Journal of Agricultural and Resource Economics 25(2):501–519

Policy Changes and the Demand for Lottery-Rationed Big Game Hunting Licenses

David Scrogin, Robert P. Berrens, and Alok K. Bohara

Lotteries are commonly used to allocate big game hunting privileges. In this study, lottery demand and consumer surplus are modeled before and after policy changes designed to increase participation. The application is to New Mexico elk hunt lotteries. Given the volume and variety of hunts, we adopt a disaggregated and flexible count modeling approach. Two welfare measures are estimated: Marshallian surplus and a proposed measure that incorporates consumer uncertainty. The Marshallian measure produces smaller and slightly less precise estimates. However, regardless of the surplus measure examined, welfare increased significantly with the policy changes, while revenues changed by less than 1%.

Key words: big game hunting, count data, lotteries

Introduction

Big game hunting privileges are a type of quasi-private good. While the right to harvest a species can be defined by the license and allocated by some mechanism (such as an auction, lottery, or queue), the right is typically not transferable. The numbers of licenses issued are determined by the herd management objectives of state game managers and are generally fixed quantities. A primary concern for game managers is to allocate hunting rights in an equitable fashion, with special concern to protecting access for resident hunters. As such, license prices are typically fixed below what would prevail in a market setting so as not to deny access based upon ability to pay; such price ceilings result in license shortages. Because lotteries distribute licenses without regard to income, this mechanism is often used to deal with these shortages. In this analysis, we model the demand for and welfare derived from lottery-rationed recreational goods. The application is to the New Mexico lotteries for elk hunting licenses before and after a set of policy changes that had a substantial effect on participation.

New Mexico is one of many states that operate a lottery system for big game hunting licenses. Established in 1933 as a tool for managing dwindling elk herds, the New Mexico lottery currently distributes licenses to hunt antelope, bighorn sheep, deer, elk, ibex,

Scrogin is postdoctoral research associate, Department of Resource Economics and Policy, University of Maine; Berrens and Bohara are assistant professor and professor, respectively, Department of Economics, University of New Mexico.

Detailed comments by two anonymous reviewers are gratefully acknowledged. We also thank V. Kerry Smith for commenting on an earlier draft and bringing several relevant cites to our attention, and participants at the 1999 meetings of the USDA W-133. Appreciation is extended to the New Mexico Department of Game and Fish for providing the data. This study was funded in part by the Maine Agriculture and Forest Experiment Station, University of Maine. This is Maine Agriculture and Forest Experiment Station Publication No. 2402. All errors and interpretations are solely the responsibility of the authors.

javelina, and oryx. Three amendments to the lottery effective in the 1997–98 season were intended to increase resident access to the hunts.[1] Subsequent to the combined policy changes, there was a 58% increase in the number of resident applications for elk licenses processed by the New Mexico Department of Game and Fish. As nonmarket values are associated with the right to hunt, an immediate question that arises is how resident welfare was altered.

Given the various statistical and choice-set issues surrounding random utility models (RUMs), we model lottery demand in a multi-site zonal travel cost framework by treating observations as counts. After demonstrating how counts may be derived from lottery applicant data, we use the generalized negative binomial regression model for estimating lottery demand and welfare. The approach also allows for the testing of several nested alternatives. Our results show that the traditional surplus measure produces underestimates of welfare relative to the proposed measure of lottery surplus in the New Mexico case. Further, regardless of the two surplus measures examined, resident consumer surplus substantially increased following implementation of the policy changes, while there was less than a 1% change in resident lottery revenues.

Lottery Participation and Welfare

Lottery Participation

In this section, we present a model of lottery participation to provide insight about the choices made by individuals in the lottery application process. We extend the work of Nickerson by deriving the consumer surplus obtained from the lottery system. This surplus measure is shown to be equivalent to those proposed in the literature on underpriced public goods rationed by lottery.

Assume that (*a*) applicants are randomly drawn in the lottery, (*b*) the supply of licenses for each hunt is fixed, (*c*) an individual can apply for only one license, (*d*) licenses are nontransferable, (*e*) applicants are risk neutral and seek to maximize the expected (net) value of participating, and (*f*) participants have full information about the characteristics and regulations of the various licenses to be issued and the total number of applicants for each hunt.[2]

Let S_j represent the number of licenses to be issued in the lottery for hunt j, and N_j represent total applications for hunt j licenses. Thus, the probability of being drawn is S_j/N_j, denoted δ_j. An individual, i, is assumed to be willing to pay $V_{j,i}(Y_i, P_i, \mathbf{H}_i, \mathbf{Z}_j)$ to receive a j license with certainty. The terms Y_i, P_i, and $\mathbf{H}_i$ represent individual i's income, the price level of the goods in i's consumption set, and a vector of his/her household characteristics, respectively, and the term $\mathbf{Z}_j$ is a vector of attributes associated with the jth hunt.[3] Also, assume there is a nonrefundable entry fee (P_L) paid by all

[1] The first amendment was the imposition of a nonresident supply quota guaranteeing residents at least 78% of the lottery-issued licenses for several species (including elk). The second was lowered fees for all elk licenses; the average fee declined by about 17%. Third, applicants were allowed to submit only the entry fee with their applications; for the 20 years prior, both the entry fee and license fee were required for participation. Applicants not drawn were refunded the license fee.

[2] Assumptions (*a*)–(*d*) apply to all New Mexico lotteries; assumptions (*e*) and (*f*) are for convenience.

[3] Thus, $V_{j,i}$ is interpreted as a money metric indirect utility function. It is the amount of money that individual i would need at price level P_i to be as well off as foregoing a unit of j and having income Y_i.

lottery participants, a hunt-specific license fee (P_j) incurred on an awarded license, and individual-specific expected travel costs ($P_{j,i}$) incurred from trip taking.[4]

The expected value of entering lottery j and being drawn is $\delta_j[V_{j,i}(Y_i, P_i, H_i, \mathbf{Z}_j) - P_L - P_j - P_{j,i}]$, and the expected value of not being drawn is $-(1 - \delta_j)P_L$. Adding these values yields individual i's expected (net) value of a hunt j license:

$$(1) \qquad E(V_{j,i}) = \delta_j[V_{j,i}(Y_i, P_i, H_i, \mathbf{Z}_j) - P_L - P_j - P_{j,i}] - (1 - \delta_j)P_L.$$

Under the assumption of risk neutrality, an individual will participate in the drawing if his/her expected value is nonnegative. Hence, the lottery for hunt j licenses is feasible if:

$$(2) \qquad E(V_{j,i}) = \delta_j[V_{j,i}(Y_i, P_i, H_i, \mathbf{Z}_j) - P_j - P_{j,i}] - P_L \geq 0.$$

Since an individual can choose only a single hunt, he or she selects the hunt providing the greatest expected value. The ith individual's decision on the optimal lottery in which to participate can then be represented by the set $d_{1,i}, d_{2,i}, \ldots, d_{J,i}$, where J represents the total number of hunts from which to choose; $d_{j,i} = 1$ if j is preferred to the other $J - 1$ hunts, and $d_{j,i} = 0$ otherwise. Specifically, individual i's choice of hunt is given by:

$$(3) \qquad d_{j,i} = \begin{cases} 1 & \text{if } \delta_j[V_{j,i}(Y_i, P_i, H_i, \mathbf{Z}_j) - P_j - P_{j,i}] - P_L \geq 0 \\ & \text{and} \\ & \delta_j[V_{j,i}(Y_i, P_i, H_i, \mathbf{Z}_j) - P_j - P_{j,i}] - P_L \geq \\ & \delta_f[V_{f,i}(Y_i, P_i, H_i, \mathbf{Z}_f) - P_f - P_{f,i}] - P_L; \\ 0 & \text{otherwise} \qquad \forall j, f \in J, \quad j \neq f. \end{cases}$$

As P_L is constant for all J, a change in its value will not cause substitution within J, but may influence the decision of whether or not to participate. Alternatively, P_j and $P_{j,i}$ are hunt specific, so changes in these amounts can influence participation and lead to substitution within J.

Welfare from Lottery-Rationed Goods

Measures of consumer welfare obtained from goods rationed by lottery have been proposed in various theoretical papers. In an early work, Seneca demonstrates how the traditional Marshallian measure of consumer surplus must be modified in order to correctly measure consumer surplus from underpriced and randomly allocated public goods (e.g., hunting licenses). In another early investigation, Mumy and Hanke consider the situation more generally by examining the amount of the good that should be rationed in order to maximize consumer surplus, given demand and cost conditions. These works address aggregate, market-level issues and do not model individual-level

[4] As an anonymous reviewer noted, expected travel costs may be mean trips multiplied by the expected price per trip. Since a license typically allows the holder several days or weeks to hunt, multiple trips may be taken, and thus travel costs incurred on each of these trips.

behavior. More recently, Boyce considers lottery welfare from an expected utility framework. Results are compared under different lottery structures (e.g., transferable and nontransferable lotteries). Welfare from our lottery participation model (3) is obtained in a fashion that is consistent with this literature. After deriving consumer surplus, we note the equivalence of our measure to the measures proposed in these works.

Because an individual can choose only a single hunt, the expected value associated with the chosen hunt is the maximum expected value obtainable through the lotteries. This expected value is also the relevant value for welfare analysis. Summing the expected value of hunt j across applicants, N_j, yields the total expected value of the hunt:

$$\sum_{i=1}^{N_j} \left[\delta_j\left(V_{j,i}(\cdot) - P_j - P_{j,i}\right) - P_L\right]. \tag{4}$$

Rewriting (4) yields a more familiar expression of total expected net benefits of hunt j licenses:

$$\delta_j \sum_{i=1}^{N_j} V_{j,i} - \delta_j \sum_{i=1}^{N_j} P_{j,i} - (S_jP_j - N_jP_L) = \text{total expected net benefits of hunt } j. \tag{5}$$

The first term in (5) is the sum of the values individuals would be willing to pay for a hunt j license with certainty, weighted by the proportion of individuals awarded licenses. Similarly, the second term is the portion of total applicant expected travel costs that are incurred. In parentheses is the total revenue collected from hunt j licenses by the management agency, where S_jP_j and N_jP_L are the license revenues and entry fee revenues, respectively. Note that (5) is identical to the traditional expression of consumer surplus in the case where the number of licenses is not constrained to be less than the number of applications (i.e., when $\delta_j = 1$).

If $P_L = P_j = P_{j,i} = 0$, then (5) is equal to the welfare measure proposed by Seneca [i.e., his expression (5)]. This is also equal to the welfare measures proposed by Mumy and Hanke [i.e., their expression (4) in the zero-price case and expression (6) in the underpriced case, with price consisting of P_j, P_L, and $P_{j,i}$], given a quantity (S_j) to be rationed. And if $P_j = P_{j,i} = 0$, and assuming no portion of revenues is rebated to society, then (5) is equal to expression (15) in Boyce for the welfare derived from a nontransferable lottery. Thus, the differences across the literature in the welfare expressions are primarily in the structure of price.

Similar to Boyce, we depict in figure 1 the lottery for a fixed supply of licenses in applicant-value (N, V) space.[5] Ordering the applicants for hunt j licenses, N_j, by the value each places on a license yields the demand curve for hunt j, denoted by V_j. If the price of a license (i.e., sum of the entry fee and license fee) is set by the agency at P_j^A (the clearing price), the results are identical to that of an auction.[6] Consumer surplus would

---

[5] We have suppressed expected travel costs from this graphical depiction of the lottery. Since $P_{j,i}$ differs across individuals (unlike P_L and P_j), and its relation to $V_{j,i}$ is unknown, it cannot be depicted conveniently in figure 1. However, *average* expected travel costs would enter graphically by an amount added to the expected fees ($P_L + \delta_jP_j$) that is equal to the averaged probability-weighted sum of total applicant expected travel costs.

[6] Note in figure 1 that for illustrative purposes we represent supply as a fixed curve. However, as both the quantity and price are fixed in the lottery, there is no supply curve, but instead a single price-quantity point.

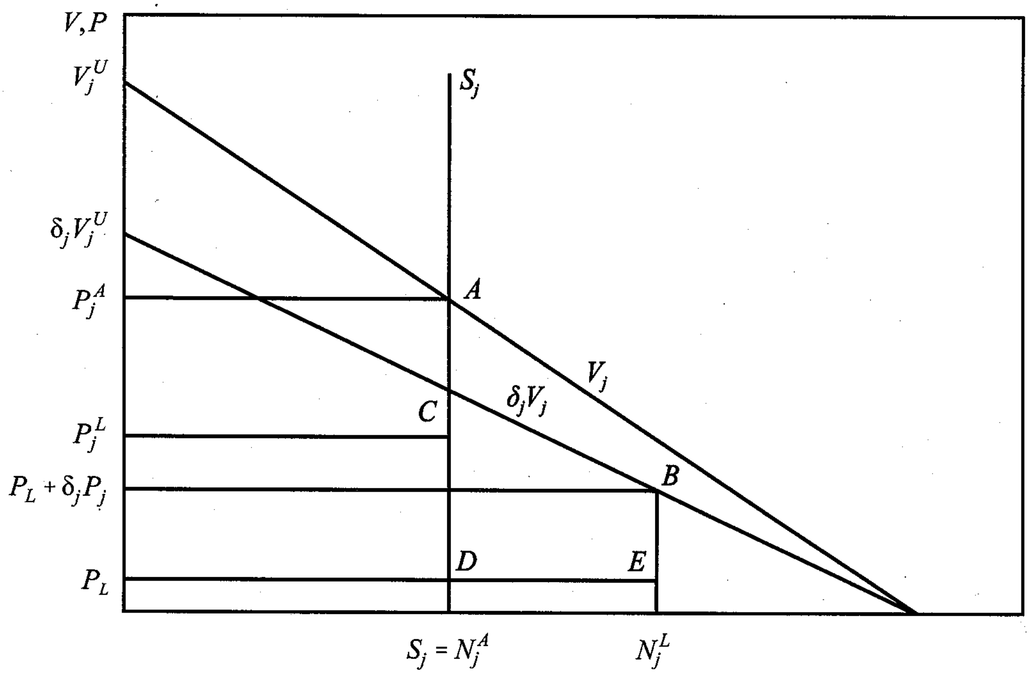

Figure 1. The lottery for hunt *j* licenses

be equal to the area $V_j^U A P_j^A$ in figure 1. Also, total revenues collected by the agency would be the same under both allocation methods, depicted by the area $P_j^A A N_j^A 0$.

However, if the price is set by the agency below the clearing price, say at P_j^L, a shortage equal to $N_j^L - S_j$ licenses results. A lottery to allocate the S_j licenses then implies a probability of receiving a permit, $\delta_j < 1$. Weighting V_j by δ_j yields the function $\delta_j V_j$, corresponding to the first term in (5). The lottery price, P_j^L, consists of the entry fee, P_L, and the license fee, P_j, so the agency collects entry fee revenues equal to the area $P_L E N_j^L 0$, and license revenues equal to the area $P_j^L CDP_L$. Assuming the expected net value obtained by the last of the ordered applicants is zero, then consumer surplus derived from the S_j lottery-distributed licenses is equal to the area $\delta_j V_j^U B(P_L + \delta_j P_j)$ in figure 1. Altering the lottery prices will influence revenues collected, applications received, and the welfare obtained from participation. Similarly, altering the supply of licenses awarded (e.g., imposing a quota) can be expected to influence revenues, applications, and consumer surplus.

In the New Mexico case for lottery-rationed elk hunts, there were several simultaneous policy changes. Our focus is on evaluating their effects on resident welfare (and agency revenues). The next section turns to developing a demand modeling approach to explain lottery applications received and the welfare generated through the rationing.

Empirical Analysis

Modeling Considerations

Big game hunting opportunities rationed through a lottery system can be described as a quasi-private good (Boxall). An individual can only receive a single permit granting the right to hunt, and this permit cannot typically be traded in a competitive market. The implication is that there are some nonmarket values attached to big game hunting opportunities, and nonmarket measurement techniques must be pursued for demand analysis. As detailed in the historical development of the travel cost literature on nonmarket recreational goods, an important choice for the analyst is the decision to use aggregate or individual-level data. The dominant trend over the last decade or more has been to use individual-level data constructed from surveys.

The economic literature specific to lottery-rationed big game hunting is rather sparse. In early work on demand analysis for lottery-rationed big game hunting, Loomis argued that for a variety of practical and theoretical reasons the appropriate approach is to use lottery applications rather than the realized hunts or trips. While Nickerson econometrically examined total lottery applications across big game hunts, welfare was not estimated due to the absence of a price proxy (i.e., a travel cost variable). Boxall provides a strong argument for the use of RUMs to more accurately characterize behavior. The single choice occasion of the lottery eliminates the need to link site choice to seasonal trip demand, an issue of concern in the literature. Boxall also notes the problem of handling zero observations in the traditional aggregate-model framework. However, as Hellerstein (1991, 1995) discusses, the choice between individual and aggregate-level data for recreational demand analysis involves tradeoffs between different types of estimation biases that may be encountered.

The reliance on aggregate data in early zonal travel cost models was largely driven by availability and statistical convenience; however, it introduced potential aggregation biases and had weak behavioral foundations, relying on the assumption of the "representative consumer model" (Hellerstein 1995).[7] With increasingly available micro-level data from nonmarket valuation surveys, researchers now typically eschew aggregate models and favor individual travel cost models or RUMs. However, individual-level models come with the potential for sample selection and nonresponse bias (see Cameron, Shaw, and Ragland) and often require the use of limited-dependent variable estimators with strong distributional assumptions. For RUMs there is also the issue of choice set definition. Boxall models lottery-rationed antelope hunts using a RUM with choice sets fixed at eight hunts. In contrast, in our New Mexico case there are 215 annual elk hunts. Inclusion of all hunts in the choice set when individuals consider less than the full set can lead to biased parameter and welfare estimates (Peters, Adamowicz, and Boxall).[8]

Thus, the choice between aggregate and individual-level data is an open empirical issue, and may well depend on the purposes of the study and available data. In simulation studies of this issue, both Kling and Hellerstein (1995) show that aggregate demand models may be more reliable than individual-level models. With sufficient variation in the dependent variable, aggregate models can perform relatively well for statistical inference and estimating welfare values. Further, Hellerstein (1998) notes that the richness of a data set with respect to the topic of interest may warrant its use, despite limitations in other dimensions.

---

[7] Potential statistical biases in aggregate travel cost models for big game hunting have been recognized for over 25 years. Brown and Nawas were concerned with the increased correlations among explanatory variables arising with aggregation, and argued for disaggregation to reduce potential multicollinearity.

[8] Choice sets may alternatively be defined through an aggregation scheme, by random draw, or through some nesting structure. Such approaches have the potential to introduce specification error, and the selection of an appropriate choice set remains an unresolved issue.

The lottery participation model given in (3) is comparable to that underlying the random utility design (see, e.g., Ben-Akiva and Lerman, p. 101). Adding error terms and defining individuals' choice sets leads to a random *expected* utility model. The alternative discrete-value approach for estimating lottery demand and welfare is count data modeling. Counts associated with discrete-choice occasions have been analyzed in select contexts, including recreational demand modeling (see, e.g., Hausman, Leonard, and McFadden; Hellerstein and Mendelsohn). A Poisson-distributed random variable results when independent and identically distributed outcomes (i.e., zeros and ones) of a Bernoulli random variable are summed over trials. Relaxing the assumption that the trials are identically distributed (i.e., allowing the probability of "success" to differ across trials) leads to a non-Poisson random variable. Draws from the underlying distribution (Poisson or otherwise) can be conditioned on a set of explanatory variables and parameters, and the latter robustly estimated using pseudo maximum-likelihood methods (Gourieroux, Monfort, and Trognon). Further, unlike the traditional least squares models, count models produce unbiased parameter estimates while accounting for nonparticipation (e.g., zero observations) in the analysis (Hellerstein 1992).

Given the volume of annual hunts from which individuals may choose (215), and the number of applicants to assign potentially erroneous choice sets (29,263 and 46,430 in the 1996–97 and 1997–98 seasons, respectively), we adopt the count modeling approach for analyzing lottery demand. To reduce the potential for aggregation biases, we develop our model in a highly disaggregated fashion. Zones of trip origin are defined as residential zip codes rather than, for example, the county or hunt level.[9] Counts on applications from each zip code population (i) for each hunt (j) allow resident demand for each of these hunts to be modeled. Combining for each season I = 273 residential New Mexico zip codes and J = 215 annual elk hunts leads to 58,695 annual observations on applications. For nonresident applicants this approach is not feasible due to the volume of combined Unites States zip codes and hunts. Further, the spatial limits of the model (Smith and Kopp) may be exceeded in the nonresident case, regardless of the adopted modeling approach.

Table 1 reports summary statistics on the dependent variable—lottery applications for each hunt received from each residential zip code—including the frequencies of the observations in the 1996–97 and 1997–98 seasons. Despite the volume of resident applications in both seasons, less than one application was received on average annually from each zip code. However, mean applications increased by over 58% in the latter season. The size of the standard deviation-to-mean ratio in each season (approximately 6.0) is an indication of overdispersion, resulting from a preponderance of zero observations.[10] The increase in applications in the 1997–98 season only slightly offsets the volume of zeros. Overall, the frequency distributions have considerable mass near zero and long right tails.

The count model we adopt is the generalized negative binomial (GNB), which accommodates overdispersed and heterogeneous data. It can also be readily used as a benchmark for testing several restricted and commonly used count models, such as the Poisson

[9] Frequencies, summary statistics, and estimation results for county-level applicant data are available upon request from the authors.

[10] The proportion of zeros in our data is comparable to that examined by others. Sixty percent of the 695 observations on boating trips were zeros in Seller, Stoll, and Chavas' data (used also in Ozuna and Gomez; Gurmu and Trivedi; and Saha and Dong). About 75% of the 527 observations on beach visits were zeros in Haab and McConnell.

Table 1. The Dependent Variables: Summary Statistics and Frequencies of Lottery Applications per Zip Code

A. 1996–97 SEASON, APPLICATIONS PER ZIP CODE (N = 58,695)

	FREQUENCIES										
	0	1	2	3	4	5	6–10	11–25	26–50	≥51	Max
Obs.	51,372	3,005	1,458	810	481	342	717	379	101	30	196
Cum.	0.875	0.926	0.951	0.965	0.973	0.979	0.991	0.998	0.999	1.000	

Mean = 0.499 Std. Dev. = 2.967

B. 1997–98 SEASON, APPLICATIONS PER ZIP CODE (N = 58,695)

	FREQUENCIES										
	0	1	2	3	4	5	6–10	11–25	26–50	≥51	Max
Obs.	49,946	3,221	1,634	937	619	408	986	683	164	97	263
Cum.	0.851	0.906	0.934	0.950	0.960	0.967	0.984	0.996	0.998	1.000	

Mean = 0.791 Std. Dev. = 4.854

and type I and type II negative binomial models (denoted by NB-I and NB-II, respectively). Under the GNB approach, the quantity of lottery applications for hunt j licenses received from zip code i ($Q_{j,i}$) is assumed to be an NB distributed random variable.[11] The probability density function can be expressed as:

$$(6)\qquad P(Q_{j,i} = c_{j,i}) = \frac{\theta_{j,i}^{c_{j,i}} e^{-\theta_{j,i}}}{c_{j,i}!} v_{j,i}, \qquad c_{j,i} = 0, 1, 2, \ldots,$$

where $v_{j,i}$ is a gamma-distributed error term, and the remainder is the Poisson density, where $\theta_{j,i}$ is both the Poisson mean and variance. Then, the NB density can be written as:

$$(7)\qquad \frac{\Gamma(c_{j,i} + \gamma_{j,i})}{\Gamma(c_{j,i} + 1)\Gamma(\gamma_{j,i})} \left(\frac{\gamma_{j,i}}{\gamma_{j,i} + \theta_{j,i}} \right)^{\gamma_{j,i}} \left(\frac{\theta_{j,i}}{\gamma_{j,i} + \theta_{j,i}} \right)^{c_{j,i}},$$

where $\Gamma(\cdot)$ is the gamma density and $\gamma_{j,i}$ is a dispersion parameter. Following Cameron and Trivedi, we conditionalize $\theta_{j,i} = \exp(\mathbf{x}_{j,i}\beta)$ and $\gamma_{j,i} = \exp(\kappa\mathbf{x}_{j,i}\beta)/\alpha$, where $\mathbf{x}_{j,i}$ is a row vector of k explanatory variables and a constant term, β is the corresponding vector of $k+1$ parameters to be estimated, and α and κ are two additional parameters to be estimated.

The roles of α and κ in the modeling are apparent upon deriving the conditional mean and conditional variance. These moments are related such that:

$$(8)\qquad \mathrm{Var}(Q_{j,i}|\mathbf{x}_{j,i}) = E(Q_{j,i}|\mathbf{x}_{j,i}) + \alpha E(Q_{j,i}|\mathbf{x}_{j,i})^{2-\kappa} = \theta_{j,i} + \alpha\theta_{j,i}^{2-\kappa}.$$

[11] We can use the $Q_{j,i}$ disaggregation to differentiate our approach from previous aggregate demand approaches for lottery-rationed big game hunting. Loomis modeled lottery applications for hunts for antelope, bighorn sheep, and buffalo by zone of trip origin, i, using from 9 to 15 observations; the only explanatory variable evaluated was a travel cost variable (defined on i). Alternatively, Nickerson modeled total lottery applications using observations on 368 elk hunts and 242 deer hunts; explanatory variables included various hunt characteristics (defined on j), but not a travel cost variable.

Note the ability of the GNB model to accommodate overdispersion, as $\mathrm{Var}(Q_{j,i}\,|\,\mathbf{x}_{j,i}) > E(Q_{j,i}\,|\,\mathbf{x}_{j,i})$. The coefficient α is an overdispersion parameter, and the κ parameter allows the relation between the conditional mean and the conditional variance to take a variety of forms. The $k+1$ parameter Poisson model, with equal first and second (conditional) moments, is obtained with the restriction $\alpha = 0$. The restriction $\kappa = 1$ leads to a linear relation between the conditional moments and the $k+2$ parameter NB-I model; the restriction $\kappa = 0$ results in a quadratic conditional moment relation and the $k+2$ parameter NB-II model. The absence of these restrictions on α and κ yields the highly flexible, $k+3$ parameter GNB model. The log-likelihood function of the GNB model is specified as follows:

$$\text{(9)} \quad \sum_{j,i=1}^{J\times I} \left\{ \ln\Gamma\left(c_{j,i} + \frac{\Theta_{j,i}}{\alpha}\right) - \ln\Gamma\left(\frac{\Theta_{j,i}}{\alpha}\right) - \ln\Gamma(c_{j,i}+1) - \left(c_{j,i} + \frac{\Theta_{j,i}}{\alpha}\right)\ln\left(\frac{\Theta_{j,i}}{\alpha} + e^{\mathbf{x}_{j,i}\beta}\right) + c_{j,i}(\mathbf{x}_{j,i}\beta) + \frac{\Theta_{j,i}}{\alpha}\left(\kappa(\mathbf{x}_{j,i}\beta) - \ln\alpha\right) \right\},$$

where $\Theta_{j,i} = \theta_{j,i}^{\kappa}/\alpha$.

The appropriateness of the NB-I and NB-II models can be gauged by testing hypotheses about κ from the GNB model or with likelihood-ratio tests after estimating the three models. Model performance can also be gauged by several goodness-of-fit criteria, such as the consistent Akaike information criterion (see Gurmu and Trivedi) or Maddala's R^2 (see Maddala, p. 39).

Explanatory Variables

Table 2 presents definitions and summary statistics for the explanatory variables. These include variables for hunt *price*, time and location, bag limit, weapon restrictions, the probability of being drawn in the lottery, the probability of harvesting an elk (conditional on being awarded a license), and average applicant age. To control for unequal populations across zip codes, we also include the logarithm of population as an explanatory variable. As Boxall, McFarlane, and Gartrell note, the inclusion of this variable is similar to weighting the dependent variable by the population, yet as a regressor it is able to capture variation in the dependent variable.

The first and most substantive change occurring in the 1997–98 season was the imposition of the nonresident supply quota guaranteeing residents 78% of the licenses awarded for each elk hunt. The quota was designed, in part, to increase the number of resident license holders. We construct the variable *PROB* to capture the effects of perceived lottery odds, pre- and post-quota, on resident applications. As shown in table 2, mean *PROB* increased by about five and one-half percentage points with the quota.

A key issue in the estimation of any recreational demand model without market prices available is the construction of a price proxy. Typically this is a constructed travel cost measure, where distance is assumed to be costly. Across aggregate models and individual-level models, the literature contains a variety of specifications of travel cost.[12]

[12] Examples from other aggregate demand models for big game hunting include: Nickerson, who excludes travel cost from aggregate lottery participation equations; Sandrey, Buccola, and Brown, who include entry fees and mileage costs; and Balkan and Kahn, who include mileage costs and opportunity costs, valued at one-third the hourly wage rate. For a recent review of the opportunity cost of time issue and its treatment in travel cost models, see Feather and Shaw.

Table 2. The Independent Variables: Definitions and Summary Statistics

Variable	Definition	1996–97	1997–98
LNPOP	Natural logarithm of population	6.93 (2.11)	6.93 (2.11)
*TC*1	Lottery fee + license fee + \$0.526 × round-trip miles, scaled by 100	3.37 (1.31)	3.24 (1.31)
*TC*2	Lottery fee + license fee + \$0.526 × round-trip miles + 1/3 × average hourly wage, scaled by 100	3.51 (1.38)	3.39 (1.38)
AGE	Average applicant age, scaled by 100	0.40 (0.04)	0.40 (0.04)
LICENSES	Number of licenses to be drawn, scaled by 100	1.13 (1.10)	1.10 (1.07)
PROB	1996–97: Ratio of *LICENSES* to 1995–96 applicants 1997–98: Ratio of 0.78 × *LICENSES* to 1996–97 resident applicants	0.57 (0.31)	0.63 (0.30)
HARVEST	Ratio of elk harvest to total hunters in 1995–96	0.33 (0.26)	0.33 (0.26)
QUALITY	1 if "quality" hunt; 0 otherwise	0.13 (0.34)	0.13 (0.34)
BULL	1 if mature bull elk hunt; 0 otherwise	0.41 (0.49)	0.40 (0.49)
BOW	1 if bow-only hunt; 0 otherwise	0.20 (0.40)	0.20 (0.40)
MUZZLE	1 if muzzle-loader-only hunt; 0 otherwise	0.15 (0.36)	0.15 (0.36)
NOLIMIT	1 if unlimited license hunt; 0 otherwise	0.07 (0.26)	0.07 (0.26)
MARQUEZ	1 if hunt includes the Marquez wildlife area; 0 otherwise	0.03 (0.18)	0.03 (0.18)
HANDICAP	1 if impaired-hunter-only hunt; 0 otherwise	0.01 (0.12)	0.01 (0.12)
SE	1 if hunt is in the southeastern quadrant of New Mexico; 0 otherwise	0.05 (0.21)	0.05 (0.21)
NW	1 if hunt is in the northwestern quadrant of New Mexico; 0 otherwise	0.39 (0.49)	0.39 (0.49)
OPENING	1 if opening week rifle hunt, bow hunt, or muzzle-loader hunt; 0 otherwise	0.22 (0.41)	0.22 (0.41)
HOLIDAY	1 if hunt occurs during Thanksgiving or the end of December; 0 otherwise	0.04 (0.19)	0.04 (0.19)
LAST	1 if hunt occurs during the final week of the season; 0 otherwise	0.01 (0.12)	0.01 (0.12)

Note: Numbers in parentheses are standard deviations.

As shown in table 2, we construct two alternative measures of travel cost (labeled *TC*1 and *TC*2) to serve as price proxies in our aggregate models.[13] *TC*1 is the sum of the lottery entry fee, license fee, and an estimate of mileage costs; *TC*2 equals *TC*1 plus an estimate

[13] Thus, an implicit assumption in the definitions of the travel cost variables is that applicants expect to take a single trip if awarded a license. However, as Creel and Loomis note, given a bag limit allowing the harvest of a single animal and that a license is typically valid for a hunting season (e.g., multiple days or weeks), license holders may choose to take multiple trips.

of the opportunity cost of time, valued at one-third of the average hourly wage rate.[14] The decline in the means of the associated travel cost variables reflects a second policy change: resident license fees were reduced by about 17% on average in the 1997–98 season.[15] A substitute-price variable is not included because, given the variety of hunts around any particular hunt (in location and time), the choice of a substitute would be ad hoc and expected to be highly correlated with the own-price variable.[16]

Of the explanatory variables summarized in table 2, only *PROB*, *TC*1, and *TC*2 were altered across the seasons. It is important to note that the third policy change, the requirement that only the lottery entry fee was needed to participate, is not reflected in the variables. Isolating the effect of this policy change requires the pooling of the observations and controlling for all other cross-seasonal effects. After statistically selecting an appropriate count model, we begin by examining the determinants of lottery demand in the individual seasons. For completeness, we then proceed by pooling the observations in order to further examine the effects of the altered, policy-relevant variables on lottery applications.

Estimation Results

We begin by selecting a count model to examine the determinants of lottery demand.[17] Table 3 reports the results of our model selection process.[18] The four candidates are the Poisson, NB-I, NB-II, and GNB models. Note in each case that the estimated α is highly significant, so the null of Poisson (H_0: $\alpha = 0$) is rejected. However, rejection of a null does not imply the alternative is correct, as Saha and Dong emphasize in a GNB context. Thus, we test the NB-I and NB-II conditional moment restrictions (H_0: $\kappa = 1$, and H_0: $\kappa = 0$, respectively) from the GNB model. For each season we reject these restrictions in favor of the GNB model using asymptotic t-tests and likelihood-ratio tests. The goodness-of-fit criteria also reported in table 3 suggest the GNB model is superior, with the NB-I model providing the next-best fit. In conclusion, the evidence in table 3 supports the use of the least restrictive specification: the GNB model.[19]

---

[14] We calculated miles traveled as the round-trip road distance between each residential zip code and the zip code associated with the hunt (CACI Marketing Systems), using the ZIPFIP program (Hellerstein et al.). This was multiplied by $0.526 per mile, an estimate of the cost per mile of operating an average American car in 1996 (U.S. Department of Transportation), to arrive at an estimate of explicit travel cost. The opportunity cost of time is computed by dividing the 1990 census estimate of the per capita income associated with each zip code (CACI Marketing Systems) by 2,000 to arrive at an estimate of the hourly wage, and multiplying this by one-third to arrive at an estimate of the opportunity cost of one hour of time. This is multiplied by the number of round-trip hours traveled, calculated as total miles driven at an average rate of 50 miles per hour, to arrive at the total opportunity cost of travel time.

[15] Resident license fees are a function of the bag limit. Fees for antlerless elk declined from $45 to $37, and for mature bull elk from $75 to $60 in the 1997–98 season.

[16] While applicants are allowed to select a first and second choice of hunt, about half choose a single hunt. Further, because observations are defined for *i*, *j* combinations, if the second choice of hunt was for the same location (but different time of the season) or nearby, then the own- and substitute-price proxies would be highly collinear.

[17] We also attempted to estimate the model proposed by Haab and McConnell; in each case, the model failed to converge. Double-hurdle models generally use individual characteristics to distinguish between zero and nonzero observations. In our zonal context, however, individual characteristics can be included only as zip code averages. The GNB model accommodates zero observations without the behavioral foundation implicit in the hurdle models.

[18] For brevity, we report the results of our model selection process for the specifications using *TC*1, as estimation results using this proxy are superior to those using the *TC*2 price proxy.

[19] Estimation results for the NB-I and NB-II models are available upon request from the authors.

Table 3. Model Selection

A. 1996–97 SEASON (N = 58,695)

Description	Generalized Negative Binomial	Type I Negative Binomial	Type II Negative Binomial
κ	0.638*	[κ = 1.0]	[κ = 0.0]
	(26.23)		
α	4.332*	4.961*	3.947*
	(34.67)	(24.64)	(31.23)
LnL	-29,485.14	-29,772.04	-30,492.99
CAIC	59,221.86	59,783.68	61,225.59
Maddala's R^2	0.236	0.229	0.209

Selection Tests from the GNB Model:

t-test for NB-I [H_0: κ = 1], t = 15.08* LR test for NB-I [H_0: κ = 1], χ^2 = 573.80*
t-test for NB-II [H_0: κ = 0], t = 26.23* LR test for NB-II [H_0: κ = 0], χ^2 = 2,015.70*

B. 1997–98 SEASON (N = 58,695)

Description	Generalized Negative Binomial	Type I Negative Binomial	Type II Negative Binomial
κ	0.634*	[κ = 1.0]	[κ = 0.0]
	(25.56)		
α	5.823*	7.811*	4.614*
	(31.44)	(25.43)	(31.79)
LnL	-36,376.64	-36,758.62	-37,795.71
CAIC	73,004.86	73,756.85	75,831.01
Maddala's R^2	0.261	0.251	0.224

Selection Tests from the GNB Model:

t-test for NB-I [H_0: κ = 1], t = 14.64* LR test for NB-I [H_0: κ = 1], χ^2 = 763.96*
t-test for NB-II [H_0: κ = 0], t = 25.56* LR test for NB-II [H_0: κ = 0], χ^2 = 2,838.14*

Notes: An asterisk (*) denotes the estimate or test statistic is significantly different from zero at the 1% level. Numbers in parentheses are t-scores. Numbers in brackets are the implied restrictions on the GNB model. The LR test statistic is defined as $-2(\text{LnL}^R - \text{LnL}^U)$, where R refers to the restricted model (NB-I or NB-II), and U indicates the unrestricted GNB model. The CAIC (consistent Akaike information criterion) statistic is defined as $-2\text{LnL}^U + (k+1)[\text{Ln}(N)+1]$, where k is the number of independent variables, and N is the number of observations. Maddala's R^2 is defined as $1 - (\text{L}^U/\text{L}^R)^{2/N}$.

Table 4 presents the estimation results for the GNB lottery demand models.[20] Overall, the models perform quite well. Consider first the effects of the policy-relevant variables (*TC*1, *TC*2, and *PROB*) on applications in each season. The estimates on the price proxies, *TC*1 and *TC*2, are of the expected sign, though statistically different in each season at the 10% level. However, the models are robust to the alternative definitions of travel cost, as the remaining estimates do not statistically differ across the specifications in

[20] We tested for multicollinearity using the condition number method (see, e.g., Kmenta, p. 439). The test uses the ratio of the largest-to-smallest characteristic roots of the determinant of the moment matrix, **X′X**; a condition number greater than 30 is a sign of substantial multicollinearity. The condition numbers for our set of explanatory variables are 26.64 and 25.94 in the 1996–97 and 1997–98 seasons, respectively.

Table 4. Generalized Negative Binomial Estimates of Zip Code-Level Applications, 1996–97 and 1997–98 Seasons (N = 58,695)

	1996–97				1997–98			
Variable	Estimate	*t*-Score	Estimate	*t*-Score	Estimate	*t*-Score	Estimate	*t*-Score
CONSTANT	-5.348***	-34.35	-5.446***	-35.78	-4.904***	-35.49	-4.994***	-36.08
LNPOP	0.722***	70.29	0.728***	70.71	0.680***	67.77	0.686***	68.19
*TC*1	-0.708***	-39.69	—	—	-0.749***	-41.66	—	—
*TC*2	—	—	-0.661***	-39.25	—	—	-0.701***	-41.24
AGE	0.332	1.22	0.353	1.36	0.344	1.51	0.365	1.60
LICENSES	0.656***	44.34	0.655***	44.30	0.725***	42.76	0.724***	42.59
PROB	-0.792***	-13.69	-0.789***	-13.66	-0.497***	-8.27	-0.498***	-8.06
HARVEST	0.397***	6.80	0.395***	6.77	0.717***	13.61	0.716***	13.57
QUALITY	0.222***	5.02	0.221***	4.99	0.903***	23.91	0.901***	23.86
BULL	0.062*	1.89	0.050	1.52	0.245***	7.73	0.236***	7.30
BOW	-0.282***	-4.85	-0.294***	-5.05	-0.742***	-12.08	-0.750***	-12.31
MUZZLE	0.104**	2.44	0.101**	2.41	-0.270***	-6.76	-0.271***	-6.82
NOLIMIT	-0.631***	-9.02	-0.641***	-9.16	-0.008	-0.27	-0.016	-0.25
MARQUEZ	0.484***	7.41	0.486***	7.45	0.415***	6.24	0.416***	6.25
HANDICAP	0.295**	2.37	0.281**	2.26	-0.252**	-2.30	-0.263**	-2.37
SE	0.237***	3.46	0.238***	3.47	0.271***	4.18	0.271***	4.20
NW	-0.531***	-15.28	-0.530***	-15.25	-0.626***	-18.36	-0.625***	-18.28
OPENING	-0.337***	-7.27	-0.337***	-7.27	-0.055	-1.16	-0.055	-1.22
LAST	1.384***	15.07	1.381***	15.02	0.811***	9.06	0.810***	9.02
HOLIDAY	-0.614***	-5.50	-0.611***	-5.48	-0.385***	-4.12	-0.382***	-4.09
α	4.332***	34.67	4.349***	34.73	5.823***	31.79	5.838***	31.89
κ	0.638***	26.23	0.638***	26.29	0.634***	25.56	0.633***	25.57
LnL	-29,485.14		-29,525.93		-36,376.64		-36,418.37	
Maddala's R^2	0.236		0.235		0.261		0.259	

Note: Single, double, and triple asterisks (*) denote the estimate is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

each season. The estimated coefficients on *PROB* are significantly negative in all regressions. This finding suggests that applicants systematically prefer "long shots" in the lottery, all else constant. A plausible explanation is that perceived probability may proxy hunt attributes absent from our set of explanatory variables, such as measures of remoteness and geography.

Also of note, *LICENSES* is positively related to applications in both seasons, perhaps serving as an indicator of the sizes of the elk herds. *QUALITY* hunts are relatively desirable, and particularly so in the 1997–98 season. Similarly, mature bull hunts (*BULL*) had a more sizable positive effect in the 1997–98 season. The marginal applicants in this season may have largely favored these two classes of hunts. The variable *AGE* is consistently an insignificant determinant, perhaps lacking sufficient variation given that the average of applicant age is used when the corresponding dependent observations are zero. The estimated coefficients on *BOW* are significantly negative in all cases, suggesting that the number of applications for hunts allowing use of a firearm are distinct from these primitive-weapon hunts. Considering location, hunts in the Capitan Mountains of south-central New Mexico (*SE*) received significantly more applications in both seasons. Only 10 of the 215 annual hunts are in this region, and generally these hunts are perceived as remote and uncongested—both favorable attributes. Alternatively, *NW* hunts received significantly fewer applications. Early season hunts (*OPENING*) and hunts during Thanksgiving and the end of December (*HOLIDAY*) received significantly fewer applications. The final annual hunts (*LAST*), beginning in mid-March, more than two months after all other elk hunts have concluded, received significantly more applications.

In summary, the GNB results reported in table 4 demonstrate that lottery applications are influenced by a variety of elements. The specifications including the price proxy of explicit costs, *TC*1, slightly outperform those including *TC*2. Also, likelihood-ratio tests indicate the estimates jointly differ across the seasons. The question arises regarding the dimension in which the seasons differ. Testing the equality of the 1996–97 season estimates with the corresponding 1997–98 season estimates, we reject the null of equality at the 10% level or less in all cases except *TC*1, *AGE*, *MARQUEZ*, and *SE*.

Because the third policy change, the entry-fee-only requirement, is not reflected in the explanatory variables, we examine its effect with a pooled regression. A variable, *TIME*, is created that takes the value of zero in the 1996–97 season, and the value of one in the 1997–98 season. Interaction variables are also created by multiplying *TIME* by each explanatory variable to control for all other cross-seasonal effects. Table 5 reports selected pooled estimates. Of note, the positive coefficient on *TIME* suggests that after controlling for all other influences, more applications are associated with the 1997–98 season. To the extent that the variables reflect the components of the lottery system altered by the policy changes, we conclude that these determinants had significantly different effects on resident applications across the two seasons.

Evaluating the Effects of Policy Changes

In this section, we estimate consumer (applicant) surplus from the 1996–97 and 1997–98 lotteries. Consumer surplus estimates from the proposed measure [given by (5) and depicted graphically in figure 1 by the area below $\delta_j V_j$ and above $P_L + \delta_j P_j$] are compared to those from the traditional Marshallian measure (which assumes $\delta_j = 1$). Thus, comparisons are made across approaches and seasons and dollar values assigned to the three policy changes affecting the 1997–98 season. As noted earlier, the policy changes have implications for lottery revenues, so we also report resident entry fee revenues and license revenues in both seasons.

For a given specification of demand to be used in calculating nonmarket values, an assumption is needed about the source of the error component in the regression model. Bockstael and Strand show that consumer surplus calculations from regression estimates may differ between the error assumption of omitted variables and that of measurement error. We estimate consumer surplus following the conservative standard of assuming measurement errors.

Following (5) and figure 1, the empirical measure of expected consumer surplus that accounts for the rationing of the licenses by a lottery is:

Table 5. Generalized Negative Binomial Estimates of the Policy-Relevant Parameters and Their Seasonal Interactions: Pooled Regression

Variable	Estimate	t-Score	Interaction Variable	Estimate	t-Score
PROB	-0.780**	-13.65	*PROB***TIME*	0.272**	3.26
*TC*1	-0.709**	-41.57	*TC*1**TIME*	-0.043*	-1.89
TIME	0.440*	1.94	—	—	—
α	5.138**	46.32	—	—	—
κ	0.628**	35.17	—	—	—
N	117,390				
LnL	-65,922.94				
Maddala's R^2	0.250				

Note: Single and double asterisks (*) denote the estimate is significantly different from zero at the 10% and 1% levels, respectively.

$$E(CS_{lottery}) = \int_{P_L+\delta_j(P_j+P_{j,i})}^{\delta_j V_j^U} \delta_j^{-1} e^{\mathbf{x}\beta}\, d\mathbf{x}_{TC1} = \mu_{lottery}. \tag{10}$$

The surplus estimate is obtained by substituting the GNB estimates of β into (10) and selecting upper and lower limits of integration and a δ_j value. We choose infinity as the upper limit, and the sum of the entry fee (P_L = \$6) and the mean of *TC*1 (net P_L) weighted by the mean of *PROB* (reported in table 2) as the lower limit. The remaining explanatory variables are set equal to their sample means, resulting in the vector $\mathbf{x}_l$. The estimate of consumer surplus derived from the lottery is then given by:

$$\hat{\mu}_{lottery} = -\frac{e^{\mathbf{x}_l\hat{\beta}}}{\delta_j\hat{\beta}_{TC1}}. \tag{11}$$

We compare estimates obtained from (11) to those produced by the traditional Marshallian surplus measure. In the latter case, $\delta_j = 1$, so the uncertainty associated with receiving a license is absent. With respect to (10), this leads to an empirical equivalent of the Marshallian consumer surplus. The upper and lower integration limits are equated to infinity and mean *TC*1, respectively. The remaining explanatory variables in $\mathbf{x}$ are set equal to their sample means, resulting in the vector $\mathbf{x}_m$. The estimate of consumer surplus in this "market" setting is then:

$$\hat{\mu}_{market} = -\frac{e^{\mathbf{x}_m\hat{\beta}}}{\hat{\beta}_{TC1}}. \tag{12}$$

Note that it is unclear whether (11) or (12) will yield larger estimates, since δ_j enters both the numerator and denominator in (11).

Considering the aggregate setting, consumer surplus is defined for observations on applications from a zip code i to a hunt j, and may be interpreted as the net value of the opportunity of receiving a license in an average hunt by residents from an average zip code. To place monetary values on the change in total resident welfare across the two seasons, we multiply (11) and (12) by the total number of annual observations.

Table 6. Expected Resident Consumer Surplus and Lottery Revenues, 1996–97 and 1997–98 Seasons

Description	1996–97	1997–98	% Δ
Lottery-Rationed Consumer Surplus [a]	\$57.72*	\$71.71*	+ 24.2
	(2.12)	(3.00)	
Total Consumer Surplus [b]	\$3,387,875	\$4,209,019	+ 24.2
Hypothesis Tests $[H_0: \mu_{1996\text{–}97} = \mu_{1997\text{–}98}]$	$z = 3.80^*$	$\chi^2 = 219.24^*$	
Marshallian Consumer Surplus [c]	\$12.01*	\$18.72*	+ 55.9
	(0.65)	(1.08)	
Total Consumer Surplus [b]	\$704,927	\$1,098,770	+ 55.9
Hypothesis Tests $[H_0: \mu_{1996\text{–}97} = \mu_{1997\text{–}98}]$	$z = 5.30^*$	$\chi^2 = 187.95^*$	
Lottery Revenues:	\$1,369,152	\$1,377,358	+ 0.60
Entry Fee Revenue	\$178,692	\$282,372	+ 58.0
License Fee Revenue	\$1,190,460	\$1,094,986	- 8.0
No. of Resident Applicants	29,782	47,062	+ 58.0
No. of Resident License Holders	17,998	19,951	+ 10.9

Notes: An asterisk (*) denotes the estimate is significant at the 1% level. Standard errors are reported in parentheses.
[a] The estimates are calculated from equation (11).
[b] The total is calculated by multiplying the respective zip code estimate by $N = 58{,}695$ annual observations.
[c] The estimates are calculated from equation (12).

The standard error of estimated consumer surplus calculated under either approach is given by the square root of:

$$\text{(13)} \qquad \text{Estimated Var}(\hat{\mu}) = \left.\frac{\partial f}{\partial \beta}\right|_{\hat{\beta}}' \hat{\Sigma}_{\hat{\beta}} \left.\frac{\partial f}{\partial \beta}\right|_{\hat{\beta}},$$

where f denotes (11) and (12) in the lottery case and market case, respectively, and $\hat{\Sigma}_{\hat{\beta}}$ the $\{19 \times 19\}$ covariance matrix of estimates.

Table 6 reports the estimated values of average and total consumer surplus and the accompanying standard errors calculated using both approaches for the 1996–97 and 1997–98 seasons. In all cases, the estimates are significantly different from zero at the 1% level. However, the t-statistics of the lottery-rationed estimates are about 50% larger than those of the Marshallian measure. Testing the equality of the estimates (H_0: $\mu_{1996\text{–}97} = \mu_{1997\text{–}98}$), we reject the hypothesis in both cases using a z-test and a Wald test (see, e.g., Kmenta, pp. 492–93).[21] Annual estimates of total resident surplus are obtained by multiplying the zip code estimates by N = 58,695 observations. The proposed measure of lottery surplus produces larger estimates of total surplus. However,

[21] The Wald statistic is as follows, distributed as χ^2 with one degree of freedom:

$$f|_{\hat{\beta}}' \left[\left.\frac{\partial f}{\partial \beta}\right|_{\hat{\beta}}' \hat{\Sigma}_{\hat{\beta}} \left.\frac{\partial f}{\partial \beta}\right|_{\hat{\beta}} \right]^{-1} f|_{\hat{\beta}}.$$

the percentage increase across the seasons is less than half of that predicted by the Marshallian measure.[22]

Table 6 also reports lottery revenues collected from residents in the two seasons. Total revenue collected from residents increased by less than 1% in the 1997–98 season. The percentage reduction in license fees exceeded the percentage increase in resident-awarded licenses, so license revenues necessarily declined.[23] However, resident entry fee revenues increased with the substantial increase in applications, offsetting the lost license revenue.

Of final note from table 6, the relative number of resident license holders to resident applicants declined considerably in the 1997–98 season. Although the nonresident license quota guaranteed an increase in the number of resident license holders, the 58% increase in resident applications in the 1997–98 season exceeded the increase in resident-awarded licenses and reduced resident odds of being awarded licenses in the majority of the elk hunts.

Conclusions

Lotteries are commonly used by state game management agencies to distribute fixed numbers of big game licenses across resident and nonresident hunters. Several policies effective in the 1997–98 hunting season in New Mexico were designed to increase resident participation in the lottery and the number of resident license holders. Modeling the demand for these quasi-private goods and estimating the accompanying nonmarket values requires that applicant data, rather than trip data, be examined, and the uncertainty of the lottery accounted for. Using resident applicant zip codes as the points of expected trip origin, we estimate multi-site lottery demand for the entire set of 215 annual hunts before and after the policy changes. Given the discreteness of lottery applications and overdispersion due to "excess zeros," we use the highly flexible generalized negative binomial regression model. Two welfare measures are estimated: Marshallian surplus and a proposed measure that incorporates consumer uncertainty. The Marshallian measure produces smaller and slightly less precise estimates. However, regardless of the surplus measure examined, welfare increased significantly with the policy changes, while there was less than a 1% change in lottery revenues.

As a final caveat, it can be expected that individual-level demand models will remain the preferred modeling choice in most nonmarket valuation applications. However, as recognized by Hellerstein (1991, 1995) and others, there are tradeoffs between individual and aggregate-level demand models, and some applications may warrant the latter. In this study, given a rich data set and the dimensions of site choice, we illustrate the use of count data travel cost models for evaluating policy changes to a lottery system for rationing recreational opportunities.

[*Received February 1999; final revision received May 2000.*]

---

[22] The welfare analysis was also performed using county data. Similar to that from the zip code data, the Marshallian measure produces smaller estimates of total consumer surplus for both seasons and a larger percentage increase in the 1997–98 season. In all cases, the estimates produced from the county data are approximately 50% larger than those of the zip code data. Results are available upon request from the authors.

[23] License revenues declined from 86.9% of lottery revenues in the 1996–97 season to 79.5% of lottery revenues in the 1997–98 season.

References

Balkan, E., and J. R. Kahn. "The Value of Changes in Deer Hunting Quality: A Travel Cost Approach." *Appl. Econ.* 20(April 1988):533–39.

Ben-Akiva, M., and S. R. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand.* Cambridge MA: The MIT Press, 1985.

Bockstael, N., and I. Strand. "The Effect of Common Sources of Regression Error on Benefit Estimates." *Land Econ.* 63(February 1987):11–20.

Boxall, P. "The Economic Value of Lottery-Rationed Recreational Hunting." *Can. J. Agr. Econ.* 43(1995): 119–31.

Boxall, P. C., B. L McFarlane, and M. Gartrell. "An Aggregate Travel Cost Approach to Valuing Forest Recreation at Managed Sites." *Forestry Chronicle* 72(November/December 1996):615–21.

Boyce, J. R. "Allocation of Goods by Lottery." *Econ. Inquiry* 32(July 1994):457–76.

Brown, W. G., and F. Nawas. "Impact of Aggregation on the Estimation of Outdoor Recreation Demand Functions." *Amer. J. Agr. Econ.* 55(May 1973):246–49.

CACI Marketing Systems. *The Sourcebook of Zip Code Demographics.* La Jolla CA: CACI Marketing Systems, 1994.

Cameron, A. C., and P. K. Trivedi. *Regression Analysis of Count Data.* London/New York: Cambridge University Press, 1998.

Cameron, T. A., W. D. Shaw, and S. R. Ragland. "Nonresponse Bias in Mail Survey Data: Salience vs. Endogenous Survey Complexity." In *Valuing Recreational Resources Using Revealed Preference Methods*, eds., J. Herriges and C. Kling, pp. 1–36. Cambridge MA: New Horizons, 1998.

Creel, M. D., and J. B. Loomis. "Modeling Hunting Demand in the Presence of a Bag Limit, with Tests of Alternative Specifications." *J. Environ. Econ. and Manage.* 22(March 1992):99–113.

Feather, P., and W. D. Shaw. "Estimating the Cost of Leisure Time for Recreation Demand Models." *J. Environ. Econ. and Manage.* 38(July 1999):49–65.

Gourieroux, C., A. Monfort, and A. Trognon. "Pseudo Maximum Likelihood Methods: Applications to Poisson Models." *Econometrica* 52(May 1984):701–20.

Gurmu, S., and P. K. Trivedi. "Excess Zeros in Count Models for Recreational Trips." *J. Bus. and Econ. Statis.* 14(October 1996):469–77.

Haab, T. C., and K. McConnell. "Count Data Models and the Problem of Zeros in Recreation Demand Analysis." *Amer. J. Agr. Econ.* 78(February 1996):89–102.

Hausman, J. A., G. K. Leonard, and D. McFadden. "A Utility Consistent, Combined Discrete Choice and Count Data Model: Assessing Recreational Use Losses Due to Natural Resource Damage." *J. Public Econ.* 56(1995):1–30.

Hellerstein, D. "An Analysis of Wildlife Recreation Using the FHWAR." In *W-133 Benefits and Costs of Resource Policies Affecting Public and Private Land, Eleventh Interim Report*, pp. 103–18. Knoxville TN: University of Tennessee, 1998.

———. "The Treatment of Nonparticipants in Travel Cost Analysis and Other Demand Models." *Water Resour. Res.* 28(August 1992):1999–2004.

———. "Using Count Data Models in Travel Cost Analysis with Aggregate Data." *Amer. J. Agr. Econ.* 73(August 1991):860–66.

———. "Welfare Estimation Using Aggregate and Individual-Observation Models: A Comparison Using Monte Carlo Techniques." *Amer. J. Agr. Econ.* 77(August 1995):620–30.

Hellerstein, D., and R. Mendelsohn. "A Theoretical Foundation for Count Data Models." *Amer. J. Agr. Econ.* 75(August 1993):604–11.

Hellerstein, D., D. Woo, D. McCollum, and D. Donnelly. "ZIPFIP: A Zip and FIPS Database." U.S. Department of Agriculture, ERS-RTD, Washington DC, 1993.

Kling, C. L. "Comparing Welfare Estimates of Environmental Quality Changes from Recreation Demand Models." *J. Environ. Econ. and Manage.* 15(September 1988):331–40.

Kmenta, J. *Elements of Econometrics.* Ann Arbor MI: The University of Michigan Press, 1997.

Loomis, J. "Use of Travel Cost Models for Evaluating Lottery Rationed Recreation: Application to Big Game Hunting." *J. Leisure Res.* 14(1982):117–24.

Maddala, G. S. *Limited-Dependent and Qualitative Variables in Econometrics.* London/New York: Cambridge University Press, 1983.

Mumy, G. E., and S. H. Hanke. "Public Investment Criteria for Underpriced Public Products." *Amer. Econ. Rev.* 65(September 1975):712–20.

Nickerson, P. "Demand for the Regulation of Recreation: The Case of Elk and Deer Hunting in Washington State." *Land Econ.* 66(November 1990):437–47.

Ozuna, T., Jr., and I. A. Gomez. "Specification and Testing of Count Data Recreation Demand Functions." *Empirical Econ.* 20(1995):543–50.

Peters, T., W. Adamowicz, and P. Boxall. "The Influence of Choice Set Considerations in Modeling the Benefits of Improved Water Quality." *Water Resour. Res.* 31(July 1995):1781–87.

Saha, A., and D. Dong. "Estimating Nested Count Data Models." *Oxford Bull. Econ. and Statis.* 59(August 1997):423–30.

Sandrey, R. A., S. T. Buccola, and W. G. Brown. "Pricing Policies for Antlerless Elk Hunting Permits." *Land Econ.* 59(November 1983):432–43.

Seller, C., J. R. Stoll, and J.-P. Chavas. "Validation of Empirical Measures of Welfare Change: A Comparison of Nonmarket Techniques." *Land Econ.* 61(May 1985):156–75.

Seneca, J. J. "The Welfare Effects of Zero Pricing of Public Goods." *Public Choice* 8(Spring 1970):101–10.

Smith, V. K., and R. J. Kopp. "The Spatial Limits of the Travel Cost Recreational Demand Model." *Land Econ.* 56(February 1980):64–72.

U.S. Department of Transportation, Bureau of Transportation Statistics. "Table 2-13: Cost of Owning and Operating an Automobile." In *National Transportation Statistics 1997.* Online. Available at: http://www.bts.gov/programs/btsprod/nts/tbl2x13.html.