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The effect of offshore wind power projects on recreational beach use on the east coast of the United States: Evidence from contingent-behavior data

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ABSTRACT

We use contingent-behavior data from a stated-preference survey to estimate the effect of offshore wind power projects on recreational beach use on the East Coast of the United States. The data are from an internet-based probabilistic sample of beachgoers (n = 1725) visiting beaches from Massachusetts to South Carolina in 2015. The contingent-behavior data are based on responses to visual simulations of wind power projects at seven different distances offshore (2.5–20 miles) in clear and hazy conditions and at night. We consider the effect on beach enjoyment/experienceand trips taken to a beach. As expected the nearer the projects are to shore, the greater their negative effect. For example, at 2.5-miles offshore, 29% of the sample state they would not visit the beach compared to only 5% at 20-miles offshore. Offsetting the negative effects, we also find evidence of potentially a large numbers of curiosity trips to view offshore wind power projects.

1. Introduction

The first offshore wind power project in the United States began operation in December 2016 near Block Island, Rhode Island (Firestone et al., 2020; Firestone et al., 2018). This five-turbine, 30 MW (MW project, which is located about 5 km from Block Island and 26 km from the mainland Rhode Island coast will be followed by much larger projects. There are offshore wind-specific targets in most states from Virginia to Massachusetts cumulatively totaling almost 26 000 MW as of March 2020. There are also thirteen active commercial wind leases on the outer continental shelf[1] (OCS) and the Bureau of Ocean Energy Management (BOEM) has issued at least one wind energy lease adjacent to every state from Massachusetts to North Carolina except Connecticut. All of this, along with declining cost in the industry, suggests growth in offshore wind power in the coming decades.

Along with this interest comes a concern about the potential effect such projects may have on coastal tourism and recreational beach use. The East Coast is a major tourist destination and altering the seascape may be consequential. Well-known conflicts with local populations over proposed projects, such as Massachusetts' Cape Wind power project, highlight this concern. At the same time, wind power projects may attract visitors curious to see wind turbines in operation and/or to be on a beach with a "green" outlook. The purpose of this paper is to estimate the effect of large offshore wind projects on recreational beach use on the East Coast of the United States.[2] The primary focus is on the negative external effects, which are the most prominent in the debate about offshore wind power, but we also have estimates to report on wind turbines as tourist attractions.

Since there are no large-scale offshore wind power projects on the East Coast for which we might observe impacts, we use contingent-behavior data wherein we ask East Coast beachgoers their reactions to visual simulations of what the wind power projects might like look. Specifically, they were shown simulations and asked to report if the presence of such projects would have: (1) affected their beach experience/enjoyment, (2) caused them to change trip plans, and/or (3) caused them to take a special trip to see the turbines. This paper presents an analysis of the response data to these questions. It covers ocean beaches from Massachusetts to South Carolina and respondents from the

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[1] The OCS, with some exceptions (none of which apply to the Atlantic of the east coast states), begins at 3 nautical miles from shore.

[2] The research was done for the Bureau of Ocean Energy Management (BOEM) under contract M12AC00017 and received additional funding from the and the National Oceanic and Atmospheric Administration (NOAA) Sea Grant Program at the University of Delaware.

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twenty East Coast states (plus Washington, DC) shown in Fig. 1.

Understanding the effect of wind power projects at different distances offshore is an important feature of our research. While siting turbines further from the shore is feasible and reduces the visual disamenity, it comes at an increase in construction, maintenance, and energy-delivery cost (Samoteskul et al., 2014). Understanding this tradeoff has important policy implications for project location and size. Another important feature of our research is having a model capable of measuring effects on any beach on the East Coast, since where the projects will be located is uncertain and nearly the entire coastline is in play. We are also interested in predicting how the effects may vary between day-versus overnight trips since this has implications for local effects. Finally, we have an interest in heterogeneity: Do effects vary by income class? Education? Attitude toward wind power? Recreation uses? We explore all of these questions in this paper, which includes a non-parametric presentation of the response data and parametric models for predicting trip loss.

Our work is preceded by at least six studies using stated-preference data to understand the effects of offshore wind power on beach use: Lilley et al. (2010), Landry et al. (2012), Fooks et al. (2017), Voltaire et al. (2107), Lutzeyer et al. (2018), and Westerberg et al. (2013). We will discuss these later and compare them to our results. There are also stated-preference studies that consider offshore and onshore wind in a broader context,but are not focused on beach use. These include Ladenburg and Dubgaard (2007), Ladenberg (2009), Krueger et al. (2011), and Boyle et al. (2019). And finally, there are hedonic price studies aimed at understanding the effects of wind power projects on property values. Some examples are Sunak and Madlener (2016) and Heintzelman and Tuttle (2012).

Fig. 1. Ocean beaches covered in the survey and states sampled.

2. Sample and study design

The survey design and sampling strategy was done at the University of Delaware. It involve a four-way interacton with Qualtrics, Macroworks, GfK Interantional, and the University of Delaware.[3] It included economists, statisticians, survey researchers, and programers. Qualtrics is the web-based platform we used to create the survey. Macroworks created the photomontages – the seascape-panning simulations of the wind power projects. GfK International implemented the survey using their KnowledgePanel – the largest online panel representative of the US population. The four-way interaction was required to get the photomontages from Macroworks operating in a Qualtrics survey seemleesly to respondents on the GfK platform where the survey was launched and the privacy of its sample was protected. After several interations, code swapping, and numerous tests, the final product satisfied our needs.

We used Qualtrics, because it to allowed us to use complex skip patterns and to reference the "external" photomontages in a simple way. We pretested the survey with faculty, staff, and graduate students. Later it was pretested with a GfK sample. The photomontages were created by Nik Hennessy in Ireland at Macroworks. Macroworks specializes in the creation of images of wind power (and other) large energy projects. The simulation we use was created on a beach at Assateague Island, VA. We choose Assateague Island because of the natural setting and its physical representativeness of East Coast beaches. Also, we wanted simulations to exclude people to avoid bias and unwanted anchoring effects. The natural setting at Assateague made this easy. We chose GfK International because it is one of a few survey research firms that provide probabilistic samples – samples from the population that mimic random draws. We drew samples of beachgoers and non-beachgoers from the 20 states shown in Fig. 1. We sampled from each state in proportion to its population (respondents over 18 years old) and oversampled beachgoers.[4] A beachgoer is anyone who had visited a beach in 2015. GfK was responsible for contacting the respondents and directing them to our survey using their protocol, which includes incentives, follow ups, etc. See GfK International (2017) for details on their methodology. We focus on the beachgoer sample (n = 1725) in this article. The core of the survey asks respondents about their trips to ocean beaches from Massachusetts (as far north as Cape Cod) to South Carolina. Hereafter, an "East Coast Beach" is any ocean beach from Massachusetts (as far north as Cape Cod) to South Carolina, and a "beachgoer" is a respondent who visited at least one of these beaches in 2015.

Part 1 of the survey asked respondents to report the frequency with which they typically visit East Coast ocean beaches, the type of activities they participate in while there (e.g., swimming, sunbathing, shopping, and so forth), and whether they or anyone they know owns property near the beach. Part 2 asked respondents to report all the East Coast ocean beaches they visited at least once in 2015. Then, one beach was randomly drawn from the set of chosen beaches for detailed questioning. The details included type of trip (day, short-overnight, long-overnight, extended stay, or side trip), length of stay, activities while there, and expenditures.

Part 3 focused on contingent-behavior questions. Using the beach randomly drawn in Part 2, respondents were asked to imagine that a wind power project was present offshore and that they were aware of its presence before making the trip. Respondents were then shown the panning photomontages that included views in clear weather, hazy weather, and at nighttime. A visual with no wind power project was also shown as a point of comparison. The hypothetical project depicted in all photomontages included 100 turbines: each turbine was 6 MW and was 175 m high (blade at apex) with a rotor diameter of 150 m. They were spaced eight rotor diameters from one another, or 1.2 km apart, in a 10 by 10 grid format. Respondents were also provided instructions on the

[3] The relevant links are: GfK (http://www.gfk.com), Macroworks (http://www.macroworks.ie), and Qualtrics (https://www.qualtrics.com/).

[4] GfK provided relevant sampling weights, which we used throughout this paper.

distance to the screen from which they should view the images—a distance which is dependent on the size of the screen. Respondents guided their way through a series of portals in which the different views were possible. Each respondent was asked to view the project at three distances offshore – near, medium and far. The viewing order was randomly chosen with distances ranging from 2.5 to 20 miles.[5]

After each distance was viewed, respondents were asked whether the presence of the wind power project would have affected their beach experience/enjoyment – making it worse, somewhat worse, neither worse nor better, somewhat better, or better. If they responded worse or somewhat worse, they were then asked if it would have affected their trip—that is, would they have made the same trip, visited another beach instead (and if so which beach) or done something else. If they reported better or somewhat better, they were asked if they would have visited another beach if the wind power project had been there instead. Finally, if they responded neither worse nor better to the enjoyment/experience question, they moved on in the survey. Respondents were also asked whether they would make a special trip just to see an offshore wind power project. This question was intended to get at the idea that the projects themselves may generate curiosity trips. Finally, in Parts 4 and 5 of the survey we gathered more data on beach trips and demographic data not available through GfK.

3. Background data

Table 1 shows the sample demographics for age, income, education, and gender over the beachgoer samples. The U.S. Census Bureau data are included in the table for comparison. Of course, the beachgoing population is not distributed the same as the general population.

By state, New Jersey had the highest visitation rate, followed by South Carolina and North Carolina. Delaware had the lowest rate and Rhode Island was second from the bottom. The most visited beach was Myrtle Beach (SC), followed by Ocean City (MD), Virginia Beach (VA), Atlantic City (NJ), Rehoboth Beach (DE), and Jones Beach (NY). The top-ten beaches accounted for 36% of all trips. Table 2 shows the frequency of beach visitation by the beachgoer sample. As shown, 21% go more than five times per year, 57% go between 1 and 5 times per year, and 22% go less than once per year.

The most important activities when visiting the beach were sand activities (sunbathing, beachcombing, etc.) at 37%, water activities (swimming, surfing, etc.) at 28%, and boardwalk/community activities (shopping, sightseeing, etc.) at 25%. The summer months (June, July, and August) dominated the time periods for trip taking at nearly two-thirds of all trips. The distribution of respondents by types of trips taken is: 42% daytrips, 26% short-overnight trips (three or fewer nights), and 28% long-overnight trips (four to 29 days). The remaining 4% are side trips (trips made to a beach while visiting the area for other purposes), extended stays (over 30 days away from home), or excursions (trips to the beach that are part of a longer multiple-purpose trip).

Finally, respondents were asked if they favor the idea of expanded use of wind power in the United States – 42% favor, 26% somewhat favor, and 27% neither favor nor oppose while only 3% somewhat oppose and 2% oppose. About 58% reported that they were aware that offshore wind power on the East Coast was being considered as an energy source; 61% reported having seen a land-based or ocean-based wind power project.

Table 1
Sample demographics.

Demographic Category	Beachgoers (n = 1725) Percent	Census Data 2015 Percent
Age		
18-24 years	11.9	12.6
25-34 years	19.7	17.1
35-44 years	19.6	16.4
45-54 years	15.6	18.1
55-64 years	18.6	16.7
65-74 years	11.3	11.0
75 + years	3.3	8.2
Education		
Less than High School or GED	6.9	12.3
High School or GED	25.8	29.5
Some College or Assoc. Degree	26.9	26.4
College or Higher	40.4	31.8
Household Income (thousands)		
Less than $10 per year	4.5	7.4
$10 – 14.9 per year	1.9	5.3
$15 – 24.9 per year	3.7	10.4
$25 – 34.9 per year	7.2	9.8
$35 – 49.9 per year	10.5	13.0
$50 – 74.9 per year	15.0	17.4
$75 – 99.9 per year	20.0	12.1
$100 – 149.9 per year	24.8	13.4
$150 + per year	12.3	11.1
Male	51.6	48.8

[5] The simulations may be viewed at www.macroworks.ie/boem/. An active version of the survey may be viewed at https://delaware.ca1.qualtrics.com/SE/?SID=SV_3TKJE5B2QKR6B1z.

4. Beach experience/enjoyment

Fig. 2 shows the response data for the first contingent-behavior question: the reported effect of offshore wind power projects on experience/enjoyment while visiting the beach. The figure separates the responses according to whether the wind power project would have made the experience worse, better, or neither worse nor better. The line labeled "worse" combines the responses somewhat worse and worse and the line labeled "better" combines somewhat better and better.

The figure shows that the closer the turbines are to shore, the more likely a respondent is to report a worse beach experience. At 2.5 miles offshore, 53% of our respondents reported that turbines would have made their experience/enjoyment somewhat worse or worse. The percentage drops monotonically till we reach 10% at 20 miles. Conversely, the percent reporting that turbines would have made their experience somewhat better or better increases as the turbines are placed further offshore. At 2.5 and 5 miles offshore, 10% and 4% report somewhat better or better. At 20 miles, 17% report somewhat better or better. Similarly, those reporting no effect (neither worse nor better) increases as the wind turbines are placed further from the coast, at 2.5 miles 37% percent report neither worse nor better, and at 20 miles 73% report neither worse nor better. At distances of 5 miles and greater, neither worse nor better is the largest response category. The effect of distance is less pronounced (in absolute terms) on those respondents reporting somewhat better or better than it is on those reporting somewhat worse

Table 2
Frequency of beach visitation by respondents.

Frequency of Beach Visits	Beachgoers	
	Number of Respondents	Percent
More than 5 times per year	366	21.3
Between 1 and 5 times per year	988	57.4
Once every 2 years	206	12.0
Once every 3 to 5 years	73	4.3
Less than once every 5 years	57	3.3
Almost never	28	1.6
Never	5	0.3
Total	**1723**	**100**

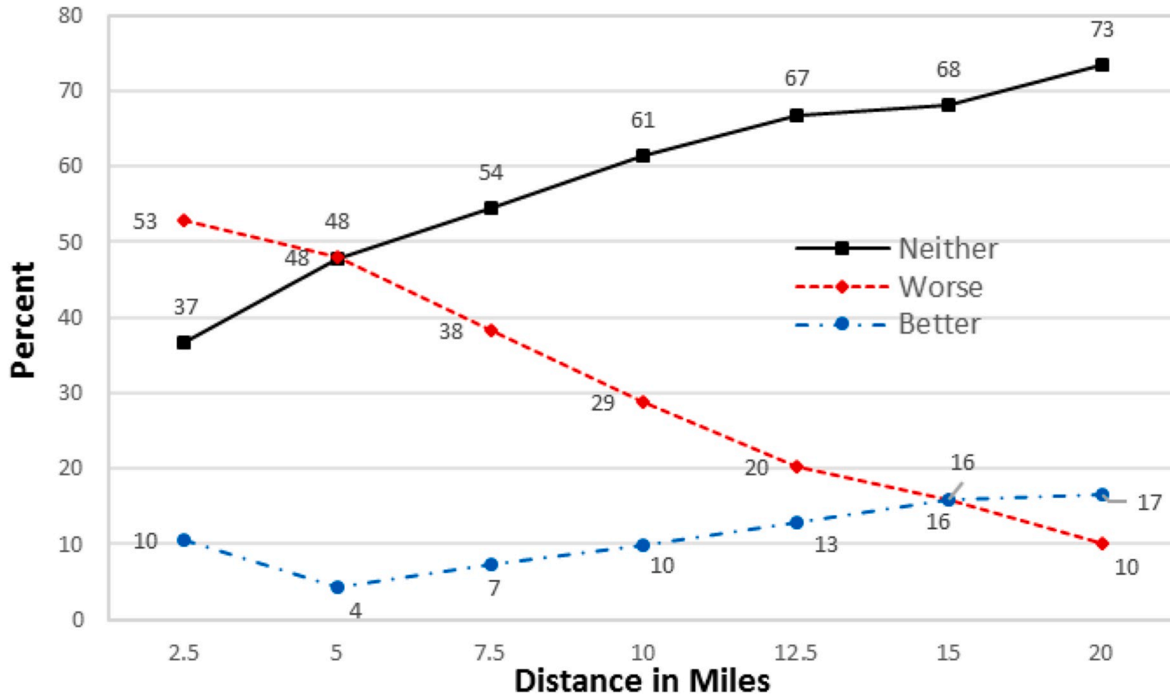

Fig. 2. The Effect of Offshore Wind Power Projects on Experience/Enjoyment on RecreationalBeach Trips: Making Experience
Worse, Better, or Having No Effect (Neither) – Somewhat Worse is Included with Worse and Somewhat Better Included with Better.

or worse. Consider the difference between the percentage of respondents reporting worse and better—the net-worse effect—as a function of distance. It is 43% at 2.5 miles, 19% at 10 miles, 0% at 15 miles, and −7% at 20 miles (i.e., more respondents reported better off than worse off). The break-even point is at 15 miles, where an equal number reporting worse as better.

Table 3 disaggregates the worse responses by somewhat worse and worse and does the same for the better responses. This gives us a sense of the intensity of the effects on experience. First, we see that the somewhat responses are larger than their non-somewhat counterparts in all cases but for worse at 2.5 miles. This is where the turbines are the most intrusive and where a more intense response might be expected. Otherwise, the results indicate a more muted response than Fig. 2. The better and worse responses (without the somewhats) are in single digits at every distance but for worse at 2.5, 5, and 7.5 miles. And the better responses are not significantly different from zero at any distance. This all suggests that but for the worse impacts at the nearest distances, the effects are not large. Fig. 3 reimagines the table by combining the somewhat responses with neither – treating them as "soft" responses. Again, with the expectation of worse responses at near distances the impacts are not large using this interpretation.

If respondents reported that their experience would be made worse or better due to the presence of offshore wind turbines, they were asked why? As shown in Table 4, the list of responses provided to respondents differed between those answering worse and those answering better. The most common reason given for worse was "the impact of wind turbines on the natural view of the seascape." About 61% of the respondents reported this response followed by 29% reporting harm to marine life. The most common response given for better is "knowing something positive is being done for the environment (examples: climate change, air pollution)" at 52% followed by "knowing something positive is being done for energy security" at 24%, "knowing something positive is being done for the economy" at 11%, and "the visual appeal of wind turbines on the seascape" also at 11%. Negative effects appeared to be precipitated by aesthetics and to a lesser extent concerns over harm to the marine environment, while positive effects were precipitated by feelings of doing good for society. These responses are consistent with Figs. 2 and 3. The worse lines increase with proximity (sensitive to view), while the better lines are rather flat (not sensitive to view).

5. Trip loss

5.1. Trip-loss rates

If respondents reported that the presence of a wind power project would make their experience somewhat worse or worse, they were asked if the presence of the turbines would have caused them to visit another beach or do something else. If the respondent reported that the wind turbines would have made their experience/enjoyment neither worse nor better, somewhat better, or better, it is assumed that they would have continued to visit the same beach and were not asked the follow-up question. These response data are used to define trip loss. It is important to keep in mind that "trip loss" pertains to the beach where a wind power project was to be located. It goes without saying that a lost trip at one beach may be a gained trip at another, which we will discuss shortly.

The trip loss contingent-behavior question was followed by a certainty-response question. Specifically, we asked "How certain are you that this is what you would have actually done?" The response format ranges from 0 to 10, where 0 = extremely uncertain, and 10 = extremely certain. We used the response to this question to construct a certainty-adjusted trip loss (c_{jk}) that ranged between 0.5 and 1 for changing trip plans and between 0 and 0.5 for not changing trip plans. So, for example, a person who reports not taking a trip with a certainty level of 10 has a $c_{jk} = 1$. A person who reports not taking a trip with certainty 0, has a $c_{jk} = .5$. That is, a person with extreme uncertainty about changing trip plans is treated as a tossup – .5 chance of trip loss and .5 chance of no trip loss. Similarly, a person who reports no trip change (no trip loss) with a certainty level of 10 has a $c_{jk} = 0$. If a person reports no trip loss with a

Table 3
The effect of offshore wind power projects on experience/enjoyment on recreational beach trips.

Distance Turbines are Miles from shore	Percent of Respondents Reporting that Experience Would Be …					Sample Size
	Worse	Somewhat Worse	Neither Worse nor Better	Somewhat Better	Better	
2.5	28.2	24.8	36.6	6.3	4.1	708
5	22.9	25.0	47.8	2.1	2.1	725
7.5	14.2	24.1	54.3	5.3	2.1	767
10	8.6	20.2	61.4	6.1	3.7	717
12.5	7.0	13.3	66.7	7.7	5.2	767
15	4.9	11.1	68.2	9.6	6.3	710
20	3.7	6.3	73.3	9.4	7.3	759
Total	**12.7**	**17.8**	**58.5**	**6.7**	**4.4**	**5153**

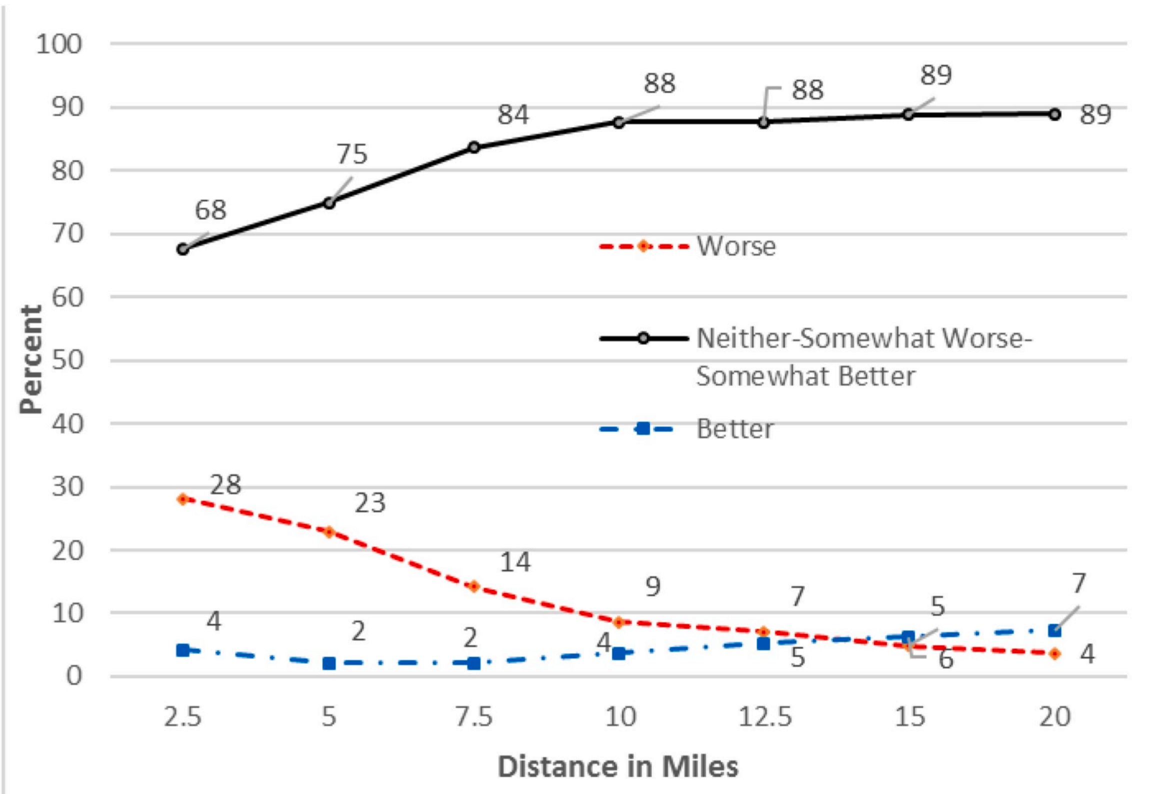

Fig. 3. The Effect of Offshore Wind Power Projects on Experience/Enjoyment on Recreational.
Beach Trips: Making Experience Worse, Better, or Having No Effect (Neither) – Somewhat Worse and Somewhat Better included with Neither.

certainly level of 0, the trip loss is $c_{jk} = .5$. Again, extreme uncertainty implies a tossup for trip loss. For no trip change, the probabilities range from 0 to 0.5. Certainty levels between 0 and 10 produce intermediate c_{jk}'s – giving a continuous variable ranging from 0 to 10.[6]

Fig. 4 shows the average certainty-adjusted trip-loss rate for wind power projects located at different distances offshore. The solid line is the base trip-loss rate – the percentage of respondents who reported that they would not have visited the beach if a wind power project were present. This includes those who replace the trip with a trip to another beach and those who would do something else instead. The dashed line depicts only those who reported that they would do something else instead (other activities such as going to a park, movie or simply staying home). We call this full trip loss, since the person would not have replaced the current beach trip with a trip to another beach. Base and full trip loss increase with wind-project proximity – the closer to shore, the higher the trip loss. Base trip-loss is 29% at 2.5 miles from shore, 14% at 10 miles, and 5% at 20 miles – all are statistically significantly different than 0%. Also, as shown by the Full Trip Loss line, most lost trips would have resulted in individuals switching to other beaches as opposed to staying home. So, in terms of community impacts, they appear to be mostly transfers from one beach to another.

5.2. Predicting trip loss by beach

This section presents an approach for predicting trip loss at individual beaches. Because it is unknown where offshore wind power projects will be located, having the flexibility to predict trip loss by beach is useful. It also provides a model wherein the correlation of beach characteristics with trip loss can be analyzed (e.g., is trip loss more likely on developed or undeveloped beaches?). We purposely exclude demographic data on our respondents as regressors because most of the beaches have few, even single digit or zero visits. In this case, incorporating individual characteristic in the model *and simulating it* could easily

[6] For those changing trip plans, 60% report a certainty level of 8 or higher and 84% report 6 or higher. For reporting no change, 57% report 8 or higher and 84% report 6 or higher.

Table 4
Reasons Respondents Gave for Why Offshore Wind power projects Would Make Their Experience/Enjoyment Worse or Better.

	Number of Respondents	Percent
Reasons for Better or Somewhat Better		
Knowing something positive is being done for the environment	175	52.3
Knowing something positive is being done for energy security	80	23.7
Knowing something positive is being done for the economy	38	11.2
The visual appeal of wind turbines on the seascape	37	11.2
Other	5	1.5
Reasons for Worse or Somewhat Worse		
The impact of wind turbines on the natural view of the seascape	545	61.5
Harm to marine environment	256	28.9
Waste of taxpayer's dollars	35	3.9
Interference with navigation	23	2.6
Other	28	3.1

result in misleading prediction. So, we opted for a model with beach characteristics believing beaches of similar type in similar areas would have similar visitation rates. The next section introduces demographic and attitudinal variables into the model.

The Trip-Loss Prediction Model has the form:

$$c_{jk} = \delta_d distance_{jk} + \delta_s state_{jk} + \delta_t triptype_{jk} + \delta_b beachch_{jk} + \varepsilon_{jk} \quad (1)$$

c_{jk} = probability of visiting another beach or doing something else (ranges from 0 to 1as described above),$distance_{jk}$ = vector of stepwise dummies for distance wind farm is offshore (2.5 to 20 miles),$state_{jk}$ = vector of dummies for state where wind farm is located offshore,$triptype_{jk}$ = vector of dummies for trip type (day, short overnight, etc.),$beahch_{jk}$ = vector of beach characteristics (width, boardwalk, etc.), and, ε_{jk} = error term.

All variables are subscripted by *jk* since the unit of observation is person *k*'s response to one of three contingent-behavior trip-loss questions at distances indexed by *j*. The idea is that like beaches in similar areas and with similar characteristics should have similar trip loss rates that can be predicted using equation (2). The model was estimated by ordinary least squares.[7]

The behavior underlying the Trip-Loss Prediction Model follows discrete choice theory. On each choice occasion, a respondent faces the choice of going to one of M beaches or staying home. Define that choice set as $B = \{b_0, b_1, b_2, b_3, \ldots, b_M\}$ where b_0 is the stay-at-home option and the other elements in the set are the beaches. We assume each beach and the stay-at-home option gives the respondent some utility and that the respondent chooses the beach that maximizes utility. That choice is defined as $Max\{U_0, U_1, U_2, U_3, \ldots, U_M\}$, where U_m is the utility of visiting beach *m* (or staying at home). For simplicity, assume a respondent chooses beach b_1, so $U_1 = Max\{U_0, U_1, U_2, U_3, \ldots, U_M\}$.

Our contingent behavior question asks respondents to reimagine their beach choice where the set of beaches is the same but the beach with the maximum utility is now assumed to have a wind power project located offshore. The reimagined choice set is $B^{wp} = \{b_0, b_1^{wp}, b_2, b_3, \ldots, b_M\}$. Now, define an indicator function $I[U_1^{wp} > Max\{U_0, U_2, U_3, \ldots, U_M\}]$ that takes the value of 1 if the statement in brackets is true and 0 if false. That is, is the utility at the chosen beach still the highest even though a wind power project is now located there offshore? If yes, then $I = 1$, if no $I = 0$. So, $I = 0$ if the respondent reports that he or she would have changed trip plans if a wind power project had been located offshore – either going to another beach or staying home (or doing something else). The Trip-Loss Model models this choice.

Using random utility theory, we rewrite our indicator function including a random component. This recognizes that there are aspects of the choice made in the contingent behavior question unknown to us as researchers so the choice is not deterministic. Now we define $I[U_1^{wp} - Max\{U_0, U_2, U_3, \ldots, U_M\} + \varepsilon > 0]$, where ε is the random component and again $I = 1$ if true and $I = 0$ if not. Now the problem is set in a probalistic form, where the probability that the person changes a trip is $pr(Change\ Trip) = pr(I[U_1^{wp} - Max\{U_0, U_2, U_3, \ldots, U_M\} + \varepsilon > 0] = 0)$. Since the only thing that changes in a person's choice set when the wind project is introduced is the presence of the project (at different

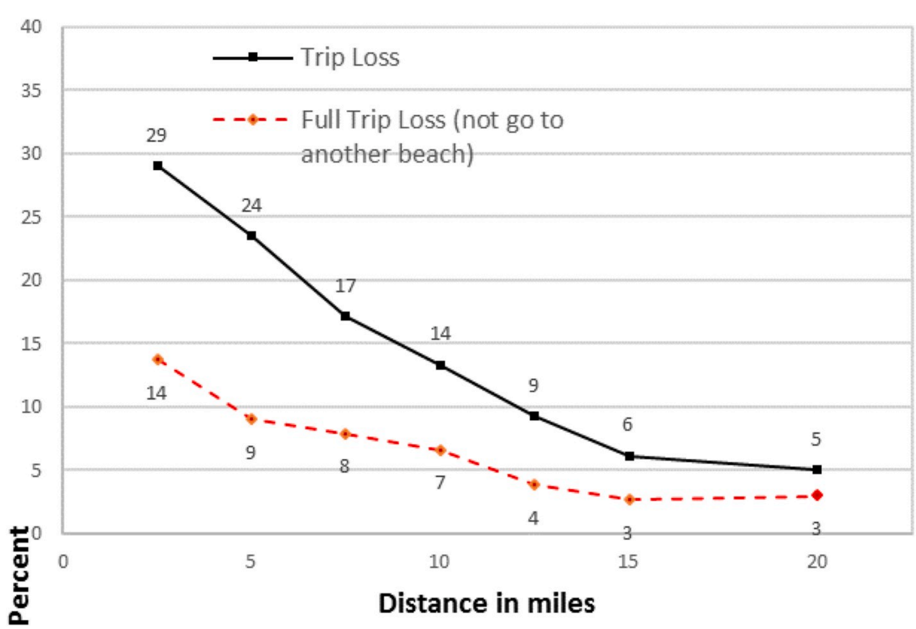

Fig. 4. Trip loss due the presence of an offshore wind power project.

[7] A random effects fractional binary logit model and a random effects OLS model were also estimated. The random effects were included to account for correlation among an individual respondent's three responses. Neither model predicted as well as the simple linear OLS model.

distances), we can write this probability for person k for contingent behavior question j as

$$pr_{jk}(Change\ Trip) = \delta_d distance_{jk} + \varepsilon_{jk}, \tag{2}$$

which is equation (1) without the covariates other than $distance_{jk}$. The other covariates are included in equation (1) to account for a difference in preferences at different beaches and to facilitate prediction. Later we add individual characteristics as covariates.

The OLS Trip-Loss Prediction Model is shown in Table 5. The coefficients on the distance dummies show an increase in the probability of trip loss as turbines are located closer to shore – consistent with Fig. 3. The distance coefficients are relative to 20 miles offshore and are statistically significant at 10 miles and closer. These coefficients are interpreted as an increase in the probability of trip loss for an increment in a specific variable. For example, moving from 20 to 10 miles offshore, all else constant, added 8.9 percentage points to the probability of trip loss. A large amount of variation is explained by unobserved regional (state) effects in the model. For example, Virginia and New Jersey have cancellation rates that are 8.5 and 6.2 percentage points higher than North Carolina, all else constant. The northern states tend to have somewhat higher unobserved regional effects (more trip loss).

With respect to trip length, the probability of trip loss for long-overnight trips (away four nights or more) is 3.7 percentage points higher than on day trips. The probability for short-overnight trips (away three nights or less) is 3.6 percentage points higher than day trips. Individuals may be more sensitive to the character of the beach given the larger investments in money and time made in an overnight trip.

Three variables are used to distinguish the degree of development on a beach – presence of boardwalk, high density housing, and designation as a local, state, or national park. The presence of a boardwalk decreases the probability of trip loss by 7.4 percentage points. This is the single most important attribute in the beach characteristics. Beaches with boardwalks are the most developed on the East Coast and have the most non-beach related activities for beachgoers (amusements, shopping, restaurants, etc.). Perhaps beachgoers at these beaches are less concerned about the natural features of the beach. At the same time, beaches designated as parks have 3.3 percentage point lower trip loss, all else constant. Beachgoers at park beaches tend to be more favorable toward wind power and correspondingly appear less inclined to report trip loss. Housing density has little predictive power. In sum, trip loss is lowest on both the more developed and the more natural beaches and highest on the beaches of intermediate development. The remaining variables in the model mostly have small and insignificant effects. The presence of a seawall has a relatively large effect, reducing trip loss by 3.8 percentage points, but is insignificant. It may be another factor acting as a proxy for developed beaches.

Table 5
OLS trip-loss prediction model.

Variables	Coefficient	T-Statistic
Constant	0.047	0.83
Distance Offshore (20 Offshore Miles Excluded):		
Distance Offshore 2.5 miles	0.240***	11.1
Distance Offshore 5 miles	0.187***	8.7
Distance Offshore 7.5 miles	0.111***	5.2
Distance Offshore 10 miles	0.089***	4.1
Distance Offshore 12.5 miles	0.021	0.99
Distance Offshore 15 miles	0.011	0.49
States (North Carolina Excluded):		
Massachusetts	0.034	0.96
Rhode Island	0.045	1.6
New York	0.054	1.6
New Jersey	0.062*	2.2
Delaware	0.043	1.2
Maryland	0.009	0.27
Virginia	0.085*	2.6
South Carolina	0.019	0.83
Trip Type (Day Trip Excluded):		
Short Overnight Trip	0.036**	2.3
Long Overnight Trip	0.037**	2.4
Any Other Trip	0.005	0.18
Other Variables (all are dummies except ln(beach width)):		
Ln*(Beach Width)*	−0.007	−0.54
Local, National, or State Park	−0.033*	−1.68
Summer	0.008	0.61
High Density Housing	0.006	0.65
Boardwalk	−0.074***	−3.29
Fish Pier	0.018	1.02
Vehicle Access	0.012	0.53
Seawall	−0.038	−0.73

Note: The dependent variable is certainty-adjusted trip-loss for each respondent, ranging from 0 to 1. Sample size = 5168. Adjusted R^2 = 0.43. *** indicates statistical significance at a 99% level, ** at 95% level and * at 90% level.

Table 6 shows predicted trip loss using the model at nine selected beaches, one in each coastal state in our study. This gives a good sense of the variability the model generates and the reasons for that variability. The table also shows our estimate for aggregate number of trips to each beach, to get a sense of the extent of the effect on a given beach. Trip loss here is a weighted average of day, short-overnight, and long-overnight trips. Jones Beach (NY) has the lowest trip loss rate and Hyannis Port (MA) the highest. The four Mid-Atlantic beaches—Jones Beach (NY), Ocean City (NJ), Rehoboth (DE), and Ocean City (MD)—are all developed beaches with boardwalks and in some cases seawalls and this appears to be driving down trip loss on those beaches relative to the others. Myrtle Beach (SC) and Wrightsville Beach (NC) have somewhat higher trip loss; these are developed beaches but do not have boardwalks, so any development effect they may have is not picked up in the prediction model.

These results assume a single wind power project is constructed and no others exist. Assuming stable preferences, as wind power projects are added, our expectation is that similar trip loss would occur as new wind projects are added. To the extent that fewer wind-project-free beaches would be available, trip losses may decrease as wind power projects are built, since the available substitutes without turbines would be shrinking, but eventually saturation would set in (few or no wind-project-free beaches) and trip loss may actually stabilize (see Landry et al. (2012) for stated-preference evidence of this effect). Welfare losses would presumably increase due the lack of good substitutes, even though trip loss declines.

5.3. Heterogeneity of preferences

The Trip-Loss Prediction Model in the previous section works well for the purpose of predicting trips across different beaches. But we also have an interest in the heterogeneity of preferences toward offshore wind projects. That is, how do preferences vary by income, education, age, recreation type, etc. To this end we also estimated a Trip-Loss Heterogeneity Model that includes demographics and attitudes.

We use the same OLS form with the same dependent variable but drop the beach characteristic variables and now include individual characteristics such as income, age, education, beach attachment, recreation type, general attitude toward wind power, residency, and a few other related variables. The results are in Table 7.[8]

With respective to the demographic variables, we see trip loss rising with income and education and declining with age. This is controlling for other factors, most notably general attitude toward wind power, so it implies offshore wind is more disruptive to higher income and better educated groups and perhaps surprisingly to younger people. The education impact is largest – with college graduates being 11% more likely to change trip plans due the presence of a wind power project than those

[8] We have not included interactive models here (age with distance offshore, income with distance offshore, etc.). There is little or no added insight beyond the non-interactive models and the number of coefficients becomes rather unwieldy.

Table 6
Weighted Average Predicted Trip-Loss Rates (%) at Nine Selected Ocean Beaches Trip losses are weighted averages of day, short-overnight, and long-overnight trips.

Beach	Distance in miles							Number of Trips (Millions)		
	2.5	5	7.5	10	12.5	15	20	Day	Short	Long
Hyannis Port, MA	35.5	30.1	22.5	20.3	13.5	12.5	11.4	0.28	0.11	0.03
Sachuset, RI	30.2	24.8	17.2	15.1	8.2	7.3	6.2	1.09	N/A	N/A
Jones Beach, NY	21.3	16.0	8.3	6.2	0.2	0.1	0.0	3.12	0.18	0.06
Ocean City, NJ	36.0	27.5	18.7	16.3	8.4	7.3	6.0	1.01	0.31	0.20
Rehoboth, DE	27.0	21.7	14.0	11.9	5.1	4.1	3.0	0.74	0.86	0.28
Ocean City, MD	26.0	20.6	13.0	10.8	4.0	3.0	1.9	2.58	1.05	1.01
Chincoteague, VA	34.4	29.1	21.4	19.3	12.5	11.5	10.4	0.32	0.14	0.07
Wrightsville, NC	30.8	25.5	17.8	15.7	8.9	7.9	6.8	0.85	0.12	0.16
Myrtle Beach, SC	34.6	29.2	21.6	19.4	12.6	11.6	10.5	1.89	2.33	3.17

with less than a high school education. The age effect, on the other hand, is not large and is just below significance at 90%. For example, lowering age from 50 to 30 years of age increases the chances of changing trip plans by about 1%. The income effect, while significant, is also not large. Increasing annual income from $50 to $100 thousand increases the chances of changing plans by 1.25%.

Attitudes toward wind power as an alternative source of energy are highly correlated with trip loss. Approximately 2% of the sample reported that they oppose wind power and another 3% reported that they somewhat oppose wind power. (Note: this is oppostion to the idea of wind power generally in the US as a source of alternative energy.) These respondents are 51% and 22% more likely to change trip plans if a wind power project was present than individuals who are indifferent to wind power. On the other hand, the 42% who favor and 26% who somewhat favor wind power are 10% and 1% (without significance) more likely to not change trip plans than those who are indifferent. There is an asymmetry in intensity here where the negative attitudes are a larger driving force than positive attitudes. It is important to note that many people in the sample who favor wind power contribute to our trip loss result. They like the idea wind power but really don't want the interference on a beach trip. A sort of NIMBY for recreation trips. This creates the asymmetry in intensity.

Type of recreation is also correlated with trip loss. The activities on or near the water show greater loss than those less involved with the beach. So, for example, those whose most important activity while at the beach is boating are 10% more likely to change trip plans versus those who report boardwalk and other community activities as most important. Those reporting activities on the water (swimming, surfing, etc.) as most important are 8% more likely. And, those reporting sand activities (sunbathing, reading, etc.) as most important are 5% more likely. Shorefishing and four-wheel driving on the beach also have effects near 5% (without statistical significance) and visiting nearby waterways near 10% (without significance). Since all of these are relative to boardwalk/local community, this group is by implication the least affected by the wind power projects.

A difficulty with stated preference surveys is that they are not based on actual experiences by respondents. In our study, the beach trips are actual experiences but the beach with a wind power project present is hypothetical. To account, at least in part, for experience with wind turbines, we asked respondents if they had seen turbines in the past and how frequently. The idea here is that individuals with past experience may have a more realistic perception of what offshore wind power projects may look like and hence have more fixed and reliable revelation of preferences. Our results show that the more visual experience respondents have with wind power projects, the more likely they are to change trip plans if an offshore project were present. These effects range from an approximate 3% increase in trip loss for those seeing turbines between 1 and 25 days annually to a 6% increase in trip loss for those seeing turbines more that 25 days. These results run counter to Boyle et al. (2019) and Ladenberg (2009), who find past experience correlated with higher acceptance.

We hypothesized that owning property near to a beach or "attachment" to a beach, which may come from a long history or family experience of visiting a beach, might be correlated with trip loss.[9] For both, the cost of changing trip plans is a larger proposition than for an occasional visitor. We find for respondents with residences within five miles of the shore that the likelihood of trip loss is 2% less all else

Table 7
OLS trip-loss heterogeneity model.

Variables	Coefficient	T-Statistic
Constant	−0.159	−1.6
Distance Offshore (20 Offshore Miles Excluded):		
Distance Offshore 2.5 miles	0.247***	12.3
Distance Offshore 5 miles	0.193***	9.7
Distance Offshore 7.5 miles	0.113***	5.7
Distance Offshore 10 miles	0.083***	4.1
Distance Offshore 12.5 miles	0.025	1.3
Distance Offshore 15 miles	0.015	0.8
Trip Type (Day Trip Excluded):		
Short Overnight Trip	0.042***	3.0
Long Overnight Trip	0.035**	2.5
Any Other Trip	0.021	0.8
Level of Attachment Self-Reported (No Attachment Excluded):		
Modest Attachment	−0.017	−1.4
Strong Attachment	0.023	1.5
Wind Preference (Neither Favor nor Oppose Excluded):		
Favor Wind Power	−0.096***	−6.9
Somewhat Favor Wind Power	−0.013	−0.9
Somewhat Against Wind Power	0.224***	6.7
Against Wind Power	0.512***	12.9
Most Preferred Activity (Boardwalk Activities Excluded):		
Water Activities (Swim, Surf, etc.)	0.077***	5.2
Sand Activities (Sunbath, read, etc.)	0.053***	3.8
Boating	0.105***	3.1
Nearby Waterbodies (Clamming etc.)	0.102***	2.8
Shore Fishing & 4-Wheel Drive	0.047	1.6
Frequency of Beach Visits Per Year (Never or Almost Never Excluded):		
More than 5 times per year	−0.058	−1.3
Between 1 to 5 times per year	−0.055	−1.3
Once every 2 years to less than once every 5 Years	−0.047	−1.1
Education (Less than High School Excluded):		
High School	0.060**	2.5
Some College	0.102***	4.2
Bachelor's Degree or Higher	0.112***	4.6
Days Wind Turbine Seen (Never Seen Excluded):		
1–10 days	0.038***	3.1
10–25 days	0.029	1.2
More Than 25 days	0.056***	2.7
Residence less than 5 miles from ocean beach	−0.039**	−2.3
Summer	−0.001	−0.1
Log Age	−0.021	−1.5
Log Income	0.018***	2.6

Note: The dependent variable is certainty-adjusted trip-loss for each respondent, ranging from 0 to 1. Sample size = 5168. Adjusted R^2 = 0.43. *** indicates statistical significance at a 99% level, ** at 95% level and * at 90% level.

[9] See Devine-Wright and Batel (2017) and Lewicka (2010) for more on place attachment.

constant. We also see some effect for those reporting "strong attachment" – again about 2% trip loss (just below statistical significance), but none for those reporting "modest attachment." A major reason these effect may not be large is the large number of substitutes beaches nearby – similar in location and physical character.

Finally, we explored the effects of trip type (day versus overnight) and trip frequency. We have already reported on the effect of trip type in our Trip-Loss Prediction Model. These are stable across the model with overnight trips showing roughly 4% higher trip loss. Trip frequency is weakly correlated with a decrease in trip loss but potentially large – about 5% higher trip loss for frequent versus infrequent visitors (but without statistical significance).

5.4. *Trip-loss findings in other studies & a robustness check*

Here we compare our trip-loss results with four other contingent-behavior studies (Lilley et al., 2010, Landry et al. (2012), Voltaire et al. (2017), and Fooks et al. (2017)) and with a robustness check we conducted with in-person data using the same visuals used in our internet-based survey. The comparison is shown in Fig. 5.

Lilley et al. (2010) conduct on-site surveys at several beaches in Delaware of out-of-state beachgoers. Their visual simulation has 130 430-foot turbines. As shown, their trip-loss rate tracks reasonably well with ours. Landry et al. (2012) gather phone-survey data in North Carolina (Outer Banks) over a sample of coastal-county residents. They ask people if they would change their next trip to the beach if there were 100 400-foot high turbines located one-mile offshore at their preferred beach. Later they ask respondents how many fewer (or more) trips they would take to all beaches in the region if there were similar wind power projects along the entire coastline (31 beaches in North Carolina). Respondents are not shown a visual; they are simply told to imagine a wind power project is present. Their trip-loss at for wind turbines at one-mile offshore is 11% for their single-beach case and about 1% for the many-beaches case. These are the lowest trip-loss rates of all five studies.

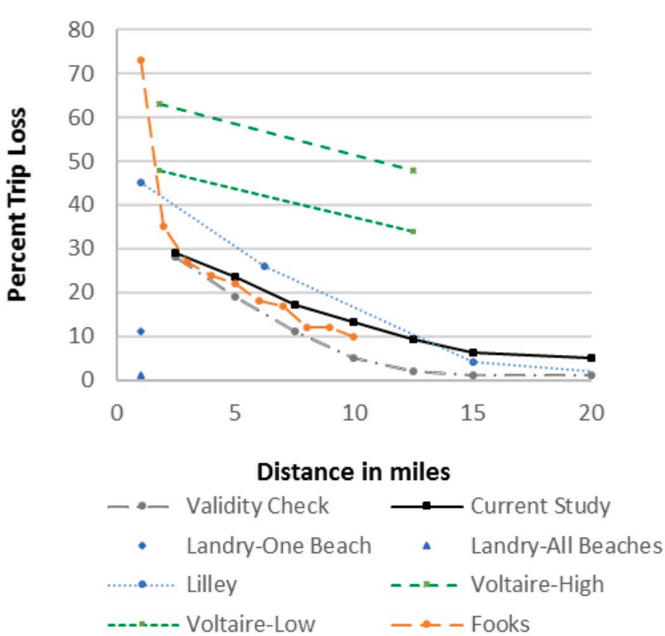

Fig. 5. Comparison of trip-loss in recent studies.

Their results are shown as points, since they do not consider different distances. Fooks et al. (2017) analyze on-site data from two Delaware beaches. Respondents are asked to participate in a laptop exercise where they can move a photo-simulated offshore wind power project to a point where it would cause them to no longer visit the beach. Their photo-simulations show 100 90-m tall turbines. Voltaire et al. (2017) setting is the Catalan coastline in Spain along the Mediterranean Sea. Individuals are intercepted at eight different beaches and given a contingent-behavior survey. The analysis has two distinct density scenarios for respondents to consider: 2 large wind power projects or 8 small wind power projects. Both projects are shown at 1.8 miles and 12.5 miles offshore. Their results are close to Fooks et al. (2017) and Lilley et al. (2010) at near distances and are much larger than all studies at far distances. Fig. 5 also includes the results for an in-person validity check we conducted using the same visuals as in our internet survey. We incepted people at a large all-day university event highlighting research and enhancing understanding of the coastal and ocean environment and showed them a four-foot poster board of the visuals similar to the ones used in our internet survey. Individuals (n = 392) viewed wind turbines at the same seven distances and answered similar contingent behavior questions. The results show mostly a lower trip-loss in response to wind power projects but are not dramatically different than the internet survey. There are innumerable reasons why differences might show up across these studies including context/setting, affected populations, methodology, time periods, sample sizes, statistics, and so forth. With so few studies to date, we do not (in effect) have the degrees of freedom needed to understand why these differences emerge. It is interesting to note that there is some convergence among Mid-Atlantic studies and the outliers (Landry et al. (2012) and Voltaire et al. (2017)) maybe explained by respondents seeing no visuals (in the case of Landry et al. (2012)) and by the setting being in the Mediterranean (Voltaire et al. (2017)), which is different dramatically in context/setting than the Mid-Atlantic. Nevertheless, transferring these result wholesale is risky business and should be done only with caution.

Finally, there are three choice experiments where trip loss can be inferred for large-scale offshore wind power projects: Landry et al. (2012), Westerberg et al. (2013), and Lutzeyer et al. (2018). These studies are less amenable to predicting trip loss *from current levels* given how their experiments are constructed but all show potential for a loss. Landry et al. (2012) finds a potential for losses at one mile offshore on ocean beaches in North Carolina and no loss at one and four miles offshore on the neighboring estuary. This analysis is done alongside the contingent behavior analysis described above. Westerberg et al. (2013) results on the French Mediterranean show large effects at 3.1 and 5 miles offshore but taper at 7.5 miles and Lutzeyer et al. (2018) report that "[w]e find that 55 percent of existing customers would not re-rent their most recent vacation property if wind turbines were placed offshore." The latter is for beach rentals in North Carolina and is probably an overstatement but it unquestionably the study finding the largest potential impact. Counterbalancing this is a revealed preference study by Carr-Harris and Lang (2019) using a difference-in-difference hedonic-like analysis of rental properties before and after the construction of the Block Island project. They find positive effects on visitation from the new project.

6. Trip gain

Our survey was designed primarily to understand the potential negative effects, if any, of offshore wind power projects on beach use and tourism since this is the issue mostly discussed in policy formation. However, policy makers also have an interest in understanding the likelihood that offshore wind power projects may (at least in the short run) be viewed as tourist attractions and generate additional curiosity trips.

With this in mind, we asked beachgoers if they would take a curiosity trip to see a wind power project if one was constructed offshore, and if so, how many trips they expect to take. For each respondent, the wind power project was randomly placed on one of eighteen East Coast beaches (two for each coastal state) and placed at one of our seven distances offshore. For the most part, curiosity trips are insensitive to offshore distance, though there is a significant drop off at 20 miles where visibility is limited. The share of respondents reporting that they would take a curiosity trip ranges from a low of 3.6% at 20 miles offshore to a high of 11.4% at 12.5 miles offshore. A few points to keep in mind with this response data. First, respondents taking curiosity trips could be traveling from home, could be on a visit to another beach, or could be visiting the area for another reason. Second, the question did not specify when in the future the trip(s) might be taken. Of the respondents reporting that they would take a special trip, 75% report that they expected to take only one trip, 24% reported 2 to 5 trips, and 1% more than five trips. Most are one-time trips.

This response data imples that a wind power project may generate on the order of 10–12 million trips just for curiosity. If this is spread over 10 years, that is 1 million special/curiosity trips per year – a large number for most East Coast beaches. As a point of reference, the most popular beaches have 7.4 million (Mrytle Beach, SC) to 4.6 million (Ocean City, MD) trips per year, while the least visited have under 100 thousand per year. This implies the potential for a large offsetting impact on the local beach community installing a wind power project. We expect these effects to dissipate for successively added wind power projects as their novelty wears off. But, keep in mind that our research does not speak directly to this effect. Still, this result along with the findings by Carr-Harris and Lang (2019) imply early trip gain would not be a surprise.[10]

We also asked respondents who reported somewhat better or better in response to the effect of wind turbines on their beach experience (our first contingent behavior question) if they would have visited another nearby beach if the wind power project had been located there instead of at the beach they visited. About 2% report that they would seek out the such beaches for recreation. While this number is small relative to the percent who report leaving a beach if a wind power project was present, the number of other beaches with possible switches is large so the total effect may be larger than expected. Based on several of the open-ended responses we received in the survey, we believe many of these trips are like curiosity trips and may double count the special trips reported above. Still, some fraction may be new recreation trips to wind-project-based beaches and this reinforces our preliminary finding that there may be large offsetting effects to the losses reported in the previous section at least in the early years.

7. Conclusion and policy implications

Our results imply that large-scale offshore wind power projects (100 turbines) will affect recreational beach use on the East Coast of the United States in negative and positive ways. The nearer a wind power project is located to shore, the larger the negative effect. At 2.5-miles offshore, 53% of the respondents report that their beach experience would be made somewhat worse or worse and 29% report that they would seek out another beach or do something else (most seeking out another ocean beach). At 20-miles offshore only 10% of the respondents report that their experience would be made somewhat worse or worse and only 5% report changing trip plans. Of respondents who reported that wind power projects would make them worse off, 62% said the effect on the visual seascape was the most important reason.

A smaller, but significant share of the sample report that wind turbines would make their experience somewhat better or better – 10% if a wind power project is 2.5-miles offshore and 17% if a wind power project is 20-miles offshore. At 15-miles and further offshore, more respondents report being made better than worse off. Of those made better off, 52% report the most reason is knowing something positive is being done for the environment.

We also find that offshore projects are likely to generate a significant number of curiosity trips (at the first generation of projects) and serve as tourist attractions. This could be on the order of one million trips annually, which is a large upswing for smaller beaches on the East Coast.

When we compare our trip-loss estimates to other studies in the literature, we find reasonable correspondence with some but they vary considerably from others. Landry et al. (2012) find very low trip loss for wind power projects even as close at one-mile offshore (11%) and Carr-Harris and Lang (2019) find positive effects on rentals on Block Island, while Lutzeyer et al. (2018) and Voltaire et al. (2017) find losses exceeding 50% even at distances of over 15-miles offshore. We are some ways from a consensus on what the effects from offshore wind power projects will be on recreational beach use. And, clearly there is no single answer – it will be context depend.

Moreover, the landscape of US offshore wind power has changed somewhat since our study: States have ramped up demand for offshore wind power with both policies and commitments; developers, as the part of contracts for sale of offshore wind-derived electricity projects, have commitment to economic development in those states; the states in turn have made bets on infrastructure (e.g., ports), supply chain development, and worker training; projects have grown in size from a mere 30 MW to over 1000 MW; costs have come down dramatically and concerns over coastal hazards, including storm surge, sea level rise, and precipitation events and the need for mitigation, resiliency and adaptation have only become more acute, which themselves greatly threaten coastal tourism economies. These changes suggest that the states and coastal tourists may be more likely to accept some degree of visual intrustion. At the same time, the visual effects are likely to be different (maybe larger) than the ones we modeled here. The wind turbines to be installed will be between 9 and 12 MW rather than 6 MW. The 12 MW wind turbine is 49% higher, but society will require roughly half as many wind turbines (the precise ratio will depend on the relative capacity factors of the turbines) to generate the same amount of electricity, and the space between wind turbines will be 47% greater, assuming similar spacing, which is based on rotor diameter. With the present study providing an appropriate baseline, these changes suggest additional research into the question of tourism effects is warranted.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

George Parsons: Conceptualization, Methodology, Writing - original draft. **Jeremy Firestone:** Conceptualization, Methodology, Writing - original draft. **Lingxiao Yan:** Data curation, Methodology, Visualization. **Jenna Toussaint:** Software, Data curation, Methodology.

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