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The Value of Beach Conditions Information

Daniel R. Petrolia (corresponding author)
Mississippi State University
d.petrolia@msstate.edu

Jerrod Penn
Louisiana State University AgCenter
jpenn@agcenter.lsu.edu

Ruth Quainoo
East Carolina University
quainoor18@students.ecu.edu

Rex H. Caffey
Louisiana State University AgCenter
rcaffey@agcenter lsu.edu

J. Matthew Fannin
Louisiana State University AgCenter
mfannin@agcenter lsu.edu

Department of Agricultural Economics
Mississippi State University
Box 5187 Mississippi State, MS 39762
Phone: (662) 325-2049
Fax: (662) 325-8777
www.agecon.msstate.edu

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Daniel R. Petrolia (corresponding author)
Professor
Department of Agricultural Economics
Mississippi State University
Box 5187
Mississippi State, MS 39762
d.petrolia@msstate.edu / 662.325.2888

Jerrod Penn
Assistant Professor
Dept. of Ag. Economics and Agribusiness
Louisiana State University AgCenter
101 Martin D. Woodin Hall
Baton Rouge, LA 70803
jpenn@agcenter.lsu.edu

Ruth Quainoo
Research Assistant
Coastal Resources Management Program
East Carolina University
379 Flanagan
Greenville, NC 27858
quainoor18@students.ecu.edu

Rex H. Caffey
Donald E. Welge Endowed Professor
Dept. of Ag. Economics and Agribusiness
Louisiana State University AgCenter
101 Martin D. Woodin Hall
Baton Rouge, LA 70803
rcaffey@agcenter lsu.edu

J. Matthew Fannin
William H. Alexander & J. Nelson Fairbanks Endowed Professor
Dept. of Ag. Economics and Agribusiness
Louisiana State University AgCenter
101 Martin D. Woodin Hall
Baton Rouge, LA 70803
mfannin@agcenter lsu.edu

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The Value of Beach Conditions Information

Abstract

We estimate the value of beach conditions information in the hands of the public prior to taking beach trips. We designed and administered a contingent-valuation survey to the beach-going population of the five U.S. Gulf Coast states that features a region-wide beach conditions monitoring system currently proposed by the Gulf of Mexico Coastal Ocean Observing System (GCOOS). We also test two hypothetical-bias mitigation strategies: a "budget and substitutes Q&A" treatment, and a "cheap talk Q&A" treatment. To preview our results, we find that although respondents perceive that such a service would be beneficial, many perceive that the information provided is already available elsewhere, and so the proportion of respondents willing to pay for access to the service is quite low. Nevertheless, we estimate that the aggregate value of the benefits associated with the service would still exceed the estimated cost of provision.

Keywords: budget and substitutes reminder, cheap talk, contingent valuation, GfK, hypothetical bias, KnowledgePanel, ocean observing information

JEL Codes: C83, D83, L86, Q51

The Value of Beach Conditions Information

Introduction

It is well-documented that the value of a recreational beach visit depends upon a variety of factors. These include the weather; crowds; surf conditions; water quality; beach debris; parking; the view; services provided; beach length and width, sand quality, and renourishment; and red tide events.[1] However, given that these factors affect the value of a beach visit, what is the value of knowing their status prior to visiting the beach? If one was aware of adverse conditions, one could reschedule or visit a different beach, resulting in a higher-quality visit relative to not having the information. Positive economic value for real-time or web-enabled information services have been demonstrated in areas such as transportation (Molin and Timmermans 2006) and agriculture (Kenkel and Norris 1995), and the literature provides some

[1] See: weather (Sabir, van Ommeren, and Rietveld 2013); crowds (McConnell 1977; Penn et al. 2015; Tratalos et al. 2013); surf conditions (Kaminski et al. 2017); water quality (Awondo, Egan, and Dwyer 2011; Beharry-Borg and Scarpa 2010; Hynes, Tinch, and Hanley 2013; Peng and Oleson 2017; Penn et al. 2014); beach debris (Smith, Zhang, and Palmquist 1997; Loomis and Santiago 2013; Leggett et al. 2013); parking (Braun and Soskin 2002; Whitehead et al. 2008); the view (Fooks et al. 2017; Ladenburg 2010); services provided (Lew and Larson 2005, 2008; Garcia-Morales et al. 2018); beach length and width, sand quality, and renourishment (Parsons et al. 2013; Gopalakrishnan et al. 2011; Parsons, Massey, and Tomasi 1999; Pendleton et al. 2012; Shivlani, Letson, and Theis 2003; Silberman and Klock 1988); and red tide events (Larkin and Adams 2007; Parsons et al. 2009; Morgan, Larkin, and Adams 2010).

evidence that this may be the case for beach visits (Kaminski et al. 2017; Murray, Sohngen, and Pendleton 2001; Pendleton, Martin, and Webster 2001; and Penn et al. 2014).

Current efforts to provide beach conditions information to the public are a mixed bag. One issue is that individual information items are scattered across sources. Take, for example, Siesta Beach, a popular and award-winning beach in Sarasota, Florida: fecal counts and advisories are reported by the Florida Department of Health's Healthy Beaches Program; rip current alerts, by the National Weather Service; flag status, by the United States Lifesaving Association; and red tide information, by NOAA's National Ocean Service and the Florida Fish and Wildlife Conservation Commission. In other locations, although there are sites reporting real-time beach information, most are very limited in scope, usually reporting only legislatively-mandated water-quality information, such as Texas Beach Watch, The Beach Report Card in Southern California, and The Beach & Bay Water Quality program in San Diego. On the other hand, there are examples of similar services that are no longer available, such as myBeachCast for the Great Lakes and How's the Beach for South Carolina.

Some entities have begun to consider these diverse elements more holistically in the form of integrated ocean observing systems and relaying it to the public in a more convenient and timelier manner (Kirkpatrick et al., 2008). And although not specific to beach conditions information, the private sector offers a number of closely-related examples. These include free sites such as Weather Underground, Carrot Weather, and Ventusky that repackage publically-available data for the general public, and for-pay sites and services for specific users, such as Surfline for surfers, and Buoyweather for boaters.

Our objective was to estimate the value of beach conditions information in the hands of the public prior to taking beach trips. We designed and administered a contingent-valuation

(CV) survey to the beach-going population of the five U.S. Gulf Coast states that features a region-wide beach conditions monitoring system as currently proposed by the Gulf of Mexico Coastal Ocean Observing System (GCOOS-RA 2014). Our estimates should serve as a gauge of the value of nascent information-aggregation efforts by both the public and private sector, and the extent to which additional investment in this direction is warranted, especially in the context of a beach-specific tool. Additionally, our work contributes to the limited literature aimed at understanding the benefits of ocean observing systems (Plummer 2017; Dumas and Whitehead 2008; Kite-Powell, Colgan, and Weiher 2008; Pendleton 2008; Richert, Bogden, and Quintrell 2008; Wellman and Hartley 2008; Wieand 2008).

In the context of our survey, we also test two hypothetical-bias mitigation strategies: a "budget and substitutes Q&A" (BSQA) treatment that is more in-depth and engaging than the standard budget reminder used in most CV studies; and a "cheap talk Q&A" (CTQA) treatment that features a much shorter script than is used in most CV studies, but that also includes a required response to a question. To preview our results, we find that although respondents perceive that such a service would be beneficial, many perceive that the information provided is already available elsewhere, and so the proportion of respondents willing to pay for access to the service is quite low. Nevertheless, we estimate that the aggregate value of the benefits associated with the service would still exceed the estimated cost of provision. Also, we find only very limited effects of our hypothetical-bias mitigation treatments, and no effects when combined with *ex post* certainty adjustments.

Conceptual Framework

We model the probability of an agent being willing to pay for access to beach conditions information using random-utility theory. Assume that a utility-maximizing agent j will purchase access to beach conditions information only if the utility associated with improved beach trips, and incurring cost t_j for information access, exceeds status-quo utility. The utility-difference expression is $U_j^1 - U_j^0 = U_j^1\left(Y_j - t_j, \pi_j, \mathbf{Z}_j, \varepsilon_j^1\right) - U_j^0\left(Y_j, \mathbf{Z}_j, \varepsilon_j^0\right)$, where U_j^1 represents utility associated with the state of nature where the agent has access to beach conditions information and U_j^0 is status-quo utility. Y_j is income of agent *j*. We model explicitly the agent's perceived usefulness of the information, represented by π_j. $\mathbf{Z}_j$ is a vector of observable individual-specific characteristics, including both visit-specific indicators, such as which beaches are visited, days spent, and reasons for visiting; and demographic indicators,. ε_j^i represents unobservable factors affecting utility.

Assuming a linear utility function, the utility-difference expression can be written as: $U_j^1 - U_j^0 = \left(\beta_Y^1 - \beta_Y^0\right)Y_j - \beta_Y^1 t_j + \beta_\pi \pi_j + \left(\boldsymbol{\beta}_Z^1 - \boldsymbol{\beta}_Z^0\right)'\mathbf{Z_j} + \left(\varepsilon_j^1 - \varepsilon_j^0\right)$. Given the low cost of the information relative to income, we assume constant marginal utility of income across states of nature, which results in the term associated with income to drop out. We then define $\beta_t \equiv -\beta_Y^1$. Also, given that the $\boldsymbol{\beta}_j^i$ and ε_j^i cannot be individually identified, the expression simplifies to $U_j^1 - U_j^0 = \beta_t t_j + \beta_\pi \pi_j + \boldsymbol{\beta}_Z{}'\mathbf{Z_j} + \varepsilon_j$.

Experimental Design

The CV survey consisted of a maximum of 28 questions, with most respondents seeing substantially fewer based on treatments, responses, and skip logic. The survey was divided into three sections: 1) collection of basic beach visit information and introduction to beach conditions information; 2) hypothetical bias mitigation treatments; and 3) the contingent scenario, referendum question, and follow-ups. The Appendix contains the full survey instrument.

Collection of basic beach visit information and introduction to beach conditions information

The questionnaire began with a screening question to identify those who had visited a Gulf Coast beach during the last 12 months. Those who qualified were then asked about which Gulf Coast beaches they had visited, total days spent, whether they took day-trips or overnight trips, and beach activities engaged in. The survey then introduced the issue of beach conditions and its provision. Respondents were asked about their awareness and use of an existing website for some Florida beaches, and shown a screen-shot of the beach conditions information currently reported on it. They were then asked whether they thought they could obtain the same or similar information elsewhere, and asked to indicate the specific conditions that they would be most interested in knowing when planning a beach visit.

This line of questioning led naturally into the elicitation of a measure of perceived usefulness of the beach conditions information. We elicited an expected increase in the number of good days at the beach associated with knowing beach conditions. We first established a baseline using the following verbiage:

"Some days at the beach we might call "good": the weather is good, it is not too crowded, the water is clear, the waves are not too rough, and so on. But other days, for one reason or another, we might call "bad".

Out of 10 days at the beaches that you usually visit, how many would you expect to be "good"? (0-10)

When answering, consider only conditions at the beach that would make it good or bad. Ignore things like bad traffic on the drive to the beach, or someone getting sick on the way, and so on.

The proposed beach conditions service was then described, and thereafter we elicited a measure of the expected increase in good beach days as a result of access to the beach conditions information using the following verbiage:

"Do you think using the beach monitoring website and app would increase your chances for a "good" day at the beach? (Yes/No/Not Sure)

Respondents who selected 'No' or 'Not Sure' were assigned $\pi_j = 0$. Those that selected 'Yes' were then asked:

"Earlier, you said you expect [X] out of 10 days at the beach to be "good". How many days at the beach would you expect to be "good" if you had access to the beach monitoring website and app? (0-10)

For these respondents, π_j was set as the difference between the above response and the baseline response.

Hypothetical bias mitigation treatments

Two hypothetical bias mitigation treatments were tested in this study, and were included in one-third of all surveys, respectively, with one-third serving as the control group. The first was a budget and substitutes Q&A (BSQA) treatment. There are only a few studies that have tested the effect of budget and substitutes reminders explicitly, and results have been mixed. Loomis, Gonzalez-Caba, and Gregory (1994) and Kotchen and Reiling (1999) tested budget and substitutes reminders, but found no significant effect. Whitehead and Blomquist (1991, 1995) tested a substitutes reminder, and Loomis et al. (1996) tested a budget reminder, and found significant effects. Whitehead and Cherry (2007) tested a combined income and substitutes reminder with a "short" cheap talk script, and found an effect, although significance depended upon how Don't Know responses were modeled, and whether certainty of response was accounted for. Our treatment departs from all of these in that we attempt to engage responses more thoroughly by requiring them to answer questions regarding their own budget situation and their own perception of available substitutes. All respondents received a standard budget and substitutes reminder:

> *We would like to know if you would be willing to pay for access to this website and app if the subscription fee were $[X] per month. But before you answer, think about your budget, whether you could afford it, and about the other things you could spend this money on instead. Also think about other ways you might access the same or similar information without having to pay for it.*

In addition to the above, those assigned to the BSQA treatment were presented with the following three questions:

1) So thinking about your budget, is $[X] per month really affordable for you? (Yes/No/Not Sure);

2) Are there other things that you are more likely to spend your money on first? (Yes/No/Not Sure); and

3) Do you think you could access the same or similar information just as easily without having to pay for it? (Yes/No/Not Sure)

The second treatment was a cheap talk Q&A (CTQA) treatment. The use of cheap talk, introduced by Cummings and Taylor (1999) is ubiquitous, and Penn and Hu (2019a) provide a thorough inventory of papers and meta-analysis of the method. One design issue with cheap talk is the length of the script. The original script of Cummings and Taylor exceeded 950 words, read aloud in a lab setting. Lusk's (2003) script was 577 words in a mail survey. Later researchers tested shorter scripts, including Aadland and Caplan (2003) and Whitehead and Cherry (2007). We chose the route of a shorter script, but our treatment departs from previous uses of cheap talk in that we attempted to better engage respondents by requiring them to answer a question regarding the script. In this way, our cheap talk script is a kind of hybrid between typical cheap talk scripts and the oath treatment used by Jacquemet et al. (2013) and Carlsson et al. (2013), which requires respondents to confirm explicitly that they will answer honestly. Those assigned to the CTQA treatment were presented the following verbiage:

When answering survey questions like this, some people say Yes even though they are not very sure whether they would actually pay for something. We would like you to answer as if you were deciding about a real purchase. Can you answer as if you were deciding about a real purchase? (Yes, I can answer as if I were deciding about a real purchase. /

No, I don't think I can answer as if I were deciding about a real purchase. / I'm not sure if I can answer as if I were deciding about a real purchase.)

Contingent scenario, referendum question, and follow-ups

The contingent scenario was framed as follows:

> *With the expanded beach conditions monitoring website and app, the conditions at any of the 28 currently monitored beaches in Florida plus the 48 additional beaches in Alabama, Florida, Louisiana, Mississippi, and Texas would be accessible from your smart-phone, laptop, or other device. Beach conditions would be updated daily. There would be a subscription fee to access the website and app. The fee would be paid online, to the provider of the service, just like you would pay for any other subscription to an online service or app. Access would require a log-in name and password, provided to you after payment. The subscription would be month-to-month, so you could subscribe for as few or as many months as you like.*

Respondents were then asked if the details of the proposed website and app were clear to them and if not, were asked to state what was unclear to them. The questionnaire continued:

> *So based on what we've told you about the beach conditions monitoring website and app, would you be willing to pay $[X] per month for access? (Remember that the subscription would be month-to-month. So you could subscribe to as few or as many months as you like.)*
>
> > *Yes, I would pay $[X] per month to use it.*
> >
> > *No, I would not pay $[X] per month to use it.*

Selected bids for our survey were $1, $5, and $10 per-month. Although many weather sites and mobile apps are free, these bids were based on the prices of current rates for similar services and mobile apps that provide targeted information. For example, Buoyweather's premium rate is $14.99 per month, and Surfline's is $9.99 per month.[2] The convenience sample on which we tested a draft version of the survey (see Quainoo 2018), indicated that only 10% of respondents would pay $10 per month, so we did not add any higher bids. Those responding "Yes" were then presented a certainty follow-up: *"On a scale from 1 to 10, how sure are you about being willing to pay $[X] per month?"*, as well as a question asking which specific months out of the year they were most likely to subscribe. The final two questions asked about smartphone usage and elicited a measure of perceived consequentiality[3]:

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[2] Schick (2014), summarizing the findings of a 2014 marketing survey conducted by Branchfire, reports that 48% of those sampled would pay less than $25 per month for "an app they love", and 31% would pay less than $10. The mobile-marketing firm Liftoff (2017) reports three categories of typical app monthly subscription rates: low ($6.99 or less), medium ($7-$20), and high ($20-$50).

[3] Consequentiality is an important trait of any CV survey (Carson and Groves 2007, 2011; Johnston et al. 2017). It refers to the degree to which a respondent believes that his responses to the survey have a positive probability of affecting a real-world outcome he cares about. Generally, the literature indicates that consequentiality can affect WTP estimates (Herriges at al. 2010; Interis and Petrolia 2014; Vossler, Doyon, and Rondeau 2012). To maximize the likelihood of our questionnaire being perceived as consequential, we designed and fielded it in a

How confident are you that this survey will influence whether this app is made available? (Not at all confident (1) … Very confident (10)).

A draft survey instrument was adapted from earlier work of Plummer (2017), who applied similar methods to estimating the value of coastal-marine information for boaters. The draft instrument was tested in March and April 2018 using a convenience sample composed of 2,471 individuals deemed likely to be or have access to members of our population of interest, and requested that they complete and/or share the questionnaire link with others.[4] Further details on this version and econometric analysis can be found in Quainoo (2018). The survey instrument was then revised based on responses, comments, and other feedback of this initial fielding. The final version was then turned over to The GfK Group for fielding.

Sampling

The population of interest was adults (18 years and over) that visit U.S. Gulf Coast (Alabama, Florida, Louisiana, Mississippi, and Texas) beaches. The GfK Group administered the survey instrument online to a sample of households participating in their KnowledgePanel. This panel,

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way that mitigates against the four *in*consequentiality principles posited by Carson and Groves (2007).

[4] Organizations that aided our testing efforts included: City of Biloxi, Gulf of Mexico Coastal Ocean Observing System (GCOOS), Gulf Shores and Orange Beach Tourism Bureau, Louisiana State University, Mississippi-Alabama Sea Grant Consortium, Mississippi State University, Mobile Bay National Estuary Program, Texas A&M University-Galveston, University of Florida, and University of Texas-Rio Grande Valley.

which GfK began in 1999, is representative of the entire U.S. population. Panel members are randomly recruited through probability-based sampling, and households are provided with access to the internet and hardware if needed. GfK recruits panel members by using address-based sampling methods. A penultimate version of the survey instrument was pretested on 25 panelists May 10-18, 2018, and the final version administered May 16-23, 2018. A total of 4,396 panelists were sampled from GfK's Knowledge Panel, and of these, 2,477 agreed to be interviewed. A total of 1,151 responded affirmatively to the screening question, for a 46% incidence rate (i.e., the rate of those that have visited a Gulf Coast beach in the past 12 months), and continued to complete the main survey. The median duration was 6 minutes.

Table 1 reports a comparison of sample demographic indicators to the population, with and without sampling weights. Sampling weights, constructed using the population benchmarks reported in the table, were provided by GfK as part of the data collection agreement. The sampling weights generally improve representativeness; of the 28 measures reported in the table, the sampling weights result in an improvement in nineteen of them. Improvements generally occur in the tails of the distributions, especially for the age-gender categories and education categories. Improvements are observed across all race categories and three of the five state-residency categories. Improvements in income categories are more mixed, with three intermediate categories seeing improvements, but the second-lowest and highest categories actually being better-represented in the unweighted sample. There are a few other categories across the other measures that are slightly better in the unweighted sample as well. The analyses discussed in the next sections were conducted with and without sampling weights.

Results

Summary of Responses

Table 2 reports definitions for all variables and Table 3 reports the associated summary statistics. Focusing on the unweighted data, the mean number of beach days per year per respondent is 8.42, and about one-third of respondents indicated that they take overnight trips to the beach, rather than day-trips or a mix of both. Forty-eight percent of respondents are Florida residents, 34% live in Texas, and 13% live in Alabama. Less than 10% live in Louisiana or Mississippi. Corresponding to those shares, 60% of respondents visit Florida beaches, 30% visit Texas beaches, and 13% visit Alabama beaches. Less than 10% visit either Louisiana or Mississippi beaches. Between 54% and 57% of all respondents indicated that they go to the beach to exercise, swim, and/or sunbathe, whereas 20% go to fish, and 17% go for other reasons, such as camping. Note that “other reasons” also includes write-in responses not necessarily associated with actually stepping foot on the beach, such as dining and “driving by”. Regarding beach conditions information, 15% of respondents indicated that they were aware of the existing beach conditions website in Florida, though only 7% indicated that they used it before. Fourteen percent indicated that they thought they could already access the information provided by the proposed app elsewhere. The mean reported increase in good beach days due to information access was 1.1, and the mean level of confidence that the survey would influence availability of the app was 5.9 (out of 10).

The mean number of information types of interest to respondents was 4.3 (out of 9 listed, plus write-ins). Preliminary models indicated that responses were not significantly affected by which specific types of beach conditions information respondents were interested in, but rather by the total number of conditions in which they were interested. This result is intuitive, given that the proposed app does not necessarily provide unique information, but rather provides a convenient means for accessing a variety of information types in one place. However, to provide readers with some understanding of the types of information proposed and the relative interest of respondents to each type, Figure 1 reports a summary of the responses to the question *"Which beach conditions would you be MOST interested in knowing before going to the beach? (check all that apply)"* . The leading category was weather information, being chosen by 76% of respondents, followed by swim hazards (62%). Interest in red drift / red tide information was tied for third along with water-quality information (54% each). The remaining categories of crowd information, beach debris, flag color, surf information, and live video feed were chosen by less than 50% of respondents.

Table 4 reports the WTP responses in more detail, including distribution of responses by bid, both unadjusted and adjusted for certainty of WTP response. As expected, the proportion of affirmative WTP responses declines as bid increases, from 34% at the $1 bid to 10% at the $10 bid for the unadjusted data, and from 20% to 3% for the certainty-adjusted data.

Hypothetical Bias Treatments

Budget and substitutes Q&A (BSQA) treatment

Table 5 reports a summary of the hypothetical bias treatments, including verbiage, distribution of responses to treatment questions, and distribution of WTP responses by treatment, with and without certainty adjustment. Each treatment received about one-third of respondents. We use a certainty cutoff of 8 (on a scale of 1-10), so that an affirmative WTP response with a certainty response of 7 or lower is re-coded as a negative WTP response. This cutoff is based on the findings of Penn and Hu's (2019b) meta-analysis of studies using certainty adjustment. Champ and Bishop (2001) found that this same cutoff resulted in responses closer to real-payment responses, although others have found that this cutoff did not result in a significant difference (Loomis and Ekstrand 1998; Whitehead and Cherry 2007), and resorted to a lower cutoff of 7. This was not the case for us, as certainty adjustment using the cutoff of 8 resulted in the conversion of 49% of initial affirmative responses.

The BSQA treatment included three questions. The first focused on affordability, with 40% indicating the good was affordable, 45% said it was not, and 16% were not sure. As expected, only 4% of those who indicated the good was not affordable voted in favor of purchasing it, and when adjusted for certainty of WTP response, it fell to 1%. Of those who were unsure, 19% voted in favor, although that number fell to just 2% when certainty-adjusted.

The second question dealt with spending money on other goods rather than the one offered. Seventy-eight percent of treatment respondents indicated that they were more likely to spend money on other things first. Of these, 13% actually voted in favor of purchase, and only 4% when certainty-adjusted. Slightly more than half of those who indicated they were not sure were WTP, although that number fell to 13% when certainty-adjusted.

The third question dealt with accessing the same or similar information elsewhere without having to pay for it. Just over half indicated that they thought they could, and 41% indicated they were not sure. Of those that thought they could, 13% were WTP (3% when certainty-adjusted). Of those not sure, 32% were WTP (13% when certainty-adjusted).

Overall, responses to BSQA treatment questions were consistent with voting behavior: those who thought the good unaffordable generally were not WTP, those more likely to spend their money on other things first were generally not WTP, and those who thought they could access the same information elsewhere for free were generally not willing to pay for it. Further, these relationships held very strongly when certainty of WTP responses was accounted for. Nevertheless, the proportion of affirmative WTP responses was higher overall for the BSQA treatment relative to the control (22% versus 16%). A reasonable conjecture is that it is possible that for those for which the good *was* affordable, for those who were *not* more likely to spend money on other things first, and/or for those where did *not* think they could access the information elsewhere for free, the treatment actually nudged them further in the affirmative direction. The treatment may have had a similar positive effect on those responding “not sure” to the questions as well. However, it also appears that the effect resulted in low-certainty affirmative responses, because when certainty of WTP responses is accounted for, the overall share of affirmative WTP responses is lower among the BSQA treatment relative to the control. Further, there appears to have been even greater WTP uncertainty associated with those responding “not sure” to the treatment questions, because the drop in the share of affirmative WTP responses is even greater when certainty-adjusted for these respondents. In short, our best explanation is that the treatment may have worked as intended for those for whom affordability, other spending priorities, and easily-available substitutes were an issue. But for others for which these were not issues, as well as for those unsure about these issues, the treatment may have nudged respondents to cast weak, but affirmative, WTP responses. Once certainty of WTP responses was accounted for however, the positive effect is eliminated.

Cheap talk Q&A (CTQA) treatment

The CTQA treatment was designed to impose the “cheap talk” effect using a very short script, as well as to better engage respondents by requiring a response to a question about it. Three-fourths of respondents assigned to this treatment responded that they could answer as if deciding about a real purchase, whereas the remainder were evenly split between responding that they could not or were not sure if they could. Overall, the share of affirmative WTP responses among those assigned to the treatment was higher than that of the control group (19% versus 16%), apparently driven by the large share of respondents who responded “yes” and “not sure” to the treatment question. When certainty-adjusted, however, the effect is mitigated, with the “not sure” respondents having a slightly lower share of affirmative WTP responses. Here, we conjecture that the treatment had the unintended effect of nudging respondents toward weak affirmative WTP responses. This finding is not unique, as Aadland and Caplan (2006) and Blumenschein et al. (2008) also found that their cheap talk script had the unintended effect of increasing WTP. Additionally, we speculate that this question may have been interpreted by respondents differently than intended, and consequently had the opposite effect. The initial wording of the question used during the test fielding was revised for this reason, and it is quite possibly true of the present wording as well. Designing a brief cheap talk script is difficult, and designing a question regarding it more difficult. The econometric analysis presented in the following section takes up the question of whether the apparent treatment effects are significant when modeled alongside all other factors.

Econometric Model

We use a probit model to estimate the effects of covariates on the probability of a respondent being WTP for the proposed beach conditions information app. The dependent variable is a binary indicator = 1 where an affirmative WTP response is observed, and = 0 otherwise. The log-likelihood of the probit model is

$$
\begin{aligned}
LL = & \sum_{WTP=1} w_j \ln\left\{\Phi\left(\beta_t t_j + \beta_\pi \pi_j + \boldsymbol{\beta}_Z{}'\mathbf{Z_j} + \varepsilon_j\right)\right\} \\
& + \sum_{WTP=0} w_j \ln\left\{1-\Phi\left(\beta_t t_j + \beta_\pi \pi_j + \boldsymbol{\beta}_Z{}'\mathbf{Z_j} + \varepsilon_j\right)\right.
\end{aligned}
$$

where w_j are weights and Φ is the cumulative normal.

For those variables for which we have a clear expected directional effect, Table 2 reports the direction in parentheses next to the variable name. We expect the two treatments and bid to have negative effects. We also expect that respondents who failed to report number of days spent, those who visit the beach for other reasons, and those who think they can obtain the offered beach conditions information elsewhere to be less likely to give an affirmative WTP response. We expect the likelihood of an affirmative WTP response to increase with the expected increase in the number of good days due to knowing the beach conditions; with the number of beach conditions information types of interest to the respondent; for those who have used the existing Florida website; with perceived consequentiality; and with income.

Table 6 reports the estimates of four models, which differ according to whether sampling weights are used, and whether WTP responses are certainty-adjusted. The BSQA treatment effect is significant only when WTP responses are not certainty-adjusted, which is consistent with the discussion of treatments in the previous section. The CTQA treatment is significant only when WTP responses are not certainty-adjusted and the model includes sampling weights. Bid is significant and negative, as expected, with similar magnitude across models. Confirming our assumption of constant marginal utility across states of nature, the coefficient on income is not significant.

The significance of only a handful of other covariates was robust across at least three of the four models. Louisiana residents (5% of the sample), and those who fish while at the beach (20% of the sample) were significantly more likely to be WTP for access to the proposed beach conditions information app. The Louisiana resident effect is perhaps because they have longer travel times (higher investments) for beach visits. Seventy-two percent of their trips were reported as out of state. By comparison, Alabama had the next-highest proportion of out-of-state trips, which was only 30%. So the economic consequences of poor or scant information is likely greater. Although the number of days spent at the beach was not significant, the control for respondents who failed to report days spent was significant and negative. Given the negative effect, we speculate that this variable is a proxy for uninterested respondents. Also, respondents visiting the beach for reasons not involving contact with the water and/or less-influenced by weather were less likely to give an affirmative WTP response. The effect of reason for visiting is consistent with the findings of Kaminski et al. (2017), who found that beachgoers who engage in activities that do not involve contact with water tend not to seek out beach conditions information. The likelihood of an affirmative WTP response increases significantly with the number of information types of interest to respondents, the expected number of additional good beach days resulting from access to beach information, and the level of confidence that the survey will influence availability of the app.

Although not consistently significant across models, several variables exhibited the expected directional effect. Those who had used the existing Florida website were more likely to give an affirmative WTP response, as were those with larger households. Those who thought they could access the same information elsewhere, as well as respondents under the age of 40, were less likely to given an affirmative WTP response.

Maximum WTP

We opted for a measure of maximum WTP that is both conservative (i.e., tends toward a lower value) but that also constrains WTP to be non-negative. The Turnbull lower-bound method (Haab and McConnell 2002) satisfies both requirements. Expected lower-bound WTP is defined as $E_{LB}(WTP)=\sum_{b=0}^{B} t_b\left(\frac{N_{b+1}}{T_{b+1}}-\frac{N_b}{T_b}\right)$, where $b=0,\dots,B$ indexes the ranges between offered bids (in our case, the ranges are \$0-\$1, \$1-\$5, \$5-\$10, and \$10+), N is the number of negative WTP responses, and T is the total number of WTP responses. The variance is calculated as

$$V\left(E_{LB}(WTP)\right)=\sum_{b=1}^{B}\left(\frac{N_b}{T_b}\left(1-\frac{N_b}{T_b}\right)/T_b\right)\left(t_b-t_{b-1}\right)^2.$$

The mean lower-bound of WTP based on certainty-adjusted data is estimated to be \$0.64 per month per respondent, with a 95-percent confidence interval of (\$0.50, \$0.78). The unadjusted estimate is \$1.41 (\$1.20, \$1.62).[5] Given the behavior of respondents assigned to the two hypothetical bias mitigation treatments, we argue that the certainty-adjusted estimate, which mitigates the treatment effects, is the better estimate. Using the mean number of months that respondents indicated they would subscribe to the app (4.72-4.90), we arrive at an annual mean WTP of \$3.12 (\$2.44 - \$3.81).

[5] Using an interval-regression model, which easily accommodates a zero lower-bound but underperforms here in terms of estimating individual covariate effects, mean WTP across models ranges between \$2.23 and \$3.39 per month. Estimated mean WTP implied by the probit models reported here range between -\$0.14 and \$0.76 per month, but these are driven by the lack of a zero lower-bound, which does not apply here.

Benefit-Cost Analysis

The population of interest for this service is Gulf Coast beachgoers. We are aware of no well-defined estimates of the beach-going population, although Houston (2018), who states that beaches are the "leading U.S. tourist destination" (p. 5), reports the results of a recent survey that about 46% of Americans had visited a beach is the past 12 months. Coincidentally, this is the exact incidence rate for our GfK sample. If we apply 46% to the number of households in the five Gulf Coast states (21,071,654), which is conservative, given that the population of Gulf Coast beach visitors extends beyond these states, we have an estimated number of Gulf Coast beach-going households of 9,692,961. Using the certainty-adjusted mean WTP of $3.12 per household per year, we have an aggregate WTP of $30.27 million per year. Estimated cost of the beach conditions information service is reported to be as low as $2,500 per beach per year (personal communication with GCOOS Executive Director Barb Kirkpatrick) and as high as $20.8 million in capital costs, with $20.1 million annual costs (GCOOS-RA 2014). Assuming a 15-year project life and 3% rate of discount, these estimates yield a present-value of $372 million in aggregate benefits and a range of present-value costs between $30,740 and $247.8 million. Even the upper range of costs does not exceed the estimated present value of benefits. In fact, annual WTP per household would need to be $2.08 (which is still below the lower-bound of our Turnbull estimate, which is, by definition, a lower bound itself) for aggregate benefits to just equal the upper bound of aggregate costs. So, from a pure BCA efficiency perspective, based on the benefits estimates of this study and the estimated costs provided by the agency considering it, a Gulf-Coast-wide beach conditions monitoring service is a net-efficiency gain.

Discussion

Although over 60% of our respondents had visited one or more Florida beaches in the past year, only 15% were aware of Florida's existing beach conditions monitoring system. At the same time, 7% indicate that they had used it before, and these respondents tended to be more likely to pay for access, implying that roughly 7 out of 10 households that were aware of it benefited from it. Additionally, 50% of respondents believed that access to the proposed beach conditions information system would increase the probability of a good beach trip. In other words, our results provide fairly strong evidence that both the existing and the proposed system are likely to be beneficial to those that use it, but awareness may be a major challenge, given that most Florida beach-goers in our sample were not even aware of the existing system.

Another apparent challenge is demonstrating the unique benefits of the system, which is primarily one of convenience by agglomerating multiple measures, although it could offer information not available from other sources. When the entire sample was asked whether they could access the same or similar information elsewhere, only 14% responded they could, but 62% indicated they were not sure. (Note that those assigned to the BSQA treatment were asked a similar question, only this time about whether they could access it *without having to pay for it*, 54% responded that they could, with 41% not sure.) Although we ultimately dropped a control for unsure respondents to this question due to lack of significance, the BSQA responses indicate that the unsure respondents tended to give weak affirmative WTP responses. In total, this implies that 76% of respondents see its unique benefits as at least questionable.

Regarding WTP, our results can be interpreted in different ways. On the one hand, only 19% of respondents indicated they are willing to pay for access to the information (10% if certainty-adjusted): only 34% were willing to pay $1 per month, the lowest bid offered; 14%

were willing to pay $5 per month; and only 10% were willing to pay $10 per month (with even lower shares if certainty-adjusted). On the other hand, the estimated WTP based on these responses still exceeds the estimated cost of the system. In short, even with a high percentage of respondents not convinced that the service is uniquely useful and a very low percentage of respondents willing to pay for it, the benefits are still estimated to outweigh the relatively low costs of implementation. The remaining challenge then, appears to be marketing, that is, in making the public aware of it, and providing an adequate scope of conditions, so that beachgoers can benefit from it.

Regarding our hypothetical bias mitigation treatments, we found mixed results, and when effects were significant, they were in the direction opposite our expectations. Summarizing the reasons given in an earlier section, it appears that for those already in a position to buy the app, the BSQA treatment seems to have nudged them further in the affirmative direction, albeit with weak affirmative responses that were reversed with certainty adjusting. When certainty of WTP responses was accounted for, the overall share of affirmative WTP responses was in fact lower among the BSQA treatment relative to the control, although the effect was not significant in the regression models. This result corroborates the findings of Whitehead and Cherry (2007) that *ex-ante* treatments may perform better when combined with *ex-post* certainty adjustments. Similarly, the CTQA treatment appears to have had a positive effect, but again the effect was largely eliminated with certainty adjusting. Again, our finding is not unique, as Aadland and Caplan (2006) and Blumenschein et al. (2008) also found that their cheap talk script had the unintended effect of increasing WTP. More general reasons given in the literature include List (2001), who found that cheap talk tends to work better among respondents unfamiliar with the good. By design, everyone in our sample was familiar with the issues discussed in the survey.

Additionally, Murphy, Stevens, and Weatherhead (2005) found that cheap talk tends to work better at high dollar amounts, which is not true of our bids, and Penn and Hu (2019a) found that cheap talk is less effective for private goods, which our good was. Given that we had no real-payment group, there is, of course, no way to confirm whether any hypothetical bias existed in the first place.

Conclusions

Houston (2018) argues that beaches are by far the leading tourist attraction in the U.S., with almost half of all Americans having visited a beach in the past year, with more day visits than are made to all national and state parks and government lands combined, supporting 2.5 million jobs, and generating $45 billion annually in taxes. Furthermore, several papers make the case that the conditions at the beach can have a significant impact on the quality of the visit, and others make the case that providing accessible, timely information on beach conditions can improve beach visits. This paper takes the next step, by presenting the results of what we believe to be the first study quantifying public preferences for providing such information, including welfare estimates. Overall, we find that in spite of a relatively small share of respondents willing to pay for it, the benefits nevertheless are estimated to outweigh the cost of implementing a program to provide the information. We also identify some of the key challenges in providing such information, including making the public aware of the information so that they may utilize and benefit from it.

Based on respondent comments at the end of the survey, there is anecdotal evidence that respondents perceive that apps should always be free, or nearly so. Some studies show that in 2018 the average paid smartphone app was as low as $1 (Singh 2018) or $4 (Statista 2019), so our respondents may have been conditioned to expect a free- or low-priced apps, despite the fact that apps for targeted users, such as Buoyweather and Surfline, have much higher subscription rates. Given that beachgoers are likely a somewhat less-targeted group relative to boaters and surfers, we would peg the price of a beach conditions app somewhere in-between, which is what our results indicate.

Also, although the contingent scenario used here presented a for-pay service, which is a necessary component of the scenario to extract welfare estimates, the service, if actually implemented, would not necessarily need to be a for-pay service. Some respondents commented that local beach communities, hotels, and/or other tourist attractions could fund it. Another indicated that local beach-related businesses could pay for advertising on it. We would not necessarily conclude that these are protest votes, but they could help in explaining the relatively high share of respondents perceiving the service as beneficial combined with the low share of affirmative WTP responses. Our results could be interpreted to suggest that a "freemium" model, where a base level of features is provided at no cost, with additional features available for a premium, may be the way forward. These alternative arrangements are as likely to work as any other arrangement, and so should be considered by the agencies and communities interested in implementing it.

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Table 1. Benchmark population (Source: 2016 American Community Survey) and sample distributions, as proportions. Sampling weights constructed by GfK.

	Population benchmarks (N = 45,291,644)	Sample sampling weights (N = 1,151)	Sample unweighted (N = 1,151)
Age 18-29 Male	0.10	0.10	0.03
Age 18-29 Female	0.10	0.10	0.07
Age 30-44 Male	0.13	0.15	0.09
Age 30-44 Female	0.13	0.16	0.13
Age 45-59 Male	0.12	0.13	0.13
Age 45-59 Female	0.13	0.11	0.12
Age 60+ Male	0.13	0.11	0.20
Age 60+ Female	0.15	0.14	0.22
White, Non-Hispanic	0.54	0.58	0.70
Black, Non-Hispanic	0.16	0.14	0.08
Other, Non-Hispanic	0.04	0.03	0.02
Hispanic	0.25	0.24	0.17
2+ Race, Non-Hispanic	0.01	0.01	0.02
Less than HS	0.15	0.09	0.03
HS	0.28	0.28	0.25
Some college	0.31	0.34	0.32
Bachelor or higher	0.26	0.29	0.40
FL resident	0.35	0.42	0.48
AL resident	0.08	0.10	0.08
MS resident	0.05	0.06	0.04
LA resident	0.08	0.07	0.05
TX resident	0.44	0.35	0.34
Under $25,000	0.17	0.14	0.14
$25,000-$49,999	0.23	0.20	0.21
$50,000-$74,999	0.19	0.19	0.20
$75,000-$99,999	0.13	0.14	0.15
$100,000-$149,999	0.15	0.18	0.19
$150,000 and over	0.12	0.14	0.12

Table 2. Variable names and definitions

Variable Name	Definition
WTP	dependent variable; = 1 if affirmative WTP response, = 0 otherwise
certainty	ordinal scale (1 - 10); used to construct certainty-adjusted WTP response where WTP = 1 if certainty ≥ 8, = 0 otherwise
BSQA (-)	= 1 if assigned to budget Q&A treatment, = 0 otherwise
CTQA (-)	= 1 if assigned to cheap talk Q&A treatment, = 0 otherwise
bid (-)	= $1, $5, or $10; offered bid in contingent scenario
visit AL/LA/MS/TX	= 1 if visited AL/LA/MS/TX beach in past 12 months, resp., = 0 otherwise; visit FL omitted base
trips	= days spent at Gulf Coast beaches in past 12 months
unreported trips (-)	= 1 if days spent not reported, = 0 otherwise
overniter	= 1 if usually takes over night-trips to the beach, = 0 otherwise
boating	= 1 if engaged in boating or fishing at last beach visit, = 0 otherwise
other reason (-)	= 1 if visited beach for reason other than swimming, sunbathing, exercising, or fishing, = 0 otherwise
conditions (+)	= count of beach conditions indicated as being most interested in knowing
used website (+)	= 1 if used existing FL beach conditions website, = 0 otherwise
other sources (-)	= 1 if thinks can get same or similar information from other sources, = 0 otherwise
good days (+)	= number of additional good beach days (out of 10) with beach conditions information
consequentiality (+)	ordinal scale (1 - 10); confidence that survey will affect app availability
resident AL/LA/MS/TX	= 1 if AL/LA/MS/TX resident, resp., = 0 otherwise; resident FL omitted base
income (+)	ordinal income categories (21 categories from "less than $5,000" to "$250,000 or more")
household	= number of individuals living in household
under40	= 1 respondent is less than 40 years old, = 0 otherwise
education	ordinal education categories (from "no formal education" to "professional or doctorate degree")
male	= 1 if respondent is male, = 0 otherwise

Table 3. Summary statistics of variables used in the regression analysis with and without sampling weights. N = 1,106.

	With sampling weights		*Unweighted*			
	Mean	Std. Dev.	Mean	Std. Dev.	Minimum	Maximum
WTP	0.203	0.403	0.189	0.392	0	1
WTP (certainty-adjusted)	0.106	0.308	0.097	0.297	0	1
BSQA	0.326	0.469	0.326	0.469	0	1
CTQA	0.345	0.475	0.329	0.470	0	1
bid	5.551	3.736	5.597	3.724	1	10
visit AL	0.152	0.359	0.130	0.337	0	1
visit LA	0.061	0.240	0.049	0.216	0	1
visit MS	0.110	0.313	0.088	0.283	0	1
visit TX	0.307	0.461	0.299	0.458	0	1
trips	8.673	26.149	8.421	27.403	0	365
unreported trips	0.128	0.334	0.146	0.353	0	1
overniter	0.300	0.459	0.297	0.457	0	1
boating	0.220	0.414	0.196	0.397	0	1
other reason	0.160	0.367	0.169	0.375	0	1
conditions	4.254	2.226	4.271	2.229	0	9
used website	0.070	0.256	0.070	0.255	0	1
other sources	0.167	0.373	0.139	0.346	0	1
good days	1.220	1.535	1.100	1.396	0	8
consequentiality	6.086	2.405	5.868	2.352	1	10
resident AL	0.098	0.297	0.080	0.272	0	1
resident LA	0.069	0.254	0.052	0.221	0	1
resident MS	0.055	0.229	0.042	0.200	0	1
resident TX	0.358	0.479	0.346	0.476	0	1
income	12.733	4.747	12.760	4.459	1	21
household	2.863	1.439	2.557	1.370	1	10
under40	0.400	0.490	0.245	0.430	0	1
education	10.173	2.102	10.738	1.743	1	14
male	0.489	0.500	0.453	0.498	0	1

Table 4. Distribution of WTP responses.

		Yes responses			
		certainty-adjusted		**unadjusted**	
bid	**N**	***n***	***%***	***n***	***%***
$1	353	70	0.20	121	0.34
$5	367	25	0.07	52	0.14
$10	420	14	0.03	42	0.10
Total	*1,140*	*109*	*0.10*	*215*	*0.19*
Turnbull Lower-bound maximum WTP					
mean (per month)		$0.64		$1.41	
(95% conf. int.)		($0.50 - $0.78)		($1.20 - $1.62)	
mean months subscribed		*4.90*		*4.72*	
mean (per year)		$3.12		$6.65	
(95% conf. int.)		($2.44 - $3.81)		($5.67 - $7.64)	

Table 5. Summary of Treatments, treatment Q&A, and distribution of responses.

		% response to questions	Yes WTP response unadjusted	Yes WTP response certainty-adjusted
Control (N = 395)			*0.16*	*0.10*
Budget and substitutes Q&A (N = 370)			*0.22*	*0.08*
So thinking about your budget, is $[X] per month really affordable for you?	Yes	0.40	0.44	0.18
	No	0.45	0.04	0.01
	Not sure	0.16	0.19	0.02
Are there other things that you are more likely to spend your money on first?	Yes	0.78	0.13	0.04
	No	0.09	0.55	0.36
	Not sure	0.13	0.54	0.13
Do you think you could access the same or similar information just as easily without having to pay for it?	Yes	0.54	0.13	0.03
	No	0.05	0.33	0.22
	Not sure	0.41	0.32	0.13
Cheap talk Q&A (N = 369)			*0.19*	*0.11*
When answering survey questions like this, some people say Yes even though they are not very sure whether they would actually pay for something. We would like you to answer as if you were deciding about a real purchase. Can you answer as if you were deciding about a real purchase?	Yes, I can answer as if I were deciding about a real purchase.	0.75	0.21	0.13
	No, I don't think I can answer as if I were deciding about a real purchase.	0.12	0.09	0.02
	I'm not sure if I can answer as if I were deciding about a real purchase.	0.13	0.17	0.09

Table 6. Probit regression results for certainty-adjusted and unadjusted data, with and without sampling weights. Standard errors in parentheses (robust with sampling weights). N = 1,106.

	certainty-adjusted sampling weights		certainty-adjusted unweighted		unadjusted sampling weights		unadjusted unweighted	
BSQA	0.022	(0.189)	(0.069)	(0.164)	0.290**	(0.147)	0.269**	(0.122)
CTQA	0.159	(0.184)	0.093	(0.154)	0.362**	(0.150)	0.113	(0.123)
bid	-0.154***	(0.024)	-0.159***	(0.020)	-0.124***	(0.018)	-0.126***	(0.014)
visit AL	-0.132	(0.244)	0.186	(0.219)	0.079	(0.198)	0.223	(0.174)
visit LA	-0.534	(0.370)	-0.684*	(0.360)	0.049	(0.249)	-0.052	(0.225)
visit MS	-0.620	(0.383)	-0.343	(0.300)	-0.395	(0.288)	-0.23	(0.220)
visit TX	0.198	(0.303)	0.126	(0.266)	0.250	(0.247)	0.232	(0.195)
trips	0.002	(0.002)	0.001	(0.003)	0.003**	(0.002)	0.002	(0.002)
unreported trips	-0.633*	(0.359)	-1.054***	(0.300)	-0.539***	(0.203)	-0.576***	(0.175)
overniter	0.241	(0.180)	0.167	(0.150)	0.176	(0.132)	0.316***	(0.114)
boating	0.346*	(0.188)	0.262*	(0.154)	0.243*	(0.145)	0.124	(0.122)
other reason	-0.413**	(0.193)	-0.232	(0.189)	-0.407**	(0.162)	-0.312**	(0.144)
conditions	0.092***	(0.032)	0.082***	(0.029)	0.050*	(0.026)	0.051**	(0.023)
used website	0.541**	(0.236)	0.440*	(0.227)	0.277	(0.212)	0.297	(0.184)
other sources	-0.390**	(0.194)	-0.245	(0.218)	-0.354**	(0.157)	-0.238	(0.158)
good days	0.127**	(0.052)	0.114***	(0.043)	0.134***	(0.041)	0.144***	(0.034)
consequentialilty	0.306***	(0.038)	0.262***	(0.033)	0.170***	(0.028)	0.151***	(0.023)
resident AL	0.544*	(0.309)	0.192	(0.279)	0.192	(0.246)	-0.007	(0.225)
resident LA	1.206***	(0.335)	0.978***	(0.294)	0.822***	(0.267)	0.506**	(0.236)
resident MS	0.613	(0.474)	0.422	(0.407)	0.332	(0.406)	0.2	(0.304)
resident TX	-0.09	(0.333)	0.151	(0.265)	0.02	(0.250)	0.104	(0.197)
income	0.018	(0.021)	0.01	(0.017)	-0.01	(0.014)	-0.013	(0.013)
household	0.048	(0.047)	0.034	(0.045)	0.098**	(0.038)	0.079**	(0.035)
under40	-0.330*	(0.183)	-0.400**	(0.159)	-0.175	(0.132)	-0.166	(0.119)
education	0.005	(0.041)	0.038	(0.043)	0.063*	(0.032)	0.043	(0.033)
male	0.151	(0.159)	-0.054	(0.132)	0.041	(0.120)	0.019	(0.102)
constant	-3.927***	(0.491)	-3.565***	(0.551)	-2.881***	(0.399)	-2.400***	(0.395)
LL	-245.836		-242.684		-430.124		-424.288	

* p<0.10, ** p<0.05, *** p<0.01

Figure 1. Sample responses regarding beach conditions of greatest interest