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# An Improved Method for Calibrating Purchase Intentions in Stated Preference Demand Models

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The Orbit demand model allows the magnitude of the calibration to stated purchase intentions to vary based on the magnitude of the stated quantities. Using an empirical example of stated trips, we find that the extent of calibration varies substantially with less correction needed at small stated trips (–25%) but larger corrections at higher quantities of stated visits (–48%). We extend the Orbit model to calculate consumer surplus per stated trip of $26. Combining the calibrations in stated trips and value per trip, the Orbit model provides estimates of annual benefits from 60% to 111% less than the count data model.

*Key Words:* hypothetical bias, Orbit, ordered probit model, travel cost model, recreation, stated preference

**JEL Classifications:** D12, H44, Q26, Q51

Agricultural and applied economists are frequently asked to estimate the demand for new consumer goods or services for which no market data exist. For example, in response to changing consumer preferences, firms desire new information on the demand for nontraditionally raised meat (Fox et al., 1998), ecolabeled products (Loureiro, McCluskey, and Mittelhammer, 2003), new wood products (Donovan and Nicholls, 2003), and new forms of public transit such as light rail (Louviere, 1988). Other times, firms or policymakers wish to know how consumers will react to new, higher prices that are outside the current range such as when large price, tax, or fee increases are planned. For example, industry and governments may want to know how the magnitude of cigarette sales and related tax revenues would change with enactment of large increases in the federal and state excise taxes on cigarettes.

Typically, agricultural economists answer this challenge by using surveys that ask about the various margins of consumer decisions. These surveys include: 1) discrete purchase intentions regarding whether to buy a new product or not (Louviere, Hensher, and Swait, 2000); 2) intended purchase quantities in the face of price changes (Englin and Cameron, 1996) or quality variation (Ward, 1987); or 3) willingness to pay for various price and quality attributes (Carson et al., 1996). This type of data has become known as "stated preference" data to contrast it with traditional economic data based on actual market purchases, i.e., "revealed preference" data.

The first concern that arises in using the stated preference data is the issue of validity: Just how accurate are these expressions of intended purchases? Although hypothetical

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bias is not as rampant as was originally supposed, there is mixed evidence on this point. Some research (Carlsson and Martinsson, 2001; Grivalva et al., 2002; Whitehead, 2005) shows good correspondence between stated preference (SP) and actual behavior. Grivalva et al. analysis is similar to our analysis because it deals with intended behavior of visitors. She finds that actual visitation behavior after closure of one of the rocking climbing site matches intended behavior elicited before the closure. One older analysis shows that not only is there no statistical difference between revealed and stated preference, but that stated preference estimates of willingness-to-pay (WTP) are slightly less than revealed preference (RP) estimates (Carson et al., 1996). However, other individual studies show significant differences (Azevedo, Herriges, and Kling, 2003; Bishop, Heberlein, and Kealy, 1983; Loomis, Gonzalez-Caban, and Englin, 2001; Whitehead et al., 2008) and so do meta-analyses on hypothetical bias by Murphy et al. (2005). However, as Murphy et al. note: "Despite an abundance of studies, there is no consensus about the underlying causes of hypothetical bias. . ."

One solution to the concern over hypothetical bias is to combine SP data on the proposed policy with RP data on the existing condition (Adamowicz, Louviere, and Williams, 1994; Layman, Boyce, and Criddle, 1996; Whitehead, Haab and Huang, 2000). However, this is not always a panacea, as Azevedo, Herriges, and Kling (2003, pp. 534–35) 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?" Although these authors offer some general suggestions, they conclude that "this research agenda has only begun. . ."

We agree with Azevedo, Herriges, and Kling but offer an alternative approach to the suggestions given in their article, one of which is in the spirit of the calibration work of Fox et al. (1998). In particular, we propose a calibration method that allows the extent of the adjustment to vary with the magnitude of stated quantities. This method has advantages over simplistic calibrations that have been used in past RP–SP recreation demand studies such as in Loomis, Gonzalez-Caban, and Englin (2001) and Whitehead et al. (2008). These prior studies pooled SP and RP recreation demand data on the number of trips taken by individuals and then included an intercept shift dummy for the SP responses. The coefficient on the SP dummy variable was positive and statistically significant, which indicated that stated quantities were, *ceteris paribus*, higher than actual quantities. One simple adjustment used by Whitehead et al. (2008) to improve predictions from SP responses was to zero out the SP dummy. However, this assumes the magnitude of hypothetical bias is the same at every price and quantity level. Additionally, the coefficients in the Loomis, Gonzalez-Caban, and Englin study are weighted averages of the SP and RP data and therefore are affected by the proportions of RP versus SP data used in the analysis and the presence of influential outliers (Belsey, Kuh, and Welsch, 1980). The typical approaches to estimation of these demand functions also implicitly weight outliers highly, because negative binomial count data and Poisson models contain factorial terms that raise the relative influence of values far from the sample mean.

When hypothetical bias exists, it usually results in overstating the expected purchases or trips (Loomis, Gonzalez-Caban, and Englin, 2001; Whitehead et al., 2008) and thus creates outliers that can have a significant effect on estimation results when the usual estimators are used. A recent meta-analysis of hypothetical bias by Murphy et al. (2005) found the mean ratio of hypothetical to actual WTP was 2.6. Although some studies cited find no hypothetical bias, a review of the studies used in Murphy et al.'s meta-analysis suggests some degree of overstatement is present in many of the studies. However, Murphy et al. note that no comprehensive theory of hypothetical bias has been developed. One of the more plausible explanations of hypothetical bias is that of preference uncertainty (Akter, Bennet, and Akhter, 2008; Champ et al., 1997). This explanation suggests that respondents state their best, but uncertain, intentions in the hypothetical scenario. However, in the real scenario, they act more conservatively because real money is involved and the opportunity costs of spending this money on the good looms larger. Our view is that individuals report their planned number of trips and then their or family members health issues, adverse weather, or other uncontrollable events result in fewer trips actually being taken.

This article offers an improved solution that allows the magnitude of the calibration correction to vary directly with the magnitude of the stated quantities so that it differentially corrects for overreporting. The Orbit procedure of Klein and Sherman (1997) contains elements of two popular techniques, the two-limit Tobit model and the ordered probit model. As such, it represents a unique (but somewhat complicated) merger of estimation approaches used with ordinal and cardinal data. Our main task in this article is to present the Orbit procedure, show its links to these other procedures, and discuss its advantages. We argue that it systematically corrects for overreporting resulting from hypothetical bias, and it is an estimator that is not sensitive to outliers. In addition, we give an empirical illustration of the model using travel cost data from three national forests in Colorado and compare the Orbit results with a generalized count data model that is frequently used (Hellerstein, 1991). Finally, we extend the original work of Klein and Sherman by developing the consumer surplus estimates from the Orbit model and then compare these results with those estimated from a negative binomial count data model.

## Modeling Approaches

Limited dependent and qualitative response models are often presented together because they contain a number of similar characteristics (Madalla, 1983). First, although there is considerable diversity in the types of data used, a central similarity is that these models are based on qualitative dependent variables with discrete data (in the case of dichotomous choice models) or the range of cardinal data used is limited as in the case of censored or truncated models. Moreover, each range, or discrete response, is attached to a specific probability of occurrence. Thus, a second commonality is that these models are estimated from a likelihood function based on the joint probabilities of occurrence of each category or range of data.

A third similarity is that the models are often developed with respect to a latent variable relationship so that observed data are thought to be a proxy for the true variable. The Orbit procedure proposed by Klein and Sherman is a unique merger of a number of these models and data types. To set up the discussion of the Orbit estimator, we first present the likelihood functions of the two related estimators, the two-limit Tobit model and the Ordered Probit model. We then present the Orbit model itself and compare it with these two previous models.

### *Related Models and Data Characteristics*

The data used in qualitative response models are usually based on dichotomous or polychotomous variables with the former leading to well-known logit and probit models and the latter further separated into models for unordered and ordered variables such as multinomial versus ordered probit models. Multinomial models are based on discrete data that is unordered such as employment categories (where 1 = blue collar, 2 = professional, etc.). However, our interest is with data that are ordered and ordinal (and cardinal from selected vantage points). Respondents to a survey might have three levels of education: 1 = less than high school; 2 = high school; and 3 = college education. The data are ordered in terms of increasing education, so 1 is logically less than 3, but the distance between the first value and third value has no intrinsic interpretation (versus, say, years of education), so the data are ordinal. Many surveys also provide results from questions based on a Likert scale, which requires the use of some kind of ordered response model. Fully cardinal data, of course, would be seen in a series such as the number of trips taken by a hiker to some destination (the case in our example), in which the data are ordered and distances between values are meaningful. These data also can be discrete or continuous.

Given these data types, two approaches are often developed, and their likelihood functions are constructed by attaching probabilities to each category or range implied in the data. The dependent variable in an ordered probit model might consist of $m$ responses that are ordered but based on ordinal data, in which each has a unique probability of occurring so that $P_1, P_2, \ldots, P_m$ would represent the probabilities of the $m$ categories. Suppose that $y_i = B'x_i + u_i$, where $y_i$ is an ordered dependent variable and $u_i$ is a random variable with zero mean and variance σ. A particular individual will fall into category 1 if $u_i < B'x_i$, in category 2 if $B'x_i < u_i < B'x_i + c$, and in category 3 if $u_i > B'x_i + c$. In essence, the fitted line $y = B'x$ defines the break between categories 1 and 2, and the addition of the constant $c$ separates the latter two categories.

$$\begin{aligned} Log\ L(\beta,\sigma,\alpha \mid y,x) &= \{y=1\} \log \Phi\left(\frac{\alpha_1 - x'\beta}{\sigma}\right) \\ &+ \{y=2\} \log\left[\Phi\left(\frac{\alpha_2 - x'\beta}{\sigma}\right) - \Phi\left(\frac{\alpha_1 - x'\beta}{\sigma}\right)\right] \\ &+ \{y=3\} \log\left[1 - \Phi\left(\frac{\alpha_2 - x'\beta}{\sigma}\right)\right] \end{aligned} \tag{1}$$

For this structure, with three response categories, the probabilities are defined as $P_1 = F(B'x)$, $P_2 = F(B'x + c)\text{-}F(B'x)$, and $P_3 = 1\text{-}F(B'x + c)$, which sum to 1 and thus cover the full event space. The F(.) is the cumulative probability function, whereas the resulting log of the likelihood function (LLF) is shown in Equation (1). There are three partitions in that equation, one for each response, where Φ(.) is the appropriate CDF. We present the LLF for this model in Equation (1) with just three values to facilitate the comparison with the Orbit model, but an extension to more categories is straightforward and is referred to in the later discussion of possible extensions of the model.[1]

To estimate an ordered probit model, it is conventional to have $\sigma = 1$ and estimate values for β and $\alpha_i$. The $\alpha_i$ are individual intercepts for the various categories and are not usually examined. Indeed, if there are three categories, then $\alpha_1$ can be set to zero so that just one value needs to be estimated, an estimate of the value for $c$ in the previous probability statement.

If the data for the dependent variable are discrete but cardinal, like in the case of the number of trips taken or the number of hypothetical purchases of a new product, then count data models such as the Poisson or negative binomial are usually used. The latter is more prevalent because the restriction that the variance equals the mean is not required (Creel and Loomis, 1990). The LLF in these models has a factorial included, and thus the problem of an accelerating influence of outliers from biased survey responses is still a potential problem.

If the data are cardinal and continuous but censored, a Tobit model is often used. In this case, the model is developed based on the relationship, $y_i^* = B'x_i + u_i$, where $y_i^*$ is a latent variable that is only observed within certain ranges. Thus, upper and lower limits, $L_1$ and $L_2$, exist, as

$Y_i = L_1$ if $y_i^* \le L_1$,
$Y_i = y_i^*$ if
$L_1 < y_i^* < L_2$,
and $Y_i = L_2$ if $y_i^* => L_2$.

The probability space is constructed as follows: $P(y_i = L_1) = P(y_i^* \le L_1) = F([L_1 - B'x]/\sigma)$ for observations lying below the lower limit. Then, $P(L_1 < y_i^* < L_2) = 1/\sigma^* f([y_i - B'x_i]/\sigma)$, where f(.) is the normal density function and F(.) is the normal CDF as before. Finally, the probability of $y_i^*$ exceeding the upper limit is given as $P(y_i = \mathrm{L}_2) = P(y_i^* => L_2) = 1 - F([L_2 - B'x]/\sigma)$. The resulting LLF is:

$$\begin{aligned} Log\ L(\beta,\sigma \mid y, x, L_1, L_2) &= \{y = L_1\} \\ &\times \log \Phi\left(\frac{L_1 - x'\beta}{\sigma}\right) + \{y = y^*\} \\ &\times \log\left[\frac{1}{\sigma}\Phi\left(\frac{y - x'\beta}{\sigma}\right)\right] \\ &+ \{y = L_2\} \log\left[1 - \Phi\left(\frac{L_2 - x'\beta}{\sigma}\right)\right] \end{aligned} \tag{2}$$

These first and third partitions are similar to the ordered probit LLF, but the middle term is

[1] An interesting parallel approach to our Orbit correction analysis suggested by a reviewer would be to use a cheap talk script before asking the stated number of trips at the new higher price. This would draw on the approach pioneered by Cummings and Taylor (1999) in CVM to combat hypothetical bias and potentially provide an ex ante means of calibration of the stated trips. An avenue for future research would be to compare how well the cheap talk design does at reducing hypothetical bias relative to the Orbit model ex post calibration.

based on a continuous variable drawn from a normal distribution. A second difference is that the values for the limits are not usually estimated in the Tobit model, whereas in the ordered probit, the breaks between partitions are determined endogenously in the estimation. The lower limit is usually set to zero, and the limits for $L_2$ are often evident from the data construction such as when a respondent is asked to report whether their income is $100,000 or above.

The estimation of this model by MLE is now standard in most software packages along with functions that permit $\sigma$ to vary by observation to account for heteroscedasticity.

It should be clear from this discussion that the two models reviewed here are similar in several important respects but are based on different data types. In the next section, the Orbit model is introduced and compared with the other approaches reported here.

## The Orbit Approach

Klein and Sherman (1997) proposed an improved estimator to correct, or adjust, SP responses derived from questions about quantity demanded. Importantly, that new estimator allows the magnitude of the correction to vary with conditionals such as the price level. They call their approach the "Orbit" because it uses elements from both ordered probit and Tobit models and because its main purpose is to keep estimated quantities based on SP responses from going off into space (Orbit!) by correcting for hypothetical bias.

The Orbit approach first estimates coefficients for slopes and variances conditional on safety points like the $L_1$ and $L_2$ limits in Equation (2). These safety points, or "trusted" quantities, partition the data into three groups (those equal to zero, greater than zero but less than a second safety point, and finally, those greater than the safety point). Based on the estimated demand coefficients, a correction is made for selected, representative quantities demanded in the second stage. This second step is essentially a forecasting exercise. The Orbit model seems to have been overlooked by agricultural economists despite its main purpose of estimating new product demand from survey data.

Our article extends the original Orbit procedure of Klein and Sherman by:

1. In the second stage, applying the correction to reported intended purchase quantities at hypothetically higher prices;
2. Incorporating a correction for heteroscedasticity into the estimated first stage;
3. Adapting a method that allows calculation of WTP for Orbit model estimates of corrected quantities; and
4. Conducting a simple internal validity test by comparing the Orbit's estimate of trips at the original travel cost to the actual trips taken at this original travel cost.

The Orbit procedure is a two-step estimation of the following likelihood function, which is constructed in a manner similar to the earlier ordered probit and Tobit models:

$$\begin{aligned} f_t(z,\lambda,\theta) = {} & \{Q=0\}\ \log\ \Phi\left([-x'B]/\sigma\right) \\ & + \{0 < Q \le t\}\log\ [\Phi([\lambda - x'B]/\sigma)] \\ & - \Phi\left([-x'B]/\sigma)\right]\{Q > t\} \\ & \times \log\ [1 - \Phi([\lambda - x'B]/\sigma] \end{aligned} \tag{3}$$

The likelihood function sums three segments together that contain portions of the total data based on ranges of quantities a consumer states he or she would purchase ($Q$). The first segment includes observations where $Q = 0$ or when respondents state they would not buy the good in question at all; the second partition includes observations where $Q > 0$ but less than $t$, where $t$ is a second threshold, or safety point, of known demand. $\Phi$ is a standard normal cumulative distribution function, the $x$*'s* are independent variables, the $B$*'s* are slope parameters to be estimated, and $\sigma$ is the variance. The third partition contains all observations from respondents who indicated they would buy quantities greater than $t$. In the first stage of the estimation, $t$ is equated with $s$, which is the same as the second safety point, but $t$ takes on a different role in the second-stage estimation. Inspection of this LLF suggests that the Orbit elements are taken from both of the previous models. The ranges of the three partitions are similar to the construction of a Tobit model, because the middle partition captures a range of data that is cardinal (albeit in the examples, discrete) rather than being a statement of the probabilities of a series of ordered but ordinal observations. Additionally, the safety points are fixed rather than being estimated, like in the Tobit model. On the other hand, the middle partition is related to a fixed parameter ($\lambda$) rather than a range of possibly continuous data, which is more suggestive of the ordered probit LLF.

The first stage of the Orbit demand estimator uses the safety points to help "anchor" the estimation of the demand coefficients by making sure that the estimates of $B$ and $\sigma$ are consistent with the two known values (0 and the second safety point, $s$). To implement the first stage, $\lambda$ and $t$ are set to the predetermined safety point, $s$, and the $B$ and $\sigma$ are estimated by MLE using the likelihood function in Equation (3). Like with all models reviewed here, the data are effectively sorted into three categories. The first category in the Orbit procedure 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 first partition, where $Q = 0$, is treated as the first safety point. Zero is a logical safety point because the typical concern with SP data are one of overstatement (Murphy et al., 2005). The second partition uses observations between zero and the next safety point or when $Q$ takes on values between 0 and $t$. Klein and Sherman (1997) use the median of their data as the second safety point, whereas we use the mean for the value of $s$. This choice of the second safety point can be subject to a sensitivity analysis, and we report such an analysis later in the article to show the robustness of our results over a reasonable range of safety points. Finally, the third partition in the Orbit is for reported quantities above this second safety point (where $Q > t$).

The second stage of the Orbit analysis involves changing the value of $t$ to differ from $s$ so that the data are sorted into two newly defined upper partitions for the second-stage analysis. For example, by raising $t$ above $s$, e.g., $t^* = s + 1$, the data going into each partition change in the upper two segments of the likelihood function. Thus, more observations are now in the second, as opposed to the third partition, because the new $t^*$ dictates that purchases need to be higher by one to be in the third partition. The objective of the second stage is to estimate $\lambda$, conditional on the new $t^*$, with the data regrouped and with $\beta$ and $\sigma$ fixed from step one. This estimated value of $\lambda$ is then used as the unbiased and adjusted quantity of purchases or trips. The process is repeated for each reported quantity to be calibrated. (If $t^* = s$, the estimated value of $\lambda$ will be the same as the fixed value from the first stage.)

The second stage appears to be more in common with the Tobit model and can best be seen as a forecasting exercise. Because the new $\lambda$ creates a value for the number of trips, it therefore is equivalent to forecasting the dependent variable. Although the numbers of trips are cardinal but discrete, as $t$ becomes large, the number of possible values that could be forecasted grows, and the possible values, taken in aggregate across the simulations, begins to reflect the proportion of the sample in the middle partition shown in Equation (2). As $t$ is increased, the number of observations in each partition changes, and hence even with the same likelihood function, the estimate of $\lambda$ varies with each value of $t$. Klein and Sherman make mention to the Tobit model in their presentation of the Orbit approach. The two stages together show a clear merger of the two types of models into a unique approach.

One advantage of the Tobit and ordered probit models in the face of potential hypothetical bias is that previous stated quantities above the second safety point are treated as ordinal and have less influence on the coefficient estimates in the first stage than they would in an Ordinary Least Squares (OLS)-based estimator. In the count data estimator, in which the stated quantities enter as a factorial, higher stated quantities have a strong nonlinear effect on the estimator. Thus, the third partition of the Orbit model helps to minimize the influence that these optimistically stated quantities (e.g., "this is the number of trips I would like or ex ante I plan to take at these prices") have on the demand estimates. It should be noted, however, in the second-stage forecast of the corrected trips that the third or upper partition is weighted less and less as one forecasts higher and higher stated trips. This occurs because when one wants to forecast say the corrected number of trips when the respondent stated five trips, the five trips is now used as the cutoff between the second and third partition rather than the original lower safety point between the second and third partitions. The data set then gets resorted at this new higher cutoff between the second and third partitions. As a result, more of the data now lie in the second partition, rather than the third, and as such, data in the third (upper) has less influence on the forecasted stated trips.

We additionally correct for heteroscedasticity by replacing Klein and Sherman's constant $\sigma$ with $\sigma_{i,}$ which can potentially vary by observation. Of course, insufficient degrees of freedom exist to estimate a unique $\sigma_{i,}$ for each observation, so $\sigma_{i,}$ is replaced by a function of variables thought to cause the changing variance. Thus, $\sigma_i = \acute{\alpha} Z_i$, where $Z_i$ is a set of variables that may or may not be in the demand specification itself. The $\alpha$ is a vector of coefficients that are estimated along with the other parameters in the Orbit model so that the number of extra estimates is reduced to just the number of variables in $Z_i$ rather than one for each observation. The $Z_i$ usually include a constant term so that a test for the presence of heteroscedasticity can be done by a likelihood ratio test asking whether all slope variables equal zero. This approach is essentially a Breusch-Pagan correction for heteroscedasticity, which has been used in other relatively elaborate likelihood functions such as accounting for heteroscedasticity in stochastic frontier likelihood functions (Caudill, Ford, and Gropper, 1995).

*Asymptotic Properties of the Orbit Estimator*

Klein and Sherman demonstrate the asymptotic properties of the Orbit model in the sixth section of their article. After noting several standard distributional assumptions, they present the asymptotic distributions for the parameters of the Orbit model given in Equation (3).

The estimates of the key parameters in the first stage are asymptotically normal with the following distribution:

$$(4) \qquad \sqrt{n}\left[\hat{\theta}(s) - \theta_0\right] \Rightarrow \mathrm{N}\left(0, -[\mathrm{H}_s(\theta_0)]^{-1}\right)$$

where $n$ is the number of observations, $\hat{\theta}(s)$ is the vector of parameter estimates made in the first stage, and $\theta_o$ is the true but unknown vector of parameters (the $\beta$ and $\sigma$ values in Equation [3]). The asymptotic covariance matrix, $[H_s(\theta_o)]^{-1}$ is a $(k + 1) \times (k + 1)$ inverse of the Hessian matrix of second derivatives with respect to each parameter in the Orbit LLF. Therefore, the estimators of the parameters in the LLF in Equation (3) provide unbiased estimates of the true, underlying parameters.

Of most interest are estimators for the values of $\lambda$, which are only estimated in the second stage of the Orbit procedure. The Klein and Sherman estimator is called $\hat{\Lambda}(t;s)$, which is a vector of $\lambda$ values, where each estimate of $\lambda$ is forecasted by changing the value of $t$ so that observations are sorted into different partitions (or probability ranges) of the model, as we mentioned. Re-estimation of the model yields an individual $\lambda$ associated with each $t$. The $s$ refers to the fact that each $\lambda$ is estimated conditional on the estimation of the $\beta$ and $\sigma$ values from the first stage.

Again, assuming standard distributional assumptions, the estimates are asymptotically normal with the following distribution:

$$(5) \qquad \sqrt{n}\left[\hat{\Lambda}(t;s) - \Lambda(t)\right] \Rightarrow \mathrm{N}(0, V_t(\Lambda(t), \theta_0; s))$$

where $\Lambda(t)$ is the true but unknown vector of $\lambda$ with $t$ varied across relevant values to sort the data into the three probability ranges shown in the LLF. The other parts of the equation have been defined earlier. The covariance matrix, $V_t(\Lambda(t), \theta_0; s)$, is a function of both true but unknown parameters $\theta_0$ and $\lambda$ and contains a series of matrices that include various first and second derivatives of the Orbit LLF in Equation (3). Moreover, the covariance matrix includes an adjustment factor to reflect the fact that the estimates of each $\lambda$ are based on estimates of $\theta_0$, not the true values (see Klein and Sherman, 1997, p. 72).

In the next section, we illustrate how the Orbit procedure can be used to calibrate or adjust stated visitor trip responses at hypothetically higher travel costs. Oftentimes, respondents are asked about these hypothetically higher travel costs in a survey to address a policy issue such as proposed increases in entrance fees (i.e., the Federal Fee Demonstration program). This application shares many similarities to a wide range of issues faced by agricultural economists, including asking consumers purchase intentions regarding new variations in agricultural products (e.g., organic products), whether consumers would pay more for environmentally friendly products, or asking farmers the number of times they would attend cooperative extension presentations if a fee was charged. We compare estimated trip quantities and consumer surplus from the Orbit model with a standard econometric model of demand, the generalized count data model (i.e., the negative binomial model).

*Empirical Specification of the Travel Cost Demand Model*

Our application involves the valuation of hiking in national forests using the hiker's stated trip quantities collected in response to hypothetically higher travel costs. We use the Travel Cost Model (TCM) as the modeling framework. TCM have are used extensively to value outdoor recreation not only nationwide, but also in the south (Arcarya, Hatch, and Clonts, 2003; Bowker, English, and Donovan, 1996; Casey, Vukina, and Danielson, 1995) and to value hiking in particular (Arcarya, Hatch, and Clonts, 2003; Casey, Vukina, and Danielson, 1995; Loomis, Gonzalez-Caban, and Englin, 2001). This model is commonly used to estimate the recreation demand function with only RP data or combined RP and SP data (Englin and Cameron, 1996; Loomis, Gonzalez-Caban, and Englin, 2001). This method's primary assumption is that even when there is no current entry fee to a public recreation site, recreationists pay an "implicit price" for the site's attributes, or services, when they incur travel costs to visit the site. The implicit price includes vehicle-related costs, which are primarily gasoline costs. To better understand how visitors would respond to fee increases, we included a scenario with hypothetical increases in trip costs. The hiker's intended trip responses to these hypothetical price increments yield the stated number of annual trips, which becomes the content of our SP data.

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

$$\text{Annual Trips}_{ij} = f(\text{Gascost}_{ij}, \text{Age}_i, \text{Income}_i, \text{Elevation}_j, \text{Lodgepole}_j) \quad (6)$$

Annual $\text{Trips}_{ij}$ is the stated or intended number of trips at the higher cost by individual i to site j.

$\text{Gascosts}_{ij}$ are the gasoline costs (i.e., variable costs) of a trip by individual (i) to site (j). (These costs include the respondents reported gas cost plus the hypothetical increase.)

Age and Income are the visitor's age and income, respectively.

Elevation is the feet above sea level of the recreation site, which is added to the model to reflect a variety of amenities associated with high elevation sites during the summer recreation season (e.g., cooler, views).

Lodgepole represents lodgepole pine forests, which is a dummy variable taking on the value of one if this is the dominant forest type at site j.

*Overall Study Design*

Visitors to three national forests in Colorado were interviewed over the course of the summer of 1998, in which the three sites included the Arapaho-Roosevelt, Gunnison-Uncompaghre, and Pike-San Isabel National Forests. We sampled over 35 days during the main summer recreation season at a total of 10 sites in the three national forests. This schedule generally allowed one sampling rotation of 2 days (1 weekday and 1 weekend day) at nearly all recreation sites during July and August. The interviewer gave a survey packet to all individuals in a group who were 16 years of age or older. The interviewer indicated that the survey could be completed at home and returned in a postage-paid return envelope enclosed in the packet.

*Survey Structure*

First, visitors were asked about their travel costs for the current trip. Then, individuals were asked about their annual number of trips to the site that year. Finally, to assess how sensitive the quantity of trips were to an addition of a new entrance fee, we asked how trips would change if trip costs increased. The wording of the intended behavior question was: "The cost of recreation changes with gas prices, equipment costs, etc. If the cost of visiting this site had been $X per trip higher tell us how many trips you would take. . .?"

As can be seen, this is a typical contingent behavior, or intended visitation question. The hypothetical increases in trip costs were $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 (or entrance fees) increased. The increments were randomly assigned to each respondent so that hypothetically higher costs faced by visitors could be very high even when the current trip had a very low actual cost. These intended trip responses yield the SP data used in this study, whereas the raw RP data are not used in the actual estimation of the coefficients in Orbit model.

The surveys were pretested at two of the national forests. Individuals were asked to fill out the survey and provide any comments or feedback, and minor revisions to the final survey were made accordingly. In the administration of the survey, there were only 14 refusals out of 541 contacts made and a total of 527 surveys handed out. Of these surveys distributed, 354 were returned after the reminder postcard and second mailing to nonrespondents for an overall response rate of 67 percent. Table 1 shows the descriptive statistics for the stated preference data used in the regression analysis.

The revealed preference data on the number of trips taken were only used to determine the second safety point in the first-stage estimation. On average, respondents actually took 2.78 trips per year during 1998. The average age of the respondents was 37 years old, and average income was $64,760. Approximately 20% of the hikes were taken in areas with lodgepole pine, which are often so thick as to block much of the view of scenery and crowd out any wildflowers.

The stated preference data used to estimate the Orbit model shows the average gas cost of close to $23 per person so that the travel cost is tripled in the hypothetical data compared with the actual revealed preference data. This increase in cost has a fairly sizable impact on the number of trips taken; as the mean number of trips drops from 2.78 to 1.66, a decrease of 1.12 trips resulting from higher trip costs, or by 59.7% at the new travel cost of $23. Thus, the direction of quantity responses in the stated preference data reflect a negative own price effect as expected from economic theory. However, the question remains whether the amount of reduction in trips with the higher cost in the stated preference data are correct. To answer this question, we turn to the results of the Orbit model estimated using just the stated preference data.

*Estimation Results*

Like Klein and Sherman, we use zero stated trips as the first known safety point. Although Klein and Sherman used the median of their stated trips for the second safety point, we use the mean of the actual trips (2.78) as the second safety point, because in our case, we have these data. However, no revealed preference data are actually needed for the second safety point. We discuss in a later section entitled "Sensitivity Analysis" that our Orbit estimates are similar over a wide range of values of the second safety points, e.g., four trips, five trips, and six trips.

**Table 1.** Descriptive Statistics of the Stated Preference Data

| Variable | Units | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Stated Antrips | Number | 1.66 | 3.14 | 0 | 13 |
| Gascost | $(1998) | 22.69 | 15.39 | 2 | 55 |
| Age | Years | 37.11 | 11.49 | 19 | 73 |
| Elevation | Thousand feet | 7.22 | 1.50 | 5.4 | 9.4 |
| Lodgepole | Yes = 1, No = 0 | 0.21 | 0.41 | 0 | 1 |
| Income | Thousand $ | 64.76 | 43.10 | 5 | 175 |

In this section we also compare our results from the Orbit approach with results from a commonly used count data model. The first stage of the Orbit model was estimated with and without the heteroscedasticity function correction with the results shown in Table 2A. The signs on the variables are as expected with Gascost (our travel cost variable) being negative and significant in both Orbit models. Age is negative and significant in both Orbit models, whereas Income is positive and significant in both Orbit regressions. Elevation is positive, because for summer recreation, higher elevations are cooler but the coefficient is not significant in either Orbit model. In the Orbit heteroscedasticity correction function, the reciprocal of Age and Gascost was highly significant.

For comparison with the Orbit model, Table 2B presents the travel cost model on stated quantities of trips based on the typical approach, the negative binomial count data model (Hellerstein, 1991). Price is also negative and statistically significant in this model as well, although only the age shift variable is significant in the count data estimation.

**Table 2B.** Negative Binomial Count Data Regression Results for Stated Annual Trips at Higher Gas Costs

| | Negative Binomial | | |
|---|---|---|---|
| Variable | Coefficient | t-Statistic | Probability |
| B1 (Constant) | 1.167 | 1.323 | 0.186 |
| B2 (Gas $Cost_{ij}$) | –0.031 | –3.563 | 0.000 |
| B3 ($Age_i$) | –0.025 | –1.957 | 0.050 |
| B4 ($Income_i$) | 0.003 | 0.842 | 0.400 |
| B5 ($LodgePole_j$) | –0.205 | –0.492 | 0.623 |
| B6 ($Elevation_j$) | 0.094 | 0.775 | 0.438 |
| Overdispersion | 1.448 | 4.217 | 0.000 |

*Orbit 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 is re-estimated at each increased price level for selected stated quantities of trips. In our analysis, each estimated λ is statistically significant at the 1% level. Table 3 illustrates the estimation of λ for stated quantity equal to 4. In this second-stage estimation, a stated quantity of four trips is corrected to 3.26 trips. From Table 3 it is evident that all slope parameters have been fixed at values from the original stage one regression, and the separate coefficient λ is the sole parameter estimated at each stated quantity. The different estimates of λ reflect the fact that as stated trips rise ($t$), the proportion of the sampling going into the second partition increases, and there is a corresponding drop in the proportion of the sample in the third partition. Because the number of observations in each partition changes with a changing $t$, this yields a different forecast of λ for each stated trip ($t$).

Table 4 reports each estimated λ for other stated quantities along with their corresponding

**Table 2A.** First-Stage Orbit Estimates with and without Correction for Heteroscedasticity for Stated Annual Trips at Higher Gas Cost

| | With Heteroscedasticity Correction | | | Without Heteroscedasticity Correction | | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | t-Statistic | Probability | Coefficient | t-Statistic | Probability |
| B1 (Constant) | 1.604 | 1.082 | 0.279 | 1.549 | 1.006 | 0.315 |
| B2 (Gas $Cost_{ij}$) | –0.068 | –3.217 | 0.001 | –0.046 | –3.007 | 0.003 |
| B3 ($Age_i$) | –0.046 | –1.910 | 0.056 | –0.049 | –2.306 | 0.021 |
| B4 ($Income_i$) | 0.010 | 1.957 | 0.050 | 0.012 | 2.018 | 0.044 |
| B5 ($LodgePole_j$) | –1.191 | –1.829 | 0.068 | –0.547 | –0.721 | 0.471 |
| B6 ($Elevation_j$) | 0.205 | 1.094 | 0.274 | 0.147 | 0.716 | 0.474 |
| Heteroscedastic Function | | | | | | |
| Z1 (Constant) | –2.013 | –1.643 | 0.101 | | | |
| Z2 (1/Age) | 123.95 | 2.675 | 0.008 | | | |
| Z3 (Gas Cost) | 0.053 | 2.401 | 0.016 | | | |

**Table 3.** Example of Estimation of λ (Corrected Trips) in the Second Stage at Stated Trips = 4

| Variable | Coefficient | Standard Error | t-Statistic | Probability |
|---|---|---|---|---|
| B1 (Constant) | 1.549 | | (Fixed parameter from first stage) | |
| B2 (Gas Cost) | –.046 | | (Fixed parameter from first stage) | |
| B3 (Age) | –.049 | | (Fixed parameter from first stage) | |
| B4 (Income) | .012 | | (Fixed parameter from first stage) | |
| B5 (LodgePole) | –.547 | | (Fixed parameter from first stage) | |
| B6 (Elevation) | .147 | | (Fixed parameter from first stage) | |
| λ | 3.26 | .308 | 10.58 | .0000 |

t-statistics and the difference between stated and corrected trips. The table makes clear that the Orbit correction procedure results in substantial correction to stated trips when stated trips are three or more times larger than the mean stated trips. 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.

In particular, at reported quantities 3.5 times the mean stated trips, the correction is 25%, whereas at six times the mean number of stated trips, the adjustment is 48%. The differential calibration is likely to be important when attempting to provide a valid estimate of the quantity of existing products that might be purchased at higher prices (e.g., extension presentations attended) or quantity demanded of new products.

*Consumer Surplus Comparisons*

Besides estimating the quantity demanded of new products, estimating the economic benefits associated with the introduction of new products is often part of economists' benefit–cost calculations. Therefore, we calculate the net WTP (consumer surplus) per trip from the Orbit empirical demand models in Table 2A. Then we compare these Orbit estimates of consumer surplus with those calculated from the negative binomial count data model in Table 2B. The consumer surplus per trip from the negative binomial count data model has a convenient form of $1/-B_{GasCost}$. Thus, the consumer surplus is directly derived from the Gascost coefficient in Table 2B as $32 per trip with a 90% confidence interval of $22–60 per trip.

The first stage of the Orbit model is quite similar to the ordered probit model in its structure and estimation. As Roe, Boyle, and Teisl (1996) state, the binary logit is just a special case of the ordered probit model, in which there are just two categories in the former rather than n categories in the latter. Stevens et al. (2000) note in their comparison of welfare estimates of conjoint and contingent valuation, WTP is derived from an ordered model by increasing the dollar amount until the point of indifference or until the individual is at

**Table 4A.** Stated Trips (SP) and Corrected Number of Trips (λ) from the Second-Stage Orbit Model without Heteroskedasticity Correction at Higher Gas Costs

| Stated Trips | Corrected Trips (λ) | Corrected Trips t-Statistic | Corrected Trips P Value | Difference in Trips |
|---|---|---|---|---|
| 1 | 1.55 | 6.6 | 0.0 | –0.55 |
| 1.66 | 1.66 | 7.5 | 0.0 | 0.00 |
| 3 | 2.87 | 10.2 | 0.0 | 0.13 |
| 4 | 3.26 | 10.6 | 0.0 | 0.74 |
| 6 | 4.48 | 10.7 | 0.0 | 1.52 |
| 8 | 4.61 | 10.8 | 0.0 | 3.39 |
| 10 | 5.21 | 10.5 | 0.0 | 4.79 |
| 12 | 5.50 | 10.2 | 0.0 | 6.50 |

**Table 4B.** Stated Trips (SP) and Corrected Number of Trips from the Second-Stage Orbit Model with Heteroscedasticity Correction at Higher Gas Costs

| Stated Trips | Corrected Trips (λ) | Corrected Trips t-Statistic | Corrected Trips P Value | Difference in Trips |
|---|---|---|---|---|
| 1 | 1.60 | 9.4 | 0.0 | –0.60 |
| 1.66 | 1.66 | 8.4 | 0.0 | 0.00 |
| 3 | 2.60 | 14.9 | 0.0 | 0.40 |
| 4 | 3.02 | 16.8 | 0.0 | 0.98 |
| 6 | 4.58 | 14.1 | 0.0 | 1.42 |
| 8 | 4.66 | 14.5 | 0.0 | 3.34 |
| 10 | 5.22 | 16.0 | 0.0 | 4.78 |
| 12 | 5.40 | 16.8 | 0.0 | 6.60 |

the interval boundary. This is the definition of WTP as well with a binary model as well. Therefore, we adopt the WTP expression for the probit model from Hanemann (1984) to calculate mean WTP. Following Loomis (1997), who estimated a probit model by pooling revealed preference trip information at the current travel costs with intended visitation behavior at a hypothetical increased travel cost, we interpret the hypothetical increased travel cost in the Orbit model as the bid variable because we are only using the SP data. Therefore, mean WTP is:

$$\text{Mean WTP} = [\beta o + \beta_2(Xm_2) + \beta_3(Xm_3) + \beta_4(Xm_4) + \beta_5(Xm_5)]/(-\beta_1) \tag{7}$$

where $Xm_n$ is the mean of the nonprice variables; and $n = 2, 3, 4$, and 5 corresponding to Age, Income, LodgePole, and Recreation Site Elevation variables, respectively. $B_1$ is the coefficient on the hypothetical increase in gas cost. Applying the respective formulas to calculate mean WTP using the Orbit model (with and without correcting for heteroscedasticity) yields per-trip estimates of $26.10 and $21.39, respectively. The consumer surplus for the count data model is $32 per trip. The per-trip WTP differences between the Negative Binomial and the Orbit with correction for heteroscedasticity is at 23% and 50% for the Orbit without the adjustment for heteroscedasticity. However, these substantial differences in average net WTP per trip between the negative binomial and the Orbit models are not statistically different as a result of the wide confidence interval around the negative binomial estimate of consumer surplus ($22–60). The 90% confidence interval overlaps the mean estimate of the Orbit model heteroscedasticity correcting for and is close to the mean estimate of the Orbit model without correcting for heteroscedasticity.

Although these differences in per-trip net WTP are substantial but not significantly different, the primary purpose of the Orbit model is to correct for overestimation of the number of stated trips or quantities purchased. To obtain the full effect of the Orbit correction involves combining the Orbit net WTP per trip and the Orbit-corrected number of trips. Table 5 compares the annual WTP calculated from the negative count data model to the Orbit corrected trips and Orbit WTP per trip. Although the negative binomial model trip prediction is accurate at estimating the mean of stated trips, Loomis, Gonzalez-Caban, and Englin (2001, p. 516) found using the same stated preference data that we use here that stated trips were significantly biased upward compared with the corresponding revealed preference number of trips holding travel cost constant. As can be seen in Table 5, the overestimation of annual WTP grows substantially at higher stated trip quantities as a result of the combined effect of the count data model's higher consumer surplus per trip together with the inflated number of stated trips. Annual benefits are roughly two times higher with the count data model than with the Orbit-corrected model at high levels of stated trips.

**Table 5.** Comparison Annual Consumer Surplus (CS) of Negative Binomial (NB) and Orbit (with Heteroscedasticity Correction)

| Stated Trips | Annual NB CS | Orbit Corrected Trips | Annual Orbit CS | Percent Difference in Annual CS |
|---|---|---|---|---|
| 1 | $32 | 1.66 | $43 | 26% |
| 3 | $96 | 2.60 | $68 | –42% |
| 4 | $128 | 3.02 | $79 | –63% |
| 6 | $192 | 4.58 | $119 | –61% |
| 8 | $256 | 4.66 | $121 | –111% |
| 10 | $320 | 5.22 | $136 | –136% |

*Sensitivity Analysis*

Our Orbit corrections using the mean of the RP trips as the second safety point have adjusted the SP intended trip responses downward substantially. However, it is also possible that using the mean number of trips as the second safety point is too low, so there is an "overcorrection" in the calibration. Therefore, our first stage of the Orbit model was re-estimated using trip levels for the second safety point of up to six trips (more than double the mean of the RP trips of 2.78). Within this range of second safety points, there was no perceptible change in any of the first-stage slope coefficients. This suggests that within a reasonable range of our data, the selection of the specific second safety point was not an issue. However, using a second safety point that was greater than six trips, the mean number of trips did yield insignificance of key Orbit model coefficients.

*Evaluating the Accuracy of the Orbit Estimates*

Although the Orbit model systematically corrects stated trips downward, especially at very high levels of stated trips, the question remains if this is too much or too little calibration relative to actual demand. To address this question of the accuracy of the estimated corrected trips from the Orbit model, we used the Orbit model's function to forecast what trips would be at the original actual data travel cost. These results are compared with the distribution of trips in the actual data that occurred at that same original actual data travel cost. In particular, we conduct an observation-by-observation comparison of respondents' reported actual number of trips and the Orbits-predicted number of trips at the same original travel costs. The mean number of trips in the actual trip data[2] is 2.78 with a standard error of 0.21. The Orbit model-estimated mean number of trips is 2.50 with a standard error of 0.11. A $t$ test of the differences in respondents' reported trips and the Orbit model estimated trips yields a $t$ statistic of 0.247, which is not statistically significant. Thus, the trip estimates of the Orbit model at the original travel cost are not significantly different than the reported trips at the original travel costs. This indicates that with our data, the Orbit model provided a valid estimate of stated trips and that the corrected number of stated trips is likely to be an accurate estimate of stated trips at the higher trip costs.

*Possible Extensions*

This Orbit procedure should also 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.). As noted by Ward (1987), 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

[2] The sample used in the Orbit analysis was truncated at a maximum of 13 trips to facilitate estimation of the highly nonlinear Orbit likelihood function. Thus, for comparison with the actual trip data and the Orbit predictions, we capped the number of trips in the actual data at 13 as well. Only 3.7% of the sample reported more than actual 13 trips.

consistent with revealed preference data on existing quality. It may also be that the correction to SP responses could be moderated by having more than one nonzero safety point and, consequently, a greater number of partitions in the likelihood function, because there is nothing in the ordered probit model that would rule out this adjustment. Then, some of the higher values could be seen as correct rather than as overstatements.

## Conclusion

This article extends the original Orbit model of Klein and Sherman to include correction for heteroscedasticity and calculation of WTP. The resulting Orbit model appears to be a promising approach for calibrating stated preference responses. In our example, it uses known safety points such as zero stated quantities as one anchor and mean quantity of trips from the revealed preference data as another anchor. Furthermore, like an ordered probit estimator, stated quantities, especially those above the second safety point, are treated in an ordinal fashion, implicitly giving these points less influence than would a normal parametric approach like OLS or count data models. Once the coefficients in the first stage are estimated, they are used in a second-stage analysis to estimate a coefficient ($\lambda$) that yields the estimated corrected stated quantities. Our results show that at low stated quantities, there is minimal correction needed to the stated quantities, but as the stated quantity grows, the correction factor increases, but not monotonically. The Orbit model also yields lower estimates of consumer surplus per unit than does the count data approach.

When the corrected quantities from the Orbit model are combined with the Orbit estimates of consumer surplus per trip, the implied annual consumer surplus can be substantially smaller than annual benefits derived from a conventional count data model using stated quantities. Comparing the Orbit model-estimated number of trips at the original gas cost with respondents' reported trips at that same original gas costs indicated that the Orbit model estimates of trips are not statistically different than actual reported trips. This gives some confidence that the correction to the stated trips is likely to be a valid downward calibration.

Thus, the Orbit models appears to be a promising technique for economists who must estimate likely quantities demanded and WTP for new products or the quantities of existing products or services that would be demanded at higher prices outside the range of existing prices or with varying qualities. Nonetheless, there is certainly room for further refinement in the two variants of the Orbit model presented here.

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