

HUNTERS LIKE SKEWNESS, NOT RISK: EVIDENCE OF GAMBLING
BEHAVIORS IN THE ALASKA HUNTING PERMIT LOTTERY

By

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A Thesis Submitted in Partial Fulfillment of the Requirements

for the Degree of

Master of Science

in

Resource and Applied Economics

University of Alaska Fairbanks

May 2018

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Abstract

In Alaska, hunting permits are distributed by traditional lottery. The absence of a preference point system means that applicants have little invested in their applications, and there are a variety of fallback hunting opportunities. Not unlike a jackpot-style state lottery, the cost to play is low relative to the potential prize winnings. These factors may cause risk-averse or risk-neutral individuals to exhibit a preference for positive skewness in their bets. Analysis in this paper is focused on four prevalent game species: moose, dall sheep, mountain goat, and bison. Pooled Ordinary Least Squares regression models were constructed to predict permit application levels as a function of various hunt characteristics, qualities, and restrictions. Permit descriptions are provided to applicants in a published document called the drawing supplement, which is the primary source of data for this study. Additional hunter-reported data is obtained from the Alaska Department of Fish and Game website. A comparison of calculated permit values and private ranch hunting opportunities validates many of the observations drawn from the models. Permit values are also used to fit a cubic model of bettor utility. Even when awarded prizes are not monetary, applicants exhibit a preference for positive skewness and aversion from risk that is typically associated with gambling.

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1.0 Introduction

The purpose of this study is to perform an analysis on the Alaska hunting permit lottery through two independent methods. The first is a development of pooled OLS regression models that predict application levels for lottery-rationed hunting permits in Alaska. Dependent variables will focus on hunt quality and other hunt characteristics, as well as proxies for individual hunting expenditure, and factors related to likelihood of obtaining a particular permit. The second is an investigation of gambling behavior among applicants in the lottery. Methods include nonparametric modeling of expected utility, and fitting a cubic model of applicant utility.

Big game hunting is a popular activity for recreation and as a method of harvesting food. Hunters may participate either through general season or by obtaining specific hunting permits, which limit their activities by species, location, and season dates. In Alaska, most hunters pursue moose and caribou as important food sources, especially in remote areas of the state. Economic studies in the continental US have estimated the demand levels for various hunting permits using traditional econometric modeling methods. No similar analyses have been conducted for the State of Alaska, which offers a large number of hunting permits through a lottery system. The distribution method also presents a unique opportunity to search for evidence of applicant behavior that is often associated with gambling

Economists widely recognize the effect of diminishing marginal utility of wealth on the marketplace, which dictates that bettors should avoid unfair bets and maximize expected outcomes. *Friedman and Savage (1948)* noted that bettors should decline bets with negative marginal returns, even though it is not observed in the marketplace [1]. *Golec and Tamarkin (1998)* and *Garrett and Sobel (1999)* conducted research on gambling behavior in the context of horse racing and state lotteries. They too, noted that factors other than expected utility must influence the decision to play unfair bets [2], [3]. The value of entertainment may be a partial explanation, but an observed preference for risk and/or skewness is best explained with a cubic model of bettor utility. The structure of the Alaska hunting permit lottery is unique because it does not use any equity-balancing tools that are common in other states. Alaska hunting permits are distributed by traditional lottery and the data is publicly available, making it possible to evaluate the risk-preference behavior of participants. Emphasis is placed on differences between game species and differences between Alaska resident vs nonresident hunters. *Golec and Tamarkin (1998)* suggested that individuals who place a series of bets balance their wagers like a portfolio, maximizing utility and also preserving their chance to ‘win big’ on riskier bets. This betting

strategy may be present in the permit lottery, with applicants mixing low-risk moose and bear permits with high-risk sheep, goat, and bison permits.

2.0 Background Information on Hunting Permit Distribution

Wildlife management policies differ greatly between states. In Alaska, regulatory agencies must rely on a variety of mechanisms to facilitate the harvest of big game. The predominate purpose of agencies such as the Alaska Department of Fish and Game (ADFG) is to allocate natural resources for the public at sustainable levels and to promote economic prosperity for commercial sectors [4]. Maintaining sustainable levels of fish and wildlife generally means restricting harvest through limits, seasons, animal size, and gender restrictions. General season hunting is the simplest and most recognizable venue for hunters to harvest game. General season tags (nonresident) or harvest tags (resident) are available to hunters for purchase, or sometimes at no cost over the counter. Fee levels and the number of distributed tags are determined by state agency or by federal agency in special cases. The number of tags for an area or species is decided based on a wide array of biological factors. Wildlife biologists' survey and model wildlife populations to choose optimal level of harvest from year to year. Issuing harvest tags allows management agencies to track the number of hunters. Hunters are also required to report successful harvest of big game animals for general season and permit hunts. This information is compiled and published electronically.

In some instances, the demand for big game tags is substantially greater than the supply and a different method of tag distribution is required to ensure equity among participants. The most common method is a modified lottery sometimes referred to as a 'preference point' system. These systems are implemented in many of the continental U.S. states to distribute tags for specific hunting areas or species that are highly sought after. Tags are awarded to applicants with the most preference points in descending order until all tags have been distributed. Each year that an applicant is unsuccessful in drawing a tag they receive a preference point. The system is intended to distribute tags with a greater level of equity than a traditional lottery, and applicants who have applied for many years without success are rewarded for their persistence.

Tags in high demand are distributed by traditional lottery in Alaska, and are available to both residents and nonresidents. However, a separate system is in place to provide hunting opportunities for subsistence and personal use resident hunters. The Tier I and Tier II class permits are reserved

specifically for Alaska residents and are issued when “there is not enough game for a general season and the population of animals has historically been an important source of human food” [4]. Tier I hunting permits are provided when the resource is expected to allow harvest for all interested parties. Tier II hunting permits are awarded on a scoring basis and provides preference to individuals who have lived in Alaska the longest or who depend on the resource for survival and/or heritage. Tier II permits are used for game populations where the number of interested parties greatly exceed the optimal target level. The Alaska Board of Game approves tier I and Tier II allocations. These systems function independently from the traditional lottery.

The publicly available hunt supplement¹ and reported harvest data² are sufficient to construct a prediction model of applications to each draw permit. Such a model could be valuable to management agencies in estimating the demand for prospective new or existing hunting permits. It may also demonstrate which particular hunt qualities explain the preferences of hunters. Observations such as these could improve overall public benefit from the resource, especially considering the large number of applicant-restricted and method-of-take restricted permits. Permit demand is directly related to revenue through the collection of application fees. A permit demand model could therefore be used to predict future revenue.

Each year, ADFG publishes a *draw hunt supplement* which lists the permits available for application [5]. The supplemental publication provides some information to hunters to aid them in the application process. Each hunt has a prescribed species, season, boundary, and other stipulations like weapon type or animal gender. Method-of-take restrictions are common and varied in the lottery. Common method-of-take restrictions include bow only or muzzleloader only take. Other permits are restricted by qualities of the applicant. This includes resident or nonresident only permits, as well as permits for youth and disabled veterans. ADFG also publishes harvest statistics like hunt participation and success rate online, and hunters can cross reference this data with the hunt supplement. Hunters have near perfect information about the quality and participation in permit hunting opportunities, as well as general season, Tier I and Tier II hunting opportunities. ‘Perfect knowledge’ implicitly includes travel costs and other expenditures related to hunt participation. The models assume the hunter knows how far they will need to travel and the approximate value of participating in the hunt.

ADFG received over 190,000 applications in the Nov. 2016 application period. A \$5 to \$10 application fee is submitted with each application, depending on the species applied for. After the

¹ ADFG drawing supplement <http://www.adfg.alaska.gov/index.cfm?adfg=huntlicense.drawsupplements>

² ADFG hunter reported harvest statistics <http://www.adfg.alaska.gov/index.cfm?adfg=moosehunting.harvest>

application period has closed, the winners are selected at random and the results are published online. Each year the number of draw permits is adjusted for each hunt based on biological factors. If wildlife populations are too low, permit hunts can be eliminated. ADFG may also generate new draw permits if game populations or demand levels change dramatically. Applicants can file for up to 3 different hunt permits per species, with the exception of moose which can be applied for up to 6 times. Only one permit may be obtained for each species, and applicants list their applications in order of preference. An amendment to the policy later allowed applicants to apply for the same permit multiple times. This amendment took effect in the 2016 application period and affected observations are included in the constructed data sets.

3.0 Literature Review

Economic theory has helped to improve policy decisions regarding recreational hunting and fishing opportunities. One of the earliest contributors to environmental and resource economics was *Krutilla (1975)*, who formally described option values and existence values. He recognized the rapidly growing demand for natural resources. As a public good, recreational hunting opportunities must be limited by regulation to prevent over-allocation of the natural resource [6]. Determining the sustainable level of harvest has traditionally relied on biological science and methods. This style of management is effective for developing method-of-take restrictions such as size, gender, and season limits for harvest. The benefit of a method-of-take restriction is that there is no limitation to who can participate. By restricting the method-of-take, management agencies reduce the level of harvest without directly limiting participation. Population growth, particularly around urban centers, has rendered method-of-take methods practically ineffective. The level of participation is so great that harvest levels exceed the sustainable level even when method-of-take restrictions are in place. In regions where demand for a resource substantially exceeds supply, management agencies restrict participation through permit application processes.

The innate problem with public goods is that marginal benefits decline dramatically with use. This is especially true of a permit lottery, where application fees (\$5-\$10) are essentially zero compared to the utility gained from the harvest of a big game animal. *Mumy and Hanke (1975)* described the issue mathematically using a simple cost-benefit analysis to model the choices of individuals. They demonstrate that the ‘zero-pricing case’ will always result in over allocation of the resource [7]. The conclusion is dependent on assuming that resource quality is a function of the level of resource use, as described by *Hardin (1968)* [8]. After aggregating the resource demand, *Mumy and Hanke (1975)*

illustrate that “the number of demanded consumption units is always greater than capacity” [7] in the case where cost is zero. It is for this reason that access to resources with no cost or very low cost of use must be restricted. Fish and wildlife populations are actually far more fragile than the public infrastructure projects evaluated by *Mummy and Hanke (1975)*. When the resource is overused it can become irreparably damaged, providing further incentive to restrict access.

When hunters travel to hunting areas they incur some cost from traveling. It represents the primary cost of outdoor recreational activities in the form of expenditures on gasoline, automobiles and maintenance. Although there is other cost associated with hunting (eg equipment, opportunity costs) travel costs can be estimated or measured with some degree of certainty. *Boxall (1994)* described the modified travel cost method (TCM). He used the modified TCM to model trophy antelope hunting in Alberta at eight particular hunting locations. Antelope permits were distributed to hunters through a traditional lottery and the hunting season was specific to each permit. The structure of the lottery system was generally similar to the structure of the Alaska hunting lottery. His model estimated application choices using multinomial logit regression. Travel costs in the model were estimated by measuring distance from the applicant’s zip code to the prescribed hunting area. A \$/Km figure was applied to each distance to determine the cost to each hunter. In addition to the travel cost parameter, the model included “site characteristics or qualities... and characteristics of the recreationists themselves” [9]. The model combined characteristics of the hunt and characteristics of the applicant.

A similar study was conducted by *Scrogin Et al (2000)* modeled demand for elk hunts in New Mexico over a 2 season time period. The focus of the study was a policy change “intended to increase resident access to the hunts” [10] . Using the estimated demand, *Scrogin Et al (2000)* calculated changes in individual recreationist utility levels and net social welfare. Critical assumptions for their model are included here.

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. [10]

Their model included a TCM price proxy variable very similar to that of *Boxall (1994)*. The base model includes indicator variables for various hunt restrictions, hunt quality, hunt region and unique qualities such as opening and closing weeks of the season. Parts (e) and (f) are especially relevant to the analysis presented later in this paper. Accurate estimation of the permit values depends heavily on the knowledge of the applicant.

Scrogin et al (2000) model derived its methodology from *Hellerstein (1993)* which described the use of count data and appropriate modeling distributions. Count data is unique in its occurrence and method of treatment. He explains, “price variation occurs across individuals, where each individual in the sample possesses a unique set of unobservable factors. At any price, these factors (*ceteris paribus*) determine the quantity each individual consumes,” [11]. In the absence of individual level data there are some limitations to inference. Hunters have the opportunity to hunt whenever they want within the prescribed permit season. In most instances the hunting period is long enough that hunters may make multiple hunting trips. After each decision to hunt “the probability of choice decreases proportionally, [and] this binomial distribution will asymptotically converge to a Poisson distribution,” [11].

Buschena et al (2001) modeled the distribution of elk permits by a preference point system, with particular emphasis on policy implications. Their models controlled for typical hunt characteristics such as success rate, animal gender, weapon type, land access, time period of the hunt, and the likelihood of harvesting a trophy animal. They estimated the number of preference points needed to obtain a hunting permit, and used those estimates to calculate marginal permit values. By modeling permit values rather than expenditures or number of hunting trips, they were able to comment on the effect of changes to the structure of the permitting process. For example, the study was able to compare the permit value of unrestricted permits to muzzleloader-only permits and make recommendations on how to increase the net public benefit of harvested animals [12]. This method also creates an opportunity for management agencies to increase revenues by maximizing the number of applicants, though this is typically not an agency goal.

The fundamental assumption of lottery based permit distribution is that applicants are risk-neutral wealth maximizers. *Nickerson (1990)* elaborates on this assumption. He presents the certain value of an application as a function of income, price, household characteristics, and hunt parameters [13]. He assumes a positive marginal expected value when the applicant is drawn and a negative marginal expected value when the applicant is not drawn. The justification is intuitive. Nickerson explains;

“A risk-neutral wealth maximizer is willing to participate in any lottery only if the expected value of the outcome is greater than or equal to zero. The rules allow participation in only one drawing and hence the individual will enter the drawing with the highest expected value.” [13]

Similarly, the number of applications for a particular permit will continue to increase as long as the expected marginal value of applying is positive. Applicants will also apply to those hunts with the largest expected marginal value until the marginal values of all permits are approximately equal. But lotteries involving cash prizes depend on players to purchase tickets when their expected outcome is negative. This is what makes the lottery profitable for the owner. *Friedman and Savage (1948)* noted the discrepancy between what traditional economic theory predicts and what is observed in the marketplace. The assumption of diminishing marginal utility dictates that for a lottery player, an earned dollar brings less utility than a dollar lost. Lottery players should therefore decline unfair bets, but this behavior is not seen in the real world [1].

Walther (2002) provides a qualitative explanation of why risk-neutral or risk-averse individuals sometimes accept unfair bets. The most common and intuitive reason is that individuals derive utility from the act of gambling. Walther describes the effect as a change in utility that arises from “the resolution of uncertainty” [14]. In simpler terms, betting can be fun. The individual generates some utility as a product of simply playing the game, and experiencing elation or disappointment when the outcome of the bet is realized. This effect is well known to the public as the ‘Lottery Dream.’ The probability of winning a multi-million dollar lottery jackpot is dismally small, but lottery players derive utility from imagining or discussing their plans for the prize money. Walther explains why individuals are willing to forgo the cost to play.

“Small probabilities to win are systematically overvalued. The reason is simple. If one loses with “certainty” no disappointment effect will arise. On the other hand, elation will be strong, if one gets a large gain – against all odds.’ [14]

The ‘nothing to lose’ explanation may play an important role in hunting permit lotteries. There are striking parallels. The low cost of applying and large number of fallback hunting opportunities may allow applicants to rationalize applying to hunts that do not maximize their expected outcome. *Clotfelter and Cook (1990)* discuss alternative explanations for risk-loving behavior of lottery players, and the

demographic distribution of players. They found that low-income players were more strongly motivated by potential gains, and high-income players were more motivated by playing ‘for fun’. Typically lottery tickets cost around \$1, and the expected payout is about half of the cost to play [15]. Utility gains from playing the lottery or the ‘dream’ effect must make up a portion of that difference.

Golec and Tamarkin (1998) explore similar questions in the context of horseracing. They too recognized the value of entertainment as a partial explanation to why bettors accept ‘overall negative returns’ after a day at the track. They improve upon their analyses with an empirical study of bets placed. They suggest that bettors want to maximize their expected outcome while also maintaining a chance to win big on a ‘long-shot.’ The tradeoff between negative expected return and skewness can be explained by a betting strategy that balances ‘favorites’ and ‘longshots’:

When Gamblers make their bets, they are considering the utility of an evening’s outcome rather than the utility of a single wager... Of course, they are more likely to lose part or all of their stakes, but the possibility of a large win is what lures them. (pg 221) [2]

Garrett and Sobel (1999) expand upon the work of *Golec and Tamarkin (1998)* by applying their reasoning and methodology to a wider population base. They examined state lottery data for similar evidence of positive skewness preference. They estimate lottery player utility using a cubic utility function, and confirm previous findings. At high win probabilities, players tend to behave as risk-averse individuals. At low win probabilities, they tend to behave as risk-loving individuals [3]. *Garrett and Sobel (1999)* reiterate the observations of *Golec and Tamarkin (1998)* and explain that large jackpot prizes seem to ‘entice’ players who are normally risk averse.

4.1 Application Model Data

The drawing supplement is organized primarily by game species, and secondarily by geographic location of the listed hunts. Each hunt can be identified with a standardized hunt ID containing 5 characters. *Figure 1* contains the supplement listing of a draw moose hunting permit in 2016, DM041, as indicated by the first two digits DM. Hunts are listed by ascending ID, and there are significant gaps in the ID numbers. As hunts are altered, added, or removed they are assigned new hunt ID numbers. The ID

numbers serve an important function in the organization of the data set, which spans 6 years and 8 species.


Game Management Unit, Area	Hunt No.	Number of Permits	Season Dates 2016	Legal Moose	Specimens Required (Return with permit report)	Reporting Requirements If Successful	Additional Requirements and Information
1C, Berners Bay	DM041	up to 5	Sept. 15-Oct. 15	Bull	 5-inch section of lower jaw with front teeth	In person or by mail to Douglas within 10 days of kill	Hunt Area: Unit 1C within the Berners Bay drainages.

Figure 1: Example of Moose Drawing Supplement Entry [5]

Table 1: Example of Application Model Data

	year	new hunt	species	Hunt Num.	hunt	Num. Apps	Num. Permits	GMU	subunit	sex	Residency	Restrictions	srate	expected draw	Concatenated
moose	2016	0	DM	41	DM041	723	5	1	c	1	0	0	80	1	1C

The data set is constructed from the drawing supplement and is used to estimate predictive models for the permit lottery. It contains observations for the hunting permits offered from 2011-2016. *Table 1* contains the application model data as derived from the supplement entry shown in *Figure 1*. *Table 1* also contains the success rate (srate) obtained from ADFG’s online database, and the number of received applications which is obtained from the 2017 drawing supplement.

Table 2: Summary Statistics of Application Model Data

Species	Observations	Min Number Apps	Max Number Apps	Mean Number Permits	Mean Success Rate	Mean Draw Probability
Moose	984	0	6267	29.1	39%	18%
Sheep	281	6	3341	10.4	41%	3%
Goat	221	15	1372	18.9	4280%	6%
Bison	34	363	14114	20.4	72%	0%
Elk	71	65	1042	53.9	33%	15%
Musk Ox	13	196	1586	18.1	99%	3%
Black Bear	56	1	266	39.5	40%	90%
Caribou	43	167	13597	146.4	56%	8%

Table 2 contains brief summary statistics for the application model data set. There are natural limitations in the abundance of certain species, and therefore sustainable harvest levels. Regression modeling is restricted mainly to moose and Dall sheep permits. Most of these hunts take place in relatively small hunt boundaries and are road accessible from Anchorage or Fairbanks, where most applicants reside. Hunting opportunities for these species are competitive and there are a sufficient number of observations for each. For some other species, such as bison, there are only 4-6 observations per year. They are generally homogenous in terms of hunt quality and other parameters, and model estimation is less reliable. The large number of moose and sheep hunts, and their proximity to urban centers constrain the variation among the samples and allows the model to isolate the effects of estimated parameters. The data includes observations from 2011 to 2016, or 6 application periods [5].

There are some breaks in the data set due to structural changes and publishing gaps.³ The affected observations were dropped from the data set. The second main source of breaks in the data is an inability to separate the effect of restrictions on resident vs nonresident hunters. Approximately 30 moose hunts in

³ In 2014 there was a restructuring of moose hunts in unit 20, where several hunts were split to create permits available only to youth. In doing so, ADFG changed the ID numbers of 44 moose hunts from 2014 to 2015. The change resulted in a publishing gap the following year and the application levels for those 44 hunts are not known.

units 21, 24 and 26 allow applications from residents and nonresidents, but there are separate hunting restrictions for the applicants.⁴

4.2 Application Model Methods

The model parameters not drawn from the hunt supplement are hunter reported success rate and approximate travel distance to the hunt Game Management Unit (GMU). Hunter reported success rate was obtained from the ADFG website harvest statistics. The travel distance term is estimated using a combination of ArcMap analysis tools and Google Maps.⁵ Many hunters use ATV's, snow-machines (snowmobiles), or boats to access hunting territory further from the highway. The models discussed later in the paper do not account for off-road vehicles, but the travel distance terms represent ordinal differences. Fairbanks was chosen as the travel distance origin because nearly all road-accessible permit hunts are located south of Fairbanks. Although permit demand is driven by Anchorage residents, a distance term implies no directionality. A distance-from-Anchorage term would create ambiguity because there are hunt locations both north and south of Anchorage. A summary of the variables used for analysis is presented in *Table 3*, below.

⁴ Nonresident hunters are required to take a large bull (minimum 50 inch spread or 4 brow tines) but residents may take any bull. The *bigbull*, *bull*, *resident*, and *nonresident* indicators are all important sources of inference in the model but their effect on the dependent variable cannot be isolated in these observations, so they are not included.

⁵Using ArcMap, The centroid of each game unit and subunit were generated and snapped to the nearest highway. The coordinates of the snapped points were exported to Google Maps and used to calculate a highway travel distance. A sum of the highway distance and distance from the snapped points to the appropriate GMU centroid were combined to form a total travel distance.

Table 3: Application Model Variable Names and Descriptions

Variable Name	Type	Description
NumApps	Continuous	current year number of applications received
NumPermits	Continuous	published maximum number of permits to be distributed
srate	Percentage	previous year success rate of hunters who went hunting
y2011-2016	Dichotomous	indicator for years 2011 through 2016
resident	Dichotomous	1 if an Alaska resident
nonresident	Dichotomous	1 if not an Alaska resident
bow	Dichotomous	1 if bowhunter certification is required
muzzle	Dichotomous	1 if muzzleloader certification required
youth	Dichotomous	1 if applicant must be 14 years of age or younger
vet	Dichotomous	1 if applicant must be a disabled veteran
DFAIR	Continuous	calculated travel distance from Fairbanks to centroid of permit Game Management Unit
DANCH	Continuous	calculated travel distance from Anchorage to centroid of permit Game Management Unit
DFAIRsq	Continuous	squared Fairbanks travel distance
DANCHsq	Continuous	squared Anchorage travel distance
Moose specific		
antlerless	Dichotomous	1 if moose must not have antlers
bull	Dichotomous	1 if moose must be male
bigbull	Dichotomous	1 if moose must be male, with antler spread
sheep specific		
fullcurl	Dichotomous	1 if sheep horns must be full curl
g12, g7, g20	Dichotomous	indicator variable for Game Management Unit
goat specific		
remote	Dichotomous	1 if no road access
southeast	Dichotomous	1 if hunt Game Management Unit = 1,2,3,4 or 5
punish	Dichotomous	1 if hunt punishes hunters who take nanny goat with kids

Travel cost is a significant expense for outdoor recreationists, and should be accounted for in the predictive models [16]. In the absence of a travel cost term, a travel distance variable should be among the more significant parameters in the model. Nonresidents have substantially greater travel costs because they must first travel to either Anchorage or Fairbanks before traveling to their prescribed hunt area. Nonresidents also have greater costs if they hire a hunting guide and/or pay for accommodations like hotel, rental car, etc. A hunting guide is required for nonresident hunters who pursue brown bear, dall sheep, or mountain goat. Theory would dictate that the *resident* and *nonresident* terms would capture these effects. In the absence of individual level data, these indicator variables are the best method to account for travel costs for out of state hunters.

The data contains three sets of categorical variables. The *resident* and *nonresident* indicator variable are compared to a baseline where either residents or nonresidents may apply. The remaining two variable sets both relate to hunt restrictions. One set contains dummy variables to indicate additional restrictions including bow only, muzzleloader only, youth only, and disabled veterans only. These restrictions should all limit the number of prospective applicants and incur a negative effect on the

dependent variable, *apps*. The remaining set varies for each species, but relates to animal gender or size restrictions. Together, these variables will attempt to capture preferences of hunters. There is little theory to dictate expectations for these terms. However, the baseline is an either sex tag, which allows for the greatest flexibility in hunting strategy. Either-sex tags function similarly to antlerless tags, but stipulate that hunters may not take a female animal with young.

The draw hunt supplement used to compile the Alaska permit lottery data set does not contain individual demographic data or characteristics. This is a critical element of estimating demand relationships with count data, and was noted by both *Boxall (1994)* and *Scrogin (2000)*. Count data for the Alaska permit lottery would ideally be modeled with a repeated discrete choice model. The permit rationing system modeling by *Boxall (1994)* and *Scrogin (2000)* closely resembles the Alaska hunting permit lottery. But in the absence of individual characteristics of the hunters and demographic information about applicants, modeling methods are limited to prediction-type Pooled OLS models. *Equations 1* through *3* represent the generalized models with quadratic terms included for each of the three modeled species.

$$\begin{aligned}
 \text{Number of Applications Moose Permit } \beta = & \beta_0 + \beta_1 X_{\text{Num.Permits}} + \beta_2 X_{\text{NewHunt}} + \\
 & \beta_3 X_{\text{SRate}} + \beta_4 X_{\text{GenSeasSRate}} + \beta_5 X_{y2016} + \beta_6 X_{y2015} + \beta_7 X_{y2014} + \beta_8 X_{y2013} + \beta_9 X_{y2012} + \\
 & \beta_{10} X_{\text{Bull}} + \beta_{11} X_{\text{Antlerless}} + \beta_{12} X_{\text{BigBull}} + \beta_{13} X_{\text{Resident}} + \beta_{14} X_{\text{NonResident}} + \beta_{15} X_{\text{Bow}} + \\
 & \beta_{16} X_{\text{Muzzle}} + \beta_{17} X_{\text{Youth}} + \beta_{18} X_{\text{Vet}} + \beta_{19} X_{\text{DANCH}} + \beta_{20} X_{\text{DFAIR}} + \beta_{21} X_{\text{NumPermitsSQ}} + \\
 & \beta_{22} X_{\text{SRateSQ}} + \beta_{23} X_{\text{DANCHSQ}} + \beta_{24} X_{\text{DFAIRSQ}}
 \end{aligned}
 \tag{Eq. 1}$$

$$\begin{aligned}
 \text{Number of Applications Sheep Permit } \beta = & \beta_0 + \beta_1 X_{\text{Num.Permits}} + \beta_2 X_{\text{SRate}} + \\
 & \beta_3 X_{\text{GenSeasSRate}} + \beta_4 X_{\text{DANCH}} + \beta_5 X_{\text{DFAIR}} + \beta_6 X_{y2016} + \beta_7 X_{y2015} + \beta_8 X_{y2014} + \beta_9 X_{y2013} + \\
 & \beta_{10} X_{y2012} + \beta_{11} X_{\text{Resident}} + \beta_{12} X_{\text{NonResident}} + \beta_{13} X_{\text{FullCurl}} + \beta_{14} X_{\text{AnySheep}} + \beta_{15} X_{\text{Bow}} + \\
 & \beta_{16} X_{\text{Youth}} + \beta_{17} X_{\text{NumPermitsSQ}} + \beta_{18} X_{\text{SRateSQ}} + \beta_{19} X_{\text{DANCHSQ}} + \beta_{20} X_{\text{DFAIRSQ}} + \beta_{21} X_{g12} \\
 & + \beta_{22} X_{g7} + \beta_{23} X_{g20}
 \end{aligned}
 \tag{Eq. 2}$$

$$\begin{aligned}
\text{Number of Applications Goat Permit } \beta = & \beta_0 + \beta_1 X_{\text{Num.Permits}} + \beta_2 X_{\text{NewHunt}} + \\
& \beta_3 X_{\text{SRate}} + \beta_4 X_{y2016} + \beta_5 X_{y2015} + \beta_6 X_{y2014} + \beta_7 X_{y2013} + \beta_8 X_{y2012} + \beta_9 X_{\text{NonResident}} + \\
& \beta_{10} X_{\text{Punish}} + \beta_{11} X_{\text{DANCH}} + \beta_{12} X_{\text{DFAIR}} + \beta_{13} X_{\text{NumPermitsSQ}} + \beta_{14} X_{\text{SRateSQ}} + \\
& \beta_{15} X_{\text{DANCHSQ}} + \beta_{16} X_{\text{DFAIRSQ}} + \beta_{17} X_{\text{Southeast}} + \beta_{18} X_{\text{Remote}}
\end{aligned}
\tag{Eq. 3}$$

4.3 Application Model Results

The travel distance proxy variables have some limitations in the model. The method of measurement does not account for travel costs incurred by the hunters and it approximates travel distances off the road system. However, the distance terms do capture ordinal preferences, which are sufficient for inference. Without individual data it is not possible to comment on individual demand or welfare changes in the lottery system.

Preliminary models are heavily influenced by heteroscedasticity in the data. Models for moose, sheep, and goat permits all tested positively for heteroscedasticity using the Breusch-Pagan test. Changes to the functional form of the models improved the adjusted R-squared fit of the model but created problems for inference. It is simpler to comment on permit demand in terms of the number of applications rather than percentage changes in applications. From a management perspective, it is also easier to estimate revenue changes for predicted application levels. Instead, the models are estimated with robust standard errors.

Table 4: Application Models for Moose Permits Using Robust Standard Errors

Alaska Hunting Permit Lottery - Moose Permits			
	Basic	Quadratic	Limited
Num. Permits	6.661*** (1.076)	15.65*** (1.806)	7.610*** (0.973)
new hunt	5.764 (137.6)	-99.27 (143.9)	
srate	2.885* (1.455)	4.468*** (0.931)	2.278* (1.092)
GenSeasSuccess	-9.280 (8.993)	-1.158 (8.747)	
y2016	238.6** (87.41)	288.9*** (81.60)	263.2** (84.56)
y2015	360.1*** (79.23)	399.3*** (67.21)	340.7*** (77.80)
y2014	222.0** (68.23)	204.4*** (58.71)	194.2** (71.65)
y2013	0 (.)	0 (.)	39.24 (55.68)
y2012	-107.8 (56.38)	-92.81 (56.64)	-84.21 (51.19)
bull	-30.43 (131.8)	-40.74 (113.1)	
antlerless	343.4** (121.0)	484.0*** (101.9)	679.1*** (107.0)
bigbull	-391.1 (202.6)	-24.00 (170.4)	
resident	298.0* (138.9)	108.6 (125.0)	
nonresident	443.2** (144.7)	-352.8* (157.1)	-672.0*** (114.4)
bow	-377.6** (128.3)	-363.3** (120.1)	-338.4*** (72.53)
mussle	-378.7* (154.1)	-377.9** (146.1)	-419.8** (134.5)
youth	-428.4*** (106.0)	-308.2** (102.1)	-338.7*** (65.38)
vet	-538.1** (177.4)	-636.3*** (143.9)	-597.7*** (85.91)
DANCH	-2.931*** (0.410)	-1.478 (1.151)	
DFAIR	0.967** (0.383)	6.404*** (1.119)	10.33*** (1.021)
NumPermitsq		-0.0362*** (0.00664)	
sratesq		-0.00496*** (0.00111)	
DANCHsq		-0.000614 (0.00178)	
DFAIRsq		-0.0104*** (0.00203)	-0.0157*** (0.00185)
Constant	598.4 (305.4)	-403.8 (311.0)	-1100.9*** (142.6)
Observations	763	763	763
Adjusted R-squared	0.518	0.602	0.532

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The moose permits pooled OLS cross section in *Table 4* explains 52% of the variation in application levels for 763 observations. The number of permits offered is highly significant, with each additional permit increasing the number of applications by 6.7. Hunter reported success rate was included in the model to serve as a proxy for unobserved hunt qualities relating to specific geographic regions. We assume that hunters have perfect knowledge of the areas they choose to hunt in and are able to compare the quality of the available permits. Success rate is significant and each additional percentage point increases the number of apps received by 2.9. The resident indicator is significant to the 10% level and the nonresident indicator is significant to the 5% level. They are compared to a baseline permit where either residents or nonresidents may apply. Weapon restrictions decrease the number of applicants, as do youth-only and vet-only permits. Note that the year 2013 indicator is omitted in models that include the general season success rate variable. The general season success rate in 2013 and the base year 2013 are perfectly correlated.

Travel represents the primary cost component for hunters. The distance terms (distance from Anchorage and distance from Fairbanks) are highly significant to the pooled OLS model. The negative coefficient of the ‘distance from Anchorage’ term is consistent with the expectation that permit demand is driven by Anchorage residents. As the largest city in Alaska, Anchorage’s residents comprise the largest portion of aggregate demand for hunting permits. With 298,000 residents, Anchorage makes up 40% of the state’s total population [17]. Because the travel distance terms do not imply directionality, inferences from models with the Fairbanks distance and Anchorage distance terms are unreliable. In the Limited model, application levels increase by 10.2 apps per mile of distance away from Fairbanks. The quadratic term indicates an inflection point at a distance of 307 miles from Fairbanks. Anchorage is approximately 366 miles from Fairbanks by highway. At distances greater than 307 miles from Fairbanks, application levels will begin to decrease. The distance roughly corresponds with the length of the Parks Highway (323 miles), the primary route for travel between Anchorage/Matsu Valley and Fairbanks. At the relative maximum predicted by the Limited model, 3,166 applications will be received for any given moose hunt, *ceteris paribus*. The maximum dependent variable value in the data set is 6,267 applications.

In terms of animal gender, we can make some interesting inferences. Antlerless moose permits receive an additional 343 applications over the baseline. Antlerless moose, although smaller, are more common and make better table fare than rutting bulls. For comparison, the large bull permit indicator was included. It is not significant to the model, and has a negative coefficient. If hunters were pursuing trophy moose or hunting purely for sport, we would expect a positive and significant coefficient for the ‘bigbull’ term. It seems that antlerless permits are preferred to bull or trophy bull permits. This is not surprising considering moose are an important source of food for many Alaskans. The finding is notable compared

to studies of lotteries in the lower-48 states where demand for hunting permits is generally driven by trophy hunting opportunities for elk, pronghorn antelope, and other species [10].

Table 5: Application Models for Dall Sheep Permits Using Robust Standard Errors

Alaska Hunting Permit Lottery - Dall Sheep Permits			
	Basic	Quadratic	Alternate
Num. Permits	17.48*** (5.043)	88.67*** (13.11)	18.62*** (1.756)
srate	0.152 (0.561)	0.0492 (2.514)	
GenSeasSuccess	-33.15 (17.78)	-21.52 (14.14)	
DANCH	0.446 (0.284)	-7.913* (3.462)	
DFAIR	-0.261 (0.986)	-24.24** (7.892)	
y2016	66.54 (79.16)	36.03 (66.72)	
y2015	0 (.)	0 (.)	108.6* (45.71)
y2014	-68.71 (86.91)	-90.59 (69.64)	
y2013	-170.1 (87.99)	-147.2* (69.83)	
y2012	-60.34 (73.59)	-71.72 (61.19)	
resident	-742.2*** (101.6)	-378.5* (189.7)	250.5*** (26.25)
nonresident	-1021.9*** (132.0)	-307.7 (235.6)	
fullcurl	-91.73 (79.63)	-116.0 (121.5)	-107.3** (34.06)
anysheep	44.52 (154.0)	19.70 (177.5)	
bow	-421.4* (195.7)	-716.0** (221.2)	-400.7*** (71.39)
youth	-464.4 (297.4)	-753.9* (315.9)	-370.2* (156.5)
NumPermits ²		-1.140*** (0.192)	
srates ²		0.000398 (0.0276)	
DANCH ²		0.0200* (0.00953)	
DFAIR ²		0.0361** (0.0123)	
g12			2003.4*** (153.6)
g7			860.2*** (80.04)
g20			451.5*** (111.0)
Constant	2259.6** (738.1)	5377.4*** (1262.0)	114.8*** (25.83)
Observations	242	242	280
Adjusted R-squared	0.695	0.794	0.862

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The pooled OLS cross sectional model of dall sheep hunts in *Table 5* explains 69.5% of the variation in application levels of 242 observations. Each additional permit offered increases the number of received applications by 17.5. The Fairbanks distance term is less appropriate for the dall sheep model. Dall sheep live in steep mountainous terrain [18], and many of the permit hunts can be accessed by multiple highway routes. Instead, an alternate set of dummy variables are developed from the ADFG designated Game Management Units (GMU). An alternate regional sheep permit model has an R-squared value of 0.86. Sheep hunters exhibit a strong preference for hunts in GMU 12 and 7. An investigation of these permits reveals that easy road access to 4 specific hunts may be the motivating factor. *Appendix F* shows the hunt boundary for two particular sheep hunts (DS102 and DS103) in GMU 12, outside of Tok, AK. State highways represent nearly 50% of the hunt boundary perimeter, and applicants simply prefer hunts with the best access. Note that the year 2013 indicator is omitted in models that include the general season success rate variable. The general season success rate in 2013 and the base year 2013 are perfectly correlated.

An indicator for full-curl restricted hunts in the alternate model is significant to the 5% level and decreases the number of applications by 107. We noted that antlerless moose hunts were preferred to bull hunts because it allowed for greater flexibility and likely relates to hunting for food. A similar relationship may be present in sheep hunters. Full curl rams are less common, and much harder to identify. Permit applicants may prefer an either-sex or any-ram permit to provide greater flexibility while hunting. If a full curl ram is spotted, it can still be harvested within these broader tag categories.

Hunter reported success rate is not statistically significant in the model. The result is interesting because it illustrates differences in hunting strategy by species. Dall sheep are small animals compared to moose, giving little meat relative to the arduous hunting conditions that must be endured to harvest one. Sheep hunters may be motivated more by prestige than by subsistence. This may indicate a higher level of competition or risk preference among sheep hunters.

Table 6: Application Models for Mountain Goat Permits Using Robust Standard Errors

Alaska Hunting Permit Lottery - Mountain Goat Permits			
	Basic	Quadratic	Alternate
Num. Permits	1.461 (2.175)	23.12** (7.163)	5.551** (1.930)
new hunt	-96.20 (64.67)	-101.5 (95.29)	
srate	1.436 (0.812)	6.469** (2.010)	
y2016	-21.67 (63.60)	-45.34 (61.55)	
y2015	38.98 (93.28)	33.56 (90.39)	150.4** (49.91)
y2014	18.54 (73.40)	31.98 (65.73)	
y2013	-9.935 (67.66)	-2.610 (61.88)	
y2012	-0.513 (69.18)	-1.291 (64.47)	
nonresident	-575.2*** (76.92)	-396.9** (122.4)	-427.0*** (33.52)
punish	-25.86 (65.30)	-29.39 (100.0)	-179.5*** (35.28)
DANCH	-0.734* (0.317)	-2.273 (2.504)	
DFAIR	-0.820* (0.363)	7.828** (2.401)	
NumPermits ²		-0.657** (0.203)	
srate ²		-0.0728** (0.0242)	
DANCH ²		0.00684 (0.00710)	
DFAIR ²		-0.00942*** (0.00263)	
southeast			-271.4*** (60.09)
remote			-194.8*** (46.71)
Constant	863.1*** (156.9)	-1156.7* (517.2)	430.1*** (42.25)
Observations	130	130	214
Adjusted R-squared	0.181	0.312	0.233

Standard errors in parentheses
 * p<0.05, ** p<0.01, *** p<0.001

A model of mountain goat permits in *Table 6* explains little of the variation in applications, but provides valuable inference. Adjusted R-squared goodness of fit ranges from 0.18 to 0.31 for the presented models. Similar to sheep permits, hunter reported success rate is not significant in the model. Mountain goats and dall sheep live in steep and rocky habitat, and hunting for mountain goat poses many of the same challenges. Success rate is often low. Also, note that there are no general season hunting opportunities for mountain goats in Alaska. Goat hunters have few substitute opportunities, so hunt quality is not relevant compared to other parameters. Applicants accept greater risk in order to pursue a rare quarry.

The dummy variable ‘punish’ represents a management tool for either-sex goat permits. A hunter may harvest a nanny goat, but the hunter will be prohibited from goat hunting for 5 years if the nanny has kids. This interesting stipulation is highly significant in the model. Permits with the punishment receive 180 fewer applications in the Alternate model. Apparently, hunters are wary of the possibility of losing their hunting privileges.

5.1 Behavioral Model Data

The behavioral model data is constructed from the results document of the 2016 hunting permit lottery. It is used to test for gambling behavior in hunters, their permit bundles, and the tradeoff of risk and expected utility among applicants. *Table 7* contains data for three individual applicants, with their names removed for anonymity. The data indicates which permit was applied for, whether the applicant was drawn, and the applicant state of residency.

Table 7: Example of Behavioral Model Data

Year	Species	ID	Y/N	First	Middle	Last	Suffix	City	State	Zip Code
2017	YM	616	No					JUNEAU	AK	99801
2017	DM	871	No					BROOKHAVEN	MS	39601
2017	DC	485	No					CHUGIAK	AK	99567

An analysis of risk behavior is conducted on the behavioral data set. Calculations and modeling are performed on a 10% sample of the 2016 permit application results population, comprised of nearly

160,000 observations [19]. The sample contains information for 3,698 individual applicants. The data include the hunt permit ID, applicant name, state code, zip code, and a yes/no field for successful applicants. *Table 8* and *Figure 2* represent the preferences of applicants in the 10% sample by species.⁶ Permit values are estimated for 455 unique permits. 44% of the unique permits are for moose, and 43% of the applications in the sample are for moose permits. Of the 3,698 applicants in the sample, 75% applied for at least 1 moose permit.

Table 8: Summary Statistics of the 10% Behavioral Data Sample

	Youth (<14 yrs old)	Alaska Resident	Nonresident	Anchorage Address	Fairbanks Address
Count by Applications	203	15996	904	4044	1132
Percentage by Applications	1.20%	94.65%	5.35%	23.93%	6.70%
Count by Applicant	122	3349	369	813	275
Percentage by Applicant	3.30%	90.56%	9.98%	21.98%	7.44%

	Moose	Sheep	Goat	Bison	Elk	Musk Ox	Brown Bear	Black Bear	Caribou	Count
Count by Applications	7208	2411	1439	1955	617	215	802	93	2160	16901
Percentage by Applications	42.65%	14.27%	8.51%	11.57%	3.65%	1.27%	4.75%	0.55%	12.78%	
Count by Applicant	2774	1069	743	1563	318	170	388	75	1720	3698
Percentage by Applicant	75.01%	28.91%	20.09%	42.27%	8.60%	4.60%	10.49%	2.03%	46.51%	

⁶ Additional summary statistics of the 10% sample can be found in *Appendices B* and *C*.

Participation of Applicants by Permit Species

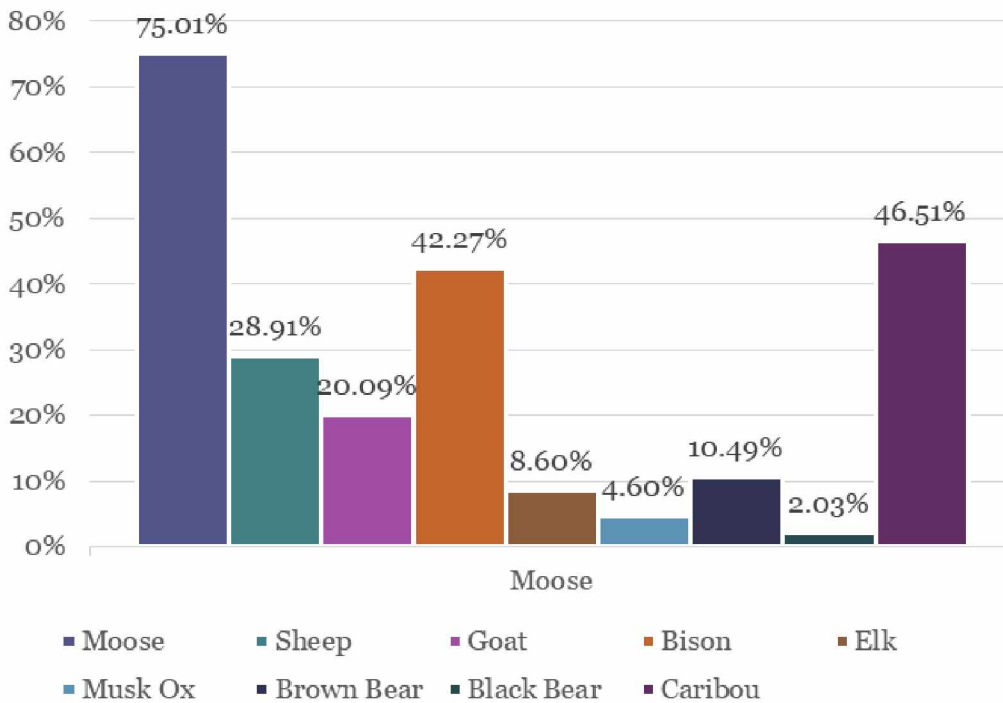


Figure 2: Relative Participation of Individuals in the Permit Lottery with Respect to Species

Although a large proportion of hunters apply for caribou permits, inference from models is difficult considering the structure of the permit lottery. Caribou are an important source of food in many rural communities and caribou management is unique. For example, the well-known Nelchina caribou herd contains about 40,000 animals at any given time and it represents a critical food source for residents of the Copper River Basin [20]. The number of permits varies substantially each year, based on ADFG management goals and the size of the herd. To further complicate the issue, Nelchina caribou permits are distributed by Tier I lottery, draw lottery, and by registration hunts. The complexity of caribou hunting opportunities, and the inability to identify users of different distribution channels makes caribou permit modeling prohibitively difficult.

5.2 Permit Values Estimation and Validation

A risk-averse/wealth maximizing hunter should only apply if their expected utility (a factor of the probability of receiving the permit, the probability of a successful harvest, and utility gained from playing the lottery) is equal to or greater than the application fee. A procedure for generating permit values is shown in *equation 4*. The resulting estimates represent values that a hunter would pay for a permit given certainty of obtaining the permit and harvesting the animal, with no gain in utility from the act of obtaining the permit.

$$F_{\text{app}} = V_{\text{permit}} * P_{\text{harvest}} * P_{\text{draw}} \Rightarrow V_{\text{permit}} = F_{\text{app}} / (P_{\text{harvest}} * P_{\text{draw}}) \quad \text{Eq. 4}$$

F_{app} = Application Fee

- Moose, Sheep, Goat, Elk, Brown Bear, Black Bear -> \$5
- Bison, Musk Ox -> \$10

P_{harvest} = Hunter Reported Success Rate During 2016

P_{draw} = Expected Permit Draw Probability (draw probability in 2015)

V_{permit} = Permit Value, 100% certainty of harvest

The expected value of each permit is then the permit value multiplied by the draw probability. Expected utilities are calculated for each permit using the Arrow-Pratt constant relative risk aversion utility function, where utility is a function only of wealth (W) [21].

$$U(W) = \ln(W) \quad \text{Eq. 5}$$

The calculated permit values represent the dollar value an applicant would be willing to pay for a hunting permit, given a 100% chance of being drawn and a 100% chance of successfully harvesting the animal. The permit values do not reflect the cost of guiding services, land access, or other amenities. Calculations are performed using *equation 4*. The permit values are presented in *Figure 3*. There is an asymptotic relationship between permit value and draw probability. A plot of expected permit value by species is included in *Appendix A*.

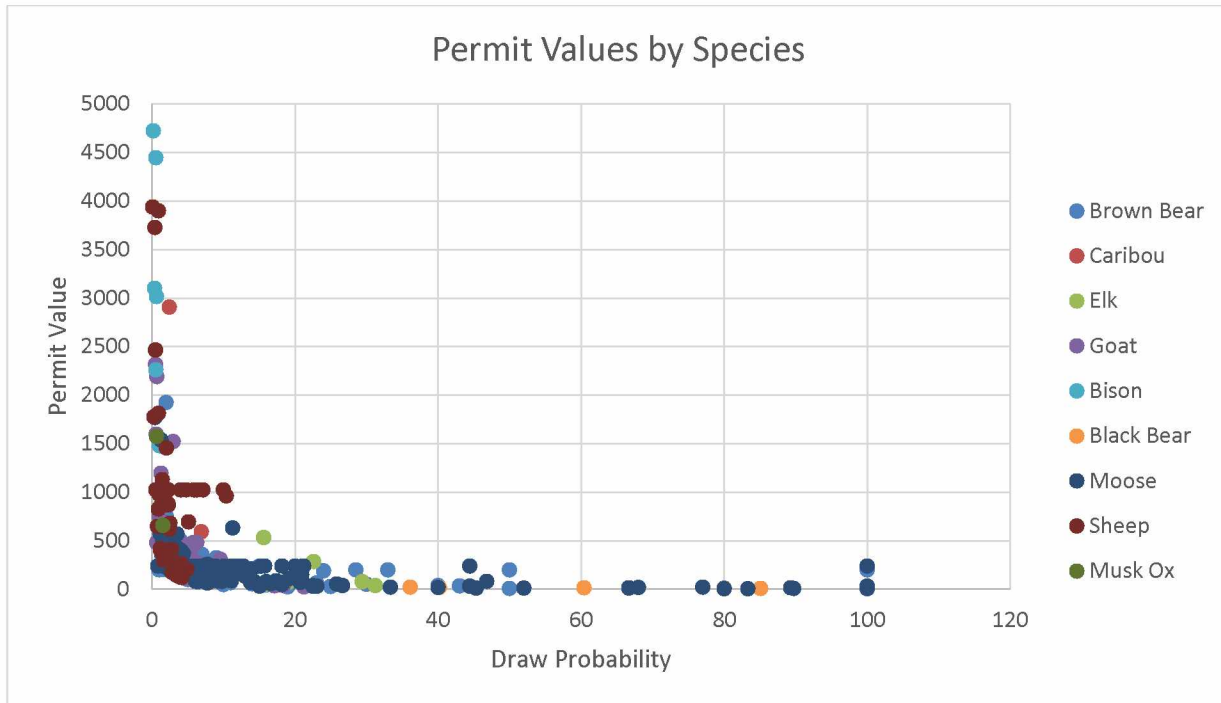


Figure 3: Permit Value over Draw Probability by Species for Behavioral Model Data

Moose and black bear permits make up the majority of the low value/high probability hunts. Permits with a 100% draw probability are designated ‘undersubscribed,’ having fewer applicants than number of available permits. The remaining permits are offered online on a first-come first-serve basis. Some moose and sheep hunts relied heavily on imputed values for hunter reported success rate, and a few undersubscribed hunts make up the small vertical trend at a draw probability of 100%. The highest value permits are generally composed of bison and sheep hunts. These hunts are extremely competitive. Some bison hunts draw as many as 15,000 applicants each year, and successful applicants are prohibited from reapplying for 10 years.

American bison hunting opportunities are extremely limited, which provides an opportunity for comparison with private hunting ranches around the USA. Private hunting ranches provide the animal, land access, guide services, and accommodations to hunters with a 100% guarantee of successful harvest. Their fee schedules are often available online. To compare these rates with the calculated permit values, we must compensate for land access fees, guide service costs, and overnight accommodations. One Alaska firm, *Interior Alaska Guides and Outfitters*, offers guided services to bison permit holders for a \$3,400 fee. Although they do not guarantee their services, they claim a 100% bison harvest success rate with their clients. We assume an accommodations cost of \$200/day, and add land trespass fees where

appropriate. We adjust the permit values and ranch fees to a standard 3 day/2 night hunt, and separate the hunts by animal gender and age. The values are listed in *Table 9*. We find that the adjusted permit values align surprisingly well with the private ranch hunting opportunities. In particular, the ‘DI403 bull only’ permit differs from the ‘ranch trophy-bull’ mean by only \$24 (less than 1%).

Table 9: Comparison of Adjusted Permit Values and Ranch Hunts for American Bison ⁷

bull - trophy	net cost	bull - young	net cost
DI403	\$ 7,016	DI403	\$ 7,016
Ox ranch Texas	\$ 7,500	Brown's Lodge & Hunting Ranch	\$ 7,000
Brown's Lodge & Hunting Ranch	\$ 8,000	Bearpaw Outfitters	\$ 4,250
Bearpaw Outfitters	\$ 7,250	Jim River Guide Service	\$ 5,100
Jim River Guide Service	\$ 6,100	EIA Outdoors	\$ 6,600
Moutain View Ranch	\$ 7,700	Mountain View Ranch	\$ 5,700
Alaska Interior Game Ranch	\$ 5,400	Alaska Interior Game Ranch	\$ 4,400
bull - trophy - mean	\$ 6,995	bull - young - mean	\$ 5,724

either sex	net cost	cow	net cost
DI450	\$ 8,725	DI404	\$ 8,447
DI454	\$ 6,980	Brown's Lodge & Hunting Ranch	\$ 6,000
DI351	\$ 6,262	Bearpaw Outfitters	\$ 3,250
DI352	\$ 7,100	EIA Outdoors	\$ 5,600
High Adventure Ranch	\$ 4,295	Mountain View Ranch	\$ 4,700
The Bison Ranch	\$ 3,600	Alaska Interior Game Ranch	\$ 3,600
Rockin 7 Ranch	\$ 7,150	cow - mean	\$ 5,266
either sex - mean	\$ 6,302		

Summary of Means	net cost
Draw Mean	\$ 7,172
Ranch Hunt - trophy bull - mean	\$ 6,992
Ranch Hunt - young bull - mean	\$ 5,508
Ranch Hunt - either - mean	\$ 5,015
Ranch Hunt - cow - mean	\$ 4,630
Overall Mean	\$ 5,863

⁷ Note that hunting permit DI403 specifies only that the animal be a bull, so it is included in the “trophy bull” and “young bull” categories for comparison.

Overall, ranch hunting opportunities range in adjusted cost from \$3,250 to \$8,000. Adjusted permit values range from \$6,262 to \$8,725. Ranch hunts typically appeal to a ‘trophy hunting’ audience. Ranches often promote their lavish accommodations, gourmet meals, fully stocked bar, and the unparalleled size of their animals. Mature bulls are in high demand and prospective clients are encouraged to book their hunt well in advance. Sometimes the hunter will have chosen the exact animal they plan to harvest, months prior to the actual hunt. Not surprisingly, private ranch bulls fetch the highest price with younger ‘meat’ animals bringing gradually less based on size and gender. We observe that ‘either sex’ and ‘cow only’ adjusted permit values are notably higher than their ranch-hunt substitutes. The finding is not surprising, considering the known preference of Alaskan hunters for high success rates and animals that make better table fare. Both of these are likely true of ‘either sex’ and ‘cow only’ permits. A comparison of the mean values confirms this observation. We find that the adjusted permit value mean is only slightly higher than mean ranch hunt costs, at \$7,172. The adjusted permit mean is heavily influenced by the value of ‘either sex’ tags, which are offered in far greater numbers. The premium for Alaska bison hunting permits may also be explained by the higher cost of living in Alaska, reflected in higher travel costs, retail good prices, and guide service fees. The analysis of the bison permit values provides validity to the calculation method described in *equations 4 and 5*.

5.3 Non-Parametric Evidence of Gambling Behaviors

Nickerson (1990) explained that an applicant will apply to the hunt with ‘the highest expected value’ [13]. This assumption is not totally appropriate for modeling the Alaska permit lottery. The primary issue lies in the structure of the lottery, which allows applicants to apply for multiple permits across 8 different big game species (though only 1 permit may be obtained for each species). Analysis must instead be focused on the expected value for a bundle of applications. Another complication arises when one considers the myriad of substitutable hunting opportunities in Alaska. Hunters may be able to harvest an animal during the general season, by obtaining a Tier I or Tier II permit, or with assistance of a professional guide. The unique structure of the distribution system and immense variety of hunting opportunities may not lead to wealth maximization of lottery applicants; it may instead lead to gambling behaviors.

Garrett and Sobel (1999) demonstrated that state lottery players changed their behavior when the win odds and top prize varied. The same may be true of hunting permits in unusually high demand. For example, wild bison hunting opportunities are extremely limited. This unique opportunity will attract up

to 15,000 applicants for each Alaska permit. The estimated permit values are much greater for bison than for other species, and the corresponding draw probabilities are small. These “long-shot” type permits might entice applicants who normally behave as risk-averse individuals. Hunters may increase the likelihood of being drawn by mixing high and low probability applications in their permit bundle. In a state lottery, players may purchase multiple tickets to increase their odds of winning. In the hunting permit lottery applicants may apply for up to 3 different permits per species (6 for moose). The key difference from a state lottery is that each unique hunting permit application has different win odds and expected utility. The cost to play is also low (\$10 or less) relative to the potential gains. Hunters stand to lose very little, making the lottery seem even more like a betting game.

Non-parametric modeling methods are used to search for evidence of gambling type behavior in the bundle of Alaskan hunt lottery applications. The Alaska hunting permit lottery differs substantially from other hunting permit distribution methods and from typical state lotteries. There is no empirical standard for distributions to model the data. In order to fit curves for visualization and for economic inference, it is necessary to utilize a kernel density estimation (KDE) technique. However, there are natural limitations in the abundance of certain species and therefore sustainable harvest levels. Due to the limited number of observations in the other game species, KDE is restricted to moose, dall sheep, and mountain goats. Hunting opportunities for these species are competitive, and there are a sufficient number of observations for each. For some other species, such as bison, there are only 4-6 observations per year. Any model will probably over-fit the data and inference will be limited. There are also some limitations to the hunter-reported data (success rate). For instance, a large number of brown bear permits relied on imputed success rates to estimate permit values and a fitted model was not appropriate. Imputed values were calculated as an average of up to five previous years of reported data, when available.

In addition to the calculated permit values, a variable is generated to reflect the risk associated with unique permit bundles. Each permit within a bundle has an associated expected draw probability, as published in each year’s supplement. Multiplying the probability of not winning each permit in the bundle results in a cumulative probability of receiving no permits from the application bundle. This metric, *probability of no permits drawn*, reflects the risk of the entire application, using existing information.

$$P_{\text{no permits drawn}} = (1 - P_{\text{draw } 1}) * (1 - P_{\text{draw } 2}) * (1 - P_{\text{draw } 3}) \dots *(1 - P_{\text{draw } x}) \quad \text{Eq. 6}$$

Using the Gaussian distribution and the normal reference bandwidth, plots are created for the expected utility bundles given the probability that the applicant obtains no permits.⁸ This metric is intended to reflect the relative risk of unique permit bundles. An aversion to risk is inferred when the distribution is more positively skewed, corresponding to lower levels of expected utility.

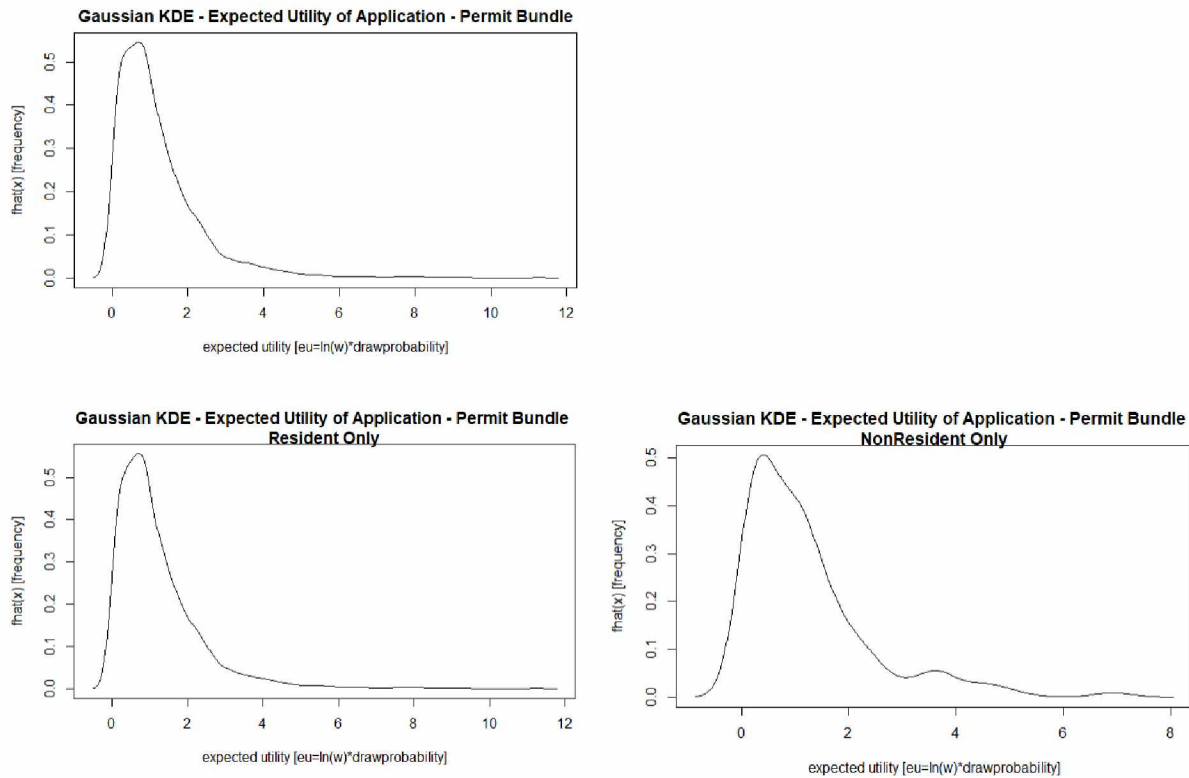


Figure 4: Fitted KDE for Full Application Expected Utility Bundles

In *Figure 4* the full nonresident bundles exhibit far less positive skew than the resident only bundles. The same is true of the moose permit bundles in *Figure 5*. In the moose permit bundles the effect is actually far more pronounced. The nonresident-only plot appears relatively normal in shape. The willingness to accept lower expected utilities in Alaska residents is immediately apparent.

⁸ The 'R Project for Statistical Computing' offers a free software package for download on a variety of operating systems. The R function *Density* is used to fit the generated utility bundles. The 'from' and 'to' options are used to limit the curves to the appropriate bounds (0 and 1 for a percentage).

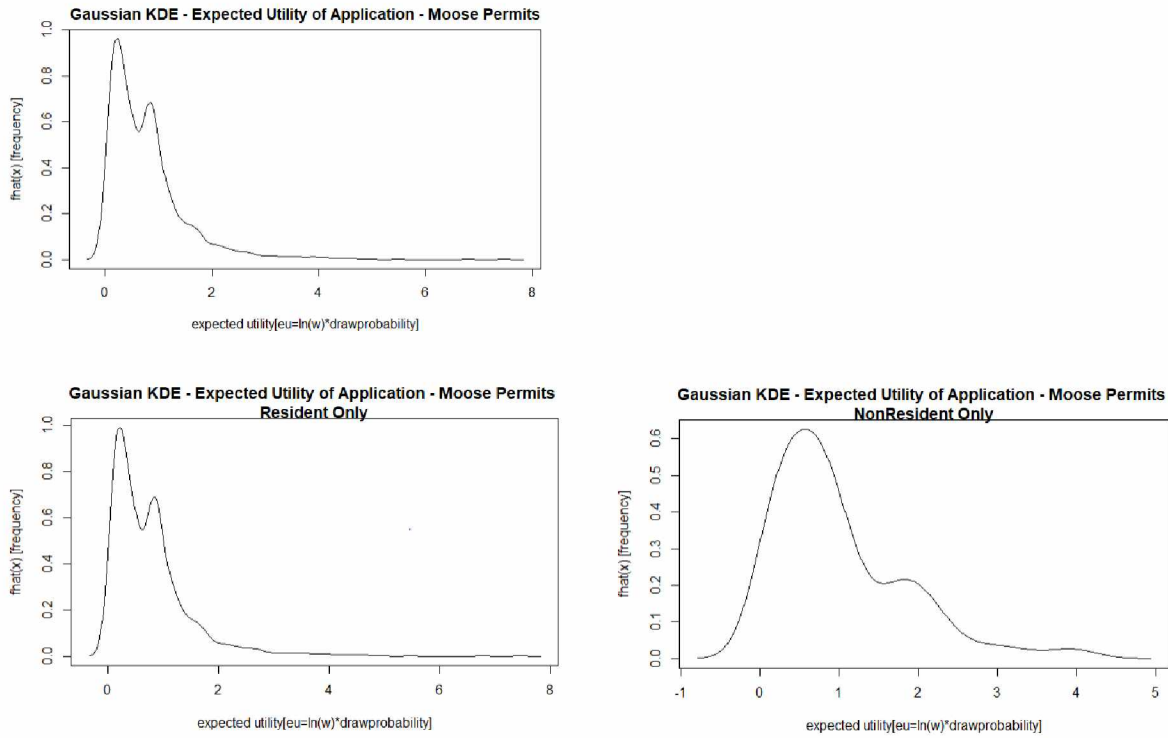


Figure 5: Fitted KDE for Expected Utility Bundles of Moose Permits

As shown in *Figure 6*, the degree of positive skew is far greater in both sheep and goat permit bundles than in moose permit bundles. There are far fewer of these hunting permits offered, and substitute hunting opportunities are limited as well.

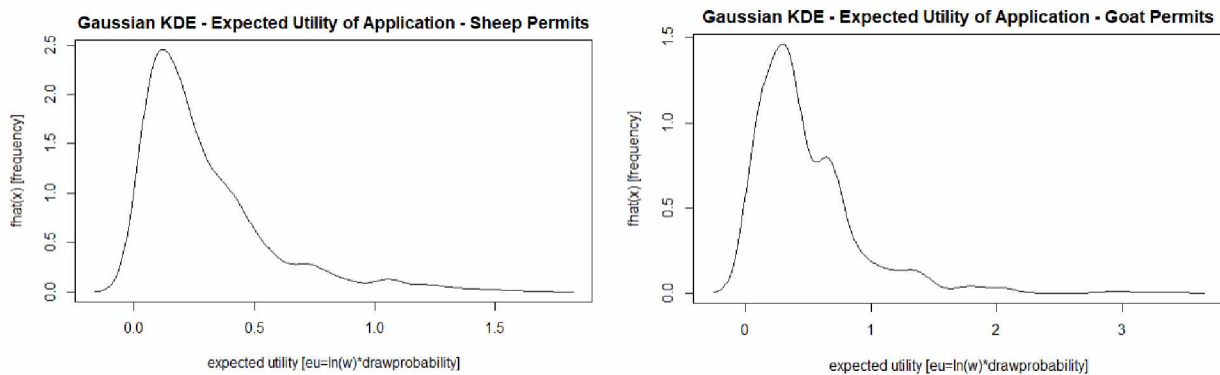


Figure 6: Fitted KDE for Expected Utility Bundles of Sheep and Goat Permits

Figures 7 through 9 are generated using the risk measure presented in equation 6. A preference for risk is inferred when the distribution is more negatively skewed, corresponding to higher probability that the applicant will draw none of the permits in their bundle. The differences in the plots of the full application bundle are small. Risk preference does not seem to vary between residents and nonresidents at this level.

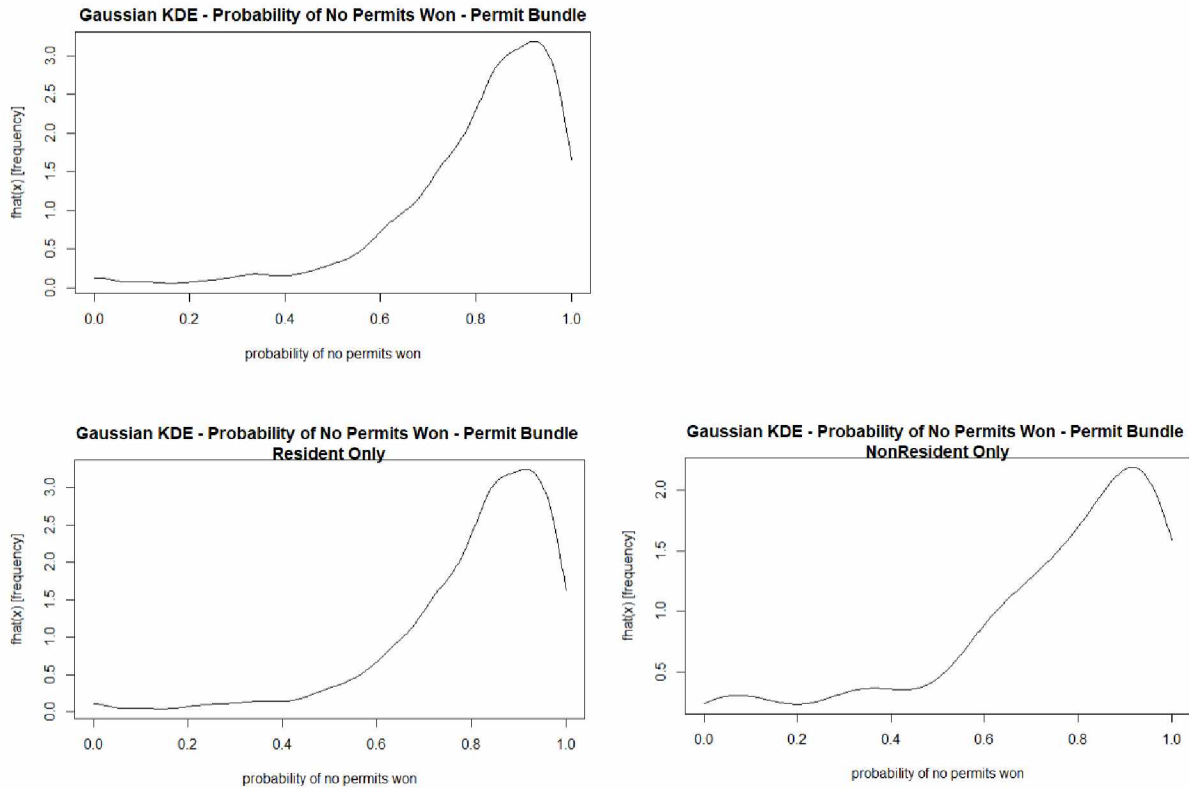


Figure 7: Fitted KDE - Probability of Winning None of the Permits in the Full Application Bundle

In Figure 8 a bimodal distribution is again observed in moose permit application bundles. Separating the resident and nonresident applications yields some interesting results. Resident moose permit bundles are more positively skewed than nonresident moose permit bundles. Resident hunters accept higher levels of risk for moose permits in the lottery. The finding can be explained by two factors. First, there are more substitute moose hunting opportunities for resident hunters. If an applicant is unsuccessful, they can easily hunt moose during the general season. This provides an opportunity for applicants to take an ‘all or nothing’ approach to their application strategy. Since resident hunters have little to lose, they are more likely to apply for high value moose hunts with the highest success rates and

lowest travel costs. Nonresidents have substantially fewer opportunities to hunt moose. If a nonresident hunter plans to take a moose in Alaska, they will need to pay for travel to the state and other costs like lodging, guide services, etc. They will likely prefer to maximize their chances of obtaining a permit, since other opportunities are limited.

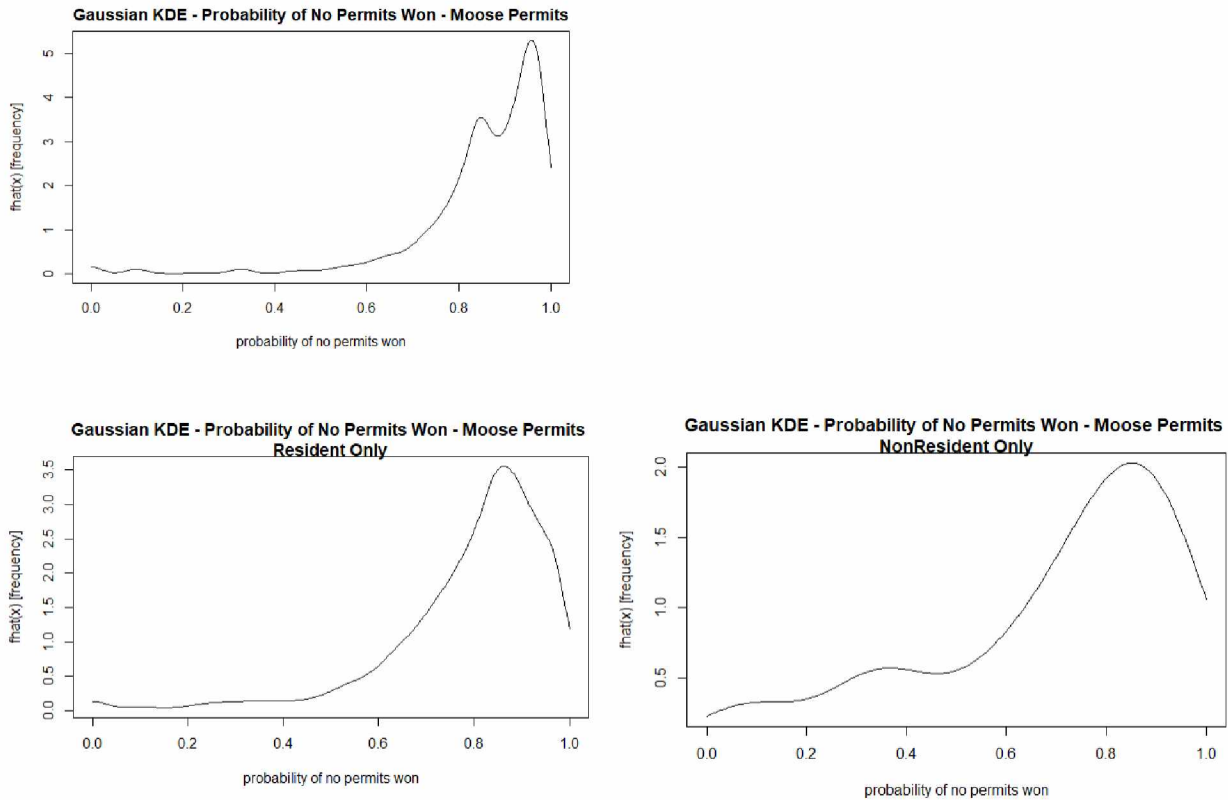


Figure 8: Fitted KDE - Probability of Winning None of the Permits in the Moose Application Bundle

In *Figure 9* the distributions of sheep and goat permit bundles are strongly skewed. The KDE's for sheep and goat permit bundles are heavily skewed toward the upper bound. Moose are a better source of food than either dall sheep or mountain goats. It is likely that sheep and goat hunters seek trophy animals, or simply hunt for sport. This may influence the strategy of the applicant. If the animal is not needed for subsistence, the applicant may accept more risk in order to get a chance at a high value permit.

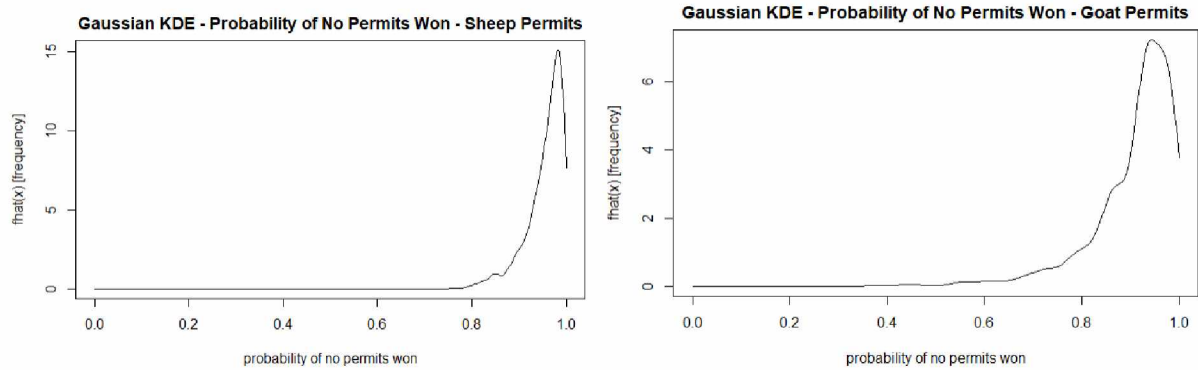


Figure 9: Fitted KDE - Probability of Winning None of the Permits in the Sheep and Goat Application Bundle

Bivariate KDE plots are generated with *expected utility* and *probability of no permits drawn* as the input variables.⁹ Contour lines on the plot represent the probability density of the plotted points relative to the plot area. The area between any two contour lines represents 2% of the probability mass of the plotted points. *Figure 10* shows some interesting differences in the application bundles of residents vs nonresidents. Nonresident application bundles are less densely distributed. A greater proportion of nonresident hunters apply to low-return, low-risk permits than resident hunters. The differences between the plots are striking and conclusive. Nonresident hunters have larger expenses and opportunity costs associated with planning a hunting trip to Alaska. It is likely that they prefer to apply to permits with a higher level of certainty that they will obtain at least one permit.

⁹ The *MASS* package contains the function *kde2d* which is used to compute bivariate kernel density estimates in R [22].

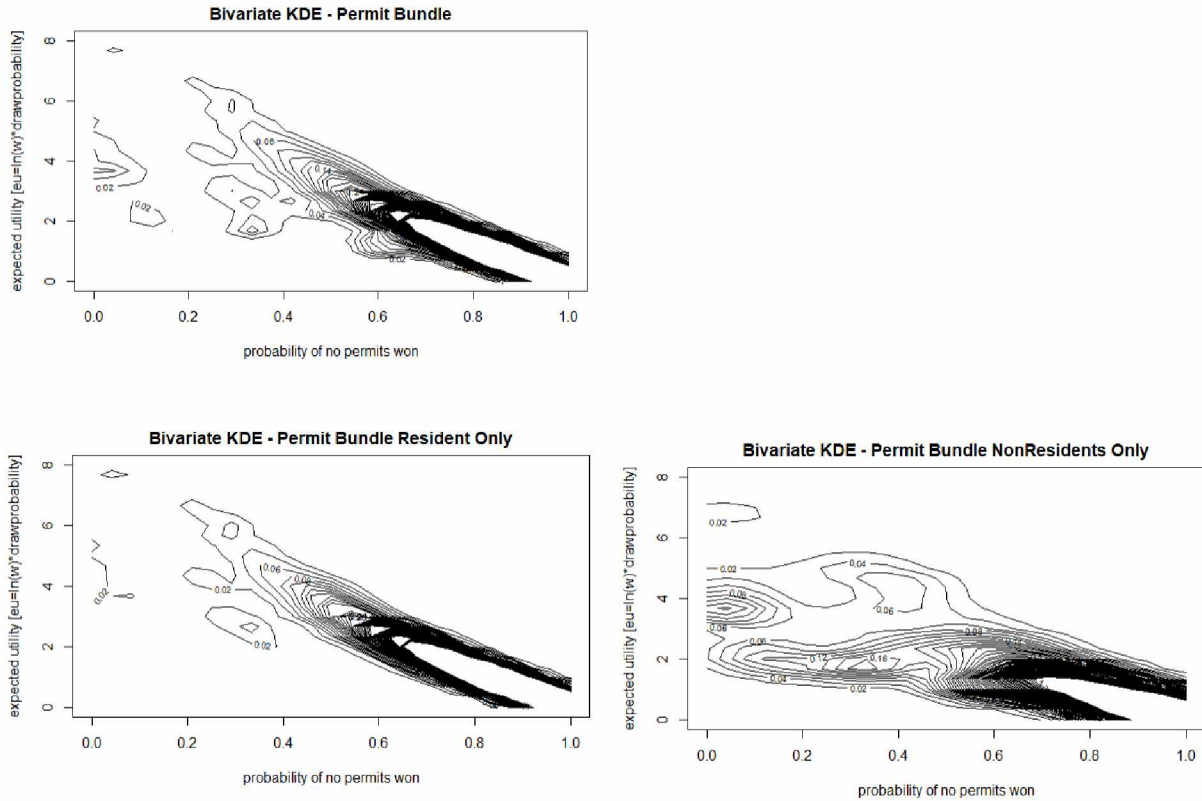


Figure 10: Plots of Bivariate KDE for Full Permit Bundle

Bivariate KDE plots of the moose permit bundles exhibit a similar relationship. *Figure 11* shows nonresident application bundles are more evenly distributed over the probability range. A larger proportion of nonresidents prefer application bundles with a *probability of no permits drawn* less than 40%. There is some overlap between the resident and nonresident bundles in the *probability of no permits drawn* range greater than 70%. The observed bimodality in permit bundles may be due to factors outside the scope of this investigation. For example, there is no data on income for permit applicants. Household income probably has a significant effect on which hunts an individual can afford to participate in.

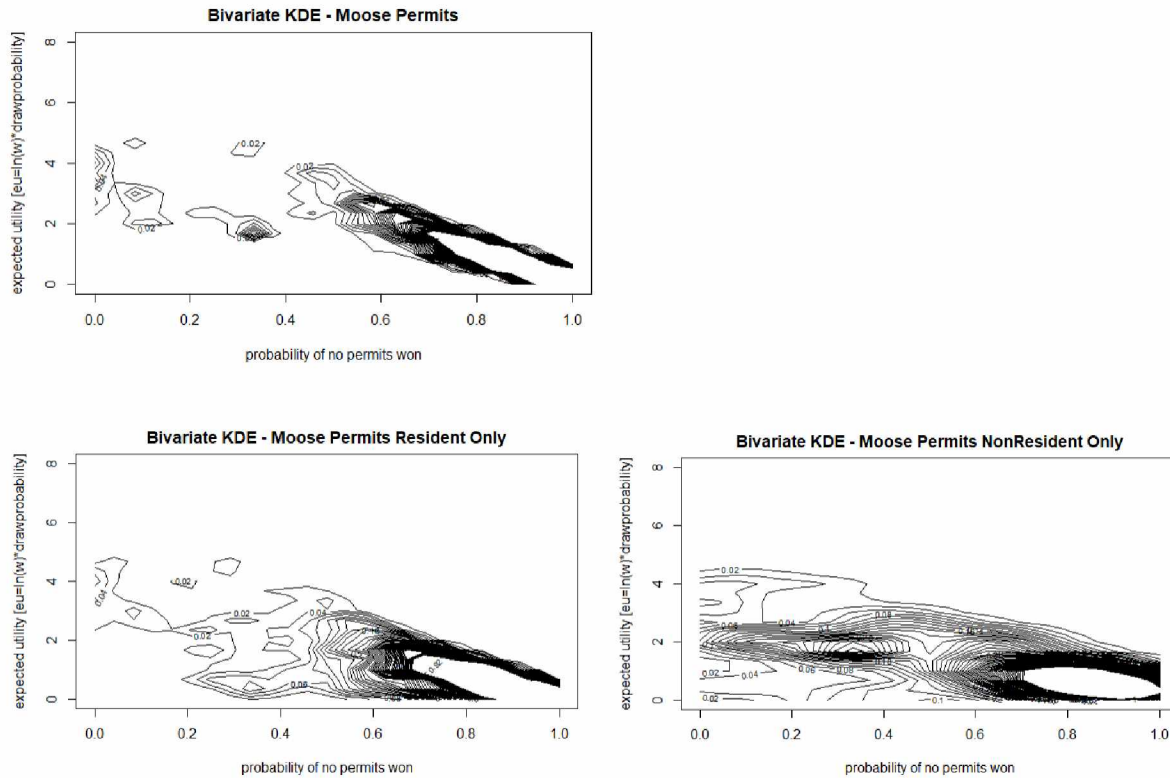


Figure 11: Plots of Bivariate KDE for Moose Permit Bundle

The nonparametric analyses seem to align with the observations of Golec and Tamarkin in the context of horserace betting. Applicants balance their application bundle with a mixture of low probability/low return and high probability/high return permit applications. Bivariate plots of sheep and goat permit bundles are included in *Appendix D*.

5.4 Fitted Cubic Applicant Utility Model

Friedman and Savage (1948) originally hypothesized that the aggregated utility curve of bettors may take a cubic shape, explaining the risk aversion of some players at higher win probabilities and risk loving behavior at lower win probabilities.¹⁰ Those players would “behave as if they calculated and compared expected utility and as if they knew the odds” [1]. *Golec and Tamarkin (1998)* and *Garrett and Sobel (1999)*, used ordinary least squares regression (OLS) to fit a cubic utility function to horse racing

¹⁰ A figure of the cubic utility function from *Golec and Tamarkin (1998)* is included in *Appendix E*.

bet payouts and lottery winnings. *Golec and Tamarkin (1998)* hypothesized that gamblers actually optimize the outcome of a series of bets over a day, rather than the outcome of singular wagers. Using a cubic utility model, *Golec and Tamarkin (1998)* demonstrate a preference for ‘long-shot’ bets on horses with low win probabilities. Risk-neutral or risk averse individuals should prefer betting on ‘favorites’, horses with higher win probabilities but lower expected mean returns. They propose that what bettors actually prefer is an increase in skewness over an increase in risk. Following their methodology, the 2016 permit application results data can be fitted with a cubic utility model to test for gambling behavior. ‘Favorites’ are represented by low risk moose, bear, and elk permit hunts. ‘Long-shots’ are synonymous to high risk permits for bison and some dall sheep. The general shape of the cubic utility model is shown in *appendix E*. The model implies that at low draw probabilities applicants will behave as though they are risk loving. The convex portion of the curve represents the risk loving range where applicants trade utility for positive skewness. The concave portion of the curve represents the risk averse range, where applicants favor higher utility and decreased skewness.

First, an odds-ratio is generated for each unique permit by dividing the draw probability of the of the highest payout bet by the draw probability of the unique permit. In the case of the hunting permit data, the highest valued permit (no adjustments) is a bison hunt (*DI454*) with a generated permit value of \$4,725. Variables for squared permit value and cubic permit value are generated to represent the second and third moment of bet returns. The three moment utility model represents coefficients for mean expected return, variance, and skewness. If the ‘long shot’ hypothesis holds true for the Alaska permit lottery data, we expect positive coefficients for the first and third moment and a negative coefficient for the second moment. The hypothesized result is interpreted as a preference for positive returns and skewness.

$$\text{Odds Ratio } (P_G/P_g) = \beta_0 + \beta_1 X_h + \beta_2 X_h^2 + \beta_3 X_h^3 \quad \text{Eq. 7}$$

Expected signs for moments:

(Mean of Returns) $\beta_1 > 0$

(Variance) $\beta_2 < 0$

(Skewness) $\beta_3 > 0$

The regression models in *Table 10* confirm the findings in literature. The dependent variables take on the expected signs with an inferred preference for positive returns and skewness, and an aversion for variance. Note that the magnitudes of the estimated coefficients are much smaller than anything estimated by *Golec and Tamarkin (1998)* or *Garrett and Sobel (1999)*. This is due to the smaller values of the awarded prizes/bet payouts and significantly larger win probabilities, both of which effect the odds ratio dependent variable.

Table 10: Fitted Cubic Utility Models for Bettor Utility by Permit Species

Alaska Hunting Permit Lottery - Fitted Cubic Bettor Utility				
Odds Ratio	All Permits	Moose Permits	Sheep Permits	Goat Permits
Mean of Returns	0.000213*** (5.81)	0.000405*** (7.61)	0.000164 (0.49)	0.000286*** (2.89)
Variance	-4.89e-08* (-1.86)	-0.000000471*** (-4.17)	-3.01e-08 (-0.12)	-0.000000186 (-1.62)
Skewness	9.25e-12** (2.06)	2.13e-10*** (4.19)	1.08e-11 (0.25)	5.91e-11 (1.70)
Constant	0.00406 (0.47)	-0.0104* (-1.81)	0.0310 (0.27)	-0.00650 (-0.37)
Observations	278	110	33	33
Adjusted R-squared	0.637	0.781	0.467	0.811

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The three moments of the moose permit utility model are statistically significant to the 1% level. Hunters exhibit a strong preference for positive mean of returns and positive skewness in moose permits. Unsuccessful applicants can harvest a moose through the general season, but may have to spend more in terms of travel expenses and opportunity costs. This is particularly true of resident hunters. With little to lose, hunters apply to moose hunts of the highest quality and ease of access. Naturally, these permits are highly sought after and are easily over-valued.

None of the independent variables are statistically significant in the sheep permit model, and only mean of returns is significant in the goat permit model. Although the coefficients take on the expected sign, skewness is not significant in the cubic utility model including only sheep or goat permits. Sheep

and goat hunting areas are geographically limited to the Alaska Range and the Brooks Range, constraining the variation in travel cost and hunter preferences. Because the hunting opportunities are so competitive, there is also little variation in the range of draw probability. Moose permit draw probabilities range from 0.45% to 100%, but goat permit probabilities range from 0.5% to 21.3%. Similarly, Sheep permit draw probabilities range from 0.13% to 10.4%. A cubic utility model fails to represent the distribution of sheep and goat permits because the observations represent a small portion of the draw probability range.

6.0 Conclusions and Future Research

The three predictive models generally confirm the findings of previous hunting permit lottery studies. Travel costs represent the primary expenditures of hunters, and the number of applications decreases as travel distance increases. Restrictions on weapon type or applicant characteristics (age, veteran status, state residency, etc.) also decrease application levels by reducing the eligible pool of applicants. Hunters are consistent in their preferences with regard to hunt quality, but hunting permit demand varies substantially with species and residency of the applicant. Resident hunters are motivated to hunt for food, which influences their permit preferences. Nonresident hunters are more likely to pursue ‘trophy’ animals, and hunt primarily for sport. Additional information like applicant income could be used to search for additional evidence of what motivates hunters. Improvements could also be made to the pooled OLS models by incorporating a variable to account for the season/dates of the hunting permit. However, there is little basis for comparison between permits. The hunt dates span throughout the fall and winter, and vary in length. An indicator variable for opening month of the hunt would be an appropriate starting place. Duration of season may also be useful.

It may be valuable from a policy standpoint to determine what motivates lottery applicants. It may be possible to increase lottery revenues and/or public benefit from the lottery. Further research is necessary to demonstrate what motivates applicants. One potential solution would be to compare the calculated permit values with auctioned permits. Nonprofit organizations may submit requests to the Alaska Department of Fish and Game for hunting permits. These permits are auctioned at charity events to the highest bidder.

Kernel density estimation is an excellent technique for analysis when data has no known empirical distribution and no foundations in literature. In the case of this paper, it proved instrumental in

generating a variety of plots for economic inference. Current methods to test for risk-preference behavior rely on parametric methods. In this paper, a non-parametric method of analysis for risk-preference behavior is based on skewness of expected utility and the net probability of a loss. ‘Skewness’ is poorly defined in literature, and there are several measures used to quantify it. Future research in this area may benefit from testing other characteristics of a probability density function. Kurtosis, for example, is a measure of lateral density in the probability density function. It is influenced less by the position of the mean and median than a skewness coefficient, and may reveal more significant differences in the data plots.

In the case of the hunting permit lottery data, analysis may benefit from a boundary-corrected KDE. Because the estimated parameter *probability of no permits drawn* is bounded at 0 and 1, it may be more appropriate to use a boundary-corrected KDE over a Gaussian KDE. This method may help to preserve the relative position of the mean and median in the data. It may also be helpful to demonstrate risk-preference behavior through a third variable. Multivariate KDE functions are available in several R-packages. Rather than testing the properties of distributions, it may be easier to demonstrate a multivariate relationship to some other variable that indicates risk-preference. Additional data would have to be collected to pursue these avenues.

In general, applicants do not maximize their expected outcomes. Applicants accept lower expected returns and higher probabilities that they will obtain no permits. The effect is more pronounced in sheep and goat permits than in the unaltered application bundle. The observed differences in individual species plots and the full utility bundle plot show some evidence of the ‘portfolio’ approach to balancing return and risk. Where possible, we expect applicants to choose to apply for permits with the greatest expected outcome and lowest risk. The work of *Golec and Tamarkin (1998)* suggests that when individuals are presented with a range of bets they often choose a combination that maximizes expected utility while also preserving their chance to ‘win big’.

Alaska’s permit distribution is unique, primarily because there are so many hunting opportunities outside of the permit lottery. Although other US states distribute hunting permits by lottery, few do so without the aid of some equity-balancing tool such as preference points. In the absence of a preference point system, applicants stand to lose only their application fee (\$5-\$10 per application). With very little invested in the application process and a large number of substitute hunting opportunities, it seems likely that lottery applicants would exhibit stronger gambling behaviors. The primary evidence of this comes from an observed proclivity for low draw probability/high permit value hunts. When a hunter does not draw any permits, they can still harvest moose, sheep, black bear, brown bear, and caribou during the general season. The moose pooled cross section revealed a preference for antlerless moose and permits

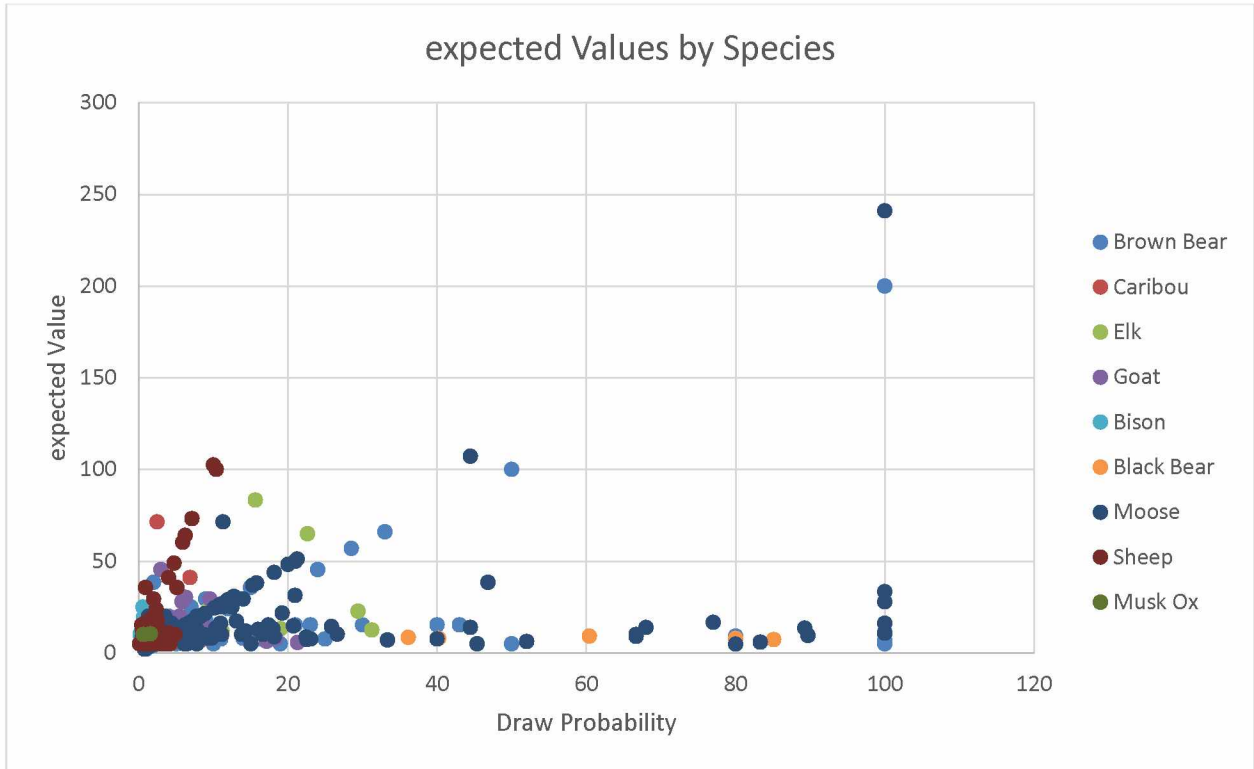
with higher success probabilities. For most resident hunters, the primary purpose of hunting is for recreation and for food. Bivariate KDE's demonstrated that resident hunters accept a higher level of risk than nonresident hunters, probably due to substitute opportunities and lower travel costs. The fitted cubic utility models demonstrate that even when the awarded prize has a relatively small value (compared to a jackpot type state lottery), participants are risk-averse but prefer a 'positive skewness of returns' [3]. Following the methodology of *Golec and Tamarkin (1998)* and *Garrett and Sobel (1999)*, the analysis reveals that bettors behave similarly, even when the awarded prize is not monetary.

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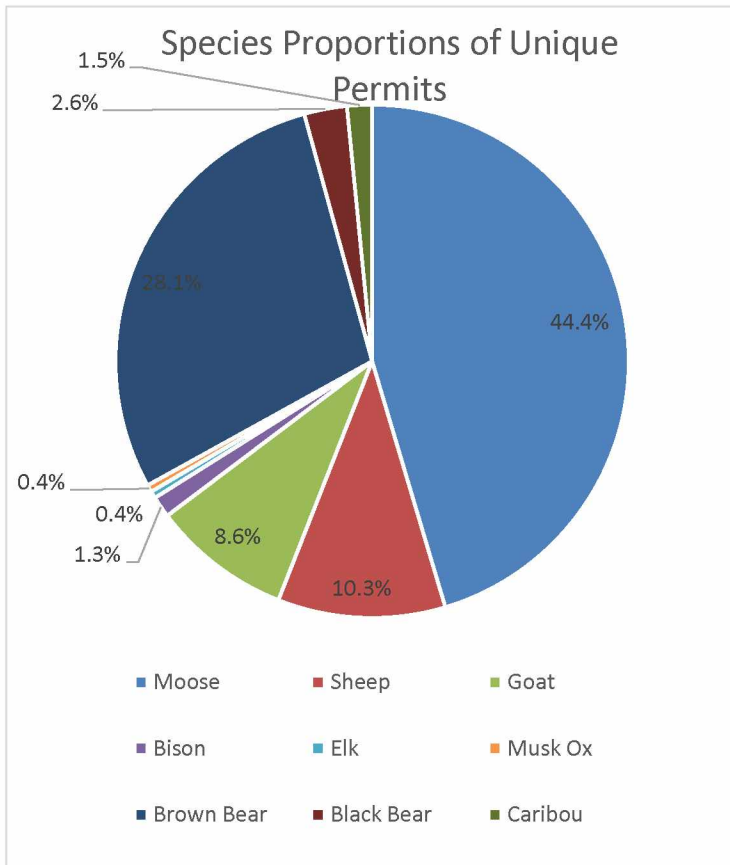
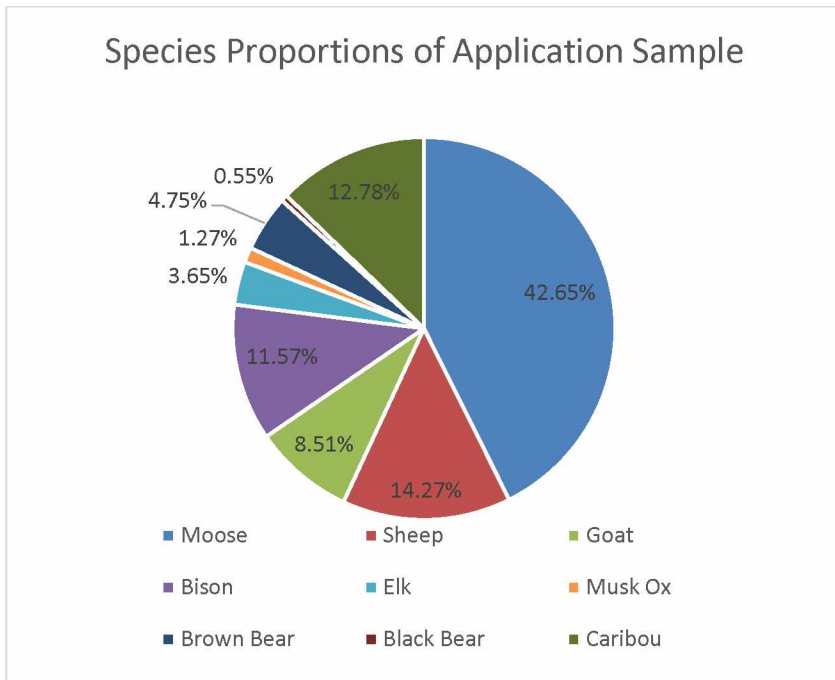
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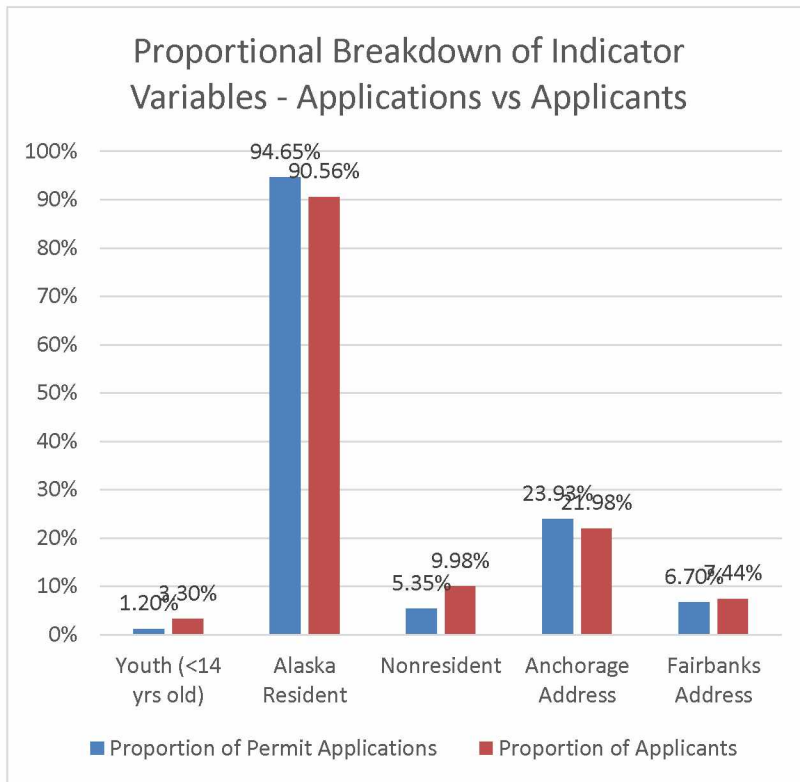
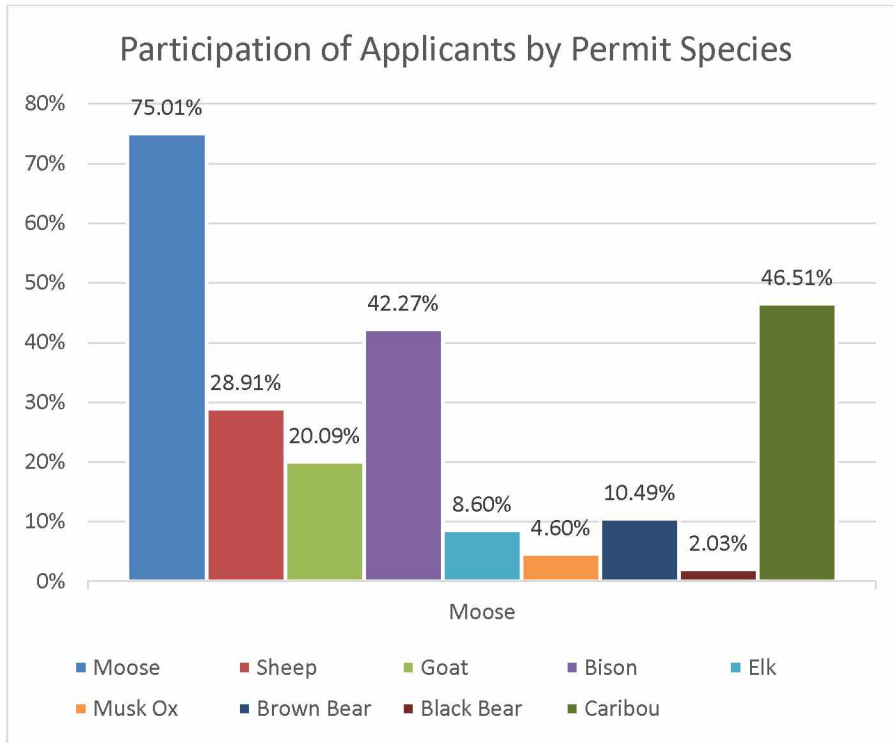
Appendix A: Expected Value over Draw Probability by Species for Behavioral Model Data



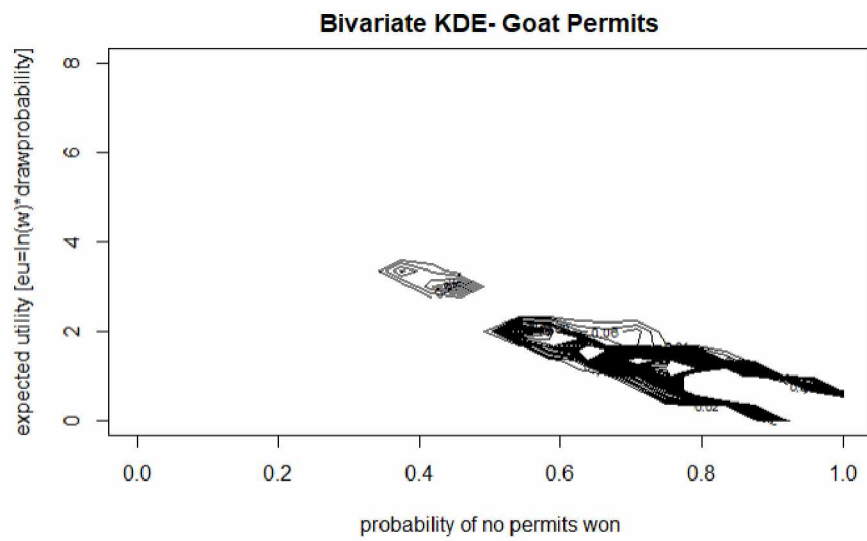
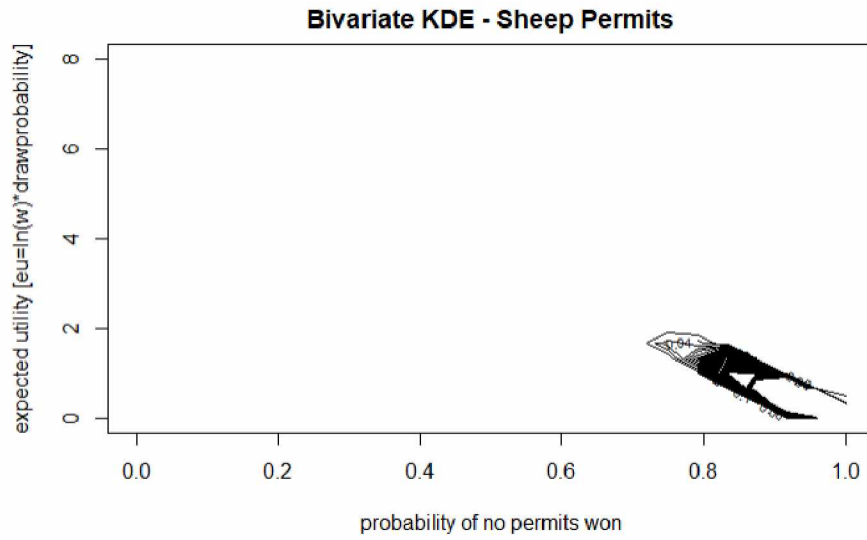
Appendix B: Proportional Application Breakdown of 10% Behavioral Model Data by Species



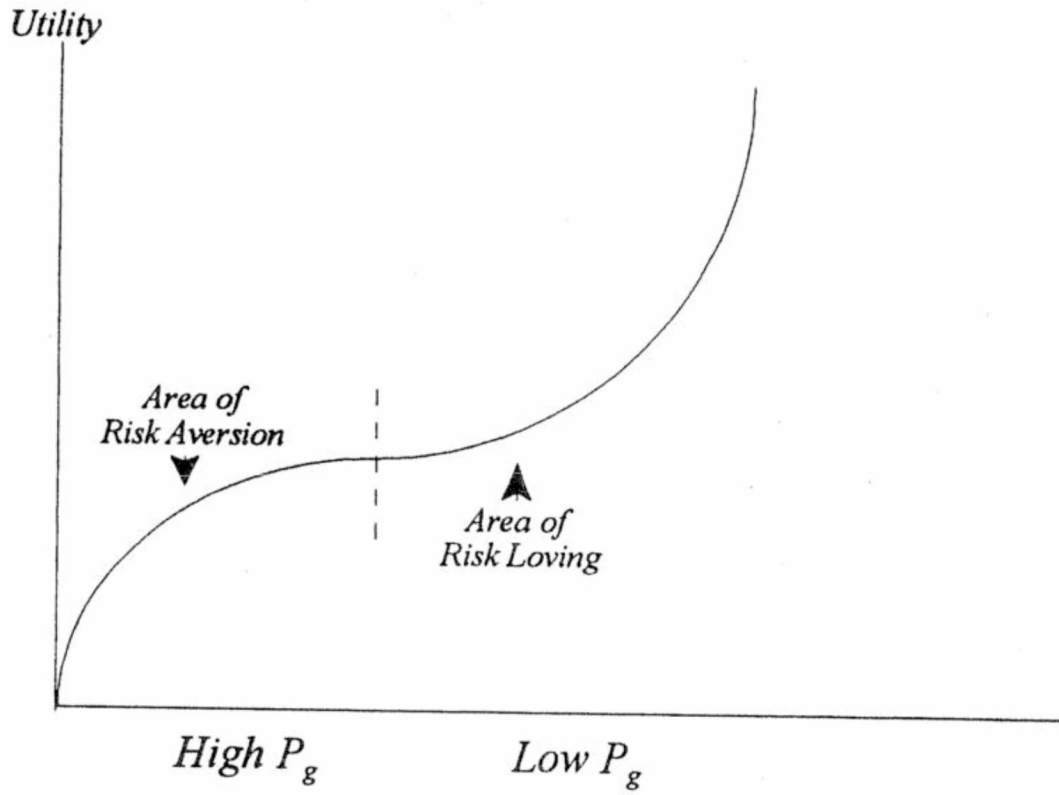
Appendix C: Lottery Participation of Applicants by Species and Frequency of Indicator Variables



Appendix D: Plots of Bivariate KDE for Sheep and Goat Permit Bundles



Appendix E: Golec and Tamarkin's Illustrated Shape of Cubic Bettor Utility Function



Source: [3] pg 89

Appendix F: ADFG Dall Sheep Hunt GMU Map

