A New Approach to Correct for Hypothetical Bias in Stated Preference Models

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Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California, July 23-26, 2006.

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Abstract

Many times economists are asked to estimate the demand for new consumer goods or services for which no market data exists. Typically market researchers and economists answer this challenge using surveys that ask about intended purchases (Louviere, et al. 2000) or what has become known as stated preference (SP) data. Tying this data to revealed preference (RP), or actual behavior, has been a target in a number of studies. Simplistic calibrations have been investigated in past RP-SP studies, such as Loomis, et al. 2001. This paper offers an alternative solution that allows the magnitude of the calibration correction to vary based on Klein and Sherman's (1997) Orbit procedure. This paper extends the original Orbit procedure of Klein and Sherman by Combining stated and revealed preference data on quantities and prices in the first stage, incorporating a correction for heteroskedasticity, and developing methods to calculate consumer surplus and elasticities.

Problem Statement

Many times economists are asked to estimate the demand for new consumer goods or services for which no market data exists. For example, recent changes in consumer preferences have resulted in firms desiring information on the demand for non-traditionally raised meat products (Fox, et al., 1998), ecolabeled products (Loureiro, McCluskey and Mittelhammer 2003), new wood products (Donovan and Nicholls, 2003) or introduction of new forms of public transit such as light rail (Louviere, 1988). Other times firms or policy makers wish to know how consumers will react to new higher prices that are outside the range of current prices such as when large price or fee increases are planned. For example, the new Federal Lands Recreation Enhancement Act, agencies wish to know how visitors will react to higher but hypothetical entrance fees.

Typically market researchers and economists answer this challenge using surveys that ask about intended purchases (Louviere, et al. 2000) or what has become known as stated preference data.

The first concern that arises in using the quantities that a consumer states she would purchase rather than what she actually has purchased is the issue of validity: Just how accurate are these expressions of intended purchases? There is mixed evidence on this point. Some research (Carson, et al. 1994; Carlsson and Martinson 2001) shows good correspondence between stated preference (SP) and actual behavior (often called revealed preference or RP). However, other studies show significant differences (Loomis, et al., 2001; Azevedo, Herriges and Kling, 2003).

One solution to the concern over hypothetical bias is to combine stated preference (SP) data on the proposed policy with revealed preference (RP) data on the existing condition (Adamowicz, et al. 1994; Layman, Boyce and Criddle, 1996; Whitehead, Haab and Huang, 2000). However, this is not always a panacea, as Azevedo, Herriges and Kling (2003: 534-535) note: "Consistency between RP and SP data is not borne out by (our) data…The problem, of course, is where do we go from here?". While these authors offer some general suggestions, they conclude that "this research agenda has only begun…"

We agree with Azevedo, et al., and offer an alternative approach to the ones suggested in their paper. This alternative is in the spirit of the calibration work of Fox, et al. (1998). Simplistic calibrations have been investigated in past RP-SP studies, such as Loomis, et al. 2001. That study pooled SP and RP recreation demand data on the number of trips and then included an intercept shift dummy for the SP responses. The coefficient on the SP dummy variable was positive and statistically significant (Loomis, et al.). This indicated that stated quantities, were *ceteris paribus*, higher than the actual quantities. While one simple adjustment to improve predictions from SP responses would be to zero out the SP dummy, this assumes the magnitude of hypothetical bias is the same at every price and quantity level. This paper offers an alternative solution that allows the magnitude of the calibration correction to vary with the price and quantity, and allows for under or over reporting.

The Orbit Correction Approach

Klein and Sherman (1997) propose a more sophisticated approach than using dummy variables to correct for, adjust or calibrate SP responses of quantity demanded, which allows the magnitude of the correction to vary with conditionals such as the price level. They call their approach the Orbit because it utilizes an **or**dered pro**bit** model that first estimates the demand coefficients using safety points (e.g., accept zero quantities as true) that partition the data into three groups (those equal to zero, greater than zero but less than second safety point, and finally, those greater than the safety point). Based on the estimated demand coefficients, the correction factor is estimated for selected, **representative** quantities demanded in the second stage. This approach seems to have been overlooked by agricultural and environmental economists, despite its stated purpose of estimating new product demand from survey data.

This paper extends the original Orbit procedure of Klein and Sherman by:

1. Combining stated and revealed preference data on quantities and prices in the first stage.
2. In the second stage, applies the correction to reported intended purchase quantities at hypothetically higher prices.
3. Incorporates correction for heteroskedasticity into the estimated first stage.

4. We develop methods to calculate consumer surplus and elasticities for various uncorrected and corrected quantities to show differences.

The Orbit procedure is a two-step estimation of the following likelihood function that involves partitioning the data into three segments:

(1) $f(z,\lambda,\theta)=\{Q=0)\}\ \log \Phi\ ((-x'B)/\sigma)\ +\{0<Q\leq t\}\log\ [\Phi((\lambda-x'B)/\sigma)-\Phi\ ((-x'B)/\sigma)]+$

$\{Q>t\}\ \log\ [1-\ \Phi\ ((\lambda-x'B)/\sigma)$

The likelihood function is the sum of the three segments that contain data based on ranges of the number of trips (Q) taken, where the first segment includes those observations that have Q=0, or for those visitors who took no trips; t= a second threshold or safety point of known demand; and Φ= standard normal cumulative distribution function. The λ is the corrected value for reported Q's. The first stage of the Orbit demand estimator uses safety points (0 and s) help to "anchor" the demand coefficients, by making sure the estimates go through two known values. To implement the first stage, λ and t are set to s, and B and σ are estimated via MLE. Then, using the estimated B and σ values, t is varied to capture different reported Qs, and the model is re-estimated in the second stage to get predicted values of λ.

Specifically, the first estimation step is begun by choosing $t=s$ (where s is the safety point or is known to be a true response in the data as an anchor point) and putting the data into three categories. The first category in Klein and Sherman's procedure and in ours, treats respondents who indicate they would not buy any of the good (or take any trips) at the new higher prices as true zeros. This becomes first partition in the ordered probit model, essentially where $y=0$. The second partition is between zero and the next safety point (when y takes on values between 0 and s). In Klein and Sherman (1997) they use the median of their data, and we use the mean.

Finally, the third partition in the ordered probit is for reported quantities above this second safety point (where $y > s$). The λ in the second and third terms above is set to s (a scalar value) as well. Then we use MLE to get β and σ.

One advantage of the ordered probit model is that quantities above the second safety point, are treated ordinally, and have less influence on the coefficient estimates than they would in more OLS based estimator. We additionally correct for heteroskedasticity by making the constant σ vary by observation, thereby creating σ_i, which is replaced by a set of variables thought to drive the changing variance. Thus $\sigma_i = f(Zi)$, where Zi is a set of variables that may or may not be in the original model specification. This adjustment yields a typical Breusch-Pagan type correction for heteroskedasticity, which has been used in many more elaborate likelihood functions. (Caudill, Ford and Gropper, 1995).

The second stage involves changing the value of t, and therefore sorting the data into different probability ranges, rerun the model with β and σ fixed from step one and getting a single coefficient estimate of λ. This value is then used to adjust the stated quantities from the survey to what is estimated to be unbiased quantities.

In the next section of the paper we illustrate how the Orbit procedure can be used to calibrate or adjust stated visitor trip responses at hypothetically higher travel costs. Often times these hypothetically higher travel costs are asked in a survey to address a policy issues such as proposed increases in entrance fees (i.e., the Federal Fee Demonstration program).

Specification of the Travel Cost Demand Model

Our application involves trips to National Forests for hiking. The Travel Cost Method (TCM) is commonly used to estimate the recreation demand function. This method is based on the premise that even when there is no entry fee to use a public recreation site, recreationists pay an "implicit price" for the site's attributes or services when they travel to the site. The implicit price includes vehicle-related costs.

The basic form of the travel cost method demand function is:

Trips = function (travel cost, age, trail characteristics: elevation, dirt access road, presence of lodgepole pine)

Overall Sample Design

Visitors to three National Forests were selected over the course of the summer of 1998, including the Arapaho-Roosevelt, Gunnison-Uncompaghre and Pike-San Isabel National Forests. We sampled 35 days during the main summer recreation season at a total of 10 sites over the three National Forests. This schedule generally allowed one sampling rotation of two days (one weekday and one weekend day) at nearly all recreation sites during July and August.

Survey Protocol

The interviewers stopped individuals as they returned to their cars at the parking area. The interviewers introduced themselves, gave their university affiliation, and gave a statement of purpose. Then the interviewer gave a survey packet to all individuals in the group 16 years of age and older. The interviewer indicated that the survey could be completed at home and mailed by in a postage paid return envelope that was enclosed in the packet.

Survey Structure

Visitors were asked their travel distance to the site and their travel costs. Then, individuals were asked about their annual number of trips to the site, which was treated as the RP data. In fact, because the surveys were administered in June and July of 1998, but respondents were asked about their intended trips during the remainder of the summer, this data still includes values that might be considered SP responses. In order to assess how sensitive trips were to an increase in costs, we asked how visits would change if trip costs increased, which is the explicit SP part of the data. In particular, a typical contingent behavior or intended visitation question on trips was asked using increases in trip costs of $3, 7, 9, 12, 15, 19, 25, 30, 35, 40 and 70 to elicit how trips to their current site would change if travel costs increased. The surveys were pretested at two of the National Forests. Individuals were asked to fill out the survey and provide any comments or feedback.

Survey Returns

There were only 14 refusals out of 541 contacts made. A total of 527 surveys were handed out. Of these, 354 were returned after the reminder postcard and second mailing to non-respondents, for an overall response rate of 67 percent.

Empirical Results of the Case Study

In setting up the first stage estimation, if a respondent indicated they would no longer visit or would take zero trips at the higher prices, we treated this zero as the first known safety point. Similar to Klein and Sherman, we used the mean of trips as the second safety point.

Results of the first stage estimation of Orbit Model along with the coefficients on heteroskedastic function correction are shown in Table 1. The signs on the variables are as expected with gasoline cost (our travel cost variable) being negative and significant. Site elevation is positive, since for summer recreation, higher elevations are cooler. Having to drive off a paved road to get to the trailhead is negative as it is an undesired feature due to the rough roads and dust. With regard to heteroskedasticity, the first variable chosen, 1/Age, was highly significant, and while Gas Cost was not, it was an important factor in providing a significant coefficient on the Gas Cost variable in the main model.

Table 1 First Stage Orbit Estimates

Variable	Coefficient	T-stat	P-value
B1 (Constant)	1.7191	1.382	0.166
B2 (Gas Cost_{ij})	-0.0071	-2.393	0.016
B3 (Age_i)	-0.0396	-2.489	0.012
B4 (SiteElevation_j)	0.2472	1.406	0.159
B5 (Dirt Road_j)	-1.2384	-2.454	0.014
B6 (LodgePole_j)	-0.4810	-0.899	0.368
Heteroskedastic Function			
Z1 (Constant)	0.2256	0.339	0.7344
Z2 (1/Age)	81.3490	3.126	0.0018
Z3 (Gas Cost)	-0.0078	-1.185	0.236

Second Stage Estimation of the Calibrated Stated Preference Quantities (λ)

In the second stage the estimated coefficients from the first stage are fixed, and λ estimated at each increased price level for each stated quantity of trips of interest. In our analysis, the estimated λ's are all statistically significant at the 1% level. Table 2 presents these corrected estimates of the number of trips along with the reported number of trips and the difference in trips.

Table 2. Reported Trips (SP) and Corrected Number of Trips from the 2nd stage Orbit Model

Stated Trips	Corrected Trips	Difference
3	3.15	0.15
4	3.59	-0.41
6	5.44	-0.56
8	5.56	-2.44
10	6.13	-3.87
12	6.33	-5.67
14	6.95	-7.05

The Orbit correction procedure results in substantial correction to stated trips that are three or more times larger than the mean. Note that in contrast with simply using a SP dummy variable, which would imply the same magnitude of correction at all, levels of stated trips, the size of the correction gets larger as the number of stated trips grows larger.

Discussion

We see that the Orbit approach allows for tailored calibration of stated quantities from survey responses based on coefficients that can be derived from similar revealed preference data. In our example, the magnitude of the correction in intended trips at higher prices varied with the number of trips a visitor took. For small numbers, the adjustment was small, suggesting that when few trips were involved, the stated and actual trips were quite similar. However, as the number of trips grew, the differences grew larger, although not monotonically.

The usefulness of our approach for policy purposes will be in part to create measures of elasticities and consumer surplus. It must be stressed that the calibrated values reported in Table 2 are not price-quantity pairs, but are a recalibration of stated preferences to be consistent with restrictions with revealed preference data. Therefore, other steps must be taken to create elasticities and consumer surplus. As the underlying model is linear, the coefficient on Gas Cost of -.0071 contains the key information for the calculation of these measures. (The model could be estimated in a semi-log form by converting Antrips, the dependent variable, to log values and basing the ranges on them.) This slope leads to an very small elasticity of -.024, suggesting a quite inelastic response to changes in Gas Cost. However, the values of consumer surplus can be calculated easily given the slope, the known safety point on the line and the mean price. With those figures, we get \$64 of consumer surplus between Gas Costs of \$5 and \$100 dollars. This is large relative to the values in the literature, which appear to be closer to \$30-\$40 (Loomis, et al., 2001), and that is mostly due to the low elasticity.

It might be that these values reflect something inherent to the model, although we feel this is not the case. The data used is actual data by and large, with some stated preference results included. The pseudo R^2 is also quite low, at .05. The corrections probably have adjusted this SP response but it is also possible that the safety point is too low, so there is an "over correction" in the estimation. Therefore, the model was re estimated for points up to six trips without any change in the slope at all, suggesting that the safety point is not the issue. Above that, the significance of key coefficients fell apart. We also tried the model on a completely hypothetical data set from the same survey, and found much higher elasticities, and presumably a moderated consumer surplus. We will consider using these results for the presentation in Long Beach.

Future extensions

This approach should be useful for adjusting intended quantities arising from hypothetical changes in demand shifters such as quality of the product (e.g., meat tenderness, health attributes, water quality at the recreation site, etc.). Estimating these demand shifts often requires stated preference responses, but the Orbit procedure offers an avenue for calibrating the increase in quantity with the demand shifters to be more consistent with revealed preference data on existing quality. It may be that the correction to SP responses could be moderated by having more than one non-zero safety point, and, consequently, a greater number of partitions in the likelihood function. There is nothing in the ordered probit model that would prohibit this, and it would add a type of spline function that might allows at least some of the higher values to be correct rather than be seen as overstatements.

Conclusion

The orbit model appears to be a promising approach for calibrating stated preference responses. The orbit model uses known safety points such as zero stated quantities as one anchor and portions of the revealed preference data thought to be reasonable (e.g., mean or median quantities) as another anchor. Further the ordered probit estimator that treats stated quantities, especially those above the safety points in an ordinal fashion implicitly giving these points less influence than would a normal parametric approach like OLS. Once the coefficients in the ordered probit model are estimated, they are used to forecast corrected quantities. Our results show that at low quantities there is minimal calibration or correction of the stated quantities. However, as the stated quantity grows, the correction factor increases, but not monotonically.

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