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A Convergent Validity Test of Recreation Use Value Estimates from the Contingent Valuation and Travel Cost Methods with Opt-in Panel Data

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Abstract:

This paper tests convergent validity between the travel cost method and contingent valuation method using opt-in panel data on recreation trips to South Florida. Data come from four survey waves administered through the Dynata panel between April 2024 and March 2025, yielding a final sample of 2103 Florida residents who took a recent recreation trip and plan another. Respondents are split into day trippers and overnight trippers. Travel cost models estimate recreation demand with a truncated negative binomial specification, using both average and minimum travel cost to 11 South Florida sites as the price measure. Contingent valuation models use a panel logit specification with two dependent variables, an initial yes/no response to a hypothetical trip cost increase and a version adjusted for respondent certainty. Consumer surplus and willingness to pay estimates, along with Krinsky-Robb confidence intervals, are computed for all eight models. Willingness to pay exceeds consumer surplus in six of eight comparisons, but only one difference is statistically significant. The results suggest that Travel Cost Method and Contingent Valuation Method welfare estimates from opt-in panel data are largely convergent valid. The findings support continued, cautious use of opt-in panel data for recreation valuation.

Key words: travel cost method, contingent valuation method, convergent validity, opt-in panel data.

JEL Code: Q51

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Introduction

Estimating losses to nonmarket goods such as recreation requires methods capable of recovering individuals' willingness to pay for changes in access or quality of the recreation activity. Two widely used approaches are the travel cost method (TCM), a revealed preference approach, and the contingent valuation method (CVM), a stated preference approach. The TCM infers values from observed travel behavior by treating travel costs as the implicit price of site access, while the CVM elicits willingness to pay directly through survey responses to hypothetical scenarios. These approaches provide complementary measures of recreation value and are frequently used in policy analysis.

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

The CVM measures use values associated by eliciting preferences directly from individuals through hypothetical survey questions (Boyle 2017). When using the CVM to estimate recreation values, researchers ask survey respondents if they would have paid more for their trip (Cameron and James 1987, Whitehead et al. 2025). Based on survey responses, researchers calculate the average willingness to pay (WTP) for the recreation trip.

Since the TCM and CVM are nonmarket valuation methods, there have been concerns about the accuracy of the value estimates (Bishop and Boyle 2019). Accuracy of a measure of a theoretical construct (e.g., willingness to pay) is comprised of validity and reliability. Validity is the extent to which a valuation method generates a measure that is unbiased, that is, provides an estimate centered around the true value, if it were known. Reliability is the extent to which a valuation method consistently generates the same measure.

There are several types of validity tests that have been considered in the CVM literature. Convergent validity is the extent that a measure is correlated with a similar measure of an underlying theoretical construct. One approach for establishing convergent validity is through a valuation comparison study in which theoretically similar valuation estimates from two or more methodologies, such as CVM and the TCM, are compared (Sellar, Stoll and Chavas 1985, Loomis, Creel and Park 1991). Estimates that are statistically similar achieve convergent validity, increasing the confidence in both valuation estimates. There is some consensus that CVM and TCM are convergent valid (Carson et al. 1996, Bishop and Boyle 2019).

Johnston et al. (2017) assert that the highest quality surveys use probability-based sampling but many nonmarket valuation applications use opt-in panel samples since they are less expensive than probability-based samples. However, a drawback of data from an opt-in sample is that respondents may pay little attention to the details of the valuation questions, resulting in relatively low-quality data. Probability-based internet samples are more expensive but respondents may pay more attention to the surveys and may generate higher quality data.

Differences between probability-based and opt-in samples may arise from several mechanisms. Opt-in respondents self-select into panels and may differ systematically in

unobserved preferences, engagement levels, and response behaviors. These differences may lead to higher stated willingness to pay (WTP) due to factors such as yea-saying, reduced attention to budget constraints, or survey satisficing. In contrast, probability-based samples are designed to better represent the underlying population but may still be subject to nonresponse and measurement error. These mechanisms generate testable hypotheses about both the direction and magnitude of differences in estimated recreation values.

There are only a few studies, to our knowledge, that have compared probability-based and opt-in data in the nonmarket valuation literature. Whitehead et al. (2023) evaluates CVM data quality by examining differences in results between probability-based and opt-in internet samples using data from another BP/Deepwater Horizon oil spill survey estimating passive use losses. Both samples pass the internal validity tests of negative price coefficients and positive income effects but only the probability-based sample passed the scope test. Sandstrom-Mistry et al. (2023) compared two opt-in panels, MTurk and Qualtrics, with a mixed mode mail/internet sample. They found that each sample produced expected results but found that MTurk respondents were more likely to vote in favor of the policy at each cost amount, which led to differences in WTP estimates. No study to date has conducted convergent validity tests of recreation use values with probability-based and opt-in panel data.

Whitehead et al. (2026) compare probability-based and opt-in samples using TCM and CVM estimates of recreation losses from the BP/Deepwater Horizon oil spill in northwest Florida. Opt-in estimates exceed probability-based estimates by 26% under TCM and by 20% to 32% under CVM. Restricting CVM "yes" responses to those respondents most certain they

would pay narrows the gap, but it remains larger than the TCM gap. Only the probability-based TCM and CVM estimates are convergent valid.

This paper contributes to the nonmarket valuation literature by providing another test of convergent validity between contingent valuation method (CVM) and travel cost method (TCM) estimates using opt-in data. In the next section of this paper we describe the survey development and implementation. Then we describe the TCM and CVM data and empirical results. Conclusions follow.

Survey Development and Implementation

We developed the survey using Qualtrics, Inc software. The survey targeted those who participate in recreation activities across South Florida. Four three-month waves of the survey were administered to respondents through the Dynata panel between April 2024 and March 2025. To improve the quality of the data we removed respondents who inconsistently answered income and age questions posed at different points in the survey. Responses are also removed for inconsistencies regarding place of residence. In total, over 8000 Dynata panelists completed one of the survey waves.

A stratified sampling approach included residents from every state in the U.S. Almost three-fourths of the sample are Florida residents with the other most-sampled states being California, New York, and Texas. We focus on Florida residents ($n=5906$) in order to increase the likelihood that the survey respondent traveled by automobile, enhancing the validity of the travel cost method. Of these, we include only respondents who took trips during the past 3 months ($n=3847$) and plan to take a recreation during the next 3 months ($n=2561$). Further, we

exclude respondents who did not report income or a valid ZIP code (n=2405). The average distance to the 11 South Florida recreation sites is the mean of the 11 distances. We delete those in the top 1% of the average distance distribution leaving the maximum distance of 574 one-way miles. Those 24 deleted respondents have a range of average distances from 575 to 2727 with a mean of 863. We also drop respondents in the 90th percentile of trip spending since these may not be trips but temporary relocations, respondents who did not answer the CVM questions and those overnight respondents who did not report party size or nights stayed. Unfortunately we did not elicit party size for respondents who report that their next trip is a day trip. The final sample size is n=2103.

Most respondents (57%) are aged between 18 and 44 years. Slightly under half (48%) are female. 47% of respondents earned over \$75,000 in pre-tax income in 2023. About one quarter of respondents have a bachelor's degree and 18% have earned a master's degree or higher.

The survey asked respondents a series of revealed (actual) preference (RP) and stated (expected) preference (SP) trip questions regarding the number and location of RP and SP recreation trips to the south Florida area. All RP/SP trip questions are posed over a 3-month period. With respect to RP trips, respondents were asked the types of recreation activities they participated in on their most-recent trip. The most popular recreation activity is a beach recreation trip (53.6%) that could include swimming, sunbathing, picnicking, beach sports or walking on the beach. Wildlife observation (24%) and saltwater fishing (24%) are the next most popular, followed by sailing (19%) – including boating, jet-skiing, waterskiing, or wake boarding – kayaking (16%), and scuba diving (15%).

Those that participated in saltwater fishing were also asked how they primarily fished. Slightly over half of those respondents (51%) report fishing from the shore with 25% reporting taking a charter boat trip and 23% taking a private or rental boat. Further, for those taking a private or rental boat trip, the majority (81%) fished in in the ocean (as opposed to the sound, river, or bay). Of this ocean group, one-half (50%) fished offshore (defined as more than 3 miles from the shore).

Travel Cost Method

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

$$(1) \quad x = x(p, y)$$

where x is the number of trips to South Florida, p is the travel cost to South Florida, and y is income. Visits refer to any trips that involved saltwater-related recreation including day trips and trips involving one or more nights away from home.¹

¹ Single-site TCM models should include substitute site(s). Our attempts to do so led to counter-intuitive results, perhaps given to the unique geography of the South Florida site, so we do not include a substitute travel cost in our model.

Both the money cost of travel and the opportunity cost of travel time are included in the travel cost measures. Distance traveled was calculated from the mid-point of household i 's home zip code to the midpoint of the coast in the j^{th} destination:

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

where c is the cost per mile, d_{ij} is round trip distance, γ is a fraction of the hourly wage rate in order to account for the cost of leisure time, w_i is the hourly wage rate, mph is miles per hour, $i = 1, \dots, N$ respondent households; and $j = 1, \dots, 11$ sites.

We use two estimates of the travel cost. The first is the average travel cost to each of the 11 sites. The second is the minimum travel cost to the 11 sites. Attempts were made to include various measures of substitute travel cost from three alternatives: the Florida Gulf Panhandle region, the Florida Gulf Peninsula region and the Northeast Florida coast. Including a substitute travel cost variable, in general, did not improve the models. For example, inclusion of a substitute travel cost variable led to either (a) higher consumer surplus estimates when the opposite is expected, (b) less statistically significant own travel cost coefficients or (c) both. We proceed with a recreation demand models with omitted substitute travel cost variables.

We use variable travel cost from AAA's 2023 Edition of "Your Driving Costs: Behind the Numbers." The variable cost estimate is based on gas, maintenance and tire costs. The variable cost estimates of c is \$0.32 per mile. The opportunity cost of travel time is assumed to be 33% ($\gamma = 0.33$), which is standard in the TCM literature (Lew, forthcoming), to account for the disutility of travel time. The wage rate is measured as household income divided by 2000 annual work hours.

We estimate the determinants of trips with the truncated Negative Binomial count data model (Haab and McConnell 2002):

$$(3) \quad P(X_i = x_i | p_i, y_i) = \frac{\Gamma(x_{1i} + (1/\alpha))}{\Gamma(1/\alpha) x_{1i}!} \left(\frac{1/\alpha}{(1/\alpha) + \mu_i} \right)^{\frac{1}{\alpha}} \left(\frac{\mu_i}{(1/\alpha) + \mu_i} \right)^{x_{1i}}$$

where $\Gamma(\cdot)$ is the gamma function, α is the dispersion parameter, μ_i is the conditional mean and $x_{1i} = 1, \dots, 63$. The conditional mean equation is:

$$(4) \quad E(X_{1i}) = \mu_i = \exp(\gamma_0 + \gamma_1 p_i + \gamma_2 y_i)$$

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

The consumer surplus per trip estimate from a log-linear model is (Bockstael and Strand 1987):

$$(5) \quad \frac{CS}{trip} = -\frac{1}{\gamma_1}$$

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

Contingent Valuation Method

For SP trips, we elicit information on the next outdoor recreation trip that respondents think they will take in South Florida. Here, respondents were presented with a map of South Florida and asked to identify the expected location of their next trip. The map breaks out the south Florida area into 11 regions, ranging from Charlotte County on the Gulf coast, down to the Keys area, and up to St. Lucie and Martin counties on the east coast. The most popular

destination across all waves for the next trip is Palm Beach County (20% across all waves). A further 12% of respondents expect to take their next trip to Marco and Naples, with 10% expecting to go to Middle and Lower Keys. The Ten Thousand Islands region (3%) is expected to be the least-frequented area for respondents' next trip.

Respondents are also asked about the number of nights stayed, the size of the travel party and the amount of money that will be spent on this planned next trip. About two-thirds of the next trips are overnight trips and the average trip length is a 2.5-night stay, with two nights as the modal response. Most (58%) stayed in a hotel or motel, and on average, there are 3 people in the party, spending \$910 per trip. The highest spending category is lodging with an average of \$198 on the most-recent trip.

Respondents are then told: "Trip costs such as travel and other expenses change over time. For example, gas prices fell from 2014 to 2016 and rose from 2020 to 2022. Overall inflation was high in 2021 and 2022. Now suppose that travel and other expenses are $A\%$ higher in South Florida." A is one of six percentage values that is randomly presented to respondents: $A = 25, 40, 55, 70, 85, 100$. By survey design, the percent increase is also converted to the corresponding change in dollar trip cost. Respondents are then told: "Based on your expected trip costs of $\{S\}$, this would mean that the cost of your trip would increase by $\{S \times A\%\}$ to $\{(S \times A\%) + S\}$." S is the amount of money that respondents think they will spend, obtained from the answer to the earlier question. Respondents are then asked: "Would you still plan to go to $\{SF_j\}$ on your next trip?" where SF_j is the location of the next South Florida outdoor

recreation trip obtained from the earlier question, $j = 1, \dots, 11$. We use a follow-up certainty question to mitigate hypothetical bias (Penn and Hu 2023).

Suppose that consumers have a quasi-concave, monotonic utility function defined over recreation trips, x (with baseline cost, p , and quality, q), and consumption of a numeraire composite commodity, h , with $p_h = 1$. The resulting indirect utility function depends upon trip quality and numeraire consumption: $v(q, y - p)$, where y denotes income. If the consumer is observed taking the trip under conditions q then $v(q, y - p) > v(y)$. When faced with additional trip cost, $c = S \times A\%$, the consumer will continue to take the trip if $v(q, y - p - c) \geq v(y)$, where the trip cost is less than the reservation price (implicitly defined as $x(\bar{p}, q) = 0$), $p + c < \bar{p}$.

The theoretical model can be operationalized empirically following Hanemann (1984), McConnell, Weninger and Strand (1999) and Loomis (1997). The individual utility from the choice is expected to be increasing in quality and income (and decreasing in price). Let the utility from alternative j be denoted as $v_j(q, y) + \varepsilon_j$, where v_j is the non-stochastic portion of utility for alternatives $j = 0, 1$ (i.e., $x = 0, 1$), and ε is the corresponding error term. The random utility model assumes that the individual chooses the alternative that gives the highest utility, $\pi_1 = \Pr(v_1 + \varepsilon_1 > v_0 + \varepsilon_0)$, where π_1 is the probability that the respondent would choose alternative $j = 1$. The probability can be rearranged to show that it depends on the difference in utilities, $\pi_1 = \Pr(v_1 - v_0 > \varepsilon_0 - \varepsilon_1)$, relative to the difference in error terms.

If the indirect utility function is assumed to be linear-in-parameters, $v = \beta + \beta_q q + \beta_y y + \varepsilon$, then the difference in utility for the two trip scenario (where quality is constant and the

trip cost changes) is $\Delta v = \beta_1 + \beta_q q + \beta_y(y - p - c) - [\beta_0 + \beta_q q + \beta_y(y - p)] + (\varepsilon_1 - \varepsilon_0)$ and $\Delta v = \tilde{\beta} - \beta_y c + \tilde{\varepsilon}$, where $\tilde{\beta} = \beta_1 - \beta_0$, and $\tilde{\varepsilon} = \varepsilon_1 - \varepsilon_0$. Under the linear-in-parameters structure, quality, income and baseline trip cost (p) drop out of the differenced utility equation.

Estimation of the parameters is achieved by stacking the change in indirect utility functions considering the $t = 2$ SP observations (choice occasions) for each respondent, $i = 1, \dots, N$, $\Delta v_{it} = \tilde{\beta} - \beta_y c + \tilde{\varepsilon}_{it}$ when utility is linear. Assuming ε are drawn from a joint logistic distribution, the probability that individual i will choose to take the trip in occasion t is

$$(6) \quad Pr(Yes_{it} = 1) = \frac{1}{1 + \exp(-\Delta v_{it})}$$

In general, if the estimated utility model is $\Delta v = \tilde{\beta} - \beta_y c$, then the willingness to pay (WTP) for a recreation trip with baseline quality is

$$(7) \quad WTP = -\tilde{\beta} / \beta_y.$$

This is the mean (and median) WTP estimate where respondents are indifferent between taking the trip or not, and can be found by solving for the price that leads to indifference, $\pi(x = 1) = 0.50$, in the logit (Hanemann 1984).

We analyze the contingent valuation data with the logistic regression model in a pseudo-panel. The dependent variable is $Yes = 1$ if the respondent would still take the trip and $Yes = 0$ if not. We stack the data so that each respondent has 2 trip observations: (1) next trip under baseline quality conditions: $c = 0$ and (2) next trip with higher cost: $c > 0$. In the first observation all of the respondents take the trip ($Yes = 1$).

Empirical Results

Forty-six percent of respondents report that their next trip will be a day trip. We split the analysis according to these “day trippers” and “overnight trippers.” The data are summarized in Table 1. The average number of RP trips taken to the South Florida region is 4.95 for day trippers and 4.07 for overnight trippers. The average number of SP trips that will be taken to the South Florida region is similar, 4.07, for day trippers but lower, 2.76, for overnight trippers. The average travel cost to the South Florida region is \$153 and \$191 for day and overnight trippers. The minimum travel cost to the South Florida region is \$38 and \$74 for day and overnight trippers. The average annual household income is similar for day and overnight trippers, \$87.8 thousand and \$88.5 thousand, respectively.

The own-price coefficients are negative and statistically significant in each of the four TCM models ($p < 0.01$). Recreation demand own-price elasticities are -0.52 and -0.20 for the average and minimum travel cost in the day tripper models. The own-price elasticities are lower, -0.29 and -0.12, for the average and minimum travel cost in the overnight tripper models.² Income has a positive effect on trips in each of the models ($p < 0.01$), indicating that South Florida trips are normal goods, with income elasticities of 0.32 (average) and 0.18 (minimum) in the day tripper models and 0.20 (average) and 0.13 (minimum) in the overnight tripper models. The AIC statistics suggest that the minimum travel cost model statistically outperforms the average travel cost model but there is very little difference in the overnight trip model AICs.

² Elasticity in the NB model is estimated as: $e_z = \beta_z^* z$, where β^* is the estimated effect of the Poisson coefficient and z is the mean of the variable.

The dependent variables for the regression models are Yes1 and Yes2 where Yes2 is adjusted for the follow-up certainty question (by recoding uncertain yes responses to no responses). The only independent variable in the model is the increase in the cost of the trip. The summary of these variables is presented in Table 1. Seventy percent of day trippers state that they would continue taking their next trip with an average additional cost of \$117. Fifty-seven percent of respondents are certain that they would take this next trip. Seventy-six percent of overnight trippers state that they would continue taking their next trip with an average additional cost of \$319 with 62% of these certain.

In both the day and overnight trip models, survey respondents are less likely to continue taking the trip as the trip cost increases ($p < 0.01$, Table 3). The AIC statistic is lower for the Yes1 day trip model relative to the Yes 2 day trip model. The Yes1 and Yes2 overnight trip models are very similar except for the intercept estimates. The intercept estimates in Yes 1 models are larger, capturing the higher number of respondents who would still take the trip.

The consumer surplus and willingness to pay estimates are presented in Table 4. We conduct 100,000 Krinsky-Robb simulations for each welfare measure (Park, Loomis, and Creel 1991). The CS and WTP estimates are the medians with lower and upper 95% confidence intervals resulting from trimming the lowest and highest 2.5% of the estimates. The range of value estimates is wide: \$188 for the day trip CS estimate from the minimum travel cost model to \$830 from the overnight trip WTP estimate from the Yes1 model. For both methods the overnight trip values are larger than the day trip estimates. But, adjusting the overnight value estimates for the number of nights stayed (average nights = 2.5) assuming equal party size makes the day vs overnight estimates, within valuation method comparison, similar. The per person per

day value estimates from the overnight trip models ranges from \$86 to \$113 from the overnight trip models (the average party size is 2.96). The Krinsky-Robb confidence intervals are asymmetric with wider upper tails. The ratio of the upper to lower tail ranges from 128% to 237%. The asymmetry ratios are larger in the TCM models.

In Table 5 we conduct convergent validity tests by comparing the WTP estimates from the CVM and CS estimates from the TCM. With four welfare estimates from each method, we conduct eight convergent validity tests. Willingness to pay is larger than consumer surplus in 6 of the 8 comparisons. The difference for the six instances where WTP is greater than CS per trip ranges from \$5 (Yes2 and minimum TC) to \$194 (Yes1 and minimum TC). Only one of these differences is statistically significant according to the convolutions test (Poe, Giraud, and Loomis, 2005). The \$174 difference between the Yes1 willingness to pay and the minimum TC consumer surplus estimates for day trippers is statistically significant at the $p < 0.01$ level. The Yes2 willingness to pay estimate and both consumer surplus estimates exhibit the greatest convergent validity with $p < 0.48$ for both tests. All other p values are between $p = 0.12$ and $p = 0.21$.

Conclusions

In this paper we compare CVM and TCM recreation values with opt-in data collected with a recent South Florida recreation survey. We find that the opt-in panel data produces valid recreation demand and willingness to pay models. Willingness to pay is higher than consumer surplus in 75% of the 8 comparisons but only one difference is statistically significant suggesting that the welfare estimates from the two methods are convergent valid. This result is in contrast to that found by Whitehead et al. (2026) for opt-in panel data.

These results have important implications for policy analysis. Probability-based samples remain the preferred standard when resources allow, particularly for high-stakes decisions where representativeness is critical. However, use of opt-in panel data is likely to persist due to lower cost and faster implementation. Whitehead et al. (2026) find that opt-in estimates of recreation values are systematically higher than those from probability-based data panels but fall within the range of errors commonly observed in benefit transfer applications (Rosenberger and Loomis 2017).. As such, opt-in data may be appropriate for preliminary or lower-stakes analyses, particularly when combined with calibration strategies based on probability-based benchmarks. The evidence in this paper strengthens the case for the use of opt-in panel data.

Future research should be conducted to investigate the internal and external validity of opt-in panel data. Valuation research should explore the development of systematic calibration approaches that adjust opt-in panel estimates to better approximate probability-based benchmarks. Additional work is also needed to evaluate whether valuation research conducted with opt-in panel data is a potential substitute to benefit transfer, or better seen as a complement when the time and money budgets do not allow research with preferred data sources.

References

- Bishop, Richard C., and Kevin J. Boyle. "Reliability and validity in nonmarket valuation." *Environmental and Resource Economics* 72, no. 2 (2019): 559-582.
- Bockstael, Nancy E., and Ivar E. Strand. "The effect of common sources of regression error on benefit estimates." *Land economics* 63, no. 1 (1987): 11-20.
- Boyle, Kevin J. "Contingent valuation in practice." In *A Primer on Nonmarket Valuation*, Editors, Patricia A. Champ, Kevin J. Boyle, Thomas C. Brown, pp. 83-131. Dordrecht: Springer Netherlands, 2017.
- Cameron, Trudy Ann, and Michelle D. James. "Efficient estimation methods for 'closed-ended' contingent valuation surveys." *Review of Economics and Statistics* (1987): 269-276.
- Carson, Richard T., Nicholas E. Flores, Kerry M. Martin, and Jennifer L. Wright. "Contingent valuation and revealed preference methodologies: comparing the estimates for quasi-public goods." *Land economics* (1996): 80-99.
- Haab, Timothy C., and Kenneth E. McConnell. *Valuing Environmental and Natural Resources: The Econometrics of Non-market Valuation*. Edward Elgar Publishing, 2002.
- Hanemann, W. Michael. "Welfare evaluations in contingent valuation experiments with discrete responses." *American Journal of Agricultural Economics* 66, no. 3 (1984): 332-341.

Johnston, Robert J., Kevin J. Boyle, Wiktor Adamowicz, Jeff Bennett, Roy Brouwer, Trudy Ann Cameron, W. Michael Hanemann et al. "Contemporary guidance for stated preference studies." *Journal of the Association of Environmental and Resource Economists* 4, no. 2 (2017): 319-405.

Landry, Craig E. and Travis A. Smith. "Single-site recreation demand models." Chapter 8 in *Handbook of Environmental Valuation*, edited by Timothy C. Haab, Lala Ma and John C. Whitehead, forthcoming.

Lew, Daniel K. "The opportunity cost of time in travel cost models." Chapter 9 in *Handbook of Environmental Valuation*, edited by Timothy C. Haab, Lala Ma and John C. Whitehead, forthcoming.

Loomis, John B. "Panel estimators to combine revealed and stated preference dichotomous choice data." *Journal of Agricultural and Resource Economics* (1997): 233-245.

Loomis, John, Michael Creel, and Timothy Park. "Comparing benefit estimates from travel cost and contingent valuation using confidence intervals for Hicksian welfare measures." *Applied Economics* 23, no. 11 (1991): 1725-1731.

McConnell, Kenneth E., Quinn Weninger, and Ivar E. Strand. "Joint estimation of contingent valuation and truncated recreational demands." In *Valuing Recreation and the Environment*, pp. 199-216. Edward Elgar Publishing, 1999.

Park, Timothy, John B. Loomis, and Michael Creel. "Confidence intervals for evaluating benefits estimates from dichotomous choice contingent valuation studies." *Land Economics* 67, no. 1 (1991): 64-73.

Parsons, George R. "Travel cost models." In *A Primer on Nonmarket Valuation*, Editors, Patricia A. Champ, Kevin J. Boyle, Thomas C. Brown, pp. 187-233. Dordrecht: Springer Netherlands, 2017.

Penn, Jerrod, and Wuyang Hu. "Adjusting and calibrating elicited values based on follow-up certainty questions: a meta-analysis." *Environmental and Resource Economics* 84, no. 4 (2023): 919-946.

Poe, Gregory L., Kelly L. Giraud, and John B. Loomis. "Computational methods for measuring the difference of empirical distributions." *American Journal of Agricultural Economics* 87, no. 2 (2005): 353-365.

Rosenberger, R.S. and J.B. Loomis (2017). "Benefit Transfer." Chapter 12 in *A Primer on Nonmarket Valuation*, 2nd ed., Patricia A. Champ, Kevin J. Boyle, and Thomas C. Brown (eds.). Springer, Dordrecht.

Sandstrom-Mistry, Kaitlynn, Frank Lupi, Hyunjung Kim, and Joseph A. Herriges. "Comparing water quality valuation across probability and non-probability samples." *Applied Economic Perspectives and Policy* 45, no. 2 (2023): 744-761.

Sellar, Christine, John R. Stoll, and Jean-Paul Chavas. "Validation of empirical measures of welfare change: a comparison of nonmarket techniques." *Land economics* 61, no. 2 (1985): 156-175.

Whitehead, John C., Andrew Ropicki, John Loomis, Sherry Larkin, Tim Haab, and Sergio Alvarez. "Estimating the benefits to Florida households from avoiding another Gulf oil spill

using the contingent valuation method: Internal validity tests with probability-based and opt-in samples." *Applied Economic Perspectives and Policy* 45, no. 2 (2023): 705-720.

Whitehead, John C., Louis Cornicelli, Lisa Bragg, and Rob Southwick. "The aggregate economic value of Great Lakes recreation fishing trips." *Journal of Great Lakes Research* 51, no. 2 (2025): 102529.

Whitehead, John C., Tim Haab, Sherry L. Larkin, John B. Loomis, Sergio Alvarez and Andrew Ropicki, 2026. "Do Any Differences in Estimated Recreation Benefits from Probability and Opt-in Samples Vary with Valuation Method?" Working Papers 26-09, Department of Economics, Appalachian State University.

Table 1. Data Summary								
	Day Trip				Overnight Trip			
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
RP Trips	4.954	7.004	1	63	4.069	5.794	1.0	63
SP Trips	4.066	6.158	1	63	2.761	3.370	1.0	63
TC average	153.462	61.944	72.21	521.22	191.398	96.330	71.88	798.20
TC minimum	38.031	44.148	0.63	414.56	74.009	83.292	0.90	619.36
Income	87.831	56.329	20.00	225.00	88.465	55.798	20.00	225.00
Yes1	0.701	0.458	0	1	0.767	0.423	0	1
Yes2	0.574	0.495	0	1	0.616	0.487	0	1
Cost	116.88	137.32	12.50	1250	318.81	256.13	12.50	1300
Sample Size	968				1135			

Table 2. Negative Binomial Travel Cost Method Models								
	Day Trip				Overnight Trip			
	TC average		TC minimum		TC average		TC minimum	
Parameter	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Intercept	1.5884	0.0855	1.4019	0.0585	1.0946	0.0565	0.9901	0.0476
Travel cost	-0.0034	0.0007	-0.0053	0.0008	-0.0015	0.0003	-0.0016	0.0003
Income	0.0036	0.0007	0.002	0.0005	0.0023	0.0005	0.0015	0.0004
Dispersion	0.6464	0.0367	0.629	0.0360	0.2928	0.0236	0.2932	0.0237
AIC	4798.33		4776.32		4624.62		4626.06	
Sample Size	968		968		1135		1135	

Table 3. Panel Logit Contingent Valuation Method Models								
	Day Trip				Overnight Trip			
	Yes1		Yes2		Yes1		Yes2	
Parameter	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Intercept	2.2098	0.0775	1.8641	0.0734	2.8392	0.0823	2.1225	0.0621
Cost	-0.0061	0.0008	-0.0080	0.0010	-0.0034	0.0002	-0.0033	0.0002
AIC	1489.58		1776.99		1406.93		1407.93	
Sample Size	968		968		1135		1135	
Time periods	2		2		2		2	

Table 4. CS and WTP Estimates from Krinsky-Robb Simulations				
		Median	Lower 95%	Upper 95%
Day	TC average	295.84	210.67	497.89
Day	TC minimum	187.98	145.71	265.21
Overnight	TC average	645.93	473.58	1017.74
Overnight	TC minimum	635.63	462.59	1017.77
Day	Yes1	362.82	299.80	466.86
Day	Yes2	233.53	194.83	297.82
Overnight	Yes1	830.14	749.06	933.86
Overnight	Yes2	641.09	575.44	725.93

Table 5. Convolutions Tests				
Trip Type	CVM	TCM	Difference (WTP - CS)	p-value
Day	Yes1	TC average	66.45	0.21
Day	Yes1	TC minimum	173.67	0.00
Day	Yes2	TC average	-61.58	0.14
Day	Yes2	TC minimum	45.41	0.13
Overnight	Yes1	TC average	183.36	0.12
Overnight	Yes1	TC minimum	193.58	0.12
Overnight	Yes2	TC average	-4.90	0.48
Overnight	Yes2	TC minimum	5.34	0.48