VALUATION OF ENVIRONMENTAL RESOURCES: STRUCTURAL ESTIMATION WITH RECREATION DEMAND AND CONTINGENT VALUATION DATA FOR CONSISTENT WELFARE MEASUREMENT

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Abstract This paper extends the existing theoretical and empirical framework to consistently estimate the welfare change due to change in environmental quality by relaxing the assumption of weak complementarity to estimate both use and passive-use values. With an online survey, we recorded respondent' past visits to springs in Florida and elicited their intended trip frequency to a representative springs under current and proposed restored conditions with an one-and-one-half-bound dichotomous choice format. The intended recreation demand is then jointly estimated with the trip demand under current condition to recover the indirect utility function in which environmental quality of the springs is a contributing factor. The recovered indirect utility function allows us to derive the total willingness to pay (WTP) for quality improvement as a function that can be decomposed into use and passive-use values. Using maximum likelihood estimation, we find that imposing weak complementarity in estimating change in environmental quality through recreation demand models leads to lower welfare measures. The mean total WTP is around $205 per household per year for springs restoration, which includes passive use that is between $85 and $105. In contrast, the estimated consumer surplus is around $ 141 per household per year, underestimating the economic value of springs. Compared to non-visitors, visitors have a higher WTP for springs restoration.

Keywords: Contingent Valuation, Recreation Demand, Weak Complementarity, Willig Condition, Welfare.

JEL: Q51, Q26

BACKGROUND

Valuation of environmental resources often uses revealed preference data to estimate the Marshallian demand for related goods, such as demand for recreation supported by environmental resources. To derive consistent welfare measures through changes in Marshallian consumer surplus as a result of changes in environmental quality, researchers assume zero non-use value (NUV) or passive use values of environmental resources (e.g., weak complementarity) and weak separability of income in the underly indirect utility function (e.g., Willig condition) (Maler, 1974; Willig, 1978) in almost all empirical valuation studies. Change in Marshallian consumer surplus is often a biased welfare estimation with the standard practice of imposing weak complementarity and Willig condition, since many environmental resources have passive use values. However, assumptions on weak complementarity and Willig conditions cannot be tested when estimating recreation demand models with revealed preference data alone. Though many studies have combined demand data and willingness to pay data for quality improvement to improve the efficiency of estimation, they still impose weak complementarity and Willig conditions.

To consistently estimate the welfare change due to change in environmental quality, a unified model of preference for environmental quality improvement has been proposed in which revealed preference data and stated willingness to pay data are combined to test the weak complementarity assumption, recover the parameters of the underlying indirect utility function, and estimate total values (TV) that include both use values (UV) and passive-use values (Eom & Larson, 2006; Huang et al., 2016; Landry et al., 2018). This type of framework can be extended to study all types of nonmarket valuation of environmental resources through consumption of related goods, such as hedonic housing model.

This paper extends the existing theoretical and empirical framework to consistently estimate the welfare change due to change in environmental quality in three important aspects. In contrast to existing studies that have used single-bound contingent valuation (CV) format to elicit willingness to pay (WTP) following environmental quality improvement, we introduce an intermediate CV format: one-and-one-half-bound dichotomous choice (OOHBDC) that is more efficient than single-bound valuation and reduces response bias on the follow-up bid often seen in double-bounded valuation (Cooper et al., 2002). Second, we focus on natural springs in Florida under threats from economic development, water withdrawal, and pollution. As one of the State's unique freshwater resources, they are likely to present non-negligible passive use value or NUV due to their historical and cultural significance. While existing studies focus on one dimension of environmental quality, such as water quality, our study uses artistic representations taken by a professional photographer over the past three decades to visualize the complex change in springs ecosystems in terms of water clarity, abundance of aquatic plants, and presence of algae. Third, we elicit the intended trip frequency under two scenarios, restoring the springs to the conditions of mid 2000s, restoring the conditions to the early 1990s, vs. the status quo. We then elicit their willingness to pay under these scenarios of restoration. In contrast to existing studies that model past recreation demand with stated WTP jointly, we jointly estimate the intended recreation demand under status quo and the restoration scenarios with stated willingness to pay to recover the indirect utility function in which environmental quality of springs is a contributing factor. The recovered indirect utility function allows us to derive the total WTP for quality improvement as a function that can be decomposed into UV and NUV. Specifically, we specified one commonly used functional form (e.g., the semi-log form) as the reference utility to recover the underlying preference function for environmental quality improvement.

The rest of the chapter is structured as follows. The next section reviews related literature of valuation methods. We then describe the econometric models in detail, followed by a section that describes our survey and data. The results are then reported, followed by conclusion and discussion.

RELATED LITERATURE

In environmental economics, there is a wide recognition that environmental goods can provides various benefits, and that NUV may be an important component of TV of these nonmarket goods in addition to UV (e.g., Freeman III et al., 2014; Krutilla, 1967; Loomis & White, 1996). Various nonmarket valuation methods have been developed in the last several decades. Travel cost method (TCM) is the most commonly used method in the estimation of use value of total nonmarket benefits linked to outdoor recreation in public and semi-public natural spaces (Whitehead et al., 2008). The stated preference approach, such as contingent valuation (CV), usually estimates the total benefits of both NUV and UV. Many studies have combined CV data with observed travel behavior to estimate the change in the recreational use value of natural resources due to quality improvements or price changes, where past trip frequency is jointly analyzed with intended trip frequency to estimate recreation values using TCM. Table 1 summarizes the relevant literature of TCM-CV analysis. The data format for these studies can be either pooled or panel data. For example, in the CV question, a dichotomous choice question is usually included in the survey to elicit the intended trip frequency in response to the hypothetical change. A recreation demand function can be estimated by pooling the intended trip frequency and the data on past trip frequency.

However the above framework assumes that the change in environmental quality only affects recreation values, thus does not estimate NUV of environmental quality changes. Eom and Larson (2006) developed and demonstrated a consistent empirical framework for estimating UV, NUV, TV of quality changes under semi-log specification for recreation models. They found that annual total WTP to restore water quality to the fishable level in MKR basin in Korea was $26.56. UV was $16.35 while NUV was estimated to be $10.21. For improvements in water quality to the swimmable level, the total WTP was $47.64 with UV $29.78 and NUV $17.86. Huang et al. (2016) extended Eom and Larson (2006) framework to more specifications in demand models. Based on their models, they found that the estimated annual individual WTP for improving water quality in a river from boatable to suitable for irrigation was $7.64; for improving it from suitable for irrigation to fishable level 2 was $10.67; from fishable level 2 to fishable level 1 was $7.11. Because of the presence of nonuse value, the consumer surplus computed from the jointly estimated trip demand equation underestimated the consumer surplus implied by the inverse demand for water quality. Landry et al. (2018) showed the existence of NUV associated with coastal erosion managements. Shoreline retreat exhibits much larger estimates of NUV while NUV for shoreline armoring are negative.

In our study, a joint structural model is built on Ebert (1998), Huang et al. (2016) and Landry et al. (2018). We aim to elicit UV and NUV for improvement in springs conditions and seek to provide information on household preferences for attributes.

METHODOLOGY

Ebert (1998) points out that the recreation demand function for the quality-related public good and the function of marginal willingness to pay for that quality form a recreation demand system that is sufficient for recovering the complete underlying preference structure. A structural function was built on microeconomic models from Eom and Larson (2006), Huang et al. (2016) and Landry et al. (2018). Eom and Larson (2006) developed an empirical framework for estimating NUV, UV and total values of quality changes by combining revealed and stated preference data for quality improvement. They started with Marshallian demand function (in the semi-log specification) and integrated back to recover the quasi-expenditure function. The quasi-expenditure function comprised travel cost p, water quality Q and a constant of integration $c(Q,u)$ where u represents utility, and c depends on quality Q and can generate NUV. In their analysis, it is assumed that $c(Q,u) = e^{\delta\psi Q}u$. If appropriate, the quasi-expenditure function can be applied to estimate the welfare of price or quality changes and test for weak complementary that indicates no NUV when $\psi = 0$.

Huang et al. (2016) examines three alternative specifications for $c(Q,u)$: constant, exponential, and quadratic. In their paper, they focus on the semi-log function while other functional forms are derived in their appendix. Landry et al. (2018) examines similar alternatives for $c(Q,u)$: constant, exponential and linear, but the quadratic specification cannot produce a convergence result.

In our study, our Marshallian demand specification is as follows:

$$\ln(X^M) = \alpha_0 + \beta P + \delta \ln(M) + \gamma Q + \alpha_1 Z + \eta \qquad (1)$$

where X^M is the number of trips, P is travel cost of the trip, M is income, Q is environmental quality influencing X, Z is a set of individual characteristics, η is the stochastic component of the empirical demand model, and $\alpha_0, \alpha_1, \beta, \gamma\ and\ \delta$ are parameters.

By the duality theorem, the quasi-expenditure function derived from semi-log equation (1) is given as:

$$\mathrm{I(P, Q, Z}, c, \eta) = (\frac{1-\delta}{\beta} e^{\alpha_0+\beta P+\delta \ln(M)+\gamma Q+\alpha_1 Z+\eta} + (1-\delta)c)^{\frac{1}{1-\delta}} \quad (2)$$

Where c stands for constant of integration derived from ordinary differential equations with an exact and closed form result in our demand specification.

We start with two different specifications for constant of integration.

(a) constant: $c(Q, u) = u$ (3)

(b) exponential: $c(Q, u) = ue^{-\sum_j \emptyset_j W_j Q}$ (4)

In the equation 4, W_j is a set of variables including individual characteristics that influence the utility of Q. A special case is to set W_j equal to 1 thus c is merely an exponential function of Q.

Using these two specifications for constant of integration, the resulting indirect utility functions are as follows:

(a) constant: $\mathrm{V} = M^{1-\delta}(\frac{1}{1-\delta} - \frac{1}{\beta}\frac{X^M}{M})$ (3)

(b) exponential: $\mathrm{V} = e^{\sum_j \emptyset_j W_j Q} M^{1-\delta}(\frac{1}{1-\delta} - \frac{1}{\beta}\frac{X^M}{M})$ (4)

The NUVs for different specification are:

(a) $NUV = 0$ (5)

(b) $NUV = ((1-\delta)u_0 e^{-\sum_j \emptyset_j W_j Q_0})^{\frac{1}{1-\delta}} - ((1-\delta)u_0 e^{-\sum_j \emptyset_j W_j Q_1})^{\frac{1}{1-\delta}}$ (6)

The corresponding WTP functions for the incremental quality are:

(a) $\text{WTP} = \text{m} - \text{m}[1 + \frac{1-\delta}{\beta}(\frac{X_1^M}{m} - \frac{X_0^M}{m})]^{\frac{1}{1-\delta}} + \varepsilon$ (7)

(b) $\text{WTP} = \text{m} - \text{m}[e^{-\sum_j \emptyset_j W_j (Q_1 - Q_0)} + \frac{1-\delta}{\beta}(\frac{X_1^M}{m} -$

$e^{-\sum_j \emptyset_j W_j (Q_1 - Q_0)} \frac{X_0^M}{m})]^{\frac{1}{1-\delta}} + \varepsilon$ (8)

The parameters $\alpha_0, \alpha_1, \beta, \gamma \ and\ \delta$ appear in both the demand and WTP functions, while the nonuse-related parameter $\emptyset_j$ enters only into WTP function. It is likely that some unobservable factors associated with these two functions. Thus, the error η in the recreation demand function (1) and the error ε in the WTP function (7) or (8) can be assumed to follow a bivariate normal distribution N $(0,0,\sigma_\eta^2, \sigma_\varepsilon^2, \rho)$ with different scale parameters and correlation ρ. Assume that the individual knows her/his own WTP C_i, to the researcher, it is a random variable with a given cumulative distribution function denoted as $\text{G}(C_{i;}\theta)$ where θ are the parameters of the distribution. In our study, we assume $\text{G}(C_{i;}\theta)$ follow a normal distribution.

Combing respondent's reported trip frequency and WTP responses, the likelihood function for the joint distribution can be shown as the following, when we use the WTP response from a single-bound dichotomous choice (SBDC) format:

$$L = \prod_{i \in no} P(X = x, Y = 0) \prod_{i \in yes} P(X = x, Y = 1)$$

$$= \prod_{i \in no} P(X = x) P(Y = 0|X) \prod_{i \in yes} P(X = y) P(Y = 1|X)$$

$$= \prod_{i \in no} P(X = x) P(Y = 0|X) \prod_{i \in yes} P(X = y)[1 - P(Y = 0|X)] \quad (9)$$

where $P(X = x)$ is the marginal distribution of trips and $P(Y = 0|X)$ is the conditional function of response =”no” to the bid value B_i^* given X. We denote the corresponding response probabilities as π_i^N.

$$\pi_i^N = P(Y = 0|X) = P(C_i \leq B_i^*|X) = P(TV + \varepsilon < B_i^*|X)$$

$$= \phi\left(\frac{\varepsilon}{\sigma_\varepsilon} < \frac{B_i^* - TV}{\sigma_\varepsilon}\middle|X\right) = \phi\left(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}}\right) \tag{10}$$

$P(Y = 1|X)$ is the conditional function of response =” yes” given X. We denote the corresponding response probabilities as π_i^Y.

$$\pi_i^Y = P(Y = 1|X) = P(C_i \geq B_i^*|X) = P(TV + \upsilon > B_i^*|X)$$

$$= \phi\left(\frac{\varepsilon}{\sigma_\varepsilon} > \frac{B_i^* - TV}{\sigma_\varepsilon}\middle|X\right) = 1 - \phi\left(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}}\right) \tag{11}$$

The resulting log-likelihood function for the responses to a SBDC format is:

$$\text{logL} = \sum_i d_i^Y\, \pi_i^Y + \sum_i d_i^N\, \pi_i^N \tag{12}$$

where $d_i^Y = 1$ if response is yes and 0 otherwise, $d_i^N = 1$ if response is no and 0 otherwise.

Applying this process of the conditional distribution, we can get the joint distribution that can be expressed as:

$$P(X = x, Y = 0) = P(X = x) * \Phi\left(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}}\right) \tag{13}$$

If we define X^M to be normally distributed, then the joint distribution function is given by:

$$P(X = x, Y = 0) \tag{14}$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(X^M-(\alpha_0+\alpha_1 D+\beta P+\delta M+\gamma Q))^2}{2\sigma_\eta{}^2}} * \Phi(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}})$$

Applying the SBDC format to the intended trip demand, the joint log-likelihood function between trip demand and WTP function is:

$$\text{LogL} = -\frac{n}{2}\log\left(2\pi\sigma_\eta{}^2\right) - \frac{1}{2}\sum_i [\frac{X^M - (\alpha_0 + \alpha_1 D + \beta P + \delta M + \gamma Q)}{\sigma_\eta}]^2$$

$$+ \sum_i d_i^N \log[\Phi(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}})] + \sum_i d_i^Y \log[1 - \Phi(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}})] \quad (15)$$

In addition to normal distribution assumption of X^M, Poisson and Negative Binomial (NB) distributions are two mostly common used for the recreation data. If X^M is Poisson distributed, we need to apply this process to the joint distribution to find its expression. Moreover, if there exists overdispersion, we need to use NB or Poisson log-normal to correct for overdispersion. Multiple forms of distribution and their joint distribution function in SBDC format are summarized in Table 2.

Built on the Eom and Larson (2006) framework, our model is revised to adapt the One-and-one-half-bound dichotomous choice (OOHBDC) format developed by Cooper et al. (2002). Cooper et al. (2002) finds that efficiency gains from SBDC to OOHBDC capture a large portion of the gains from single-bounded to double-bound dichotomous choice (DBDC), but OOHBDC uses less information than double-bounded choice. OOHBDC may serve as an alternative to the DBDC in which follow-up questions may induce response bias, while OOHBDC could gain more efficiency than SBDC.

In the OOHBDC format, the respondent is presented with a range $[B_i^-, B_i^+]$, where $B_i^- < B_i^+$. If B_i^- (e.g., the lower bound) is drawn at random as the starting bid, followed by the bid of B_i^+ only when the response to the starting bid is yes, three possible response outcomes are (no), (yes, no), (yes, yes); we denote the corresponding response probabilities by π_i^N, π_i^{YN} and π_i^{YY}. If B_i^+ is randomly drawn as the starting bid, followed by the lower bid B_i^- only when the response to the starting bid is no, the possible response outcomes are (yes), (no, yes), and (no, no), denoted as π_i^Y, π_i^{NY} and π_i^{NN}. Observe that there is a symmetry between the ascending sequence and the descending sequence of CV questions.

$$\pi_i^N = \pi_i^{NN} = \Pr\{C_i \le B_i^-\} = \mathrm{G}(B_i^-; \theta) \tag{16}$$

$$\pi_i^{YY} = \pi_i^Y = \Pr\{C_i \ge B_i^+\} = 1 - \mathrm{G}(B_i^+; \theta) \tag{17}$$

$$\pi_i^{YN} = \pi_i^{NY} = \Pr\{B_i^- \le C_i \le B_i^+\} = \mathrm{G}(B_i^+; \theta) - \mathrm{G}(B_i^-; \theta) \tag{18}$$

Let $d_i^N = 1$ if either the first bid is B_i^- and the corresponding response is no, or the first bid is B_i^+, second bid is B_i^- and response is (no, no), 0 otherwise. Let $d_i^{YN} = 1$ if either the first bid is B_i^-, second bid is B_i^+ and the corresponding response is (yes, no), or the first bid is B_i^+, second bid is B_i^- and response is (no, yes), 0 otherwise. Let $d_i^Y = 1$ if either the first bid is B_i^+ and the corresponding response is yes, or the first bid is B_i^-, second bid is B_i^+ and response is (yes, yes), 0 otherwise. The log-likelihood function is:

$$\mathrm{logL} = \sum_i d_i^Y \pi_i^Y + \sum_i d_i^{YN} \pi_i^{YN} + \sum_i d_i^N \pi_i^N \tag{19}$$

Applying the OOHBDC format to the intended trip demand, the joint log-likelihood between trip demand and WTP function is

$$\mathrm{LogL} = -\frac{n}{2}\log\left(2\pi{\sigma_\eta}^2\right) - \frac{1}{2}\sum_i [\frac{X^M - (\alpha_0 + \alpha_1 D + \beta P + \delta M + \gamma Q)}{\sigma_\eta}]^2 \tag{20}$$

$$+\sum_i d_i^Y \log\left[1-\Phi\left(\frac{\frac{B_i^+ - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}}\right)\right]$$

$$+\sum_i d_i^{YN} \log\left[\Phi\left(\frac{\frac{B_i^+ - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}}\right) - \Phi\left(\frac{\frac{B_i^- - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}}\right)\right]$$

$$+\sum_i d_i^N \log\left[\Phi\left(\frac{\frac{B_i^- - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}}\right)\right]$$

Where TV = $m - m[1 + \frac{1-\delta}{\beta}(\frac{X_1^M}{m} - \frac{X_0^M}{m})]^{\frac{1}{1-\delta}}$ with a constant specification of $c(Q,u)$, and

TV = $m - m[e^{-\sum_j \emptyset_j W_j (Q_1 - Q_0)} + \frac{1-\delta}{\beta}(\frac{X_1^M}{m} - e^{-\sum_j \emptyset_j W_j (Q_1 - Q_0)} \frac{X_0^M}{m})]^{\frac{1}{1-\delta}}$ with an exponential specification of $c(Q,u)$.

Note that in this joint estimation with trip demand function and WTP function, the parameters $\alpha_0, \alpha_1, \beta, \delta, \gamma$ appear in both the demand and WTP function, while the nonuse-related parameter $\emptyset_j$ only enters into the WTP function. Quasi-preferences are weakly complementary if $\partial E(\hat{P}, Q, c(Q,u)/\partial Q = 0$. In other words, we can test for weak complementarity assumption by testing that ϕ = 0 since $\partial E(\hat{P}, Q, c(Q,u)/\partial Q = -\phi$.

SURVEY AND DATA

An online survey was administered in November 2018 to panel members managed by Qualtrics, following prior focus groups with local residents and a week of survey pre-test. To qualify for the survey, respondents need to be at least 18 years old and year-around residents of Florida. Additionally, a quota-based sampling method was used to obtain 800 completed responses and the respondents represent the Florida adult population in terms of gender, age, and racial composition. In addition, 50% of the survey respondents had above household income above the median income of the State. For this analysis, we focus on 432 respondents that were presented to the contingent valuation questions.

The online survey contains four main sections. The first section includes screening questions on social demographic characteristics of respondents. The second section asks about the recreation experience of visitors in the past 2 years. The third section asks all respondents (visitors and non-visitors) about their opinions and attitudes about environmental protection pertaining springs and rivers in Florida. We also included a question on whether the recreational site was congested during respondents' past visits to ensure that the quality change is exogenous to the respondents. The fourth section refers to the intended behavior (planned future trips and WTP) in the next 12 months under two conditions: the current condition (status quo) and the improved condition after an environmental improvement plan is assumed to be implemented.

For the proposed improved condition, the respondents were asked: "*Suppose that with a restoration program, the density of aquatic plants would increase from 30% to 70% and algae coverage would be reduced from 70% to 10% on the bottom of the spring. Water in the spring would become crystal clear and the water flow in the spring would be increased to its historical level. In the next 12 months, how many recreation trips would you take to springs in the Lower Suwannee and Santa Fe River Basin, if the average conditions of springs changed to those described above?*" See Figure 1 below for an artistic illustration.

In the fifth section, contingent valuation questions were asked in the format of OOHBDC. Details in the OOHBDC CV survey are as follows: (1) The respondent was told that in order to help fund the restoration program to achieve the outcome described in specific scenario, a surcharge would be added to their household's monthly utility bills. The respondent is presented with a range $[B_i^-, B_i^+]$ and told that the cost is known to lie somewhere within that range bounded by an upper bound B_i^+ and a lower bound B_i^-. In our study, we have four range groups [$36, $60], [$60, $96], [$96, $120], [$120, $144]. Each respondent was presented with a range that was randomly selected from the four ranges. (2) Under the presented price range, the upper bound B_i^+ or the lower bound B_i^- is randomly chosen as the starting bid, and the respondent is asked to if she/he is willingness to pay that bid amount for the next 10 years to help fund the restoration programs (the first round). (3) If the respondent answered 'yes' in the first bid when the lower bound B_i^- was presented in the first round, the respondent was presented with the upper bound B_i^+ in the second round of dichotomous choice. Similarly, if the respondent answered 'no' when the upper bound $B_i^+$was present in the first stage, the respondent was presented with the lower bound bound B_i^- in the second-round of dichotomous choice.

The final sample consists of 432 respondents and the descriptive statistics of the sample are presented in Table 3. We see that 63% of the sample has visited springs for at least once and 29% of the sample has visited the targeted springs in our research areas. In the past 12 months, the average trip to springs is 0.98 while the average planned trip frequency to springs in the next 12 months increases to 2.01. In the sample, respondents are almost balanced in terms of gender, and the mean age is around 48, which is a bit of higher to that of Florida population (40). We also find that 26% of the respondents belongs to environmental groups and 37% of them voluntarily make donation for social causes. On average, respondents live 140 miles to the nearest springs in our study area.

Table 4 and Table 5 present the OOHBCD format and SBDC format data, respectively, showing the bid value and response summaries in different scenarios. We use the first response from the OOHBDC questions as a single-bound CV response. In general, respondents are less likely to say ‘yes’ when the price increases except at the bid price of $120. When $36, $60, $96, $120 and $144 are offered in the first stage, the percentage of “yes” response is 67%, 66%, 58%, 62% and 45%, respectively.

ECONOMETRIC RESULTS

We present a series of results in this section: 1) estimating recreation demand only pooling current trip and intended trip data; 2) estimating the contingent valuation questions alone with the first-step response as single-bound discrete choice and with responses from both two steps of the OOHB; 3) estimating recreation demand and contingent valuation response jointly.

Recreational Demand Analysis

For the recreation demand data, we have a panel of stacked preference responses by current and restored conditions of springs. We estimate a commonly used semi-log demand function and use a dummy variable “*Quality*” to denote the improved (restored) condition in the demand function. The results are presented in Table 6. The travel cost variable is defined by the cost of visiting the nearest spring in the study area. It was estimated using the monetary cost of driving round-trip from the centroid of the respondent’s home zip code to the nearest spring and the opportunity cost of travel time evaluated at the 1/3 of the implicit wage rate that was estimated by the reported household income divided by 2000 working hours a year. Travel costs to the nearest Florida springs has a negative effect while income has a positive effect. The coefficient for *Quality* is positive and statistically significant, indicating that respondents take fewer trips to deteriorated springs. Turning to economic welfare measures, the WTP is around $500 per household/year.

Contingent Valuation Estimates

Table 7 presents the maximum likelihood estimates for the contingent valuation responses, in which we first analyzed the responses in the first round of OOHBDC as a single-bound dichotomous choice followed by the analysis on all responses to the OOHBDC. Additional explanatory variables include age, gender, household income, distance to the nearest spring, and visitation experience. Coefficients are statistically significant and have the expected signs in single-bound and OOHBDC. An increase in bid value reduce the probability of voting “yes”. As shown by the value of t-statistics, OOHBDC coefficient exhibits more efficiency than SBDC parameters.

For brevity and for the sake of comparison with results, we only estimate mean and median WTP for respondents. Krinsky-Robb procedure is used to calculate the 95% confidence intervals for WTP from the status quo to the improved condition (Scenario A) and Table 8 presents the results. The WTPs from the OOHBDC estimates are lower than the measures deduced from the SBDC model. In OOHB, the mean WTP of the sample is $148 compared with $193 in SBDC models. The upper bound for mean WTP in OOHB is $180 while SBDC is $672.

Joint Estimation

The next step is to combine the recreational demand and OOHBDC data in a joint model. Built on the framework of Eom and Larson (2007) and Huang et al. (2016), we jointly estimate models and test for weak complementarity. By combining demand and CV behavior data, we can employ the same behavioral models and make use of demand theory to relate observed demand to potential NUV. We integrate the demand equation over travel cost to recover the quasi-expenditure function that gives the level of payment to achieve a certain utility, which is a function of travel cost and environmental quality. The integration needs to introduce a constant term that can be theoretically defined to reflect NUV. In our models, that constant term of integration is presented as three specifications discussed in the methodology section, including $c = u$, $c = ue^{-\phi_1 Q}$ and $c = ue^{-\sum_j \emptyset_j W_j Q}$.

Estimation results in Table 9 and Table 10 indicate that the effect of travel cost on trip demand is negative and statistically significant, as expected. We use a dummy variable to represent the quality improvement, in which it equals zero for status quo and 1 for the restored/improved conditions. The result shows a positive and significant impact of springs quality on trip demand in all specifications. Household income is significant in the OOHB format in all three specifications and insignificant in the SBDC format.

Akaike Information Criterion (AIC) is employed to choose the best fit among alternative specifications. We compute AIC for six models (Table 9 and Table 10). The selected model is specification 3 in which the constant is defined as $c = ue^{-\sum_j \emptyset_j W_j Q}$ in both SBDC and OOHB format.

We then test weak complementarity and the Willig condition in these specifications with Wald test. The results are shown at the bottom of Table 9 and Table 10. In model A.2 and model B.2, we test for $\phi_1 = 0$. In model A.3 and model B.3, the average of W_j is used to test if $\sum_j \emptyset_j W_j = 0$. In other words, the Wald test on the joint significance of $\emptyset_1 + \emptyset_2 W_2 + \emptyset_3 W_3$ are tested holding the vector of W variables constant at the sample means. W_2 represents the respondent's gender (male=1 otherwise 0), and

W_3 represents the respondent's past visit to springs and equals to 1 if the respondent has visited any springs and 0 otherwise. In both CV formats, parameter restrictions to impose weak complementarity and the Willig condition are rejected with Wald test, indicating that the welfare measures for quality improvement based on the travel cost models alone could not be used to reflect the overall values of water quality improvement. Imposing these two conditions in the model A.1 and model B.1 may result in misspecification and biased welfare measures.

Figure 3 shows WTP calculated from Krinsky–Robb procedure with SBDC and OOHBDC formats and the three specifications of the indirect utility functions. In all specifications, WTP estimated in the OOHBDC format is always significantly lower than the WTP in the SBDC format, indicating that the joint estimation with the SBDC format would overestimates consumer surplus. Thus, we focus on the model B.3 with OOHBDC format and $c = ue^{-\sum_j \emptyset_j W_j Q}$. The model rejects the zero NUV assumption and finds that visitors have significantly higher utility than non-visitors when keeping other conditions constant. The welfare measures in Model B.3 are shown in Table 12 (Column 4) with the proposed improvement condition as shown in Figure 1. The mean NUV is $119 per household per year while the total value is around $205 .

CONCLUSION

Using online survey administered through consumer panels by Qualtrics, we obtained a sample of 432 completed responses with quota-based sampling to ensure the sample's representativeness s of Florida's adult residents in terms of age, gender, and ethnicity composition. Since the survey sample includes both visitors and non-visitors, we are able to represent diverse groups and conduct a comprehensive and comparative analysis of economic welfare and statistical tests on the magnitudes of use s and nonuse values of springs.

Using maximum likelihood estimation on joint function of recreation demand and WTP, we find that imposing weak complementarity in the demand models results in misspecification and biased welfare measures. The joint estimation rejects the assumption of weak complementarity indicating positive nonuse values for the improvement in springs conditions. The mean total WTP for springs condition improvement from the status quo to Scenario A, as shown in Figure 1, is around $205 per household per year using the model with the best fit. This includes passive use or non-use value between $89 and $105. Imposing weak complementarity leads to much lower estimation on the mean consumer surplus, which is around $141. Compared to non-visitors, visitors have a higher WTP for springs restoration. Our results suggest that loss of recreational benefits due to degradation will be underestimated if passive-use values are ignored. By recovering underlying preference structure for welfare analysis based on demand models, we can illustrate the implications of a wider perspective regarding the impacts of spring restoration. For example, there are 6.3 million households in Florida. Restoring all springs to their conditions around mid-1990s would provide $1,291 million in total economic values to all Florida residents annually, which is about 13% of the GDP contributed by tourism industry in Florida.

We also find that, compared to SBDC format, the result from joint estimation with OOHB format shows that welfare estimates are significantly lower than values estimated from SBDC format. Specifically, OOHBDC may be more successful in reducing hypothetical bias in stated preference study. However, there are a few limitations of this study. Existing studies use revealed trip data and intended trip data under various scenarios. In our study, the trip information used in estimating the demand function are stated trip frequency to a representative springs under the status quo and under hypothetical improvement. We were not able to use revealed trip frequency directly, because the study area includes hundreds of springs with varying conditions under status quo. While most respondents visited springs in the past, the number of respondents that visited any particular spring is low. Furthermore, the joint maximum likelihood estimation on recreation demand and WTP is complex, and the convergence depends on starting values as well as functional form assumptions. We recommend researchers to explore Bayesian parameter estimation when using other datasets in future studies.

Table 1. Study using both travel cost recreation demand and contingent valuation in recreation analysis.

Study	Topic	Change	Econometric model[c]
Lankia et al. (2019)	Swimming trips in Finland	Water quality changes +[a]	NB; RE-Poisson
Wicker et al. (2017)	Sports attendance	Sports success and management failure*[b]	Poole-Poisson
Simões et al. (2013)	Bussaco National Forest	Price and quality+	Pooled NB; RE-NB; RE-Poisson-Gamma
Grossmann (2011)	Boating recreation	Water level*	Pooled Poisson
Lienhoop & Ansmann (2011)	Water reservoirs recreation	Quality decline+	Pooled NB
Whitehead et al. (2010)	Beach recreation	Improved access; beach width increase+	RE-Poisson; Kuhn-Tucker Demand system
Jeon & Herriges (2010)	Lake recreation	Quality improvement+	Repeated mixed logit
Landry & Liu (2009)	Beach recreation	Quality and access improvements +	Generaized RE-NB
Alberini et al. (2007)	Lagoon sports fishing	Travel cost; quality improvement +	RE-GLS
Egan & Herriges (2006)	Lake recreation	Travel cost +	SUNB
Hesseln et al. (2004)	Hiking trails	Travel cost +	Poisson
Bergstrom et al. (2004)	Estuary recreational fishing	Freshwater flows and fish catch +	Pooled GLS
Bhat (2003)	Marine reserve	Reef quality improvement*	RE Poisson
Azevedo et al. (2003)	Wetland recreation	Travel cost*	ML eq. Demand System
Grijalva et al. (2002)	Rock climbing	Access condition +	SU Poisson; Generalized NB
Englin et al. (2001)	Hiking trails and mountain biking	Travel cost; fire effect +	NB
Whitehead et al. (2000)	Water-based recreation in estuaries	Quality improvement	RE-Poisson
Rosenberger & Loomis (1999)	Ranch open space	Characteristics*	RE-Poisson
Chase et al. (1998)	National parks	Entrance fee*	RE Probit; Tobit
Loomis (1997)	River recreational activities	Travel cost; quality improvement +	Pooled Probit; RE probit

Table 1. Continued

Study	Topic	Change	Econometric model
Layman et al. (1996)	Recreational fishing	Fishing management*	Pooled OLS; Tobit
Englin and Cameron (1996)	Recreational fishing	Travel cost*	Pooled Poisson; FE Poisson
Loomis (1993)	Lake visits	Water level +	Chi-squared statistics; t-test
Ward (1987)	Water recreation	Quality*	Restricted OLS
Ribaudo and Epp (1984)	Water recreation	Water quality improvement +	OLS

(a) + indicates that the CV question is an intended contingent behavior. Respondents are asked to predict how they would behave under proposed conditions.
(b) *indicates that the CV question is a reassessed contingent behavior. In this format, respondents reassess their trip behavior as they are asked about how they would have behaved in the past under a hypothetical quality or price level.
(c) FE denotes fixed effects; RE denotes Random effects; GLS denotes generalized least squares; OLS denotes ordinary least squares; ML denotes maximum likelihood; SU denotes seemingly unrelated; and NB denotes negative binomial.

Table 2. Distribution assumptions and probability functions of joint estimation

Distribution	$P(X = x, Y = 0)$
Eom and Larson (2006); Huang et al. (2016) Normal	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(lnX^M-(\alpha_0+\alpha_1 D+\beta P+\delta lnM+\gamma Q))^2}{2\sigma_\eta{}^2}} * \Phi(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}})$
Gonzalez et al. (2008) Negative binomial	$\frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y+1)}(1+\alpha\mu)^{-(y+\alpha^{-1})}(\alpha\mu)^y * \Phi(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}})$
Landry et al. (2018) Poisson-Log normal	$\int_{-\infty}^{+\infty} \frac{e^{-\lambda}\lambda^y}{y!} \frac{e^{-\frac{\eta^2}{2}}}{\sqrt{2\pi}} * \Phi(\frac{\frac{B_i^* - TV}{\sigma_\varepsilon} - \rho\frac{\eta}{\sigma_\eta}}{(1-\rho^2)^{1/2}})d\eta$

Note that X indicates the number of trips while Y indicates the response to the contingent valuation question, where Y =1 if response is Yes, 0 otherwise. Other parameters shown in these probability functions can be found in methodology section.

Table 3. Sample descriptive statistics

Variable	Value
Ever visited springs in the past	63%
Ever visited springs in Lower Suwannee and Santa Fe River Basin (LSSFR)	29%
Number of trips in the last 12 months in LSSFR	0.98
Number of planned trips in the future 12 months	2.01
Average rate in the importance of preserve springs (from 1 to 5)	4.39
Percent in the member of environmental groups	26%
Percent in donation for social causes	37%
Male	52%
Age	48
Education	
High school graduate or higher degree	89%
Bachelor's degree or higher	30%
Percent in full-time or part-time employment	71%
Household Income	$62,000
Distance to the nearest springs in LSSFR	140 miles
Travel cost to the nearest springs in LSSFR	$98

[a] Household income was a categorical response. Following previous studies, we used the mid-points of the categorical responses as the level of household income.

Table 4. Summary of the responses to the OOHBDC questions in scenario A

Bid [B-; B+]	Lower Bond Bid (B-) offered first			Upper bond bid (B+) offered first			Sample Size
	No. of 'No' responses	No. of 'Yes-No' Response	No. of 'Yes-Yes' Response	No. of 'Yes' responses	No. of 'No-Yes' Response	No. of 'No-No' Response	
36;60	18	6	30	39	4	11	108
60;96	21	4	28	35	2	17	107
96;120	26	3	25	36	5	15	110
120;144	21	5	26	25	5	25	107

Table 5. Summary of the responses using the first response from the OOHBDC questions as a single-bound CV response under the springs restoration scenario A

Bid [B- or B+]	Sample Size	No. of 'Yes' responses	% of 'Yes' responses	No. of 'No' responses	% of 'No' responses
36	54	36	67%	18	33%
60	107	71	66%	36	34%
96	108	63	58%	45	42%
120	108	67	62%	41	38%
144	55	25	45%	30	55%

Table 6. Regression results from semi-log demand function using existing and intended trip data

Variable	Coefficient	Std. Error
Constant	-0.513	0.475
Travel cost	-0.002	0.002
Income	0.068	0.044
Quality	1.244***	0.121
LL		-930
AIC		1871

Note: N=864. ***p<0.01, **p<0.05, *p<0.1

Table 7. Regression results from probit model using CV questions alone

Variable	Coefficient (t-stat)	
	Single bound	OOH bound
Constant	0.76(1.42)	1.25***(2.68)
Bid amount	-0.007**(-2.44)	-0.01***(-6.98)
Age	-0.006(-0.82)	-0.008(-1.14)
Gender (male)	0.20(0.92)	0.18(0.88)
Income	0.007*(2.58)	0.007***(2.63)
Distance to the nearest spring	-0.001(-0.98)	-0.0009(-0.83)
Ever visited springs	0.50**(2.33)	0.50**(2.44)
LL	-277.85	-374.41
AIC	569.71	762.82
BIC	598.19	791.29

Note: N=432. ***p<0.01, **p<0.05, *p<0.1

Table 8. Estimates of mean WTP ($) for restoring Springs using CV questions alone

Format		WTP Estimation ($)		
		Estimate	LB	UB
SB	Mean	193.73	136.54	672.37
	Median	155.17	117.72	383.56
OOHB	Mean	147.86	128.99	180.53
	Median	131.07	113.41	156.07

Table 9. Joint Estimation of Semi-log Trip demand and Nonlinear WTP Equations in SBDC format

Constant of Integration	Model A.1 ($c = u$)	Model A.2 ($c = ue^{-\phi_1 Q}$)	Model A.3 ($c = ue^{-\sum_j \emptyset_j W_j Q}$)
α_0 intercept	0.394 (0.365)	-1.782 (0.415)***	-1.737(0.444)***
β travel cost	-0.003 (0.001)***	-0.008(0.001)***	-0.008(0.001)***
δ ln(income)	-0.014 (0.033)	0.187(0.038)***	0.182(0.041)***
γ quality	1.164 (0.113)***	1.241(0.121)***	1.243(0.121)***
ϕ_1 or τ_1		0.002 (0.0002)***	-0.002 (0.001)
ϕ_2 or τ_2 male			0.001 (0.001)
ϕ_3 or τ_3 experience			0.004(0.001)***
Observation	432	432	432
AIC	3756	3357	3334
Test of WC	Implied	Wald stat = 7.221***	Wald stat = 32.030***
Test of Willig condition	Implied	Wald stat = 7.221***	Wald stat = 32.030***

Note: Standard errors are in parentheses. *** P<0.01, ** P<0.05, and * P<0.1. The sample average of W_j is used to test the WC and Willig condition in model A.3. Specifically, $W_1 = 1$, W_2 represents gender (male=1,otherwise 0) and W_3 represent respondent's past visit (respondents have ever visited springs in the past years=1, otherwise 0). Wald tests on the joint significance of $\sum_j \emptyset_j W_j = 0$ are performed holding gender and past visit at the sample means.

Table 10. Joint Estimation of Semi-log Trip demand and Nonlinear WTP Equations in OOHB format

Constant of Integration	Model B.1 ($c = u$)	Model B.2 ($c = ue^{-\phi_1 Q}$)	Model B.3 ($c = ue^{-\sum_j \emptyset_j W_j Q}$)
α_0 intercept	-1.515 (0.354)***	-2.637 (0.366)***	-2.785(0.401)***
β travel cost	-0.007 (0.001)***	-0.012 (0.001)***	-0.012(0.001)***
δ ln(income)	0.160 (0.032)***	0.264 (0.033)***	0.280(0.037)***
γ quality	1.241 (0.120)***	1.271 (0.122)***	1.236(0.123)***
ϕ_1 or τ_1		0.001 (0.0001)*	0.0002(0.001)
ϕ_2 or τ_2 gender			-0.0004(0.001)
ϕ_3 or τ_3 experience			0.002(0.001)***
Observation	432	432	432
AIC	3892	3808	3790
Test of WC	Implied	Wald stat = 9.718***	Wald stat = 64.278***
Test of Willig condition	Implied	Wald stat = 9.718***	Wald stat = 64.278***

Note: Standard errors are in parentheses. *** P<0.01, ** P<0.05, and * P<0.1. The average of W_j is used to test the WC and Willig condition in model B.3. Specifically, $W_1 = 1$, W_2 represents gender (male=1,otherwise 0) and W_3 represent respondent's past visit (respondents have ever visited springs in the past years=1, otherwise 0). Wald tests on the joint significance of $\sum_j \emptyset_j W_j = 0$ are performed holding gender and past visit at the sample means.

Table 11. Welfare Measures based on Various Estimation Specifications in SBDC format from status quo to scenario A

	Model A.1 ($c = u$) Mean/Median (Std. dev.) [95% c.i./quantile range]	Model A.2 ($c = ue^{-\phi_1 Q}$) Mean/Median (Std. dev.) [95% c.i./quantile range]	Model A.3 ($c = ue^{-\sum_j \emptyset_j W_j Q}$) Mean/Median (Std. dev.) [95% c.i./quantile range]
CS_A	369.928 / 335.654 (623.330) [213.755, 748.760]	132.995/129.630 (22.548) [99.198,186.389]	142.321/137.355 (30.137) [99.549,215.012]
CS_T	369.928 / 335.654 (623.330) [213.755, 748.760]	263.303/260.779 (30.457) [210.669,328.621]	269.480/266.839 (37.472) [205.193,351.486]
WTP	370.197/ 335.651 (609.856) [213.756, 748.894]	263.573/261.323 (30.418) [209.776,330.259]	269.641/266.984 (37.545) [205.217,351.797]
NUV	0	130.779/130.545 (16.801) [97.908,163.783]	127.525/127.331 (21.815) [85.787,171.60]

Note: The Krinsky–Robb procedure was used to compute the standard deviation and confidence interval. CS_A is the consumer surplus computed based on the estimated trip demand equation while CS_T is calculated based on the recovered underlying inverse demand question for quality. The NUV associated with specification $c = u$ is always zero because weak complementarity is automatically implied in this case.

Table 12. Welfare Measures based on Various Estimation Specifications in OOHBDC format

	Model B.1 ($c = u$) Mean/Median (Std. dev.) [95% c.i./quantile range]	Model B.2 ($c = ue^{-\phi_1 Q}$) Mean/Median (Std. dev.) [95% c.i./quantile range]	Model B.3 ($c = ue^{-\sum_j \emptyset_j W_j Q}$) Mean/Median (Std. dev.) [95% c.i./quantile range]
CS_A	141.210/ 140.010 (12.438) [119.836, 168.594]	87.639/87.096 (7.395) [74.684,103.646]	85.750/84.889 (8.710) [71.171,104.954]
CS_T	141.210/ 140.010 (12.438) [119.836, 168.594]	203.134/203.052 (13.042) [178.067,228.826]	204.710/204.427 (14.954) [175.870,234.273]
WTP	141.184/139.983 (12.436) [119.820,168.556]	203.157/203.083 (13.044) [178.084,228.887]	204.716/204.425 (14.947) [175.888,234.198]
NUV	0	115.681/115.660 (11.494) [93.368,138.053]	119.138/118.968 (15.660) [89.705,150.363]

Note: The Krinsky–Robb procedure was used to compute the standard deviation and confidence interval of welfare under the scenario A. CS_A is the consumer surplus computed based on the estimated trip demand equation while CS_T is calculated based on the recovered underlying inverse demand question for quality. The NUV associated with specification $c = u$ is always zero because weak complementarity is automatically implied in this case.

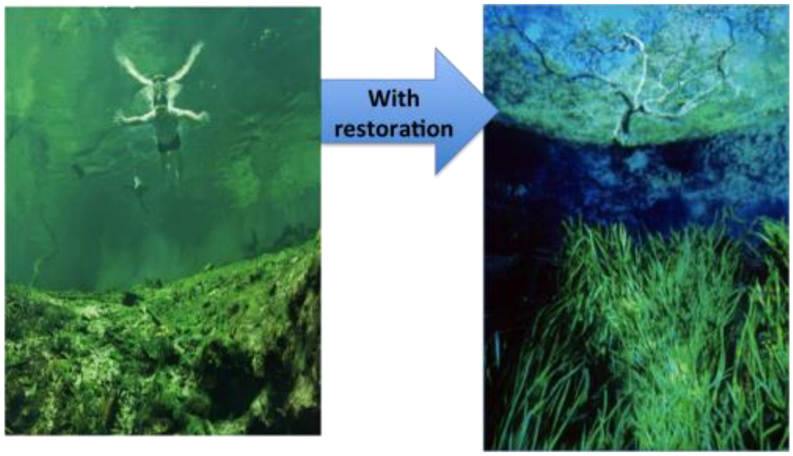

Figure 1. Spring pictures in scenario A: the current situation and the improved situation where an environmental improvement plan is assumed to be implemented. Photo credit: John Moran.

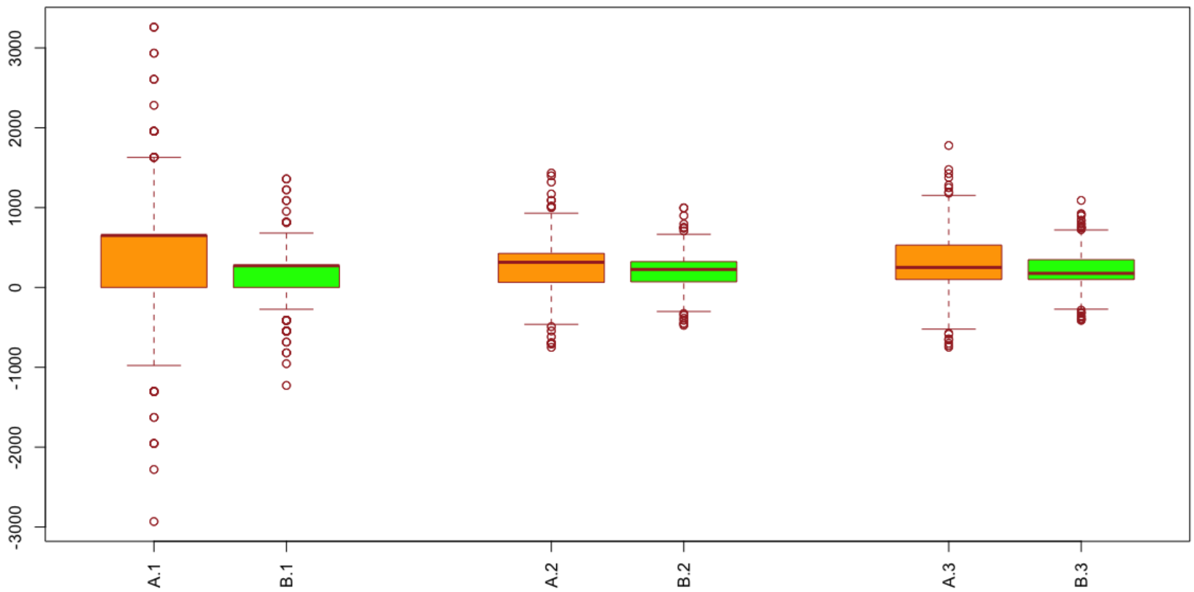

Figure 2. Multiple boxplots of individual WTPs with different CV formats and specifications. In the x axis, A stands for SBDC format while B represents OOHBDC format. In terms of the constant of integration specification, A.1 (B.1), A.2 (B.2) and A.3 (B.3) indicate $c = u$, $c = ue^{-\phi_1 Q}$ and $c = ue^{-\sum_j \emptyset_j W_j Q}$, respectively.

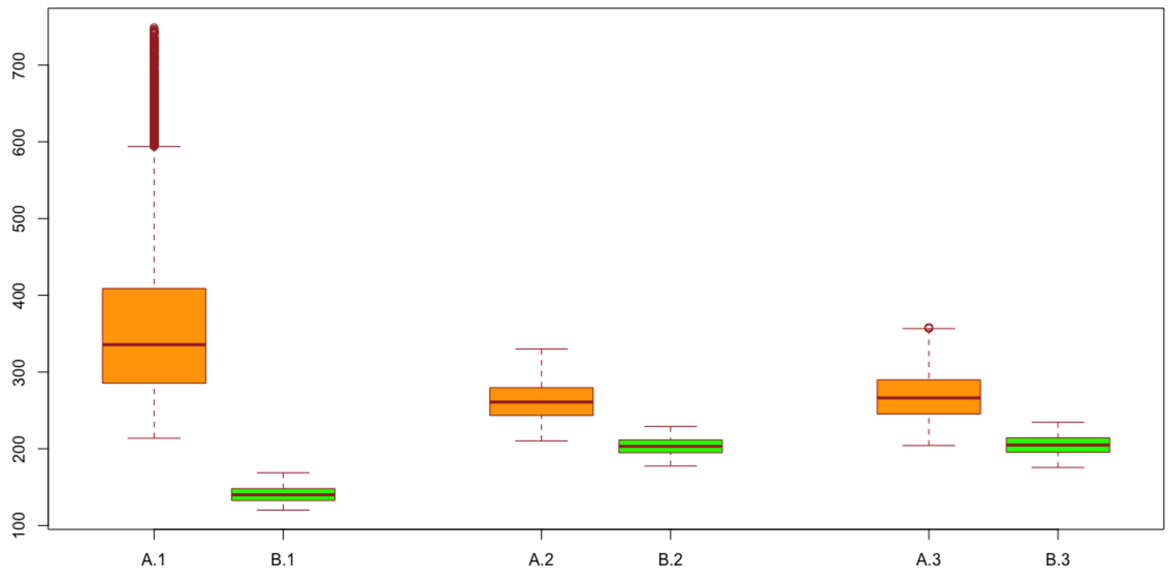

Figure 3. Multiple boxplots of WTPs calculated from Krinsky–Robb procedure with different CV formats and specifications. In the x axis, A stands for SBDC format while B represents OOHBDC format. In terms of the constant of integration specification, A.1 (B.1), A.2 (B.2) and A.3 (B.3) indicate $c = u$, $c = ue^{-\phi_1 Q}$ and $c = ue^{-\sum_j \emptyset_j W_j Q}$, respectively.