Respondent experience and willingness to pay: Reconciling stated preference data with scientific evidence

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Abstract

Stated preference research to elicit respondents' values, or willingness-to-pay (WTP), to avoid or mitigate a detrimental environmental outcome or change often collects information on past experience with the adverse event in the underlying survey. Traditionally, this information on past experience is then incorporated into a given Random Utility Model (RUM) used for welfare estimation as an explanatory modifier of WTP. The quality or accuracy of these measurements of "past experience" has, to date, been given limited attention. This study presents a unique opportunity to validate stated experiences by Florida Gulf coast residents with red tide-related air toxins with satellite imagery of chlorophyll-a concentration, as well as field data on respiratory irritation at local beaches. We find that respondents are more likely to choose our proposed new harmful algal blooms forecast system when the chlorophyll-a concentration or respiratory irritation is higher at nearby coastal locations. Moreover, we illustrate that this ancillary scientific information can be efficiently combined with choice experimental data and works as a truly exogenous instrument for survey-elicited experiences. Looking further, we consider this research a first step in a broader effort to directly link scientific data on environmental conditions with nonmarket economic outcomes.

Keywords: Harmful algal blooms; stated preferences; choice experiments; chlorophyll-a; respiratory irritation

Introduction

As observed globally, harmful algal blooms (HABs) have severe economic effects on fisheries (Jardine et al., 2020; Sakamoto et al., 2020), aquaculture (Matsuyama and Shumway, 2009; Karlson et al., 2021), seafood (Bechard, 2020), tourism (Bechard, 2020), property prices (Bechard, 2020), and human health (Young et al., 2020). It is estimated that the economic loss caused by HAB events was $364 million in China from 2008 to 2012 (Guo et al., 2014). Along the U.S west coast an estimated $97.5 million were lost in commercial crab fishery, and $40 million were lost to the tourism sector in 2015 due to HABs[1]. In South Korea, the direct losses due to HABs from 2001 to 2012 were estimated at 52 million USD by Lee et al. (2014). Due to the considerable economic losses caused by HABs, predicting their occurrence and intensity has gained great attention (Lee and Lee, 2018; Zohdi and Abbaspour, 2019; Hennon and Dyhrman, 2020). As discussed in Jin et al. (2020a), prediction of HABs can enable decision makers to adjust economic activities to mitigate HAB effects. Therefore, economic values carried by HAB predictions need to be understood to develop and refine HAB forecasting system.

Because of the non-market characteristics for HAB forecasting, Stated-Preference (SP) methods are attractive to construct models to value HAB forecasts. SP studies have been used to elicit respondents' willingness to pay (WTP) for avoiding adverse events, such as floods (Navrud and Vondolia, 2020), power outages (Cohen et al., 2018), hurricanes (Chatterjee et al., 2019), food or water contamination (Sanou et al., 2021; Brouwer et al., 2015) and air pollution (Jin et al., 2020b). In general, SP methods elicit the monetary value of a given environmental commodity or service with a hypothetical market, thus allowing to capture respondents' decisions.

In SP studies, such as those based on a choice experiment (CE) or contingent valuation (CV), past experience with the resource in question may shape respondents' WTP. This is especially true when it comes to adverse environmental events, such as erosive runoff events (Crastes et al., 2014), water interruptions (MacDonald et al., 2005), water quality concerns

[1] https://www.fisheries.noaa.gov/west-coast/science-data/hitting-us-where-it-hurts-untold-story-harmful-algal-blooms

(Dupont and Bateman, 2012), storm water management (Kim et al., 2016), flooding disaster (Zhai et al., 2006) and beach erosion (Windle and Rolfe, 2014). In essence, past experience can be captured by the analyst in two fundamental ways: (i) Directly from the respondent, as part of the survey and (ii) Based on scientific sources that are extraneous to the survey instrument but can be linked in some other ways to the respondent. In existing studies, the first strategy has been more common than the second.

In terms of modeling, some CE studies incorporate respondents' past experience by adding interaction terms between personal experience and the status quo (SQ) indicator, and/or specific CE attributes. For example, Dupont and Bateman (2012) investigate preferences for tap water quality by adding an interaction between indicators capturing bad experiences with tap water and the SQ dummy. The corresponding estimated coefficients for these interactions emerged as positive but insignificant. In a similar vein, MacDonald et al. (2005) add an interaction term between respondents' past experience of water interruptions and the alternative specific constant in the econometric model. The estimated coefficient for this interaction is not significant, and significance levels and signs of CE attributes are the same compared to baseline model without this interaction. In addition to interactions with the SQ, Crastes et al. (2014) incorporated interaction terms between self-rated exposure to erosive runoff events and actual CE attributes. They find that respondents with a high level of past exposure to erosive runoff events are willing to pay significantly more for the implementation of good farming practices and communication about erosive runoff events. Londono Cadavid and Ando (2013) include an interaction between a dummy variable of past flooding experience, basement ownership, and a CE attribute specifying the number of the expected future basement flooding and find this interaction to be negative and significant.

In addition to CE studies, many other CV studies incorporated survey-elicited experience as dummy variables to investigate WTP for non-market goods or services in their econometric model, such as farmers with experience in waste compost in Ghana (Danso et al., 2006), vegetable farmers with previous experience in pesticide poisoning in Nicaraguan (Garming and Waibel, 2009), experience with visiting wetland in Taiwan (Hammitt et al., 2001), experience of damage to property from wildfire in Michigan (Winter and Fried, 2001), experience with suffering from respiratory cases related to air pollution in South Korea (Kwak et al., 2001), and experience with sand erosion at a visited beach in Australia (Windle and Rolfe, 2014).

In addition to survey-elicited experience, outside scientific information was also incorporated in some existing studies. For example, Cohen et al. (2018) include the number of power outages in the past 12 months as reported by the corresponding utility company in a CV-type model to investigate customers' WTP to avoid power interruptions and find that the number of power outages is estimated to be insignificantly negative. Fahad and Jing (2018) examine Pakistani farmers' WTP for hypothesized crop insurance program to mitigate disaster risks by incorporating scientific information, such as distance from farmland to the river, farmland height and occurrence of flooding in years. They find that distance and farmland height have a significantly negative effect on WTP for crop insurance and occurrence of flooding has a significantly positive effect.

The objective scientific information which can be spatially and temporally linked to respondents is more generally desirable to reflect respondents' experience compared to survey-elicited experience in the following ways. First, survey-elicited experience has potential recall problems. For example, Wollburg et al. (2021) find that farmers in Malawi and Tanzania report higher quantities of harvest, labor and fertilizer inputs and fewer plots when recall periods are longer. More specifically, Kjellsson et al. (2014) use self-reported hospitalization data to study length of recall periods influence recall error and find that overall level of recall error increases with longer periods. The survey-elicited information can also lead to strategic bias problems in discrete CE (Scheufele and Bennett, 2012; Nguyen et al., 2021). Meginnis et al. (2018) find that 27% respondents behave strategically, as they can understand information and comprehend the payoff scheme associated with relative probabilities with provision outcomes so that their decision will switch to the second-best outcome. In our application, respondents may be strategically over- or under-reporting their outdoor activities influenced by air contamination from red tide. In addition to recall and strategic mis-reporting problems, survey-elicited experience can introduce endogeneity problems in the choice model. In our case, avid beach goers or people with stronger preferences for outdoor activities may both be more influenced by red tide, but also have a higher WTP for the proposed new HABs forecast system as they would use it more often. Another advantage of linking objective scientific information to WTP models is that we can predict both impacts from the red tide and WTP values directly from outside scientific data without having to do another survey in the future.

In this study, we implement a choice experiment (CE) survey that incorporates respondent's self-stated experience with HABs and outside scientific information based on remote sensing data as well as lifeguard reports to investigate the economic value to residents in five southwest Florida counties of a hypothetical improved red tide (RT) air quality forecast system. Survey-elicited experience related to RT air contamination, includes having had to cancel, postpone, or shorten outdoor activities, as well as bigger impact activities such as having moved away from the shore or having sold off boating and water-sports gear. The outside scientific information, in turn, comprises environmental conditions such as respiratory irritation (RI) levels from Mote Marine Laboratory's Beach Conditions Reporting System (Mote's BCRS) and satellite imagery of chlorophyll-a (Chl-a) concentration from the National Oceanic and Atmospheric Administration (NOAA).

We first model stated impacts as a function of scientific data and find that reported adverse effects are significantly related to both higher levels of Chl-a and RI. Thus, We are able to establish a positive link between the survey-elicited experience and scientific information. We then estimate a first choice model that incorporates interaction terms between the SQ indicator and survey-elicited experience and reveals that, not surprisingly, respondents are less likely to be content with current forecasting tools when their outdoor activities have been affected by RT air contamination. In a second choice model, we include interaction terms between the SQ indicator and scientific information, and find that respondents prefer choosing our proposed new HABs forecast system to the current status when their closest beach destinations have been experienced relatively high historic levels of Chl-a and RI. All choice models produce similar WTP estimates for the new HABs forecast system with different attribute settings, ranging from \$18 to \$45. As the estimated coefficients for attribute and bid value remain stable and WTP estimates are similar, we conclude that the ancillary scientific information collected outside of the survey can be efficiently combined with choice experimental data and works as a truly exogenous instrument for survey-elicited experiences.

The quality and accuracy of survey-elicited past experience with adverse events has, to date, been given limited attention. This study contributes to the nonmarket valuation literature by validating survey-elicited experience with scientific information collected from satellite images as well as the local beach reports. This study also adds to literature by incorporating both survey-elicited experience and scientific information into choice modeling to investigate the impact of outside scientific information on respondents' choice. We consider this research a first step in a broader effort to directly link scientific data on environmental conditions with nonmarket economic outcomes.

Respiratory irritation and chlorophyll-a concentrations

Recent years have witnessed increased intensity, frequency, and geographical coverage of RT blooms along the Florida Gulf Coast (Carvalho et al., 2010; Fleming et al., 2011; Phlips et al., 2011; Wolny et al., 2015) that can cause human respiratory irritation (Schaefer et al., 2020; Anderson et al., 2021), deteriorate water quality (Lapointe et al., 2017; Mitsch, 2019), kill marine animals in large quantities (Gravinese et al., 2020), as well as degenerate watercolor (Wynne et al., 2005; Carvalho et al., 2011).

Florida red tide, the HAB under consideration in this study, is known for leading to respiratory illness for humans via aerosolized toxins. Kirkpatrick et al. (2008) find that brevetoxins produced by Karenia brevis can cause RI in people who inhale it, and asthmatics experience measurable changes in pulmonary function. Kirkpatrick et al. (2011) suggest that even a one-hour exposure to an active red tide for asthmatics may lead to increased symptoms and respiratory function suppression that can last for up to five days. Poor air quality due to red tide can also affect local beach and water activities. Larkin and Adams (2007) investigate the impacts of HABs on coastal business and find that reduction of beach and water-related activities due to RT blooms leads to a negative impact on business revenues. Bechard (2020) argues that beaches are closed and waters activities are no longer safe because of irritable effects on the throat and eyes from high concentrations of HABs, and find that an additional day of red tide leads to a decrease of 1-2% and 0.5-1% for lodging and restaurant sector, respectively.

Chlorophyll-a is a green pigment in plants and algae which is used in oxygenic photosynthesis. Chl-a acts as a bridge between algal production and nutrient concentration (Gholizadeh et al., 2016). Many studies find that Chl-a is closely related to HABs or RT events. For example, McGowan et al. (2017) argue that Chl-a is a standard proxy for phytoplankton abundance and can be used to verify the predominance of HABs. In a similar vein, McGowan et al. (2017) find Chl-a concentration is directly associated with phytoplankton biomass and is an indicator of RT. More specifically, Yunus et al. (2015) investigate the Chl-a and RT detection in Tokyo Bay water using satellite reflectance data and find that Chl-a maps correspond with RT events. However, Chl-a and RT are not perfectly correlated with each other. As pointed out by NOAA[2], high concentrations of Chl-a from NOAA satellite images could be Chl-a and other substance that influence the color and intensity of the light reflected by the water. Therefore, high concentrations of Chl-a are not necessarily or always indicative of RT. This speaks to the benefits of utilizing a more direct source of RT aerosol concentrations at local beaches via Mote's BCRS, in addition to satellite-based Chl-a data.

In essence, there are two fundamental differences between RI from Monte's BCRS and Chl-a concentrations from NOAA satellite images. On the one hand, RI is the air-based toxins and tells us what is already in the air, while Chl-a concentrations is the water-based biomass and tells us what is in the water. On the other hand, these two sources of information are key to different types of visitors. For example, RI is more key to beach visitors while Chl-a is more vital to offshore angler because fish will die in the RT water even if air-based toxins are not in the air.

[2] https://earthobservatory.nasa.gov/images/5071/red-tide-off-florida

Data

Survey instrument

The CE survey was implemented in June and September 2020 by a professional polling firm (Qualtrics) in five Florida counties: Sarasota, Collier, Lee, Charlotte and Manatee. Respondents over the age of 18 and permanent residents of five counties were eligible to participate in the survey. The sample of respondents was stratified according to age, income groups, and presence of children under the age of 18 based on official census data for these five counties to ensure the representativeness of the sample. There are 502 respondents who properly completed questionnaires. The number of respondents for each ZIP code area in the five counties are given in Figure 1, showing that most respondents are from coastal areas of southwest Florida. More details on survey design and implementation are provided in Moeltner et al. (2020).

The questionnaire consisted of four sections. The first section presented detailed background on RT blooms along the South Florida Gulf Coast. This section also asked respondents how RT air contamination affected life such as cancel, postpone or shorten outdoor activities, personal health, moved away from the shore, sold boat/water equipment and changed job. As presented in Table 5 and 6 from Moeltner et al. (2020), the survey listed 16 activities that could potentially be impacted by RT air contamination. For each activity, respondents were provided with five choices: never, sometimes, often, almost daily and cannot recall or not applicable. After imposing missing value to "cannot recall" and "not applicable", we recode the frequency of effects for these activities by making "never" equal to 0 and all other choices equal to 1. Table 1 presents recoded percentages for activities impacted by RT air contamination. As is evident from Table 1, majority of households (over 50%) had to cancel/postpone, shorten or re-locate outdoor activities due to RT air contamination. Over 40% households had to cancel/postpone or shorten outside activities around home. In terms of health effects, over 60% households have experienced RI and approximately 12% households were even affected by severe irritation. A large share of households (over 60%) indicated that they have been bothered/sickened by dead fish smell.

As is shown in the last row of the table, over 80% households reported that they have been impacted by one of the above activities or effects.

The second section of the survey provides existing public information systems related to RT cell counts and irritation levels, such as Monte's BCRS, NOAA's HAB forecast and Florida Fish & Wildlife and Conservation Commission (FWC). The third section introduces the new proposed forecast system and detailed information related to the new forecast system can be found in Figure 1 and 2 from Moeltner et al. (2020). Each respondent was presented with four choice sets, each with three choice options (Option A, Option B and Status quo). Option A and B are characterized by a set of attribute levels related to the new forecast system. Three attributes capture the most salient features of the proposed system. The first attribute is the width of spatial coverage along the coastline, which is either six or 12 miles. The second and third attributes are the percentages of accuracy of the forecast system for the first and second 12 hours, which are 50%, 75% and 100%. Each choice set also includes a price variable, which is specified at four uniformly spaced levels: \$5, \$15, \$25, \$35 for Option A and Option B, and \$0 for SQ. According to Moeltner et al. (2020), these bids were informed by focus groups and are specified as payable in the form of additional annual taxes per household. Figure 2 shows an example of a choice set as presented to survey respondents.

The last survey section collected demographic information, such as ZIP code of residence, household size, education level and income category. The sample demographics can be found in Table 2 from Moeltner et al. (2020). As is evident from the table, the survey produced a representative sample for the underlying target population in terms of key demographics.

Scientific information

The first source of scientific information is daily observations of RI from Monte's BCRS from 2018 to 2019. The daily RI was reported by citizen scientists who are usually lifeguards on 37 local beaches in terms of frequency of observed coughing by beach visitors: none, slight, moderate and intense. We categorized none and slight as low RI and moderate and intense as high RI[3], and count the number of days with high RI for each beach from 2018 to 2019. To link this information to survey respondents, we identify the three nearest beaches[4] to the centroid of each respondent's ZIP code, and then calculate the average number of days with high RI across these three locations for the entire time period (2018-2019).

The second source of scientific information is based on the daily satellite images of Chl-a concentrations from NOAA's HAB forecast from 2018 to 2019. Using exact beach coordinates from Monte's BCRS, we create two-mile buffer for each beach and calculate the average Chl-a concentrations based on the satellite data[5]. We calculate the two-year's (2018 and 2019) average Chl-a concentrations for each beach and then average across the three nearest beaches as for the RI data.

Table 2 presents the correlation between Chl-a and RI across all beaches. Column (1) shows the number of available days with Chl-a satellite images from NOAA's HAB forecast and Column (2) shows the number of days with RI from Mote's BCRS. Column (3) presents the number of days that both have Chl-a and RI and are thus suitable for inclusion in the construction of the corresponding correlation coefficient. Column (4) shows the correlation between Chl-a and binary RI while Column (5) shows the correlation between Chl-a and four-levels RI. As is evident from the table, correlations between Chl-a and RI in Column (4) and (5) are predominately positive for most beaches. Also, the overall average correlation across all beaches as shown in the last row of the table is positive. While these correlations are far from unity, as can be expected given the imperfect link between Chl-a and RT water concentrations discussed above, and the unobservable factors that translate RT water concentrations in measurable concentrations of air toxin, such as local wind patterns and wave action, the table provides at least evidence of a positive relationship, as would be expected. We thus proceed as planned considering both data sources for inclusion in our choice model.

[3]We also categorized none as low RI and slight, moderate and intense as high RI for robustness checks. All detailed results related to different categorized RI are shown in Table A1 and Table A2

[4]We also calculate the first nearest beach, two nearest beaches, four nearest beaches and five nearest beaches for robustness checks. All detailed results related to number of beaches are shown in Table A5.

[5]Chl-a satellite images were downloaded from https://www.ncei.noaa.gov/data/oceans/co-ops/hab/gomex/ in Hierarchical Data Format (HDF) and extracted Chl-a layer to convert as Tag Image File Format (TIFF). Using these daily Chl-a TIFF files, we can get average Chl-a within a buffer area.

Method

As outlined in Moeltner et al. (2020), the indirect utility function (IUF) with or without choosing the proposed forecast system for individual i, choice situation t and forecast alternative j is given as:

$$\begin{aligned} U^*_{it0} &= \beta_{sq} * sq + \lambda m_i + \epsilon_{it0} \\ U^*_{itp} &= \mathbf{z}'_{itp}\boldsymbol{\theta} + \lambda\left(m_i - P_{itp}\right) + \epsilon_{itp} \\ \epsilon_{itj} &\sim EV(0,1), \quad j = p, 0 \end{aligned} \tag{1}$$

where subscripts p denotes the Option A/B and 0 denotes SQ status, respectively, sq is the SQ indicator and β_{sq} is the corresponding coefficient, $\mathbf{z}_{itp}$ is a vector of forecast attributes, such as coverage and accuracy in this application, m_i represents annual income, P_{itp} is the bid value associated with forecast scenario, ϵ_{itj} captures all other components that influence utility but are invisible to the analyst, $\boldsymbol{\theta}$ is the vector of coefficients for forecast attributes and λ is the marginal utility of income.

We incorporate interaction terms between SQ and survey-elicited experience related to RT or scientific information, such as Chl-a and RI. The IUF of this model for person i, choice situation t and forecast alternative j can be expressed as:

$$\begin{aligned} U^*_{it0} &= \beta_{sq} * sq + \mathbf{sq\_int}' * \boldsymbol{\beta}_{sq\_int} + \lambda m_i + \epsilon_{it0} \\ U^*_{itp} &= \mathbf{z}'_{itp}\boldsymbol{\theta} + \lambda\left(m_i - P_{itp}\right) + \epsilon_{itp} \\ \epsilon_{itj} &\sim EV(0,1), \quad j = p, 0 \end{aligned} \tag{2}$$

where **sq_int** is the vector for interaction terms between SQ and survey-elicited experience or scientific information, and $\boldsymbol{\beta}_{sq\_int}$ is the corresponding coefficients vector.

As has been shown before (McFadden et al., 1973; Greene, 2012), the probability of person i choosing alternative j at choice situation t can be conveniently expressed as follows:

$$
\begin{aligned}
&prob(y_{itj}=1)=\frac{exp\left(\mathbf{x}'_{itj}\boldsymbol{\beta}\right)}{\sum_{j=1}^{J} exp\left(\mathbf{x}'_{itj}\boldsymbol{\beta}\right)}, \quad \text{where} \\
&\boldsymbol{\beta}=\begin{bmatrix}\boldsymbol{\theta} & -\lambda & \beta_{sq} & \boldsymbol{\beta}_{sq\_int}\end{bmatrix}' \\
&\mathbf{x}_{itj}=\begin{bmatrix}\mathbf{z}'_{itj} & P_{itj} & -sq & -\mathbf{sq\_int}'\end{bmatrix}', \quad \text{and}
\end{aligned} \tag{3}
$$

where y_{itj} is a binary indicator that equals 1 if person i chooses alternative alternative j at choice situation t, and equals 0 otherwise.

The choice model expressed by Eq.2 and Eq.3 is generally called the "Conditional Logit Model" (CLM) in applied economics (McFadden et al., 1973; Greene, 2012). Based on the above probability functions, the sample likelihood function for N independent respondents $i = 1, ..., N$, each respondent facing $t = 1, ..., T$ independent choice situations with $j = 1, ..., J$ alternatives is given as follows:

$$
p\left(\mathbf{y}|\boldsymbol{\beta},\mathbf{X}\right)=\prod_{i=1}^{N}\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{exp\left(\mathbf{x}'_{itj}\boldsymbol{\beta}\right)}{\sum_{j=1}^{J} exp\left(\mathbf{x}'_{itj}\boldsymbol{\beta}\right)}\right)^{y_{itj}} \tag{4}
$$

The sample likelihood function expressed as Eq.4 is traditionally estimated via Maximum Likelihood Estimation (MLE) using the first and second derivatives to determine the optimal coefficient vectors that maximizes the probability of choosing the combined choices of sample.

Based on the estimated coefficients, we are able to obtain the value w_{ip} of a forecast system with attribute settings $\mathbf{z}_p$ implicitly by a equation that links the indirect utility for the SQ at full income m_i and indirect utility for the forecast at reduced income $m_i - w_i$. Separating $\boldsymbol{\beta}$ into $\boldsymbol{\beta}_z$, β_{sq} and $\boldsymbol{\beta}_{sq\_int}$ based on IUF Eq.2, the willingness to pay for the proposed HAB forecast can then be derived as:

$$w_{ip}|\mathbf{z}_p, \boldsymbol{\beta} = -\frac{1}{\lambda}\left(\mathbf{z}'_p * \boldsymbol{\beta}_z - \beta_{sq} - \boldsymbol{\beta}_{sq\_int} * \bar{int}\right) \tag{5}$$

where $\bar{int}$ is the average of interaction terms across all respondents.

Results

Impact model

To fully investigate the relationship between scientific information, such as Chl-a and RI, and survey-elicited experience impacted by RT air contamination, we apply a simple binary logit model for all effects presented in Table 1. In each regression, we also add the demographic variables including gender, age, household size, number of family members under seven, number of family members ages seven to 18, family members with respiratory conditions, years lived at current address, years lived at current county, income, and two education categories (highest degree is college and highest degree is above college), with high-school education taken as the baseline.

Table 3 shows the marginal effects of Chl-a and RI from simple binary logit models holding all other variables at the sample mean. As is evident from Table 3, the Chl-a concentrations and RI are estimated to be significantly positive for most models, indicating that probability of activities effected by RT air contamination increases when the Chl-a concentrations or the number of high RI days increases. Given the marginal effects, we can conclude the magnitude of probability changes. For example, Column (1) in Table 3 shows the probability of at least one activity impacted by RT air contamination goes up by 0.32% for one additional day of high RI. Similarly, Column (2) indicates the probability of canceling outdoor activity increases by 0.22% with one additional day of high RI or goes up by 0.76% when the Chl-a concentration increases by one mg/m^3.

Choice model

To examine the impact of survey-elicited experience and scientific information on the proposed new HAB forecast, we apply the CLM with five different model specifications. Model 1, which is taken as the baseline model, only includes the SQ indicator, forecast attributes, and bid value. Model 2 adds interaction terms between the SQ indicator and survey-elicited activities impacted by RT air contamination to examine how respondents' potential exposure to RT risks influences their choice of forecasting systems. Model 3 and Model 4 include interaction terms between the SQ indicator and Chl-a or RI, respectively, to examine the impact of scientific information on respondents' choice. Model 5 adds both interaction terms between the SQ indicator and scientific information to examine the joint effect of scientific information on respondents' choice.

Table 4 presents CLM estimation results. In our application, three forecast attributes are included in the CLM: spatial coverage, accuracy for the first 12 hour,s and accuracy for the second 12 hours. We express the forecast attributes as binary level indicators by omitting the lowest setting and treat the bid variable as a single continuous regressor. In Table 4, *sq* is the SQ indicator; *cov12* is the 12-mile coverage; *acc175* and *acc1100* are the 75% and 100% accuracy, respectively for the first 12 hours; *acc275* and *acc2100* are the 75% and 100% accuracy, respectively for the second 12 hours; *bid* is the bid value; *sq_RTimpact*, *sq_Chla*, and *sq_resp* are the interaction terms between the SQ indicator and survey-elicited activities impacted by RT contamination, Chl-a concentration, and the number of high RI days, respectively.

Column (1) in Table 4 shows results for "Model 1" which replicates results given in Moeltner et al. (2020) and is shown here to provide a baseline setting. Column (2) shows results for "Model 2", which includes an interaction term between the SQ indicator and survey-elicited activities impacted by RT air contamination. Estimated coefficients for attributes and bid value are similar to those from Model 1. Importantly, the interaction term is estimated to be significantly negative, indicating respondents are less likely to settle for existing forecasting systems when their past activities were affected by RT air contamination. This result is consistent with our intuition that respondents will be in support of the new proposed HAB forecast system if their activities are more likely to be influenced by RT.

The next two models in Table 4 shown in Columns (3) and (4), respectively include individual interaction terms between the SQ indicator and outside information on historic RT concentrations[6]. We first note that estimated coefficients for forecast attributes and bid value are similar to those from Model 1 and Model 2. The estimated coefficients for the interaction terms are both insignificantly negative in Model 3 and Model 4. The final column in the table shows results for "Model 5" which includes both interaction terms between the SQ indicator and scientific information. In this case, estimated coefficients for interaction terms are significantly negative, indicating respondents are less likely to choose the current status when high Chl-a concentrations are found in nearby coastal waters or RI from airborne toxins, as measured by number of high RI days, is high. Compared to Model 3 and 4, estimated coefficients for Chl-a and RI in Model 5 become significant. One possible explanation is that Chl-a and RI are positively correlated as discussed above. We are able to control for Chl-a to investigate the effect of RI on respondents' choice and vice versa, which is different from the sole effect of Chl-a and RI from Model 3 and 4.

Value predictions

Based on the econometric steps outlined in Eq.5, we compute the WTP for all 18 possible combinations of attribute settings for spatial coverage and accuracy. Results are presented in Table 5 for all five model specifications discussed above. For each model, the table shows the mean as well as the lower and upper bounds of 95% confidence interval for WTP estimates.

Similar to WTP estimates in Moeltner et al. (2020), we observe that the typical household is willing to pay approximately $18 per year for the least refined forecast system with six-mile coverage and 50% accuracy for the first and second 12-hour segment. The WTP

[6]Robustness checks for interaction terms between the SQ indicator and each individual outdoor activity are shown in Table A3 and Table A4

estimates increase to $40-$45 per year for forecast systems with higher accuracy. The confidence bounds for WTP estimates are tight, approximately $10 between the lower and upper bounds. It is worthwhile to note that WTP estimates across all model specifications are stable, ranging from $18 to $45. For example, in Model 5 which includes both interaction terms between the SQ indicator and scientific information, the minimal WTP estimate is $17.66 and the maximal WTP increases to $44.91.

Conclusion

Building on a survey-based choice experiment for a new proposed HABs forecast system in southwest Florida, this study focuses on augmenting survey-elicited information with external scientific data on RT occurrences and concentrations. Specifically, we investigate both the influence of survey-elicited experience related to RT air contamination and the impact of scientific information such as RI from Mote's BCRS and satellite images of chlorophyll-a concentrations from NOAA.

Based on logit regression, we first investigate the relationship between outside scientific information and survey-elicited experience. We conclude that the probability of activities affected by RT air contamination increases when the Chl-a concentration increases or the number of high RI days increases. This result is consistent with our intuition that poor water quality measured by Chl-a concentration and poor air quality measured by the number of high RI days tend to increase the probability of respondents' activities affected by RT risks.

We then apply a CLM with different model specifications including interaction terms between the SQ indicator and survey-elicited experience or scientific information. We find that respondents are less likely to choose the current status when outdoor activities are more influenced by RT air contamination. We also find that interaction terms between the SQ indicator and scientific information are jointly estimated to be significantly negative, which is different from insignificantly negative results when adding interaction terms separately. One possible explanation is that Chl-a and RI are positively correlated with each other and the standard deviation is smaller when controlling for one of them, leading to a higher significance level. Therefore, we can conclude that respondents are more favorable of the new HABs forecast system when the water quality is poor or RI from airborne toxins is severe.

Given CLM estimates, we can obtain WTP estimates for the new HABs forecast system. For model specifications including interaction terms with the SQ indicator and survey-elicited experience or scientific information, the WTP estimates for the new HABs forecast system are stable, ranging from \$18 to \$45.

Based on estimation results from the impact model, we find strong evidence for the validity of self-reported RT impacts as the probability of outdoor activities affected by RT air contamination increases when Chl-a concentrations and the number of high RI days increases. As estimated coefficients for attributes and bid value are stable and WTP estimates are similar, we conclude that including interaction terms between the SQ indicator and scientific information does not impose endogeneity issues in the choice model. Additionally, the ancillary scientific information works as a truly exogenous instrument for survey-elicited experiences.

In terms of policy implication our stable estimated coefficients and similar WTP estimates show, first and foremost, that outside objective scientific information can be effectively combined with choice experimental data, suggesting a further link between the scientific data on environmental conditions and nonmarket economic outcomes. Another policy implication is that we can predict both impacts of survey-elicited experience and WTP estimates directly from scientific data without asking related questions for respondents or even without having to do another survey.

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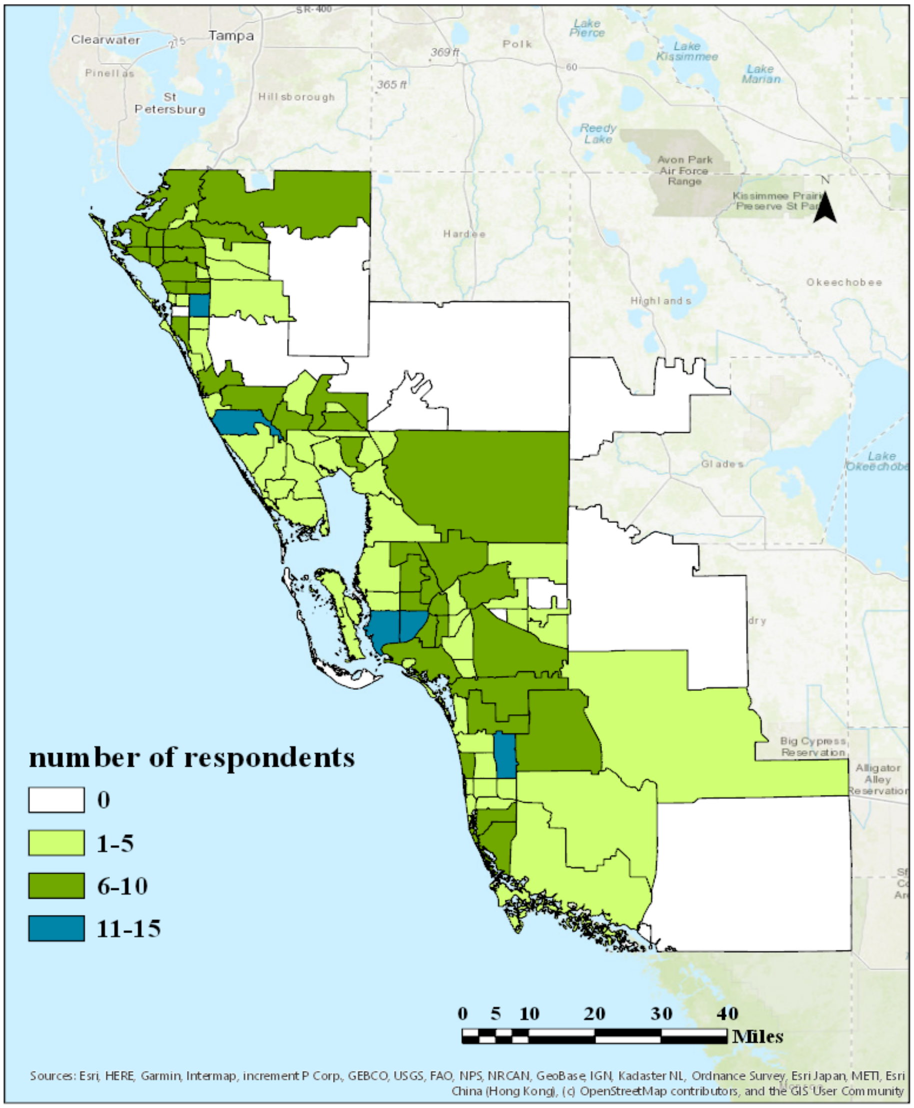

Figure 1: The number of respondents in ZIP code areas

Table 1: Activities impacted by RT air contamination

effect	variable	% NO	% YES
outdoor activities:			
cancel / postpone	outcancel2	38.26	61.74
shorten	outshort2	37.85	62.15
re-locate	outreloc2	48.7	51.3
around house outside activities			
cancel / postpone	yardcancel2	57.17	42.83
shorten	yardshort2	53.73	46.27
health effects:			
irritation (but no doctor)	irritation2	38.99	61.01
severe irriation, see doctor	doctor2	87.66	12.34
bothered / sickened by dead fish smell	fishsmell2	48.52	51.48
other effects:			
guests cancelled visits	visitcancel2	66.67	33.33
unable to open windows (home or car)	windows2	48.1	51.9
unable to let pets out	pets2	75.13	24.87
toxins enered home / car via A/C system	accar2	69.44	30.56
additional actions in response to RT:			
moved away from coast	moved2	78.15	21.85
sold boat / water sport equipment	soldboat2	91.11	8.89
put house / condo on market	sellhouse2	92.93	7.07
changed job / retired early	changejob2	92.1	7.9
any activities were impacted	RTimpact2	17.6	82.4

$N = 502$

Figure 2: Choice set example

Table 2: Correlation between Chl-a and RI

beach name	(1) # of days for Chl-a	(2) # of days for RI	(3) # of days for matched Chl-a and RI	(4) correlation (Chl-a and binary RI)	(5) correlation (Chl-a and four-levels RI)
Barefoot Beach	140	317	134	0.13	0.15
Bonita Beach	144	307	132	0.09	0.05
Bowmans Beach	189	313	183	0.00	0.23
Caladesi Island	167	132	68	0.00	0.45
Captiva	213	142	89	0.08	0.05
Causeway Islands	144	186	79	N/A	0.06
Coquina Beach	163	296	146	0.42	0.43
GI Range Light	213	189	119	0.06	0.11
GI State Park (South Lighthouse)	203	97	56	0.39	0.45
Henderson Beach State Park	136	202	77	N/A	0.27
Indian Shores	163	142	73	0.07	0.35
Lake Worth Beach	138	62	22	N/A	N/A
Lido Key	154	301	143	0.21	0.32
Light House Beach Sanibel Island	159	113	57	N/A	0.31
Lovers Key State Park	126	237	88	N/A	-0.03
Lynn Hall Beach Park	161	218	114	0.15	0.15
Madeira Beach	167	125	67	N/A	0.05
Manasota Beach	147	300	128	0.32	0.37
Manatee Beach	166	315	160	0.33	0.48
Newton Park	145	259	110	0.05	0.17
Nokomis	110	302	100	0.12	0.22
Pass-a-Grille	196	110	64	0.33	0.52
Pensacola Beach	145	305	138	N/A	N/A
Seagate Beach	142	260	117	-0.02	-0.01
Siesta Key	155	279	135	0.16	0.40
South Marco Beach	182	321	177	0.01	0.04
St George Island Bayside	160	175	85	N/A	N/A
St George Island Gulfside	175	178	95	N/A	N/A
St Joseph Bayside	142	100	36	N/A	-0.07
St Joseph Gulfside	138	98	38	N/A	-0.03
St Pete Beach	173	123	69	N/A	0.00
Treasure Island	169	125	64	N/A	0.31
Vanderbilt Beach	115	236	86	-0.02	0.09
Venice Beach	131	292	114	0.49	0.52
Venice North Jetty	139	302	128	0.23	0.37
overall average	157	213	100	0.16	0.22

The binary RI indicates high and low RI.
The four-levels RI indicates none, slight, moderate and intense.
Correlations between Chl-a and RI for some beaches are "N/A" as RI for those beaches have the same value on every single day from 2018 to 2019, leading to incalculable standard deviation for RI.

Table 3: Estimation results I: Marginal effects of impact model

	RTimpact2	outcancel2	outshort2	outreloc2	yardcancel2	yardshort2	visitcancel2	windows2	pets2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
chlora	0.0284***	0.0099	0.0307***	0.0108	0.0532***	0.0590***	0.0190***	0.0680***	0.0528***
	(0.0046)	(0.0074)	(0.0074)	(0.0078)	(0.0078)	(0.0078)	(0.0073)	(0.0078)	(0.0072)
RI	0.0028***	0.0029***	0.0046***	0.0014**	0.0052***	0.0054***	0.0031***	0.0080***	0.0050***
	(0.0004)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Observations	5940	5460	5520	5484	5628	5568	5376	5628	4632

	accar2	irritation2	doctor2	fishsmell2	moved2	soldboat2	sellhouse2	changejob2
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
chlora	0.0614***	-0.0027	0.0230***	0.0307***	-0.0120*	-0.0043	-0.0124***	-0.0022
	(0.0075)	(0.0072)	(0.0042)	(0.0078)	(0.0065)	(0.0037)	(0.0029)	(0.0033)
RI	0.0066***	0.0023***	0.0014***	0.0056***	-0.0023***	-0.0008***	-0.0009***	-0.0005**
	(0.0006)	(0.0006)	(0.0003)	(0.0006)	(0.0005)	(0.0003)	(0.0002)	(0.0003)
Observations	5292	5676	5592	5604	4992	4404	4872	4812

Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.0.05$, $^{***}p < 0.01$
Estimated coefficients for demographics are available upon request.

Table 4: Estimation II: Choice model

	Model 1	Model 2	Model 3	Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)
sq	-0.8017***	-0.4012***	0.2994	-0.8282***	4.3274***
	(0.1041)	(0.1289)	(0.6392)	(0.1443)	(1.5578)
cov12	0.1097	0.1097	0.1117	0.1101	0.1103
	(0.0940)	(0.0945)	(0.0941)	(0.0940)	(0.0942)
acc175	0.2628**	0.2655**	0.2579**	0.2619**	0.2622**
	(0.1294)	(0.1297)	(0.1294)	(0.1295)	(0.1296)
acc1100	0.9346***	0.9364***	0.9305***	0.9339***	0.9348***
	(0.1429)	(0.1432)	(0.1428)	(0.1429)	(0.1431)
acc275	0.2219**	0.2187**	0.2224**	0.2220**	0.2223**
	(0.0954)	(0.0955)	(0.0954)	(0.0954)	(0.0955)
acc2100	-0.0069	-0.0067	-0.0018	-0.0061	-0.0052
	(0.1286)	(0.1289)	(0.1286)	(0.1287)	(0.1288)
bid	-0.0464***	-0.0464***	-0.0465***	-0.0465***	-0.0465***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
sq_RTimpact		-0.0789***			
		(0.0160)			
sq_chlora			-0.0545*		-0.2234***
			(0.0313)		(0.0673)
sq_resp				0.0006	-0.0150***
				(0.0024)	(0.0053)
Observations	4416	4416	4416	4416	4416
Pseudo R-squared	0.0668	0.0747	0.0678	0.0668	0.0702

Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.0.05$, $^{***}p < 0.01$

Table 5: WTP estimates ($'s per household per year)

forecast scenario			Model 1			Model 2			Model 3			Model 4			Model 5		
coverage	accurancy 1st 12 hrs	accurancy 2nd 12 hrs	mean	low	high	mean	low	high	mean	low	high	mean	low	high	mean	low	high
6	50	50	17.26	17.26	17.26	17.59	17.59	17.59	17.40	17.40	17.40	17.27	17.27	17.27	17.66	17.66	17.66
6	50	75	22.04	22.04	22.04	22.30	22.30	22.30	22.18	22.18	22.18	22.05	22.05	22.05	22.44	22.44	22.44
6	50	100	17.11	17.11	17.11	17.44	17.44	17.44	17.36	17.36	17.36	17.14	17.14	17.14	17.55	17.55	17.55
6	75	50	22.92	22.92	22.92	23.31	23.31	23.31	22.94	22.94	22.94	22.91	22.91	22.91	23.30	23.30	23.30
6	75	75	27.70	27.70	27.70	28.03	28.03	28.03	27.72	27.72	27.72	27.68	27.68	27.68	28.08	28.08	28.08
6	75	100	22.77	22.77	22.77	23.17	23.17	23.17	22.90	22.90	22.90	22.78	22.78	22.78	23.19	23.19	23.19
6	100	50	37.38	37.38	37.38	37.78	37.78	37.78	37.40	37.40	37.40	37.37	37.37	37.37	37.76	37.76	37.76
6	100	75	42.16	42.16	42.16	42.49	42.49	42.49	42.18	42.18	42.18	42.15	42.15	42.15	42.54	42.54	42.54
6	100	100	37.24	37.24	37.24	37.63	37.63	37.63	37.36	37.36	37.36	37.24	37.24	37.24	37.65	37.65	37.65
12	50	50	19.62	19.62	19.62	19.95	19.95	19.95	19.80	19.80	19.80	19.64	19.64	19.64	20.03	20.03	20.03
12	50	75	24.40	24.40	24.40	24.67	24.67	24.67	24.58	24.58	24.58	24.42	24.42	24.42	24.81	24.81	24.81
12	50	100	19.48	19.48	19.48	19.81	19.81	19.81	19.76	19.76	19.76	19.51	19.51	19.51	19.92	19.92	19.92
12	75	50	25.28	25.28	25.28	25.68	25.68	25.68	25.34	25.34	25.34	25.28	25.28	25.28	25.67	25.67	25.67
12	75	75	30.06	30.06	30.06	30.39	30.39	30.39	30.12	30.12	30.12	30.05	30.05	30.05	30.45	30.45	30.45
12	75	100	25.13	25.13	25.13	25.53	25.53	25.53	25.30	25.30	25.30	25.14	25.14	25.14	25.56	25.56	25.56
12	100	50	39.75	39.75	39.75	40.14	40.14	40.14	39.80	39.80	39.80	39.74	39.74	39.74	40.13	40.13	40.13
12	100	75	44.52	44.52	44.52	44.86	44.86	44.86	44.58	44.58	44.58	44.52	44.52	44.52	44.91	44.91	44.91
12	100	100	39.60	39.60	39.60	40.00	40.00	40.00	39.76	39.76	39.76	39.61	39.61	39.61	40.02	40.02	40.02

Appendix

Table A1: Robustness check: Choice model of RI

	Model 1	Model 2	Model 3	Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)
sq	-0.8017***	-0.4012***	0.2994	-0.8388***	3.4587**
	(0.1041)	(0.1289)	(0.6392)	(0.1514)	(1.4601)
cov12	0.1097	0.1097	0.1117	0.1102	0.1104
	(0.0940)	(0.0945)	(0.0941)	(0.0940)	(0.0941)
acc175	0.2628**	0.2655**	0.2579**	0.2617**	0.2616**
	(0.1294)	(0.1297)	(0.1294)	(0.1295)	(0.1295)
acc1100	0.9346***	0.9364***	0.9305***	0.9337***	0.9340***
	(0.1429)	(0.1432)	(0.1428)	(0.1429)	(0.1430)
acc275	0.2219**	0.2187**	0.2224**	0.2219**	0.2228**
	(0.0954)	(0.0955)	(0.0954)	(0.0954)	(0.0955)
acc2100	-0.0069	-0.0067	-0.0018	-0.0059	-0.0046
	(0.1286)	(0.1289)	(0.1286)	(0.1286)	(0.1288)
bid	-0.0464***	-0.0464***	-0.0465***	-0.0465***	-0.0465***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
sq_RTimpact		-0.0789***			
		(0.0160)			
sq_chlora			-0.0545*		-0.1845***
			(0.0313)		(0.0624)
sq_resprobust				0.0003	-0.0044**
				(0.0009)	(0.0018)
Observations	4416	4416	4416	4416	4416
Pseudo R-squared	0.0668	0.0747	0.0678	0.0669	0.0695

Standard errors in parentheses.
$*p < 0.1$, $**p < 0.0.05$, $***p < 0.01$
sq_resprobust is the interaction term between the SQ indicator and new recoded RI (none=0, slight=1, moderate=1 and intense=1).

Table A2: Robustness check: Marginal effects of RI

	RTimpact2	outcancel2	outshort2	outreloc2	yardcancel2	yardshort2	visitcancel2	windows2	pets2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
chlora	0.0379***	0.0077	0.0354***	0.0138*	0.0393***	0.0385***	0.0254***	0.0618***	0.0494***
	(0.0043)	(0.0076)	(0.0075)	(0.0082)	(0.0083)	(0.0082)	(0.0082)	(0.0084)	(0.0082)
RI2	0.0013***	0.0009***	0.0018***	0.0007***	0.0016***	0.0014***	0.0013***	0.0030***	0.0017***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
demographic variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4764	4380	4452	4404	4512	4452	4260	4476	3708

	accar2	irritation2	doctor2	fishsmell2	moved2	soldboat2	sellhouse2	changejob2
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
chlora	0.0416***	-0.0054	0.0356***	0.0090	-0.0023	0.0026	-0.0131***	-0.0009
	(0.0082)	(0.0076)	(0.0050)	(0.0082)	(0.0071)	(0.0039)	(0.0030)	(0.0033)
RI2	0.0018***	0.0010***	0.0008***	0.0016***	-0.0007***	-0.0001	-0.0004***	-0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
demographic variables	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4212	4548	4464	4476	3984	3528	3888	3828

Standard errors in parentheses.
*$p < 0.1$, **$p < 0.0.05$, ***$p < 0.01$
RI2 is the new recoded RI (none=0, slight=1, moderate=1 and intense=1).
Estimated coefficients for demographics are available upon request.

Table A3: Robustness check: Choice model of individual outdoor activities

	outcancel2	outshort2	outreloc2	yardcancel2	yardshort2	visitcancel2	windows2	pets2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sq	-0.5073***	-0.5924***	-0.5945***	-0.5568***	-0.5368***	-0.6358***	-0.5918***	-0.7624***
	(0.1296)	(0.1310)	(0.1214)	(0.1151)	(0.1170)	(0.1144)	(0.1195)	(0.1225)
cov12	0.1066	0.1306	0.1177	0.1172	0.1212	0.1460	0.1020	0.0995
	(0.0944)	(0.0937)	(0.0943)	(0.0931)	(0.0939)	(0.0960)	(0.0937)	(0.1028)
acc175	0.3189**	0.2561**	0.2428*	0.2889**	0.2826**	0.2379*	0.2895**	0.2131
	(0.1301)	(0.1291)	(0.1295)	(0.1280)	(0.1289)	(0.1318)	(0.1285)	(0.1414)
acc1100	0.9150***	0.8954***	0.8749***	0.8913***	0.8889***	0.8502***	0.9004***	0.8073***
	(0.1418)	(0.1407)	(0.1409)	(0.1400)	(0.1409)	(0.1434)	(0.1407)	(0.1519)
acc275	0.1863**	0.2403**	0.2010**	0.2086**	0.2147**	0.2071**	0.2330**	0.2332**
	(0.0948)	(0.0940)	(0.0946)	(0.0934)	(0.0943)	(0.0960)	(0.0940)	(0.1024)
acc2100	-0.0280	-0.0112	0.0121	0.0199	0.0570	-0.0180	0.0476	0.0925
	(0.1274)	(0.1264)	(0.1271)	(0.1260)	(0.1269)	(0.1292)	(0.1265)	(0.1366)
bid	-0.0432***	-0.0446***	-0.0442***	-0.0441***	-0.0455***	-0.0434***	-0.0449***	-0.0393***
	(0.0048)	(0.0048)	(0.0048)	(0.0047)	(0.0048)	(0.0049)	(0.0048)	(0.0052)
Interaction term (SQ and activity)	-0.4143***	-0.3408***	-0.5000***	-0.5348***	-0.5266***	-0.5648***	-0.4705***	-0.3203*
	(0.1284)	(0.1294)	(0.1281)	(0.1284)	(0.1267)	(0.1428)	(0.1271)	(0.1640)
Observations	4416	4488	4440	4548	4488	4296	4512	3744
Pseudo R-squared	0.0664	0.0689	0.0730	0.0697	0.0693	0.0691	0.0739	0.0709

Standard errors in parentheses.
$*p < 0.1$, $**p < 0.0.05$, $***p < 0.01$
Interaction term (SQ and activity) indicates the interaction term between the SQ indicator and individual outdoor activities.

Table A4: Robustness check: Choice model of individual outdoor activities, continued

	accar2	irritation2	doctor2	fishsmell2	moved2	soldboat2	sellhouse2	changejob2
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
sq	-0.8453***	-0.6335***	-0.7463***	-0.5646***	-0.7413***	-0.9852***	-0.8771***	-0.9753***
	(0.1153)	(0.1252)	(0.1053)	(0.1193)	(0.1143)	(0.1193)	(0.1116)	(0.1133)
cov12	0.1341	0.1137	0.1209	0.1299	0.1592	0.1264	0.1300	0.1103
	(0.0960)	(0.0926)	(0.0936)	(0.0935)	(0.0987)	(0.1056)	(0.1001)	(0.1008)
acc175	0.2346*	0.2269*	0.2330*	0.2352*	0.2601*	0.2442*	0.2419*	0.2393*
	(0.1318)	(0.1271)	(0.1281)	(0.1283)	(0.1352)	(0.1434)	(0.1362)	(0.1374)
acc1100	0.8272***	0.8691***	0.8714***	0.8641***	0.9060***	0.8719***	0.8978***	0.8175***
	(0.1437)	(0.1395)	(0.1398)	(0.1404)	(0.1472)	(0.1561)	(0.1489)	(0.1506)
acc275	0.1950**	0.2362**	0.2123**	0.2024**	0.1799*	0.1947*	0.1518	0.1662
	(0.0969)	(0.0935)	(0.0947)	(0.0943)	(0.1008)	(0.1063)	(0.1023)	(0.1023)
acc2100	0.0363	0.0181	0.0143	0.0751	0.0250	0.0316	-0.0632	0.0641
	(0.1303)	(0.1262)	(0.1269)	(0.1269)	(0.1336)	(0.1420)	(0.1362)	(0.1375)
bid	-0.0449***	-0.0469***	-0.0461***	-0.0466***	-0.0451***	-0.0456***	-0.0468***	-0.0462***
	(0.0049)	(0.0048)	(0.0048)	(0.0048)	(0.0051)	(0.0054)	(0.0052)	(0.0052)
Interaction term (SQ and activity)	-0.0705	-0.3677***	-0.7574***	-0.5088***	-0.1899	0.2679	-0.0848	0.3288
	(0.1388)	(0.1252)	(0.2140)	(0.1250)	(0.1622)	(0.2367)	(0.2570)	(0.2343)
Observations	4248	4584	4500	4512	4020	3564	3924	3864
Pseudo R-squared	0.0667	0.0703	0.0705	0.0702	0.0645	0.0789	0.0688	0.0730

Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.0.05$, $^{***}p < 0.01$
Interaction term (SQ and activity) indicates the interaction term between the SQ indicator and individual outdoor activities.

Table A5: Robustness check: Multiple nearest beaches

	Model 3	Model 4	Model 5	Model 3	Model 4	Model 5	Model 3	Model 4	Model 5	Model 3	Model 4	Model 5	Model 3	Model 4	Model 5
	(3)	(4)	(5)	(3)	(4)	(5)	(3)	(4)	(5)	(3)	(4)	(5)	(3)	(4)	(5)
		First nearest beach only			two nearest beaches			three nearest beaches			four nearest beaches			five nearest beaches	
sq	-1.2102***	-0.8435***	-1.7340***	-0.4266	-0.9270***	-1.3024	0.2994	-0.8282***	4.3274***	0.4423	-0.8570***	3.6265**	0.8195	-0.8726***	6.0443***
	(0.4512)	(0.1441)	(0.6375)	(0.5403)	(0.1464)	(0.9788)	(0.6392)	(0.1443)	(1.5578)	(0.7203)	(0.1436)	(1.7004)	(0.6890)	(0.1442)	(1.7477)
cov12	0.1087	0.1104	0.1100	0.1106	0.1113	0.1111	0.1117	0.1101	0.1103	0.1116	0.1105	0.1100	0.1120	0.1106	0.1100
	(0.0940)	(0.0940)	(0.0941)	(0.0940)	(0.0940)	(0.0940)	(0.0941)	(0.0940)	(0.0942)	(0.0941)	(0.0940)	(0.0942)	(0.0942)	(0.0940)	(0.0943)
acc175	0.2648**	0.2612**	0.2610**	0.2610**	0.2590**	0.2591**	0.2579**	0.2619**	0.2622**	0.2575**	0.2610**	0.2593**	0.2564**	0.2606**	0.2610**
	(0.1295)	(0.1295)	(0.1295)	(0.1294)	(0.1294)	(0.1294)	(0.1294)	(0.1295)	(0.1296)	(0.1294)	(0.1294)	(0.1294)	(0.1294)	(0.1294)	(0.1295)
acc1100	0.9365***	0.9334***	0.9341***	0.9330***	0.9316***	0.9318***	0.9305***	0.9339***	0.9348***	0.9299***	0.9332***	0.9307***	0.9286***	0.9327***	0.9318***
	(0.1430)	(0.1429)	(0.1429)	(0.1429)	(0.1429)	(0.1429)	(0.1428)	(0.1429)	(0.1431)	(0.1428)	(0.1429)	(0.1429)	(0.1428)	(0.1429)	(0.1431)
acc275	0.2214**	0.2221**	0.2216**	0.2223**	0.2222**	0.2220**	0.2224**	0.2220**	0.2223**	0.2227**	0.2221**	0.2227**	0.2225**	0.2221**	0.2218**
	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0955)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0955)
acc2100	-0.0091	-0.0055	-0.0059	-0.0050	-0.0032	-0.0035	-0.0018	-0.0061	-0.0052	-0.0012	-0.0052	-0.0019	0.0004	-0.0047	-0.0021
	(0.1287)	(0.1287)	(0.1287)	(0.1286)	(0.1286)	(0.1286)	(0.1286)	(0.1287)	(0.1288)	(0.1286)	(0.1286)	(0.1287)	(0.1286)	(0.1286)	(0.1288)
bid	-0.0464***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***	-0.0465***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
sq_chlora	0.0201		0.0388	-0.0185		0.0161	-0.0545*		-0.2234***	-0.0616*		-0.1978***	-0.0803**		-0.3026***
	(0.0216)		(0.0270)	(0.0262)		(0.0416)	(0.0313)		(0.0673)	(0.0354)		(0.0748)	(0.0339)		(0.0763)
sq_resp		0.0010	0.0033		0.0030	0.0041		0.0006	-0.0150***		0.0014	-0.0106**		0.0018	-0.0188***
		(0.0023)	(0.0028)		(0.0024)	(0.0038)		(0.0024)	(0.0053)		(0.0024)	(0.0051)		(0.0025)	(0.0058)
Observations	4416	4416	4416	4416	4416	4416	4416	4416	4416	4416	4416	4416	4416	4416	4416
Pseudo R-squared	0.0671	0.0669	0.0675	0.0670	0.0673	0.0673	0.0678	0.0668	0.0702	0.0678	0.0669	0.0691	0.0686	0.0670	0.0718

Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.0.05$, $^{***}p < 0.01$