

WELFARE LOSSES DUE TO LIVESTOCK GRAZING ON PUBLIC LANDS: A COUNT DATA SYSTEMWIDE TREATMENT

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Backcountry hikers' willingness-to-pay for removing grazing from trails in the Hoover Wilderness is analyzed using a multinomial Dirichlet negative binomial distribution. This multivariate discrete distribution allows the direct calculation of seasonal welfare measures that are derived from an incomplete demand specification. The welfare maximizing choice of activities is examined on a trail-by-trail basis using the results of the analysis. Our findings suggest that a mix of hiking and grazing activities provide the greatest social welfare.

Key words: grazing, incomplete demand system, multinomial Dirichlet, multivariate counts, negative binomial, public lands.

A pressing public issue in the United States is the competition between grazing and other uses for public lands. While the price of grazing permits is an administrative decision, the values of the public lands in other uses is a nonmarket issue. One of the competing recreational uses is backcountry hiking. Backcountry hiking is an especially interesting competing use because the conflict is so direct. The issue is that people are viewing cattle or sheep and sharing the ecosystems with these animals.

An example of this conflict is the Hoover Wilderness of eastern California. When the Hoover Wilderness was created, the enabling legislative act grandfathered historical grazing activities. While hiking had been going on for some time in this area, the designation as wilderness brought with it an administrative structure that now accounted for hiking as well as grazing in the area's management. As a result, both grazing and backcountry hiking are managed by the Forest Service. Thus, the Hoover Wilderness represents an ideal microcosm of a phenomenon that has surfaced throughout the

West as federal grazing lands are converted to more general use. Our analysis utilizes data from the Hoover Wilderness to estimate the willingness-to-pay by backcountry hikers to reduce grazing and to provide estimates of the value of several ecosystems and other trail characteristics.

This study synthesizes the elements necessary to treat multiple site travel cost models of recreation demand, when the decision variables are measured as trip counts. A multivariate count data probability model is shown to provide a link between conventional logit models of trip allocation and count data models of trip demand. Because this model generates conditional demands with exponential form, a proper incomplete demand structure (LaFrance and Hanemann, 1984; von Haefen) is imposed to insure that exact welfare analysis can be performed.

We proceed by discussing recreation demand-modeling approaches and establishing the relationship between conditional logit models of site choice and incomplete demand systems of exponential form. Next, the multinomial Dirichlet (MnD) model is introduced and linked with an aggregate count data distribution in order to address the system wide count data structure admitted by the incomplete demand model. Then data from backcountry hiking trips in the Hoover Wilderness are fitted to a linear exponential demand model using this distribution. Welfare measures associated with changes in grazing

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activities are derived and certain policy implications are considered.

Behavioral Models and Econometric Methods

A conventional recreation site choice model is the conditional multinomial logit model of McFadden. McFadden's conditional logit model (and generalizations such as the random parameter logit model; Train) possesses useful properties for analyzing the site-allocation problem because visitation data are discrete and the model can be easily used to estimate exact per trip welfare measures for site quality changes under the notion of random utility. This model, while quite popular because of its attractive features in dealing with multiple sites, is problematic when seasonal welfare changes are of interest since the logit's site-specific demands are estimated conditional on total demand for all sites. A number of researchers (Bockstael, Hanemann, and Kling; Hausman, Leonard, and McFadden; Feather, Hellerstein, and Tomasi; Shaw and Shonkwiler, *inter alia*) have raised the point that consumer's surplus measures should come from some aggregate or unconditional demand function rather than from the site-specific conditional demands, because the former allows total seasonal consumption to change in response to site quality and price changes and the latter does not.

We are interested in the techniques that generate a demand system that allows calculation of unconditional welfare measures and can accommodate the discrete nature of the demand quantities. An incomplete demand system appears to be a tractable candidate. The incomplete demand system specification is attractive because the preference structure it identifies is consistent with rational models of consumer behavior. Incomplete demand models can be related to an underlying utility maximization subject to a linear budget constraint and can be used to conduct well-defined welfare analyses (LaFrance and Hanemann 1989). The key assumption of an incomplete demand system is that prices outside the set of goods of interest do not vary. If this maintained hypothesis is reasonable, then unconditional welfare measures can be computed from a properly specified incomplete demand system. Given that prices of other goods are constant, the utility maximization problem under a linear budget constraint yields a system of incomplete demands that satisfy Slutsky symmetry and pro-

vide exact welfare measures for price changes of the goods of interest.

Behavioral Model

The functional form chosen for modeling the relationship between expected demands and conditioning variables dictates the restrictions needed to assure the integrability of the incomplete demand system. Fortunately, LaFrance and Hanemann (1984) and von Haefen (2002) have considered a number of functional forms and have detailed the restrictions consistent with integrability.

If the site-specific expected demands for $j = 1, 2, \dots, J$ sites take the form

$$(1) \quad E(y_j) = \alpha_j \exp\left(\sum_{k=1}^J \beta_{jk} p_k + \theta_j I\right) = \gamma_j$$

where p_k represents the price of the k th ($k = 1, 2, \dots, J$) site, I denotes household income and the observational index has been suppressed, one set of restrictions consistent with an incomplete demand system of this form is (LaFrance and Hanemann 1984): $\alpha_j > 0$ and $\beta_{jj} (0 \forall j, \beta_{jk} = 0 \forall j \neq k, \text{ and } \theta_j = \theta \forall j$. These restrictions result in this incomplete demand system having J free own-price parameters and one income coefficient. Therefore there are $(1 + 1/2J) \times (J - 1)$ price and income parameter restrictions implied by this functional form if it is to be consistent with the optimizing behavior underlying the incomplete demands. The requirement of zero Marshallian (not Hicksian) cross-price effects is a necessary restriction for integrability just as the restriction that Marshallian cross-price effects equal Hicksian cross-price effects is required in a linear incomplete demand system. As von Haefen points out, the requirement that expected demands be integrable and possess strictly positive values results in models, which do not admit both flexible income and Marshallian cross-price effects.

Individual-specific factors can enter the incomplete demand model and still satisfy the integrability restriction that $\alpha_j > 0$ by recognizing that we can specify $\alpha_j = \exp(a_j)$ where a_j is itself a function of conditioning variables that may correspond to an individual or household. Note that this specification may be restricted to reproduce the basic form of the standard conditional multinomial logit model (see equation (6)) which does not admit different own-price coefficients, income, or other individual-specific shifters. This is easily accomplished by requiring that $\beta_{jj} = \beta$ and

$\theta_j = 0 \forall j$ so a single price coefficient is obtained. These additional restrictions result in the model

$$(2) \quad E(y_j) = \alpha_j \exp(\beta p_j) = \gamma_j.$$

These restrictions imply a quasi-indirect utility function and expenditure function associated with this demand system which are (LaFrance and Hanemann 1984), respectively

$$(3) \quad v(p, I) = I - \beta^{-1} \sum_{j=1}^J \alpha_j \exp(\beta p_j) \\ = I - \beta^{-1} \sum_{j=1}^J \gamma_j$$

$$(4) \quad e(p, u) = u + \beta^{-1} \sum_{j=1}^J \alpha_j \exp(\beta p_j) \\ = u + \beta^{-1} \sum_{j=1}^J \gamma_j$$

where u denotes utility.

Now these expressions can be used to estimate the welfare effects of changes in prices and, under certain circumstances, changes in environmental goods. This leads to consideration of the comparison of these welfare measures to those obtained from the more familiar conditional logit model. To illustrate the relationship among welfare measures, assume one or more of the α_j include an environmental amenity which when increased yields a new level $\alpha_j^* \geq \alpha_j$. The change in consumer's surplus under the incomplete demand specification is

$$(5) \quad S_1 = \beta^{-1} \left(\sum_{j=1}^J \alpha_j \exp(\beta p_j) - \sum_{j=1}^J \alpha_j^* \exp(\beta p_j) \right) \\ = \beta^{-1} \left(\sum_{j=1}^J E(y_j) - \sum_{j=1}^J E(y_j^*) \right) \\ = \beta^{-1} \left(\sum \gamma_j - \sum \gamma_j^* \right).$$

The logit model may be parameterized so that

$$(6) \quad E(\pi_j) = \frac{\alpha_j \exp(\beta p_j)}{\sum_{j=1}^J \alpha_j \exp(\beta p_j)} = \frac{\gamma_j}{\sum_{j=1}^J \gamma_j}$$

with the $E(\pi_j^*)$ defined analogously. This formulation leads to the well-known per trip surplus measure (Small and Rosen)

$$S_t = \beta^{-1} \left(\ln \sum_{j=1}^J \alpha_j \exp(\beta p_j) - \ln \sum_{j=1}^J \alpha_j^* \exp(\beta p_j) \right) \\ = \beta^{-1} \left(\ln \sum \gamma_j - \ln \sum \gamma_j^* \right).$$

Two choices exist for scaling up the per trip surplus measure S_t . They are (i) multiply S_t by total expected trips before the amenity change, or (ii) multiply by total trips after the amenity change. These measures are defined as

$$S_0 = S_t \sum_{j=1}^J E(y_j) = S_t \sum \gamma_j$$

and

$$S_2 = S_t \sum_{j=1}^J E(y_j^*) = S_t \sum \gamma_j^*.$$

Note that γ_j have been scaled such that the expected value of their sum equals the sum of y_j .

It may be shown that when $\gamma_j > 0$ and $\gamma_j^* \geq \gamma_j \forall j$ then $S_0 \leq S_1 \leq S_2$.¹ Thus scaling up the per trip consumers surplus measure from the random utility model by expected demand either before or after the amenity change provides bounds to the surplus measure obtained from the restricted incomplete demand system given in equation (2). Of course these results may be applied to the valuation of nonmarket goods only if the welfare effects of amenity changes can be completely recovered from the site-specific demands (LaFrance 1994). This notion is further developed by Ebert (1998) who shows that if the marginal willingness-to-pay functions for the environmental goods can be inferred from the specification of the incomplete demand system then unambiguous

¹ The proof follows by expressing each S_i in terms of β , $(\sum \gamma_j)$, and $\sum \gamma_j^*$. Let c and c^* represent the two summations and multiply the inequality by the positive quantity $-\beta$ to yield $\ln(c^*/c) \leq c^* - c \leq c^* \ln(c^*/c)$. To prove the left-hand side of the inequality, divide by c to obtain $\ln(c^*/c) \leq c^*/c - 1$. Since $\ln k \leq k - 1$ ($k > 0$), let $k = c^*/c$. To prove the right-hand side of the inequality, divide by c^* , recognize that $\ln(c^*/c) = -\ln(c/c^*)$, and arrange terms to obtain $\ln(c/c^*) \leq c/c^* - 1$. The proof follows from substituting $k = c/c^*$.

welfare measures can be determined for these environmental goods.²

Econometric Approach

Our objective in this analysis is to model counts of trips without assuming the independence of each trip or conditioning on total seasonal trips. Let Y_{nj} denote the number of trips from the n th ($n = 1, 2, \dots, N$) origin to the j th ($j = 1, 2, \dots, J$) individual site. Let $Y_n = \sum_{j=1}^J Y_{nj}$ denote aggregate trips to the wilderness area from the n th origin. A common approach to deriving a multivariate distribution is to express it as the product of a conditional distribution and a marginal distribution. In the present context, suppressing the observational index n , this may be represented by $P(Y_1 = y_1, Y_2 = y_2, \dots, Y_J = y_J | Y) \cdot P(Y = y)$. The multinomial logit model is a popular choice for the conditional probability mass function; however Johnson, Kotz, and Balakrishnan show that this implies that the marginal distributions of each Y_j are Poisson distributed and perforce the distribution of aggregate trips is also Poisson distributed. Yet, as Cameron and Trivedi (p. 60) point out, it is commonplace for count data to be overdispersed. In this case, the data generating process is not truly Poisson.

Suppose instead that the distribution of Y is negative binomial, $Nb(\mu, \theta)$, such that $V(Y) = \mu(1 + \mu\theta)$. Now overdispersion can be accommodated. Further, suppose the joint conditional distribution for the y_1, y_2, \dots, y_J is taken to be multinomial, $Mn(\pi_1, \pi_2, \dots, \pi_J | Y)$. Then it follows that the unconditional results are $E(y_j) = \mu_j$, $V(y_j) = \mu_j(1 + \mu_j\theta)$, and $cov(y_i, y_j) = \theta\mu_i\mu_j$. This will be termed the multinomial-negative binomial model (Mn-Nb). However, as Shonkwiler and Hanley have

pointed out, the marginal distributions of the counts should be Poisson distributed under the multinomial model. Yet if the sum of the y_j , Y , is specified to be $Nb(\mu, \theta)$ then the marginal distributions of its components, the y_j , are consequently $Nb(\mu_j, \theta)$. As a consequence, the multinomial-negative binomial joint probability mass function is not internally consistent unless $\theta = 0$.

To derive a more general conditional distribution of y_j , consider that the trips are independently distributed with probability generating function $pgf_j = (1 + \rho - \rho t)^{-\gamma_j}$. The probability generating function of Σy_j is then of the form $(1 + \rho - \rho t)^{-\Sigma \gamma_j}$. The marginal probability mass function is

$$P(Y_j = y_j) = \frac{\Gamma(\gamma_j + y_j)}{\Gamma(\gamma_j)\Gamma(y_j + 1)} q^{y_j} (1 - q)^{\gamma_j}$$

where $q = \rho/(1 + \rho)$. Thus, $y_j \sim Nb(\gamma_j, \rho)$ and $E(Y_j) = \gamma_j\rho$ and $V(Y_j) = \gamma_j\rho(1 + \rho)$. The joint conditional distribution $P(Y_1 = y_1, Y_2 = y_2, \dots, Y_J = y_J | Y)$ is

$$\prod_{j=1}^J \frac{\Gamma(\gamma_j + y_j)}{\Gamma(\gamma_j)\Gamma(y_j + 1)} q^{y_j} (1 - q)^{\gamma_j} / \frac{\Gamma(\Sigma \gamma_j + \Sigma y_j)}{\Gamma(\Sigma \gamma_j)\Gamma(\Sigma y_j + 1)} q^{\Sigma y_j} (1 - q)^{\Sigma \gamma_j}$$

or equivalently

$$(7) \quad P(Y_1 = y_1, Y_2 = y_2, \dots, Y_J = y_J | Y) = \frac{Y! \Gamma(\Sigma \gamma_j)}{\Gamma(Y + \Sigma \gamma_j)} \times \prod_{j=1}^J \frac{\Gamma(\gamma_j + y_j)}{\Gamma(\gamma_j)\Gamma(y_j + 1)}$$

Termed the compound multinomial (Mosi-mann) or the fixed-effects negative binomial (Hausman, Hall, and Griliches) or multinomial Dirichlet (Mnd), Mosimann derived this distribution by assuming the multinomial probabilities $Mn(\pi_1, \pi_2, \dots, \pi_J | Y)$ have Dirichlet distribution and noted that

$$E(\pi_j) = \gamma_j / \Sigma \gamma_j$$

and

$$cov(\pi_i, \pi_j) = \gamma_i \gamma_j \left(\frac{1}{(\Sigma \gamma_j + (\Sigma \gamma_j)^2)} - \frac{1}{(\Sigma \gamma_j)^2} \right) < 0.$$

² For example, consider the case where an environmental good, g , enters the quasi-indirect utility and expenditure functions through the parameter α_j . We explicitly adopt the form $\alpha_j = \exp(a_j + a_g g)$. Following Ebert, the marginal willingness-to-pay function, w_g , may be inferred from the quasi-indirect utility function equation (3) according to

$$w_g = \frac{\partial v / \partial g}{\partial v / \partial I} = -a_g B^{-1} \sum_{j=1}^J \alpha_j \exp(\beta p_j).$$

However, this additional unknown parameter, a_g , may be estimated directly because differentiation of the implied quasi-indirect expenditure function yields a demand system having the form $E(y_j) = \exp(a_j + a_g g + \beta p_j)$. Further, the conditions for weak integrability are met since $\partial y_j / \partial g = -\partial w_g / \partial p_j$, a requirement under the no-income effects model. This system conforms to the third example considered by Ebert (p. 252), who notes that estimation of welfare effects is possible as long as the prices of the market commodities excluded from the incomplete demand system are held constant.

Woodland has recognized the ability of the Dirichlet distribution to limit shares to the unit simplex and gives several compelling arguments why the shares would likely be negatively correlated. Morey et al. have extended this discussion to the case where shares lie on the boundaries of the unit simplex and correctly noted that the Dirichlet cannot be applied to data where zero shares are observed.

The multivariate multinomial Dirichlet can, however, be used in the boundary case problem because the multinomial parameters do not have a degenerate distribution in this situation. The multinomial Dirichlet, $MnD(\gamma_1, \gamma_2, \dots, \gamma_J | Y)$, in equation (7) is a conditional distribution. Recently, Shonkwiler and Hanley have applied this distribution in a random utility modeling context. In this context, γ_j are scaled to lie in the unit interval and sum to unity. Shonkwiler and Hanley introduced an additional parameter they called α (distinct from the current usage of α) to replace the term $\Sigma\gamma_j$. This representation of the multinomial Dirichlet nests the conventional conditional logit model and can accommodate data that are more variable than what would be expected under multinomial sampling. Similarly, we are concerned with discrete data series that are not likely individually Poisson distributed—a necessary property if their joint conditional distribution is to be multinomial.

The multinomial Dirichlet can be considered an allocation model that suggests the relationship $E(Y_j) \Sigma\gamma_j = \gamma_j Y$ resulting in an implicit link between Y and $\Sigma\gamma_j$. An unconditional distribution results when this conditional distribution is multiplied by a probability mass function of the conditioning variable Y . Exploiting the link to the distributions of the y_j we require that $Y \sim Nb(\Sigma\gamma_j, \theta)$ and the product of this marginal times the conditional distribution in equation (7) yields the joint unconditional probability mass function:

$$(8) \quad \frac{\Gamma(Y + \theta^{-1}) \Gamma(\Sigma\gamma_j)}{\Gamma(\theta^{-1}) \Gamma(Y + \Sigma\gamma_j)} \left(\frac{\theta^{-1}}{\Sigma\gamma_j + \theta^{-1}} \right)^{\theta^{-1}} \times \left(\frac{\Sigma\gamma_j}{\Sigma\gamma_j + \theta^{-1}} \right)^Y \prod_{j=1}^J \frac{\Gamma(\gamma_j + y_j)}{\Gamma(\gamma_j) \Gamma(y_j + 1)}.$$

Now the γ_j parameters directly affect the expected values of y_j and thus will likely be specified to depend on a set of predetermined variables according to $\gamma_j = \exp(X_j\beta_j)$. Additional flexibility can be obtained by modeling

the $E(Y) = \delta \Sigma\gamma_j = \mu$. This simply scales the sum of the hyperparameters by δ or, alternatively, $\ln(\delta)$ may be interpreted as a common intercept appearing in each expression for γ_j . This gives the multinomial Dirichlet-negative binomial, $MnD-Nb$, distribution

$$(9) \quad \frac{\Gamma(Y + \theta^{-1}) \Gamma(\Sigma\gamma_j)}{\Gamma(\theta^{-1}) \Gamma(Y + \Sigma\gamma_j)} \left(\frac{\theta^{-1}}{\mu + \theta^{-1}} \right)^{\theta^{-1}} \times \left(\frac{\mu}{\mu + \theta^{-1}} \right)^Y \prod_{j=1}^J \frac{\Gamma(\gamma_j + y_j)}{\Gamma(\gamma_j) \Gamma(y_j + 1)}.$$

Note that this is a valid joint probability density mass function when θ and $\delta > 0$ and $\gamma_j > 0 \forall j$. In principle, maximum likelihood estimation of this joint probability mass function should be no more difficult than that of the joint multinomial-negative binomial model. The log likelihood for the i th ($i = 1, 2, \dots, N$) independent observation would have the form

$$\begin{aligned} \ell_i = & \ln \Gamma(Y_i + \theta^{-1}) + \ln \Gamma\left(\sum_j \gamma_{ij}\right) \\ & - \ln \Gamma(\theta^{-1}) - \ln \Gamma\left(Y_i + \sum_j \gamma_{ij}\right) \\ & + \theta^{-1} \ln(\theta) + Y_i \ln\left(\delta \sum_j \gamma_{ij}\right) \\ & - (\theta^{-1} + Y_i) \ln\left(\delta \sum_j \gamma_{ij} + \theta^{-1}\right) \\ & + \sum_j \{\ln \Gamma(\gamma_{ij} + y_{ij}) \\ & - \ln \Gamma(\gamma_{ij}) - \ln \Gamma(y_{ij} + 1)\} \end{aligned}$$

where $Y_i = \sum_j y_{ij}$ and conditioning variables would be incorporated using the parameterization $\gamma_{ij} = e^{X_{ij}\beta_j}$. This distribution of both the allocation of trips and the sum of the trips across alternatives can be compared to the aforementioned multinomial-negative binomial model that has a scaled form as well.

Table 1 shows the moments of the $MnD-Nb$ distribution. The $MnD-Nb$ has additional flexibility to model the variance within and covariance between equations due to the fact that the scale parameter enters these equations in a more complicated fashion. Note that for certain parametric combinations of θ and ω , the $MnD-Nb$ can generate negative

Table 1. Moments of the MnD-Nb and the Mn-Nb Distributions with Scale Parameter

	MnD-Nb	Mn-Nb
$E(Y_j)$	$\delta\gamma_j$	$\delta\mu_j$
$V(Y_j)$	$\delta\gamma_j[1 + (1 + \theta)\omega(\delta + \delta\gamma_j) - \delta\gamma_j]$	$\delta\mu_j[1 + \theta\delta\mu_j]$
$\text{cov}(Y_i, Y_j)$	$\delta^2\gamma_i\gamma_j(1 + \theta)\omega - 1$	$\theta\delta^2\mu_i\mu_j$

Note: $\omega = \Sigma\gamma_j/(1 + \Sigma\gamma_j)$.

covariances across equations, whereas the Mn-Nb formulation restricts these to be everywhere positive. The ability to flexibly handle the interdependence between the count variables represents an important advancement in multivariate count data modeling. Notice that there is a relationship between the MnD-Nb and Mn-Nb models in the limit. If $\Sigma\gamma_j \rightarrow \infty$ then this implies that $\omega \rightarrow 1$, $\delta \rightarrow 0$, and $\delta\gamma_j \rightarrow \delta\mu_j$. In these circumstances, the multinomial Dirichlet negative binomial converges to the multinomial negative binomial.

To date most multivariate models of seasonal recreation demand have been derived either as extensions of the conditional logit model (repeated nested logit [e.g., Morey, Watson, and Rowe] and linked models [Terza and Wilson; Bockstael, Hanemann, and Kling; Hausman, Leonard, and McFadden; Feather, Hellerstein, and Tomasi]) or from incomplete demand systems (Englin, Boxall, and Watson; Shonkwiler). The multinomial Dirichlet negative binomial represents a more flexible estimator than the model of Englin, Boxall, and Watson which does not allow for overdispersion and non-zero correlations between trips. Additionally, this likelihood based approach to estimation is likely to be more familiar to practitioners than the generalized linear model formulation adopted by Shonkwiler. This makes the model an attractive alternative to existing approaches.

Data and Estimation

The study area is the Hoover Wilderness area. The Hoover Wilderness area is located on the east side of the Sierra Nevada Mountain range, close to the California-Nevada state borders. The primary wilderness recreation taking place in Hoover is backcountry hiking. One of the requirements for backcountry hiking is that a backcountry hiking permit be filled out. This analysis is based on permits for 1990, 1991, and 1992.

A total of 7,661 complete permits were submitted during these three years. Of these, 7,136

were for backcountry hiking, the activity under study here. The permits included the entry point of the hiking party and the originating zip code of the party. Using these pieces of information, travel distances were calculated using both computer programs and U.S. Forest Service maps. A total of 598 residential zip code origins in Nevada and California were used in this analysis in order to more reasonably infer that the main purpose of the trip to the wilderness area was for recreation there. Consequently, for the slightly more than 2,000 trips that originated outside California and Nevada, we assume that hiking in the Hoover Wilderness was not the sole purpose of these trips. This classification resulted in a sample of 5,113 permitted trips to the 14 trails.³

Trail characteristics were developed from U.S. Forest Service geographic information system information (GIS) and U.S. Forest Service and U.S. Geological Survey maps. The maps primarily provided information about campgrounds in the area of the trailhead, grazing allotments, and trail elevation. Vegetative characteristics were obtained from the timber inventory GIS. The ecosystems found in the Hoover Wilderness include Ponderosa/Jeffrey pine, mixed pine, riparian/meadow, and rocky alpine areas. These data were merged together by digitizing the trail maps and then laying the trail map layer onto the vegetative characteristics GIS layers. This allowed us to accurately calculate the number of acres of each ecosystem that were on each trail. Grazing allotments were then added to the data base by using a U.S. Forest Service grazing allotment map in conjunction with historical grazing figures.

Since the analysis is based on permit data there is no individual travel cost information. (Hellerstein has discussed the rationale for using aggregate trip data.) Following Englin and Mendelsohn (1991) who also worked with permit data like these, travel costs were calculated at \$0.25 per mile. While this is arbitrary, the

³ The trails are ordered according to the number of trips observed (trail number-trips): 1-2; 2-3; 3-8; 4-11; 5-16; 6-33; 7-53; 8-97; 9-128; 10-417; 11-799; 12-1,004; 13-1,125; 14-1,417.

welfare estimates can easily be converted by multiplying reported estimates by the ratio of a selected travel cost divided by the assumed travel cost of \$0.25 per mile.

Estimation Results

The multinomial Dirichlet negative binomial model was estimated using a maximum likelihood routine programmed in GAUSS. Table 2 reports the log likelihood of the estimated model, estimated coefficients, and associated standard errors. The likelihood estimates that are presented in table 2 are from a so-called penalized model. This likelihood includes a term to ensure that the estimated aggregate average number of trips to the Hoover Wilderness closely matches that of the observed average (if this is not the case, subsequent welfare calculations will not be able to reflect the average visitation rates of the sample). This factor is necessitated by the consequence that the negative binomial model, while a member of the linear exponential family for fixed and known θ (Gourieroux, Monfort, and Trognon), need not reproduce the average count when θ is estimated simultaneously with the conditional mean. In the empirical model, this penalty function only slightly decreases the likelihood from the unconstrained specification.⁴ Further, the impact of this penalty on the calculated robust (as per White) standard errors is investigated by also obtaining bootstrap standard errors. Table 2 indicates that both sets of standard errors correspond closely. In the one case, where they differ substantially (the Mixed Pine variable), the calculated standard error suggests a more liberal confidence interval.

The multinomial Dirichlet negative binomial was compared to the corresponding multinomial negative binomial model with the identical number of parameters and penalty. This latter model's log likelihood value was

-1351.92 at convergence. The models differ only in the distributional assumption underlying the conditional distribution of site-specific trips and thus are nonnested. Vuong's test of the superiority of the multinomial Dirichlet versus the multinomial specification yielded at test statistic of 3.04, which is distributed as standard normal under the null of no difference between the models. The test leads us to conclude with greater than 99% confidence that the multinomial Dirichlet better represents the data generating process. A direct consequence of the different specifications is the estimator of the covariances between the trip counts. While no average correlation from the multinomial Dirichlet is negative, they are uniformly smaller than those of the multinomial negative binomial.

Most of the ecosystems are positively valued as are high trails and campgrounds near the trailhead. Both sheep and cattle grazing have a negative impact on the utility of a backcountry hiking trip. Because the unit of observation is the residential zip code, the logarithms of the populations of these zip codes entered the model and were assigned parameters that could vary by trail. The rationale for the inclusion of the population variable centered on the idea that the more metropolitan origins likely focused their trips on the more well-known trails. The estimated parameters ($\beta_{n1}, \dots, \beta_{n14}$) for the population variable (n_j) show a diverse pattern of preferences for trails based on population of the zip code origin and generally support the notion that those from more populated areas have the propensity to visit the better-known trails. This observation is based on the fact that the six least visited trails have negative coefficients associated with the origin population; while the more popular remaining eight trails have positive coefficients associated with their origin populations.

Welfare Analysis

The econometric analysis provides estimates of the values of several natural features of the Hoover Wilderness Area trails. The value of the ecosystems will depend on what other characteristics are on the trail. For ecosystem valuation, the value of the ecosystem across pertinent trails is calculated rather than the total value of all ecosystems found on a given trail. The values are estimated by increasing the quantity of each ecosystem on trails, where

⁴ The penalized log likelihood for the i th observation was of the form $\ell_i - 0.5(Y - \bar{\mu})^2/N$. Agresti (pp. 614-15) considers the theoretical and empirical implications of penalized likelihood models. Since the penalized estimator is a quasi-likelihood and is in the spirit of a generalized estimator given that the objective function includes a function of the means of the data, the use of the robust or sandwich estimator of the parameter variance-covariance matrix is prescribed. The unpenalized and penalized estimators may be considered overlapping models in the terminology of Vuong and, as a consequence, a test of whether these two distributions are observationally identical can be constructed. This amounts to testing whether the variance statistic, ω_s^2 , is equal to zero (Vuong, pp. 320-21). The test statistic, $n\hat{\omega}^2$, is distributed as a weighted sum of chi-square distributions and its calculated value was 3.33 ($p = 0.238$). Therefore, we conclude that the penalized estimator is observationally equivalent to the unpenalized estimator.

Table 2. Multinomial Dirichlet–Negative Binomial Model. Log-Likelihood: –1244.98

Variable/Parameter	Coefficient	Standard Error	Asymptotic <i>t</i> -Value	Bootstrap ^a Standard Error ^a
Travel cost	–0.0183	0.0016	–11.3865	0.0018
Cattle AUMs (100) ^{1/2}	–0.8846	0.1766	–5.0083	0.1921
Sheep AUMs (100) ^{1/2}	–0.5892	0.0756	–7.7886	0.0588
Jeffrey/ponderosa pine (100 acre)	0.2653	0.0577	4.5953	0.0565
Riparian/meadow (100 acre)	2.0737	0.5422	3.8243	0.3559
Mixed pine (100 acre)	–0.0152	0.0163	–0.9316	0.0082
Rocky alpine (100 acre)	0.0672	0.0150	4.4648	0.0142
Highest elevation (100 ft)	0.0047	0.0026	1.7968	0.0025
Campground (yes = 1)	0.2910	0.1907	1.5260	0.2192
Log of scale (δ)	–1.0333	0.1641	–6.2982	0.1543
Variance (θ)	0.6318	0.0439	14.4029	0.0434
β_{n1}	–0.6127	0.1926	–3.1810	0.2203
β_{n2}	–0.4187	0.1983	–2.1118	0.2191
β_{n3}	–0.8110	0.1136	–7.1419	0.1256
β_{n4}	–0.4257	0.1212	–3.5133	0.1202
β_{n5}	–0.4241	0.1004	–4.2238	0.0993
β_{n6}	–0.3215	0.0868	–3.7057	0.0863
β_{n7}	0.6662	0.1399	4.7620	0.1245
β_{n8}	0.1020	0.1355	0.7524	0.1291
β_{n9}	0.1407	0.0964	1.4604	0.0973
β_{n10}	0.2957	0.0697	4.2403	0.0731
β_{n11}	0.2998	0.0682	4.3937	0.0705
β_{n12}	0.3856	0.0793	4.8604	0.0842
β_{n13}	0.6216	0.0663	9.3749	0.0671
β_{n14}	0.3399	0.0790	4.3007	0.0811

Note: Penalized estimator. Unpenalized log-likelihood: –1243.86.

^aBased on 400 samples.

Table 3. Per-Season Surplus for 1 Acre Increases in Existing Ecosystems

	Jeffrey/Ponderosa Pine	Riparian	Mixed Pine	Rocky Alpine
Total surplus	\$75.04	\$869.90	–\$7.16	\$60.78
Acres added	3	5	5	12
Surplus/acre	\$25.01 (6.60) ^a	\$173.98 (57.59)	–\$1.43 (1.05)	\$5.06 (1.80)

^aBootstrap standard error based on 200 samples.

that ecosystem is present by 1 acre and calculating the change in aggregate willingness-to-pay using the measure $S_1 = \beta^{-1} \delta (\sum \gamma_j - \sum \gamma_j^*)$. Standard errors around each surplus measure are obtained using a bootstrap approach. Table 3 shows these results. The surplus/acre measure represents an average (across trails) marginal value of a 1 acre increase in the ecosystem since as many acres are added as there are trails possessing that ecosystem. These results sharply illustrate the value of riparian or meadowland to back country hikers.

A variety of grazing scenarios could be examined using this model. We chose to examine the impacts of grazing bans on a trail-by-trail basis looking at sheep and cattle both individually and jointly. The reason

for analyzing the impacts on a trail-by-trail basis is that the impacts of grazing depend in part on what other characteristics are on the trail. Its not only how many animals but where they are grazed. Table 4 provides these results. The first two columns of table 4 show the current level of grazing by trail. Trails not listed in the table currently do not allow grazing. Cattle grazing is limited to Burt Canyon, Molybdenite Creek, and Buckeye Creek. An annual average of 1,354.2 cattle AUMs (animal unit months) per year were allowed in the early 1990s. Sheep are grazed on Burt Canyon (in addition to the cattle), Leavitt Meadows, Poore Lake, Emma Lake, and Tamarack Lake. A total of 4,153.5 sheep AUMs per year of sheep have been permitted in the wilderness over the last three years. It

Table 4. Annual Recreational and Nonrecreational Benefit Measures

Trail Name	Permitted Grazing		Recreational Values			Revenues and Surplus Measures Accruing to Non-Recreationists		
	Current Cattle AUMs	Current Sheep AUMs	Remove Cattle	Remove Sheep	Remove Cattle and/or Sheep	Agency Revenue ^a	Surplus of Producers ^b	Total
Burt Canyon	545.6	780.0	\$7,316 (3097-23278) ^c	\$4,437 (2,423-6,847)	\$42,354 ^d (19,703-147,059)	\$2,651	\$19,957	\$22,608
Molydenite Creek	545.6		14,542 (6,511-45,828)		14,542	1,091	15,277	16,368
Buckeye Creek	263.0		8,306 (3,999-20,339)		8,306	526	7,364	7,890
Leavitt Meadows		1,189.0		123,862 (72,658-20,0274)	123,862	2,378	7,134	9,512
Poore Lake		780.0		353 (157-824)	353	1,560	4,680	6,240
Emma Lake		780.0		360 (148-701)	360	1,560	4,680	6,240
Tamarack Lake		624.5		1,055 (609-1,750)	1,055	1,249	3,747	4,996
Wilderness totals	1,354.2	4,153.5	\$30,164 ^d (14,042-90,380)	\$130,067 ^d (77,727-209,895)	\$190,832 ^d (115,053-356,910)	\$11,015	\$62,839	\$73,854

^aComputed at \$2 per AUM.^bComputed at \$28 per AUM for cattle and \$6 per AUM for sheep (Lambert and Shonkwiler).^cBootstrap 95% confidence interval based on 200 samples and empirical 2.5% and 97.5% quantiles.^dValue reflects multiple amenity changes.

should be noted that while a cattle AUM is usually about one animal, a sheep AUM consists of five head of sheep. So the total number of sheep in the wilderness could approach 20,000 head depending on the number of days that animals are grazed.

As the third column of table 4 clearly shows that the willingness-to-pay by hikers to remove cattle from the wilderness varies widely by trail. These surplus measures were obtained from equation (5) scaled by the parameter δ , i.e. $S_1 = \beta^{-1}\delta(\sum \gamma_j - \sum \gamma_j^*)$.⁵ Burt Canyon shows a loss of \$7,316 for all hikers visiting the Hoover Wilderness Area. Cattle grazing at Molybdenite Creek, with same number of cattle AUMs, results in losses of over \$14,542. The total recreational losses from all cattle grazing are estimated to be about \$30,000. Sheep pose a more extreme picture. Leavitt Meadows is currently grazed by 1,189 AUMs of sheep each year (the number of animals present at any given time would depend on the number of months sheep are grazed). The total welfare losses incurred by hikers due to grazing at Leavitt Meadows are almost \$124,000 per year. The reason for this substantial loss, and probably the large number of sheep, is that Leavitt Meadows contains a 100 acre riparian meadow. As demonstrated by the results reported in table 3, riparian areas are highly valued by hikers. Removing sheep from Leavitt Meadows results in a large increase in the value of Leavitt Meadows to hikers. Comparatively speaking, the other losses are small.

A final observation about the Burt Canyon trail is useful. The cattle and sheep estimates presented above were for removing one kind of grazing but leaving the other. The final column shows the value of removing both kinds of grazing simultaneously. As one can see the value is about \$42,000. This is sharply higher than the combined individual cattle and sheep estimates. This result has a straightforward interpretation, however. Given that 780 AUMs of sheep are still there, removing the cattle is only worth \$10,975. The marginal effect of removing cattle alone is small. The same argu-

ment applies to sheep. If, however, all grazing is curtailed at this site, then the joint influence of the two effects dominates the welfare change since now there is a complete absence of grazing on the trail.

The final three columns of table 4 provide measures of the grazing permit revenue and the producer surplus that accrue from the grazing. These costs recognize that removing grazing generates direct economic losses to permit holders and government agencies. While the loss in agency revenue can be easily calculated, welfare losses of permit holders require special treatment. A paper by Lambert and Shonkwiler has estimated the surplus under the derived demand curves associated with grazing permits over the time period analyzed. Their methods implicitly account for the costs in addition to fees incurred by grazing permit holders. This is an important consideration since these costs are typically substantial relative to the grazing fee. The direct permitting revenue totals \$11,015 and the producer surplus totals nearly \$63,000.

Columns five and eight in table 4 provide a trail-by-trail comparison of the recreational and market values. Welfare losses of hikers exceed the revenues of the agency and the surpluses of the livestock grazers at two sites, Burt Canyon and Leavitt Meadows.⁶ And of those two, only grazing at Leavitt Meadows results in statistically significant net welfare losses to hikers (i.e., the 95% confidence interval for hiker welfare losses does not include the estimated losses in agency revenues and producer surplus). This result is a consequence of the ecosystem components that comprise each of the trails. Recognize, though, that our analysis cannot account for changes in other ecosystem components that may occur given changes in grazing. Further, the estimated producer surplus measure adapted from Lambert and Shonkwiler represents an average per AUM across all grazing lands. It is quite likely that the producer surplus associated with the Leavitt Meadows permit exceeds this average value. Nevertheless, our methodology does present a compelling case for agency review of grazing at this particular site.

More broadly, there are several policy implications that seem clear based on our analysis. First, large riparian areas are highly valued by

⁵ The incomplete demand welfare measures can be compared to the scaled conditional welfare measures S_0 and S_2 . For example, in the case of Burt Canyon S_0 - S_2 are 7034-7587, 4327-4533, and 34874-50734 for the remove cattle, remove sheep, and remove both scenarios. Note that the midpoints of these ranges are quite close to the corresponding S_1 values. On the other hand the, S_0 - S_2 range is 78736-183516 for Leavitt Meadows. In this case, the midpoint differs by about 6% from the calculated S_1 value.

⁶ The analysis can account for changes at both the intensive and extensive margins for hikers; however, grazing behavior must be viewed in a partial equilibrium context.

recreational users of Hoover Wilderness. Net social welfare for the wilderness could be dramatically increased simply by curtailing grazing in Leavitt Meadows. Second, mixing sheep and cattle grazing as at Burt Canyon is a poor policy from a recreational perspective. A likely reason that mixed grazing is shown to have such a large cumulative impact on recreational values is due to its extending the total time that animals occupy the trail area—as cattle and sheep are not normally grazed together. Third, there is evidence that sheep grazing at relatively unattractive sites (Poore, Emma, and Tamarack Lakes) and even cattle grazing at the relatively more attractive sites of Molybenite and Buckeye Creeks (but without riparian areas) can be tolerated by recreational users because it is not as concentrated as at Leavitt Meadows. Finally, the variability of welfare results across sites makes blanket prescriptions imprudent. The welfare impacts depend on site qualities and the density and types of grazing.

Conclusions

One of the issues facing public land managers is the prioritization of activities that may simultaneously compete for the same public areas. A pressing issue today is the appropriate level of grazing on public lands, especially those that have alternative uses. This analysis has examined (i) the willingness-to-pay by backcountry hikers in the Hoover Wilderness Area to remove grazing from hiking trails, and (ii) the value of some Sierra ecosystems to backcountry hikers. The results indicate that the damages hikers incur vary considerably from trail-to-trail in the wilderness. The differences are primarily driven by the other characteristics at the trail. High country grazing by either sheep or cattle causes much lower damages than competition in riparian areas. On the Leavitt Meadows, trail losses from sheep grazing are estimated to be about \$124,000 annually. This is the direct result of the high value that hikers place on the 100 acre Leavitt Meadow. Welfare losses due to sheep grazing in other areas, while certainly constituting statistically significant damages, are at least an order of magnitude smaller. The increase in hiking activity is generally modest except for the change forecasted for Leavitt Meadows.

The econometric model proposed in this paper has several advantages. Most importantly, it permits arbitrary covariance structures. The

model also allows researchers to work with unconditional site demands so meaningful welfare measures of increases as well as decreases in quality can be calculated. The restriction that all sites have the same demand slope coefficient is used in this analysis, but it need not be used in subsequent work. Finally, it should be pointed out that the apparent gains in adopting an incomplete demand system specification and estimating it using the multinomial Dirichlet negative binomial joint probability mass function do not necessarily validate the results obtained.

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