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Incentive Payment Programs for Environmental Protection

A Framework for Eliciting and Estimating Landowners' Willingness to Participate

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Incentive Payment Programs for Environmental Protection: A Framework for Eliciting and Estimating Landowners' Willingness to Participate

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Abstract

This paper considers the role of incentive payment programs in eliciting, estimating, and predicting landowners' conservation enrollments. Using both program participation and the amount of land enrolled, we develop two econometric approaches for predicting enrollments. The first is a multivariate censored regression model that handles zero enrollments and heterogeneity in the opportunity cost of enrollments by combining an inverse hyperbolic sine transformation of enrollments with alternative-specific correlation and random parameters. The second is a beta-binomial model, which recognizes that in practice elicited enrollments are essentially integer valued. We apply these approaches to Finland, where the protection of private nonindustrial forests is an important environmental policy problem. We compare both econometric approaches via cross-validation and find that the beta-binomial model predicts as well as the multivariate censored model yet has fewer parameters. The beta-binomial model also facilitates policy predictions and simulations, which we use to illustrate the framework.

Key Words: protection, endangered, voluntary, incentive, tobit, beta-binomial, stated preferences

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David F. Layton and Juha Siikamäki *

1. Introduction

Incentive payment programs are increasingly popular mechanisms for achieving environmental policy goals. They are used, for example, in the United States, European Union, and Australia to encourage soil and water conservation and the adoption of environmentally friendly agricultural practices (OECD 2003). The protection of endangered species and habitat on private lands, which this paper addresses, is another important environmental policy problem, one which incentive payment programs, if properly designed, may help to resolve.

The conceptual framework for using incentive payment programs and, more generally, voluntary approaches for achieving environmental policy goals have been investigated by Smith (1995), Wu and Babcock (1995, 1996, and 1999), Polasky and Doremus (1998), Segerson and Miceli (1998), Innes (2000), and Smith and Shogren (2002).[1] Empirical research on landowners' willingness to participate in environmental policy programs has focused almost entirely on discrete-choice econometric models, which explain landowners' willingness to participate in various environmental and agricultural policy programs. These studies include Cooper and Keim (1996), which estimates farmers' willingness to adopt practices that improve water quality; Cooper and Osborne (1998), which estimates a model for the participation of farmers in the Conservation Reserve Program; Lynch and Lovell (2003), which analyzes the willingness of landowners to participate in a conservation easement program by purchasing or transferring development rights; and Cooper (2003), which jointly estimates farmers' participation in multiple environmental stewardship programs. All model their program participation as a binary choice. Lohr and Park (1995) extend the standard binary-choice model using Roy's identity,

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[1] Alberini and Segerson (2002) review economic issues related to voluntary programs.

deriving a discrete-continuous model of participation and its intensity. Their focus is on modeling participation.[2]

Although it is natural to begin with a pure discrete-choice participation problem, policymakers are not interested solely in the number of participants in a given program, but also in how much land will be protected under varying policy configurations. It is particularly important, when designing a large-scale program that may have tens or hundreds of thousands of participants, to know the number of hectares that may be enrolled under a specific program configuration.

Our goal in this paper is to provide a methodology for eliciting enrollments in incentive payment programs; flexible econometric models for analyzing the resulting data; and an approach for generating expected enrollments for different combinations of program attributes. Our results estimate potential enrollment in an incentive payment program for protecting certain small-scale, species-rich forest areas in Finland. Our model focuses on estimating participation as a function of two key attributes of the program: payment amount and contract length.

Finnish forests are an especially interesting and compelling setting for our application. *In situ* species conservation on private lands is a particular problem in Finland's conservation policy, as forests cover about three-quarters of the country's total land area, and most forests are nonindustrial, private holdings. Such holdings make up about 60 percent of the forestland and provide approximately three-quarters of the industrial timber supply in Finland. Forest ownership is widespread, as approximately 10 percent of Finland's population owns at least some forest area. Finland already has an active, if small, incentive payment program in place for the protection of forests that have particular ecological importance. Finland is currently considering employing this program in a large expansion of conservation efforts.[3]

We use a stated-preference (SP) survey of nonindustrial, private forest owners to collect data on the expected enrollment in alternatively configured incentive payment programs. Instead of simply posing binary participation questions, the survey asks forest owners also for the number of hectares they would enroll in different incentive payment programs. Consequently,

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[2] Parks and Kramer (1995) estimate participation in the Wetlands Reserve Program, but they use county-level, not individual-level, data on participation.

[3] To enroll a sufficiently large amount of land, many landowners will need to be convinced to set aside all or a portion of their lands. Voluntary participation is considered to be a key element of the new conservation program as non-voluntary approaches using command-and-control mechanisms would be politically difficult. The potential for conflict is easily understood when one considers that one in ten Finns might expect to be directly affected.

our data are a combination of discrete participation decisions enriched by continuous data on enrolled hectares**.**

Since data on enrollment in incentive payment programs are often censored, we start by developing a censored regression model of enrollment. To facilitate modeling multiple program responses for each landowner, we use a panel-type multivariate censored regression model. Using this as our base model, we then specify a rich correlation structure based on alternative-specific correlation components and random coefficients.

As an alternative to the censored regression model, we develop a beta-binomial model for enrollments. The beta-binomial model treats enrollments of different stands in a forest holding as separate choice occasions. Total enrollment by a landowner is then determined by the sum of stand-specific enrollment decisions over all available stands. Consequently, the structure of the beta-binomial model constrains total enrollment to a range between zero and the total hectares in the holding.

To our knowledge, the beta-binomial model has not been applied in this context before. It has been applied in marketing research since Chatfield and Goodhardt (1970), but in environmental economics, the econometric model most closely related to the beta-binomial model seems to be the Dirichlet model of recreational trip demand, which has been developed and estimated recently by Shonkwiler and Hanley (2003) and Moeltner and Shonkwiler (2005).

Comparing the beta-binomial model with the censored regression model using cross-validation and a mean square error (MSE) criterion, we find that although the beta-binomial model has fewer parameters to estimate, it performs either equally well or better than the censored regression model. Other properties of the beta-binomial model are also useful for policy design and analysis: the model provides closed-form predicted enrollments, and predicted enrollments are a smooth function of program attributes. Since the analyst's choice between the two models may vary depending on the application, we describe both econometric models in some detail.

Methods developed in this study are not limited to SP applications and forestry but may apply to a broader set of applications associated with predicting land-use decisions. Incentive payment programs are increasing in popularity, and methods for analyzing them are therefore important. The methods developed and analyzed in this study can also accommodate the analyses of agricultural and environmental policy programs, of which a vast range is in place around the world. Understanding and predicting landowners' decisions are indispensable when assessing such policy programs.

This paper is organized in seven sections. The second section (below) describes Finland's forest-conservation policy problem. The third develops the censored regression and beta-binomial econometric models for analyzing the survey responses. The fourth explains our SP survey design, implementation, and the resulting data. The fifth section presents estimation results and model comparisons using cross-validation. The sixth demonstrates how our methodology can be used in policy analysis. The seventh section concludes the paper.

2. Finland's Forest-Conservation Policy Problem

Forests provide the primary living environment for more than half the endangered native species in Finland. The endangerment of forest species is associated with forest-management practices that have changed forest composition, caused the loss of old-growth forests, fragmented remaining old-growth forests, and decreased the number of decaying trees in the forests (Hanski and Hammond 1995). Old-growth forests and so-called key habitats, hereafter termed biodiversity hotspots, are considered the primary targets of endangered-species protection. These areas, in particular the biodiversity hotspots, are typically small holdings—often less than a hectare—but they provide a habitat for many threatened species. Overall, about 6 percent of Finland's forests can be classified as either old-growth or biodiversity hotspots.

Finland has more than 400,000 privately owned, nonindustrial forest holdings, which on average are approximately 37 hectares (Finnish Forest Research Institute 2000). These are typically small units of managed forest stands—often not more than a hectare or two, and usually fewer than 10 hectares. Management of a forest stand typically follows a 60- to 120-year rotation cycle, depending on geographical location, soil conditions, and tree species.

Beginning in 1997 Finland implemented an incentive payment program for landowners to promote the protection of old-growth forests and biodiversity hotspots. Currently, a landowner who enrolls qualified forest habitat in the program for 10 to 30 years is eligible for an incentive payment, a cost-sharing compensation that is determined by the surface area and timber stock of the protected forest. By enrolling in the program the landowner is precluded from harvesting or managing the enrolled forest, although the program allows for nondisruptive uses, such as hiking and wildlife viewing. A participating landowner receives the incentive payment in full at the beginning of the protection period. The program has only a few participants to date, but it will nevertheless play a central role in Finland's plans to expand its protection of privately owned, nonindustrial forests (Ministry of Agriculture and Forestry 2001). Finland has already placed under protection contiguous areas that make up more than 10 percent of its total land area; those areas are mostly in the north, where state ownership is more common and land values are lower. The current program proposes to supplement existing conservation areas by establishing a network of many smaller protected forest habitats dispersed in a mosaic pattern throughout the country.

3. Modeling Participation in Incentive-Payment Programs

The landowner's decision about how much eligible land to enroll depends on several variables—among them the forest owner's planning horizon and motives for making the bequest, the age of the forest, its stand structure, nonforest income, interest rates, other land uses, and possible liquidity constraints. The private valuation of a forest stand under *in situ* landowner preferences is examined thoroughly by the multiple-stand forest-rotation model of Tahvonen and Salo (1999). Their study illustrates that participation decisions involving multiple stands (tens or hundreds per each forest holding in our application), substantial nonforest income, and *in situ* preferences are so complex that a rotation-based structural model is infeasible and not likely to provide much guidance for empirical decisions such as functional form. For this reason, we pursue estimating a predictive model for enrollments as a function of program attributes.

We develop alternative econometric models—a multivariate censored regression model and a beta-binomial model—of landowners' participation and enrollment in incentive payment programs. These models respond to and address different aspects of the data. The multivariate censored regression model focuses on the many zero enrollments one often finds in the data and views enrollments as an approximately continuous variable. The beta-binomial model is applicable to integer-valued enrollments, which is what we observe in our actual data set. In principle, enrollments are continuous, but because in practice they are often integer valued, both models may be useful in different applications.

Multivariate Censored Regression Model

We first model enrollment y using a multivariate censored regression specification (described in more detail by Cornick et al. 1994, Feenberg and Skinner 1994, and Moeltner and Layton 2002):

$$
\begin{aligned}
y_{it}^{*} &= f(x_{it}, \beta, \varepsilon_{it}) \\
y_{it} &= \max(0, y_{it}^{*})
\end{aligned}
\tag{1}
$$

where y^*_{it} denotes the latent dependent variable for landowner i and program t, y_{it} is the observed enrollment (hectares), x_{it} represents the contract (program) attributes, β is a vector of coefficients, and ε_{it} is a random error term.[4] If the landowner enrolls any forest area in a certain program, we observe y^*_{it} as the hectares enrolled, otherwise, a zero enrollment is observed.

The typical approach is to assume that ε_{it} are multivariate normal, perhaps after a transformation. Here we first transform the dependent variable using the standard inverse hyperbolic sine (IHS) transformation $IHS(y) = \ln(y + (y^2 + 1)^{1/2})$ of y. The IHS is similar to the log transformation, with two main differences: it is well defined at zero with IHS(0) = 0 and does not constrain the dependent variable to be positive before transformation.[5]

When potential enrollment is elicited using SP surveys with multiple enrollment questions involving alternative program configurations, or when actual enrollments in more than one program are modeled jointly, the analyst can benefit from applying a multivariate approach, perhaps with random coefficients. Define Y_i^* as a T-dimensional vector of enrollments to T program configurations by landowner i, and X_i as the T by k matrix of explanatory variables, such as program attributes and landowner and parcel characteristics. Y_i^* can be modeled as multivariate normal and as a function of random coefficients and correlated alternative specific errors:

$$IHS\left(Y_i^*\right) = X_i\bar{\beta} + \varepsilon_i \tag{2}$$

where ε_i is a function of normally distributed random coefficients $\tilde{\beta}_i$ interacted with independent variables and normally distributed alternative specific errors ν_i, so that $\varepsilon_i = X_i\tilde{\beta}_i + \nu_i$, where $\tilde{\beta} \sim MVN(0, \Delta)$ *and* $\nu \sim MVN(0, \Sigma)$, $\tilde{\beta}$ and ν are independent. Consequently, the final multivariate censored regression specification for enrollments is:

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[4] One could also incorporate upper censoring of enrollments. Given the nature of our data with a preponderance of zeros enrollments but nearly all enrollments below the upper limit, upper censoring is not crucial for this analysis.

[5] Moeltner and Layton (2002) assume multivariate normality after taking the natural logarithm of the dependent variable which treats the non-negativity of enrollments nicely but creates some difficulty in managing zero enrollments as the log of zero is undefined. Burbidge et al. (1988) used the IHS transformation as an alternative to the Box and Cox (1964) for handling extreme values of the dependent variable. It has been previously used in the double-hurdle demand model by Yen and Jones (1997) and as a functional form for SP data by Layton (2001).

$$IHS\left(Y_i^*\right) \sim MVN\left(\bar{\beta},\Omega\right),\ where\ \Omega = X_i \Delta X_i' + \Sigma \tag{3}$$

The vector $\bar{\beta}$ is k by 1 and Δ is a w by w dimensional covariance matrix of random coefficients, where $w \leq k$ so that not all coefficients need be random. Σ is a T-dimensional covariance matrix for the alternative specific errors.

The T enrollments by each landowner can consist of up to T censored enrollments, or T uncensored enrollments, or any combination in between. The likelihood of the model as defined by (1) and (3) is easiest to write by noting that the multivariate normal density can be written as a censored component conditioned on the uncensored component, where either the censored or uncensored components might be null vectors for any given landowner. The censoring of Y_i^* induces censoring on the ε_i. Denoting the normal density by $f(\cdot)$, its cdf by $F(\cdot)$, the uncensored components of ε_i as ε_i^{uc}, and the censored components as ε_i^{c}, the individual likelihood is:

$$\ell_i = F\left(\varepsilon_i^c \mid \varepsilon_i^{uc}\right) f\left(\varepsilon_i^{uc}\right) \tag{4}$$

The log likelihood is

$$\ln\left(\ell_i\right) = \ln\left(F\left(\varepsilon_i^c \mid \varepsilon_i^{uc}\right)\right) + \ln\left(f\left(\varepsilon_i^{uc}\right)\right) \tag{5}$$

The model as defined by (3) allows for a very rich correlation structure. We are aware of only one application where both random coefficients and correlated alternative specific errors are used—a multivariate probit model by McCulloch and Rossi (1994).

It is important to note that in the multivariate censored regression model scale is fully recoverable as a result of having at least some uncensored observations. Thus given the cardinal-level information on enrollments, one need not worry about the identification of Σ in principle. However, some restrictions are necessary in practice as the number of potential terms in the covariance matrix for the alternative-specific errors for t alternatives is $t(t+1)/2$, which can become prohibitively large very quickly, especially with the addition of random parameters. To address this problem, we consider specifications of the covariance matrix of alternative-specific errors that employ some natural restrictions and are easily generalized to higher dimensions.

Since our empirical application will consider enrollment in three different program configurations, our first specification is:

$$\Sigma = \begin{bmatrix} \sigma_{11}^2 & 0 & 0 \\ 0 & \sigma_{22}^2 & 0 \\ 0 & 0 & \sigma_{33}^2 \end{bmatrix} \tag{6}$$

Σ is the covariance matrix for an independent trivariate censored regression model. We extend Σ to handle at least some correlation by including a common off-diagonal component in Σ′:

$$\Sigma' = \begin{bmatrix} \sigma_{11}^2 & \sigma_{\mathrm{cov}} & \sigma_{\mathrm{cov}} \\ \sigma_{\mathrm{cov}} & \sigma_{22}^2 & \sigma_{\mathrm{cov}} \\ \sigma_{\mathrm{cov}} & \sigma_{\mathrm{cov}} & \sigma_{33}^2 \end{bmatrix} \tag{7}$$

The covariance matrix in (7) imposes restrictions on the covariance structure, in that it has four free parameters instead of the maximum possible of six. Since Σ′ nests Σ, likelihood ratio tests can be employed in determining model structure.[6]

Given the IHS-transformation of the dependent variable, the expected hectare enrollment by landowner *i* can be directly derived as:

[6] The covariance matrix in (7) can also be viewed as a generalization of the Butler and Moffitt (1982) equi-correlation structure for the panel probit model. Their covariance matrix is based on assuming that the alternative specific errors ν_i are generated by a permanent component τ_i distributed normally as $N(0, \sigma_\tau)$, and a transitory component γ_{it} distributed independent $N(0, \sigma_\gamma)$, and γ_{it} and τ_i are independent for all *i* and *t* resulting in:

$$\Sigma'' = \begin{bmatrix} \sigma_\gamma^2 + \sigma_\tau^2 & \sigma_\tau^2 & \sigma_\tau^2 \\ \sigma_\tau^2 & \sigma_\gamma^2 + \sigma_\tau^2 & \sigma_\tau^2 \\ \sigma_\tau^2 & \sigma_\tau^2 & \sigma_\gamma^2 + \sigma_\tau^2 \end{bmatrix}$$

Σ″ has two free terms, σ_τ, and σ_γ. In (6), we estimate Σ with three free terms, and Σ′ in (7) has four free terms.

$$E\left[Y_i^*\right] = \left[e^{\left(X_i\bar{\beta}\right)} - e^{-\left(X_i\bar{\beta}\right)}\right]\frac{e^{\frac{1}{2}\sigma^2}}{2} \qquad (8)$$

where σ^2 is $\mathrm{var}(\varepsilon_i) = \mathrm{var}\left(X_i\tilde{\beta}_i + v_i\right)$.

Beta-Binomial Model

The beta-binomial model is a probability mixture model of the sort that has been used to model brand-choice behavior since Chatfield and Goodhardt (1970). It is perhaps the first random-parameters model, in that it allows the probability *p* in a binomial model to have an underlying beta distribution.

In our analysis, the decision about whether to enroll one stand of forest in a certain program configuration constitutes a choice occasion. Aggregating the enrollment of all stands within each holding determines the total enrollment for each landowner. So we model the total probability of enrollment as *binomial*(n_i, p), where n_i is the number of hectares for each landowner and *p* is a *Beta(v,w)* random variable. Thus *p* is a random parameter.[7]

Next, denoting the hectares enrolled in the program by *x*, the beta-binomial probability is then calculated for landowner *i* for contract *t* as:

$$p\left(x_{it} \mid n\right) = \binom{n_i}{x_{it}}\frac{B\left(v + x_{it}, n_i + w - x_{it}\right)}{B\left(v, w\right)}, \quad Range\ 0 \le x_{it} \le n_i,\ x_{it} \text{ is integer},\ v, w > 0 \qquad (9)$$

where $B(v,w)$ is the beta function. The maximum-likelihood method can be directly applied to estimate the parameters of the beta-binomial model—no simulation or numerical integration is required. Using the estimated parameters, the expected number of hectares enrolled by landowner *i* is:

[7] The beta distribution can take a variety of shapes, which makes it useful for empirical work (see for instance Evans et al. 2000).

$$\overline{X}_i = N_i \left(\frac{v_i}{v_i + w_i} \right) \tag{10}$$

where both v and w can vary over different landowners. We will explain our empirical specification for v_i and w_i after describing our data in the next section.

4. The Stated-Preference Survey and Data

We conducted an SP survey of landowners regarding their willingness to participate in alternatively configured incentive payment programs designed to protect endangered habitat. The survey targeted 2,400 private, nonindustrial forest owners randomly sampled with a special permit from the database of the National Bureau of Taxation (NBT).[8] The NBT keeps comprehensive, up-to-date records of land property in Finland. The NBT database is updated continuously and automatically registers every real-estate transaction at closing. The NBT database updates landowners' addresses from annual tax forms, which all landowners need to file, and the census register, to which every citizen of Finland is required by law to file a new address within a week of moving. In practice, this means that our sampling population comprises the owners (at the time of the sampling) of every hectare of forest in Finland possessed by any individual with a permanent address in Finland or abroad.[9]

The survey was designed in consultation with two ecologists, five non-market survey experts, three foresters, nine forest- and farm-survey experts, and eight forest owners. Pretesting included personal interviews and a pilot survey that targeted 200 forest owners throughout the country.[10]

[8] The pilot and final samples are drawn from the total population of forest owners with at least five hectares of forestland. We used a stratified sampling scheme with province-specific quotas (250 to 350 forest owners in each of ten provinces) to guarantee collecting data from all regions.

[9] Internet samples, random-digit-dialing surveys, and surveys using other common convenience samples are considerably less general than the sampling approach used in this survey. Due to strict regulations regarding the privacy of personal information in the public domain, obtaining the sample required nearly a yearlong permitting process in which the survey, questionnaires, and confidentiality of survey responses were reviewed, assessed, and revised.

[10] The questionnaires were mailed to respondents in December 1999. A week after the first mailing, a reminder card was mailed to each respondent, and in early January each nonrespondent was mailed a new copy of the questionnaire with a reminder to respond.

The pilot survey included one questionnaire mailing and a reminder postcard, which resulted in exactly 100 responses (a 50-percent response rate).

In addition to questions about the incentive payment program, the mailing asked landowners about their forest holding and its management.[11] We focus here on explaining the section of the questionnaire that related directly to the incentive payment program. That section described the current incentive payment program and illustrated it with the help of an easy-to-follow practical example, which respondents in the pilot survey and personal interviews found particularly helpful. It described in detail the forest areas that were eligible for the current program. Those areas were classified in categories commonly used by forestry professionals and forest owners, and also in forest management plans, which form the basis for the management of many forest holdings in our sample. Identifying eligible areas was thus made as simple as possible for the respondents. Next, the respondents were asked to list the amount of land they owned in each category.

Based on our experience with landowners during the design and testing of the questionnaire and prior to the survey effort, we expected that many would refuse to divulge the extent of various endangered habitats in their forests—an understandable reaction given privacy concerns. To meet that concern, we formulated the question so that respondents could either list the amount of eligible land or check a box offering an "unable to list" alternative. Although we did not expect to receive comprehensive data on the eligible areas, we posed this question to prepare respondents for the questions that followed.

In introducing the subsequent questions on enrollment in the incentive payment program, the questionnaire first explained that three variations on the current program would be presented, each offering a different payment and contract length. The differing payments and contract lengths were specified and explained. Only then were the three variants (Programs *A*, *B*, and *C*) of the current incentive payment program described. The questionnaire then asked how many hectares, if any, of old-growth forests and biodiversity hotspots the respondent would enroll in each program. The program-participation question was formulated as follows:

[11] The respondents received no payment for participating in the survey, but they had an opportunity to sign up for a lottery. Twenty-two prizes were awarded in the lottery, including the main prize of a chainsaw valued at about $400.

Program A		
Payment	*P*	per hectare
Contract length	*T*	years

How many hectares would you enroll in the Program A?

I would enroll the following areas:

(a) ☐ ☐ ☐ hectares of old growth

(b) ☐ ☐ ☐ hectares of key habitats

(c) ☐ I would not enroll anything.

This discrete-continuous question format differs from discrete SP questions commonly used for the valuation of public goods and is similar in spirit to open-ended elicitation questions. Although the contingent-valuation literature is skeptical of open-ended questions, this application differs in important ways from the direct elicitation of willingness to pay (WTP). Our question format elicits enrollments in a way that landowners found both credible and easy to respond to. Many of the respondents are full-time farmers who are very familiar with the similar question format of land-use forms they complete annually to enroll farmland in the European Union's agricultural policy programs. Many others are landowners who know their forests in detail. The respondents are therefore well equipped to determine whether enrolling certain parcels of land in an incentive payment program for a particular length of time provides an attractive forest-management alternative. For a landowner, this matter is not necessarily different from other routine forest-management decisions, such as deciding whether to cut off, thin, plant, or otherwise manage an area of forest.

Each participation question dealt with a different modification of the incentive payment program defined by two attributes: the payment (P) and the contract length (T). The payment per hectare enrolled would be made in a lump sum upon enrollment, as under the current regime. The contract length is a binding time requirement, meaning that the enrolled land must be preserved for the required time.[12] The program alternatives actually presented to each respondent were randomly assigned from a set of 35 different questionnaire versions, which differed only in

[12] Compliance monitoring would not be problematic under the proposed program, since monitoring compliance *ex post* is highly effective. For example, satellite imaging is now commonly used for observing field-level land use and compliance with agricultural policy programs of the European Union and could be used for the proposed program.

the program attributes (*P* and *T*). The incentive payment in different programs ranged between FIM500 and FIM70,000 or about \$75–\$10,500 per hectare in U.S. dollars as one Finnish markka (FIM) ≈ US\$0.15 at the time of the survey. The contract length took values between 10 and 50 years (in 5-year increments). The wide spread in the bids reflects the pilot survey results and the heterogeneous timber stock in different eligible areas. In the pilot survey, we used 10 different bid vectors and one questionnaire version with an open-ended compensation requirement to confirm our understanding of the range of bids needed in the final survey. Low bids are very relevant to the portion of timber owners who have a very low reserve price for conserving old-growth forests and biodiversity hotspots, as some already conserve them for free. High bids are relevant to those with valuable old-growth timber that they intend to harvest.

Although experimental design is critically important in conducting discrete-choice SP surveys, it is likely to play a less pivotal role in our open-ended SP format, which elicits information at the cardinal, not ordinal, level. Still, we paid careful attention to issues of experimental design. A primary concern that arose during pretesting was that standard orthogonal designs would result in some implausible program combinations. Respondents found that only programs that included higher payments for longer contract lengths were credible. Therefore, we constrained the experimental design so that each respondent was always offered a higher payment for longer contract lengths and not vice versa. Across all respondents, however, different contract lengths were offered with a wide variety of payments, thereby minimizing the correlation between contract length and payment.[13]

The two attributes, payment and contract length, capture the essential features of the current program with one major difference. The current program computes per-hectare payments based either on the local average or on the site-specific volume of timber. Our SP-style question uses a flat lump-sum payment per hectare. This enables us to estimate participation in forest conservation for varying incentive payments without having stand-specific data on the timber stock. In addition, using a flat per-hectare payment, perhaps differentiated by region and forest type, is a practical format for future policy implementation. Obviously the same flat payment will not deliver the same benefits to each forest owner because forest stands will have different amounts of timber per hectare. But that is precisely the key benefit of voluntary participation:

[13] Although necessary in this case, using a correlated design can lower efficiency in econometric estimation (Huber and Zwerina 1996). To minimize this, we created a GAUSS program that randomly draws survey designs with 35 questionnaire versions, each with three different programs satisfying the non-dominance constraints explained in the text, designs are then ranked according to their non-orthogonality. The final design was chosen from among the least non-orthogonal designs out of 200,000 designs that satisfied the non-dominance constraints.

other things being equal, owners with less marketable timber per eligible hectare will be more likely to enroll their hectares than those with more marketable timber, thus sorting landowners according to the opportunity cost of enrollment.

A total of 2,380 landowners were reached by mail. The survey resulted in 1,129 responses (47.40-percent response rate).[14] Since 302 respondents indicated that they owned neither hotspots nor old growth, we excluded them from further analysis. We believe that many of the nonrespondent landowners do not, in fact, own hotspots or old-growth forests, but that belief cannot be verified. The final sample size consists of 828 responses to three programs each. Of these, 801 respondents own hotspots and 738 old-growth forests. Because only a small percentage of forests are hotspots or old growth, we expected and observed substantial censoring of enrollment responses. For hotspots, 86.3 percent of the respondents did not enroll any forests in any of the programs offered. For old growth, 91.3 percent of the respondent landowners did not enroll any hectares.

5. Econometric Model Results

Here we present separate results for the censored regression and beta-binomial models. We then compare these two nonnested models using cross-validation and an MSE criterion.[15] Each landowner stated enrollments in three alternative programs separately for hotspots and old growth. Since old growth and hotspots are distinctively different in their characteristics, prevalence, and value, we estimate separate models for their enrollments.

We use the weighted maximum-likelihood method for estimating model parameters, because our survey sampled responses using stratification and regional quotas. Sampling weights give more weight to observations that have a lower probability of being selected, and vice versa.[16] Independent variables in each estimated model include the per-hectare payment (*PAYMENT*) and the contract length (*TIME*).

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[14] In addition, 20 blank questionnaires were returned. A Christmas-time mailing, unavoidable for other reasons, may have reduced the response rate. The response rate is similar to two recent surveys conducted for the estimation of the public's WTP for different conservation programs in Finland. Li et al. (2004) had a 44 percent to 45 percent response rate, and Siikamäki (2001) obtained a 48 percent to 49 percent rate.

[15] All models were programmed and estimated in GAUSS. To facilitate convergence in estimation, payment and time variables were scaled by dividing them by 1,000 and 10, respectively.

[16] Given the stratified sampling procedure noted earlier, sampling probabilities are similar across regions and so using weighted instead of non-weighted estimation does not substantially modify our results.

The censored regression and beta-binomial models differ in their underlying assumptions regarding the continuity of enrollment data. The censored regression model assumes that enrollment is a continuous variable, whereas the beta-binomial model treats it as an integer variable. Unavoidably, both assumptions are approximations. However, elicited enrollment data suggest that the integer assumption of the beta-binomial model is well justified: out of the total of 286 positive enrollments, only 8 enrollments contained non-integer amounts. We therefore round these non-integer enrollments to their nearest integers and continue to apply alternative econometric models to the same data.[17]

Multivariate Censored Regression Model

The diagonal elements of the covariance matrix Σ' in (7) are denoted by coefficients σ_{11}^2, σ_{22}^2, and σ_{33}^2; σ_{cov} is the off-diagonal element. *LnHectares* is the natural logarithm of the total hectares of forest owned by the respondent, which is included because increased holding sizes are likely to increase the availability of eligible hectares.

We estimate three models of increasing complexity, separately for old-growth and hot-spot enrollments. The structure of the estimated models is as follows: Model 1 is an independent trivariate model with fixed coefficients. The least flexible of the estimated models, it assumes independent errors between different responses by the same landowner, estimates the covariance matrix Σ in (6), and does not allow for heterogeneous coefficients. Model 2 is a correlated trivariate model with fixed coefficients. It accounts for error correlation between different responses by the same landowner, estimates the covariance matrix Σ' in (7), and does not allow for heterogeneous coefficients. Model 3 is a correlated trivariate model with random coefficients, which makes it the most flexible of our models. It accounts for error correlation between different responses by the same landowner, estimates the covariance matrix Σ' in (7), and also allows for heterogeneous coefficients. In this model only the *Time* coefficient is modeled with a random coefficient, as most non-market studies that use random coefficients treat the cost coefficient as fixed (in our case *Payment*).

The estimation results are presented in Table 1. As these are not our final results, we provide only a brief discussion. All the models produce statistically significant coefficient estimates with expected signs. The *Payment* coefficients are all positive, indicating that enrolled hectares increase with the amount of compensation offered. The *Time* coefficients are all

[17] One could also simply drop these eight observations with minimal impacts on the final results.

negative, which reasonably suggests that the enrolled hectares decrease as contract length increases. The *LnHectares* coefficients are positive and statistically significant, indicating that there is a positive relationship between the size of the forest holding and the enrolled hectares.

The estimated σ_{cov} coefficients are all statistically significant except in Model 3 for old growth. The significance of the covariance coefficient demonstrates the importance of relaxing the assumption of independent errors in Model 1. The statistically significant deviation parameter σ of the *Time* coefficient suggests the heterogeneous effect of contract length on the willingness to enroll in conservation. This may be related to heterogeneous forest quality, forest owners' preferences, or a combination of the two.

Generally speaking, these results show clearly that econometric flexibility improves the statistical performance of the estimated model. The correlated trivariate model (Model 2) increases the log-likelihood value statistically significantly from the independent trivariate model (Model 1). Enriching the correlated trivariate model with random coefficients (Model 3) further enhances the log-likelihood value.[18]

Beta-Binomial Model

We estimate beta-binomial models using $w = \exp(w^*)$, and $v = \exp(\alpha + \beta z)$, where $\beta=[\beta_P\ \beta_T]$, and z consists of payment amount and contract length. This functional form will ensure that v, $w > 0$.[19] If the contract length and payment are zero, we effectively obtain a "no program" situation, and then α and w jointly determine the probability of having any hotspots or old growth available. Conditional on α and w, we can interpret β as the effect of payment and contract length. For three programs, we compute three probabilities with the same underlying parameters, but the x_{it} (enrolled hectares) and z data change between different programs. The overall probability is then computed as the product of the three sub-probabilities shown below.[20]

[18] Formal testing via likelihood ratio statistics rejects Model 1 in favor of Model 2, and Model 2 in favor of Model 3 for both the old growth and hotspots.

[19] Note that a *Beta(v,w)* random variable is identical to a *Beta(w,v)* random variable, so that the choice of whether it is v or w that depends upon covariates is not important. One can make both v and w functions of covariates, but experience suggests little practical gain from such a strategy.

[20] One can imagine dependence across the sequence of three questions, but modeling dependence is both econometrically challenging and complicates subsequent policy analysis in the context of the beta-binomial model.

$$p(x_i \mid n) = \prod_{t=1}^{t=3} p(x_{it} \mid n) = \prod_{t=1}^{t=3} \binom{n_i}{x_{it}} \frac{B(v + x_{it}, n_i + w - x_{it})}{B(v, w)} \tag{11}$$

The results of beta-binomial models using both linear (Model 1) and logarithmic (Model 2) transformations of the independent variables are presented in Table 2. In comparison with the linear models, the logarithmic models improve the maximized log-likelihood values from −730.22 to −725.18 for the old-growth models and from −1079.84 to −1075.63 for the hot-spot models, suggesting that the logarithmic transformation of *PAYMENT* and *TIME* are preferred for modeling these data.[21] Finally, see Table 2 for an illustration of how strikingly simple the beta-binomial model is compared with the multivariate censored regression model. The estimated parameters are all significant, and the *TIME* and *PAYMENT* coefficients have expected signs. We will further explain the results of the beta-binomial model after discussing cross-validation.

Model Comparison

Cross-validation can be used to compare the predictive power of the multivariate censored regression and beta-binomial models (Stone 1974; Efron and Tibshirani 1993). Formulas (8) and (10) can be used with the contract components actually offered to each respondent to predict the hectares enrolled in the survey. For a sample of *m* observations, the cross-validation technique uses *m–n* observations to estimate the model parameters, which are then used to predict the remaining observations. We implement “leave-one-out” cross-validation where *n* is set equal to 1 and each time a different observation is left out, cycling through all observations. Using individual predictions, we then calculate the MSE over the whole sample.

We present cross-validation results for the most flexible censored regression specification (Model 3), and the logarithmically specified beta-binomial model, which are the best fitting models. The cross-validation results are described in Table 3. The average MSEs of censored-regression models for old growth and hotspots are 16.05 and 58.23; the respective MSEs of beta-binomial models are 3.36 and 58.11. So, for the old-growth models, the MSE of beta-binomial models is over four times smaller than that of censored regression models, although the difference is primarily attributable to the very poor predicative performance of the latter model

[21] A linear *TIME* implies a constant compensation requirement per additional year, whereas a logarithmic *TIME* implies an increasing compensation requirement. For an individual owner the compensation required over time is likely a mixture of factors related to setting aside a specific forest stand for a predetermined time, including growth or decay of timber stock, expectation of future timber prices, rotation cycle, and landowners’ time preferences.

for question 1. For the hotspots, the beta-binomial and censored regression models result in almost exactly the same MSE (58.23 vs. 58.11). However, the beta-binomial models use only four parameters, whereas the censored regression models, with their very flexible structure, estimate a total of nine parameters. We have also confirmed that cross-validation results are robust to alternative model specifications. Our overall assessment is that the beta-binomial models are at least as good as the censored regression models; they have fewer parameters and, as we will show in the next section, they also provide closed-form predictions that are practical for policy simulations.

When investigating individual enrollment predictions, we found that censored regression models often predict either zero or complete enrollments. We find the predictions from beta-binomial models more plausible as they predict partial enrollments and provide a smooth transition between different levels of enrollment. One could explore landowners' enrollment decisions using richer econometric specifications and spatial-temporal aspects of conservation policy design. As this analysis can be become fairly extensive, we leave additional specifications for future work and instead demonstrate how the beta-binomial models can be used for evaluating conservation policy alternatives.

6. Policy Evaluation

We now consider predicting the total number of hectares enrolled when a contract with common payment and length is offered to all landowners. The question is what combination of time and payment will yield a given level of enrolled hectares. Using (10) we see that the expected total hectares enrolled are determined in the beta-binomial model as:

$$\sum_i \overline{X}_i = \sum_i N_i \left(\frac{v_i}{v_i + w_i} \right) \tag{12}$$

Substituting $\overline{X} = \sum_i \overline{X}_i, \quad N = \sum_i N_i$, and noting that landowners are homogenous in our estimated models, we find that offering a common time and payment results in constant *v* and *w* across all landowners and yields the following closed form for the expected number of hectares in enrolled:

$$\bar{X} = \left(\frac{v}{v+w} \right) N \tag{13}$$

Combinations of time and payment that will yield a given number of expected enrollments are solved by substituting estimated *v* and *w* for the parameters into (13). The payment amount that will generate enrollment $\bar{X}$ for *T* years using our preferred Model 2 with logarithmic payment and time is:

$$P = \left(\left(\frac{w\bar{X}}{N - \bar{X}} \right) \left(T^{-\beta_T} \right) \left(\exp^{-\alpha} \right) \right)^{\frac{1}{\beta_P}} \tag{14}$$

Calculating *P* for varying $\bar{X}$ yields the marginal cost curve of land enrolled for conservation in the proposed incentive payment program. The payment equation also shows how the payment requirement increases as a function of contract length.[22]

Figure 1 illustrates the effects of the enrollment time horizon (10 vs. 30 years) and forest type (hotspots vs. old growth) on the payment requirement. Per-hectare payment requirements are calculated for enrolling from 0 to 5 percent (about 550,000 hectares) of private forests in the program, of which the latter closely corresponds to the maximum amounts of hotspots and old growth available. The range of the protection time horizon embraces the proposed future conservation programs in Finland.

The estimated payment requirement for hotspots ranges from about $0 to approximately $2,000 per hectare. Payment requirements for old-growth protection are significantly higher—ranging from $0 to nearly $9,000 per hectare. Noting that the value of standing timber in old-growth forests can reach $10,000–$15,000 per hectare, and that hotspots generally contain significantly less timber than old growth, these estimates are realistic. Also noteworthy is that our results (not illustrated here) predict that the most extreme policy (protecting all old growth for 50-years) would require an approximately $14,000 incentive payment. Although this is out of the range of payments offered in the survey, the payment requirement is quite reasonable. Payment requirements for all other less extreme and plausible programs fall within the range of

[22] Note that (14) is general and that any scaling or transformations used to ensure positivity of *v* and *w* will need to be included in practice.

the experimental design. The estimated payments also illustrate that enrolling small percentages of the total forest area can be accomplished using very low payment amounts. This observation is in line with responses from some respondents, who indicated that they already effectively and voluntarily protect some specific areas of their forests (regardless of incentive payments).

The probability density functions of estimated enrollments of hotspots and old growth are illustrated in Figure 2 by employing two alternative incentive payments ($500 and $10,000) and a fixed 30-year enrollment. The graph shows that the probability density mass shifts northeast with an increase in the payment, indicating that landowners find enrollment economically more attractive as incentive payments rise. The figure also illustrates that the probability mass is mostly near zero, suggesting that enrollment probabilities are small. Although in this application the estimated probability density functions appear similar to an exponential distribution, a beta-binomial model of other enrollment data may result in very differently shaped densities, which suggests that it may be useful in a wide range of applications.

7. Discussion

This paper provides a unified framework for estimating participation in voluntary conservation programs using incentive payments. We developed a multivariate censored regression model and a beta-binomial model to predict enrollment under the alternative programs. We designed an SP survey to elicit enrollments in response to alternative configurations of an incentive payment program. Based on the cross-validation results we selected the beta-binomial model for our data. The structure of the beta-binomial model constrains enrollment to values between zero and the total hectares owned by each landowner, which is both practical and realistic.

The econometric results suggest that a beta-binomial model provides a useful alternative for modeling discrete-continuous data with natural lower and upper bounds, such as the amount of land enrolled in response to various incentive payment programs. On the whole, however, both censored regression and beta-binomial models worked well, yielding statistically significant estimates with expected signs. Which model to select might depend on the application, but in our application with a focus on predicting total enrollments under varying contractual configurations, we found the beta-binomial most useful. Both censored regression and the beta-binomial models are clearly useful for designing and analyzing conservation programs, and provide a useful foundation for additional research.

This study facilitates the estimation of the opportunity cost of conservation for all proposed spatial and temporal ranges of the conservation of endangered habitat in Finland.

Notably, the estimated payment requirements for all currently proposed policy alternatives are within our experimental design. Albeit this does not imply the estimates are infallible, it raises our confidence in the assessments of different policy alternatives.

Investigating the opportunity costs of conservation is only a partial evaluation of the conservation problem. A more comprehensive assessment would contrast the opportunity cost of conservation with its benefits. We find evaluating the conservation problem from both cost- and benefit perspectives a particularly interesting and important topic for future research. We have also found through additional and on-going analysis that regional differences in compensation requirements are substantial. Therefore, a regulator should pay particular attention to finding a policy design that attempts to equalize trade-offs between the costs and benefits of spatially balanced conservation policy. A comprehensive analysis of optimal or cost-efficient design of conservation policy, which we leave for future work, could involve an analysis, perhaps along the lines of Polasky et al. (2001), of how to incorporate ecological benefits in designing a cost-efficient spatial configuration of conservation policy.

References

Alberini, A., and K. Segerson. 2002. Assessing Voluntary Programs to Improve Environmental Quality. *Environ. Res. Econ.* 22: 157–84.

Box, G. E. P., and D. R. Cox. 1964. An Analysis of Transformations. *J. Royal Statist. Soc. B.* 26: 211–43.

Burbidge, J. B., L. Magee, and A. L. Robb. 1988. Alternative Transformations to Handle Extreme Values of the Dependent Variable. *J. Amer. Statist. Assoc.* 83: 123–27.

Butler, J. S., and R. Moffitt. 1982. A Computationally Efficient Quadrature Procedure for the One-Factor Multinomial Probit Model. *Econometrica* 50: 761–64.

Chatfield, C., and G. J. Goodhardt. 1970. The Beta-Binomial Model for Consumer Purchasing Behavior. *Applied Statistics* 19: 240–50.

Cooper, J. 2003. A Joint Framework for the Analysis of Agri-Environmental Payment Programs. *Amer. J. Agr. Econ.* 85: 976–87.

Cooper. J. and R. W. Keim. 1996. Incentive Payments to Encourage Farmer Adoption of Water Quality Protection Practices. *Amer. J. Agric. Econ.*78 (February): 56–64.

Cooper, J. and T. Osborne. 1998. Rental Rates and the Extension of CRP Contracts. *Amer. J. Agr. Econ.* 80: 184–94.

Cornick, J., T. L. Cox, and B. W. Gould. 1994. Fluid Milk Purchases: A Multivariate Tobit Analysis. *Amer. J. Agr. Econ.* 76: 74–82.

Efron, B., and R. J. Tibshirani. 1993. *An Introduction to Bootstrap.* New York: Chapman & Hall.

Evans, M., N. Hastings, and B. Peacock. 2000. *Statistical Distributions*. 3rd ed. New York: John Wiley & Sons.

Feenberg, D., and J. Skinner. 1994. The Risk and Duration of Catastrophic Health Care Expenditures, *Rev. Econ. Statist*. 76: 633–47.

Finnish Forest Research Institute. 2000. *Finnish Statistical Yearbook of Forestry.* Helsinki.

Hanski, I., and P. Hammond. 1995. Biodiversity in Boreal Forests. *Trends in Ecol. Evol.* 10: 5–6.

Huber, J., and K. Zwerina. 1996. The Importance of Utility Balance in Efficient Choice Designs. *J. Marketing Research* 33 (August): 307–17.

Kuuluvainen, J., H. Karppinen, and V. Ovaskainen. 1996. Landowner Objectives and Non-Industrial Private Timber Supply. *Forest Science* 42: 300–08.

Layton, D. F. 2001. Alternative Approaches for Modeling Concave Willingness to Pay Functions in Conjoint Valuation. *Amer. J. Agr. Econ.* 83: 1314–20.

Li, C-Z., J. Kuuluvainen, E. Pouta, M. Rekola, and O. Tahvonen. 2004. Using Choice Experiments to Value the Natura 2000 Nature Conservation Programs in Finland. *Environ. Resource Econ.* 29: 361–74.

Lohr, L., and T. R. Park. 1995. Utility-Consistent Discrete-Continuous Choices in Soil Conservation. *Land Econ.* 71(4): 474–90.

Lynch, L., and S. J. Lovell. 2003. Combining Spatial and Survey Data to Explain Participation in Agricultural Land Preservation Programs. *Land Econ*. 79(2): 259–76.

McCulloch, R. E., and P. E. Rossi. 1994. An Exact Likelihood Analysis of the Multinomial Probit Model. *J. Econometrics* 64: 207–40.

Ministry of Agriculture and Forestry. 2001. Finland's National Forest Program 2010—Follow-Up Report. Helsinki.

Moeltner, K., J., and S. Shonkwiler. 2005. Correcting for On-Site Sampling in Random Utility Models. *Amer. J. Agr. Econ.*, 87: 327-339.

Moeltner, K., and D. F. Layton. 2002. A Censored Random Coefficient Model for Pooled Surveys Data with Application to the Estimation of Power Outage Costs. *Rev. Econ. Stat.* 84: 552–61.

OECD (Organisation for Economic Co-operation and Development). 2003. *Agri-Environmental Policy Measures: Overview of Developments.* Paris.

Parks P. J., and R. A. Kramer, 1995. A Policy Simulation of Wetlands Reserve Program. *J. Environ. Econ. Management* 28:223–40.

Polasky, S., and H. Doremus. 1998. When the Truth Hurts: Endangered Species Policy on Private Lands with Imperfect Information. *J. Environ. Econ. Management* 35: 22–47.

Polasky, S., J. D. Camm, and B. Garber-Yonts. 2001. Selecting Biological Reserves Cost-Efficiently: An Application to Terrestrial Vertebrate Conservation in Oregon. *Land Econ.* 77(1): 68–78.

Segerson, K., and T. Miceli. 1998. Voluntary Environmental Agreements: Good or Bad News for Environmental Protection? *J. Environ. Econ. Management* 36: 109–30.

Shonkwiler, J. S., and N. D. Hanley. 2003. A New Approach to Random Utility Modeling Using the Dirichlet Multinomial Distribution. *Environ. Resource Econ.* 26: 401–16.

Siikamäki, J. 2001. Discrete Choice Experiments for Valuing Biodiversity Conservation in Finland. Unpublished Ph.D. Dissertation, University of California, Davis.

Smith, R. 1995. The Conservation Reserve Program as a Least-Costs Land Retirement Mechanism. *Amer. J. Agr. Econ.* 77: 93–105.

Smith, R., and J. F. Shogren. 2002. Voluntary Incentive Design for Endangered Species Protection, *J. Environ. Econ. Management* 43:169–87.

Tahvonen, O., and S. Salo. 1999. Optimal Forest Rotation with In Situ Preferences. *J. Environ. Econ. Management* 37: 106–28.

Wu, J., and B. A. Babcock. 1995. Optimal Design of a Voluntary Green Payment Program Under Asymmetric Information. *J. Agric. Resource Econ.* 20 (2): 316–27.

———. 1996. Contract Design for the Purchase of Environmental Goods from Agriculture. *Amer. J. Agr. Econ.* 78: 935–45.

———. 1999. The Relative Efficiency of Voluntary vs. Mandatory Environmental Regulations. *J. Environ. Econ. Management* 38: 158–75.

Yen, S. T., and A. M. Jones. 1997. Household Consumption of Cheese: An Inverse Hyperbolic Sine Double-Hurdle Model with Dependent Errors. *Amer. J. Agr. Econ.* 79: 246–51.

Tables and Figures

Table 1. Censored Regression Model Results (t-statistics in parentheses)

		Old growth (N=738)			**Hotspots (N=801)**		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
CONSTANT		**–4. 3253** (4.333)	**–4.6983** (4.519)	**0.6370** (0.795)	**–2.3217** (2.888)	**–2.7917** (4.529)	**1.4997** (2.844)
LNHECTARES		**0.3724** (1.919)	**0.7241** (2.718)	**0.6040** (2.532)	**0.4042** (2.575)	**0.5530** (2.749)	**0.4591** (2.580)
PAYMENT		**0.0447** (3.261)	**0.0541** (3.165)	**0.0644** (3.796)	**0.0505** (4.251)	**0.0522** (3.559)	**0.0593** (4.445)
TIME	μ	**–0.9600** (2.993)	**–1.1813** (4.290)	**–3.0529** (7.512)	**–1.4222** (4.782)	**–1.3991** (5.280)	**-3.0776** (10.289)
	σ			**1.0995** (8.401)			**1.1404** (10.967)
σ_{11}^2		**6.2831** (7.292)	**4.2767** (7.696)	**2.5145** (5.555)	**4.8691** (8.322)	**3.5326** (10.999)	**1.8081** (7.305)
σ_{11}^2		**3.5832** (10.749)	**2.8815** (8.640)	**1.4001** (4.488)	**3.4089** (13.332)	**2.5728** (12.543)	**1.0254** (3.514)
σ_{11}^2		**3.3930** (10.407)	**2.2919** (9.039)	**1.5892** (3.950)	**3.6797** (12.339)	**2.3964** (9.714)	**1.9827** (6.249)
σ_{cov}			**2.2128** (6.838)	**–0.3487** (0.879)		**2.2436** (8.479)	**–0.6796** (2.024)
LL		**–557.53**	**–492.37**	**–479.27**	**–836.93**	**–737.18**	**–713.89**

Table 2. Beta Binomial Model Results (t-statistics in parentheses)

	Old growth (N=738)		**Hotspots (N=801)**	
	Model 1	**Model 2**	**Model 1**	**Model 2**
PAYMENT	**0.0237**	**0.5400**	**0.0193**	**0.3893**
	(3.557)	(4.106)	(3.494)	(4.074)
TIME	**–0.1906**	**–0.5147**	**–0.1638**	**–0.4561**
	(2.302)	(2.568)	(2.346)	(2.849)
ALPHA	**–4.2127**	**–5.2650**	**–4.0964**	**–4.7874**
	(17.715)	(14.438)	(21.389)	(18.422)
W	**0.3650**	**0.3693**	**–0.3331**	**–0.3313**
	(2.000)	(2.099)	(2.599)	(2.515)
LL	**–730.22**	**–725.18**	**–1,079.84**	**–1,075.63**

Table 3. Mean Square Errors Using Cross-Validation

Model		*Censored regression*	*Beta-binomial*
Old growth	Question 1	41.26	3.12
	Question 2	2.20	2.20
	Question 3	4.68	4.76
	Average MSE	*16.05*	*3.36*
Hotspots	Question 1	61.01	60.64
	Question 2	55.96	55.72
	Question 3	57.74	57.96
	Average MSE	*58.23*	*58.11*

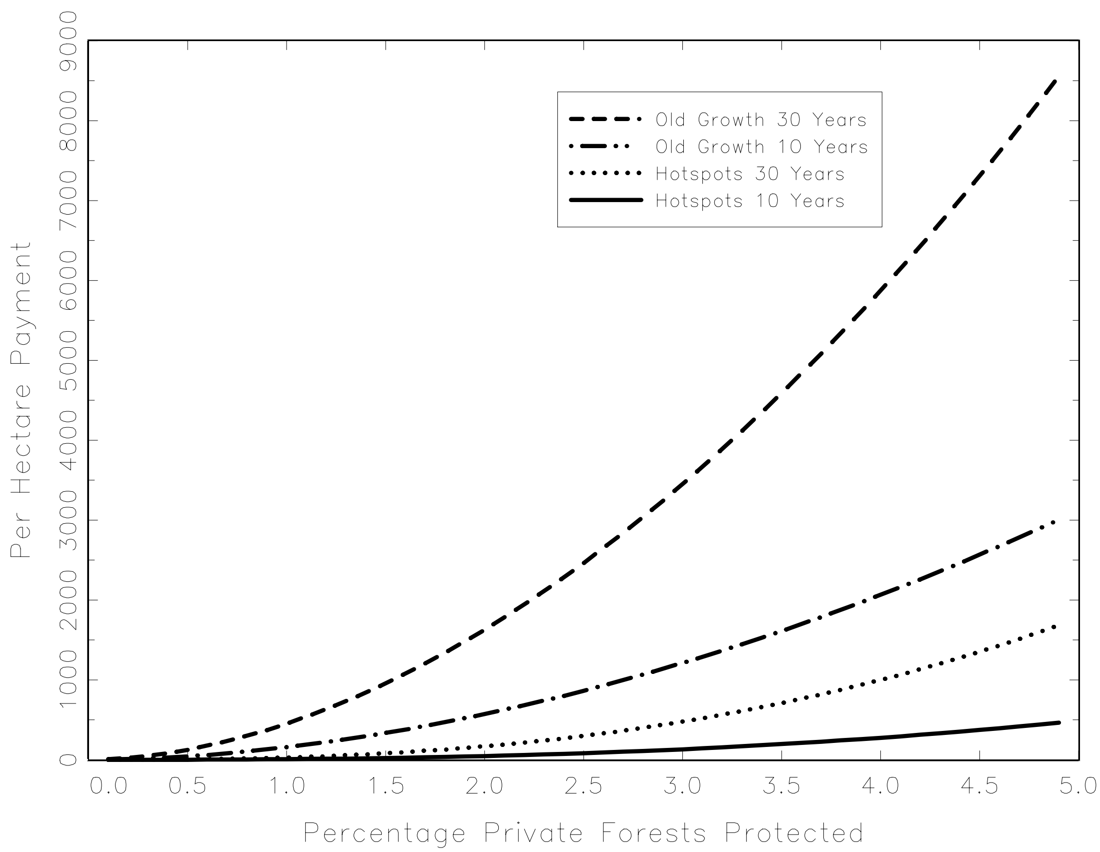

Figure 1. Compensation Requirement per Hectare by Forest Type and Protection Time

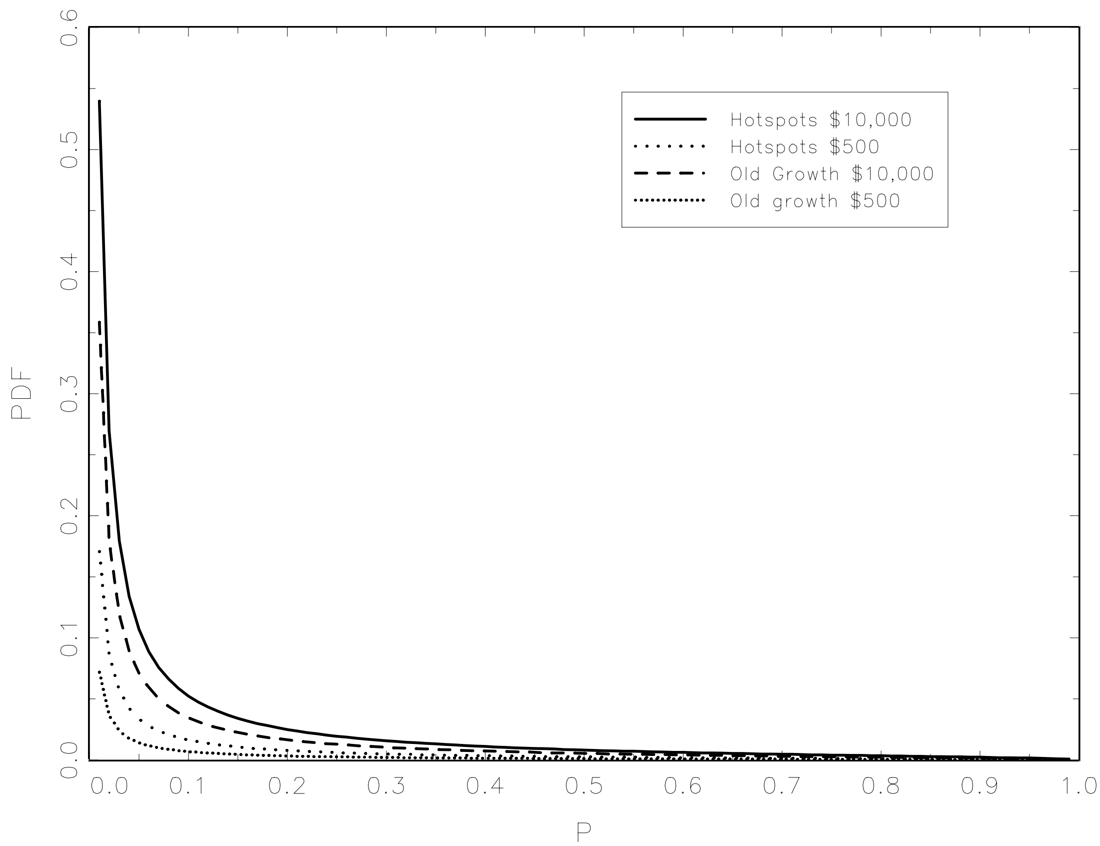

Figure 2. Estimated Probability Density Functions (Beta Distribution) of the Enrollment of Hotspots and Old Growth into Incentive Payment Programs with Alternative Payment Amounts and a Fixed 30-Year Enrollment Requirement