

Anchoring on Visual Cues in a Stated Preference Survey: The Case of Siting Offshore Wind Power Projects

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Abstract

We consider anchoring on visual cues in a contingent-behavior study of the effects of offshore wind power projects on beach use on the East Coast of the United States. In an internet-based survey of beachgoers, we show respondents visual simulations of wind power projects at three offshore distances and vary the order in which respondents see the visuals -- so some see near visuals first and some see far visuals first. Respondents are asked how their trip-taking behavior may be affected by the projects. In parametric and non-parametric analyses, we find strong anchoring in the far-to-near ordering of the visuals and weak anchoring in the near-to-far ordering. We also find greater dependence on the first-shown visual versus the most-recent-shown visual. Finally, we find some effects of having viewed wind turbines in real life before entering the survey. The size of the anchoring effect has important policy implications insofar as it affects the predicted change in visitation and hence measured impact of offshore wind power projects. It also has implications for the interpretation of results from other stated preference surveys using visuals and on how surveys are designed.

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1. Introduction

In classical economic models, decision makers' preferences are regarded as predefined, consistent, and stable. In contrast, Tversky and Kahneman (1974) describe a heuristic wherein individuals use prior information, such as initial values shown in a survey or advertisement, to guide preferences. This phenomenon is referred to alternatively as anchoring, reference-dependence, or ordering effect (Ariely et al., 2003).

In this paper, we consider anchoring on visual cues in a stated preference survey. We conducted a large-scale revealed-preference/contingent-behavior study using an internet survey. The purpose of the study was to understand the effect of offshore wind power projects on beach recreation on the East Coast of the United States (Parsons et al., 2020). In the survey, respondents (beachgoers) were shown visual computer simulations of offshore wind power projects and asked how it might affect their behavior. Each respondent was shown a simulation at a near, mid, and far distance, and then for each distance asked to report how it might affect their trip taking behavior. The order in which a respondent saw the visual simulations varied. For example, they might see near-mid-far, far-mid-near, or some other combination. The respondents know in advance that they will see the wind turbines at different distances offshore.

Our research question then is: Does the order in which respondents see visual simulations affect their stated change in trip taking? Or, put differently, do respondents anchor in some way on the first distance they are shown? We also consider the potential for anchoring on information respondents have as they enter the survey, since some respondents have prior experience viewing wind power projects and others not.

At the outset, we were uncertain whether visuals would serve as an anchor or not and, if so, how the anchor might manifest itself. We had two competing hypotheses assimilation and contrast. Our null hypothesis is no anchoring – perhaps the clarity visuals bring to the choice setting obviates anchoring

effects. In the assimilation hypothesis, a respondent's initial level of satisfaction with a wind power project is carried forward in the survey. If, for example, a respondent happened to see a non-intrusive field of turbines at a far distance first, they would be prone throughout the survey to have a positive view of turbines even if the positioning worsened. A tone would be set by the initial view, carried forward by the respondent with perhaps some adjustments as new views are shown, and ultimately assimilated into later responses. These responses are pulled toward the preference held in the initial view. The assimilation theory is like the psychometric descriptions of behavior discussed by Green et al. (1998). In the contrast hypothesis respondents see the current viewing of turbines relative to or in contrast to the earlier views. In the previous example, the non-intrusive first view of turbines would be carried forward as a comparator for current views. If current views are worsening, then respondents are less favorable than they would have been otherwise. They see the current view in contrast to what might be possible – a less intrusive view. The contrast hypothesis is like the reference-effect hypothesis discussed by Day et al. (2012). Dillman et al. (2014, p. 234) discusses these competing anchoring effects in surveys.

We find anchoring in our results and they align best with the contrast hypothesis. Respondents appear to treat their early visual as a “possibility” or “deal” and go on to compare their later visuals relative to that first view. So, if the sequence of visuals is such that circumstances are improving, respondents tend to see a relative “gain” and react more favorably toward later visuals versus a case without an earlier view. If, on the other hand, the sequence is such that circumstances are worsening, respondents tend to see a relative “loss” and react less favorably toward later visuals versus a case without the earlier view. While both effects are observed in our data, the loss is larger in absolute value. We interpret this as loss aversion, which we discuss later.

We begin with a brief review of the literature and then discuss our study design, results, robustness, and overall findings.

2. Literature Review

Visual information is used widely in stated preference surveys. Visuals can help respondents better understand questions and scenarios being considered. Their effect on psychological processes is well established. Compared with the text, visual cues are accessed faster (Barry, 1997), easier to recall (Nelson et al., 1976), and grab attention (Scheufele and Tewksbury, 2006; Wanta, 1988). Social psychologists find that visual messages are more effective in attitude change when information processing is heuristic rather than systematic (Chaiken and Eagly, 1977; Chaiken, 1981; Sojka and Giese, 2006). With the advent of internet surveys and improved software, the use of visuals in stated preference surveys has been increasing noticeably. Two examples where visuals figure prominently are Jansen et al. (2009) with housing and Sylcott et al., (2016) with flatware. In both cases, the visuals matter and whether they are preferred over simple text is mixed. For example, Jansen et al. (2009) find that visuals with accompanying text results in respondents spending less time with the text and may be less informed. So, what may seem like an obvious positive incremental improvement to choice design, is not.

There are many other stated preference studies on the effect of visual information (virtual reality, virtual environments, film, 3D, static images) on choice. Meyerhoff et al. (2019) has a good summary table of these studies. The results are mixed on the extent to which visuals have an effect final choice and value estimates and on the extent to which they are used by respondents. The variation in context and methods across the studies make it difficult to draw firm conclusions. Consider some recent examples. Bateman et al. (2009), Matthews et al. (2017), and Shr et al. (2019) consider landscape visuals in the context of a choice experiment. All three compare visuals to non-visuals and find differences in their final valuation estimates and variance of the estimates (visuals tend to reduce variance). Patterson et al. (2017) consider visual representations of neighborhoods and Rid et al. (2019) consider visuals of housing developments. In these cases, the visuals did not change the results appreciably versus non-visuals and even seemed to generate some inconsistencies. Meyerhoff et al. (2019) consider landscape visuals and although they find some differences (in attribute non-attendance and some marginal willingness-to-pay estimates), they write that “..visual and text-based choice sets do not lead to substantially different

outcomes". Here again, no single consistent story emerges. Visuals and their effects seem to be context specific. They may or may not affect choice and whether they are preferred is not always clear.

Given the increasing use of visuals and concerns about anchoring effects generally (which we discuss below), it is natural to ask if visual information might itself have an anchoring effect or even alleviate anchoring effects. To the best of our knowledge, this question has not been explored. The closest is a study by Meyerhoff and Glenk (2015). They consider the effect of instructional choice sets preceding an actual vote in a choice experiment. Their choice set include maps depicting water quality levels, so they implicitly have a visual anchor, which turns out to matter in choice¹.

Anchoring has been studied in various domains in the economic literature, including general theory, probability estimates, valuation elicitation, legal judgements, etc. Furnham and Boo (2011) provide a good review. In both stated and revealed preference applications researchers find a persistent anchor-and-adjust heuristic, where the anchor is the price or quantity of a previously observed good (or attribute of the good). In the stated preference case, the previous price or quantity is what is shown early in the survey. In the revealed preference case, it is what is observed previously in the market (e.g., listing price for a house). In both settings, the previously observed price/quantity usually affects the current choice and is stronger for goods for which respondents have less experience.

The context closest to our analysis is the stated preference non-market valuation literature where respondents are observed anchoring on bid amounts shown first in a survey. This was originally called starting-point bias. Since these studies usually question participants about unfamiliar (nonmarket goods), they are especially prone to anchoring. Respondents in these studies seemingly look for guidance and use cues that may be available (perhaps offered inadvertently) in the survey (Boyle et al., 1985; Herriges and Shogren, 1996; Green et al., 1998; Frykblom and Shogren, 2000). In the contingent valuation context (e.g., Are you willing to pay \$X to protect environment Y?) researchers consistently find bids (prices) shown early on in survey influence how respondents reacted to bids shown later. They use the early bids as cues. Willingness to pay levels in these studies are consistently pulled in the direction of the starting bid – the higher the starting bid, the higher the final willingness to pay estimate. These findings fit the

contrast theory of anchoring discussed above. Respondents are more likely to vote yes to a given bid amount, if they previously viewed a higher bid, because the new bid looks comparatively (by contrast) better. Also, if the conditions become worse for the respondent in the sequence of questions (bid rising), there appears to be a stronger tendency to anchor than when conditions are becoming better. This is a form of loss aversion. A good example of this finding is DeShazo's (2010) contingent valuation study. He finds a stronger anchor in the price rising versus price falling case. Similarly, Day and Prades (2010) in a choice experiment finds stronger anchoring with price rising or quantity falling versus the reverse.

The stated preference literature is also populated with articles on question ordering effects concerned with learning, preference stability, and fatigue (Day et al. 2012, Carlsson et al. 2012, and Swait and Adamowicz 2001). These are related but different from pure anchoring effects. Dillman et al. (2014) divides question-ordering effects in two types: cognitive-based and normative-based. Cognitive-based effects include priming, carryover, subtraction, and anchoring. Priming is where earlier questions shape later responses by bringing certain elements of a choice to mind more readily than if the earlier question had not been asked. Carryover and subtraction are where respondents treat earlier questions (especially if nearby) as related to a current question and use similar considerations in answering the current question. Again, these are considerations that are not used if the earlier question is excluded. They refer to anchoring as "setting a standard" by which later responses are compared and give examples of assimilation and contrast. The normative-based question-order effects include evenhandedness, consistency, and appearing moderate. These all evoke some type of norm in answering questions – being fair, being consistent, and appearing moderate. Respondents are believed to consciously exercise these norms across questions and so one can observe different responses depending on inclusion/exclusion of questions or order of questions. They use the example of asking students about punishment of their fellow undergraduates for plagiarism. If they are previously asked about punishment for professors, their responses may be different than if not asked, as they attempt to use a consistent norm.

There are also revealed preference studies of anchoring. We discuss only a few here. They include price and non-price anchoring. Good examples of price anchoring are Beggs and Graddy (2009) in fine

art auctions, Bucchianeri and Minson (2013) in real estate, and Gergaud et al. (2017) in vineyard transactions. All three find anchoring effects. Beggs and Grady (2009) find that final sales prices at art auctions are anchored on previously observed prices at the auction – a higher observed earlier price yields a higher final bid. Bucchianeri and Minson (2013) find that the final selling price of a house anchors on its listing price – so a higher listing price yields a higher sales price. Gergaud et al. (2017) find that grape and vineyard prices anchor strongly on an obsolete, but once widely used, pricing system – sales price is moved in the direction of the published price. McAlvanah and Moul, (2013) is a good example of non-price anchoring in horse-racing – betting odds are slow to adjust away from previously reported odds.

To summarize, there is wide use of visuals in surveys in choice modelling and the visuals are growing in complexity, such as films, simulations, 3Ds, virtual realities etc. The visuals are actively used by respondents and they often matter in choice. There is also a large literature on anchoring effects in surveys wherein researchers find a persistent anchor-and-adjust heuristic at work. In this paper we ask if that same heuristic is at work with visuals. Do respondents anchor on visuals or do visuals bring clarity to the choice situation that obviates anchoring? To our knowledge ours is first formally explore this effect.

3. Study Design & Data

As noted earlier, the purpose of our survey is to evaluate the effect of offshore wind power projects on beach use. We sampled households from 20 states near beaches on the East Coast and asked them about their trips to beaches from Massachusetts to South Carolina over the past year. The sample was screened for beachgoers (i.e., individuals who took at least one trip in the past year to an East Coast beach), was done by internet, conducted in 2015, and done using GfK's probabilistic-based Knowledge Panel that was weighted to mimic a random draw from the population ($n = 1725$)². There are several stated preference studies related to siting offshore wind power projects we drew on to design our study.³ These include Ladenburg and Dubgaard (2007), Ladenburg (2009), Krueger et al., (2011), and Westerberg et al., (2013). But, closest in design to ours are Landry et al. (2012), Voltaire et al. (2010),

and Voltaire et al. (2020) – all asked beachgoers to report how current trip plans might change if wind power projects were present using contingent-behavior questions.

Our survey began by questioning respondents about the specifics of beaches they had visited in the past year. Then it turned to a contingent-behavior question in which respondents were asked to consider a trip to one of the beaches they had visited in the past year (randomly drawn) and to imagine that a wind power project had been located offshore on that beach. Then, they were asked how the presence of the project would have affected their beach experience/enjoyment and if it would have caused them to change their trip plans.

Each respondent was shown a simulation at three different distances offshore.⁴ The simulations panned over images of the turbines to give a realistic view. The visuals were shown in all cases in three conditions: clear, hazy, and at night. The distances were classified as near, mid, and far. Near distance was at 2.5, 5, or 7.5 miles offshore; mid distance at 7.5, 10, or 12.5 miles; and far distance at 12.5, 15, or 20 miles. Respondents were randomly assigned one of the three mileages in each distance category. The assignment was programmed so the same respondent would not see 7.5 at both near and mid distance or 12.5 at both mid and far distance – the two overlapping distances. Critical in our analysis was the order in which the visuals were shown. Respondents were assigned randomly to one of four order groupings (sample size in parenthesis):

- Near-Mid-Far (575)
- Far-Mid-Near (575)
- Mid-Near-Far (287)
- Mid-Far-Near (288).

The sample was split roughly into thirds into the groupings near-first, far-first, and two mid-first groups. Two possible groupings were excluded: Near-Far-Mid and Far-Near-Mid. This was done to increase the sample sizes ending with near and far responses. In hindsight and given some of our findings, it might have been useful to include these groupings as well. It would have allowed us to gain a better reading on intermediate positioning and competing anchors. In the current structure, the last visual is always preceded by visuals uniformly closer (Near-Mid-Far, Mid-Near-Far) or uniformly farther (Far-

Mid-Near, Mid-Far-Near). Breaking that uniformity might have been interesting. Does one anchor dominate the other? Or, are these offsetting effects? Finally, respondents were shown the same wind power project at each distance: 100 turbines, each of which was 6 MW, 175 meters high with a rotor diameter of 150 meters. The turbines were displayed 1.2 km apart from each other in a 10 by 10 grid format. As noted, the visuals were shown in clear and hazy conditions and at nighttime in all cases so respondents would have idea of how the turbines appear in different conditions.

After each simulated wind power project was viewed, respondents were asked whether the presence of the turbines would have affected their beach experience/enjoyment relative to no wind power project – making it worse, somewhat worse, neither worse nor better, somewhat better, or better. If they answered worse or somewhat worse to the experience question, they were asked whether they would have made the same trip, visited another beach instead, or done something else, with the assumption that they would have known in advance about the presence of the turbines. We refer to this as our “cancel” question (see Figure 1). If respondents responded better or somewhat better to the experience question, they were asked if they would have gone to a different beach in the same state if the wind power project was installed there instead (see Figure 2).⁵ We refer to this as our “seek” question, as in seeking out wind power projects. Finally, if they reported neither, they would move to the next set of questions.

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Assuming you had been aware of the wind power project before taking your last day-trip to Rehoboth Beach, DE, would its presence at 20 miles offshore have caused you to visit another beach or do something else instead?

Assume the wind power project would have been visible from other beaches located near Rehoboth Beach, DE.

This is not a vote for or against wind power. We simply want to know how your beach trips would have been affected.

I would still have visited Rehoboth Beach, DE

I would have visited another beach instead

I would have done something else

How certain are you that this is what you would have actually done?

Extremely Uncertain Somewhat Uncertain Somewhat Certain Extremely Certain

0 1 2 3 4 5 6 7 8 9 10

Level

Go [here](#) if you would like to see the simulations at 20 miles offshore again.

Back Next

Survey Powered By **Qualtrics**

Figure 1: Sample Question from the Survey Regarding Respondents' Trip Cancellation Decision after Seeing the Simulation

The screenshot shows a survey question from the University of Delaware. The question asks if respondents would have visited Rehoboth Beach instead of Dewey Beach if a wind power project were located there. It includes radio button options for 'No' and 'Yes', a certainty scale from 0 to 10, and a 'Back Next' button.

UNIVERSITY OF DELAWARE

Suppose the wind power project at 12.5 miles offshore was instead located at Rehoboth Beach in Delaware. Assuming you had been aware of the project before taking your last long overnight-trip, would you have visited Rehoboth Beach instead of Dewey Beach, DE to be on a beach where a wind power project is located?

This is not a vote for or against wind power. We simply want to know how your beach trips would have been affected.

No, I would still have visited Dewey Beach, DE

Yes, I would have visited Rehoboth Beach

How certain are you that this is what you would have actually done?

Extremely Uncertain Somewhat Uncertain Somewhat Certain Extremely Certain

0 1 2 3 4 5 6 7 8 9 10

Level

Go [here](#) if you would like to see the simulations at 12.5 miles offshore again.

Back Next

Survey Powered By Quizzgo

Figure 2: Sample Question from the Survey Regarding Respondents' Trip Seeking Decision after Seeing the Simulation

4. Analytical Approach

4.1 Assimilation Versus Contrast

To test for anchoring in the stated cancel and seek responses described above, we use non-parametric (simple mean differences) and parametric (regression) analyses to test for dependence. Our analysis is done by grouping the data by responses to the visuals at near views only and then by responses to visuals at far views only. Then, within each group we test whether the viewing order shown matters to respondents. So, in the near-view-only data did it matter if respondents had previously seen a far view? And, then similarly for the far-view-only data.

Figure 3 shows how our competing hypotheses would be realized in the data. The figure assumes respondents prefer wind turbines further from shore. The solid line labeled “When Viewed First” is what the response data would look like for responses to the visuals shown first – the vertical axis is the share of the population cancelling at each distance. Cancellation declines with distance. Since this is the hypothetical response data for the first-time turbines are viewed, it is free of anchoring. The dashed and dotted lines show the expected anchoring effects for the assimilation and contrast hypotheses. These are what responses would look like at each distance if respondents had had a previous view and if each hypothesis held true. In the case of the near distances, the previous views would have been far distances and for far distances would have been near distances.

The dotted line labeled “When Viewed Last: Assimilation Hypothesis” is the anchoring effect expected if the assimilation hypothesis is at work. At near distances the effects are damped causing the line to drop (less cancelling) because a positive tone is set by the previous distant views. At far distances, the effects work in the other direction. The line rises (more cancelling) because a negative tone is set by the previous near views. In both cases the previous view is assimilated into the current response.

The dashed line labeled “When Viewed Last: Contrast Hypothesis” is the anchoring effect expected if the contrast hypothesis is at work. At near distances the line is lifted because respondents compare the near views to the better previous more distant view and sense a loss. There is higher cancellation. At far distances the line drops because respondents compare the current far view to a worse near view seen earlier and see circumstances by contrast as improved and cancel less. The anchoring effect lines are shaded over middle distances since we never observe these in the last position and so cannot test for anchoring. We will return to this figure in our results sections.

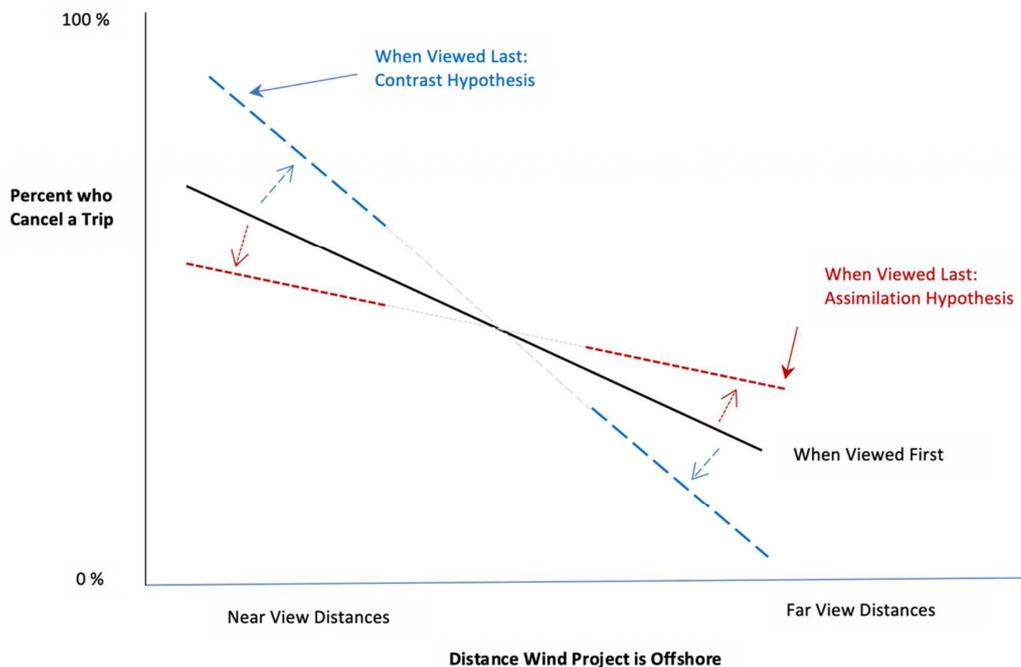


Figure 3: Assimilation and Contrast Theories of Anchoring on Visuals

4.2 Net-Trip-Cancellation

In the upcoming analyses we combine our cancel and seek responses into a single variable we call net-cancel. Net-cancel takes on a value from 1 to -1, where 1 is cancel, -1 is seek, and 0 is neither cancel nor seek. Fractional values between 1 and -1 are determined by a certainty-of-response question that follows the cancel and seek questions. We begin by describing how net-cancel is constructed.

Respondents fall in one of three groups based on how they respond to the effect-of-turbines-on-beach-experience question: (1) neither worse nor better, (2) worse or somewhat worse, or (3) better or somewhat better. For respondents in Group 1, we assume that they neither cancel nor seek, since they report that their experience is unaffected by turbines. For respondents in Group 2, we ask if their experience would cause them to visit another beach if turbines were present on a beach they wanted to visit (cancel question in Figure 2). For respondents in Group 3, we ask if their experience would cause them to seek a beach with turbines present (seek question in Figure 3). This gives us a trichotomous

response. The final step is to convert this response into a continuous variable using the certainty-of-response follow-up question asked after the cancel and seek questions. This adjusts our response for the degree of respondent certainty.

Following the Group 2 cancellation question, we asked respondents: “How certain are you that this is what you would have actually done?”. People responded on a scale from 0 to 10, where 0 is extremely uncertain and 10 is extremely certain. If a person reports that they would have cancelled a trip with a certainty level of 10, the person is assigned a cancel probability of 1. If the person reports that they would have cancelled a trip with a certainty level of 0, they are assigned a cancel probability of .5. That is, if the person is extremely uncertain of cancelling, their probability of taking a trip is treated as a toss-up. Continuing in this vein, respondents who reported that they would have cancelled a trip with a certainty level greater than 0 but less than 10, are assigned a cancel probability arrayed between .5 and 1. So, for example, a cancel response with a certainty level of .5, would be assigned a cancel probability of .75. For respondents who reported that they would not have cancelled a trip, we follow the same reasoning but array people between a probability of 0 (not cancel with certainty 10) and .5 (not cancel with certainty level 0). In effect, we transform the cancel variable into a “probability of cancel” ranging from 0 to 1.

For the seek variable, we make the same transformation, but put the response on a negative unit interval (-1 = seek, 0 = not seek). Putting these adjusted response variables together gives the net-cancel variable that ranges from 1 to -1, where 1 is a certain cancel, -1 is a certain seek, 0 is a certain neither cancel nor seek, and fractional values capture a respondent’s degree of uncertainty in either cancelling or seeking. Mathematically, net-cancel takes the form

$$c_{nj}^{net} = z_{nj}^{worse} \cdot \{[y_{nj}^c \cdot (1 - w_{nj}^c)] + [(1 - y_{nj}^c) \cdot w_{nj}^c]\} + z_{nj}^{better} \cdot \{[y_{nj}^s \cdot (1 - w_{nj}^s)] + [(1 + y_{nj}^s) \cdot w_{nj}^s]\} \quad (1)$$

where

$n = 1, \dots, 1691$ denotes the n th respondent,

$j = 1, 2, 3$ denotes the j th contingent behavior question,

c_{nj}^{net} = net-cancel probability,

$z_{nj}^{worse} = 1$ if respondent n reported that her beach experience would be made worse by turbines,

$z_{nj}^{better} = 1$ if respondent n reported that her beach experience would be made better by turbines,

$y_{nj}^c = 1$ if respondent n reported that she would not take trip j and 0 otherwise,

$Y_{nj}^s = -1$ if respondent n reported that she would seek another site on trip j and 0 otherwise,

$w_{nj}^{c'} = 0, \dots, 10$, where 0 is extremely uncertain and 10 is extremely certain to cancel,

$$w_{nj}^c = .5 \cdot \left\{ 1 - \frac{w_{nj}^{c'}}{10} \right\}$$

$w_{nj}^{s'} = 0, \dots, 10$, where 0 is extremely uncertain and 10 is extremely certain to seek,

$$w_{nj}^s = .5 \cdot \left\{ 1 - \frac{w_{nj}^{s'}}{10} \right\},$$

$$z_{nj}^{worse} \cdot z_{nj}^{better} = 0.$$

So, c_{nj}^{net} ranges from 1 to -1. $z_{nj}^{worse} \cdot z_{nj}^{better} = 0$ implies that respondents cannot find turbines both worse and better (this is forced in construction of the survey).⁶ Equation (1) also implies that for respondents who find turbines neither worse nor better, that is when $z_{nj}^{worse} = z_{nj}^{better} = 0$, $c_{nj}^{net} = 0$.

In the non-parametric analysis then, we consider the mean value of c_{nj}^{net} at each of our seven distances (from 2.5 to 20 miles offshore) and test for view-order effects. Our null hypothesis is that the mean values will be invariant with the order in which the visual was shown. The difference is tested statistically for each distance.

In the parametric analysis, we use ordinary least squares (OLS) with c_{nj}^{net} as our dependent variable. We also estimated a fractional logit version model, but the simpler OLS version gives a better fit and is easier to interpret in this context. Recall that each respondent is shown a wind power project at a

near, mid, and far distance. With these data, we consider three sub-models: a near-distance model that only uses response data to views of turbines near to shore, a mid-distance model that only uses response data to views of turbines at mid-distances from shore, and a far-distance model that only uses response data to views of turbines far from shore. Since we stack these three data set and estimate the models as one, we refer them separately as sub-models. Each sub-model then takes the form

$$c_{nj}^{net} = \mathbf{D}'_{nj}\beta + \mathbf{X}'_{nj}\delta + \mathbf{R}'_{nj}\gamma + \epsilon_{nj} \quad (2)$$

where c_{nj}^{net} is defined in equation (1), \mathbf{D}'_{nj} , \mathbf{X}'_{nj} , and \mathbf{R}'_{nj} are covariates, ϵ_{nj} is an OLS error term, and β , δ , and γ parameters to be estimated. The covariates are described below.

\mathbf{D}'_{nj} is a vector of dummy variables controlling for the offshore distance of the wind power project. There are three levels in each sub-model. For example, in the Near-Distance Sub-Model, which only uses response data when turbines are near to shore, there are variables for *Distance 2.5* and *Distance 5.0*, with *Distance 7.5* excluded. These variables control for varying offshore distances *within each model*. Similar dummy variables are used in the Far-Distance and Mid-Distance Sub-Models.

\mathbf{X}'_{nj} is a vector of dummy variables indicating the question order. The coefficients on these variables are used to test for anchoring. We use three dummy variables: *First Question*, *Second Question*, and *Third Question* to indicate order. *First Question* is excluded for identification. With no anchoring, $\delta = 0$. In this case, stated cancellation is stable with respect to question order. Since there are two possible orderings for view distances preceding questions in the third position, we define two separate variables to see if the sub-ordering matters. So, for example, in the Near-Distance Sub-Model, respondents view of near-distance may be preceded by far- then mid-distance or by mid- then far-distance. It may matter which came first. To test for sub-ordering effects, we have separate third-question variables: *Third Question with Far-Mid Before* and *Third Question with Mid-Far Before*.

R'_{nj} is vector of variables intended to capture anchoring by respondents on actual past experiences with wind power projects. People who have seen or frequently see wind turbines may have different reference points as they begin the survey and hence may have different reactions to the wind-power simulations. *Real-Life View*, which is a categorical variable for how many days a respondent reports having seen a wind power project (or even a single turbine) in the past year. It has four categories: *Never Seen, 1 - 10 Days, 10 – 25 Days and More than 25 days*. The real-life coefficients are constrained to be the same across our three sub-models.

To recap, the coefficients δ on the question order variables X'_{nj} are used to test for anchoring. They will signal whether or not question order affects the probability of cancelling. The coefficients γ on R'_{nj} pick up the effect of actual experience viewing wind projects. D'_{nj} is a control variable for distance – within each subgroup turbines are viewed at three different distances and this must be controlled.

Finally, in our model anchoring may surface by altering cancelling or seeking behavior. So, for example, an anchor that causes an increase in reported cancellation might also cause a decrease in seeking (if the effect is working in the same direction). Conversely if the anchor decreases reported cancellation, it might increase seeking. In this way we see cancel and seek on the same continuum.

4.3 Robustness Checks

As a robustness check, we conducted an in-person survey with a similar question structure to our internet-based survey but instead used hand-held visual simulations of the wind power projects. The in-person survey was conducted in October 2017 at the University of Delaware Coast Day, an annual open exhibition in Lewes, DE. This event attracts thousands of visitors from nearby regions for a fun/educational experience. Among the many activities available to visitors in 2017 was a short survey replicating a portion of our internet-based survey. Those agreeing to participate were given brief instructions, a self-guided survey, and an image booklet, which included seven simulated offshore wind project photos at seven offshore distances (the same considered in our internet survey), and free ice cream

for participating. Participants (n = 559) were assigned to one of two types of image booklets: one with ascending view order (2.5 miles to 20 miles) and the other with descending view order (20 miles to 2.5 miles). In both cases, respondents flipped through the booklets in which each page showed the same wind power project but at a different distance. Like the internet survey, respondents could be in a near-to-far sample or a far-to-near sample. Respondents were free to flip through the booklet in advance and were told the survey was about the effects of views at different distances. Unlike the internet survey, people viewed wind power projects at all seven distances. Also, unlike the internet survey we did not ask about seeking, so the robustness check only considers cancelling.

As a second robustness check we estimated the Net-cancel Model dropping all observations where wind power projects at either 7.5 and 12.5 miles offshore are used. These are the distances where overlap is possible – 7.5 may appear in the Near- or Mid- Distance groupings and 12.5 may appear in the Mid- or Far-Distant grouping. This never happens for any given observation, but it can across observations.

5. Results

5.1 Non-Parametric

Figure 4 shows our net-cancellation results. The solid line shows the percent of respondents who net-cancel when the viewing distance (on the horizontal axis) is first-in-order and the dashed line for when it is last-in-order. In the absence of anchoring, these lines should be the same or nearly so. This graph only uses the near-mid-far and far-mid-near responses. There is no result for 10 miles offshore because it is never shown first or last in these responses. Figure 4 is the empirical version of Figure 3.

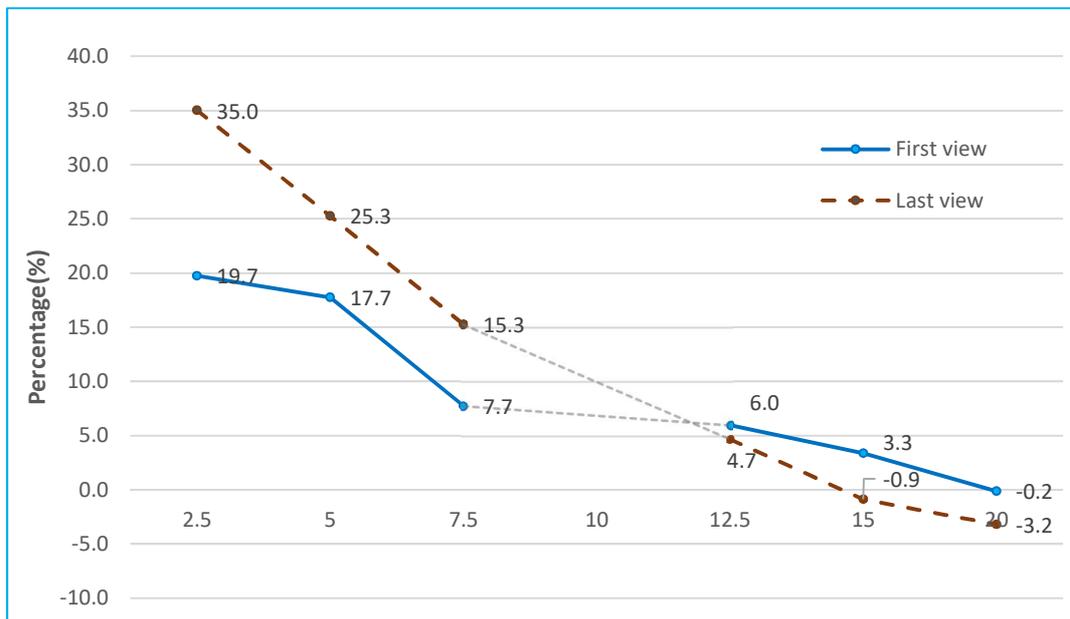


Figure 4: Proportion of the Sample Net-Cancelling a Trip by Distance Comparing First-in-Order and Last-in-Order Viewing.

Notes: Net-cancel is the proportion of the sample that cancels a trip minus the proportion that seeks a trip. The solid line is the response data when the view was shown first. The dashed line is the response data when it was shown last. Separation between lines is evidence of anchoring. The lines become negative over some of the more distant view, because seeking outweighs cancelling.

First, the shape of the graph in Figure 4 makes sense. Net-cancellation rates are higher the nearer a wind power project is to shore -- that is, the impact on beachgoers is greater (more negative) at nearer distances. It is interesting to note (and important from a policy perspective) that at 20 miles offshore net-cancellation is negative in both view orders, implying more seekers than cancellers at that distance.

Second, net-cancellation rates for near-distance wind power projects (left-side of the figure) are higher if respondents had previously viewed turbines at a far distance -- the Last-View line lies above the First-View. This shows anchoring in far-to-near distance ordering that fits our contrast theory -- seeing an earlier more favorable view makes the current view seem by contrast worse, lifting the line. Third, net-cancellation rates for far-distance wind power projects (right-side of the figure) are also affected by view order but to lesser extent -- the Last-View line lies below the First-View line at far distances but the difference is much smaller. Again, this is anchoring that fits our contrast theory.

Table 1 presents t-statistics testing the anchoring effect. As shown, statistical significance is present for the anchoring with both far-to-near and near-to-far ordering, but the statistical significance is lower for the near-to-far anchoring, consistent with the smaller spread between the lines at far distances in Figure 4. The difference is insignificant at 12.5 miles and significant but only at 90% at 15 and 20 miles.

Distance	Net-Cancel: When Viewed First (%)	Net-Cancel: When Viewed Last (%)	t-stat for difference in means	Sample size
2.5 miles (4.0 km)	19.7%	35.0%	3.61	593
5 miles (8.0 km)	17.7	25.3	2.31	613
7.5 miles (12.1 km)	7.7	15.3	2.53	376
12.5 miles (20.1 km)	6.0	4.7	0.13	372
15 miles (24.1 km)	3.3	-0.9	1.95	601
20 miles (32.2 km)	-0.2	-3.2	1.68	600

Table 1: Mean Reported Net-Cancel Rate by Distance by View Order

Note: t-statistics for significance at 90%, 95%, and 99% are 1.645, 1.96, and 2.576.

As far our competing hypotheses are concerned, the results fit the contrast theory (compare Figures 3 and 4). Respondents at near distances who had previously viewed turbines at a far distance, appear to compare the current *high-intrusive* (up-close) view with the previous *low-intrusive* (far-away) view and report more net-cancellation than they do without the contrast. Things appear worse by contrast, so there is more cancellation and less seeking. Respondents at far distances who had previously viewed turbines at near distance do something similar. In this case, they compare the current *low-intrusive* far view with the previous *high-intrusive* near view and reduce net-cancellation. Things appear better by contrast in this case. Indeed, seeking increases enough at 15 and 20 miles so that net-cancelling is negative when it accompanied with an anchor effect.

Before moving on to the parametric results, the seeking part of net-cancellation needs more discussion here. It is useful to separate the seekers into two groups: green seekers and view seekers. Green seekers like the idea of being on a beach where a turbine is present (knowing something good is being done for the environment in their judgment) but prefer they be placed at more distance locations from the shore. A green seeker's net-cancel likelihood increases with the proximity of turbines to shore. They seek turbines at far distances but cancel if they are too close.

View seekers are different. View seekers like the view of turbines and seek them out for the view. For this group, if turbines are too far offshore to see (or at least to see well), the likelihood of seeking decreases contributing to an increase in net-cancel. View seekers work as an offset in our analysis. In Figure 4, they tend to pull the dashed Last-View line down somewhat at near distances (left side) and pull it up at far distances (right side). For example, consider the right-side of the figure at far distances. View seekers that view distant wind power projects after having view near ones have a reference that is *better* than their current view (*high-intrusion* is good because they can see the turbines) and so are less likely to seek. This gives some uplift to the dash line. The same offsetting effect is true on left side of the figure. All said this effect is not large -- only a small fraction of the sample are seekers and most are green seekers.

Finally, the larger spread between the lines at near distances versus far distances in Figure 4, may be a form of loss aversion. At near distances the anchoring effect is working in the direction of a perceived loss – it is a contrast is between the current *high-intrusive* (up-close) near view versus the earlier *low-intrusive* (far-away) view. In contrast to the earlier view things are getting worse in the current view. At far-distances the anchoring effect is working in the direction of a perceived gain – the contrast is between the current *low-intrusive* (far-away) view versus the *high-intrusive* (up-close) near view. Now, the current view looks better than the previous view so there is a gain. This result is consistent with a theory of loss aversion – avoided losses are valued more than acquired gains of equal magnitude.

5.2 Parametric

The parametric results are shown in Table 2 and are broken down into three sub-models: near-distance, mid-distance, and far-distance. The model is shown in equation (2). Each sub-model considers observations in one distance grouping. So, the Near-Distance Sub-Model includes responses only for the near-distance observations and those responses vary by order: first, second, or third question. The same is true for the Mid-Distance and Far-Distance Sub-Models. The sub-models were estimated simultaneously using interactive terms and allowing for correlation across a single respondent’s three choices. We constrain the variable for real-life views of wind projects to be constant across the three sub-models.

In the parametric results all possible orders are included: near-mid-far, far-mid-near, mid-far-near, mid-near-far. In the non-parametric data, we excluded the last two orderings – those beginning with mid-distances. The parametric results then tell a broader story and, in particular, pick-up the effects of intermediate ordering. Also, all three sub-models include *Distance* variables – these are controls to account for respondents seeing different distances in their near, mid, and far treatments.

We consider the variable groups in turn. The *Distance* variables (our controls) are positive and statistically significant in all cases (the most distance placement in a grouping is the excluded variable). The effect is largest moving from 7.5 to 2.5 miles in the Near-Distance Sub-Model, a 12-percentage point increase in net-cancellation, and from 7.5 to 5, a 6-percentage point increase. In the other models we see the same effect – more net-cancellation the closer the turbines are to shore. All are statistically significant.

Variable	Coefficient	p-value
Near-Distance (7.5 Miles and First Question Excluded)		
<i>2.5 Miles Offshore</i>	0.121***	0.000
<i>5 Miles Offshore</i>	0.057**	0.023
<i>Second Question with Mid Before</i>	0.099***	0.000
<i>Third Question with Far-Mid Before</i>	0.119***	0.000
<i>Third Question with Mid-Far Before</i>	0.081***	0.001
Far-Distance (20 Miles and First Question Excluded)		
<i>12.5 Miles Offshore</i>	0.073***	0.004

<i>15 Miles Offshore</i>	0.034*	0.059
<i>Second Question with Mid Before</i>	0.002	0.943
<i>Third Question with Near-Mid Before</i>	-0.045**	0.029
<i>Third Question with Mid-Near Before</i>	-0.019	0.438
Mid-Distance (12.5 Miles and First Question Excluded)		
<i>7.5 Miles Offshore</i>	0.077***	0.000
<i>10 Miles Offshore</i>	0.058***	0.004
<i>Second Question with Far Before</i>	0.035**	0.044
<i>Second Question with Near Before</i>	-0.017	0.558
<i>(Real-Life View: 0 Days Excluded)</i>		
<i>Real-Life View: 1 - 10 Days</i>	0.008	0.417
<i>Real-Life View: 10 - 25 Days</i>	0.013	0.502
<i>Real-Life View: More Than 25 Days</i>	0.026	0.154
<i>Number of Respondents</i>		1,691
<i>Adjusted R²</i>		0.168

Table 2: Coefficient Estimates for Net-Cancel Model (OLS)

Notes: The Near-Distance Model includes all response data for the near-distance cancellation questions – respondents may see turbines at 2.5, 5.0, 7.5 miles offshore. The Far-Distance Model includes all response data for the far-distance questions – respondents may see turbines at 12.5, 15, 20 miles offshore. The Mid-Distance Model includes all response data for mid-distance questions – respondents may see turbines at 7.5, 10, 12.5 miles offshore. The real-life views variables are constrained to be constant across the models. Significance at 90, 95, and 99% are denoted with *, **, and ***.

Let's turn to the anchoring results. If there is no anchoring, the question-order variables would have coefficient estimates near zero. As shown in Table 2, this is not the case. Indeed, the Near-Distance Sub-Model shows evidence of far-to-near anchoring, like we see in the non-parametric results. All of the question-order variables are significant and positive (First Question is the excluded variable). The sign on the coefficients suggest that having previously viewed turbines at a far-distance, respondents are *more* inclined to find near-distance turbines intrusive and to cancel or not seek a trip. The anchoring effect pushes net-cancellation up 8 to 12 percentage points, depending on question order. The largest effect is realized in the case where respondents see far-distance turbines first. The coefficient is on *Third Question with Far-Mid Before* is .12 and on *Second Question with Mid-Before* and *Third Question with Mid-Far Before* are .10 and .08. This suggests something like a “first-encounter” or “starting-point” effect (Boyle et al. 1985, Herriges & Shogren 1996, and Ladenburg & Olsen 2008). But, in all cases anchoring is present.

The Far-Distance Sub-Model is shown in the second group of coefficients in Table 2. Here we see a near-to-far anchoring but it is significantly weaker than that far-to-near anchor. Two of the three question-order variables are insignificant and small. Only the *Third Question with Near-Mid Before* is significant with a coefficient of -.05. The negative sign indicates a lower likelihood of cancelling and higher likelihood of seeking. The distance view looks relative good in contrast to *high-intrusive* nearshore wind power projects. But again, the effect is only seen when near view is first in order (so there appears to be a “first encounter effect” here too) and is not present if mid-distance views come first or are the only previous view.

Finally, the Mid-Distance Sub-Model shares traits of the Near- and Far-Distance Sub-Models and confirms the anchoring we find in these models. By construction, mid-distance is only observed first or second in order, never third. When it is in the second position, it is preceded by either a near- or far-view – a clean comparison with no intermediate views. A single coefficient in each case provides the test: *Second Question with Far-Before* and *Second Question with Near-Before*. Like in the other sub-models we see strong far-to-near anchoring and weak (and insignificant) near-to-far anchoring, which is good validation. The far-to-near anchoring effect increases net-cancelling by 3.5% with significance. The near-to-far anchor decreases net-cancelling by 1.7% without significance. So, the Mid-Distance Sub-Model gives us the same one-sided anchoring seen in the other sub-models and in the non-parametric results.

The Real-Life variables *Real-Life: 10-25 days* and *Real-Life: More than 25 days* are positive but insignificant in each case. This is weak evidence that people who have viewed turbines in the past are more likely to report that the offshore wind power projects make their experience worse and cause them to cancel to a trip. This may be anchoring or simply that people with real life views have a clearer reference for translating the true effect of the simulations and a hence a different reaction. Ladenburg (2015), Knapp and Ladenburg (2015), and Ladenburg et al. (2020) study the effects of past encounters on attitudes toward new projects and willingness to pay for new projects. Their results show that past encounters can work in either direction – making people either more or less accepting of a new project – suggesting the effect is context dependent. Again, our results are without statistical significance.

Finally, it is interesting to note that in our survey we included a view simulation of offshore wind turbines as the survey begins as a test to see if they could view it. People were randomly shown either 7.5 or 12 miles offshore. There was no context for the visual other than testing – so it was not tied to a recreation trip. When we tested for anchoring with this view, we see no effect. It was shown early (so probably received a lot of attention) but again was not shown in the context of our choice question. This result along with the weak *Real-Life* results suggests that the saliency of the anchor (and proximity in time) to the decision may be important.

6. Robustness Checks

Using the in-person data described in section 4.3, we split the sample into two groups based on their viewing order: near-to-far or far-to-near. The cancel rate at each distance for the two groups is shown at Figure 5. In this case, we show cancel only since the in-person survey did not include seeking. At 2.5, 5, 7.5 and 10 miles offshore, we have a higher cancellation rate for those who see far-distance turbines first. At 12.5, 15, and 20 miles offshore, the view order does not matter – the lines converge. So again, for trip cancellation, we observe far-to-near anchoring effects, but seemingly no near-to-far anchoring effects. Like the internet data, the in-person data has advance notice, and making this point even stronger, respondents are free to look through the images in their booklet to make comparisons. Still, the order in which the visuals are presented matters. It is also interesting to note that the in-person data, in general, produced higher cancellation rates at each distance than the internet-based data. The lightly shaded grey line shows the internet-based response data for first-view cancel only for comparison.

As a second robustness check, we re-estimated Net-Cancellation Models dropping observations using 7.5 and 12.5 miles offshore. These are the two groups where some overlap (across but within observations) is possible. The sample size drops to 712 and the Mid-Distance group now includes only 10 miles offshore. The results change modestly, but probably due mostly to sample size. No coefficient changes sign and most are close in magnitude. The variable that changed the most was the *Second Question with Far Before* is lost in the Mid-Distance Cancellation Model -- it drops from .035 to .012 and loses

significance. We also looked at mean differences between cancellation at 7.5 when it appears first in the survey as a member of the near-group and first in the survey but as a member of the mid-group. Then we did the same for 12.5 – first as a member of the far and then first as a member of mid. There is no difference in either case.

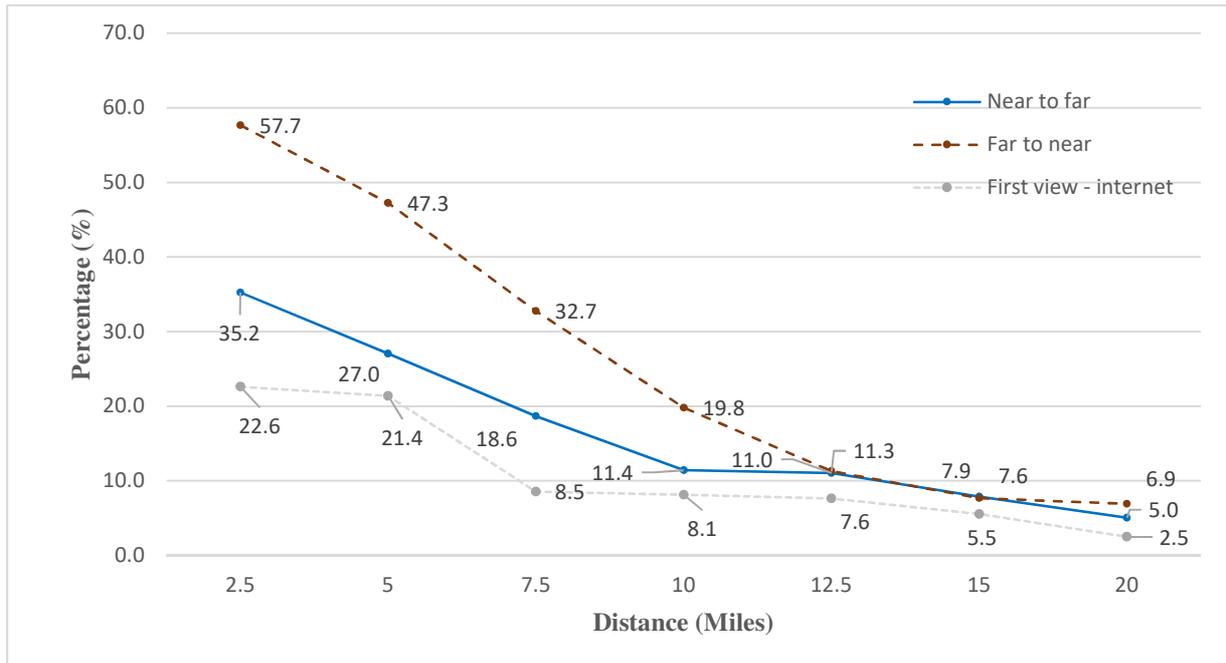


Figure 5: Proportion of the In-Person Sample Cancelling a Trip by Distance for Near-to-Far and Far-to-Near View Order

Note: This figure corresponds to (is a validity check for) Figure 4 above.

7. Conclusion

Visual representations of consumer choices are common in stated preference studies to clarify, simplify, and make the survey experience more pleasing. For some respondents, these visuals (film, pictures, graphs, etc.) may be the main way in which they process information. In this paper, we present an example where visual simulations are used and indeed are the centerpiece of the choice problem being studied and show that respondents have a tendency to anchor on the visuals using them as cues. That is,

visuals shown first in the choice experiment influence choices later in the experiment. Since the visuals are introduced, presumably, to clarify and improve the accuracy of responses, this is of concern.

More specifically in our context, respondents who view offshore wind power projects at near distances are more likely to cancel a trip due their presence if they had previously viewed a project at a far distance. We call this a far-to-near anchor. Similarly, respondents who view projects at far distances are less likely to cancel at trip if they had previously viewed a project at a near distance, but the effect in this direction is significantly smaller (and in some cases vanishes). We call this a near-to-far anchor.

We argue that this result is consistent with a contrast hypothesis of anchoring wherein respondents compare their current visual to their previous visual and, in effect, ask “am I better or worse off”. If worse, there is a tendency to find the current view worse than otherwise since it looks bad in contrast, and if better to find the current view better than otherwise since it looks good in contrast. The competing hypothesis of anchoring is the assimilative theory wherein respondents initial view sets a tone, so to speak, and respondents react by carrying that feeling forward onto future responses. Seeing a good view in the beginning makes bad views seem better in later views and vis-a-versa. Respondents assimilate their earlier experience into their later choices. This is a psychometric effect, which we do not observe in our data.

There is an asymmetry in our results. The far-to-near anchor is stronger than the near-to-far anchor. The former produces a larger increase in cancellation than the latter does an decrease in cancellation. We argue that this is loss-aversion, since the directional change in the far-to-near anchor is a loss and for the near-to-far anchor is a gain.

Our results include seeking behavior. That is, where respondents seek out a beach because a wind project is located there. There are green seekers and views seeks. The former seek a beach for the positive feeling they get on a beach where they perceive something good is being done for the environment. For view seekers, the seascape is improved by the turbines. We incorporate seeking in the analysis by treating it as a negative cancel. This gives rise to a measure we use called net-cancel. Seekers make up less than 3% of the sample and have very little effect on the final analysis.

Other findings include a larger effect from first-shown versus second-shown visuals. So, the first visual appears to serve as a stronger anchor, which perhaps detracts somewhat from a pure contrast hypothesis and lends some weight within our broader findings to a psychometric effect. Also, having seen a wind turbine in real life leads to a slight, but statistically insignificant, increase in the chance that a respondent will have a negative view toward turbines in their beach experience and be more inclined to cancel.

Finally, the impact of anchoring on trip cancellation has policy implications. At 2.5 miles offshore, the net-cancellation rate is 20% if it is viewed first and 35% if last. The effect is not as large for projects 5 and 7.5 miles offshore, but the effects are still large and statistically significant. At far distances this is also an understatement of cancelling in the anchored results but not as large. Since many beaches on the East Coast have millions of visitors per year, some over 10 million, the anchoring effects can be large and possibly sway analyses (benefit-cost or locational analyses) one way or the other.

Our purpose is not to dissuade the use of visuals, they are no doubt useful tools, but rather to alert researchers to a possible effect they may have not been considering. Meyerhoff and Glenk (2015) have similar findings and we expect the result will hold in further experimentation. As far as advice, in our judgment first-view is a better measure of effect. It is free of anchoring effects, does not invite strategic behavior (respondents possibly gaming their choice over distances to get a preferred policy outcome), and is consistent with one-shot (single binary question) recommendations in the valuation literature (Johnston et al. 2017). Of course, the obvious tradeoff with more response data must be weighed against this advice.

8. Reference List

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¹ Ladenberg and Olsen (2008) also find anchoring on instructional choice sets but without visuals.

² GfK maintains a probabilistic sample of household in the United States and provides weights to mimic draws based on the properties of their initial sampling procedure. GfK (2017) provides a good discussion of their approach.

³ Here is the active survey: https://delaware.ca1.qualtrics.com/SE/?SID=SV_3TKJE5B2QKR6B1z.

⁴ The simulations were created by [Macroworks Inc](#). Here a link to see the simulations we use [enviroviz.ie/offshore-survey-1](#). When viewing the simulations from this site use your forward and backward browser buttons to navigate and not the embedded navigation tool labeled “Retrun to Survey”. The visuals were imbedded individually in the survey as needed.

⁵ A beach was designated in each state for assignment of the alternate location. If that location happened to be the chosen beach, each state had a backup beach.

⁶ It is possible for a respondent to report turbines make their experience worse at once distance and better at another, but not worse and better at the same distance.