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A tale of two samples: Understanding WTP differences in the age of social media☆

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ABSTRACT

Social media platforms represent a potentially cost-effective solution to obtaining stated preference data. We use data from a representative sample and a sample of convenience to investigate how willingness to pay (WTP) for increased cultural (recreational) use of an ecologically unique site differs across the two groups. We find mixed evidence of differences in WTP estimates between the two samples depending on the survey attribute. Where differences exist, the most effective selection correction mechanism is the ordered probit with weights. Our results suggest caution about extrapolating results to the general population from samples of conveniences without correcting for sample selection.

1. Introduction

The internet has reduced the cost of data collection for nonmarket valuation researchers, creating opportunities to estimate values for ecosystem services previously not estimated or for which there are few studies in the existing literature. One area of growth in the nonmarket valuation literature is estimating values associated with the cultural ecosystem service of outdoor recreation. Studies have leveraged crowdsourced data from social media (Ghermandi, 2018; Keeler et al., 2015; Pickering et al., 2020; Sinclair et al., 2018; Sinclair et al., 2020) and citizen and community science (Kolstoe et al., 2018; Kolstoe and Cameron, 2017; Roberts et al., 2017) to gather revealed preference data on actual behavior to estimate recreational cultural ecosystem service values. Stated preference researchers have also leveraged the internet to gather samples of convenience to answer specific research questions that revealed preference data cannot or are less well-suited to answer (Loomis et al., 2018; Richardson and Lewis, 2021). Stated preference information, which is based upon stated choice rather than actual behavior, has benefits over revealed preference studies. Researchers can, for example, use it to estimate non-use values[1] or ask questions that are outside the range of historical data.

The results of revealed and stated preference studies using samples of convenience may not generalize to the broader population because their samples are not necessarily representative.[2] Several studies have compared results estimated from representative and crowdsourced data. Sinclair et al. (2020), for example, compared willingness to pay (WTP) estimates from Flickr and on-site survey data for a network of German national parks. While they were able to obtain similar results between social media and in-person samples, similarities depended on whether the visitation data patterns matched. Outside of the nonmarket

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[1] Non-use values are obtained without direct use of a good or resource, and include bequest and existence values. In contrast, use values require one to take an action to gain value from a good or resource. This category includes direct use value and indirect use value.

[2] Users of social media opt into using social media, thus social media usage varies over time and place. For example, a fact sheet released by the Pew Research Center in April 2021 found 72% of Americans use social media, but back in 2005 this was only 5%. (Pew Research Center, 2021). In addition, the underlying population of users of crowdsourced platform is not always known to the researcher.

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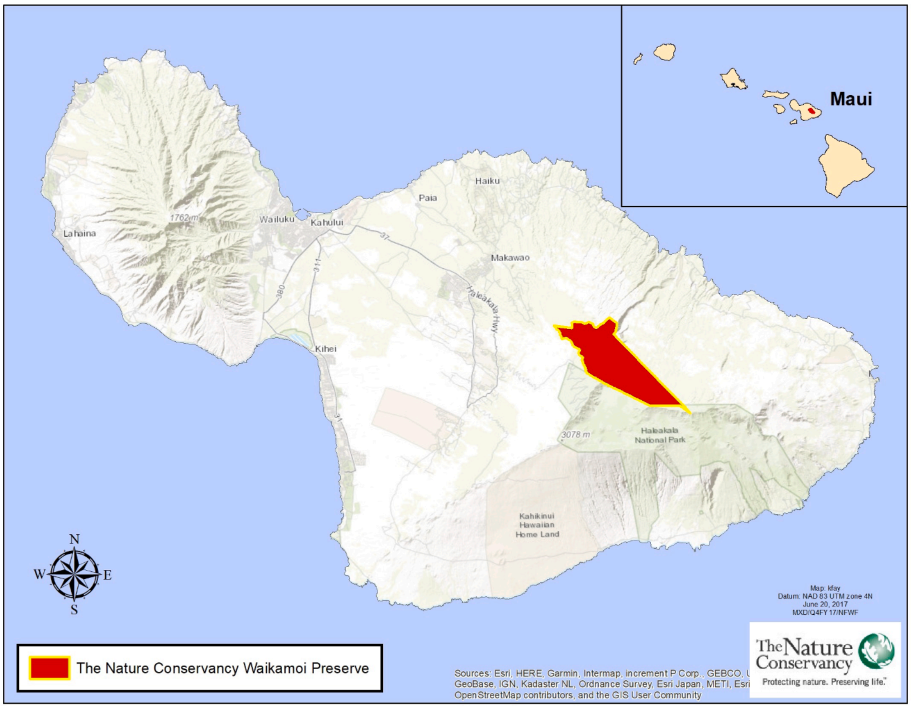


Fig. 1. Map of Maui indicating location of Waikamoi.

valuation literature, several visitation studies have compared social media posts and on-site count estimates, largely arriving at similar conclusions (Hausmann et al., 2018; Heikinheimo et al., 2017; Fisher et al., 2018; Mancini et al., 2018; Wood et al., 2013). These studies did not, however, attempt to correct for the differences between their representative samples and samples of convenience.

This research contributes to two different strands of the nonmarket valuation literature. First, we provide the first evidence of how the WTP distribution estimated from responses gathered through social media differ systematically from a representative sample of the population. This is distinct from other research, which has found that mean WTP and WTP distributions differs across survey mode (Lindhjem and Navrud, 2011; Lindhjem and Navrud, 2011; Skeie et al., 2019; Poe et al., 2005; Olsen, 2009), recreational user groups (Roberts et al., 2017; Landry et al., 2020), between users and non-users, (Jørgensen et al., 2013) and between residents and tourists (English et al., 2018; Oh et al., 2010). Our second contribution builds on the nascent sample selection literature for choice models in two ways (Cameron and DeShazo, 2013; Cameron and Kolstoe, 2021; Johnston and Abdulrahman, 2017; Kolstoe and Cameron, 2017). First, we illustrate the types of data that must be gathered to apply sample selection techniques. Second, using data from a representative sample of the population, we provide technical guidance on how to correct for the sample selection present in our sample of convenience.

Recently, Cameron and Kolstoe (2021) developed a method to correct for sample selection in samples of convenience from citizen and community science projects using an auxiliary representative sample. This method corrects both for whether respondents engaged in the activity, and also how intensively they engaged. Modeling the market extent for a birding day trip, they found their approach outperformed the standard approach that only accounts for whether respondents engaged in the activity. In this paper, we adapt the method developed by Cameron and Kolstoe (2021) to analyze data from a stated preference survey guided by the following questions: (1) how does WTP for a fee-based hike into an ecologically unique site compare across a social media sample and a representative sample from the U.S. population?; and (2) what types of data must be collected in order to apply the sample selection correction technique developed by Cameron and Kolstoe (2021)? Our representative sample is gathered through Qualtrics' online survey panel, and our sample of convenience is gathered from social media.[3] Where WTP differences exist between the two samples, we find that an ordered probit with intensity weights is the preferred sample selection correction model.

The rest of this paper is structured as follows. Section 2 outlines the experimental design and model we use for analysis, Section 3 presents the results and associated discussion, and Section 4 presents our conclusions.

2. Material and methods

2.1. Background

The ecologically unique site used for context in this study is Waikamoi Preserve, which is managed by The Nature Conservancy (TNC) of Hawaiʻi. The survey was designed to understand preferences over introducing a fee-based guided hike in Waikamoi Preserve, which is currently offered monthly for free on a first-come, first-served basis. Two competing phenomena complicate this potential policy change. First, a recently discovered invasive disease, Rapid ʻŌhiʻa Death (ROD), is more likely to be introduced to Waikamoi Preserve as more people are granted access. In light of this, TNC has restricted visitor access to protect against spreading ROD.

Second, in 2017 the American Birding Association added the state of Hawaiʻi to the North American Birding List (Swick, 2016), which created a large increase in demand for access to Waikamoi Preserve. This countervailing momentum led TNC to commission a study to explore the potential for a fee-based hiking program to increase recreational access to Waikamoi Preserve. The goals are to have the program be self-sustaining, as well as mitigate the risks associated with having more people enter Waikamoi Preserve.

[3] Qualtrics is an online survey company which maintains an online panel of respondents. For additional information on this platform see https://www.qualtrics.com/research-services/online-sample/.

Hike Attributes	Current Program	Fee-Based Program
Chance of Securing a Spot on a Waikamoi Hike	10 %	75 %
Chance Of Encountering Native Hawaiian Forest Birds	90 %	90 %
Chance of Introducing ROD & Other Invasive Species	5 %	30 %
Cost Per Person	$ 0	$ 500

Fig. 2. Example of a choice card.

Waikamoi Preserve is on the windward slopes of Haleakalā on the Island of Maui (see Fig. 1). The Preserve is managed by The Nature Conservancy (TNC), and is the largest privately held nature preserve in the state of Hawai'i. Waikamoi Preserve is dominated by 'ōhi'a trees, which provide habitat to many unique species found only in the state of Hawai'i and Maui, to include several bird species that are listed as either endangered or threatened species under the U.S. Endangered Species Act (ESA).[4]

2.2. Experimental design

We designed the discrete choice experiment (DCE) based on best practices listed in Johnston et al. (2017).[5] To determine the proper sample size, we used Orme's Rule (de Bekker-Grob et al., 2015). A critical issue in experimental design and stated preference design is using incentive compatible value elicitation methods (Vossler et al., 2012). Under mild assumptions, the binary choice elicitation format is shown to be incentive compatible (Interis and Petrolia, 2014; Vossler and Holladay, 2018; Vossler and Zawojska, 2020). For this reason, we decided to administer a repeated binary choice experiment.

To select the relevant attributes for the two different types of choice cards, we relied upon experts at, and affiliated with, TNC's Maui Nui Forest Program. For the past several years, they have managed and facilitated the volunteer docent-led hikes in Waikamoi Preserve. The general hike choice tasks, each alternative was described according to four attributes: the probability of being able to sign up for a hike (25%, 50%, 75%), the probability of encountering native Hawaiian forest birds (70%, 80%, 90%), the chance of introducing invasives (including ROD) (10%, 20%, 30%), and cost per person to go on the hike ($100, $250, $500, $1000, $1500). We used a D-optimal fractional factorial design to create 36 different choice tasks, which were then split into six blocks of six tasks. Each respondent was randomly allocated to one of the six blocks, and presented six tasks with two alternatives. One "action" alternative containing a combination of attributes and levels different from the status quo, and one status quo alternative, containing attribute levels that remained constant at current hiking program levels across choice tasks. See Fig. 2 for an example choice card. The survey was tailored to TNC's specific research questions based on interviews and feedback from TNC Maui Nui Staff and select experts who work with the TNC Maui Nui Program in 2019 and early 2020. In June 2020 a pretest sample (N = 125) from Qualtrics' online sample was used to make final adjustments and refinements to the survey prior to the launch of the main survey.

2.3. Discrete choice experiment (DCE) estimation

Analysis of the DCE data is based upon the Random Utility Maximization (RUM) Model, in which respondents are given a menu of alternatives comprised of different attributes and levels, and then maximize their utility by choosing the alternative (in each choice task in this case) that gives them the greatest satisfaction (McFadden, 1974). U_{ijt}, which is the utility for individual i when faced with alternative j in choice task t, is given by:

$$U_{ijt} = \alpha c_{ijt} + \boldsymbol{\beta}' \mathbf{x}_{ijt} + \epsilon_{ijt} \tag{1}$$

where α is the coefficient on the cost of alternative $c, \boldsymbol{\beta}'$ is a vector of coefficients on non-cost attribute levels $\mathbf{x}_{ijt}$, and ϵ_{ijt} is a stochastic error term. Assuming the stochastic term is distributed i.i.d. extreme value, parameters can be estimated using the conditional logit model (McFadden, 1974). The conditional logit assumes that within the choice scenarios, respondent utility is based solely upon the attributes of the choices and not upon the characteristics of the respondent. The conditional logit also assumes that choice probabilities are constant across individuals, so that coefficients are fixed.

An important limitation of the conditional logit is that it is subject to the independence from irrelevant alternatives (IIA) assumption (Greene, 2012). The mixed logit (ML) relaxes the IIA assumption. In it, some or all parameters are allowed to vary randomly based on heterogeneity in the sample population. This allows the model to capture unobserved heterogeneity in preferences. It is also possible for utility to be correlated across alternatives in the ML model (Train, 2009). To construct the ML, the traditional CLM is adjusted in two ways. First, for each covariate allowed to vary randomly, a parameter value is estimated for each individual, so instead of estimating a single β, each individual gets their own (β_i). Second, we include a scale parameter, σ_i, which allows for correlation among the coefficients in the utility function (Hess and Train, 2017):

$$U_{ijt} = \alpha c_{ijt} + \boldsymbol{\beta}_{\mathbf{i}}' \mathbf{x}_{ijt} + \frac{1}{\sigma_i} \epsilon_{ijt} \tag{2}$$

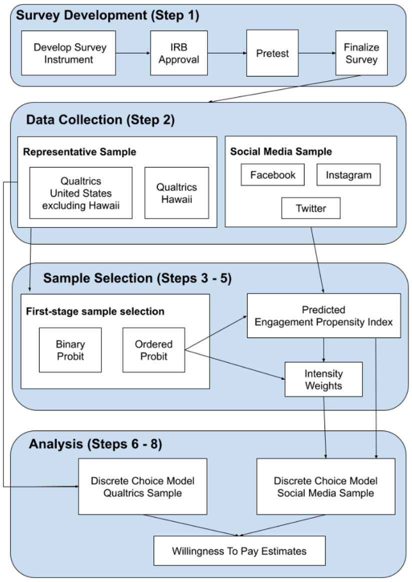
The indirect utility function is linear in parameters, and the disutility of no change in the status quo is normalized to zero. For statistically significant parameters, willingness to pay for a marginal change in attribute k can be calculated as the attribute's estimated coefficient divided by the estimated cost coefficient: $WTP_k = \frac{\beta_k}{\alpha}$. In the ML model, β_k is the mean of the distribution of estimated coefficients of the k^{th} attribute.

2.4. Selection correction for the social media sample

One weakness of sampling using social media posts or surveys is the

[4] Bird species listed as either endangered or threatened under the ESA that visitors may see in Waikamoi Preserve include: the Maui Parrotbill (in Hawaiian, kiwikiu), the Crested Honeycreeper (in Hawaiian, 'ākohekohe), and the Hawaiian Short-Eared Owl (in Hawaiian, pueo), the nēnē and Scarlet Honeycreeper (in Hawaiian, 'iiw'i).

[5] Because the survey was fielded during the COVID-19 pandemic, we included two sets of questions about how the pandemic has affected them. The first set of questions was about their future travel plans over the next two years, and the second set of questions was about how their household income has changed as a result of the pandemic.Respondents were first asked for the 2019 household income, then they were asked if their household income for 2020 would increase, decrease or stay the same as a result of the pandemic. If respondents selected either "increase" or "decrease" then shown a follow-up question about the percentage. Other design features included an oath promising to answer questions honestly (Jacquemet et al., 2017), a certainty followup (Faccioli et al., 2019), an attention trap (Malone and Lusk, 2019), and a question on consequentiality (Groothuis et al., 2017; Carson et al., 2014).



Implementing the Sample Selection Approach using Two Auxiliary Samples: One Representative and the other a Sample of Convenience

Step 1	Develop survey instrument to be used and follow best practices in the development and testing of the survey instrument prior to fielding the survey. See Champ (2017) for best practices about collecting primary and secondary data and Johnston et al. (2017) for best practices developing a stated preference survey.
Step 2	Collect data from a representative sample and the sample of convenience, in this case social media.
Step 3	Estimate the first-stage sample selection model using the representative sample. To proceed with this method requires a common set of variables on about the individual (e.g. sociodemographics, income, etc.) with the level of engagement with social media as the outcome variable.
Step 3a	Estimating the first-stage sample selection mode using a binary probit addresses sample selection along the extensive margin using the representative sample.
Step 3b	Estimating the first-stage sample selection model using an ordered probit address sample selection on the extensive and intensive margin using the representative sample. Use the ordered probit sample selection results for the subsequent steps.
Step 4	Assume the sample selection process is the same between the representative sample and the sample of convenience. Use the parameters from the first stage equation (from step 3b) to calculate the fitted propensity of engaging with social media for each member of the sample of convenience.
Step 5	Calculate the predicted engagement probabilities and construct the predicted engagement propensity index..
Step 5a	Use the estimates from step 3b to estimate the predicted engagement probabilities for the social media from step 3b.
Step 5b	Estimate an ordered probit using the same equation from step 3b and calculate the fitted probabilities for the levels of engagement observed in the social media sample.
Step 5c	Estimate the weight by taking the predicted engagement probabilities from step 5a and divide them through for each individual in the social media sample by the fitted probabilities for the level of engagement for the social media sample in step 5b. This normalizes the weights so they sum to the sample size of the social media sample.
Step 6	Interact the demeaned fitted engagement propensity with the independent variables in the discrete model.
Step 7	Include the variables from step 6 and the intensity weights from step 5c in the discrete choice model estimated with the social media sample.
Step 8	Estimate willingness to pay estimates from the discrete choice model.

Fig. 3. Flow Diagram and Steps to Incorporate Sample Selection into the Model.

limited amount of data about the individual and the population of users. To overcome this issue, one can use two data sets, where one must be from a representative sample to identify users of the social media platform for the desired purpose (e.g. posting of trips, etc). The idea is to draw samples from each of the underlying populations of interest and then model the sample selection present in the social media sample.

To formally correct for sample selection in the main choice model requires estimating a first-stage where we model the sample selection in order to calculate fitted or predicted propensities to be used in the second-stage choice model (Cameron and DeShazo, 2013; Johnston and Abdulrahman, 2017). We adapt the sample selection correction approach used by Cameron and Kolstoe (2021) to use two samples: a representative sample of the population of interest and the sample of convenience to the case where the sample of convenience comes from social media.[6]

Fig. 3 provides an overview of the work flow for the sample selection approach used in this study and that is described below.

We use data from a representative sample (Qualtrics) of $i = 1, \ldots, N$ individuals and $j = 1, \ldots, J$ individuals from a sample of convenience (social media) who were given the same survey and for whom we have the same set of information to explain engagement intensity with social media. This allows us to correct for the selection into using social media since not all people are users, and may differ in their intensity of engagement with it. For the first-stage selection model, propensity to engage is estimated using an ordered probit. In it, we calculate the fitted propensity of engaging with social media (in this case Facebook, Instagram and Twitter) with seven levels of engagement with social media (N/A, annually, semi-annually, monthly, weekly, daily, multiple times per day) according to the following equation:

$$S_i = \eta + \gamma' \mathbf{Z}_i + \epsilon_i \quad (3)$$

where S_i is the fitted propensity to engage in social media and can assume a value of 1–7; and Z_i is a vector including sociodemographic information, income, and other variables to explain engagement intensity.

We assume the underlying sample selection process between the representative sample and the sample of convenience is the same. For each member of the social media sample, j, we use $\gamma_{Qualtrics}$ to calculate the fitted propensities of engaging with social media based on observables in the social media sample, Z_j used to construct the predicted engagement propensities and construct the predicted engagement propensity index. Next, we incorporate this "predicted engagement propensity" index into the second-stage choice model. This is done like any other type of individual-specific heterogeneity by interacting the demeaned predicted engagement propensity with the key variables of interest in the second stage. Then when estimating WTP, these interaction terms can be set to zero so that estimated WTP results are for the respondent with the mean propensity to be in the sample (Cameron and DeShazo, 2013; Johnston and Abdulrahman, 2017; Kolstoe and Cameron, 2017). Fig. 3 illustrates the workflow to our sample selection approach.

Finally, we construct intensity weights to re-weight our sample based on the estimated engagement with social media propensity model following the approach used by Cameron and Kolstoe (2021). To do this we (1) estimate a seven-level ordered probit model with the Qualtrics data, (2) use $\hat{\gamma}_{Qualtrics}$ to calculate the predicted probabilities for the social media data $\hat{p}_e^*$ for engagement levels $e = 1, \ldots, 4$), (3) estimate a three-level ordered probit model with the social media data and calculate the fitted probabilities $\hat{q}_e^*$ for engagement levels $e = 2, \ldots, 4$.[7] Every observation in the choice model is then weighted by $\hat{p}_e^* / \hat{q}_e^*, e = 2, \ldots, 4$, normalized so these weights sum to the sample size of the social media sample.

3. Results and discussion

3.1. Sample selection data

The data for this study was collected in the summer of 2020. The Qualtrics sample is made up of a representative sample of the U.S. (N = 781) and a representative sample of the state of Hawaiʻi (N = 246). Descriptive statistics for both samples are presented in Table 1. After cleaning the sample from social media, 162 usable surveys remained to be used for the sample selection corrections.[8] 64.6% of the Qualtrics sample is under 54 years old, compared with 72.9% of the social media

[6] Cameron and Kolstoe (2021) use data a survey question given to both a representative sample (Qualtrics' qBus panel) and members of Cornell's citizen and community science project, eBird.

[7] In the social media sample, we only observe respondents who report using Facebook, Instagram and/or Twitter weekly, daily or multiple times per day.

[8] There were 172 surveys completed through social media.

Table 1
Summary Statistics Qualtrics & Social Media Samples.

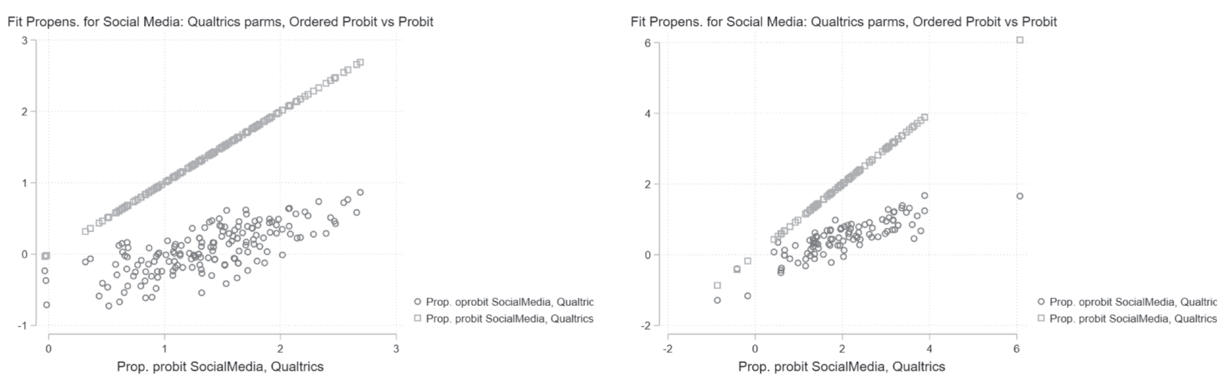
Variable	Qualtrics Full	Qualtrics Hawai'i	Social Media Full	Social Media Hawai'i
	Mean			
1(Female)	0.504	0.526	0.548	0.619
Age	46.30	48	44.04	43.24
1(Race: White)	0.682	0.378	0.568	0.476
1(Race: Nonwhite)	0.318	0.622	0.432	0.524
1(Ethnicity: Hispanic)	0.070	0.052	0.068	0.095
Household Income	85.59	86.	86.25	84.64
1(Region: West)	0.373	1	0.366	1
1(Region: Northeast)	0.176	0	0.027	0
1(Region: Midwest)	0.147	0	0.062	0
1(Region: South)	0.304	0	0.055	0
1(Conservative Politics)	0.318	0.297	0.075	0.067
1(Unemployed)	0.087	0.092	0.076	0.096
1(Retired)	0.208	0.221	0.236	0.058
1(Education: College)	0.257	0.329	0.349	0.362
1(Kids > 0)	0.396	0.309	0.204	0.225
Member of an environmental organization	0.212	0.116	0.671	0.59
Observations	1030	249	146	105

sample. Roughly half of the Qualtrics sample is female, compared with 54% of the social media sample. The social media sample has a substantially higher proportion of individuals having obtained at least a bachelor's degree than the Qualtrics sample (71% versus 51.3%). Strikingly, a much higher proportion of respondents in the Qualtrics sample self-identify as conservative than the social media sample.

3.2. Sample selection model results

Fig. 4 displays scatter plots comparing the fitted propensity index from the conventional binary probit and the ordered probit for both the full and the Hawai'i only samples. The binary probit adjusts only at the extensive margin, whereas the ordered probit adjusts at both the extensive and intensive margin, thus correcting for engagement intensity.[9] We find that the estimated fitted propensities are systematically lower for our engagement-intensity models for both the full sample and the Hawai'i only sample. This is consistent with Cameron and Kolstoe (2021), whose fitted propensities from the engagement-intensity model were also lower. An important difference between these two studies is only about 10 percent of the representative sample used in Cameron and Kolstoe (2021) report being eBird members, whereas only 12.5 percent of our representative sample report *not* using Facebook, Instagram or Twitter. The comparison of the fitted propensities from the binary versus the ordered probit results suggests a failure of the binary probit to account for the intensity of engagement results in higher fitted propensities, even when the majority of population uses the medium through which the data was collected.

The ordered probit, on the other hand, allows us to use multiple categories of information to account for differences of engagement with social media. Fig. 5 shows how the kernel densities of the fitted engagement probabilities differ between the Qualtrics (Panels A) and social media (Panels B) samples. Panels C of Fig. 5 show how we can use the parameters of the sample selection model estimated with the Qualtrics sample to predict the engagement probabilities with the social media data. Recall, the intention of the sample selection correction approach is twofold: 1) estimate the key parameters in the outcome equation at the mean propensity of the representative sample and 2) calculate weights which will reweight the sample of convenience to match the distribution in the representative sample (as captured in Panels C in Fig. 5 for both the full sample and Hawai'i subsample).



(a) Full Sample (b) Hawai'i Sample

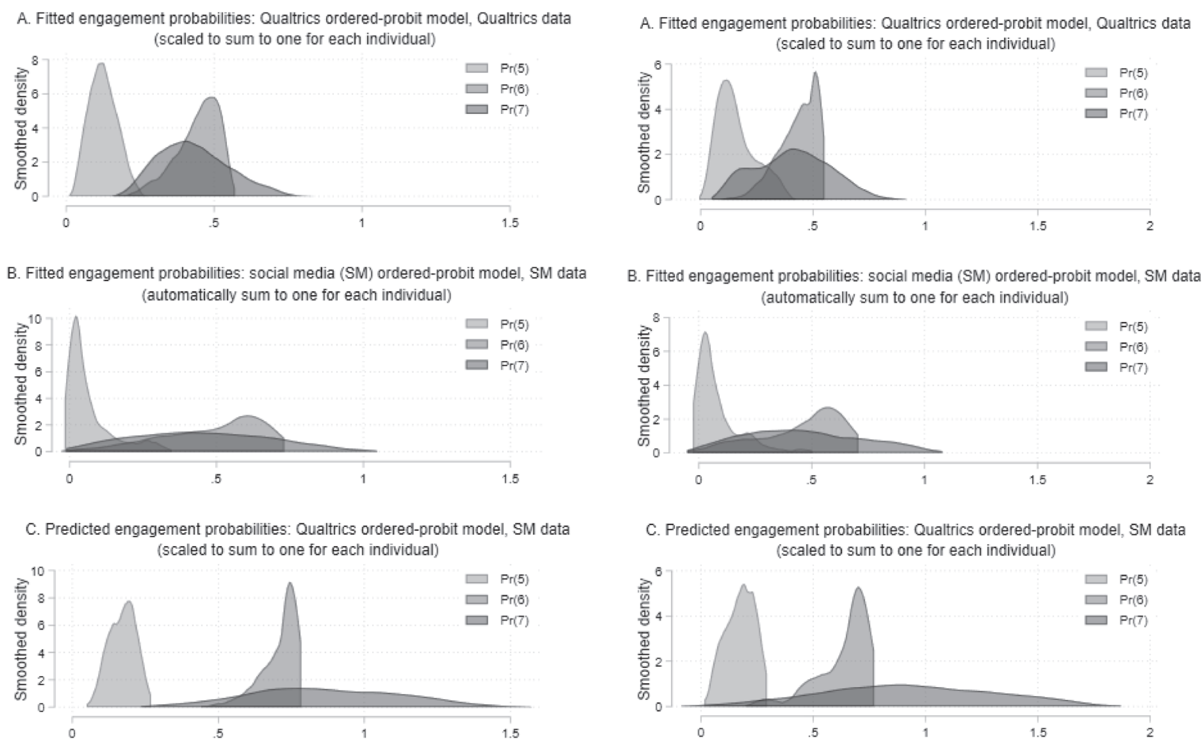
Fig. 4. Scatter plot of the predicted propensity index estimated using the Qualtrics data, ordered probit selection propensity index against the binary probit selection propensity index for both the full and Hawai'i only sample.

3.3. DCE data

Tables 2 and 3 contain descriptions of the choices made by respondents in the Qualtrics and social media samples of the DCE for the full sample and Hawai'i subsample respectively. We include only responses where respondents indicated they believed the results of the survey would be consequential, and would actually take the hike if presented with the option.[10] Across both survey mediums, respondents saw six choice scenarios, each with two options. This resulted in 9,036 total alternatives from 753 respondents in the Qualtrics sample, and 1,860 total alternatives from 155 respondents in the social media sample. Our sample includes an oversampling of residents of the state of Hawai'i which makes up 25 percent of the full sample. To correct for

[9] The results of our engagement-intensity models for the whole U.S. as well residents of the state of Hawai'i are available in the Appendix in Tables A4 and A5, respectively.

[10] To understand whether respondents saw the survey as consequential, they were asked "To what extent do you believe TNC will pay attention to people's preferences, as expressed in this study, as they make their decisions about future hiking programs?"



(a) Full Samples (b) Hawai‘i Samples

Fig. 5. Kernel density graphs showing the predicted probabilities for engagement levels 5, 6 and 7 with social media (SM). Panel A shows the fitted engagement level probabilities for the representative Qualtrics sample; Panel B shows fitted engagement probabilities for the SM sample; Panel C shows the predicted engagement probabilities for the social sample, based on an ordered-probit model estimated using the Qualtrics sample.

Table 2
Summary Statistics & Definition of Variables – DCE Model – Full Sample.

	Definition of Variable	Qualtircs				Social Media			
		Mean	SD	Min	Max	Mean	SD	Min	Max
Cost Hike	Cost per person to go on the hike	304.83	466.72	0.00	1500.00	300.91	465.02	0.00	1500.00
Chance Spot on Hike – Adj.	Probability of being able to sign up for a hike adjusted by status quo probability of 10%	19.96	24.61	0.00	65.00	20.05	24.74	0.00	65.00
Chance Hawaiian Forest Birds – Adj.	Probability of encountering native Hawaiian forest birds adjusted by status quo probability of 90%	−4.97	7.63	−20.00	0.00	−4.92	7.56	−20.00	0.00
Chance ROD/Invasives – Adj.	Probability of introducing invasives (including ROD) adjusted by status quo probability of 5%	7.44	9.39	0.00	25.00	7.48	9.44	0.00	25.00
1(Resident of State of Hawai‘i)	Indicator resident of the state of Hawai’i	0.25	-	0.00	1.00	0.73	-	0.00	1.00
1(Previously visited Waikamoi)	Indicator for previous visitor to Waikamoi Preserve	0.26	-	0.00	1.00	0.52	-	0.00	1.00
1(ANA Cost Hike)	ANA indicator for cost attribute	0.60	-	0.00	1.00	0.54	-	0.00	1.00
1(ANA Chance Spot on Hike)	ANA indicator for chance spot on hike	0.71	-	0.00	1.00	0.86	-	0.00	1.00
1(ANA Chance Hawaiian Forest Birds)	ANA indicator for chance Hawaiian forest birds	0.73	-	0.00	1.00	0.83	-	0.00	1.00
1(ANA Chance ROD/ Invasives)	ANA indicator for chance ROD/invasives	0.72	-	0.00	1.00	0.57	-	0.00	1.00
Fit Propens. probit	Fitted demeaned propensity estimated using binary probit					1.51	0.56	0.08	2.80
Fit Propens. oprobit	Fitted demeaned propensity estimated using ordered probit					0.19	0.33	−0.62	0.98
Intensity Weight – Full US	Intensity weight					1.01	2.40	0.22	30.26
Observations		9,036				1,860			

this, we use a base weight (population/sample size) to re-weight the sample to reflect the proportion in the overall US population based on the 2018 American Community Survey, which are the same data used to set the quotas for the representative sample.

3.4. DCE model results

Parameter estimates for the mixed logit results are displayed in Tables 4 and 5. The simulated likelihood is maximized in each model using

Table 3
Summary Statistics – DCE Model – Hawai'i Sample

	Qualtrics				Social Media			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Cost Hike	303.90	466.21	0.00	1500.00	301.33	465.06	0.00	1500.00
Chance Spot on Hike – Adj.	20.08	24.77	0.00	65.00	19.96	24.62	0.00	65.00
Chance Hawaiian Forest Birds – Adj.	−5.03	7.70	−20.00	0.00	−4.91	7.55	−20.00	0.00
Chance ROD/Invasives – Adj.	7.50	9.43	0.00	25.00	7.44	9.41	0.00	25.00
1(Previously visited Waikamoi)	0.15	–	0.00	1.00	0.50	–	0.00	1.00
1(ANA Cost Hike)	0.53	–	0.00	1.00	0.50	–	0.00	1.00
1(ANA Chance Spot on Hike)	0.86	–	0.00	1.00	0.87	–	0.00	1.00
1(ANA Chance Hawaiian Forest Birds)	0.83	–	0.00	1.00	0.86	–	0.00	1.00
1(ANA Chance ROD/Invasives)	0.73	–	0.00	1.00	0.58	–	0.00	1.00
Fit Propens. probit					1.47	0.56	0.08	2.80
Fit Propens. oprobit					0.17	0.33	−0.62	0.98
Intensity Weight – Hawai'i					1.06	1.60	0.09	12.40
Total Alternatives	2,292				1,356			

Table 4
Mixed Logit Results – Qualtrics – Key Parameters.

	(1) Weighted Qualtrics Sample	(2) + Attribute Non-Attendance	(3) Hawai'i Qualtrics Sample	(4) + Attribute Non-Attendance
Mean				
Cost Hike	−0.00109***	−0.00144***	−0.00161***	−0.00223***
	(0.000149)	(0.000239)	(0.000271)	(0.000415)
Chance Spot on Hike – Adj.	−0.000240	0.00806**	−0.00302	0.0169+
	(0.00322)	(0.00405)	(0.00597)	(0.0104)
… × 1(Resident of Hawaii)	−0.0131***	−0.0108**		
	(0.00442)	(0.00460)		
… × 1(Previously Visited Waikamoi)	−0.00301	−0.00773+	0.0135	0.0102
	(0.00446)	(0.00470)	(0.00946)	(0.00956)
Chance Hawaiian Forest Birds – Adj.	0.0150*	0.0135+	0.0368*	0.0377*
	(0.00846)	(0.00872)	(0.0223)	(0.0223)
… × 1(Resident of Hawaii)	0.0112	0.0103		
	(0.0124)	(0.0124)		
… × 1(Previously Visited Waikamoi)	0.0279**	0.0297**	0.0367	0.0458
	(0.0126)	(0.0135)	(0.0327)	(0.0337)
Chance ROD/Invasives – Adj.	−0.0598***	−0.0808***	−0.122***	−0.133***
	(0.00871)	(0.0128)	(0.0264)	(0.0326)
… × 1(Resident of Hawaii)	−0.0213*	−0.0209*		
	(0.0123)	(0.0121)		
… × 1(Previously Visited Waikamoi)	0.0273**	0.0345***	0.0975***	0.0996***
	(0.0112)	(0.0116)	(0.0341)	(0.0333)
var(Chance Spot on Hike – Adj.)	0.0204***	−0.0227***	0.00485	0.00441
	(0.00424)	(0.00382)	(0.00739)	(0.00753)
cov(Chance Spot on Hike – Adj.,	0.0296*	0.0255**	0.0524**	0.0496*
Chance Hawaiian Forest Birds – Adj.)	(0.0169)	(0.0124)	(0.0261)	(0.0255)
cov(Chance Spot on Hike – Adj.,	−0.0527***	−0.0493***	−0.0740**	−0.0689**
Chance ROD/Invasives – Adj.)	(0.0113)	(0.00890)	(0.0327)	(0.0289)
var(Chance Hawaiian Forest Birds – Adj.)	0.0200	0.0218	0.0414	0.0387
	(0.0360)	(0.0215)	(0.0293)	(0.0289)
cov(Chance Hawaiian Forest Birds – Adj.,	−0.0172	−0.0164	−0.0541+	−0.0508*
Chance ROD/Invasives – Adj.)	(0.0281)	(0.0133)	(0.0370)	(0.0299)
var(Chance ROD/Invasives – Adj.)	0.00220	0.00488	0.0244	0.0264
	(0.0324)	(0.00893)	(0.0547)	(0.0428)
Correct ANA?	No	Yes	No	Yes
Weighted?	Yes	Yes	No	No
Total Alternatives	9036	9036	2292	2292
Log Likelihood	−6.98e + 08	−6.94e + 08	−421.50	−416.73
AIC	1.40e + 09	1.39e + 09	869.01	867.45
BIC	1.40e + 09	1.39e + 09	943.59	964.98

Standard errors in parentheses below parameter estimates.
Estimated via STATA 16 with 500 Halton draws (mixlogit).
*** p<0.01, ** p<0.05, * p<0.1, + p<0.15.

Table 5
Mixed Logit Results – Social Media, Key Parameters.

	(1) Attribute Non-Attendance – U.S.	(2) Ordered Probit & Weighted – U.S.	(3) Attribute Non-Attendance – Hawai'i	(4) Ordered Probit & Weighted – Hawai'i
Mean				
Cost Hike	−0.00427***	−0.00407***	−0.00428***	−0.00408***
	(0.000740)	(0.000946)	(0.000830)	(0.00109)
… × (Fitted Propensity oprobit $\hat{\gamma}$)		0.0000591		0.000811
		(0.00177)		(0.00196)
Chance Spot on Hike – Adj.	0.0281**	0.0376**	0.0236+	0.0478**
	(0.0138)	(0.0153)	(0.0153)	(0.0235)
… × 1 (Resident of Hawai'i)	−0.00823	−0.0240**		
	(0.0104)	(0.0108)		
… × 1 (Previously Visited Waikamoi)	0.00581	0.0132	0.0122	0.00820
	(0.00942)	(0.0103)	(0.0112)	(0.0127)
… × (Fitted Propensity oprobit $\hat{\gamma}$)		−0.0199		−0.0452**
		(0.0202)		(0.0228)
Chance Hawaiian Forest Birds – Adj.	0.0307	0.0703	0.0205	0.0618
	(0.0441)	(0.0705)	(0.0415)	(0.0739)
… × 1 (Resident of Hawai'i)	−0.00806	−0.0198		
	(0.0433)	(0.0546)		
… × 1 (Previously Visited Waikamoi)	−0.00952	−0.0355	−0.0148	−0.0366
	(0.0380)	(0.0462)	(0.0485)	(0.0535)
… × (Fitted Propensity oprobit $\hat{\gamma}$)		−0.110		−0.0823
		(0.0866)		(0.0901)
Chance ROD/ Invasives – Adj.	−0.150***	−0.271***	−0.173***	−0.291***
	(0.0515)	(0.0948)	(0.0519)	(0.105)
… × 1 (Resident of Hawai'i)	−0.0151	0.0173		
	(0.0444)	(0.0381)		
… × 1 (Previously Visited Waikamoi)	−0.00158	0.0126	−0.000810	0.0413
	(0.0378)	(0.0405)	(0.0502)	(0.0804)
… × (Fitted Propensity oprobit $\hat{\gamma}$)		0.0501		0.0197
		(0.0548)		(0.0855)
var(Chance Spot on Hike – Adj.)	0.0101	0.0125	0.00789	−0.0111
	(0.00842)	(0.00903)	(0.0155)	(0.0166)
cov(Chance Spot on Hike – Adj., Chance Hawaiian Forest Bird – Adj.)	−0.0783**	−0.0520	−0.0876+	−0.146
	(0.0360)	(0.0410)	(0.0561)	(0.102)
cov(Chance Spot on Hike – Adj., Chance ROD/ Invasives – Adj.)	0.0782**	0.119***	0.0465	0.125**
	(0.0317)	(0.0373)	(0.0378)	(0.0617)
var(Chance Hawaiian Forest Birds – Adj.)	0.0617*	0.108***	0.0692	0.0681
	(0.0342)	(0.0419)	(0.0494)	(0.0720)
cov(Chance Hawaiian Forest Birds – Adj., Chance ROD/ Invasives – Adj.)	0.0861***	0.0583***	0.0658*	0.0501
	(0.0298)	(0.0211)	(0.0351)	(0.0508)
var(Chance ROD/ Invasives – Adj.)	0.0330	−0.0528**	0.129***	0.244***
	(0.0458)	(0.0216)	(0.0362)	(0.0759)
Correct ANA?	Yes	Yes	Yes	Yes
Ordered Probit Sample Selection?	No	Yes	No	Yes
Weighted?	No	Yes	No	Yes
Observations	1860	1860	1356	1356
Log Likelihood	−315.47	−265.42	−222.66	−198.51
AIC	670.94	578.85	479.32	439.02

Standard errors in parentheses below parameter estimates.
Estimated via STATA 16 with 500 Halton draws (mixlogit).
*** p<0.01, ** p<0.05, * p<0.1, + p<0.15.

500 Halton draws. Cost is estimated as a fixed parameter, as are all of the interaction effects. The main parameters of interest are estimated randomly. The underlying distribution of each random parameter is assumed to be normal. The coefficients of the random parameters are the means of the normal distribution of estimates. The estimated elements of the Cholesky matrix, which appear below the parameter estimates, describe the distributions around the mean values, as well as the correlations between the parameters. In each model, the standard errors are calculated using the delta method (Hole, 2007; Train, 2009).

3.4.1. *Representative sample*

Table 4 contains the results from the Qualtrics panel, the quota-based representative sample. Model 1 shows the results of the full Qualtrics sample. This model is state population-weighted to reflect the population distribution of the U.S. It also includes controls for consequentiality and whether the respondent would actually take the hike if presented with the option. Model 2 shows the results of the same model, but with additional controls for attribute non-attendance. Models 3 and 4 are the versions of Models 1 and 2, but estimated with only the Hawai'i subsample. The Akaike Information Criterion (AIC) and log likelihood statistics favor the models with corrections for attribute nonattendance (ANA).[11] These correspond with Models 2 and 4, which are the preferred set of results for the full and Hawai'i subsamples, respectively. We focus our discussion for the Qualtrics sample on these results.

The cost parameter represents the private cost to the respondent for obtaining the mix of attributes and levels in the alternative. As expected, the estimated parameter on cost is negative and statistically significant across all models. This indicates respondents were less likely to choose an alternative as its cost (i.e., price) increased. The chance of being able to sign-up to go on the hike was positive and statistically significant for the full sample, and marginally significant in Hawai'i subsample, once we control for ANA. This indicates that folks are more likely to choose an alternative where the probability of being able to sign-up for a hike (i.e. there being available spots) is higher. Also as expected, the estimated parameter on chance of encountering native Hawaiian forest birds is positive and statistically significant across all models. This indicates that respondents are more likely to choose an alternative as the chance of encountering a native forest bird increases. The estimated parameter on chance of introducing ROD and other invasive species is negative, statistically significant, and an order of magnitude larger than the estimated coefficient in front of encountering native forest birds. This suggests that respondents are more likely to choose an alternative as the chance of introducing ROD or other invasive species decreases, and indicates disutilty for increasing the risk of the introduction of ROD or other invasives to Waikamoi Preserve. Interestingly, we see multiple instances of familiarity with Waikamoi Preserve making a difference in peoples' attitudes in Model 2. First, the chance of securing a spot on a general hike was not statistically different from zero until Model 2, in which we controlled for ANA. Even then, the estimated parameter is small in magnitude relative to the other hike attributes. The estimated parameter in front of the interaction term between those that have previously visited Waikamoi and chance of getting a spot on the hike is negatively and marginally statistically significant. This suggests that relative to a person from the general U.S. population, those who have previously visited Waikamoi have a lower utility of going on a hike into Waikamoi again. Second, the interaction of previously visited and chance of introducing ROD or other invasives is positive and statistically significant, suggesting that there is less disutility for increasing the risk for those who have visited Waikamoi preserve compared to those who have not. This result may be due to a difference in risk perception of the risk. Third, the interaction between previously visited and chance of encountering native forest birds is positive and statistically significant, suggesting that those who visited Waikamoi previously gain even more utility from the chance of seeing birds than the entire sample.

3.4.2. Social media sample

Table 5 contains the results from the social media sample. Models 1 and 2 are from the full sample; Models 3 and 4 are from the Hawai'i subsample. Controls for ANA, consequentiality, and whether the respondent would actually take the hike if presented with the option are applied in all models. The first and third models do not correct for sample selection, while Models 2 and 4 use an ordered probit with weights for how intensively respondents use social media. The goodness of fit measures indicate a preference for Models 2 and 4; we base our discussion going forward on those models.

In some ways, results are similar to those from the Qualtrics panel. The estimated parameters on cost, chance of being able to sign up for the hike and chance of introducing ROD or other invasives have the same signs and significance, though different magnitudes. Three differences between the social media and Qualtrics samples are notable. First, "Chance of Encountering Native Hawaiian Forest Birds" is not statistically significant in the social media group. Most of the social media sample is familiar with native Hawaiian forest birds and thus the draw to the hike may be more location specific, such that it is in a large intact native forest. Second, the magnitude of the coefficient on ROD for the social media group is, for most models, nearly twice that of the Qualtrics panel. One reason for this is that ROD may be more salient to social media respondents. Third, familiarity with Waikamoi Preserve does not seem to affect responses in the social media sample, as evidenced by the lack of statistical significance in the interaction terms of having previously visited Waikamoi Preserve.

Comparing Models 2 and 4 allow us to explore whether differences between the Qualtrics and social media samples might be driven by a higher proportion of Hawai'i residents in the social media sample. The major insight arising from this comparison is Hawai'i residents are more concerned about reducing ROD risk than they are about gaining access to the hike or encountering birds, relative to the full social media sample or the Qualtrics sample. One explanation for this is that Hawai'i residents may be more familiar with ROD because of its effect on native forests on the Big Island of Hawai'i and Kauai'i, where the outbreaks have been the worst. As with the full social media sample, the results for the interaction terms of having previously visited Waikamoi Preserve are not statistically significant in this sample.

Because the cost coefficient in the social media sample is larger than in the Qualtrics sample, and since it enters into the denominator of the WTP ratio, we turn our attention to comparing WTP estimates and their distributions to gain more insight into differences between the two samples and the effectiveness of the sample selection mechanism.

Table 6
WTP for Choice Attributes.

Attribute	Full Sample Median (2.5%, 97.5%)	Hawai'i Sample Median (2.5%, 97.5%)
Chance Spot on Hike		
Qualtrics	5.56 (0.10, 11.67)**	7.59 (−1.70, 17.83)*
Social Media, No Corrections	6.58 (0.15,13.36)**	5.52 (−1.75, 13.28)
Social Media, Ordered Probit Demeaned Prop. w/ weights	9.39 (2.07, 19.40)**	11.81 (0.68, 23.80) **
Chance Hawaiian Forest Birds		
Qualtrics	9.22 (−1.98, 24.91)*	16.97 (−2.83, 42.50) *
Social Media, No Corrections	7.28 (−13.55, 30.34)	4.84 (−14.65, 26.11)
Social Media, Ordered Probit Demeaned Prop. w/ weights	17.70 (−19.02, 59.43)	15.53 (−22.88, 60.93)
Chance ROD/Invasives		
Qualtrics	−56.08 (−88.85, −35.22)***	−59.86 (−109.17, −28.98)***
Social Media, No Corrections	−35.08 (−65.04, −11.97)***+	−40.55 (−77.53, −16.24)***
Social Media, Ordered Probit Demeaned Prop. w/ weights	−66.67 (−125.46, −24.62)***	−71.61 (−133.24, −26.36)***

95% CI next to WTP estimates.
*** WTP distributions are different from zero at the 1% level or better.
** WTP distributions are different from zero at the 5% level or better.
* WTP distributions are different from zero at the 10% level or better.
+ WTP distribution is different from Qualtrics sample distribution at the 15% level.

3.5. Willingness to pay

Estimating WTP, and comparing WTP distributions, is a central focus of this research. Mean WTP estimates are calculated as the estimated

[11] The ANA control is from a stated ANA question. The question can be asked as either what respondents attributes paid the most or least attention to in the DCEs. We asked respondents to which attributes they paid the most attention.

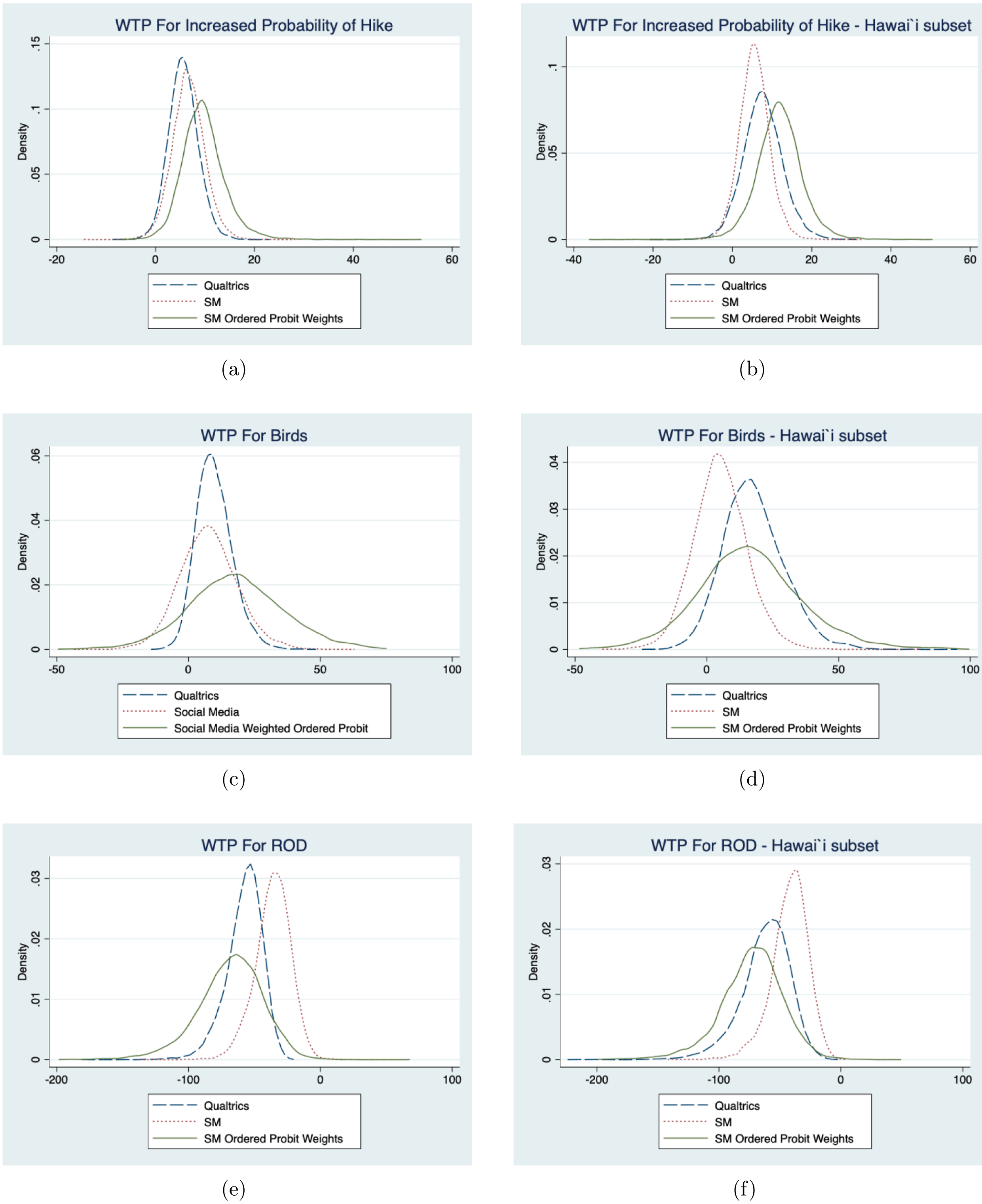


Fig. 6. Comparison of WTP distributions.

coefficient on attributes divided by the estimated cost coefficient ($\widehat{WTP}_k = \frac{\widehat{\beta_k}}{\alpha}$). Distributions are constructed by taking 10,000 random draws of the data, multiplying by the parameter estimates from the model, and calculating mean WTP values. The medians of these distributions, along with 95% confidence intervals in parentheses, are shown in Table 6. To formally test whether the WTP distributions differ from one another and from zero, the complete combinatorial approach of Poe et al. (2005), in which two independent distributions obtained from simulation methods are compared for equality, is used. A two-sided test of differences between WTP distributions is conducted and, where statistically significant, is noted.

In both the full Qualtrics sample and the Hawai‘i Qualtrics subsamples, WTP for each attribute is significantly distinguishable from zero. In the social media sample, WTP for an increased chance of encountering native Hawaiian forest birds is not different from zero in any of the models. However, WTP for ROD is different from zero in every model, and WTP for an increased chance of securing a spot on a hike is statistically significantly different than zero for most models. A few interesting observations are present. First, for nearly every attribute, WTP estimates are different from one another, though not by a statistically significant margin. One exception is that for "Chance of ROD/Invasives," the WTP distribution from the full Qualtrics sample is statistically different from the full social media sample. The difference in this particular attribute, and not the others, may be tied to the difference in familiarity with the risk of ROD/invasives to Hawaiian native forests. Only about 60 percent of respondents in the representative Qualtrics sample knew about ROD, whereas almost everyone in the social media sample knew of ROD (all but about 5 percent). The results for our uncorrected stated preference estimates echo findings of other revealed preference or visitation studies comparing results from crowdsourced and representative data: similarities may be found, but caution in using these estimates is still warranted. Respondents on social media self-select into using social media, so it is critical that researchers address sample selection if intending to make inference about the general population. To phrase it differently, crowdsourced samples may serve as complements to data sets sampling the general population, but should not be viewed substitutes, particularly in the absence of sample selection corrections (Cameron and Kolstoe, 2021; Keeler et al., 2015; Kolstoe and Cameron, 2017; Fisher et al., 2018; Sinclair et al., 2020).

Fig. 6 shows WTP distributions for a one percentage point increase of each of our key attributes for the full U.S. sample and the Hawaiʻi subsample. In panels (a)-(c), it is visibly evident that the uncorrected social media and Qualtrics WTP estimates are similar prior to applying the selection correction method. In panels (d)-(f), however, it is clear that the uncorrected social media and Qualtrics WTP estimates are different. In each of the instances in which differences exist, the ordered probit with intensity weights is effective at pulling the social media WTP estimates closer to the representative Qualtrics WTP estimates.

4. Conclusion

In this paper we used a DCE to show how WTP distributions for attributes of a recreational hike, a cultural ecosystem service, compare between a representative sample and a sample of convenience from social media. While social media platforms present an opportunity to gather data at a lower cost, the sample is non-random, and the underlying selection mechanism into the sample must be considered. To account for the sample selection portion of that difference, we advance the state of the art by extending the method developed by Cameron and Kolstoe (2021) for citizen and community science projects to social media and correct for sample selection present in discrete choice data. Some of the WTP distributions from our social media sample were not statistically different from the WTP distributions from our representative sample. Where differences were found, such as for "Chance of ROD/Invasives," the most effective sample selection correction model was the ordered probit with intensity weights. This finding is consistent with Cameron and Kolstoe (2021), who find the dominant selection correction method for revealed preference data includes ordered probit with intensity weights.

In addition to identifying the most effective selection correction mechanism, we provide technical guidance on how to use a representative sample of a population to estimate sample selection corrections when using DCE data collected from social media platforms. One complication is that the method requires access to data from a representative sample, as well as respondents' levels of engagement with social media and sociodemographic information. While we were able to administer the DCE to both samples, it may be cost prohibitive for other researchers to replicate the effort with a representative sample. In that case, a smaller survey with more targeted questions can be fielded to gather the necessary data to conduct the sample selection. Moving forward, we suggest researchers who use social media data either: (1) collect data that allows them to correct for the problem; or (2) if collecting more data is not an option, acknowledge the results may not generalize beyond the sample in question, as done in Keeler et al. (2015) and Kolstoe and Cameron (2017).

Social media is a valuable source of data for understanding how people engage with nature and value cultural ecosystem services. It provides researchers with a potentially more cost-effective way to identify peoples' interests based on what they choose to follow, post, or reply to on social media. This study demonstrated that researchers need to carefully consider whether values estimated using social media or other crowdsourced data can be extrapolated to a more general population without first addressing the sample selection problem. Our research provides an avenue through which the selection problem present in such samples may be corrected, which makes the resulting inference more useful in planning and policy decisions. Future research should consider exploring the conditions under which WTP differences between social media and representative samples arise, and when they likely will not. Our work suggests familiarity with the good may play a role, but this and other mechanisms merit further study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecoser.2022.101420.

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