NCEE Working Paper

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Working Paper 25-05
December, 2025

U.S. Environmental Protection Agency
National Center for Environmental Economics
https://www.epa.gov/environmental-economics

NCEE
NATIONAL CENTER FOR ENVIRONMENTAL ECONOMICS

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This Version: December 4, 2025

Abstract

Nonmarket valuation surveys are designed to ask the who, what, when, where and why for a population of interest to understand preferences for environmental goods. Recent declines in survey response rates and high costs associated with traditional survey modes (e.g., mail), along with recent advances in online sampling have led to increased use of non-probability sample frames. This raises an important question for stated preference surveys about potential differences in willingness to pay (WTP) based on data collected by probability versus non-probability samples. We develop a layered, sequential approach to test whether data processing and adjustments to estimation strategies can lead to similar welfare distributions for nonmarket attributes. Using a survey on the protection of safe recreation hours at ocean beaches, we find that our proposed process decreases the variance of marginal WTP for the non-probability sample and produces WTP distributions that overlap with the probability sample for our key attribute of interest.

JEL classification: Q57, Q51
Keywords: Stated preference, binary choice referendum, WTP distributions, erosion management

1 Introduction

Nonmarket valuation surveys are increasingly administered online due to the multiple advantages this survey mode offers researchers, such as the inclusion of videos or interactive elements, conditioning questions on prior responses, and the ability to track the time it takes respondents to complete tasks. This trend towards online samples has raised important questions about how these online data are collected and the implications for welfare analysis (e.g., Penn et al. 2023). Although probability-based samples are often considered best practice for data collection (Johnston et al., 2017), there are significant concerns about declining response rates and the overall quality of response data to surveys in general (Meyer et al., 2015; Dutwin and Buskirk, 2021), which are likely driven by social changes in modes of communication. Probability-based samples are also notably more expensive than non-probability samples offered by online panels or through samples of convenience. As a response to these challenges, some federal agencies in the United States (U.S.) are beginning to change the way they collect data. For example, the U.S. Fish and Wildlife Service revamped their 2022 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation to combine responses from non-probability online panels with probability samples (U.S. Fish and Wildlife Service, 2023). Further complicating this issue, recent research on the value of information provided by nonmarket valuation studies, including those of differing quality that may deviate from best practices, suggests any study estimating welfare impacts is likely to have net benefits from a decision-support perspective (Newbold and Johnston, 2020; Pannell et al., 2025).

The broader literature on public opinion surveys demonstrates consistent differences in accuracy of estimates generated from non-probability samples relative to probability-based ones (e.g., Yeager et al. 2011). While such direct comparisons are relatively new in the nonmarket valuation space (e.g., Penn et al. 2023; Sandstrom-Mistry et al. 2023; Whitehead et al. 2023), these studies suggest potential for welfare estimates to be similar across sample types. Concerns remain about data quality and the resulting impacts on willingness-to-pay (WTP) estimates when using non-probability samples due to the potential for fraudulent responses (e.g., bots completing surveys) in addition to known behavioral response anomalies that may differ depending on the data collection process (Boyle et al., 2016; Campbell et al., 2018; Lindhjem and Navrud, 2011; Moore et al., 2023; Penn and

Hu, 2018; Sandstrom-Mistry et al., 2023; Goodrich et al., 2023). Our motivation is the idea that developing a systematic, consistent and generalizable approach to address the above concerns may provide a pathway to put more trust in welfare estimates from non-probability samples. We aim to test this by examining responses to the same online survey conducted at the same time across two different sample collection methods: 1) an address-based push-to-web probability sample and 2) an opt-in quota-based non-probability sample from an online panel. Guidelines for dealing with some of these concerns do not yet exist for non-probability samples, despite the uptick in their use due to lower costs and ease of data collection. Such guidelines could help provide transparency in how raw survey data are processed (i.e., cleaned) prior to analysis, which would facilitate comparison of results across studies and applications, promote future meta-analyses or systematic reviews, and potentially improve the value of such studies to environmental policy decisions (Johnston et al., 2017; Newbold and Johnston, 2020).

In this paper, we investigate whether there are systematic differences in marginal WTP estimates for attributes of a proposed policy and total WTP estimates for policy scenarios from a binary choice advisory referendum collected by two different sample frames. The survey instrument was designed to estimate WTP for coastal erosion management affecting safe recreation access to beaches conditional on differences in shoreline armoring policy for private landowners. We propose a three-layer sequential approach to processing response data and adjusting estimation strategies: (1) clean the data by removing observations from bots, duplicates, and other invalid data; (2) address behavioral response anomalies (e.g., speeding, inattention, attribute non-attendance (ANA)) of respondents; and (3) account for hypothetical bias (i.e., consequentiality or certainty follow-up corrections). Through our analysis, we show that all three layers have impacts on the estimated marginal WTP for the environmental quality change, the policy treatment, and the status quo. Importantly, we find that this layered approach decreased the variance of the marginal WTP distributions estimated from the non-probability sample for all attributes and shifted both samples' marginal WTP distributions away from zero for the environmental quality change. This shift increased their overlap such that the welfare distribution for the attribute of interest is not statistically different across probability and non-probability sample frames.

Stated preference guidelines or textbooks, like Johnston et al. (2017) and Mariel et al. (2021), are often referenced by researchers because they outline best practices for conducting a stated preference survey and analyzing the collected data. However, the increasing use of online panels and mixed-mode surveys points to the need to also have clearer guidelines for ex-post data cleaning (Johnston et al., 2023; Penn et al., 2023) to facilitate comparison of studies and their findings (Johnston et al., 2017). Several prior studies comparing value estimates across survey modes found differences were not significant (e.g., Campbell et al. 2018; Lindhjem and Navrud 2011). However this is not always the case (e.g., Boyle et al. 2016; Sandstrom-Mistry et al. 2023), thus prompting the need for further research in this area.

Our findings in this paper highlight the importance of establishing a systematic approach to cleaning survey response data, especially from non-probability samples. We show the impact of careful data cleaning alongside following guidance from the literature on accounting for known response behavior anomalies has significant effects on model estimates and welfare estimates. With the non-probability sample, we find that careful cleaning and accounting for ANA (and to a lesser extent other response anomalies) decreased the variance of the distribution of marginal WTP estimates for each attribute. Whereas in the probability-based sample, the decrease in variance arising from these corrections does not outweigh the loss of power from removing potentially valid responses from the estimating sample. We also note that while the non-probability online panel sample was twice as large as the probability sample, the address-based sample had smaller variance in marginal WTP distributions for all attributes.

We used a combinatorial test (Poe et al., 2005) to assess the difference in marginal WTP distributions across samples for each attribute at each layer of the process. We find no statistical difference between sample frames for preservation of safe recreation hours. The median marginal WTP of preventing a 1% loss of safe hours is approximately \$5 per year for respondents in both samples who attended to the attributes and were certain about their referendum vote (*vote-certain* hereafter). However, after applying these corrections we still observe a difference in preferences between samples for changing Oregon's existing shoreline armoring policy to allow more armoring by private landowners. Only the online panel sample has a statistically significant WTP to relax the armoring policy, which was on average $90 per year for attending and vote-certain respondents. For both samples, we find accounting for whether respondents were certain about how they voted and whether they paid attention to attributes mattered – reinforcing the importance of best practices as outlined in Johnston et al. (2017) given that stated preference surveys ask hypothetical questions and respondents may or may not pay attention to all attributes.

Lastly, this study also contributes to the literature by providing new estimates of a metric relevant for future coastal planning to address sea level rise and erosion: the value of hours of safe recreation access. Prior valuation efforts focus on valuing beach width and policies that lead to wider beaches (Dundas, 2017; Landry et al., 2003, 2020; Pendleton et al., 2012; Penn et al., 2023; Whitehead et al., 2008). However, in Oregon, current beach conditions with large spatial variance in widths (Leung et al., 2024) and the state's increasing vulnerability to coastal hazards (Ruggiero et al., 2013) suggest that *safe* recreation access is likely a more salient attribute to state residents than beach width in relation to a proposed hypothetical coastal management plan (Plybon, 2021). Back-of-the-envelope calculations from the probability sample suggest that an aggregate WTP for a management program that prevents a 10% loss of safe recreation hours in Oregon ranges from a lower bound of $41.9 million to an upper bound of $402 million per year.

2 Survey

The primary focus of our survey is estimating preferences for a coastal sediment management program in Oregon that would offset losses in beach width due to erosion and sea level rise (SLR). The key attribute of interest is the proposed policy's ability to prevent the loss of hours for safe recreation time on the state's developed ocean shoreline.[1] The valuation question is framed as a binary choice referendum, a commonly understood format for Oregon residents as statewide initiatives are often on ballots during major elections (e.g., five separate measures, ranging from ranked-choice voting to a new corporate revenue tax to partially fund citizen rebates, appeared on voter ballots in the November 2024 election). We also apply a policy treatment based on a state

[1] One such management option is beach nourishment where sand is dredged from another location and spread on a beach to increase width. To date in Oregon, there have been no federal or state efforts to manage sediment on ocean beaches (Elko et al., 2021; Program for the Study of Developed Shorelines, n.d.).

land-use regulation (Statewide Planning Goal 18) that prohibits shoreline armoring (e.g., rip-rap revetments, seawalls) on private oceanfront property for any home constructed after 1976. Half of the sample in each survey mode is randomly shown a valuation question where the state maintains this land-use regulation and the other half are shown a valuation question that relaxes the policy to allow more armoring of vulnerable private property.

Erosion and SLR are inducing significant negative transformations to both the amenity and risk profiles of Oregon's beaches (Ruggiero et al., 2013) and these changes are generating conflict between the general public who enjoy beach recreation and oceanfront residents. Prior valuation work has focused on housing market participants (Dundas and Lewis, 2020) but both groups have vested interests and property rights associated with these beaches. For the general public, Oregon's 1967 Beach Bill created a permanent public easement to access and recreate on all beaches seaward of the existing line of vegetation, regardless of ownership (Oregon Department of Land Conservation and Development, n.d.). Safe recreation access, a key concern for people making recreation trips to the Oregon Coast, implies that beaches are sufficiently wide so that recreators can avoid common safety hazards such as sneaker waves (i.e., waves that surge high up on the beach often without warning).[2] This particular risk on the U.S. West Coast results in more fatal accidents than all other weather hazards combined (NOAA National Weather Service, n.d.).

For oceanfront residents, Oregon's Statewide Planning Goal 18 (*Goal 18* hereafter) restricts eligibility for installing hardened shorelines for erosion protection to private parcels where development existed prior to 1977. Approximately 50 percent of Oregon's 9,050 oceanfront parcels are eligible for armoring and, as of 2015, approximately 1,000 of these eligible parcels have installed armoring (Beasley and Dundas, 2021). Since the option to armor is not available to every oceanfront property owner and erosion is an escalating threat to private property, there is increased interest from those currently ineligible to relax Goal 18 to allow more armoring options. Furthermore, some properties have recently received exceptions from the state to armor their shorelines despite ineligibility under Goal 18 (Foden-Vencil, 2022).[3] While relaxing the prohibition on armoring would allow more pri-

[2] An example warning sign posted at a beach access point in the Cape Perpetua Scenic Area in Oregon can be found in Figure A1 in the Online Appendix.

[3] If Goal 18 is maintained, projections suggest that another 300 eligible parcels will install shoreline armoring in the next 30 years. If Goal 18 is relaxed, up to 550 parcels will armor within 30 years, including many currently ineligible (Beasley and Dundas, 2021).

vate landowners to protect their properties from erosion, the armoring structures may take up space on the public recreation easement and further reduce beach width and subsequently, safe recreation hours.

2.1 Sample Frame and Implementation

The focus of this work is comparing results from an online survey provided to residents of the same U.S. state at the same time from two different sample frames: 1) a probability-based sample using a push-to-web format and the Dillman (2011) repeat contact method via address-based mailings (*Address* sample hereafter); and 2) an opt-in quota-based (i.e., non-probability) sample from an online panel (*Qualtrics* sample hereafter). Our survey's binary choice referendum question can be considered a text discrete choice experiment (DCE) in that it has multiple attributes (i.e., prevented loss of safe recreation hours, armoring policy treatment, cost to households) so a minimum sample size for each frame was determined using Orme's Rule of Thumb for DCEs (de Bekker-Grob et al., 2015). For the Address sample, the population of interest was all Oregon residents and participants were identified through a randomized address list with individuals' names obtained from a market research firm (Dynata) by Oregon State University's Survey Research Center (OSU SRC).[4] Participants were contacted four times during the recruitment process. First, a pre-letter from the research team describing the survey topic was sent via the U.S. Postal Service to 10,000 households who reside in the state of Oregon. Potential participants then received a letter from the OSU SRC about a week later with instructions on how to access the online survey with a URL and an individual-specific access code. A third mailing (postcard) followed one week later as a reminder to complete the survey and a final letter two weeks later to encourage completion. Conversely, for the Qualtrics sample, respondents come from the set of Oregon residents identified, recruited and compensated by Qualtrics to complete online surveys. Using this opt-in approach, we purchased 1,800 completed surveys from respondents with demographics matching Oregon's gender and age percentages from the 2016-2020 American Community Survey's 5-year estimates (U.S. Census Bureau, 2022).

[4]The number and type of contacts was chosen according to Dillman (2011)'s guidelines for mail surveys. We purchased address records with names to enable us to personalize these contacts, establish trust, and potentially increase response rates (Dillman, 2011, p. 20).

In both sample frames, the survey was administered online through the Qualtrics platform. The only difference between survey versions was the inclusion of three screening questions at the beginning of the survey in the Qualtrics sample to obtain zip code of residence and ask about age and gender to ensure the sample meets our demographic quotas. The next question – and the first question in the Address sample version – is a consent to participate, which is where Qualtrics sample respondents learn the topic of the survey. Thus, the difference in contact mode creates a difference in the order of assumptions about 1) whether a respondent had access to internet, which precludes an invitation to the Qualtrics sample, and 2) when a respondent learns about the topic of the survey, which only Address sample respondents know before accessing the survey. Figure 1 presents a flow diagram of the steps for each survey mode, starting from the selection of the target population to the selection of the final set of respondents.

Prior to implementing the survey, we conducted three online focus groups and a pre-test using the first 180 respondents (10%) of the Qualtrics panel sample.[5] Data collection occurred over a two-month period in Spring 2022 (April to June). For the Address sample, the pre-letter mailing began in early April and the online survey opened for responses in the third week of April, corresponding with the second mailing containing the link to the online survey. This survey was closed in early June, approximately two weeks after the fourth and final mailings were sent. For the Qualtrics sample, Qualtrics began inviting participants to the survey in mid-April and the survey was closed when our pre-arranged goal of 1800 completed surveys was met in mid-June.

2.2 Description of the Survey Instrument

After consenting to participate, respondents in both sample frames were provided with a summary of the 1967 Oregon Beach Bill, which codified the permanent public access easement to all coastal beaches in the state.[6] The survey proceeded to provide respondents with background information about the policy setting by describing shoreline armoring, the state's armoring policy (Goal 18), and

[5]Focus group participants were recruited and compensated by InsightsNow, a Corvallis, OR-based behavioral research firm, using a screener questionnaire provided by the research team. Pre-test responses were analyzed every 30-respondent increment so that multiple survey adjustments could be made, if needed.

[6]Two survey elements, a familiarity question (LaRiviere et al., 2014) and a color photo (Labao et al., 2008), were used to partition the flow of long sections of text, engage respondents as they read, and improve respondents' ability to digest information. For example, this page included a photo of a surfer on a Pacific City beach a and a follow-up question about their familiarity with this recreation easement.

sediment management. We then discussed beach safety and defined our metric of environmental quality change: safe recreation hours. These safe hours are calculated as daylight hours where a minimum beach width is available for safely engaging in recreation activities. This metric was developed with input from coastal stakeholders and scientists, where conversations suggested that, given Oregon's harsh wave climate and unique coastal hazards, safe recreation access is likely to be a more salient attribute (as compared to beach width) of any proposed coastal management plan to the general population (Plybon, 2021).[7] We attempt to include enough information to make the good and context familiar and meaningful so that hypothetical bias (HB) is reduced (Schläpfer and Fischhoff, 2012) while keeping this information concise so as to avoid fatigue (Needham et al., 2018).[8] The percent loss of safe hours prevented by the proposed coastal management plan shown to respondents ranged from 10 to 40 percent, with these estimates based on projections from a stochastic climate emulator applied to Oregon beaches in 2050 (Leung et al., 2024). We use a percent change in safe hours instead of a level change because the number of daylight safe hours varies across Oregon beaches. For example, a 30 percent loss of safe hours could be two (2) hours at one beach or five (5) hours at another.

After defining our key metric of environmental quality change, we describe the dimensions of a hypothetical sediment management policy in terms of how the policy would prevent the loss of safe hours. We establish the private armoring policy context (Goal 18) and then randomly assign all respondents to an armoring policy treatment: either 1) maintaining current prohibitions or 2) relaxing the Goal 18 policy to allow more armoring of private property. Bid levels were informed by recent stated preference surveys in Oregon (Lewis et al., 2019; Nguyen et al., 2023) and adjusted for this survey based on a range of cost estimates tested in focus groups and pre-test surveys. Table 1 lists the levels of each attribute that a respondent could have seen in the valuation question.

Respondents were then told that the State of Oregon is considering future coastal management policies and are presented with two options that describe the potential outcomes of the subsequent binary (yes/no) referendum choice. A *yes* vote would implement a new coastal management policy

[7]See section A.1 in the Online Appendix for further details on measurement of safe hours for recreation.

[8]HB is the difference between stated valuations in hypothetical scenarios and actual valuations in real and binding scenarios. The valuation literature has found that WTP estimated from hypothetical valuations is often greater (Penn et al., 2023; Schläpfer and Fischhoff, 2012).

and increase household costs (Option 1 in Figure 2). A *no* vote maintains the status quo: there would be no new coastal management policy and no increase costs to the household (Option 2 in Figure 2). After the policy description we include a consequentiality statement (Vossler et al., 2012) and cheap talk with a budget reminder (Penn and Hu, 2019) to mitigate hypothetical bias before presenting the binary referendum question (Figure 3). The payment vehicle was described as an increase in each household's annual state income taxes each year for the next 30 years to fund the coastal management program. Framing our valuation question as a state ballot measure promotes policy consequentiality and using state income taxes as the payment vehicle promotes payment consequentiality since Oregon voters are accustomed to voting on state ballot measures that increase state income taxes.

The survey includes a number of follow-up questions after the valuation question to measure the extent of response anomalies and to enhance the validity of the study. After voting, respondents are first asked a certainty follow-up question (Penn et al., 2023). Our valuation approach (i.e., text DCE) contained two attributes that vary in addition to cost, so we also collect information to address attribute non-attendance (ANA).[9] To collect stated ANA information, respondents are asked to select on a 5-point Likert scale how important each ballot initiative outcome – safe hours, shoreline armoring policy, and cost – was in influencing their vote. The debriefing section also includes a question to gauge how consequential the respondent found the survey to be (Vossler et al., 2012). Additional debriefing questions attempt to identify response anomalies like scenario rejection, warm glow and protest responses as well as other motivations for value elicitation responses. This includes an attention trap question designed to identify inattentive respondents and potential bots (Jones et al., 2015). The debriefing section also collects information on attitudes about erosion risk, SLR, and climate change as well as demographics. A copy of the survey instrument is provided in section D of the Online Appendix.

[9]ANA occurs when a respondent ignores one or more of the attributes in a valuation question. ANA is a type of response anomaly (and preference heterogeneity) that biases WTP estimates when not accounted for (Giguere et al., 2020; Lew and Whitehead, 2020). Accounting for ANA often decreases WTP estimates, as found in the empirical ANA literature (Giguere et al., 2020). Lew and Whitehead (2020) provide a useful review of this topic.

3 Systematic Approach to Data Processing

Our research question centers on the hypothesis that non-probability- and probability-based non-market valuation studies may elicit similar preferences as long as effort is made to ensure estimation proceeds with valid response data. We define *valid* as complete or incomplete responses representing survey takers with well-behaved preferences and no evidence of fraudulent behavior (e.g., Goodrich et al. 2023). *Complete* and *incomplete* responses are differentiated by whether the respondent answered the binary choice referendum question and could thus be in the estimating sample. We apply three layers of exclusion criteria to show the impact of incorporating successively stricter requirements for a response to provide valid data. A detailed description of this process and total observations dropped by each element of the three layers can be found in section B.1 of the Online Appendix.

The first and broadest layer of exclusion criteria removed likely bots, duplicate responses, and participants not part of the target population of adult Oregon residents. The second layer removes participants whose response behavior suggests they had incomplete comprehension or were not truthful in their responses. This includes respondents who sped through the survey or who were flagged by debriefing questions as providing inattentive or protest responses. Our estimation strategies applied to this layer of exclusion criteria also account for ANA as another behavioral response anomaly using respondents' stated ANA information. We estimate separate coefficients for attending and non-attending respondents in the modeling stage instead of removing likely non-attending respondents from the sample during data cleaning. In the third layer, we address HB using debriefing questions about policy consequentiality or vote certainty. As with ANA, HB correction is primarily applied during discrete choice model estimation, as described in section 4. Section B.2 of the Online Appendix describes how we construct and use the ANA and HB variables.

Data cleaned using the first exclusion criteria yields the largest valid sample: 2386 complete responses in the Qualtrics sample and 1047 complete responses in the Address sample. Applying all three layers of exclusion criteria yields the smallest sample of valid responses: 1173 in the Qualtrics sample and 736 in the Address sample. As expected, when requiring the strictest criteria for valid complete responses, a greater proportion of the Qualtrics online panel sample is flagged as providing potentially invalid data (51 percent) compared to the proportion flagged in the Address sample (30 percent). Table 2 reports summary statistics by sample frame for the total number of alternatives in the valid data.[10] The *First Criteria* column summarizes the attribute, HB, and ANA variables for all alternatives after applying the broadest exclusion criteria. The *All Criteria* column reports these statistics after applying all exclusion criteria.

The proportion of respondents who found the survey to be consequential is approximately 85-90 percent across samples and exclusion criteria layers, with this proportion being higher in the Qualtrics sample and increasing (slightly) for both samples after all exclusion criteria are applied. Respondents were, on average, less certain about their vote (50 to 60 percent). This proportion is again higher in the Qualtrics sample (60-61 percent) but increases more in the Address sample (50 to 55 percent). Generally, as exclusion criteria are layered on to remove behavioral response anomalies other than HB (e.g., ANA), perceived consequentiality and certainty in the remaining sample increases, suggesting that some respondents exhibit multiple response behaviors flagged by our exclusion criteria.

ANA varied more than the HB measures across all dimensions. ANA was highest for the Goal 18 private armoring policy - consistently 44 percent in the Address sample and 41 percent in the Qualtrics sample after applying all corrections. Accounting for other exclusion criteria decreases mean ANA by 5 percentage points in the Qualtrics sample, implying some overlap of response behaviors within that sample. Average ANA to the cost of the policy and to preventing safe hours loss was also different between samples before accounting for behavioral response anomalies - 36 percent in the Address sample for both attributes and 45 percent (40 percent) for cost (safe hours) in the Qualtrics sample. After all exclusion criteria are applied, ANA again aligns across samples to 37 percent for cost and 31 percent for safe hours. For most attributes and in both sample frames, ANA decreased with additional layers of exclusion criteria.[11]

The spatial variation in response rates aggregated by county using respondent zip codes is

[10] We report total alternatives instead of complete responses because our estimation strategy uses information from both alternatives (options) that respondents choose over: the *do nothing* option that maintains the status quo and the policy option. Thus, the number of alternatives is twice the number of complete responses in each cleaned data set.

[11] The one exception to this was ANA to cost in the Address sample, which increased from 36 to 38 percent after applying the second and third exclusion criteria.

illustrated in Figure 4. Counties shown in green are where the percent of respondents and the percent of the state population from that county are similar (within 0.5 percent). In the yellow (purple) counties, the percent of respondents is higher (lower) than the percent of the state population by at least 0.5 percent. Although these cutoffs are arbitrary and the simple difference does not hold other sources of variation constant, the illustrative differences between the maps suggest that the counties with the state's largest cities had higher relative representation in the Address sample whereas some coastal counties had higher relative representation in the Qualtrics sample.

The cost of the Qualtrics online panel sample was \$7.83 per contracted response. The cost per valid response ranged from \$5.91 to \$12.01 depending on the layers of exclusion criteria applied (first to all, respectively). The per completed response cost of the Address sample ranged from \$32.01 to \$45.53. Applying only the first exclusion criteria suggests that the Address sample was approximately 5.4 times more expensive to collect than the Qualtrics sample. This multiplier decreases to 3.8 with all three exclusion criteria layered since a larger proportion of the online panel sample is flagged for behavioral response anomalies.

4 Model

To estimate WTP for safe recreation hours at developed Oregon beaches, we start with a conditional logit regression model. We assume the utility of individual i from policy alternative j can be specified as linear function of the attributes and is composed of a systematic component, v_{ij}, and a random component, ϵ_{ij}, that is assumed to be independent and identically distributed as Type 1 extreme value (i.e., Gumbel distribution):

$$V_{ij} = v_{ij} + \epsilon_{ij} \tag{1}$$

The systematic component, v_{ij}, is a linear function of the cost of the policy, c_j, and policy attribute vector, X_j, with α and vector β as estimable parameters. The indirect utility function is specified as follows:

$$v_{ij} = \alpha c_j + \beta' X_j = \alpha c_j + \beta_1 DN_j + \beta_2 SafeH_j + \beta_3 RelaxG18_j \tag{2}$$

where c_j is the cost of the policy and $\beta' X_j$ can be decomposed into the main policy attributes: $SafeH$ is the prevention of loss of safe hours, $RelaxG18$ is the relaxing of the Goal 18 private property armoring policy, and DN is the *do nothing* dummy variable. The value of $SafeH$ is specified as the expected percent loss of safe hours, and takes on negative values (e.g., -10) in the vote *no* case and 0 in the vote *yes* case as the policy was stated to prevent the loss of safe hours (i.e., it maintains current beach conditions).[12] $RelaxG18$ is set to equal 1 if the armoring policy treatment randomly assigned to the respondent relaxes the Goal 18 private property armoring policy and 0 if this policy is maintained as is (i.e., no change to current armoring prohibitions). The value of DN depends both on the alternative j and how the respondent votes since the estimation strategy uses information from both alternatives (options) that respondents choose over. Thus, in the policy option (i.e., when j equals 1), DN takes on a value of 1 in the vote *no* case and 0 in the vote *yes* case. DN is set equal to 1 in the no-action alternatives (i.e., when j equals 0) that would "let people and nature deal with the effects of erosion and sea level rise" (quote from survey, Online Appendix D).

If the error term ϵ_{ij} is distributed i.i.d. extreme value, parameters can be estimated using the conditional logit model (CLM) (McFadden, 1974). An advantage to the CLM is that it assumes that respondent's utility is based only on the attributes of the choices and not characteristics of the individual respondent. The model assumes the individual respondent will choose the alternative that will give them the highest utility and that these choices are based on utility differences between the policy alternatives. Thus the probability of an individual i choosing alternative j is

$$Pr_{ij} = \frac{exp(v_{ij})}{\sum_{j=1}^{J} exp(v_{ij})} \tag{3}$$

We can include interactions with individual-specific characteristics to account for individual response anomalies, such as ANA, by adding a vector of parameters γ to equation 1 to capture additional effects in vector Z^i that vary by individual i for each of the attributes j. For the Address

[12]Section A.1 in the Online Appendix explains how the safe hours measure is determined.

sample this vector includes behavioral response anomalies as well as sample selection correction.[13] We can build on equation 1 to explore preference heterogeneity by including respondent characteristics and their interaction with the attributes j to allow for the utility to vary systematically. We explore systematic preference heterogeneity for the following respondent characteristics: have at least one child, household income greater than $100,000, and have a college degree or more.

$$V_{ij} = \alpha c_j + \beta' X_j + \gamma' Z^i X_j + \epsilon_{ij} \tag{4}$$

We specify four discrete choice models that use different layers of exclusion criteria and different constructions of Z_i. The first (1) model specification estimates the CLM on the data after applying the first layer of exclusion criteria to remove invalid responses (the *Base Model* hereafter).[14] For the second (2) specification we apply the second layer of exclusion criteria to remove behavioral response anomalies and then estimate separate preference parameters for respondents who stated they ignore an attribute from those who stated they attend to it, as in Hess and Hensher (2010) and Scarpa et al. (2013).[15] The third (3) and fourth (4) specifications layer on the HB exclusion criteria and apply the consequentiality and certainty follow-up corrections, respectively. Both ANA and consequentiality are incorporated through interactions on the attributes such that the main parameters represent fully attending and fully consequential responses (i.e., Z_i includes interactions between the attributes X_j and binary consequential and/or attending indicators Z_i). Vote certainty is also included through interactions, but on the dependent variable, as in Penn et al. (2023).

As additional robustness checks, we relax the assumption of identical preference parameters for all respondents by specifying more flexible models: mixed logit, and latent class logit. We estimate mixed logit models to allow the preference parameters to be randomly distributed and latent class models to investigate inferred ANA. Using these models and additional debriefing questions we also explore systematic preference heterogeneity by characteristics of the individual such as income, edu-

[13] We correct for sample selection in the Address sample due to the low response rate, of approximately 10.4 percent (1042/9998), following the approach developed by Cameron and DeShazo (2013) and per guidance in Johnston et al. (2017). A detailed description of this process can be found in Section B.3 of the Online Appendix.

[14] Thus, for this specification, Z_i is empty for the Qualtrics sample and only contains sample selection corrections for the Address sample.

[15] We focused on using a stated ANA approach due to convergence issues with latent class models when estimating inferred ANA specifications. Giguere et al. (2020) suggest using stated ANA questions when not able to rely on inferred ANA latent class models.

cation and whether the respondent has a child. These characteristics are interacted with the policy attributes in some CLM and mixed logit models and also used to specify membership equations in latent class models. The results of the mixed logit and latent class logit models that we were able to estimate suggest that there may be some unobservable preference heterogeneity in each sample and that it differs between the two samples. The mixed logit results for the Address sample are qualitatively similar with the CLM, but the parameters are not significant in the Qualtrics sample. The latent class logits suggest the unobserved preferences may be different between the two samples. Whereas when we estimate the preferences on average for each sample, assuming homogeneous preferences for both samples, we find comparable results. We focus our discussion on the results of the CLM in this paper and provide the mixed and latent class logit results in the Online Appendix.

4.1 Marginal and Total Willingness to Pay

We estimate marginal WTP distributions for all models and total WTP for our preferred specifications. The parameter $-\alpha$ represents the marginal utility of net income, and the policy scenario parameters are represented by β_k for $k = SafeH$ or $RelaxG18$, corresponding to each of the parameters described in the subsection above.[16] Dividing by the policy attribute by the marginal utility of net income yields the marginal WTP ($MWTP$) for a change in policy attribute k:

$$MWTP = -\frac{\partial V_{ij}/\partial X_k}{\partial V_{ij}/\partial c_j} = -\frac{\beta_k}{\alpha} \tag{5}$$

This same exercise can be done when we have attributes interacted with respondent characteristics, to capture observed heterogeneity:

$$MWTP = -\frac{(\beta_k + \gamma_k Z^i)}{\alpha} \tag{6}$$

The total WTP ($TWTP$) as shown in equation 7 is found by setting the utility difference between the policy scenario ($j = 1$) and the no action option ($j = 0$) equal to zero, then solving for the cost

[16]Theoretically, the indirect utility function for a RUM model is $V_{ij} = v_{ij}(Z_j, y_i - c_j) + \epsilon_{ij}$ where y_i is the income of individual i (Holmes et al., 2017)[p.157-158]. The linear-in-utility assumption allows for a simplification to the form $V_{ij} = v_{ij}(Z_j, -c_j) + \epsilon_{ij}$ to facilitate the estimation of the parameter $-\alpha$, which then represents the marginal utility of net income.

that maintains the baseline level of utility (i.e., compensating variation). Assuming that all error terms ϵ_{ij} are i.i.d. and mean zero, we can evaluate the $TWTP$ at the mean value of these error differences, also assumed to be zero.[17]

$$\begin{aligned} TWTP &= -\frac{1}{\alpha}[V_{j=1} - V_{j=0}] \\ &= -\frac{1}{\alpha}[(\beta_1 DN_1 + \beta_2 SafeH_1 + \beta_3 RelaxG18_1) \\ &\qquad - (\beta_1 DN_0 + \beta_2 SafeH_0 + \beta_3 RelaxG18_0)] \end{aligned} \tag{7}$$

The $MWTP$ and $TWTP$ distributions are constructed by taking 10,000 random draws from the asymptotic joint normal distribution of the parameter estimates (Krinsky and Robb, 1986). We then use this distribution to calculate the median and 95% confidence intervals of $MWTP$ and $TWTP$ for the policy attributes and scenarios.

5 Results

We estimate the probability of voting for the coastal erosion management policy as a function of its attributes using the CLM and present the results assuming homogeneous preferences in Table 3

[17] For example, let the policy scenario shown to the respondent be a 40% expected loss of safe hours ($SafeH =$ -40) with Goal 18 armoring restrictions maintained ($RelaxG18 = 0$). In our model, we code the policy scenario to represents the no-loss case, as the policy was described as preventing the loss of those safe hours. If they voted *no*, the *no action* or *do nothing* option represents the scenario in which the loss of safe hours would be experienced. In both of these cases, the Goal 18 policy is maintained without change.
We first write out the indirect utility function, V_{ij} for each scenario:

$$\begin{aligned} V_{i,j=0} &= -\alpha(0) + \beta_1(1) + \beta_2(-40) + \beta_3(0) + \epsilon_{i,j=0} \\ V_{i,j=1} &= -\alpha(c_{j=1}) + \beta_1(0) + \beta_2(0) + \beta_3(0) + \epsilon_{i,j=1} \end{aligned}$$

Then calculate the $TWTP$ as follows for this example:

$$\begin{aligned} TWTP &= -\frac{1}{\alpha}[V_{i,j=1} - V_{i,j=0}] \\ &= -\frac{1}{\alpha}[(\beta_1(0) + \beta_2(0) + \beta_3(0) + \epsilon_{i,j=1}) - (\beta_1(1) + \beta_2(-40) + \beta_3(0)) + \epsilon_{i,j=0})] \end{aligned}$$

Rearranging to group terms together and the above assumption about the error term to simplify the above equation to the following:

$$TWTP = -\frac{1}{\alpha}E[\beta_1(0-1) + \beta_2(0-(-40)) + \beta_3(0-0) + (\epsilon_{i,j=1} - \epsilon_{i,j=0})]$$

and results allowing for systematic heterogeneity in Table 4.[18] These tables report select parameter estimates for the four main CLM specifications, by sample frame.[19] Column (1) *Base Model* reports estimates from that specification, i.e., the parameters represent all potentially valid responses. Columns (2) through (4) report the main estimates from those specifications. Specifically, the parameters represent fully-attending responses in column (2) *Base + ANA*, fully-attending and fully-consequential responses in column (3) *Base + ANA + HB(Conseq)*, and fully-attending and vote certainty-corrected responses in column (4) *Base + ANA + HB(Certain)*.[20] We refer to the percent loss of safe hours prevented attribute as *safe hours* and the relaxing of private armoring restrictions under Goal 18 as *relax Goal 18*. The *do nothing* alternative reports estimates for the no-action scenario where armoring restrictions are maintained and there is no new coastal management program.

5.1 Homogeneous Preferences

Panels A and B of Table 3 present results for the Address and Qualtrics sample, respectively. The negative relationship between the cost of the coastal management plan and respondents' WTP for it conforms to the law of demand for all models across both samples. Coefficients on the safe hours attribute vary in significance and magnitude between models but are consistent in sign and significance across sample frames. Prior to correcting for ANA, we find that the safe hours parameter in column (1) is positive but not significant and therefore would not pass the external scope test. However, after controlling for stated ANA in column (2), we find that this parameter is statistically significant.[21] Respondents were more likely to vote for the management plan as the prevented percent loss of safe hours increased, and the significance of this effect persists if HB is corrected

[18]Additional results from the investigation of preference heterogeneity are available in section C.1 of the Online Appendix.

[19]We also estimated a CLM with pooled data from both samples. These results are available upon request but are not reported here because we do not suggest pooling the data. The data generating process of the two samples may be different and it is not clear what population is represented by the pooled data because of the difference in sampling properties.

[20]Recalling that specification (1) is estimated on the data after applying the first layer of exclusion criteria, specification (2) is estimated after applying the second layer, and specifications (3) or (4) are estimated after applying the third layer. See Tables A3 (Address) and A4 (Qualtrics) in the Online Appendix for all parameter estimates including for non-attending respondents and those who did not find the survey consequential.

[21]These findings are similar to Giguere et al. (2020) after they correct for stated ANA.

for using certainty follow-up (column (4)).[22] Unlike safe hours, responses to the private armoring policy scenario differed across sample frames. In the Address sample, whether respondents were in the *Relax* or *Maintain* Goal 18 scenarios did not have a statistically significant effect on how they voted in any model. In the Qualtrics sample, however, after correcting for ANA (column (2)) the effect of the policy treatment is marginally significant, suggesting that respondents were more likely to vote for the management plan if the policy is relaxed to allow more shoreline armoring. The significance and magnitude of this effect increases if HB is corrected for using certainty follow-up (column (4)).

5.2 Systematic Heterogeneity

We also investigate potential drivers of observed response differences between sample frames with additional logit models that use respondent characteristics to incorporate systematic preference heterogeneity. Table 4 reports select results for one set of models and one driver of heterogeneity: CLM with an interaction between the safe hours attribute and whether there is a child in the respondent's household. We hypothesize that people with children may have stronger preferences for preserving safe beach access in the future. We find that the prevented percent loss of safe hours has a significant effect on the voting behavior of respondents with children across model specifications. For respondents without children, this effect is significant only in columns (2) and (4), as in the homogeneous preference results.

We explore additional elements of preference heterogeneity and report selected results in Tables A6 through A11 in the Online Appendix. We find sources of preference heterogeneity for the other attributes but do not find the exact systematic drivers. For example, two sources of heterogeneity for relaxing the private armoring policy - education and income - may be correlated but have different impacts on preferences across samples.

[22] Correcting for HB using consequentiality (column (3)) instead suggests this effect is not significant. Another difference between these two HB corrections is that the certainty follow-up correction drops two (Qualtrics) and six (Address) respondents that the consequentiality correction does not, resulting in fewer total alternatives in column (4) vs column (3). These responses are missing certainty follow-up answers which precludes correcting the dependent variable using the certainty correction. More information about how these variables are defined and used can be found in section B.2 of the Online Appendix.

5.3 Welfare Estimation and Comparison

We report the median and the 95% confidence interval (CI) for *MWTP* for each attribute and the *TWTP* for each policy scenario. To test whether the *MWTP* distributions differ from zero and across sample modes, we use the complete combinatorial method from Poe et al. (2005). This approach provides an exact measure of the difference of two independent simulated distributions, allowing for a two-sided test of differences between empirical WTP distributions.

Table 5 reports the median and 95% CI for each simulated *MWTP* distribution by attribute, sample frame, and model specification. Figure 5 plots the *MWTP* CIs for the (a) safe hours and (b) relaxing Goal 18 armoring policy attributes by sample frame and model specification to visualize how applying each layer of exclusion criteria to the survey data impacts the *MWTP* distribution for that attribute. Median annual *MWTP* to prevent a one percent loss of safe hours is approximately \$5 for the Address sample and \$5 to \$6 for the Qualtrics sample when *MWTP* is simulated using statistically significant estimates from Table 3, i.e., *Base + ANA* results in column (2) and *Base + ANA + HB(Certain)* results in column (4). Figure 5a highlights how applying only the first exclusion criteria (*Base Model*) suggests that *MWTP* for preventing a loss in safe hours is not statistically significant (at the 5% level). However, applying the second set of exclusion criteria, i.e., ANA and other response behavior corrections (*Base + ANA*), bounds the *MWTP* distributions (95% CIs) away from zero such that values become statistically significant in both samples.[23] Layering on HB corrections using certainty follow-up tightens the 95% CI in the Address sample and attenuates median *MWTP*, as expected, but slightly *increases* the Qualtrics sample's median *MWTP*.

Respondents in the Address sample do not have a statistically significant *MWTP* to relax the Goal 18 armoring policy regardless of exclusion criteria used. *MWTP* in the Qualtrics sample is only statistically significant at the 5% level after applying all exclusion criteria and suggests a median *MWTP* of \$90 per year to relax Goal 18 and allow more armoring of vulnerable oceanfront private property. Figure 5b shows how layering on exclusion criteria may reveal differences between sample frames that are otherwise obscured by the presence of behavioral response anomalies.

Table A12 and Figures A2 to A3 in the Online Appendix report the median and 95% CIs for

[23] This suggests that the safe hours estimates can pass the external scope test if ANA is accounted for, a result similar to that of Giguere et al. (2020).

the *MWTP* distributions drawn from the joint distribution of parameter estimates from Table 4.[24] After applying all exclusion criteria we find that respondents with children have a median annual *MWTP* of \$7 to \$8 to prevent a percent loss of safe hours, in the Address and Qualtrics samples respectively. Respondents without children have a lower median annual *MWTP* of \$4 to \$5 across these samples, which suggests that people with children, compared to those without, have higher WTP to preserve safe beach access for the future.

Table A5 in the Online Appendix compares *TWTP* values for different levels of the safe hours attribute. We report median *TWTP* and 95% CIs for five scenarios where the statewide armoring policy is maintained and only the prevented percent loss of safe hours changes. For each of the levels shown in the survey (10, 20, 30, and 40 percent), median *TWTP* for the Address sample increases between the *Base Model* (1) and *Base + ANA + HB(Certain)* (4) specifications. In contrast, median *TWTP* for the Qualtrics sample decreases as the exclusion criteria are layered on. These shifts have the effect of decreasing the *difference* between the two samples' median *TWTP* estimates. For example, for a 10% prevented loss of safe hours, *Base Model* (1) results suggest Qualtrics *TWTP* is about \$201 higher than the Address sample but that gap narrows to about \$25 after all exclusion criteria are applied to the data, as shown in column (4).

We use these estimates in a back-of-the-envelope calculation to quantify the value of safe beach access to state residents, and present the lower and upper bounds of the range based on the approach of Mitchell and Carson (1987) and highlighted by Loomis (1987) to use for stated preference surveys.[25] Results from the Address (probability) sample suggest the range of aggregate WTP for a sediment management program that prevents a 10% loss of safe hours is approximately \$41.9 million (lower bound) to \$402 million (upper bound) per year. For a program that prevents a 40%

[24] For the safe hours attribute we present the *MWTP* estimates for respondents with and without children after all exclusion criteria are applied (columns (3) and (4) of Table 4) to illustrate the impact of accounting for one systematic driver of preference heterogeneity without potential confounding by ANA, HB, and other response behaviors. We focus our discussion on estimates from the *Base + ANA + HB(Certain)* specification in column (4) since they are statistically significant for both groups of respondents.

[25] Loomis (1987) evaluates several approaches to the aggregation of benefits, a concern particularly when a survey has a low response rate. He highlights the approach of Mitchell and Carson (1987) to identify a range of aggregate benefits for contingent valuation estimates. Mitchell and Carson (1987) used a weighted average based on the population proportions in the sample, and differing assumptions about the proportion of the population represented by non-respondents. For the lower bound, they assume the percentage of non-respondents have a WTP of zero. For the upper bound, they assume that non-respondents' value is not different from respondents. For the lower bound, we assume only 10.42 percent of the population of Oregon households have a non-zero WTP, reflecting our response rate in the probability sample.

loss of safe hours, the range of aggregate WTP is \$68.1 million to \$654 million per year.

We formally test whether the attributes' $MWTP$ distributions differ between sample frames using the Poe et al. (2005) complete combinatorial approach. Table 6 reports the results of this two-sided test by model specification and attribute. Each attribute's combinatorial test shows a different pattern of significance as exclusion criteria are added. $MWTP$ distributions for the safe hours attribute are not statistically different between samples irrespective of model specification, suggesting that differences in $MWTP$ to prevent a percent loss of safe hours are small enough across samples that, after removing invalid data, additional corrections for ANA, HB, and other response behaviors may not be needed for the two samples to elicit similar preferences for the environmental quality change. In contrast, for the statewide armoring policy, combinatorial tests suggest that the difference between the Qualtrics and Address $MWTP$ distributions is marginally statistically significant after correcting for ANA (2) and statistically significant at the 10% level after applying all exclusion criteria (4).

To visualize the impact of data processing measures in our exclusion criteria on $MWTP$ distributions, Figure 6 plots kernel density estimates (KDEs) of each attribute's $MWTP$ distribution.[26] Each subfigure reports $MWTP$ KDEs for both sample frames (Address in black and Qualtrics in green) and for two model specifications: the *Base Model* (1) after applying the first layer of exclusion criteria in solid lines and (4) after applying all exclusion criteria (*Base + ANA + HB(Certain)*) in dashed lines. For the safe hours attribute, correcting for ANA, HB, and other response behaviors shifts the uncorrected $MWTP$ KDEs (*Base Model*) away from zero for both samples, narrows the CI of the Qualtrics $MWTP$ distribution, and increases overlap between the samples' $MWTP$ distributions, corroborating the Poe et al. (2005) test result of no significant difference. For the armoring policy, the uncorrected $MWTP$ KDEs (*Base Model*) have high overlap between samples, which results in the combinatorial test failing to reject the null hypothesis of no statistical difference between distributions. However, results from the *Base + ANA + HB(Certain)* specification induce only a small shift of the Address sample's distribution but a large shift of the Qualtrics sample's distribution, revealing a statistically significant difference between samples.

[26] $MWTP$ distributions were trimmed to their 95% CIs to facilitate plotting KDEs by removing tails.

6 Discussion and Conclusion

Surveys are a valuable tool researchers use to learn about household preferences over changes in policies and environmental quality. A set of best practices has established guidelines to follow for survey development and estimation strategies (e.g., Johnston et al. (2017); Mariel et al. (2021)). Guidance for ex-post data cleaning and validation for increasingly used non-probability samples is less established. A key takeaway from this work is the importance of increasing transparency in stated preference survey data cleaning protocols, especially when feasibility or funding limitations dictate that sample collection deviates from probability-based representative samples. These decisions are often not elaborated on in published research in sufficient detail to facilitate replicability and comparison of results or enable regulators to use estimates in benefit transfer exercises to inform policy decisions. This conclusion is similar in spirit to Banzhaf and Smith (2007) in their call for more transparency from researchers in sharing all modeling decisions and outcomes that shaped their thinking when estimating welfare effects with their preferred specifications.

To test the generalizability of welfare estimates from a non-probability sample, we use a stated preference survey sent at the same time to two different sample frames (address-based probability sample and an online panel non-probability sample) in Oregon. Our results demonstrate the importance of systematic and transparent data cleaning by layering exclusion criteria on different choice models and comparing resulting $MWTP$ estimates across models and sample frames. Specifically, we investigate differences between the two samples' $MWTP$ distributions for each attribute when (1) the data is carefully cleaned for bots, speeders and other known threats to data quality with online panels; (2) behavioral response anomalies are controlled for, especially ANA as respondents may not attend to all the attributes; (3) potential hypothetical bias is mitigated using vote certainty follow-up information; and (4) researchers consider how the difference in the order of assumptions between having access to the platform to take the survey and the topic of the survey could impact the data when designing a data cleaning protocol.

Across attributes, accounting for ANA induces the largest shift of $MWTP$ distributions relative to other exclusion criteria. For our environmental quality change, the prevented loss of safe recreation hours on ocean beaches, this bounds both samples' $MWTP$ distributions away from zero to suggest that attending respondents have a positive (median) $MWTP$ of approximately \$5 per year to prevent a 1% loss of safe hours.

However, careful cleaning can also reveal differences between sample frames that are otherwise obscured by the presence of behavioral response anomalies. For our policy treatment (relaxing private shoreline armoring restrictions under Goal 18), applying all exclusion criteria does not change the null result for the probability sample but does for the non-probability sample, suggesting that online panel respondents have a median $MWTP$ of \$90 per year to relax Goal 18 to allow more armoring of vulnerable oceanfront private property. Thus, ANA, HB, and the other behaviors our exclusion criteria account for are not the only drivers of observed response and WTP differences between our samples. However, we do not find clear systematic drivers of preference heterogeneity across samples for this attribute. Parameter differences may arise because the difference in contact mode creates a difference in the order of assumptions about survey topic and internet access. This may lead to a difference in the data-generating process between the two sample frames. The mixed results for relaxing shoreline armoring restrictions may also be due to the embedded trade-off between private armoring rights and public recreation rights resulting in complex preferences whose systematic drivers are difficult to disentangle. In comparison, for safe hours preservation we find evidence of systematic preference heterogeneity between respondents with children and those without. We hypothesize that, given the salience of beach hazards to people on the West Coast, Oregon parents may have higher WTP to preserve safe beach access for their children than people without children.

We explored more flexible choice models but convergence and power issues limit the additional insight we are able to glean from these more sophisticated models. The results suggest unobserved heterogeneity in preferences may differ across the two samples. For example, qualitatively, for the Address sample, our results for the mixed logit were similar but suggestive of a median $MWTP$ that is larger than that of the CLM, whereas for the Qualtrics sample, no parameters were statistically significant in the mixed logit, but were in the CLM.

In conclusion, this paper demonstrates that there may be systematic differences in important welfare outcomes introduced by researcher judgment with respect to data cleaning decisions. WTP differences between probability and non-probability samples can be increased or decreased depending on the cleaning approaches used, and whether they are considered on their own or in combination. In our survey setting, careful cleaning reduced differences between the two samples' WTP distributions for an environmental quality change but highlighted differences in a policy treatment. Our contribution lies in highlighting the need for transparency in data cleaning and modeling decisions in survey research so that even stated preferences studies limited by budgets or feasibility can produce useful welfare measures for benefit transfer applications and other settings useful for policy and decision makers.

7 Acknowledgments

The survey was developed and administered when A. Hadziomerspahic was affiliated with Oregon State University (OSU). IRB approval # IRB-2022-1355 was granted for this survey work by the OSU Human Research Protection Program (HRPP) and Institutional Review Board (IRB). We thank Lydia Newton and the OSU Survey Research Center for outstanding survey administration. We are grateful for comments from John Whitehead, Chris Moore and Matt Massey as well as from conference participants at the 2024 W5133 annual meeting, the 2023 and 2024 AERE Summer Conferences, the 2024 NAREA and SEA conferences, along with seminar participants at the U.S. EPA's National Center for Environmental Economics (NCEE) and Portland State University. We acknowledge funding that supported this research while A. Hadziomerspahic was affiliated with OSU came from the NOAA National Centers for Coastal Ocean Science Competitive Research Program through NOAA Cooperative Institutes Program award numbers NA11OAR4320091A and NA16OAR4320152. We also acknowledge concurrent support from NOAA's Effects of Sea Level Rise Program awards numbers NA19NOS4780180 and NA23NOS4780284 and the USDA National Institute of Food and Agriculture Hatch Multi-state project W-5133. The views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. Environmental Protection Agency (EPA). The EPA's NCEE reviewed the paper prior to its circulation. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy. This manuscript was

reviewed by S.H. Kolstoe's supervisors to ensure an assessment of technical accuracy was completed and for adherence to the USDA Forest Service and Pacific Northwest Research Station scientific publication policy.

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Figure 1: Sample frame and survey flow: Understanding sample frame differences, to include when respondents learned of the survey topic

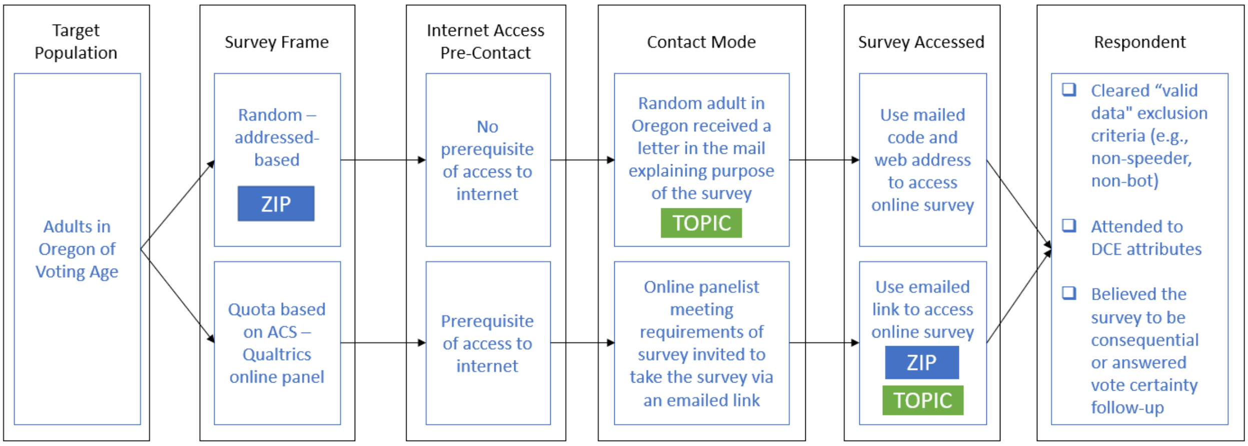


Figure 2: Example of advisory referendum options: From the *Relax Goal 18* version of the survey instrument

Below are two options that the State of Oregon is considering.

Option 1:

The **first option** would **increase your household's annual state income taxes** by a small amount to implement **a new coastal management plan**. This plan would do two (2) things:

- **Create an Oregon Public Beach Fund** to manage sediment on eroding **developed** beaches. This fund would be overseen by Oregon State Parks and used to address erosion and **preserve access and safe hours for recreation**.
- **Relax armoring restrictions** under Statewide Planning Goal 18 to address erosion issues on oceanfront parcels. Relaxing Goal 18 would mean that all oceanfront homeowners would become eligible to install shoreline armoring when their property becomes vulnerable to erosion. This represents a significant change to Oregon's current land use policy and will **increase the amount of shoreline armoring** on developed beaches. Additional armoring structures would protect more private property but will also take up space for recreation and further reduce the width of these beaches. Armoring would not be funded by the state income tax increase and will continue to be the financial responsibility of the coastal homeowners who decide to armor.

Option 2:

The **second option** is to **do nothing** and, instead, let people and nature deal with the effects of erosion and sea level rise. Under this option, there would be **no Oregon Public Beach Fund** and the **current armoring restrictions under Goal 18 remain unchanged**. There would also be **no increase to your household's annual state income taxes**.

Figure 3: Example of advisory referendum question: From the *Relax Goal 18* version of the survey instrument

Consider that the **Oregon Public Beach Fund** and **the Goal 18 policy change to relax shoreline armoring restrictions** described previously are part of a state ballot measure. This measure would increase your household's annual state income taxes **per year for the next 30 years** to allow Oregon State Parks to implement the coastal management plan so as to meet both goals of preserving safe access for recreation and protecting private property from erosion.

This ballot initiative would:

- Increase funding for sediment management to **<u>prevent</u> a 20% loss of safe hours** for recreation at developed beaches at the highest risk of erosion.
- **<u>Relax</u>** Oregon's Goal 18 shoreline armoring policy so that all oceanfront property owners become eligible to armor the shoreline in front of their homes.

The ballot initiative would **(1) preserve access to these beaches and their safe hours for the next 30 years** and **(2) relax the shoreline armoring policy**.

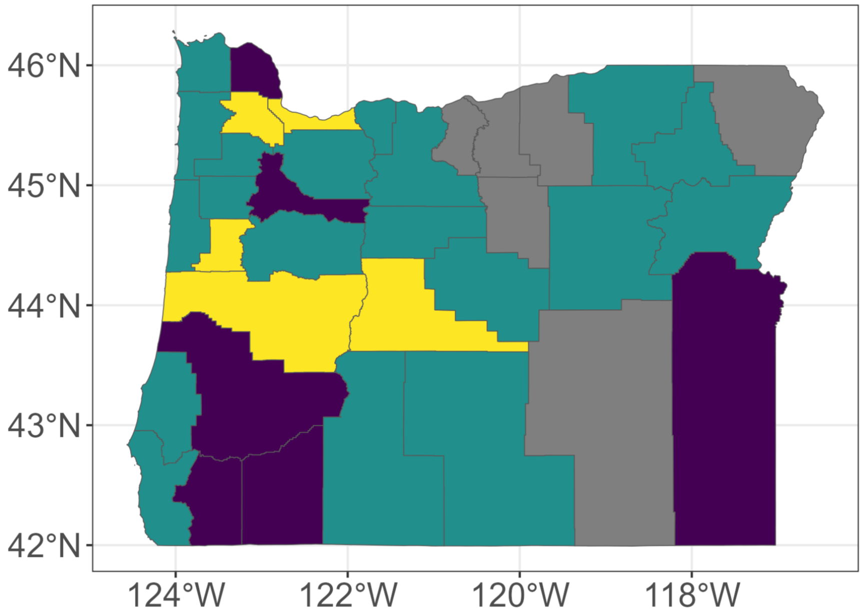
If this ballot measure passes, it would cost every household in Oregon an additional **$100 in state income taxes every year for the next 30 years**.

If this measure is on the ballot in the next election, would you vote for (yes) or against (no) the ballot measure?

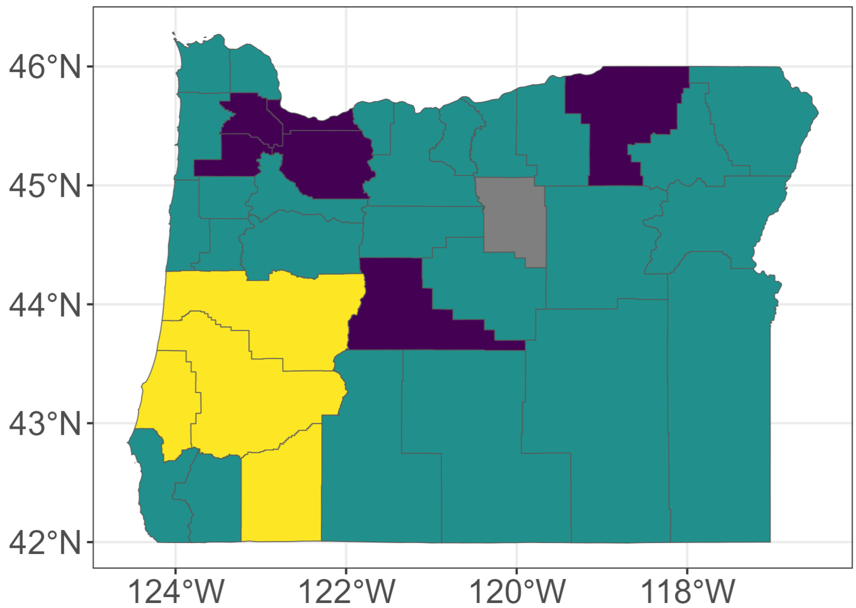
◯ I would vote "yes"

◯ I would vote "no"

Figure 4: Survey samples by contact mode: Spatial variation in responses by county



(a) Address sample (probability)

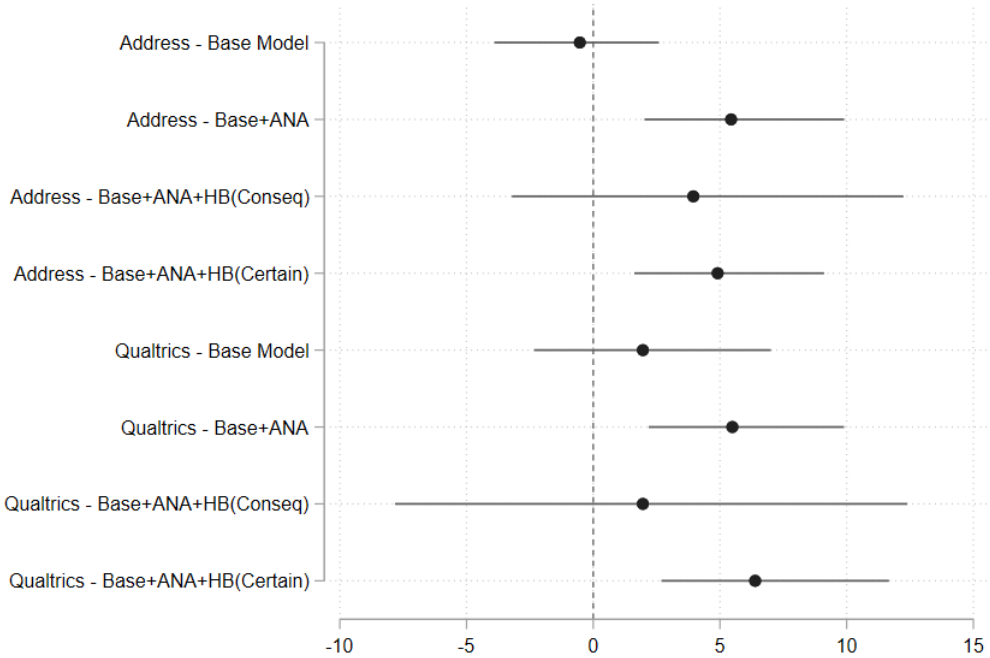


(b) Qualtrics sample (non-probability)

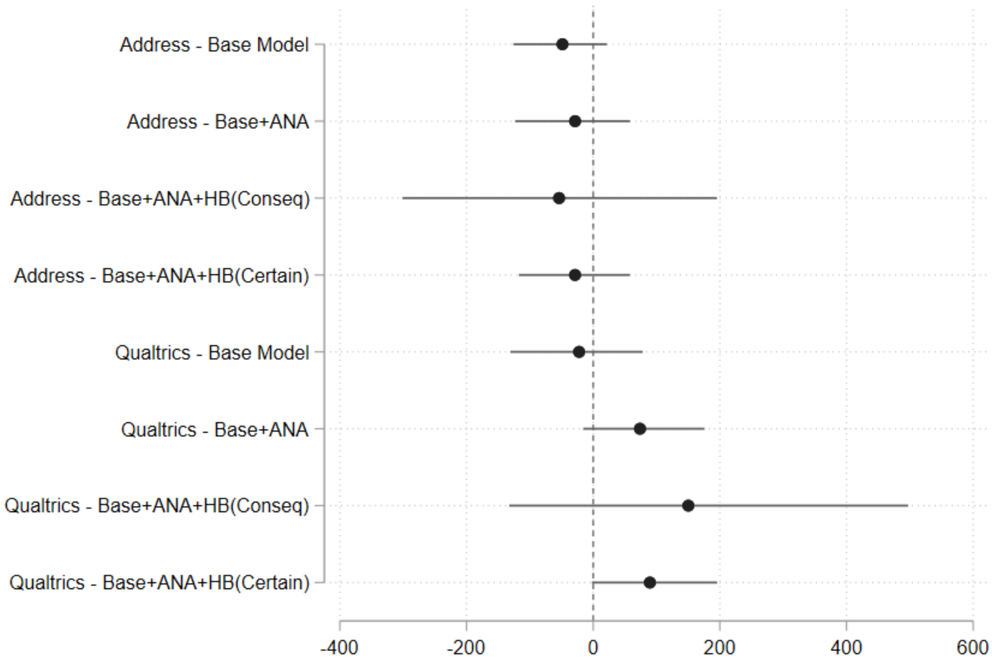
(-100,-0.5] (-0.5,0.5] (0.5,100] NA

Notes: Figure reports the difference between the percent of respondents and the percent of the state population in each county, in panel (a) for the Address sample and panel (b) for the Qualtrics sample. Colors denote the magnitude and sign of this difference. In green counties, the percent of respondents is within 0.5 percent of the percent of the state population in that county. In yellow (purple) counties, the percent of respondents is higher (lower) than the percent of the state population by at least 0.5 percent. Counties without survey responses are labeled in gray. Respondent percentages are calculated after applying the first layer of exclusion criteria to remove invalid responses.

Figure 5: Comparison of MWTP estimates across models from Table 3



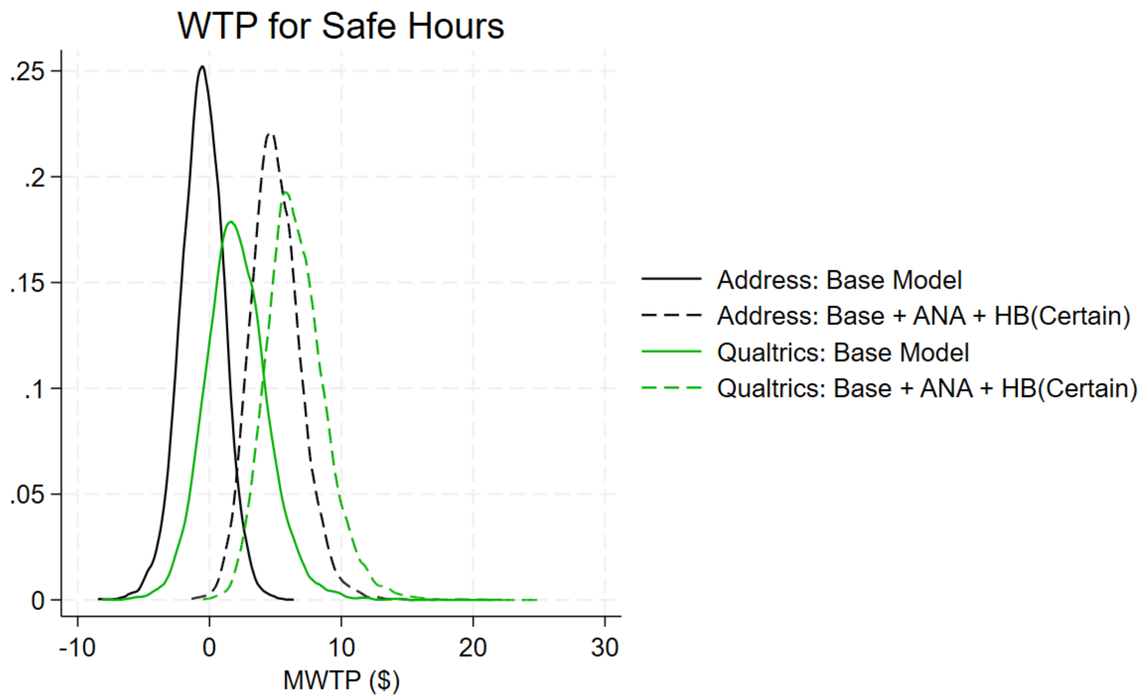
(a) For Safe Hours



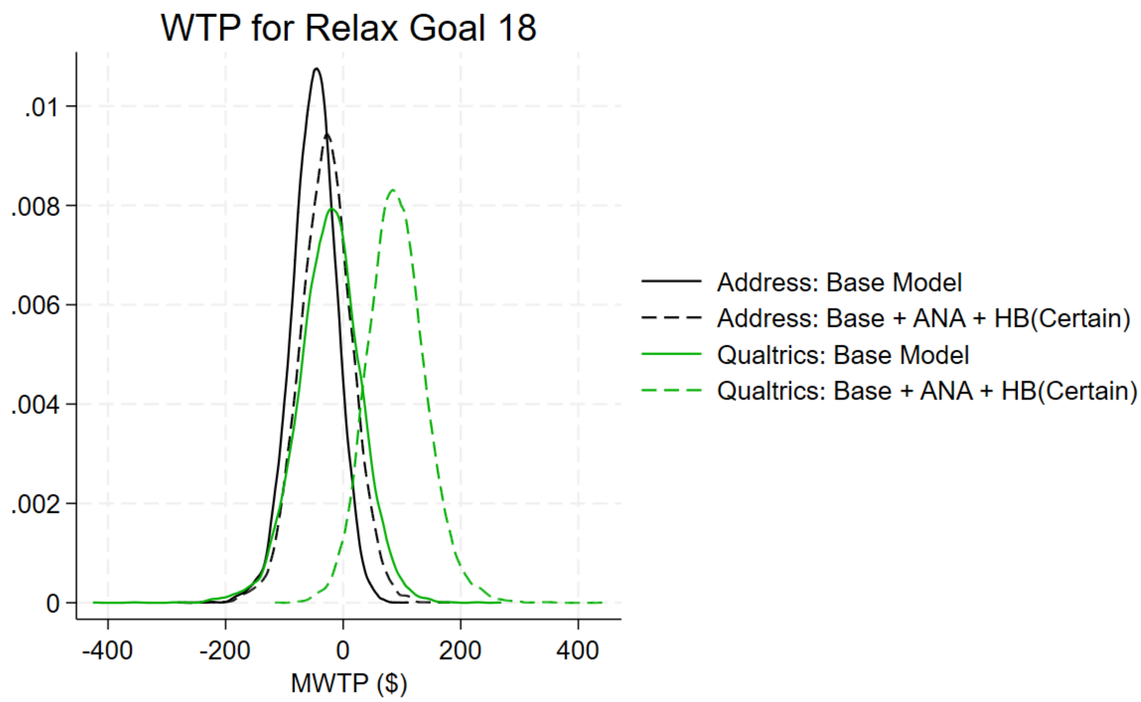
(b) For Relaxing Goal 18 Armoring Policy

Notes: Figure reports median $MWTP$ and 95% CIs for the simulated $MWTP$ distributions of the (a) safe hours and (b) relax Goal 18 armoring policy attributes, by sample frame and model. Median $MWTP$ values with CIs that do not overlap the dashed vertical line at 0 are statistically significant at the 5% significance level at least. CIs that overlap this line represent $MWTP$ values that are not statistically different from 0.

Figure 6: Comparison of kernel density plots of MWTP distributions of attributes in models in Table 3



(a)



(b)

Table 1: Attributes of the advisory referendum in the stated preference survey

Attribute	Level of Attribute
Percent loss of safe hours prevented ($\%\Delta$ *Safe Hours*)	10%, 20%, 30%, 40%
'Relax' Goal 18 scenario (*1(Relax)*)	0 or 1
Bid	$0 (Do Nothing Option Only), $10, $25, $50, $75, $100, $150, $200, $300, $400

Table 2: Summary statistics for valid responses, by sample and exclusion criteria corrections

	Address				Qualtrics			
	First Criteria		All Criteria		First Criteria		All Criteria	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Voted yes	0.50	(0.50)	0.50	(0.50)	0.50	(0.50)	0.50	(0.50)
Bid	72.81	(114.72)	70.62	(112.42)	71.38	(112.65)	72.46	(113.68)
% loss of safe hours prevented	-12.52	(14.81)	-12.55	(14.83)	-12.56	(14.85)	-12.50	(14.80)
In 'Relax' Goal 18 scenario	0.25	(0.43)	0.25	(0.43)	0.25	(0.43)	0.26	(0.44)
Results seen as consequential	0.84	(0.37)	0.88	(0.32)	0.91	(0.29)	0.92	(0.28)
Certain about vote	0.50	(0.50)	0.56	(0.50)	0.60	(0.49)	0.61	(0.49)
Likely ANA to bid	0.36	(0.48)	0.38	(0.49)	0.45	(0.50)	0.37	(0.48)
Likely ANA to % Δ safe hours	0.36	(0.48)	0.31	(0.46)	0.40	(0.49)	0.31	(0.46)
Likely ANA to Goal 18 policy	0.44	(0.50)	0.44	(0.50)	0.46	(0.50)	0.41	(0.49)
1(Have Kid(s)) $\times$ 1(Ans. Q.)	0.27	(0.44)	0.27	(0.45)	0.51	(0.50)	0.28	(0.45)
1(Educ. College+) $\times$ 1(Ans. Q.)	0.65	(0.48)	0.71	(0.46)	0.21	(0.40)	0.31	(0.46)
1(Inc. $100k+) $\times$ 1(Ans. Q.)	0.36	(0.48)	0.38	(0.49)	0.09	(0.28)	0.12	(0.32)
Total Alternatives	2094		1472		4772		2346	

Table 3: Conditional logit estimation results with homogeneous preferences

	(1) Base Model	(2) Base + ANA	(3) Base + ANA + HB(Conseq)	(4) Base + ANA + HB(Certain)
Panel A: Address Sample				
Bid	-0.004***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.000910)
Do nothing	-0.697***	-1.002***	-0.993***	-0.997***
	(0.185)	(0.234)	(0.238)	(0.247)
Percent loss of safe hours prevented	-0.002	0.028***	0.021	0.026***
	(0.006)	(0.009)	(0.019)	(0.00890)
In 'Relax' Goal 18 scenario	-0.184	-0.146	-0.284	-0.152
	(0.136)	(0.223)	(0.633)	(0.225)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	Y	Y	Y	Y
Total Alternatives	2094	1492	1484	1472
Log Likelihood	-693.40	-405.89	-401.73	-399.25
AIC	1400.80	831.78	829.46	818.50
BIC	1440.33	884.86	898.40	871.44
Panel B: Qualtrics Sample				
Bid	-0.002***	-0.004***	-0.003***	-0.003***
	(0.0003)	(0.001)	(0.001)	(0.001)
Do nothing	-0.661***	-0.786***	-0.777***	-0.673***
	(0.118)	(0.173)	(0.178)	(0.185)
Percent loss of safe hours prevented	0.003	0.019***	0.006	0.022***
	(0.004)	(0.006)	(0.015)	(0.006)
In 'Relax' Goal 18 scenario	-0.0378	0.262+	0.466	0.303*
	(0.084)	(0.160)	(0.444)	(0.156)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	N	N	N	N
Total Alternatives	4772	2378	2352	2348
Log Likelihood	-1574.92	-720.57	-703.58	-712.95
AIC	3157.84	1455.15	1427.17	1439.90
BIC	3183.72	1495.56	1484.80	1480.23

+ p<0.15, * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Table 4: Conditional logit estimation results with systematic heterogeneity

	(1) Base Model	(2) Base + ANA	(3) Base + ANA + HB(Conseq)	(4) Base + ANA + HB(Certain)
Panel A: Address Sample				
Bid	-0.004***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Do nothing	-0.710***	-1.016***	-1.015***	-1.009***
	(0.185)	(0.237)	(0.241)	(0.240)
Percent loss of safe hours prevented	-0.004	0.023**	0.009	0.022**
	(0.006)	(0.009)	(0.019)	(0.009)
%Δ Safe Hours × 1(Have Kid(s))	0.007	0.021**	0.024***	0.017**
	(0.005)	(0.008)	(0.009)	(0.008)
In 'Relax' Goal 18 scenario	-0.204+	-0.142	-0.331	-0.152
	(0.138)	(0.221)	(0.640)	(0.220)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	Y	Y	Y	Y
Total Alternatives	2094	1492	1484	1472
Log Likelihood	-692.47	-402.21	-397.21	-396.80
AIC	1400.95	826.41	822.42	815.60
BIC	1446.12	884.80	896.65	873.83
Panel B: Qualtrics Sample				
Bid	-0.002***	-0.004***	-0.003***	-0.003***
	(0.0003)	(0.001)	(0.001)	(0.001)
Do nothing	-0.674***	-0.809***	-0.804***	-0.694***
	(0.126)	(0.180)	(0.186)	(0.185)
Percent loss of safe hours prevented	-0.005	0.016***	-0.0004	0.018***
	(0.004)	(0.006)	(0.015)	(0.006)
%Δ Safe Hours × 1(Have Kid(s))	0.015***	0.010*	0.012**	0.010*
	(0.003)	(0.006)	(0.006)	(0.006)
In 'Relax' Goal 18 scenario	-0.038	0.247*	0.444	0.292*
	(0.084)	(0.150)	(0.444)	(0.154)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	N	N	N	N
Total Alternatives	4772	2378	2352	2348
Log Likelihood	-1562.57	-718.70	-701.20	-711.29
AIC	3135.13	1453.40	1424.41	1438.57
BIC	3167.48	1499.59	1487.80	1484.66

+ p<0.15, * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Table 5: Median MWTP with 95% confidence intervals from Table 3

	Median MWTP	Lower CI (2.5%)	Upper CI (97.5%)
Prevented percent loss of safe hours			
Address - (1) Base Model	-0.53	-3.90	2.59
Address - (2) Base + ANA	5.44	2.02	9.90
Address - (3) Base + ANA + HB(Conseq)	3.95	-3.21	12.24
Address - (4) Base + ANA + HB(Certain)	4.91	1.62	9.11
Qualtrics - (1) Base Model	1.96	-2.33	7.01
Qualtrics - (2) Base + ANA	5.49	2.19	9.89
Qualtrics - (3) Base + ANA + HB(Conseq)	1.96	-7.82	12.39
Qualtrics - (4) Base + ANA + HB(Certain)	6.39	2.69	11.67
Relaxing Goal 18			
Address - (1) Base Model	-48.49	-126.11	21.67
Address - (2) Base + ANA	-28.65	-123.28	58.17
Address - (3) Base + ANA + HB(Conseq)	-53.84	-301.21	195.39
Address - (4) Base + ANA + HB(Certain)	-28.71	-117.33	58.02
Qualtrics - (1) Base Model	-22.20	-130.77	78.16
Qualtrics - (2) Base + ANA	73.88	-15.70	175.70
Qualtrics - (3) Base + ANA + HB(Conseq)	150.29	-132.62	497.31
Qualtrics - (4) Base + ANA + HB(Certain)	89.60	-1.85	195.69

All estimates are in 2022 dollars.

Table 6: Combinatorial test of differences between MWTP distributions from Table 5

Comparison of Address vs Qualtrics	Safe Hours	Relax Goal 18
(1) Base Model (potentially valid responses)	NS	NS
(2) Base + ANA and other anomalies	NS	+
(3) Base + ANA + HB(Consequentiality)	NS	NS
(4) Base + ANA + HB(Certainty Follow-up)	NS	*

*** p<0.01, ** p<0.05, * p<0.1, + p<0.15, NS Not Significant

Appendix

A Advisory Referendum Development

A.1 Determining Safe Hours Measure

Daylight hours are designated as *safe* if a minimum beach width is met, which is defined as the distance between total water level elevation (i.e., the maximum elevation that water reaches on the shore) and back shore feature elevation (e.g., the elevation of the dune or cliff toe). Total water levels (TWLs) were calculated for the historical period at the county scale using deep water wave data (wave height, period, and direction) from GOW2 wave hindcast nodes (Perez et al., 2017) and water level data from NOAA tide gauges at Port Orford, South Beach, Garibaldi, and Astoria. Wave and water level data were input into nearshore surrogate models (SWAN lookup tables combined with empirical Stockdon run up formulas) following the methodology presented in Serafin et al. (2019) to extract TWLs at 1000 m resolution. This process was repeated for each site after adding three regional SLR projections for 2050 representing intermediate likelihoods for low, moderate, and high global mean SLR scenarios to the water level inputs (Sweet et al., 2017).

Daylight hours were identified for each day of the year using sunrise and sunset data for a coastal town (Newport) at approximately the midpoint (average) latitude of Oregon (NOAA Global Monitoring Laboratory, n.d.). We calculate beach width for the 16 developed beaches at multiple points for each beach to ensure a 1 km resolution. These 16 beaches were chosen with expert feedback because they are the most popular developed beaches on the Oregon Coast (Plybon, 2021). We use three different minimum beach width measures – 10 m, 15 m, and 20 m – in an attempt to capture different perceptions about what constitutes as *safe* to access and recreate on. The number of daylight safe hours are counted for each day of the year, for each of the three minimum beach width definitions, and at each of the 16 developed beaches. This number is then aggregated by season to get the present-day seasonal average of safe hours at each location for each minimum beach width definition. Seasonal average safe hours are calculated for the year 2050 using three different sea level rise scenarios corresponding to 0.5 m, 1.0 m, and 1.5 m of sea level rise by 2100.

The present-day and projected seasonal average safe hours are used to determine the percent change (loss) in safe hours by 2050 in the status quo scenario. Projected percent losses informed the range of the environmental quality change in the survey, i.e., the range of prevented percent loss of safe hours under the proposed coastal management plan. Thus, the attribute levels shown to respondents for the prevented percent loss of safe hours were 10%, 20%, 30%, and 40%.

B Data Processing

B.1 Exclusion Criteria

This section describes the exclusion criteria used to remove survey takers we determined did not provide valid data. The first layer of exclusion criteria is the broadest in that it removes the most easily-identifiable invalid data. It first removes suspected bots by dropping participants who entered gibberish or nonsensical comments in the open-ended comment box at the end of the survey (0 Address observations, 11 Qualtrics observations). The Qualtrics sample's survey includes termination points that immediately drop participants who may not be inside the sample frame. The first exclusion criteria removes failures of the first two termination points - responses with the same IP address (85 Qualtrics) and participants who provided a ZIP code outside of Oregon (220 Qualtrics). For the Address sample, duplicate responses were dropped by the unique access code instead of by

IP address, which allowed for more accurate identification of duplicates (7 Address). A key difference between sample frames is that Address participants' ZIP codes were not self-reported so this sample was not subject to ZIP code-based termination. The Qualtrics panel sample's survey also terminated responses where participants did not provide age or gender information for the demographic quotas (12 and 42 Qualtrics, respectively). Participants who did not provide age or gender information in the Address sample were not dropped since that information was not required.There were 14 respondents who did not provide age and 58 who did not provide gender in the Address sample. Another termination point in the Qualtrics sample's survey dropped participants whose IP address was not located in Oregon (422 Qualtrics). Address sample participants were not dropped according to their IP address since residing at an Oregon address was a prerequisite for having access to the survey. Participants who self-reported their age as under 18 were terminated from both sample frames (30 Qualtrics, 1 Address). An additional 387 completed responses were dropped from the Qualtrics sample that would have been terminated if not for an error made when Qualtrics established their termination points.

The second layer of exclusion criteria build on the first layer and removes participants whose response behavior suggests they had incomplete comprehension or were not truthful or sincere in their responses. We drop respondents who sped through the survey (163 Qualtrics, 0 Address), defined as having a total time to complete the survey of less than nine minutes. This was set as the speeding threshold based on the distribution of complete response times in the pretest data. We also drop inattentive respondents who failed our attention check debriefing question (729 Qualtrics, 141 Address). We drop protest responses (i.e., where participants rejected the premise or assumptions of the CV question), which were identified using debriefing questions similar to those used by Lewis et al. (2019). This drops respondents who strongly agreed with the following statements: I do not trust the Oregon State government to protect Oregon beaches; I do not believe it is the state government's responsibility to fund a coastal management plan; if applied, I do not think the proposed coastal management plan will succeed at preserving safe hours for recreation on Oregon's developed beaches. Respondents who strongly disagreed with the statement "I had enough information to make an informed vote" were also dropped as protest votes. This layer also accounts for ANA as another behavioral response anomaly using respondents' stated ANA information in the modeling stage to estimate separate coefficients for attending and non-attending respondents.

The third layer corrects for HB by removing the few respondents who exhibited warm glow and/or did not consider their budget constraint (< 20 total) and then applying the consequentiality or certainty follow-up adjustments as the primary HB mitigation technique. First, respondents who strongly agreed with the statement "I enjoy contributing to a good cause no matter what it is" but strongly disagreed with the statement "I considered whether I can afford to pay for the proposed management plan" were dropped since they did not consider their budget constraint and exhibit warm glow, which suggests they receive utility from stating a WTP but not for the change actually being valued. This layer then corrects for HB using the consequentiality or certainty follow-up debriefing question responses to create indicators that are interacted with the attributes or the dependent variable, respectively. Section B.2 of the Online Appendix describes how the stated ANA, consequentiality, and certainty follow-up variables are constructed. Section 4 of the paper describes how these variables are used in estimation.

Cleaning the data using the first layer of exclusion criteria yields 2386 and 1047 complete responses in the Qualtrics and Address samples, respectively. Applying the second layer to capture behavioral response anomalies yields 1189 and 746 complete responses in the Qualtrics and Address samples, respectively, which includes both respondents who did and did not attend to the attributes.

The third layer of exclusion criteria drops few observations regardless whether consequentiality or certainty corrections are used since HB is mitigated primarily post-cleaning in the modeling stage. Table A2 extends Table 2 in the paper and reports summary statistics for both HB correction approaches. As before, the *First Criteria* column summarizes the attribute, HB, and ANA variables for all alternatives after applying the first layer of exclusion criteria, where the number of alternatives is twice the number of complete responses in each cleaned data set. The *All - Conseq* and *All - Certain* columns report these statistics after applying all exclusion criteria using the consequentiality and certainty follow-up HB corrections, respectively. There are fewer total alternatives in the certainty-adjusted data because that correction drops two (Qualtrics) and six (Address) responses that are missing certainty follow-up answers but not consequentiality answers. Applying the third layer using the consequentiality correction yields 1175 and 742 complete responses in the Qualtrics and Address samples, respectively, whereas using the certainty follow-up correction yields 1173 and 736 complete responses in the Qualtrics and Address sample.

B.2 Hypothetical Bias and ANA Exclusion Criteria

This section describes how we determine which responses likely exhibit HB and/or ANA using debriefing questions about policy consequentiality, vote certainty, and ANA. All three sets of questions ask respondents to select their answer on a 5-point Likert scale or select a *not sure* option. The vote certainty question immediately follows the valuation question and asks respondents, "How certain are you of your vote?" with Likert scale options ranging from *extremely certain* to *not at all certain*. The ANA question subsequently asks respondents to "Please select how important each factor was in influencing your vote" with options ranging from *very important* to *not at all important* for each attribute of the advisory referendum - safe hours, shoreline armoring policy, and cost. The consequentiality question asks respondents, "How much do you agree or disagree with the following statement? The results of this survey will influence Oregon state agencies and policymakers as they make their decisions about future coastal management plans for developed beaches" on a scale from *strongly agree* to *strongly disagree*.

We group responses to create binary indicators for consequentiality, certainty, and for ANA (for each attribute). We test different thresholds of these indicators by varying how strictly we treat neutral and uncertain responses. The strictest threshold retains a response in the indicator (= 1) only when it is in strong agreement with the given statement whereas the least strict threshold also retains neutral and uncertain responses, treating them as potentially indifferent but not in disagreement with the statement. These indicators are incorporated through interactions in Models (2) to (4) as described in section 4 of the paper.

We explore the effect of different consequentiality thresholds in models where only the consequentiality correction is applied, i.e., we interact the given *consequential* indicator with each of the valuation question attributes. Our approach to accounting for stated consequentiality is similar to that of Vossler et al. (2012), except that we collapse the Likert scale response to a binary consequential indicator whereas Vossler et al. (2012) retain the Likert scale levels in a categorical consequential variable. We find that the significance and magnitude of the parameter estimates remains stable across different consequentiality thresholds, though the model with the strictest consequential threshold is underpowered due to the (effective) loss of observations that are corrected for HB. We use a similar approach to investigate the effect of varying the certainty threshold. Certainty indicators are interacted with the binary dependent variable, as in Penn et al. (2023), which recodes *yes* votes on the advisory referendum to *no* if the certainty threshold suggests the respondent was not certain about their vote. We find similar results as with consequentiality - parameter estimates remain stable as the certainty threshold is varied. Thus, when correcting for HB we use the least strict definition of policy consequentiality or vote certainty, setting these indicators to 0 for only the respondents who stated they did not think the survey was consequential or who said they were not certain about their vote, respectively.

For ANA we create a *likely attending* indicator for each attribute. The strictest version of this indicator is equal to 1 if the respondent said the attribute's outcome was *very important* or *moderately important* in influencing their vote. If the respondent chose *neutral*, *slightly important*, *not at all important*, or *not sure*, we assume that they likely did not attend to that attribute. The least strict definition does not differentiate between non-attendance and indifference, classifying *neutral* and *slightly important* (or *neutral* and *not sure* in an alternate specification) as likely attending or at least indifferent. We test these stated ANA thresholds by interacting the *neutral* and *likely attending* indicators with their respective attributes, following the ANA validation model of Hess and Hensher (2010). In contrast to the HB threshold investigations, we find differences in parameter estimates between attending and non-attending respondents as the stated ANA threshold shifts, suggesting that the difference between attending and non-attending respondents is blurred as the strictness of the attending definition decreases and respondents who are potentially indifferent are included in the *likely attending* group. So to avoid capturing potentially indifferent respondents we use the strictest ANA threshold to correct for stated ANA, treating as attending only those respondents who stated that all three attributes were *very* or *moderately* important in influencing their vote. Thus, our preferred specifications for Models (2) through (4) use the least strict definition of consequentiality or certainty and the strictest definition of ANA.

B.3 Sample Selection Correction

This section describes how we correct for sample selection in the Address sample. We follow the two-stage approach developed by Cameron and DeShazo (2013). The sample selection model is estimated in the first stage using a probit model where the outcome variable is 1 if the individual responded to the survey and 0 if they did not. We use a wide array of independent variables that could explain systematic differences in the propensity of the survey takers in the address-based sample frame to respond to the survey. Following the literature (e.g., Cameron and DeShazo 2013; Cameron and Kolstoe 2022; Johnston and Abdulrahman 2017; Kolstoe and Cameron 2017; Lewis et al. 2019), we regress whether an individual from the given sample frame responded to the survey on socioeconomic data, political ideology, geography, and availability of fast broadband for their ZIP code, where Census ZIP Code Tabulation Area (ZCTA) serves as a proxy for ZIP code. We also include a coastal county dummy and county-level fixed effects in this first stage regression. Table A1 presents ZCTA-level descriptive statistics by sample for the ZIP codes with survey responses as used in the first stage sample selection model. Sample selection correction using these variables is only applied to the Address sample. Descriptive statistics are presented for the Qualtrics sample for comparison only.

We predict the fitted response propensities from the first stage and estimate their mean. We then demean the fitted response propensities prior to incorporating them into the second stage. When the fitted response propensity variable is zero, the survey subject's predicted response propensity is the mean of the entire set of survey subjects.

In the second stage choice model, we interact the demeaned fitted response propensity from the first stage selection model with every variable. This allows all of the estimated parameters in the choice model to vary systematically with the demeaned fitted response propensities for the estimating sample. Finally, we simulate the parameter estimates that we would have obtained had everyone in the estimating sample shared the mean response propensity in the eligible population.

C Additional Tables and Figures

C.1 Additional Tables

Table A1: Descriptive statistics of ZCTAs with survey responses by sample as used in the first stage sample selection model

	Address		Qualtrics	
Variables (ZCTA-level)	Mean	Std Dev	Mean	Std Dev
Median age	40.47	(6.14)	40.49	(6.56)
% Female	50.46	(2.16)	50.51	(2.28)
% White	83.10	(8.89)	83.07	(9.00)
% Hispanic	12.61	(9.21)	12.86	(9.41)
% Bachelors or higher	34.63	(16.82)	32.46	(16.62)
% Renter occupied	36.94	(12.91)	38.37	(13.22)
Median Household income (in $10,000)	6.86	(1.89)	6.50	(1.84)
% Unemployed	3.39	(1.13)	3.48	(1.13)
% voted for Republican for 2020 OR house	0.45	(0.23)	0.46	(0.22)
% voted for minor party for 2020 OR house	0.02	(0.03)	0.02	(0.03)
1(Urban Area)	0.94	(0.24)	0.94	(0.23)
% State pop in geography	0.75	(0.45)	0.75	(0.45)
1(Coastal geography)	0.06	(0.24)	0.07	(0.26)
1(Coastal county)	0.18	(0.38)	0.23	(0.42)
1(cable broadband)	0.85	(0.36)	0.85	(0.36)
1(copper/DSL broadband)	0.52	(0.50)	0.50	(0.50)
1(fiber broadband)	0.45	(0.50)	0.40	(0.49)
1(5G broadband)	0.98	(0.13)	0.98	(0.15)
Observations	9998		3273	

Table A2: Summary statistics for valid responses, by sample and exclusion criteria corrections

	Address						Qualtrics					
	First Criteria		All - Conseq		All - Certain		First Criteria		All - Conseq		All - Certain	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Voted yes	0.50	(0.50)	0.50	(0.50)	0.50	(0.50)	0.50	(0.50)	0.50	(0.50)	0.50	(0.50)
Bid	72.81	(114.72)	70.71	(112.33)	70.62	(112.42)	71.38	(112.65)	72.43	(113.63)	72.46	(113.68)
% Δ Safe Hours	-12.52	(14.81)	-12.54	(14.82)	-12.55	(14.83)	-12.56	(14.85)	-12.49	(14.79)	-12.50	(14.80)
In 'Relax' Goal 18 scenario	0.25	(0.43)	0.25	(0.43)	0.25	(0.43)	0.25	(0.43)	0.26	(0.44)	0.26	(0.44)
Results seen as consequential	0.84	(0.37)	0.88	(0.32)	0.88	(0.32)	0.91	(0.29)	0.92	(0.28)	0.92	(0.28)
Certain about vote	0.50	(0.50)	0.56	(0.50)	0.56	(0.50)	0.60	(0.49)	0.61	(0.49)	0.61	(0.49)
Likely ANA to bid	0.36	(0.48)	0.39	(0.49)	0.38	(0.49)	0.45	(0.50)	0.38	(0.48)	0.37	(0.48)
Likely ANA to % Δ safe hours	0.36	(0.48)	0.31	(0.46)	0.31	(0.46)	0.40	(0.49)	0.31	(0.46)	0.31	(0.46)
Likely ANA to Goal 18 policy	0.44	(0.50)	0.45	(0.50)	0.44	(0.50)	0.46	(0.50)	0.41	(0.49)	0.41	(0.49)
1(Have Kid(s)) $\times$ 1(Ans. Q.)	0.27	(0.44)	0.28	(0.45)	0.27	(0.45)	0.51	(0.50)	0.28	(0.45)	0.28	(0.45)
1(College+) $\times$ 1(Ans. Q.)	0.65	(0.48)	0.70	(0.46)	0.71	(0.46)	0.21	(0.40)	0.31	(0.46)	0.31	(0.46)
1(Inc. $100k+) $\times$ 1(Ans. Q.)	0.36	(0.48)	0.38	(0.49)	0.38	(0.49)	0.09	(0.28)	0.12	(0.32)	0.12	(0.32)
Total Alternatives	2094		1484		1472		4772		2350		2346	

Table A3: Full CLM results with homogeneous preferences - Address sample

	(1) Base Model	(2) Base + ANA	(3) Base + ANA + HB(Conseq)	(4) Base + ANA + HB(Certain)
Bid	-0.004***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Do nothing	-0.697***	-1.002***	-0.993***	-0.997***
	(0.185)	(0.234)	(0.238)	(0.247)
Percent loss of safe hours prevented	-0.002	0.028***	0.021	0.026***
	(0.006)	(0.009)	(0.019)	(0.009)
In 'Relax' Goal 18 scenario	-0.184	-0.146	-0.284	-0.152
	(0.136)	(0.223)	(0.633)	(0.225)
Bid × demeaned prop. in sample	0.005**			
	(0.003)			
%Δ Safe Hours × demeaned prop.	0.027			
	(0.019)			
1(Relax) × demeaned prop.	-1.093*			
	(0.661)			
Bid × 1(ANA)		0.002*	0.002*	0.001
		(0.001)	(0.001)	(0.001)
%Δ Safe Hours × 1(ANA)		-0.083***	-0.080***	-0.086***
		(0.008)	(0.009)	(0.009)
1(Relax) × 1(ANA)		-0.166	-0.163	-0.232
		(0.258)	(0.270)	(0.251)
Bid × demeaned prop. in sample		0.002	0.003	0.004
		(0.003	(0.003)	(0.003)
%Δ Safe Hours × demeaned prop.		0.026	0.021	0.023
		(0.026)	(0.026)	(0.028)
1(Relax) × demeaned prop.		-1.263	-1.093	-1.311
		(0.818)	(0.833)	(0.844)
Bid × 1(Conseq) × 1(Ans. Q.)			-0.001	
			(0.003)	
%Δ Safe H.×1(Conseq)×1(Ans. Q.)			0.009	
			(0.018)	
1(Relax) × 1(Conseq) × 1(Ans. Q.)			0.089	
			(0.625)	
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	Y	Y	Y	Y
Total Alternatives	2094	1492	1484	1472
Log Likelihood	-693.40	-405.89	-401.73	-399.25
AIC	1400.80	831.78	829.46	818.50
BIC	1440.33	884.86	898.40	871.44

+ $p<0.15$, * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors in parentheses.

Note: Demeaned propensities are generated in the first stage of selection correction using the given Model's sample.

Table A4: Full CLM results with homogeneous preferences - Qualtrics sample

	(1) Base Model	(2) Base + ANA	(3) Base + ANA + HB(Conseq)	(4) Base + ANA + HB(Certain)
Bid	-0.002***	-0.004***	-0.003***	-0.003***
	(0.0003)	(0.001)	(0.001)	(0.001)
Do nothing	-0.661***	-0.786***	-0.777***	-0.673***
	(0.118)	(0.173)	(0.178)	(0.185)
Percent loss of safe hours prevented	0.0033	0.019***	0.006	0.022***
	(0.004)	(0.006)	(0.015)	(0.006)
In 'Relax' Goal 18 scenario	-0.038	0.262	0.466	0.303*
	(0.084)	(0.160)	(0.444)	(0.156)
Bid × 1(ANA)		0.002***	0.002***	0.002***
		(0.001)	(0.001)	(0.001)
%Δ Safe Hours × 1(ANA)		-0.046***	-0.045***	-0.049***
		(0.005)	(0.005)	(0.006)
1(Relax) × 1(ANA)		-0.500***	-0.474**	-0.530***
		(0.185)	(0.184)	(0.188)
Bid × 1(Conseq) × 1(Ans. Q.)			-0.005**	
			(0.002)	
%Δ Safe H.×1(Conseq)×1(Ans. Q.)			0.015	
			(0.014)	
1(Relax) × 1(Conseq) × 1(Ans. Q.)			-0.240	
			(0.447)	
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	N	N	N	N
Total Alternatives	4772	2378	2352	2348
Log Likelihood	-1574.92	-720.57	-703.58	-712.95
AIC	3157.84	1455.15	1427.17	1439.90
BIC	3183.72	1495.56	1484.80	1480.23

+ p<0.15, * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Table A5: Median TWTP with 95% confidence intervals for all models from Table 3

	Median TWTP	Lower CI (2.5%)	Upper CI (97.5%)
0% Prevented Loss of Safe Hours			
Address - (1) Base Model	209.64	111.67	324.25
Address - (2) Base + ANA	196.07	109.33	311.26
Address - (3) Base + ANA + HB(Cons)	188.81	100.92	307.76
Address - (4) Base + ANA + HB(Cert)	187.25	99.26	300.97
Qualtrics - (1) Base Model	387.99	257.72	609.40
Qualtrics - (2) Base + ANA	220.94	130.10	340.26
Qualtrics - (3) Base + ANA + HB(Cons)	248.15	141.22	401.79
Qualtrics - (4) Base + ANA + HB(Cert)	197.72	93.98	325.04
10% Prevented Loss of Safe Hours			
Address - (1) Base Model	206.51	135.79	291.93
Address - (2) Base + ANA	250.29	182.52	357.86
Address - (3) Base + ANA + HB(Cons)	227.81	136.88	363.08
Address - (4) Base + ANA + HB(Cert)	236.14	168.88	340.40
Qualtrics - (1) Base Model	407.09	298.42	615.88
Qualtrics - (2) Base + ANA	275.66	202.89	389.28
Qualtrics - (3) Base + ANA + HB(Cons)	267.25	154.04	434.54
Qualtrics - (4) Base + ANA + HB(Cert)	261.53	184.09	382.10
20% Prevented Loss of Safe Hours			
Address - (1) Base Model	202.90	149.35	272.98
Address - (2) Base + ANA	304.49	238.20	419.74
Address - (3) Base + ANA + HB(Cons)	267.56	130.88	457.30
Address - (4) Base + ANA + HB(Cert)	285.08	220.43	393.98
Qualtrics - (1) Base Model	426.71	326.23	637.70
Qualtrics - (2) Base + ANA	330.32	259.35	451.56
Qualtrics - (3) Base + ANA + HB(Cons)	287.13	111.72	521.92
Qualtrics - (4) Base + ANA + HB(Cert)	325.39	251.14	455.18
30% Prevented Loss of Safe Hours			
Address - (1) Base Model	199.70	144.77	269.84
Address - (2) Base + ANA	358.85	278.04	496.96
Address - (3) Base + ANA + HB(Cons)	306.10	108.15	569.21
Address - (4) Base + ANA + HB(Cert)	334.31	257.96	462.84
Qualtrics - (1) Base Model	446.36	339.91	667.63
Qualtrics - (2) Base + ANA	385.01	302.45	526.88
Qualtrics - (3) Base + ANA + HB(Cons)	305.59	42.65	633.94
Qualtrics - (4) Base + ANA + HB(Cert)	389.12	302.10	544.74
40% Prevented Loss of Safe Hours			
Address - (1) Base Model	196.15	121.99	283.36
Address - (2) Base + ANA	413.86	309.20	585.09
Address - (3) Base + ANA + HB(Cons)	346.90	81.01	683.64
Address - (4) Base + ANA + HB(Cert)	384.16	285.95	542.02
Qualtrics - (1) Base Model	465.66	340.61	707.27
Qualtrics - (2) Base + ANA	440.26	335.01	615.48
Qualtrics - (3) Base + ANA + HB(Cons)	324.72	-25.84	747.57
Qualtrics - (4) Base + ANA + HB(Cert)	453.22	341.67	649.58

Note: All estimates are for the scenario where Goal 18 is not relaxed. All estimates are in 2022 dollars.

Table A6: Additional CLM results with systematic heterogeneity - Address sample

	Base + ANA + HB(Conseq)		Base + ANA + HB(Certain)	
	Kids & Education	Kids & Income	Kids & Education	Kids & Income
Bid	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Do nothing	-0.976***	-1.017***	-0.976***	-1.017***
	(0.249)	(0.242)	(0.249)	(0.242)
%Δ Safe Hours	-0.005	0.019*	-0.005	0.019*
	(0.021)	(0.010)	(0.021)	(0.010)
In 'Relax' Goal 18 scenario	-0.112	-0.192	-0.112	-0.192
	(0.695)	(0.257)	(0.695)	(0.257)
%Δ Safe Hours × 1(Have Kid(s)) × 1(Ans. Q.)	0.027**	0.019*	0.027**	0.019*
	(0.012)	(0.011)	(0.012)	(0.011)
1(Have Kid(s)) × 1(Ans. Q.)	-0.007	-0.158	-0.007	-0.158
	(0.428)	(0.390)	(0.428)	(0.390)
%Δ Safe Hours × 1(College+) × 1(Ans. Q.)	0.025**		0.025**	
	(0.012)		(0.012)	
1(Relax) × 1(College+) × 1(Ans. Q.)	-0.397		-0.397	
	(0.408)		(0.408)	
%Δ Safe Hours × 1(Inc. \$100k+) × 1(Ans. Q.)		0.006		0.006
		(0.010)		(0.010)
1(Relax) × 1(Inc. \$100k+) × 1(Ans. Q.)		0.175		0.175
		(0.372)		(0.372)
Bid × 1(ANA)	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
%Δ Safe Hour × 1(ANA)	-0.081***	-0.088***	-0.081***	-0.088***
	(0.009)	(0.009)	(0.009)	(0.009)
1(Relax) × 1(ANA)	-0.185	-0.232	-0.185	-0.232
	(0.268)	(0.259)	(0.268)	(0.259)
Bid × 1(Conseq) × 1(Ans. Q.)	-0.001		-0.001	
	(0.004)		(0.004)	
%Δ Safe Hours × 1(Conseq) × 1(Ans. Q.)	0.012		0.012	
	(0.019)		(0.019)	
1(Relax) × 1(Conseq) × 1(Ans. Q.)	0.216		0.216	
	(0.633)		(0.633)	
Bid × demeaned prop. in sample	0.003	0.005	0.003	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
%Δ Safe Hours × demeaned prop. in sample	0.005	0.015	0.005	0.015
	(0.025)	(0.026)	(0.025)	(0.026)
1(Relax) × demeaned prop. in sample	-0.899	-1.365*	-0.899	-1.365*
	(0.853)	(0.810)	(0.853)	(0.810)
ANA	Y	Y	Y	Y
Consequentiality	Y	N	Y	N
Certainty Follow-up	N	Y	N	Y
Sample Selection	Y	Y	Y	Y
Total Alternatives	1484	1472	1484	1472
Max. log-likelihood	-393.91	-395.51	-393.91	-395.51

[+] p<0.15, * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Note: Demeaned propensities are generated in the first stage of selection correction using the given Model's sample.

Table A7: Additional CLM results with systematic heterogeneity - Qualtrics sample

	Base + ANA + HB(Conseq)		Base + ANA + HB(Certain)	
	Kids & Education	Kids & Income	Kids & Education	Kids & Income
Bid	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.00)	1 (0.001)
Do nothing	-0.799***	-0.698***	-0.799***	-0.698***
	(0.186)	(0.180)	(0.186)	(0.180)
%Δ Safe Hours	-0.004	0.017***	-0.004	0.017***
	(0.015)	(0.006)	(0.015)	(0.006
In 'Relax' Goal 18 scenario	0.574	0.390**	0.574	0.390**
	(0.453)	(0.173)	(0.453)	(0.173)
%Δ Safe Hours × 1(Have Kid(s)) × 1(Ans. Q.)	0.016**	0.012*	0.016**	0.012*
	(0.008)	(0.007)	(0.008)	(0.007)
1(Have Kid(s)) × 1(Ans. Q.)	-0.185	-0.136	-0.185	-0.136
	(0.284)	(0.275)	(0.284)	(0.275)
%Δ Safe Hours × 1(College+) × 1(Ans. Q.)	0.008		0.008	
	(0.007)		(0.007)	
1(Relax) × 1(College+) × 1(Ans. Q.)	-0.152		-0.152	
	(0.259)		(0.259)	
%Δ Safe Hours × 1(Inc. $100k+) × 1(Ans. Q.)		0.008		0.008
		(0.011)		(0.011)
1(Relax) × 1(Inc. $100k+) × 1(Ans. Q.)		-0.482		-0.482
		(0.382)		(0.382)
Bid × 1(ANA)	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
%Δ Safe Hour × 1(ANA)	-0.044***	-0.049***	-0.044***	-0.049***
	(0.006)	(0.005)	(0.006)	(0.005)
1(Relax) × 1(ANA)	-0.471**	-0.525***	-0.471**	-0.525***
	(0.195)	(0.189)	(0.195)	(0.189)
Bid × 1(Conseq) × 1(Ans. Q.)	-0.005**		-0.005**	
	(0.002)		(0.002)	
%Δ Safe Hours × 1(Conseq) × 1(Ans. Q.)	0.018		0.018	
	(0.014)		(0.014)	
1(Relax) × 1(Conseq) × 1(Ans. Q.)	-0.265		-0.265	
	(0.452)		(0.452)	
ANA	Y	Y	Y	Y
Consequentiality	Y	N	Y	N
Certainty Follow-up	N	Y	N	Y
Sample Selection	N	N	N	N
Total Alternatives	2352	2348	2352	2348
Max. log-likelihood	-700.39	-710.19	-700.39	-710.19

+ p<0.15,* p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Table A8: Latent class logit results - Inferred ANA - Address sample

	Base Model	Base + ANA	Base + ANA + HB(Certain)
Class1			
Bid	-0.014***	-0.012**	-0.011**
	(0.005)	(0.005)	(0.005)
Do nothing alternative	-1.338+	-0.848	-0.924*
	(0.839)	(0.598)	(0.519)
Percent loss of safe hours prevented	-0.017	0.011	0.008
	(0.024)	(0.014)	(0.014)
In 'Relax' Goal 18 scenario	1.016	-0.371	-0.360
	(0.796)	(0.344)	(0.325)
Class2			
Bid	0.001	0	0
	(0.003)	(.)	(.)
Do nothing alternative	-0.936	-1.385	-1.136*
	(0.980)	(0.996)	(0.634)
Percent loss of safe hours prevented	0.039	0	0
	(0.029)	(.)	(.)
In 'Relax' Goal 18 scenario	-1.876**	0	0
	(0.950)	(.)	(.)
Share1			
Have Kid(s) × 1(Ans. Q.)	-0.546	-0.507	-0.398
	(0.474)	(0.422)	(0.481)
Income $100k+ × 1(Ans. Q.)	-0.095	-0.071	-0.185
	(0.349)	(0.356)	(0.405)
College Degree+ × 1(Ans. Q.)	-1.576***	-1.271*	-1.601*
	(0.570)	(0.725)	(0.822)
Constant	1.371**	1.286*	1.596+
	(0.636)	(0.696)	(1.019)
Inferred ANA	N	Y	Y
Certainty Follow-up	N	N	Y
Total Alternatives	1486	1486	1474
Max. log-likelihood	-468.04	-474.09	-472.48

+ p<0.15,* p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.
In Class 2, parameters on Bid, Do Nothing, %Δ Safe Hours and 1(Relax Goal 18)
are constrained to zero. Consequentiality was not included, as the model did not converge.
No sample selection parameters were included as they were not statistically significant.

Table A9: Latent class logit results - Inferred ANA - Qualtrics sample

	Base Model	Base + ANA	Base + ANA + HB(Certain)
Class1			
Bid	-0.019**	-0.019**	-0.019**
	(0.008)	(0.008)	(0.008)
Do nothing alternative	0.808	-0.483	-0.440
	(0.906)	(0.934)	(0.936)
Percent loss of safe hours prevented	0.022	0.015	0.019
	(0.028)	(0.023)	(0.024)
In 'Relax' Goal 18 scenario	1.916**	0.353	0.404
	(0.957)	(0.532)	(0.534)
Class2			
Bid	0.004	0	0
	(0.003)	(.)	(.)
Do nothing alternative	-13.50	-1.162**	-1.018***
	(335.3)	(0.467)	(0.355)
Percent loss of safe hours prevented	-0.017	0	0
	(0.027)	(.)	(.)
In 'Relax' Goal 18 scenario	-12.29	0	0
	(335.3)	(.)	(.)
Share1			
Have Kid(s) × 1(Ans. Q.)	-0.442**	-0.679*	-0.745*
	(0.188)	(0.384)	(0.412)
Income \$100k+ × 1(Ans. Q.)	-0.475+	-0.399	-0.548
	(0.303)	(0.535)	(0.642)
College Degree+ × 1(Ans. Q.)	-0.389**	-0.646+	-0.623+
	(0.186)	(0.431)	(0.401)
Constant	0.046	-0.395	-0.418
	(0.169)	(0.351)	(0.336)
Inferred ANA	N	Y	Y
Certainty Follow-up	N	N	Y
Total Alternatives	2352	2352	2348
Max. log-likelihood	-756.64	-758.74	-763.00

+ p<0.15,* p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Consequentiality was not included, as the model did not converge.

Table A10: Mixed logit estimation results

	Base Model	Base + ANA	Base + ANA + HB(Conseq)	Base + ANA + HB(Certain)
Panel A: Address Sample				
Bid	-0.004***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.003)	(0.004)	(0.003)
Do nothing	-0.715***	-1.339***	-1.354***	-1.438***
	(0.197)	(0.476)	(0.504)	(0.527)
Percent loss of safe hours prevented	-0.002	0.090**	0.074+	0.087**
	(0.006)	(0.044)	(0.049)	(0.043)
In 'Relax' Goal 18 scenario	-0.189	0.007	-0.630	-0.088
	(0.140)	(0.449)	(1.072)	(0.439)
SD				
Percent loss of safe hours prevented	-0.001	0.109*	0.113*	0.119*
	(0.024)	(0.057)	(0.063)	(0.061)
In 'Relax' Goal 18 scenario	-0.591	-2.146*	-2.310+	-1.692
	(1.213)	(1.302)	(1.440)	(1.358)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	Y	Y	Y	Y
Total Alternatives	2094	1492	1484	1472
Log Likelihood	-693.35	-401.62	-397.68	-394.34
AIC	1404.71	827.24	825.37	812.69
Panel B: Qualtrics Sample				
Bid	-0.002*	-0.009*	-0.012	-0.011
	(0.001)	(0.005)	(0.013)	(0.009)
Do nothing	-0.672***	-1.223**	-1.405	-1.253
	(0.157)	(0.604)	(1.280)	(0.939)
Percent loss of safe hours prevented	0.0130	0.119	0.112	0.166
	(0.023)	(0.093)	(0.175)	(0.170)
In 'Relax' Goal 18 scenario	-0.029	1.057	3.723	1.642
	(0.153)	(0.963)	(4.951)	(1.767)
SD				
Percent loss of safe hours prevented	0.052	0.195	0.323	0.268
	(0.083)	(0.151)	(0.422)	(0.280)
In 'Relax' Goal 18 scenario	0.298	2.762	-4.266	4.035
	(2.413)	(2.585)	(5.736)	(4.474)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	N	N	N	N
Total Alternatives	4772	2378	2352	2348
Log Likelihood	-1574.71	-713.58	-693.89	-704.25
AIC	3161.41	1445.16	1411.77	1426.50

+ p<0.15, * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Table A11: Mixed logit estimation results - with kid(s)

	Base Model	Base + ANA	Base + ANA + HB(Conseq)	Base + ANA + HB(Certain)
Panel A: Address Sample				
Bid	-0.004***	-0.008***	-0.009***	-0.009***
	(0.001)	(0.003)	(0.003)	(0.003)
Do nothing	-0.732***	-1.266***	-1.267***	-1.338***
	(0.198)	(0.414)	(0.419)	(0.456)
Percent loss of safe hours prevented	-0.004	0.068**	0.039	0.067*
	(0.006)	(0.033)	(0.035)	(0.035)
%Δ Safe Hours × 1(Have Kid(s))	0.008	0.039**	0.046**	0.029+
	(0.006)	(0.019)	(0.021)	(0.018)
In 'Relax' Goal 18 scenario	-0.198	-0.014	-0.607	-0.098
	(0.142)	(0.399)	(0.913)	(0.393)
SD				
Percent loss of safe hours prevented	-0.001	0.091*	0.090*	0.100*
	(0.024)	(0.046)	(0.048)	(0.051)
In 'Relax' Goal 18 scenario	-0.654	-1.776+	-1.848+	-1.416
	(1.129)	(1.142)	(1.180)	(1.234)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	Y	Y	Y	Y
Total Alternatives	2094	1492	1484	1472
Log Likelihood	-692.30	-398.44	-393.64	-392.77
AIC	1404.59	822.88	819.27	811.54
Panel B: Qualtrics Sample				
Bid	-0.003**	-0.009*	-0.011	-0.012
	(0.002)	(0.005)	(0.009)	(0.012)
Do nothing	-0.723***	-1.261**	-1.349	-1.384
	(0.221)	(0.620)	(0.968)	(1.164)
Percent loss of safe hours prevented	0.008	0.108	0.064	0.166
	(0.017)	(0.087)	(0.102)	(0.191)
%Δ Safe Hours × 1(Have Kid(s))	0.035+	0.038	0.058	0.054
	(0.023)	(0.033)	(0.063)	(0.065)
In 'Relax' Goal 18 scenario	-0.0001	0.966	3.186	1.784
	(0.240)	(0.893)	(3.537)	(2.161)
SD				
Percent loss of safe hours prevented	-0.099	0.196	0.290	0.294
	(0.087)	(0.155)	(0.307)	(0.338)
In 'Relax' Goal 18 scenario	0.638	2.494	-2.952	-4.486
	(2.785)	(2.434)	(3.724)	(5.537)
ANA	N	Y	Y	Y
Consequentiality	N	N	Y	N
Certainty Follow-up	N	N	N	Y
Sample Selection	N	N	N	N
Total Alternatives	4772	2378	2352	2348
Log Likelihood	-1561.33	-711.75	-691.83	-702.37
AIC	3136.65	1443.50	1409.66	1424.75

+ p<0.15, * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

Table A12: Median MWTP with 95% confidence intervals from Table 4

	Median MWTP	Lower CI (2.5%)	Upper CI (97.5%)
Prevented percent loss of safe hours			
Safe H. - HB(Cons) K1 - Address	1.85	-5.65	10.36
Safe H. Kid(s) - HB(Cons) K1 - Address	6.37	-1.09	16.37
Safe H. - HB(Cert) K1 - Address	4.15	0.81	8.17
Safe H. Kid(s) - HB(Cert) K1 - Address	7.36	3.41	13.08
Safe H. - HB(Cons) K1 Qualtrics	0.05	-9.30	9.94
Safe H. Kid(s) - HB(Cons) K1 Qualtrics	3.54	-5.36	14.35
Safe H. - HB(Cert) K1 - Qualtrics	5.43	1.85	10.37
Safe H. Kid(s) - HB(Cert) K1 - Qualtrics	8.17	3.93	14.16
Relaxing Goal 18			
Address - Base Model K1	-54.20	-137.04	17.03
Address - Base+ANA K1	-28.39	-121.53	59.68
Address - Base+ANA+HB(Cons) K1	-64.17	-325.32	189.44
Address - Base+ANA+HB(Cert) K1	-29.26	-122.52	54.41
Qualtrics - Base Model K1	-21.93	-128.54	77.22
Qualtrics - Base+ANA K1	68.42	-14.12	159.33
Qualtrics - Base+ANA+HB(Cons) K1	138.94	-141.63	453.28
Qualtrics - Base+ANA+HB(Cert) K1	85.05	-4.22	194.05

All estimates are in 2022 dollars.

Table A13: Combinatorial test of differences between MWTP distributions from Table A12

Comparison of Address vs Qualtrics	Safe Hours	Safe Hours Have Kid(s)	Relax Goal 18
(1) Base Model (potentially valid responses)	NS	+	NS
(2) Base + ANA and other anomalies	NS	NS	+
(3) Base + ANA + HB(Consequentiality)	NS	NS	NS
(4) Base + ANA + HB(Certainty Follow-up)	NS	NS	*

*** p<0.01, ** p<0.05, * p<0.1, + p<0.15, NS Not Significant

C.2 Additional Figures

Figure A1: Beach entrance sign warning recreators about common safety hazards

Photograph by Steven J. Dundas

Figure A2: Comparison of MWTP estimates across models from Table 4 - For Safe Hours

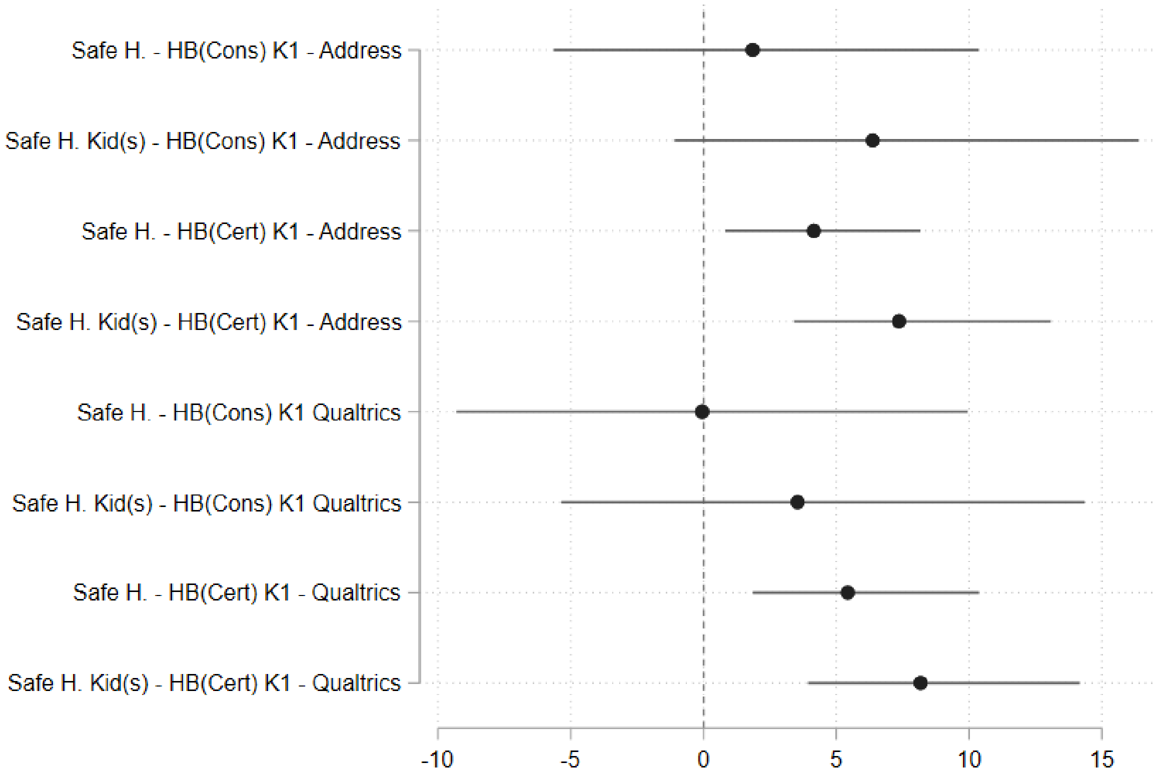
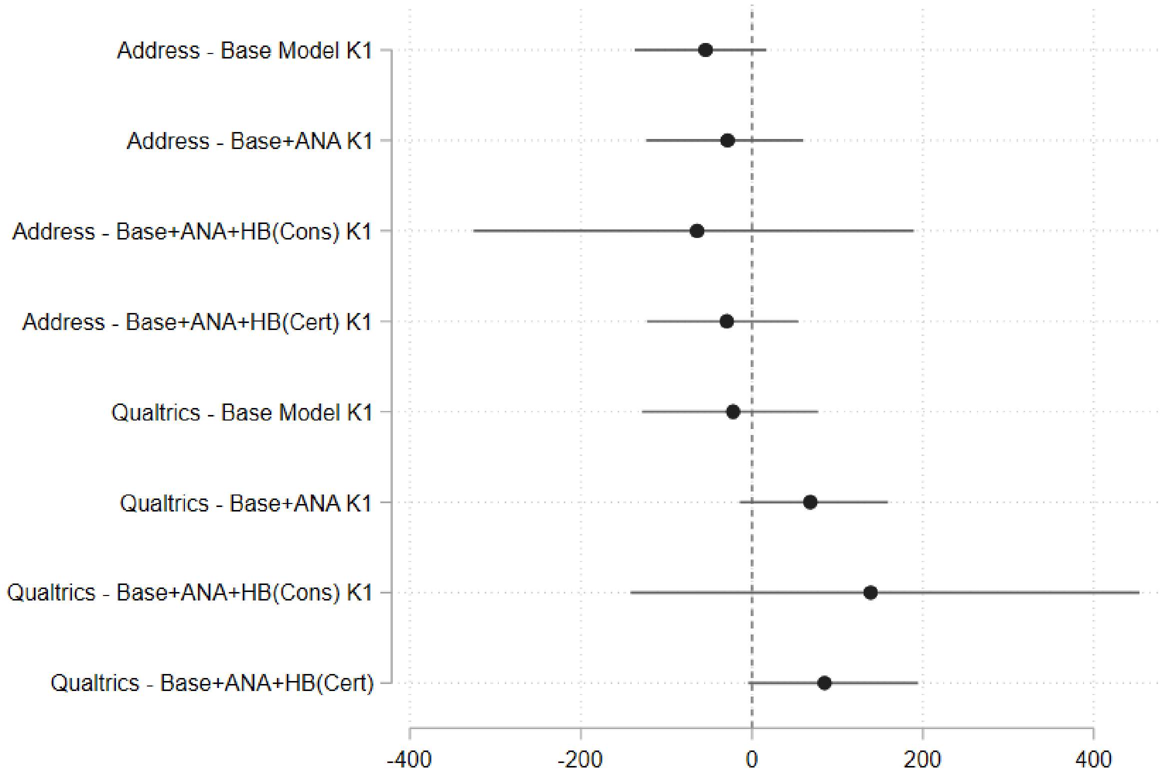


Figure A3: Comparison of MWTP estimates across models from Table 4 - For Relaxing Goal 18



D Survey Instrument

The Oregon Coast: A Survey about Coastal Recreation & Management Plans

We would like to learn more about your personal views on future management plans for Oregon's coastline and beaches. This survey provides you with key information about Oregon's beaches and will ask you a series of questions related to your experiences and vision for the future.

Lincoln City, Oregon

You might not have previous experience with this topic, but the state's beaches are a resource freely accessible to you, an Oregon resident, and your participation in this survey is very important to us.

Participation in this survey is voluntary. If you decide to participate, you will be asked to read about Oregon beaches and answer a series of questions that will take about 20 minutes. If you run out of time completing the survey, you may leave and return later to complete it. Your previous answers will be saved if you use the same device and Internet browser when returning. There are no known risks associated with participation in this survey. The benefits of this research study include providing Oregon state agencies and legislative bodies with information from the public that may help inform decisions about policies affecting Oregon's beaches.

Confidentiality of Records: Your individual responses to all questions in this survey will remain confidential. Any material linking you to your survey responses will not be released and will be destroyed at the end of the study.

Questions about this Survey? If you have any questions or concerns about this research project, please contact the principal investigator, Dr. Steven Dundas (dundas_survey@oregonstate.edu). If you have questions about your rights or welfare as a participant in this survey, please contact the Oregon State University Human Research Protection Program (HRPP) office at (541) 737-8008.

This research is sponsored by the National Oceanic and Atmospheric Administration (NOAA), a federal agency charged with managing the nation's coastal and marine resources.
Are you eligible and willing to be a participant in this study? By clicking Yes, you certify that:

- You are at least 18 years or older
- You currently live in Oregon
- You consent to have the information you provide used in this study

○ Yes

○ No

Please start by reading some background information on Oregon's beaches.

On June 7th, 1967, the Oregon Legislature passed the Beach Bill, which gave Oregonians a permanent easement to access and recreate on all beaches in the state. Unlimited access to the beach has made the Oregon Coast a source of recreation and enjoyment for residents and tourists alike.

Surfer in the water in Pacific City

Before today, were you aware that Oregon's 1967 Beach Bill guarantees permanent public access to coastal beaches in the state?

- Yes
- No
- Not sure

The first part of the survey focuses on recreation on Oregon's **developed beaches** - beaches in coastal towns with building and other structures behind the beach.

Undeveloped beaches, such as those found within Oregon's State Parks or U.S. Forest Service lands, are natural systems without significant coastal development. This type of beach is not the focus of this survey.

Both developed and undeveloped beaches can have amenities like parking, restrooms, and ramp access. However, developed beaches will have other services like restaurants, shops, and lodging facilities nearby.

Before today, have you ever visited developed and/or undeveloped beaches in Oregon?

- Yes, developed beaches only
- Yes, undeveloped beaches only
- Yes, both developed and undeveloped beaches
- No
- Not sure

*****Survey section eliciting recreation trip behavior is omitted here as this information is not used in this manuscript. A full copy of the survey instrument is available upon reasonable request.***

The second and final part of the survey focuses on future management of safe access to **Oregon's developed beaches**. Recreation opportunities on **developed** Oregon Coast beaches may be impacted by **erosion** driven by winter storms, currents, winds, rain, runoff, and elevated water levels caused by rising sea levels.

Beach erosion is a process where waves, storms, and local sea level rise remove beach sand and wear away the dunes and bluffs of the Oregon Coast, often resulting in a **narrower** beach. In the United States, beach erosion results in approximately $500 million dollars per year in property damages and loss of land.

Developed beaches (shown below on the left) tend to be **more vulnerable to the effects of erosion** than undeveloped (or natural) beaches. This is because coastal development is fixed in place and erosion narrows the beach in front of that development. These beaches may require active management to **preserve safe recreation access** in the future due to increasing erosion and sea level rise.

Undeveloped beaches (shown below on the right) are natural systems that can move and change with erosion due to a lack of development behind the beach and continue to preserve safe access for recreation.

DEVELOPED BEACH
Nye Beach in Newport.

UNDEVELOPED BEACH
South Beach State Park in Newport.

For example, erosion may cause the shoreline of an undeveloped beach to move inland but the beach can preserve width (and access) because it isn't confined by development behind the beach. On a developed beach, however, the beach gets narrower as it erodes because structures behind the beach fix the shoreline in place. As the beach loses width, beach access will decrease and oceanfront properties will become more vulnerable to erosion.

Before today, were you aware that developed beaches tend to be more vulnerable to erosion compared to undeveloped beaches?

- ○ Yes
- ○ No
- ○ Not sure

Safety is a key concern for people making recreation trips to the Oregon Coast. Three common safety hazards on the Oregon Coast are: **Sneaker waves**, which are waves that surge high up on the beach with deadly force, often appearing without warning. **Rip currents**, which are strong, narrow currents that can carry even the strongest swimmers away from shore. **King Tides**, which are extreme high tides that can reduce the amount of beach that is safely accessible and can also increase erosion to beaches and dunes.

For much of the West Coast of the U.S., sneaker waves result in more fatal accidents than all other weather hazards combined.

Waves of a winter storm near Depoe Bay

Before today, were you aware that sneaker waves are considered one of the deadliest natural hazards in Oregon?

- ◯ Yes
- ◯ No
- ◯ Not sure

These safety hazards impact the **number of daylight hours per day that people can safely access the beach and engage in recreation activities**, which we are defining here as **safe hours**. Safe hours can vary each day depending on the amount of daylight, the tides, the season (summer compared to winter), and the weather.

As an example, the images below show the **same beach** on a sunny winter day at high tide in Lincoln City. The photo on the left has a relatively wide beach with safe access for recreation. In the photo on the right, the ocean is covering the beach and it would be unsafe to walk or recreate on the beach. The photo on the right shows what this beach could look like in the future with the same tide, season, and weather conditions but with fewer safe hours.

An example of an accessible safe hour in Lincoln City.

An example of an unsafe hour on the same Lincoln City beach.

There is growing evidence that **erosion** and **rising sea levels** along the Oregon Coast have the potential to **decrease beach safe hours** now and in the future. Fewer (i.e., a loss of) safe hours on **developed** Oregon beaches will lead to a reduction in safely accessible beach areas and will increase the risks of safety hazards such as sneaker waves.

Before today, were you aware that the number of safe hours may decrease as erosion on developed beaches increases?

- ◯ Yes
- ◯ No
- ◯ Not sure

In addition to impacts to safe access for recreation, erosion also poses an increased threat to houses, businesses, roads, and other infrastructure behind **developed beaches**.

Currently, Oregon land use policy allows one option for homeowners to protect infrastructure behind developed beaches from erosion, known as **shoreline armoring**. This is a type of engineered infrastructure that involves the construction of seawalls, riprap revetments (rock piles), and other hard structures by private individuals on their own property.

Riprap in Neskowin, OR

Oregon's **Statewide Planning Goal 18 was originally implemented in 1977 to restrict armoring of private property** to conserve and protect Oregon's beaches and dunes in their natural state for all beach users. Goal 18 restricts armoring eligibility to land parcels where development existed prior to January 1st, 1977. All properties developed since that date are **not eligible** to install shoreline armoring, thus this option is not available to every homeowner. Given concerns about erosion and rising sea levels, there is currently debate across the state about relaxing, maintaining, or more strictly enforcing armoring rules.

About half (4,500) of Oregon’s 9,000 oceanfront parcels are eligible for armoring and half are not eligible. A recent study by Oregon State University found about 1,000 eligible parcels have installed shoreline armoring to date. **If Goal 18 is maintained**, projections suggest another 300 eligible parcels will install shoreline armoring in the next 30 years. **If Goal 18 is relaxed**, that number would rise to 550 parcels, including many that are not currently eligible.

Before today, were you familiar with shoreline armoring on developed Oregon beaches?

- ◯ Yes
- ◯ No
- ◯ Not sure

Reasons Oregon residents **may support shoreline armoring for private property** include:

- It may be effective at preventing land loss and damage to homes due to erosion.
- In addition to the erosion control benefits to property owners, it may also benefit beach visitors if they visit the places (for example, restaurants, hotels, shops) protected by the structures.

Reasons Oregon residents **may not support shoreline armoring for private property** include:

- It may lead to narrower and steeper beaches compared to those that are not armored, which can interfere with public access and make beaches less desirable and less safe for recreation.
- It may have negative effects such as loss of beach sand and beach habitat for native plants, birds, and wildlife.

Do you believe it is likely that Goal 18's armoring policy will be maintained in its current form for the foreseeable future?

○ Very likely

○ Somewhat likely

○ Neither likely nor unlikely

○ Somewhat unlikely

○ Very unlikely

A policy option used in other parts of the U.S. to control erosion is **sediment management**. This occurs when sand or other sediment is taken from another location and spread on a beach to increase beach width. **Beach nourishment** is the most used method along sandy coastlines in the U.S., especially along the East and Gulf Coasts.

To date, there have been **no** federal or state efforts to control erosion using sediment management on beaches in Oregon.

Beach nourishment project on Long Beach Island in New Jersey

Before today, were you familiar with beach nourishment as a sediment management option?

○ Yes

○ No

○ Not sure

Given the potential impacts to Oregon's **eroding developed beaches**, the state is considering **future policies to <u>prevent a loss of safe hours</u> for recreation while also <u>protecting property</u> from erosion**.

All beaches in Oregon (both developed and undeveloped) are **public** and managed by **Oregon State Parks** (under the Oregon Parks and Recreation Department). So, this agency may be tasked with implementing any new policy.

Oregon State Parks is currently **not funded** by tax dollars and relies on funding from the Oregon Lottery along with camping and parking fees, and RV registration fees. However, current revenue sources cannot cover the additional responsibilities created by a new policy.

Before today, did you know that Oregon State Parks manages Oregon's beaches?

- ◯ Yes
- ◯ No
- ◯ Not sure

Below are two options that the State of Oregon is considering.

<u>Option 1:</u>

The **first option** would **<u>increase</u> your household's annual state income taxes** by a small amount to implement **a new coastal management plan**. This plan would do two (2) things:

- **Create an <u>Oregon Public Beach Fund</u>** to manage sediment on eroding **developed** beaches. This fund would be overseen by Oregon State Parks and used to address erosion and **preserve access and safe hours for recreation**.
- **<u>Relax armoring restrictions</u>** under Statewide Planning Goal 18 to address erosion issues on oceanfront parcels. Relaxing Goal 18 would mean that all oceanfront homeowners would become eligible to install shoreline armoring when their property becomes vulnerable to erosion. This represents a significant change to Oregon's current land use policy and will **increase the amount of shoreline armoring** on developed beaches. Additional armoring structures would protect more private property but will also take up space for recreation and further reduce the width of these beaches. Armoring would not be funded by the state income tax increase and will continue to be the financial responsibility of the coastal homeowners who decide to armor.

<u>Option 2:</u>

The **second option** is to **do nothing** and, instead, let people and nature deal with the effects of erosion and sea level rise. Under this option, there would be **no Oregon Public Beach Fund** and the **current armoring restrictions under Goal 18 remain unchanged**. There would also be **<u>no increase</u> to your household's annual state income taxes**.


Recreation on an armored beach WITH erosion


Recreation on an armored beach WITHOUT erosion

How much do you agree or disagree with the following statement?

All properties that are vulnerable to erosion should be able to install shoreline armoring.

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree
- Not sure

***** Alternative treatment is to MAINTAIN armoring restrictions (omitted here)***

Your opinion matters. You will be asked to **vote on a new proposed coastal management plan**. Your vote **may help inform the State of Oregon** about what plan to put on a state ballot measure in an upcoming election. **The plan would be implemented if chosen by a majority of Oregon voters.**

Research suggests that people sometimes respond to questions like these one way, but then act differently. For example, people may vote “yes” on an ambitious project that involves higher costs than what they are actually willing to pay. We are interested in your opinion to best inform state policy **- there is no right or wrong answer**. Your answer will be **kept confidential**.

When making this decision, please remember your household budget and other items you may want to spend money on. Remember that **if you spend money on this coastal management plan, you will have less money for other things.**

Consider that the **Oregon Public Beach Fund** and **the Goal 18 policy change to relax shoreline armoring restrictions** described previously are part of a state ballot measure. This measure would increase your household’s annual state income taxes **per year for the next 30 years** to allow Oregon State Parks to implement the coastal management plan so as to meet both goals of preserving safe access for recreation and protecting private property from erosion.

This ballot initiative would:

- Increase funding for sediment management to **<u>prevent</u> a 20% loss of safe hours** for recreation at developed beaches at the highest risk of erosion.
- **<u>Relax</u>** Oregon’s Goal 18 shoreline armoring policy so that all oceanfront property owners become eligible to armor the shoreline in front of their homes.

The ballot initiative would **(1) preserve access to these beaches and their safe hours for the next 30 years** and **(2) relax the shoreline armoring policy**.

If this ballot measure passes, it would cost every household in Oregon an additional **$100 in state income taxes every year for the next 30 years**.

If this measure is on the ballot in the next election, would you vote for (yes) or against (no) the ballot measure?

○ I would vote "yes"

○ I would vote "no"

How certain are you of your vote?

- ◯ Extremely certain
- ◯ Very certain
- ◯ Somewhat certain
- ◯ Slightly certain
- ◯ Not at all certain

If this coastal management plan were to be implemented, would you still visit the developed beaches you visited between April 2021 and March 2022?

- ◯ Yes
- ◯ No
- ◯ Not sure

You indicated that you would **not** continue visiting these developed beaches if the coastal management plan was implemented. Would you continue to visit Oregon beaches but choose a nearby undeveloped beach instead?

- ◯ Yes
- ◯ No
- ◯ Not sure

How much do you agree or disagree with the following statement?

The results of this survey will influence Oregon state agencies and policymakers as they make their decisions about future coastal management plans for developed beaches.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree
- ◯ Not sure

We would like to understand what factors may or may not have influenced your vote on the ballot measure. Below is a list of statements people have made in similar surveys about why they responded as they did.

How much do you agree or disagree with each of the following statements:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree	Not sure
I had enough information to make an informed vote.	○	○	○	○	○	○
I do not trust the Oregon State government to protect Oregon beaches.	○	○	○	○	○	○
I do not believe it is the state government's responsibility to fund a coastal management plan.	○	○	○	○	○	○
If applied, I do not think the proposed coastal management plan will succeed at preserving safe hours for recreation on Oregon's developed beaches.	○	○	○	○	○	○
Please select Strongly Disagree here. Thank you for reading carefully.	○	○	○	○	○	○
I considered whether I can afford to pay for the proposed management plan.	○	○	○	○	○	○

How much do you agree or disagree with each of the following statements:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree	Not sure
I enjoy contributing to a good cause no matter what it is.	○	○	○	○	○	○
It is my right to have well-managed Oregon Coast beaches and I should not have to pay extra for it.	○	○	○	○	○	○
Beach erosion is a serious problem.	○	○	○	○	○	○
Sea levels are rising on most of the Oregon Coast.	○	○	○	○	○	○
The global climate is changing.	○	○	○	○	○	○
I am more sensitive to costs today than I was a couple of years ago before the economic changes brought on by the COVID-19 pandemic.	○	○	○	○	○	○

Do you think the risk of erosion to developed beaches 30 years from now will be:

- Much greater
- Somewhat greater
- Equal
- Somewhat smaller
- Much smaller
- Not sure

Why do you think erosion risk will change this way? Select all that apply.

- Coastal land use change
- Sea level rise
- Climate change
- Stronger El Niño events
- Stronger winter storms
- Other ___________________________
- Not sure

Do you believe that Oregon's climate is changing?

- Yes
- No
- Not sure

Do you believe that climate change will increase the erosion risk to developed beaches?

- Yes
- Maybe
- No
- Not sure

How do you see yourself: Are you generally a person who is fully prepared to take risks or are you unwilling to take risks? Please check a box on the scale, where the value 1 means: "always unwilling to take risks" and the value 5 means: "always prepared to take risks".

- 1 (Always unwilling to take risks)
- 2 (Somewhat unwilling to take risks)
- 3 (Neutral)
- 4 (Somewhat prepared to take risks)
- 5 (Always prepared to take risks)
- Not sure

IMPORTANT: <u>Your individual responses to all questions in this survey will be kept confidential.</u> Any material linking you to your survey responses will not be released and will be destroyed at the end of the study.

To help make our study as accurate as possible, we want to account for whether you have lived in the same 5-digit Postal/ZIP code during the time period we asked questions about, or whether you moved.

Did you move sometime between April 2021 and March 2022?

- ○ No
- ○ Yes, to the same ZIP code
- ○ Yes, to a new ZIP code
- ○ Prefer not to say

Please select the month and year you moved to your current residence.

- ○ April 2021
- ○ May 2021
- ○ June 2021
- ○ July 2021
- ○ August 2021
- ○ September 2021
- ○ October 2021
- ○ November 2021
- ○ December 2021
- ○ January 2022
- ○ February 2022
- ○ March 2022

To help make our study as accurate as possible, please provide us with the 5-digit Postal/ZIP code of your **previous** residence: ____________________

Is your primary residence a coastal property (within 1 mile of the coast)?

- ○ Yes
- ○ No
- ○ Prefer not to say

Do you own a second home on the Oregon Coast (within 1 mile of the coast)?

- ○ Yes
- ○ No
- ○ Prefer not to say

Which of the following best describes your race or origin?

- American Indian or Alaska Native
- Asian
- Black or African American
- Native Hawaiian or other Pacific Islander
- White
- From multiple races
- Prefer not to say

Are you of Hispanic, Latino, or Spanish origin?

- Yes
- No
- Prefer not to say

What was your household's total annual income (before taxes) in 2021?

- Less than $20,000
- $20,000 to $24,999
- $25, 000 to $29,999
- $30, 000 to $49,999
- $50,000 to $74,999
- $75,000 to $99,999
- $100,000 to $124,999
- $125,000 to $149,999
- $150,000 to $174,999
- $175,000 to $199,999
- $200,000 or more
- Prefer not to say

What is the highest level of education you have completed?

- Some High School or less
- High School Diploma / GED
- Some College
- Associate's Degree / Trade School
- Bachelor's Degree
- Some Graduate School
- Master's Degree
- Doctorate Degree
- Other
- Prefer not to say

Which of the following best describes your current marital/partnered status?

- Single
- Cohabiting/Living with a partner
- Married
- Widowed
- Divorced/Separated
- Prefer not to say

How many people, including yourself, currently live in your household?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7 or more
- ○ Prefer not to say

How many children under 18 years old live in your household?

- ○ None
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5 or more
- ○ Prefer not to say

Do you typically visit developed Oregon Coast beaches with children?

- ○ Yes
- ○ Sometimes
- ○ No
- ○ Prefer not to say

How old are the children that visit developed Oregon Coast beaches with you? Select all that apply.

- ☐ 0-3 years old
- ☐ 4-7 years old
- ☐ 8-11 years old
- ☐ 12 or older
- ☐ Prefer not to say

Which of the following best describes your current employment situation?

- ○ Self-employed or small business owner
- ○ Employed, working full time
- ○ Employed, working part time
- ○ Not employed, looking for work
- ○ Not employed, not looking for work
- ○ Retired
- ○ Disabled, not able to work
- ○ Full-time student
- ○ Full-time caregiver or parent
- ○ Other
- ○ Prefer not to say

In terms of politics, how would you describe yourself?

- ○ Extremely liberal
- ○ Moderately liberal
- ○ Slightly liberal
- ○ Neither liberal nor conservative
- ○ Slightly conservative
- ○ Moderately conservative
- ○ Extremely conservative
- ○ Prefer not to say

Have you ever engaged with a coastal advocacy group like the Surfrider Foundation or the Oregon Shores Conservation Coalition? Engagement can include activities like donating to, being a member of, or participating in an event put on by that organization.

- ○ Yes
- ○ No
- ○ Prefer not to say

In the last 12 months (between April 2021 and March 2022), have you engaged in any of the following activities with a coastal advocacy group? Please select all that apply.

- ☐ Followed them on social media
- ☐ Received their newsletters
- ☐ Donated to them
- ☐ Attended an event put on by them
- ☐ Attended their meeting
- ☐ Became or remained a dues-paying member
- ☐ Volunteered at or helped organize an event put on by them
- ☐ Other ___________________________
- ☐ Prefer not to say

Do you use social media?

- ○ Yes
- ○ No
- ○ Prefer not to say

Do you post to social media about your trips to the Oregon Coast? Select the option that **best** fits how frequently you post.

- ◯ Yes, for all my trips
- ◯ Yes, for more than half my trips
- ◯ Yes, for less than half my trips
- ◯ Yes, but only occasionally
- ◯ Never
- ◯ Prefer not to say

Please indicate which social media platforms you use to post about your trips:

- ☐ Twitter
- ☐ Instagram
- ☐ Facebook
- ☐ Flickr
- ☐ Other ____
- ☐ Prefer not to say

Did we overlook anything that is important to you?
Would you like to make a comment?
Please use the space below.

Oregon State University