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Abstract: This research measures the welfare losses to beachgoers from the visual disamenity associated with offshore energy projects. We use a contingent-behavior approach in a field setting wherein respondents use a simulation to control the placement of offshore wind turbines and/or oil platforms in their choices. Our model allows for valuation results with continuous, instead of discrete, spatial resolution. We analyze the data using a duration or survival model consistent with random utility theory and recover an expression for willingness-to-pay as a function of distance of shore. We find three distinct clusters of participant responses. Most participants were relatively accepting of the wind turbines and had a much more elastic damage function as compared to oil platforms. On the other hand, a minority of participants displayed a strong aversion to any offshore installations, and had a higher level of damage from turbines instead of oil platforms.

Keywords: Offshore energy; Nonmarket valuation; Renewable Energy

Introduction

Conventional approaches characterize the valuation of non-market amenities and disamenities in terms of Stated Preferences (SP) and Revealed Preferences (RP). Historically, SP studies have been the domain of survey instruments like contingent valuation and choice experiments, while RP approaches, like hedonics and defensive expenditures have relied on observed market data. Travel cost studies fall somewhere in between, using survey instruments to generate observed data. Recently, both lab and field experiments have become more common in both the RP and SP literature both as a way of testing the validity of SP methodologies and as a way of using a high degree of control and precise value elicitation mechanisms to create preference revealing "markets" that would not otherwise exist.

This paper proposes a novel elicitation and estimation approach that draws from SP surveys, RP data, and lab-experimental style design[1]. It is essentially a contingent-behavior model using a continuous variation in an attribute of a non-market amenity to generate a data-efficient estimate of the value of that attribute. We apply this approach to estimate the effect of off-shore distance of wind turbines and oil platforms on beach goers. This issue that has been of increasing interest, yet has received only modest attention (Landenburg, 2009; Landry et al., 2012). Our approach integrates baseline RP travel-cost data, and uses realistic, controlled and replicable, lab-experiment style simulation that allows users to vary distance from shore of both wind turbines and oil platforms, in response to price signal. The data generated allows for

[1] It is important to note, that the language around "experiments" in economics is sometimes muddled. An economic experiment traditionally indicates the use of real financial incentives, either money or goods, to motivate decisions and reveal real (as compared to expressed or hypothetical) behavior or values. This contrasts with other uses of the term such as "choice experiment" or statistical "design of experiments" which have different meanings. We use the langue of "experiment style" here because this is expressly not an economic experiment as there is no observation of behavior motivated by real incentives, but does adopt the idea of control, manipulation, and comparison within a synthetic environment which is the hallmark of experimental designs.

estimation in a duration model context, from which WTP as a function of distance may be recovered.

Past efforts combining both SP and RP into a single analysis have taken many approaches, which are reviewed in Whitehead, et al. (2008a). Typical approaches to this include "stacking" RP and SP data with identical structures into a pooled dataset to extend sample size, or estimating separate models, often within subjects, to test for "convergent validity" or biases in methods. Recent approaches more directly integrate RP and SP by taking participants' observed behavior as a baseline, and then extending that with hypothetical variations of attributes (Train and Wilson, 2008; von Haefen and Phaneuf, 2008[2]; Parsons and Thur, 2008). The idea of eliciting the knowledge base of research participants and framing the remainder of the study around that knowledge base is used in "pivot designs" frequently applied in the transportation literature (e.g. Hensher and Greene, 2003; Hensher, 2004). Our research is similar to this approach, but is has important differences in both the elicitation and the analysis. The elicitation instrument was designed for participants to control computer simulations of the offshore distance of turbines and rigs at the beach they were visiting while being surveyed. The response data was structured as "spells", or adjacent spans of distance over which the offshore energy facilities would be acceptable at a given price, instead of the customary set of dichotomous choice, or referendum responses. Non-market goods often have this continuous. Other examples include proximity to amenities such as open space and farm land (Ready and Abdalla, 2005; Bergstrom and Ready, 2009), or protected habitat (Pate and Loomis, 1997; Loomis 2000; Neumann, Boyle, and Bell, 2009), or to disamenities, such as contaminated sites (Ihlanfeldt and Taylor, 2004;

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[2]

Messer et al, 2006), or the width of nourished beaches (Shivlani, Letson, and Theis, 2003; Whitehead, et al.; 2008b, Parsons, et al., 2013).

Dichotomous choice questions have been the de facto elicitation format for environmental valuation studies since Arrow et al.'s (1995) report to the National Oceanic and Atmospheric Administration (NOAA) on contingent valuation endorsed it as the standard for such work. This referendum-style choice format has persisted for two decades through the extensions of contingent valuation into the science of choice modeling. This contrasts with direct response formats such as open-ended -elicitation questions that seek responses in terms of willingness-to-pay (WTP) given a set of attributes. The upside of questions that directly measure WTP is precise observations, generally either points or small intervals Dichotomous choice responses offer only yes/no responses at a few fixed prices so studies that use them typically require much larger samples to obtain a similar level of accuracy (Cameron and Quiggin, 1994). Given the marginal cost of additional participants in some stated preference research, it is not atypical for surveys to have samples that are quite large, often in the several hundred to thousands range. For more sophisticated designs this can become prohibitively resource intensive. Ex ante power analysis has become an increasingly important in experimental economics (Rutstrom and Wilcox, 2009; Ferraro and Price, 2013), and methodological concerns about appropriately sized samples have been increasingly common within the wider community of experimental disciplines (Bacchetti et al 2005). However, as consumers, research participants typically are much more familiar with posted-price decision-making. They are comfortable assessing whether they would be willing to accept an offered deal. The question of exactly how much they would be willing to pay for a hypothetical package of attributes is a far less familiar task and thus is more cognitively taxing. It is possible that studies of willingness-to-pay for a bundle of a large number of attributes are prone to bias (Balistreri et al., 2001, Carson and Groves, 2007). Exactly how substantial such bias may be is the subject of debate and likely depends on how familiar the situations presented and the design of the elicitation instrument are to participants.

Attempts have been made to improve the efficiency of dichotomous choice instruments. A notable example is the double bound (or interval) method, which poses a yes/no WTP question at a particular price level and then, depending on the response, presents a follow-up question involving a different price level (Albeini, 1995). Thus, the decision remains in the posted-price decision space, and the structure considerably improves the statistical efficiency of data collected (Hanemann, Loomis, and Kanninen, 1991). However, Cameron et al. (1996) observed a degree of inconsistency between the distributions of WTP for the initial and follow-up questions and speculated that introducing a new price-point may have caused participants to update their degree of WTP, which would be consistent with theories of value formation (Plott, 1996; Braga and Starmer, 2005; Kingsley and Brown, 2011).

In this research, we approach this using computer technology and drawing on approaches from lab experiment techniques, we developed a simulation related to offshore energy development off the Mid-Atlantic coast in the United Sates in which participants respond to the level of attribute provided at a given price. The simulation can be repeated using various price levels and attributes to obtain a series of observed intervals of attribute acceptance, which can be modeled with standard duration (or survival) models that estimate effects on the time required to achieve an event. When time is replaced by cost, duration models generate estimates of demand curves (Steinberg and Carson, 1989). Duration models are commonly used to estimate WTP from both payment-ladder valuation data (Wang and He, 2011), interval censored response data

(Carson et al., 2003), and medical treatment data (Luchini, Daoud, and Moatti, 2007). The approach recovers WTP as functions of attribute levels at the mean, at the median, or for a specific consumer when the model is specified in terms of attribute level with cost as a covariate.

Duration models offer new options in addressing issues like censoring and modeling unobserved heterogeneity. As shown below, they are consistent with the random utility model, the approach that motivates empirical analyses of dichotomous choice data, while also providing greater statistical power in the face of data collection constraints. We use a Monte Carlo experiment to compare estimates of WTP recovered from a duration model to WTP estimated from a simulation experiment involving multiple dichotomous choices using a logit model. We find a significant difference between the two sets of estimates. With small sample sizes, the difference is quite large, while even with what would be considered "moderately" sized samples for lab and artefactual field experiments, in the 50 to 100 respondent range, the magnitudes of the standard errors produced by the duration model are on the order of half of those of the dichotomous choice data. We then apply the two models to data collected from beach visitors to estimate the value of the visual disamenity generated by offshore energy production (wind turbines and drilling platforms).

Data were collected from an intercept survey of visitors at two popular Delaware beaches. Respondents reported information on their trip costs[3] and then were asked to participate

[3] The use of self-reported cost data creates some issues of concerns. Individuals may not remember or may not have known details on prices, times, or distance. Different individuals may have considered things like depreciation or time value that are typically included in such calculations differently, or have unobservable heterogeneous values. Still, in this research, we are more concerned about the individual's perception of cost than the actual costs. Also, by asking about different cost categories separately, we hopefully get a more consistent measurement across participants, and also make the participant give more careful reflection on the costs associated with their trip. By formatting the question in discrete increments instead of open-ended prices it leads the participant to think through the range of possible values and reduces the cognitive pressure of trying to recall exact values. We did collect data on both zip codes and nights of lodging, and found a high correlation between out expenditure data and time spend traveling to and on the beach.

in the computer-simulation, which involved a picture of the same beach on which they were standing with computer-generated wind turbines or oil platforms superimposed on the horizon. Participants were asked to adjust (i.e., enlarge or bring closer) the location of the turbines or platforms until they would no longer be willing to visit the beach at a randomly assigned price discount. The distance choice data allowed estimation of a model of visitor attrition based on proximity to energy infrastructure using co-varying costs of the trip, type of energy generated, and demographic characteristics. Results show that beach visitors are relatively indifferent to wind turbines that are at least two to three miles offshore, are less accepting of oil platforms, and have a smaller price elasticity of demand for drilling platforms than for turbines. Further analysis of heterogeneity using cluster analysis shows that most of the disamenity is concentrated on 20% of the sample—a group that is relatively wealthy, is most likely to prefer water activities, is most likely to visit the more developed beaches, and is mostly female.

Methods

Our model uses a dichotomous-choice referendum (accept or reject) for a fixed attribute bundle but allows participants to adjust their bundles after making an initial choice by decreasing the bundle to indifference. This point is such that they would no longer make the same choice and thus equivalent to reducing their surplus to zero. Instead of making decisions based on the price they are willing to pay, participants face a fixed price and instead “choose” by adjusting a continuously varying attribute to achieve a fixed (reservation) level of utility. In our case the “attribute” is the distance from shore of offshore wind turbines or oil platforms.

The survey takes each respondent through four steps. First the respondent is asked if he/she would have made the trip with turbines located at some random distance offshore where distances varied from 1 mile to 13 miles. Depending on their answer to this question, they were asked in the controlled simulation to move the turbines either closer towards shore or further towards the horizon to the distance at which they would no longer make that trip. Third, we offer a random discount, and again ask respondents to adjust the offshore distance of turbines to the point at which they would cancel their trip. Finally, respondents were given another, larger discount and asked to go through the exercise a final time.

Given that respondents are faced with an initial image of the objects, a potential concern is that respondents would anchor on these initial positions as "normal" which could affect their response. To control for this potential effect, we randomized the starting point over the entire possible range of locations, so that while this could potentially add noise to the estimated, it should not bias them. Additionally, we collected the data on the random starting point for each participant so that we could test the extent to which this affected responses. Using this data we tested decisions on both the initial decision and across all decisions (both the initial decision and the subsequent two decision) and did not find a significant effect. The two subsequent decisions are made relative to each prior placement, so are conditional on prior choices. This is taken into account through a repeated events statistical modeling approach, as described below.

By observing several price/distance pairs at the reservation utility level, we can trace the shape of an indifference curve through the reservation utility and locate it in price/distance space. The survey instrument allowed participants to adjust the distance and gave them a realistic visual depiction of the results of their choices. As a result, the decision environment was more concrete than decisions made in terms of hypothetical monetary values.

Estimation Approach

Consider individual i's choice of an outcome from a set of several options. According to the random utility model, individuals choose an outcome of interest, $j = 1$, when they believe that the utility associated with outcome $j = 1$ exceeds the utility of all other outcomes and, in particular, the outcome of their next best option, $j = 0$,

$$U_{i,1} \geq U_{i,0}$$

The indirect utility functions for both *j* = 1 and *j* = 0 are a function of the price associated with the outcome, $p_{i,j}$, and a vector of other individual, outcome-specific attributes, $z_{i,j}$. Suppose that outcome *j* = 1 includes a continuous variable such as distance, which can take values within a fixed range, $w_d \in [\underline{w}, \overline{w}]$, and has an effect on the utility of the outcome but not on utility of the other alternatives.[4] In our case, if we assume that the utility of the beach visit is linear in the distance of an object from shore, w_d, then

$$U_{i,1} = V\left(p_{i,1}, z_{i,1}\right) - \alpha w_d + \varepsilon_{i,1},$$

$$U_{i,0} = T\left(p_{i,0}, z_{i,0}\right) + \varepsilon_{i,0}.$$

The probability of an individual choosing option *j* = 1 can be expressed as:

$$\Pr\left[U_{i,1}(w) > U_{i,0} \middle| p_i, z_i\right] = \Pr\left[V\left(p_{i,1}, z_{i,1}\right) - \alpha w_d + \varepsilon_{i,1} > T(p_i, z_i) + \varepsilon_{i,0} \middle| p_i, z_i\right]$$

$$= \Pr\left[\frac{1}{\alpha}\left[V(p_i, z_i) - T(p_i, z_i) + \varepsilon_{i,1} - \varepsilon_{i,0} > w_d\right] \middle| p_i, z_i\right]$$

$$= \Pr[U^* > w_d | p_i, z_i]$$

$$= S(w_d)$$

conditional on the alternatives' prices and the attributes.

$U_{i,0}$ thus acts as a reservation utility with the distribution $U_{i,0} | p_i, z_i$ inherited from $\varepsilon_{i,0}$. U^* is a random variable representing a scaled premium in utility for *j* = 1 when w_d is at the furthest bound of its range, $\overline{w}$. This U^* will be a random variable with a cumulative distribution

[4] In this case, we assume that decreasing values of attribute *w* have a negative effect on utility. The opposite could be easily accommodated by switching signs in the derivation of WTP from the hazard functions specified.

of $F(w_d) = \int_0^w f(s)ds$. The function $S(w_d)$ is nearly identical to the survival function used in duration analysis except that in this case it is a function of w_d instead of time. An instrument that can solicit participant decisions in terms of a "withdrawal point" can be used to estimate the random utility model under a duration approach using standard econometric software. It is also useful to consider the hazard function: $\lambda(w_d) = f(w_d) / S(w_d)$. The survival function, $S(w_d)$, indicates the probability that an individual will continue to choose outcome $j = 1$ for $w < (w_d)$ while $\lambda(w_d)$ indicates an instantaneous likelihood of switching to the next best option at w_d.

The distribution of $U^* | p_i, z_i$—and hence the parametric specification of the duration model—depends on the distributions of $\varepsilon_{i,1}$ and $\varepsilon_{i,0}$. Under the common assumption that these are both extreme value type I (EVI) distributions, $U^* | p_i, z_i$ will be logistic and the estimated duration model will be log-logistic. If we assume that both are normal distributions, $U^* | p_i, z_i$ will be normal, and the estimated duration model will be log-normal. If we assume that the disturbance on the utility of outcome $j = 1$ is EVI while the reservation utility is normal, then the difference will be an extreme value distribution, and the duration model can be specified as a Weibull model.[5] In practice, the choice between these models is often guided by the data, either through parameter significance tests for nested distributions (several of the distributions used in duration analysis are exponential and nested through restrictions on estimated parameters) or, more generally, through comparisons of Akaike information criteria (AICs).

For most of these specifications, a hazard model can be easily recovered from an estimated duration model. When the results are specified in hazard form, WTP is calculated from

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[5] A Weibull specification is a more commonly used formulations in duration analysis and has the advantage of a relatively clean hazard function, and a resulting WTP function that depends only on *p* and *w*.

the estimation by calculating the payment required to maintain the hazard level for a change in attributes, as follows. With payment included as a covariate in the model, the fully augmented hazard function is $\lambda(w_{d;}\, p_{i,} z_i)$. At which point the compensation required to maintain the probability of a switch to the alternative—and hence the same level of utility–solves $\lambda(\underline{w};\ p_i, z_i) =\ \lambda(w_d;\ (p_i + C), z_i)$. A solution for C as a function of w_d will depend on the distribution assumptions. Notably, if we consider $\boldsymbol{X}$ to be the full covariate vector, β to be the vector of the regression coefficients, β_p to be the price coefficient, ρ to be the shape parameter of the Weibull distribution, and γ to be the shape parameter of the log-logistic distribution, then

- for a Weibull model, the hazard ratio is

$$\lambda(w; X) = \rho e^{X\beta} w^{\rho-1}$$

  and WTP will satisfy

$$C\big(w_d; \beta_p, \rho, \underline{w}\big) = \left[\frac{\rho - 1}{-\beta_p}\right] \ln\left[\frac{w_d}{\underline{w}}\right].$$

- for a log-logistic model, the hazard ratio is

$$\lambda(w; X) = \frac{e^{X\beta} w^{(1/\gamma - 1)}}{\gamma[1 + e^{\left(-X\beta/\gamma\right)} w^{\left(\frac{1}{\gamma}\right)}]}$$

  and WTP will satisfy

$$C\big(w_d; X, \beta, \gamma, \underline{w}\big) = \frac{\gamma}{\beta_p} \ln\left\{\left[\frac{w_d}{\underline{w}}\right]^{\left(\frac{1}{\gamma}-1\right)} \left[1 + e^{-\frac{X\beta}{\gamma}} \underline{w}^{\frac{1}{\gamma}}\right] - \left[w_d^{\frac{1}{\gamma}}\right] \left[\mathrm{e}^{-X\beta}\right]\right\}.$$

Note that C, in the case of the Weibull distribution, is a function only of the price parameter and will be constant across the population; for the log-logistic distribution, C is a function of the full parameter vector and individual attributes so it will vary across individuals. Therefore, we must consider C functions for a mean, median, or specific individual. The functions will describe iso-payment lines that maintain a given level of utility. Based on the WTP function for a particular (or average) participant, one can add a constant to satisfy a cost/distance point.

Estimator Efficiency

This approach is an alternative to dichotomous-choice/mixed-logit estimations because the data per observation have a higher resolution and thus should provide greater efficiency in terms of the ratio of sampling effort to statistical power. We test this hypothesis using a Monte Carlo experiment using realistic data generated based on data from beach visitors, described in the next section, similar to the approach in Kumioff, Parmeter and Pope (2010).

In this study, true parameters are assumed to represent individual participants' price and attribute parameters in the indirect utility function for the outcome of interest and for distributions for individuals' costs, disturbances on the utility function, and reservation utilities (see Table 1). The values were chosen reflect a distribution of costs, and a proportion of decisions that was similar to the data collected from on-site experiments with Delaware beach visitors, as described in the next section. The utility parameters and trip costs are used to describe the particular individual and the cost factors and attribute levels describe the points used in sampling.

Using these values, a sample of *n* participants is drawn. For each participant, we calculate a reservation utility, $\overline{U_i} \sim N(0, 1)$, and a utility level for each combination of sampling D_j and W_k:

$$U_{i,j,k} = \alpha + \beta C_i D_j + \gamma W_k + \varepsilon_i$$

where $U_{i,j,k}$ is the level of utility associated with the cost for the participant, C_i. C_i is a multiple of the cost for observation, D_j, and a value for the continuous attribute for the observation, which is represented by W_k. We then calculate nine responses from a dichotomous choice experiment using a response variable of $Y_{DC;i,j,k} = 1$ if $U_{i,j,k} > \bar{U}_i$ and $Y_{DC;i,j,k} = 0$ otherwise. Using the response variable, the cost, and sampling variables, we estimate a fixed effects logit model and WTP_{DC}, which represents the marginal WTP for the attribute under the dichotomous model. We then calculate the 95% confidence interval and standard error using a parametric bootstrap method (Krinsky-Robb, 1986).

After estimating WTP_{DC}, we calculate the continuous response that will be modeled with a Weibull specification $Y_{W;i,j}$) by solving for the value of W_k that satisfies $U_{i,j,k} = \bar{U}_i$ for each value of D_j:

$$Y_{W;i,j} = \frac{1}{\gamma}[\bar{U}_i - \alpha - \beta C_i D_j - \varepsilon_i].$$

This calculation generates three observations whereas the dichotomous choice experiment generated nine. We use these three observations to estimate a Weibull duration model and WTP under that model, designated as $\mathrm{WTP_W}$, using the same system as for $\mathrm{WTP_{DC}}$. Standard errors for the Weibull estimate are calculated using the delta method. This differs from the bootstrap used for $\mathrm{WTP_{DC}}$ because the delta method is inappropriate for ratios of variables with positive density at zero (Gleser and Hwanh, 1987). This procedure repeats 10,000 times for each value of *n*.

Figure 1 displays the results of our calculations in terms of standard errors as a function of sample size for the dichotomous choice (WTP_{DC}) and continuous response (WTP_W) estimates. Based on the parameterization, the true WTP is 120, and all calculations for each value of *n* generated average WTP estimates that were extremely close to this value. Consequently, WTP_W consistently generates smaller standard errors but the standard errors appear to converge as the sample size increases.[6] At $n = 20$, WTP_W is significantly greater than zero at a 95% significance level. WTP_{DC} does not achieve that level of significance until $40 < n < 50$. If we consider a "moderate" sample size of $n = 100$, WTP_W has a standard error of about 9.5. WTP_{DC} does not achieve that standard error until $n > 150$. This would still be a fairly small sample for much survey based research, but this margin can be very valuable for more administrator intensive designs. Thus, if we consider a typical sample range for this case, WTP_W requires a sample size one-half to two-thirds of the sample size required by WTP_{DC} to achieve a given level of precision.

Application: Offshore Energy Production and Beach Tourism in the Mid-Atlantic

To reduce dependence on fossil fuels, agencies in many coastal areas have proposed offshore wind projects as alternative sources of energy. An issue that arises for virtually all wind projects is whether wind turbines disfigure the natural seascape, thereby reducing residents' utility and tourism. A typical offshore wind project can include more than 100 turbines, each more than 400 feet tall, within sight of the shore. Similarly, oil platforms generate domestic fossil fuel, such as those established about one mile off the Gulf of Mexico's coast, and are visible from the shore. The potential disamenity impact of both structures drives some opposition to offshore energy projects. Perhaps the best-known conflict involves the Cape Wind project in Nantucket Sound off Cape Cod in Massachusetts. It was delayed for more than a decade because of objections from local residents whose ocean views would be interrupted. Similar objections to the

[6] In general, the ratio of standard errors, r_s, will converge to some $c \leq 1$. In this case, $c = 0.75$. It achieves $r_s > 0.74$ at around $n = 200$.

appearance of wind turbines have recently been raised for by resort developers off the coast of Scotland, and as a potential keystone campaign issue by UK prime minister David Cameron and the conservative party.

One proposed solution is to locate such projects far enough away to alleviate the visual disamenity. The visibility driver of the conflict can be resolved entirely if the structures can be placed beyond the view of the horizon. Unfortunately, constructing turbines farther away increases capital and maintenance costs because the depth to the ocean floor increases. In addition, the cost of delivering the energy generated rises farther from the coast.

We estimate visual externalities associated with wind turbines and drilling platforms and investigate how such costs are affected by placing the structures farther from the shore. In the Mid-Atlantic, opening the state's coastline to offshore oil exploration also has been given consideration, and a recently proposed offshore wind projects has generated controversy. Thus the problem setting is rooted in live, recent debates.

Ladenburg (2009) provides an overview of the literature on amenity valuation related to wind projects, with more recent contributions from Gee (2010) and Landry et al. (2012). Less work has focused on the visual impacts of offshore oil and natural gas production (Nassuaer and Benner, 1984 being a notable counterexample), even though many of the same coastal areas that have considered adapting wind energy have been also considered for fossil fuel exploration (US MMS, 2010). Of particular interest, Krueger, Parsons, and Firestone (2011) studied offshore wind projects and the effect of how distant they would be from the coast in Delaware using a stated preference choice experiment involving projects situated 0.9, 3.6, 6.0, and 9.0 miles offshore for inland, bay, and ocean projects. Their results showed an annual disamenity value for beach residents of $19, $9, $1, and $0, respectively. Given that the value of a beach visit varies continuously with respect to the distance of such structures from shore and that the marginal social cost of moving a project back is of direct interest in determining optimal siting, this setting provides a useful application of our methodology.

Design

Iterative survey design occurred over two years, first, with semi-structured testing with a focus group composed of administrative staff members at a large public university in the Mid-Atlantic and, second, with an on-site pilot survey conducted with beachgoers at Rehoboth Beach, Delaware. These efforts produced feedback that led to refinements of instrument format and wording, but also allowed for testing the usability of the computer interface to ensure that subjects found the interface usable and unbiased. On-site beach intercept sessions with a four mobile computer interfaces produced many practical challenges (especially, sun, heat, and sand), which required significant time and effort to overcome.

The final version of the survey consisted of a computer exercise and a written survey instrument. The computer portion of the session elicited travel cost information and presented images of the beach that participants were at with realistic wind turbines or oil platforms on the horizon. Participants were able to adjust the distance of these objects from shore, in response to variations in price, implemented as a discount on the cost of their trip. Participants first responded to onscreen questions about the various costs associated with their vacation at the beach, including travel, food, lodging, retail spending, and amusements. This was similar in design to a revealed preference travel cost study. For each category of costs, respondents were provided with a pull-down list of values ranging between $0 and $5,000 in $50 increments. The sum of the cost responses (using midpoints of the $50 increments) from each category was calculated. Respondents were shown this total on their computer screen and could either accept it as reasonably accurate or adjust it to better represent the trip's total cost.

Final enumeration occurred with visitors to two popular Delaware beaches, Rehoboth Beach and Cape Henlopen (Figure 2), on July 12 through 15 and July 29 through August 1, 2012. Rehoboth Beach is a resort town with a beach and boardwalk while Cape Henlopen is a less developed, more natural beach in a state park. Rehoboth Beach is highly developed with hotels fronting on a boardwalk, restaurants, and other attractions. It mainly draws visitors from Delaware, Maryland, and the Washington DC metro area. A fenced-off dune area punctuated by intermittent access walkways separates the boardwalk from the beach. A large public parking lot serves as the primary spot for beach access to at Cape Henlopen as foot traffic is funneled on a single boardwalk a public bathhouse and small concession stand.

In both settings, enumerators approached the lead adult individual in every third group of visitors entering the beach on an access path and asked this individual to participate in a twenty-minute survey about his or her beach experiences. Pilot experiments showed a high refusal rate because of the high time commitment. So, in the final survey, those who declined were offered the opportunity to participate in a short two-minute survey about their opinions regarding a series of images of wind turbines and platforms offshore at various distances. The data from the short survey were used to test for any indication of nonresponse bias (see further discussion in the section below). Individuals who agreed to take the full survey proceeded to a tent containing four survey stations and were offered a bottle of water. To ensure privacy, the stations were placed several feet apart and had privacy screens, which also helped mitigate glare.

Participants were seated and instructed to put on headphones. They then watched a two-minute video demonstrating the interface and showing the full range of possible placements for offshore turbines and oil platforms on their computer screen. Respondents then answered onscreen questions about the costs associated with their beach visit. The final computerized section of the survey showed each participant a photo of the beach they were visiting with either 100, 90 meter wind turbines or two oil platforms (thus providing equivalent amounts of energy) on the horizon. Figure 3 shows examples of images used in the research.

Using cursor keys, participants could scroll to change the size of the energy structures in intervals small enough to be essentially continuous (on the order of several feet). This program allowed participants to locate the turbines/platforms anywhere between ten miles and one-quarter mile. The one-quarter mile range was set as it still enabled the image of the structures to remain mostly within the computer screen). Participants watched a short video that instructed them on the use of the software, and were then shown an image of the object at an initial starting distance. The starting spot for the turbines/platforms observed by the participants was varied randomly. Participants were asked whether the object enhanced or detracted from their view. If they responded that it detracted they were asked whether it would have led to them not visit the beach. They were then asked to relocate the turbines to the point of indifference. Specifically, if participants responded that would still have visited the beach, they were then asked to move the object towards the shore until they no longer would have visited the beach. In contrast, if the respondent indicated that the objects would have caused them not to come to the beach they were asked to move them towards the horizon until they would have.

Respondents were then asked to consider a scenario in which the local chamber of commerce offered travel discounts to increase tourism after construction of the energy project, thus reducing the cost of their trips, and were asked to move the turbines/platforms to make their proximity consistent with the discounted trip cost. Finally, participants repeated the exercise in response to a second discount, generating three price-level observations per object per participant. For each of these discounts, the starting location was the point that they chose for the previous choice. The potential discounts (25%, 37%, 48%, 58%, 67%, 75%, 82%, 88%, 93%, and 97%) were drawn at random without replacement, and the higher of the two discounts selected was offered first. This meant that the discounts were always increasing, which assumes that values were strictly non-positive. Participants completed the process for one type of project and then repeated it for the other installation type. The type of installation (wind turbines or oil platforms) shown first was alternated each day. The same two discounts applied to both wind turbines and oil platforms. Once they finished the computer survey, participants filled out a written survey (see the Appendix) that requested demographic and attitude information measured.

Results

The full survey results were compared to those of the abridged survey to test for sample response validity. The sample for the full survey consisted of 149 participants. Of those, only 112 had well-defined spells (i.e. did not answer either 10 miles or .25 miles for all values) that could be included in the Andersen-Gill model. The sample for the abridged survey was 375. In both, participants were shown wind turbines and oil platforms at random distances from the shoreline and asked if those structures would have enhanced, detracted, or made no difference to their beach experiences. Figure 4 displays the results of this comparison. The distributions of attitudes for the two samples are similar and are not statistically different.

Table 2 offers some basic summary statistics of participants that completed the full exercise. On average participants were slightly older than Delaware and national medians (36.7 and 36.8 years respectively). The income was somewhat higher than the national median ($51,759) but in line with the state median ($58,763). The general impressions of the initial images shown to participants were surprisingly similar for wind turbines and oil platforms. For both structures, around of participants 50% report that it would not make a difference to their beach experience, and about 25% say that while it would detract it would not cause them to alter their vacation plans. Only about 15% said it would have caused them not to have visited that beach. In spite of the similarity in stated attitude, when asked to move the structure to the point at which they would not have been willing to visit at their current trip price (before any discount was offered), the average placement for wind turbines was between 2.5 and 3 miles from shore, while the average initial placement for oil platforms was about 5.9 miles from shore. Figure 5 shows the distribution of participants' initial (pre-discount) placement of the turbines/platforms relative to the cost of their trips. Note that placement of both turbines and platforms spikes at ten miles, because respondents were not allowed to place the structures more than ten miles from the shore. The spike is significant for both structures but was much larger for oil platforms (22.3% of all responses) than wind turbines (8.9% of all responses). For the uncensored observations (within 10 miles), oil platforms are fairly uniformly distributed throughout the distance range while turbines are generally clustered within three miles of the shore, a result that is consistent with Krueger, Parsons, and Firestone's (2011) finding that disamenity values for offshore ocean wind turbines decreased drastically between 4 and 6 miles from the beach.

Figure 6 depicts kernel-smoothed hazard curves that represent the relative probability of a visitor choosing an alternate travel destination at a given distance of the structures from the shore. Figure 7 shows Kaplan-Meier survival curves that represent the share of visitors who would continue to visit the beach at a given distance for the structures. The curves show a greater hazard and a smaller beachgoer population for oil platforms than for wind turbines. Again, the results illustrate the dramatic increase in attrition of visitors in response to structures placed within two to three miles of the shore.

We estimate the full duration model as a multi-sequential event model (Andersen-Gill, 1982). Duration models represent data as "spells", or logged distance between (possibly censored) staring points and events. Sequential event models control for endogenous starting points when there are a series of events, such that each spell begins when the proceeding one ends (i.e. after the initial placement of wind turbines or oil platforms by participants, the distance spell for each price level begins at the end of the prior price spell). A key assumption for this model is that the baseline hazard is identical across spells, i.e. that the participants' fundamental disamenity values do not change after each decision. If we did not believe this were the case (perhaps we suspect that participants' increasing frustration at being asked the same question repeatedly spills over to their disamenity values) an alternative might be the Prentice-Williams-Peterson model (1981) which allows for stratification of risk across events.

Since the convenience sample was collected over a week in mid-July at the beach, there is concern that there might be sampling bias. We would tend to oversample individuals who were more frequent visitors or who stayed for a longer period of time, and they might have systematically different values than non-frequent visitors (Egan and Herriges, 2006). To correct for this we use data collected on the number of days between Memorial Day and Labor Day that the participant had visited or was planning on visiting to calculate the likelihood of that individual being sampled on a given day (note that this assumes that there is not significant heterogeneity over this period). These are used as inverse probability weights in estimating the model.

Table 3 shows the results of the estimates, with coefficients reported in standard, instead of exponentiated (or hazard ratio) form. The coefficients represent the effect of the covariates on the acceptable placement of the structure relative to the horizon, with negative numbers indicating movement closer to the beach. The significant negative constant for wind turbines indicate a baseline acceptance significantly closer than the horizon, while the coefficient on oil platforms is not significant, indicating a baseline placement at the horizon line. The coefficients can be interpreted as marginal movements toward the shore and away from the horizon. So, for instance those who do not own beach property will be willing to have oil platforms closer than individuals that do own beach properties. Age, trip cost, and visitors to the less developed destination tend to push oil platforms towards the horizon, while there is a small and borderline significant marginal increase in acceptance of platforms for males. Individuals with higher incomes are generally more willing to allow wind turbines closer to shore. Since the Weibull specification is appropriate in this case, the demographic covariates are only relevant as controls, and will not affect WTP estimates (as they might in a log-logistic model as described above). To recover WTP we need the price elasticity, the shape parameter, and the maximum distance ($\beta_{p,}\rho$, and $\underline{w}$ above). Then we can build a function for WTP as a function of distance. The maximum distance (ten miles) is a constant determined by the design. The estimated shape parameter, rho, is important in recovering WTP estimates, and serves as a test of specification versus an exponential model when rho equals 1 (or ln(rho) equals 0). The primary parameter of interest from this model is the elasticity of distance with respect to trip cost. We specify here in terms of percent discount so that we get a constant elasticity term that is increasing in the same direction as distance. This is very significant for both wind turbines and oil platforms. It is also negative for both, indicating a percentage movement closer per percentage point trip discount.

Figure 8 shows our estimates of the total surplus of a beach trip with either wind turbines or oil platforms on the horizon for the mean beach visitor. Note that the distance intersections at about three and six miles denote the point at which such a visitor would choose an alternate destination over visiting the beach. As miles from shore increases, each curve approaches the "over the horizon" value for each installation type. The difference between the two curves at around 10 miles would indicate the baseline difference in disamenity value for each type being off-shore, capturing things like concern for a relatively higher environmental risk from the oil platforms.[7]

Given the controversial nature of offshore energy development it may be the case that there are multiple sets of discrete opinions represented in the data. For instance, there may be some individuals who identify with political positions that are strongly for either oil or renewable energy development. We use cluster analysis to further explore the data and see if there are any obvious divisions in responses. Both from participant feedback and in looking at the distribution of responses (Figure 5) it appears that there are multiple, distinct, heterogeneous groups that have fundamentally different attitudes towards offshore energy production. To further explore heterogeneity, we construct k-means clusters of decision types, based on the vector of each individual's decisions across both wind turbines and oil platforms.

[7] Given the premise of this paper, one might be interested in comparable estimates that might be obtained from dichotomous choice responses. Using the initial responses and the first sets of follow-ups we obtained WTP estimates from ingle choice probit and double bounded bivariate probit (Cameron and Quiggin, 1994) and obtained estimates that were quite insignificant, with confidence intervals on the order of several hundred dollars per mile.

For a given value of k, k-means starts off with k distinct vectors corresponding to the means of the elements of each observations. Then each observation is iteratively assigned to a group corresponding to the closest mean vector and new means based on the newly assigned groups until the means converge to constant values. This results in the assignment of observations to k groups such that each individual belongs to the group with the closest mean. The proper number of clusters (k) can be predetermined, or chosen based on statistical criteria. Using the Calinski-Harabasz decision criterion (Table 5) we find three clusters.

Figure 9 shows Kernel Densities of the decisions for each of these clusters for both wind turbines and oil platforms. The Choice 1 curve represents the distribution of choices made by members of that cluster for first, non-discounted decision. Again, decisions further to the right indicate placement of turbines or platforms closer to the horizon. Choice 2 and 3 represent placement distributions after successive discounts. The further apart these curves are, the more responsive members of that cluster are to compensating discounts. Descriptive statistics for the initial choice of each cluster are offered below the corresponding graph. Cluster 1 and 2 are both quite accepting of wind turbines, being initially willing to place them close to the beach, but not responding strongly to the following discounts. Cluster 1 initially strongly dislikes oil platforms, placing them relatively far away, but tends to be receptive to compensating discounts, with many bringing them very close to shore. Cluster 2, on the other hand, initially places the platforms relatively closer, but is somewhat less responsive to the discounts. Cluster 3, immediately has a strong aversion to both wind turbines and oil platforms, but is very responsive to compensating discounts. Cluster 1 and 2 both represent about 40% of the sample, while cluster 3 represents about 20% of the sample. Table 6 reports the relevant coefficients from the duration model to calculate WTP by cluster. Figure 10 shows how willingness-to-pay for a beach trip changes with distance for each of these clusters. Cluster 1 and 2 are very similar, with the notable difference being that Cluster 2 has the platforms start at a negative value at the horizon. Cluster 3 on the other hand is more interesting. Members of this cluster have much more negative values, and are much more sensitive to changes in distance. Also it is notable that they are more affected by turbines then by platforms.

Table 7 describes members of each of the clusters. Cluster demographics are fairly uniform across age and education. There does not appear to be a substantial difference in treatment ordering. Cluster 1 members are least likely to own beach properties, most likely to be rural residents, and report the highest trip costs. Cluster 2 members are more likely to be primarily “sand” users relative to the other clusters, have the lowest income, be most likely to be visitors to Cape Henlopen, and the least likely to be rural residents. Cluster 3, which had the strongest negative reaction to both turbines and platforms, were more likely to prefer water activities and less likely to prefer sand activities relative to the other clusters. They had the highest income, lowest trip costs, were most likely to be visitors to Rehoboth (the more developed beach) and are much more likely to be female.

Conclusions

Our research proposes a new contingent-behavior approach to valuing some kinds of nonmarket goods by taking advantage of continuous variation in attributes of those goods. Observations from a continuous variation model typically are more precise than observations from dichotomous choice surveys and avoid some cognitive challenges associated with approaches that ask consumers how much they are willing to pay for a good (which is why such open ended questions are no longer typically used in SP research). Our approach provides a series of “spell” data over the continuous attribute for different price levels that can be estimated using a duration model. A Monte-Carlo simulation demonstrates that the approach can reduce standard errors by 50% for small to moderate sample sizes relative to dichotomous choice questions with a gap in efficiency persisting asymptotically.

We applied our approach to a survey of visitors to Mid-Atlantic beaches to value the visual disamenity of potential offshore wind turbine and oil drilling projects. In the study, a computer simulation allowed beachgoers to adjust the distance between the beach and turbines/platforms based on the disamenity of the structures for several trip costs. The majority of the beach visitors were generally indifferent to the appearance of wind turbines that were at least two miles from shore and were more resistant to oil platforms. The disamenity associated with the oil platforms is also less price-elastic.

This simulation based continuous attribute acceptance elicitation approach could potentially be applied to any number of non-market valuation scenarios. Possibilities include physical distance related attributes like beach width and proximity to hazardous sites; however the approach can also be extended to other amenities or disamenities that could be presented and adjusted in a simulation environment, like water turbidity, traffic or recreational congestion, view impediments like haze or development, or even noise pollution.

Acknowledgements

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Table 1.Monte Carlo Parameters

Variable	**Description**	**Value**
Α	U Intercept	15
Β	U Cost Parameter	-1.2
Γ	U Attribute Parameter	-0.01
C_i	Individual’s Trip Cost	Normal(500, 1000)
D_j	Price Factor	{0.5, 0.75, 1}
W_k	Sampling Values for the Continuous Attribute	{6, 12, 18}

Table 2. Descriptive Statistics

	Sample Means of Participant Characteristics	
	Rehoboth	Cape Henlopen
Sample Size	126	98
Age	43	49
Income (Median)	$55,001-$65,000	$55,001-$65,000
Percent Male	50.8	44.9
Total Trip Cost	996	416
Years of Education	15.6	15.2
Number of Days at Beach this Season	6.0	16.3
Primarily Water Activities	0.47	0.59
Primarily Beach Activities	0.29	0.20
Primarily Boardwalk/Town Activities	0.24	0.20
Owns Property in Beach Town	0.07	0.34
Initial Impression (at random distance from shore)		
Wind Turbines		
Enhance	0.143	0.143
No difference	0.508	0.408
Detract - Would still visit	0.206	0.265
Detract - Would not still visit	0.143	0.184
Initial placement (miles from shore)	2.52	3.06
First Discount	0.82	0.84
Placement at First Discount	1.65	2.22
Second Discount	0.57	0.57
Placement at Second Discount	1.06	1.78
Oil Platforms		
Enhance	0.063	0.102
No difference	0.525	0.470
Detract - Would still visit	0.254	0.265
Detract - Would not visit	0.158	0.163
Initial placement (miles from shore)	5.87	5.89
First Discount	0.82	0.84
Placement at First Discount	4.29	5.34
Second Discount	0.57	0.57
Placement at Second Discount	3.92	5.03

Table 3. Sequential Event Weibull Regressions

Miles from horizon ($\beta < 0$ => closer to shore)	Wind Turbines	Oil Platforms
Constant	-6.633*** (1.896)	-3.799*** (0.307)
Percent Trip Discount	-0.0298*** (0.0083)	-0.0193*** (0.0086)
Primarily Water Activities	0.549 (0.609)	0.066 (0.362)
Primarily Sand Activities	0.632 (0.404)	0.458 (0.519)
Own Property at DE Beaches	2.050** (0.841)	0.948* (0.514)
Income ($10,000)	-0.015 (0.012)	0.006 (0.018)
Years of Education	0.046 (0.041)	-0.029 (0.042)
Age	0.012 (0.008)	0.029*** (0.010)
Male	0.221 (0.296)	-0.314 (0.206)
Trip Cost ($100)	0.008 (0.010)	0.017** (0.008)
Turbines First	0.247 (0.202)	0.070 (0.209)
Henlopen	-0.340 (0.431)	0.348* (0.209)
Initial Placement	0.003 (0.042)	0.020 (0.055)
Ln(Rho)	2.140*** (0.995)	2.58*** (0.791)
N	112	112

Note: *, **, and *** represent significance at a 10%, 5%, and 1% level. Standard errors are clustered by participants. Controls for survey recruiter and day were included but are not reported. Model is estimated using sampling probability weights based on the number of days spent at the beach during the beach season.

Table 4. WTP Confidence Intervals from Dichotomous Choice Data

	Probit		Double Bounded	
	Wind Turbines	Oil Platforms	Wind Turbines	Oil Platforms
Upper Limit	837	1432	1213	1059
WTP	310	304	498	119
Lower Limit	-216	-823	-216	-820

Table 5. Calinski-Harabasz Criteria for Number of Clusters

Number of Clusters	Pseudo-F
2	97.12
3	**122.76**
4	84.25
5	121.90

Table 6. WTP Coefficients by Cluster

	Turbines			Platforms		
	b	chi-2	Median	b	chi-2	Median
c1	-0.0259***	28.07	0.76	-0.0259**	4.99	10.00
c2	-0.0320**	5.23	0.59	-0.0320***	26.64	1.60
c3	-0.0130***	30.33	10.00	-0.0191**	4.56	10.00
rho	2.71222			1.617136		

Table 7. Cluster Member Demographics

	Cluster 1		Cluster 2		Cluster 3	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Primarily Water Activities	0.458	0.499	0.435	0.498	0.659	0.475
Primarily Sand Activities	0.250	0.434	0.391	0.490	0.171	0.377
Own Property at DE Beaches	0.166	0.373	0.217	0.414	0.220	0.415
Income ($1000)	70.28	63.55	57.66	41.24	86.30	75.01
Years of Education	15.42	3.23	15.57	2.19	15.23	2.43
Age	43.94	14.37	45.70	14.31	45.61	15.30
Male	0.563	0.497	0.522	0.501	0.366	0.483
Trip Cost ($100)	915.67	1413.12	773.91	1025.80	523.54	648.66
Turbines First	0.521	0.500	0.652	0.478	0.488	0.501
Henlopen	0.438	0.497	0.565	0.498	0.366	0.483
Rural Resident	0.708	0.455	0.435	0.498	0.610	0.488
N		41		48		23

Figure 1. Results of Monte-Carlo Experiment

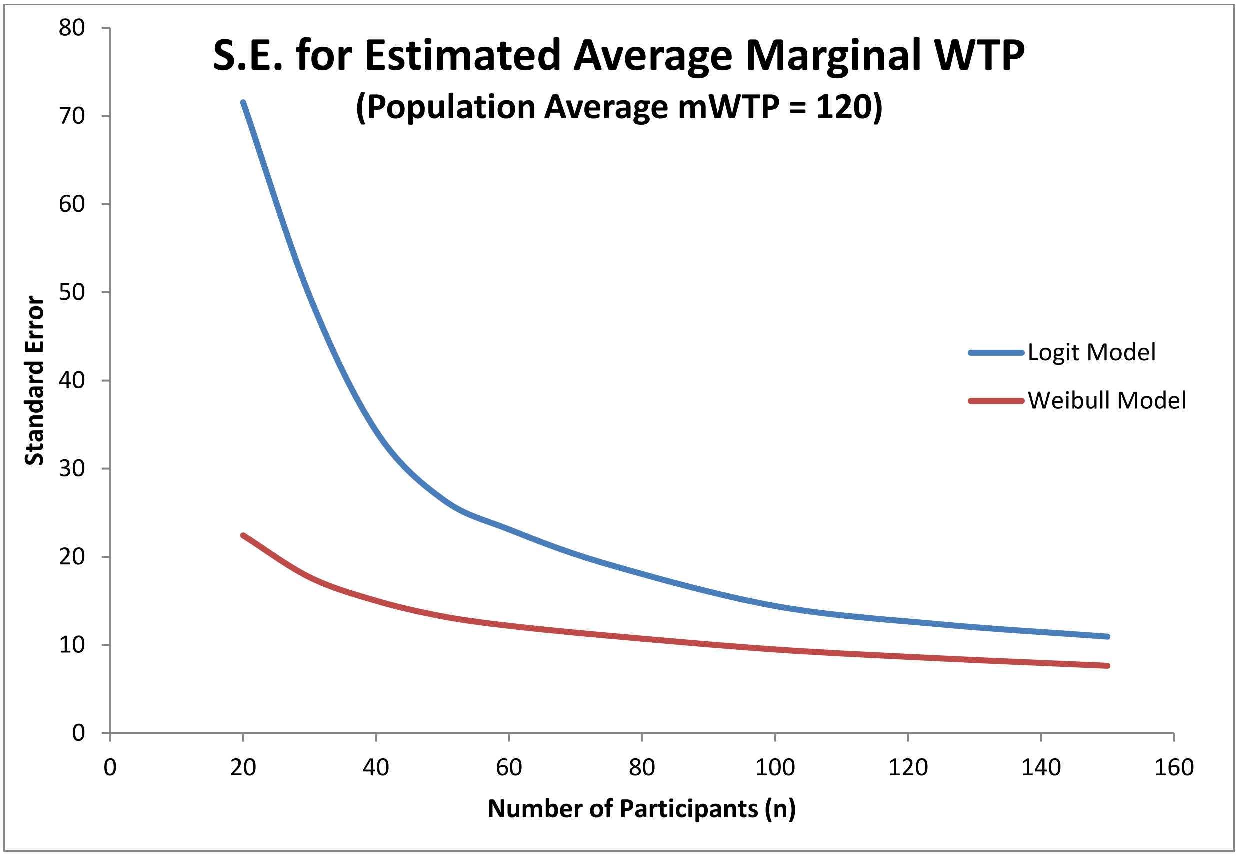


Figure 2. Map of Survey Sites

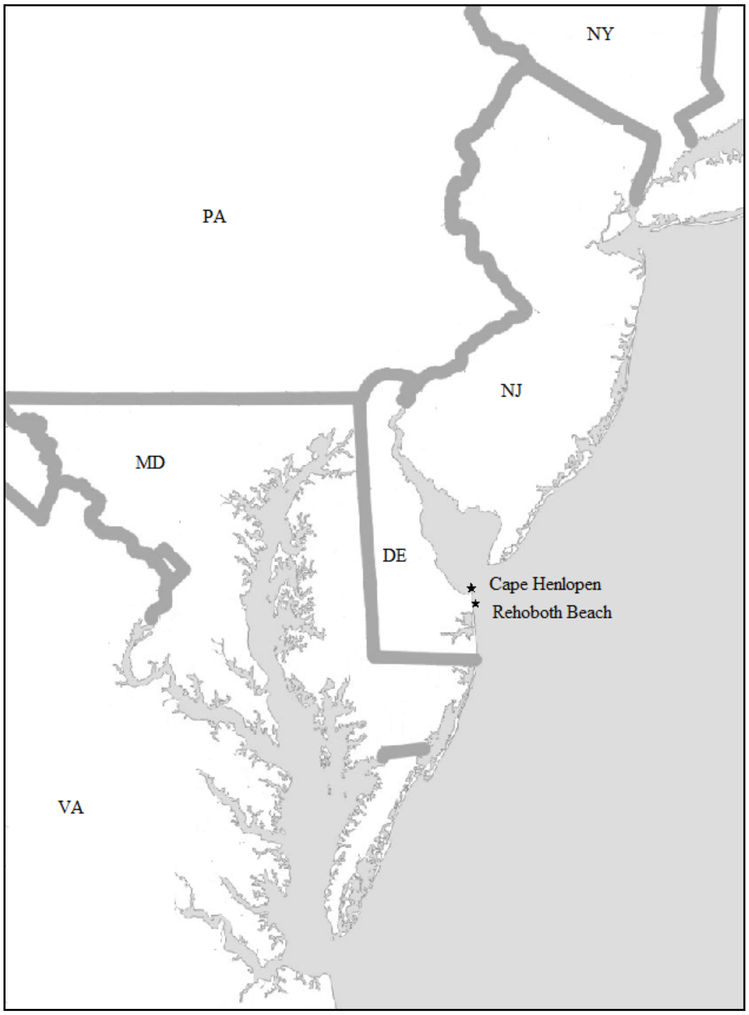
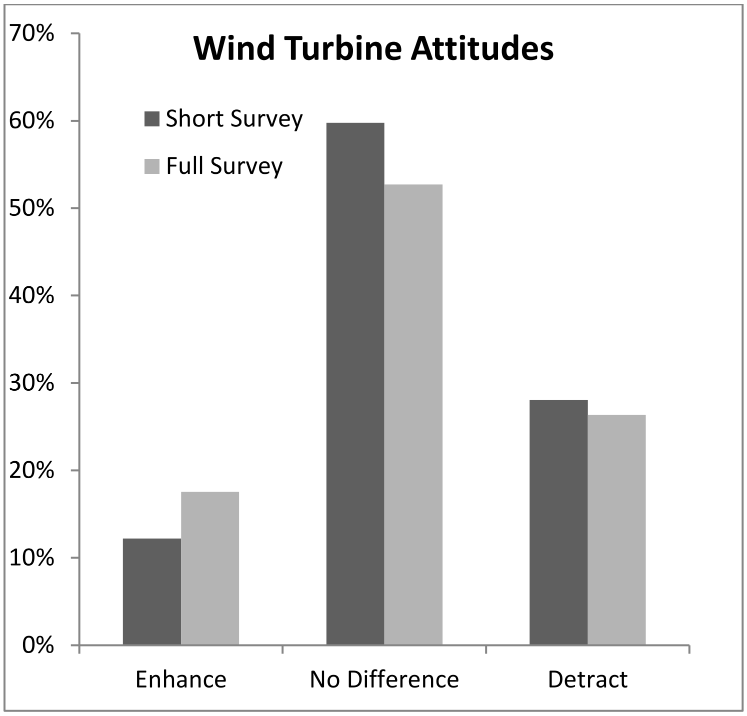


Figure 3. Images of Wind Turbines and Oil Platforms at 5 miles used in the Interface

Figure 4. Basic Attitudes in Survey and Validation Samples



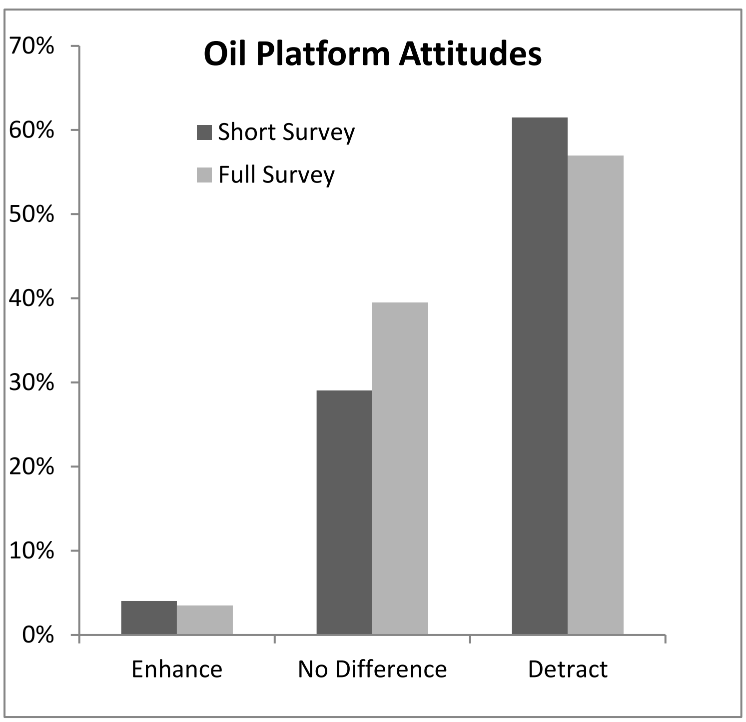
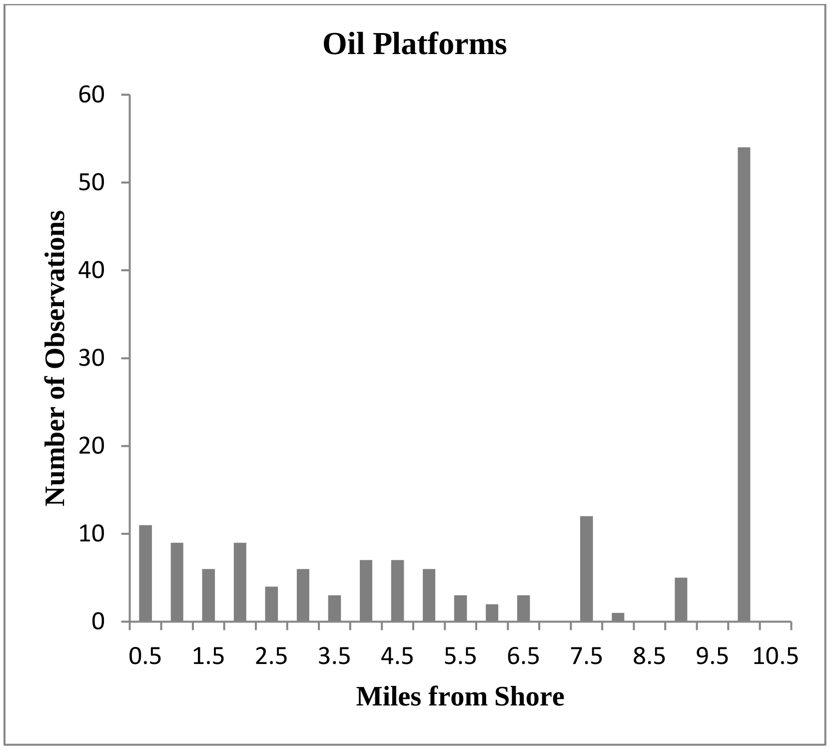


Figure 5. Histogram of Participants' Initial Placement at Reported Trip Costs



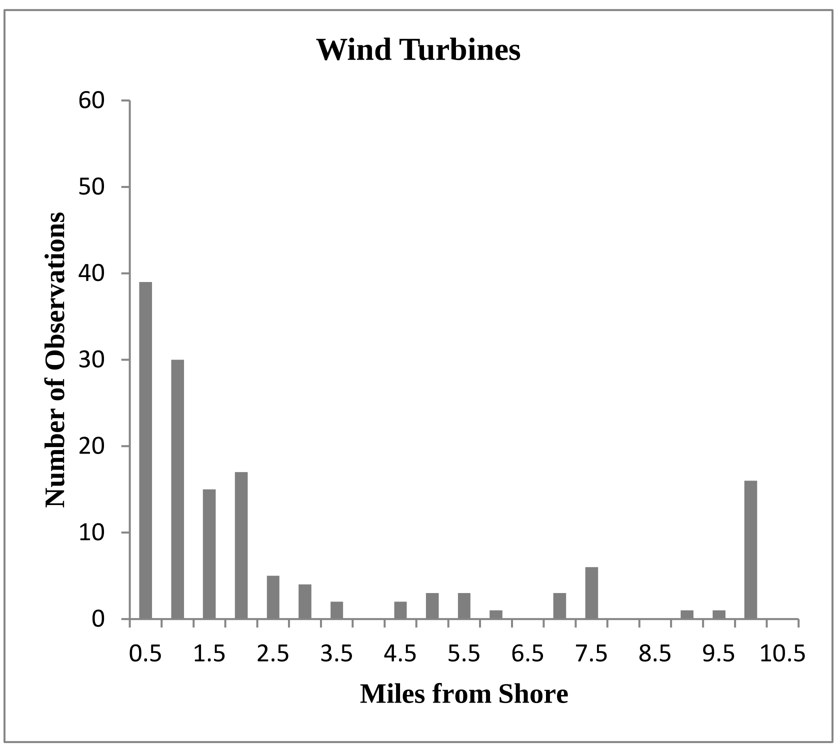


Figure 6. Average Smoothed Hazard Functions at Reported Trip Cost

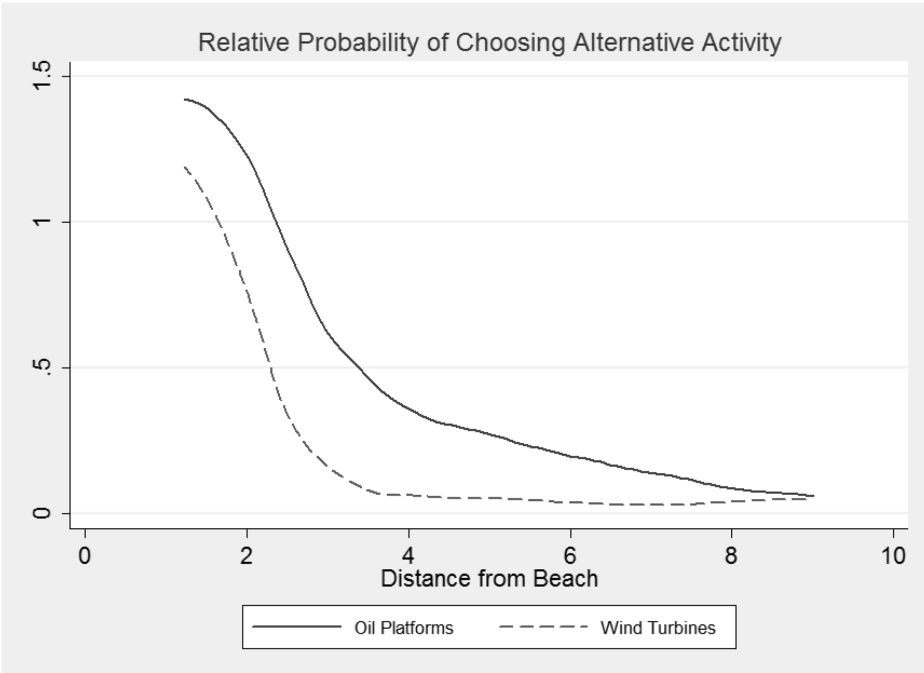


Figure 7. Kaplan-Meier Survival Curves at Reported Trip Cost

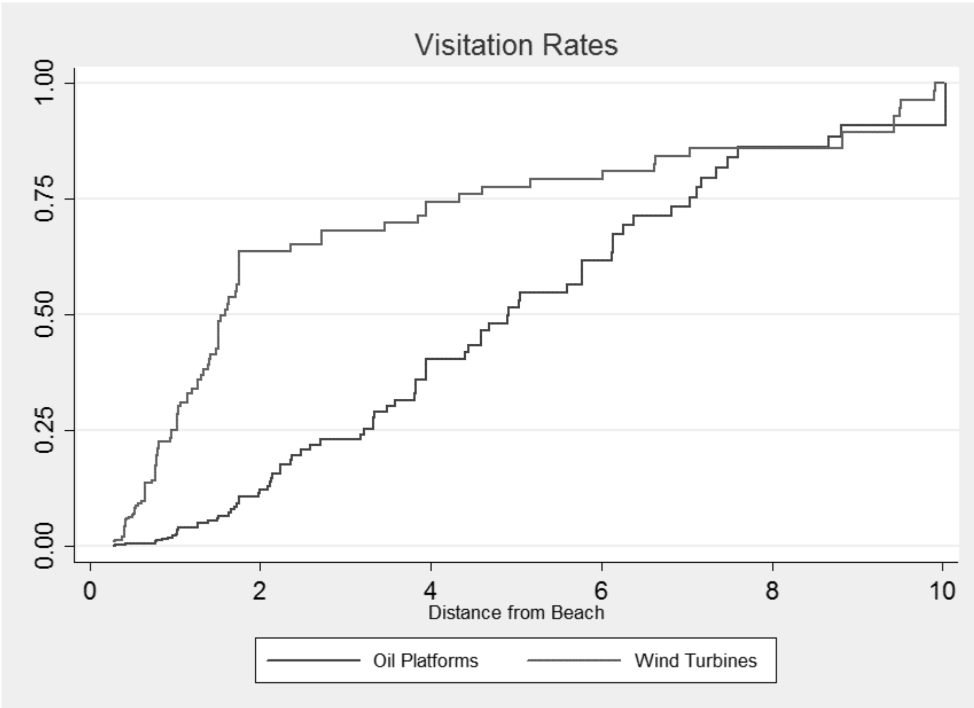
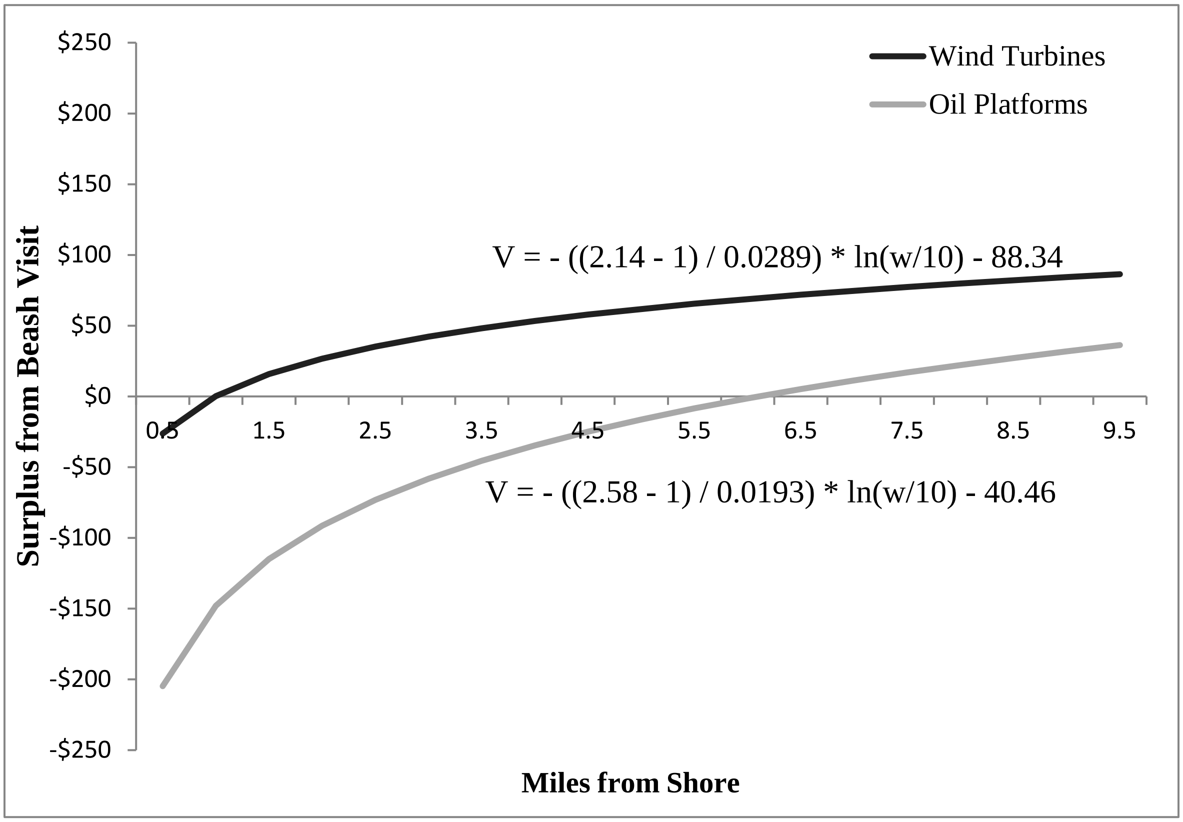
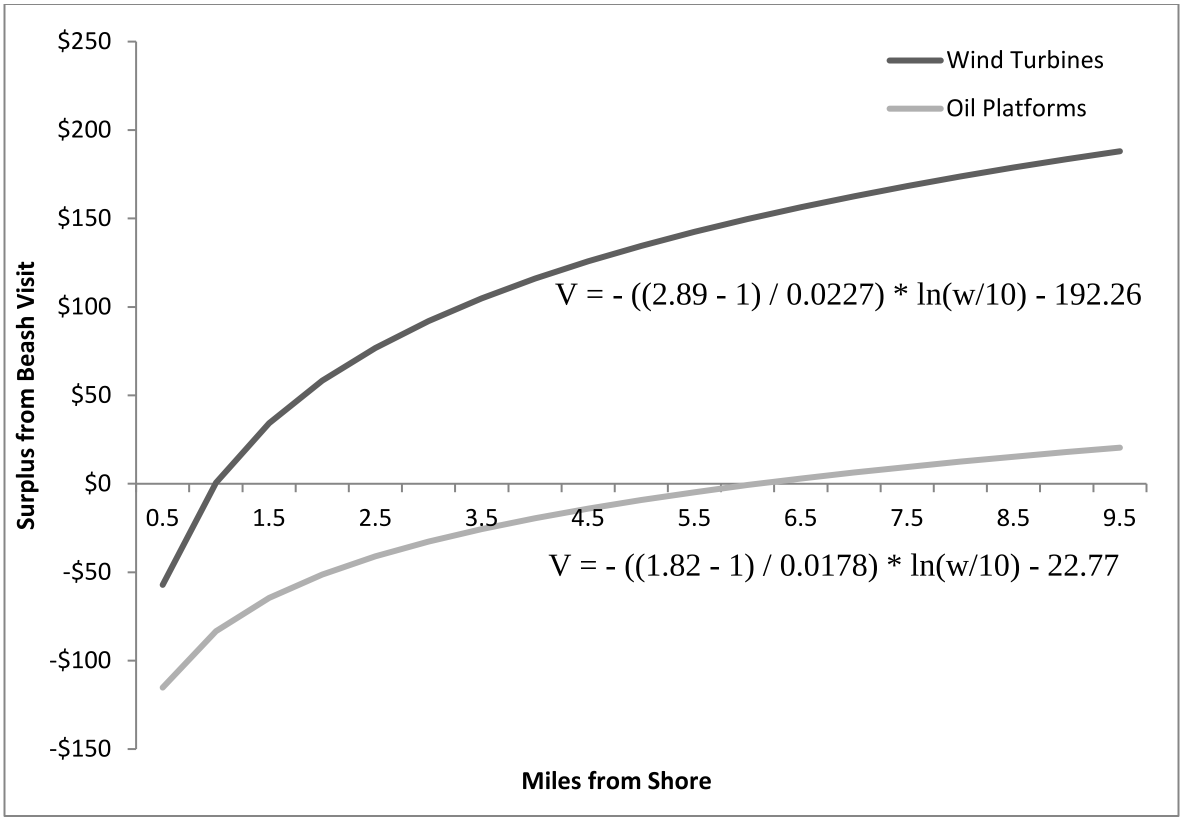


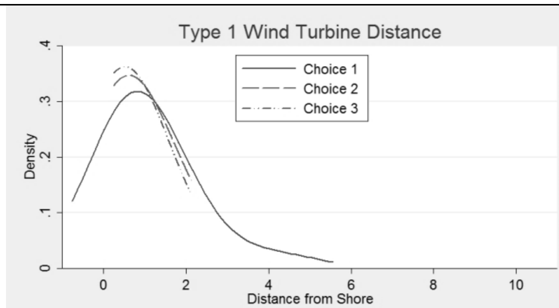
Figure 8. WTP as a Function of Distance

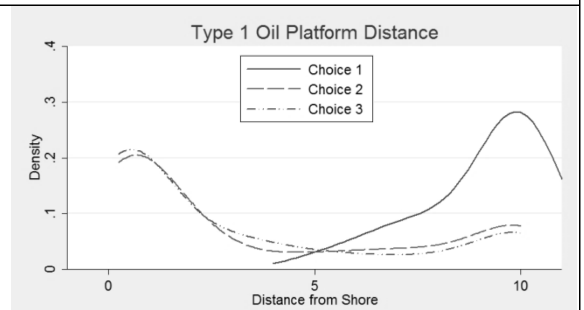


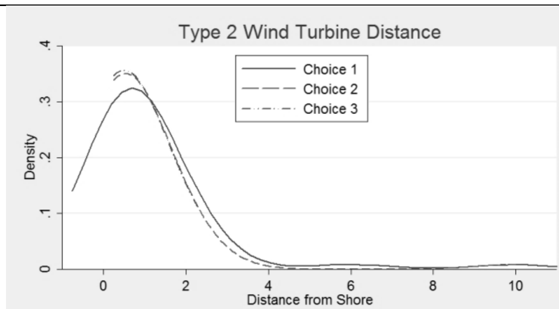


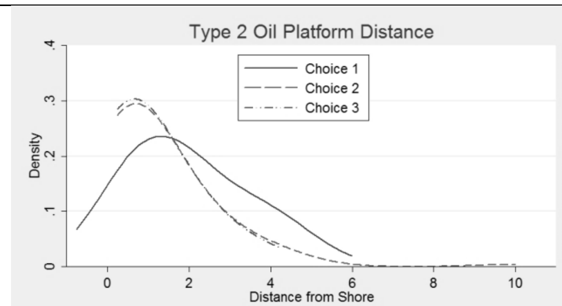
$250
$200
$150
$100
$50
$0
-$50
-$100
-$150
Surplus from Beash Visit
0.5
1.5
2.5
3.5
4.5
5.5
6.5
7.5
8.5
9.5
Miles from Shore
Wind Turbines
Oil Platforms
V = - ((2.89 - 1) / 0.0227) * ln(w/10) - 192.26
V = - ((1.82 - 1) / 0.0178) * ln(w/10) - 22.77

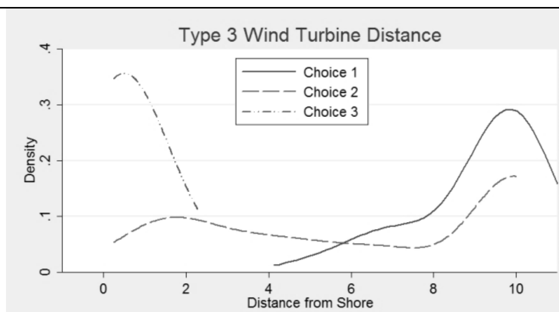
Figure 9. Kernel Densities of Decision Clusters

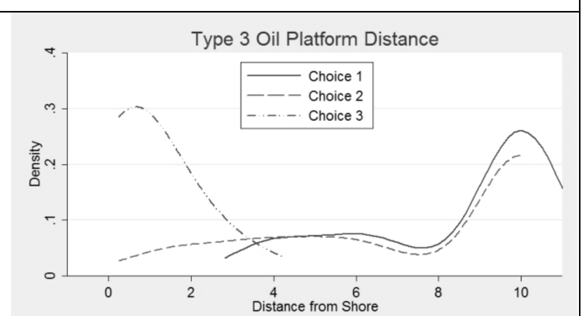
<table>
<tr><td>Cluster</td><td>Turbines</td><td>Platforms</td></tr>
<tr><td>1</td><td>

Mean = 1.121 St. Dev. = 1.027
Median = 0.762 N = 41</td><td>

Mean = 9.073 St. Dev. = 1.469
Median = 10.00 N = 41</td></tr>
<tr><td>2</td><td>

Mean = 1.115 St. Dev. = 1.027
Median = 0.585 N = 48</td><td>

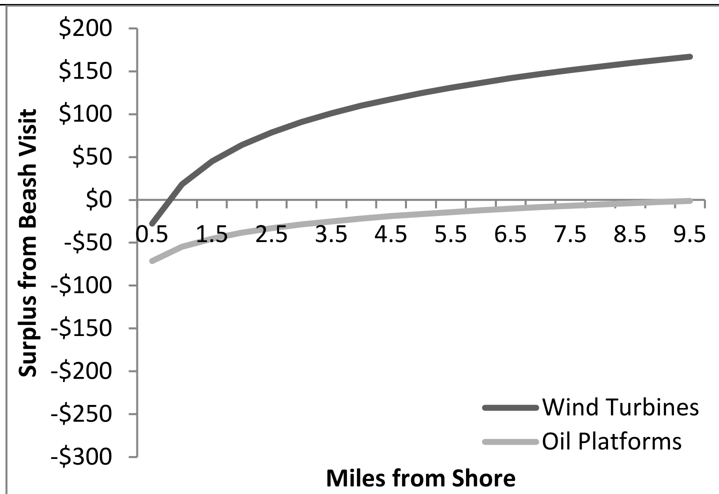
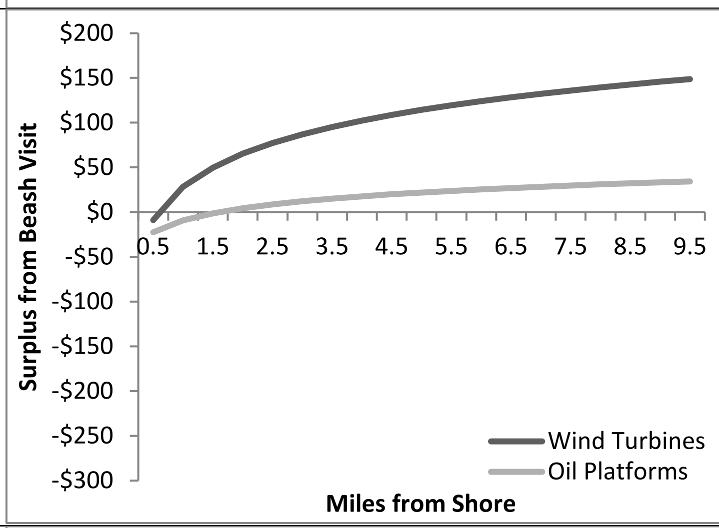
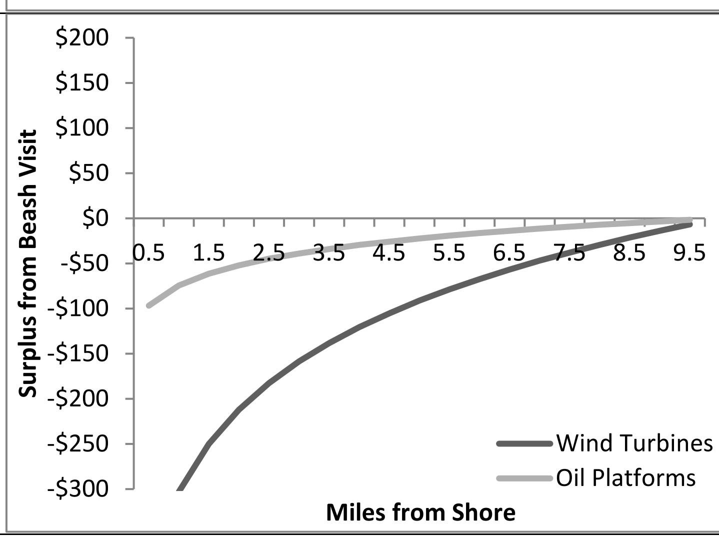
Mean = 1.962 St. Dev. = 1.395
Median = 1.597 N = 48</td></tr>
<tr><td>3</td><td>

Mean = 9.084 St. Dev. = 1.460
Median = 10.00 N = 23</td><td>

Mean = 8.358 St. Dev. = 2.416
Median = 10.00 N = 23</td></tr>
</table>

Statistics listed are for the first choice.

Figure 10. WTP over Distance by Cluster

<table>
<tr><td>Cluster</td><td></td></tr>
<tr><td>1</td><td>
</td></tr>
<tr><td>2</td><td>
</td></tr>
<tr><td>3</td><td>
</td></tr>
</table>

Appendix: Paper Survey

Date: __________

Subject #:_______

Please answer the following questions. Your responses will be kept confidential. Please do not put your name on any of the materials. Any questions may be addressed to the study administrator.

1. Please indicate your sex.
   _______M _______F

2. In what year were you born?_____________

3. What is the zip code at your primary residence? _________

4. How would you describe your area of residence?
   _______Urban _______ Suburban_______Rural

5. How years of formal schooling do you have? (Completed high school = 12 years)?__________

6. Are you currently…?

_______Employed Full Time	_______Employed Part Time	_______Self Employed
_______ Student	_______ Homemaker	_______ Retired
_______ Unemployed		

7. What is your total household gross annual income?

_______ Less than$25,000	_______ $95,001-$105,000	_______ $175,001-$185,000
_______ $25,001-$35,000	_______ $105,001-$115,000	_______ $185,001-$195,000
_______ $35,001-$45,000	_______ $115,001-$125,000	_______ $195,001-$205,000
_______ $45,001-$55,000	_______ $125,001-$135,000	_______ $205,001-$215,000
_______ $55,001-$65,000	_______ $135,001-$145,000	_______ $215,001-$225,000
_______ $65,001-$75,000	_______ $145,001-$155,000	_______ $225,001-$235,000
_______ $75,001-$85,000	_______ $155,001-$165,000	_______ Greater than $235,000
_______ $85,001-$95,000	_______ $165,001-$175,000	_______ Prefer not to say

8. Do you own property in a Delaware beach community (within 5 miles of an ocean beach)? (Exclude investment properties)
   _______Yes, my primary residence
   Yes, my secondary residence
   _______No

9. Which activities are most important to you when visiting anocean beach or beach community in Delaware? (If you engage or more than one, pick the one that is most important.)
   _______Activities in or on the water

_______Activities on the sand
_______Activities at the boardwalk or in town

10. Are you staying here for more than one night on your current trip? (Please skip if your primary residence in a Delaware beach community)
_______Yes _______No
If yes, for how many nights are you staying? _______

11. How many hours do you expect to spend on the beach and boardwalk today? ________

12. Including yourself how many people are you traveling with? ________
- How many children under age 18? _______

13. How many days have you spent on Delaware's ocean beaches (including time on the beach as well as in the community) since Memorial Day? (Please skip if your primary residence in a Delaware beach community)
(Days on the beach since May 28th)? _______

14. How many more days do you expect to spend on Delaware's ocean beaches before Labor Day
(Day on the beach between now and Sept. 3th)? _______

15. Are these primarily day trips or overnight trips?
_______ Day _______ Overnight

16. How many years have you been coming to Delaware's ocean beaches? _______

17. What would you most likely do with your time if the beach you were visiting on your current trip was closed for some reason for an extended period of time?
_______ Visit another beach in Delaware
_______ Visit the same beach community in Delaware but not go on the beach
_______ Visit a beach in Maryland
_______ Visit a beach in Virginia
_______ Visit a beach in New Jersey
_______ Visit a beach outside the mid-Atlantic (not MD, VA, NJ pr DE)
_______ Visit a bay beach in Delaware
_______ Engage in some other non-beach recreation
_______ Stay home
_______Other: ______________________________

18. On a scale of 1 to 5, how favorable are you toward the development offshore wind power in the Mid-Atlantic region?

On a scale of 1 to 5, how favorable are you toward the development of offshore oil production in the Mid-Atlantic region?

Rank your level of agreement with each of the following statements based on the this scale:		STRONGLY STRONGLY AGREE	MILDLY AGREE	UNSURE	MILDLY DISAGREE	DISAGREE
19.	How aware are you of the proposed wind farms off the coast of Delaware?	1	2	3	4	5
20.	How aware are you of oil drilling regulations on the Atlantic Outer Continental Shelf?	1	2	3	4	5
21.	Wind power is a financially viable energy source for our country.	1	2	3	4	5
22.	Offshore oil is a financially viable energy source for our country.	1	2	3	4	5
23.	Wind turbines have a negative impact on the landscape.	1	2	3	4	5
24.	Offshore oil platforms have a negative impact on the landscape.	1	2	3	4	5
25.	When humans interfere with nature it often produces disastrous consequences.	1	2	3	4	5
26.	Human ingenuity will insure that we do NOT make the earth unlivable.	1	2	3	4	5
27.	Humans are severely abusing the environment.	1	2	3	4	5
28.	The earth has plenty of natural resources if we just learn how to develop them.	1	2	3	4	5
29.	Plants and animals have as much right as humans to exist.	1	2	3	4	5
30.	The balance of nature is strong enough to cope with the impacts of modern industrial nations.	1	2	3	4	5
31.	Despite our special abilities humans are still subject to the laws of nature.	1	2	3	4	5
32.	The so-called "ecological crisis" facing humankind has been greatly exaggerated.	1	2	3	4	5
33.	The earth is like a spaceship with very limited room and resources.	1	2	3	4	5
34.	Humans were meant to rule over the rest of nature.	1	2	3	4	5
35.	The balance of nature is very delicate and easily upset.	1	2	3	4	5
36.	Humans will eventually learn enough about how nature works to be able to control it.	1	2	3	4	5
37.	If things continue on their present course, we will soon experience a major ecological catastrophe.	1	2	3	4	5

The Department of Applied Economics and Statistics
College of Agriculture and Natural Resources
University of Delaware

The Department of Applied Economics and Statistics carries on an extensive and coordinated program of teaching, organized research, and public service in a wide variety of the following professional subject matter areas:

Subject Matter Areas

Agricultural Policy	Environmental and Resource Economics
Food and Agribusiness Management and Marketing	International Agricultural Trade
Natural Resource Management	Price and Demand Analysis
Rural and Community Development	Statistical Analysis and Research Methods

The department's research in these areas is part of the organized research program of the Delaware Agricultural Experiment Station, College of Agriculture and Natural Resources. Much of the research is in cooperation with industry partners, the USDA, and other State and Federal agencies. The combination of teaching, research, and service provides an efficient, effective, and productive use of resources invested in higher education and service to the public. Emphasis in research is on solving practical problems important to various segments of the economy.

The mission and goals of our department are to provide quality education to undergraduate and graduate students, foster free exchange of ideas, and engage in scholarly and outreach activities that generate new knowledge capital that could help inform policy and business decisions in the public and private sectors of the society. APEC has a strong record and tradition of productive programs and personnel who are engaged in innovative teaching, cutting-edge social science research, and public service in a wide variety of professional areas. The areas of expertise include: agricultural policy; environmental and resource economics; food and agribusiness marketing and management; international agricultural trade; natural resource management; operations research and decision analysis; rural and community development; and statistical analysis and research methods.

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