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THE AMENITY COSTS OF OFFSHORE WIND FARMS: EVIDENCE FROM A CHOICE EXPERIMENT

Sanja Lutzeyer, Daniel J. Phaneuf and Laura O. Taylor[1]

Abstract

We conduct a choice-experiment with individuals that recently rented a vacation property along the North Carolina coastline to assess the impacts of a utility-scale wind farm on their rental decisions. Visualizations were presented to survey respondents that varied both the number of turbines and their proximity to shore. Results indicate that there is not a scenario for which respondents would be willing to pay *more* to rent a home with turbines in view, as compared to the baseline view with no turbines in sight. Further, there is a substantial portion of the survey population that would change their vacation destination if wind farms were placed within visual range of the beach. The rental discounts required to attract the segment of the survey population most amenable to viewing wind farms still indicate that rental value losses of up to ten percent are possible if a utility-scale wind farm is placed within 8 miles of shore.

Keywords: Offshore wind farms, choice experiment, rental market, latent class models

JEL Codes: Q4, Q51

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1) Introduction

Wind power is a fast growing source of renewable energy in the United States. Land-based wind energy capacity has grown at an average rate of 25 percent per year, resulting in an installed base of over 66 gigawatts.[2] While this growth places the US among the global leaders in installed capacity, offshore wind energy remains largely unexploited. Estimates suggest that wind energy potential off US coastlines is more than 4,000 gigawatts – roughly enough to power 2.8 billion homes for a year (Schwartz, et al., 2010). To date, however, there are no utility-scale offshore wind facilities in the country.

The absence of offshore wind development in the US can be explained by two factors. First, offshore wind costs are still substantially higher than land-based fossil-fuel alternatives. For example, the levelized cost of offshore electricity generation is currently estimated to be nearly twice that of an advanced natural gas-fired plant with carbon capture and storage (US EIA, 2015). Second, local opposition to offshore wind farms can be a significant impediment. The best-publicized example of this is the Cape Wind project that called for a 130 turbine array covering 24 square miles in Nantucket Sound, Massachusetts. The project attracted vigorous opposition from a wide range of stakeholders, including fishermen, local Native American tribes, high income oceanfront communities, and nearby inland townships where incomes closely match the state average.[3]

One important driver of the opposition to offshore wind farms is concern about visual

[2] US Department of Energy, Energy Efficiency and Renewable Energy, Wind Exchange, Installed Wind Capacity, http://apps2.eere.energy.gov/wind/windexchange/wind_installed_capacity.asp, last accessed August 4, 2017.

[3] Eileen McNamara, "What Really Toppled Cape Wind's Plans for Nantucket Sound," January 30, 2015, last accessed August 4, 2017, https://www.bostonglobe.com/magazine/2015/01/30/what-really-toppled-cape-wind-plans-for-nantucket-sound/mGJnw0PbCdfzZHtITxq1aN/story.html.

disamenities. To understand the potential visual impact of an offshore wind farm, it is important to recognize that the current vintage of offshore wind turbine extends over 500 feet above the water – approximately the height of a fifty story building. The turbines are required to be lit at night with red beacons that flash in unison every two seconds, and their height makes them technically visible out to thirty miles from shore. Turbines are also spaced 0.5 miles apart from each other, so that even a medium sized array can have a large footprint. For instance, a 144 turbine array laid out in a twelve by twelve grid with the nearest row 5 miles from shore, would fill the peripheral vision of a person standing on the beach. Thus different combinations of height, footprint, and distance from shore can lead to substantially altered viewsheds.

In a benefit-cost evaluation framework, it is critical to understand how alternative placements of offshore wind turbines impact the welfare of both residents and visitors to the coast, where the latter drive local tourism-based economies. While a number of studies in Europe have documented, through stated preference surveys, the negative visual impacts of offshore wind farms perceived by residents and tourists, there is little evidence on their welfare impacts in the US (see Ladenburg and Lutzeyer, 2012, for a review of European studies). Two published exceptions are Landry et al. (2012) and Krueger et al. (2011), who explore the impacts of offshore wind development in North Carolina and Delaware, respectively. Landry et al. consider recreation decisions over the number of day trips to a beach. They find little sensitivity in trip taking to the presence of wind farms when people were queried without viewing images of turbines during the survey. For a subset of respondents who completed an internet component with visualizations, there is some evidence that turbines less than one mile from shore would affect recreation choices.[4] Krueger et al. (2011), on the other hand, find that residents in Delaware are willing to pay higher electricity bills to move turbines further offshore. The magnitude of their estimates are difficult to interpret, however, because the welfare measures confound reductions in visual disamenities with reductions in the carbon intensity of electricity produced for the state.[5] Furthermore, the Krueger et al. study does not address how alterations in ocean viewsheds may impact the tourism markets that underpin coastal economies. We fill this research gap by examining how offshore wind farms impact welfare through coastal property markets. In this regard, the studies that come closest to ours use hedonic models to show that utility-scale *land-based* wind farms in close proximity can reduce residential property values by up to 14 percent (e.g., Sunak and Madlener, 2016; Gibbons, 2015; Heintzleman and Tuttle, 2012; Jensen et al., 2014).[6] Results from land-based wind farms may not transfer to the offshore context for a variety of reasons, however, including the unique nature of an expansive, unobstructed ocean view.

We partner with three local vacation property rental agencies in North Carolina to conduct a choice experiment with their customers. Vacationers that rented a beach home were surveyed to determine how a utility-scale offshore wind farm would affect their future vacation choices. Respondents viewed images depicting wind farms of different sizes, arrayed at different

[4] In a recent working paper, Fooks et al. (2014) also examine how recreation beach visits are affected by wind turbines. Using a sample of visitors intercepted at two Delaware beaches, they find that visitors are on average relatively indifferent to turbines placed 2-3 miles offshore, but a minority of people would alter their behavior in response to an offshore wind farm.

[5] This confounding arises because the alternative to building an offshore wind farm (at any distance from shore) is to increase fossil fuel production, thus making it impossible to econometrically identify willingness to pay to reduce visual disamenities as separate from willingness to pay for carbon reductions. Other studies that nest carbon reductions with viewshed impacts include Westerberg et al. (2014) and Strazzera et al. (2012).

[6] Lang et al. (2014) examine the property value impacts of a *single turbine*, and find no evidence of a statistically significant negative effect.

distances from the shore, and were asked to select from rental properties that varied in their rental price and ocean viewshed. Within this basic framework, we present several noteworthy features. First, the sample for our choice experiment consists of known beach house renters. We observe the specific property rented and the price paid, which allows us to ground our counterfactual options as deviations from the respondent's revealed choice. Second, our experimental design is the first to include a treatment in which respondents are shown both daytime *and* nighttime images of wind turbines, which provides an important perspective absent in earlier work. Third, similar to Ladenburg and Dubgaard (2007), our experimental design includes the same amount of aggregate wind energy produced in all of the scenarios – only the number of turbines *visible from shore* varies. In this way, we are able to disentangle pure viewshed externalities from preferences people may have for renewable energy in general. Finally, ours is the first choice experiment to focus on week-long beach home renters, which is a critical segment of the mid-Atlantic coastal tourism industry.[7]

Our focus on North Carolina (NC) is also policy-relevant, as the Bureau of Ocean Energy Management (BOEM) includes the state among the most suitable regions for offshore wind development. The NC coast has the best wind resources among all eastern states, with an estimated 300 gigawatts of potentially recoverable energy (Schwartz et al., 2010). However, the NC coast is heavily reliant on tourism, and potential impacts of a near-shore wind farm have been the subject of local debates with townships along the entire coast expressing concerns about possible viewshed impacts. In this regard, our study area is representative of other regions

[7] As an illustration of the importance of this tourism segment, vacation rental home occupancy receipts in the northern part of our study area comprised 82 percent of all occupancy receipts from any source, including hotels and motels. Bennett (2013) notes that most of the US Atlantic coast is similar to our study area, with coastal development patterns (and thus tourism lodging) being dominated by seasonal vacation rental homes.

facing tradeoffs between the climate change advantages of offshore wind development, and the negative local externalities that may arise.

We find several striking results. In general, renters have strong preferences for an ocean view at their rental location that does not include visible turbines, despite general support for wind energy among the sampled individuals. There is no population segment that would be willing to pay *more* to rent a home with turbines in view. At best, the results indicate that some respondents would not require a discount to rent a home with turbines in view, so long as the farm is further than 5 miles from shore (only 21 percent of respondents fall into this category). For other respondents, even large discounts would not be sufficient to induce them to accept a viewshed that included near or distant turbines. Specifically, we find that 55 percent of existing customers would not re-rent their most recent vacation property if wind turbines were placed offshore. Lastly, using a split-sample design, we find that respondents who only view daytime images of turbines react less negatively to them than respondents who viewed both daytime and nighttime images. This result is important as it indicates that past studies may have understated the impact of offshore wind energy development on coastal tourism, since all previous studies only include daytime images in their surveys.

These findings have several policy implications. First, we find that the welfare gains of moving wind farms as little as 3 miles further from shore (from 5 to 8 miles) could outweigh the increased capital costs of doing so for an area with as few as 1,000 rental homes.[8] Second, we find that the negative effects of wind farms are primarily attributable to proximity of the farm to shore, rather than the number of turbines. In general, images showing more than double the number of turbines did not result in statistically significant changes in choices. This fact,

[8] The average number of rental units in our study area that lie within a 2-mile radius of the center point of a turbine array proposed in our survey is 200 oceanfront and 800 non-oceanfront (but close to the shore) homes.

combined with our finding that the negative effects of any size turbine array diminish rapidly once placed more than 8 miles from shore, implies that wind farm developers can take advantage of economies of scale with large arrays, while avoiding negative external costs, by placing large wind farms more than 8 miles from shore.

2) Study Area and Choice Experiment Design

North Carolina has over 300 miles of shoreline, much of which is barrier islands. Developed shorelines are dominated by single-family residential dwellings that serve as vacation rental properties. Indeed, North Carolina beaches are known for their unique 'cottage-only' development patterns, which have long attracted repeat visits from extended-family parties. This 'attachment to place' is an important component of visitors' experience, and hence an asset to the local economy.

We sample visitors from three regions of the NC coast: the northern Outer Banks, the southern Outer Banks, and the southern Brunswick County islands.[9] These three regions span the NC shoreline, and importantly, each of the sample regions has been identified as feasible for utility-scale, offshore wind farm development. Two of the three areas were included in the Bureau of Ocean Energy Management's call for expressions of interest for commercial leasing (BOEM, 2012), and continue to be considered for potential leasing (BOEM, 2015).

A mail survey of households that rented a beach home along the NC coast during the summer of 2011 was conducted in January 2012. Mailing addresses for renters of specific, oceanfront and non-oceanfront (but ocean view) properties were obtained from three realty

[9] Specifically, we sampled visitors to the towns of Corolla to Nags Head in the Northern Outer Banks, Emerald Isle in the southern Outer Banks area, and Ocean Isle Beach representing the southern Brunswick County islands.

agencies, serving the three different regions of the NC coastline described above. The sample was evenly split among the three locations. In addition, we over-sampled oceanfront rentals by splitting oceanfront and non-oceanfront rentals evenly to ensure sufficient responses from the important oceanfront category of renters.

We designed our choice experiment to be relatively simple, so as to directly focus on the viewshed impacts of offshore wind energy development. Our objective was to measure the demand for vacation beach homes with different configurations of visible wind turbines. For this we generated high quality images of different beach views, which varied in the number and distance from shore of visible turbines, and asked about rental choices, conditional on the views. Specifically, survey participants considered a beach home rental scenario designed around their actual rental choice from the previous summer. They compared the cottage they rented to two counterfactual alternatives, which were described by three attributes: (*i*) the number of turbines visible from shore; (*ii*) the distance of the visible turbines from shore; and (*iii*) the rental price of the beach house. The levels for each attribute are presented in Table 1.[10] The number of turbines and their distance from shore together form the basis for the specific wind farm visualizations that we created. Figure 1 shows two examples of images used in the survey.

Our images depict 5-megawatt (MW) turbines, which were thought to be the most likely turbines for offshore deployment at the time of our survey. Images included either 64, 100, or 144 turbines placed between 5 and 18 miles from shore, which overlaps the policy-relevant

[10] Four focus groups, each comprised of individuals who had vacationed along the North Carolina coastline in the past five years, were conducted between March and September of 2011 to determine the appropriate levels for the choice question attributes, and to ensure that instructions were clear and that respondents understood all aspects of the survey and choice task.

ranges for the size and location of potential offshore wind farms in the eastern US.[11] In NC, wind turbines are feasible as close as 5 miles from shore in one of the three areas being proposed for lease sale (UNC, 2009). Furthermore, visualizations used in public engagement forums in NC by BOEM used 7 MW turbines placed 10 miles from shore; our 5MW turbines at 5 miles from shore are visually indistinguishable from the larger turbines at greater distance.[12]

Our images show turbines that are spaced 0.5 miles apart, and laid out in a square grid, which is considered one of the least visually intrusive layouts (UK DTI, 2005). For perspective, if a person were standing on the beach at the center of a 144 turbine farm placed 5 miles from shore (the most visually intrusive image used in our survey), the turbines would completely fill her peripheral vision while looking out to sea. In contrast, if there is no haze, 144 turbines at 18 miles from shore would appear as a small, unified object on the horizon. Visualizations were developed using the software WindPRO (version 2.7), which allows users to insert scale-accurate wind turbines into digital photographs. The photographs used to construct our images were taken in May 2010 from the beach at one of the study areas by a professional photographer. A generic seascape was used, and for scale, two people are shown in the foreground sitting on beach chairs. In order to construct both day and night wind turbine visuals, photos were taken at noon and late dusk; these provided the background images for the daytime and nighttime

[11] Communication with industry experts suggested initial projects are not likely to be smaller than 350MW (70 turbines) in North Carolina, due to economies of scale in production, which guided our choice of the lower-bound visible array (64 turbines). Our upper-bound is similar to current projects in various stages of development in Massachusetts, including the Cape Wind project, with 130 turbines placed as close as 5.6 miles from Cape Cod (www.capewind.org) and the Deepwater ONE project, with 150 to 200 turbines placed 15 miles from Martha's Vineyard (www.dwwind.com). In addition, the distances of turbines from shore in our survey are similar to those used in previous studies (Krueger et al. 2011; Ladenburg, 2007).

[12] Visualizations from the public forums are available at www.boem.gov/Renewable-Energy-Program/State-Activities/NC/003-Kitty-Hawk-Afternoon.aspx. Last accessed August 2017.

visualizations. The day and night photos were taken at the same location, with the same two people in the same two chairs, which had not been moved. In the nighttime visualizations, the perimeter turbines are shown lit with a red beacon.

As part of our experimental design, half of the surveyed households received a booklet containing only daytime images of wind turbines, and the other half received both day- and nighttime images. For ease of exposition, we refer to the survey that includes both day and night images as the *nighttime* treatment, and the survey with only day images as the *daytime* treatment. All participants received a description in the survey that turbines are lit at night and flash in unison every two seconds, regardless of whether or not nighttime visualizations were included.

The distance from shore and turbine count attributes (and associated visualizations) were combined with a change in the rental price of the beach home that the person had previously rented. Specifically, people were asked to interpret the visualizations as the view that they would have when standing on the beach after walking to it from their rental unit. Thus people were asked to consider configurations of a familiar property that varied only in the rental price and the view from the beach near the property. Seven levels were used for the price change attribute, ranging from a 5 percent increase to a 25 percent decrease (see Table 1 for the levels).[13] Though we used a percentage price change in our experimental design, survey respondents were given the actual dollar amount of the rental increase/reduction implied by the percentage change. Rental rates for our sampled properties ranged from $2,000 to $10,000 per week, which is the

[13] Focus groups and the previous literature have suggested that visible offshore wind turbines are a negative amenity, and so only one rental price increase was considered (Krueger et al. 2011; Ladenburg and Dubgaard, 2007; Westerberg, Jacobsen and Lifran, 2011).

typical range along the NC coast during peak summer season.[14]

Figure 1 shows an example choice question. Each choice task paired two designed alternatives with a status quo or 'baseline' option. The baseline option is 144 turbines placed out of visible range and no change in rental price. This was done so the amount of wind energy produced was identical across all choices, which allows us to isolate the impact of the viewshed change without the confounding effect of preferences people may have for renewable wind energy production. The designed scenarios paired visible wind turbines with rental price changes. Subjects were asked to rank each alternative from 1 to 3 and since there are only three alternatives, this is equivalent to a best-worst scaling design (Finn and Louviere, 1992; Marley and Louviere, 2005).

To control the visual cues that respondents received, the survey was professionally printed on high-quality paper. An internet survey was ruled out because wind turbines are small features in a photographic context, and the visual impact varies dramatically across computers, depending on the monitor size, type, and quality, as well as the viewing angle. Instead, each choice question was presented on an 8.5 by 11 inch (letter size) page, which contained images for the two designed alternatives as well as the attribute levels. The baseline image (no turbines in view) was included as a separate photo that was clipped to the page with the sample choice question. Respondents were asked to remove the image and place it next to the booklet as they made their choice decisions. All images in the survey, including the baseline image, were 4 by 6 inches. In the nighttime treatment, day and night images were paired with each other by placing them on facing pages, with a connecting line placed between them. A Bayesian efficient design

[14] Survey respondents were also asked to report the rental price for their recent trip, both as a reminder of the baseline cost and as a device for us to check that the rental prices we have on record match the renter's recall. Respondents' answers almost always matched our records.

enabling estimation of all main effects and attribute interactions was used to construct the choice tasks presented to respondents (Hensher et al., 2005; Ferrini and Scarpa, 2007). The final design consisted of 16 choice questions divided into two blocks, so that each respondent completed eight choice tasks.

The survey booklet contained five main sections. To begin, respondents reported their visitation patterns to the North Carolina coast, and their experience with both onshore and offshore wind energy. An introduction to offshore wind energy was then given, consisting of a discussion of wind turbine size and design, wind farm layouts, and the technical visibility parameters of wind farms including a description of how they are lit at night. Following the wind energy introduction, attributes of the choice questions and their levels were described, and respondents were shown an example question. They then completed the eight choice tasks and several debriefing and attitudinal questions. Finally, a set of demographic questions ended the survey.[15]

3) Summary statistics

A total of 792 surveys were mailed in January, 2012 and 484 completed, usable surveys were ultimately returned, implying a response rate of 62 percent. There are no statistically significant differences in the response rates by rental location along the coast, by daytime or nighttime treatments, or between oceanfront versus non-oceanfront homes.

Table 2 presents characteristics of our sample. Beach home renters are a relatively homogeneous group of white, highly-educated, high-income, working-age adults who are either somewhat or very interested in environmental issues (98 percent). The majority of vacationers

[15] Complete survey booklets for both the daytime and nighttime treatments are available as online supplemental material.

are residents of North Carolina (26 percent) or neighboring Virginia (30 percent). Additional summary statistics show that respondents have a strong affinity for vacationing at North Carolina beaches. Over half of respondents have visited the North Carolina coast every year since 2007. Eighty percent indicated they usually visit the same general location, and nearly a third of respondents report renting the same house from year to year. Additionally, 99 percent of respondents indicated that their vacation time is mainly spent on the beach in front of, or within walking distance of, their rental unit (not reported in the table).

Respondents indicated reasonable levels of prior experience with wind farms, in that 53 percent reported having seen a wind farm with more than ten turbines. Not surprisingly, only 18 people (less than 4 percent) indicated that they had seen an offshore wind farm. After reviewing the survey's technical information on wind energy and viewing the images, respondents were asked to report how they thought an offshore wind farm in North Carolina would impact the environment and economy.[16] Survey participants first filled out a five-point Likert scale indicating if they believed offshore wind would have a positive, neutral or negative effect on marine life, bird life, recreational boating and fishing, and climate change. Figure 2 presents a summary of these responses. The largest proportion of respondents were unsure about the environmental impacts of offshore wind energy, with the exception of climate change, where 47 percent of respondents answered there would be no impact.[17] Among the environmental impacts listed, respondents thought that bird life would be most negatively impacted (47 percent indicated a somewhat negative or negative impact), followed closely by recreational boating and

[16] During the technical discussion of wind turbines, potential impacts on environmental outcomes were not discussed.

[17] This latter result is sensible, since the survey focused on the development of a single offshore wind farm, and not national-scale energy policy.

fishing (43 percent expected a somewhat negative or negative impact).

Survey participants also completed a Likert scale recording their beliefs about how an offshore wind farm might impact coastal tourism, coastal property values, and electricity prices in North Carolina. Fifty-five percent of respondents felt electricity prices in North Carolina would at least somewhat decrease as a result of offshore wind energy development, which is contrary to international experience thus far. Very few respondents felt there would be an increase in coastal tourism (<6 percent) or property values (<5 percent) as a result of developing offshore wind energy, and the majority thought coastal tourism and property values would decline at least somewhat (44 and 58 percent, respectively).

Choice question summary

Figure 3 presents a summary of answers to the choice questions for the entire sample (first row) and for separate subsamples of the respondents. Several clear patterns emerge. First, a plurality of respondents (42 percent of the sample) revealed a strong preference for not seeing wind turbines by always selecting the option with all 144 wind turbines placed out of visual range and no change in rental price.[18] Approximately 40 percent of the people in this group indicated in follow-up questions that the rent reduction was not important in their choices, and that they would not select a wind farm view even if the price decrease was larger than presented in the survey. Figure 3 also shows that 47 percent of nighttime treatment respondents always chose the baseline scenario with no turbines visible. This is statistically different from the 38 percent of daytime treatment respondents who always chose the baseline scenario. There is also a significant difference in the proportion of respondents always choosing the baseline scenario

[18] The summaries that follow use 476 respondents because eight people left more than two choice tasks blank or answered the choice questions incorrectly.

for oceanfront home renters (47 percent), and those renting non-oceanfront homes (37 percent).

Figure 3 further shows that 17 percent of the full sample always chose an alternative with visible wind turbines, and there is no statistical difference in this proportion across the sample segments. Of the 80 individuals always choosing an alternative with visible wind turbines, 61 percent reported that they did not mind seeing turbines so long as they also received a price discount, 15 percent indicated they did so because they liked the way wind turbines look, and 41 percent reported they did so because they were strong supporters of wind energy. Finally, Figure 3 also indicates that 41 percent of respondents selected status quo and visible turbine options at some point in their sequence of choices (the 'Mixed Choices' category in Figure 3), and there is not a statistical difference in this proportion across the sample segments.

Table 3 presents an additional summary of choice question responses, examining instances when a respondent had the opportunity to pay more for a wind turbine view, or could select a wind turbine view with no price change. Across all surveys, there were 1,849 completed choice questions that included an option with a wind farm view paired with either no change in rental price or a 5 percent increase in rental price. Overall, these alternatives were ranked first by respondents only 5.6 percent of the time. The last column indicates that just over 15 percent of respondents ranked a view first when it included a view of turbines without a price discount. These summaries support the notion that wind turbines are a visual disamenity, and that the majority of vacationers surveyed have an unambiguous preference for viewsheds that do not include offshore wind turbines.

4) Econometric model

The summary statistics in the previous section suggest the likelihood of heterogeneity in preferences regarding offshore wind farms, and so our empirical approach should accommodate this. There are two dimensions to consider. The first is preference heterogeneity, which is our primary interest. Different types of people are likely to experience differential impacts from wind turbine views, and so our estimates need to reflect variation in the marginal utilities associated with the different levels of our choice experiment attributes. The second is scale heterogeneity, which is important insofar as it affects our ability to estimate preference heterogeneity. In the discrete choice econometric models used with choice experiments, it is common practice to assume that the random component of utility has a normalized variance that is equal for all decision makers. This normalization implies that any variation in utility function parameter estimates is attributed to preference heterogeneity. However, the relative precision ('scale') of respondents' answers may vary, even when preferences are homogenous. To identify preference heterogeneity that is not confounded with scale heterogeneity, we need to explicitly incorporate both into our analysis. For this reason we apply a scale-adjusted latent class model.[19]

We begin by specifying the utility a person *n* receives from alternative *j* during choice situation *c* as

$$U_{njc|q,s} = \beta_q' X_{njc} + \varepsilon_{njc|q,s}, \tag{1}$$

where β_q is a vector of utility function parameters, and X_{njc} is a vector that includes characteristics of the choice alternative, often interacted with characteristics of the individual. The index q denotes membership in one of q=1,…,Q preference classes, and the index s denotes

[19] The use of latent class discrete choice models for preference heterogeneity is now fairly common; see Train (2009, p. 365) for a textbook discussion. Latent class models that accommodate both preference and scale heterogeneity are newer and less common. Thiene et al. (2015) include a detailed discussion of modeling preference and scale heterogeneity, and Thiene et al. (2012) provide an application valuing forest biodiversity that estimates both types. Other examples of studies examining scale and preference heterogeneity include Flynn et al. (2010), Fiebig et al. (2010), and Burke et al. (2010).

membership in one of s=1,…,S scale classes. Thus heterogeneity in preferences is given by the discrete range of values that β_q and λ_s can take, where λ_s is the scale parameter associated with the type I extreme value distributed random variable $\varepsilon_{njc|q,s}$. This distributional assumption implies we are working with the logit class of discrete choice models. For estimation, it is necessary to normalize one of the scale parameters to one. Without loss of generality, we assume that λ_1=1, so that scale classes s=2,…,S are relative to scale class s=1.

If we know the preference and scale classes to which each person belongs, as well as the number of classes Q and S, estimation is via the usual conditional logit framework, which gives rise to probabilities of the form

$$\begin{aligned}
\Pr_{njc|q,s} &= \frac{\exp(\beta_q' X_{njc})}{\sum_{k=1}^{J} \exp(\beta_q' X_{nkc})}, \quad s=1, \\
\Pr_{njc|q,s} &= \frac{\exp(\lambda_s \beta_q' X_{njc})}{\sum_{k=1}^{J} \exp(\lambda_s \beta_q' X_{nkc})}, \quad s=2,\ldots,S,
\end{aligned} \tag{2}$$

where J is the number of choice alternatives. Full sample maximum likelihood estimation based on these probabilities allows identification of preference class-specific utility parameters, which are not confounded with any potential scale differences.

Of course, we do not know the total number of preference and scale classes, nor the specific classes to which each person belongs. Class memberships are therefore latent, and need to be estimated as part of the model. To this end, we assume that the probability that person n belongs to latent preference class q is determined according to the expression

$$\Pr_{nq} = \frac{\exp(\theta_{q0} + \theta_q' Z_n)}{\sum_{k=1}^{Q} \exp(\theta_{k0} + \theta_k' Z_n)}, \quad q=1,\ldots,Q, \tag{3}$$

where θ_{q0} is a scalar, Z_n is an R-dimensional vector of individual covariates (referred to as 'active covariates'), and θ_q=(θ_{q1},… θ_{qR}) is a vector of coefficients that is compatible with Z_n. For identification we use the common restrictions

$$\begin{aligned}&\sum\nolimits_{q=1}^{Q}\theta_{q0}=0,\\&\sum\nolimits_{q=1}^{Q}\theta_{qr}=0,\quad r=1,\ldots,R.\end{aligned}\tag{4}$$

Likewise, membership in a latent scale class *s* is determined by

$$\Pr_{ns}=\frac{\exp(\gamma_{s0}+\gamma_s' Z_n)}{\sum\nolimits_{k=1}^{S}\exp(\gamma_{k0}+\gamma_k' Z_n)},\quad s=1,\ldots,S,\tag{5}$$

where $\gamma_s=(\gamma_{s1},\ldots\gamma_{sR})$ and

$$\begin{aligned}&\sum\nolimits_{s=1}^{S}\gamma_{s0}=0,\\&\sum\nolimits_{s=1}^{S}\gamma_{sr}=0,\quad r=1,\ldots,R.\end{aligned}\tag{6}$$

The expressions in (2) are conditional probabilities. To derive estimating equations we need to state the unconditional probabilities and a person's contribution to the likelihood function. Since the probability of membership in a latent preference and scale class are independent, conditional on values for *Q* and *S*, the probability of observing person *n* choosing alternative *j* on choice occasion *c* is:

$$\Pr_{njc}=\sum\nolimits_{q=1}^{Q}\sum\nolimits_{s=1}^{S}\Pr_{nq}\cdot\Pr_{ns}\cdot\Pr_{njc|q,s}.\tag{7}$$

To derive the likelihood for person *n*, let $y_{njc}=1$ indicate that the person chose alternative *j* on occasion *c*, with $y_{njc}=0$ otherwise. Conditional on the model parameters and structure, the likelihood of observing person *n*'s sequence of choices is

$$L_n=\sum\nolimits_{q=1}^{Q}\sum\nolimits_{s=1}^{S}\Pr_{nq}\cdot\Pr_{ns}\cdot\prod\nolimits_{c=1}^{C}\prod\nolimits_{j=1}^{J}\left(\Pr_{njc|q,s}\right)^{y_{njc}}.\tag{8}$$

From this we can see that the log-likelihood function for a sample of *N* people has the form

$$\ln L=\sum\nolimits_{n=1}^{N}\ln\left[\sum_{q=1}^{Q}\sum\nolimits_{s=1}^{S}\Pr_{nq}\cdot\Pr_{ns}\cdot\prod\nolimits_{c=1}^{C}\prod\nolimits_{j=1}^{J}\left(\Pr_{njc|q,s}\right)^{y_{njc}}\right].\tag{9}$$

Estimation of the parameters in (2), (3), and (5) is by maximum likelihood, though the nonlinearities inherent in (9) preclude the use of standard numerical search routines. As such, it is now standard to estimate latent class models using the expectation-maximization (EM) algorithm (see Train, 2009, chapter 14). Routines for estimating latent class models are available in commercial software packages; for this study we used Latent Gold Choice Version 5.1.[20]

The model just described uses information only on the respondent's most-preferred option. When ranking information is available additional information can be extracted from the sample. In our case we know the first and second most-preferred options (and hence the full ranking of all three alternatives offered in each choice), and so the log-likelihood function needs to be adjusted to accommodate the additional ranking.[21] In addition, the estimation routine is for a model conditional on values for Q and S (the number of preference and scale classes). Ideally the estimation routine would search for the optimal number of classes, but this is not computationally or practically feasible, given the large number of possible combinations. Instead, researchers estimate several models conditional on specific assertions for the class sizes, and then use information criteria, such as AIC and BIC, along with intuition and knowledge of the needs of the study, to select the best model. We discuss the specifics of our selection criteria in the next section.

[20] The user manual for Latent Gold, available from http://www.statisticalinnovations.com/user-guides/, contains technical descriptions of the model and estimation. Thiene et al. (2015) and Burke et al. (2010) provide accessible descriptions on how estimation of the scale adjusted latent class model proceeds.

[21] With three choice options, the adjustment effectively uses the rankings to construct two outcomes per choice scenario: the most preferred among three options, and the preferred option among the remaining two. The product of corresponding conditional logit probabilities is used to construct the likelihood function.

5) Estimation and Results

Specification

The conditional utility function specification we use is

$$U_{njc|q,s} = \sum_{d=1}^{4}\sum_{l=1}^{3}\kappa_q^{d,l} dist_{njc}^{d} \times size_{njc}^{l} + \sum_{d=1}^{4}\eta_q^{d} dist_{njc}^{d} \times OF_n + \beta_q p_{njc} + \varepsilon_{njc|q,s}, \tag{10}$$

where *dist* and *size* denote the categorical 'distance from shore' and 'visible turbines' attribute values, respectively. Specifically, $dist_{njc}^{d}$ and $size_{njc}^{l}$ are dummy variables indicating the attribute levels presented to person *n* for alternative *j* on choice task *c*. The variable p_{njc} is the rent for alternative *j* on choice task *c*, calculated based on a percentage adjustment from the actual price paid during the previous summer and recorded as a continuous dollar value for each survey respondent (see Table 1 for the attribute levels for distance, visible turbine, and price). Finally, OF_n is a dummy variable equal to one if the person rented an oceanfront home.

For a preference class *q*, we are interested in estimates for each $\kappa_q^{d,l}$, which is the utility level for a non-oceanfront renter from a specific combination of windfarm distance and visible turbine count. For oceanfront renters, utility is differentiated by η_q^{d}, which shifts utility based on the distance attribute. The left out category in equation (10) is the status quo of no visible turbines.[22] Thus the observable utility *V* from selecting a configuration with visible turbines,

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[22] We arrived at this specification via a systematic process of starting with the simplest models and gradually adding additional complexity. Comparison of a rank ordered logit model with only main effects for distance and visible turbines, and a rank ordered logit model with the full set of interactions as in (10), confirmed that interactions were important for both our daytime and nighttime treatments. Staying with the ordered logit model, we then examined observable preference heterogeneity via interactions between the distance and visible turbines attributes, and household/survey design/household activity characteristics. While interactions in general did not reveal substantial observable heterogeneity, there was some indication that oceanfront property renters reacted differently to the distance attribute than non-oceanfront renters. Since the simple models suggested the important

relative to no visible turbines, is

$$\begin{aligned} V_{njc,q}^{d,l}\,|_{OF=1} &= \kappa_q^{d,l} + \eta_q^d + \beta_q p_{njc} \\ V_q^{d,l}\,|_{OF=0} &= \kappa_q^{d,l} + \beta_q p_{njc}, \quad d = 1,\ldots,4, \quad l = 1,\ldots,3, \end{aligned} \tag{11}$$

where the *d* and *l* indices correspond to the distance and visible turbines attribute levels shown in Table 1.

Latent class analysis requires decisions on which covariates to use for parameterizing the probabilities of class membership (the active covariates). Researchers often use socio-demographic variables for this, but the homogeneity of our sample in standard socio-demographic measures (see Table 2), and our preliminary examination of observable heterogeneity, suggested these were not likely to be important for distinguishing among classes. Instead, we use the survey questions on respondents' beliefs about the environmental and economic impact of offshore wind farms in North Carolina, to construct our active covariates (see section 3 and appendix Figure 1). Specifically, we use factor analysis to reduce the information contained in the Likert scale questions down to a two factor variables, which we then employ as active covariates. Appendix Table 1A shows factor loadings from our analysis, which reflect correlations between the constructed factors and respondents' Likert scale answers. For reasons described in the notes to Table 1A, we refer to Factors 1 and 2 as the 'environmental factor' and 'public factor', respectively. Scores for the two factor variables are calculated for each individual in the sample, yielding two variables for use as active covariates in the latent class models. Specifically, we use the environmental and public factors as covariates explaining

heterogeneity was likely to be unobserved, we pursued latent class analysis within a relatively parsimonious parametric utility function. A detailed record of our specification analysis is provided in Lutzeyer (2013, pp. 184-188). Stata programs and data for estimating main effects and full interaction ordered logit models are available for download at the journal webpage, along with example Latent Gold scripts.

preference class membership, and do not use active covariates for the scale class membership.[23]

The final specification decision concerns the number of preference and scale classes. As is standard for latent class models, we explored a series of models with an incrementally increasing number of preference classes, where each model was estimated multiple times using randomly generated starting values. To determine our final number of classes, we used comparisons based on information criterion, the stability of models to different starting values, and intuition. Appendix Table 2A presents information statistics for the nighttime and daytime treatments for models with two to five preference classes and two scale classes. Based on these statistics and other criterion described in the table notes, we use three preference and two scale classes for our primary models.

Model Estimates

In this subsection we present parameter estimates for our nighttime-treatment, scale-adjusted latent class model that is estimated using respondents' full ranking of choice alternatives. The latent class models and membership probabilities are similar across the daytime and nighttime treatments, and so for succinctness we only discuss parameter estimates for the nighttime treatment. Parallel results for the daytime treatment are presented in the Appendix in Tables A3 and A4 and are briefly described in a later section.

We first describe the general composition and choice behavior of respondents in each latent class. Individuals are assigned to one of the three latent classes based on their largest class

[23] In preliminary analysis we examined models that included the constructed factors as well as other household characteristics as active predictors of preference class membership. We consistently found that the environmental and public factors were strong predictors of class membership, and that other variables were not significant. Details on our factor analysis and specification decisions are provided in Lutzeyer (2013, pp. 135-138).

membership probability. Table 4 reports summary statistics describing respondents' choices and demographic characteristics by each latent class. Panel A indicates that latent class 1 (LC1) captures almost 87 percent of respondents that always chose a view with visible turbines as their most preferred scenario. We refer to this group as the *All View* class. Latent class 2 (LC2), referred to as the *Some View* class, contains the majority of respondents that sometimes picked a view of turbines as their most preferred scenario, as well as 13 percent of those who always did. Finally, latent class 3 (LC3) captures the respondents that always ranked the baseline view as their most preferred scenario, as well as 19.5 percent of those who occasionally chose a view of turbines as their most preferred scenario. The LC3 respondents reveal a strong preference for the status quo and accordingly are referred to as the *Never View* class. The final row in Panel A reports that 55 percent of respondents are in the *Never View* class, indicating a strong preference among the majority of respondents for a view from their rental property that is free from turbines. Panel B of Table 4 presents the membership in each latent class by household characteristics. The proportion of people in each latent class is generally not statistically different across the different socioeconomic profiles. Using Pearson Chi-squared tests and a five percent significance level, the only difference among latent classes is the greater proportion of females in the *Some View* class. The similar demographics across latent classes confirms that class membership is generally determined by unobserved preferences rather than observable individual characteristics.

Model estimates are shown in Table 5. Panel A presents utility parameters for a simple ordered logit model (first column), and for the latent class model (last three columns). The ordered logit estimates provide a useful baseline and show that, on average, visible turbines in all configurations generate negative utility relative to the status quo of no visible turbines.[24] The disutility of viewing turbines is attenuated as they are moved further offshore. For example, the disutility associated with viewing a 64 turbine array at 5 miles is reduced by 58 percent when the array is placed 18 miles from shore. This attenuation is even greater for the larger arrays (e.g. the disutility of viewing 144 turbines at 5 miles decreases by 82 percent when it is moved to 18 miles). Furthermore, fewer visible turbines reduce the disutility of the view relative to the baseline, holding constant the distant of the turbines from shore. This effect is most pronounced for arrays placed at either 5 or 8 miles from shore. The model also shows that oceanfront renters receive greater disutility from close-in turbine arrays (5 and 8 miles), relative to their non-oceanfront counterparts, and that there is no statistically significant heterogeneity for the further-out arrays.

While the ordered logit results are intuitive and strong statistically, they mask important heterogeneity that becomes clear in the latent class model. The second column of Table 5 shows that individuals in the *All View* class receive disutility from visible turbines only in their most intrusive configurations, albeit not in a statistically significant way. Specifically, wind farms 5 miles from shore with 144 visible turbines generate negative utility relative to the status quo of no visible turbines, but the point estimate is not statistically significant. The other non-price attribute parameters are insignificant, with the exception of the 8 and 12 mile configurations with 144 visible turbines, which provide positive utility relative to no visible turbines. While the estimates indicate this group is indifferent or possibly positively inclined towards all but the

[24] We conducted a Hausman test comparing estimates from the ordered logit model and a similarly-specified conditional logit model. We reject the hypothesis of equal parameters from the two models ($\chi^2_{16} = 246$, *p*-value=0.000). We decided to rely on the ordered version in our latent class analysis so as to extract more information from the class of respondent who always chose the opt-out as their most preferred option.

nearest and largest windfarms, as we note later when presenting welfare estimates, the coefficient estimates never result in a statistically significant willingness to pay to move visible turbines closer to shore. Lastly, the price coefficient for the *All View* class is negative and an order of magnitude larger than for the other two classes, suggesting members of this latent class are the most price conscious respondents.[25]

The last column of Table 5 contains estimates for the *Never View* class. The large, negative, and statistically significant estimates for all combinations of distance and visible turbines imply a strong preference for the status quo with no visible turbines, and a large disutility associated with the choice of any designed scenario. The relative magnitudes of the utility parameters are intuitive. The disutility from wind farms 5 miles offshore is larger than the disutility from wind farms 8 miles away, and the configurations 18 miles offshore provide the smallest, albeit still statistically significant, utility decrease. The price coefficient estimate, though negative and significant, is the smallest among the three groups, suggesting that rental price is comparatively unimportant for this class of respondents. This finding is driven by the fact that the members of the *Never View* class almost always chose the baseline option as most preferred, even when the price discount for a designed scenario was substantial. Taken together, the utility parameter estimates imply that members of the *Never View* class are not willing to trade rental price reductions for viewing turbines that they consider a negative change in the viewshed.

Finally, Table 5 indicates that preferences are more nuanced among the *Some View* class.

[25] The magnitudes of marginal utilities are not formally comparable across latent classes due to the scale normalization. However, a comparison of the size of the price effect for LC1 relative to the size of the other marginal utilities in LC1 supports the assertion that the *All View* respondents are the most attentive to price. Similar logic suggests that respondents in the *Never View* class are the least price responsive.

The estimates show that, relative to the status quo, this group receives statistically significant and negative utility for windfarms out to 12 miles distant, but is largely indifferent to windfarms 18 miles away. The magnitude of disutility decreases noticeably for the 8 and 12 mile distances relative to the more intrusive 5 mile distance for small and medium arrays of 64 or 100 turbines. However, the disutility of viewing 144 turbines at 8 miles is similar to the disutility of viewing 144 turbines at 5 miles for this class of respondents. More generally for this latent class, the disutility of views with 144 visible turbines leads to higher disutility than those with 64 or 100 visible for the 5, 8, and 12 mile distances.

For all three classes, the point estimates suggest that oceanfront renters have a higher disutility for close-in wind farms relative to non-oceanfront renters, though few of the coefficients are statistically significant. Nonetheless, the magnitudes of oceanfront interactions for the 5 and 8 mile distances suggest there may be economically important differences between the two groups. We examine this in more detail when we present welfare estimates.

Panels B and C in Table 5 show estimates for the latent class membership probabilities. Panel B indicates that people who believe wind energy will have a positive impact on environmental and public factors were significantly more likely to be in the *All View* class and significantly less likely to be in the *Never View* class. Neither of the factors was significant in determining class assignment for the *Some View* class. Panel C presents estimates for the two scale classes. Each preference class can contain respondents belonging to either scale class. Here we see that the log of the relative scale parameter is significantly larger for respondents in the second scale class (SC2), indicating that they have a lower error variance than the reference scale class (SC1), and the sample is split approximately equally among the two scale classes.

Welfare Estimates for Changes in the Viewshed

We use the latent class model parameter estimates from Table 5 to compute point estimates and confidence intervals for respondents' willingness to accept (WTA) rental discounts for a range of changes in viewsheds.[26] In what follows we first summarize estimates for the nighttime treatment as our main findings, and then discuss comparisons with the daytime treatment. Table 6 presents WTA point estimates and significance levels for the three latent classes. The welfare estimates show the price discount needed to rent the same property, with visible turbines moved closer to shore.[27] The WTA estimates are presented by latent class and number of visible turbines for both the oceanfront and non-oceanfront renters in Panels A and B, respectively. The first row for each sample in Table 6 reports the WTA to move turbines from out of visible range at 30 miles (the status quo option) to 5 miles from shore – the most intrusive view shown in the survey. The remaining rows present the necessary price discounts for four scenarios that change turbine distances incrementally from the status quo of 30 miles (too far out to see) to 18 miles, 18 to 12 miles, 12 to 8 miles, or 8 to 5 miles.[28] These measures thus

[26] Point estimates for MWTA are computed as the ratio of estimated coefficients for the characteristics of interest, and the estimated coefficient for the price variable. Specifically, the MWTA for latent class q for a change from distance d and visible turbine count l to distance e and visible turbine count m is

$$MWTA^{q}_{d,l\rightarrow e,m} = \frac{\left(\kappa_q^{d,l} + \eta_q^{d} \times OF\right) - \left(\kappa_q^{e,m} + \eta_q^{e} \times OF\right)}{-\beta_q},$$

where OF=1 if the welfare measure is for an oceanfront renter. Note that, although utility parameter estimates are not directly comparable across latent classes due to the scale parameter, MWTAs *are* comparable, because the scale parameter drops out when taking the ratio of parameters (see Phaneuf and Requate, 2017, chapter 16 for a discussion of the MWTA derivation within this context). Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where, for example, the 2.5th and 97.5th percentiles of the resulting empirical distribution is used to construct a 95 percent confidence interval.

[27] A negative WTA estimate in Table 6 indicates a positive willingness to pay (WTP) to view turbines.

[28] The WTA point estimate in the first row is simply the sum of the remaining four point estimates in each column.

represent marginal willingness to accept (MWTA).

Table 6 reveals several patterns. First, WTA is always positive when it is statistically significant. There are no wind farm scenarios, for any of the latent classes, in which respondents would be willing to pay *more* to rent a property with turbines incrementally closer to shore (i.e., have a statistically significant *negative* MWTA). At best, some respondents under some scenarios would not require a discount to rent a home with turbines in view. Second, the point estimates imply an ordering in which

$$MWTA_{NeverView} \geq MWTA_{SomeView} \geq MWTA_{AllView}$$

holds for almost all combinations of turbine distance change, array size, and property location (oceanfront or non-oceanfront).

Third, conditional on a preference class, the MWTA for a distance change scenario is generally not statistically different across the number of visible turbines. Similarly, comparisons of the top and bottom panels in Table 6 indicate that, with some exceptions, the estimates are not statistically different for oceanfront and non-oceanfront rental locations, though the magnitude of some differences may be economically important.

Lastly, the large disutility associated with viewing turbines at any distance for the *Never View* class is made clear in Table 6. Because respondents in this latent class almost always chose the status quo as the most preferred option, there is significant disutility when any configuration of turbines is visible. This is reflected in the large WTA estimates for viewing turbines at 18 miles as compared to having them out of visible range. Even for the least intrusive view of 64 turbines at 18 miles, the WTA estimates are nearly double the mean rental price for the sample (mean rental price is $4,100 per week). The impact of incremental movements of visible turbines closer to shore for the *Never View* class, such as from 18 to 12 or 12 to 8 miles, depends on the size of the turbine array in question. For example, moving 144 turbines closer to shore requires additional discounts until 8 miles. However, the welfare impact of viewing 144 turbines at 8 miles is not statistically different from the welfare impact of viewing them at 5 miles. A 100 turbine view provides similarly negative welfare impacts for *Never View* respondents when the turbines are 18, 12 or 8 miles from shore, and the rental discounts needed to view turbines incrementally closer to shore (MWTA) are generally not statistically significant within this range.[29] It is not until 100 turbines are placed close to shore (5 miles) that a large and statistically significant additional discount is needed. Finally, the utility parameters and MWTA estimates indicate that views of the smallest array (64 turbines) are approximately equally disliked at 12, 8 or 5 miles.

Overall, the WTA estimates for the *Never View* class imply that these respondents would likely exit the local rental market if turbines were present, rather than make intensive margin tradeoffs among rental price and characteristics of the viewshed. As such, we focus the remainder of our discussion in this section on the economically relevant respondents – the *All View* and *Some View* classes – as they are the groups that are making tradeoffs at the intensive margin, and thus could affect market rental prices if discounts are needed to attract them to the same location. We do, however, return to a discussion of the *Never View* class when discussing market and policy implications in the concluding section.

To further understand the impact of visible turbines on the *All View* and *Some View* latent classes, we present welfare measure point estimates and 95 percent confidence intervals in Figures 4 and 5 for oceanfront and non-oceanfront renters, respectively. Panel A in Figures 4

[29] Note that the price parameter for this latent class is identified from respondents' second and third choice ranks. As such, the estimate is both small and somewhat imprecisely estimated, which leads to larger standard errors for the welfare measures.

and 5 presents WTA measures to move turbines from the status quo to either 18, 12, 8 or 5 miles from shore. Panel B in Figures 4 and 5 presents the MWTA point estimates from Table 6 to move turbines incrementally closer to shore, along with their 95 percent confidence intervals. The estimates are distinguished by the number of visible turbines and latent class (*All View* or *Some View*). Figures 4 and 5 make clear that the *All View* class would generally not require a discount for viewing turbines at any distance as compared to not viewing them at all, but nor would they pay *extra* to see turbines closer to shore (see Figures 4 and 5, Panel A). The exception is oceanfront renters, who would require a moderate discount of $412, or approximately a 10 percent reduction in the mean rental price of $4,100, although this is only statistically significant at the 90 percent level (see also Table 6). However, when comparing among different views of turbines, both oceanfront and non-oceanfront renters would require a moderate discount ($534 and $413, respectively) to view the largest array of 144 turbines at 5 miles as compared to 8 miles from shore. A small discount may also be needed for oceanfront renters to accept a 100 turbine array at 5 miles as compared to 8 miles ($193, or about 5 percent of the mean rental price).

The estimates for the *Some View* class indicate that large, but in some cases plausible, discounts are needed for these respondents to stay in the market if turbine arrays are brought into view or moved closer to shore. Bringing turbines into view (from 30 to 18 miles) does not result in a statistically significant MWTA for oceanfront and non-oceanfront renters in the majority of cases, suggesting little if any discount would be needed for viewing a distant array. However, as compared to viewing no turbines, the implied discounts increase substantially at 12 and especially 8 miles (see Panel A, Figures 4 and 5). Specifically, when compared to the status quo of no visible turbines, viewing turbines at 12 miles requires statistically significant discounts of approximately $500 to $750, depending on the number of visible turbines. These discounts increase to $1,000 or more for a view of turbines at 8 miles as compared to the status quo. For the largest turbine array, Panels A and B in Figures 4 and 5 also highlight that the welfare impact of viewing the largest array of 144 turbines at 8 miles is approximately the same as viewing them at 5 miles for the *Some View* latent class, which was also the case generally with the *Never View* class. Overall, the WTA and MWTA estimates for the *Some View* class suggest that *i*) there is not a welfare impact of viewing an array of any size if the turbines are placed 18 miles from shore, *ii*) economically plausible discounts could entice the *Some View* class to view turbines at 12 miles from shore, but *iii*) renters in this latent class are likely to leave the market if turbines are built 8 or 5 miles from shore, since the implied discounts to attract them are generally 25 percent or more of mean rental price.

Nighttime versus daytime treatments

We report results for the daytime treatment in a parallel format to the nighttime treatment in appendix Tables 3A, 4A and 5A. The results for the daytime treatment are qualitatively similar to the nighttime treatments, although there are a few differences of note. Overall, the same pattern of choices is observed across the three latent classes as for the nighttime treatment, and the proportion of respondents in each of the three latent classes is similar for the two treatments (Table 3A). Furthermore, the proportion of people in each latent class for the daytime treatment does not vary across the different socioeconomic profiles, again suggesting that class membership is determined by unobserved preferences, rather than observable individual characteristics. For the utility parameter estimates (Table A4), the daytime treatment results reveal similar patterns as their nighttime treatment counterparts, with the point estimates again implying that: *i*) turbines further offshore are preferred by all latent classes, *ii*) smaller turbine arrays are usually preferred to larger arrays, and *iii*) there is a clear progression in disutility of visible turbines among the three classes, with the *All View* class having the least disutility and *Never View* having the largest.

Table 5A presents MWTA estimates and significance levels for the daytime treatment that are akin to those in Table 6. A comparison indicates that the pattern of estimates is similar to the nighttime treatment, although in the majority of cases, the MWTA estimates from the nighttime treatment are <u>larger</u> than for the daytime treatment. For example, the *All View* class in the daytime treatment exhibits even more willingness to view turbines than their counterparts in the nighttime treatment, as evidenced by the economically small and rarely significant MWTA estimates, even for moving turbines as close as 5 miles from shore.[30] In addition, the WTA and MWTA point estimates for the *Some View* class in the daytime treatment are often only half those of the nighttime treatment. Interestingly, there is a clear progression in disutility among the *Never View* class in the daytime treatment, with each incremental movement of turbines toward shore implying a positive, significant MWTA (see Panels A and B, Table 5a). This contrasts somewhat with the *Never View* latent class in the nighttime treatment, in which the primary welfare impact came from moving the turbines into view, with the specific distance/turbine-number pairing mattering somewhat less to that group of respondents.

Overall, the comparison of daytime to the nighttime treatment results suggest similar patterns in responses, but that the disutility of viewing turbines is attenuated when only daytime

[30] Indeed, we note that there is one instance for the *All View* class in the daytime treatment in which there is a statistically significant (at the 90 percent level) but economically small marginal willingness to pay to move turbines closer to shore (an $86 increase in weekly rent for a viewshed containing 64 turbines at 12 miles as compared to 18 miles).

images are shown to respondents. This is the case despite the fact that respondents in the daytime treatment are shown a diagram of a wind turbine that describes how the turbines nacelles are lit at night with red beacons that flash in unison every two seconds, as required by U.S. federal aviation law. This result is important because it indicates that past studies have likely understated the potential impact of wind farms in tourism settings since all previous surveys only present daytime images of turbines (e.g., Ladenburg and Dubgaard 2007; Ladenburg and Dubgaard 2009; Krueger 2007; Westerberg et al. 2011; Landry et al. 2012).

6) Conclusions

Offshore wind energy development can create global public benefits by offsetting carbon-intensive energy sources, yet these benefits come with locally-borne costs. Our choice experiment with customers renting coastal vacation properties unambiguously indicates that viewing a utility-scale offshore wind farm from a beach rental property is a disamenity for these individuals. There was no wind farm scenario, for any group of respondents, in which visitors to the coast indicated that they would be willing to pay *more* to rent a property with turbines in view, as compared to one with no turbines in sight. Even more striking is that over 50 percent of those surveyed indicated they would not return to the same property for their next rental should a utility-scale wind farm be placed offshore. This is true despite wide-spread support for wind energy development among these same respondents.

Although our results are broadly consistent with the majority of stated and revealed preference studies, our respondents exhibit a more pronounced negative reaction to altering the viewshed than has been reported in the past.[31] Three main factors likely contribute to this result.

[31] For example, Krueger et al. (2011).

First, our survey includes nighttime images of turbines whose nacelles are lit, presented side-by-side with daytime images of the same turbines. Our study is the first to include nighttime images and in a split-sample design, and we find that individuals react more negatively to wind farms when nighttime images are included. Thus, past studies have likely understated the potential impact of wind farms in tourism settings.[32] Second, our survey design holds constant the amount of wind energy produced in all scenarios, including those where all turbines are too far out to see. As such, we are able to distinguish pure viewshed preferences from preferences for green energy. Lastly, the North Carolina beaches, like many eastern US coastal communities, enjoy a loyal customer base that engages in repeat visitations. Fifty-five percent of respondents indicated that they had rented a home in the same area each summer for the past five years. Given this strong affinity for the in-situ amenities at these communities, it is not surprising that respondents indicated a strong preference for the status quo.[33]

What do our results imply for actual rental prices in the event that a utility scale wind farm were constructed? The answer depends on how the different preference classes in the renting population re-sort in response to a wind farm, and how far out from shore the turbines are placed. If the turbines are placed further than 8 miles from shore, our results suggest rental demand by the segment of the population most amenable to viewing turbines, referred to as the *All View* group of respondents, will not be affected. While the others may exit the local market, perhaps causing rental prices to fall in the short-run, other potential renters similar to the *All*

[32] Although aviation safety dictates lighting requirements for wind turbines in the US, the results of our split-sample design also suggests that the negative welfare effects of visible offshore wind farms can be ameliorated somewhat by minimizing nighttime lights.

[33] We received 121 open ended written comments to our survey. Among these, 38 percent of respondents explicitly emphasized that the natural beauty of the open ocean vistas are very important to their vacation and/or explicitly stated that they would move their vacation to a different beach if visible turbines were present.

View group will be attracted by these lower prices and will sort into the affected local market. If the wind farm effect is localized, this re-sorting – small in comparison to the overall North Carolina coastal rental market – will result in unchanged equilibrium prices. In this scenario, the welfare effects consists only of short term adjustment costs to the new sorting equilibrium: property owners may need to incur costs to attract new customers and could incur costs related to decreased occupancy rates during the transition period, and renters who change vacation locations will need to bear search costs when selecting an alternative vacation home. Given the *All View* group represented only 20% of our survey respondents, these transition costs could be substantial.

If turbines are built 5 miles from shore, our results indicate that rental rates will decrease, and once again, property owners and renters will bear non-zero transactions costs during the adjustment to the new equilibrium. Among the *All View* rental group, the willingness to accept for a 144 turbine array located 5 miles from shore is approximately $400 for oceanfront renters, relative to the status quo. This represents approximately 8 percent of the average rental rate for oceanfront homes rented by our respondents ($5,250), and standard hedonic property value theory thus suggests that local oceanfront home prices would fall by 8 percent if a 144 turbine array were placed 5 miles from shore. The logic here is as follows. Assuming the number of rental homes affected by turbine views is small relative to the overall North Carolina market, renters with similar preferences to the *All View* group will replace those who exit the local market in response to the turbines. However, since the demand among existing renters in the *All View* group, and potential renters with preferences similar to the *All View* group, are also affected by the altered viewshed, a discount is required to attract this group to rental homes with turbines placed 5 miles from shore. Our models suggest the discount required is 8 percent (see Taylor, 2016, and Phaneuf and Requate, 2107, chapter 12 for overviews of the hedonic framework and market sorting).

From a state or national policy perspective, the welfare losses associated with a single wind array close to shore will be small. However, from a local jurisdictional perspective, the losses could be substantial. A review of coastal townships in North Carolina indicates that the majority are small jurisdictions with less than six square miles of land within their municipality borders. For context, the first row of a 144 turbine array set in a twelve by twelve grid pattern would span 5.5 linear miles. When placed 5 miles from shore directly in front of a jurisdiction, the turbine array would imply significant viewshed impacts for most of the properties in an average-sized North Carolina beach town. An 8 percent reduction in rental price, and the commensurate reductions in property values, occupancy taxes, and property taxes, would apply to most of the rental properties located within the jurisdiction's borders.

The potential for high localized costs leads naturally to the question of whether moving visible turbines further offshore would pass a benefit-cost test. Given the minimal utility impacts of arrays further than 8 miles from shore on the *All View* group of respondents, our models suggest that moving turbines beyond 8 miles are unlikely to generate positive net benefits from this baseline (exclusive of transition costs that we are unable to quantify). However, for projects that are proposing distances closer than 8 miles from shore, things may be different. As a first order approximation exploring this issue, we use tax parcel maps for the northern North Carolina coastline to determine the average number of rental properties that would be directly impacted by a 144 turbine array placed 5 miles from shore. We compute the average number of oceanfront homes and the average number of non-oceanfront homes within a two-mile radius of the center-point of the array, and assume they are directly impacted by the viewshed change. Rental discounts required to move an array from 8 miles to 5 miles from shore (based on the *All View* class in last row of Panels A and B in Table 5) are then applied to the average rental prices for these homes. The net present value of the total annual rental losses is then computed using an 8 percent discount rate over 20 years.[34] The resulting calculations suggest estimated losses for a beach community of average development density are $61 million.

To pass a benefit-cost test, the upfront capital costs associated with moving 144 turbines three miles further out to sea would need to be less than $61 million. Myhr (2014) suggests that export cables bringing offshore energy to shore cost approximately $782,000 per mile, on average, with lower and upper bounds of $626,000 to $938,000. Without other changes in costs, it is clear that moving turbines from 5 to 8 miles would generate positive net benefits. Of course, there are many factors that impact siting decisions, including water depth, seabed materials and topography, access to onshore support facilities, and potential locational conflicts such as interference with shipping lanes. Nonetheless, our results plausibly suggest the potential for both efficiency and distributional gains from the reduction of visual impacts of near-shore wind farms.

Our conclusions are subject to two caveats. First, our population contains a significant base of loyal, repeat customers. Our experimental design sought to maximize internal validity by asking respondents to consider re-renting the same house – a realistic choice in our context. However, the external validity of our findings beyond North Carolina is limited to locations that that have similar conditions. This said, Bennett (2013) demonstrates that most of the US Atlantic coast has seasonal vacation rental homes as the dominant development pattern, similar to in North Carolina. To the extent that coastal communities share the same characteristics as those along the NC coast – i.e. dominated by vacation rental homes with a significant base of

[34] An eight percent discount rate and 20 year time horizon was chosen to be consistent with recent estimates that calculate the costs of moving wind farms further from shore (Myhr, 2014).

repeat customers – our estimates may be transferable. Indeed, the local opposition to every proposed offshore wind project thus far in the US is indicative that our results may be representative for households that own or rent weekly vacation homes along the eastern seaboard. Of course, similar studies in other locations would need to be conducted to conclude this with confidence.

Second, our price analysis relies on the standard competitive hedonic model that assumes a continuum of available options, implying that renters who leave the local market in response to a change in the viewshed are able to move to an identical property elsewhere, thereby suffering no permanent welfare loss. If, however, the location conveys amenities that are not present elsewhere – i.e. local markets are not perfectly substitutable – this re-sorting will involve a welfare cost. The welfare loss could arise from selecting a less-preferred option within the same location, or moving to a different (less-preferred) location on the coast. Understanding the local price and welfare consequences in this context would require knowing if people who would not re-rent the same property would rent elsewhere in the same location, thereby potentially reducing the overall local impacts of a windfarm, or move to a new location. Our design does not allow us to distinguish among these two possibilities.

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Table 1. Attributes and attribute levels used in choice experiment

Attribute	**Levels**	**Status Quo**
Distance of turbines from the shore	5, 8, 12, 18, 30[a] miles	30[a] miles
Total number of turbines built	144[b]	144
Number of turbines visible from the shore (implied number built too far out to see)	64 (80), 100 (44), 144 (0)	0 (144)
Change in rental price[c]	+5%, 0%, −5%, −10%, −15%, −20%, −25%	0%

[a]Turbines 30 miles from shore are not visible.

[b]The total number of turbines built does not vary across choices, only the number visible from shore.

[c]Percentages are used to generate the experimental design. The percentages were converted into absolute price changes for respondents in the choice questions, based on each home's actual rental price.

Table 2: Summary statistics of demographic characteristics

Variable (definition)	Count (Total Responses)	Percent
College = 1 (four-year college degree or higher)	408 (465)	87.7
White = 1 (Caucasian, not of Hispanic origin)	445 (462)	96.5
Working age = 1 (age between 26 and 65)	353 (463)	76.3
Female = 1	270 (465)	58.1
Employed = 1 (employed, including self-employed)	298 (462)	64.5
Retired = 1 (retired or not working by choice)	163 (462)	35.3[a]
Environmental =1 (somewhat interested or interested in environmental issues)	456 (465)	98.0
Household income:		
less than 70,000 = 1	47 (432)	10.9
$70,000 to $100,000 = 1	94 (432)	21.8
$100,000 to $150,000 = 1	115 (432)	26.6
greater than $150,000 = 1	176 (432)	40.7
State of residence:		
North Carolina = 1	127 (484)	26.2
Virginia =1	144 (484)	29.8
Owner = 1 (own a beach house along the NC coast)	13 (465)	2.8
Always rent = 1 (visited NC coast each year since 2007)	270 (484)	55.7
Same area = 1 (when at NC coast, usually vacation in the same township or locality)	386 (484)	79.7
Same house = 1 (when at NC coast, rent same house each vacation)	150 (484)	31.0

[a]The categories ‘employed’ and ‘retired’ do not sum to 100, as 2 percent of respondents indicated they were unemployed seeking work.

Table 3. Summary of question responses when a wind turbine viewshed was accompanied by a price increase or no price discount

Rental price change	**# of choice questions**	**# of times option was ranked highest (%)**	**Individuals ranking the option first (% of sample)**
+ 5 percent	913	36 (3.8%)	28 (6.1%)
No price change	1,080	76 (7.0%)	61 (13.3%)
Total[a]	1,849	112 (5.6%)	77 (16.8%)

[a]Total includes all questions containing a view of turbines paired with price a price increase or no change. Total for number of choice questions is less than the sum of individual categories because a price increase could be paired with an option having no change in price, with both having visible turbines.

Table 4. Summary of latent classes by choices and characteristics

Panel A: Number of Individuals in Each Category

Frequency a turbine view is most preferred	*All View* (LC1)	*Some View* (LC2)	*Never View* (LC3)	Total
Always	26	4	0	30
(percent of total)	(86.7)	(13.3)	(0)	(100)
Sometimes	20	46	16	82
(percent of total)	(24.4)	(56.1)	(19.5)	(100)
Never	0	0	103	103
(percent of total)	(0)	(0)	(100)	(100)
Total	46	50	119	215
(percent)	(21.4)	(23.2)	(55.3)	(100)

Panel B: Proportion of individuals in each class by respondent characteristics[a]

	All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
Area rented			
No. Outer Banks	0.22	0.22	0.55
So. Outer Banks	0.19	0.24	0.57
So. Brunswick	0.23	0.23	0.53
Gender			
female	0.19	0.29	0.53
male	0.26	0.17	0.57
Residence			
Outside NC	0.22	0.24	0.54
NC	0.19	0.21	0.60
Retirement status			
Not retired	0.19	0.23	0.57
Retired	0.26	0.23	0.51
Annual Income:			
≤ $150,000	0.20	0.27	0.53
> $150,000	0.24	0.20	0.56

[a]Rows may not sum to one due to rounding.

Table 5. Choice model parameter estimates (nighttime treatment)

	Panel A: Preference Parameters			
	Rank Ordered Logit Model	Latent Class Model		
		All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
5miles×64 turbines $(\kappa^{1,1})$	-1.588*** (0.278)	0.1047 (0.3122)	-2.707*** (0.4404)	-4.394*** (0.8709)
5miles×100 turbines $(\kappa^{1,2})$	-1.7123*** (0.327)	-0.0559 (0.2505)	-3.504*** (0.503)	-5.100*** (1.1552)
5miles×144 turbines $(\kappa^{1,3})$	-2.3700*** (0.346)	-0.6039 (0.509)	-3.482*** (0.5822)	-5.427*** (1.4598)
8miles×64 turbines $(\kappa^{2,1})$	-0.9903*** (0.220)	0.1335 (0.1716)	-0.864*** (0.3116)	-3.746*** (0.6814)
8miles×100 turbines $(\kappa^{2,2})$	-0.6511*** (0.203)	0.1549 (0.1647)	-0.617*** (0.2248)	-3.262*** (0.6548)
8miles×144 turbines $(\kappa^{2,3})$	-1.5469*** (0.285)	0.5942** (0.2625)	-3.058*** (0.451)	-4.691*** (0.7671)
12miles×64 turbines $(\kappa^{3,1})$	-0.9557*** (0.210)	0.1812 (0.1916)	-0.570*** (0.1543)	-3.720*** (0.5553)
12miles×100 turbines $(\kappa^{3,2})$	-0.9544*** (0.195)	0.4131 (0.4088)	-0.462*** (0.1543)	-3.395*** (0.5956)
12miles×144 turbines $(\kappa^{3,3})$	-1.0040*** (0.209)	0.2489* (0.1523)	-0.764*** (0.2195)	-3.602*** (0.5137)
18miles×64 turbines $(\kappa^{4,1})$	-0.6537*** (0.151)	0.2334 (0.3804)	-0.239** (0.1007)	-2.848*** (0.1749)
18miles×100 turbines $(\kappa^{4,2})$	-0.3956** (0.178)	0.1552 (0.1003)	0.1059 (0.3804)	-3.151*** (0.215)
18miles×144 turbines $(\kappa^{4,3})$	-0.4222** (0.165)	0.1213 (0.1834)	0.0758 (0.5752)	-2.903*** (0.1834)
5miles×oceanfront (η^{1})	-1.0184** (0.457)	-0.5915 (0.393)	-0.6048 (0.5183)	-1.198 (0.9287)
8miles×oceanfront (η^{2})	-0.8319*** (0.320)	-0.2414 (0.2316)	-0.225 (0.3087)	-1.257* (0.7289)
12miles×oceanfront (η^{3})	-0.4338 (0.281)	-0.0395 (0.205)	0.0352 (0.2402)	-0.819 (0.7313)
18miles×oceanfront (η^{4})	-0.2805 (0.215)	-0.1842 (0.2427)	-0.0369 (0.2015)	-0.4052 (0.7269)
Price (β)	-0.0006*** (0.0001)	-0.0029*** (0.0008)	-0.001*** (0.0002)	-0.0004** (0.0002)

Table 5 continued

	Rank Ordered Logit Model	Latent Class Model		
		All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
Panel B: Active Covariates				
Environmental Factor	NA	0.6724*** (0.1762)	-0.1747 (0.1319)	-0.4977*** (0.1459)
Public Factor	NA	0.8143*** (0.1755)	0.1309 (0.1549)	-0.9452*** (0.1541)
Panel C: Scale Classes				
			Estimate	Class size
		Scale 1 ($\ln\lambda_1$)	0	0.526
		Scale 2 ($\ln\lambda_2$)	1.484*** (0.210)	0.474

Table 6. Marginal willingness to accept estimates in rental discounts for moving turbines closer to shore (nighttime treatment)[a]

	All View (LC1)			*Some View* (LC2)			*Never View* (LC3)		
# Visible Turbines:	64	100	144	64	100	144	64	100	144
Panel A: Oceanfront Sample[b]									
Turbines 30 → 5 mi.	$168	$223	$412*	$3,313***	$4,109***	$4,087***	$13,982***	$15,750***	$16,567***
Turbines 30 → 18 mi.	-$17	$10	$22	$277*	-$69	-$39	$8,133***	$8,890***	$8,272***
Turbines 18 → 12 mi.	-$32	-$139	-$94	$259*	$496	$768***	$3,218***	$1,648	$2,782***
Turbines 12 → 8 mi.	$86	$159	-$49	$554***	$415*	$2,554***	$1,159	$762	$3,817***
Turbines 8 → 5 mi.	$131	$193**	$534**	$2,224***	$3,267***	$804	$1,473	$4,450***	$1,695
Panel B: Non-Oceanfront Sample[b]									
Turbines 30 → 5 mi.	-$36	$19	$208	$2,708***	$3,504***	$3,483***	$10,985***	$12,752***	$13,570***
Turbines 30 → 18 mi.	-$80	-$54	-$42	$240**	-$106	-$76	$7,120***	$7,877***	$7,259***
Turbines 18 → 12 mi.	$18	-$89	-$44	$331***	$568*	$841***	$2,181***	$612*	$1,746**
Turbines 12 → 8 mi.	$16	$89	-$119	$294	$155	$2,294***	$64	-$333	$2,722*
Turbines 8 → 5 mi.	$10	$73	$413*	$1,844***	$2,887***	$424	$1,620	$4,597**	$1,842

[a]MWTA for latent class q for a change from distance d and visible turbine count l to distance e and visible turbine count m is

$MWTA^{q}_{d,l\rightarrow e,m} = -\beta_q^{-1}\left(\left(\kappa_q^{d,l} + \eta_q^{d} \times OF\right) - \left(\kappa_q^{e,m} + \eta_q^{e} \times OF\right)\right)$, where OF=0,1 for non-oceanfront or oceanfront renters, respectively. Significant levels are computed using the Krinsky and Robb (1986) procedure, where the empirical distribution is used to construct confidence intervals, and a *, **, or *** indicates that the 90, 95, and 99 percent confidence intervals do not overlap zero.

[b]Point estimates based on latent class model results presented in Table 5.

Figure 1. Example choice question

Choice 1: Imagine you are re-renting your beach house. Please rank the following scenarios with a 1, 2 and 3 in order of your preference (1= Most preferred, 3= Least preferred). Use each number only once.
Remember, 144 turbines are always built – only the number visible from shore varies across scenarios.

_____ **Scenario 1A:** 64 turbines visible at 8 miles & rent reduced by $160.

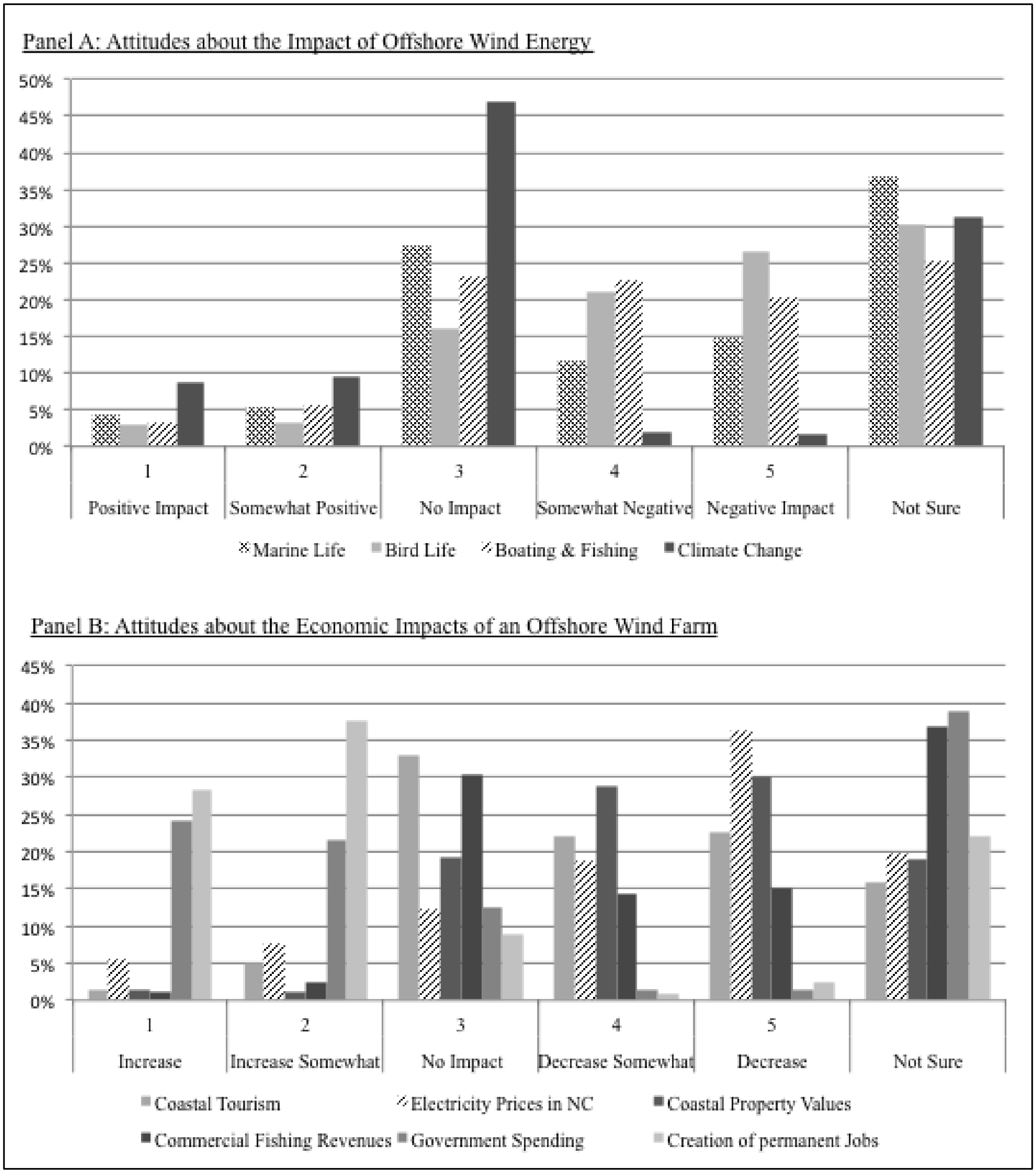
_____ **Scenario 1B:** 100 turbines visible at 5 miles & rent reduced by $620.

_____ **Baseline view:** No turbines are visible from shore & no rent change.

Scenario 1A: This view from the beach closest to your house & a **$160** **reduction in rent**

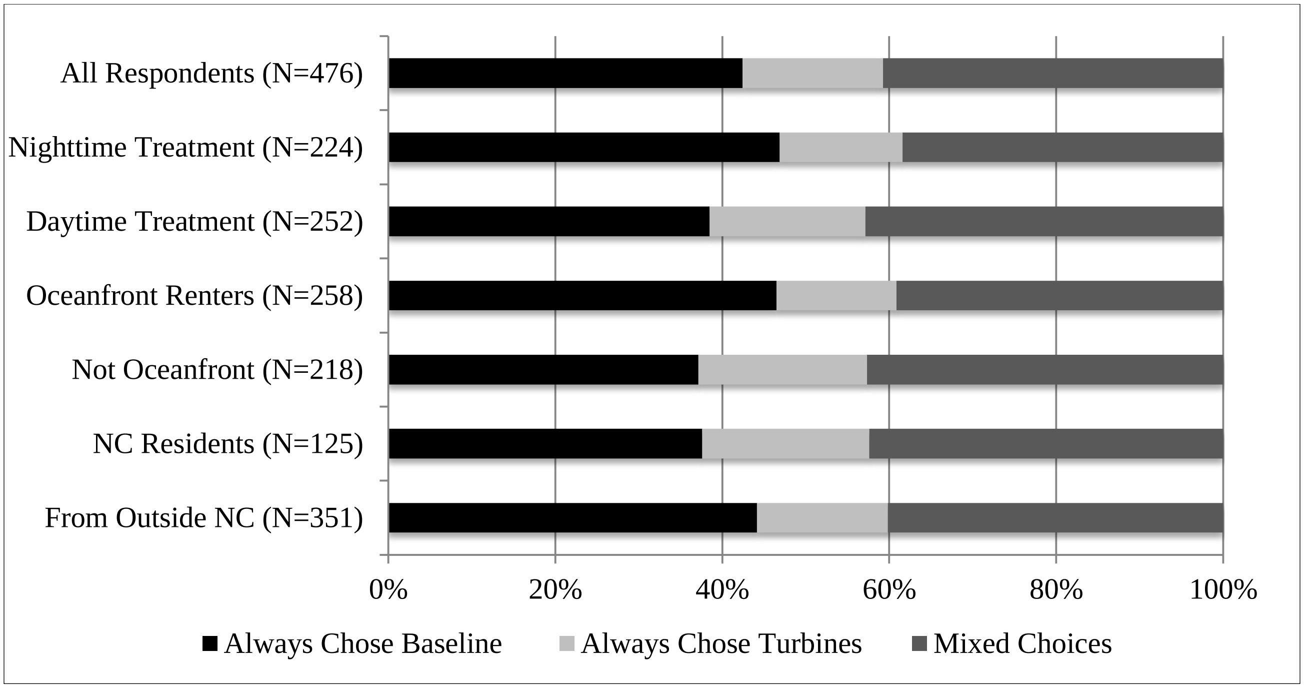
Scenario 1B: This view from the beach closest to your house & a **$620** **reduction in rent**

Figure 2. Respondents' Attitudes Towards Wind Energy[a]



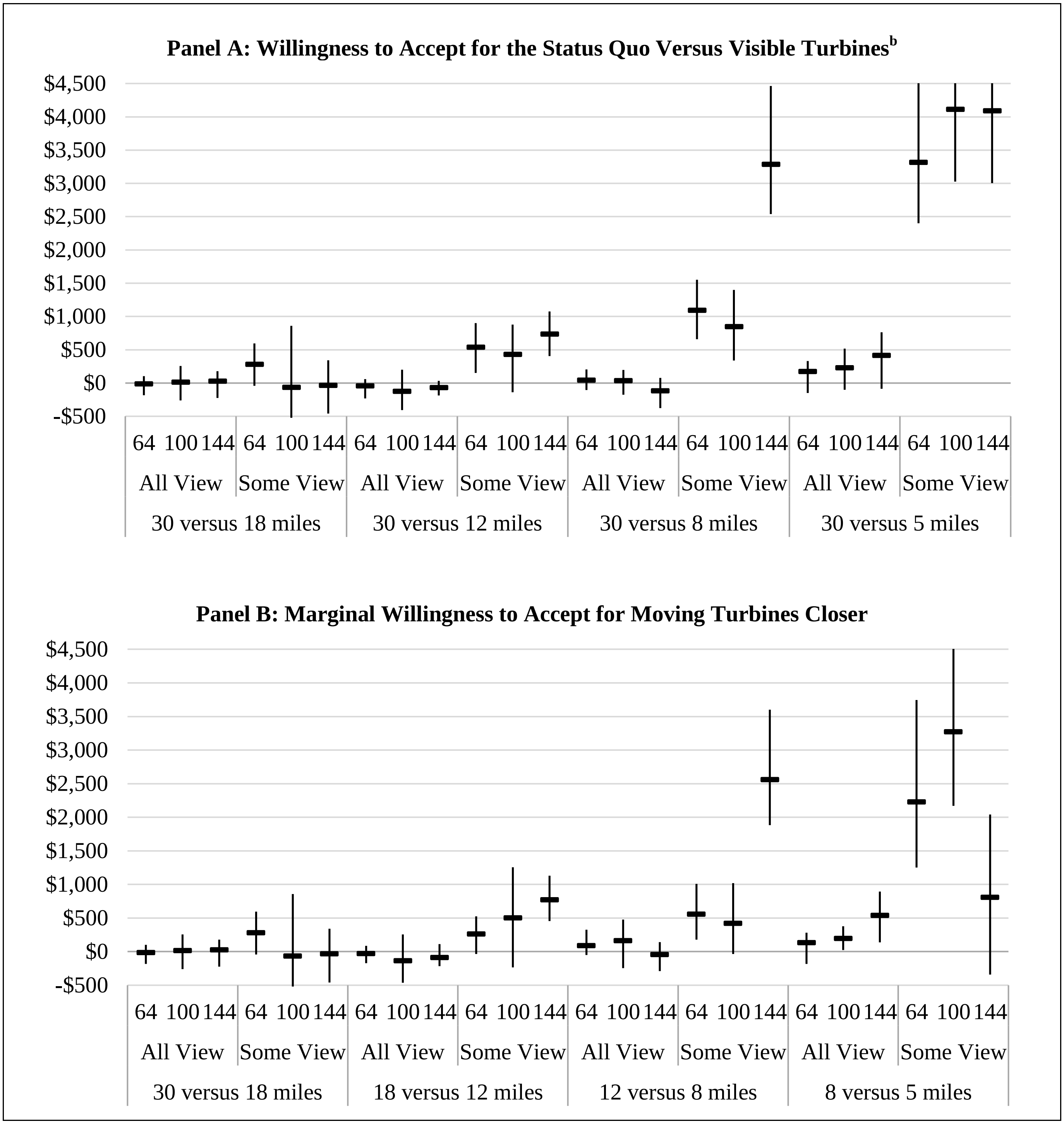
[a]Between 473 and 478 respondents answered each question. Bar heights represent the proportion of respondents choosing each point on the 1 to 5 Likert scale indicated on the horizontal axis in each panel.

Figure 3. Percent of Respondents Who Always/Never/Sometimes Chose the Baseline Scenario as the Most Preferred Option[a]



[a]Total number of respondents by category are given in parentheses.

Figure 4. Willingness to accept (in rental discounts) to move turbines closer to shore, by number of turbines visible, for oceanfront renters in the nighttime treatment and *All View* and *Some View* classes.[a]



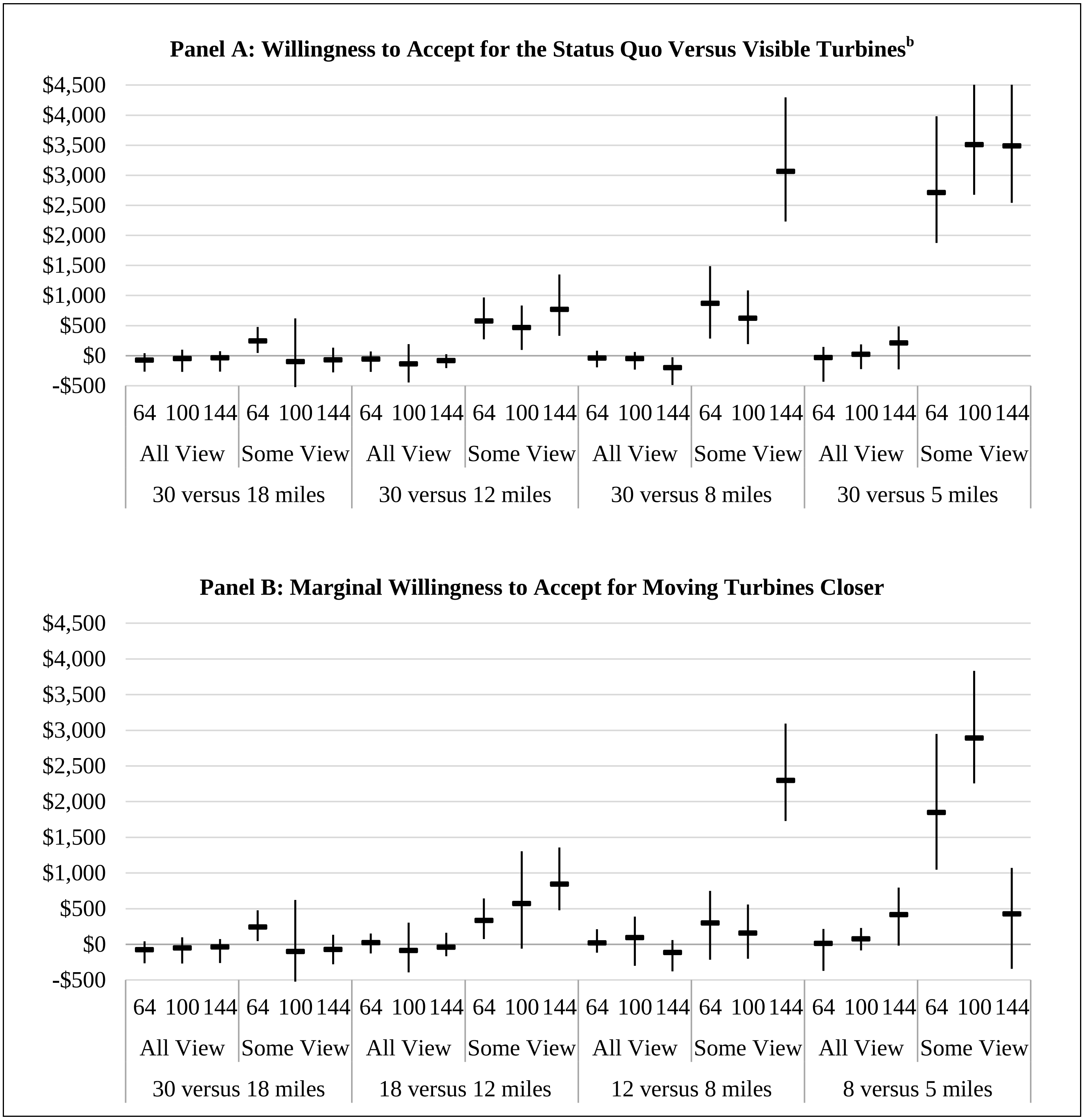
[a]Point estimates are based on ratios of parameters shown in Table 5. The MWTA for latent class q for a change from distance d to distance e for a given number of visible turbines l is

$$MWTA^{q}_{d,l\rightarrow e,m} = -\beta_q^{-1}\left(\left(\kappa_q^{d,l} + \eta_q^{d} \times OF\right) - \left(\kappa_q^{e,m} + \eta_q^{e} \times OF\right)\right),$$

where *OF*=1 indicates an oceanfront property. Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where the 2.5th and 97.5th percentiles of the empirical distribution are used to construct 95 percent confidence intervals.

[b]Upper bound confidence intervals are not shown for the *Some View* class' willingness to accept to move turbines from 30 to 5 miles in order to keep the figure scaled appropriately for other comparisons. The upper-bound of the 95% confidence interval is $4,818, $5,761 and $5,763 for 64, 100 and 144 turbines, respectively.

Figure 5. Willingness to accept (in rental discounts) to move turbines closer to shore, by number of turbines visible, for non-oceanfront renters in the nighttime treatment and *All View* and *Some View* classes.[a]



[a]Point estimates are based on ratios of parameters shown in Table 5. The MWTA for latent class q for a change from distance d to distance e for a given number of visible turbines l is

$$MWTA^{q}_{d,l\rightarrow e,m} = -\beta_q^{-1}\left(\kappa_q^{d,l} - \kappa_q^{e,m}\right),$$

Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where the 2.5th and 97.5th percentiles of the empirical distribution are used to construct 95 percent confidence intervals.

[b]Upper bound confidence intervals are not shown for the *Some View* class' willingness to accept to move turbines from 8 to 5 miles in order to keep the figure scaled appropriately for other comparisons. The upper-bound of the 95% confidence interval is $4,706 and $4,681 for 100 and 144 turbines, respectively.

APPENDIX

Table 1A. Likert scale questions and factor loadings[a]

	Factor 1[b] "Environmental Factor"	Factor 2[b] "Public Factor"
Effect on…(*positive, no impact, negative impact*)		
Marine life	0.7524	-0.0212
Bird life	0.6062	0.1005
Recreational boating & fishing	0.7996	-0.12
Climate change	0.1561	0.0842
Effect on…(*increase, no impact, decrease*)		
Coastal tourism	0.6289	0.3794
Creation of permanent jobs	0.1826	0.5706
Electricity prices in NC	0.1213	-0.7293
Coastal property values	0.602	0.4115
Commercial fishing revenues	0.7296	0.0675
Government spending	-0.1529	-0.4435

[a]Factor loadings computed using principle components analysis with varimax rotation, conducted using the *factor* command in Stata. Two factors were retained based on a Cattell (1966) scree plot (see Lutzeyer, 2013, p. 213). Factor variables for inclusion in the latent class specification were computed for each respondent based on linear combinations of the factor loadings and respondents' Likert scale answers.

[b]Factor loadings reflect correlations between individuals' Likert scale answers and the constructed variables. For example, the perceived impact on marine life has correlation with the Factor 1 variable of 0.75, and the perceived impact on electricity prices has correlation with the Factor 2 variable of −0.73. Since Factor 1 is correlated with perceptions of wind farms related to environmental outcomes, we refer to it as the 'environmental factor'. Likewise, since Factor 2 is correlated with perception of wind farms related to fiscal and economic outcomes, we refer to it as the 'public factor'.

Table 2A. Information criteria values of estimated models[a,b]

Classes	Log Likelihood	BIC	AIC	AIC3	CAIC	Parameters	R^2
Nighttime Treatment							
Preference heterogeneity and covariates							
2	-1638.8	3476.3	3351.5	3388.5	3513.3	37	0.54
3	-1413.7	3133.5	2941.3	2998.3	3190.5	57	0.69
4	-1366.0	3145.5	2886.0	2963.0	3222.5	77	0.72
5	-1318.0	3157.0	2830.1	2927.1	3254.0	97	0.73
Preference- and two scale heterogeneity and covariates							
2	-1522.8	3255.1	3123.7	3162.7	3294.1	39	0.61
3	-1369.8	3056.4	2857.6	2916.6	3115.4	59	0.73
4	-1318.0	3060.2	2793.9	2872.9	3139.2	79	0.74
5	-1271.4	3074.5	2740.8	2839.8	3173.5	99	0.76
Preference- and two scale heterogeneity							
2	-1647.0	3494.3	3368.0	3405.0	3531.3	37	0.61
3	-1493.7	3285.0	3097.4	3152.4	3340.0	55	0.72
4	-1442.8	3280.6	3031.6	3104.6	3353.6	73	0.73
5	-1398.0	3288.4	2977.9	3068.9	3379.4	91	0.75
Daytime Treatment							
Preference heterogeneity and covariates							
2	-2079.3	4361.8	4232.5	4269.5	4398.8	37	0.55
3	-1839.9	3992.9	3793.8	3850.8	4049.9	57	0.66
4	-1754.1	3931.1	3662.2	3739.2	4008.1	77	0.69
5	-1692.1	3917.0	3578.1	3675.1	4014.0	97	0.72
Preference and two scale heterogeneity and covariates							
2	-1968.3	4150.8	4014.5	4053.5	4189.8	39	0.59
3	-1756.1	3836.3	3630.2	3689.2	3895.3	59	0.69
4	-1693.6	3821.2	3545.3	3624.3	3900.2	79	0.72
5	-1635.3	3814.4	3468.6	3567.6	3913.4	99	0.76
Preference- and two scale heterogeneity							
2	-2062.3	4329.3	4198.7	4235.7	4366.3	37	0.5897
3	-1850.1	4004.2	3810.1	3865.1	4059.2	55	0.6949
4	-1787.4	3978.4	3720.8	3793.8	4051.4	73	0.7161
5	-1726.1	3955.4	3634.2	3725.2	4046.4	91	0.7351

[a]Information criteria (IC) include Bayesian (BIC), Akaike (AIC), Akaike-3 (AIC3), and corrected-AIC (CAIC). Values are presented for models that only include preference heterogeneity, and preference and scale heterogeneity, distinguished by treatment. For both treatments, including preference and scale heterogeneity with active covariates leads to the lower (preferred) IC values for any number of preference classes.

[b]For models that include scale and preference heterogeneity with covariates, BIC and CAIC criteria indicate 3 latent classes are preferred for the nighttime treatment, while a higher number is preferred based on AIC and AIC3 measures. For the daytime treatment, the criteria generally decrease with additional classes. However,

for both treatments, we found that models with four or more classes are not robust to starting values, while three class models are always robust. Based on (a) the BIC and CAIC tests for the nighttime treatment; (b) the numerical instability of models with more than 3 classes; and (c) our goal of representing heterogeneity in an intuitive and interpretable way, we settled on 3 latent preferences classes as our preferred specification. Additional details on the iterative process used to evaluate different class structures is given in Lutzeyer (2013, pp. 140-141).

Table 3A. Summary of latent classes by choices and characteristics (daytime treatment)

Panel A: Number of Individuals in Each Category

Frequency a turbine view is most preferred	*All View* (LC1)	*Some View* (LC2)	*Never View* (LC3)	Total
Always	41	3	0	44
(percent of total)	(93.18)	(6.82)	(0)	(100)
Sometimes	24	63	19	106
(percent of total)	(22.64)	(59.43)	(17.92)	(100)
Never	0	0	93	93
(percent of total)	(0)	(0)	(100)	(100)
Total	65	66	112	243
(percent)	(26.75)	(27.16)	(46.10)	(100)

Panel B: Proportion of individuals in each class by respondent characteristics[a]

	All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
Area rented			
No. Outer Banks	0.26	0.29	0.46
So. Outer Banks	0.27	0.25	0.48
So. Brunswick	0.27	0.27	0.46
Gender			
female	0.28	0.27	0.44
male	0.27	0.26	0.47
Residence			
Outside NC	0.25	0.26	0.49
NC	0.33	0.31	0.36
Retirement status			
Not retired	0.25	0.26	0.49
Retired	0.32	0.31	0.37
Annual Income:			
≤ $150,000	0.30	0.28	0.43
> $150,000	0.25	0.25	0.50

[a]Rows may not sum to one due to rounding.

Table 4A. Choice model parameter estimates (daytime treatment)

	Panel A: Preference Parameters			
	Rank Ordered Logit Model	Latent Class Model		
		All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
5miles×64 turbines ($\kappa^{1,1}$)	-1.3774*** (0.2682)	-0.1483 (0.2259)	-1.795*** (0.2739)	-5.897*** (1.0458)
5miles×100 turbines ($\kappa^{1,2}$)	-1.6793*** (0.264)	-0.2974 (0.1948)	-2.478*** (0.3337)	-6.281*** (1.0355)
5miles×144 turbines ($\kappa^{1,3}$)	-2.1445*** (0.2822)	-0.4099* (0.2157)	-3.378*** (0.4968)	-6.558*** (1.0381)
8miles×64 turbines ($\kappa^{2,1}$)	-0.9804*** (0.1919)	0.0147 (0.118)	-0.9544*** (0.2942)	-5.722*** (1.0116)
8miles×100 turbines ($\kappa^{2,2}$)	-0.9063*** (0.194)	-0.1555 (0.1222)	-0.8999*** (0.2104)	-5.510*** (1.0412)
8miles×144 turbines ($\kappa^{2,3}$)	-1.4941*** (0.221)	-0.167 (0.1856)	-1.824*** (0.3737)	-5.955*** (1.0474)
12miles×64 turbines ($\kappa^{3,1}$)	-0.9317*** (0.2129)	0.0768 (0.1269)	-0.8909** (0.3958)	-4.897*** (1.0449)
12miles×100 turbines ($\kappa^{3,2}$)	-0.8279*** (0.1938)	0.1352 (0.1427)	-0.6412*** (0.2126)	-5.012*** (1.0278)
12miles×144 turbines ($\kappa^{3,3}$)	-0.7299*** (0.1817)	0.0539 (0.1254)	-1.006*** (0.2775)	-5.133*** (0.9752)
18miles×64 turbines ($\kappa^{4,1}$)	-0.3905*** (0.1441)	0.0354 (0.102)	-0.3371** (0.1399)	-3.925*** (1.0362)
18miles×100 turbines ($\kappa^{4,2}$)	-0.3512** (0.138)	0.014 (0.1163)	-0.1839 (0.1274)	-4.226*** (0.9859)
18miles×144 turbines ($\kappa^{4,3}$)	-0.4434*** (0.1472)	0.0977 (0.1084)	-0.26** (0.1161)	-4.131*** (1.0659)
5miles×oceanfront (η^{1})	-0.4761 (0.3844)	0.1131 (0.2494)	-0.3026 (0.4981)	1.622 (1.1273)
8miles×oceanfront (η^{2})	-0.2609 (0.2783)	0.1097 (0.1562)	-0.0921 (0.2668)	2.034 (1.1172)
12miles×oceanfront (η^{3})	0.0151 (0.2573)	0.0833 (0.171)	0.3862 (0.2653)	2.155 (1.0844)
18miles×oceanfront (η^{4})	-0.0291 (0.1834)	-0.0812 (0.1126)	0.1465 (0.1223)	1.987 (1.072)
Price (β)	-0.0007*** (0.0001)	-0.0024*** (0.0004)	-0.0017*** (0.0002)	-0.0005*** (0.0001)

Table 4A continued

	Panel B: Active Covariates			
	Rank Ordered Logit Model	Latent Class Model		
		All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
Environmental Factor	NA	0.5603*** (0.1739)	0.0472 (0.1340)	-0.6075*** (0.1455)
Public Factor	NA	0.2920** (0.1368)	0.2180* (0.1180)	-0.5100*** (0.1215)
	Panel C: Scale Classes			
			Estimate	Class size
		Scale 1 ($\ln\lambda_1$)	0	0.543
		Scale 2 ($\ln\lambda_2$)	1.697*** (0.1926)	0.457

Table 5A. Marginal willingness to accept estimates in rental discounts for moving turbines closer to shore (daytime treatment)[a]

	All View (LC1)			*Some View* (LC2)			*Never View* (LC3)		
# Visible Turbines:	64	100	144	64	100	144	64	100	144
Oceanfront Sample[b]									
Turbines 30 → 5 mi.	\$15	\$77	\$124	\$1,234***	\$1,636***	\$2,165***	\$8,550***	\$9,318***	\$9,873***
Turbines 30 → 18 mi.	\$19	\$28	-\$7	\$112*	\$22	\$67	\$3,876***	\$4,479***	\$4,289***
Turbines 18 → 12 mi.	-\$86*	-\$119	-\$50	\$185	\$128	\$298***	\$1,608***	\$1,235***	\$1,668***
Turbines 12 → 8 mi.	\$15	\$110	\$81	\$319*	\$434***	\$762**	\$1,892***	\$1,238**	\$1,886***
Turbines 8 → 5 mi.	\$67	\$58	\$100	\$619**	\$1,052***	\$1,038***	\$1,174**	\$2,366***	\$2,030***
Non-oceanfront Sample[b]									
Turbines 30 → 5 mi.	\$62	\$124	\$171*	\$1,056***	\$1,458***	\$1,987***	\$11,794***	\$12,562***	\$13,117***
Turbines 30 → 18 mi.	-\$15	-\$6	\$41	\$198**	\$108	\$153**	\$7,851***	\$8,453***	\$8,246***
Turbines 18 → 12 mi.	-\$17	-\$51	\$18	\$326	\$269***	\$439***	\$1,944***	\$1,571***	\$2,004***
Turbines 12 → 8 mi.	\$26	\$121*	\$92	\$37	\$152	\$481*	\$1,650***	\$996**	\$1,644***
Turbines 8 → 5 mi.	\$68	\$59	\$101	\$495**	\$928***	\$914***	\$349	\$1,541***	\$1,205**

[a]MWTA for latent class *q* for a change from distance *d* and visible turbine count *l* to distance *e* and visible turbine count *m* is

$MWTA^{q}_{d,l\to e,m} = -\beta_q^{-1}\left(\left(\kappa_q^{d,l} + \eta_q^{d} \times OF\right) - \left(\kappa_q^{e,m} + \eta_q^{e} \times OF\right)\right)$, where OF=0,1 for non-oceanfront or oceanfront renters, respectively. Significant levels are computed using the Krinsky and Robb (1986) procedure, where the empirical distribution is used to construct confidence intervals, and a *, **, or *** indicates that the 90, 95, and 99 percent confidence intervals do not overlap zero.

[b]Point estimates based on latent class model results presented in Table 4A.