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 five percent or more are possible if a utility-scale wind farm is placed within eight miles of shore.

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

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[1] *Lutzeyer:* McKinsey and Company, Johannesburg, South Africa and Center for Environmental and Resource Economic Policy, North Carolina State University, slutzey@ncsu.edu. *Phaneuf:* Department of Agricultural and Applied Economics, University of Wisconsin, dphaneuf@wisc.edu. *Taylor*: Center for Environmental and Resource Economic Policy, North Carolina State University, laura_taylor@ncsu.edu. We thank Kevin Boyle, Bob Koger, Roger von Haefen, Brian O'Hara, John Rose, and Marty Smith for helpful comments throughout this project. We also thank S Suda Thao for excellent assistance with survey administration and coding.

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

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[2] U.S. 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 July 30, 2015.

[3] Eileen McNamara, "What Really Toppled Cape Wind's Plans for Nantucket Sound," January 30, 2015, accessed August 5, 2015, 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 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 five 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 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, and find little sensitivity to the presence of wind farms. Their results may be because the majority of study participants received no visual images of offshore turbines when answering the survey. 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.[4] 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).[5] 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 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 novel features. First, the sample for our choice experiment consists of known beach house users. 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 includes a treatment in which respondents are shown both daytime *and* nighttime images of wind turbines, which provides an important perspective absent in earlier

[4] 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.

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

work. Also, 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.

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 debate.[6] In this regard, our study area is representative of other regions 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 eight miles from shore (20 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 54 percent of existing

[6] For example, the coastal town of Kitty Hawk, NC, which is located in an area where BOEM had identified turbines could be placed as close as 5-6 miles from shore, passed a resolution opposing BOEM allowing turbines to be placed closer than 20 miles from its shoreline.

customers would change their vacation location if wind turbines were placed offshore. Lastly, in a related context, less than half of respondents reported they would drive thirty minutes to see an offshore wind farm. This indicates that wind farms are not likely to be a draw for daytrip tourism, given the distance of NC beaches from major population areas.

These findings have several policy implications. First, we find that placement of turbines further out to sea to eliminate their negative visual impacts could very well pass a benefit-cost test. We find that the welfare gains of moving wind farms as little as three miles further from shore (from five to eight miles) can outweigh the increased capital costs of doing so for an area with as few as 1,000 rental homes (200 oceanfront, 800 non-oceanfront).[7] Since no actual proposals exist in our study area, our cost estimates are speculative and we only consider the capital costs of increased cabling, holding constant the cost of constructing the individual turbines. 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. With the exception of distances of five miles or less, images showing more than double the number of turbines did not result in statistically significant changes in demand. This fact, combined with our finding that the negative effects of any size turbine array diminish rapidly once placed more than eight 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 eight miles from shore.

[7] 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 ocean-side homes. We conservatively assume these to be the "impacted" homes since the leading edge of our turbine array has twelve turbines, and thus creates a 5.5 mile wide facing edge for the wind farm as seen 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.[8] 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 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

[8] 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.

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 of 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.[9] 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 five-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 ranges for the size and location of potential offshore wind farms in the eastern US.[10] In

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[9] 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.

[10] 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).

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.[11]

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 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 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

[11] Visualizations from the public forums are available at www.boem.gov/Renewable-Energy-Program/State-Activities/NC/003-Kitty-Hawk-Afternoon.aspx. Last accessed June 2015.

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 three 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 visited. Specifically, people were asked to interpret the visualizations as the view that they would have when standing on the beach, after walking 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 unit. 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).[12] Though we used percentage change in our 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 typical range along the NC coast during peak summer season.[13]

Figure 1 shows an example choice question. Each choice task paired two designed alternatives with a status quo or 'baseline' option. The baseline included 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

[12] 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).

[13] 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.

energy production. The designed scenarios paired visible wind turbines with rental price changes. Subjects were asked to rank each alternative from best to worst, which is equivalent to a best-worst scaling design when there are only three alternatives (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 (Hensher et al., 2005) was used to construct the choice tasks presented to respondents. The final main effects and interactions 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 also 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.[14]

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 62.27 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 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,

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

however, 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.[15] 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 1A in the appendix 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, in which 47 percent of respondents answered there would be no impact.[16] 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 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

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

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

decline at least somewhat (44 and 58 percent, respectively).

Choice question summary

Figure 2 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.[17] 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 2 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 for oceanfront home renters (47 percent), and those renting non-oceanfront homes (37 percent).

Figure 2 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 2 also indicates that 41 percent of respondents selected status quo and visible turbine options at

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

some point in their sequence of choices (the 'Mixed Choices' category in Figure 2), 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, and no change in rental price or a five 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.[18]

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 individual and the choice alternative. The index q denotes membership in one of q=1,…,Q preference classes, and the index s denotes 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 $\lambda_1=1$, 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

[18] 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).

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 membership is therefore latent, and needs 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 a vector of individual covariates (referred to as 'active covariates'), and $\theta_q=(\theta_{q1},\ldots\theta_{qR})$ is a vector of coefficients that is compatible with Z_n. For identification we use the common restrictions

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

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

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

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

$$\sum_{s=1}^{S} \gamma_{s0} = 0, \qquad \sum_{s=1}^{S} \gamma_{sr} = 0, \quad r = 1,\ldots,R. \tag{6}$$

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:

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

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

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

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

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

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 4.5.[19]

[19] 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.

The estimation routine just described is 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.

5) Estimation and Results

Specification

The conditional utility function specification we use is

$$\begin{aligned} U_{njc|q,s} = &\sum_{d=1}^{4}\omega_q^d dist_{njc}^d + \sum_{l=1}^{3}\phi_q^l size_{njc}^l + \sum_{d=1}^{4}\sum_{l=1}^{3}\kappa_q^{d,l} dist_{njc}^d \times size_{njc}^l + \sum_{d=1}^{4}\eta_q^d dist_{njc}^d \times OF_n \\ &+ \beta_q p_{njc} + \delta_q ASC_j + \alpha_q ASC_j \times OF_n + \varepsilon_{njc|q,s}, \end{aligned} \tag{10}$$

where *dist* and *size* denote the distance from shore and visible turbine attribute values. Specifically, $dist_{njc}^d$ and $size_{njc}^l$ are effects-coded discrete variables indicating the attribute levels presented to person n for alternative j on choice task c. In addition, 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). The term ASC_j is a dummy variable equal to one if alternative j is a turbines-visible designed option and equal to zero if the alternative is the baseline with no turbines in view and no change in rental price, which is commonly referred to as the alternative-specific constant, or ASC. Finally, OF_n is a dummy variable equal to one if the person rented an oceanfront home.

For each preference class q, we are interested in estimating the attribute main effects $(\omega_q^d, \phi_q^l, \beta_q)$, attribute interactions effects $(\kappa_q^{d,l}, \eta_q^d)$, the ASC parameter δ_q for options with viewable turbines, and a term α_q that shifts the ASC if the person rented an oceanfront property.[20] Identification of effects-coded variables requires normalization; we follow convention and use

$$\begin{aligned} &\sum_{d=1}^{4} \omega_q^d = 0, \quad \sum_{l=1}^{3} \phi_q^l = 0, \quad \sum_{d=1}^{4} \eta_q^d = 0, \\ &\sum_{l=1}^{3} \kappa_q^{d,l} = 0, \quad d = 1,\ldots,4. \end{aligned} \tag{11}$$

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 1A). Specifically, we use factor analysis to reduce the

[20] We arrived at this specification via a systematic process of starting with the simplest models and gradually adding additional complexity. Comparison of a conditional logit model with main effects and a conditional logit model with main effects and interactions confirmed that interactions were important for both our daytime and nighttime treatments. Staying with the conditional logit model, we then examined observable preference heterogeneity via interactions between the main effects and ASC, 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 visible turbines than non-oceanfront renters. Since the simple models suggested the important 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 (2012, pp. 184-188).

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 preference class membership, and do not use active covariates for the scale class membership.[21]

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 primary nighttime treatment

[21] 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 (2012, pp. 135-138).

model.[22] We first describe the general composition and choice behavior of respondents in each latent class. Individuals are assigned to one of the three classes based on their largest class 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 17 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 54.4 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 not statistically different across the different socioeconomic profiles. This confirms that class membership is generally determined by unobserved preferences, rather than observable individual characteristics.

The utility function parameter estimates are presented in Table 5. Panel A presents estimates of the utility parameters for each class. The first two columns show that only the price coefficient and turbine distance main effects for 5, 8, and 12 miles from shore are significant for

[22] The latent class models and membership probabilities are very 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 Appendix Tables A3 and A4 and are briefly described in the next section.

the *All View* class. The distance main effects indicate that utility increases monotonically when visible turbines are moved further offshore, out to 12 miles. For this class, the number of turbines does not influence choice, and there is no utility gained when visible turbines are moved from 12 to 18 miles offshore. Finally, the price coefficient for the *All View* class is an order of magnitude larger than for the other two classes, suggesting members of this latent class are the most price conscious respondents.[23]

The last two columns of Table 5 contain estimates for the *Never View* class. The estimate for the ASC is large, negative, and significant, which stands in dramatic contrast to the ASC estimate for the *All View* class. This implies a strong preference for the status quo with no visible turbines, and a large disutility associated with the choice of any designed scenario. 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. Importantly for our interpretations, it also means that utility function parameters for the array size and distance attributes for this latent class are estimated from respondents' rankings of non-preferred options (i.e. their second and third place choices), an important point we return to when describing welfare measure results in the next section. Nonetheless, several of the size and distance main effects and interactions are statistically significant for the *Never View* class. For a given windfarm size, utility increases monotonically in the distance of visible

[23] 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.

turbines from shore. Similarly, for a given distance from shore, utility is decreasing in the size of the windfarm. The results also indicate that the oceanfront location impacts preferences, in that respondents who rented an oceanfront property generally have a stronger preference for moving wind farms further offshore. The exception is for turbines placed five miles out, for which the disutility is not statistically different among oceanfront and non-oceanfront renters.

Table 5 also shows that the ASC for the *Some View* class negative and significant, suggesting this class also prefers a viewshed without visible turbines. However, the magnitude of the ASC suggests that preferences are more nuanced for this group, as compared to the *Never View* class. As with the other classes, *Some View* respondents have a clear preference for moving visible turbines further offshore, and they prefer smaller farms. The negative and significant estimate on the interaction term *5miles*×*oceanfront* indicates that the disutility from close-in wind farms is larger for oceanfront renters in the *Some View* class, relative to those who rented further inland. Moreover, the negative and significant interaction between the ASC and an oceanfront location suggests that respondents in this class who had rented an oceanfront property are less likely to choose a designed scenario as their most preferred scenario as compared to non-oceanfront renters.

Finally, panels B and C in Table 5 show estimates for the 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. Only the environmental factor was significant in determining class assignment for the *Some View* class, where the estimate indicates that respondents who believe offshore wind energy would have positive environmental impacts are somewhat less likely to be in 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 relative scale parameter is significantly smaller for respondents in the second scale class (SC2), indicating that they have a higher 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 parameter estimates from Table 5 to compute point estimates and 90 percent confidence intervals for the marginal willingness to accept (MWTA) among the three preference classes for a range of changes in viewsheds.[24] In what follows we first summarize estimates for the nighttime treatment as our main findings, and then discuss comparisons with the daytime treatment below. Figures 3 and 4 present our estimates for the nighttime treatment respondents who either rented oceanfront or non-oceanfront (‘ocean side’) homes, respectively. The figures show the price discount needed to rent the same property, with visible turbines moved incrementally closer to shore (i.e., the marginal willingness to accept a price discount). Estimates for three scenarios that change turbine distance from 18 to 12 miles, 12 to 8 miles, or 8 to 5 miles, are presented by latent class and number of turbines visible.

[24] 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* to distance *e* for a given number of visible turbines *l* is

$$MWTA^{q}_{d \to e|l} = \frac{\left(\omega_q^d + \phi_q^l + \kappa_q^{d,l}\right) - \left(\omega_q^e + \phi_q^l + \kappa_q^{e,l}\right)}{-\beta_q}.$$

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, 2016, chapter 16 for a discussion of the MWTA derivation within this context). Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where the 5th and 95th percentiles of the resulting empirical distribution are used to construct 90 percent confidence intervals.

Inspection of Figures 3 and 4 reveals several patterns. First, MWTA is always positive when it is statistically significant. There are no wind farm scenarios, for any of the latent classes, in which respondents indicated they would be willing to pay *more* to rent a property with turbines in view (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 ocean side). However, the estimates for the *All View* and *Some View* classes are much more precise than the estimates for the *Never View* class. This is due to the fact that respondents in the latter category almost always selected the status quo option as their most preferred alternative, and thus there is little response to price and view changes upon which the coefficients are identified. Instead, identification comes from the respondents second and third choices, which are expected to be noisier given the strong preference for not viewing turbines.

The third pattern that emerges is that the *Never View* respondents would likely exit the rental market if turbines were present, rather than make intensive margin tradeoffs among rental price and characteristics of the viewshed. This follows from the large point estimates, wide confidence intervals, and strong preference for the status quo among this class of respondents. In contrast, the estimates suggest that the *All View* and *Some View* classes would, in some scenarios, stay in the market in exchange for small to moderate sized reductions in rent. Lastly, conditional on a preference class, the MWTA for a distance change scenarios is not statistically different across the number of visible turbines. Similarly, comparisons of Figure 3 to Figure 4 indicate that, with some exceptions, the estimates are not statistically different for oceanfront and ocean side rental locations, though the magnitude differences are often economically important. See appendix Figure 2A for a side-by-side comparison of MWTA for oceanfront and ocean side renters, for the *All View* and *Some View* preference classes.

Overall, the combined results suggest the negative visual effects lie in the existence of turbines and their distance from shore, rather than the array size. Further, they imply that the oceanfront versus ocean side (near-beach) distinction may matter, but to a lesser extent than distance. These general patterns can be further appreciated via reference to specific estimates. The figures show that the *All View* class would not require a discount for the scenarios moving turbines 18 to 12 miles or 12 to 8 miles, but nor would they pay *extra* to see turbines closer to shore. For the more intrusive case of moving turbines from 8 to 5 miles from shore, ocean side renters continue to have zero MWTA, while ocean front renters would require a small discount. For example, a discount of $300 is required for a 144 turbine array at five miles (as compared to eight miles), which is approximately six percent of the average rental price of $4,700. In contrast, there are no scenarios in which the *Never View* respondents would accept an economically plausible discount to stay in the market: the point estimates for moving 144 visible turbines from 18 to 12 miles distance from shore are close to $3,000 for both the ocean front and ocean side renters in this class. Since the *Never View* class predominantly chose the baseline view as the most preference choice, these figures indicate this group is not making choices at the intensive margin between rental price and viewshed characteristics. Instead, they are more likely to make an extensive margin decision to exit the local market by vacationing at a substitute beach town.

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. Discounts of nearly $1,500 and $500 are required for oceanfront and ocean side renters, respectively, to re-rent their unit with 144 visible turbines brought from 8 to 5 miles of shore. Given that the estimates are not sensitive to the number of visible turbines, the figures suggest oceanfront renters in the *Some View* class are likely to exit the market if any number of visible turbines were placed 5 miles from shore. In contrast, discounts in the ten percent range may be sufficient for ocean side renters to continue in the market.

For distances of eight miles or greater, smaller discounts are required for the *Some View* class to re-rent with turbines in the viewshed. For example, oceanfront renters would require an average discount centered around $500 to rent a home with 144 visible turbines 12 miles from shore, as compared to 18 miles. If the comparison is between homes with 144 turbines 8 miles from shore rather than12 miles, they would require a $900 discount to rent the home. For the 100 and 64 turbine scenarios, these point estimates fall to $250 and $400, respectively (see appendix Figure 2A).

Nighttime versus daytime treatments

The results for the daytime treatment are qualitatively similar to the nighttime treatments, and so the parallel estimates are presented appendix Tables A3 and A4. Inspection of the estimates suggests the same pattern of choices across 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. 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. Finally, the daytime treatment utility parameter estimates reveal similar patterns as their nighttime treatment counterparts. Parameter estimates again imply that turbines further offshore are preferred by all latent classes, and that smaller turbine arrays are preferred to larger arrays, although the coefficient estimates are not significant for the *All View* class.[25]

Appendix Figures 3A and 4A present MWTA estimates for the daytime treatment that are akin to those presented for the nighttime treatment in Figures 3 and 4. A comparison indicates that the MWTA estimates are generally larger for the nighttime treatment, with most substantial differences found in the *Some View* class – especially as turbines are moved closer to shore. In two of the three distance changes considered, the discounts required by the *Some View* class in the nighttime treatment were nearly twice as large as those from the daytime treatment. Although 90 percent confidence intervals for many MWTA estimates overlap, the economic differences are significant. The results suggest that past studies may have understated the potential impact of wind farms in tourism settings, since all previous surveys only consider 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

[25] The nighttime and daytime latent class and utility parameters comparisons are based on information in Tables 4 and A3 and Tables 5 and 4A, respectively.

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 beach 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.[26] Three main factors likely contribute to this result. First, 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 in a way past studies have not (e.g., Krueger et al., 2011). Second, 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. Lastly, we are the first to include nighttime images of turbines whose nacelles are lit, presented side-by-side with daytime images of the same turbines. In a split-sample design, we find that individuals react more negatively to wind farms when nighttime images are included in the survey (as compared to just a verbal description of the turbines being lit at night).

What do our results imply for actual rental prices in that event that a utility scale windfarm were constructed? The answer depends on how the different preference classes in the

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

renting population re-sort in response to a windfarm, and how far out from shore the turbines are placed. If the turbines are further than 8 miles from shore, our results suggest rental demand by one segment of the population will not be affected (the *All View* class). The other segments may exit the market, perhaps causing the rental price to fall. However, other potential renters similar to the *All 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 NC coastal rental market – will result in unchanged equilibrium prices. In this scenario, the welfare effects consist of adjustment costs to the new equilibrium: property owners may need to incur costs to attract new customers, and long-time renters will need to bear search costs when selecting an alternative vacation home.

If turbines are built closer than eight miles from shore, our results indicate that rental rates will decrease by five percent in equilibrium since a five percent discount is the average discount required by the *All View* latent class to accept a view of turbines 5 miles from shore as opposed to 8 miles from shore. Our assumption here is that demand among existing and potential *All View* renters in the local market is affected by the altered viewshed and that the overall number of affected rental homes is small relative to the overall NC market. Thus there is re-sorting among different preference classes, with *All View* renters remaining in, or sorting to, the affected area and requiring a discount to rent a home. Once again, property owners and renters will bear non-zero transactions costs during the adjustment to the new equilibrium.

From a state or national policy perspective, the welfare losses associated 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 five 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 NC beach town. A five percent reduction in rental value, and 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 price impacts for arrays further than eight miles from shore, it is unlikely that moving turbines beyond eight miles will generate net benefits from this baseline. 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 five 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 eight miles to five miles from shore are then applied to the average rental prices for these homes, and we compute the net present value of the total annual rental losses using an eight percent discount rate over 20 years.[27] Our calculations suggest estimated losses for a beach community of average development density are $31 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 $31 million. Myhr (2014) suggests that

[27] 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).

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 five to eight 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 results are likely to apply beyond North Carolina. As Bennett (2013) demonstrates, 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 repeat customers – our estimates are likely to 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 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.

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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	17	51	14	82
(percent of total)	(20.7)	(62.2)	(17.1)	(100)
Never	0	0	103	103
(percent of total)	(0)	(0)	(100)	(100)
Total	43	55	117	215
(percent)	(20.0)	(25.6)	(54.4)	(100)

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

	All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
Area rented			
No. Outer Banks	0.20	0.24	0.56
So. Outer Banks	0.19	0.27	0.55
So. Brunswick	0.21	0.26	0.52
Gender			
female	0.18	0.30	0.53
male	0.25	0.19	0.56
Residence			
Outside NC	0.21	0.26	0.53
NC	0.18	0.24	0.58
Retirement status			
Not retired	0.19	0.26	0.55
Retired	0.23	0.25	0.51
Annual Income:			
≤ \$150,000	0.18	0.28	0.54
> \$150,000	0.23	0.22	0.55

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Table 5. Final scale adjusted latent class model (nighttime treatment)

	All View (LC1)		*Some View* (LC2)		*Never View* (LC3)	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Panel A: Preference classes						
5 miles (ω^1)	-2.032**	0.878	-7.401***	1.166	-4.956***	0.911
8 miles (ω^2)	0.665**	0.337	0.345	0.431	-0.527	0.366
12 miles (ω^3)	1.049*	0.584	2.365***	0.409	1.398***	0.295
18 miles (ω^4)	0.319	0.404	4.692***	0.535	4.085***	0.776
64 turbines (ϕ^1)	-0.080	0.326	0.626**	0.307	0.612*	0.335
100 turbines (ϕ^2)	-0.020	0.411	-0.080	0.388	0.365	0.222
144 turbines (ϕ^3)	0.100	0.391	-0.546	0.369	-0.977***	0.329
5miles×64 turbines ($\kappa^{1,1}$)	0.285	0.59	1.434*	0.766	1.718**	0.839
5miles×100 turbines ($\kappa^{1,2}$)	0.226	0.856	-2.248**	0.917	-0.723	0.551
5miles×144 turbines ($\kappa^{1,3}$)	-0.511	1.079	0.814	1.265	-0.995*	0.546
8miles×64 turbines ($\kappa^{2,1}$)	-0.114	0.526	0.726*	0.420	-0.747	0.735
8miles×100 turbines ($\kappa^{2,2}$)	-0.829	0.694	1.391**	0.604	1.692***	0.641
8miles×144 turbines ($\kappa^{2,3}$)	0.943	0.863	-2.117***	0.819	-0.945	0.783
12miles×64 turbines ($\kappa^{3,1}$)	0.033	0.580	-1.25***	0.430	-0.777	0.940
12miles×100 turbines ($\kappa^{3,2}$)	-0.141	1.020	0.745*	0.438	0.195	0.565
12miles×144 turbines ($\kappa^{3,3}$)	0.108	0.772	0.506	0.391	0.582	0.635
18miles×64 turbines ($\kappa^{4,1}$)	-0.204	0.600	-0.909**	0.377	-0.193	0.438
18miles×100 turbines ($\kappa^{4,2}$)	0.744	0.868	0.112	0.398	-1.165*	0.696
18miles×144 turbines ($\kappa^{4,3}$)	-0.540	0.728	0.798	0.506	1.358**	0.586
5miles×oceanfront (η^1)	-0.716	0.761	-2.953***	1.069	-0.616	0.688
8miles×oceanfront (η^2)	0.380	0.356	0.238	0.413	-0.931***	0.341
12miles×oceanfront (η^3)	-0.174	0.467	1.044***	0.375	0.416*	0.225
18miles×oceanfront (η^4)	0.510	0.337	1.671***	0.490	1.131**	0.525
Price (β)	-0.017***	0.003	-0.006***	0.001	-0.002***	>0.001
ASC (δ)	-0.264	0.535	-5.324***	0.699	-19.336***	3.286
ASC×oceanfront (α)	-0.467	0.357	-1.699***	0.530	-2.408	1.628
Panel B: Active Covariates						
Environmental Factor	0.713***	0.181	-0.217*	0.125	-0.496***	0.133
Public Factor	0.655***	0.159	0.113	0.134	-0.768***	0.142

Panel C: Scale classes

	Est.	Std. Err.	Class size
Scale(1)	1	Fixed	0.51
Scale(2)	0.224***	0.032	0.49

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.

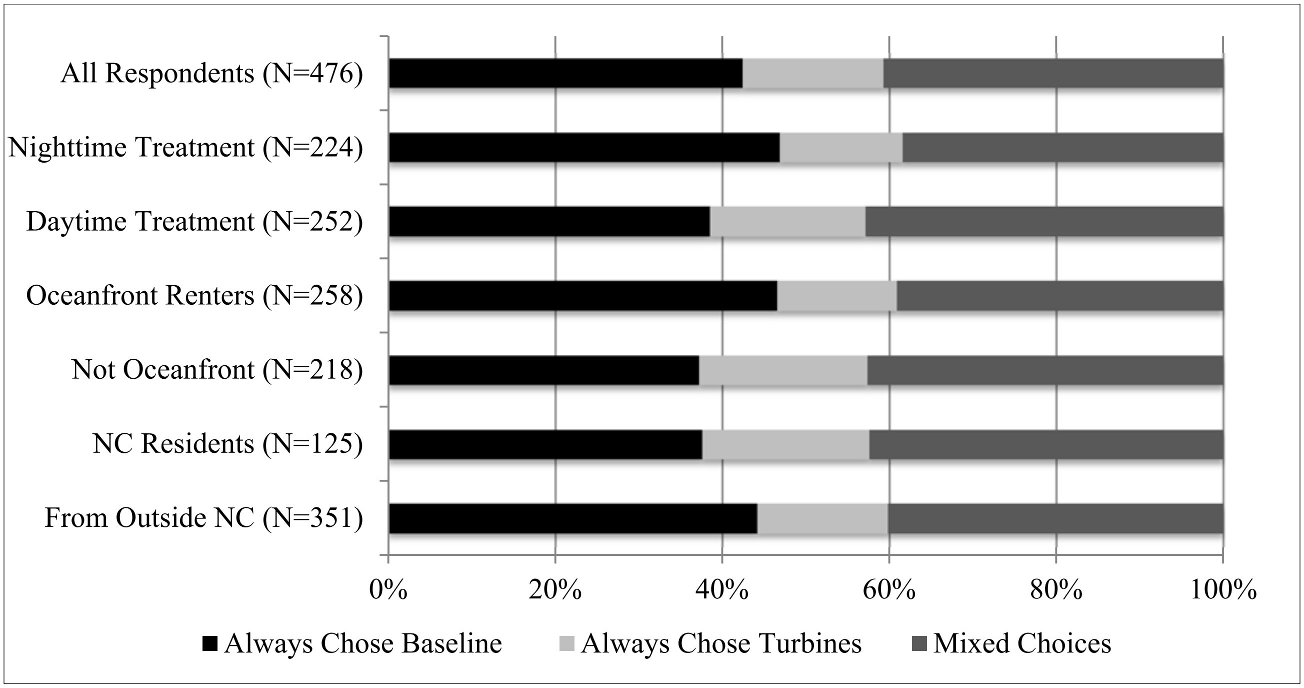
_____ **Scenario 1B:** 100 turbines visible at 5 miles & rent reduced by $620.

_____ **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**

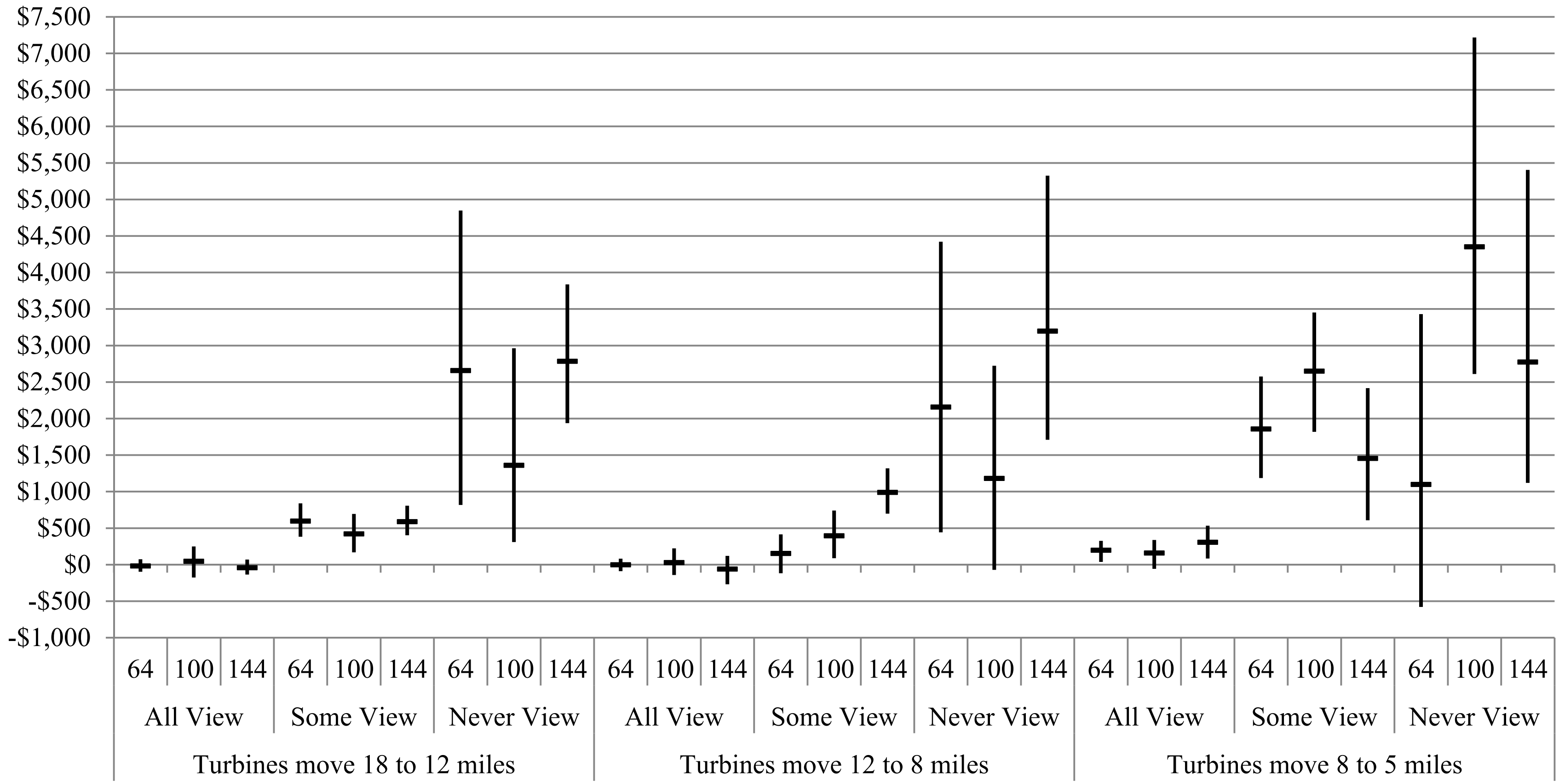
Scenario 1B: This view from the beach closest to your house & a **$620 reduction in rent**

Figure 2. Percent of Respondents Who Always/Never/Sometimes Chose the Baseline Scenario as the Most Preferred Option[a]



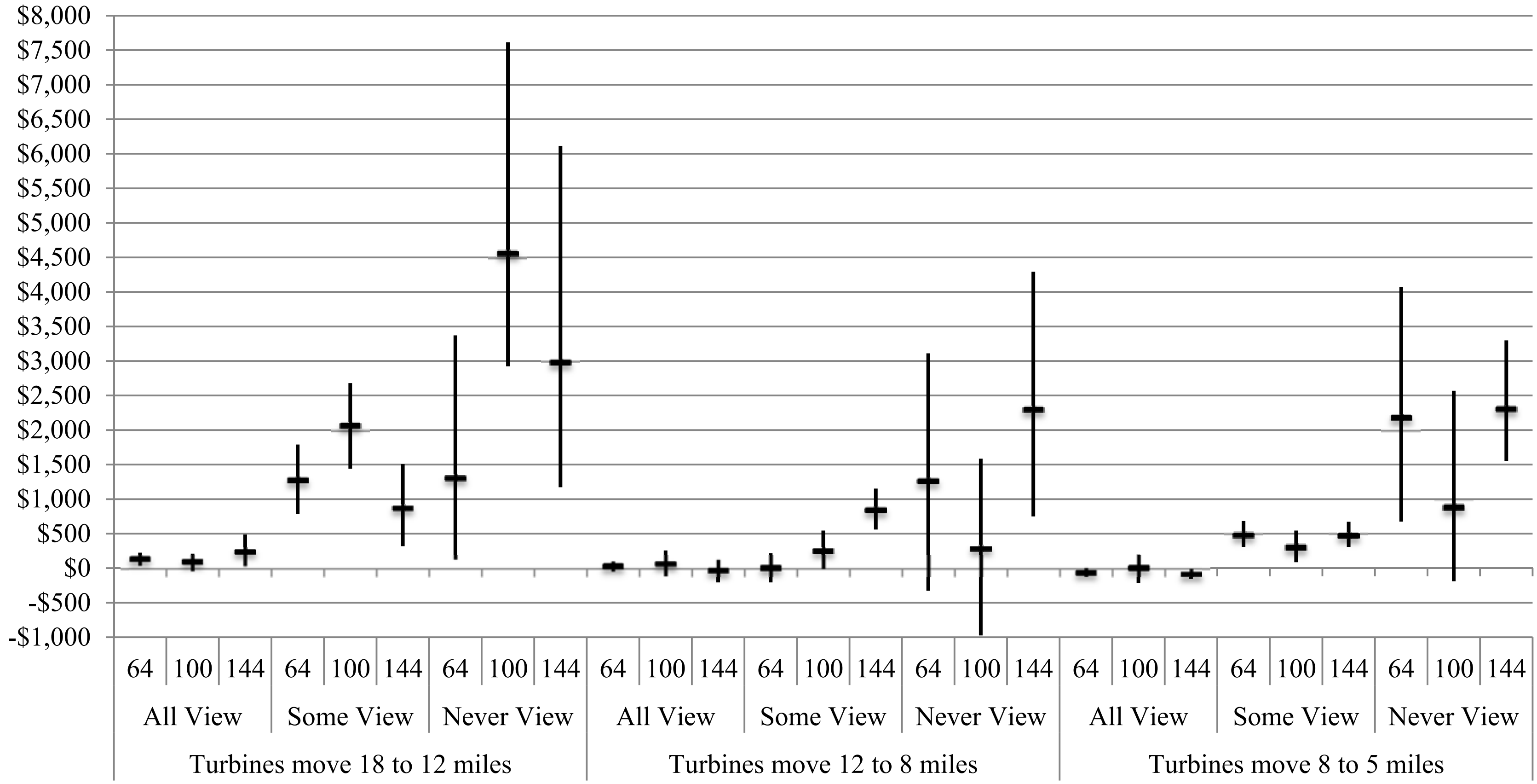
[a]Total number of respondents by category are given in parentheses.

Figure 3. Marginal willingness to accept (in rental discounts) for <u>oceanfront</u> renters to move turbines closer to shore, by number of turbines visible and latent class category[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 $MWTA^{q}_{d\to e|l} = -\left(\omega^{d}_{q} + \phi^{l}_{q} + \kappa^{d,l}_{q}\right) - \left(\omega^{e}_{q} + \phi^{l}_{q} + \kappa^{e,l}_{q}\right) / \beta_{q}$. Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where the 5th and 95th percentiles of the empirical distribution are used to construct 90 percent confidence intervals.

Figure 4. Marginal willingness to accept (in rental discounts) for <u>non-oceanfront</u> renters to move turbines closer to shore, by number of turbines visible and latent class category[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 $MWTA^{q}_{d \to e|l} = -\left(\omega^{d}_{q} + \phi^{l}_{q} + \kappa^{d,l}_{q}\right) - \left(\omega^{e}_{q} + \phi^{l}_{q} + \kappa^{e,l}_{q}\right) / \beta_{q}$. Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where the 5th and 95th percentiles of the empirical distribution are used to construct 90 percent confidence intervals.

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, 2012, 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 (2012, 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	27	55	24	106
(percent of total)	(25.47)	(51.89)	(22.64)	(100)
Never	0	0	93	93
(percent of total)	(0)	(0)	(100)	(100)
Total	68	58	117	243
(percent)	(27.98)	(23.87)	(48.15)	(100)

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

	All View (LC1)	*Some View* (LC2)	*Never View* (LC3)
Area rented			
No. Outer Banks	0.26	0.26	0.48
So. Outer Banks	0.29	0.22	0.49
So. Brunswick	0.29	0.24	0.47
Gender			
female	0.3	0.23	0.48
male	0.27	0.25	0.48
Residence			
Outside NC	0.26	0.23	0.51
NC	0.35	0.27	0.38
Retirement status			
Not retired	0.26	0.23	0.51
Retired	0.33	0.27	0.4
Annual Income:			
≤ $150,000	0.31	0.23	0.45
> $150,000	0.24	0.24	0.52

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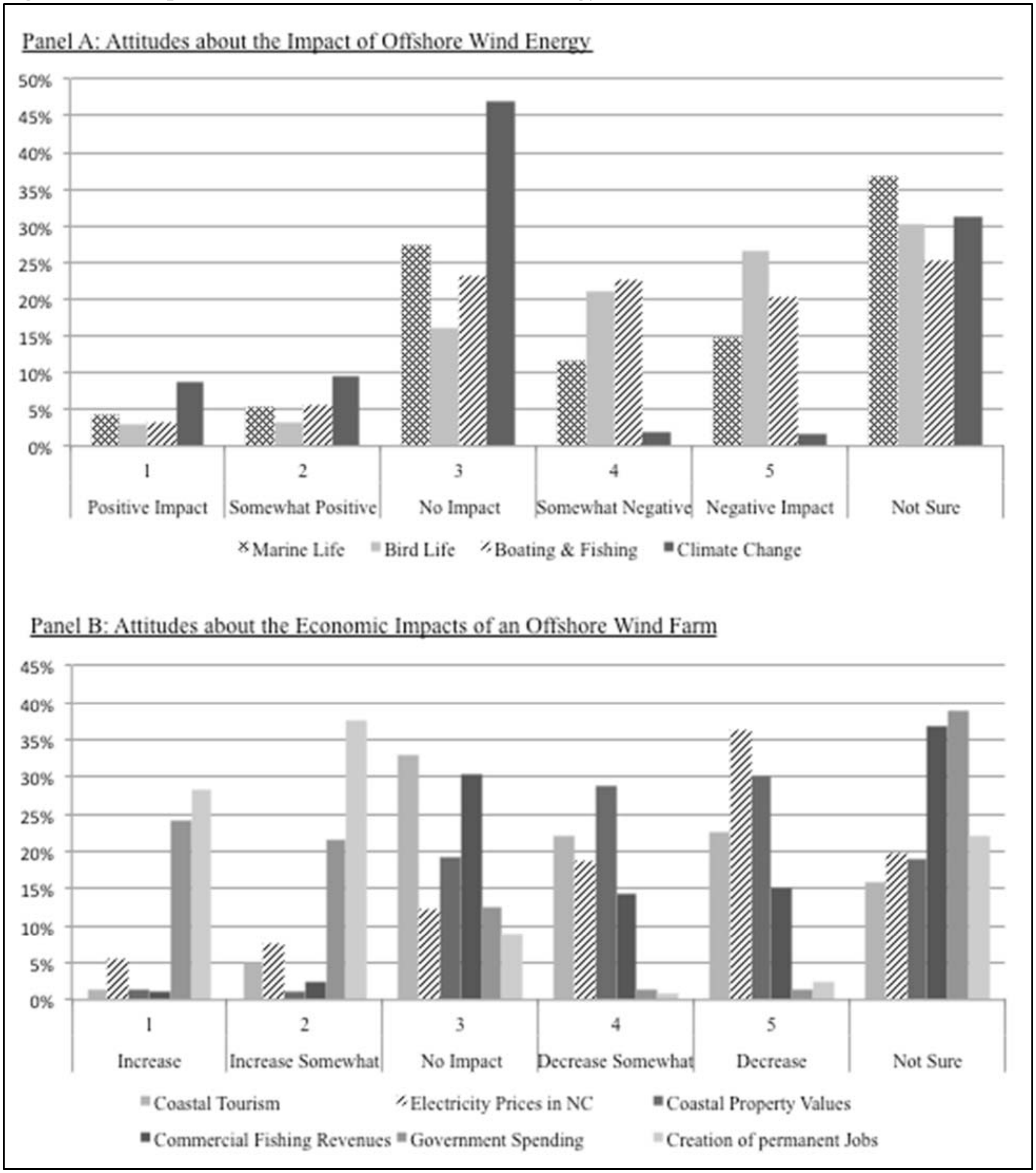
Table 4A. Final scale adjusted latent class model (daytime treatment)

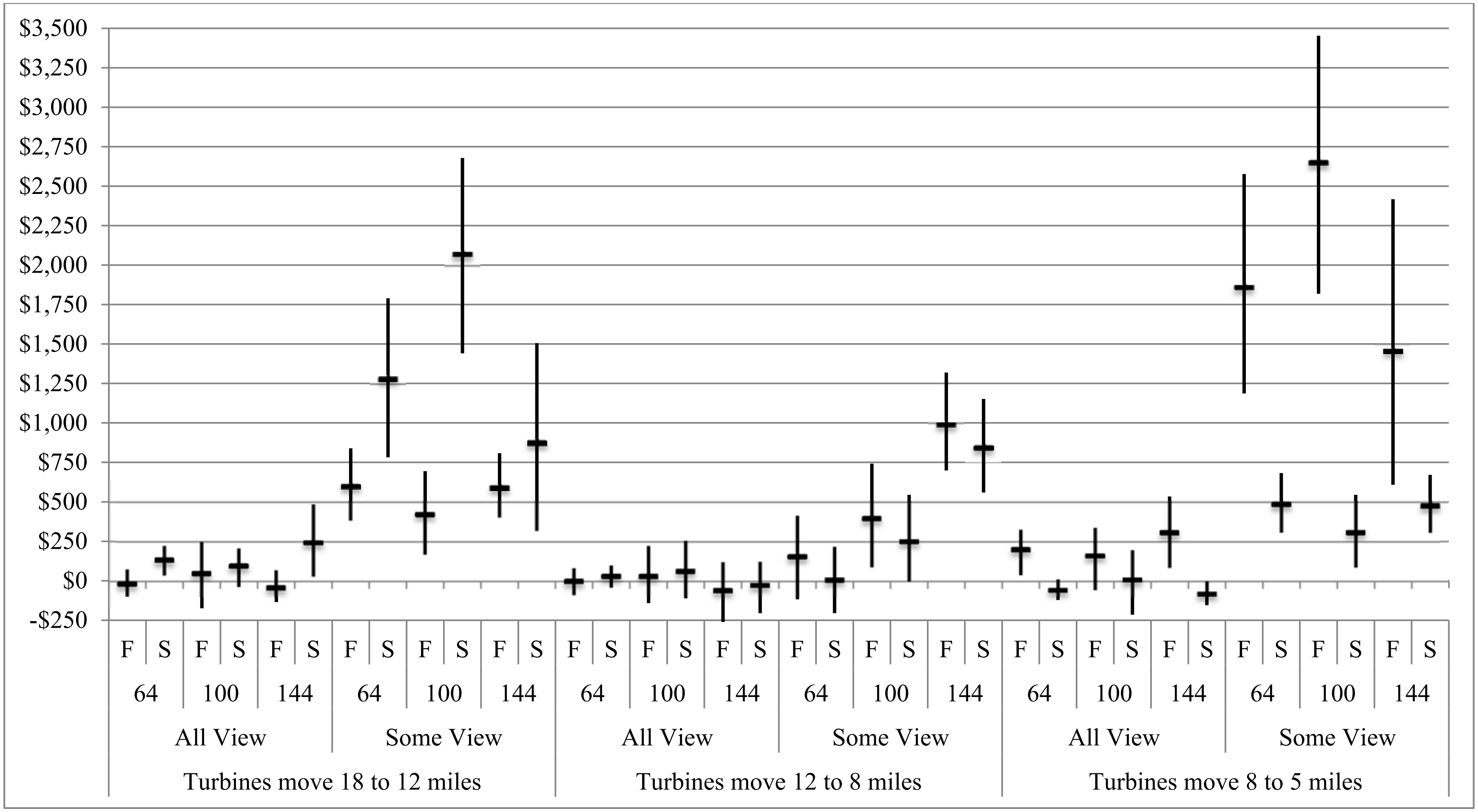
	All View (LC1)		*Some View* (LC2)		*Never View* (LC3)	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Panel A: Preference classes						
5 miles (ω^1)	-0.396***	0.131	-1.77***	0.652	-0.883***	0.188
8 miles (ω^2)	0.039	0.068	-0.133*	0.076	-0.122*	0.063
12 miles (ω^3)	0.21***	0.069	0.717***	0.169	0.258***	0.087
18 miles (ω^4)	0.147***	0.051	1.187**	0.485	0.747***	0.174
64 turbines (ϕ^1)	0.041	0.047	0.292*	0.151	0.088**	0.043
100 turbines (ϕ^2)	0.062	0.115	0.161*	0.087	0.057	0.039
144 turbines (ϕ^3)	-0.103	0.129	-0.453**	0.223	-0.145***	0.054
5miles×64 turbines ($\kappa^{1,1}$)	0.168	0.182	0.429**	0.193	0.241**	0.097
5miles×100 turbines ($\kappa^{1,2}$)	0.023	0.376	-0.125	0.088	0.066	0.079
5miles×144 turbines ($\kappa^{1,3}$)	-0.192	0.265	-0.304*	0.164	-0.306**	0.122
8miles×64 turbines ($\kappa^{2,1}$)	0.203**	0.102	0.07	0.095	-0.035	0.096
8miles×100 turbines ($\kappa^{2,2}$)	-0.1	0.103	0.187**	0.091	0.038	0.082
8miles×144 turbines ($\kappa^{2,3}$)	-0.103	0.147	-0.258**	0.128	-0.003	0.096
12miles×64 turbines ($\kappa^{3,1}$)	-0.276*	0.165	-0.182	0.168	-0.114	0.102
12miles×100 turbines ($\kappa^{3,2}$)	0.124	0.222	-0.029	0.149	-0.008	0.086
12miles×144 turbines ($\kappa^{3,3}$)	0.152	0.106	0.211**	0.099	0.122	0.079
18miles×64 turbines ($\kappa^{4,1}$)	-0.096	0.083	-0.317***	0.104	-0.092	0.095
18miles×100 turbines ($\kappa^{4,2}$)	-0.047	0.157	-0.034	0.14	-0.095	0.114
18miles×144 turbines ($\kappa^{4,3}$)	0.143	0.156	0.351**	0.156	0.187	0.116
5miles×oceanfront (η^1)	0.144	0.137	-0.176	0.217	-0.117	0.1
8miles×oceanfront (η^2)	-0.029	0.062	0.027	0.102	-0.018	0.043
12miles×oceanfront (η^3)	-0.012	0.146	0.024	0.118	0.043	0.065
18miles×oceanfront (η^4)	-0.103**	0.042	0.126	0.175	0.092	0.091
Price (β)	-0.003*	0.002	-0.002*	0.001	-0.0003***	0.0001
ASC (δ)	-0.033	0.103	-1.325*	0.707	-3.08***	0.687
ASC×oceanfront (α)	0.07	0.08	-0.068	0.243	0.541	0.652
Panel B: Active Covariates						
Environmental Factor	0.598***	0.147	0.027	0.148	-0.625***	0.128
Public Factor	0.38***	0.129	0.141	0.147	-0.522***	0.16
Panel C: Scale classes						
	Est.	Std. Err.	Class size			
Scale(1)	1	Fixed	0.65			
Scale(2)	0.272***	0.047	0.35			

Figure 1A. Respondent Attitudes Towards Wind Energy[a]



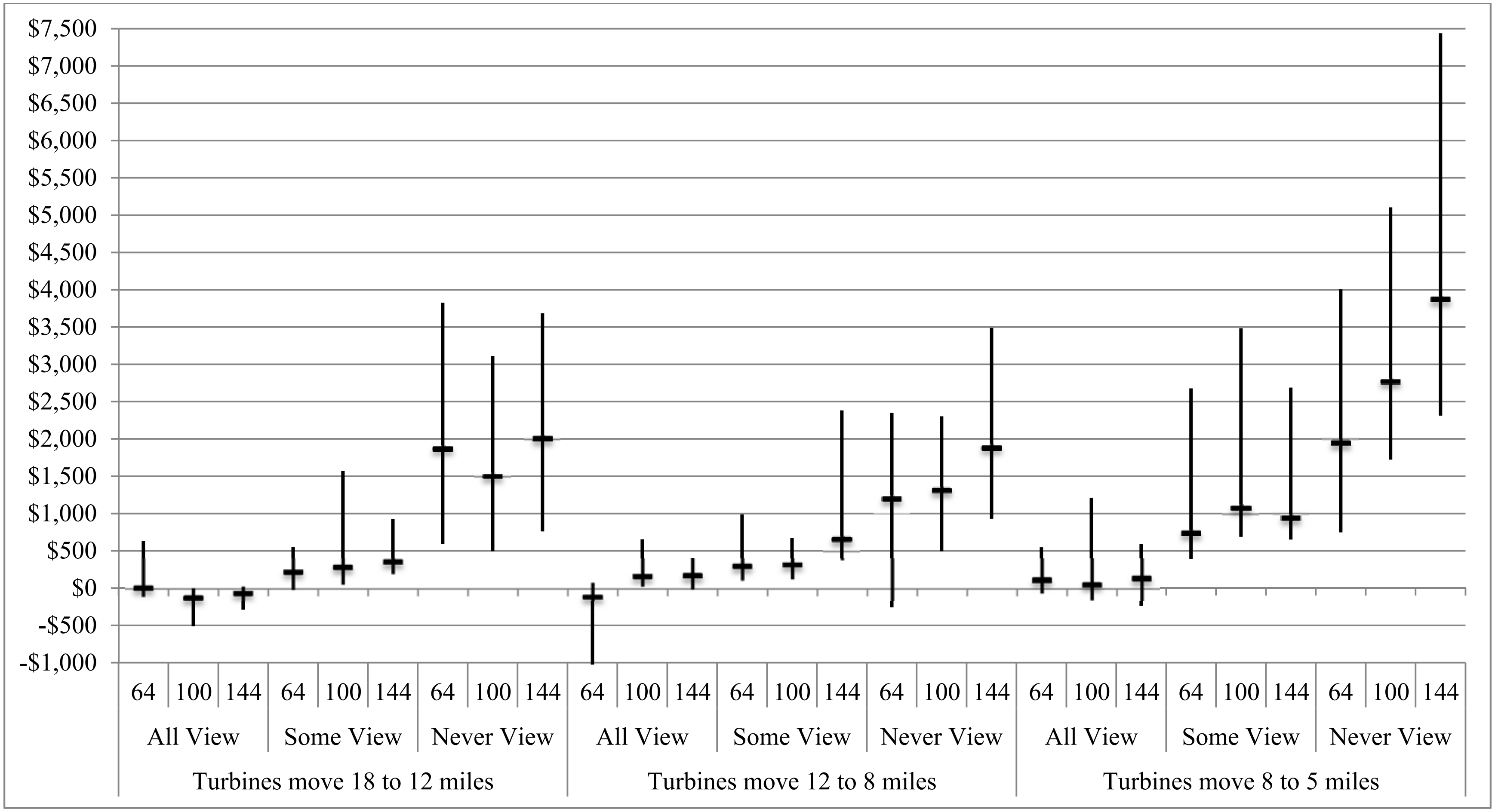
[a] Between 473 and 478 respondents answered each question. Bar heights represent the proportion of respondents choosing each point on the 1 to 5 Likert scale indicated on the horizontal axis in each panel.

Figure 2A. Marginal willingness to accept (in rental discounts) for *All View* and *Some View* latent classes (nighttime treatment), to move turbines closer to shore, by number of turbines visible and by whether they rented an oceanfront home (F) or non-oceanfront home (oceanside, S).[a]



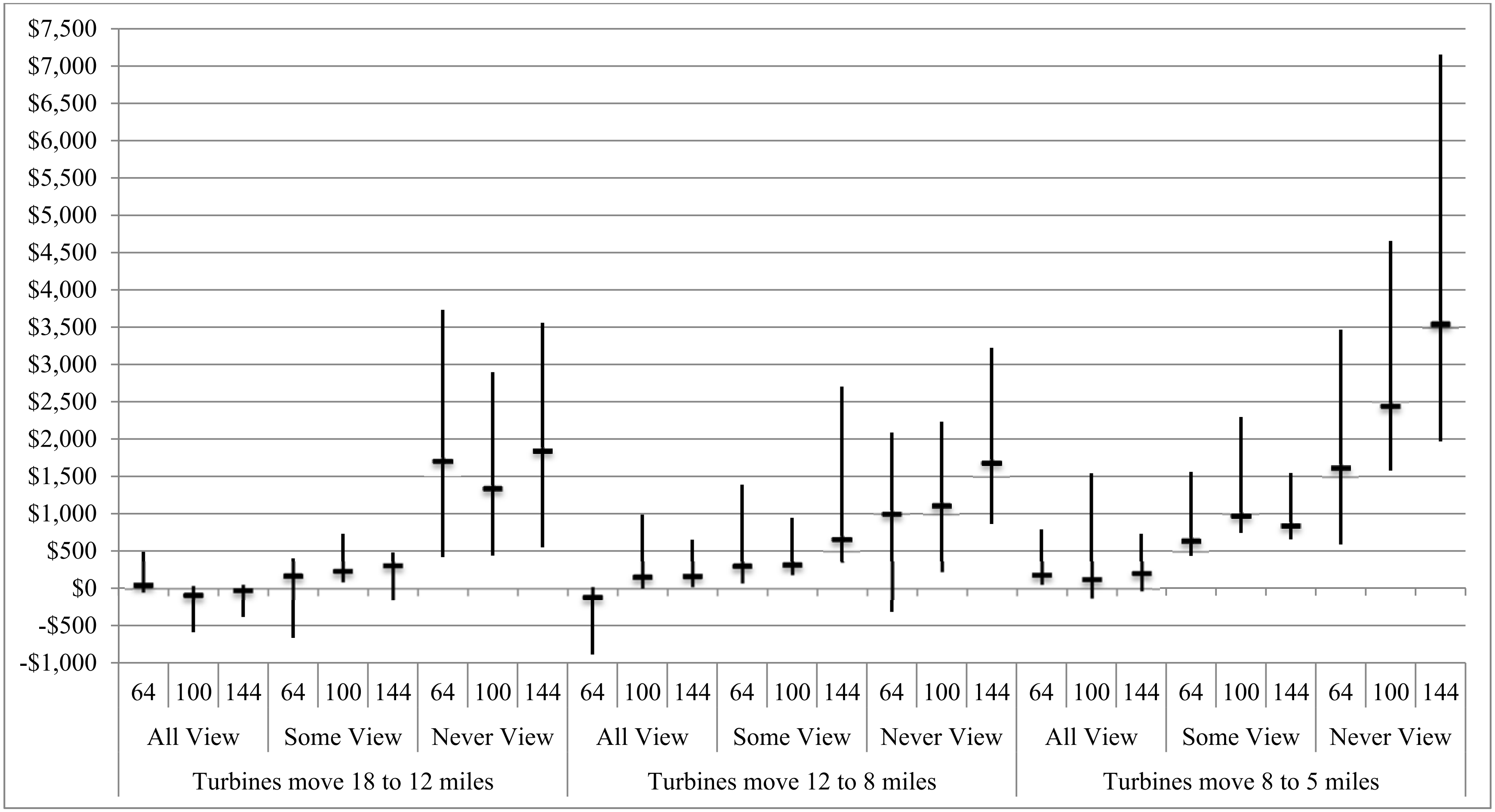
[a]MWTA point estimates and confidence intervals are computed as described in footnote a to Figure 3.

Figure 3A. Marginal willingness to accept (in rental discounts) for <u>oceanfront</u> renters receiving daytime images of turbines only, to move turbines closer to shore, by number of turbines visible and latent class category[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 $MWTA^q_{d\to e|l} = -\left(\omega^d_q + \phi^l_q + \kappa^{d,l}_q\right) - \left(\omega^e_q + \phi^l_q + \kappa^{e,l}_q\right) / \beta_q$. Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where the 5th and 95th percentiles are used to construct 90 percent confidence intervals.

Figure 4A. Marginal willingness to accept (in rental discounts) for non-oceanfront renters receiving daytime images of turbines only, to move turbines closer to shore, by number of turbines visible and latent class category[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 $MWTA^{q}_{d\rightarrow e|l} = -\left(\omega^{d}_{q} + \phi^{l}_{q} + \kappa^{d,l}_{q}\right) - \left(\omega^{e}_{q} + \phi^{l}_{q} + \kappa^{e,l}_{q}\right) / \beta_{q}$. Confidence intervals are computed using the Krinsky and Robb (1986) procedure, where the 5th and 95th percentiles are used to construct 90 percent confidence intervals.