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Do CVM Welfare Estimates Suffer from On-Site Sampling Bias? A Comparison of On-Site and Household Visitor Surveys

Juan Marcos González-Sepúlveda and John B. Loomis

The problem of endogenous stratification associated with on-site sampling has been overlooked in the Contingent Valuation Method (CVM). We find that using on-site samples of visitors overstates visitor willingness to pay (WTP) estimates relative to a household sample of visitors, and substantially overstates the unconditional population values. We provide two methods of correcting WTP of on-site samples. The uncorrected on-site sample CVM yields WTP of \$132 per trip, while visitor WTP obtained from a random sample of households had a value of \$66 per trip. Adaptation of choice-based sampling correction estimator to the on-site CVM data yields \$73 per trip, *not* statistically different from the visitor value from the household survey, but significantly different from the uncorrected on-site sample value.

Key Words: contingent valuation method, endogenous stratification, on-site sampling bias

On-site sampling is a useful and cost-efficient sampling technique that has been used for years by transportation planners and recreation economists. Because users of a particular site (e.g., bus stop, recreation site) represent a small portion of the total population, obtaining a large enough user sample from a general population survey can be expensive. On-site surveying is an inexpensive alternative way to obtain a large number of users at the sites of interest. The problem is that these on-site sampling benefits come at the expense of creating other sampling issues. These sampling issues may lead to overestimates of not only the general population's value of a new proposed recreation site but even visitors' value of the existing site. In this paper we argue that this lack of generalizability of on-site samples also applies to the Contingent Valuation Method (CVM) derived willingness to pay (WTP) values.

Endogenous stratification has been a concern in recreation valuation since Shaw (1988) first pointed out the problem. The effect of on-site sampling on WTP has been documented in the Travel Cost Method (TCM) literature (e.g., Moeltner and Shonkwiler 2005, Martinez-Espineira, Amoako-Tuffour, and Hilbe 2006) and corrections devel-

oped for TCM econometric estimators. However, these on-site sampling concerns have been largely ignored in other recreation valuation methods such as CVM, which also utilizes on-site samples to estimate visitor WTP. This paper tests whether CVM suffers from endogenous stratification, and if so, we show how to correct for it.

When Shaw proposed a statistical correction for on-site sampling in the TCM, the correction addressed two sources of bias: *endogenous stratification* and *truncation*. If the researcher is relying on interviewing only people that visited the site, the sample will be endogenously stratified and truncated at zero because no zero visits will be observed.

Throughout the years, economists have embraced the idea that the corrections proposed by Shaw provide useful information that extends TCM estimates of WTP results to the general population. Relevant empirical applications of Shaw's correction in the TCM literature include the use of "corrected" count data models (Poisson and Negative Binomial particularly) to study deer hunting (Creel and Loomis 1990), hiking (Englin and Shonkwiler 1995), river recreation (Loomis 2003), marine recreation (Bhat 2003), and ecotourism (Chase et al. 1998), among many others.

While dichotomous choice CVM models are different from TCM in terms of the parametric

Juan Marcos González-Sepúlveda is an economist at RTI Solutions in Research Triangle Park, North Carolina. John Loomis is Professor at Colorado State University in Fort Collins, Colorado.

distributional assumptions and the approach CVM uses to assess visitors' WTP, we argue that the sampling issues that affect TCM may also affect CVM estimates of WTP. Despite the domain of the distributions assumed in many CVM studies not being directly affected by the nature of collected-on-site data, on-site sampling can still over-represent more avid users, and certainly those more avid than the general population. To our knowledge, no research has been published where these sampling issues and the alternative solutions to this problem are presented and formally tested against CVM WTP obtained from a household sample.

This paper takes advantage of a rare opportunity in which we have access to both a CVM visitor on-site survey and a CVM household survey. We use these two data sets to estimate WTP per trip for visitors from the on-site sample, WTP of visitors from the household survey, and total population WTP from the household survey. We then compare the resulting WTP from each sample and test whether the on-site CVM WTP per trip is statistically different from the value per trip obtained from visitors in a household survey. We then propose two methods to correct CVM estimates of WTP to obtain unconditional WTP that can be used to estimate or calculate more representative visitor values. To statistically test for significant differences in WTP values with on-site versus household sampling, and to test for equivalence of our corrected estimate of WTP and household WTP values, we use an empirical convolutions method (Poe, Giraud, and Loomis 2005).

Where Does the Sampling Bias Come From?

Sample-selection bias resulting from on-site surveying has long been studied by economists in fields outside of recreation. In 1979 Heckman provided an explanation of the source of on-site sampling bias. He did so by explicitly presenting the probability of an event conditioned on the sampling method used by the researcher. Heckman showed that a biased estimate can be obtained whenever observing a random variable depends on observing a particular state of a different random variable. By explicitly modeling the conditional nature of the data, Heckman demonstrated that the potential bias is caused by the

omission of information contained in the inverse mills ratio (Greene 2003). Including this ratio in a linear specification captures the effect that is left out of the parameter estimates when the researcher has access only to observations that match a state of a second random variable.

Following Heckman, we can show analytically how our CVM estimate of WTP from an on-site sample is incidentally conditioned on observing non-zero visits to the site of interest (a particular state of a different random variable). The general form of each individual model equation is as follows:

$$(1) \quad q_i = f(tc_{ij}, z_i, v_j) = x_i\beta + \mu_i,$$

where $x = (tc_{ij}, z_i, v_j)$, and

$$(2) \quad bid_answer_i = g(b_i, z_i, v_j) = z_i\delta + \varepsilon_i,$$

where $z = (b_i, z_i, v_j)$, q_i represents the number of trips taken by individual i , tc_{ij} is the cost of traveling that the i th individual faces to visit site j , z_i is a set of individual characteristics, v_j is a set of site characteristics, bid_answer_i is the answer that individual i gave to the stated preference question, and b_i is the bid amount offered to each individual.

Relating these equations in a conditional framework we note that the expected value of the dependent variable in the CVM model can be expressed as

$$\begin{aligned} (3) \quad & E[bid_answer_i | bid_answer_i \text{ is observed}] \\ &= E[bid_answer_i | q_i > 0] \\ &= E[bid_answer_i | E[q_i] > 0] \\ &= z_i\delta + E[\varepsilon_i | \mu_i > -x_i\beta] \\ &= z_i\delta + \zeta_i \lambda_i(\alpha_\mu), \end{aligned}$$

where $\alpha_\mu = -x_i\beta/\sigma_\mu$ and $\lambda_i(\alpha_\mu) = \phi(-x_i\beta/\sigma_\mu)/\Phi(-x_i\beta/\sigma_\mu)$. As a consequence, without some correction, an on-site CVM fails to recognize that we have only visitors in our sample. Ignoring this conditioning has the effect of overestimating WTP visitors and the general population. In the following sections, we focus on testing whether this bias is present in our particular application and ex-

plore two different options to correct WTP estimates obtained with on-site data.

Testing for On-Site Sampling Bias in CVM

Part of the problem of sampling on-site is that more frequent visitors (i.e., more avid) have a higher probability of being sampled relative to infrequent users (endogenous stratification). If, as expected, more avid users have higher WTP than infrequent visitors, the on-site sample may overstate the typical visitor's WTP. Statistically speaking, this means that the visitors intercepted have a different visit's probability distribution than that of the general population, violating the random sampling requirement to make results externally valid (Moeltner and Shonkwiler 2005). Englin and Shonkwiler (1995) found that not paying attention to such sampling concerns could lead to biased TCM welfare estimates when modeling demand for recreation at a single site. Further efforts by Moeltner and Shonkwiler (2005) consider the same issues for multiple sites in a multivariate random utility model framework.

Discussion of endogenous stratification in the CVM literature is, to our knowledge, rare at best. In 1988, Nowell, Evans, and McDonald recognized a length-of-stay bias sampling problem in CVM. They showed that not accounting for the higher probability of sampling visitors with greater length of stays at a site results in biased WTP estimates. Their claim was that at a site where multiple-day stays are common, the probability of interviewing someone on-site is directly related to the length of his or her visit.

Parallel to the intuition presented by Nowell, Evans, and McDonald (1988), the probability of intercepting an individual at a site where only single-day visits are taken is affected by the number of trips a visitor takes. This is the case because sampling an individual is *conditional* on his or her decision to visit the site. People that take more trips to a site may also place greater value on visiting the site due to an avidity for that site. Thus, an on-site sample may not provide a representative value per visitor, let alone for individuals in the population.

Having conditional measures of WTP (i.e., on-site estimates of WTP) could become a serious issue when policymakers need valuation information to apply to a reported or estimated number

of visitors to a site, or to the general population living within a few hours' drive of a proposed recreation site. In situations like this, the WTP estimate derived from an on-site sample is likely to be too large. Furthermore, transferring WTP values from an on-site visitor sample at a study site to a policy site with an estimated number of visitors could also be misleading. One contribution of this paper is to provide statistical methods to correct WTP estimates obtained from cost-effective on-site samples so they can be generalized to a visitor population, and to provide an unconditional measure of the general population WTP (not conditional on being a visitor). Accounting for the bias caused by endogenous stratification may allow researchers to transfer WTP estimates to other policy sites with greater confidence.

Method to Test for On-Site Sampling Bias in CVM

To test whether there is on-site sampling bias in dichotomous choice CVM-derived estimates of WTP, we compare WTP results from an on-site sample to those obtained by using a household survey. By using a logit regression we estimate the WTP for each data set. First we test the equivalence of on-site visitor WTP to that of the WTP of the underlying population:

$$(4a) \quad H_o : WTP_{pop} = WTP_{on-site}$$

$$(4b) \quad H_a : WTP_{pop} < WTP_{on-site}$$

We also test whether the on-site sample yields equivalent estimates of visitors' WTP as estimated from a sample of visitors obtained from a household survey [*hhvisitor* in equations (5a) and (5b)]:

$$(5a) \quad H_o : WTP_{hhvisitor} = WTP_{on-site}$$

$$(5b) \quad H_a : WTP_{hhvisitor} < WTP_{on-site}$$

It is worth noting that we are implicitly relying upon the idea that the household survey provides a representative estimate of WTP. While the original sample frame may be representative of the population of households, non-response to the survey (Whitehead, Groothuis, and Blomquist 1993) or to the WTP question (Haab 1999) can undermine the representativeness of the resulting household WTP estimates. In Whitehead, Grooth-

uis, and Blomquist (1993), survey non-response resulted in an over-estimate of household WTP by 33 percent. Of course, the on-site surveys are also subject to non-response bias. Therefore, it may be that on-site sampling adds yet another factor in addition to non-response bias pushing up the estimates of WTP.

To statistically test these two null hypotheses, an empirical convolutions method is used to determine the statistical significance of any difference between the WTP measures estimated using the on-site sample, the household population [equation (4a)], and the visitors from the household sample [equation (5a)]. We use the parameters generated with the representative population sample (from the household survey) and the representative visitors (from the household survey) along with their corresponding standard errors to calculate a random vector of WTP for households (WTP_{pop}) and visitors ($WTP_{hvisitor}$) with their own confidence interval. A similar random WTP vector is calculated ($WTP_{on-site}$) from the parameters and standard errors from the on-site CVM data and estimation. The convolutions method takes all possible differences between these two random vectors and determines the probability that they are different. The proportion of the differences that are less than zero as a result of this convolutions procedure is believed to be overlapping values between the corresponding distributions, and used to determine the empirical probability of finding the same WTP in both distributions (empirical p-values).

Results from these tests provide us with empirical evidence to indicate whether this particular application of on-site CVM sampling suffers from endogenous stratification. If the differences in WTP are statistically significant, then methods to correct WTP estimated from on-site samples are needed to allow continued use of these cost-effective, but biased on-site samples.

Two Approaches to Correcting On-Site Conditional WTP

We explore two different corrections to the on-site CVM WTP and compare them based on how well they recover the general population values and household visitor values.

Correction using probability of visitation. A relatively simple way to correct for on-site sampling bias is to use an adjustment factor that is equal to the percentage of a general population that visits the site or would visit a new site of policy interest. This fraction is multiplied by the on-site WTP to provide the unconditional population WTP value. This two-step procedure is performed by first obtaining conditional estimates for the parameters of the model from the on-site sample. Then, second, by correcting the resulting on-site WTP measure after the estimation process by using the percentage of the general population that would visit. An advantage of this approach is that the calculated WTP is adjusted to the population based on expected visitation, thus allowing researchers to obtain a transferable value that is more flexible to accommodate to populations that may have different levels of participation in the recreation activity. In other words, the researcher does not need to assume that the level of avidity around the study site is equal to that of the population around the policy site when conducting a benefit transfer.

To justify the use of the adjustment factor, we can think of what is obtained when calculating net WTP for the on-site sample. The on-site net WTP calculation is a conditional value that depends on whether the respondent has visited the site of interest. With this in mind, the visitor net WTP is just part of the population net WTP for the site. Analytically we can say that

$$(6) \quad E[WTP_{pop}] = [WTP_v \times P_v] + [WTP_{nv} \times (1 - P_v)],$$

where $E[WTP_{pop}]$ is the expected value of the population net WTP, WTP_v is the net WTP or consumer surplus that visitors have, P_v is the probability of being a visitor, and WTP_{nv} is the net WTP of non-visitors. The equation above says that the expected population net WTP equals the net WTP of each of the two possible groups (visitors and non-visitors) multiplied by the respective probability of being in that group.

First, we have shown already that the net WTP_v is obtained with the on-site survey. Furthermore, because non-visitors face a travel cost that is already higher than what they are willing to pay for their first trip, we know that net WTP_{nv} is likely to be zero (unless there is an option value, which we

have omitted to simplify the analysis¹). Due to the non-divisible nature of trips, non-visitors' optimal choice is to not visit the site at all, and hence they have no consumer surplus or zero net WTP. With this in mind, equation (6) above becomes

$$(7a) \quad E[WTP_{pop}] = [WTP_v \times P_v] + [0 \times (1 - P_v)]$$

or

$$(7b) \quad E[WTP_{pop}] = [WTP_v \times P_v].$$

This shows that we can use the probability of being a visitor to adjust our conditional WTP measure and use our on-site results to infer something about the general population. The percentage of the population that visits the site can be easily calculated if the researcher knows total site visitation. This can then be divided by the population in the surrounding geographic region to calculate the participation rate for that site.

For benefit transfer purposes, the researcher can approximate this visitation probability at the new policy site to transfer on-site WTP measures from other sites. This probability can be an informed estimate based on existing studies like the U.S. Fish and Wildlife Service (USFWS) National Survey² or the National Survey of Recreation Use and the Environment,³ or simple survey information on what percentage of the population of interest might visit the new site.

Weighted exogenous sampling maximum likelihood. The second option is to use what Manski and Lerman called Weighted Exogenous Sampling Maximum Likelihood (WESML) (Manski and Lerman 1977). In a choice-based sample, such as the ones we obtain on-site, one type of answer

may be oversampled. A maximum likelihood estimator will transfer this bias to the parameters and mimic the on-site data. The estimator that Manski and Lerman derived uses the observed or assumed relationship between the sample and population proportions to correct the parameter estimates and adjust them to the appropriate population means. It is a weighting scheme that approaches the Choice Based Sampling Maximum Likelihood (CBSML)⁴ estimator using the following likelihood function:

$$(8) \quad \ln L = \sum_{i=1}^N w_i \ln F(x_i | \beta),$$

where

$$w_i = y_i \left(\frac{\omega_1}{p_1} \right) + (1 - y_i) \left(\frac{\omega_0}{p_0} \right),$$

ω_1 and ω_0 are the population proportions of visitors and non-visitors, and p_1 and p_0 are the observed proportions of participation and non-participation observed in the CVM responses.

A practical limitation with this approach is that we need to know (or assume) the correct proportion of users in the population of interest. Just as with the first adjustment approach described above, this information can be obtained with a simple participation survey that is often conducted by agencies or other existing studies of participation in the particular activity under study (e.g., USFWS National Survey).

We will use the method of convolutions to test whether the corrected estimates of WTP from these two correction methods are equivalent to the underlying general population:

$$(9a) \quad H_o : WTP_{pop} = WTP_{on-site \text{ correction}}$$

$$(9b) \quad H_a : WTP_{pop} \neq WTP_{on-site \text{ correction}}$$

¹ It is of course possible that some of the non-visiting households may hold an option value for future visitation. To the extent this is true, then our $E[WTP_{pop}]$ as defined in equation (6) would understate the true societal $E[WTP_{pop}]$. Conceptually this could be dealt with in one of two ways in equation (6). One way would be to re-label our WTP_{pop} as Current Use Value WTP_{pop} to make clear that equation (6) does not include option value or any other non-use values (e.g., existence value). More satisfying would be to add another term to equation (6) to reflect the proportion of the non-visitors that have an option value for future use times their $WTP_{option-value}$. For this option value group, an additional option value WTP question would need to be asked of non-visitors to obtain the fraction of non-visitors with option value and the monetary amount of that option value.

² See http://library.fws.gov/nat_survey2006.pdf.

³ See <http://www.srs.fs.usda.gov/trends/Nsre/Round1t4rptuw.pdf>.

⁴ CBSML uses Bayes' Rule to incorporate the choice-based sampling process. This estimation requires at least marginally tractable integrals in the likelihood function (Manski and Lerman 1977, McFadden and Reid 1975, and Westin 1974). Although a case with two alternatives (like the one at hand) would require the least number of evaluations of integrals, it is still more complicated than the WESML proposed by Manski and Lerman.

We also test whether the two correction methods yield WTP equivalent to the visitor WTP obtained from the household sample:

$$(10a) \quad H_o : WTP_{hhvisitor} = WTP_{on-site\ correction}$$

$$(10b) \quad H_a : WTP_{hhvisitor} \neq WTP_{on-site\ correction}$$

In the next section, we conduct empirical tests to determine if there is on-site sampling bias in a dichotomous choice CVM data set, and if so, how well our two proposed correction procedures do in approximating the WTP values from the household survey that includes visitors.

Data Sources

The Snake River in Jackson Hole, Wyoming, is the recreation site of interest for this analysis. This stretch of the Snake River south of Grand Teton National Park provides a wide spectrum of day use recreational activities. These activities include fishing from shore, fishing from boats, scenic raft trips, and hiking along the levees.

Visitors to one of four areas along the Snake River were given a mail-back survey packet. Sampling took place on weekdays and weekends during the month of August through Labor Day weekend in September of 2000. The four sampling locations included a boat put-in and take-out point used by private and commercial rafters, as well as two levee areas used for fishing and hiking. A random sample of visitors was intercepted as they returned to their vehicles at each location. Visitor names and addresses were recorded so that a reminder postcard and second mailing of the survey to non-respondents could be performed. We had only 19 on-site refusals to take a survey, for a refusal rate of just 3 percent. There were 657 surveys handed out, and the overall response rate was 65 percent.

The same 12-page survey booklet that was given to visitors on-site was also mailed to 800 randomly selected Teton County residents and 800 randomly selected Wyoming residents, along with a \$1 incentive on the first mailing. After two mailings, the response rate, net of undeliverable surveys and deceased, for the sample of Teton County residents was 59 percent, or 372 returned surveys. For Wyoming residents, the net response rate was 52.2 percent, or 386 returned surveys.

The same dichotomous choice CVM recreation WTP question was asked of on-site visitors and visitors from the household sample. About half those sampled in the household survey were *not* visitors to this section of the Snake River and therefore were not asked the WTP question, since this question asked about direct use value and was not phrased to obtain any option value (see footnote 1 for more discussion of option value). The WTP question was asked immediately following the questions asking the respondent to record his or her trip expenses. The exact wording of the question was: "As you know, some of the costs of travel, such as gasoline, have been increasing. If the cost of this most recent visit to this section of the Snake River had been \$X higher, would you have still made this visit?" The \$X varied from a low end of \$1 and \$2 to a high end of \$90 to \$150.

Results

Econometric Results

Table 1 displays the estimation results using the dichotomous choice CVM data. The first column shows the logit model results for the uncorrected or naïve on-site sample analysis (what we call the naïve on-site model). The second column shows the results from the analysis using WESML with the on-site data. The third and fourth columns show the logit model results estimated using data from the household survey, first for the full sample of households (i.e., visitors and non-visiting households), and then for only visitors within our household sample. Results from our models in Table 1 all have a negative and statistically significant bid coefficient.

WTP Results for the Comparison of On-Site Samples to the Household Visitors and Unconditional Population Values

Table 2 presents the mean WTP for each of the four econometric models, plus the correction of the on-site naïve model WTP using the probability of participation. The uncorrected naïve on-site model yields a mean WTP per trip of \$131.89, which is about double the mean WTP per trip estimated from the sample of visitors within the household survey (\$66.49). This large difference

Table 1. Results from Dichotomous Choice Contingent Valuation Method Logit Models for Snake River Recreation

	Naïve (on-site data)	WESML (on-site data)	Household	Household Visitors
Constant	0.4434 (0.1624)	-0.4578 (0.2744)	-0.8007* (0.1679)	0.8279* 0.2330
Bid	-0.0140* (0.0036)	-0.0141* (0.0039)	-0.0153* (0.0033)	-0.0203* (0.0039)
Income	0.0134* (0.0034)	0.0113* (0.0025)	0.0085* (0.0017)	0.0018 (0.0021)
Log-likelihood	-141.2694	-144.7326	-344.5955	-141.2694

Note: * indicates significant at the 99 percent confidence level. Standard errors are in parentheses.

Table 2. Willingness to Pay Confidence Intervals for 95 Percent and 90 Percent Confidence Levels

		95%	90%
Naïve (on-site)	L Bound	\$96.05	\$100.10
	Mean	\$131.89	\$131.89
	U Bound	\$226.20	\$204.00
WESML (on-site)	L Bound	\$51.93	\$54.66
	Mean	\$73.08	\$73.08
	U Bound	\$137.97	\$120.54
Naïve with correction	L Bound	\$47.02	\$49.08
	Mean	\$64.19	\$64.19
	U Bound	\$115.90	\$101.50
Visitor household	L Bound	\$53.06	\$54.79
	Mean	\$66.49	\$66.49
	U Bound	\$95.31	\$88.27
Household	L Bound	\$33.00	\$34.19
	Mean	\$42.50	\$42.50
	U Bound	\$64.76	\$59.94

between the naïve on-site model WTP and the WTP of visitors obtained within the household survey suggests the presence of endogenous stratification in the naïve on-site dichotomous choice CVM WTP estimates. The uncorrected naïve on-site model estimate of WTP (\$131.89) is more than triple the unconditional WTP obtained from the household survey (\$42.50).

To correct the naïve on-site WTP estimate, we use the visitor participation rate of 48.67 percent obtained from the household survey. The resulting expected WTP drops to \$64.19 per trip. This

corrected estimate is nearly identical to the \$66.49 per trip from the visitor data obtained from the household survey. Since the household sample is a random one, results for the visitors in this group do not suffer from the avidity problem that the on-site observations have. Thus, even if the researcher is primarily interested in WTP conditional on being a visitor, the naïve on-site sample estimate of WTP overstates a representative sample of visitor WTP. Such endogenous stratification in the naïve model related to on-site sampling would undermine benefit transfer since the WTP

estimates would depend on how the data was collected.

However, this probability of visitor participation correction estimate of WTP per trip (\$64.19) is higher than the unconditional population WTP of \$42.50. Nonetheless this correction yields a WTP per trip that is much closer to the unconditional WTP than does the uncorrected on-site naïve model.

The WESML model also provides a lower WTP measure (\$73.08) than the naïve on-site data model (\$131.89). The WESML estimate of \$73.08 per trip is much closer to the \$66.49 per trip estimated with the visitor portion of the household survey. Thus for benefit transfer purposes the WESML estimate would be more generalizable despite having been estimated using on-site data. However, the WESML estimate of \$73.08 is substantially higher than the unconditional household sample of \$42.50. This divergence between WESML and the unconditional household value could be due to the presence of incidental truncation.

Testing Differences in WTP

In order to formally test our hypotheses regarding whether these differences in WTP are statistically significant, we compared the calculated mean WTP with each model using the method of convolutions. We applied the (complete combinatorial) convolutions to the WTP simulated confidence intervals presented in Table 2 to test the statistical difference between calculated WTP for each model. Table 3 shows the results of this process. Eight pair-wise comparisons were done between the alternative sampling frames and the

correction approaches. The first column, labeled P-Value vs. Household, tests the null hypothesis of equality of the WTP for all models versus the WTP of the unconditional population household sample. The next column, labeled P-Value vs. HH Visitors, tests the null hypothesis of equality of the WTP for all models versus the WTP of the visitor portion of the household sample.

Tests of equality of WTP with unconditional population. The results of the convolutions method in Table 3 indicate that two of the WTP measures obtained with an on-site sample are statistically different from the unconditional household sample WTP. Specifically, the result of the first hypothesis test is that the conditional on-site sample WTP (naïve on-site model) is statistically different from the unconditional household population WTP ($P = 0.00008$). In addition, WTP obtained using the WESML with the on-site visitor data is statistically different at the 5 percent level ($P = 0.04$) from the WTP for the unconditional household population. This of course raises a flag for researchers that would want to use on-site WTP calculations to say something about the general population (non-visitors included) or to transfer the on-site benefit estimates to a new proposed site, which might have a different proportion of the population as visitors. As for the simple adjustment factor approach, we obtain the percentage of visitors to the site by looking at the household sample and calculating the portion of the sample that visited the site of interest. Multiplying this percentage by the on-site WTP reduces the net WTP from \$131.89 to \$64.19. This corrected WTP is closer to the one in the household general sample (\$42.50) and not statistically different at the 5 percent or 10 percent level ($P = 0.12$) from the unconditional population estimate of WTP.

Tests of equality of WTP with visitors from the household sample. Of greater concern is the fact that the WTP of the naïve on-site model is also statistically different from the WTP obtained from the visitor portion of the household sample ($P = 0.0072$). This suggests that traditional models for on-site visitor samples can misrepresent the WTP of visitors, the specific group the on-site sample is intended to model. Thus, endogenous stratification seems to affect not only the assessment of the

Table 3. Willingness to Pay Convolutions and P-Values for Pair-Wise Differences Between Samples

	P-Value vs. Household	P-Value vs. HH Visitors
Naïve (on-site)	0.00008	0.0072
WESML (on-site)	0.04	0.86
Naïve with correction	0.12	0.86
Visitor household	0.06	1
Household	1	0.06

Note: Reported p -values are obtained using empirical convolutions methods.

general population's WTP but also that of visitors as well. In contrast to the WTP from the naïve model, the WTP obtained using the WESML is not statistically different from that of the sample of visitors in the household sample ($P = 0.86$). Thus the WESML estimator provides an accurate estimate of the visitor WTP value. The simple correction of the naïve on-site data model WTP for percentage participation also yields a WTP estimate that is not statistically different ($P = 0.86$) from the visitor portion of the household sample. This suggests that our simple correction to an on-site sample is a tenable approximation to a visitor WTP obtained from a household sample. Thus, both correction methods proposed in this paper provide estimates of WTP that are free from the effects of endogenous stratification, and hence more accurately represent WTP of visitors. This suggests that visitor WTP derived from these two correction methods would be more suitable for benefit transfer than WTP calculated from the uncorrected naïve on-site samples.

Conclusions

Results from this study show that on-site dichotomous choice CVM WTP estimates have a conditional nature that has to be recognized when using the estimated parameters to infer WTP about the general population or even a population-based sample of visitors. The proposed correction presented here is a useful tool to extend on-site sampling results to the general population and for benefit transfer. The unconditional mean WTP in our household sample was roughly \$42.50. The estimate of visitor WTP obtained from the household sample is \$66.49, about half of the \$131.89 estimate from the uncorrected on-site sample. Even if the researcher is interested in just visitor values, the on-site sample greatly overstates the visitor values, let alone the unconditional population values. The WESML model produces a \$73 estimate of per trip value that, while statistically greater than the unconditional population value, is not statistically different from the \$66.49 visitor value obtained from the household sample. The on-site WTP estimate, when corrected by the probability of participation, is also not statistically different from the unconditional household estimate of WTP [as noted earlier, the unconditional household estimate of WTP from a house-

hold survey may still be biased upward due to household survey non response bias (Whitehead, Grootuis, and Blomquist 1993)].

If the analyst wishes to estimate generalizable visitor WTP values from an on-site sample, our two correction methods appear capable of obtaining visitor WTP values from an on-site sample not statistically different from visitor WTP obtained from a household survey that does not suffer from endogenous stratification. If the analyst wishes an estimate of the population WTP for benefit transfer purposes, then multiplying the on-site visitor WTP value by the probability of participation will yield an estimate of WTP not significantly different from that obtained from a household survey of visiting and non-visiting households. However, the WESML adjustment method appears to overstate the unconditional population WTP, although by far less than the conditional on-site sample. Future research should attempt to explore what other methods might be available to better correct on-site sample visitor WTP and better approximate the general population WTP.

References

- Bhat, M.G. 2003. "Application of Non-Market Valuation to the Florida Keys Marine Reserve Management." *Journal of Environmental Management* 67(4): 315–325.
- Chase, L.C., D.R. Lee, W.D. Schulze, and D.J. Anderson. 1998. "Ecotourism Demand and Differential Pricing of National Park Access in Costa Rica." *Land Economics* 74(4): 466–482.
- Creel, M., and J. Loomis. 1990. "Theoretical and Empirical Advantages of Truncated Count Data Estimating for Analysis of Deer Hunting in California." *American Journal of Agricultural Economics* 72(4): 434–441.
- Englin, J., and J.S. Shonkwiler. 1995. "Estimating Social Welfare Using Count Data Models: An Application to Long-Run Recreation Demand Under Conditions of Endogenous Stratification and Truncation." *Review of Economics and Statistics* 77(1): 104–112.
- Greene, W.H. 2003. *Econometric Analysis* (5th edition). Upper Saddle River, NJ: Prentice Hall.
- Haab, T. 1999. "Nonparticipation or Misspecification? The Impacts of Nonparticipation on Dichotomous Choice Contingent Valuation." *Environmental and Resource Economics* 14(4): 443–461.
- Heckman, J. 1979. "Sample Selection Bias as Specification Error." *Econometrica* 47(1): 153–161.
- Loomis, J. 2003. "Travel Cost Demand Model Based River Recreation Benefit Estimates with On-Site and Household

- Surveys: Comparative Results and a Correction Procedure.” *Water Resources Research* 39(4): 1105–1108.
- Manski, C., and S. Lerman. 1977. “The Estimation of Choice Probabilities from Choice Based Samples.” *Econometrica* 45(8): 1977–1988.
- Martinez-Espineira, R., J. Amoako-Tuffour, and J. Hilbe. 2006. “Travel Cost Demand Model Based Recreation Benefit Estimates with On-Site and Household Surveys: Comparative Results and a Correction Procedure: Reevaluation.” *Water Resources Research* 42 (doi:10.1029/2005WR004798).
- McFadden, D., and F. Reid. 1975. “Aggregate Travel Demand Forecasting from Disaggregate Behavioral Models.” *Transportation Research Record* 534(1): 24–37.
- Moeltner, K., and J.S. Shonkwiler. 2005. “Correcting for On-Site Sampling in Random Utility Models.” *American Journal of Agricultural Economics* 87(2): 327–339.
- Nowell, C., M.A. Evans, and L. McDonald. 1988. “Length-Biased Sampling in Contingent Valuation Studies.” *Land Economics* 64(4): 367–371.
- Poe, G.L., K.L. Giraud, and J.B. Loomis. 2005. “Computational Methods for Measuring the Difference of Empirical Distributions.” *American Journal of Agricultural Economics* 87(2): 353–365.
- Shaw, D. 1988. “On-Site Samples Regression: Problems of Non Negative Integers, Truncation and Endogenous Stratification.” *Journal of Econometrics* 37(2): 211–223.
- Westin, R. 1974. “Predictions from Binary Choice Models.” *Journal of Econometrics* 2(1): 1–16.
- Whitehead, J., P. Grootuis, and G. Blomquist. 1993. “Testing for Non-Response and Sample Selection Bias in Contingent Valuation.” *Economic Letters* 41(2): 215–230.