'Adopt a hypothetical pup': A count data approach to the valuation of wildlife.

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Abstract

The willingness to pay for a coyote conservation program is estimated using a novel payment-vehicle, based on how many coyotes respondents would be willing to sponsor. This hypothetical scenario mimics an increasingly popular type of actual market. Data from a phone survey conducted in Prince Edward Island are analyzed using count data models that consider different processes explaining zero responses and the level of positive responses. This is particularly important in the case of coyotes, often regarded as a bad. Estimates of willingness to pay per coyote around \$18-\$20 and annual consumer surplus per respondent of about \$35-\$42 are obtained.

Keywords: coyotes, wildlife, contingent valuation, count data, zero-inflation

JEL codes: Q20, Q26

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1 Introduction

Fully assessing the economic desirability of wildlife management policies, such as population control or reintroduction of species, requires the estimation of the value of wildlife species. However, like most environmental amenities and natural resources, the preservation of wildlife is not traded in the open market, so its non-consumptive values can rarely be elicited from the observation of market transactions. This problem constitutes a key aspect of the valuation of wildlife species.

For example, the value placed by the general public on coyotes would represent a key input in the cost-benefit analysis of any type of coyote management program. This, together with the measures of consumptive benefits from exploiting the species, the damage or nuisance costs inflicted by coyotes, the direct costs of coyote control, and any disutility associated with the control method of choice, would make it possible to estimate the optimal level of coyote control or coyote conservation, depending on the case

In this paper we estimate the willingness to pay by residents in Prince Edward Island (PEI) for a coyote conservation program based on compensating farmers for depredation losses using the contingent valuation method.[2] Recently, there has been some debate in this Canadian province about the management policies that the authorities should implement in order to reduce the costs they allegedly impose on the sheep-farming industry (Environmental Advisory Council, 2001).

A novel payment-vehicle is employed to elicit individuals' willingness to pay. Respondents are asked how many coyotes they would be willing to sponsor, given a certain cost of sponsorship per year, knowing that this contribution would be used to compensate farmers for coyote damage, so that the animal would not have to be killed. This payment format is advantageous because, contrary to most instances in which non-use values are estimated, it is based on a hypothetical market scenario that mimics an actual market,[3] which could

[2] Eastern coyote, or *canis latrans var* would be a more scientific way to refer to the variety of coyote in this part of Canada (Parker, 1995, p.10).

[3] For example, *T&D's Cats of the World, Wildlife Associates*, and the *Kerwood Wolf Education Centre* have 'adopt a coyote' programs. Other examples of species that can be adopted include bears, wolves, sea otters, dolphins, whales, tigers, panthers, and elephants. Other organizations with similar programs include *Defenders of Wildlife*, *Adoption.co.uk*, *World Wildlife Fund*, etc. Outside the wildlife arena, one can, for example, also adopt a stretch of highway in most of North America, and since 2003 also in PEI.

be eventually used to analyze the validity of the results. In this sense, the payment-vehicle turns the contingent valuation question into something closer to the contingent trip models of recreation demand (e. g. Betz et al., 2003).

The methodology adopted departs from that used in most previous contingent valuation studies. This is because the nature of the valuation question results in a strictly positive integer response. For this reason, count data models, often employed in the recreation demand literature (Englin et al., 2003; Englin and Moeltner, 2004), are used to conduct the econometric exercises described below. Crucially, the more basic among these methods are expanded to account for the presence of two potentially different processes explaining zero responses (versus positive responses) and the magnitude of positive responses. This is particularly important in the case of coyotes, because while some individuals will consider them a good, others will likely think of them as a bad.

The following section presents a brief background on the valuation of nuisance wildlife species, with special attention to the valuation of wild canids in North America. Section 3 describes the data collection process and the survey instrument. Section 4 presents the econometric methodology, describing the different types of count data models considered. Section 5 presents the results of the analysis, including tests of the different count data specifications and calculations of price-elasticities and welfare estimates. The total willingness to pay per coyote is estimated at around \$18-\$20 and the corresponding extrapolation to annual consumer surplus per respondent results in \$35-\$42.[4] Demand for sponsored coyotes appears to be price-inelastic.

2 The valuation of coyotes

Non-use values are not revealed through observation of data on market economic transactions. Therefore, the valuation of wildlife species, which are not owned by any economic agent, but still provide economic effects (sometimes both negative and positive, Bostedt, 1999), requires the use of stated-preference methods. Perhaps the most common is the contingent valuation method (CVM). This consists of directly asking people to state the value

[4] All monetary figures are expressed in CAN\$.

they place on the change of quantity or quality of a certain environmental resource and it has been widely applied during the last decades (see, for further theoretical details and reviews of empirical applications, Mitchell and Carson, 1989; Braden and Kolstad, 1991; Freeman, 1993; Hanemann, 1994; Diamond and Hausman, 1994).

Previous studies have addressed the valuation of other wildlife species, endangered species in particular (Brookshire et al., 1983; Boyle and Bishop, 1987; Jakobsson and Dragun, 2001)[5] but only a couple of them focus on coyotes. Stevens et al. (1991, 1994) find that twenty-three percent of respondents would pay US$ 5.35 to protect coyotes. More plentiful are examples of valuation of another, perhaps more glamorous, wild canid: the wolf. These include Duffield (1992); Duffield and Neher (1996); Boman and Bostedt (1999); Jorgensen et al. (2001); and Chambers and Whitehead (2003).

This is, to the author's knowledge, the first time that a contingent valuation study of coyotes has been conducted in Canada.

3 Data collection

A phone survey was conducted on a random sample of listed and unlisted residential phone numbers from all the counties in Prince Edward Island, the smallest Canadian province, with a population of around $135,000$. The latest edition of the Island's phone book was complemented with direct information from the phone company to find out about the up-to-date three-digit prefixes (exchanges) operative in each county. Calls were made from the hours of 12:00 to 21:00, during both weekdays and Saturdays. One male and one female student research assistants obtained 63% of the observations, while a professional research center obtained the rest. No significant differences were found between the data obtained from the two subsamples. The guidelines suggested by Dillman (1978) were followed during the different stages of the surveying process. A total of 438 contacts with eligible respondents were made, resulting in 255 completed questionnaires, which represents a response rate of

[5] See Loomis and White (1996) for a meta-analysis of contingent valuation studies concerned with endangered species.

about 58%[6] (Dillman, 1978, p. 50). This response rate is quite reasonable in a survey targeting the general public.

Some targeted individuals refused to participate in the survey, leaving open the possibility of non-response bias or sample selection bias. If respondents significantly differed from non-respondents in characteristics that influence WTP for the valued good, non-response bias may arise. The average age of the respondents was 45.6. The average level of education of the respondents (variable *educat*) was 2.6 while the average for PEI is 2.[7] The average family *income* level was $\$39,004$, while it is $\$46,543$ in PEI (Stats Canada). 59.57% of the respondents were female and 40.42% were male, while the average for PEI is 51% versus 49%. Other summary variables are provided in Table 1. Comparing the sample's summary statistics with those applicable to the whole of Prince Edward Island suggests that no serious systematic non-response bias should be expected, given the variables entering the econometric models. However, there might be an oversampling of female respondents and the typical individual in the sample seems more educated and the average family slightly poorer than their average counterparts in the population.[8]

Apart from the questions on sociodemographic characteristics of the respondent, additional questions about livestock and pet ownership, attitudes towards hunting, and direct or indirect experiences with coyotes were asked.[9] The final models contained only a subset of the variables obtained. The analysis in this paper focuses on one of a last type of questions, namely questions about the respondents' willingness to pay to support publicly funded programs of coyote conservation based on compensating farmers for predation losses. Respondents were asked how many coyotes they would be willing to sponsor, given a certain cost of sponsorship per year (the values[10] of \$5, \$10, \$15, \$20, and \$25 were randomly proposed as *spobid*), knowing that this contribution would be used to compensate farmers,

[6] Out-of-service numbers and commercial numbers were discarded (see Dillman, 1978, page 238-239). Calls meeting answering machines, busy signals, or no answer after five dial tones were retried once on a different day and discarded after two new failed attempts.

[7] Calculated from Stats Canada data for 2001 referring to individuals 15 years and older (Statistics Canada, Census of Population). Refer to the Appendix for an explanation of the scale (see variable *educat*).

[8] This concern will be considered when reporting the final results; in Section 5.3 reported estimates of annual consumer surplus are calculated using both sample means and predicted means.

[9] The text of the full questionnaire is available upon request.

[10] These values were chosen after pretesting the questionnaire with open-ended questions about how much the respondent would be willing to pay yearly to sponsor a coyote.

so that the coyote would be spared. In this sense, respondents were asked about their hypothetical willingness to adopt or sponsor a number of coyotes. Given the increasing number of conservation programs that offer the possibility of adopting members of wildlife species, the question format was expected to help the respondent formulate an answer. It was expected that with this question format respondents should perceive as plausible the description of how the service would be provided and paid for, so that they would search their preferences and income when deciding whether to pay or not (Mitchell, 2002).

Additionally, and contrary to most question formats employed in the contingent valuation literature, this one asks respondents to choose, as it is most usual in the marketplace, a quantity at a given price, rather than come up with a price for a quantity or quality change. The question format chosen, although enjoying the advantages of discrete analysis described above, is also more statistically efficient than the often used dichotomous-choice format.

Since some respondents refused to answer some of the questions, some variables had missing values.[11] These observations were removed, so the final sample contained 235 observations. A summary of the variables involved in the survey can be found in Table 1. The Appendix contains also a list of definitions and descriptions of each variable.

4 Econometric methods

Given the type of valuation question used, the dependent variable (*sponsored*) was a nonnegative integer or *count*. The econometric exercises described below aim at explaining the variability of this count among respondents in terms of a set of covariates (denoted x). Regression models for counts[12] differ from the classical regression model in that the response variable is discrete with a distribution that places probability mass at nonnegative integer values only. Count data distributions are characterized by exhibiting a concentration of values on a few small discrete values (such as 0, 1 and 2), skewness to the left, and intrinsic heteroskedasticity with variance increasing with the mean (Cameron and Trivedi, 2001).

[11] However, for 5.5% of the observations the missing value of *income* was substituted by its sample mean of $39,000.

[12] The presentation in this section borrows heavily from Gurmu and Trivedi (1996) and Cameron and Trivedi (1998 and 2001).

Table 1: Variables summary

Variable	N	Mean	St. Dev.	Min.	Max
age	235	45.579	17.682	12	85
cats	235	0.3234	0.4687	0	1
coyote	235	0.5702	0.4961	0	1
density	235	159.86	229.62	6.0626	923.11
dogs	235	0.3660	0.4827	0	1
dumspo	235	0.4000	0.4909	0	1
educat	235	2.6000	1.0669	1	4
hunt	235	0.1021	0.3035	0	1
income	235	3.9004	1.2213	2.5	5.5
incometown	235	1.8871	0.2740	0.1782	2.4213
lastseen	235	2.7489	1.7543	1	6
livestock	235	0.0809	0.2732	0	1
male	235	0.4043	0.4918	0	1
neighbours	235	0.2723	0.4461	0	1
pet killed	235	0.0255	0.1581	0	1
pets	235	0.5830	0.4941	0	1
problems	235	0.0638	0.2450	0	1
selshoot	235	0.6596	0.4749	0	1
sheep	235	0.0085	0.0921	0	1
spobid	235	12.553	5.3781	5	25
sponsored	235	1.8894	6.9685	0	100

This methodology has been widely employed in the area of non-market valuation within the context of recreational demand analyses, since these often seek to place a value on natural resources such as national parks by modeling the number of trips to a recreational site (Englin and Shonkwiler, 1995; Gurmu and Trivedi, 1996).

4.1 Poisson regression

Although it more often than not proves inadequate, the Poisson is the starting point for most count data analyses. The density of the Poisson distribution for the number of occurrences (y) of an event is given by:

$$\Pr[Y = y] = \frac{e^{-\mu}\mu^y}{y!}, \qquad y = 0, 1, 2, ... \tag{1}$$

where μ is the intensity or rate parameter. In our case, Y would be the variable *sponsored* and μ the mean of the distribution of *sponsored* across individuals.[13] The first two moments of this distribution are equal to each other ($E[Y] = \mu = V[Y]$), a property known as equidispersion.

This model can be extended to a regression framework by parametrizing the relation between the mean parameter μ and a set of regressors x. The Poisson regression model is commonly based on an exponential mean parametrization:

$$\mu_i = \exp(x'\beta), \qquad i = 1, ..., n \tag{2}$$

where x is the matrix of k regressors and β is a comformable matrix of coefficients to be estimated. Since $V[y_i|x_i] = exp(x_i'\beta)$, the Poisson regression is intrinsically heteroskedastic. Given (1) and (2), the Poisson regression model can be estimated, under the assumption that $(y_i|x_i)$ are independent, by maximum likelihood. The log-likelihood function is:

$$\ln L(\beta) = \sum_{i=1}^{n} \{y_i x_i' - \exp(x_i'\beta) - \ln y_i!\} \tag{3}$$

The Poisson maximum-likelihood estimator (MLE) is the solution to k nonlinear equations corresponding to the first-order condition for maximum likelihood:

$$\sum_{i=1}^{n} \{y_i - \exp(x_i'\beta)x_i\} = 0 \tag{4}$$

This log-likelihood function is globally concave, so unique parameter estimates can be found.

4.2 The Negative Binomial Model ($NBREG$)

The Poisson regression model provides a standard framework for the analysis of count data. In practice, however, count data are often overdispersed relative to the Poisson distribution. That is, the variance is larger than the mean for the data, so the Poisson model becomes overly restrictive. Overdispersion has qualitatively similar consequences to heteroskedastic-

[13] A more general Poisson model would account for different time intervals or exposure lengths, but in our case, this parameter takes the value of one.

ity in the linear regression model. Therefore, as long as the conditional mean is correctly specified, the Poisson MLE with overdispersion is still consistent, but it underestimates standard errors and inflates t-statistics in the usual maximum-likelihood output.

Overdispersion in count data may be due to unobserved heterogeneity. Then counts are viewed as being generated by a Poisson process, but the researcher is unable to correctly specify the rate parameter of this process. Instead the rate parameter is itself a random variable. This approach leads to the widely-used negative binomial model.

The negative binomial model can be obtained in many different ways. A common approach is to add an additional parameter that reflects the unobserved heterogeneity that the Poisson fails to capture. Let the distribution of a random count y be Poisson, conditional on the parameter λ, so that $f(y|\lambda) = exp(-\lambda)\lambda y/y!$. Suppose now that the parameter λ is random, rather than being a completely deterministic function of the regressors x. In particular, let $\lambda = \mu\nu$, where μ is a deterministic function of x, in particular we adopt $\mu = exp(x'\beta)$, letting $\nu > 0$ be iid distributed with density $g(\nu|\alpha)$. This is an example of unobserved heterogeneity, as different observations may have different λ (heterogeneity) but part of this difference is due to a random (unobserved) component ν, which would not be captured by the Poisson regression model.

If $f(y|\lambda)$ is the Poisson density and $g(\nu)$, $\nu > 0$ is assumed to be the gamma density with $E[\nu] = 1$ and $V[\nu] = \alpha$, we obtain the negative binomial density:

$$h(y|\mu, \alpha) = \frac{\Gamma(\alpha^{-1} + y)}{\Gamma(\alpha^{-1})\Gamma(y+1)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\mu + \alpha^{-1}}\right)^{y} \qquad \alpha > 0 \tag{5}$$

where $\Gamma(\cdot)$ is the gamma function. In the context of count regression models, the negative binomial distribution can be thought of as a Poisson distribution with unobserved heterogeneity which, in turn, can be understood as a mixture of two probability distributions, Poisson and gamma. In the negative binomial, the parameter α determines the degree of dispersion in the predictions. Special cases of the negative binomial include the Poisson ($\alpha = 0$) and the geometric ($\alpha = 1$).

The first two moments of the negative binomial distribution are:

$$\begin{aligned} E[y|\mu, \alpha] &= \mu \\ V[y|\mu, \alpha] &= \mu(1 + \alpha\mu). \end{aligned} \tag{6}$$

The variance therefore exceeds the mean, since $\alpha > 0$ and $\mu > 0$.

Two standard variants of the negative binomial are commonly used. Both specify $\mu_i = exp(x_i'\beta)$. The most common variant, sometimes referred to as the negative binomial 2 ($NB2$) lets α be a parameter to be estimated, in which case the conditional variance function, $\mu + \alpha\mu^2$ from (6) is quadratic in the mean. The other variant ($NB1$) has a linear variance function, $V[y|\mu, \alpha] = (1+\delta)\mu$, obtained by replacing α by δ/μ throughout (5). In both cases, the log-likelihood is obtained from (5) to estimate the parameters by maximum likelihood. In most cases, both parametrizations will yield similar results, and the parametrizations will not significantly differ from each other. The $NB2$ model has been widely used in cross-section models for counts. A likelihood-ratio test based on the parameter α (or δ) can be employed to test the hypothesis of no overdispersion.[14]

4.3 Treatment of excess zeros

One frequent manifestation of the overdispersion is that the incidence of zero counts in the data is greater than expected for the Poisson distribution. This *excess-zeros* or *zero inflation* problem is often of interest because zero counts frequently have special meaning. In our case, an individual may respond with a zero because she finds the protection of coyotes objectionable or, instead, because, while being a potential supporter of coyote conservation, her socioeconomic circumstances lead her to choose a corner solution.

Using a mixed Poisson distribution as described above might ameliorate the problem (Mullahy, 1997), but it is unlikely to solve it. The Poisson and negative binomial models do not extract information about the participation decision from the zeros in the data. They simply treat the zeros as being generated by the same process that generates positive observations (Englin et al., 2003, p. 350).

[14]See Cameron and Trivedi (2001, p. 336) for details.

The use of models that deal explicitly with excess zeros has increased during recent years. Again, no examples are available in the context of contingent valuation, but examples from the area of recreation demand analysis include Gurmu and Trivedi (1996) and Shonkwiler and Shaw (1996). The following subsections describe the theoretical features of these methods.

4.3.1 Hurdle models

To address the problem of excess zeros, Mullahy (1986) proposed the use of a *hurdle* or two-part model, a modified count model that relaxes the assumption that the zeros and the positives in the data set come from the same data generating process (Cameron and Trivedi, 1998, pp. 123-125, Greene, 2000, pp. 889-891).[15] The zeros are determined by the density $f_1(\cdot)$, so that $Pr[y = 0] = f_1(0)$. The positive counts come from the truncated density $f_2(y|y > 0) = f_2(y)/(1 - f_2(0))$, which is multiplied by $Pr[y > 0] = 1 - f1(0)$ to ensure that probabilities sum to unity. Thus

$$g(y) = \begin{cases} f_1(0) & \text{if } y = 0 \\ \frac{1-f_1(0)}{1-f_2(0)} f_2(y) & \text{if } y \geq 1 \end{cases}$$

Maximum likelihood estimation of the hurdle model involves separate maximization of the two terms in the likelihood, one corresponding to the zeros and the other to the positives.

The moments of the hurdle model are given by the probability of crossing the threshold (being a potential supporter of coyote conservation) and by the moments of the truncated density governing the positive counts:

$$E[y|x] = Pr[y > 0|x] \cdot E_{y>0}[y|y > 0, x]$$

where the second expectation is taken relative to the zero-truncated density. The variance is given by

$$V[y|x] = Pr[y > 0|x] \cdot V_{y>0}[y|y > 0, x] + Pr[y = 0|x] \cdot E_{y>0}[y|y > 0, x]$$

[15] This model is the count data equivalent of the one proposed by Cragg (1971) for continuous data.

The hurdle model is widely used, and the hurdle negative binomial model is quite flexible. However, the model is not very parsimonious, typically the number of parameters is doubled, and parameter interpretation is not as easy as in the same model without hurdle. The binomial determination of the zeros can be analyzed in a variety of ways (such as with a Logit or Probit) and the positive counts can be modelled separately with a zero-truncated Poisson or a zero-truncated negative binomial.

4.3.2 Zero-inflated models (ZIP and $ZINB$)

Another way to address the problem of underprediction of zeros is to use an extension of the hurdle model, namely the zero-inflated count model, introduced by Mullahy (1986) and Lambert (1992). These change the mean structure to allow zeros to be generated by two different processes (Cameron and Trivedi, 1998, p. 126).

$$
\begin{aligned}
Pr[y &= 0] = \varphi_i + (1-\varphi_i)e^{-\mu} \\
Pr[y &= r] = (1-\varphi_i)\frac{e^{-\mu}\mu_i^r}{r!}
\end{aligned}
$$

Lambert (1992) proposed a zero-inflated Poisson (ZIP)[16] in which $\mu_i = \mu(x_i, \beta)$ and the probability φ_i is parametrized as a logistic function of a set of covariates. This can be extended to the negative binomial case, resulting in the zero-inflated negative binomial ($ZINB$) and also employ alternative parametrizations of φ_i (Lambert, 1992; Greene, 1994).

The basic count model and the zero-inflated models are not nested, so it is not easy to conduct specification tests. Greene (1994) adapted one of the tests of non-nested models developed by Vuong (1989) to the cases of ZIP versus Poisson and $ZINB$ versus negative binomial models. As described in Long and Freese (2003, 285-286), this statistic has a standard normal distribution with large positive values favoring the zero-inflated model and large negative values favoring the nonzero-inflated version. Values close to zero (smaller than 1.96 in absolute value) favor neither model (Greene, 2000, p. 891). There are also Wald and likelihood-ratio (LR) tests for evaluating the relative fits of ZIP and $ZINB$.

[16] Alternative labels for variants of this model found in the literature include *with zeros* (Mullahy, 1986) and zero-altered Poisson (Greene, 1994).

5 Results

Exactly 60% of the respondents stated that they would not sponsor any coyotes. The mean count of *sponsored* coyotes predicted by the estimated model is 1.9 (while the average for nonzero respondents was 4.72) The following sections explain how the number of *sponsored* varied with changes in the values of a series of covariates. The general model estimated was of the form:

$$sponsored = f(spobid, S, E, A)$$

where *spobid* is the proposed price for one sponsored coyote proposed in the questionnaire; S includes socioeconomic variables of the household and its county of residence (*age*, *agesq*, *male*, *income*, *educat*, *livestock*, *sheep*, *pets*, *cats*, *dogs*, *incometown*, *density*); E are variables about respondents' previous experience with coyotes (*coyote*, *lastseen*, *problems*, *neighbours*, *petkilled*); and A are variables about respondents' attitudes towards wildlife and coyote control (*hunt*, *selshoot*). A detailed description of these variables can be found in the Appendix.

A selection of these variables was included in the final models reported. These explain the relationship between the different variables and the value of *sponsored*. Particular attention was paid to the effect of *spobid*, since most economic implications have to do with that parameter. Table 1 lists summary statistics for a number of variables in the questionnaire related to the analysis presented below. Results from the different estimated demand models are presented in Table 2.[17] All the analysis was conducted using STATA 8.1 (Statacorp, 2003).

5.1 Model choice

Usually, the first step in the analysis of count data is to consider how well the Poisson distribution fits the data. Visual inspection suggests that a simple univariate Poisson specification (with μ equal to the sample mean for the dependent variable *sponsored*) fails to

[17] BIC is the Bayesian information criterion equal to -2ln L-ln $N \cdot k$, where N is the number of observations and k the number of parameters (which exceeds the number of regressors for some of the models). The more negative the BIC measure, the better the fit. Note that in Table 2 the log-likelihood reported for $TRPOIS$ and $TRNBIN$ includes also the component associated with the binary equation ($LOGIT$).

Table 2: Results of the different count data estimations

Variable	POISSON	POISSR	NBREG	ZIP	ZINB	TRPOIS	TRNBIN
spobid	-0.054	-0.054	-0.053	-0.047	-0.045	-0.046	-0.045
	0.0000*	0.0271*	0.0164*	0.0000*	0.0201*	0.0000*	0.0689*
age	0.017	0.017	0.020	0.095	0.011	0.106	0.061
	0.2909	0.6465	0.6355	0.0000	0.7930	0.0000	0.2716
agesq	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001	-0.001
	0.0009	0.1925	0.1209	0.0000	0.6001	0.0000	0.2867
educat	0.105	0.105	0.027	0.126	0.191	0.126	0.197
	0.0584	0.4722	0.8609	0.0398	0.1882	0.0447	0.3068
income	0.237	0.237	-0.001	0.197	0.070	0.202	0.092
	0.0000	0.1540	0.9937	0.0001	0.5573	0.0001	0.5602
incometown	-0.083	-0.083	-0.076	-1.540	-1.065	-1.623	-0.764
	0.6493	0.8760	0.9132	0.0000	0.1396	0.0000	0.4524
lastseen	0.005	0.005	-0.053	-0.003	0.018	-0.007	0.052
	0.9421	0.9767	0.7296	0.9652	0.8941	0.9165	0.7740
hunt	-1.115	-1.115	-1.275	-0.874	-0.924	-0.930	-1.107
	0.0000	0.0318*	0.0078*	0.0011*	0.0504*	0.0001*	0.0646*
problems	-0.697	-0.697	-0.812	-0.180	-0.458	-0.210	-0.574
	0.0092*	0.0934*	0.0899*	0.2897*	0.2153*	0.2784*	0.2390*
coyote	-0.633	-0.633	-0.229	-1.020	-0.501	-1.051	-0.689
	0.0029	0.3942	0.6668	0.0000	0.2909	0.0000	0.2844
pets	-0.361	-0.361	-0.263	-0.247	-0.222	-0.232	-0.076
	0.0002*	0.1059*	0.1926*	0.0094*	0.2008*	0.0157*	0.4174*
male	0.556	0.556	0.208	0.949	0.249	0.988	0.363
	0.0000	0.2694	0.5000	0.0000	0.3744	0.0000	0.3376
cons	1.081	1.081	2.317	2.600	3.340	2.511	1.082
	0.0189	0.2233	0.2023	0.0000	0.0672	0.0000	0.6711
$\ln(\alpha)$			1.157		0.189		0.954
			0.0000		0.4884		0.1123
N	235	235	235	235	235	235	235
log-likelihood	-695	-695	-358	-456	-337	-433	-332
AIC·n	1418	1418	745	953	718		
BIC	180	180	-490	-260	-493		
CS/year	\$35.19	\$35.19	\$35.82	\$40.20	\$41.85	\$40.66	\$41.92
$\widehat{CS}$/year	\$35.19	\$35.19	\$35.84	\$45.09	\$40.29	\$25.44	\$15.71
CS/coyote	\$18.63	\$18.63	\$18.96	\$21.28	\$22.15	\$21.52	\$22.19
ξ(spobid)	-0.67	-0.67	-0.66	-0.59	-0.57	-0.58	-0.57
$\overline{\mu}$	1.89	1.89	1.89	2.12	1.82	1.18	0.71

The second row reports the P-values. A * signifies that the value correspond to a one-tailed test, since the coefficient presents the expected sign. The second row reports the P-values. A * signifies that the value correspond to a one-tailed test, since the coefficient presents the expected sign.

fit the data. Figure 1 shows that the Poisson would substantially underpredict zeros and overpredict the values of 1, 2, 3, and 4 for *sponsored*. Note also that the counts 5 and 10 appear underestimated by the theoretical prediction, because respondents tended to cluster their stated preferences on these *round* numbers.

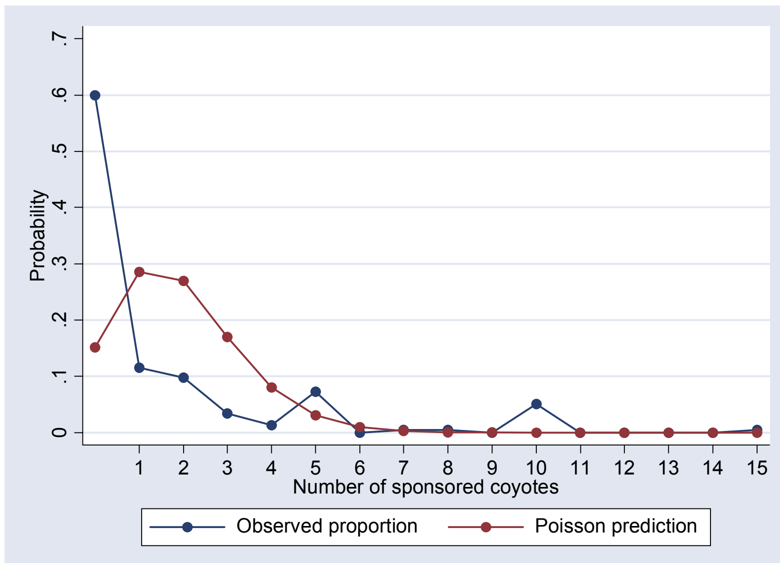

Figure 1: Observed distribution of the counts for *sponsored* versus the predictions obtained from a Poisson univariate model.

Next, still within the Poisson framework, each observation is allowed to have a different value of μ (the mean and variance). This Poisson regression model ($POISSON$), which makes μ a function of a series of covariates (see Table 2), fits the data better, but, as shown by Figure 2, still leaves a lot of room for improvement. The goodness of fit test $\chi^2 = 1116$ (Prob $> \chi^2$ (222) $= 0.0000$) clearly rejects the hypothesis that the Poisson regression model is adequate to model the counts of *sponsored*. In addition, there is a strong suspicion that the data present overdispersion relative to the Poisson distribution (the mean of *sponsored* is 1.89 and the standard deviation is 6.97). Finally, a robust estimation of the Poisson using the Huber/White/sandwich estimator of variance (Huber, 1967; White, 1980), denoted $POISSR$ in Table 2, also reveals that the simple Poisson might overestimate the t-statistics. Therefore, a negative binomial specification is considered next.

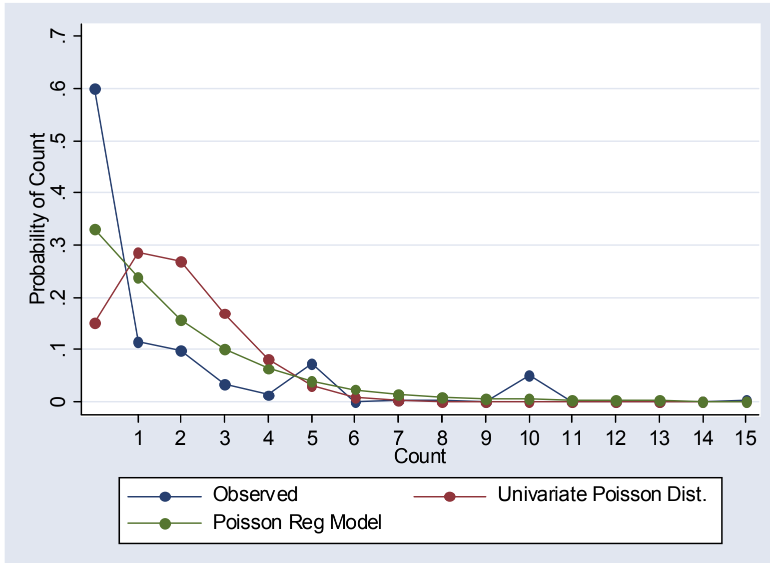

Figure 2: Observed distribution of the counts for *sponsored* versus the predictions obtained by the multivariate Poisson regression model and the Poisson univariate model.

Figure 3 plots the variable *sponsored* against a Poisson distribution with the same mean and a negative binomial distribution with the same mean and variance. It can be seen that the negative binomial distribution fits the data much better than the Poisson. In particular, the negative binomial predicts the number of zero responses very accurately. The proportion of zeros in the sample is 60.00% and the negative binomial would predict a 60.54% while the Poisson would predict only a 15.11%. The suspicion of overdispersion in the data relative to the Poisson is confirmed (the overdispersion parameter is 4.477).

The negative binomial regression ($NBREG$) results are shown also in Table 2, while Figure 4 plots the predicted probabilities of the first different values of *sponsored*. Crucially, there is very little difference between the estimated coefficient for *spobid* under $NBREG$ and under $POISSON$. Therefore, estimates of welfare both per coyote spared and per annum for the average respondent (see bottom of Table 2) will not differ much between both specifications, since they both have the same mean structure (Long and Freese, p. 266). However, and as expected, the estimated coefficients exhibit lower levels of significance under $NBREG$ than under $POISSON$, which suggests that the $POISSON$ t-ratios are

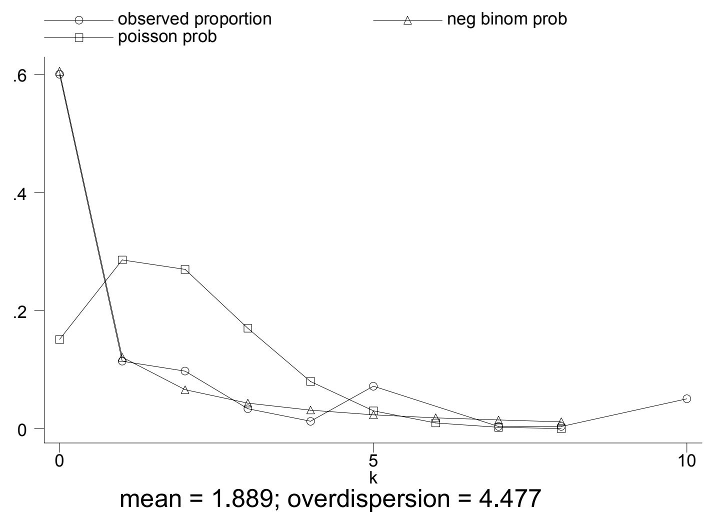

Figure 3: Predicted probabilities from Negative Binomial and Poisson versus observed probabilities.

biased.

The estimate of the over-dispersion parameter[18] ($\alpha = 3.18$) is highly significant, as reported in Table 2. This suggests that $NBREG$ is superior to $POISSON$. The likelihood-ratio improves substantially when the more flexible approach in the negative binomial is adopted. In fact, a likelihood ratio test[19] of the null hypothesis of no overdispersion (H_0 : $\alpha = 0$) confirms that the overdispersion is significant: $G^2 = 2(\ln L_{NBREG} - \ln L_{POISSON}) = 675.03$ with Prob>= $\chi^2(01) = 0.000$.

It is possible to generalize the negative binomial model by allowing α to be modelled as a function of one or more variables. This option was attempted, but the results (not reported, but available upon request) did not improve substantially over the negative binomial. Instead, the high proportion of zeros in the sample and the fact that coyotes are considered a nuisance species by some respondents, suggests that explicitly modelling the zeros could be desirable. That is, the over-dispersion in the data and the significance of α in the $NBREG$

[18] When $\alpha = 0$ the negative binomial distribution is equivalent to a Poisson distribution.

[19] In this case, this tests whether an estimated variance component (something that is always greater than zero) is different from zero. Therefore, the limiting distribution that applies is a normal distribution that is halved at zero. As a result, the distribution of the LR test statistic is not the usual $\chi 2$ with 1 degree of freedom, but instead a 50:50 mixture of a $\chi 2(0)$ (i.e. a point mass at zero) and a $\chi 2(1)$. The p-value of the LR test reported takes this into account (Long and Freese, 2003, p. 270; Gutiérrez et al., 2001).

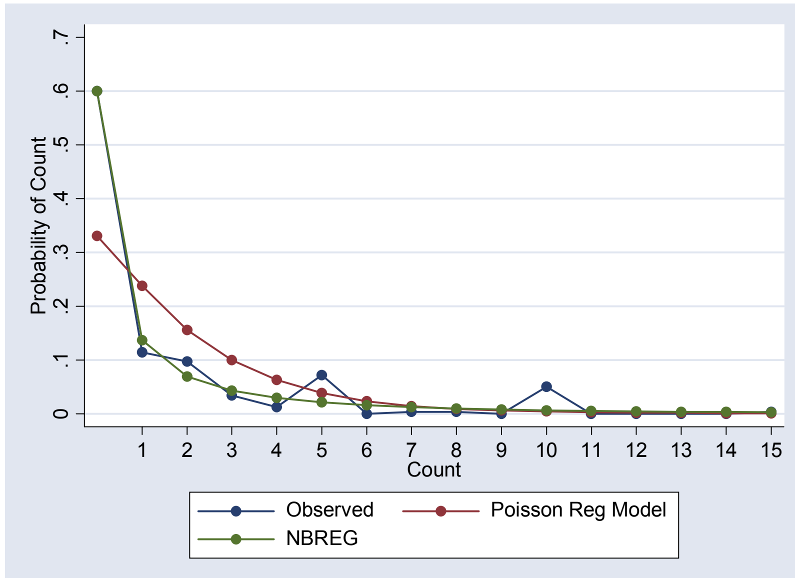

Figure 4: Predicted probabilities for sponsored from multivariate Poisson and Negative Binomial versus observed probabilities.

output could be due to zero-inflation.

The results of the zero-inflated Poisson model (ZIP) reported in Table 2 show that the coefficient on *spobid* is slightly smaller than in the previous models. It can be seen that the likelihood-ratio improves substantially relative to the standard $POISSON$, but is not better than the one obtained by the $NBREG$. A Vuong (Vuong, 1989; Greene, 1994) test of ZIP versus the standard $POISSON$ (see Section 4.3.2) yields a value of $z = 5.44$ (Prob> $z = 0.0000$), rejecting the null of the validity of the Poisson model.

If both a separate process for the zero and nonzero values of *sponsored* and between-respondent heterogeneity were affecting the data, a $ZINB$ model would be superior to the ZIP. Table 2 shows that the coefficient on *spobid* under $ZINB$ is just slightly smaller than the one under ZIP. The likelihood-ratio, however, improves considerably. More formally, the likelihood ratio test of the null hypothesis of no overdispersion ($H_0 : \alpha = 0$) confirms that the overdispersion is significant: the statistic takes the value 237.89, so Prob>= $\chi^2(01) =$ 0.000. When comparing the $ZINB$ versus the $NBREG$, the Vuong (Vuong, 1989; Greene, 1994; Long and Freese, 2003, p. 285) test statistic takes the value of 4.25 (Prob> $z = 0.0000$).

This reveals that the $ZINB$ significantly improves the fit over the ZIP model.

A different treatment of the excess-zeros feature consists of using a separate truncated Poisson ($TRPOIS$) plus a Logit (or Probit) or a truncated negative binomial plus a Logit (or Probit).[20] These hurdle specifications were attempted too. In the case of the Poisson, a likelihood-ratio test comparing the combination of $TRPOIS$ and $LOGIT$ to ZIP only just rejects the hypothesis of no significant differences between both specifications: the test statistic takes the value 5.815 (Prob>= 0.016). The equivalent test between the $ZINB$ and the hurdle model combining a truncated negative binomial ($TRBIN$) and a $LOGIT$ would yield a statistic value of 11.938 Prob>= 0.001. Therefore, it could be argued that the hurdle model fits the data better. However, as shown in Table 2, the coefficient of *spobid*, in which the analysis focuses, is remarkably close under both approaches (-0.0451453 under $ZINB$ and -0.0450708 under $TRNBIN$ in the hurdle model). More importantly, the hurdle model implies that once a respondent passes the hurdle (belongs to the nonzero-respondents group) the *sponsored* will be necessarily positive, hence the use of the truncated count models (Gurmu and Trivedi, 1996; Zorn, 1996). This is reasonable in some settings,[21] but not in the one considered here, since some of the potential supporters of coyote conservation might still choose a corner solution and state a zero response, due to their economic circumstances, particularly their *income* and the value of *spobid* they face. On the other hand, the zero-inflation models handle this situation better, since they separate the sample between an 'always zero' group and a 'not-always zero' group, which allows for corner solutions for the latter. Therefore, the rest of the results will be described in terms of the $ZINB$. Table 2 includes the results of $TRPOIS$ and $TRNBIN$ for reference.

Figure 5 provides a final visual aid to compare the goodness of fit of four of the different count data models. The mean predicted probability for each count (up to nine) is computed for each model by averaging the predicted probability for all the observations in the sample. Then the difference between these expected probabilities and the observed probability is

[20] This analysis was implemented in STATA using separately the commands *trpois*0 and *trnbin*0 (Hilbe, 1999) and the standard *logit*. This is equivalent to the joint maximum likelihood regression proposed by McDowell (2003).

[21] A good example in the continuous setting: it is reasonable to assume that once an individual decides to smoke, consumption takes place (García and Labeaga, 1996). That is, there are no *smokers* who do not smoke.

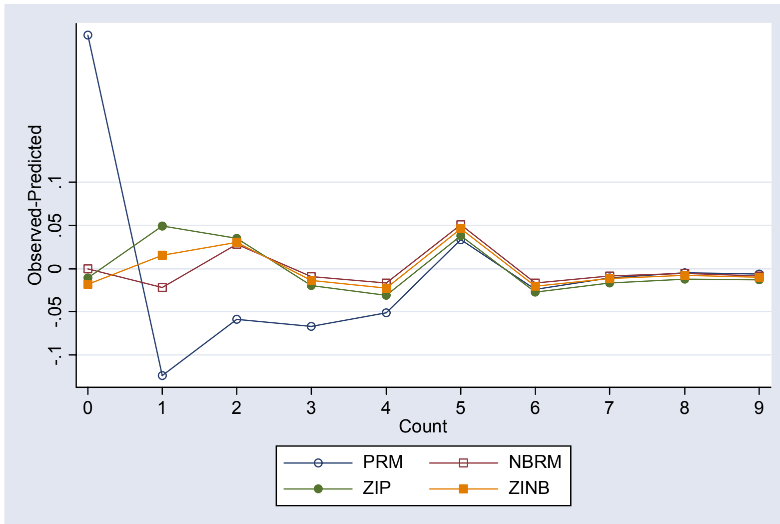

Figure 5: Deviations between the observed probabilities and the predicted probabilities for each count.

calculated. This difference for $POISSON$, $NBREG$, ZIP, and $ZINB$ is plotted, with points above zero on the vertical axis reflecting an underestimation of the observed counts by the respective model. This plots clearly show that only the $POISSON$ fails to predict correctly the average number of zero responses. Although most counts higher than five are quite accurately predicted by all models, the superiority of the $ZINB$ model is apparent in the case of lower counts.

The variable *spobid* presents a significant coefficient in almost all models, with a negative sign consistent with a downward-sloping demand. Its magnitude is also strikingly close among the different count models. Very little of the effect of *spobid* is on the decision to sponsor or not. Most of it is, as expected, on the decision about the number of coyotes to sponsor. Therefore, it was dropped from the binary equations in ZIP and $ZINB$.

5.2 COEFFICIENT INTERPRETATION

The interpretation of the coefficients in Table 2 is different from that of a standard least squares model, due to the nonlinearities underlying the relationships between the independent variables and *sponsored*. It can be shown that:

$$\frac{\partial E[y_i|x_i]}{\partial x_{ji}} = \beta_j \exp(x_i'\beta) = \beta_j \cdot E[y_i|x_i] \tag{7}$$

Therefore, a one unit change in the j^{th} regressor leads to a change in the conditional mean by $\beta_j \cdot E[y_i|x_i]$ (whereas in the linear model we would have simply β_j). The partial effect of a regressor depends on $\exp(x_i'\beta)$, which varies across individuals. β_j measures the relative change in $E[y_i|x_i]$ induced by a unit change in x_j. This effect is usually reported at the sample mean (Cameron and Trivedi, 2001, p. 324), which can be calculated in two alternative ways (as explained in Section 5.3).

Alternatively, one could consider that a unit change in x_j changes *sponsored* by a factor of $\exp \beta_j$. That is, the marginal effect of each variable depends on the value of the count. However, one unit change in j^{th} regressor leads to a proportionate change in $E[y_i|x_i]$ that is constant and equal to β_j. This is because:

$$\frac{\partial E[y_i|x_i]/\partial x_{ji}}{\partial x_{ji}} = \beta_j$$

Therefore, β_j could be referred to as a half-elasticity or semielasticity (Cameron and Trivedi, 1998, p.81). A full elasticity can be calculated, parting from the usual elasticity formula:

$$\xi = \frac{\partial E[y_i|x_i]}{\partial x_{ji}} \cdot \frac{x_{ji}}{E[y_i|x_i]}$$

combining it with Expression 7 and simplifying it into:

$$\xi = \beta_j \cdot E[y_i|x_i] \cdot \frac{x_{ji}}{E[y_i|x_i]} = \beta_j \cdot x_{ji} \tag{8}$$

Therefore the full-elasticity is a function of the independent variable (Cameron and Trivedi, 1998, p. 82; Haab and McConnell, 2002, pp. 165-166).

For example, according to the estimated coefficients for $ZINB$ reported in Table 2 being a *male*, given the values of all the rest of independent variables, would increase the expected value of *sponsored* by a factor of $\exp(0.24873) = 1.2824$ of the value of *sponsored*. Thus, everything else the same, the typical *male* would be expected to state a value of *sponsored* 28% higher than the typical female. Similarly, a $10,000 increase in household *income* would lead, *ceteris paribus*, to an increase in *sponsored* by a factor of $\exp(0.07030) = 1.0728$. Therefore, everything else the same, having $10,000 extra income would increase the expected number of sponsored coyotes by about 7.3%. In the case of the continuous variables, the estimated coefficients are readily interpretable as the proportional change in *sponsored* when the value of the variable increases in one unit.

Table 3: Results of modelling the binary choice: dumspo =1 if sponsored>0 under Logit and Probit. ZIP and ZINB model the opposite probabilties

	ZIP	ZINB	Logit	Probit
age	0.058	0.071	-0.061	-0.037
	0.0000	0.0002	0.0000	0.0000
educat	0.251	0.437	-0.181	-0.112
	0.1327	0.1023	0.2314	0.2075
incometown	-1.639	-2.459	1.256	0.739
	0.0249	0.0228	0.0518	0.0505
hunt	0.641	0.523	-0.922	-0.560
	0.3349	0.6123	0.1143	0.0960
selshoot	1.365	1.804	-1.182	-0.721
	0.0003	0.0080	0.0004	0.0003
livestock	0.773	-1.717	0.747	0.490
	0.2276	0.2509	0.2107	0.1565
cons	-0.765	-1.237	1.164	0.738
	0.5889	0.5039	0.3672	0.3380
N	235	235	235	235
log-likelihood	-	-	-121	-121
AIC$\cdot n$	-	-	256	256
BIC	-	-	-1003	-1003
$\widehat{Prob}(dumspo{=}0)$	0.5798	0.4063	0.6329	0.6241

The coefficients of the zero-inflation part of the $ZINB$ model (Table 3) determine the factor change in the odds of being a *zero-respondent* compared to being a *nonzero-respondent.* These coefficients can be interpreted just as the coefficients for a binary Logit model. For example, in the case of *age*, $\exp(0.07143) = 1.074$, so being one year older increases in 7.4% the odds of belonging to the *zero-respondent* group. Similarly, since $\exp(0.52345) = 1.688$, being a hunter increases the odds of belonging to the *zero-respondent* group in 68.8%.

Alternatively, the marginal effects can be calculated at some pre-specified value of each

Table 4: Marginal effects evaluated at the sample means for ZINB. For binary (starred) variables $\partial y/\partial x$ is for discrete change of dummy variable from 0 to 1

Variable	$\partial y/\partial x$	Prob>z
spobid	-0.0729762	0.045
age	-0.0296387	0.673
agesq	-0.0004269	0.588
educat	0.0215923	0.928
income	0.1136352	0.562
incometown	-0.1063758	0.930
lastseen	.0287767	0.894
hunt*	-1.248013	0.003
problems*	-0.6113805	0.333
coyote*	-0.8482641	0.330
pets*	-0.366122	0.416
male*	0.412812	0.387
selshoot*	-1.051108	0.002
livestock*	0.8615157	0.057

regressor (corresponding to a certain value of the expected count). For the Zero-inflated negative binomial model ($ZINB$) marginal effects, calculated at sample means, with appropriate significance levels are reported in Table 4.

When one variable enters both equations in $ZINB$, it often takes opposite signs in each. This is because the zero-inflation part for the ZIP and $ZINB$ (Table 3) models the odds of being in the *zero-respondent* group,[22] while the count equation (Table 2) refers to the value stated for *sponsored*. Often, if a factor increases the likelihood of a zero response, it will have a negative effect on the value of *sponsored* for *nonzero-respondents*. However, the reason to model the excess zeros separately is that some factors will exert different effects on the likelihood of stating a positive response and on the value of *sponsored* given that is positive (see Lin and Schmidt, 1984, for an illustration of this notion in the continuous case). In particular, it is noteworthy to see how the variables *age*, *educat*, and *incometown* present the same sign in both equations in $ZINB$, suggesting that being older and more educated reduces the likelihood of stating a positive value for *sponsored*, but for those who state a positive value, being older and more educated increases the expected value of *sponsored*. Living in a richer county (higher *incometown*) makes it more likely for the respondent to

[22] This explains while the sign of the coefficients of the binary equation of ZIP and $ZINB$ systematically present opposite signs relative to the Logit and Probit (Table 3).

give a positive response, but affects downwards the value of sponsored for those who state a positive value. These asymmetries are ignored by the more basic models that do not account for the process explaining the zero responses. On the other hand, a variable like *hunt* appears to affect the likelihood of stating a positive *sponsored* and the value of *sponsored* in the same direction (negative in both cases).

The results show that the influence of most variables agrees with *a priori* expectations.[23] The estimated coefficient on *spobid* is negative, resulting in the conventional downward-sloping demand curve. Household *income* presents a positive sign, confirming that this type of wildlife conservation is a normal good. However, *incometown* presents a negative sign in the count equation. This might be because it is correlated with other variables like the *density* or the degree of urbanization in the county. Having seen a *coyote* negatively affects *sponsored*, but having seen it more recently (*lastseen*) has a positive effect.

Respondents who *hunt* are less willing to sponsor coyotes (a similar result to that found by Walsh et al., 1984). This could reflect the influence of attitudes toward wildlife in general but also the fact that they consider coyotes a competitor for game. As expected, those who have experienced *problems* attributed to coyotes and those who own *pets*[24] are willing to sponsor the conservation of fewer coyotes. A somewhat surprising result[25] is that *male* respondents appear more willing to support conservation. This could be because they have different attitudes from women's towards wildlife in general. However, it could also reflect the fact that coyotes are particularly blamed for killing cats, and this could be expected to result in ill-feelings towards them held mainly by women. Although the individual level of significance is quite low for most variables, it can be rejected with a high level of confidence that the combined effect of the reported variables on *sponsored* is null.

The binary equation (Table 3) also shows that respondents who agreed to measures of coyote control (*selshoot*) were less likely to belong to state a positive value for *sponsored* (a

[23] Kellert (1985) studied the public's attitudes towards coyotes and wolves. Stevens et al. (1994) studied perceptions about coyotes. These works, among others, suggest that young, urban, female, wealthy, and more educated individuals tend to exhibit more favorable attitudes towards predators.

[24] Ownership of *cats* and *dogs* was also considered separately during the model selection process, but the results did not differ substantially.

[25] Stern et al. (1993) propose that females would exhibit a more protective attitude toward nature than males. Boman and Bostedt (1999) and Chambers and Whitehead (2003) find males less likely to support wolf conservation.

result that agrees with the finds in Arthur, 1981). Owning *livestock* had the opposite effect. This is because, although some farmers might be against coyote conservation, they would agree with supporting a program that actually compensates them for losses from predation.

5.3 Measures of Price Elasticity and Consumer Surplus

Two economic measures can be derived from the estimated demand model: price elasticity of demand ξ and consumer surplus (CS). In this case, the price elasticity measures the response of *sponsored* to changes in *spobid.* Calculated as per Expression 8 in Section 5.2, the value of the price elasticity at the sample mean is given by the product of the sample mean of *spobid* times the corresponding estimated coefficient ($12.55319 \cdot \widehat{\beta}_{spobid}$). For the $ZINB$, this price-elasticity is -0.57. At the average *spobid*, the hypothetical demand for sponsored coyotes is inelastic. This means that, at that price, an increase in the annual price of adopting or sponsoring a coyote for one year would be expected to result in an increase in the total revenue for the conservation program.

Additionally, in all the count data models reported in Table 2 the consumer surplus per coyote can be calculated as -$1/\beta_{spobid}$ (Creel and Loomis, 1990). If this expression is multiplied times the predicted count of coyotes, the predicted CS per year for the typical respondent in the sample results (Englin et al., 2003, p. 345). This is the correct measure for policy analysis if it is assumed that the dominant source of error in the analysis is measurement error (Bockstael and Strand 1987, Haab and McConnell 2002, p. 162). This predicted mean count can be calculated in two alternative ways (Cameron and Trivedi, pp.80-82). Since respondent characteristics vary across individuals, there will be a different predicted count for every respondent. One way to calculate the mean predicted count is to aggregate over all individuals and calculate the average count[26] obtaining:

$$\frac{1}{n}\sum_{i=1}^{n}{}_j \exp(x_i'\beta) \tag{9}$$

which in the case of the Poisson simplifies into $\overline{y}$, the sample mean.

[26] This can be simply done using the conventional commands *predict* and *summarize* in STATA (Statacorp, 2003).

An alternative procedure is to calculate the predicted count for the typical respondent (the respondent with the average characteristics):[27]

$$\exp(\overline{x}_i'\beta) \tag{10}$$

Since $\exp(\cdot)$ is a convex function its average calculated at several points exceeds the $\exp(\cdot)$ at the average of the same points. Therefore, Expression 10 yields a predicted mean smaller than Expression 9. Following Cameron and Trivedi's recommendation, the first procedure was used to compute $\widehat{CS}$/year, reported in Table 2.

If instead the error is expected to be mainly specification error, -1/β_{spobid} should be multiplied times the sample average. This is why we focus in this second measure for annual consumer surplus per respondent.

The value of consumer surplus per coyote or total willingness to pay per coyote ranges from \$18.63 in the $POISSON$ to \$22.19 in the $TRNBIN$, while it takes the value of \$22.15 under $ZINB$. The extrapolation to the annual consumer surplus per respondent (based on Expression 9) would, accordingly, range from \$35.19 to \$41.92, being \$41.85 under $ZINB$.[28] Annual consumer surplus measures based on the predicted number of *sponsored* coyotes, rather than the observed number, would be substantially lower (\$21.26 under $ZINB$).

If it were considered that the population of PEI defined the relevant market boundary for the willingness to pay for the coyotes living in the province, these measures of consumer surplus could be extrapolated by multiplying them times the number of households in PEI (around 50,000). This would amount to around two million dollars. However, it is entirely possible that the population of Eastern Coyote in this province provides non-use values to residents of other provinces, whose tax payments contribute to manage the species and the damage it creates (Chambers and Whitehead, 2003). On the other hand, it is somewhat problematic to extend individual value measures to population levels (Jakobsson and Dragun, 2001), so this figure should be considered with caution.

[27] This can be easily obtained using the STATA commands *prvalue* (Long and Freese, 2003, p. 259) or mfx (Statacorp, 2003).

[28] Note that for ZIP and $ZINB$ the reported values of the expected consumer surplus per year takes into account the expected probability of stating a positive value for *sponsored*.

The predicted counts of *sponsored* for the typical respondent can be derived for any given value of any given variable by choosing the value of that variable and leaving the rest of variables at their sample mean levels. This exercise was done for *spobid*. The predicted number of *sponsored* coyotes at each value of *spobid* between \$0 and \$100 (which, it should be noted, is not a *choke* price) is plotted in Figure 6. This could be understood as the predicted inverse demand curve for hypothetical *sponsored* coyotes by the typical respondent.

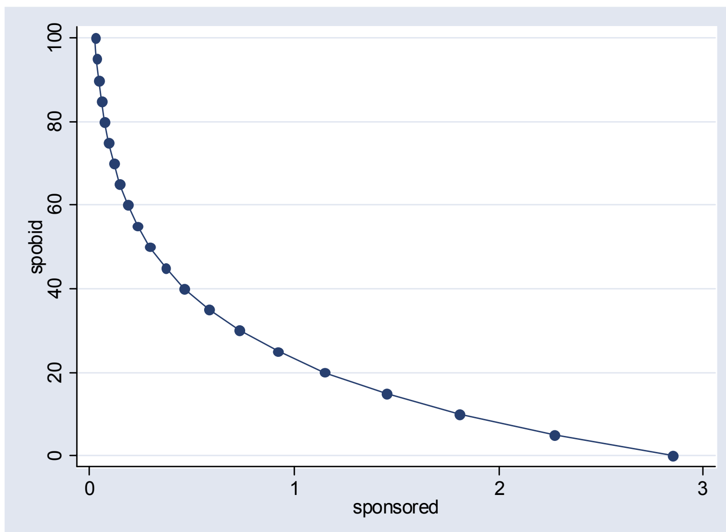

Figure 6: Predicted demand curve for the typical respondent.

6 Conclusions and suggestions for further research

In this paper, the willingness to pay for coyote a conservation program by sponsoring individuals of the species has been estimated. The results show that, save a couple of exceptions, the number of coyotes that would be *sponsored* depend in a expected manner on a series of respondent characteristics and, more clearly, on the price of sponsorship. The estimated values of price-elasticity appear highly robust to the choice of econometric specification and reveal that the number of coyotes sponsored would less than proportionately decrease when the price of sponsorship increased from its sample mean value of \$12.5. The total individual willingness to pay per coyote is estimated at about \$18-\$20. The corresponding extrapolation to annual consumer surplus per respondent results in \$35-\$42. These figures probably reflect largely non-use values.

Since coyotes are considered a nuisance species, care was taken to account for respondents who would never, as a matter of principle, sponsor any coyotes. The results confirm the advisability of modelling separately the decision about whether to state a positive response or not and the decision about the stated number of coyotes to sponsor improves .

It is important, when considering the results, to remember that, as usual in the contingent valuation context, responses relate to hypothetical, rather than revealed, demand. It would be reasonable to assume than to a certain extent these hypothetical responses may be exaggerating the true responses in a real situation (Getzner, 2000). However, in this case, given the existence of many instances of real sponsorship markets, it would be possible to test the validity of the hypothetical responses by analyzing the pattern of real sponsorships.

Another interesting extension would consist of considering the differences between different species. In particular, comparing the willingness to pay for conservation of less controversial species, or less well-known ones, would be interesting.

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7 Appendix:

7.1 Variable definitions

Note that some of these where considered but removed from the finally reported models.

age age of the respondent

cats binary=1 if respondent has any cats

coyote binary=1 if respondent ever saw a coyote in Prince Edward Island

density (population density in the county according to STATS CANADA)

dogs binary=1 if respondent has any dogs

dumspo (binary variable: 1 if *sponsored*>0 and 0 otherwise). This would be the dependent variable for the Logit and Probit models.

educat education level (ordered dummies from 1= less than high school, 2= high school; 3 = some college to 4 = college degree)

hunt binary=1 if respondent hunts

income household gross income categories, mean points of interval used ($25000, $35000, $45000, and $55000)

incometown (average annual income in the county according to STATS CANADA)

lastseen when the respondent saw the coyote last 1 = never 2, 3, 4, 5, 6 = very recently

livestock binary=1 if respondent has any livestock

male binary variable regarding sex of the respondent

neighbours binary=1 if respondent ever heard about trouble with coyotes in Prince Edward Island

sheep binary=1 if respondent has any sheep

petkilled binary=1 if respondent lost a pet to coyotes

pets binary=1 if respondent owns pets (including cats dogs and 'other pets')

problems binary=1 if respondent ever had trouble with coyotes in PEI

selshoot binary=1 if respondent agrees with the selective shooting of coyotes

sheep binary=1 if respondent owns sheep

spobid amount of dollars suggested as the annual cost of sponsoring a coyote so that farmers could be compensated for predation losses and the coyote would not have to be eliminated. The values $5, $10 $15 $20 and $25 were used randomly.

sponsored number of coyotes the respondent would be willing to sponsor. This is the dependent variable in all the count regressions.