Preference Heterogeneity in a Count Data Model of Demand for Off-Highway Vehicle Recreation

Thomas P. Holmes and Jeffrey E. Englin

This paper examines heterogeneity in the preferences for OHV recreation by applying the random parameters Poisson model to a data set of off-highway vehicle (OHV) users at four National Forest sites in North Carolina. The analysis develops estimates of individual consumer surplus and finds that estimates are systematically affected by the random parameter specification. There is also substantial evidence that accounting for individual heterogeneity improves the statistical fit of the models and provides a more informative description of OHV riders.

Key Words: consumer surplus, off-highway vehicles, outdoor recreation, Poisson model, random parameters

The demand for off-highway vehicle (OHV) use on public land is not new—motorcycles have been used off-road for nearly a century (Havlick 2002).[1] However, the growth in popularity of OHV use is primarily due to the introduction of all-terrain vehicles (ATVs), which began gaining popularity after being introduced in 1983, and ATV riding has become one of the fastest growing outdoor recreation activities in the country.[2] Between 1982 and 2001, OHV use increased by more than 100 percent, and by 2004 roughly 24 percent of people 16 years old and older (more than 50 million people) reported that they participated in OHV recreation (Cordell et al. 2005).

The rapid growth in the use of OHVs suggests that substantial economic benefits are generated by OHV recreation. Between 1993 and 2003, the number of OHVs in the United States grew from less than 3 million vehicles to over 8 million vehicles (Cordell et al. 2005). Although national data on expenditures related to OHV use are not generally available, a recent study in Wyoming showed that OHV visitors to that state each spent more than $900 on their most recent trip for travel-related expenses, providing substantial revenues for service providers (Foulke et al. 2008). Another study, undertaken in Utah (Jakus, Keith, and Liu 2008), found that although OHV-related expenditures are a small part of regional economies—never exceeding about 1.5 percent of employment, income, or value added—a significant number of jobs and millions of dollars of output can be added to rural economies from OHV recreation.

A second measure of the economic benefits of OHV recreation is the net economic benefit received by participants in this recreational activity. The net economic benefit of recreation can be measured by consumer surplus, which is

Thomas P. Holmes is a Research Forest Economist with the Southern Research Station of the USDA Forest Service in Research Triangle Park, North Carolina. Jeffrey E. Englin is Professor with the Department of Resource Economics at the University of Nevada in Reno, Nevada. The authors acknowledge the invaluable assistance provided by USDA Forest Service employees Bonnie Amaral, Chad Boniface, Jake Cebula, Bill Champion, and Kathy Ludlow. This research was partially supported by the USDA Forest Service and the Nevada Agricultural Experiment Station.

[1] We use the term "off-highway vehicle" use rather than "off-road vehicle," as the former term avoids ambiguity surrounding the definition of a road. OHV use is made up of three classes of vehicles: (1) motorcycles, (2) all-terrain vehicles, and (3) four-wheel drive jeeps and sport utility vehicles.

[2] Three-wheel ATVs were dangerous to drive and were banned in 1988 for safety reasons.

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the difference between the total economic benefits received by participants and their costs associated with participating in an activity. A few studies have been conducted to evaluate consumer surplus associated with OHV recreation, using the travel cost method. Bergstrom and Cordell (1991) reported a daily consumer surplus value of $15.06 per person based on a national zonal travel cost model (roughly $21.60 in 2005 dollars). Bowker, Miles, and Randall (1997) estimated consumer surplus to range between $12 and $66 for a fee-based recreation area in Florida ($14.60 to $80.32 in 2005 dollars). Loomis (2006) estimated a consumer surplus value of $29 for the Little Snake River Resource Area in Colorado. Englin, Holmes, and Niell (2006) estimated a demand system for four OHV sites in North Carolina. Their estimates of consumer surplus varied widely depending upon the recreation site, the functional form of demand functions, and the restrictions placed on the demand system. For example, consumer surplus varied from $25.51 to $131.58 across sites in the best-fitting demand system. It should be recognized that no effort was made in Englin, Holmes, and Niell (2006) to control for single day/single purpose trips, so the reported values may not be directly comparable to other studies.

Consumer surplus can also be estimated by willingness to pay in contingent valuation (CV) studies. Using a CV study of OHV users in Arizona, Silberman and Andereck (2006) reported a consumer surplus value of $54 to $96 per trip. Snyder and Smail (2009) used CV to evaluate the annual consumer surplus to OHV users in Wisconsin, and found that median annual consumer surplus varied from $30.39 to $67.48 depending on the specification of the econometric model. Another CV study, conducted in Larimer County, Colorado, estimated a consumer surplus value of $78 per person per day (Deisenroth, Loomis, and Bond 2009).

Despite the economic benefits generated by OHV recreation, both to rural economies and to OHV riders themselves, OHV use on public lands is controversial due to environmental and social impacts associated with this activity. OHV use creates negative externalities to the environment (Priskin 2003) and to other potential users of multiple-use recreation areas, who may be affected by smoke, noise, disturbed trail conditions, and the presence of large machines. Given the growing popularity of OHV recreation, the economic benefits it generates, and its controversial nature, it is important to understand the characteristics of the people who participate in this activity and, specifically, what type of participants generate the greatest use of OHV recreational areas. In addition, many OHV sites currently charge user fees, the revenues from which can be used to manage environmental impacts of OHV riding. Consequently, it is important to obtain reliable estimates of consumer surplus so that the degree to which consumer surplus exceeds existing or anticipated use fees can be evaluated.

Recognizing that the mix of OHV users may affect recreation demand parameters in a complex fashion, we investigate the heterogeneity of user preferences for OHV sites. In the next section, we summarize the use of count data approaches for modeling recreation demand and provide the motivation for considering heterogeneous preferences in a count data framework. Then, in the third section, we describe the study area and the data collection methods. Results are presented in the fourth section, and the final section presents our conclusions.

Count Demand Functions

During the past decade, there has been a surge of interest in the application of count data models based on the Poisson distribution to estimate parameters of outdoor recreation demand (Englin, Holmes, and Sills 2003). In contrast to prior recreation demand modeling efforts using ordinary least-squares regression, count data models emphasize the non-negative, integer nature of data on the number of trips taken. Count data estimators place positive probability only on possible, discrete events, whereas OLS estimators can place positive probability on fractional and negative events (Creel and Loomis 1990). For counts of recreational trips, a count data distribution is more likely to represent the true data-generating process than is a normal distribution.

A functional form that guarantees positive mean values is the linear exponential (semi-log) demand function:

(1) $$E[Q_i] = \exp(X_i\beta)$$

where $E[Q_i]$ is the expected number of visits to a site by individual i, X_i is a vector of observations on independent variables associated with individual i, and the βs are parameters to be estimated. For count data models, the demand function is linked with a count data distribution by the relationship:

(2) $$\lambda_i = E[Q_i] = \exp(X_i\beta)$$

where λ_i is the mean of the count data distribution. A popular specification for count data models of recreation demand is the Poisson model. The probability density function (pdf) for the Poisson is a one-parameter distribution and is written:

(3) $$\Pr(Q_i = q_i) = \exp(-\lambda_i^{q_i})/q_i$$

where q_i is a nonnegative integer.

One limitation of the Poisson model is that it restricts the mean (λ_i) of the distribution to equal its variance. In economic count data in which the variance exceeds the mean, "over-dispersion" of the data may arise from heterogeneity in the mean event rate of the Poisson distribution (Mullahy 1997). A popular method to account for over-dispersion in recreation demand data is to add a stochastic random variable (ε) to the expression for the mean: $\lambda_i = \exp(X_i\beta + \varepsilon_i)$. Cameron and Trivedi (1986) show that if $\exp(\varepsilon)$ follows a gamma distribution, then the compound count data generation process follows a negative binomial distribution.

One limitation of the negative binomial model is that it assumes that heterogeneity arises solely in the mean event rate of the Poisson parameter λ. More recent models have been developed that account for heterogeneity in the mean event rate and the regression parameters β. If the mixing function g(β) is discrete, where β takes only a limited number of classes, it is referred to as a latent class (or finite mixture) model. Wedel et al. (1993) presented a latent class Poisson model that accounts for heterogeneity in both the base mean event rate (constant term) and the regression coefficients. The parameters of the model can be estimated using maximum likelihood estimation and numerical methods. Using data on consumer purchases of books through direct mail, they found that the latent class Poisson model had greater explanatory power than the negative binomial model and was able to identify the sources of heterogeneity in the parameters for the latent groups.

During the past several years, a rapid increase in computing power has provided new, simulation-based tools for conducting econometric analysis that allows heterogeneity to be modeled as parameters that are randomly distributed across individuals (Gouriéroux and Monfort 1996). In the Poisson model with heterogeneity, the pdf has the general form (Gouriéroux and Monfort 1991):

(4) $$\Pr(q_i | X_i, \nu_i; \theta) = (1/q_i!)\exp[-\exp(X_i\beta + \Gamma\nu_i)]\exp[q_i(X_i\beta + \Gamma\nu_i)]$$

where ν_i is a vector of unobserved heterogeneity factors associated with β; Γ is a diagonal matrix of standard errors that scale the heterogeneity factors; and θ is the full parameter vector of βs and their standard errors (e.g., for parameter k, $\beta_{k,i} = \beta_k^0 + \gamma_k \nu_{k,i}$). Because ν_i is unobserved, equation (4) cannot be used to define a likelihood function, and it is necessary to integrate this factor out. This can be accomplished by specifying a parametric pdf, $g(\nu_i)$, that has a known distribution.

Given this structure, the log-likelihood for the random parameters count data model is:

(5) $$\log L = \Sigma_i \log \int_{\nu i} \Pr(q_i | X_i, \nu_i; \theta) g(\nu_i) d\nu_i$$

where $g(\nu_i)$ is the mixing function. Except for some special cases, such as the gamma distribution that produces the closed-form negative binomial distribution, the integral in equation (5) cannot be computed analytically. Integration of the random parameter model encounters numerical problems arising from the large number of integrals that must be evaluated, which are equal to the number of individuals in the sample.

The problem of an intractable number of integrals can be solved using simulated maximum likelihood methods (Gouriéroux and Monfort 1996). Define an unbiased simulator of $\Pr(q_i | X_i, \nu_i; \theta)$ as $\Pr^*(q_i | X_i, \nu_i; \theta)$. Then, a simulated maximum likelihood estimator for the parameter vector θ is

(6) $\max_\theta \Sigma_i \log[(1/R)\Sigma_r \Pr^*(q_i | X_i, \nu_i; \theta)]$

where a large number R of simulated draws (r = 1, …, R) from the distribution of ν_i replace the integral in equation (5) with a simulated average, which is approximately equivalent when the number of simulated draws is large. Maximization of the simulated maximum likelihood function produces a vector of mean values for the random parameters β and a diagonal matrix of standard errors Γ that describe the distribution of β across the sample of individuals.

In the analysis reported below, we evaluate the stability of parameter estimates by conducting R = 50, 100, 250, 500, 750, and 1,000 draws for the simulations. As it is generally unknown which parameters might exhibit statistically significant random variation, we test for heterogeneity across a small set of individual characteristics that are likely to be of interest to recreation managers (age, education, income, and experience). However, we do not test for heterogeneity in the travel cost variable. Consumer surplus per trip can then be computed as $1/\beta_{tc}$, where β_{tc} is the parameter estimate associated with travel cost.[3] We anticipate that accounting for unobserved heterogeneity will improve the fit of the random parameter model relative to the model in which heterogeneity is ignored. Further, by explaining some of the variation in the dependent variable (number of trips) via inclusion of the heterogeneity factors, we anticipate that the (non-stochastic) parameter estimate of the travel cost variable (β_{tc}) might be altered, thus affecting consumer surplus estimates. Further, based on descriptive statistics characterizing OHV participants in the South (Cordell et al. 2005), we anticipate that demand may be inversely related to age, income, and education.

Study Area and Data Collection

Data were collected at four OHV recreation sites within National Forests in North Carolina. Three sites are located in the Southern Appalachian Mountains (Upper Tellico, Wayehutta, and Brown Mountain) and one site is located in the Uwharrie Mountains of the Piedmont (Badin Lake). Upper Tellico OHV is a premier regional site covering 8,000 acres in the Nantahala National Forest. This site is highly scenic and the steep, rugged trails are designed for use by experienced riders only. Wayehutta OHV is located in the Roy Taylor section of the Nantahala National Forest and has 28 miles of trails ranging from easy to most difficult. Brown Mountain OHV is located in the Pisgah National Forest and has 34 miles of trails offering recreational opportunities for beginning to advanced riders. Badin Lake OHV is located in the Uwharrie National Forest and is not as high in elevation as the other sites. This site offers over 20 miles of trails that are suited for all classes of riders.

Data were collected using a paper and pencil survey administered on-site to riders as they were exiting the trail system during the summer of 2000. Volunteers from local trail riding organizations were used to solicit respondents and to monitor the data collection process. The use of volunteers was thought to increase the likelihood that riders would agree to participate in the survey.[4] Data were collected over several weekends at various times during the day with the goal of obtaining 100 complete surveys per site. Only one rider per party was asked to respond to the survey. Although random sampling procedures were not used, an attempt was made to obtain data from a diverse sample.

The survey consisted of an eight-page booklet and twenty-five 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. For the analysis reported here, an attempt was made to isolate respondents making single day trips to individual sites. This was accomplished by excluding multi-

[3] Annual consumer surplus can be computed as (predicted trips/ β_{tc}) where the predicted number of trips will vary across the sample due to parameter heterogeneity.

[4] Data were not recorded regarding the number of refusals, so a response rate could not be computed.

ple day trips from the analysis.[5] Also, in an attempt to minimize recall bias, trips taken to sites other than the site at which the survey was administered were not used in the analysis. Thus, a maximum of three observations per respondent regarding the number of trips taken were available for analysis. A single-site model was specified for each OHV site.[6]

Respondents provided information regarding their zip code, which allowed us to compute their two-way travel distance. Travel costs were computed using a cost of 31 cents per mile, plus an opportunity cost of time based on one-third of their hourly wage or salary for the estimated time spent traveling.[7] Respondents were also asked to provide responses to attitudinal questions, the number of years they had been riding OHVs, type(s) of vehicle(s) used, OHV related expenses, age, education, and income.

Because it is generally unknown which parameters in a travel cost model of recreation demand might exhibit significant heterogeneity, we specified a simple demand model with travel cost (COST); years of riding experience (YEARS); years of education (SCHOOL); age (AGE); and income (INCOME) included as explanatory variables. All of the explanatory variables except COST were specified to have normally distributed random parameters. For the random parameter models, 1,000 Halton draws were used for the simulated maximum likelihood algorithm. Halton draws can reduce computer time relative to simple random draws, while at the same time improving accuracy (Train 2003).

Results

Overall, 357 questionnaires were collected. Surveys with complete responses for the variables included in the model specification were available for 90 respondents at Upper Tellico OHV site (114 observations across years); 31 respondents at Wayehutta OHV site (68 observations across years); 70 respondents at Brown Mountain OHV site (138 observations across years); and 82 respondents at Badin Lake OHV site (120 observations across years).

Descriptive statistics from the sample of respondents shows that, on average, OHV riders are generally young (32 years old); predominantly male (88 percent); middle-class ($50,100 annual family income); and have some college education (13.6 years of education) (Table 1). These results are quite similar to the demographic characteristics reported by Cordell et al. (2005) for OHV riders in the southern United States and provide some confidence that the sampling procedure used at the National Forest sites was not grossly biased. Categorized by demographic class, the largest number of OHV participants in the South were from the 30-50 year old age group; they were male, had some college education, and had family incomes of $25,000-$49,999. However, the proportion of male riders obtained in the sample of respondents at North Carolina National Forests (88 percent) exceeded the proportion reported by Cordell et al. (2005) for the South (61 percent).

The descriptive statistics from the sample showed that ATVs (52 percent) and four-wheel drive vehicles (55 percent) were more commonly used than trail bikes (19 percent) at these sites. A small proportion of respondents had handicap parking permits (2 percent). Notably, a significant proportion of riders had received injuries while riding that required medical attention (13 percent). A moderate number of riders reported that drinking alcoholic beverages at OHV sites was a typical part of their OHV trip (21 percent). Respondents had, on average, nearly a decade of riding experience (9.8 years) and self-reported their skill level as mid-way between Intermediate and Advanced. Nearly one-half of the sample (45 percent) had volunteered to help maintain OHV trails, and the majority (77 percent) responded favorably when they were asked whether they thought user fees could be a good tool for managing public recreation areas. Average annual expenses incurred in pursuit of OHV riding were about $1,811 and riders spent about $7,053 on

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5 The data used in the analysis reported here constitute a subset of the data analyzed in Englin and Holmes (2006).

6 The sampling method may have over-sampled more avid riders, who were more likely to be riding during the sampling period than riders who frequent the sites less often. Given the structure of the data, it was not possible to adjust for endogenous stratification.

7 Mileage costs were based on standard rates reported by the Internal Revenue Service for 1999. Opportunity costs of time were computed based on an assumed average travel speed of 50 miles per hour.

Table 1. Descriptive Statistics for a Sample of OHV Riders in North Carolina

Variable	Description	Mean	Std. dev.	N
INCOME	$1,000	50.1	0.01	282
AGE	Years	32	10.36	351
Male	Percent	88	0.33	345
SCHOOL	Years	13.6	2.47	354
Injury	Percent needing medical attention	13	0.33	354
Drinking	Percent responding drinking alcohol at OHV site is typical part of trip	21	0.41	354
Handicap	Percent having a Handicapped Parking Permit	2	0.13	357
YEARS	Number of years riding experience	9.8	8.5	354
Skill	Self-reported 3-point scale (Beg.-Int.-Adv.)	2.5	0.6	342
ATV	Percent of respondents who ride this vehicle	52	0.50	354
4WD	Percent of respondents who ride this vehicle	55	0.49	354
Trail bike	Percent of respondents who ride this vehicle	19	0.39	354
Annual expense	Average spent per year on OHV equipment and gear, dollars	1,811	2,240	315
Most recent purchase	Expenditure on most recent OHV, dollars	7,053	6,816	327
User fee	Percent agreeing user fees are a good idea	77	0.43	342
Volunteer	Percent volunteered to maintain trails	45	0.50	351

Note: Variables in all capital letters are included in the econometric models.

their most recent OHV purchase. The relatively high outlay of equipment-related expenses differentiates OHV riding from many other forms of outdoor recreation.

For each of the OHV sites studied, the McFadden pseudo-R^2 goodness-of-fit statistic for the random parameter model greatly exceeded the corresponding value for the non-random parameter model (Tables 2-5).[8] Over-dispersion tests for the non-random Poisson model, which follow a χ^2 distribution with one degree of freedom, all exceeded the critical level, suggesting the presence of unobserved heterogeneity in the data. The random parameter models were all successful in identifying heterogeneity in the recreation demand parameters.[9] The mean of the random parameter, the standard deviation of the random parameter, or both, were statistically different than zero at the 0.05 level or higher for all respondent characteristics at every OHV site. In contrast, some of the parameters for respondent characteristics were not significantly different than zero (at conventional levels) in some of the non-random Poisson models.

The signs on the parameter estimates in the non-random Poisson model were not always consistent with our expectations [which were based on a description of demographic characteristics associated with OHV participation in Cordell et al. (2005)]. Consistent with our expectations, the

[8] The McFadden pseudo-R^2 is computed as $(1\text{-}L_0/L_1)$ where L_0 is the log-likelihood with constraints (constants only) and L_1 is the log-likelihood for the unconstrained model.

[9] In results not reported here (but available from the authors), we note that the random parameter Poisson model also consistently fit the data better than the negative binomial model.

Table 2. Count Data Models for Brown Mountain OHV Area

Variable	Poisson model parameters	Poisson model parameters with heterogeneity
	Non-random parameters	
Constant	1.023** (0.492)	--
COST	-0.146** (0.007)	-0.042*** (0.007)
YEARS	-0.160* (0.010)	--
AGE	-0.023*** (0.007)	--
SCHOOL	0.030 (0.041)	--
INCOME	0.009*** (0.002)	--
	Means for random parameters	
Constant	--	0.279 (0.691)
YEARS	--	-0.009 (0.010)
AGE	--	-0.021*** (0.008)
SCHOOL	--	-0.016 (0.059)
INCOME	--	0.005* (0.003)
	Standard deviation for random parameters	
Constant	--	0.032 (0.070)
YEARS	--	0.031*** (0.006)
AGE	--	0.013*** (0.002)
SCHOOL	--	0.157*** (0.011)
INCOME	--	0.037*** (0.003)
Nobs	138	138
$1-L_1/L_0$	0.05	0.67
Consumer surplus, per trip	$68.49	$24.04

Note: Numbers in parentheses are standard errors. * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; and *** denotes significance at the 0.01 level.

demand for trips was inversely related to respondent age (younger riders were found to be more avid)—statistically significant (negative) parameters on AGE were found for two sites. Likewise, the demand for trips was consistent with our expectation for education—statistically significant (negative) parameters were estimated for the variable SCHOOL at two sites. However, the nonrandom Poisson model consistently found a positive, and statistically significant, parameter estimate on income, which was contrary to our expectation.

The Poisson model with random parameters provided a richer description of OHV preferences than the standard Poisson model (Table 6). For example, consider the impact of income on recreation demand. The standard Poisson model indicated a statistically significant income effect,

Table 3. Count Data Models for Badin Lake OHV Area

Variable	Poisson model parameters	Poisson model parameters with heterogeneity
	Non-random parameters	
Constant	2.727*** (0.354)	--
COST	-0.046*** (0.006)	-0.095*** (0.010)
YEARS	0.012 (0.008)	--
AGE	-0.004 (0.007)	--
SCHOOL	-0.114*** (0.030)	--
INCOME	0.023*** (0.003)	--
	Means for random parameters	
Constant	--	2.179 (0.394)
YEARS	--	-0.023*** (0.009)
AGE	--	-0.041*** (0.012)
SCHOOL	--	-0.041 (0.026)
INCOME	--	0.035*** (0.004)
	Standard deviation for random parameters	
Constant	--	0.448*** (0.064)
YEARS	--	0.053*** (0.005)
AGE	--	0.074*** (0.005)
SCHOOL	--	0.030*** (0.005)
INCOME	--	0.002** (0.001)
Nobs	120	120
$1\text{-}L_1/L_0$	0.16	0.77
Consumer surplus, per trip	$21.74	$10.11

Note: Numbers in parentheses are standard errors. * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; and *** denotes significance at the 0.01 level.

Table 4. Count Data Models for Upper Tellico OHV Area

Variable	Poisson model parameters	Poisson model parameters with heterogeneity
	Non-random parameters	
Constant	3.075*** (0.496)	--
COST	-0.0115*** (0.002)	-0.048*** (0.005)
YEARS	0.097*** (0.010)	--
AGE	-0.023*** (0.009)	--
SCHOOL	-0.196*** (0.045)	--
INCOME	0.015*** (0.002)	--
	Means for random parameters	
Constant	--	4.078*** (0.745)
YEARS	--	0.072*** (0.013)
AGE	--	0.012 (0.012)
SCHOOL	--	-0.369*** (0.064)
INCOME	--	0.013*** (0.004)
	Standard deviation for random parameters	
Constant	--	0.206*** (0.071)
YEARS	--	0.026*** (0.006)
AGE	--	0.027*** (0.003)
SCHOOL	--	0.082*** (0.008)
INCOME	--	0.034*** (0.003)
Nobs		114
$1\text{-}L_1/L_0$	0.21	0.75
Consumer surplus, per trip		$20.96

Note: Numbers in parentheses are standard errors. * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; and *** denotes significance at the 0.01 level.

Table 5. Count Data Models for Wayehutta OHV Area

Variable	Poisson model parameters	Poisson model parameters with heterogeneity
Non-random parameters		
Constant	0.687 (0.894)	--
COST	-0.008** (0.003)	-0.025*** (0.005)
YEARS	0.017** (0.008)	--
AGE	-0.001 (0.007)	--
SCHOOL	0.019 (0.067)	--
INCOME	0.001 (0.002)	--
Means for random parameters		
Constant	--	0.556 (0.884)
YEARS	--	-0.005 (0.008)
AGE	--	-0.023*** (0.012)
SCHOOL	--	0.073 (0.063)
INCOME	--	0.013*** (0.004)
Standard deviation for random parameters		
Constant	--	0.400*** (0.083)
YEARS	--	0.037*** (0.005)
AGE	--	0.052*** (0.005)
SCHOOL	--	0.032*** (0.006)
INCOME	--	0.004*** (0.001)
Nobs	65	65
$1\text{-}L_1/L_0$	0.03	0.72
Consumer surplus, per trip	$65.00	$40.50

Note: Numbers in parentheses are standard errors. * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; and *** denotes significance at the 0.01 level.

at the 0.01 level of significance, for three of the four OHV sites. The signs on the estimated parameters were all positive, indicating that the number of trips increased along with income (each $1,000 increase in income added about 0.9–2.3 trips per year). The random parameter estimates of the income effect, however, present a more nuanced interpretation. First, note that the random parameter estimate on income at Badin Lake OHV has the same sign as the non-random model, although the magnitude is somewhat larger, and the standard error estimate indicates

Table 6. Impact of Respondent Heterogeneity on Sign of Estimated Preference Parameters in Comparison with Sign of Estimated Preference Parameters in Non-Random Model

	Brown Mtn.	**Badin Lake**	**Upper Tellico**	**Wayehutta**
YEARS	**61% - | 39% +**	**67% - | 33% +**	**1% - | 99% +**	**55% - | 45% +**
	(-)	(+)	**(+)**	**(+)**
AGE	**95% - | 5% +**	**71% | 29% +**	**33% - | 67% +**	**67% - | 33% +**
	(-)	(-)	**(-)**	(-)
SCHOOL	**54% - | 46% +**	**91% - | 9% +**	**99% - | 1% +**	**1% | 99% +**
	(+)	**(-)**	**(-)**	(+)
INCOME	**45% - | 55% +**	**0% | 100% +**	**35% | 65% +**	**0% | 100% +**
	(+)	**(+)**	**(+)**	(+)

Note: Estimated sign of preference parameters for non-random model shown in parentheses; **bold** indicates statistical significance at the 0.10 level or higher.

that the positive income effect applied to all respondents. Second, a positive income effect applying to all respondents was also identified in the random parameter model for Wayehutta OHV, although the non-random model indicated that income did not have an effect on the demand for trips. Third, a bimodal income effect was identified for Upper Tellico and Brown Mountain OHV sites. Plotting a normal distribution with the estimated mean and standard deviation for Upper Tellico, it can be seen that roughly 35 percent of the respondents have a negative income effect (Figure 1). At both Upper Tellico and Brown Mountain OHV sites, the most avid riders were found among those respondents with the lowest and the highest income levels. This bimodal distribution of the income effect was not evident in the non-random parameter model. Bimodal use patterns associated with other respondent characteristics were identified at each of the OHV

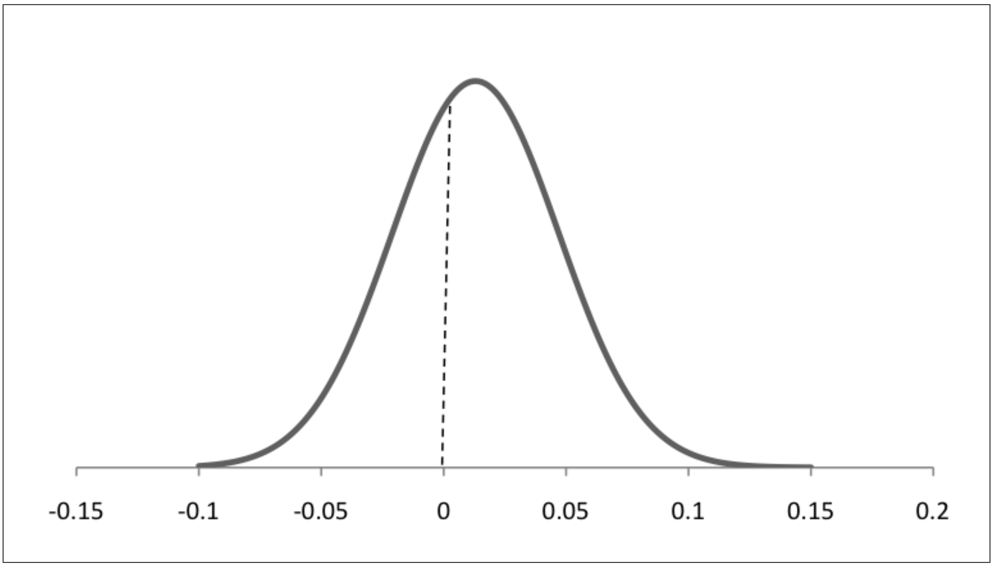
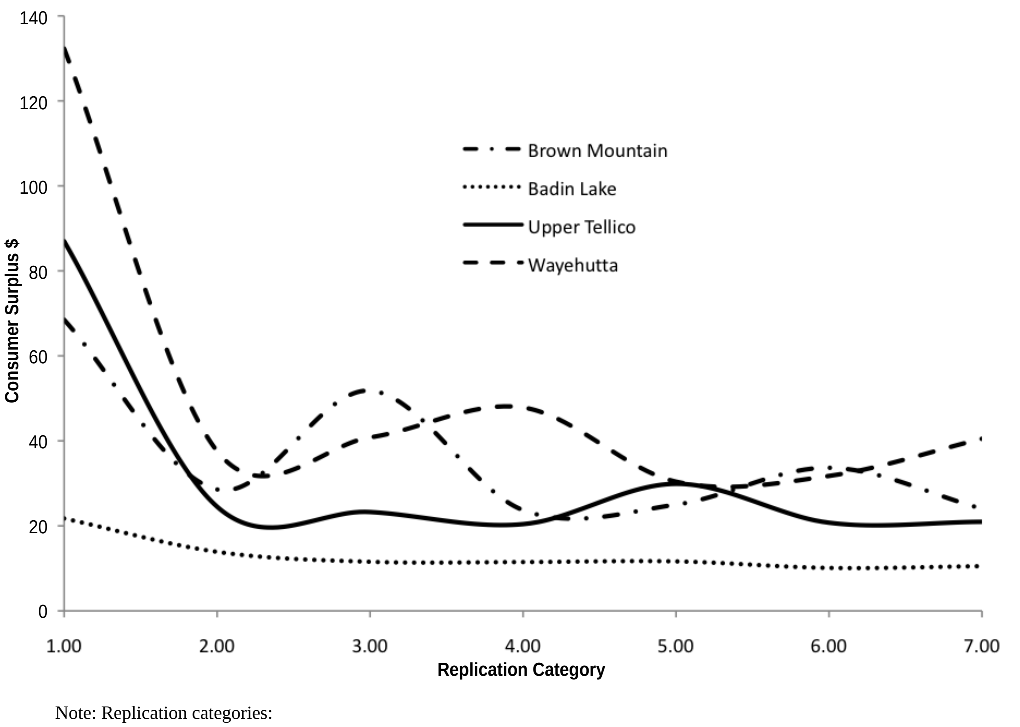


Figure 1. Distribution of Heterogeneous Income Parameter Estimated for Upper Tellico OHV Area

sites, and the degree of bimodality varied substantially across sites for each respondent characteristic studied (Table 6).

Parameter estimates on the travel cost variable (β_{tc}) were negative and statistically significant at the 0.05 level or greater in each of the non-random parameter model specifications, and at the 0.01 level in each of the random parameter model specifications (Tables 2-5). Estimates of consumer surplus per trip ($1/\beta_{tc}$) were found to be lower in each of the random parameter models relative to the corresponding non-random parameter model. Although it is unclear exactly why this result occurred, it may be due to the effect of omitted explanatory variables in the non-random parameter model, which are included in the random parameter model in terms of a vector of heterogeneity factors. Consumer surplus estimates appeared to stabilize as the number of Halton draws increased from 50 to 1,000 (Figure 2). The consumer surplus estimates in the random parameter model with 1,000 Halton draws ranged from roughly \$10–\$40 per trip (\$11.72–\$46.88 in 2005 dollars). These values are similar to the revealed preference consumer surplus estimates reported by Bergstrom and Cordell (1991), Bowker, Miles, and Randall (1997), and Loomis (2006), although they are lower than some of the estimates reported by Englin, Holmes, and Sills (2006). When comparing values across sites, it should be kept in mind that data for the study reported here were structured so that only single-day trips were used for analysis.



Note: Replication categories:
(1) non-random parameter model, (2) 50 draws, (3) 100 draws, (4) 250 draws, (5) 500 draws, (6) 750 draws, (7) 1,000 draws.

Figure 2. Consumer Surplus Estimates as a Function of the Number of Halton Draws for Non-Price Heterogeneity Factors

Conclusions

The demand for OHV recreation on public land is growing rapidly and is anticipated to continue along a steep trajectory for the foreseeable future. The use of public land for this form of recreation is controversial due to the negative environmental impacts it creates and the necessary exclusion of other forms of recreation at OHV sites. Better information regarding the characteristics of OHV riders and the economic benefits generated by OHV recreation is needed by public land managers to help them formulate strategies for serving this segment of the population while protecting environmental quality.

Revenues collected via user fees at recreation sites provide one means of maintaining environmental quality at OHV sites. A large majority of the respondents to this survey indicated that they thought user fees could be a good tool for managing public recreation areas. Consumer surplus estimates per trip indicated that per trip user fees should be kept at a modest level to prevent the exclusion of potential riders. Further, a substantial number of respondents disagreed with the imposition of user fees to manage public recreation areas. Due to the fact that many respondents indicated they had volunteered to help maintain trails at public OHV areas, alternative approaches to site protection might be considered, such as the provision of user fee vouchers for volunteers in lieu of payment.

The random parameter Poisson model provides an attractive alternative for modeling heterogeneity in count data recreation demand. In this study, accounting for individual heterogeneity in parameter estimates associated with respondent characteristics greatly improved the statistical fit of the models at each OHV site. Further, a more nuanced description of OHV recreation demand parameters emerged from the random parameter analysis. Segments of the sample that contributed strongly to OHV demand at some sites, such as lower income riders, were identified in the random parameter models, whereas they would not have been evident in standard count data analysis. Understanding the degree of heterogeneity in recreation demand, both at OHV sites and more broadly, is an important and emerging arena for economic analysis.

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