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John C. Whitehead
Appalachian State University

Tim Haab
The Ohio State University

Sherry L. Larkin
University of Florida

John B. Loomis
Colorado State University

Sergio Alvarez
University of Central Florida

Andrew Ropicki
University of Florida

Department of Economics
Appalachian State University
Boone, NC 28608
Phone: (828) 262-2148
Fax: (828) 262-6105
www.business.appstate.edu/economics

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John C. Whitehead[a], Tim Haab[b], Sherry L. Larkin[c],

John B. Loomis[d], Sergio Alvarez[e] and Andrew Ropicki[f]

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[a] Professor, Department of Economics, Appalachian State University, Boone, NC 28608 USA.

[b] Professor, Department of Agricultural, Environmental and Development Economics, The Ohio State University, Columbus, OH 43210 USA.

[c] Professor, Department of Food and Resource Economics, University of Florida, Gainesville, FL 32611 USA.

[d] Emeritus Professor, Department of Agricultural and Resource Economics, Colorado State University, Fort Collins, CO 80523 USA.

[e] Associate Professor, Rossen College of Hospitality Management and Center for Integrated Coastal Research, University of Central Florida, Orlando, FL 32816 USA.

[f] Associate Professor, Department of Food and Resource Economics, University of Florida, Gainesville, FL 32611 USA.

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Abstract

Estimating recreation benefits from environmental events or regulatory actions often requires household survey data. Probability-based sampling is preferred but costly; opt-in panels cost less but their welfare estimates may be biased. This paper compares probability-based and opt-in samples using travel cost method (TCM) and contingent valuation method (CVM) estimates of recreation losses from the BP/Deepwater Horizon oil spill in northwest Florida. Opt-in estimates exceed probability-based estimates by 26% under TCM and by 20% to 32% under CVM. Restricting CVM "yes" responses to those respondents most certain they would pay narrows the gap, but it remains larger than the TCM gap.

Key words: contingent valuation method, opt-in panel data, probability-based panel data, travel cost method.

JEL Code: Q51

Introduction

If the purpose of a nonmarket valuation study is to generalize the estimated values beyond the sample to the population of interest, then probability sampling is needed (Champ, 2017: 58). Probability sampling involves the researcher selecting the elements of the sample, with each element having a known probability. This contrasts with non-probability samples, where often times data is collected from people who volunteer or "opt-in" to be included in the sample. As noted by Johnston, et al. (2017) these samples may reflect "...unknown selection biases related to people's unobserved characteristics." Usually probability-based samples also provide a known sampling frame, and typically make possible calculating a survey response rate. Opt-in samples usually lack comparable response rate information. This difference hinders the ability to accurately generalize the opt-in sample values to the population.

After reviewing the empirical evidence on comparisons of probability and non-probability surveys, Cornesse et al. (2020: 22) state that the majority of the evidence is that use of weighting cannot reliably solve the inaccuracy of non-probability samples, i.e., only a few studies show that demographic weighting will sufficiently reduce differences between the two types of samples. The authors end their article indicating "Based on the accumulated empirical evidence, our key recommendation is to continue to rely on probability sample surveys." Cornesse et al. (2020: 22). While non-probability samples are useful for methodological studies (Champ, 2017:58), if the purpose of the study is to generalize the results to benefit-cost analysis, Regulatory Impact Analysis or damage assessment then probability samples are key.

Nonmarket values can be estimated by using a variety of techniques including the contingent valuation method (CVM), discrete choice experiments, the hedonic price method, and the travel cost method (TCM). All but the hedonic price method usually require collection of survey data. As such the generalizability of the results for real world decision making requires probability sampling. However, despite the significance of many of these decisions, time and budget constraints sometimes require the use of non-probability samples, such as opt-in panel data. Thus, it is important for researchers to understand the differences in nonmarket valuation benefit estimates between probability-based and opt-in samples.

At present, there appears to be only three published non-market valuation studies that have addressed the differences between probability and non-probability samples and all use stated preference methods (Berrens, et a. 2003; Whitehead, et al. 2023; Sandstrom-Mistry, et al. 2023). The Berrens, et al. (2003) study involved a comparison of random digit dialing phone surveys (nationally representative), an opt-in internet panel survey, and a probability-based internet survey. The topic was attitudes toward climate change and ratification of a global treaty. While CVM was not the main focus on their analysis, the study did find that respondents in all three survey sampling approaches support ratification, with such support significantly decreasing with the higher the price respondents were asked to pay. Nonetheless, the two probability samples had greater sensitivity to price, hence lower willingness to pay (WTP) than the opt-in sample. The authors indicate that this difference largely disappears once demographic variables such as income, age, and education are included in the model. Sandstrom-Mistry et al. (2023) compared two opt-in panels, MTurk and Qualtrics, with a mixed mode addressed-based mail/internet probability sample. Respondents to all three identical surveys showed a lower likelihood of paying as cost of the water quality program increased. However, the WTP of the

MTurk opt-in sample for non-marginal changes in water quality related features of the program were always significantly higher than in the probability sample (Sandstrom-Mistry et al. 2023). The pattern of higher WTP was less pronounced in the Qualtrics sample, but still greater than the probability sample.

The Whitehead et al. study used the CVM to estimate passive use value for Florida households using a probability-based internet panel versus an opt-in panel. While both samples response to stated price was negative and significant, the benefit estimates from the opt-in panel data were 166% higher than the probability-based panel data. The opt-in sample also had a much higher variance resulting in a standard error 5.59 times greater than the probability-based internet panel. Such a large variance makes a meaningful statistical test of differences misleading.

This study compares the sensitivity of TCM and CVM welfare estimates to survey sampling frame, using probability-based estimates as the benchmark for comparison. The existing valuation literature that compares probability and opt-in samples makes such comparisons using just one valuation method. The advantage with making the comparison using a single method is in isolating the valuation method when making the comparison between probability vs opt-in sampling. However, in the case of recreation there is often the option to use either TCM or CVM. An unanswered question in the existing literature is which valuation method would minimize any bias introduced by opt-in samples. We are not aware of any published studies that have addressed this issue. The purpose of this research is to fill this gap by conducting an empirical analysis comparing WTP obtained from probability and opt-in samples using both the TCM and CVM.

This paper contributes to the literature in three ways. First, it provides one of the few direct comparisons of probability-based and opt-in samples in nonmarket valuation. Second, it is the first study, to our knowledge, to compare these sampling-frame differences across both revealed-preference (TCM) and stated-preference (CVM) approaches within a common empirical setting. Third, it provides practical guidance regarding the magnitude of sampling-frame effects when probability-based sampling is infeasible.

In the next section of this paper we describe the data which are from the BP/Deepwater Horizon study conducted by the state of Florida in 2011. We exploit a feature of the data where Knowledge Networks supplemented the probability-based panel with separate opt-in panel data. Next, we describe the models that are estimated: a single-site recreation demand TCM model for the Panhandle region of Florida that estimates consumer surplus per trip (CS) and a CVM model from a survey question that elicits the WTP for the most recent trip to the same region. We compare the CS and WTP per trip estimates across sample. We find that the opt-in panel data results in higher CS and WTP per trip estimates with both TCM and CVM. Finally, we conclude that, while opt-in panel data produces welfare estimates greater than probability-based panel data, situations may arise where opt-in panel data is still useful for researchers and policy-makers. In these cases, knowing the expected magnitude of overstatement of CS and WTP would be important, so additional comparisons are needed so as to adjust opt-in sample welfare estimates in the future.

Data

The data for this analysis is derived from survey conducted to estimate the recreational losses associated with the BP/Deepwater Horizon oil spill in the Gulf of Mexico. This spill constitutes the largest marine oil spill in U.S. history. The magnitude of the spill generated substantial concern about losses to coastal recreation in Florida. To quantify these effects, a research project was undertaken to estimate economic losses to the State of Florida, including losses associated with affected recreation trips. The data used in this current research was collected as part of that broader effort (Huffaker et al. 2012).

The BP/Deepwater Horizon recreation survey was implemented in 2011 via the internet by Knowledge Networks Inc. (KN). Survey respondents were drawn from a sample of households residing in the 13 states that comprise the primary market area for domestic visitors to Northwest Florida, drawn from the KN KnowledgePanel® using a probability-based panel designed to be representative of the United States. To obtain the opt-in sample KN sent email invitations through another firm that manages opt-in online panels.

This study sought to determine the economic losses experienced by recreation visitors to coastal regions in Florida impacted by the BP/Deepwater Horizon oil spill, primarily the Panhandle region of Northwest Florida (NWFL). The affected area was defined to include Escambia, Santa Rosa, Okaloosa, Walton, Bay, Gulf, Franklin, Wakulla, Jefferson, Taylor, Dixie, and Levy Counties. The target population of the survey was non-institutionalized adults age 18 and over who have visited the Northwest Florida coast in the last 24 months, or canceled at least one trip to the Gulf of Mexico since June 1, 2010 due to the oil spill. The survey gathered information on past visitation to coastal destinations, saltwater-based recreation activities, details on their past trip to the study region, trip cancellations due to the oil spill (past and future), and respondent information.

Since there is no sampling frame for recreation visitors planning saltwater-based trips to this broad coastal region from which to sample, two sources of secondary data were used to assess the domestic market area for recreation visitation to the study region. The first secondary data source was VISIT FLORIDA®, which is the official tourism marketing organization for the State of Florida. The second was the Marine Recreation Fisheries Statistics Survey (MRFSS) program, since renamed the Marine Recreation Information Program (MRIP), which is administered by NOAA's National Marine Fisheries Service. VISIT FLORIDA® and the MRFSS both report the number of annual visitors to Florida by state of residence. Results from each source for the three years prior to the oil spill (2007, 2008, and 2009) were used to determine the top states for visitation to the study region.

The top non-Florida states in 2007-2009 included a total of 17 states. Restricting the market area only to states that appear in lists compiled from both VISIT FLORIDA® and the MRFSS yielded 13 states that in 2009 accounted for 88% of non-Florida general overnight visitors, as well as 89% of marine anglers. The resulting 13-state market area is comprised of southern states and extends north through the Midwest: Georgia, Alabama, Tennessee, Louisiana, Texas, Missouri, Mississippi, Kentucky, Arkansas, Ohio, Indiana, Illinois, and Florida.

The survey was conducted by KN from August 12 through September 24, 2011. Each respondent's eligibility for the full survey was determined by a series of screening questions at the beginning of the questionnaire. Eligible participants completed the survey in a median time of 14 minutes. To enhance survey response rates, KN emailed reminders to non-responders. The response rate was 79 percent for KN panelists. The response rate for the opt-in panelists could not be obtained.

Of the 15,014 individuals that began the survey, 2108 were either past or potential recreation visitors to the NMFL study region. The CVM and TCM analyses are conducted based on surveys with the 1,518 households that are past visitors. Almost 52% of the respondents are from the KN probability-based panel (n=788) and 48% are from the opt-in panel (n=740). KN provided a weight that reflects each respondent's representativeness in the overall sample based on their socio-demographic information.

Valuation Methods

Estimating gains or losses to nonmarket goods, such as recreation, requires methods capable of recovering individuals' willingness to pay for changes in environmental quality. Two widely used approaches are the travel cost method (TCM), a revealed preference approach, and the contingent valuation method (CVM), a stated preference approach.

Travel Cost Method

The underlying principle of the TCM is that the costs individuals (consumers) incur to take a recreation trip can be used as a proxy for the "price" of the recreation opportunities at the site (Parsons 2017). The single-site version of the TCM assumes that consumers' willingness to pay these travel expenses can be estimated from the number of trips taken at different travel costs (Landry and Smith, forthcoming). This approach is comparable to estimating the demand for any market good or service based on the quantities demanded by consumers at different prices.

The single-site TCM is used to estimate recreation demand functions in this analysis. In the single-site model, recreation trips to a specific site over a given period of time represents the quantity demanded by a given respondent, and the travel cost to that site is considered the implicit own-price of that same person. We included the following two additional independent variables: a measure of the travel cost to a substitute site (i.e., the implicit cross-price), and the respondent's income. Assuming just two sites, the model of demand for recreation trips to a single-site becomes:

$$(1) \qquad x_1 = x(p_1, p_2, y)$$

where x_1 is the number of trips to NWFL made by the respondent, p_1 is their travel cost to NWFL, p_2 is their travel cost to a substitute site, and y is their income. Trips refer to any trips that involved saltwater-related recreation including day trips and trips involving one or more nights away from home.

In order to employ the TCM we developed an estimate of the travel cost for each respondent to travel to the site they visited and estimates of the costs they would have incurred to travel to each substitute site. Both the money variable cost of travel and the opportunity cost of travel time are included in the travel cost measures. Distance traveled was calculated from the mid-point of household i's home zip code to the midpoint of the coast in the j^{th} destination:

$$(2) \qquad tc_{ij} = cd_{ij} + \gamma w_i \left(\frac{d_{ij}}{mph}\right),$$

where c is the cost per mile, d_{ij} is round trip distance, γ is a fraction of the hourly wage rate in order to account for the cost of disutility of travel time, w_i, is the hourly wage rate, mph is miles per hour, i = 1, …, 1518 respondent households; and j = 1, …, 12 counties.

The own-price travel cost is the minimum travel cost to the 12 NWFL counties. The substitute sites are Gulf of Mexico and South Atlantic coastal states of Texas, Louisiana, Mississippi, Alabama, Georgia, South Carolina and North Carolina. Each non-Florida state was considered a separate site because within each state the coastal areas are similar. The remainder of the state of Florida was divided into three substitute sites: Southwest Florida, the Florida Keys, and the Florida Atlantic Coast. The substitute travel cost is the minimum travel cost of the 10 non-NWFL site travel costs, i.e., the seven non-Florida states and three Florida areas outside of NWFL.

We use variable cost of travel estimates from AAA's 2011 Edition of "Your Driving Costs: Behind the Numbers." The variable cost estimate is based on gas, maintenance and tire costs. These costs vary by small, medium and large sedan, sport-utility vehicles and mini-vans. The variable cost estimate is the weighted average of the cost per mile for each type of vehicle and estimates of the market shares of the vehicle fleets in Georgia and Florida (49% of the respondents). The weighted variable cost is \$0.1962 per mile. The opportunity cost of travel time is assumed to be 33% ($\gamma = 0.33$) of the wage rate, standard in the TCM literature (Lew, forthcoming), to account for the disutility of travel time. The average of 50 miles per hour is based on a trip from Atlanta, GA, to Destin, FL, with two 20-minute stops (estimated from Mapquest in 2011). The wage rate is measured as household income divided by 2000 annual work hours.

The unweighted TCM data are summarized in Table 1. The average number of trips taken to the NWFL region is 2.25 in the probability-based (PB) data and 2.46 in the opt-in (OI) data. These means are not statistically different according to a t-test. The calculated travel cost to the nearest of five NWFL sub-regions is $298 and $285 in the probability-based and opt-in data. The calculated travel cost to the households' nearest alternative site is $228 (PB) and $220 (OI). None of the differences in the travel cost estimates across data type are statistically significant. The assumption of automobile travel for all respondents is a simplifying assumption necessitated by data limitations. Although some respondents may have used alternative modes (e.g., air travel), prior research suggests that automobile travel dominates regional coastal recreation. We acknowledge that this assumption may introduce measurement error. The average annual household income is higher in the probability-based data, $72 thousand, relative to the opt-in data, $53 thousand. This difference is significant at the $p<0.01$ level.

Contingent Valuation Method

The CVM measures values by eliciting preferences directly from individuals through simulated market survey questions (Boyle 2017). A commonly used CVM question format to estimate recreation values asks survey respondents if they would pay $A more for their trip, where the amount of $A varies across the sample (Cameron and James 1987). Based on survey responses, researchers calculate the average willingness to pay (WTP) for the recreation trip. In this study CVM is used to estimate the value of recreation trips by asking past visitors if they "would have visited Northwest Florida for your most recent trip if your travel and lodging expenses were $A higher?" The variable A is the product of the respondent's reported travel and lodging expenses, and a randomly assigned percentage from five alternatives: 25%, 50%, 75%, 100% or 125%. The average change in trip cost (A) is $581 with the probability-based data and $439 with the opt-in data. The difference in the cost amounts across samples is significant at the $p<0.01$ level.

The frequencies of "yes" responses by percentage increase in the cost amount are reported in Table 2. The majority of these respondent households, 66% (PB) and 70% (OI), indicated that they still would have taken the trip with higher costs (Yes1). These households were then asked a follow up question about certainty. Prior research starting with Champ, et al. (1997) suggests recoding respondents' "Yes" answer to a "No" when the follow up question indicates that they are unsure about whether they would pay the cost amount. Champ, et al. found this improved the consistency between stated WTP and actual WTP. This finding has been replicated by others (see Penn and Hu 2023). We adopt the certainty delineation approach of Blumenschein, et al. (2008) who uses a series of adjectives such as "probably sure" and "very sure" rather than the numeric scale of Champ, et al. (1997).

Consistent with the Champ, et al. (1997) recoding to improve consistency between stated and actual WTP, those Yes1 respondents that were *not* at least "somewhat sure" (Yes2) or "very sure" (Yes3) of their Yes responses were coded as "No's". Fifty-five percent of both the probability-based and opt-in respondents were "somewhat sure" that they would actually be willing to pay the change in trip costs (Yes2). Twenty-eight percent of probability-based and 25% of opt-in respondents were "very sure" that they would actually be willing to pay the change in trip costs (Yes3). According to Champ, et al. (1997) this group would have the highest likelihood of actually following through their stated intentions to pay with an actual payment. As such those respondents indicating "Yes" but unsure, somewhat unsure, neither sure or unsure were recoded as "No" responses.

The probability of a yes response (Yes1) in the probability-based data decreases from 80% to 52% as the percentage cost increase from 25% 125%. The probability of a yes response in the opt-in data decreases from 79% to 57% as the percentage cost increases from 25% to 125. Both of these decreasing patterns of frequency of yes responses are statistically significant at the p<0.01 level. However, the frequencies across the probability-based and opt-in data are statistically different according to the Cochrane-Mantel-Haenszel (CMH) test with a slower decrease in the opt-in data.

The probability of a somewhat sure “yes” response (Yes2) decreases from 67% to 44% as the percentage cost increases from 25% to 125% in the probability-based data. The probability of a somewhat sure “yes” response with the opt-in data decreases from 63% to 46% as the percentage cost increases from 25% to 125% (with a non-monotonicity at 75%). The decreases in the frequency of the somewhat sure “yes” (Yes2) responses are statistically significant at the p<0.01 level in both data sets. However, the frequencies across the PB and OI data are statistically different according to the Cochrane-Mantel-Haenszel (CMH) test with, again, a slower decrease in the opt-in data.

The probability of a very sure “yes” response (Yes3) in the probability-based data decreases from 31% to 21% as the cost increases from 25% to 125%. There are non-monotonicities in these data at the 50% cost increase (41% yes) and the 100% cost increase (27% yes). The probability of a very sure “yes” response in the OI data decreases from 30% to 23% as the percentage cost increases from 25% to 125%, with non-monotonicities at 75% and 100% cost increases. The decreases in the frequency of very sure “yes” responses are statistically significant at the p<0.01 level in the probability-based data but statistically insignificant in the opt-in data. The frequencies across the PB and OI data are statistically different according to the Cochrane-Mantel-Haenszel (CMH) test.

Empirical Results

Travel Cost Model

We estimate the determinants of trips with the truncated Negative Binomial count data model since all respondents took at least one trip (Haab and McConnell 2002):

(3) $$P(X_{1i} = x_{1i}|p_{1i}, p_{2i}, y_i) = \frac{\Gamma(x_{1i}+(1/\alpha))}{\Gamma(1/\alpha)x_{1i}!}\left(\frac{1/\alpha}{(1/\alpha)+\mu_i}\right)^{\frac{1}{\alpha}}\left(\frac{\mu_i}{(1/\alpha)+\mu_i}\right)^{x_{1i}}$$

where $\Gamma(\cdot)$ is the gamma function, α is the dispersion parameter, μ_i is the conditional mean and $x_{1i} = 1, \ldots, 49$. The conditional mean equation is:

(4) $$E(X_{1i}) = \mu_i = exp(\beta_0 + \beta_1 p_{1i} + \beta_2 p_{2i} + \beta_3 y_i)$$

The variance is $E(X_{1i}) = \mu_i + \alpha\mu_i^2$ which is greater than the mean when $\alpha > 0$.

Elasticity in the Negative Binomial model is estimated as: $e_z = \beta_z^* z$, where β^* is the estimated effect of the Poisson coefficient and *z* is the mean of the variable. The consumer surplus per trip estimate from a log-linear model is (Bockstael and Strand 1987):

(5) $$\frac{CS}{trip} = -\frac{1}{\beta_1}$$

CS confidence intervals are estimated with the Krinsky-Robb simulation (Park, Loomis and Creel 1991).

The models are weighted and the data sources are pooled because the weighting factor is designed for use with the combined sample. Estimating separate models for each data source would require reweighting or unweighted estimation, potentially introducing inconsistencies. Thus, we estimate just one model with pooled probability-based and opt-in data where differences across data sources are captured by interacting the constant and each independent variable with PB=1 and OI=1 indicators in a switching specification. The model is statistically significant according to the model chi-square statistic ($p < 0.01$).

Results of the TCM estimation are shown in Table 3. The own-price (travel cost) coefficients are negative and statistically significant in each data model. Recreation demand own-price elasticities are -1.04 and -0.77 in the probability-based and opt-in data models.[1] The cross-price (substitute travel cost) coefficient has a positive effect on trips, indicating that the alternative site is a substitute, with cross-price elasticities of 0.41 (PB) and 0.26 (OI). Income has a positive effect on trips, indicating that NWFL trips are normal goods, with income elasticities of 0.24 (PB) and 0.34 (OI). The coefficients on the travel cost and income variables are statistically different across the PB and OI data sources with χ^2 statistics on equality constraints of 2.90 ($p= 0.09$) and 5.14 ($p=0.023$), respectively. The joint test indicates that the constants, own-price, cross-price, and income coefficients are statistically different across the PB and OI data sources $\chi^2=20.85$ ($p< 0.01$).

Consumer surplus per trip estimates are presented in Table 4. The CS for each household is estimated at $287 and $374 in the probability-based and opt-in data, respectively, a 26%

[1] Elasticity in the Negative Binomial model is estimated as: $e_z = \beta_z^* z$, where β^* is the estimated effect of the Poisson coefficient and z is the mean of the variable.

difference. The differences are statistically significant at the p=0.04 level according to the convolutions test (Poe et al. 2005).

Taken together, the TCM results indicate that both probability-based and opt-in data yield theoretically consistent demand models. However, the systematically higher consumer surplus estimates obtained from the opt-in sample suggest that sampling frame may influence the magnitude of welfare estimates even when behavioral relationships are preserved.

Contingent Valuation Method

Following Loomis (1997) and McConnell, Weninger, and Strand (1999), respondents who take a recreation trip enjoy utility, v, with income, y, and travel cost, p. The indirect utility function is $v(y - p \mid x)$. Each respondent in the sample has made the revealed preference choice to take the trip, $x = 1$.

(6) $$v(y - p \mid x = 1) > v(y \mid x = 0)$$

Respondents are then presented with a situation with higher travel costs and asked if they would still have taken the recreation trip:

(7) $$v(y - (p + A) \mid x = 1) \underset{<}{\overset{>}{=}} v(y \mid x = 0)$$

Given that (a) income is constant across states of the world and (b) the own-price of a trip is constant across time, these two variables drop from the analysis with a linear approximation of the utility function and simple binary logit models are estimated (Hanemann 1984, Haab and McConnell 2002):

$$(8) \qquad \Pr(YesC = 1) = \Pr(\alpha_0 - \alpha_1 A + e_i)$$

where $C = 1, 2, 3$ certainty levels. The probability function is operationalized with the logistic regression model:

$$(9) \qquad \Pr(\Delta v \geq 0) = \frac{1}{1+\mathrm{e}^{-(\alpha_0 - \alpha_1 A + e_i)}}.$$

The empirical model is a panel with one revealed preference observation, Yes = 1, A = 0, and one stated preference observation, Yes = 0, 1, A > 0. Given that the empirical model is a panel, the standard errors are clustered at the respondent level to account for within-subject correlation.

Three separate logistic regression models are estimated, one each for Yes1, Yes2 Yes3 dependent variables (Table 5). Each model pools the probability-based and opt-in data. In each model the constant is not statistically different across data source which is driven by the revealed preference panel where probability of a trip is 100% when the change in trip cost is zero. The cost amount is interacted with the probability-based and opt-in data indicators. The change in the cost amount for both the probability-based and opt-in data has a negative and statistically significant effect on the probability of a yes response for the Yes1, somewhat sure Yes2 and very sure Yes3 coding of the dependent variable. In each model, the differences in PB and OI cost coefficients are statistically significant and the probability-based cost amount coefficient indicates a steeper slope. The Yes1 model represents the worst statistical fit according to the model Wald F statistics.

With a linear functional form for utility, the mean (and median) WTP estimate is the cost amount that makes the probability that the change in utility is equal to 0.50 (Hanemann 1984).

(10) $WTP = -\frac{\alpha_0}{\alpha_1}$.

The willingness to pay estimates are presented in Table 6. The probability-based willingness to pay per trip estimates are $1146, $850 and $335 from the Yes1, somewhat sure Yes2, and very sure Yes3 models, respectively. The opt-in willingness to pay per trip estimates are $1397, $1053 and $462 from the Yes1, Yes2 and Yes3 models, respectively. The opt-in WTP estimates are 20% (Yes1), 21% (Yes2) and 32% (Yes3) greater than the corresponding estimates with the probability-based data. The convolutions test p-values for dollar differences in the WTP between probability-based and opt-in data for Yes1, Yes2, and Yes3 estimates are p = 0.071, p = 0.051 and p = 0.012, respectively.

Comparison of TCM and CVM and Probability and Opt-in Samples

In Table 7 we compare the six WTP estimates from the CVM and two CS estimates from the TCM. There are three WTP estimates and one CS per trip estimate for probability-based data, and likewise for the opt-in data. Since our main focus is on relative accuracy (as judged by comparing the probability sample to the opt-in sample) for TCM and CVM, these comparisons are discussed first. The most consistent finding is that benefit estimates from the opt-in sample are higher than those from the probability-based sample. The overstatement is at least 20%. For TCM it is 26%, but it is the smallest dollar difference in Table 7 at $87. Interestingly, the greatest PB vs OI percentage overstatement (32%) is with (Yes3) which only includes Yes responses if the respondent is very sure they would pay their bid amount. However, the dollar amount of the difference is the smallest with the CVM (Yes3) PB vs OI comparison. This is due to the very sure Yes3 being the most stringent criteria for accepting a yes response, it has a substantially smaller dollar value of the CVM opt-in WTP estimates.

Table 7 also compares CS and WTP estimates in a convergent validity test (Loomis, Creel, and Park, 1991). The traditional dichotomous choice WTP (Yes1) analysis leads to the largest percentage and dollar value disparity between CVM and TCM. In particular, WTP Yes1 estimates are 120% and 116% higher than CS estimates in the probability-based and opt-in panel data, representing \$860 and \$1023 differences ($p<0.01$). The WTP Yes2 estimates are 99% and 95% higher than CS estimates in the probability-based and opt-in panel data, \$564 and \$679 differences ($p<0.01$). In contrast, screening the yes responses by allowing only very sure Yes3 responses to be counted as a Yes, the CVM WTP and the TCM CS estimates with the opt-in panel data have a difference of \$88 which is just marginally significantly different from zero according to the convolutions test ($p = 0.09$). Only one of the comparisons exhibits a definitive lack of statistical differences. The very sure Yes3 WTP per trip probability-based estimate of \$335 and the TCM CS per trip probability-based estimate of \$287, have a difference of \$48 which is not statistically significant from zero according to the convolutions test ($p = 0.15$). These last two results suggest that if the analyst must rely on opt-in data and use dichotomous choice CVM, that counting only "very certain" yes responses as yes would be advisable.

Conclusions

In this paper we compare CVM and TCM recreation values with probability-based and opt-in data collected with the BP/Deepwater Horizon oil spill Northwest Florida recreation survey. Our results indicate that welfare estimates derived from opt-in samples differ systematically from those derived from probability-based samples, regardless of valuation method. The results indicate that recreation benefit estimates are 26% larger with the TCM opt-in panel data and the dollar amounts are statistically different at the 0.04 level of significance. The CVM opt-in panel values relative to the probability-based values are between 20% and 32% larger, with all three comparisons being statistically different at significance levels ranging from 0.07 to 0.01. Perhaps the most notable finding is that sampling-frame differences result in estimates of recreation benefits that are of similar magnitude across revealed- and stated-preference approaches. While opt-in samples consistently generate larger welfare estimates, the percentage divergence from probability-based estimates does not appear to be unique to either valuation method, although the dollar amount of divergence is smallest with TCM. With the probability-based data the CVM very sure WTP (Yes3) per trip estimate and the TCM CS per trip estimate are not statistically different from each other, another indicator that probability-based data are preferred.

The consistently higher benefit estimates derived from the opt-in sample across all four models suggest that differences in sampling frame affect CS and WTP estimates in a systematic manner. The observed differences in our study may arise from several sources, including self-selection of more recreation-oriented respondents into opt-in panels, differences in survey engagement, panel conditioning, or other unobserved characteristics correlated with recreation preferences. While we cannot isolate these mechanisms with the available data, the consistency of the findings across valuation methods suggests that sampling-frame effects warrant consideration regardless of the valuation approach employed.

In terms of sample composition, we find only significant differences in respondent income, with opt-in panel data income significantly lower. In our models, income is a positive predictor of trips and WTP. Thus, the difference between CS and WTP estimates adjusting for these income differences are somewhat larger between probability-based and opt-in data than the estimates reported above. So, the differences in recreation benefits reported in this paper are a conservative lower bound on the differences between probability and opt-in samples.

The overall results of this paper have important implications for policy analysis. Probability-based samples remain the preferred standard when resources allow, particularly for high-stakes decisions where representativeness is critical. However, opt-in panel data are likely to persist due to lower cost and faster implementation. The magnitude of the sampling-frame differences observed here are comparable to ranges often discussed in the benefit-transfer literature, suggesting that opt-in survey estimates may remain informative when probability-based sampling is infeasible (Kaul, et al. 2013, Rosenberger and Loomis 2017). Opt-in data may be appropriate for preliminary or lower-stakes analyses, particularly when combined with calibration strategies based on probability-based benchmarks or as a complement to benefit transfer. However, an opt-in panel data survey often has one advantage over benefit transfer in that an opt-in survey would directly focus on the policy site rather than the usual benefit transfer challenge of trying to find a study site similar to the policy site.

The findings of our study should be interpreted within the context of a single recreation application based on internet survey administration. Additional comparisons across resources, recreation contexts, and survey populations would be useful for assessing the broader generality of the results. Specifically, two avenues for future research would be to develop additional comparisons of opt-in samples to probability-based samples in similar or different contexts for both valuation methods. In the future, with a substantial number of such comparisons for both TCM and CVM, a meta-analysis may provide a method for quantitatively identifying what factors matter to each method, and if so by how much, for calibrating opt-in sample derived benefit estimates to what probability-based samples would likely yield.

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Table 1. Travel Cost Model Descriptive Statistics									
	Probability-based				Opt-in				
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Difference
Trips (x)	2.25	4.09	1	49	2.46	4.83	1	49	0.20
Travel cost (op)	298.46	245.18	1.34	1458.44	284.76	216.65	1.25	1163.37	13.70
Substitute travel cost (cp)	228.09	202.01	0.12	1197.01	220.15	191.63	0.86	1109.47	7.93
Income (y)	72.09	44.85	2.5	175	53.46	36.00	2.5	175	18.63***
Observations	788				740				

***The difference is statistically significant at the $p < 0.01$ level.

Table 2. Contingent Valuation Yes/No responses								
	Yes1							
	Probability-based				Opt-in			
Percent	Yes	No	Total	%Yes	Yes	No	Total	%Yes
25	130	33	163	79.8	118	32	150	78.7
50	116	27	143	81.1	107	44	151	70.9
75	103	64	167	61.7	98	43	141	69.5
100	81	59	140	57.9	90	64	154	58.4
125	86	79	165	52.1	82	62	144	56.9
Total	516	262	*778*	66.3	495	245	740	66.9
χ^2 (df=4)	48.18				22.30			
CMH χ^2 (df=1)	62.33							
	Yes2 (Somewhat Sure)							
	Probability-based				Opt-in			
Percent	Yes	No	Total	%Yes	Yes	No	Total	%Yes
25	109	54	163	66.9	94	56	150	62.7
50	96	47	143	67.1	84	67	151	55.6
75	84	83	167	50.3	84	57	141	59.6
100	68	72	140	48.6	81	73	154	52.6
125	72	93	165	43.6	66	78	144	45.8
Total	429	349	778	55.1	409	331	740	55.3
χ^2 (df=4)	30.24				10.16			
CMH χ^2 (df=1)	32.19							
	Yes3 (Very Sure)							
	Probability-based				Opt-in			
Percent	Yes	No	Total	%Yes	Yes	No	Total	%Yes
25	50	113	163	30.7	45	105	150	30.0
50	59	84	143	41.3	30	121	151	19.9
75	37	130	167	22.2	36	105	141	25.5
100	38	102	140	27.1	40	114	154	26.0
125	35	130	165	21.2	33	111	144	22.9
Total	219	559	778	28.1	184	556	740	24.9
χ^2 (df=4)	19.63				4.56			
CMH χ^2 (df=1)	6.62							

Table 3. Negative Binomial Recreation Demand Model						
Dependent variable = Trips						
	Probability-based			Opt-in		
Parameter	Coeff	SE	z-stat	Coeff	SE	z-stat
Constant	1.1189	0.0665	16.83	0.9934	0.0621	16.00
Travel cost	-0.0035	0.0003	-11.67	-0.0027	0.0003	-9.00
Substitute travel cost	0.0018	0.0004	4.50	0.0012	0.0004	3.00
Income	0.0033	0.0009	3.67	0.0064	0.001	6.40
Dispersion (α)	0.3055	0.0187				
Observations	1518					
Log Likelihood	-3107.56					

Table 4. Travel Cost Model Consumer Surplus per Trip						
Probability-based			Opt-in			
CS per trip	Lower 95%	Upper 95%	CS per trip	Lower 95%	Upper 95%	Difference
286.62	240.74	353.79	373.98	299.95	498.30	87.36***

***The difference is statistically significant at the $p < 0.01$ level.

Table 5. Logistic Regression Models									
	Yes1			Yes2 (Somewhat sure)			Yes3 (Very sure)		
Variable	Coeff	SE	z-stat	Coeff	SE	z-stat	Coeff	SE	z-stat
Constant	2.3119	0.089	25.98	1.9617	0.0752	26.09	1.5266	0.0584	26.14
Cost × Probability-based	-0.0020	0.0002	-9.95	-0.0023	0.0002	-9.96	-0.0046	0.0005	-8.96
Cost × Opt-in	-0.0017	0.0001	-12.03	-0.0019	0.0001	-13.68	-0.0033	0.0002	-14.21
Observations	1518			1518			1518		
LL	-1223.03			-1411.74			-1442.44		
Wald F(2,1516)	102.82			123.73			124.73		

Table 6. CVM Willingness to pay per trip							
	Probability-based			Opt-in			
	WTP/trip	Lower 95%	Upper 95%	WTP/trip	Lower 95%	Upper 95%	Difference
Yes1	1146.19	942.19	1446.30	1396.76	1178.23	1691.82	249.08*
Yes2	850.58	699.10	1073.65	1052.79	902.20	1246.71	201.13*
Yes3	335.34	271.20	434.39	461.85	397.30	544.19	125.78**

*, ** Differences are statistically significant at the $p < 0.10$ and $p < 0.05$ levels.

Table 7. Probability-based (PB) and Opt-in (OI) comparisons					
			OI to PB	PB to PB	OI to OI
	Probability-based	Opt-In	Difference	Difference to TCM	
TCM	$286.62	$373.98	$87.36***		
CVM (YES1)	$1,146.19	$1,396.79	$250.60*	$859.66***	$1,022.92***
CVM (YES2)	$850.58	$1,052.68	$202.10*	$564.05***	$678.81***
CVM(YES3)	$335.34	$461.83	$126.49**	$48.81	$87.96*

*, **, *** Differences are statistically significant at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels.