Wind Turbines and Coastal Recreation Demand

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Abstract

We examine the impact of coastal wind turbines on coastal tourism and recreation for residents of the northern CAMA counties in North Carolina. A combination of telephone and web survey data are used to assess the impact of coastal wind farms on trip behavior and site choice. Most of the respondents to our telephone survey claim to support offshore wind energy development, and independent survey data suggest that the observed levels of support may be indicative of the broader population in this region. Overall, we find very little impact of coastal wind turbines on aggregate recreational visitation; loss in consumer surplus associated with wide spread wind development in the coastal zone is insignificant at $17 (or about 1.5%). Results suggest that NC coastal residents are averse to wind farms in the near-shore zone; average compensating variation for wind farms one mile from the shore is estimated at $55 per household. On average, we find no evidence of aversion to wind farms 4 miles out in the ocean, or for wind farms located in coastal estuaries. For all wind farm scenarios, we find evidence of preference heterogeneity– some respondents find this appealing while others find it aversive.

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Dependence on fossil fuels has induced significant and diverse risks associated with climate change, while potentially compromising U.S. national security through reliance on foreign providers. As global energy demand rises and fossil fuel sources decline, energy price levels and volatility have been on the rise. These forces have created a groundswell of pressure for further consideration and exploration of options for renewable energy sources. In 2007, North Carolina became the first state in the Southeast to adopt a Renewable Energy Portfolio Standard (http://www.ncuc.commerce.state.nc.us/reps/reps.htm). Under this new law, electric utilities in North Carolina will be required to produce up to 12.5% of their energy supply through renewable energy resources such as wind, solar, and geothermal. Wind energy potential is great in North Carolina, and while the upfront capital costs can be quite high, variable costs associated with maintenance and distribution are relatively small and fairly stable. As prices for oil, coal, and gas rise, wind energy becomes economically viable. Wind power is also attractive due to its ability to provide long-term price stability for electric power.[1]

Wind power installations typically consist of a grouping of turbines mounted on towers and accompanying transmission infrastructure. These so-called "wind farms" can include anywhere from around a dozen to as many as one hundred (or more) turbines placed on large contiguous tracts within the landscape. The harvesting of wind energy, however, is not without potential drawbacks. Wind farms, with their imposing towers and whirling turbines, can create a visual dis-amenity (Álvarez-Farizo and Hanley 2002; Ladenburg and Dubgaard 2007), can engender negative environmental and avian impacts (Blaszquez, de Hoces, and Lehtine 2003; Pasqualetti 2004; Bergmann, Colombo, and Hanley 2008), and may entail social justice and equity issues if local citizens' concerns are not integrated into planning, placement, design, or operation (Dimitropoulos and Kontoleon 2008). Numerous studies have employed stated preference (SP) nonmarket valuation methods to estimate stakeholder's economic value for wind farms (Álvarez-Farizo and Hanley 2002; Ladenburg and Dubgaard 2007; Bergmann, Colombo, and Hanley 2008; Koundouri, Kountouris, and Remoundou 2009; Meyerhoff, Ohl, and Hartje 2010; Krueger, Parsons, and Firestone 2011). In this context, economic value is typically defined as individuals' willingness to pay (WTP) to convert electricity generation to renewable wind energy facilities or individuals' willingness to accept (WTA) compensation for negative impacts associated with wind turbines. The existing literature has considered many important issues in wind farm development, including negative impacts on flora and fauna, landscape and placement effects, impacts on environmental quality, local economic effects, and heterogeneity in individual preferences for wind energy development.

In a comprehensive analysis of 7,500 single-family home sales across nine U.S. states, Hoen, et al. (2009) use revealed preference (RP) nonmarket valuation methods to assess the impact that wind power facilities have on property values. Their analysis focuses on properties within 10 miles of 24 wind energy facilities. Whether examining view of or distance from wind energy facilities, their findings strongly suggest that wind

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[1] The Wall Street Journal reports that the city of Houston is saving money on municipal power after switching one quarter of its generation to fixed-price wind-power contracts (Johnson 2008).

Electronic copy available at: https://ssrn.com/abstract=1824397

turbines have no statistically significant impact on the value of surrounding residential properties. Nonetheless, opposition to wind energy facilities often reflects a concern over visual disamenities. The recent controversy over the Cape Wind project in Massachusetts provides a microcosm of the issues. Proponents of the project tout the positive environmental impacts (less carbon emissions and improved fishery habitat) and economic benefits of wind power for Cape Cod (CPN 2010), while opponents cite concern over impacts on birds, potential navigation problems, and negative effects on view amenities (Save Our Sound 2010).

In North Carolina, Massachusetts, and many other states, the potential for negative impacts is exacerbated by the fact that some of the places with the highest wind energy potential, such as mountaintops and coastal waters, are distinguished by their scenic vistas. A synthesis conducted by the U.S. Minerals Management Service (2007) indicates that the primary concern of the general public relates to visual impacts of wind turbines on the aesthetics of the coastal environment. Diminution of scenic vistas could affect the everyday welfare of local people and inhibit tourism and recreation.

In this paper, we examine the impact of coastal wind turbines on coastal tourism and recreation. A combination of telephone and web survey data are used to assess the impact of coastal wind farms on trip behavior and site choice for a sample of North Carolina coastal tourists. Overall, we find very little impact of coastal wind turbines on aggregate recreational visitation of residents in the northern coastal counties of North Carolina (focusing exclusively on the northern CAMA (Coastal Area Management Act) counties). Most of the respondents to our telephone survey claim to support offshore wind energy development; about half indicate that wind farms could enhance coastal views, and we see little evidence that wind farms influence visitation intensity. We estimate that under a scenario of widespread coastal wind energy development, consumer surplus of NC coastal residents remains virtually the same. Using an internet survey with visual representations of coastal wind turbines, we explore the impact of wind turbine placement on beach site selection. Results suggest that NC coastal residents are averse to wind farms in the near-shore zone; average compensating variation for wind farms one mile from the shore is estimated at $55 per household. We find evidence of preference heterogeneity for other wind farm placement scenarios, but the mean effects are statistically insignificant.

Background and Previous Literature
Given current technology, offshore wind turbines are feasible to a water depth of 30 meters. New technology exists to site wind turbines to a depth of 50 meters, while 100 meter technology is on the horizon. Considering this, offshore wind turbines are feasible from Cape Cod, Massachusetts to Cape Hatteras, North Carolina. Kempton et al. (2007) find that much of the energy needed in New England and the Mid-Atlantic could be supplied with wind turbines once the 100 meter technology is developed. Offshore plants in the east have capacity factors on par with Great Plains resources, but the cost of energy is greater because capital costs are higher (EnerNex Corp. 2010).

The benefits and costs of wind farms in coastal North Carolina should be considered as part of the North Carolina energy policy-making process. Wind farm benefits include reductions in carbon emissions and improved fishery habitat. Wind farm costs include a potential diminution in visual amenities, bird and bat mortality, possible decreases in coastal property values, and impacts on coastal recreation and tourism. The

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magnitudes of these benefits and costs for coastal North Carolina are currently unknown. In this paper, we focus on the projected impacts of widespread coastal wind energy development on tourist trips and tourists' preferences for wind turbine placement in the coastal zone, because the literature is largely lacking analysis of these aspects of offshore wind development.

Assessing Visual Impact

The potential for wind energy development in coastal locations has been assessed in studies by the National Renewable Energies Laboratory (NREL), and other state, regional, and local commercial feasibility studies. One study commissioned by the North Carolina General Assembly concluded there is potential for utility-scale wind energy production in North Carolina, particularly the eastern Pamlico Sound (UNC 2009.) While this study assessed the relevant meteorological, ecological, statutory, and infrastructure requirements, limitations, and synergies, the study did not evaluate the potential direct or indirect aesthetic and visual impacts, particularly in the intensive tourist economy of the Outer Banks. The potential for visual impact of wind turbines creates possible conflict and debate, including *Not in My Back Yard* (*NIMBY*) and *Not in My Beautiful Ocean* (*NIMBO*) effects. In the case of the Cape Wind project of Massachusetts, visual impacts prompted assessments, including nighttime and field-of-view of the proposed project, resulting in redesign, such as the number of turbines, removal of daytime aviation lighting, and narrowing the field of view visible from shore, to reduce visual effects (Rodgers and Olmsted 2008.) Although major utility-scale wind energy projects in nearshore marine locations such as Cape Wind have elicited ardent opposition (Phadke 2010), recent surveys in other regions with offshore potential (such as the Mid-Atlantic) have shown far lower potential opposition or substantial support (Firestone, et al. 2009).

Delineating technical feasibility zones is often the first step in assessing wind farm development. In this phase, early location selection policy may elicit public reaction or participation. Technical feasibility and public acceptability typically reduce the potential wind energy development areas to a small set of alternative sites. In this process, multi-criterion evaluation (MCE) techniques have been deployed to objectively compare alternatives (Gamboa and Munda 2007). This method has been illustrated to serve as more than a technical refinement procedure, but also as a learning process to reveal tradeoffs and comprehensive assessments of impacts. One quantifiable parameter of interest is the *viewshed*, or the zone of visual impact of the development. *Viewshed mapping* is a technique that provides for the estimation of the extent of viewshed across a landscape. Viewshed mapping can identify a binary *visual basin* area and has the capability of doing so for numerous alternative sites across a landscape and for measuring spatially coincident geographic features and summarizing impacts (e.g., land use, population, habitats) using a Geographic Information Systems (GIS) (Möller 2006.) In a published comparison of visual preferences based on landscape simulations, Oh (1994) evaluates four alternative visualizations (wireframes, surface models, combined wireframe and surface models, and image processing simulations.) Image processing-based simulations provided the highest realism among the methods.

Assessing Economic Value

Most existing valuation research has focused on Europe and has employed stated preference (SP) methods to estimate WTP or WTA compensation for new wind energy facilities (Álvarez-Farizo and Hanley 2002; Ladenburg and Dubgaard 2007; Bergmann, Colombo, and Hanley 2008; Koundouri, Kountouris, and Remoundou 2009; Meyerhoff, Ohl, and Hartje 2010). Exceptions include Hanley and Nevin (1999) – a comprehensive cost benefit analyses of renewable energy alternatives in Scotland; Dimitropoulos and Kontoleon (2008) – which employs SP methods to examine political factors which influence local acceptance of wind farm investments in Greece; and Krueger, Parsons, and Firestone (2011) – which estimates external costs of coastal wind turbines (at varying distances) on inland and coastal residents in Delaware. Our analysis is most similar to that of Ladenburg and Dubgaard (2007, 2009) and Krueger, Parsons, and Firestone (2011).

The placement of turbines further offshore can limit their visual impact on coastal populations, but moving the turbines into deeper water increases construction, maintenance, and transmission costs. Recognizing these tradeoffs, Ladenburg and Dubgaard (2007) use a choice experiment (CE) to examine the preferences of Danish residents for locating turbines further offshore. They find positive willingness to pay (WTP) for locating wind farms further from land (distances of 12km, 18km, and 50km, relative to an 8km baseline). Also, they find that residents that are more likely to see offshore wind farms – either from their residence or while engaged in recreational boating, fishing, or beach visitation – exhibit significantly higher WTP for locating turbines further offshore (Ladenburg and Dubgaard 2009). They express concern over the viability of coastal recreation and tourism in the presence of offshore wind turbines.

Krueger, Parsons, and Firestone (2011) use CE to measure Delaware residents' WTP for offshore wind farms (relative to a fossil fuel status quo). They find increasing WTP to locate turbines further offshore (up to a distance that is too far to see), but no significant value for specific locations along the Delaware coastline. Krueger, Parsons, and Firestone estimate separate choice models for inland residents, those residents with close proximity to Delaware Bay, and those residents with close proximity to the ocean. Still, they find some evidence of heterogeneity within these groups. The distance one lives from the coast increases the probability of selecting offshore wind farms over fossil fuels for the inland and ocean samples, but decreases the probability for the bay sample. Annual costs per inland Delaware household of observable offshore wind farms at a distance of 0.9 miles, 3.6 miles, 6 miles, and 9 miles are $19, $9, $1, and $0 (all values of WTP are relative to a distance too far to see). Corresponding costs for ocean (bay) residents are $80, $69, $35, and $27 ($34, $11, $6, and $2), respectively. Krueger, Parsons, and Firestone allow for royalties stemming from wind power generation to be paid to the state of Delaware, and they find a preference for payments to green energy and beach replenishment funds (over the general state fund). Surprisingly, they find diminishing utility associated with increased royalty payments.

Given the lack of attention to the projected impacts of offshore wind farms on coastal tourism, we focus on recreational beach visitation in North Carolina. We use travel cost models and combine revealed preference (RP) and stated preference (SP) methods in order to measure the impact of widespread coastal wind farms on the economic value of beach visitation. The primary model is estimated with data collected

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via telephone. With a sub-sample of internet data, we conduct a CE to examine the influence of the location of wind turbines on coastal recreation site choice.

Methods
We examine the impact of offshore wind turbines on coastal tourism within the framework of recreation demand models. We first consider the aggregate demand for trips to the North Carolina coast under current conditions, how this demand would change in the future if current conditions persisted, and how demand would change in the future under a scenario in which wind turbines are located offshore at all 31 major beach destinations in North Carolina. As such, we combine revealed (RP) and stated (SP) preference data to analyze the impact of widespread wind farm development on the economic value of coastal visitation. Our second application considers site choice on a single beach trip occasion. We examine the influence of beach site characteristics, such as the presence and location of wind farms, on site choice probabilities. We discuss the econometric methods behind each of these analyses in turn.

Pooled Site-Frequency Demand Model
      For analysis of aggregate NC beach recreation demand, we specify individual utility for coastal visitor i during period j as $u_{ij} = u(y_{ij}, z_{ij}, q_j)$, where y_{ij} is the number of recreation trips to the North Carolina coast in period j, z_{ij} represents consumption of a numeraire good during period j, and q_j is the quality of NC recreation trips during period j (assumed to be exogenous to individual choice).   Assume $u(\bullet)$ is quasi-concave, bounded, and twice differentiable. The budget constraint is given by $m_{ij} = y'_{ij} c_{ij} + z_{ij}$, where, m_{ij} is income for individual i during period j, c_{ij} is individual i's travel cost to NC coast – a combination of explicit (gas and vehicle wear-and-tear) and implicit (opportunity cost of time) costs of travel to a site – during period j, and numeraire price is normalized to unity. Constrained optimization produces the demand function for recreation trips:

$$y_{ij} = f(c_{ij},\ q_i,\ m_{ij}), \tag{1}$$

for individual i during period j.
      We consider a 3×1-vector of recreation demand counts, $y_i = [y_{ij}]$, with one observation per individual on RP ($j = 1$) and the remaining observations pertaining to SP ($j = 2, 3$) under current ($j = 2$) or projected ($j = 3$) conditions. Landry and Liu (2011) review a number of econometric models available for the analysis of stacked site-frequency demand models. All of these approaches make use of count models for panel data. We define $E[y_{ij}/x_{ij}] = \exp(\beta' x_{ij} + \varepsilon_i) = \mu_{ij}\exp(\varepsilon_i)$, where x_{ij} includes travel costs to NC beaches (c_{ij}), travel costs to substitute beach recreation sites, income(m_{ij}), demographic factors, and dummy variables for $j = 2$ and $j = 3$. We assume $\exp(\varepsilon_i)$ follows a Gamma(α^{-1}, α) distribution with a mean of 1 and a variance of α, producing the following probability density function:

$$f(y_i \mid x_i) = \frac{\Gamma\left(\sum_{j=1}^{J} y_{ij} + \alpha\right) \alpha^{\alpha} \left(\sum_{j=1}^{J} \mu_{ij} + \alpha\right)^{-\left(\sum_{j=1}^{J} y_{ij} + \alpha\right)}}{\Gamma(\alpha)} \prod_{j=1}^{J} \frac{\mu_{ij}^{\ y_{ij}}}{y_{ij}!}, \tag{2}$$

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with the likelihood function given as the sum of (2) over all individuals in the sample. The model is commonly known as the multivariate Poisson-Gamma or random effects Poisson model.[2] The conditional mean and variance are given by $E(y_{ij}|x_{ij}) = \mu_{ij}$ and $\text{Var}(y_{ij}|x_{ij}) = \mu_{ij} + \alpha^{-1}(\mu_{ij})^2$, respectively. This model allows for positive correlation among recreation demand across the j periods. The model has a closed-form solution and is estimated by maximum likelihood.

With y_{ij} measuring trips per year, annual consumer surplus (CS) for individual i under conditions q_j is the integral of expected recreation demand over travel cost, from the current level of cost (c^0) to infinity:

$$CS_{ij} = \int_{c^0}^{\infty} \exp(\widetilde{\beta}'\widetilde{x}_{ij} + \beta_c c)dc$$
$$= -\frac{E(y_{ij} \mid x_{ij})}{\beta_c} \tag{3}$$

where β_c is the NC travel cost parameter, and $\widetilde{\beta}'\widetilde{x}_{ij}$ represents the inner produce of covariates and parameters other than NC travel cost. CS under conditions j is a measure of the economic value of access to NC beaches. For $j = 1$, we have an RP measure of economic value under current conditions. Assuming income, travel costs, the overall price level, and beach conditions remain constant over time, CS under $j = 2$ is an SP measure of economic value associated with projected future demand under current conditions. On the other hand, if individuals expect changes in income, travel costs, prices, or beach conditions relative to $j = 1$, CS under $j = 2$ is an SP measure of economic value associated with projected future demand and expected future conditions. The $j = 2$ treatment provides a baseline for which to compare economic value under the scenario of interest, $j = 3$. Our $j = 3$ scenario entails widespread installation of wind farms at all 31 major beach destinations along the NC coast. As both involve projected demand under common conditions, the only induced difference between economic welfare associated with $j = 2$ and $j = 3$ is the presence of wind farms along the NC coast (Whitehead, Haab, and Huang 2000). Thus, $CS_{i2} - CS_{i3}$ provides a measure of the annual loss in economic value attributable to coastal wind farms in NC. Confidence intervals for consumer surplus are estimated with the Krinsky-Robb Procedure (1986).

Site Choice Model

For analysis of NC beach site choices, we employ the random utility model (RUM). We assume that individuals choose beach sites that yield the highest level of utility. Individual i's utility associated with a choice j among a set of choices t, denoted U_{ijt}, is a function of site characteristics, x_{ijt}, and travel costs, c_{ijt}. Our application of RUM uses the method of choice experiments (CE), an SP method that allows the researcher to select elements and levels of site characteristics x_{ijt} and to define levels of c_{ijt} in order to learn about preferences for beach site characteristics. (More on this method below.) Individual utility can be decomposed into an observable portion, $V_{ijt}(x_{ijt}, c_{ijt}; \widetilde{\alpha}, \widetilde{\beta})$, and an unobservable portion known only by the subject, ε_{ijt}:

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[2] We also attempted to estimate the Discrete Factor Method model (Landry and Liu 2011), but the factor loading parameters were not statistically significant.

$$U_{ijt} = V_{ijt}(x_{ijt}, c_{ijt}; \tilde{\alpha}, \tilde{\beta}) + \varepsilon_{ijt}, \quad \text{if site } j \text{ is selected}$$

$$U_{i0t} = \varepsilon_{i0t}, \qquad\qquad\qquad \text{if no trip is taken} \qquad\qquad (4)$$

where $\tilde{\alpha}$ and $\tilde{\beta}$ are unknown parameters, associated with site characteristics and travel costs, respectively, to be estimated. The probability of individual i choosing a site j over other choices h in set t, is thus:

$$P_{ijt} = \Pr[V_{ijt}(x_{ijt}, c_{ijt}; \tilde{\alpha}, \tilde{\beta}) + \varepsilon_{ijt} > V_{iht}(x_{iht}, c_{iht}; \tilde{\alpha}, \tilde{\beta}) + \varepsilon_{iht}, \forall h \neq j]$$

$$P_{ijt} = \Pr[\varepsilon_{iht} - \varepsilon_{ijt} < V_{ijt}(x_{ijt}, c_{ijt}; \tilde{\alpha}, \tilde{\beta}) - V_{iht}(x_{iht}, c_{iht}; \tilde{\alpha}, \tilde{\beta}), \forall h \neq j]. \qquad (5)$$

Expression (5) is a cumulative probability distribution, indicating the likelihood that the difference in the error terms (ε_i) is below the differences in the observable portions of utility (Train 2003). Given an assumption about the distribution of the difference in errors $g(\varepsilon_i)$, the choice probability can be obtained as:

$$P_{ijt} = \int_e I[\varepsilon_{iht} - \varepsilon_{ijt} < V_{ijt} - V_{iht}, \forall h \neq j] g(\varepsilon_i) d\varepsilon_i, \qquad (6)$$

where $I(\bullet)$ equals one when the expression in brackets is true, zero otherwise.

Various choice models can be developed by making different assumptions about the distribution $g(\varepsilon_i)$ (and possibly introducing other elements of random variation). We assume the observable portion of utility is additive: $V_{ijt} = \tilde{\alpha}' x_{ijt} + \tilde{\beta} c_{ijt}$. We choose to employ the repeated mixed logit (RXL) model (Herriges and Phaneuf 2002; Train 1999). We assume the ε_{ijt} are i.i.d. extreme value variates for all $i, j,$ and t, and the choice probabilities for any set t are conditional on an individual-specific vector β_i. Including alternative specific constants for J - 1 alternatives in the choice set, the conditional choice probabilities are given by:

$$\breve{P}_{ijt}(\psi, \alpha, \beta) = \frac{\exp(\psi' d_{ijt} + \alpha_i' x_{ijt} + \beta c_{ijt})}{\sum_h \exp(\psi' d_{iht} + \alpha_i' x_{iht} + \beta c_{iht})}, \qquad (7)$$

where $d_{ijt} = 1$ for choice alternative $j = 1, \ldots J$ - 1, zero otherwise, and $\alpha = \tilde{\alpha}/\sigma$ and $\beta = \tilde{\beta}/\sigma$ (where σ is the scale parameter of the extreme value distribution). We assume $\alpha_i \sim \phi(\alpha \mid \mu, \Omega)$, where ϕ is a multivariate normal probability density with mean μ and diagonal covariance matrix Ω. Since ε_{ijt} are i.i.d. for all t, the conditional probabilities for a series of choices $\boldsymbol{j} = \{j_1, \ldots j_T\}$ is given by the product of (7) across the T choice occasions:

$$\breve{P}_{ij}(\psi, \alpha, \beta) = \prod_{t=1}^{T} \frac{\exp(\psi' d_{j_t t} + \alpha_i' x_{ij_t t} + \beta c_{ij_t t})}{\sum_h \exp(\psi' d_{ih_t t} + \alpha_i' x_{ih_t t} + \beta' c_{ih_t t})} \qquad (8)$$

The unconditional choice probabilities are:

$$P_{ij} = \int \breve{P}_{ij}(\psi, \alpha, \beta) \phi(\alpha \mid \mu, \Omega) d\alpha \qquad (9)$$

The likelihood function is the product of (9) over all individuals in the sample. The means of the ψ and β parameters, as well as the means and variance terms for α are recovered from Simulated Maximum Likelihood estimates.

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Compensating variation (CV) provides a measure of the incremental change in economic value associated with changes in beach site characteristics (e.g., the presence of wind turbines). Conditional on $\alpha_{ik,}$ CV for a small change in site characteristic k is defined as:

$$CV_{ik} = \frac{\Delta x_k(\alpha_{ik})}{-\beta},\qquad(10)$$

for each k element of the vector x. The distribution of CV is simulated by repeatedly drawing from the posterior distribution of α. Mean, median, standard deviation, and confidence intervals can be calculated from the simulated distribution. Details on the CE are provided in the next section.

Visualization Techniques

Terrestrial photographs were used as the image background for daylight-hours, summertime landscape visualization. Photos were taken using a 10megapixel digital camera and converted to Tagged Image File Format (TIFF) on a personal computer. Next, various object models of wind turbines were evaluated for overlaying on a superimposed image plane onto the background photograph, with inclusion of associated haze, illumination, reflectance, and shadowing for the relevant solar geometry. The CanVIS software program and turbine models from the NOAA Coastal Services Center (NOAA 2010) were used to develop the prototype images. To estimate the height of the turbine in each image, a calibration photo of the feature (reference) at a known distance and height is needed. Equation (11) was used to calculate the appropriately scaled height for visualizing a large utility scale 3+ MW, 80m tall turbine with 50m blade diameter:

$$If = \frac{Af}{Ar} \times \frac{Dr}{Df} \times Ir \qquad(11)$$

where the desired image height of feature, *If,* is determined from estimating $Dr =$ Distance from reference feature, $Df =$ distance from feature, $Ar =$ actual height of reference feature, $Af =$ actual height of feature, $Ir =$ image height of reference feature. At distances greater than 4-5 kilometers, the curvature of the earth is factored by estimating the height of the feature that is obscured by the horizon and cropping the image height of the feature.

Data
Given budget limitations, we chose to focus our study on households in the designated "CAMA" (Coastal Area Management Act) counties of North Carolina's Outer Banks (OBX) region. This includes 16 counties in all – four coastal (Carteret, Hyde, Dare, and Currituck) and twelve adjacent to the coast (Beaufort, Bertie, Camden, Chowan, Craven, Gates, Hertford, Pamlico, Pasquotank, Perquimans, Tyrell, and Washington) as shown in Figure 1. Our rationale for this approach is practical; we have a limited budget and want to focus on a limited geographic region. We expect that single-day trips (with no overnight stay) are the most common type of trip to NC beaches for households in this region. Thus, we are more comfortable producing models of economic behavior with a common preference structure.

The East Carolina University Center for Survey Research implemented a telephone survey in the summer of 2009. Twenty dollar gift cards to local merchants were used as an incentive for respondents. Contact was made with 1,162 households, of

which 361 completed the telephone survey (for an overall response rate of 31%). Those that completed the telephone interview were invited to participate in an internet survey that included wind turbine visualizations. Of the 361 telephone respondents, 118 households participated in the internet survey (33% of the telephone respondents; 10% of the households contacted). Given the differences in sample sizes, we treat the telephone and internet surveys separately in this paper. We discuss each dataset in turn.

Telephone Data

The telephone survey collected information on respondents' knowledge & perceptions of climate change and opinions about and support for wind energy projects. Data was collected on number of trips to NC beaches in the previous 12 months and how many of these trips were single-day and overnight visits (RP data). The survey inquired about intentions to visit NC beaches in the next 12-months, specifically eliciting the beach the respondent would likely visit on their next trip and the overall planned number of trips (SP data). The contingent scenarios were then described as follows:

"Now we are interested in how your beach trips might change if there are wind farms in North Carolina.

Scenario 1: Suppose that a wind farm is built at _____ [*insert beach respondent is most likely to visit*]. The wind farm has 100 windmills, standing about 400 feet high and 1 mile from the shore. The next time you go to the beach would you still go to this beach, a different beach without a view of a wind farm, or would you take no beach trip at all?

Scenario 2: Now suppose that similar wind farms are built at each of the 31 major beach towns in North Carolina. How many total beach trips would you expect to take to North Carolina beaches in the next 12 months?"

The survey included a question to identify those that live at a NC beach and those that own property at a NC beach. Lastly, demographic factors, such as education, income, age, household size, marital status, and political ideology, were collected.

The first column of table 1 includes raw descriptive statistics for the 313 respondents that did not live at the beach or own beach property and made no more than 150 trips in the previous 12 months. (As we are interested in estimating models of recreation demand within the travel cost framework, we focus on beach tourists.) The average respondent took almost 12 trips to NC beaches in the previous 12 months, 9 of which were day trips and 3 of which involved overnight stay. The average respondent planned almost 15 trips for the next 12 months. Eighty-nine percent of respondents indicated that they would maintain their planned beach visit on their next trip, with 100 wind turbines present 1 mile offshore (**scenario 1**, above). Over 6% indicated they would visit a different beach (without wind turbines) under this scenario, while almost 5% indicated they would not make a beach trip. Overall trips under the contingent scenario of widespread wind farms at all major 31 beach destinations (**scenario 2**, above) is slightly over 14.

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The most common RP site visited was Nags Head (26.7%), followed by Atlantic Beach (26.3%), Kill Devil Hills (8.4%), and Emerald Isle (7.8%). As such, travel cost for aggregate trips to the NC coast is measured using distance to Nags Head or Atlantic Beach, whichever is smaller. Travel costs to substitute sites are measured using distance to Myrtle Beach, SC and Virginia Beach, VA. All travel costs are calculated using monetary costs of $0.54 per mile (AAA 2009). Travel time costs are calculated assuming average speed of 50 miles per hour and using 1/3 of the implicit hourly wage as a measure of the opportunity cost of time.

Seventy-two percent of respondents expressed concern over potential climate change (either "very concerned" or "somewhat concerned"), and 82% "strongly agreed" or "somewhat agreed" with the statement, "most of the increase in temperature during the past 50 years has been caused by manmade pollution". Ninety-one percent claim to support wind energy development, in general, and, somewhat surprisingly, about half of respondents thought that offshore wind farms could have a *positive* impact on the overall view at the beach. About 87% (84%) expressed support for wind energy development at the nearest beach to their house (all NC beaches).

An independent survey of property owners in Kitty Hawk, NC supports the notion of widespread support for wind energy development on the coast (91% affirmative response) (Town of Kitty Hawk 2010). Only 9% of Kitty Hawk survey respondents expressed concern over the unattractive appearance of wind turbines, while 7% were concerned about obstructed scenic views. The majority of Kitty Hawk survey respondents considered wind turbines attractive (20%) or 'neither attractive nor unattractive' (65%).

Nonetheless, the demographic statistics in table 1 suggest that our sample is not representative of the overall population in the 16 northern CAMA counties of NC. In particular, our sample appears to be older, more educated, have greater income, and more heavily weighted towards females than the overall population when compared to U.S. Census data for these counties (third column of table 1.) We correct for these factors using normalized inverse probability weights, composed of the population proportions divided by sample proportions (where the proportion is above or below the median for age and income level). The corrected descriptive statistics can be found in column 2 of table 1. The weighted means exhibit lower past trips (9) and planned trips (around 9.75 under current and wind scenario conditions). The effect of wind turbines on intended visitation for the next beach visit diminishes somewhat in the weighted sample, as 92% indicate they would visit the same beach (with 4% visiting a different beach and 4% engaging in some other activity). Weighted descriptive statistics indicate slightly more concern over climate change (78%) and greater support for wind energy (92%). It is noteworthy that the majority of respondents (44%) consider themselves politically conservative; if our sample were biased towards supporters of wind energy, we might expect a higher proportion of respondents that self identify as liberal or moderate. Overall, while perspectives on wind energy appear in line with the Kitty Hawk survey data (Town of Kitty Hawk 2010), the potential for unobserved differences between the sample and population, in terms of climate change concern and support for wind energy projects, remain in the data.

Internet Data

We turn next to the internet survey data. Telephone respondents that agreed to participate in the internet portion of the study were given a URL (via telephone and e-mail) to access the survey, which was programmed using Perseus software. Each respondent had a unique identification number so that data could be linked across the survey instruments. The $20 incentive (gift card) was only provided to those that completed both surveys, and this was made clear at the initiation of the telephone survey.

The primary component of the internet survey was a choice experiment (CE) that included visualizations to depict conditions at NC beaches with and without wind farms in the sounds or offshore waters. The CE examines tradeoffs that tourists make when selecting a destination for coastal recreation, using generic beach destinations that vary only along dimensions specified by the researcher. The dimensions of site characteristics (the x_{ijt} matrix, above) that we chose to analyze are: i) presence/absence of wind farms in offshore waters and distance from the shore (when present); ii) presence/absence of wind farms in sound waters and distance from the shore (when present); iii) number of people on the beach (beach congestion); and iv) onsite fees for parking. Travel distance, which determines travel cost, was also included as a site attribute. The initial instructions for the CE were as follows:

> "Imagine you are deciding on a destination for a single-day beach trip (i.e. no overnight stay). In what follows we have laid out a set of alternatives for this decision. Each alternative is described by characteristics of the available sites. The characteristics have a number of levels. The characteristics and possible levels are below:"

The attributes and levels for the CE are depicted in table 2. The levels of travel distance ("Distance from Home") varied by proximity to the coast. For those respondents in the four coastal counties (Carteret, Hyde, Dare, and Currituck), the possible distances were 20, 40, and 60 miles, while for those in the twelve adjacent counties (Beaufort, Bertie, Camden, Chowan, Craven, Gates, Hertford, Pamlico, Pasquotank, Perquimans, Tyrell, and Washington), the possible distances were 60, 90, and 120 miles. Parking fees varied at $0, $4, and $8 per day. Ocean and sound view, the last two site attributes, took three levels each: unobstructed by wind turbines, turbines one mile from the shore, or turbines 4 miles from the shore. Visualizations were developed to provide a sense of what the ocean and sound would look like under each condition. An example of a choice set is included in Figure 2; this figure depicts conditions for each level of visual obstruction in the sound and on the ocean. Each visualization presents an array of wind turbines (if applicable) along the horizon and includes a pier to provide a scale of reference.[3] The instructions continued:

> "We would like to know how these characteristics affect your choice of destination for a single-day beach trip. For each choice that you make, you will be shown three alternative sites. Pick the site that you would most like to visit. Assume that the sites are completely the same except for the differences in characteristics that are listed.

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[3] We thank Laurynas Gedminas and the Renaissance Computing Institute at ECU for producing the visualizations.

You can also choose to make no trip (or stay home). For each choice, please indicate which trip you would take or whether you would rather stay home than visit one of the sites offered.

You will make six choices overall. Please treat each choice as if it is independent of the other choices that you've made. That is, when making your second choice, treat it as if it is the only choice you are making."

Our experimental design implies 3^5 possible choice profiles. We choose a fractional factorial design of 36 profiles, designed with SAS Macros *%MktEx* and *%ChoiceEff*, which is fully efficient for a linear experimental design and from which main effects can be estimated (Huber and Zwerina 1996; Kuhfeld 2005). The *%MktBlock* SAS Macro was used to efficiently partition our 36 profiles into 2 blocks of 6 choice sets with 3 profiles each. Each choice set also included a no-trip (stay home) option. (See Figure 2.)

Table 3 presents descriptive statistics for the internet sample. Again, we find evidence that our sample is skewed towards older females, with greater education and income. Given the relatively small dataset, inverse probability weights that take all of these factors into account proved to be somewhat imprecise (leading to higher model standard errors), so we only correct for income and education level. The weighted descriptive statistics are presented in the second column of table 3, with U.S. Census data in the third column for comparison. The internet data are more heavily skewed towards adjacent (77%) rather than coastal (23%) counties. The internet sample also appears more avid than the telephone sample, with 28 NC beach trips, on average, in the previous 12 months. Again, the majority of respondents consider themselves politically conservative.

Results

Table 4 contains regression results for the multivariate Poisson-Gamma mixture model (AKA Random Effects Poisson). Each model includes intercept shifters and own-price interaction terms for the SP scenarios ($j = 2, 3$).[4] The first column presents results for the raw data, and the second column presents results for the weighted data. Results indicate statistically significant and negative own-price effects, and responsiveness to price is greater under the SP scenarios. Substitute price coefficients are positive and statistically significant in both models, while the income coefficients are negative and significant. The negative age coefficient for the weighted model indicates an inverse relationship between beach recreation demand and age. Gender and education coefficients are not statistically significant in either model. The SP intercept shifters are statistically significant and indicate an upward shift of the demand function under both SP scenarios. The parameter for SP demand under current conditions is greater than the parameter for SP demand under the wind scenario for the raw data model, while the opposite pattern holds for the weighted data. The alpha dispersion parameter is statistically significant in each model.

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[4] Likelihood ratio tests support the inclusion of own-price-SP interaction parameters: $\chi^2_{(df=2)} = 44.70$ for the raw data and $\chi^2_{(df=2)} = 24.16$ for the weighted data; both *p*-values are less than 0.0001.

Table 5 presents conditional expectations of demand and elasticity & welfare estimates. Measures of expected demand consistently exceed the raw moments (as expected given the functional form). But, following the raw data, demand appears to diminish slightly for the SP wind scenario relative to the SP baseline for the raw data model, while SP demand is virtually the same for the two SP scenarios for the weighted model. Price elasticity of demand for trips to North Carolina beaches is -1.4 to -1.9, indicating somewhat high responsiveness of recreation demand to changes in travel cost. Estimates of price elasticity derived from SP data indicate greater responsiveness, -1.6 to -2.2. Cross-price elasticity for trips to Myrtle Beach (Virginia Beach) is around 1.8 (1.07 to 1.31), and the income elasticity is negative (-0.25 to -0.32) indicating beach recreation is an inferior good.

Annual consumer surplus (CS) is calculated via equation (3) using sample enumeration, and confidence intervals are produced by the Krinsky-Robb bootstrapping procedure. CS from the RP data is estimated at $1456 per household, per year for the raw data or $1082 for the weighted data; these correspond with welfare estimates of $113 per trip for the raw data model and $94 per trip for the weighted data model. CS for the projected demand (SP data) under current conditions is $1636 per household, per year for the raw data or $1068 for the weighted data. Notably, the raw data model indicates greater stated intensity of expected visitation and higher economic value under current resource quality conditions. The weighted model, however, indicates greater stated visitation, but slightly lower overall economic value. The lower value reflects more price responsive (elastic) demand (as the price coefficient is present in the denominator of (3)). The change in demand and economic value across RP and SP data associated with current resource conditions may indicate expected changes in income or price levels or could indicate hypothetical bias – a possible lack of reliability inherent in data on projected behavior. In any event, SP demand under current conditions provides a baseline against which we can compare behavior under the wind farm scenario (wind farms at all 31 major beach destinations in North Carolina). Annual CS for the wind scenario is $1540 per household for the raw data or $1051 per household for the weighted data. The wind scenario welfare point estimate for the raw data is $96 (5.8%) below the baseline, but only $17 (1.5%) below for the weighted model.

We turn next to results for the Choice Experiment (CE). The parameters of the choice model are estimated using Simulated Maximum Likelihood using 1500 Halton draws at the individual level. We 'burn' the first 20 draws in order to reduce the correlation between the Halton sequences for each random parameter. The parameter estimates are displayed in table 6. The first column presents results for the raw data, while the second column presents results for the weighted model.

For both models, the no-trip option has a large negative coefficient, indicating a loss in utility relative to the trip alternatives. Dummy variables for trip alternatives A and B are not statistically significant for the raw data, but are significant in the weighted model; the excluded category is trip alternative C. For the weighted model, findings suggest some sort of ordering effect in the data – respondents in the weighted model were more likely to choose the first or second alternative over the third. This could be evidence of bias stemming from fatigue due to respondents making repeated choices, as profile ordering is orthogonal to site attributes by design. The travel cost and parking

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cost parameters are negative and statistically significant in each model. The parking cost parameters are an order of magnitude larger than the travel cost parameters.

The coefficients for site characteristics (level of beach congestion and the presence of wind turbines in the sound or ocean (at varying distances)) were assumed to follow a multivariate normal distribution with diagonal covariance matrix. Dummy variables are included for medium and high beach congestion, with low congestion as the excluded category. The mean parameter for medium congestion is not statistically significant in either model. The mean parameter for high congestion, however, is negative and statistically significant in the raw data model (negative and not statistically significant for the weighted data). This indicates that high beach congestion can decrease the probability of site visitation. The standard deviation parameters for site congestion are generally estimated with precision and tend to be rather large.[5] We construe this as evidence of heterogeneity of preferences for beach congestion.

Dummy variables are included for wind turbine scenarios: turbines in the ocean, 1 mile out; turbines in the ocean, 4 miles out; turbines in the sound, 1 mile out; and turbines in the sound, 4 miles out. The excluded categories are 'no wind turbines in the ocean' and 'no wind turbines in the sound'. Only the coefficient for 'ocean wind turbine, 1 mile out' is statistically significant. The mean parameter for one-mile-ocean is negative and statistically significant in each model, indicating a reduction in site utility when wind turbines are located in close proximity to the beach on the ocean side. The mean parameters for other wind turbine scenarios are positive (with the exception of sound placement, 1 mile out, in the weighted model), but not statistically significant. The standard deviation parameters for wind farm location are precisely estimated and indicate significant variability in preferences for placement of wind turbines.

Estimates of compensating variation are presented in table 7. Compensating variation for not taking a trip is $270 ($341) for the weighted (raw) model. We interpret this as average value of a hypothetical beach trip in our choice experiment. Compensating variation for a $1 increase in the onsite parking fee is $10 to $12. This result likely reflects the widespread lack of paid parking on the Outer Banks of North Carolina and a strong preference for this status quo. The result indicates that the average beach visitor is willing to drive a significant distance (incurring additional travel cost) to avoid beach parking fees.

Willingness-to-pay to avoid moderate congestion is around $21 for the raw data model, but negative for the weighted data model (-$6). The modest negative value indicates a slight preference, on average, for moderate levels of beach congestion. Willingness-to-pay to avoid high congestion is $105 for the raw data model and $32 for the weighted model. Confidence intervals for these welfare estimates (and those associated with wind turbines, discussed below) are estimated using the standard deviation parameters associated with the multivariate normal mixing distribution (rather than the standard error of the mean coefficient). As such, there is much larger variability in the confidence intervals. For willingness-to-pay to avoid congestion, in all cases there is significant variability in utility parameters. The magnitudes of the estimated standard deviations are rather large relative to the means, indicating significant heterogeneity of congestion preferences among the sampled population.

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[5] Standard tests for statistical significance of standard deviation parameters are biased because the null hypothesis is on the boundary of the parameter space.

Compensating variation for the presence of wind turbines one mile off the beach is $55 ($102) for the weighted (raw) data model. The estimated standard deviations imply significant variability in the aversion to this placement scenario. Point estimates for the other wind turbine scenarios tend to be smaller in magnitude and highly variable (reflecting low statistical significance of the mean parameters and relatively large standard deviations).

Discussion

Overall, we find little impact of offshore/sound wind turbines on recreational visitation of residents in the northern CAMA counties of North Carolina. Respondents to the telephone survey took around 9 trips to North Carolina beaches in the previous 12-monthsl, plan to take almost 10 trips in the next year, and will take approximately the same number of trips if wind turbines were built at each of the 31 major beach towns in North Carolina. Hanley and Nevin (1999) find similar results for the installation of wind turbines on a rural estate in Scotland; none of their respondents indicated that they would avoid the estate entirely if there was a wind farm, and over 90% indicated that the wind farm would have no effect on future trips.

The average planned trips masks individual level variation in our data, however. While some respondents indicated that they would take less trips under the wind farm scenario, others indicated that they would increase trips under this scenario. Approximately half of the respondents "strongly agreed" or "somewhat agreed" that wind turbines could have a *positive* impact on the overall view at the beach. The overall insensitivity of aggregate recreation demand to our contingent wind farm scenario could be evidence of sample selection bias, as the effect persists with inverse probability weights to correct for non-response bias. In particular, we are concerned that our sample may be skewed towards individuals that support wind farms. We note, however, that the majority of respondents (44%) self-identify as politically conservative, rather than liberal (13%), moderate (19%), or 'other' (22%). If our telephone sample were skewed towards wind energy supporters, we might expect a higher proportion of liberals and moderates in the sample (though our sample still could be skewed relative to population proportions). Also, an independent survey of Kitty Hawk residents reveals similar patterns of support for wind energy development (Kitty Hawk 2010).

Regression results for annual aggregate NC beach demand indicate price elasticity that increases (becomes more elastic) under the SP scenarios. The increasing sensitivity to travel cost is at odds with standard conjecture regarding hypothetical bias, which would suggest less sensitivity to price in SP measures. This could be construed as evidence of the perceived validity of our SP scenarios, and may also reflect poor macroeconomic outlook that induces greater price sensitivity among respondents. NC beach demand in the northern CAMA counties is sensitive to travel costs to both Virginia Beach, VA and Myrtle Beach, SC, with both substitute site travel costs increasing demand for NC beach visitation, *ceteris paribus*. Results suggest that demand is decreasing in age and that NC beach trips are an inferior good.

Consumer surplus (CS) estimates for NC beach trips are about $1082 per year for our preferred model (weighted for non-response bias), or around $94 per trip. Most of the respondents in our dataset took day trips to the beach, so the per-trip estimate primarily applies to a single beach day. This is similar to previous results in the literature

(Bin et al. 2005; Whitehead et al. 2008; Lew and Larson 2008). Projected future CS under current conditions is slightly lower at $1068 per year, which is reduced to $1051 under the wind scenario. The $17 loss in CS is slightly more than 1% of the SP baseline. This suggests very small (if not inconsequential) costs associated with the installation of wind energy facilities at all major North Carolina beach destinations.

While this result is encouraging for the economic viability of offshore wind in North Carolina, we bring attention to the important caveat that our sample only includes residents from the coastal region of North Carolina. Most of these residents make day trips to the beach, and thus create less economic impact per trip. Moreover, this population has very limited substitution possibilities relative to those that travel greater distances for beach recreation. Tourists from the Mid-Atlantic, Northeast, and Midwest regions of the U.S. often travel significant distances to access warm water beaches. This population is much more likely to spend a week or more onsite, thus creating greater economic impact. Also, this population has a larger set of viable alternatives for beach recreation. If these coastal tourists are averse to wind farms and recognize alternative sites that do not have visible turbines, we might expect a greater diminution in tourism in coastal North Carolina. The impact of offshore wind turbines on recreation decisions of this group of tourists remains an important topic for future research.

Having wind turbines at every major beach destination is a somewhat drastic scenario given current tentative plans for limited development of offshore wind energy. By exploring this scenario, we attain a sense of the impacts of what we might construe as a worst-case scenario for coastal recreation and tourism. Under this characterization, the cost estimates derived can be construed as an upper bound on the likely costs. Our SP scenario, however, does not explore the relationship between turbine placement (i.e. location, offshore or in the sounds, and distance from the shore) and recreation behavior. To this end, we gathered additional internet data that made use of visual depictions of offshore wind turbines (a capability that was not possible with the telephone instrument). Recent research indicates that visual representations can be effectively integrated within choice experiments and that visual attributes perform better, in terms of reducing biases, than numerical representations of visual phenomena (Bateman et al. 2006).

Our choice experiment (CE) examines the impact of wind farms, offshore and located in the sound, on beach site choice. In each trip profile, offshore conditions are either free of wind farms, wind farms can be seen 1 mile from the shore, or wind farms can be seen 4 miles from the shore. Conditions in the sound receive a similar treatment: either the sound is free of wind farms, wind farms can be seen a mile from the shore, or 4 miles from the shore. Offshore and sound conditions are treated independently in the CE. The experiment is designed so that these two trip attributes are orthogonal, and thus both offshore and sound conditions can be evaluated independently. Each trip profile also includes travel distance to the beach site, beach congestion, and parking fees. Participants in the CE evaluated six choice sets which were composed of three trip profiles and included a no-trip option.

Results from the mixed logit model indicate that parking fees and travel costs both have a negative impact on site choice, with the parking fee parameter differing from the travel cost parameter by an order of magnitude. Compensating variation for a $1 increase in parking fee is around $10 to $12, indicating that beach visitors will incur greater travel cost in order to avoid parking fees. This could suggest that there is some

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utility in travel to the beach that is not being accounted for in our travel cost measure, or may be indicative of a strong negative disposition towards beach parking fees in North Carolina. The latter interpretation could reflect a strong preference for the status quo conditions on the Outer Banks in which parking fees are rare.

The coefficients for beach congestion and the presence of wind turbines were assumed to follow a multivariate normal distribution with diagonal covariance matrix. We find some evidence that high beach congestion reduced the probability of site selection, but standard deviations of the congestion parameters were generally large, indicating significant heterogeneity in utility associated congestion. Willingness-to-pay to avoid high congestion is $105 for the raw data model (but statistically insignificant for the weighted model).

Offshore wind farms one mile from the shore induce a significant and negative mean utility effect on beach visitors (relative to the excluded category of no wind turbines offshore), while the mean effects of other placement options are not statistically significant. Compensating variation for wind farms one mile from the shore is $55. Given the large estimated standard deviation, the 95% confidence interval of compensating variation is -$71.97 to $177.17. If, however, we use the standard error of the mean effect to estimate the 95% confidence interval, the range does not include negative values. Thus, the choice experiment data indicate that beach visitors from the northern CAMA counties in North Carolina are aversive to ocean wind farms in close proximity to the beach, and the compensating variation for the presence of wind farms is large relative to the average value of a beach visit (around $94). For ocean wind farms further out (4 miles) and for wind farms located in the sounds, however, we do not find a statistically significant effect. For all scenarios the standard deviation of the wind farm utility effect is large, indicating significant heterogeneity within the sample. Overall, our results suggest that the installation of wind farms in the sounds of North Carolina's coastal region or far out in the ocean will have the no appreciable effect on recreation and tourism. Nonetheless, the caveat that we are focusing on coastal NC residents has gravity. More research on other types of visitors is needed to explore whether the pattern of results we find can be interpreted more broadly.

Conclusions

The push towards renewable energy sources raises many important questions about the economic viability of alternative energy sources and the external effects of alternative energy development. Wind energy is a promising prospect for many parts of the U.S. Wind turbines, however, can create a visual dis-amenity that may affect property values, local residents, tourist behavior, or other factors. From a practical perspective, this dis-amenity can create a significant dilemma, as areas with greatest wind energy potential are often those with scenic vistas (mountain ridges and coastal landscapes).

We use a combination of telephone and web survey data to assess the impacts of coastal wind farms on trip behavior and site choice, focusing on residents in the northern CAMA counties of North Carolina (adjacent to North Carolina's Outer Banks). Overall, we find little impact of widespread coastal wind energy development on aggregate recreational visitation. Most telephone survey respondents (92%) claim to support offshore wind energy development, and over half (60%) indicate that wind farms could have a *positive* impact on the overall view at the beach. Further, we see little evidence of

impact on trip-taking. The average household made about 9 trips to North Carolina beaches in the previous 12-months, planned to take almost 10 trips in the next year, and would take approximately the same number of trips if wind turbines were built at each of the 31 major beach towns in North Carolina. Accordingly, we estimate that lost consumer surplus under the wind energy scenario is about $17, or 1.5% per year.

Our internet survey employs visual representations of coastal wind turbines to examine the effect of wind turbine placement on beach site selection. We find evidence that NC coastal residents are averse to wind farms in the near-shore zone; average compensating variation for wind farms one mile from the shore is estimated at $55 per household. For all wind farm scenarios, we find evidence of preference heterogeneity – some respondents find the scenario appealing while others find it aversive. For wind farms located further out in the ocean or located in the sounds we find no evidence of negative impacts on recreation visitation, on average. Future research that focuses on local residents could explore the extent to which "place theory" influences acceptability of what some may considerable undesirable land uses (Devine-Wright 2005).

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Table 1: Descriptive Statistics for Telephone Survey Data

Variable	Definition	Obs	Raw	Weight	Census
t_trips1	Total trips to NC beaches in previous 12-months (RP)	312	11.81 (18.08)	9.09 (14.74)	
d_trips1	Single-day trips to NC beaches in previous 12-months (RP)	313	8.57 (16.36)	7.28 (13.06)	
on_trips1	Overnight trips to NC beaches in previous 12-months (RP)	313	3.12 (6.74)	1.86 (5.11)	
t_trips2	Trips to NC beaches over next12-months under current conditions (SP)	304	14.76 (40.84)	9.76 (23.85)	
t_trips3	Trips to NC beaches over next12-months w/ wind farms (SP)	302	14.10 (41.48)	9.77 (25.30)	
same_beach	Respondent would visit same beach under wind farm scenario	313	0.89 (0.32)	0.92 (0.27)	
diff_beach	Respondent would visit different beach under wind farm scenario	313	0.06 (0.24)	0.04 (0.19)	
no_beach	Respondent would visit no beach under wind farm scenario	313	0.05 (0.21)	0.04 (0.19)	
concern_cc	Very or somewhat concerned over climate change	313	0.72 (0.45)	0.79 (0.41)	
anthro_cc	Strongly or somewhat agreed that most recent climate change is due to manmade pollution	313	0.91 (0.39)	0.86 (0.35)	
wind_support	Strongly or somewhat support coastal wind energy development	313	0.91 (0.28)	0.92 (0.27)	
wind_impact	Very positive or positive impact of wind farms on view at the beach	313	0.53 (0.50)	0.60 (0.49)	
wind_support _near	Strongly or somewhat support wind energy development at nearest beach	313	0.88 (0.33)	0.90 (0.30)	
wind_support _all	Strongly or somewhat support wind energy development at all NC beaches	313	0.84 (0.37)	0.86 (0.35)	
ptr	Travel cost to NC beach (closest of Nags Head or Atlantic beach)	313	160.86 (477.44)	176.90 (235.03)	
MBsub_ptr	Travel cost to Myrtle Beach, SC	313	435.52 (444.56)	306.82 (368.31)	
VBsub_ptr	Travel cost to Virginia Beach, VA	313	262.77 (469.08)	190.76 (224.88)	
inc	Household income (in thousands)	258	78.80 (50.27)	52.00 (43.81)	42.2
male	Male respondent	312	0.38 (0.48)	0.49 (0.50)	0.48
age	Respondent age	308	54.65 (15.34)	44.45 (19.68)	39.66
less_hschool	Less than High School education	313	0.03 (0.16)	0.30 (0.46)	0.21
hschool	High School is highest educational attainment	313	0.24 (0.43)	0.29 (0.46)	0.32
some_coll	Some college is highest educational attainment	313	0.31 (0.46)	0.27 (0.44)	0.28

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college	College or graduate school is highest educational attainment	313	0.42 (0.49)	0.13 (0.34)	0.17
env_org	Member of environmental organization	310	0.11 (0.31)	0.51 (0.22)	
liberal	Respondent considers themselves politically liberal	313	0.17 (0.37)	0.13 (0.33)	
moderate	Respondent considers themselves politically moderate	313	0.30 (0.46)	0.19 (0.40)	
conservative	Respondent considers themselves politically conservative	313	0.37 (0.48)	0.44 (0.50)	
other_poly	Respondent considers themselves something other than liberal, moderate, or conservative	313	0.15 (0.36)	0.22 (0.42)	

Note: Standard deviations in parentheses

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Table 2: Attributes and Levels for the Beach Site Choice Experiment

Attribute	Levels
Distance from Home - number of one-way miles travelled to get to the beach	"Coastal" counties: 20 miles; 40 miles; 60 miles "Adjacent" counties: 60 miles; 90 miles; 120 miles
People on the Beach – number of people per mile on the surrounding beach	low (1 – 20 people per mile); moderate (20 – 80 people per mile); high (more than 80 people per mile)
Parking Fees – the amount you have to pay to park your car	$0 per day, $4 per day, $8 per day
Ocean View	a clear view of the ocean; wind farm 1 mile out; wind farm 4 miles out
Sound View	a clear view of the sound; wind farm 1 mile out; wind farm 4 miles out

Table 3: Descriptive Statistics for Internet Survey Data

Variable	Definition	Obs	Raw	Weight	Census
adjacent	Resident of adjacent county	118	.64 (.48)	.77 (.42)	
ocean	Resident of ocean county	118	.36 (.48)	.23 (.42)	
t_trips1	Total trips to NC beaches in previous 12-months (RP)	112	43.16 (95.77)	27.77 (73.57)	
inc	Household income (in thousands)	97	88.56 (46.16)	63.11 (43.26)	42.25
male	Male respondent	111	.37 (.48)	.33 (.47)	0.486
age	Respondent age	109	51.38 (13.86)	51.96 17.73	39.662
hschool	High School is highest educational attainment	112	.13 (.34)	.49 (.50)	0.323
some_coll	Some college is highest educational attainment	112	.27 (.44)	.29 (.45)	0.287
college	College or graduate school is highest educational attainment	112	.58 (.50)	.18 (.38)	0.170
env_org	Member of environmental organization	108	.14 (.35)	.12 (.32)	
liberal	Respondent considers themselves politically liberal	112	.19 (.39)	.10 (.30)	
moderate	Respondent considers themselves politically moderate	112	.29 (.46)	.29 (.46)	
conservative	Respondent considers themselves politically conservative	112	.35 (.48)	.44 (.50)	
other_poly	Respondent considers themselves something other than liberal, moderate, or conservative	112	.14 (.35)	.13 (.34)	

Note: Standard deviations in parentheses.

Table 4: Random Effects Poisson Regression Model Results

Variable	Raw Data		Weighted Data	
	Coefficient	Standard Error	Coefficient	Standard Error
ptr	-0.0088***	0.0010	-0.0107***	0.0014
ptr×future	-0.0012***	0.0003	-0.0015***	0.0004
ptr×future_wind	-0.0013***	0.0003	-0.0018***	0.0004
MBsub_ptr	0.0042***	0.0006	0.0057***	0.0009
VBsub_ptr	0.0050***	0.0006	0.0056***	0.0009
inc	-0.0032*	0.0018	-0.0061***	0.0023
male	0.1235	0.1471	0.2583	0.1655
age	-0.0016	0.0050	-0.0127***	0.0043
hschool	0.0835	0.5246	-0.1870	0.2288
some_coll	0.5190	0.5215	-0.0056	0.2327
college	0.4548	0.5208	0.1953	0.2950
future	0.3251***	0.0287	0.2135***	0.0399
future_wind	0.2819***	0.0292	0.2403***	0.0406
constant	0.4534	0.5540	1.0072***	0.3284
alpha	1.1672***	0.0939	0.9947***	0.0928
observations	757 (256 individual responses)		757 (256 individual responses)	
lnL	-2901.10		-1911.90	
LRT (df) p-value	1119.14 (13) $p<0.0001$		1469.36 (13) $p<0.0001$	

Note: *** - statistically significant for 1% chance of Type I error; ** - statistically
significant for 5% chance of Type I error; * - statistically significant for 10% chance of
Type I error.

Table 5: Conditional Expected Demands, Elasticities, and Welfare Estimates

	Raw Data	Weighted Data
$E[y_1/x_{ij}]$ (RP)	12.88	11.54
$E[y_2/x_{ij}]$ (SP)	16.40	12.96
$E[y_3/x_{ij}]$ (SP_wind)	15.60	13.07
ε_{op}: own-price elasticity (RP)	-1.41	-1.89
ε_{op_future}: own-price elasticity (SP)	-1.61	-2.16
$\varepsilon_{op\_future\_wind}$: own-price elasticity (SP_wind)	-1.62	-2.21
ε_{cp_MB}: cross-price elasticity for Myrtle Beach	1.83	1.75
ε_{cp_VB}: cross-price elasticity for Virginia Beach	1.31	1.07
ε_{inc}: income elasticity	-0.25	-0.32
Consumer Surplus (RP) (95% confidence interval)	$1456.30 ($1227.73 - $1784.90)	$1082.08 ($890.49 - $1375.25)
Consumer Surplus (SP) (95% confidence interval)	$1635.86 ($1387.86 - $1988.40)	$1068.41 ($888.63 - $1336.75)
Consumer Surplus (SP_wind) (95% confidence interval)	$1539.91 ($1313.48 - $1865.61)	$1050.70 ($877.86 - $1312.05)

Table 6: Mixed Logit Model Results

Variable	Raw Data		Weighted Data	
	Coefficient	Standard Error	Variable	Coefficient
Mean: no_trip	-3.7155***	0.3448	-3.3026***	0.5350
Mean: altA	-0.1064	0.2747	0.5863***	0.2415
Mean: altB	0.2067	0.1630	0.4491***	0.1605
Mean: ptr	-0.0109***	0.0020	-0.0122***	0.0029
Mean: park_fee	-0.1302***	0.0221	-0.1221***	0.0285
Mean: med_cong	-0.2166	0.1851	0.0864	0.2145
Mean: hi_cong	-1.1583***	0.2245	-0.4124	0.2629
Mean: oceanw1	-1.0772***	0.2775	-0.6693*	0.3604
Mean: oceanw4	0.0412	0.2171	0.1933	0.3067
Mean: soundw1	0.0177	0.1961	-0.3473	0.2759
Mean: soundw4	0.4484	0.2810	0.0747	0.2455
SD: med_cong	1.0398***	0.2363	0.4439	0.3129
SD: hi_cong	1.3635***	0.2946	0.6862***	0. 2956
SD: oceanw1	1.6901***	0.2914	0.9194***	0.3460
SD: oceanw4	1.7021***	0.2601	1.2585***	0.3853
SD: soundw1	1.2086***	0.2445	0.8211***	0.2648
SD: soundw4	1.0481***	0.2359	0.7109*	0.3670
observations	2768 profiles; 692 choices (118 individual responses)		2768 profiles; 692 choices (118 individual responses)	
lnL	-744.634		-748.544	
LRT (df) p-value	94.61 (11) < 0.0001		98.92 (11) < 0.0001	

Note: *** - statistically significant for 1% chance of Type I error; ** - statistically significant for 5% chance of Type I error; * - statistically significant for 10% chance of Type I error.

Table 7: Welfare Estimates for Visualization Choice Experiment

	Raw Data	Weighted Data
No-trip	$341.25 ($290.24, $394.22)	$270.14 ($196.81, $342.89)
Park_fee	$11.99 ($8.59, $15.38)	$9.95 ($6.16, $13.93)
Medium Congestion	$20.81 (-$138.13, $175.90)	-$6.24 (-$67.70, $52.98)
High Congestion	$104.69 (-$91.74. $313.73)	$32.39 (-$59.40, $127.35)
Ocean1	$102.48 (-$160.58, $360.65)	$54.58 (-$71.97, $177.17)
Ocean4	-$2.24 (-$260.35, $254.34)	-$18.77 (-$191.25, $147.16)
Sound1	-$1.03 (-$186.17, $180.45)	$26.25 (-$82.12, $136.64)
Sound4	-$42.25 (-$200.49, $117.75)	-$6.92 (-$103.39, $91.60)

Note: Confidence intervals for 'no-trip' and 'park_fee' are estimated using the variability in fixed mean parameters to boot strap the mean. Confidence intervals for the other site attributes are estimated using the mean and standard deviation parameters to simulate the distribution of willingness-to-pay. The latter gives rise to larger confidence intervals that reflect individual heterogeneity.
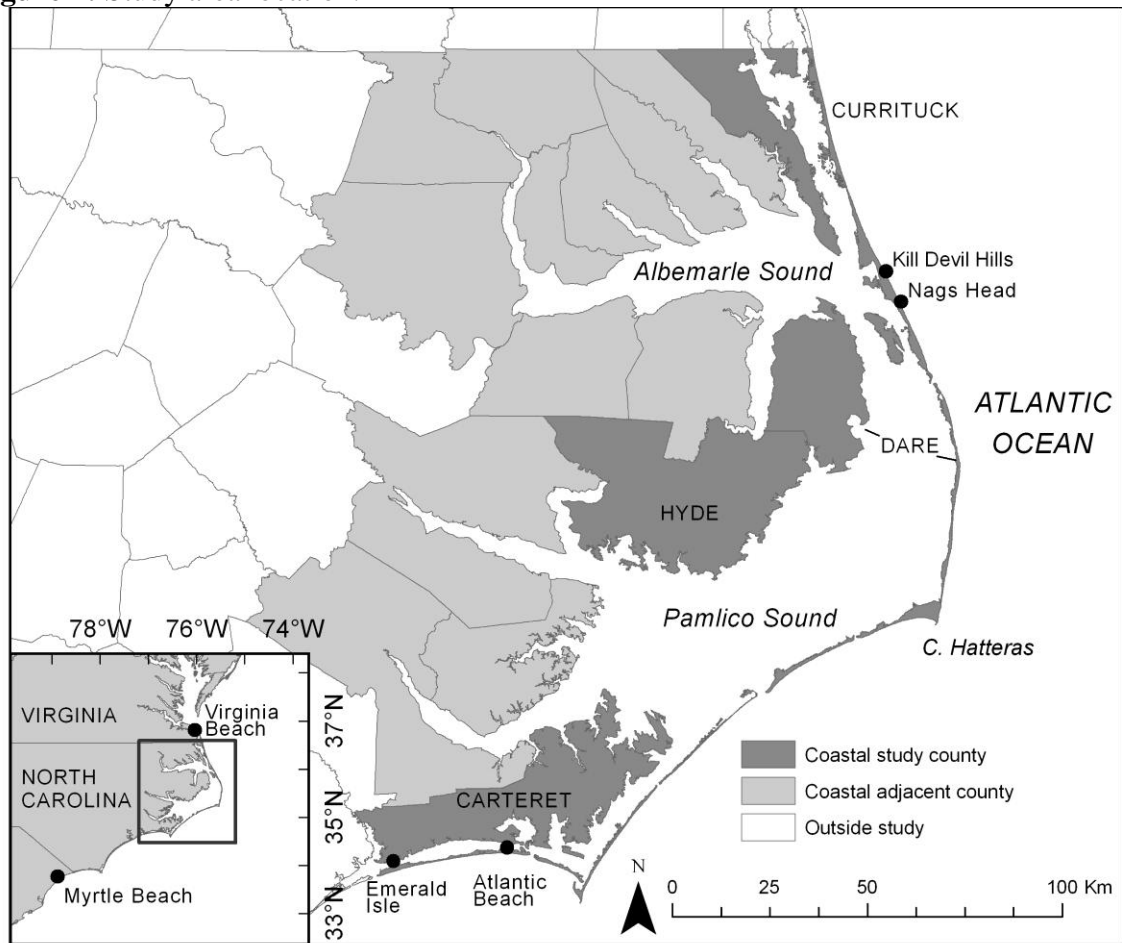
Figure 1: Study area location.

Figure 2: Example of Choice Set for Beach Site Choice Experiment

No Trip (stay home)	Trip A	Trip B	Trip C
	People on the Beach: 40 - 200	**People on the Beach:** more than 200	**People on the Beach:** less than 40
	Distance from home: 120 miles	**Distance from home:** 90 miles	**Distance from home:** 60 miles
	Parking Fee: $0	**Parking Fee:** $4	**Parking Fee:** $8
	Ocean View: 1-mile wind farms	**Ocean View:** 4-mile wind farms	**Ocean View:** no wind farms
	Sound View: 4-mile wind farms	**Sound View:** no wind farms	**Sound View:** 1-mile wind farms