Using stated preference responses to address endogeneity in the single site travel cost equation

Adan L. Martinez-Cruz[1], Valeria Gracia-Olvera[2], and Yadira Peralta[3]

[1] *Assistant Professor, Department of Economics, Centro de Investigación y Docencia Económicas, Región Centro (CIDE-RC), México*
[1] *Research Affiliate, Centre for Energy Policy and Economics (CEPE), ETH-Zurich, Switzerland*
[2] *Research assistant, Department of Economics, Centro de Investigación y Docencia Económicas, Región Centro (CIDE-RC), México*
[3] *Visiting Professor, Programa de Estudios Longitudinales, Experimentos y Encuestas (PANEL), Centro de Investigación y Docencia Económicas, Región Centro (CIDE-RC), México*

January 2019

Abstract

The travel cost (TC) method models the number of trips to a recreation site as a function of the costs to reach that site. The single site TC equation is particularly vulnerable to endogeneity since travel costs are chosen by the visitor. This paper suggests a control function approach that breaks the correlation between travel costs and the error term by plugging inferred omitted variables into the TC equation. Inference of omitted variables is carried out on an endogenous free, stated preference equation that, arguably, shares omitted variables with the TC equation. By revisiting the TC and contingent valuation (CV) data analyzed by Fix and Loomis (1998), this paper infers the omitted variables from the CV equation via a finite mixture specification —an inference strategy whose justification resembles the use of heteroscedastic errors to construct instruments as suggested by Lewbel (2012). Results show that not controlling for endogeneity in this particular case produces an overestimation of welfare measures. Importantly, this *infer and plug-in* strategy is pursuable in a number of contexts beyond recreation demand applications.

1 Introduction

More than sixty years ago, Hotelling (1947) made the observation that the cost of travelling to a recreation site can serve as a reasonable proxy for the price of a trip to that site. Consequently, his reasoning follows, a demand curve for the recreational services provided by the site can be inferred by modelling the number of (seasonal or annual) trips to the site as a function of the costs to reach it.

The travel cost (TC) method's strength and weakness both lay at the core of Hotelling's observation. On one hand, the possibility of using travel costs as proxy of entry fees for non-market public goods explains why the TC method has become a staple in the economists' toolkit to estimate willingness to pay (WTP) values.

On the other hand, travel costs are not determined in a competitive market but instead chosen by the visitor, and consequently are endogenous to number of trips.[1] Handling TC endogeneity has proved troublesome because collecting an instrument for travel cost is particularly difficult due to its inherent individual-specific nature (Moeltner and Von Haefen, 2011). In addition, modern recreation demand models are nonlinear constructs —e.g. count data densities, or site choice logit probabilities. Consequently, the conventional instrumental variable (IV) approach, developed for the linear regression case, no longer apply —a situation labeled the nonlinear instrumental variable problem by Berry (1994).

IV approaches have recently been proposed to handle endogeneity in a multi-site context (see Moeltner and Von Haefen, 2011, for a review). These approaches rely on a rich variation in site attributes to exploit the trade-offs between travel time and site attributes. However, these methods are not feasible in the single site context because valuing a single site is equivalent to valuing a bundle of attributes at once, and therefore no rich variation in site attributes is available.

To the best of our knowledge, Fix et al. (2000) is the only previous study that has developed an econometric strategy to tackle endogeneity in a single site context. They estimate a three-equation system of seemingly unrelated regressions (SUR) to empirically test the theoretical distinction made by Ward (1984) between endogenous and exogenous travel costs. Accordingly, one equation models number of trips as a function of total travel costs which include both exogenous and endogenous components; a second equation models endogenously determined out of pocket costs as a function of total exogenously determined out of pocket costs; and the third function models endogenously determined on-site time as a function of total exogenously determined out of pocket costs. This SUR strategy unavoidably runs into nuisances when justifying the specific items to be included or not in the endogenous component of the travel costs. These nuisances may partially explain why this SUR strategy has not taken off.

This paper proposes a strategy that controls for endogeneity in single site TC equations by exploiting the information embedded in answers to stated preference (SP) questions. We take availability of SP data for granted since there is a substantial non-market valuation literature that gathers TC and SP data via a single survey with the aim of either testing convergent validity or drawing on their relative strengths to improve WTP estimates (see Jeon and

[1] Early studies discussing TC endogeneity include Allen et al. (1981); Caulkins et al. (1985); McConnell (1975); McConnell and Duff (1976).

Herriges, 2017; Wang and Zhao, 2019; Whitehead et al., 2008).

This paper departs from the intuition that, if respondents are presented to TC and SP questions via a single survey, unobserved variables in the single site TC equation must be similar, if not identical, to the unobserved factors in the SP equation. This intuition is more likely to hold when the SP scenario is designed to obtain use values associated to the recreation site that the respondent is visiting at the time the survey is implemented. An example of such a SP scenario is the dichotomous contingent valuation (CV) question implemented by Fix and Loomis (1998) as part of an on-site TC survey: *If your share of the costs to visit [this recreation site] were X dollars higher, would you still have come on this trip?*.

A key component of SP protocols is the experimental variation in the price attribute. This feature implies that, in contrast to the TC equation, the price attribute in the SP equation is not correlated with the omitted variables. Consequently, omitted variables in the SP equation produce unobserved heterogeneity in preferences but does not imply the presence of endogeneity.

If only we could infer/estimate the omitted variables from the endogenous free equation and plug them into the endogenous one. This *infer and plug-in* strategy would break the correlation between travel costs and the error terms by eliminating the source of such a correlation —i.e. by *cleaning* the error term *out* of the variables that generate correlation with the travel costs. Sticking to the definition that a control function (CF) "is a variable that, when added to a regression, renders a policy variable appropriately exogenous" (Wooldridge, 2015, p. 420), the inferred omitted variables that are added to the TC equation can be characterized as CF variables.

Notice that the presence of omitted variables in the endogenous free equation implies that the error term is heteroscedatic. An error-components representation of such a heteroscedasticity motivates the use of finite mixture models (FMM) (Train, 2009). The error structure of FMM opens the door to the inference of omitted variables because these models test for the existence of a categorical omitted variable impacting the outcome variable either directly (via changes in intercept) or indirectly (via changes in slopes) or both (Martinez-Cruz, 2019). This motivation to infer omitted variables via FMM specifications very much resembles Lewbel (2012)'s justification for the use of heteroscedatic errors as an IV strategy.

To test this infer and plug-in strategy, we revisit the TC and CV data analyzed by Fix and Loomis (1998). To avoid the propagation of standard errors implicit in a two-stage procedure, the estimation is carried out in a single step via a Bayesian Inference Approach. Estimates suggest that not controlling for endogeneity implies an overestimation of welfare measures —a result that should be treated as context-specific.

The rest of this document is organized as follows. Section 2 describes the jointly distributed decisions modelled in this paper and the Bayesian Inference Approach used to implement the infer and plug-in strategy. Section 3 illustrates the application of the proposed strategy by revisiting the data obtained by Fix and Loomis (1998). Section 4 concludes and discusses the potential of this strategy in a number of contexts beyond recreation demand applications —e.g. residential electricity demand, hedonic price applications, etc.

2 Infer and plug-in strategy

This sections, first, describes a single site travel cost (TC) equation as sharing omitted variables with a contingent valuation (CV) equation, and the implications in terms of probabilistic modelling. Then, this section presents the Bayesian Inference Approach implemented to estimate both equations simultaneously which helps in avoiding the propagation of standard errors implicit in a two-stage procedure.

2.1 Jointly distributed decisions

Today's single site applications of the TC method rely on Poisson or Negative Binomial econometric specifications. Here we focus on the Poisson specification because, as it will become clear later on, our econometric approach allows for a discretely distributed intercept which is an alternative to the Gamma distribution assumed by the Negative Binomial.

Theoretically rooted by Hellerstein and Mendelsohn (1993), a Poisson specification deals with the non-negative, integer nature of the number of trips (y_i) chosen by individual i at the beginning of a season/year. The probability density function of a Poisson distribution is defined as

$$P(Y = y_i) = \frac{e^{-\lambda}\lambda^{y_i}}{y_i!} \tag{1}$$

The λ parameter represents the mean and the variance of Y, and is assumed to behave in an exponential manner. That is, $\lambda = E(Y) = exp(\alpha_0 + \alpha_c C + \gamma'\mathbf{X_1})$ —where α_0 is an intercept; α_c is the parameter capturing the response to changes in travel costs; and γ is a $k \times 1$ vector of coefficients associated to the $k \times 1$ vector of control variables $\mathbf{X_1}$.

Hanemann (1984) provides the theoretical link between the dichotomous CV question and the utility maximization framework. Accordingly, the probability that an individual answers yes to a dichotomous CV question is equivalent to the probability that the individual's indirect utility under the CV scenario (U_i^{cv}) is larger than under current conditions (U_i^{cc}), i.e. $P(\Delta U_i^* = U_i^{cv} - U_i^{cc} > 0)$. Since ΔU_i^* is well known by the decision maker but only observable up to certain degree from the researcher's point of view, it is necessary to incorporate an error term, i.e. $\Delta U_i^* = \Delta U_i + \epsilon_i$. Assume that ΔU_i can be expressed in a linear manner, $\Delta U_i = \beta_0 + \beta_b B + \nu'\mathbf{X_2}$ —where β_0 is an intercept; β_b is the parameter capturing the response to changes in the bid presented in the CV scenario; and ν is a $k \times 1$ vector of coefficients associated to the $k \times 1$ vector of control variables $\mathbf{X_2}$. The vectors of control variables in both equations, $\mathbf{X_1}$ and $\mathbf{X_2}$, may include identical variables.

We can express the probability of individual i answering yes to a dichotomous CV question as

$$P(D_i = 1) = P(\Delta U_i^* > 0) = P(\epsilon_i > -(\beta_0 + \beta_b B + \nu' \mathbf{X_2})) \quad (2)$$

Since ϵ_i is assumed normally distributed with mean zero and variance σ^2, dividing the components of expression (2) by σ is equivalent to obtain the standard normal distribution with cumulative density function Φ which generates the probit specification:

$$P(\epsilon_i > -(\beta_0 + \beta_b B + \nu' \mathbf{X_2})) = \Phi((\beta_0 + \beta_b B + \nu' \mathbf{X_2})/\sigma) \quad (3)$$

Up to this point, nothing deters us from treating both probabilities as independent of each other —i.e. $P(Y = y_i, D_i = 1) = P(Y = y_i)P(D_i = 1)$.

Now assume that O is also a relevant control variable when modelling both the mean parameter of the Poisson distribution and the change in utility in the probit model. This variable, however, is not observed by the researcher. This implies that the Poisson distribution of trips as well as the normal distribution of the willingness to pay implicit in the probit model are both correlated with O, and therefore are jointly distributed —i.e. $P(Y = y_i, D_i = 1) \neq P(Y = y_i)P(D_i = 1)$.

Assume O is a variable with G categories (or a continuous one that can be categorized in G categories). Then $P(D_i = 1)$ can be modelled via a finite mixture specification, i.e.

$$P(D_i = 1) = \sum_{g=1}^{G} \pi_g \Phi_g((\beta_{0,g} + \beta_{b,g} B + \nu_{\mathbf{g}}' \mathbf{X_2})/\sigma_g) = \sum_{g=1}^{G} \pi_g \Phi_g(\mu_g/\sigma_g) \quad (4)$$

where π_g is the relative size of the category g, and each category is described by a mean characterized by parameters $\beta_{0,g}, \beta_{b,g}$, and ν_g. This modelling strategy is equivalent to model unobserved heterogeneity in preferences.

For the case of expected trips, $E(Y)$, O is an omitted variable that provokes endogeneity and, consequently, when controlled for, parameter estimates are unbiased. Thus an expression that controls for O looks as follows

$$E(Y) = exp(\alpha_0 + \alpha_c C + \gamma' \mathbf{X_1} + \alpha_o O) \quad (5)$$

Equation (5) assumes O is observed. But if O is not observed, then

$$E(Y) = \sum_{g=1}^{G} \pi_g exp(\alpha_{0,g} + \alpha_c C + \gamma' \mathbf{X_1}) = \sum_{g=1}^{G} \pi_g \lambda_g \quad (6)$$

Consequently, the joint probabilities can be expressed as follows

$$P(Y = y_i, D_i = 1) = \sum_{g=1}^{G} \pi_g \frac{e^{-\lambda_g} \lambda_g^{y_i}}{y_i!} \Phi_g(\mu_g/\sigma_g) \quad (7)$$

2.2 Bayesian Inference Approach

The EM (Expectation-Maximization) algorithm is a common approach to estimate equation (7). An EM's step involves updating the posterior probabilities. However, a posterior probability cannot analytically be derived in our case. A Bayesian Inference Approach is useful in this context because Markov chain Monte Carlo (MCMC) methods are implemented to simulate the posterior distribution.

A Gibbs sampling procedure was implemented to simulate the posterior distribution.[2] As an iterative algorithm, Gibbs sampling requires a set of starting values for all model parameter to begin the process. It is common to discard the first posterior draws because they might not be representative of the target distribution. This period is called burn-in. The subsequent posterior draws are used for inference by creating summary statistics. For this study, three chains were run in parallel and convergence was assessed by using the potential scale reduction factor (PSRF) (Gelman et al., 1992). A mean PSRF of less than 1.2 is a common threshold to grant convergence (Brooks and Gelman, 1998; Sinharay, 2004).

Non-informative prior distributions were considered for all model parameters. The prior distribution for all model parameters concerning the on-site Poisson model was normal with mean zero and variance 1,000. The prior distribution of model parameters concerning the probit model was normal with mean zero and variance 10 because the independent variable (bid) was standardized.

In order to model the mixtures, the marginal probabilities of each mixing proportions were modeled as a Dirichlet(1,...,1) process, which is a typical choice as a noninformative prior. In addition, a categorical prior for the number of classes was also used.

A total of 30,000 total iterations were used for Gibbs sampling, 10,000 of them were for the burn-in period. The model converged successfully according to the mean PSRF. When using Gibbs sampling for a finite mixture model, there is a risk of label switching. To address this issue, we applied the Equivalence Classes Representativeness (ECR) algorithm as implemented in the label.switching R package (Papastamoulis, 2015).

3 Results

This section revisits the data gathered by Fix and Loomis (1998). Their travel cost data refers to mountain bikers visiting Moab, Utah, in mid-March 1996. Fix and Loomis (1998)'s goal was to test whether the TC method and the CV method yield similar WTP estimates. Thus mountain bikers were faced to the dichotomous contingent valuation question *if your share of the costs to visit Moab area, on this trip, were X dollars higher, would you still have come to the Moab area on this trip?*.

[2]Coding was carried out in JAGS, taking advantage of the rjags package in R.

Table 1 presents the variables used in the estimations reported by Fix and Loomis (1998). In this paper, we take these variables as they were calculated by Fix and Loomis (1998) and implement the infer and plug-in strategy.

We first carry out a two step-procedure. Table 2 reports the estimates of the first stage. Resembling the specifications by Fix and Loomis (1998), Bid is the only regressor included. Results of the finite mixture specification on the answers to the CV question are reported in the first two columns. For comparison purposes, the probit specification is reported in the third column. While the coefficients for class 2 are not significant, this is not a feature that deters us from carrying out the second stage. That is, we use the posterior probabilities from the finite mixture specification to infer the dichotomous omitted variable implicit in the presence of classes.

Table 3 reports a conventional on-site Poisson specification in the first column. In the second column, we can see the results from the second stage of the infer and plug-in strategy. Notice that there is an alternative strategy to directly plugging an omitted variable. Instead, we can use the posterior probabilities themselves as control variables. The third column in table 3 reports the results of such a strategy.

Four features in table 3 are worth highlighting. First, the point estimates of the travel cost parameter are larger in absolute value when the infer and plug-in strategy is implemented (columns II and III) in comparison to the estimate from the conventional specification (column I) —i.e. -2.64 and -2.49 versus -2.03. This would imply that the half price elasticity is underestimated when endogeneity is not controlled for.

A second feature in table 3 is the high statistical significance of the inferred omitted variable —i.e. the omitted variable is variable relevant when informing the travel cost equation. The third feature refers to the magnitude and sign of the coefficient associated to the inferred omitted variable under both strategies —0.62 and 0.69.

Finally, the fourth feature in table 3 is the indication that the inclusion of the omitted variable improves the statistical fit of the specifications. This conclusion can be reached through the AIC, BIC and pseudo-R^2 criteria. In particular, the best statistical fit is provided by the specification that includes the dichotomous inferred omitted variable.

Indeed, a two-stage procedure implies a propagation of standard errors that makes statistical inference difficult. Thus we implement the Bayesian Inference Approach described in section 2.2. The mean of the posterior draws and the 95% credible interval are reported in table 4.

Four features are worth noticing in table 4. First, in line with estimates from the two-stage approach, the specification that controls for endogeneity (column II) yields larger estimates (in absolute value) of the travel cost parameter — -2.82 versus -2.06. Second, the variables biking skills and income, that are not significant in the two-stage procedure, become significant due to their smaller standard errors. Third, the inferred omitted variable (class 2) is highly significant —as in the two-stage procedure. Finally, the statistical fit of the simultaneous specification is preferred over the concentional on-site Poisson, based on on the deviance information criterion (DIC) which is a hierarchical modeling generalization of the Akaike information criterion (AIC).

4 Conclusions and discussion

This paper illustrates how the endogeneity inherent to single travel cost equations can be handled by plugging omitted variables that are inferred from an endogenous free, stated preferences equation. The key assumption to implement this infer and plug-in strategy is that both equations share omitted variables —or, alternatively, that they can be described as two seemingly unrelated regressions.

This infer and plug-in strategy can be implemented in a number of research fields where combination of stated and revealed preferences is common practice. For instance, transportation (Helveston et al., 2018), health (Lambooij et al., 2015; Mark and Swait, 2004), and hedonic applications (Phaneuf et al., 2013). Also, we believe that the potential of this strategy goes beyond those fields. For instance, a recurrent topic in energy economics is the estimation of the demand for residential electricity. Following Shin (1985), researchers usually model electricity consumption as a function of the average price instead of the marginal fee (e.g. Alberini and Filippini, 2011; Blázquez et al., 2013). Indeed, this modelling decision is under suspicion of endogeneity. Assume that a sample of household heads is presented to a discrete choice experiment (or other stated preference question) in which they must choose among refrigerators with varying levels of energy efficiency. The stated decisions, arguably, share omitted variables with the electricity consumption and, therefore, the infer and plug-in strategy described here would represent an alternative to control for endogeneity.

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Table 1: Descriptive statistics (N=187)

Variable		Mean	Std. Dev.	Min	Max
Bid	Randomly assigned bid (dollars)	178.21	148.83	5	500
Age	Age of respondent	27	8	15	56
Trips	Number of trips per year	2.90	6.45	1	80
Travel Cost	Travel costs of round trip[a] (thousand dollars)	0.277	0.726	0.003	8.985
Biking skill	Auto reported biking skill[b]	2.75	0.82	1	4
Income	Annual income (thousand dollars)	24.09	26.26	5	150
Price of substitutes	Prices to mountain bike sites with similar weather [c]	0.474	0.396	0	1.322

[a]Including out-of-pocket expenditures and one third opportunity cost of time.
[b]With 1 indicating novice and 4 indicating expert.
[c]Measured in thousand miles from respondent's home to the substitute site.

Table 2: Probit and finite mixture estimates on answer of contingent valuation question[a]

	(I)		(II)
	class 1	class 2	probit
Bid	-0.0329*	-0.0128	-0.0102***
	(0.007)	(0.007)	(0.001)
Intercept	3.380***	5.040	2.310***
	(0.688)	(3.444)	(0.337)
share	0.65	0.35	
AIC	184.91		187.17
BIC	201.06		193.63
N	187		187

[a] *"If your share of the costs to visit the Moab area, on this trip, where x dollars higher would you still have come to the Moab area on this trip?"*
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: On-site Poisson specification on number of trips per year

	I	II	III
Travel Cost	-2.028***	-2.642***	-2.399***
	(0.384)	(0.423)	(0.406)
Biking skills	0.0141	0.00836	-0.00439
	(0.066)	(0.065)	(0.067)
Income	0.000116	0.00102	0.000323
	(0.003)	(0.003)	(0.003)
Substitute sites	0.501***	0.562***	0.527***
	(0.140)	(0.141)	(0.141)
Class 2		0.617***	
		(0.110)	
Prob of class 2			0.691***
			(0.184)
Intercept	0.705**	0.501*	0.463*
	(0.219)	(0.220)	(0.230)
N	187	187	187
Log likelihood	-661.97	-655.01	-653.58
AIC	1333.93	1305.40	1322.01
BIC	1350.09	1324.79	1341.40
Pseudo-R^2	0.045	0.067	0.055

I: without endogeneity control.

II: controlling for endogeneity, dummy strategy.

III: controlling for endogeneity, posterior probability strategy.

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Simultaneous estimation of on-site Poisson and probit specifications via Bayesian Inference Approach

	I	II
On-site Poisson equation		
Travel Cost	-2.065	-2.819
	[-2.828, -1.324]	[-4.092, -1.445]
Biking skills	0.014	-0.686
	[-0.115, 0.147]	[-0.854, -0.524]
Income	0.00001	-0.009
	[-0.005, 0.005]	[-0.018, -0.001]
Substitute sites	0.500	0.653
	[0.223, 0.774]	[0.247, 1.092]
Class 2		4.838
		[4.240, 5.433]
Intercept	0.706	1.469
	[0.257, 1.135]	[0.939, 1.992]
Probit equation		
Class1		
Bid		-1.595
		[-2.149, -1.101]
Intercept		0.554
		[0.157, 0.972]
Share		0.84
Class2		
Bid		-1.689
		[-4.179, -0.338]
Intercept		0.143
		[-1.069, 1.159]
Share		0.16
Mean PSRF	1.002	1.002
DIC	1333.928	838.638

I: without endogeneity control.

II: simultaneous estimation.

95% credible interval in parenthesis