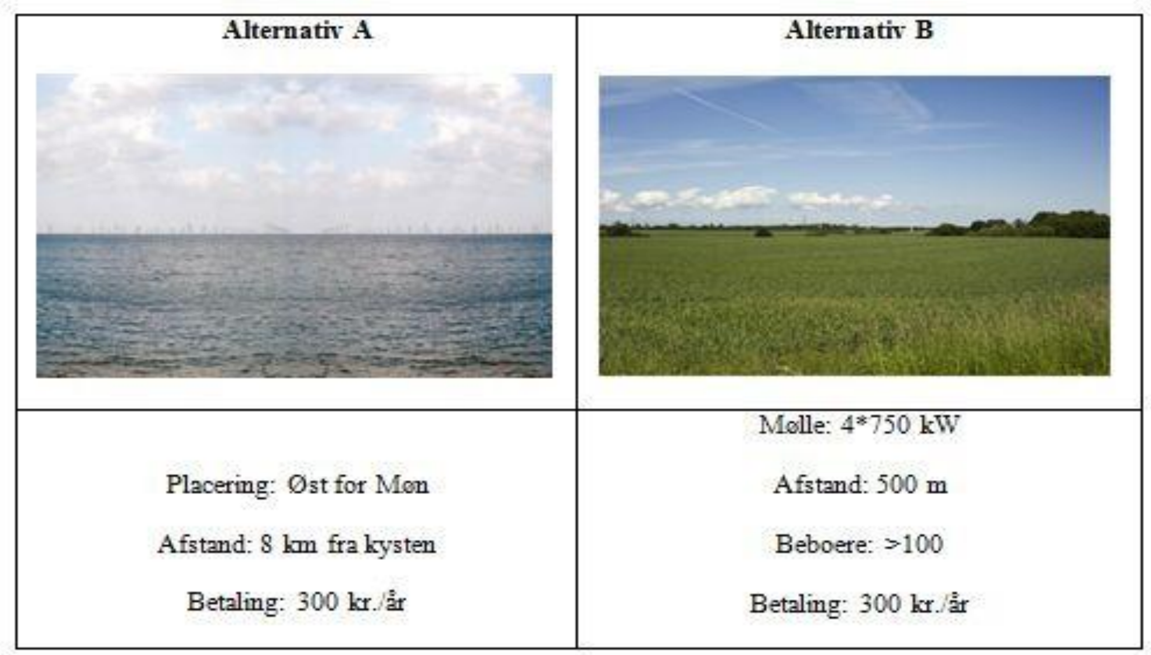
The response rate was 8.57 % which is far from decent response rates but not uncommon in web-surveys. Many of the respondents did not complete the survey. The main reason seems to be that the respondents loss their interest halfway through the questionnaire. However, since we have invited a large number of respondents to participate in the survey we still have 17, 848 usable observations which is enough to draw conclusions.

3.1.3. Experimental Design

Experimental design deals with the way to combine attributes and attributes levels into alternatives and alternatives in to choice set (Alpizar et al., 2003). The ultimate objective of the experimental design is to create efficient choice sets. The choice experiment was designed using D-efficient design with utility priors. Finally, 36 choice sets remained after accounting for unreasonable and identical combinations which we subsequently randomly assigned in to 9 blocks of 4 choice sets each. This implies a respondent faced 4 choice sets each with two alternatives.

3.1.4. The choice Experiment

In the choice experiment, every respondent faced two hypothetical wind farm alternatives in every choice set one offshore wind farm and the other onshore wind farm. The choice scenario was developed in a way that resembles the real life choices. Both alternatives were varied in terms attributes and attribute levels. Due to the political devotion to develop more of both offshore and onshore wind power projects in Denmark, an opt-out alternative was not included in the choice set. Given the Danish governments devotion to develop more wind power projects, the policy-relevant question to ask is how the planned wind power development should be carried out at a minimum external cost. Hence, the respondents were "forced" to choose either the offshore alternative or the onshore alternative. Therefore, our willingness to pay estimates will be interpreted conditional on development of onshore and offshore wind power projects.



Alternativ A	Alternativ B
Placering: Øst for Møn Afstand: 8 km fra kysten Betaling: 300 kr./år	Mølle: 4*750 kW Afstand: 500 m Beboere: >100 Betaling: 300 kr./år

If you only have to choose between alternative A and B, which one will you choose?

( ) Alternative A ( ) Alternative B

Figure 2: Sample Choice Set

An example of a choice set to which respondents faced in their choice is given in Figure 2. As you can see from the picture, both alternatives were supported by simulated pictures which shows the changes in the landscape or seascape when the wind farm settings change. Moreover, the respondents were instructed to tap on the pictures prior to their choice so that the pictures were enlarged.

3.2. The Random Utility theory and Econometric Model

The choice experiment method is based on the theoretical framework of the Lancaster's characteristics of value which asserts that the utility for a good can be decomposed in to the attributes that make up the good (Lancaster, 1966). The econometric model used to analyze a discrete choice data like the one in choice experiment surveys was developed by McFadden (1973) based on the random utility theory (Luce, 1959, Manski, 1977, McFadden, 1973). The random utility model is based on a random utility index of alternatives. In a random utility model with exclusive alternatives, an individual chooses the alternative with highest level of utility i.e., the preferred option from the given choice set (Louviere et al., 2000, Train, 2009). The utility (U) of each alternative is supposed to be the sum of a systematic component (V) which is a function of different observed variables and an unobserved component (ε) which can be represented as a random variable (Train, 2009).

Following Hole (2007) and Train (2009), the utility that a decision maker *n* gets by choosing alternative *j* is given as in equation 4:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{4}$$

Where V_{nj} is a function of observable attributes of the alternatives, $\mathbf{X}_{nj}$, and of the decision maker, $\mathbf{Z}_n$ where as ε_{nj} is unknown and treated as random. The subscripts $j = 1, 2, \ldots J$, and $n = 1, 2, 3, \ldots, N$ designates the alternatives and decision makers, respectively.

Given the random utility function in equation 4, the probability that decision maker *n* chooses alternative *i* is given by:

$$\begin{aligned} P_{ni} &= \Pr(U_{ni} > U_{nj})\ \forall j \neq i \\ &= \Pr(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj})\ \forall j \neq i \\ &= \Pr(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj})\ \forall j \neq i \end{aligned} \tag{5}$$

Given equation 5, the choice of the suitable econometric model that fit the data better depends on the assumption of the distribution of the random terms and on how the random terms enter the indirect utility function (Train, 2009, Hoyos, 2010, Hole, 2007, Ben-Akiva & Lerman, 1985). Two alternative models with their different assumptions: the conditional logit (CL) model and mixed logit (the random parameter logit (RPL)) model are presented in the subsequent sections.

3.2.1. The conditional Logit Model

The conditional logit model assumes an independently and identically distributed (IID) and type I extreme value (Gumbel) distributed random term (Alpizar et al., 2003, McFadden, 1973, Train, 2009). After some algebraic digestion, the conditional logit model is specified as in equation 6:

$$P_{ni} = \frac{\exp(\sigma_n V_{ni})}{\sum_{j=1}^{J} \exp(\sigma_n V_{nj})} \tag{6}$$

σ_n is a scale parameter which is typically normalized to 1. Normally, the linear-in parameter utility function is used to capture utility. The linear-in parameter utility function is specified as in equation 7:

$$V_{ni} = \mathbf{X}_{ni}' \boldsymbol{\beta} + \mathbf{Z}_n' \gamma i \tag{7}$$

However, attributed to Train (2009), conditional logit model has several caveats. First, the conditional logit model can only represent the systematic taste variation but not a random taste variation. The conditional logit model does not allow random taste variation and thus the variance of the random term should be the same over alternatives. Second, conditional logit assumes independence from irrelevant alternatives (IIA). This implies the ratio of probabilities of two alternatives should not be affected by the removal or introduction of another alternative which is a very restrictive assumption. Given two alternatives, *i* and *k*, the CL assumes

$$\frac{P_{ni}}{P_{nk}} = \frac{\exp(V_{ni}) / \sum_{j=1}^{J} \exp(V_{nj})}{\exp(V_{nk}) / \sum_{j=1}^{J} \exp(V_{nj})} = \frac{\exp(V_{ni})}{\exp(V_{nk})}$$

Whether an alternative is introduced or removed, there would be a proportionate shift in the probabilities of the other alternatives.

Finally, the CL model cannot handle dynamics associated with unobserved factors because the unobserved factors are assumed to be unrelated over choices (t). The CL assumes the random term is IID extreme value type I, independent over individuals (n), alternatives (j), and choices (t). The CL model does not allow the unobserved factors to be correlated over time. This implies that the conditional logit model cannot handle panel data sets.

3.2.2. The Mixed Logit Model

The mixed logit model is a more flexible model than the CL model. It has the power of overcoming the limitations mentioned in the CL model (Train, 2009, Wooldridge, 2010). The mixed logit model allows for random taste variation, correlation of unobserved factors over time, and unrestricted substitution pattern. After some algebraic digestion, the mixed logit choice probability is specified as follows (Train, 2009):

$$P_{ni} = \int \frac{\exp(\mathbf{X}'_{ni}\boldsymbol{\beta})}{\sum_{J=1}^{J}.\exp(\mathbf{X}'_{nj}\boldsymbol{\beta})} f(\boldsymbol{\beta}|\theta)d\boldsymbol{\beta} \qquad \textbf{(8)}$$

Where f(β|θ) is the density function of β (a mixing distribution). θ represents the parameters of the density function such as mean (b) and covariance (W).

The mixed logit probability is a weighted average of the logit formula evaluated at different values of β, with the weights given by the density f(β|θ) (Train, 2009). In a mixed logit model, we have a random coefficients with density f(β|θ). The coefficients vary over individuals and thus are not fixed. f(β|θ) is specified to be continuous with mean b and covariance W. The mixed logit choice probabilities do not depend on the value of β as the parameters β are integrated out like the random error term.

Given repeated choices (panel data), the mixed logit choice probability (S_n) for a decision maker *n* is specified as follows (Train, 2009):

$$S_n = \int \prod_{t=1}^{T}\prod_{j=1}^{J} \left[\frac{\exp(\mathbf{X}'_{njt}\boldsymbol{\beta})}{\sum_{j=1}^{J} \exp(\mathbf{X}'_{njt}\boldsymbol{\beta})}\right]^{y_{njt}} f(\boldsymbol{\beta}|\theta)d\boldsymbol{\beta} \qquad \textbf{(9)}$$

Where y_{njt} =1 if the individual choose alternative j in choice situation t and 0 otherwise.

A simulation method is applied when estimating the mixed logit model given in equation 9. Given any value of θ, the choice probabilities are approximated using simulation (Train, 2009). The θ parameters can be estimated by maximizing the simulated log-likelihood (SLL) function given in equation 10 (Train, 2009, Hole, 2007, Wooldridge, 2010).

$$SLL = \sum_{n=1}^{N} \text{In} \left\{ \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp\left(\mathbf{x}'_{njt} \boldsymbol{\beta}_n^{[r]}\right)}{\sum_{j=1}^{J} \exp\left(\mathbf{x}'_{njt} \boldsymbol{\beta}_n^{[r]}\right)} \right]^{y_{njt}} \right\} \quad (10)$$

Where $\beta_n^{[r]}$ is the r-th draw for individual n from the distribution of β

As stated in Train (2009), the simulation task proceeds through three steps. First, draw a value of $\boldsymbol{\beta}$ from $f(\boldsymbol{\beta}|\theta)$ and label it as $\beta_n^{[r]}$ with the subscript r=1 referring to the first draw. Second, calculate the logit formula P_{ni} with this draw. Finally, repeat first and second steps many times and average the results to get the average simulated probability.

The mixed logit model allows a choice of different distributions for the attributes (Hensher & Greene, 2002). Train (2009) noted that the random parameter model and the error component model of the mixed logit are formally equivalent although the random coefficient is most undemanding and widely used in applications (Hensher & Greene, 2003). Having the appropriate variable and mixing distribution, the mixed logit model can approximate any random utiliy model (McFadden & Train, 2000). Hoyos (2010) noted that it is very important to focus on three specification issues when using the mixed logit model: the randomness of the parameters, choice of mixing distribution, and finally the interpretation of the coefficients. Given its flexible properties, we applied the Random parameter logit model in estimating our models instead of conditional logit.

When estimating either a conditional logit or a mixed logit model, the inclusion and interpretation of the ASC is debated. According to Meyerhoff & Liebe (2009), the interpretation of the ASC estimate depends on whether one sees it mainly as a technical parameter capturing the average effect of all relevant unobserved factors, or one rather chooses to associate the ASC parameter with a behavioral assumption as suggested by Adamowicz et al. (1998). Therefore, there is disagreement in the literature about which interpretation is most correct. However, attributed to Train (2009) & Hensher et al. (2005), the ASC captures the average effect on utility of all unaccounted variables in the model. Hensher et al. (2005) noted that the interpretation of the ASC in branded alternatives actually makes sense. Train (2009) and Hoyos (2010) also recommended to have the ASC while estimating the model. Therefore, the present study has estimated and given a behavioral interpretation to the ASC.

3.2.3. Welfare Measure

The Hicksian surplus/variation for a price change is the theoretical framework behind the measure of welfare changes. The welfare measures for a price change developed by Hicks can also apply for environmental quantity/quality changes (Pearce et al., 2006). According to Mitchell & Carson (1989), given an individual right to the *initial situation,* the compensating surplus (CS) measures are fit to measure an environmental quantity/quality change. In such cases, the CS is either the maximum WTP to for an improvement or the minimum compensation to tolerate loss (Pearce et al., 2006).

Even though the property right is a debatable issue, many argue that it is feasible to have a right to the future states of the environment, perhaps, through environmental legislations (Pearce et al., 2006). In such cases, it is sensible to use the equivalent surplus (ES) measure. The ES then measures either households' willingness to pay to avoid loss or willingness to accept to forgo the benefits of post change (Ibid). Although choice between a WTP or WTA measure is a context based, the WTP format should be used over the WTA as the later is a conservative measure (Arrow et al., 1993).

In the present study, the municipalities were asked by the government to find suitable locations for the wind farm installments. Moreover, the choice set presented to the respondents does not include an opt-out alternative. Therefore, it is reasonable to assume that the households have the right to the post policy change. Specifically, households' have the right to a landscape or seascape with wind farms. Given, households' right to the new situation, they have to pay to secure a quality improvement to the landscape/seascape. Therefore, the appropriate measure would be the equivalent surplus (ES) measure.

Given a logit model, Small and Rosen (1981) specified the ES measure as follows

$$\boldsymbol{ES = WTP = \frac{1}{\beta_P}\left\{ln\sum_{j=1}^{J} e^{v_j^0} - ln\sum_{j=1}^{J} e^{v_j^1}\right\}} \qquad (\mathbf{11})$$

Where,

β_P is the marginal utility of income which assumed to be independent of income

$e^{v_j^0}$ and $e^{v_j^1}$ are the utility values for each choice alternative before and after the quality change respectively

And J is the number of alternatives in the choice set.

Therefore, the ES is a WTP of the households for an improvement in the quality of the landscape or seascape. Given a linear-in parameter utility function, calculating the WTP estimates for landscape/seascape quality improvement is straightforward. Following Hole (2007), the marginal willingness to pay (MWTP) formula is specified as in equation 9:

$$\boldsymbol{MWTP} = \frac{\partial \boldsymbol{V} / \partial \boldsymbol{NP}}{\partial \boldsymbol{V} / \partial \boldsymbol{P}} = \frac{-\boldsymbol{\beta_{NP}}}{\boldsymbol{\beta_P}} \qquad (\mathbf{12})$$

Where NP and P represents a non-price and price coefficients respectively.

The total willingness to pay for all attributes is specified as follows (Hole, 2007).

$$\boldsymbol{WTP} = \sum\nolimits_{\boldsymbol{k}} \frac{\boldsymbol{\beta_k}}{-\boldsymbol{\beta}\boldsymbol{\beta_P}} (\Delta \boldsymbol{x_k}) \qquad (\mathbf{13})$$

Where k referes to the attributes of the landscape or seascape quality improvement.

According to Hole (2007), four standard methods can be applied to compute the standard error of the WTP estimates. These methods are the Delta method, Krinsky-Roob method, Fieller Method, and Bootstrap method. Each of the methods has their own pros and cons (a detailed explanation can be referred in Hole (2007)). The Delta method is most accurate when the data is well conditioned even though all methods can produce similar results (Ibid). The Delta method assumes that the WTP is normally distributed and symmetric around its mean (Ibid).

Therefore, the WTP estimates presented in the present study were computed using the Delata method. We also calculated the WTP estimates and their standard errors using the Krinsky-Roob method but the results were almost identical to the Delta method estimates. According to Hole (2007), the variance of the WTP estimates using the Delta method is specified as follows:

$$\boldsymbol{Var}\left(\frac{\boldsymbol{\beta_{NP}}}{\boldsymbol{\beta_P}}\right) = \left(\frac{\boldsymbol{\beta_{NP}}}{\boldsymbol{\beta_P}}\right)^{\mathbf{2}} \left(\frac{\boldsymbol{Var}(\boldsymbol{\beta_{NP}})}{\boldsymbol{\beta_{NP}}^{\mathbf{2}}} + \frac{\boldsymbol{var}(\boldsymbol{\beta_P})}{\boldsymbol{\beta_P}^{\mathbf{2}}} - \frac{\mathbf{2}\boldsymbol{cov}(\boldsymbol{\beta_{NP}}, \boldsymbol{\beta_P})}{\boldsymbol{\beta_{NP}}\boldsymbol{\beta_P}}\right) \qquad (\mathbf{14})$$

Where Var and cov stands for variance and covariance respectively.

4. Presentation and Discussion of Results

This section is dedicated to the presentation and discussion of the findings of the present study. In the subsequent sections, we discuss both descriptive statistics of the sample and the random parameter logit results broadly.

4.1. Sample characteristics

The respondents socio-demographic and economic characteristics and prior experience with wind turbines are presented in table 3.

Table 3: Characteristics of the sample. Total observation: 17,848 (2331 respondents)

Variable	**Sample(%)**	**Variable coding**
Age30 (share of <=30 years old)	15	=1if age<=30, else =0
Income (DKK) (share)		
Low: <=299,999	23.1	=1if income <=299,999, else =0
Middle: >=300,000-<=599,999	40.1	=1 if income >=300,000 but <=599,999, else =0
High: >=600,000	36.8	=1if income >=600,000,else= 0
Education (share)		
Primary-high school (incl. vocational)	35.1	=1 if educ. is primary-high school, else= 0
Shorter secondary education and Bachelor	44.6	=1 if educ. is shorter sec. educ. & bachelor, else =0
Master and above	20.3	=1if educ is master or above, else =0
Gender		
Female	50.4	=1 if gender is female, else =0
Male	49.6	=1 if gender is male, else=0
View to offshore wind farms		
Offshore View	3	=1if they have a view, else =0
No offshore View	96.7	=1 if they don’t have a view, else =0
I don’t Know	0.3	=1 if they stated ”I don’t know”, else= 0
View to onshore wind farms		
Onshore View	11.93	=1if they have a view, else =0
No onshore View	87.67	=1 if they don’t have a view, else =0
I don’t know	0.4	=1 if they stated ”I don’t know”, else =0
Number of turbines seen on a daily basis		
dailysee0	50	= 1 if they can see none, else =0
dailysee5	18	=1 if they can see 1-5 turb., else =0
dailysee15	5.5	=1 if they can see 6-15 turb., else =0
dailysee16	26.5	=1 if they can see 16 or more, else =0
Number of turbines daily seen from a residence or a summerhouse		
homesee0	86	= 1 if they can see none, else =0
home see3	7.9	=1 if they can see 1-3 turb., else =0
homesee4	6.1	=1 if they can see 4 or more, else =0

A web-based survey could result in overrepresentation/underrepresentation of a certain segment of the population in the sample and low response rates (Bateman et al., 2002, Hoyos, 2010, Ek, 2006).

The response rate in the present study is only 8.57 % which is far from satisfactory response rate but not uncommon in web-surveys (Bateman et al., 2002). All the 26032 respondents who were invited to participate in the present survey were drawn based on quota sampling. Accordingly, the respondent could not self-select into the survey. Nevertheless, it is reasonable to assume that there might be self-selection in responding to the questionnaire and this may result in self-selection bias (Ek, 2006). Table 3 presents the distribution of the respondents' characteristics and the coding of the variables.

In table 4, the respondents' socio-demographic and economic characteristics are compared with the Danish nationwide figures. As we can see from table 4, the distributions of the respondents' age and gender are found to be representative of the Danish population. Within the sample, 15 percent of the respondents stated that they are 30 years old or younger. Actually, the minimum age in the sample was 20 years of age so that the comparison was made based on this figure. In addition, within the sample, 50.4 percent of the respondents stated that they are female which is quite representative. However, the level of completed education and average annual income of the respondents are significantly higher compared to the distribution of these characteristics in the Danish population and this might have consequences on the findings. For example, if the sample constitutes higher proportion of respondents with high income, the willingness to pay estimates might be overestimated.

Table 4: Comparing the sample to Danish nationwide figures

Socio-demographic and economic characteristics	Sample (percentage)	Denmark (percentage)	Significance (Chi-square test)
Age30(share of <=30)	15	15.62	0.2723
Income (DKK) (share)			
Low: <=299,999	23.1	42	8.63366E-74
Middle: >=300,000-<=599,999	40.1	31	
High: >=600,000	36.8	27	
Education (share)			
Primary-high school (incl. vocational)	35.1	73.15	≈0
Shorter secondary education and Bachelor	44.6	19.54	
Master and above	20.3	7.31	
Gender			
Female	50.4	50.29	0.9172
Male	49.6	49.71	

Due to lack of national data on the exposure to wind turbines, comparison of these characteristics was not possible. As we can see in table 3, only 3 percent of the respondents have a view to offshore wind farms from their permanent residence or summerhouse while approximately 12 percent of the sample has stated that they have onshore wind farms in the view shed from their permanent residence/summerhouse. Ladenburg & Dubgaard (2007) found that approximately 5 % of the respondents in their sample had a view to offshore wind turbines from their either permanent residence or summerhouse. Ladenburg et al. (2013) also found that 4.9 % and 24 % of their sample had a view to offshore and onshore wind turbines respectively either from a permanent residence or summerhouse. Moreover, frequency of turbine encounters on a daily basis (0, 1-5, 6-15, & 16 or more) and frequency of turbine encounters on a daily basis from residential area/ summerhouse (0, 1-3, and 4 or more) are also presented in table 3. The frequencies of daily turbine encounter variables are important to test the cumulative effect of wind turbine on preferences for offshore versus onshore. Ladenburg et al. (2013) found out that 23.6, 13.9, 7.8, and 5.5 percent of the respondents in their sample had a daily turbine encounter of 0-5, 6-10, 11-20, and more than 20 respectively while 49.3 percent of the respondents stated that they do not recall the daily encounter.

4.2. Econometric Results: The Random Parameter Logit Model

In this section, we present and discuss different estimation results of mixed logit models. Firstly, an attribute only model, which includes the different attributes of wind farms is presented and discussed. Secondly, estimations including the socio-demographic and economic characteristics of the respondents are presented and discussed. These types of models enable us to identify preference heterogeneity among the respondents with respect to these characteristics. Thirdly, in an attempt to test the effect of exposure to wind farms on preference, we ran group of models incorporating variables related to experience of respondents with wind farms.

When estimating the attributes-only model, all attribute parameters including the ASC but the cost parameter were set to be random. This is because the random parameter approach allows correlation across alternatives, defines degree of unobserved heterogeneity and preference heterogeneity around the mean (Hensher & Green, 2002, Train, 2009, Hoyos, 2010). However, when estimating the other models, the parameters with insignificant standard deviations in the attributes-only model were set to fixed-point estimates. In all estimations, the normal distribution was used as the mixing distribution. Hensher & Green suggested a uniform distribution with (0,1) bound when we have dummy variables. Accordingly, the same model was ran using a uniform distribution as the mixing distribution but the estimation with normal distribution outperforms the estimation with uniform distribution (the estimation result using a uniform distribution can be found in the appendix section A, table A7). Moreover, all the estimations were ran using 500 Halton draws. As noted in Hensher & Greene (2002), in a three alternative choice model with one or two random coefficients a 25 intelligent draws can produce stable parameters although 100 appears to be a “good” draw. Therefore, in the present study, with a large data set 500 draws were assumed to be enough to produce stable parameters.

The cost parameter was estimated as a fixed-point estimate. With constant cost coefficient, the distribution of the willingness to pay for the other attributes will be continuous and have the distribution of their respective coefficients. This is because the ratio of two normally distributed parameters has a discontinuous distribution with the denominator having singularity at zero (Hensher & Green, 2002, Train, 2009). Therefore, keeping the cost coefficient constant ensures a continuous and normally distributed willingness to pay estimates given a normally distributed non-price coefficients.

4.2.1. The Attributes-only Model

We attempted to estimate two separate models with and without an interaction between the distance and size attributes of the onshore alternative. However, the log-Likelihood value at the convergence point of the model shows the model with interactions outperforms the model without interactions. Thus, table 5 presents the estimation results for the interaction model. (The model without interactions can be found in the appendix section A, table A5). The chi-square value indicates that the random parameter model (RPL) is significant. The attributes-only model shows the average preference of the sample. However, we does not take in to account the overrepresentation of highly educated and high-income groups. The implied willingness to pay (WTP) estimates and their 95 % confidence interval computed based on the coefficients of the attributes-only model are presented in table 6 and table 9.

The standard deviation estimates on the random parameters indicate that there is a considerable degree of unobserved heterogeneity in preference among the respondents. The standard deviation estimates of 8 random parameters out of the 15 are statistically significant and large relative to their respective means. This indicates that the random parameter do vary across respondents. For some of the attributes, while the mean of the random parameters are not significant the standard deviations of the random parameters are still significant

Table 5: Estimation results of the attributes-only model

Variable		Parameter	Pvalue
Cost		-0.0062	< 2.2e-16 ***
Offshore			
ASC		3.3466	3.331e-15 ***
Distance (Km):	8 vs 12	1.1107	4.635e-05 ***
	8 vs 18	1.4473	1.891e-05 ***
	8 vs 50	1.0407	0.0004758 ***
Location:	Bornholm vs Moen	1.0112	0.0156403 *
	Bornholm vs Anholt	0.2946	0.2506886
	Bornholm vs Jammer	0.3492	0.2845985
	Bornholm vs Vester	0.4721	0.2163547
Onshore			
Distance (M)	500 vs 1000	1.2185	7.942e-05 ***
Size(KW, MW)	4X750 vs 2X1.5	1.2281	0.0009072 ***
	4X750 vs 1X3	1.9669	1.556e-09 ***
Distance:Size	500 vs 1000: 4X750 vs 2X1.5	-2.0473	4.100e-05 ***
	500 vs 1000: 4X750 vs 1X3	-3.3211	2.620e-09 ***
No of Residents:	Below10 vs 10-100	0.0524	0.8321102
	Below 10 vs above 100	-0.5616	0.0810153 .
Standard deviations			
ASC		2.6469	< 2.2e-16 ***
Distance (Km):	8 vs 12	-2.044	1.046e-06 ***
	8 vs 18	0.6434	0.4736664
	8 vs 50	0.0369	0.9666183
Location:	Bornholm vs Moen	-3.746	3.800e-10 ***
	Bornholm vs Anholt	-0.2744	0.8210934
	Bornholm vs Jammer	2.1495	7.378e-05 ***
	Bornholm vs Vester	1.9583	0.0064462 **
Distance (M)	500 vs 1000	0.5834	0.2488362
Size(KW, MW)	4X750 vs 2X1.5	-0.6113	0.4125626
	4X750 vs 1X3	1.728	4.911e-05 ***
Distance:Size	500 vs 1000: 4X750 vs 2X1.5	0.5713	0.5893276
	500 vs 1000: 4X750 vs 1X3	0.1819	0.8828748
No of Residents:	Below10 vs 10-100	-2.0727	1.840e-07 ***
	Below 10 vs above 100	3.3054	2.988e-10 ***
Log-Likelihood (β):		-3674.1	
McFadden R^2:		0.26149	
Likelihood ratio test :		chisq = 2601.8 (p.value = < 2.22e-16)	
No of observations:		17,848	
No of respondents:		2331	

' *** ', ' ** ', ' * ', ' · ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

As expected, the cost coefficient is negative and statistically significant. This implies that the households' demand/ preference for externality reduction decreases as the cost of externality reduction increases. The non-price attributes of both offshore and onshore wind power farms will be discussed in the subsquent sections in detail.

4.2.1.1. Analysis and discussion of the offshore parameters

1. Distance of the offshore wind farms from the coast

The variables representing the distance of the offshore wind farms to the coast (disti) are dummy coded. The 12 Km, 18 Km, and 50 Km distances are compared to the baseline distance of 8 Km from the shoreline. The gradient shows that the coefficients are all significant. A brief look at the coefficients tell us that the coefficient on the 50 Km distance is less than the coefficients on both the 12 Km and 18 Km distances. Nevertheless, a Wald-test indicates that the three coefficients are not significantly different from each other: $\beta_{dist12} = \beta_{dist18} = \beta_{dist50}$ (the test results can be referred in the appendix section B, table B1). This implies that, all else equal, an average respondent prefers the 12 Km distance to 8 Km distance whereas both the 18 Km distance and 50 Km distance are not preferred to the 12 Km distance.

The standard deviation on these random parameters indicates a reasonable degree of unobserved heterogeneity in the preference for the 12 Km distance relative to the baseline 8 Km distance. The standard deviation estimate of the parameter shows that some of the respondents preferred 8 km to 12 km while still others preferred 12 km to the 8 Km distance. The standard deviations for the 18 Km and 50 Km distances are not significant. This implies that no unobserved heterogeneity in preference is detected for the 8 Km versus 18 Km and 8 Km versus 50 Km distances.

The WTP values for the distance variables and other variables have been calculated based on the coefficients in table 5. These WTP estimates are presented in table 6. The WTP estimates were computed using the delta method (The WTP calculating methods are explained in the methodology section). On average, the respondents are willing to pay 179.3, 233.6, and 168 DKK/household/year for sitting the offshore wind farms at 12 Km, 18 Km, and 50 Km, respectively, relative to the 8 Km distance. However, the households' willingness to pay for the 12 Km, 18 Km, and 50 Km distances are in fact not significantly different from each other. Therefore, statistically, households have the same WTP values for the three distances relative to the 8 Km distance. The willingness to pay estimates are household's annual external cost in the form of surcharge to electricity bill. The WTP estimates may capture other effects beyond visual disamenity so that we continue to refer the estimates as costs/benefits. For instance, the concern for boaters and anglers could be well beyond visual disamenity.

The possible reason for having the same WTP for the three distances ($WTP_{dist12} = WTP_{dist18} = WTP_{dist50}$) as explained in Lilley et al (2010) and Westerberg et al (2013) could be that people have both amenity and disamenity value from offshore wind farms. At shorter distances, the disamenity value is greater than the amenity value triggering respondents to prefer distant locations. However, if a wind farm is situated at a reasonably longer distance and it is impossible to see the wind turbines from the coast, the diamenity value would be less than the amenity value encouraging respondents to even prefer the shorter distance to the longer distances. In the present study, peoples prefer wind farms to be located further away from the shore but not beyond 12 Km. According to Lilley et al (2010), it is likely that an offshore wind farm situated at 10 km from the coast would increase coastal recreation than reduce it. In our case too, people do not prefer the wind turbines to be placed at too distant locations.

Table 6: WTP Estimates for the offshore attributes (incl. the ASC) (DKK/household/year)

Variables	Mean WTP	95 % Confidence interval	
		Lower Limit	Upper Limit
ASC	540.309	427.588	653.029
8 vs 12	179.317	102.020	256.615
8 vs 18	233.666	128.583	338.749
8 vs 50	168.020	80.604	255.436
Bornholm vs Moen	163.253	39.482	287.024
Bornholm vs Anholt	47.569	-34.574	129.713
Bornholm vs Jammer	56.379	-44.223	156.981
Bornholm vs Vester	76.214	-42.123	194.550

The implication of the finding is that the benefit that the society could gain by moving the wind farms further away offshore beyond the 12 Km distance is negligible. On the other side, the costs per kWh produced rises as the distance from the coast increases (Ladenburg & Dubgaard, 2007). Therefore, based on our findings we could suggest that wind farms should not be located beyond a 12 Km distance because there would not be gain to the society in terms of externality reduction while it increases wind power generation costs. As Lilley et al. (2010) notes, wind power production cost increases (like cable costs) as the distance of the offshore wind turbines increases. Ladenburg & Lutzeyer (2012) also argued that the capital cost of offshore wind power generation increases when the wind farm is placed in deep waters and the distance of the wind farm from the shoreline increases. However, for a decision making to depend on a solid ground, further studies in the area are warranted.

The findings of the present study are compared with the findings of Ladenburg & Knapp (2014), Ladenburg et al. (2011), and Ladenburg & Dubgaard (2007) hereunder. The WTP estimates from the four studies for the 12 Km, 18 Km, and 50 Km as opposed to 8 Km distance are presented in table 7.

Table 7: Comparing the willingness to pay estimate of the present study with other studies (DKK/household/year)

Studies	Dist12	Dist18	Dist50
Present study*	179.3	233.6	168
Ladenburg & Knapp (2014)	142.65	227	368
Ladenburg et al. (2011)	153[NS]	216[NS]	385
Ladenburg & Dubgaard (2007)	342.7	715.2	908.9

NS=not significantly different from the 8 Km distance.
* indicates that $WTP_{dist12} = WTP_{dist18} = WTP_{dist50}$

The valuation scenario in Ladenburg et al. (2011) entails establishment of 3500 MW wind power in 7 wind farms using a 5 MW turbines (100 m nacelle and 60 m blades). Using a survey was carried out in July 2006, the study analyzed the effect of the so-called “Cheap Talk” on visual impact of offshore wind farms. The effective samples for the Cheap Talk and Non-Cheap Talk samples were 367 and 338 respondents, respectively. The 8 Km distance with no extra costs to the households defined the *status quo* option. Therefore, the WTP estimates used in this study are the ones for the Cheap Talk sample. The valuation scenario in Ladenburg & Dubgaard (2007) stipulated a development of 3600 MW win power offshore using 5 MW turbines (100 m nacelle and 60 m blades) and the survey was carried out in may 2004. They had an effective sample of 362. Similarly, Ladenburg & Knapp (2014) stipulated a total offshore wind power establishment of 3500 MW, 100 turbines per wind farm, using 5 MW turbines in five potential areas which was presented to the respondents on a map. The survey was carried out in 2006. The A graphical demonstration of the willingness to pay estimates in table 7 is given in figure 3.

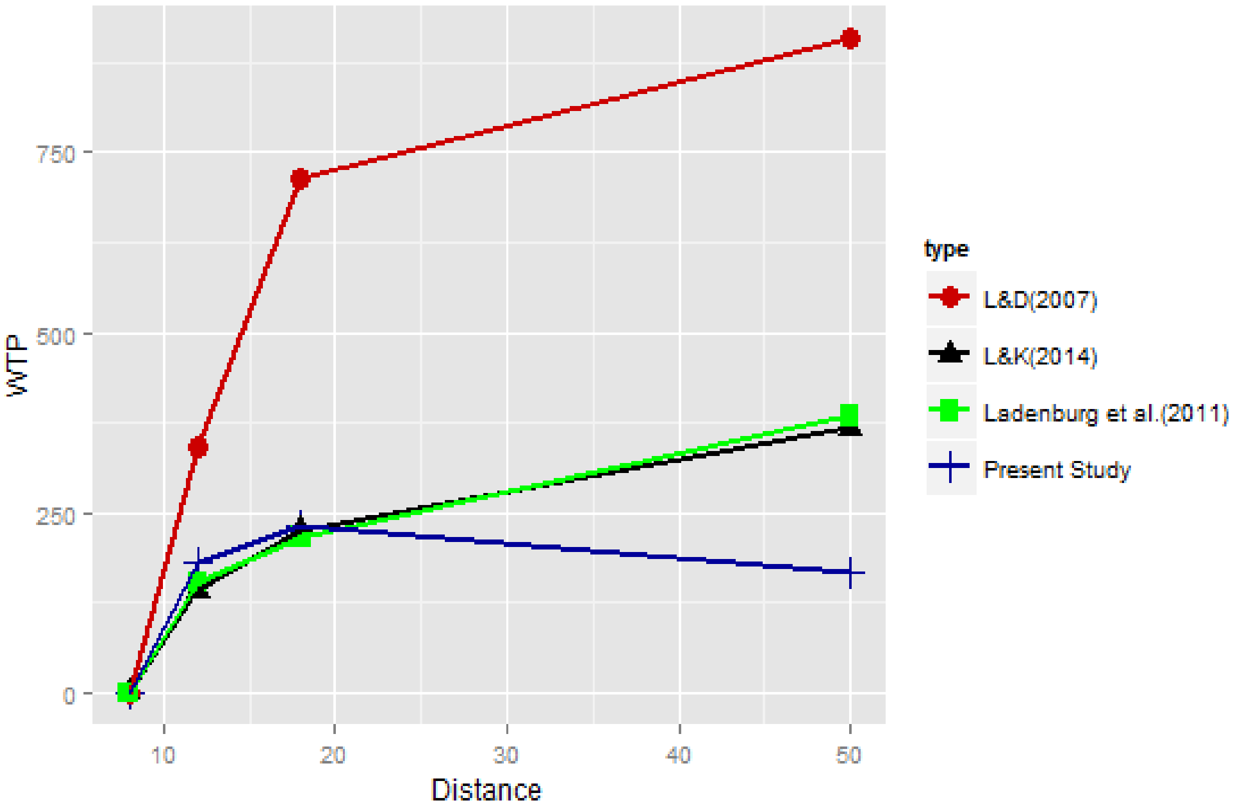


Figure 3: Comparing the WTP for the offshore distances with other studies

In Both Ladenburg & Dubgaard (2007) and Ladenburg & Knapp (2014) the WTP for the three distances are different from each other ($WTP_{dist12} \neq WTP_{dist18} \neq WTP_{dist50}$, $WTP_{dist18} \neq WTP_{dist50}$). The only significant WTP in the Ladenburg et al. (2011) study is the estimate for the 50 Km distance while in the present study the three WTP estimates are not different from each other ($WTP_{dist12} = WTP_{dist18} = WTP_{dist50}$). As we can see from figure 3, the WTP estimates in Ladenburg and Dubgaard (2007) are higher than the WTP estimates of the other three studies and the willingness to pay increases with distance although at a decreasing rate. Ladenburg & Dubgaard (2007) found out that disamenity cost persists beyond the 18 Km distance albeit many studies point out that the disamenity cost from offshore wind farms tends to zero at a larger distances (Bishop & Miller, 2007, Krueger et al., 2011, Landry et al., 2012).

Given the 12 Km distance, the WTP estimates of the present study are higher than the WTP estimates of Ladenburg et al.(2011) and Ladenburg & Knapp (2014) but much lower than the Ladenburg & Dubgaard (2007) WTP estimates. Moreover, the three studies other than the present study reveal that there is an external cost at the 50 Km distance. Given the 50 Km distance, the

Ladenburg & Dubgaard WTP estimates are the highest followed by Ladenburg et al., (2011) and then by Ladenburg & Knapp (2014). The WTP estimates in the present study for the 18 Km and 50 Km distances are in fact not significantly different from the WTP estimate for the 12 Km distance.

Various factors could have resulted in WTP disparity between the four studies. The huge disparity between the Ladenburg & Dubgaard (2007) and the other three studies could partially be due to difference in timing of the studies. Compared to Ladenburg & Dubgaard (2007), the other three studies conducted at a time when Danish population got an exposure to offshore wind farms. As noted in Wolsink (2007), people actually develop a positive inclination towards wind farms after a reasonable time after the establishment of wind farms. If the Wolsink's argument holds true, the low WTP estimates of the three studies compared to Ladenburg & Dubgaard might be reasonable.

The difference could also be due to difference in valuation scenarios. For instance, the present study entails a development of only 450 MW (90 turbines X 5 MW) in one of the five site-specific locations while the valuation scenario in Ladenburg & Dubgaard (2007) stipulated the establishment of 3600 MW using a 5 MW turbines. However, the three studies except the present study have almost the same valuation scenarios but there still is a huge disparity between the WTP estimates of Ladenberg & Dubgaard (2007) and the other two studies. The locations of future wind farm in Ladenburg & Dubgaard were not site-specific while in our case we have five site-specific locations. Therefore, Knowledge of the site-specific locations might affect the respondents WTP negatively, for instance, if most the respondents in our sample live further away from these site-specific locations. Finally, unlike the other studies, the choice experiment in the present study was designed in a way that respondents were able to choose between an offshore and onshore alternative each with different settings.

2. The site-specific locations of the offshore wind farms

The site-specific locations are all dummy coded and the coefficients for the four sites are estimated relative to the Bornholm site. As we can see from table 5, the coefficient on the Moen site is the only statistically significant estimate. The model results indicate that, on average, there is a clear preference for the future offshore wind farms to be located in the Moen site. As we can see from table 6, the average WTP to site the future wind farm in the Moen site relative to the Bornholm site is 163.2 DKK/household/year. The coefficients for the other three sites are not significantly different from the Bornholm site: $\beta_{Bornholm} = \beta_{Anholt} = \beta_{Jammer} = \beta_{Vester}$. This implies that households have indifferent preferences for the four sites. Krueger et al. (2011) also found no significantly different preference for the site-specific locations.

In our case, it could be because our respondents are drawn from all over the nation and they might not have any special attachments to the site-specific locations. Moreover, the preference for these specific geographical locations might depend on the distance and number of population who live around those sites. Had we had enough information on such variables, perhaps, we could have found different preferences for the different sites. Besides, for such group of populations, the willingness to pay for situating the wind farms further offshore might have been higher compared to the other respondents. Nevertheless, we have not collected the data on such variables making it impossible to indicate their preferences.

However, the standard deviation estimates on the random parameters of the sites except the Anaholt site are large compared to the coefficients and statistically significant. This indicates the presence of a reasonable degree of unobserved preference heterogeneity among the respondents. This implies that although the mean of the random parameters are not significant, the respondents had different preferences for the sites relative to Bornholm. For example, the significant standard error on the random parameter of the Jammer site indicates that some of the respondents preferred Jammer to Bornholm while still others preferred Bornholm to Jammer. The standard deviation estimate for the Anholt site is insignificant indicating that the respondents had similar preferences for the two sites.

4.2.1.2. Presentation and discussion of the onshore attributes

1. **Interdependence Between distance and size of the wind farms**

It is reasonable to assume that the preference for the different size of the onshore wind turbines may vary with the distance of the wind turbines from the residential areas. Therefore, the two attributes were interacted during the estimation. The size attribute is dummy coded: the 2X1.5 MW turbines and 1X3 MW turbine are compared to the baseline size, 4X750KW turbines. The distance attribute is also dummy coded taking the value “1” when 1000 M distance from the residential area is chosen and “0” when the 500 M distance is chosen. The design of the size attribute ensures the preference for the different size of the wind turbines is, in principle, free of potential “installed capacity demand effect”. This is because the design enabled to weed out the potential installed capacity demand by keeping the installed capacity constant across choice sets. This ensures that the demand for installed generating capacity would not be confounded with wind farm settings. There was no *a priori* expectation about the size attribute. This is because some respondents might prefer “few large” turbines while still others might prefer “many small” turbines (Ladenburg & Dubgaard, 2007). We expected *a priori* that distance increases acceptance. We ran the attributes-only model with fixed-point estimates of the two attributes but the coefficients show no significant difference to attributes-only model with all attributes random (see table A6 in the appendix).

The interaction coefficients for the distance and size of turbines (which actually indicate both size and number of turbines) which are based on the coefficients in table 5 are presented in table 8.

Table 8: Interdependence of distance and the size of the turbines

Distance	Size		
	4X750 KW	2X1.5 MW	1X 3 MW
500 M	0	1.2281 ***	1.9669 ***
1000 M	1.2185 ***	0.3993	-0.1357

' *** ', ' ** ', ' * ', ' ˙ ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

As it is evident from table 8, the distance and size attribute are indeed interdependent. Given the 500 M distance, the coefficients on the 2X1.5 MW turbines and 1X3 MW turbine are positive and statistically significant. Specifically, the 1X3 MW turbine is preferred to 2X1.5 MW turbine and the 2X1.5 MW turbines are in turn preferred to the 4X750 KW turbines. This signifies that, at the 500 M distance, the average respondent prefers “few large” turbines to “many small” turbines. However, conditional on the 1000 M distance, only the coefficient on the 4X750 KW turbines is significant. This implies that, at the 1000 M distance “many small” turbines are preferred to “few large” turbines. The standard deviation estimate on the random parameter 1X3MW turbine is the only significant estimate. This implies that the respondents have similar preferences for the distance-size relations. Our findings are not comparable with previous studies because the present study is the first study to control the installed generating capacity constant across choice sets. For instance, Meyerhoff et al.(2010) and Vecchiato (2014) included the size of a wind farm, in terms of the numbers of turbines per wind farm, and found that people prefer small wind farms to large wind farms. Nevertheless, in their study, it was not possible to identify whether people preferred larger but few turbines or smaller but many turbines.

It can be inferred from the distance-size relations that at a shorter distances people prefer few large turbines whereas many small turbines are preferred at relatively longer distances. The possible reason could be that peoples’ preference for the different size wind turbines might depend on the relative visual intrusion perception of the different sizes positioned at different distances. For instance, at a shorter distance where both the few large turbines and many small turbines are clearly visible, people might prefer the few large turbines because the visual intrusion from the many small turbines might be larger than the few large turbines. However, if the wind turbines are placed at a fairly longer distances, people might perceive that the few large turbines are more visible than the many small turbines so that they prefer many small turbines to few large turbines.

The preference for the distance attribute is heterogeneous. Given the 4X750 MW turbines, as expected, the 1000 M distance is preferred to the 500 M distance. Surprisingly, give eithe the 2X1.5 MW turbines or 1X3 MW turbine, the 500 M distance is preferred to the 1000 M distance. However, the findings in the previous studies relating the distance of onshore wind farms from residential areas and attitude towards wind farms are also mixed. For instance, a review by Ladenburg et al. (2013) indicates that Anderson et al. (1997) & Warren et al. (2005) found an evidence that acceptance of wind turbines declines with distance whereas Swofford & Slattery (2010) found out that acceptance increases with distance. Still other studies found no significant effect of distance on the acceptance of wind turbines (Krohn & Dmborg, 1999, Johanssen & Laike, 2007).

A Wald-test result shows that except for the coefficients on the 2X1.5 MW turbine and 1X3 MW turbine both situated at 1000 M the coefficients on the rest of the interactions are significantly different from each other (test results can be found in the appendix section B, tables B4 and B5). Table 9 presents the conditional WTP estimates based on the interaction coefficients presented in table 8. The numbers in square brackets are 95 % confidence intervals.

Table 9: The conditional willingness to pay estimates (DKK/Household/year)

Distance	Size		
	4X750 KW	2X1.5 MW	1X 3 MW
500 M	0	198.3	317.5
		[88.3, 308.3]	[218.5, 416.6]
1000 M	196.7	64.5	-21.9
	[94.6, 298.9]	[-55.2, 184.2]	[-129.1, 85.3]

As we can see from table 9, households are willing to pay 198.3 and 317.5 DKK/household/year for having 2X1.5 MW turbines and 1X3 MW turbine, respectively as opposed to 4X750 KW turbines, if all situated at a 500 M distance. In contrast, given the 1000 M distance, the average willingness to pay for having 4X750 turbines relative to either 2X1.5 MW or 1X3 MW turbine is 196.7 DKK/ household/ year. A graphical demonstration of the conditional willingness to pay estimates is shown in figure 4.

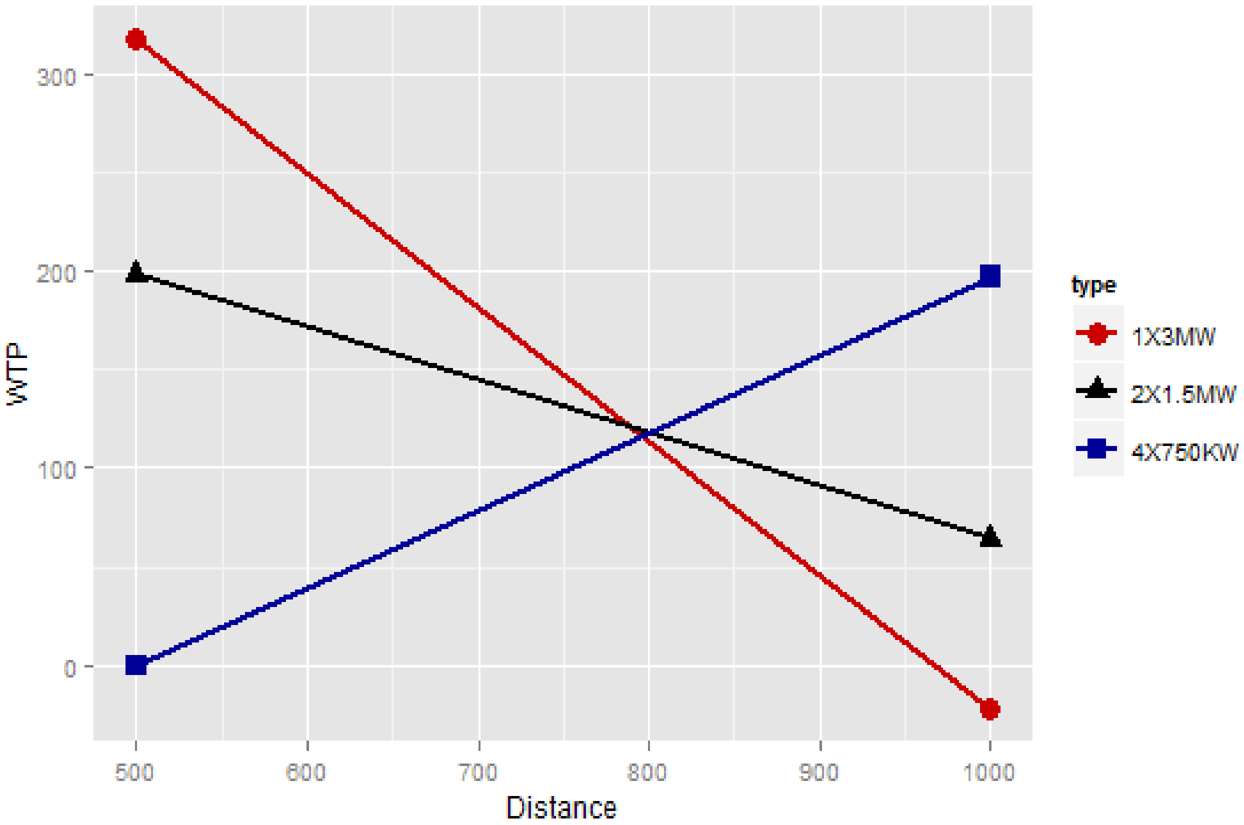


Figure 4: The WTP for the distance and size interdependence

It can be deduced from figure 4 that at shorter distances people are willing to pay more for having "few large" turbines relative to "many small" turbines while the reverse is true at relatively longer distances. Specifically, given the 500 M distance, the WTP for the 2X1.5 MW turbines (which is moderate in terms of turbine size and number) is higher than the WTP for the 4X750 KW turbines but less than the WTP for the 1X3 MW turbine. Moreover, the WTP for the 1X3 MW turbine is higher than the WTP for 2X1.5 MW turbine both located at 500 M distance. Given the 1000 M distance, the WTP for the 4X750 KW turbines is higher than the WTP of the 2X1.5 MW and 1X3 MW turbine while the WTPs for the 2X1.5 MW and 1X3 MW turbine are not different from each other (and not different from zero). This implies people have the same WTP for 4X750 KW turbine located at 500 M and 2X1.5 MW & 1X3 MW turbine both located at 1000 M distance. Finally, we can observe from the figure that people are WTP more to locate the 4X750 MW turbines at 1000 M distance relative to 500 M distance. Conversely, the respondents stated higher WTP for the 500 M distance relative to the 1000 M distance, given the 2X1.5 MW and 1X3 MW turbines.

2. **Number of households living in the locality**

This attribute is dummy coded comparing “10-100” residents and “above 100” residents living in the locality of future wind farms to the baseline number of residents which is “less than 10”. As we can see from table 5, both coefficients are not significant. The finding does not meet *a priori* expectation that wind farms situated in a locality where there are many residents would be less preferred. This is because larger number of residents living in the locality is associated with higher total external cost from the wind farms in terms of disutility. The possible reason for the insignificance of the coefficients could be that people may not consider other peoples’ welfare in their choice decision. However, even though the mean of the random parameters turns to be insignificant, the standard deviation estimates on the random parameters indicates the presence of large unobserved preference heterogeneity. The standard deviation estimates of both random parameters are large relative to the mean of the random parameter and statisticaly significant. This implies some respondents preferred wind turbines in an area with few residents while still some others prefered wind turbines in an area with many residents.

4.2.1.3. Offshore Versus onshore wind farms (The ASC)

The alternative specific constant (ASC) indicates the preference for the offshore location relative to the onshore location. The estimation and interpretation of the ASC is debated. However, Train (2009) and Hoyos (2010) recommended the estimation of the ASC along the model. Moreover, Hensher et al. (2005) argued that the estimation of the ASC when having branded alternatives actually makes sense. The interpretation of the ASC depends on whether one sees it as a technical term or rather associate it with behavioral assumptions (Meyerhoff & Liebe, 2009). Adamowicz et al. (1998) suggested associating the ASC parameter with behavioral assumption. Therefore, in the present study, the ASC parameter is associated with the behavioral assumption that it indicates the preference for the offshore location relative to onshore.

As it is presented in table 5, the ASC coefficient is positive and statistically significant. This indicates that, all else equal, an average respondent prefers offshore wind farms relative to onshore wind farms. This indicates that respondents associate offshore wind farms with a lower external cost compared to onshore locations. The standard deviation estimate on the random parameter of the ASC is significant indicating that presence of unobserved preference heterogeneity. Indeed, some of the respondents preferred the onshore while the vast majority of the respondents preferred the offshore location. As we can see from table 6, other things being equal, households are willing to pay 540.3 DKK/household/year to locate the future wind farms offshore relative to onshore.

Our finding is in line with most of the previous studies (e.g. Aravena et al. 2006, Ek, 2006, Vecchiato, 2014, Ek & Persson, 2014). These studies found out that an average respondent was willing to pay more to site the wind turbines in the *offshore* location relative to *onshore* locations. These studies evaluated the value of location of wind farms in the broader sense of whether the wind farms are located offshore or onshore. In the present study, the offshore and onshore locations are the alternatives in the choice experiment. However, the ASC can have the role of a location attribute like in the previous studies. We have to note that respondents might not consider the effects of offshore wind parks on marine life and thus show a strong preference for having the wind farms offshore relative to onshore.

The preference for offshore versus onshore location is likely to depend on site-specific locations of the future offshore wind farms. For instance, a study in Australia by McCartney (2006) found out that respondents were willing to pay more to locate the future wind farms onshore relative to offshore when the offshore site happens to be a marine park. In the present study, five site-specific locations of the future offshore wind farms were included in the choice experiment. Our results indicate that households are willing to pay more to locate the wind farms in the Moen site relative to the other four sites. The respondents were indifferent between the four sites excluding the Moen site. The reason could be that most of the households may not have any special attachment to the site-specific locations put in the choice experiment. If so, it is no surprise that most of the respondents choose the offshore alternative.

The lesson that can be drawn from our finding is that people are willing to pay more tolocate the wind farms offshore relative to onshore. Nevertheless, the decision by policy makers should depend on whether the choice is welfare maximizing. The pure capital cost, citrus paribus, of offshore wind farms is almost twice as high as the onshore wind farms and the difference gets even larger when the offshore wind farms are located in deep water and at distant locations from the coast (Ladenburg, 2009a). Similarly, a Danish study found out that the onshore wind power have a long-term marginal production cost of about 320 DKK./MWh where as the production costs of offshore wind power stands at just over 580 DKK./MWh (Energistyrelsen, 2014).

Hence, any decision should compare the benefits and costs to the society in general of locating the wind farms in either location. If the incremental production cost to the power producing companies of installing the wind farms offshore relative to onshore is lower as compared to the benefit that the society could gain, in terms of externality reduction, by locating offshore, the offshore location would be a welfare maximizing choice. On the other hand, if the external cost difference from locating wind farms onshore and offshore is quite small compared to the cost increment to the power producing companies from locating offshore, the optimal decision would be to locate the wind farms onshore.

4.2.2. Observed preference heterogeneity

This section presents and discuss preference heterogeneity with respect to respondents' socio-demographic and economic characteristics and experience with wind farms. In both cases, we ran a group of models with the variables entering the model as a shift factors interacting with the ASC and as interactions with some of the attributes. We will explore these sources of preference heterogeneity in detail in the subsquent sections.

4.2.2.1. Preference heterogeneity in the line of socio-demographic and economic characteristics

The socio-demographic and economic characteristics presented and discussed in this paper are education, income, gender, and age of the respondents. Tested as a shift factor and interacting with the distance parameters, the level of education of the respondents were an insignificant determinant of preference so that it will not be discussed further. Ladenburg & Dubgaard (2007) and Lilley et al. (2010) also found education to be an insignificant determinant of preference for wind farms.

4.2.2.1.1. Socio-demographic and economics characteristics as a shift factors

Socio-demographic and economic characteristics, specifically, gender, age, education, and income were interacted with the alternative specific constant (ASC) to test preference heterogeneity among respondents. The estimation of the coefficients as a shift factors indicates preference heterogeneity for offshore versus onshore in the line of the respective characteristics. The log-likelihood value at the point of convergence of the model shows that the fit of the interaction model is slightly improved compared to the attributes-only model. The estimation results are shown in table 10. The results in table 10 are extracted from the full model presented in the appendix section A, table A1.

The “Gender” variable is dummy coded taking the value “1” if the respondent is female and “0” if the respondent is male. It was expected that gender would affect respondents’ preference for offshore versus onshore wind farm projects. Due to lack of obvious argument, however, it was not expected *a priori* which sex prefers which location (offshore versus onshore). As we can see from table 10, the coefficient of gender is negative and significant implying that, other things being equal, female respondents have less preference for offshore wind farms compared to males.

The present findings are consistent with the findings of Ek & Persson (2014) and Ladenburg (2009b). Ek and Persson (2014) found out that female respondents have weaker preference for offshore wind farms relative to onshore compared to males. In two separate models for male and female, Ladenburg (2009b) also found that female respondents have weaker preferences to reduce visual impact from offshore wind farms compared to men. Nonetheless, the findings in the literature are not consistent. For instance, Kruger et al (2011) in their ocean sample and Ladenburg (2010) found out that female respondents have stronger preferences for offshore wind farm development. Yet, Lilley et al. (2010) found out that the likelihood of continuing to visit a specific beach if a new wind farm would be installed around the beach was not affected by sex of the respondents.

Table 10: Socio-demographic and economic characteristics as a shift factors

		Age and Gender effect		Income effect	
Variable		Parameter	P value	Parameter	Pvalue
ASC (Offshore)		3.98298196	< 2.2e-16 ***	2.74754609	2.822e-12 ***
Socio-demographic and Economic characteristics					
Age	Age<=30	-1.15336665	1.115e-08 ***		
Income	Middle			0.58212162	0.0004848 ***
	High			0.93558826	5.272e-07 ***
Gender	Female=1	-0.89217680	1.089e-09 ***		
Log-Likelihood (β):		-3644.5		-3667.5	
McFadden R^2:		0.26744		0.26281	
Likelihood ratio test :		chisq = 2661 (p.value = < 2.22e-16)		chisq = 2615 (p.value = < 2.22e-16)	
No of observations:		17,848		17,848	
No respondents		2331		2331	

' *** ', ' ** ', ' * ', ' ˙ ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

The income variable is dummy coded comparing the middle and high-income respondents to the low-income respondents. It was hypothesized that household income may affect the preference for onshore versus offshore wind power projects. The coefficients on the middle and higher income variables are positive and statistically significant. This implies that as the level of household income increases the inclination towards offshore wind power development relative to onshore. Compared to low income groups, the middle-income and high-income groups prefer the wind farms to be placed offshore.

The income coefficients in the present study are not directly evaluating respondents' perception of wind farms. Rather, the coefficients indicate respondents' preference for the offshore versus onshore wind farms. However, if we assume that offshore wind farms are less disturbing relative to onshore wind farms, our findings are in line with the previous findings (e.g. Firestone & Kemptone, 2007, Lilley et al., 2010, Ladenburg, 2009b, and Ladenburg & Dubgaard, 2007). According to these studies, higher income respondents perceive wind farms more negatively compared to low income respondents. For instance, Ladenburg & Dubgaard (2007) found that middle and high-income group of respondents experience higher welfare loss from offshore wind farms compared to low income groups. Therefore, we could argue that middle and high-income households have strong preference for the offshore location compared to low income groups in order to avoid the visual disruptions from onshore wind farms.

The "Age" variable is also dummy coded: taking the value "1" if the age of the respondent is less than or equal to 30 years of age, 0 otherwise. Originally, this type of coding was adopted from the literature (e.g. Lilley et al., 2010, Ladenburg & Dubgaard, 2007). However, alternative age (continuous) specifications such as *age, ln (age), and* $(age + age^2)$ have been tested using conditional logit model. But, the dummy coded age variable appeared to capture preference heterogeneity very well so that the variable was used in the final random parameter logit model. The dummy coding is also preferable to capture generation effects since respondents who are 30 years of age or younger have an experience to wind turbines since childhood compared to the older group. It was expected that the preference for offshore versus onshore wind power development may vary with the age level of the respondents. However, due to lack of obvious argument it was not expected *a priori* which age group prefers which location. The age coefficient is negative and significant implying that younger group respondents have weaker preferences to offshore wind farms compared to the older age group.

If we assume that offshore wind farm is less disturbing relative to onshore; our findings are consistent with previous studies (e.g. Bishop and Miller, 2007, Krueger et al., 2011, Ladenburg and Dubgaard, 2007, Ladenburg, 2008, Westerberg et al., 2013, and Firestone & Kemptone, 2007). These previous studies found out that elderly respondents perceive wind farms more negatively and they are more concerned about the visual disamenity relative to younger age groups. Lilley et al. (2010) argued that younger generations might have less attachment to places compared to older generations so that they may encourage or at least be less risk averse to the new technology. However, the literature on the effect of age on wind farm perception is not consistent. For instance, Ladenburg (2009b) and Klick (2010) found mixed results of age effect on the acceptance of wind turbines.

4.2.2.1.2. Interaction of socio-demographic and economic characteristics with attributes

Specifically, income is interacted with the cost/price variable and age is interacted with the distance variables. The log-likelihood value indicates that there is no significant improvement in the fit of the two models compared to the attributes-only model. The estimation results are presented in table 11. There are two separate estimation results one for income and one for age since the two variables were correlated when estimated in one model.

The coefficient on the interaction of cost/price and the high-income dummy is positive and statistically significant while the coefficient on the middle-income group is positive but only significant at a 10% significance level. However, the two coefficients are jointly significant at a 5 % significance level. The result confirms *a priori* expectation that asserts high-income respondents have strong preference for externality reduction compared to low income respondents. Previous studies also point out that the welfare loss in terms of utility due to the visual impact of wind farms is higher for high-income respondents compared to low-income respondents (Firestone & Kemptone, 2007, Ladenburg, 2009b, Lilley et al., 2010, and Ladenburg & Dubgaard, 2007).

Turning to age, age is interacted with both the offshore and onshore distances. As we can see from table 11, the coefficients on the interaction of age and the 12 Km and 50 Km offshore distances are significantly negative implying that younger age respondents have weaker preferences to move the wind turbines further away offshore compared to older age respondents. Nevertheless, these two coefficients are not significantly different from each other ($dist_{12}\!:Age = dist_{50}\!:Age$).

Interestingly, the coefficient on the 18 Km and age interaction is insignificant indicating that the preference for the 18 Km distance is not different between the two groups.

For the offshore wind farm distances, the findings of the present study are consistent with previous studies (e.g. Bishop and Miller, 2007, Krueger et al., 2011, and Ladenburg and Dubgaard, 2007, Ladenburg, 2008, Westerberg et al., 2013, Firestone & Kemptone, 2007). These previous studies found out that elderly respondents perceive wind farms more negatively and they are more concerned about the visual disamenity relative to younger age groups. According to Lilley et al. (2010), the likelihood of continuing to visit a beach in Delware, USA when a new wind farm is installed increased significantly when the respondent is below 30 years of age. Lilley, Firestone, & Kempton argued that younger generations may have less attachment to places compared to older generations so that they may encourage or at least be less risk averse to the new technology.

In contrary to the findings of offshore distances, the coefficient on the interaction of age and the onshore distance ($\mathrm{dist}_{1000}\mathrm{:Age}$) indicates that the younger respondents have strong preference to site the future onshore wind farms further away from residential areas. Unexpectedly, for the older respondents, distance reduces preference. This indicates that the younger respondents prefer the future onshore wind turbines to be placed at distant locations while older respondents want to have them in their backyard. Ladenburg (2009b) and Klick (2010) also found mixed effects of age on the acceptance of wind turbines.

Table 11: Preference heterogeneity with respect to Age and income of respondents

		Age and distance interaction effect		Income and cost interaction effect	
Variable		Parameter	P value	Parameter	Pvalue
Cost		-0.0071	< 2.2e-16 ***	-0.0057	< 2.2e-16 ***
Cost: Middle income				0.0005	0.0772324 .
Cost: High income				0.0009	0.0031900 **
Offshore					
ASC (offshore)		3.1778	1.269e-12 ***	3.2331	2.220e-16 ***
Distance (Km):	8-12	1.0234	0.0003579 ***	0.9838	3.493e-05 ***
	8-12: Age	-1.5877	0.0019205 **		
	8-18	2.3577	1.448e-05 ***	1.7607	1.237e-05 ***
	8-18: Age	0.1366	0.8799109		
	8-50	0.4522	0.1066298	0.9778	0.0002327 ***
	8-50: Age	-1.2534	0.0028949 **		
Location:	Bornholm vs Moen	0.9820	0.0321894 *	0.6905	0.0666572 .
	Bornholm vs Anholt	1.0686	7.051e-07 ***	0.3596	0.0889227 .
	Bornholm vs Jammer	1.5363	2.468e-06 ***	0.0184	0.9448870
	Bornholm vs Vester	1.9866	0.0031041 **	0.3192	0.3308786
Onshore					
Distance (M)	500 vs 1000	-0.5855	0.0187588 *	1.4298	4.253e-07 ***
	500 vs 1000:Age	0.7308	0.0290261 *		
Size(KW, MW)	4X750 vs 2X1.5	0.4472	0.0690932 .	0.9270	0.0016305 **
	4X750 vs 1X3	0.5468	0.0078512 **	1.9475	8.732e-11 ***
Distance:Size	500 vs 1000: 4X750 vs 2X1.5			-1.7001	4.018e-05 ***
	500 vs 1000: 4X750 vs 1X3			-3.6178	1.243e-11 ***
No of Residents:	Below10 vs 10-100	0.6526	0.0110488 *	0.2518	0.2378074
	Below 10 vs above 100	-0.0633	0.8241862	-0.3787	0.1666881
Standard deviations					
ASC		2.9402	< 2.2e-16 ***	2.5071	< 2.2e-16 ***
Distance (Km):	8 vs 12	3.0709	6.863e-09 ***	1.5550	5.597e-05 ***
	8 vs 12:Age	-1.2234	0.4264700		
	8 vs 18	-3.6734	1.550e-08 ***	2.1299	1.676e-05 ***
	8 vs 18:Age	-1.3484	0.5162549		
	8 vs 50	-0.1512	0.8917836		

	8 vs 50:Age	0.4064	0.8151322		
Location:	Bornholm vs Moen	-3.3631	4.491e-07 ***	-3.3227	1.751e-09 ***
	Bornholm vs Vester	4.9215	1.202e-07 ***	-1.5591	0.0205181 *
Distance	500 vs 1000	0.6785	0.1759757		
	500 vs 1000: Age	-0.0211	0.9904589		
Size:	4X750 vs 1X3	-1.3546	0.0027672 **	-1.8528	1.308e-06 ***
No of Residents:	Below10 vs 10-100	2.5237	1.569e-08 ***	0.9962	0.0156350 *
	Below 10 vs above 100	2.8321	3.280e-08 ***	2.8486	2.699e-10 ***
Log-Likelihood (β):		-3684.7		-3676.3	
McFadden R^2:		0.25936		0.26105	
Likelihood ratio test:		chisq = 2580.6 (p.value = < 2.22e-16)		chisq = 2597.4 (p.value = < 2.22e-16)	
No of observations:		17,848		17,848	
No of respondents:		2331		2331	

' *** ', ' ** ', ' * ', ' ˙ ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Ladenburg & Lutzeyer (2012) nicely explained the policy implication of the age effect on the preference for optimal wind farm settings. If the present finding of the effect of age is permanent (a generation effect) because the younger age groups have an experience to this new technology since childhood, the external cost of moving the future offshore wind farms further away from the coast would be much lower in the future. Therefore, if the age effect is permanent, future investments in the sector might take low external costs in to account because the external cost will decrease overtime anyways. On the contrary, if the effect of age changes with the age level of the respondents in every generation, placing the wind farms based on the preferences of the present generation would be optimal. However, identification of whether the present finding of the effect of age is permanent (a generation effect) or an age effect (changes with age) warrants further research.

4.2.2.2. Exposure to wind turbines and preferences

Specifically, whether a respondent have a view to offshore or onshore wind turbines from a permanent residence/summerhouse, the frequency of daily turbine encounter, and the frequency of daily turbine encounter from respondents home/summerhouse are the variables representing the experience with wind turbines. All variables are dummy coded. The "view" variables take the value "1" if the respondent has a view to wind turbines and "0" if not. Regarding the daily turbine encounter, those respondents who can see 1-5 turbines, 6-15 turbines, and 16 or more turbines daily are compared to those respondents who can see none. Likewise, those who can see 1-3 turbines, and 4 or more turbines from their residential areas/summerhouse are compared to those who can see nothing.

The variables indicating whether the respondent has a view to onshore or offshore wind turbines entered in to the model both as a shift factor interacted with the ASC and interacted with the distance variables. However, the variables indicating the frequency of daily turbine encounter and the frequency of daily turbine encounter from permanent residence/summerhouse enter in to the model only as a shift factors. The estimation results which are extracted from the full model which is presented in the appendix section A, table A2 are shown in table 12. The log-likelihood values at the convergence point of the models indicate that the introduction of these variables does not significantly improve the fit of the model compared to the attributes-only model. The coefficients on both "onshore view" and "offshore view" are positive and significant. This show that those respondents having either offshore or onshore wind turbines in the view shed from either a permanent residence/summerhouse prefer the wind farms to be placed offshore compared to those who do not have any turbines in the view shed. Consistent with the present finding, Ladenburg

(2010) points out those respondents with prior exposure to onshore wind farms appeared to be more inclined towards offshore wind farms.

As it is shown in table 12, the coefficients on the dummies representing the number of turbines seen on a daily basis (dailysee5, dailysee15, dailysee16) are positive and significant. Besides, the coefficients are significantly different from each other. This implies that the preference for offshore relative to onshore gets stronger as the number of daily seen turbines increases. There are a number of previous studies which analyzed the effect of the number of daily seen turbines on respondents *attitude* towards more wind turbines (e.g. Ladenburg, 2010, Ladenburg & Möller, 2011, Ladenburg & Dahlgaard, 2012, Ladenburg et al., 2013, Thayer & Freeman, 1987, Krohn & Damborg, 1999). However, the findings of these studies are not comparable with the present study because the frequencies of daily seen turbines variables in the present study are determining the preference for offshore wind farm relative to onshore.

Following Ladenburg et al. (2013), we tested the cumulative effect (the effect of frequency of daily turbine encounter on the preference for offshore versus onshore) of daily seen turbines. However, our objective in the present study is different from that of Ladenburg, Termansen, and Hasler. Specifically, the objective is to analyze the effect of daily turbine encounter on the preference for offshore versus onshore wind farms (the dummies are interacted with the ASC). Therefore, our findings are not comparable with Ladenburg et al. (2013). We split the data in to two: one for those having an onshore view and the other for the respondents who do not have wind turbines in the view shed and then ran a model for those having an onshore view. By so doing, it is possible to identify if the effect of daily turbine encounter on the preference for offshore versus onshore wind farms is conditional on having wind turbines in the view shed. We found out that for those having onshore wind turbines in the view shed, the frequency of daily seen turbines does not affect their preference for the offshore versus onshore wind farms (see appendix section A, table A4). This indicates that there is no cumulative effect of wind turbines in the preference for the offshore versus onshore wind turbines when the respondents already have onshore wind turbines in the view shed. However, for those respondents without a view to onshore wind turbines the preference for offshore relative to onshore gets stronger as the number of turbines seen on a daily basis increases (see appendix section A, table A8).

Turning in to the coefficients on the interaction of the ASC and the dummies representing the number of turbines seen on a daily basis from home/ summer house, only those respondents who can see 1-3 turbines (dailysee3) have a strong preference for offshore wind farms compared to those who can see none. As we can see from table 12, the coefficient on the dummy indicating those respondents who can see 4 or more turbines (homesee4) is unexpectedly not significant. The number of turbines seen from home, the view variables, and the number of turbines seen on a daily basis were correlated. As a result, we ran three separate models for each category as we can observe it in table 12.

Finally, we ran a model with the interaction of onshore view and offshore view with the distance variables. The estimated coefficients show that having a view to offshore or onshore wind turbines do not affect the preference for the different distance variables (the results can be referred in the appendix section A, table A3). This indicates that prior experience with offshore or onshore wind turbines has no effect on the preference for wind farm setting. However, it should be noted that only 3 % and app. 12 % of the respondents have a view to offshore and onshore wind turbines respectively. Although not in a similar setting, Lilley et al. (2010) also found out that prior experience with offshore and/or onshore wind turbines had no effect on the likelihood of continuing to visit the Delware beach, USA or another beach in Delware when a new wind farm is situated at a 10 Km off the shore. Interestingly, Ladenburg & Knapp (2014) found out that those respondents with experience to wind farms have weaker preferences to move the future wind farms further away from the coast compared to those with no experience. Yet, Ladenburg & Dubgaard (2007) found out that the group of respondents having a view of an offshore wind farm either from permanent or summerhouse show a strong preference for moving the wind turbines further away from the offshore.

Table 12: Preference heterogeneity with regard to exposure to wind turbines

		Effect of onshore & offshore view		Effect of No of daily seen turbines		Effect of No of home seen turbines	
Variable		Parameter	P value	Parameter	Pvalue	Parameter	Pvalue
ASC (offshore)		3.2008	1.998e-15 ***	3.0188	2.061e-13 ***	3.4157	1.377e-14 ***
Exposure to wind turbines							
Dailysee	dailysee0 vs dailysee5			0.6334	9.889e-05 ***		
	dailysee0 vs dailysee15			1.0721	3.796e-07 ***		
	dailysee0 vs dailysee16			1.3421	2.285e-05 ***		
Homesee	homesee0 vs homesee3					0.823	0.0016712 **
	homesee0 vs homesee4					0.0597	0.8157843
onshore view		0.5037	0.0083214 **				
offshore view		1.2273	0.0062208 **				
Log-Likelihood (β):		-3672		-3660.1		-3672.3	
McFadden R^2:		0.2619		0.26431		0.26184	
Likelihood ratio test :		chisq = 2605.9 (p.value = < 2.22e-16)		chisq = 2629.8 (p.value = < 2.22e-16)		chisq = 2605.3 (p.value = < 2.22e-16)	
No of observations:		17,848		17,848		17,848	
No of respondents:		2331		2331		2331	

' *** ', ' ** ', ' * ', ' . ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

5. Conclusion and Recommendations

Wind energy has long been introduced to the Danish energy sector as a promising alternative energy source. Accordingly, the wind energy's share in the total energy mix of the nation has registered an impressive growth. However, the wind energy expansion has been facing social resistance throughout its development due to its potential environmental impacts. With the vast increase in onshore wind power production, finding more onshore sites remained a tough challenge for the energy planners. Therefore, recently, the trend has been diverted towards large offshore wind parks as a means to get uncontested offshore sites. Nevertheless, offshore wind power is contested as well as costly to produce relative onshore. For instance, a Danish study assessed that onshore wind turbines have a long-term marginal production cost of about 320 DKK/MWh whereas the production costs of offshore wind power stands at just over 580 DKK/MWh (Energistyrelsen, 2014). Therefore, from a welfare viewpoint, there is an economic-trade-off between offshore and onshore wind power production.

Thus, using an excellent choice experiment design, the present study focuses on the choice of the two wind power development strategies: offshore versus onshore each with location specific settings. The valuation scenario stipulated the establishment of 450 MW either in 150 different onshore locations or in one of five site-specific offshore locations. The study used a random parameter logit for estimation of the discrete choice model. The findings show that, everything being equal, households are willing to pay 540 DKK/household/year to place the future wind farms offshore as opposed to onshore. This signals that there will be less external cost to the society by developing future wind farms offshore as opposed to onshore. Nevertheless, the choice between offshore and onshore wind farms should also take into account the pure capital cost of wind power generation in the respective locations.

When households choose the offshore wind farms, they are willing to pay 173 DKK/ household/year for having the future wind farms located at 12 Km from the shoreline as opposed to 8 Km. The willingness to pay estimates for the 18 Km and 50 Km distance are not significantly different from the 12 Km distance. This signals that the socially optimal offshore distance appeared to be 12 Km from the shoreline. This signifies that there will be additional welfare gain from locating the offshore wind farms further away from the shoreline. However, the results also pose a caution that the future offshore wind farms should not be located at too distant positions from the shoreline. This is because the benefit to the society in terms of externality reduction from placing the wind farms at too far positions is negligible while the pure capital cost of offshore wind power increases with distances. The present study also considered five site-specific locations of the future offshore wind farms. Then, the households are willing to pay 163 DKK/household/year for having the future wind farms located at the Moen site as opposed to the Bornholm, Anholt, Jammer, and Vester sites.

On the other hand, when household choose the onshore wind farms, they are willing to pay 198 and 317 DKK/year/household for having the 2X1.5 MW turbines and 1X3MW turbine, respectively as opposed to 4X750 KW turbines, if all placed at 500 M distance from residential areas. On the contrary, given the 1000 M distance, households are willing to pay 196 DKK/household/year for having 4X750 KW turbines in preference to 2X1.5 MW and 1X3 MW turbines. This implies that households prefer to have large but fewer turbines at short distances whereas they prefer smaller but many turbines at a relatively longer distance. Conditional on the sizes of turbines, the preferences for the distance attribute are mixed.

Finally, the present study also found varying preferences across groups. Female respondents relative to male, high-income groups relative to low income, respondents who have wind turbines in the view shed from their home/summerhouse, and respondents who are 30 years of age or younger have weaker preferences for reducing externalities from offshore wind farms relative to onshore. Interestingly, we found out that having wind turbines in the view shed does not affect the respondents' preference for the distance of wind farms.

As mentioned in the introductory section, this study has not covered variables such as the attitude of the respondents towards Green energy in general & wind energy in particular because these variables are endogenous regressors of preference. It would have been Interesting to see the effect these attitudinal variables on the choice between onshore and offshore locations and the preference for wind farm settings. However, attitudinal variable require more advanced models such as the hybrid choice model (Ben-Akiva et al., 2002). Thus, we recommend further research to look at the effect of the attitudinal variables on people's choice using the advanced models. Moreover, the present study has not examined the effect of spatial variables such as respondents distance from residential areas to current/proposed wind farms. Thus, again, we recommend future studies to consider these variables.

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Appendix

Section A: Estimation Results

Table A1: Estimation results when socio-demographic and economic characteristics enter as a shift factors

		Age and Gender effect		Income effect	
Variable		Parameter	P value	Parameter	Pvalue
Cost		-0.00563783	< 2.2e-16 ***	-0.00543780	< 2.2e-16 ***
Offshore					
ASC		3.98298196	< 2.2e-16 ***	2.74754609	2.822e-12 ***
Distance (Km):	8-12	1.10459998	1.387e-05 ***	1.02909984	2.879e-05 ***
	8-18	2.07770094	6.511e-06 ***	1.91655587	6.917e-06 ***
	8-50	1.07222168	0.000128 ***	1.02324197	0.0002001 ***
Location:	Bornholm vs Moen	0.81998615	0.041707 *	0.77454410	0.0461333 *
	Bornholm vs Anholt	0.30942881	0.160083	0.35849557	0.0955718 .
	Bornholm vs Jammer	0.01930815	0.945719	0.01276384	0.9629481
	Bornholm vs Vester	0.30446578	0.378549	0.42814710	0.2446443
Onshore					
Distance (M)	500-1000	1.49663181	4.969e-07 ***	1.46078579	6.575e-07 ***
Size(KW, MW)	1X750-2X1.5	0.92767279	0.003120 **	0.89304781	0.0037167 **
	4X750-1X3	2.08039494	6.362e-11 ***	2.05336780	6.610e-11 ***
Distance:Size	500-1000: 4X750-2X1.5	-1.77239637	4.667e-05 ***	-1.66495765	7.941e-05 ***
	500-1000: 4X750-1X3	-3.85458480	1.275e-11 ***	-3.78642508	1.101e-11 ***
No of Residents:	Below10-10-100	0.13570902	0.555675	0.20096817	0.3727012
	Below 10-above 100	-0.47345307	0.105715	-0.43782793	0.1234693
Socio-demographic and Economic characteristics					
ASC:Age	Age<=30	-1.15336665	1.115e-08 ***	-	-
ASC:Income	Middle	-	-	0.58212162	0.0004848 ***
	Higher	-	-	0.93558826	5.272e-07 ***
ASC:Gender	Female=1	-0.89217680	1.089e-09 ***	-	-
Random parameters (dispersion)					
ASC		2.57104995	< 2.2e-16 ***	2.58288945	< 2.2e-16 ***
Distance (Km):	8-12	1.56803926	6.260e-05 ***	1.58854298	7.890e-05 ***

	8-18	2.54067484	2.197e-06 ***	2.29830164	7.281e-06 ***
Location:	Bornholm vs Moen	3.62136401	6.694e-10 ***	3.44432860	5.152e-10 ***
	Bornholm vs Vester	1.64419728	0.016339 *	1.88347056	0.0047694 **
	4X750-1X3	1.97824253	4.468e-07 ***	1.93266638	9.766e-07 ***
No of Residents:	Below10-10-100	1.68103968	4.793e-05 ***	1.40266849	0.0009360 ***
	Below 10-above 100	-3.15009501	5.332e-11 ***	3.06046886	2.593e-10 ***
		Log-Likelihood: -3644.5 McFadden R^2: 0.26744 Likelihood ratio test : chisq = 2661 (p.value = < 2.22e-16)		Log-Likelihood: -3667.5 McFadden R^2: 0.26281 Likelihood ratio test : chisq = 2615 (p.value = < 2.22e-16)	

' *** ', ' ** ', ' * ', ' ˙ ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Table A2: Estimation results when the exposure variables enter the model as a shift factors

		Effect of onshore & offshore view		No of daily seen turbines		Home seen no of turbines	
Variable		Parameter	P value	Parameter	Pvalue	Parameter	Pvalue
Cost		-0.0054	< 2.2e-16 ***	-0.0056	< 2.2e-16 ***	-0.0058	< 2.2e-16 ***
Offshore							
ASC		3.2008	1.998e-15 ***	3.0188	2.061e-13 ***	3.4157	1.377e-14 ***
Distance (Km):	8-12	1.0273	2.589e-05 ***	1.1434	1.259e-05 ***	1.1694	1.446e-05 ***
	8-18	1.9048	7.861e-06 ***	1.9741	9.309e-06 ***	2.0206	1.338e-05 ***
	8-50	0.9928	0.0002361 ***	1.0315	0.0002661 ***	1.0433	0.0003084 ***
Location:	Bornholm vs Moen	0.7542	0.0492603 *	0.7488	0.0630894 .	0.8147	0.0508139 .
	Bornholm vs Anholt	0.361	0.0910526 .	0.2735	0.2165944	0.2651	0.2409984
	Bornholm vs Jammer	0.0391	0.8855985	0.0117	0.9668244	0.0419	0.8840454
	Bornholm vs Vester	0.4163	0.252873	0.5272	0.1599021	0.484	0.2086814
Onshore							
Distance (M)	500-1000	1.4344	8.896e-07 ***	1.5691	3.226e-07 ***	1.5436	7.493e-07 ***
Size(KW, MW)	1X750-2X1.5	0.8935	0.0033149 **	0.983	0.0019454 **	0.9699	0.0025828 **
	4X750-1X3	2.0144	7.700e-11 ***	2.14	8.868e-11 ***	2.1388	2.257e-10 ***
Distance:Size	500-1000: 4X750-2X1.5	-1.6353	9.138e-05 ***	-1.8469	3.102e-05 ***	-1.8458	4.291e-05 ***
	500-1000: 4X750-1X3	-3.6721	1.923e-11 ***	-3.9447	2.843e-11 ***	-3.9228	1.003e-10 ***
No of Residents:	Below10-10-100	0.2007	0.3670117	0.2045	0.3688056	0.1921	0.4086106

	Below 10-above 100	-0.4051	0.1472452	-0.4034	0.1641849	-0.3981	0.177645
Exposure to wind turbines							
Daily see	0 vs 1-5	-	-	0.6334	9.889e-05 ***	-	-
	0 vs 6-15	-	-	1.0721	3.796e-07 ***	-	-
	0 vs 16 and above	-	-	1.3421	2.285e-05 ***	-	-
Home see	0 vs 1-3			-	-	0.823	0.0016712 **
	0 vs 4 and above			-	-	0.0597	0.8157843
Onshore view	Yes	0.5037	0.0083214 **	-	-	-	-
Offshore view	Yes	1.2273	0.0062208 **	-	-	-	-
Random parameters (dispersion)							
ASC		2.5572	< 2.2e-16 ***	2.6179	< 2.2e-16 ***	2.658	< 2.2e-16 ***
Distance (Km):	8-12	1.6309	3.551e-05 ***	-1.6863	3.792e-05 ***	-1.8145	9.510e-06 ***
	8-18	2.2916	7.992e-06 ***	2.411	5.212e-06 ***	2.4829	7.072e-06 ***
Location:	Bornholm vs Moen	3.3737	7.007e-10 ***	3.5328	3.750e-09 ***	3.6734	4.039e-09 ***
	Bornholm vs Vester	1.8358	0.0063336 **	2.229	0.0006165 ***	2.1817	0.0013402 **
	4X750-1X3	1.8371	3.039e-06 ***	2.0217	1.104e-06 ***	2.0599	1.684e-06 ***
No of Residents:	Below10-10-100	1.3991	0.0008326 ***	1.4329	0.0015650 **	1.6253	0.0002738 ***
	Below 10-above 100	2.9698	4.380e-10 ***	-3.0382	1.510e-09 ***	-3.0868	2.329e-09 ***
		Log-Likelihood: -3672		Log-Likelihood: -3660.1		Log-Likelihood: -3672.3	
		McFadden R^2: 0.2619		McFadden R^2: 0.26431		McFadden R^2: 0.26184	
		Likelihood ratio test : chisq = 2605.9 (p.value = < 2.22e-16)		Likelihood ratio test : chisq = 2629.8 (p.value = < 2.22e-16)		Likelihood ratio test : chisq = 2605.3 (p.value = < 2.22e-16)	

' *** ', ' ** ', ' * ', ' . ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Table A3: The effect of View variables on the distance gradient

		Distance and view interaction effect	
Variable		Parameter	P value
Cost		-0.00588721	< 2.2e-16 ***
Offshore			
ASC		2.61977263	4.152e-14 ***
Distance (Km):	8-12	0.48075958	0.0189580 *
	8-12: Onshore view	-0.45117829	0.3034585
	8-12: Offshore view	-0.27219007	0.8074019
	8-18	1.72729961	9.950e-06 ***
	8-18: Onshore view	-0.49495690	0.5399101
	8-18: Offshore view	1.37937522	0.5528687
	8-50	0.22989935	0.3042873
	8-50: Onshore view	0.65336649	0.2166857
	8-50: Offshore view	2.04431372	0.3973805
Location:	Bornholm vs Moen	0.77294482	0.0214043 *
	Bornholm vs Anholt	1.05135650	8.873e-08 ***
	Bornholm vs Jammer	0.92749418	0.0003612 ***
	Bornholm vs Vester	0.14994080	0.5739281
Onshore			
Distance (M)	500-1000	-0.35912882	0.0620202 .
	500-1000: Onshore view	-0.59719305	0.1261749
	500-1000: Offshore view	-0.60412965	0.5122400
Size(KW, MW)	1X750-2X1.5	0.32240425	0.1333160
	4X750-1X3	0.39126292	0.0199889 *
No of Residents:	Below10-10-100	0.43359624	0.0496955 *
	Below 10-above 100	-0.47908165	0.0803144 .
Random parameters (dispersion)			
ASC		2.48093340	< 2.2e-16 ***
Distance (Km):	8-12	-1.72059270	5.543e-08 ***
	8-12: Onshore view	1.47702162	0.0664528 .
	8-12: Offshore view	0.41220054	0.9377607
	8-18	-2.17083434	4.322e-06 ***
	8-18: Onshore view	-1.70278751	0.1014738
	8-18: Offshore view	-2.25227084	0.4504337
	8-50	0.10812227	0.8573399
	8-50: Onshore view	0.84395610	0.5675887
	8-50: Offshore view	1.79486582	0.7161055
Location:	Bornholm vs Moen	-2.74207669	4.655e-09 ***
	Bornholm vs Vester	-0.96331016	0.1461673
Distance (M)	500-1000	1.23925955	0.0002232 ***
	500-1000: Onshore view	-0.90923944	0.1955720
	500-1000: Offshore view	-0.54894894	0.8885410
Size	4X750-1X3	1.04365760	0.0015173 **
No of Residents:	Below10-10-100	-2.30974754	1.007e-10 ***
	Below 10-above 100	3.30241423	8.593e-14 ***

Log-Likelihood:	-3697.1
McFadden R^2:	0.25687
Likelihood ratio test:	chisq = 2555.8 (p.value = < 2.22e-16)
No of Observations:	17,848

' *** ', ' ** ', ' * ', ' . ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Table A4: Estimation Results for those respondents having an onshore view (2128 respondents)

Variables	Estimate	Pr(>|t|)
ASC	2.87144815	0.0001944 ***
cost	-0.00430466	0.000004703 ***
dist12	0.31630102	0.5321521
dist18	0.34605120	0.5350849
dist50	0.60484040	0.3102731
moen	-0.65087145	0.3349264
anholt	0.38864505	0.4851954
jammer	0.01695174	0.9803924
vester	-0.01608068	0.9814042
dist1000	0.44945353	0.5306236
MW1_5	-0.53829126	0.4886158
MW3	0.95060008	0.1089311
dist1000:MW1_5	0.41576404	0.6620830
dist1000:MW3	-2.21470739	0.0474063 *
bebor11_100	0.07002366	0.8900349
bebor100	-0.50394120	0.4555694
ASC:dailysee15	-0.26952152	0.4358229
ASC:dailysee16	-0.35013750	0.3996441
sd.1:(intercept)	1.85019198	0.000002869 ***
sd.dist12	1.59074909	0.0740281 .
sd.dist18	-0.01588063	0.9985305
sd.moen	-0.10044126	0.9888043
sd.vester	0.06255195	0.9960682
sd.MW3	0.75564622	0.5523042
sd.bebor11_100	-0.72221211	0.6149707
sd.bebor100	-2.14581588	0.0185357 *
	Log-Likelihood: -406.53 McFadden R^2: 0.27143 Likelihood ratio test : chisq = 302.91 (p.value = < 2.22e-16)	

' *** ', ' ** ', ' * ', ' . ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Table A5: The attribute only model without interactions

	Estimate	Pr(>|t|)
ASC	2.51099689	1.446e-12 ***
cost	-0.00611158	< 2.2e-16 ***
dist12	0.42656291	0.0500002 .
dist18	1.54553437	0.0002361 ***
dist50	0.38218638	0.0907608 .
moen	0.87266134	0.0163842 *
anholt	1.05025343	1.368e-07 ***
jammer	0.98801467	0.0010581 **
vester	0.17660373	0.5009341
dist1000	-0.52395144	0.0131350 *
MW1_5	0.43259415	0.0705273 .
MW3	0.41616708	0.0137305 *
bebor11_100	0.28597506	0.2100715
bebor100	-0.88196177	0.0092565 **
sd.1:(intercept)	2.52074836	< 2.2e-16 ***
sd.dist12	-1.72456405	2.951e-05 ***
sd.dist18	-1.60719725	0.0142926 *
sd.dist50	0.03491040	0.9770934
sd.moen	-2.88681665	3.275e-08 ***
sd.anholt	-0.02947541	0.9794426
sd.jammer	2.70882172	5.971e-08 ***
sd.vester	0.58255127	0.5482969
sd.dist1000	1.21999405	0.0012032 **
sd.MW1_5	-0.21767236	0.7690926
sd.MW3	0.44740219	0.4729725
sd.bebor11_100	2.21312325	4.845e-08 ***
sd.bebor100	3.85576279	2.001e-12 ***
	Log-Likelihood: -3701.6 McFadden R^2: 0.25596 Likelihood ratio test : chisq = 2546.8 (p.value = < 2.22e-16)	

' *** ', ' ** ', ' * ', ' · ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Table A6: The attribute-only model with fixed –point coefficients of turbine size and distance of onshore wind farms

Variables	Estimate	Pr(>|t|)
ASC	2.93678344	< 2.2e-16 ***
cost	-0.00466688	< 2.2e-16 ***
dist12	0.82386027	6.875e-05 ***
dist18	1.62864737	6.123e-06 ***
dist50	0.79717299	0.0003054 ***
moen	0.69626693	0.0340403 *
anholt	0.41710270	0.0218177 *
jammer	0.15074536	0.5083751
vester	0.35355707	0.2567903
dist1000	1.19044366	1.406e-06 ***
MW1_5	0.72583153	0.0051996 **
MW3	1.88500000	2.724e-13 ***
dist1000MW1_5	-1.21891664	0.0004096 ***
dist1000MW3	-2.89099703	2.873e-13 ***
bebor11_100	0.12259906	0.5345897
bebor100	-0.21034299	0.3631793
sd.1:(intercept)	2.25970019	< 2.2e-16 ***
sd.dist12	-1.40551956	0.0001165 ***
sd.dist18	2.04615929	5.058e-06 ***
sd.moen	-2.90996823	4.723e-11 ***
sd.vester	1.59881640	0.0071195 **
sd.bebor11_100	1.30399740	0.0007991 ***
sd.bebor100	2.31217498	9.569e-12 ***
	Log-Likelihood: -3684	
	McFadden R^2: 0.2595	
	Likelihood ratio test : chisq = 2582 (p.value = < 2.22e-16)	

' *** ', ' ** ', ' * ', ' · ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Table A7: The attribute-only model with uniform distribution

	Estimate	Pr(>|t|)
ASC	3.07930042	< 2.2e-16 ***
cost	-0.00533230	< 2.2e-16 ***
dist1000	-0.32953543	0.0647966 .
dist12	0.35204868	0.0799407 .
dist18	1.49328130	0.0001557 ***
dist50	0.22907538	0.2720581
MW3	0.50988412	0.0012342 **
MW1_5	0.40802740	0.0533806 .
bebor100	-0.11423203	0.6538316
bebor11_100	0.63189909	0.0023312 **
moen	0.77373468	0.0408809 *
anholt	0.99320946	9.037e-09 ***
jammer	1.02683804	4.104e-05 ***
vester	1.26932596	0.0199314 *
sd.1:(intercept)	4.54423352	< 2.2e-16 ***
sd.dist1000	0.58619743	0.4966929
sd.dist12	-3.41390486	2.967e-07 ***
sd.dist18	-3.55517296	0.0001802 ***
sd.dist50	-0.42433736	0.7207269
sd.MW3	0.48800108	0.5373123
sd.MW1_5	0.88584301	0.3516850
sd.bebor100	4.10092548	4.476e-09 ***
sd.bebor11_100	-2.50118700	0.0001043 ***
sd.moen	-4.32392203	3.103e-06 ***
sd.anholt	0.04533243	0.9656161
sd.jammer	-2.95698852	0.0001177 ***
sd.vester	-5.72908302	3.666e-06 ***
	Log-Likelihood: -3850.8 McFadden R^2: 0.25141 Likelihood ratio test : chisq = 2586.6 (p.value = < 2.22e-16)	

' *** ', ' ** ', ' * ', ' . ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Table A8: Estimation Results for those respondents without onshore view(15,648 respondents)

Variables	Estimate	Pr(>|t|)
ASC	3.96151431	5.998e-12 ***
cost	-0.00629370	1.554e-15 ***
dist12	1.35688090	2.445e-05 ***
dist18	2.36757833	4.083e-05 ***
dist50	1.14844496	0.0009842 ***
moen	1.26273891	0.0157874 *
anholt	0.23854095	0.3592562
jammer	0.05097734	0.8831163
vester	1.01842273	0.0611812 .
dist1000	1.77828807	3.016e-06 ***
MW1_5	1.34022216	0.0011573 **
MW3	2.46457103	5.864e-09 ***
dist1000:MW1_5	-2.36705713	2.927e-05 ***
dist1000:MW3	-4.41113991	2.145e-09 ***
bebor11_100	0.23164687	0.3920806
bebor100	-0.46154266	0.1721296
ASC:dailysee15	0.82950883	0.0031153 **
ASC:dailysee16	1.55113337	0.0031313 **
sd.ASC	2.89569729	4.663e-15 ***
sd.dist12	1.88286780	0.0001352 ***
sd.dist18	2.80341205	2.455e-05 ***
sd.moen	4.44193117	8.667e-09 ***
sd.jammer	-0.91265778	0.4161297
sd.vester	3.32258212	0.0001002 ***
sd.MW3	2.32255427	1.108e-06 ***
sd.bebor11_100	1.55508571	0.0047017 **
sd.bebor100	-3.38980788	1.116e-08 ***

Log-Likelihood: -3218.1

McFadden R^2: 0.26764

Likelihood ratio test : chisq = 2352.1 (p.value = < 2.22e-16)

' *** ', ' ** ', ' * ', ' ˙ ' represents statistical significance at 0.1% , 1%,5%, and 10% respectively.

Section B: Test Results

The tables in this section are the Wald-test results testing for a significant difference between parameters. The values in every cell of the table are P-values of a chi-square distribution.

Ho: The coefficients are not significantly different from each other

H1: The coefficients are significantly different from each other

All the tests were made at a two-tailed 5% significance level.

Table B1: Wald-test for a significant difference between the distance coefficients

	dist18	**dist50**
dist12	0.3	0.77
dist18		0.28

Table B2: Wald-test for a significant difference between the specific geographical-site coefficients

	Anaholt	**Jammer**	**Vester**
Jammer	0.85		0.79
Vester	0.68		

Table B3: T-test for a significance of the onshore distance and size interaction coefficients

Distance	**Size**		
	4XKW750	2XMW1_5	1XMW3
500	-	0.0009072	1.556e-09
1000	7.942e-05	0.2911917	0.6888957

Table B4: Wald-test for a significant difference between the onshore distance coefficients conditional on the size attribute

Size	**Ditance comparision**
	dist1000 versus dist500
KW750	7.942e-05
MW1_5	0.04803041
MW3	0.0000001398353

Table B5: Wald-test for a significant difference between the onshore size coefficients conditional on the onshore distance attribute

Distance	**Size comparision**		
	KW750 Vs MW1_5	KW750 Vs MW3	MW1_5 Vs MW3
dist500	0.0009072	1.556e-09	0.042
dist1000	0.01740696	0.0001826214	0.09

Tests of Age effect on distances

Table B6: Wald-test for a significant difference between the offshore distance coefficients (Age>30)

	dist18	**dist50**
dist12	0.006	0.055
dist18		0.00074

Table B7: Wald-test for a significant difference between the offshore distance coefficients (Age<=30)

	dist18	**dist50**
dist12	0.081	0.56
dist18		0.15

Table B8: Wald-test for a significant difference of the distance coefficients for different age categories

dist12 vs dist12:Age	**0.00014**
dist18 vs dist18:Age	0.0067
dist50 vs dist50:Age	0.003

dist1000 vs dist1000:age (0.0055)