10 Efficiency versus bias: the role of distributional parameters in count contingent behaviour models

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INTRODUCTION

One of the challenges facing many applications of non-market valuations is to find data with enough variation in the variable(s) of interest to estimate econometrically their effects on the quantity demanded. A solution to this problem was the introduction of stated preference surveys. These surveys can introduce variation into variables where there is no natural variation and, as a result, natural experiments are not possible. The problem of no or insufficient variation in naturally occurring data to estimate the effects of interest has led to a large literature on stated preference methods.

Among the methods developed, two can be linked directly to observed behaviour. Unlike contingent valuation questions, these approaches key off of actual choices that individuals have made in the past or are contemplating in the future. Consequently, the consistency of these choices with the responses to stated preference questions can be examined. The two methods are those based upon random utility theory and those based upon demand theory. While the two can be linked theoretically in practice, one either adopts a random utility framework or a demand framework. The demand framework, adopted here, is frequently identified as a 'contingent behaviour' approach.

The contingent behaviour method was proposed by Englin and Cameron (1996). Their paper suggests focusing on the number of trips an individual might make under different situations rather than how a single choice might vary (random utility model) under different situations. The advantage of the contingent behaviour model is that it includes both the intensive and the extensive margin while the random utility approach focuses solely on the intensive margin. As a result, the contingent behaviour approach can capture improvements with the extensive margin as well as quality reductions on the intensive margin.

While considerable effort has been expended examining the functional form, parametric specifications and distributional assumptions used in contingent behaviour studies, no effort has been spent examining the role of heteroscedasticity. Cameron and Englin (1997) provided the first analysis of the role that systematic differences between respondents may play in generating heteroscedasticity in a stated preference analysis. Their work examined the role of experience in the variance of dichotomous choice WTP survey responses. The analysis in this chapter examines the relationship between demographic characteristics and potential heteroscedasticity in contingent behaviour studies.

The analysis is important because of the relationship between distributional shape parameters and the demand shift parameters. The intuition of OLS models fails in the case of many count models. Unlike OLS models where simple algebra can be used to calculate the parameters and standard errors of a regression *ex post*, count models must be estimated using maximum likelihood methods and the distributional shape parameter(s) and demand parameters must be estimated simultaneously. If the shape parameters are correlated with the demand shift variables and the relationship is not properly specified, mis-specification has been introduced into the model and the demand shift parameters will be biased. This results in both a possible bias in the parameter on the travel cost variable as well as an inability to recover the mean dependent variable of the data. Subsequent estimates of welfare measures will suffer from the effects of biased parameters.

In this chapter, these methods are illustrated using data on off highway vehicle (OHV) riders in North Carolina, USA. While OHV riding generates economic benefits for riders, they also generate negative externalities. The externalities include smoke, noise, disturbed trail conditions and the presence of large machines (Jakus et al., 2008; Priskin, 2003). The combination of benefits and external costs make OHV riding a useful activity to examine. Several studies have applied travel cost models to examine the value of OHV riding. Bergstrom and Cordell (1991) apply a national zonal travel cost model to examine values and find that daily values of about $21 in 2005 US dollars. Bowker et al. (1997) suggest that consumer surplus in fee based sites in Florida to range between $14.60 and $80.32 in 2005 US dollars. Englin et al. (2006) estimated a demand system for the same four OHV sites in North Carolina used in this analysis and found consumer surplus to be between $25.51 and $131.58.

The remainder of the chapter is structured in the following way. The next section presents count models of recreational site demand that are used in this study. The third section outlines the data collection procedures and the data used in the analysis. The fourth section provides the results, and the final section provides a discussion of the limitations of the analysis and suggestions for future research.

COUNT MODELS OF RECREATIONAL SITE DEMAND

Count models have become a very popular application of the traditional travel cost model. Traditional OLS models suffered from a number of issues including negative and fractional trip forecasts. In the last decade or so count distributions have been widely applied to model this relationship. Count distributions are attractive because they naturally handle both the integer and non-negative characteristics of recreation demand. Specifically, the demand for a site is:

$$Y = f(tc, d) \tag{10.1}$$

where $f()$ is the exponential function, Y is the number of trips, tc is the travel cost to the site and d is the demographic variables that characterize the respondents.

In the case of pooled sites, the demand equation must be expanded to include site characteristics. The specification of the demand is given by:

$$Y_i = f(tc_{ij}, d_i, x_j) \tag{10.2}$$

where $f(\ )$ is the exponential function, i denotes individuals and j denotes sites, tc_{ij} is the travel cost for individual i to site j, d_i is the demographic variables that characterize the respondents, and x_j is the characteristics of the sites contained in the pooled in the data. The estimated per trip consumer surplus for the individual i is simply $\int Q^*(.)\, dp$, or $1/\beta_p$ where β_p is the parameter on the price variable. This is clearly the 'average site' in the sample and corresponds to the value at the intensive margin. To calculate values at the extensive margin or, more simply, allowing the number of trips to change, one needs to estimate the change in the number of trips. Quantity demanded for a particular site is simply found by substituting the site attributes into the demand equation. Changes in quantity that result from changing site attributes is found by substituting the new site attributes into the demand equation forecasting the new quantity demanded. Dividing the change in trips by the parameter on travel cost, β_p, gives the change in value for the extensive and intensive margins. Traditionally this calculation is performed for each respondent and the resulting mean consumer surplus and standard error are reported.

The Poisson Model

The most basic count travel cost demand is the Poisson model. The Poisson model provides an excellent reference point because it does not contain any shape parameters to be estimated. This makes it one of the distributions that is a member of the linear exponential family (Gourieroux et al., 1984)). The Poisson regression model specifies that each y_i is drawn from a Poisson distribution with parameter, λ_i. The predictive variables are linked to the latent λ using an exponential link function, $\lambda_i = \exp(tc_{ij}, d_i, x_j)$ where i denotes individuals and j denotes sites. The probability mass function for the Poisson is

$$\text{Prob}(Y_i = y_i|x_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, y_i = 0, 1, 2, \ldots \tag{10.3}$$

where x_i now includes both demographic and site variables. The expected number of y_i (trips) and the variance of trips are both given by

$$E[y_i|x_i] = Var[y_i|x_i] = \lambda_i = e^{x_i'\beta} \tag{10.4}$$

While the Poisson has the unattractive property that the mean equals the variance, it does retain the attractive linear exponential property that the parameters are unbiased as long as the underlying relationship is linear exponential. One way to address the heteroscedasticity that is usually inherent with the Poisson is to use White's (1982) standard errors with the Poisson parameter estimates. Another approach is to adopt a distributional specification that allows for more heterogeneity in the variance and presumably provides more efficient estimates.

The Negative Binomial Generalization

A popular generalization of the Poisson is the negative binomial. The negative binomial is found by mixing a gamma density with mean 1 and variance $1/\alpha$ with the Poisson. The likelihood for the negative binomial distribution is:

$$\text{Prob}(Y_i = q) = \frac{\Gamma(q + \frac{1}{\alpha})}{\Gamma(q + 1)\Gamma(\frac{1}{\alpha})}(\alpha\lambda_i)^j[1 + \alpha\lambda_i]^{-\left(q + \frac{1}{\alpha}\right)} \tag{10.5}$$

where q is the number of trips taken by individual i and α is the over-dispersion parameter. Notice that this likelihood collapses to the Poisson if α equals zero. An important point to notice is that in empirical work the α parameter is estimated from the data. As a result the distribution loses the attractive linear exponential properties held by the Poisson. The expected number of y_i (trips) is given by

$$E[y_i|x_i] = \lambda_i = e^{x_i'\beta} \tag{10.6}$$

while the variance of trips is given by

$$V[y] = \lambda(1 + \lambda\alpha) \tag{10.7}$$

Note that when α is zero, the expression collapses to the Poisson moments. The expectation is that relaxing the equivalence between the mean and variance will result in improved efficiency.

The Gaussian Random Effects Poisson generalization

Terza (1998) suggested introducing normally distributed heterogeneity to the Poisson model. Cameron and Trivedi (1998) called this density a Gaussian Random Effects Poisson. Terza utilized a two-stage method of moments estimator to avoid the full information maximum likelihood's (FIML) computational burden. In the Gaussian Random Effects Poisson the random effects follow the normal distribution. Following Terza, y_{it} are assumed to be iid $\mathrm{P}[\exp(u_i + x_{it}'\beta)]$ where the random effect u_i is iid $\mathrm{N}[0, \sigma_u^2]$:

$$y_{it} \sim \mathrm{P}[\alpha_i \exp(x_{it}'\beta)] \tag{10.8}$$

and $\alpha_i = \exp u_i$

The joint density is:

$$\Pr(y_{it}) = \int_{-\infty}^{\infty} \left[\prod_{t=1}^{T} \left(\frac{e^{-\lambda_{it}} \lambda_t^{y_{it}}}{y_{it}!} \right) \frac{e^{-\frac{1}{2}u^2}}{\sqrt{2\pi}} \right] du \tag{10.9}$$

where $\lambda_{it} = \exp(x_{it}\theta + \sigma u)$.

The expected number of trips is given by:

$$E[Y] = \exp(\mu + 0.5\sigma^2) \tag{10.10}$$

and the variance is given by:

$$V[y] = \exp(x_i'\beta + 0.5\sigma^2) + (\exp(2\lambda + \sigma^2)(\exp(\sigma^2) - 1) \tag{10.11}$$

Note that when σ^2 is zero the expressions again collapse to the Poisson moments. From a conceptual viewpoint the expectation is that loosening the equivalence between the mean and the variance will result in improved efficiency. Of course, the Gaussian Random Effects Poisson takes a very different approach to relaxing this restriction.

Heteroscedasticity and the Negative Binomial and Gaussian Random Effects models

Failure to model heteroscedasticity can lead to a variety of issues. There are the conventional problems with model testing but there are also problems which can affect the welfare results. This section provides a framework for modelling heteroscedasticity in negative binomial and Gaussian random effects Poisson models.

Modelling heteroscedasticity is accomplished by developing a relationship between the over-dispersion parameters and exogenous variables that could underlay the pattern of over-dispersion. In this case, the two over-dispersion parameters that are of interest are α from the negative binomial and σ^2 from the Gaussian random effects Poisson model. In each case an exponential link function between the over-dispersion parameters and the exogenous variables is used. An exponential link function assures that the predicted over-dispersion parameters will be positive (which is a requirement).

The exponential link function is a second equation that links the over-dispersion parameters to a set of exogenous variables. The equation for the negative binomial can be represented by:

$$\alpha_i = \exp(z_i'\delta) \tag{10.12}$$

where α is the negative binomial over-dispersion parameter, the δ are parameters to be estimated and the z's are exogenous variables. The equation for the Gaussian Random Effects Poisson can be represented by:

$$\sigma_i^2 = \exp(z_i'\rho) \tag{10.13}$$

where σ^2 is the Gaussian random effects Poisson shape parameter, the ρ are parameters to be estimated and the z is exogenous variables

The introduction of a parameterized shape parameter for α in the negative binomial and σ^2 in the Gaussian random effects Poisson model provides a way to enrich the specification of the distributional shape parameter. Clearly, if only the constant in the function is significantly different from zero then the traditional methods are perfectly adequate. If, however, other variables are significantly affecting the shape parameter then the system of two equations for each model will be mis-specified if only a constant is used. The goal is to enjoy the increased efficiency of the negative binomial or the Gaussian random effects Poisson without incurring the bias that comes from mis-specifying the shape parameter.

DATA

The study area included four US Forest Service OHV areas in western and central North Carolina, USA during the summer of 2000. These included Upper Tellico, Wayehutta, and Brown Mountain in the Southern Appalachian Mountains and Badin Lake in the Uwharrie Mountains. The areas include some of the most attractive OHV areas of southeastern USA.

Surveys were administered by volunteers from local riding clubs. The volunteers were especially helpful due to their understanding of the nuances of the sites and the types of riders that frequented each site as well as their ability to maintain a cooperative ambiance throughout the data collection process. Although the sample was a convenience sample, an attempt was made to obtain data from a diverse array of riders. Only one rider per party was asked to respond to the survey. The goal was to obtain at least 100 completed surveys per site.

The survey consisted of an eight-page booklet consisting of 25 questions. To elicit the recreation count data, respondents were presented with a table and asked to enumerate the total number of trips made to each of the four OHV sites during each of the previous three years. Although this procedure may induce some degree of recall bias, respondents commonly left blank cells for some locations and years, suggesting a possible response strategy for those who could not recall the requested information. However, it is anticipated that some respondents may have made a best (but inaccurate) guess, inducing heteroscedasticity in the responses.

In addition, respondents were presented with three contingent behaviour questions. These questions asked how many trips would have been taken if the characteristics of the sites were changed from their current level. The characteristics chosen for inclusion in the contingent behaviour questions were attributes under consideration by US Forest Service recreation managers at the four OHV sites. In particular, the site characteristics that were varied included the number of parking spaces (Parking); the trail mileage (Trail); and whether or not alcohol consumption was allowed on-site (Alcohol). The level of these characteristics was varied using a fractional factorial experimental design. Data used for analysis included only the reported actual and contingent number of trips for the site at which the survey was administered based on the rationale that those responses would be most accurate. Thus, if respondents answered all visitation questions, six observations per respondent were available for analysis. Some respondents answered fewer questions, so their panel of responses is reduced. The survey also elicited a suite of demographic variables that could be included in the analysis. For the analysis here, the age (Age), income (Income), and gender (Male = 1, Female = 0) of the respondent were included in the model specifications.

RESULTS

Table 10.1 presents the econometric results. The first column presents the Poisson parameter estimates while columns two and three present the partially parameterized and fully parameterized specifications of the negative binomial model, respectively. Columns four and five present the partially parameterized and fully parameterized versions of the Gaussian random effects Poisson, respectively. Standard errors are shown in parentheses beneath the respective parameter estimates.

Each equation satisfies the basic expectation of a downward sloping demand curve (all of the estimates of β_p are negative and statistically significant at conventional levels). The parameter estimates on the miles of trail (Trail) are consistently positive across all model specifications, as one would expect – more trails to ride increases visitation. However, there is inconsistency among the influence of other site attributes on visitation with the Poisson and negative binomial providing consistent signs on the parameter estimates and the Gaussian random effects Poisson parameter estimates telling a slightly different story. The Poisson and negative binomial models suggest that having a greater number of parking spaces (Parking) decreases visitation and that allowing alcohol consumption on site (Alcohol) also decreases visitation – both of which are somewhat counter intuitive. The Gaussian random effects Poisson model suggests that a greater number of parking spaces increases visitation (which is logical) and that allowing alcohol consumption also increases visitation (which is at least plausible.) The Poisson regression provides unbiased, although inefficient, estimates of the demand parameters. The other models should provide more efficient estimates of the parameters. The issue at hand is the utility of different methods of handling the specification of the distributional parameters.

The second and third columns provide some insight into the negative binomial model. The second column provides the standard negative binomial specification. The usual test of the desirability of the negative

Table 10.1 OHV demand parameter results

Variables	Poisson	Negative binomial		Gaussian random effects Poisson	
		Partially parameterized	Fully parameterized	Partially parameterized	Fully parameterized
Constant	0.9786***	0.9297***	0.7939***	0.0330	−0.5250***
	(0.0736)	(0.3783)	(0.3664)	(0.4505)	(0.3561)
Tc	−0.0027***	−0.0016***	−0.0015***	−0.0028***	−0.0023***
	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0002)
Parking	−0.0078***	−0.0086***	−0.0082***	0.0034***	0.0043***
	(0.0008)	(0.0036)	(0.0037)	(0.0005)	(0.0004)
Trail	0.0106***	0.0116***	0.0122***	0.0155***	0.0124***
	(0.0012)	(0.0063)	(0.0063)	(0.0009)	(0.0010)
Alcohol	−0.0598***	−0.0534	−0.0503	0.0778***	0.0594***
	(0.0307)	(0.1304)	(0.1324)	(0.0149)	(0.0147)
Age	−0.0030***	−0.0061	−0.0042	−0.0113***	−0.0052
	(0.0014)	(0.0075)	(0.0072)	(0.0102)	(0.0083)
Income (in 100s)	0.0001***	0.0001	0.0002	0.0003	0.0005***
	(5.01E−05)	(0.0002)	(0.0002)	(0.0004)	(0.0002)
Male	0.0243***	0.0872	0.0899	−0.1003	0.1239
	(0.0242)	(0.2073)	(0.2124)	(0.3664)	(0.2936)
α		7.5047***			
		(0.3696)			
α _constant			4.4646***		
			(1.61)		
α _revealed			−0.3737		
			(0.7743)		

Table 10.1 (continued)

Variables	Poisson	Negative binomial		Gaussian random effects Poisson	
		Partially parameterized	Fully parameterized	Partially parameterized	Fully parameterized
α _age			0.0950***		
			(0.0343)		
α _male			−0.1845		
			(1.2069)		
σ^2				1.0159***	
				(0.0671)	
σ^2 constant					0.0981
					(0.2951)
σ^2 revealed					0.1255***
					(0.0129)
σ^2 age					0.0195***
					(0.0052)
σ^2 male					0.2592
					(0.2607)
Log-likelihood	−9501.4	−3693.9	−3689.6	−7698.4	−7692.6

Note: Significant at: *** 1 per cent level.

binomial specification is the *t*-statistic on the over-dispersion parameter, α. The value of the test statistic is over 20, signifying that the negative binomial is the superior specification. The question remains, however, whether a simple linear specification of the dispersion parameter is, in fact, a good enough specification. Column three provides the parameter estimates for a specification that fully parameterizes α.

For the purposes of illustrating the methodology, the over-dispersion parameter is modelled with a constant and three variables. These include whether the observation is a revealed (α_revealed = 1) or stated (α_revealed = 0) observation, the age of the respondent (α_age) and the gender of the respondent (α_male). It is interesting to observe that the parameter estimates indicate that there is no (statistically significant) difference between the revealed and stated observations. Nor does gender play a role in the degree of dispersion. There remains a fixed effect but the *t*-statistic is now on the order of three instead of 20 which suggests that the constant in the simple negative binomial specification is trying to capture a great deal of variation. Age is now a statistically significant determinant with older people displaying more dispersion around the mean number of trips than younger people. In addition, the likelihood ratio test is 8.6 with three degrees of freedom which is significantly different from zero at the 5 per cent level.

The effect of multicollinearity is also clear in the results. The partially parameterized effect of male gender on demand is 0.0872 while in the fully parameterized model it is 0.0899, virtually the same. This would be expected since male gender is not a significant determinant of α. Age, however, does affect α. The partially parameterized value is −0.0061 while in the fully-parameterized model the value is −0.0042. If the shape parameter α is not fully parameterized, the regression is forced to put the net effect of age into the demand shift variable rather than apportion it among the demand shift effect and the heteroscedasticity effect.

A similar exercise is conducted with the Gaussian random effects Poisson model. The standard approach is to estimate the model by only partially parameterizing σ^2 – the fifth column reports the results for the partially parameterized model. Note that the parameter on σ^2 is very accurately measured with a *t*-statistic over 10. As noted above, the parameters on Parking, Trails and Alcohol are all positive and significant at the 1 per cent level. Age has a significant negative affect and the parameter on Income remains insignificant.

The last column shows the model with a fully-parameterized σ^2. For purposes of comparison, the parameterization is the same as the one used in the negative binomial model. This specification indicates that the revealed preference data have greater variance than the contingent behaviour responses, and that Age also significantly increases the variation

*Table 10.2 Welfare estimates for each model**

Poisson	Negative binomial		Gaussian random effects Poisson	
	Partially parameterized	Fully parameterized	Partially parameterized	Fully parameterized
\$370	\$625	\$667	\$372	\$435
(\$45)	(\$273)	(\$313)	(\$42)	(\$63)

Note: * 10% confidence interval in parentheses.

around the mean number of trips. Neither the constant nor being male has a significant effect on σ^2.

Further, it is important to note the effect of fully-parameterizing σ^2 on the demand shift variables. The parameter on Age in the demand equation is roughly halved – to −0.0052 – relative to the partially parameterized model. Being Male remains insignificant and the estimates from columns four and five remain about the same. Of particular note, the Income parameter is now statistically significant, suggesting that the partially parameterized σ^2 was correlated with the income level. This correlation may have been through the Age variable, where older people earn higher salaries. In any case, fully parameterizing σ^2 results in an equation that fits better than the base case. The likelihood-ratio test statistic is 11.6 with three degrees of freedom, which is significant at the 0.05 level.

As discussed above the estimated per trip consumer surplus for the individual i is simply $\int Q^*(.)\,dp$. One is also interested in the variance around the welfare measures so that welfare measures can be meaningfully compared. Following Englin and Shonkwiler (1995) the variance of the per trip consumer surplus estimates can be calculated as:

$$Var\left(\frac{1}{\beta_{tc}}\right) = \frac{V}{\beta_{tc}^4} + 2\frac{V^2}{\beta_{tc}^6} \tag{10.14}$$

Table 10.2 provides the per trip consumer surplus for each model and the associated 10 per cent confidence interval. For example, the 10 per cent confidence interval around the Poisson welfare measure of \$370 is \$370 plus or minus \$45. As can be seen in the table there is a wide variation in the welfare measure and the respective confidence intervals. Some observations about the results include the relatively high values yielded by the negative binomial models. These also have quite large confidence intervals and as a result they encompass every other model including each other. The other models are more precise and more interesting to explore.

The welfare and confidence intervals around the Poisson and the partially parameterized Gaussian random effects Poisson are remarkably close. While the partially parameterized Gaussian random effects Poisson sharply outperforms the Poisson in terms of fit, the welfare estimates are indistinguishable. The fully parameterized Gaussian random effects Poisson shows an increase in value of about a quarter. The partially parameterized Gaussian random effects Poisson and the Poisson welfare estimates are at the ragged edge of the bottom of the confidence interval around the fully parameterized Gaussian random effects estimate. The superiority of fit of the fully parameterized Gaussian random effects Poisson and the precision of the model seem to suggest that modelling the shape parameter of a Gaussian random effects Poisson provides the best approach to characterizing these data.

SUMMARY

An avenue of analysis that has not received attention to date is the role that shift variables play in the degree of homogeneity that is found in contingent behaviour data. This analysis presented a framework within which one can explore the importance of fully specifying distributional shape parameters. The evidence, which is not surprising upon reflection, is that there are systematic influences on distributional shape parameters that can be captured in a multi-equation framework as suggested in this chapter.

In each case, the effect of demographic or survey design variables was found to be a significant determinant of the shape parameters and, importantly, to affect the demand parameters and the resulting welfare measures. This is important because failure to capture the separate effects of an explanatory variable on demand and the imposed distributional shape parameter assures a bias in the shape parameter and in the one place the demand parameter appears. Clearly, more work remains to be done to understand the role that different demographic variables or survey designs have on demand and distributional shape parameters. One can easily consider survey complexity and respondent burden in a framework such as the one described here.

NOTE

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