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A Joint Estimation Method to Combine Dichotomous Choice CVM Models with Count Data TCM Models Corrected for Truncation and Endogenous Stratification

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We update the joint estimation of revealed and stated preference data of previously published research to allow for joint estimation of the Travel Cost Method (TCM) portion using count data models. The TCM estimation also corrects for truncation and endogenous stratification as well as overdispersion. The joint estimation allows for testing consistency of behavior between revealed and stated preference data rather than imposing it. We find little gain in estimation efficiency, but our joint estimation might make a significant improvement in estimation efficiency when the contingent valuation scenarios involve major changes in site quality not reflected in the TCM data.

Key Words: contingent valuation models, joint estimation, nonmarket valuation, recreation, travel cost models

JEL Classifications: Q51

In 1992, Cameron proposed a procedure that combined Revealed Preference (RP) and Stated Preference (SP) methods in a simultaneous estimation framework. The purpose of this was to allow communication between models and to arrive at a robust estimation of both sets of parameters. In Cameron's study, Contingent Valuation Method (CVM) estimation is combined with a Travel Cost Method (TCM) in a structural way, allowing CVM parameters to be conditional to expected demand levels for each individual. This first attempt used a probit and a normal distribution joint process. The simultaneous estimation done in Cameron's paper relates the errors in both methods assuming a bivariate normal distribution, conditioning the probit part of the estimation to the error structure in the TCM portion. Since the publication of this paper, determining the consistency of SP and RP has become an important part in the recreation economics literature (Adamowicz, Louviere, and Williams; Azevedo, Herriges, and Kling; McConnell, Weninger, and Strand).

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SP uses hypothetical scenarios to create or extend existing market conditions for a public good and assess marginal consumer behavior to changes in fees or quality. RP considers observed behavior from consumers to uncover a demand schedule, usually to arrive at the benefit consumers receive with the current price and quantity. These models are set up to look at different sides of the same problem. They differ in their approach, but aim to obtain the same information from survey data. TCM looks to estimate an ordinary demand function through which economists can calculate respondent's willingness to pay (WTP). Although CVM obtains surplus measures directly, looking at utility differentials between residual income and the visitor's stated behavior, consistency between the two models requires that the site demand function and utility difference function come from the same underlying utility function (McConnell, Wenington, and Strand). Traditionally, this theoretical expectation has been imposed through parameter restrictions (Cameron) or conversion of one type of data to the other (Englin and Cameron; Loomis 1997; McConnell, Wenington and Strand).

When looked at individually, neither of the available methods under both types of models is free of criticism. SP models, typically developed in the form of Contingent Valuation methods, are of concern because of the hypothetical nature of the "transactions" used. Although several validation studies have been done (Bowker and Stoll; Carson et al.; Loomis 1989) showing that CVM results provide welfare estimates that are comparable to RP results, criticism of CVM techniques have become more focused and direct over time (Boyle). RP models, typically in the form of Travel Cost Models (TCMs) and Random Utility Travel Cost Models (RUM-TCM) are criticized because of the sensitivity of their welfare estimates to treatment of travel time and econometric issues.

However, both SP and RP have useful properties that aid researchers in their assessment of nonmarket values. SP models allow the researcher to explicitly evaluate policy-relevant scenarios that might involve changes in resource quality beyond the levels observed in the RP data. This "data augmentations" approach avoids extrapolating beyond the range of the RP data when evaluating substantial improvements in environmental quality. RP data resembles what economists are used to dealing with when they estimate demand for a good has a market. That TCM behavior reflects actual decisions that involve real payments and thus provides very useful information for the estimation process.

For these reasons, we adopt the spirit of Randall's suggestion that we learn everything that can be learned from combining these data without imposing preconceived notions regarding the superiority of one type of data over another. As Azevedo, Herriges, and Kling mention, discrepancies between the results obtained with these two methods need not be a failure of either one. On the contrary, these differences should be taken as an indication that the two sources are correcting the limitations that the other has.

For this research, we also follow the spirit of Cameron's work by combining CVM and TCM data to estimate joint parameters. Unlike Cameron's approach, however, our attempt is primarily computational and does not use a combined utility function to channel the TCM model information into the CVM choice parameters. This leaves us with a joint error structure but eliminates the need for parameter restrictions, in that no utility function needs to be determined (thus, parameters are not to be constrained across equations). In a way, our approach looks at these equations as a pair of seemingly unrelated regressions wherein the connection between equations lies in the error structure rather than the parameters themselves. When using both models with the same group of respondents, the unobservable factors that affect respondents' number of trips demanded are also likely to affect respondents' answers to the CVM question. These unobservable factors are contained in the error term of each model, suggesting that the errors of these models could be related (McConnell, Weninger, and Strand). Bringing the two models together and allowing a correlation parameter between their respective error terms provides a way to look into this possibility and test it. Again, the purpose here is NOT to impose, but to test consistency.

This approach has a drawback that should be mentioned. That is, with no parameter restrictions, we can *potentially* obtain two different welfare measures[1] for the same policy change. Despite this potential drawback, we see value in relaxing the assumption that both models respond to a particular underlying distribution arbitrarily chosen by the researcher. Estimating separate parameters and accounting only for the potential relation in the error structure of the models represents, in our view, a looser enforcement of the known theoretical relation between the models. Furthermore, in terms of applicability of the model, this would only be a problem really if any of the WTP measures changes the balance between the costs and benefits of a project.

Another contribution of this paper is to update the joint estimation process presented by Cameron by taking advantage of the evolution in parametric estimation models for TCM data. Fully parameterized trip frequency count data models have gained ground with the use of Poisson, Negative Binomial, and Multinomial Count Distributions in recreation literature (Creel and Loomis; Hellerstein and Mendelsohn). They are seen as a logical extension to accommodate the particular properties of trip data (Shonkwiler). In fact, it has been argued that the evolution of fully parametric trip frequency models has made RP models trustworthy (Hellerstein). With this in mind, we use a Poisson and Negative Binomial distribution to exploit the count nature of the TCM data. Furthermore, these distributions are modified to account for on-site sampling, a problem also known as endogenous stratification.

To assess whether welfare calculations differ between individual and joint estimations, we use an empirical numeric procedure known as *complete combinatorial convolutions*. Poe, Giraud, and Loomis proposed this method as an alternative to empirically determine the probability that a random variable is statistically different from another. We recognize that an individual's WTP in both CVM and TCM models is a random variable, and we test whether calculated consumer surplus changes significantly from one case to another (joint and individual estimation).

The following sections will expand on the econometric estimation process and the use of the convolution method. Results and conclusions are also presented.

Alternative Ways to Combine TCM and CVM Data

TCM and CVM questions form a continuum, ranging from seasonal WTP for both (Cameron) to marginal trips for both (Loomis 1997). Loomis (1997) combined TCM and CVM in a series of dichotomous choices. In this view, the revealed trip-making behavior reflects an implicit yes to the first of the bid questions at existing travel cost, whereas the CVM question represents the second response to a higher bid in a panel. McConnell, Weninger, and Strand also look at combining TCM and CVM by treating both as utility differentials. Like Loomis, McConnell argues that the original trip decision is an implicit yes to a first dichotomous choice question with a bid equal to the actual travel cost. His RUM argument is very appealing because it also allows for a change in the visitor's preference structure after more information about the site becomes available through a visit. Although useful, the problem with using such an approach is that you need to discard the trip frequency information from the TCM to be able to use it in a dichotomous choice panel context.

Others, like Englin and Cameron, do the opposite, setting up the CVM question in a way that mimics the TCM framework. Their

[1] Carson et al. used more than 600 different CVM and TCM estimates and concluded that differences between CVM and TCM WTP were not statistically significant. If anything, CVM WTP measures are generally below TCM WTP estimates (roughly .9 of TCM estimates).

study looks at a change in trips in response to higher travel costs. The problem here is that asking visitors to reassess a full season of trips given a marginal change in price on site might be too much of a strain, thus becoming a source of possible bias or item nonresponses. The argument is basically the same used with open-ended questions in which respondents have a hard time pinpointing the actual WTP from a wide number of possible values. When visitors have to reassess the number of trips made in a season, they are in essence asked to choose a new value for trip number in an open-ended format. Certainly this problem becomes less relevant with visitors that have fewer visits because this limits the remaining number of visiting options available.

To our knowledge, the closest prior effort to test for consistency was done by Azevedo, Herriges, and Kling. However, three differences need to be pointed out. First, they use the same approach that Enlgin and Cameron had used before. They asked respondents to reassess their behavior for an entire season subject to marginal changes in costs. This provides a nice dataset in which you can readily pool RP and SP responses into a single framework. In addition, Azevedo, Herriges, and Kling still rely on the use of a censored normal distribution for their estimations. They do not take advantage of the newer, more appropriate count data models. They do this because this allows them to use a bivariate normal distribution, which provides a familiar framework to correlate the errors between the two scenarios. The third difference lies in the way they test for consistency. Because they focus on the statistical discrepancies between TCM and CVM parameters, differences in the actual variable of interest, WTP, are not addressed directly.

The objective of this paper is to simultaneously estimate both models to take advantage of the commonalities between the two methods without 1) discarding TCM trip frequency information, 2) forcing users to reassess their visits for the full season, and 3) imposing consistency between the two models (e.g., instead, allowing testing for consistency). Our paper fills an important empirical gap in the analysis of combined RP and SP data: The case of TCM, with CVM on the most recent trip. This combination is often used in the literature. Examples of separate use of these particular data setups can be found in studies that range from deer hunting (Loomis, Pierce, and Manfredo) and mountain biking (Fix and Loomis) to recreation demand in developing countries (Chase et al.).

Data

Data for this study come from a research project that is currently being conducted in the Caribbean National Forest in the northeastern part of Puerto Rico, also known as El Yunque. Surveys were administered during the summers of 2004–2005 as part of a comprehensive study on the effect of site characteristics on social and physical conditions in and around the forest streams.

In-person interviews were conducted at nine recreation sites along the Mameyes and Espíritu Santo rivers. Data include visitor's demographics, site characteristics (fixed and variable), trip information, and a contingent valuation question in the form of: "If the cost of this visit to this river was $____ more than what you have already spent, would you still have come today?" Bid amounts ranged from $1 to $200 per trip.

More than 700 observations were obtained and coded, of which 450 observations were used in this analysis. The reason for the reduction in observations is because only trips in which visiting the site was the main reason for traveling are considered valid for the TCM. This is done to deal with multiple destination problems (274 trips were not single-destination trips) that are typically pointed out as a source of distortion in travel cost models. Also, because of the complicated form of the corrected negative binomial distribution, we eliminated four visitors who took more than 12 trips because they appear to be somehow quite different from the vast majority who take a small fraction of these trips. This is not uncommon, as pointed out by Englin and Shonkwiler, who also limited their corrected Negative Binomial to visitors with fewer than 12 trips.

The same variables were chosen in both models to be able to compare "apples and apples" between the two. The variable travel cost (TC) was created from a set of variables available. Our definition of travel cost follows the conventional formula

$$\mathrm{TC} = (0.33 \times \text{per minute income})\ \text{travel time} + \left(\frac{\text{gas cost}}{\text{No. of adults}}\right),$$

where travel time (in minutes) and gas costs are round-trip measures.

The first term of this definition looks at the opportunity cost of the time spent in the trip (assuming this time was taken away from income-generating activities). The second term looks at the actual cost of traveling to the site incurred by each adult in the household.

The following are summary statistics of the sites studied and the variables considered. Table 1 presents the mean, maximum, minimum, and number of observations per site.

The price variable in the TCM is of course travel cost as defined above. The bid amount visitors were asked to pay is the price variable in the CVM. Common explanatory variables for both models were mean annual discharge (as means of flow), distance the river pools were to the bridge access and road width (as a measure of accessibility).

Likelihood Estimation

Estimating CVM Parameters

Because CVM deals directly with consumer reactions to marginal changes, they represent a straightforward way to obtain compensated welfare measures. In our study, a dichotomous choice WTP question format is used. The welfare measure from a WTP question in CVM can be summarized in the following equation,

$$v(p^0, Q^0, y) = v(p^1, Q^1, y - c), \quad (1)$$

where $v(\ )$ is an indirect utility function, p^0 is

Table 1. Summary Statistics by Site

		Angelito Trail	El Verde Bridge	Jimenez Bridge	Jimenez Waterfall	Juan Diego	La Mina	La Vega	Puente Roto	Sonadora	Waterfall
Observed		28	23	18	19	42	235	49	254	37	73
Mean annual discharge	Mean	1.272	1.282	1.632	0.219	0.106	0.238	1.667	1.365	0.273	0.665
Distance, bridge to pool	Mean	0	0	145	52	93	35	0	0	5	30
Travel cost	Mean	$17.54	$14.88	$14.57	$18.49	$13.72	$12.88	$18.09	$17.16	$24.77	$15.82
	Min	$1.65	$1.28	$1.41	$2.90	$1.24	$0.14	$1.41	$0.41	$3.05	$0.14
	Max	$55.09	$42.81	$61.50	$75.21	$63.88	$65.50	$71.88	$140.13	$92.19	$77.75
Bid	Mean	$83.93	$57.83	$69.44	$50.26	$86.19	$58.89	$63.35	$54.37	$62.43	$86.90
	Min	$5.00	$5.00	$5.00	$5.00	$5.00	$1.00	$1.00	$1.00	$5.00	$5.00
	Max	$180.00	$180.00	$200.00	$200.00	$200.00	$200.00	$200.00	$200.00	$200.00	$200.00

the current price level of the good considered, Q^0 is the current quantity of the good consumed, and y is income. On the other side of the equation, p^1 and Q^1 represent the new price and consumption level, and c is the Hicksian compensating variation, or WTP. In words, this equation states that maximum WTP is the amount that makes utility levels equal when considering different price levels, quantities, and disposable income. Note that under the current condition (*0*), disposable income is y, whereas in the alternative scenario (*1*), it is the difference between y and c.

What CVM allows us to do is determine what the visitors' WTP is for the good in question. In other words, we uncover the population parameter c. In the case of recreation or site valuation, the two levels available for consumption are typically all or nothing. Put differently, we uncover the WTP that makes the visitors indifferent between visiting a site or not on their most recent trip.

Because our WTP question format of "take it or leave it" involves a dichotomous choice of continuing to visit at the hypothetically higher travel cost or staying home, economists have used logit and probit likelihood functions to obtain WTP measures. For our purpose, we use a probit in this study for the CVM portion of the parameter estimation. The general form of a probit likelihood function is derived from the Bernoulli distribution. A probit link is associated to ensure a nonnegative and bounded probability value (between 0 and 1) while conditioning the individual probability function to the set of parameters to be estimated,

$$(2) \quad \ln L = y_{\mathrm{CVM}} \times \ln(\pi) + (1 - y_{\mathrm{CVM}}) \times \ln(1 - \pi),$$

where $\pi = \Phi(\mathbf{X}\beta)$ and y_{CVM} is the individual's response to the CVM question. It is important to point out that $\Phi(\ )$ stands for the standard normal cumulative density function, $\mathbf{X}$ refers to the set of variables we are conditioning our probability to, and β is the set of parameters to be estimated. Among the set of variables $\mathbf{X}$, we have the bid amount or price increase per trip.

Estimating the TCM Parameters

For the TCM portion of our estimation we use a Poisson and a Negative Binomial. Both of these distributions are used in the estimation of recreation demand because they are count data models. This means that they take advantage of two important characteristics that count data share: nonnegative and discrete outcomes. The Poisson and Negative Binomial distribution have been used successfully in the past to estimate seasonal demand for sites.

One important consideration that was raised by Shaw and later showed empirically by Creel and Loomis is that truncated versions of these distributions should be used when on-site sampling takes place. Truncation of the dependent variable arises because all visitors must take at least one trip to be sampled. In addition, we also correct for what is known as endogenous stratification, or that on-site sampling results in an overrepresentation of more frequent visitors in the sample data.

In general, correcting for truncation is done by dividing our probability distribution function by the probability of the outcomes ruled out (i.e., unobserved). Analytically this could be represented as

$$(3) \quad \Pr(Y = y|y > a) = \Pr(Y = y)/\Pr(Y > a).$$

In our particular case, $a = 0$, so

$$(4) \quad \Pr(Y = y|y > 0) = \Pr(Y = y)/[1 - \Pr(Y = 0)].$$

Note that because we are using count data models, we only need to find the probability that $Y = 0$ and use its complement by subtracting it from 1.

When using the Poisson distribution, the resulting truncated version looks like

$$(5) \quad \Pr(Y = y|y > 0) = \frac{(e^{-\lambda}\lambda^{y})}{y!(1 - e^{-\lambda})},$$

where $\lambda = e^{(\mathbf{X}\beta)}$ and a resulting log likelihood function that can be represented in the following way:

$$(6) \quad \ln(L_{\mathrm{poisson}}) = -\lambda \times \ln(y_{\mathrm{TCM}}!)\check{S}\ln(1 - e^{-\lambda}).$$

Alternatively, the Poisson distribution has a very particular and useful property for correcting for endogenous stratification; that is, the truncated Poisson distribution provides the same results as using a regular (without truncation) Poisson when subtracting 1 from the dependent variable Y.

However, the Poisson distribution imposes the restriction that the mean of the distribution equals its variance, something often rejected by trip data. A more general form of the Poisson count data that tests for and relaxes this mean-variance equality is the Negative Binomial model. The standard likelihood function of the on-site corrected Negative Binomial is

$$L_{\mathrm{rp}} = \left[\frac{\Gamma(\alpha + y_{\mathrm{TCM}})}{\Gamma(\alpha)(y_{\mathrm{TCM}} - 1)!}\right] \times \left[\frac{(\alpha)}{(\lambda + \alpha)}\right]^{\alpha} \frac{\lambda^{(y_{\mathrm{TCM}}-1)}}{(\lambda + \alpha)^{y_{\mathrm{TCM}}}}. \tag{7}$$

This was derived by Englin and Shonkwiler, wherein, again, $\lambda = e^{(x\beta)}$, and α is the overdispersion parameter. In the case of the Negative Binomial distribution, this convenient property of the Poisson for correcting for on-site sampling does not hold, and a more complicated correction to the likelihood function is needed. See Englin and Shonkwiler for the derivation and expression.

Simultaneous Estimation

Using Cameron's structure, we define our joint estimation process taking advantage of the known fact that a joint probability is equal to a conditional probability multiplied by a marginal probability:

$$f(x, y) = f(x|y)f(y). \tag{8}$$

Just as in her case, we define the conditional probability in a direct manner by making the CVM estimation conditional to the TCM expected outcome. This expectation is used as an avidity measure to "inform" the CVM part of the estimation. It is however a statistical convenience to be able to incorporate a correlation parameter while treating the individual likelihood functions separately. This is an ad hoc approach that simplifies the estimation process by allowing the researcher to simply multiply the two probabilities obtained from our individual models. This in turn allows the possibility of simply adding the two log likelihood functions together when using a bivariate distribution.

When choosing the bivariate distribution for this application, we are faced with a particular challenge. Because we use a count data distribution for our TCM estimation, we cannot use a regular bivariate normal distribution as has been used in the past. To accomplish the simultaneous estimation of these equations, we use the joint Poisson and probit distribution derived in Cameron and Englin. Although developed for a different purpose, the joint density is ideal for the job. Unfortunately, Cameron and Englin did not derive a Negative Binomial and probit joint density, so another contribution of this paper is to derive such a joint estimator to incorporate overdispersion into our regression. Furthermore, both our densities are also modified to incorporate endogenous stratification. Appendix A shows in detail how these distributions were derived. Analytically, our new Negative Binomial joint likelihood function for the i^{th} observation looks like

$$L_i = \left[(\theta_i)^{y_{\mathrm{CVM},i}}(1 - \theta_i)^{1-y_{\mathrm{CVM},i}}\right] \times \left[\frac{\Gamma(\alpha + y_{\mathrm{TCM},i})}{\Gamma(\alpha)(y_{\mathrm{TCM},i} - 1)!}\right] \times \left[\frac{(\alpha)}{(\lambda_i + \alpha)}\right]^{\alpha} \frac{\lambda_i^{(y_{\mathrm{TCM},i}-1)}}{(\lambda_i + \alpha)^{y_{\mathrm{TCM},i}}}, \tag{9}$$

where

$$\theta_i = \Phi\left[(x_i\beta + \sigma\rho Z_i)\Big/\left(1 - \rho^2\right)^{0.5}\right]$$

and

$$Z_i = [y_{\mathrm{TCM},i} - E(y_{\mathrm{TCMm},i})]\Big/[\mathrm{Var}(y_{\mathrm{TCM},i})]^{0.5}.$$

The log likelihood version of the joint estimation is simply the sum of the new CVM probit likelihood and the chosen TCM likelihood function. The probit portion is modified with the normalized TCM variable and accounting for individual variances and their joint covariance. Because we expect that the error term in the CVM equation should change with changes in the expected trip demand, we also allow for this heteroskedastic process by setting $\sigma = e^{[\gamma E(y_{\mathrm{TCM}})]}$.

One point of clarification is necessary before finalizing this section. Special care must be taken when using the NB modified distribution. Because we are correcting it for endogenous stratification, the first and second moments used in the definition of Z are not the ones usually considered but are also modified to account for the correction. Englin and Shonkwiler define these corrected moments for the Negative Binomial as

$$(10) \quad E(y|y > 0) = \lambda + 1 + \alpha_0$$

and

$$(11) \quad V(y|y > 0) = \lambda + \alpha_0 + \alpha_0\lambda + \alpha_0^2,$$

where $\alpha_0 = \alpha/\lambda$.

We will estimate recreation benefits with three empirical models: (1) the dichotomous choice CVM estimated with a probit model, (2) the TCM with Poisson and NB, and (3) a joint RP-SP model. From each of these models, an estimator of net WTP for a trip is calculated. Now we turn to evaluation of whether these benefit estimates are different from each other and their respective confidence intervals (CIs) as a measure of the precision of the benefit estimates with each of the 3 methods. To do this, we use a method proposed by Poe, Giraud, and Loomis called empirical convolution. The next section presents these methods and relates it to the task at hand, comparing the resulting WTP from all the models used in this paper.

Convolutions Method for Testing Differences in WTP

We use the method of convolution to compare WTP estimates. Convolution is a mathematical operator that takes two functions and produces a third function that represents the amount of overlap between them. Poe, Giraud, and Loomis proposed an alternative that can use a complete combinatorial approach to measure the differences between independent distributions. As mentioned before, convolution creates a third random variable that is formed by some relationship between the original functions considered. In Poe's example, this relationship is a difference between the two random variables of interest. This new random variable can be expressed as

$$(12) \quad Z = X - Y.$$

Although several approaches have been used to assess differences between benefit estimates, some important issues are addressed with the use of the complete combinatorial approach. With this method, we do not have sampling errors from the use of random sampling or overstate significance with the use of Nonoverlapping Confidence Intervals. More importantly, this method does not require the assumption of normality for the difference parameter obtained.

The complete combinatorial method assumes that the researcher generates two independent distributions that approximate random variables X and Y. The way in which these empirical distributions are obtained does not affect the operation by which we determine the difference between them. Poe, Giraud, and Loomis follow the argument that resampling methods approximate the underlying distribution of two independent random variables or calculated parameters. Each event in both distributions is given the same probability, although repeated outcomes are easily incorporated without losing generality. Poe, Giraud, and Loomis showed that this empirical application can be related to the summation of polynomial products, which, itself, goes back to the formal definition of the convolution method. For more details on the approach used by Poe, you can refer to Appendix B at the end of this paper.

In our study, **X** and **Y** refer to WTP vectors for the individual and joint estimations, respectively. A vector with random draws from the feasible values for each WTP is generated by the Krinsky Robb approach. A total of 4,000 draws were made and sorted. Each element of these vectors is subtracted from the other, as suggested in Appendix B. This results in 4,000! possible combinations of the elements in both vectors. To obtain the one- and two-sided *p*-value, the proportion of nonpositive values is calculated. This represents the empirical probability that $\{x - y\} \leq 0$, or the area in one distribution that overlaps the other. We use the convolution method to test consistency between CVM and TCM joint and individual estimation. This method aids us in looking beyond mean values in the WTP distributions and allows us to determine statistically whether the difference between the two estimation approaches is significant in the part that matters the most, surplus values.

Testing Efficiency Gains of Joint Estimation

As explained above, the method known as convolution allows us to assess the probability that two empirical distributions are different (whether $\text{WTP}_{\text{joint}} = \text{WTP}_{\text{individual}}$). In our particular case, we want to test whether the distribution of the WTP obtained from a joint estimation is statistically different from the one obtained in the individual estimation process. This allows us to test whether simultaneous estimation yields significantly different benefit estimates. We can evaluate in other important ways how different these results are from those obtained in separate regressions. For this matter, we rely on more traditional hypothesis-testing methods. That is, we use two different hypothesis tests to determine whether 1) the data generating processes of both equations are related in some way and 2) the resulting parameters for joint and individual estimations are equal. Formally, this would be

$$\text{(13)} \qquad \text{H}_0 : \rho = 1 \quad \text{and} \quad \text{H}_1 : \rho \neq 1$$

$$\text{(14)} \qquad \begin{array}{l} \text{H}_0 : \beta^{\text{joint}} = \beta^{\text{individual}} \quad \text{and} \\ \text{H}_1 : \beta^{\text{joint}} \neq \beta^{\text{individual}}. \end{array}$$

To determine whether to accept the null hypotheses in Tests (13) and (14), we use the traditional *t*-test and likelihood ratio approach, respectively. We assess whether Rho is statistically different from 1 with a *t*-test. To test equality of joint and individual coefficients, we use the sum of log likelihoods of individual estimations against the joint estimation likelihood value. Together with the convolution method, these set of tests should aid us in having a clearer idea of whether simultaneous estimation in this empirical case provides more efficient parameters.

Results

Results for the models estimated are summarized in Table 2. The values shown are the parameters' estimated values and their corresponding *t*-values. This table shows results for the individual and joint estimations with the use of the Negative Binomial (NB) distributions because preliminary statistical results indicated that the overdispersion parameter *alpha* was statistically significant. This suggests that the Negative Binomial is closer to the actual data-generating process and thus should be used rather than the Poisson when determining WTP.

As can be seen, theoretically consistent results were obtained for both TCM and CVM regressions. Results seem to suggest that our empirical case supports the theoretical expectation of negative slope parameters for travel cost and bid amount variables. The table not only reports the individual log likelihoods for the separate estimations, but also includes the sum of both TCM and CVM likelihood values. Results also suggest that the CVM and TCM results were very robust because all parameters from individual and joint estimations remain very close under the two estimation approaches.

Also notable is that, in both our separate and joint estimations, calculated WTP for CVM and TCM were considerably different. The two-tail *p*-value for the empirical convolution between the TCM and CVM WTP (for the joint and the individual Negative Binomial estimation) was around .02. This suggests that the disparity found between the two WTP measures is not an artifact of our joint estimation but instead could be the reason

Table 2. Results from Individual and Joint Estimations

Variable	Separate Estimation	Joint Estimation
Negative binomial		
Intercept	0.8022	1.0412
	(0.334188)	(0.4373899)
TC	−0.1250	−0.1263
	−(2.996302)	−(3.1975384)
Road	0.4683	0.3512
	(0.561003)	(0.4433266)
Mean annual discharge	−3.8705	−3.8259
	−(1.561611)	−(0.9744921)
Distance, bridge to pool	−0.0420	−0.0324
	−(0.849035)	−(0.799866)
Alpha	3.9238	3.9131
	(8.5631)	(8.1664354)
Probit		
Intercept	1.4846	1.3562
	(1.332047)	(3.3689947)
Bid	−0.0107	−0.0095
	−(8.889946)	−(4.5358031)
Road	−0.0770	−0.0556
	−(0.563755)	−(0.856263)
Mean annual discharge	−0.0142	−0.0485
	−(0.021363)	−(0.2651793)
Distance, bridge to pool	−0.0010	−0.0011
	−(0.199364)	−(0.4629103)
Rho		0.0642
		(0.390131)
Sigma		0.0253
		(0.6286091)
LL negative binomial	−764.5786	
LL probit	−236.4633	
LL joint	−1001.0418	−1000.7478
Likelihood ratio	0.588	
Implied WTP TCM	$ 8.00	$ 7.92
CVM	$ 110.12	$ 114.32

Note: Results present coefficients, with *t*-values in parentheses.

behind the little improvement found between these approaches.

Results for the likelihood ratio test performed between simultaneous and individual regressions are included in Table 2 also. The individual likelihood values for the separate regressions are reported along with the pooled log likelihood value. The difference between the sum of the individual log likelihoods and the simultaneous estimation likelihood is multiplied by 2 to obtain the likelihood ratio statistic χ^2 reported. The likelihood ratio value computed is not significant for the χ^2 test with two degrees of freedom (critical value for 90% confidence level equals 3.84). With regard to Hypothesis Tests (13) and (14), we see that in the joint estimation, rho appears to be an insignificant variable. Through both an insignificant rho value and likelihood ratio for the joint model, the joint estimation process, as used here, does not seem advantageous in our case study over the separate regressions approach. Finally, our estimate for σ also appears to be insignificant, suggesting that our error term in the CVM portion does not vary with changes in the expected number of trips.

As for the results of the convolution testing for significant differences in mean WTP, the most commonly used confidence levels (90% and 95%) are reported in Table 3. The values presented as maximum and minimum WTP in each case come from our convolution method; thus, these would vary in case of replication because of the random nature of the process. The mean values presented are the ones obtained directly from the parameters estimated using the appropriate WTP formulas.

On the other hand, we fail to reject the null hypothesis of equality or no difference in separately estimated versus joint estimation of TCM and CVM benefits. Note that the *p*-value under this test represents the probability that the difference between the two empirical distributions is less than or equal to zero. These results seem to reflect the small gain in efficiency obtained with the joint estimation process in the case for our data. In our table, the comparisons between the joint and individual empirical WTP variables appear, for all practical purposes, identical for both the TCM and the CVM. The similarity of consumer surplus estimates from the individual and joint models can be seen in the near equivalence of the Travel Cost coefficients in Table 2. In the individual Negative Binomial and Joint Negative Binomial model, the coefficients are again almost identical (−.1250 and −.1263), yielding a consumer surplus per day of $8. This also suggests that, in our particular dataset, we do not observe any significant

Table 3. Summary for Convolution WTP Confidence Intervals (CIs) for Individual and Joint Models

		Joint			Individual		
	CI	Min	Mean[a]	Max	Min	Mean[a]	Max
TCM (negative binomial)							
	95	\$4.89	\$8.00	\$9.28	\$4.84	\$7.92	\$11.96
	90	\$5.19	\$8.00	\$9.45	\$5.16	\$7.92	\$11.52
CVM (probit)							
	95	\$95.37	\$110.12	\$160.62	\$96.30	\$114.32	\$126.78
	90	\$97.33	\$110.12	\$156.13	\$98.23	\$114.32	\$123.57

[a] Means are calculated using $1/\beta_{tc}$ for the TCM and $\beta_0/\mathrm{abs}(\beta_{\mathrm{bid}})$, where β_0 is a grand constant term (it includes all nonbid coefficients multiplied by the respective mean value of the variables). Minimum and maximum values come from the convolution method. These represent the minimum and maximum values of the random WTP vectors generated and compared under each estimation type.

connection between the two models through unobservables. Perhaps, imposing a theoretical relation between the parameters in the models could increase the relation between the error structures.

Because all comparisons between joint and individual estimations show us a two-tail *p*-value close to 1 (.97 for the TCM and .98 for the CVM), we can understand that the entirety of one of the distribution tails is covered by the tail of the other distribution; thus, one empirical distribution lies on top of the other. It is important however to recall the huge difference in WTP between the two methods (CVM and TCM). Perhaps this is one reason why our results are not benefiting from the joint estimation. This might be what McConnell, Weninger, and Strand called Transitory Preference Structure, wherein the unobservables between the two equations are not related. It is called this because it is assumed that, under this situation, visitors completely update their information set, leading to a new preference structure.[2] Other possible explanations include problems with the way the CVM question was presented, with the way travel cost was determined, or both, but both of these were done following very standard assumptions.

An alternative explanation for the difference between TCM and CVM WTP could lie in the geographical characteristics of the studied area. Particularly because we are dealing with an on-site sample (no zeros or choke prices are observed), we might be facing a truncated spatial TCM market for the studied sites. We call this issue "Island effect," and it basically says that the implicit spatial market requirement in the TCM could be broken by the geographical limitations that the island dimensions impose, biasing TCM welfare measures downward. Because the maximum amount that local visitors are able to pay might be limited by the size of the island, the observed variation in the implicit price could be truncated in our application. In other words, we do not observe the full range of prices that locals are willing to pay for the services received at these sites; hence, the inverse demand function estimated by the TCM does not reflect the full benefit accrued to visitors on each visit. In fact, any point that should lie above the "spatial choke price" would not be observed. Instead, individuals with a WTP above the choke price would be found somewhere below their true demand points. If this is the case, not only our TCM WTP will be underestimated because of the portion missing above the spatial choke price, but because we are using fully parametric estimations, our results would suffer from

[2] Although unlikely, it is worth mentioning that the nature of the rainforest under study causes significant and sudden changes in precipitation and water flow levels. These sudden changes can considerably alter the nature of the scenario faced by visitors when compared with the information individuals had at hand when they made their visiting decision.

further bias because our methods will take the biased observations under the choke price as good and try to accommodate our regression results to them. Again, this could be a problem, particularly because we do not observe zeros in our data and hence do not have observations on the price axis that would tilt our regressed demand curve up toward the real demand function.

Conclusions and Future Research

In this paper, we provide an empirical modeling procedure that allows for testing whether joint estimation of stated and revealed preference models increase efficiency when compared with individual estimations and consistency between TCM and CVM responses. In our data, the CVM WTP question involved willingness to pay to visit the site under current conditions, a scenario quite conceptually similar to what is estimated with TCM. In this situation, the improvement from joint estimation was quite small. However, joint estimation could result in larger and significant efficiency gains in the situation in which the CVM WTP scenario deviates substantially from the existing situation in terms of quality of the site. Empirically testing this conjecture awaits suitably designed CVM and TCM datasets.

Another avenue of future research would be to integrate both models more, perhaps updating the joint utility theoretical approach that Cameron used to reflect the utility structure of count data models presented by Hellerstein and Mendelsohn. Another alternative is to derive the expected constraints for different utility specifications and again use the simultaneous equation or estimation only to test which utility specification is supported by the data.

For this case, our simultaneous estimation process can be seen as a general unconstrained version of Cameron's earlier work and opens the door to determine which type of joint preferences should be used before the actual constrained estimation. Because of the complexity of estimating a constraint utility theoretic specification, more information on the constraints that are supported by our empirical analysis should save researchers a great amount of effort, while providing a better understanding of the behavior that guides both stated and revealed preferences.

At the methodological level, a contribution of this paper is updating the TCM portion of the joint estimation statistical technique used by Cameron to reflect the count data models now commonly used for recreational demand modeling. The use of count data models represents an improvement over the original simultaneous estimation suggested by Cameron.

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Appendix A. Deriving the Joint Density Function

The derivation of the Joint Negative Binomial and probit distribution comes almost directly from Cameron and Englin. In that article, the authors look at two different random variables, Z_1 and Z_2, and relate them to the probit and probit distributions. For a corrected Negative Binomial and a probit, we just need to follow Cameron and Englin's steps but change the Poisson portion for a corrected Negative Binomial. So we start by defining two random variables Z_1 and Z_2 and relating them to the following moments:

$$E[Z_1] = \lambda + 1 + \alpha; \quad V[Z_1] = \lambda + \alpha + \alpha\lambda + \alpha^2;$$
$$E[Z_2] = 0; \quad V[Z_2] = 1.$$

We can relate Z_1 and Z_2 to the variables of interest in the following way:

$$\text{Trip} = Z_1;$$
$$\text{WTP} = \sigma\left\{\rho\left[(Z_1 - E[Z_1])\Big/\sqrt{V[Z_1]}\right] + \sqrt{(1-\rho^2)}Z_2\right\}$$

It can be shown that the moments of these new random variables are

$$E[Trip] = \lambda + 1 + \alpha; \quad V[Trip] = \lambda + \alpha + \alpha\lambda + \alpha^2; \quad E[WTP] = \mu; \quad V[WTP] = 1.$$

The covariance between the two random variables is determined by

$$E[(Trip - E[Trip])(WTP - E[WTP])] = E\left\{ \begin{array}{l} (Trip - E[Trip]) \times \\ \left[\sigma\left(\begin{array}{l} \rho\{(Trip - E[Trip])/\sqrt{V[\mathrm{Trip}]}\} \\ + \sqrt{(1-\rho^2)}\mathrm{WTP} \end{array}\right)\right] \end{array} \right\}$$

$$E\{(Trip - E[Trip])(WTP - E[WTP])\} = \rho\sigma\left(\lambda + \alpha + \alpha\lambda + \alpha^2\right)^2$$

Therefore the covariance term can be defined as ρ.

Now, the joint density of these two variables, assuming independence between them, is defined by

$$f(Z_1,Z_2) = \left\{\left[\frac{\Gamma(\alpha + Z_1)}{\Gamma(\alpha)(Z_1 - 1)!}\right]\left[\frac{(\alpha)}{(\lambda + \alpha)}\right]^{\alpha}\frac{\lambda^{(Z_1-1)}}{(\lambda + \alpha)^{Z_1}}\right\}\left\{\frac{1}{\sqrt{2\pi}}\exp\left[\frac{(-Z_2)^2}{2}\right]\right\}.$$

By solving Trips and WTP for Z_1 and Z_2, substituting in the joint density, and scaling by the Jacobian

$$J = \left(1 - \rho^2\right)^{-0.5},$$

we obtain the joint density function

$$f(\mathrm{Trips, WTP}) = \left[\frac{1}{\sqrt{2\pi}}\sigma^2\left(1 - \rho^2\right)\right]^{-0.5}\left\{\left[\frac{\Gamma(\alpha + \mathrm{Trips})}{\Gamma(\alpha)(\mathrm{Trips} - 1)!}\right]\left[\frac{(\alpha)}{(\lambda + \alpha)}\right]^{\alpha}\frac{\lambda^{(\mathrm{Trips}-1)}}{(\lambda + \alpha)^{\mathrm{Trips}}}\right\}$$
$$\times \exp\left\{\left[\frac{\begin{array}{l}\mathrm{WTP} - \mu - \sigma\rho \\ (\{\mathrm{Trips} - E[\mathrm{Trips}]\}/\sqrt{V[\mathrm{Trips}]})\end{array}}{\sqrt{\sigma^2(1 - \rho^2)}}\right]^2\right\}.$$

Because it is easier to deal with a joint density that is defined in terms of a conditional and a marginal density function, we try to do this for our joint distribution. We know that the marginal density of trips is defined as

$$g(\mathrm{Trips}) = \left[\frac{\Gamma(\alpha + y_{\mathrm{TCM}})}{\Gamma(\alpha)(y_{\mathrm{TCM}} - 1)!}\right]\left[\frac{(\alpha)}{(\lambda + \alpha)}\right]^{\alpha}\frac{\lambda^{(y_{\mathrm{TCM}}-1)}}{(\lambda + \alpha)^{y_{\mathrm{TCM}}}}.$$

By dividing our joint density *f*(Trips, WTP) by the marginal density of trips, we obtain the conditional density

$$h(\mathrm{WTP}|\mathrm{Trips}) = \left[\frac{1}{\sqrt{2\pi}}\sigma^2\left(1 - \rho^2\right)\right]^{-0.5} \times \exp\left\{\left[\frac{\begin{array}{l}\mathrm{WTP} - \mu - \sigma\rho \\ (\{\mathrm{Trips} - E[\mathrm{Trips}]\}/\sqrt{V[\mathrm{Trips}]})\end{array}}{\sqrt{\sigma^2(1 - \rho^2)}}\right]^2\right\}.$$

Note that this is the normal distribution with the following moments:

$$E[\text{WTP}|\text{Trips}] = \mu + \sigma\rho\{(\text{Trips} - E[\text{Trips}])/\sqrt{V[\text{Trips}]}\}, V[\text{WTP}|\text{Trips}] = \sigma(1 - \rho^2).$$

Now we have everything we need to define our joint density as a product of a marginal and a conditional probability function. Because our CVM response is really a latent variable, we know that

$$y_{\text{cvm}} = 0 \quad \text{if (Bid} < \text{WTP)}, \quad y_{\text{cvm}} = 1 \quad \text{if (Bid} \geq \text{WTP)}.$$

For this setup (and when assuming the variable WTP follows a normal distribution), we use a probit link with a Bernoulli Distribution. With this final assumption, we can present our joint likelihood function,

$$L_i = \left[(\theta_i)^{y_{\text{cvm},i}}(1 - \theta_i)^{1-y_{\text{cvm},i}}\right] \times \left[\frac{\Gamma(\alpha + y_{\text{TCM},i})}{\Gamma(\alpha)(y_{\text{TCM},i} - 1)!}\right]\left[\frac{(\alpha)}{(\lambda_i + \alpha)}\right]^{\alpha} \frac{\lambda_i^{(y_{\text{TCM},i}-1)}}{(\lambda_i + \alpha)^{y_{\text{TCM},i}}},$$

where

$$\theta_i = \Phi\left[(x_i\beta + \sigma\rho Z_i)\Big/\left(1 - \rho^2\right)^{0.5}\right]$$

and

$$Z_i = \left[y_{\text{tcm},i}\, \check{S}\, E(y_{\text{tcm},i})\right]\Big/[Var(y_{\text{tcm},i})]^{0.5}.$$

Appendix B. Empirical Convolution Method

The empirical convolution method was first proposed by Poe, Giraud, and Loomis. It uses all possible differences between randomly selected values of two random variables to determine the probability that these variables are statistically the same. Note that Equation (12) can also be presented by adding the **X** distribution to the distribution of **Y** flipped around zero (thus obtaining the negative value):

$$\mathbf{Z} = \mathbf{X} + (-\mathbf{Y}).$$

Assuming that the corresponding probability functions of **X** and **Y** are $f_x(x)$ and $g_y(y)$, respectively, the distribution of their sum is represented by the integral

$$f \otimes (-g) = h_z(z) = \int_{-\infty}^{\infty} f_x[z - (-y)]g_y(-y)dy.$$

This expression provides the probability that each combination of the original function produces. This can be shown to be related to the sum of the product of each combination from a polynomial multiplication.

The complete combinatorial approach offers a simpler way to use the empirical convolution method. The empirical distribution of the difference can be expressed as

$$\widehat{X}_i - \widehat{Y}_j = \widehat{X}_i + \left(-\widehat{Y}_j\right) \ \forall i = 1, 2, 3, ..., m, \ j = 1, 2, 3, ..., n,$$

wherein each difference is given the same weight.