DISSERTATION

MODELING HETEROGENEOUS PREFERENCES IN THE VALUATION OF ENVIRONMENTAL PUBLIC GOODS: AN ECONOMETRIC ANALYSIS OF DICHOTOMOUS CHOICE CONTINGENT VALUATION SURVEY DATA

Submitted by

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In partial fulfillment of the requirements
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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER SUPERVISION BY LAURA NAHUELHUAL MUÑOZ, ENTITLED MODELING HETEROGENEOUS PREFERENCES IN THE VALUATION OF ENVIRONMENTAL PUBLIC GOODS: AN ECONOMETRIC ANALYSIS OF DICHOTOMOUS CHOICE CONTINGENT VALUATION SURVEY DATA, BE ACCEPTED AS FULFILLING IN PART THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

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ABSTRACT OF THE DISSERTATION

MODELING HETEROGENEOUS PREFERENCES IN THE VALUATION OF ENVIRONMENTAL PUBLIC GOODS: AN ECONOMETRIC ANALYSIS OF DICHOTOMOUS CHOICE CONTINGENT VALUATION SURVEY DATA

Contingent valuation method (henceforth CVM) has become the most extensively used technique to estimate the value of non-market goods. Traditional contingent valuation studies assume that provision of environmental public goods or programs is distinctly utility increasing for everybody. In turn, this assumption has led CVM research to focus on modeling techniques that restrict welfare measures to positive levels. However, by restricting willingness to pay to be non-negative, these studies have ignored that externalities associated to the provision of environmental goods can manifest themselves as benefits for some people and as costs for others. Ignoring these heterogeneous values for the public good can lead to biased welfare measures, which in turn can affect policy decisions.

This Dissertation is composed of an introductory section and three related papers addressing the problem of how to account for the existence of positive and negative values towards environmental public goods. The introductory section discusses the appropriate welfare measures to be considered in contingent valuation when the public

good generates benefits to many but also disutility to others. The sequence of three papers discusses different modeling approaches to account for the existence of heterogeneous preferences towards environmental public goods. The first paper presents a double bounded dichotomous choice model of positive and negative preferences. In this model willingness to accept bids were coded as negative willingness to pay bids, which allowed to combine negative and positive values for the good in the estimation process. The double bounded specification was used to estimate net benefits or net losses for the prescribed burning program. In the second paper, the data structure allowed for the identification of negative and positive responses as in the first paper, but also identified the respondents with zero willingness to pay. The different response categories were modeled accordingly using parametric and non-parametric extended spike models. In the third and last paper, heterogeneous preferences were addressed using a random parameter logit (RPL) model, where individual parameters were allowed to vary across people so as to reflect variation in tastes among respondents towards the public good.

The results from all three papers indicate that accounting for heterogeneous preferences yields significantly lower welfare estimates. This information on the variation of preferences and valuation can be relevant to policy makers and natural resource managers who must balance welfare of a diverse population when making decisions.

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DEDICATION

To my parents, Veronica and Raul, for their infinite dedication and love.

To my husband Mauro and my daughter Amanda, who give the meaning to everything I do and pursue.

TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

Page

CHAPTER I

INTRODUCTION

1.1 Contingent Valuation Method to value environmental public goods

Since the NOAA Panel (Arrow et al., 1993) recognized that contingent valuation can produce reliable welfare measures to be used in damage assessment, CVM became the most widely used method to value non-market goods and currently plays an important role in public policy formulation.

Following the recommendations made by Arrow et al. (1993), most contingent valuation studies use the closed-ended format to elicit willingness to pay. This relatively recent shift from using open-ended surveys towards the use of the closed-ended approach (also known as dichotomous choice, referendum, or discrete choice) has demanded increased sophistication in modeling and estimation techniques. In this new setting, discrete choice responses are analyzed using statistical models, but as Hanemann and Kanninen (1999) observed, the models must be consistent with economic theory. This imposes important theoretical restrictions, which several models currently used violate.

A particularly complex issue is to what extent CVM can accurately elicit and represent heterogeneous preferences and still produce welfare estimates that are consistent with economic theory. Given that provision of some environmental goods generates diverse values for different people, obtaining zero and negative willingness to pay (WTP) responses is not surprising. However, contingent valuation studies typically assume that willingness to pay is positive and, therefore, the possibility of zero and negative values is ruled out (Werner, 1999). By restricting willingness to pay in this way, these studies disregard the fact that externalities associated to the provision of environmental public goods can represent benefits for some people but costs for others.

In most CVM applications, there are respondents who refuse to pay any amount for the good being valued. In this case, as Jorgensen et al. (1999) observed, a common research approach has been to treat these responses as protest votes and, therefore, exclude them from the relevant sample. Nonetheless, some of the protest responses might reflect authentic zero or negative willingness to pay for the good and their exclusion could generate unrealistic welfare estimates (Werner, 1999).

Bohara et al. (2001) pointed out that researchers downplay the importance of negative willingness to pay alluding that individuals are simply wrong in their statements. Negative responses are, therefore, attributed to misperception of the good being valued and excluded among other protest votes. Haab and McConnell (1997) stated that for most public goods negative willingness to pay is clearly a mistake. Since provision increases utility, negative estimates do not reflect true preferences and are more likely a consequence of a bad fit or the use of inappropriate functional forms. They argue that since public goods are freely disposable, those respondents who dislike the good can still ignore it without incurring losses in utility and, hence, willingness to pay for the public good should remain a positive value.

Denying the occurrence of heterogeneous preferences has led researchers to focus on modeling approaches that restrict willingness to pay measures to positive levels. Two of these approaches commonly used are the truncation of the distribution of the willingness to pay estimate at zero and the use of functional forms, such as the Weibull, log-normal, and log-logistic, which impose strictly positive estimates. However, excluding negative willingness to pay might overstate the effect of the upper tail of the distribution, increasing the sensitivity of parametric models to distributional assumptions (Haab and McConnell, 1997).

For most pure public goods, limiting willingness to pay to positive levels can be appropriate as long as provision is regarded as an improvement. Nonetheless, the same approach might not be as appropriate for public programs that provide a mix of non-market goods and bads. Here, the assumption of free disposability could be unrealistic since people will not be indifferent towards a program that they might see as a public bad. As Huhtala (2000) noted, if a respondent dislikes the public good or program, the good will actually represent a bad that generates disutility and, consequently, willingness to pay will not be positive. In this situation, the elicitation and valuation of both positive and negative responses is necessary.

1.2 Welfare measures for changes in environmental goods

Hicks (1943) defined four measures of consumer's surplus, named equivalent surplus, compensating surplus, equivalent variation, and compensating variation. While the variation measures are determined after the consumer has made adjustments in order to optimize his consumption bundle, the surplus measures do not allow such adjustments. As Brookshire et al. (1980) pointed out, when the characteristics of a public program or project are already determined, the individual must take them as given, in which case the surplus measures should be used.

In the analysis of price changes, the measures of welfare conventionally used are compensating variation and equivalent variation. For a price decrease, compensating variation measures the maximum willingness to pay to secure the change, while equivalent variation measures the minimum willingness to accept to forgo it. For a price increase the opposite situation occurs. The difference between these traditional Hicksian compensating and equivalent measures of consumer surplus lies in the level of utility or welfare level that serves as reference. The compensating measure uses the initial welfare level as reference and values the impact of the change in quantity deeming that the person has the right to stay in his initial level of utility. The equivalent measure, on the other hand, uses the subsequent welfare level as reference and therefore assumes that the person has the right only to this successive level of utility (Brookshire et al., 1980).

This analysis has been extended to the environmental economic research to measure changes in the quantity and quality of environmental public goods. According to Clinch and Murphy (2001), contingent valuation surveys elicit the following consumer surplus measures: Hicksian compensating variation, which measures both the maximum amount a person is willing to pay for an increase in the quantity of the good and the minimum amount the person is willing to accept in compensation for a decrease, and Hicksian equivalent variation, which measures the minimum amount the individual is willing to accept in compensation to forgo an increase in the quantity of the good as well as the maximum willingness to pay to avoid a decrease.

Figure 1.1 illustrates the differences and similarities among these welfare measures depending the direction of the environmental change. As depicted in panel (a), if a certain quantity (Q) of an environmental good is provided and provision is regarded as an improvement, the person moves from an initial situation (q_o) or level of utility (U') towards a more preferred situation (q_l or U"). In this scenario, compensating and equivalent variation are the usual measures of willingness to pay to have the good (compensating measure) and willingness to accept to forego it (equivalent measure) respectively. Panel (b) of Figure 1.1 depicts the scenario of the change from a preferred towards a less preferred situation. The most common example would be a reduction in the quantity or quality of the environmental good, which is considered a bad (same as a price increase). In this case, the appropriate welfare measures are willingness to pay to avoid the change (equivalent measure), and willingness to accept compensation to have the change (compensating measure).

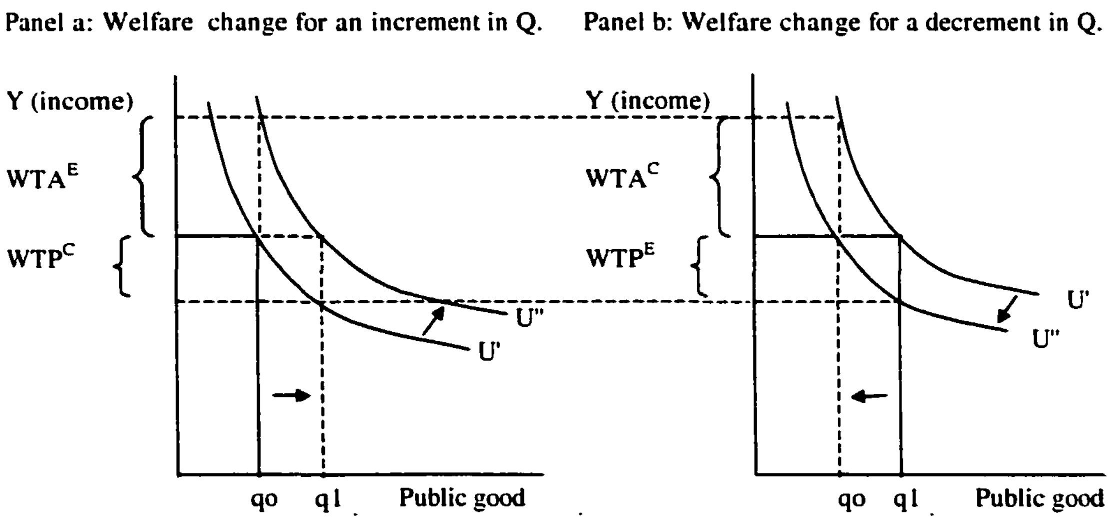

Figure 1.1 Welfare measures for increments and decrements of a public good.

Therefore, there are compensating and equivalent measures for both willingness to pay and willingness to accept. Following Brookshire et al. (1980), these measures are WTP^C (willingness to pay to secure the preferred situation), WTP^E (willingness to pay to avoid the less preferred situation), WTA^C (willingness to accept compensation to take the less preferred situation), and WTA^E (willingness to accept compensation to give up the preferred situation), where the superscripts C and E indicate compensating and equivalent variation measures respectively.

For a given change in provision of a public good when provision represents an improvement, the following equalities should hold: $WTP^C=WTP^E$ (willingness to pay for an increase in quantity is equal to willingness to pay to avoid an equivalent decrease in quantity) and $WTA^C=WTA^E$ (willingness to accept compensation for the decrease in quantity is equal to willingness to accept compensation to forgo the increase in quantity). Moreover, in presence of income effects $WTP^C=WTP^E$ will be less than $WTA^C=WTA^E$, but they will be equal if income effects are not significant.

1.3 Disparity among welfare measures

In the case of price changes, theory suggests that in the absence of significant income effects, willingness to pay and willingness to accept should be fairly close. This assumption has been carried over to the analysis of changes in environmental goods. However, according to Hanemann (1986), for changes in quantity of a public good, such equivalence might not hold, because not only income effects but also substitution effects are involved. Holding income constant, the fewer substitutes the public good has (small substitution effect) the greater the difference between the two measures.

Hanemann (1999) makes an important distinction between two types of disparity: the traditional WTA-WTP disparity and the gain-loss disparity. In the former, willingness to pay and willingness to accept are compared for the same change in quantity. Thus, for an increase in quantity WTP^C is compared with WTA^E (as in panel (a) of Figure 1.1), and for a decrease, WTP^E is compared with WTA^C (as in panel (b) of Figure 1.1). In the absence of income effects and if substitution is feasible, the welfare measures in each situation should be reasonably close in magnitude. However, the disparity is likely to occur, since most environmental goods have no close substitutes.

In the gain-loss disparity on the other hand, willingness to pay for an increase in quantity is compared with willingness to accept for a *symmetric* decrease in quantity. According to Hanemann (1999), the gain-loss disparity depends only on the substitution effect, unlike the WTA-WTP disparity that depends on both income and substitution effects. Hence, just one indifference curve is involved and its curvature will determine the direction of the disparity. With usual quasi-concave preferences and consequently convex indifference curves, willingness to accept is larger than willingness to pay as depicted in panel (a) of Figure 1.2. Contrarily, with quasi-convex preferences and, hence, concave indifference curves willingness to pay is larger than willingness to accept, as depicted in panel (b) of Figure 1.2.

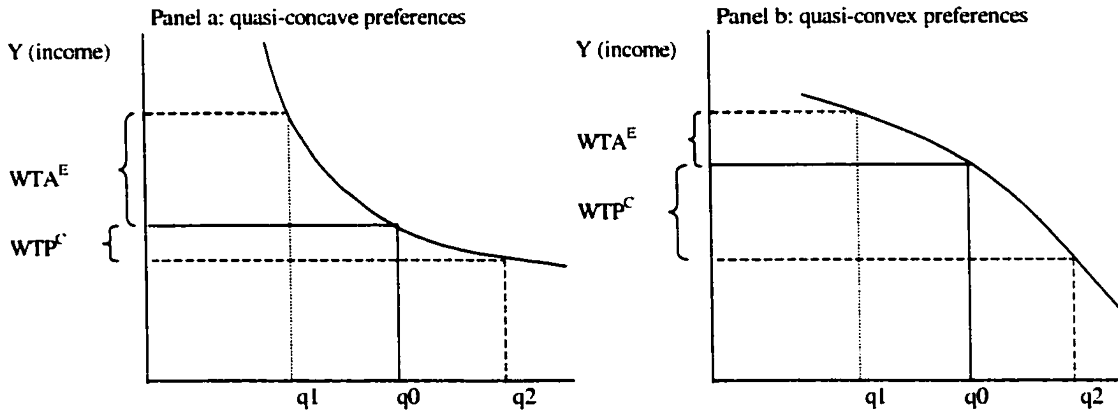

Figure 1.2. Gain-loss disparity for a symmetric change in quantity of the public good (Adapted from Hanemann, 1999).

1.4 Welfare measures for a public bad

As Clinch and Murphy (2001) observed, when valuing an improvement in the quality or quantity of a public good the appropriate measure is compensating variation or willingness to pay for that improvement. However, if the public good also exhibits characteristics of a public bad the appropriate measure must reflect the loss of utility from the increase in its provision. When the proposed environmental good or program provides a mix of goods and bads, there will be people willing to pay to have the program implemented and people who oppose it and will require compensation. For this type of public good/bad case, it can be argued that there will be two scenarios: the situation depicted in panel (a) of Figure 1.1 for those who consider the program as a good and therefore have a positive willingness to pay (WTP^C), and the situation depicted in Figure 1.3 for those who see it as a bad and, hence, have negative willingness to pay. In the case of a public bad the indifference curves are upward sloping and convex, which implies that as more of the bad is provided the more income the person requires in exchange.

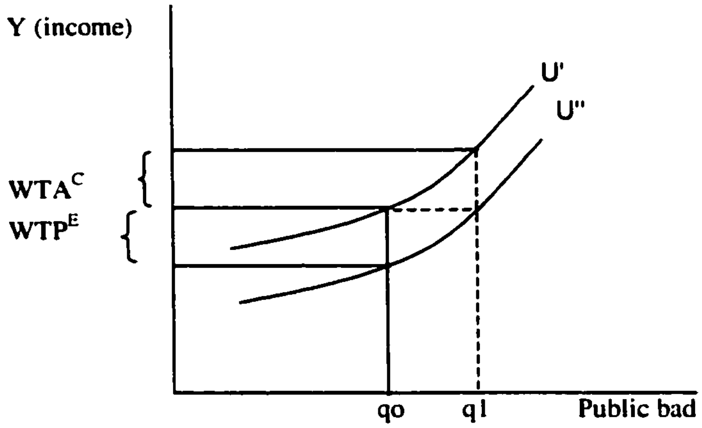

Figure 1.3. Welfare measures for a public bad.

The individual moves from a higher (U') towards a lower level of utility (U") represented by a larger quantity of the bad. Hence, willingness to pay corresponds to the amount of money the person would pay to avoid the implementation of the program (WTP^E) and willingness to accept corresponds to the minimum amount the person would accept to take the program (WTA^C). Furthermore, in absence of income effects both measures should coincide.

Clinch and Murphy (2001) pointed out that given some practical difficulties of eliciting willingness to accept compensation for a public bad in contingent valuation surveys, willingness to pay to avoid a public bad can be used as an appropriate proxy for willingness to accept. They state that when the public good/bad is not unique or irreplaceable and when willingness to pay is just a small fraction of income, willingness to pay (WTP^E) will be a valid proxy for willingness to accept (WTA^C).

According to Hanemann and Kanninen (1999), willingness to pay (WTP^E) to avoid a less preferred situation corresponds to negative willingness to pay. Furthermore, they state that "for models that do not consider income effects the (negative) willingness to pay coincides with the willingness to accept to have the less preferred situation".

Given the arguments above and if income effects are unlikely to be large, it is possible to assume a correspondence between negative willingness to pay and willingness to accept for the provision of the same public program. In this case willingness to pay corresponds to the traditional compensating variation measure of welfare, which represents the amount the person is willing to pay to secure the change. Willingness to accept on the other hand corresponds to the minimum amount of money the person would require to take the program, which is regarded as a bad, and is also a compensating variation measure.

Assuming this equivalency (WTA= -WTP) makes it possible to combine willingness to pay and willingness to accept responses as in a continuous set of preferences in order to obtain a net measure of welfare, which reflects the fact that the environmental program may generate *non-market* benefits for some people and *non-market* costs for others.

1.5 Problem statement and the studies

Most CVM studies implicitly assume that "more conservation" is always good for everybody, which translates in positive willingness to pay. However, the provision of some environmental public goods may raise contrasting attitudes and, in most cases, there will be at least a small proportion of people negatively affected who oppose the change. It is important to distinguish, however, between the pecuniary market and non-market effects associated to this provision. While the former have already been accounted for as private costs or welfare transfers in cost benefit analysis, the latter are what CVM is designed to measure. Therefore, the notion of heterogeneous preferences is related to the *non-market* benefits and costs associated to the provision of environmental public goods. If heterogeneous tastes indeed exist, they must be taken into account in the valuation process in order to obtain unbiased and reliable welfare measures that can be used in policy formulation.

This series of papers examined issues related to the existence of heterogeneous preferences for environmental public programs and presents three different approaches that account for the existence of non-positive willingness to pay. The first two papers were based on data collected to value the extension of prescribed burning programs in Florida, and Montana and California, respectively. In both cases the survey format allowed the identification of people with different values towards the good, which in turn permitted the implementation of various modeling techniques. The first of these two papers provides an empirical approach where willingness to accept bids were coded as negative willingness to pay bids in the estimation process. Both type of bids were combined in the same bid vector, such that negative and positive responses to the valuation questions could be pooled together in the same log-likelihood function. The double bounded specification was used to estimate net benefits or net losses for the prescribed burning program.

In the second paper, the data structure permitted the identification of negative and positive responses as in the first paper, as well as the segment of respondents who were indifferent towards the public good. The different response categories were modeled accordingly using parametric and non-parametric extended spike models.

In the third and last paper, heterogeneous preferences were addressed from a different perspective. In this case, a random parameter logit (RPL) model was used, where individual parameters were allowed to vary across respondents rather being fixed, so as to reflect variation in tastes among respondents towards the public good. The focus of this paper was on testing for the existence of variation among respondents' willingness to pay for the attributes associated with different strategies for managing open space and the impact of heterogeneous preferences on the valuation of these strategies.

1.6 Objectives

The overall and common objective of all three studies was two fold:

i) To develop and compare modeling techniques that explicitly consider heterogeneous preferences in the estimation of welfare measures and specifically address the problem of zero and negative willingness to pay.

ii) To provide further evidence on the advantages of these modeling techniques over standard techniques when preferences for the good being valued are indeed heterogeneous.

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CHAPTER II

COMBINING WILLINGNESS TO PAY AND WILLINGNESS TO ACCEPT RESPONSES TO VALUE A NON-REJECTABLE PUBLIC GOOD USING A POOLED ESTIMATOR

2.1 Introduction

One of the distinguishing characteristics of pure public goods that has not been studied in sufficient detail is non-rejectability. This characteristic implies that when a public good is provided, everyone will receive the same quantity of this pure public good, whether they desire it or not. For most classic public goods non-rejectability does not represent a problem, since provision will usually increase utility, as is the case of improved air and water quality. In this case, as Haab and McConnell (1997) point out, respondents who dislike the good can still remain indifferent to its provision without incurring losses in utility, which Bohara et al. (2001) refer to as free disposability. Since no loses in utility are involved, willingness to pay (willingness to pay) should remain positive.

Assuming that most public goods are in fact freely disposable has led recent research in contingent valuation to focus on parametric distribution functions or non-parametric approaches that restrict willingness to pay estimates to positive levels. However, there are some public programs that provide a joint product, which results in a mix of public goods and public bads at the same time. As Clinch and Murphy (2001) notice, while people can choose not to consume a private good if they do not like it, they can not avoid consuming a public bad. Thus, for this type of public programs, free disposability is not an appropriate assumption.

In the present case study, prescribed burning of underbrush in forests to reduce the threat of catastrophic wildfires provides such a joint product: a public good, which corresponds to the increased community safety from wildfire, and a public bad, associated to the smoke emissions released when the prescribe fire is conducted.

Valuation of such public programs must account for both gains and losses in utility. In essence, some individuals will pay for the program since they feel the benefits of the fire reduction are greater than the disutility from the smoke, while others will not be willing to pay anything for the implementation of a program that they consider a bad and, rather, will have to be compensated.

This paper presents a contingent valuation questioning sequence and an associated discrete choice model that permit the identification of both positive and negative responses. Willingness to pay for the program was contrasted with willingness to accept compensation to take the program. Unlike most contingent valuation studies where willingness to accept represents the amount of money that has to be offered to a respondent in order to forego the consumption of a specific good and remain at the same utility level (i.e., equivalent variation measure), in this application willingness to accept corresponds to the minimum amount of money that has to be offered to the respondent to put up with a less preferred situation and accept the program (i.e., compensating variation measure).

The focus of this paper was on estimating a net willingness to pay measure (willingness to pay of gainers minus willingness to accept of losers) for the non-rejectable mixed public-good/public-bad. An empirical estimator was developed that pools together positive responses (willingness to pay for the program) and negative responses (willingness to accept compensation to take the program) in order to estimate welfare measures. Explicitly, willingness to accept bids were coded as negative willingness to pay amounts such that a single vector of bids was used in the estimation.

This approach can be of particular relevance in cases where there are insufficient observations to separately estimate a willingness to accept function and directly calculate willingness to accept. The estimator developed here, which is patterned after the double bounded likelihood function, allowed to calculate a net benefit or net loss, where the net benefit would be willingness to pay net of willingness to accept and net loss would be willingness to accept net of willingness to pay. The net estimate would implicitly reflect the sample proportion of gainers and losers.

2.2 Previous studies

Valuation of natural resources or services when positive and negative willingness to pay are being observed has been addressed only recently in the literature. At the survey design stage, valuation questions are framed in a way that allows researchers to separate respondents with negative and those with positive preferences. Once the sub-samples have been differentiated by preferences, many formal modeling techniques can be used (Hanemann and Kanninen, 1999).

However, eliciting negative willingness to pay has proven a difficult task without affecting the credibility of the survey. As Kriström (1997) pointed out, it is difficult and rather artificial to set up a dichotomous question that ask people to pay -$xx for a given environmental good or project. Some approaches for eliciting negative willingness to pay include the use of valuation questions that elicit willingness to pay to avoid the change as a proxy for negative willingness to pay (Clinch and Murphy, 2001) and the use of screening attitudinal questions to separate respondents by their preferences prior to the valuation question (Kriström, 1997; Huhtala, 2000).

At the estimation stage on the other hand, different approaches are possible to deal with variation in preferences, which include parametric and non-parametric estimation techniques. Yet, specific studies that explicitly consider non-positive willingness to pay are rather limited and they usually discuss only zero willingness to pay.

Bohara et al. (2001), used Monte Carlo simulation to investigate the performance of different distributions in estimating willingness to pay under three proportions of people holding negative willingness to pay. When the proportion of respondents with negative willingness to pay was high, models that allowed only for positive willingness to pay estimates (standard log-normal and Weibull) significantly overestimated mean and median willingness to pay for all sample sizes, while the log-normal and Weibull mixture models outperformed the standard models of the same distributions.

Clinch and Murphy (2001) valued the increase in Ireland's forest estate. Primarily, the respondents were asked if they thought more forest was good for the environment. Those responding affirmatively were assumed to have a zero or positive *willingness to pay to have* the increase in forests, whereas those responding *no* were considered to have zero or positive *willingness to pay to avoid* the increase (equal to negative willingness to pay to have the increase). They estimated separate and combined models of negative and positive willingness to pay responses using a Hurdle specification and concluded that ignoring negative bids results in overestimation of net willingness to pay.

Huhtala (2000) valued two programs for waste disposal. He described the positive and negative attributes of incineration and recycling and asked people their preferred alternative after which a willingness to pay question followed for the preferred option. He used parametric and non-parametric modeling techniques and concluded that ignoring heterogeneous preferences leads to considerably larger willingness to pay estimates, bias that was more serious in the parametric estimation. Lockwood et al. (1996) also used parametric and non-parametric methods in order to estimate willingness to pay for nature conservation and heritage values in conflict with cattle-raising in the Australian Alps.

This paper contributes to this literature an additional approach for dealing with negative willingness to pay and also provides further proof of the importance of modeling negative preferences with respect to the good being valued when these preferences indeed exist. The modeling approach used is less demanding in terms of the data and estimation and provides an appropriate modeling alternative when insufficient observations of the willingness to accept population segment exist to separately estimate a willingness to accept function.

2.3 Double bounded net WTP-WTA model

In the classical double-bounded model, each participant is presented with two bids. The level of the second bid is contingent upon the response to the first bid. If the individual responds *yes*, meaning that he or she is willing to pay the amount of the initial bid (A_I), then the level of the second bid (A_H) is some amount greater than the first. On the other hand, if the individual's answer is *no*, meaning that he or she is not willing to pay the amount of the initial bid, the second bid (A_L) is some amount smaller than the first. Hence, the four possible outcomes are: (a) *no* to both bids, (b) a *no* followed by a *yes*, (c) a *yes* followed by a *no* and, (d) *yes* to both bids.

The sequence of questions isolates the range in which the respondent's true WTP lies, placing it into one of the following four intervals: $(-\infty, A_L)$, $[A_L, A_I)$, $[A_I, A_H)$, or $[A_H, +\infty)$. The second bid, in conjunction with the response to the initial preference decision, makes it possible to place both an upper and a lower bound on the respondent's unobservable true WTP. However, when the second decision is in the same direction as the first one (i.e. *yes* to both bids or *no* to both bids), the lower bound is raised and the upper bound lowered, respectively.

In the estimation problem at hand, the data followed a double-bounded format, but with a slight difference in the bid sequence. The difference is that instead of using a positive initial bid amount to allocate participants' preferences, a referendum question was asked in which participants were presented with the option of voting in favor or against the prescribed burning program at no cost to them. Thus, the first bid amount (A_I) was equal to zero. If they supported the program at no cost, the follow up dichotomous question asked whether they would be willing to pay a random positive bid amount(A_H). On the other hand, if the participants did not support the program at no cost, a follow up dichotomous WTA question asked whether they would take the program if the government paid them a positive amount (A_L).

Figure 2.1 depicts the response probability function for the double bounded model. Mean willingness to pay would be the difference between the shaded area on the positive side and the shaded area on the negative side, while median willingness to pay is given by C*. If the proportion of negative responses is small, the double bounded model might yield similar welfare estimates than a standard logit model of only positive preferences. Contrarily, if the proportion of people who dislike the program is sufficiently large, the double bounded model should generate a smaller estimate of willingness to pay than a logit model that includes only the positive bidders.

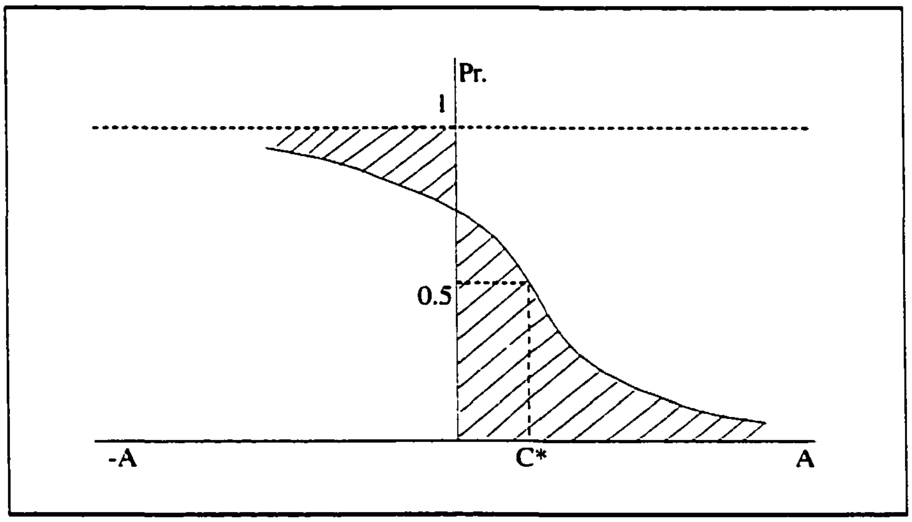

Figure 2.1. Distribution of positive and negative WTP.

For the estimation of this special case of double bounded model, willingness to pay and willingness to accept responses were pooled together by coding the dollar amount offered to the objecting household to accept the program (A_L) as a negative bid amount in the logit equation. This approach can be of particular relevance when a sufficiently small minority of the population receives disutility from the program and the sample is too small to estimate a separate willingness to accept discrete choice equation. Furthermore, it allows the calculation of a *net* measure of willingness to pay (willingness to pay net of willingness to accept) or *net* measure of willingness to accept (willingness to accept net of willingness to pay).

The discrete outcomes of the bidding process are shown in equation 2.1, where WTA= -WTP.

$$D = \begin{cases} 1 & -WTP \quad < A_L \\ 2 & A_L \leq \quad -WTP \quad < A_I, \quad \text{where} \quad A_I = 0 \\ 3 & A_I \leq \quad WTP \quad < A_H \\ 4 & A_H \leq \quad WTP, \end{cases} \tag{2.1}$$

Willingness to pay can be represented as $WTP = \alpha + \beta A + \varepsilon$, where A is the bid amount and ε is a random term accounting for unobservable characteristics. Assuming that $\varepsilon \sim G(0, \sigma^2)$ follows a logistic distribution with mean zero and variance σ^2 (which implies a standard deviation $\sigma = \pi / \sqrt{3}$), the choice probabilities for the double bounded model are the following:

$$prob(D = j) = \begin{Bmatrix} G(\tilde{\alpha} + \tilde{\beta}A_L) \\ G(\tilde{\alpha} + \tilde{\beta}A_I) - G(\tilde{\alpha} + \tilde{\beta}A_L) \\ G(\tilde{\alpha} + \tilde{\beta}A_H) - G(\tilde{\alpha} + \tilde{\beta}A_I) \\ 1 - G(\tilde{\alpha} + \tilde{\beta}A_H) \end{Bmatrix} \text{ for } j = \begin{Bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{Bmatrix} \tag{2.2}$$

Thus, the final specification of the log-likelihood function is shown in equation 2.3, where I_K is an indicator function for the event K and i denotes individual i.

$$L = \sum_i \begin{Bmatrix} I_{D_i=1} \ln G(\tilde{\alpha} + \tilde{\beta} A_{Li}) + I_{D_i=2} \ln[G(\tilde{\alpha} + \tilde{\beta} A_{Ii}) - G(\tilde{\alpha} + \tilde{\beta} A_{Li})] \\ + I_{D_i=3} \ln[G(\tilde{\alpha} + \tilde{\beta} A_{Hi}) - G(\tilde{\alpha} + \tilde{\beta} A_{Ii})] + I_{D_i=4} \ln[1 - G(\tilde{\alpha} + \tilde{\beta} A_{Hi})] \end{Bmatrix} \tag{2.3}$$

The coefficients of the double-bounded model were estimated via maximum likelihood techniques using GAUSS 3.5.[1] The advantage of the double bounded model in the face of positive and negative values is that it provides an estimate of the *net* benefits that reflect the relative proportions of willingness to pay and willingness to accept responses as long as a correspondence between negative willingness to pay and willingness to accept is assumed (WTA= -WTA). Following Hanemann (1989) the mean willingness to pay for the double bounded model was calculated as the ratio of the constant over the absolute value of the bid coefficient (α / β), which allows mean willingness to pay to be either positive or negative.

2.4 Research Hypotheses

The empirical importance of ignoring negative preferences was tested by comparing the willingness to pay estimates obtained from the double bounded model and a standard binary logit model of positive bidders only (i.e. negative responses were excluded from the estimation). The null and alternative hypotheses in this case can be expressed as follows:

[1] The Gauss code for the double bounded model is given in Appendix I.

$$H_0: WTP\ (Logit) = Net\ WTP\ (Double\ Bounded)$$
$$H_1: WTP\ (Logit) \geq Net\ WTP\ (Double\ Bounded)$$

Unlike the logit model of positive bidders that basically ignores negative responses, another logit specification was estimated in which negative bids were coded as zero bids. This model was also contrasted with the double bounded and, as in the previous hypothesis, it was expected to generate higher willingness to pay estimates than the double bounded model. Confidence intervals for the willingness to pay estimates were computed using the Krinsky and Robb approach (Park et al., 1991).

2.5 Data

The data to illustrate an application of the model and test the empirical importance of ignoring negative willingness to pay came from a survey to Florida residents following the widespread wildfires of 1998. In 1998, Florida experienced one of its most active wildfire seasons ever. From mid May to mid July, over 2,000 wildfires occurred in central and northern Florida. More than 500,000 acres burned, most of them by high intensity/high severity, stand replacing fires. More than 10,000 firefighters, many of them from other states, fought the fires. Property losses included the destruction and damage of 370 business and residences, while commercial timber losses exceeded $300 million and suppression costs topped $130 million (USDA Forest Service, 2000). In reaction to these catastrophic events a variety of policies were proposed for reducing the risk of future wildfires. Most of the proposals involved various intensities and means for implementing fuel reduction programs, such as aggressive prescribed burning programs on public lands and with private landowners to develop fuel management strategies (Mercer et al., 2000).

Although fuel reduction treatments provide benefits in terms of reducing the probability of catastrophic wildfires, the treatments (particularly if initiated on a large scale) may generate potentially large external costs, e.g. impacts of smoke on tourism, human health, and quality of life, which certainly represent important constraints for the implementation of a prescribed burning program. The survey attempted to address this issue of positive and negative joint products from prescribed fire in order to value the alternative of implementing an expanded prescribed burning program in Florida.

To develop and refine the survey instrument, four focus groups were conducted, which were videotaped and attended by one member of the research group. The videotape allowed for review by other researchers on the team. Pretests were conducted to further evaluate the survey instrument following the focus groups. Pretesting was monitored via phone interviews and revisions were made to the survey booklet and the script using this pretest information. The final survey booklet contained educational information and drawings contrasting wildfire and prescribed fire, including a discussion of smoke related issues under both situations. The booklet explained that the expanded prescribed burning program would result in a 25% decrease in the number of acres burned in a wildfire and would reduce the number of houses lost in a typical year from 43 to 25.

The survey was conducted from the late fall of 1999 to the spring of 2000 using a phone-mail-phone process. It was suspended for a short time during December and January due to the holiday season. In order to obtain a representative sample, random digit dialing was used. Once initial contact with a respondent was established, appointments were made with individuals for follow-up interviews.

During the interim time period the color survey booklet providing educational information was mailed to the household. This booklet contained definitions of some key concepts such as prescribed fire, wildfire, fire management, and health standards, along with a description of Florida's fire management standards. The issue of smoke emissions was specifically addressed as well as a description of prescribed burning (implementation procedures and costs) as a solution for diminishing incidence of wildfires.

After the description of the program was given, respondents were asked if they thought this prescribed burning program should or should not be undertaken at no cost to them, which was the screening question to separate out those that viewed the program positively from those that viewed it negatively. For those that viewed it negatively and whose answer to the previous question was *no*, the following willingness to accept question was asked: *"Because of the importance of using prescribed burning to reduce the threat and dangers from wildfire, there may be times when the state must do the prescribed burns. However, the state could pay affected citizens for adverse effects of prescribed burning such as smoke, soot, road closures, and other inconveniences; if the state paid your household $___ per year would you vote in favor of the Expanded Prescribed Burning Program?" Yes _____ No _____*

Those individuals that indicated they thought the prescribed burning program should be implemented were provided with cost information. The wording of the willingness to pay portion of the survey was: *"Your share of the Expanded Prescribed*

Burning Program would cost your household $____ a year. If the Expanded Prescribed Burning Program were on the next ballot would you vote" In favor_____ Against _____

The inclusion of an initial qualitative question permitted to separate truly negative and positive preferences before the question with monetary value was asked. Thus, there was no need to split the sample into subgroups, which has been one of the approaches for dealing with heterogeneous preferences (Huhtala, 2000). This approach is known to have problems such as the difficulty of giving the same amount and quality information to both sub-samples in order to ensure that results are not biased (Clinch and Murphy, 2001).

The bid amounts used for eliciting willingness to accept and willingness to pay corresponded to one of fifteen amounts ranging from $10 to $350.

2.6 Results

A response rate of 52.2% (779 out of 1,492 households) was obtained for individuals who completed both the pre and post educational information interviews. Individuals, who could not be reached or interviewed for reasons such as under age 18, were not included in the response rate reported. Individuals who were contacted but refused to finish the phone interview were included in the response rate as unit non-responses along with those that completed the screening but did not complete the entire survey process (Bair, 2001).

Although demographic and attitudinal questions were covered in the survey, the focus of this study was on the combination of negative and positive bid amounts in order to determine the importance of the negative responses in the final estimates of willingness to pay. For this reason the bid amount was considered as the only explanatory variable. Moreover, when included, most demographic and attitudinal variables were found statistically insignificant.

Estimation of the coefficients of the double-bounded model was conducted via maximum likelihood techniques using GAUSS for Windows version 3.5. Coefficients and their associated standard errors are presented in Table 2.1. Both coefficients were found significant at 1% and had the expected signs.

Table 2.1. Coefficients of the double bounded model.

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	129.97	0.2543	511.08	0.0000
$\tilde{\beta}$	-5.738	0.0162	-353.86	0.0000
WTP= $-\tilde{\alpha}/\tilde{\beta}$	\$226			
95% WTP C.I.	\$225-\$227[2]			

Following Hanemann (1989), mean willingness to pay for the double bounded model was calculated as the ratio of the constant over the absolute value of the bid coefficient, which allows the mean to be either positive or negative. It is possible that a negative estimate of *net* willingness to pay be obtained if a large proportion of respondents were not willing to pay any positive amount for the implementation of the prescribed burning program, but rather had to be compensated with a discounted price or tax break in order to accept the program.

In order to facilitate convergence of the model the bid amount was divided by ten. Therefore, the result obtained from calculating willingness to pay as α / β needs to be

[2] Variance-Covariance matrix is heteroskedastic-consistent

multiplied by ten. Hence, the mean *net* willingness to pay estimate for the prescribed burning program obtained from the double bounded model was equal to $226 per household per year. The resulting net benefit estimate can be generalized to Florida's population because negative willingness to pay or willingness to accept was implicitly factored in during the estimation.

The results for the logit model of only positive bidders are presented in Table 2.2. Both coefficients were found significant at the 1% level and they had the expected signs.

Table 2.2 Coefficients of the logit model.

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	1.2948	0.1343	9.637	0.0000
$\tilde{\beta}$	-0.0038	0.0008	-4.893	0.0000
WTP	$404			
95% WTP C.I.	$286-$599			

Mean willingness to pay for the standard binary logit model was calculated as $E(WTP) = \ln[1 + \exp(\tilde{\alpha})] / \tilde{\beta}$[3] since only positive bidders were considered in the estimation. This formula constrains willingness to pay to positive levels and, as Hanemann (1989) emphasized, it only applies if willingness to pay is a non-negative random variable. The results in Table 2.2 show that when negative responses were excluded from the estimation, the welfare estimate increased considerably. Mean willingness to pay for the logit of positive bidders was equal to $404 per household per

[3] The general formula $\int_0^{\infty}[1 - G(A)]dA$ reduces to E(WTP)= ln[1+exp(α)]/β for a logistic distribution and linear indirect utility function (Hanemann, 1999).

year, almost twice the size of the willingness to pay estimate obtained from the double bounded model.

For the estimation of the logit model reported in Table 2.2, the negative bids (WTA bids) were treated as protest bids and, therefore, they were excluded from the sample in the estimation process. As opposed to protest bids, which are essentially ignored, if negative bids are not allowed an alternative approach is to code all negative bids as zero bids and estimate a standard binary logit model in the usual way. The results of this estimation are shown in Table 2.3.

Table 2.3 Coefficients of the logit model with negative responses coded as zero bids.

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	1.5238	0.1279	11.910	0.0000
$\tilde{\beta}$	-0.0049	0.0007	-6.386	0.0000
WTP	$351			
95% WTP C.I.	$285-$464			

Both coefficients were highly significant and had the expected signs. Mean willingness to pay was equal to $351 per household per year. This value is smaller than the estimate obtained when negative bids were ruled out, but still higher than the willingness to pay estimate obtained from the double bounded model.

2.6.1 Hypothesis Tests

The 95% confidence intervals in Tables 2.1 and 2.2 do not overlap, indicating that the hypothesis of equality between willingness to pay of positive bidders from the logit model and net willingness to pay estimate from the double bounded model was rejected at the 5% level of significance. If negative responses were not important in the valuation process, these two measures would have been statistically equivalent. The hypothesis of equality between willingness to pay estimates of the standard logit model with negative bids coded as zeros and the double bounded model was also rejected at the 5% level, as suggested by the non-overlapping confidence intervals in Tables 2.1 and 2.3.

2.7 Conclusions

There is a class of public programs that simultaneously provide a mix of public goods and public bads. In this case study, prescribed burning of natural fuels in forests to reduce the incidence of potentially catastrophic wildfires is an example of this type of public good.

Assuming that willingness to pay is unlikely to be a large proportion of income, it was argued that willingness to accept compensation to have the program is an appropriate proxy for negative willingness to pay. This assumption allowed coding willingness to accept bids as negative willingness to pay bids in the valuation process. Based on this assumption, a double bounded model was estimated that permitted the identification of both positive (e.g.WTP) and negative (e.g. WTA) responses and the estimation of a *net* welfare measure. Furthermore, this modeling approach is particularly useful when there are insufficient willingness to accept observations to estimate a separate willingness to accept function.

In order to determine the importance of excluding negative preferences in the valuation process, the *net* willingness to pay estimate obtained from the double bounded model was contrasted against the willingness to pay estimates obtained from a standard binary logit model of positive bidders and a logit model where negative bids were coded as zero bids. The null hypothesis of equality between the willingness to pay estimates obtained from the logit models and the *net* willingness to pay estimate obtained from the double bounded was rejected at the 5% significance level. As expected, neglecting to account for negative responses resulted in significantly higher estimates of willingness to pay compared to the *net* estimate obtained from the double bounded model.

The results obtained in this paper suggest that the assessment of welfare losses is of particular relevance when the environmental good or program is likely to generate benefits for some proportion of the population but also costs for others, associated to negative externalities that can not be avoided if the public program is implemented.

When the public good or program in question can result in gainers and losers, both the elicitation format and the modeling techniques should allow to explicitly account for the existence of positive and negative values towards the good. This paper has shown a survey format that successfully elicited heterogeneous preferences for the prescribed burning program and a straightforward modeling technique that accounted for positive and negative willingness to pay.

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CHAPTER III

ADDRESSING HETEROGENEOUS PREFERENCES USING PARAMETRIC AND NON-PARAMETRIC EXTENDED SPIKE MODELS

3.1 Introduction

Most public goods are assumed to be freely disposable, i.e. if the person dislikes the good she or he can simply ignore it without incurring losses in utility. This assumption has led to modeling approaches in the contingent valuation literature that usually restrict willingness to pay (WTP) to positive values. Nonetheless, several examples of public goods suggest that the assumption of free disposability may not hold in all situations. Such is the case of prescribed burning programs, which are part of a broader Federal Wildland Fire Management Policy, whose objective is to prevent the occurrence of wildfires by means of the controlled application of fire to existing underbrush in forests.

Prescribed fire treatments have proved an efficient tool for reducing the probability of catastrophic wildfires and, thus, the risk of economic and human loses. However, they can also generate potentially large negative externalities derived from the impact of smoke emissions on tourism and human health, a "public bad" for which some people will not be willing to pay and might instead need to be compensated.

In a typical dichotomous choice contingent valuation survey, people who dislike the public good or are indifferent will show this with a *no* response to the valuation question. In the estimation process, these *no* responses will be interpreted as rejection to pay the particular bid amount, when in reality they may reflect an authentic negative or zero value for the good. Given that for this kind of mixed public good/bad heterogeneous preferences are likely to exist, they should be elicited as well as modeled appropriately in order to obtain unbiased welfare measures.

In this paper, the problem of heterogeneous preferences was addressed at the survey design as well as the modeling stage. The structure of the contingent valuation questionnaire allowed separating respondents with different preferences for the good, which were modeled accordingly using parametric and non-parametric extended spike models. In essence, both parametric and non-parametric approaches assume that a proportion of the population has positive value for the good, another proportion is indifferent, and therefore has no value for the good (willingness to pay is zero), while the remaining proportion has a negative value and therefore needs to be compensated.

In the analysis, it was assumed that willingness to accept compensation to have the prescribed burning program is a valid proxy for negative willingness to pay. This made it possible to combine the two types of answers in the same log-likelihood function and calculate a *net* measure of willingness to pay as well as a measure of willingness to accept.

The first modeling approach corresponds to a parametric extended spike model that combined in the same log likelihood function positive, zero, and negative willingness to pay responses. The second approach corresponds to a non-parametric extended spike model based on the non-parametric Turnbull estimator.

This paper contributes to the debate over negative and zero willingness to pay by providing further proof that ignoring heterogeneous preferences can result in biased welfare estimates. In order to address this issue, estimates obtained from the parametric and non-parametric extended spike models were compared with conventional modeling approaches that only account for non-negative willingness to pay.

3.2 Previous studies

The existence of zero and negative willingness to pay and the proper way to model it is still subject of much debate in the contingent valuation literature and has been explicitly addressed using both parametric and non-parametric approaches. Yet, there is no consensus on the best way to address the problem.

Among parametric applications, An and Ayala (1996) used a mixture model that accounted for the possibility that willingness to pay for the good be zero. In this model, the willingness to pay distribution was specified as a mixture of two distinct distributions, one with a point mass at zero and another with distribution on the positive side. Using a double bounded dichotomous choice survey, the category of respondents that answered *no* to the first bid offered and *no* to the second lower bid was assumed to be composed by two subgroups: those with willingness to pay less than the lower bid but greater than zero, and those with zero willingness to pay. They concluded that the mixture model performed better than the conventional double bounded model in terms of goodness of fit and welfare estimates.

Werner (1999) also showed an application of the mixture model. As in An and Ayala (1996), she argued that respondents in the *no-no* response category can be separated in those whose willingness to pay is zero and those whose willingness to pay is positive but less than the minimum bid amount. Each subgroup was assigned a probability, which was modeled as a constant as well as a function of covariates. In both cases, the mixture model produced far lower estimates of mean willingness to pay than the strictly positive willingness to pay models.

As An and Ayala (1996) pointed out, the spike model first developed by Kriström (1995) is a special case of the mixture model. The simple spike model, which accounts for positive and zero willingness to pay, assumes that willingness to pay can be either positive or negative and consequently it allows the willingness to pay distribution to range over the interval $[-\infty, +\infty]$. In the simple spike model, the mass distribution at zero (the spike) is the truncation at zero of the negative part of the willingness to pay distribution. The height of the spike represents the proportion of people with zero willingness to pay and is the integration of the probability density function (pdf) over the range $[-\infty, 0]$. Instead, in the mixture model, the point mass at zero is an extra parameter associated to the unknown proportion of people with an authentic indifference for the good.

Hanemann and Kanninen (1999) sketched out a mixture model that combined in the same log-likelihood function positive and zero willingness to pay, as well as negative willingness to pay. Unlike the mixture model that truncates willingness to pay at zero (An and Ayala, 1996; Werner, 1999), this extended mixture model included two free parameters to account for the negative and positive partitions. It is implicit in this model that the proportions of both types of responses are not known beforehand, and therefore the free parameters that represent such proportions have to be estimated from the data or can be made a function of covariates.

Among the few parametric applications of the simple spike model are Kriström (1995), Hanemann and Kriström (1995), and Kriström (1997). These studies suggest that when the proportion of zeros is likely to be large within the sample, the simple spike model is a better specification than the standard binary logit. Del Saz-Salazar and García-Menédez (2001) concluded that the simple spike model was a better specification than a standard logit, a bivariate probit, and a non-parametric estimator when a large amount of people had zero willingness to pay for social benefits from environmental and urban improvements in Spain.

A non-parametric application is Kriström (1997). He estimated an extended spike model to value traffic reduction. In the survey, the respondent was presented with two alternatives, one for a reduction in traffic and another for an increase in traffic. The election of one alternative implied that the person had negative willingness to pay for the alternative not chosen. Assuming a symmetric distribution, he found a median willingness to pay equal to zero and a mean willingness to pay near zero.

Parametric and non-parametric spike models have not been used frequently in contingent valuation studies, particularly the extended spike model. In fact, no published applications were found of the parametric extended spike in modeling positive, zero, and negative willingness to pay responses. Within this context, this paper adds to the literature by further exploring the implications of ignoring heterogeneous preferences in terms of the magnitude of welfare estimates.

3.3 Parametric Extended Spike Model

Following Kriström (1997), the distribution of willingness to pay in the extended spike model can be represented as shown in equation 3.1, where $H_{WTP}(A)$ is the distribution of negative preferences, $G_{WTP}(A)$ is the distribution of positive preferences, p^- is a mass distribution at zero when $A \to 0^-$, and p^+ is a mass distribution at zero when $A \to 0^+$. Although $H_{WTP}(A)$ and $G_{WTP}(A)$ can take different functional forms, in this study they were treated as equal and assumed to be logistic.

$$
\begin{aligned}
F_{WTP} &= H_{WTP}(A) && \text{if } A < 0 \\
F_{WTP} &= p^- && \text{if } A \to 0^- \\
F_{WTP} &= p^+ && \text{if } A \to 0^+ \\
F_{WTP} &= G_{WTP}(A) && \text{if } A > 0
\end{aligned}
\tag{3.1}
$$

The p's (p^- and p^+) correspond to the cumulative density functions when A is equal to zero (i.e. the non-zero probability that WTP is equal to zero) and can be represented graphically as depicted in Figure 3.1. The spike is given by the difference between p^+ and p^- . The notion of the "spike" is that for some people the public good does not contribute to utility and, therefore, they will not "buy" it even at zero cost. These people are considered to be "out of the market" for the public good, which from an economic theory perspective, is consistent with a corner solution.

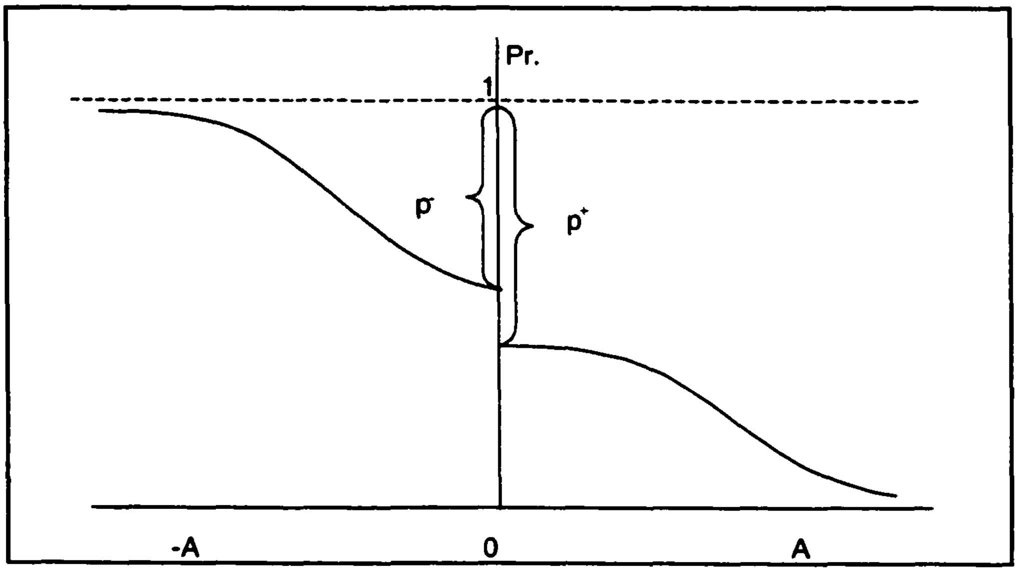

Figure 3.1. Representation of p^- and p^+ **for the extended spike model.**

In order to elicit positive, negative, and zero values for the public good, the contingent valuation questionnaire included an initial screening question, which separated respondents who favored the program (WTP≥0) from those who opposed it (WTP<0). Those in favor were asked a willingness to pay follow up question and those who opposed it were asked a willingness to accept follow up question. Respondents who refused to pay the initial willingness to pay bid (A) were asked if they would pay $1. Those who did not pay $1 were assumed to have zero willingness to pay. This question was considered equivalent to the question of willingness to pay "anything at all" used in other studies to identify indifference (Kriström, 1997; Del Saz-Salazar and García-Menédez, 2001). For those who answered *no* to the initial screening question (WTP<0), a single willingness to accept question followed. In this case, a *no* response implied that willingness to accept was greater than the bid amount offered as compensation ($\bar{A}$) and contrarily, a *yes* response implied that $\overline{A}$ >WTA>0. In order to account for the possibility that the positive and negative sides of the response distribution have different shapes, two versions of the extended spike model were estimated. The first specification, defined as Spike 1, allowed for two different intercept parameters, α for the negative side and γ for the positive side, but a single slope coefficient. The distribution of willingness to pay for this model is shown in equation 3.2.

$$\begin{aligned}
F_{WTA}(\overline{A}) &= [1+\exp(\alpha+\beta\overline{A})]^{-1} && \text{if } \overline{\mathrm{A}} < 0 \\
F_{WTA}(\overline{A}) &= [1+\exp(\alpha)]^{-1} && \text{if } \overline{\mathrm{A}} \to 0^{-} \\
F_{WTP}(A) &= [1+\exp(\gamma)]^{-1} && \text{if } \mathrm{A} \to 0^{+} \\
F_{WTP}(A) &= [1+\exp(\gamma-\beta A)]^{-1} && \text{if } \mathrm{A} > 0
\end{aligned} \tag{3.2}$$

A second version of the model, defined as Spike 2, allowed for different intercepts and different slope parameters (β for the *negative* side and λ for the positive side). This version of the model has the advantage of being more flexible, in the sense that it allows for different shapes of the response distribution at both sides of the spike. In this case, the distribution of willingness to pay was the following:

$$\begin{aligned}
F_{WTA}(\overline{A}) &= [1+\exp(\alpha+\beta\overline{A})]^{-1} && \text{if } \overline{\mathrm{A}} < 0 \\
F_{WTA}(\overline{A}) &= [1+\exp(\alpha)]^{-1} && \text{if } \overline{\mathrm{A}} \to 0^{-} \\
F_{WTP}(A) &= [1+\exp(\gamma)]^{-1} && \text{if } \mathrm{A} \to 0^{+} \\
F_{WTP}(A) &= [1+\exp(\gamma-\lambda A)]^{-1} && \text{if } \mathrm{A} > 0
\end{aligned} \tag{3.3}$$

The p's were calculated according to equation 3.4 for both versions of the model. The spike was calculated as shown in equation 3.5.

$$p^{-} = [1/1+\exp(\alpha)]$$
$$p^{+} = [1/1+\exp(\gamma)] \tag{3.4}$$

$$spike = [1/1+\exp(\gamma)] - [1/1+\exp(\alpha)] = p^{+} - p^{-} \tag{3.5}$$

The different response categories were combined in the same log-likelihood function as shown in equation 3.6.

$$l = \sum_{i}^{N} \begin{array}{l} g_i ln[F_{WTA}(\bar{A})] + h_i ln[F_{WTA}(0^{-}) - F_{WTA}(\bar{A})] + e_i \ln[F_{WTP}(0^{+}) - F_{WTA}(0^{-})] \\ + d_i ln[F_{WTP}(A) - F_{WTP}(0^{+})] + f_i ln[1 - F_{WTP}(A)] \end{array} \tag{3.6}$$

The indicators g_i, h_i, e_i, d_i, and f_i were used to separate the different partitions of respondents such that:

gi = 1 if respondent answered *no* to the WTA bid.

hi = 1 if respondent answered *yes* to WTA bid.

ei = 1 if respondent answered *no* to WTP bid and *no* to \$1 (WTP=0).

di = 1 if respondent answered *no* to WTP bid but *yes* to \$1.

fi = 1 if respondent answered *yes* to the WTP bid.

The log-likelihood functions were programmed in Limdep 7.0 and the coefficients were estimated using maximum likelihood techniques[4].

For the simple spike model that combines only zero and positive willingness to pay responses, Kriström (1997) pointed out that the slope coefficient (the marginal utility of money) must be positive in order for the mean to exist in the model. This also holds for the extended spike model. Mean willingness to pay for the Spike 1 was calculated according to equation 3.7. In turn, the result in equation 3.7 is equivalent to the expression in equation 3.8.

$$E(WTP) = \int_0^\infty 1 - F_{WTP}(A)dA - \int_{-\infty}^0 F_{WTA}(\bar{A})dA$$
$$E(WTP) = \frac{\ln[1+\exp(\gamma)]}{\beta} - \left[\frac{\ln[1+\exp(\alpha)]}{\beta} - \frac{\alpha}{\beta}\right] \tag{3.7}$$

$$E(WTP) = \frac{\ln[1+\exp(\gamma)]}{\beta} - \frac{\ln[1+\exp(-\alpha)]}{\beta} \tag{3.8}$$

For Spike 2, expected willingness to pay was calculated as shown in equation 3.9. The first integral in equations 3.7 and 3.9, defined over the positive domain, corresponds to willingness to pay of the gainers and is, therefore, a "gross" willingness to pay measure. The second integral, defined over the negative domain, corresponds to negative willingness to pay of the losers, which in turn, is equivalent to willingness to accept compensation to take the program. The difference between the two estimates gives a *net* measure of willingness to pay that takes into account the negative and positive values towards the public good.

$$E(WTP) = \int_0^\infty 1 - F_{WTP}(A)dA - \int_{-\infty}^0 F_{WTA}(\bar{A})dA$$
$$E(WTP) = \frac{\ln[1+\exp(\gamma)]}{\lambda} - \left[\frac{\ln[1+\exp(\alpha)]}{\beta} - \frac{\alpha}{\beta}\right] \tag{3.9}$$
$$E(WTP) = \frac{\ln[1+\exp(\gamma)]}{\lambda} - \frac{\ln[1+\exp(-\alpha)]}{\beta}$$

[4] The Limdep codes for the simple and extended spike models are given in Appendix II.

3.3.1 Research Hypotheses

3.3.1.1 Individual slope coefficients. In order to test for the possibility that the negative and the positive sides of the response distribution had different shapes, confidence intervals were computed for the individual slope coefficients of the extended spike models. For the Spike 2, the slope on the negative side of the response distribution was compared with the slope of the positive side. The hypothesis tested in this case was the following:

$$H_o\text{: Slope } (\beta) \text{ Spike 2} = \text{Slope } (\lambda) \text{ Spike 2}$$

$$H_1\text{: Slope } (\beta) \text{ Spike 2} \neq \text{Slope } (\lambda) \text{ Spike 2}$$

Furthermore, the two slope coefficients of the Spike 2 were compared with the single slope of the Spike 1. The hypotheses tested in this case were the following:

$$H_o\text{: Slope } (\beta) \text{ Spike 2} = \text{Slope } (\beta) \text{ Spike1}$$

$$H_1\text{: Slope } (\beta) \text{ Spike 2} \neq \text{Slope } (\beta) \text{ Spike 1}$$

and:

$$H_o\text{: Slope } (\lambda) \text{ Spike 2} = \text{Slope } (\beta) \text{ Spike1}$$

$$H_1\text{: Slope } (\lambda) \text{ Spike 2} \neq \text{Slope } (\beta) \text{ Spike 1}$$

3.3.1.2 Individual intercept coefficients. Given that the public program in question provides a mix of non-market public goods and bads, it is possible that people who refused the implementation of the program and those who favored it, may have been valuing different features of it, namely the smoke and the increased safety respectively.

Since the overall value of the program is given by netting willingness to pay for safety and willingness to accept for the smoke, it is plausible that a continuous preference function may exist. The approach to test for this was to compare the individual intercept coefficients of the Spike 1 and the Spike 2. If the two intercepts in each model are not statistically different from one another, it may be concluded that the data do not support the existence of a "spike" (i.e. discontinuity at zero) and, therefore, preferences can be seen as a continuous set ranging from negative to positive values. In order to determine this, the following hypotheses were tested:

$$H_o\text{: Intercept } (\alpha) \text{ Spike 1} = \text{Intercept } (\gamma) \text{ Spike 1}$$

$$H_1\text{: Intercept } (\alpha) \text{ Spike 1} \neq \text{Intercept } (\gamma) \text{ Spike 1}$$

and:

$$H_o\text{: Intercept } (\alpha) \text{ Spike 2} = \text{Intercept } (\gamma) \text{ Spike 2}$$

$$H_1\text{: Intercept } (\alpha) \text{ Spike 2} \neq \text{Intercept } (\gamma) \text{ Spike 2}$$

3.3.1.3 Willingness to pay estimates. Given the complicated structure of the *net* estimators presented in equations 3.7 and 3.9, the variance of the willingness to pay estimates cannot be easily computed and, consequently, confidence intervals cannot be derived using common techniques such as the adapted Krinsky and Robb approach (Park et al., 1991) or the delta method. These techniques are applicable to response probability models for which willingness to pay is a function of two coefficients, usually defined as α and β (i.e. the intercept and the slope coefficients). For a variety of discrete choice models commonly used, mean willingness to pay can be calculated as a non-linear function of these two parameters (Hanemann and Kanninen, 1999).

However, for the extended spike models presented here, *net* willingness to pay is a complicated function of more than two parameters. Given this limitation, an alternative solution was to obtain confidence intervals for the "gross" willingness to pay estimates obtained from Spike 1 and Spike 2 and compare them with the confidence intervals of the willingness to pay estimates obtained from a standard binary logit of positive bidders and a simple spike model[5]. Although these approaches are not as conclusive as constructing confidence intervals for the *net* willingness to pay estimates, they give insight about the differences among the welfare measures obtained from the distinct model specifications when heterogeneous preferences are taken into account. Thus, in order to determine the importance of ignoring negative and zero willingness to pay responses for the public program, the following hypotheses were tested:

H_o: *WTP (Binary Logit) = Gross WTP (Extended Spikes)*

H_1: *WTP (Binary Logit) > Gross WTP (Extended Spikes)*

and: H_o: *WTP (Simple Spike) = Gross WTP (Extended Spikes)*

H_1: *WTP (Simple Spike) > Gross WTP (Extended Spikes)*

Willingness to pay estimates were calculated and compared for the combined sample and for the sub-samples from Montana and California. This allowed the identification of potential differences between respondents in both locations in terms of relative preferences for the prescribed burning program and magnitude of the welfare measures.

[5] Confidence intervals for "gross" WTP were computed using the Krinsky and Robb approach (Park et al., 1991).

3.4 Non-parametric Extended Spike Model

In contrast to maximum likelihood estimation techniques, which assume a closed form distribution for the latent willingness to pay variable, an alternative approach is to assume that the analyst does not have enough information to specify the underlying distribution, in which case distribution-free estimators can be used. In this study, the Turnbull estimator was used (Turnbull, 1976), which has been described in detail in Haab and McConnell (1997) and Boman et al. (1999). For single bounded dichotomous choice data, the Turnbull can provide rigorous closed-form solutions for mean willingness to pay and its variance (Hutchinson et al., 2001).

The non-parametric Turnbull estimator has been used in many contingent valuation studies (Carson et al., 1994a and 1994b; Kriström, 1990 and 1997) and has been shown to provide a straightforward alternative to parametric models in the estimation of mean willingness to pay. Most these studies, however, have focused on modeling positive preferences. The only published application found of a non-parametric extended spike model using the Turnbull estimator is Kriström (1997).

In a typical single bounded dichotomous choice experiment, the respondent is asked to pay a particular amount A_i. Thus, k-1 bids ranging from $i=A_1,...,A_{k-1}$ (from lowest to highest) are presented to k-1 sub-groups of individuals such that responses are obtained from $n_1,n_2,...,n_{k-1}$ groups. In a particular subgroup i $(i=1,2,....,k-1)$, there will be m_i respondents accepting the bid A_i and therefore, the proportion of *yes* responses in each subgroup will be $\pi_i=m_i/n_i$. The sequence of proportions obtained, $\hat{\pi}=(\hat{\pi}_1 ..... \hat{\pi}_{k-1})$, is expected to be non-increasing in A, since as the bid presented increases fewer people will choose to pay it. However, due to small sample sizes at each bid level, it can happen sometimes that $\pi_{i+1}>\pi_i$ making the sequence increasing. If this is the case, the Kuhn-Tucker solution to the problem is to combine the i^{th} and $i+1$ cells into one cell, and to estimate again the associated p_i's (the probability density functions or pdf's). This process continues until cells are pooled enough to allow for a monotonically non-increasing cumulative density function (cdf). The procedure yields a series of points on the unknown willingness to pay function $\hat{\pi}(A)$ (i.e. the demand curve, $\hat{\pi}(A) = \hat{D}(A)$), which is related to the cumulative distribution function $\hat{F}(A)$, since $\hat{\pi}(A) = 1 - \hat{F}(A)$. Expressed in this form $\hat{\pi}(A)$ is known as the survival function (Boman et al., 1999).

In order to calculate mean willingness to pay, it was necessary to determine the lower end of the survival function (i.e. a value A_0 that makes $\hat{\pi}(A)=1$) as well as the upper end (i.e. a value of A where $\hat{\pi}(A)=0$). Given the structure of the CVM survey format used in this study, willingness to pay had support in the entire real line and, therefore, A_0 was a negative value. As in the parametric estimation of the extended spike model, in the non-parametric estimation it was assumed that willingness to pay is an appropriate proxy for negative willingness to pay. Thus, the negative quadrant of the survival function was represented by those people answering the willingness to accept valuation question.

In order to determine the upper end of the survival function, A_K, which is the maximum willingness to pay value where $\hat{\pi}(A)=0$, it was assumed that $A_K=A_{K-1}$, which implies that the estimated proportion of *yes* answers was zero for values of A greater than A_{K-1} (Boman et al., 1999). Having the lower and upper ends of the distribution, it was possible to calculate the variance of the cdf's (π_i's) and the pdf's (p_i's) as well as a lower bound estimate of willingness to pay and its variance. Following Haab and McConell (1997), the variance associated with the cdf's was calculated as follows:

$$V(\pi_i) = \frac{\pi_i(1-\pi_i)}{n_i} \tag{3.10}$$

Since π_i and π_{i+1} have zero covariance, the variance associated with the p_i's was calculated as shown in equation 3.11, where $p_i = \pi_i - \pi_{i-1}$.

$$V(p_i) = V(\pi_i) + V(\pi_{i-1}) = \frac{\pi_i(1-\pi_i)}{n_i} + \frac{\pi_{i-1}(1-\pi_{i-1})}{n_{i-1}} \tag{3.11}$$

For the p_i's to represent a valid probability density function, they have to be non-negative. This is assured if $(m_i/n_i)>(m_{i+1}/n_{i+1})$, i.e. as long as the proportion of *yes* responses to a particular bid amount A_2 is strictly smaller than the proportion of *yes* responses to a bid A_1, the probability that willingness to pay falls within $[A_1, A_2]$ will be positive and equal to the difference in the proportions (Haab and McConnell, 1997).

Replacing the bid that the respondent faced by the lower bound of each interval, it was possible to obtain a lower bound estimate of willingness to pay, which is shown in equation 3.12. This estimate is distributed asymptotically normal, because it is a linear combination of the p_i's, which are also asymptotically normal.

$$E(LB_{WTP}) = \sum_{i=A_0}^{A_K} A_{i-1} p_i \tag{3.12}$$

The variance of the mean lower bound willingness to pay ($E(LB_{WTP})$) was calculated as:

$$V\left(\sum_{i=A_0}^{A_K} p_i A_{i-1}\right) = \sum_{i=A_0}^{A_K} A_{i-1}^2 (V(\pi_i) + V(\pi_{i-1})) - 2\sum_{i=A_0}^{A_K} A_i A_{i-1} V(\pi_i) \qquad (3.13)$$

3.4.1 Research Hypotheses

With the mean and variance of willingness to pay (equations 3.12 and 3.13), confidence intervals were constructed to test hypotheses on the sample mean obtained from the non-parametric extended spike model versus a standard non-parametric Turnbull of only positive bidders which excluded the negative and zero WTP responses. The null and alternative hypotheses in this case were the following:

$$Ho: WTP\,(N.P\ Extended\ Spike) = WTP\,(Turnbull)$$
$$H_1: WTP\,(N.P\ Extended\ Spike) < WTP\,(Turnbull)$$

3.5 Data

The data to illustrate an application of the models came from a survey to California and Montana residents conducted between July 2001 and May 2002. The survey followed a phone-mail-phone procedure. The objective of the survey was to quantify attitudes and economic values toward the expansion of prescribed burning programs already in place in both states. The interest in the expansion of these public programs is derived from the active wildfire seasons that occurred in the last several years nationwide that have caused significant losses to private property and commercial timber losses. In order to obtain a representative sample, random digit dialing was used. After the initial contacts with the respondents, appointments were made to conduct a follow-up phone interview. During the interim, a color survey booklet providing educational information was mailed to the each household. This booklet contained definitions and drawings of some key aspects related to prescribed fire and wildfire. The booklet also explained that the implementation of the expanded prescribed burning program would reduce the number of acres burned in a typical year by 25% and a corresponding percentage reduction in the number of houses lost each year. After this was explained, respondents were asked if they thought this program should or should not be undertaken at zero cost to them. This screening question allowed the identification of those who viewed the program positively (WTP>0) from those who viewed it negatively (WTP<0), such that the appropriate valuation question followed. The structure of the contingent valuation questionnaire is depicted in Figure 3.2.

Respondents who answered *no* to the screening question were asked a willingness to accept question worded as follows:

"Because of the importance of using prescribed burning to reduce the threat and dangers from wildfire, there may be times when the state must do the prescribed burns. However, the state could pay affected citizens for adverse effects of prescribed burning such as smoke, soot, road closures, and other inconveniences; if the state paid your household $___ per year would you vote in favor of the Expanded Prescribed Burning Program?" In favor _____ Against _____

Respondents who answered affirmatively to the initial screening question were asked the following willingness to pay question:

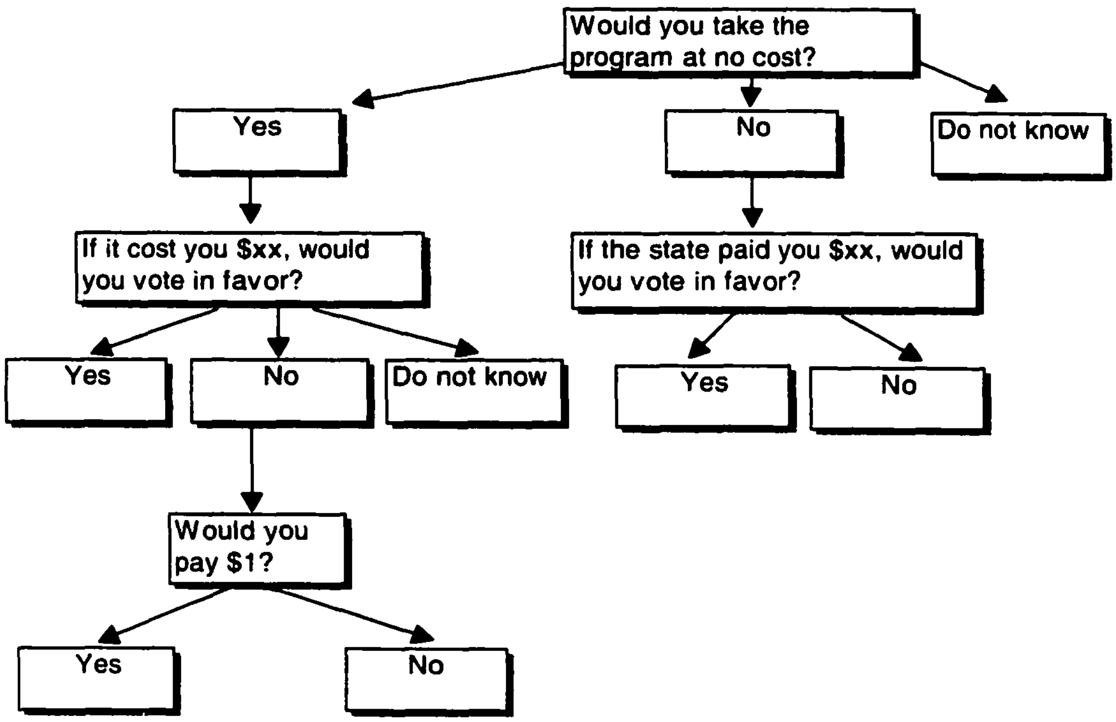

Figure 3.2. Outline of the structure of the CVM questionnaire.

"Your share of the Expanded Prescribed Burning Program would cost your household $____ a year. If the Expanded Prescribed Burning Program were on the next ballot would you vote": In favor_____ Against _____ Do not know _____

Respondents who voted *against* to this question were presented with a follow up question that asked if they would pay $1/year. Those respondents who answered *against* to the willingness to pay question and *no* to the $1 question as well as those who answered *do not know* to the willingness to pay question were assumed to have zero willingness to pay for the prescribed burning program.

The bid amount asked was one of ten amounts ranging from $15 to $480 for the willingness to pay question and from $10 to $470 for the willingness to accept question.

A total of 475 phone interviews were completed in May 2002 from comparable samples in California and Montana. This represented a combined response rate of 73% of households participating in the screener survey and 40% of all households initially contacted by random digit dialing. Of the 475 surveys completed, 48% were from California and the remaining 52% from Montana. Most respondents in the combined sample supported the implementation of the prescribed burning program at no cost, with only 14.73% expressing a negative value and only 6.52% expressing indifference.

In the California sub-sample 10.8% of the respondents expressed that they would not take the program at zero cost. In turn, 83.3% of these respondents expressed that they would not accept any compensation to take the program. In Montana, nearly 20% of respondents opposed the program at no cost and 91.6% of this 20% did not accept any compensation to take it. Respondents who expressed zero willingness to pay were 5.2% and 8.4% in California and Montana respectively.

To allow for a more direct comparison of net benefits between the non-parametric model (which does not allow for covariates) and the parametric model, no attitudinal or demographic variables were included in the parametric analysis. Hence, the bid amount was considered as the only explanatory variable.

3.6 Parametric Results

3.6.1 Coefficient estimates and spike calculation

Table 3.1 summarizes the empirical results for the binary logit and simple spike as well as both specifications of the extended spike model. In all models the slope and intercept coefficients were highly significant at conventional levels.

Table 3.1. Binary logit and spike model estimates.

Coefficient Estimates	Binary Logit	Simple Spike	Spike 1	Spike 2
$\tilde{\alpha}$ (Intercept)	1.3348[a] (0.1709)	1.1464[a] (0.1107)	1.4679[a] (0.1131)	1.6152[a] (0.1278)
$\tilde{\beta}$ (Slope)	-.0028[a] (0.0007)	0.0043[a] (0.0038)	0.0033[a] (0.0002)	0.0008[a] (0.0002)
$\tilde{\gamma}$ (Intercept Poss. Side)	-------	-------	1.0057[a] (0.0973)	1.1474[a] (0.1108)
$\tilde{\lambda}$ (Slope Poss. Side)	-------	-------	-------	0.0043[a] (0.0004)

Superscript "a" indicates significance at the 1% level.

As expected, the slope parameters β and λ carried a positive sign. The intercept parameter of the negative (α) and positive side (γ), also carried positive signs and were highly significant.

The values of p^+ and p^- for the Spike 1 and Spike 2 were obtained by inserting the estimated intercept coefficients (α and γ) in equation 3.4. For the Spike 1, p^+ was equal to p^+=[1/1+exp(1.0057)=0.2678, which nearly coincides with the proportion of people with negative and zero willingness to pay. p^- was equal to p^-=[1/1+exp(1.4679)]=0.1872, which closely corresponds to the proportion with strictly negative willingness to pay. The difference between the two yielded a spike equal to 0.2678-0.1872=0.08.

For the Spike 2, p^+ was equal to p^+ =[1/1+exp(1.1474)]=0.2409, while p^- was equal to p^-=[1/1+exp(1.6152)]=0.1658. This yielded a spike of 0.2409-0.1658=0.075.

For the simple spike model, the spike was equal to p=[1/1+exp(1.1464)]= 0.24, which combines the proportion of people with zero and negative willingness to pay.

3.6.2 Welfare estimates

For the binary logit model, mean willingness to pay was calculated as $\ln[1+\exp(\alpha)]/\beta$ since only positive bidders were considered in its estimation. The same formula was used to calculate mean willingness to pay for the simple spike model as suggested by Kriström (1997). Mean willingness to pay for the Spike 1 and Spike 2 was calculated according to equations 3.7 and 3.9 respectively.

3.6.2.1 Combined sample. The welfare estimates for the combined sample (Montana and California) and their 95% confidence intervals are reported in Table 3.2. As expected, the standard binary logit model of only positive bidders (i.e. zero and negative responses were excluded from the estimation) gave the highest willingness to pay estimate, equal to $560 per household per year. The simple spike, where negative responses were coded as zero willingness to pay bids, gave a lower mean willingness to pay than the logit, equal to $330.

Table 3.2. Binary logit and spike model willingness to pay estimates for the combined sample.

	Logit	Simple Spike	Spike 1	Spike 2
WTP of gainers "gross" WTP	$560	$330	$399	$331
WTP of losers (negative WTP or WTA)	-------	-------	$63	$226
Net WTP	-------	-------	$336	$104
95% WTP C.I*	$407-$915	$286-$390	$334-$460	$281-$378

*Confidence intervals of the "gross" WTP estimate.

In the Spike 1, willingness to pay of the gainers was $399, while negative willingness to pay of the losers (WTA) was equal to $63. This gave a *net* WTP of $336.

In the Spike 2, willingness to pay of the gainers was equal to $331 and negative willingness to pay of the losers (WTA) was $226. Since WTA of the losers was considerably larger in the Spike 2, the *net* willingness to pay estimate ($104) was lower than in the Spike 1. These findings can be explained by the fact that the slope coefficient in the Spike 1 was constrained to be the same for the positive and negative sides of the response distribution, which for the results obtained here, underestimated the negative portion (WTA) of the *net* willingness to pay estimator. This, in turn, resulted in a higher *net* welfare measure.

3.6.2.2 Individual sub-samples. The estimation was also conducted for the individual sub-samples from Montana and California[6]. The results obtained from the Montana sub-sample were fairly consistent with those obtained from the entire sample. The welfare estimates for Montana and their respective confidence intervals are reported in Table 3.3.

Table 3.3. Binary logit and spike model willingness to pay estimates for the Montana sub-sample.

	Logit	Simple Spike	Spike 1	Spike 2
WTP of gainers "gross" WTP	$532	$231	$295	$231
WTP of losers (negative WTP or WTA)	-------	-------	$78	$419
Net WTP	-------	-------	$217	($188)
95% WTP C.I*	$324-$2291	$195-$279	$236-$367	$192-$276

*Confidence intervals of the "gross" WTP estimate.

[6] The coefficient estimates of the binary logit, simple spike, and extended spike models for both sub-samples are reported in Appendix III and IV respectively.

As in the combined sample, the binary logit of only positive bidders gave the highest estimate of willingness to pay. Furthermore, the confidence interval for the logit model is notably wide indicating that the variance of the WTP is considerably large. Both the simple spike and the Spike 2 produced significantly lower gross estimates than the logit model, as indicated by the non-overlapping confidence intervals, and with a much lower variance, which suggest that these estimates are more efficient than the estimate yielded by the binary logit model. Contrarily, the gross WTP estimate produced by the Spike 1 was not statistically different from the logit estimate as indicated by the overlapping 95% confidence intervals.

An interesting finding is the large WTA estimate produced by the Spike 2, which in turn, caused the *net* estimate to be negative (-$188). This finding can be explained by the fact that in this sub-sample nearly 20% of the respondents did not take the program at no cost, and around 92% of this 20% did not accept even the highest compensations offered. Although some of these responses may be protest votes, it is also possible that the respondents who opposed the program have truly negative values given that the external costs of the smoke emissions offset by far the benefits of increased safety from having the program implemented.

In the California sub-sample, on the other hand, the willingness to pay estimates were considerably higher than those of the Montana sub-sample reported in Table 3.3, reflecting the fact that only around 11% of the respondents gave zero and negative willingness to pay responses, which translated in higher gross and net welfare estimates. Furthermore, in the sub-sample from California all 95% confidence intervals overlapped, indicating that the willingness to pay estimates produced by all four models were not statistically different from each other. These results are summarized in Table 3.4.

Table 3.4. Binary logit and spike model willingness to pay estimates for the California sub-sample.

	Logit	Simple Spike	Spike 1	Spike 2
WTP of gainers "gross" WTP	\$542	\$479	\$530	\$479
WTP of losers (negative WTP or WTA)	-------	-------	\$43	\$94
Net WTP	-------	-------	\$478	\$385
95% WTP C.I*	\$284-\$1424	\$372-\$636	\$420-\$712	\$373-\$644

*Confidence intervals of the "gross" WTP estimate.

3.6.3 Hypothesis Tests

3.6.3.1 Individual slope coefficients. The results in Table 3.5 are the 95% confidence intervals of the individual slope coefficients of the extended spike models. As the confidence intervals indicate, the hypothesis of equivalence between both slopes of the Spike 2 was rejected at the 5% level of significant. Likewise, the hypothesis of equivalence between the slope of the simple spike and the slope on the negative side of the Spike 2 was rejected at the 5% level.

Table 3.5. Confidence intervals of individual slope coefficients.

Estimate	Spike 1	Spike 2	
Slope Coefficient	0.0033	0.0008 (negative side)	0.0043 (positive side)
95% C.I.	0.0028-0.0039	0.00028-0.0013	0.0036-0.0051

These results support that the negative and positive side of the response distribution may, in fact, have different shapes. This finding may explain why the Spike 1 yielded a much lower estimate of negative WTP (or WTA of the losers) and consequently a higher net WTP estimate. Constraining the slope to be the same in Spike 1 could lead to model mispecification and, consequently, to biased welfare estimates. Contrarily, the confidence intervals of the slope coefficient of Spike 1 and the slope coefficient on the positive side of Spike 2 overlap indicating that both parameters are not significantly different from each other.

3.6.3.2 Individual intercept coefficients. In order to test whether preferences are continuous over the entire real line or they exhibit a discontinuity at zero (i.e. a spike at zero), confidence intervals were calculated and compared for the two individual intercept coefficient of both extended spike models. The results obtained are summarized in Table 3.6. The intercept coefficients of Spike 2 were statistically different at the 10% level and the coefficients of Spike 1 were statistically significant at the 5% level. These results indicate that the data support the existence of a spike at zero and that preferences for the prescribed burning program are not continuous.

Table 3.6. Confidence intervals of individual intercept coefficients.

Estimate	Spike 1		Spike 2	
Intercept Coefficient	1.4679 (negative side)	1.0057 (positive side)	1.6152 (negative side)	1.1474 (positive side)
90% C.I	1.281-1.654	0.845-1.165	1.404-1.825	0.952-1.342
95% C.I.	1.246-1.689	0.815-1.196	1.364-1.865	0.914-1.380

3.6.3.3 Comparison of gross WTP estimates. Although no direct comparison could be made between the *net* willingness to pay of the extended spike models and the logit and simple spike, the confidence intervals reported in Table 3.2 for the entire sample provide some evidence on the differences among the estimates of the four models. The 95% confidence intervals do not overlap indicating that the gross willingness to pay produced by the binary logit was significantly higher than the gross estimate of the simple spike and the Spike 2. Consequently, the *net* willingness to pay measure derived from the Spike 2 ($104) should be significantly lower than the logit estimate.

The gross willingness to pay produced by the Spike 1 instead ($399), was not significantly different from the logit and the simple spike estimates. Therefore, limited inferences can be made about the *net* willingness to pay derived from the Spike 1 as compared to the logit and simple spike estimates.

Nonetheless, the results above provide enough information towards the rejection of the null hypotheses of equality between the gross estimates derived from the extended spike models and the estimates yielded by the logit of only positive bidders and the simple spike that ignores negative preferences.

3.7 Non-parametric Results

For the non-parametric estimation, the sample was divided into three groups: the respondents with positive willingness to pay that agreed to pay the bid amount and those who rejected to pay the bid but agreed to pay $1 (78.73%); the respondents who were indifferent that refused to pay both the bid and $1 (6.52%) and those who responded *do not know* to the willingness to pay question; and finally, the respondents with negative willingness to pay who gave *no* and *do not know* answers to the screening question (14.73%). These results are summarized in Table 3.7.

Table 3.7. Summary of responses to the valuation questions.

	WTP >0		WTP=0		WTP<0	
Response	Yes to WTP bid	No to bid, Yes to $1	No to $1	Don't know	No to screening	Don't know
Yes/Total	283/475	91/475	17/475	14/475	58/475	12/475
(%)	78.73		6.52		14.73	

Table 3.8 shows the number of *yes* responses to each of the willingness to pay bids as well as the total number of responses to zero and the negative bid. Unlike in the parametric estimation, here all negative responses were aggregated around one single bid given that the sequence of willingness to accept responses was not monotonically increasing as would be expected (i.e. as the amount of money offered as compensation to take the program increases, the probability of acceptance should also increase).

Table 3.8. Number of *yes* responses to each bid amount.

Bid Amount	N° Yes Responses	Total Responses
-136	-----	70
0	-----	31
15	33	35
25	36	40
45	37	46
65	29	33
95	22	34
125	31	43
175	22	33
260	26	34
360	25	36
480	22	40
Total		475

This finding may be related to either small sample size in the negative portion of the data (n=70) or to a population for which the program truly represents a bad. Previous to the willingness to accept question these respondents had already stated that they would not take the program at zero cost and, consequently, many of them did not take it even at the highest compensation offered in the survey.

Had the willingness to accept sequence been increasing, the highest willingness to accept amount would have been a natural lower end of the survival curve, such that $\hat{\pi}(A)=1$ at this bid. Instead, given the non-increasing nature of the sequence and the broad willingness to accept bid interval, the Turnbull pdf and cdf's were evaluated at a predicted bid, which was calculated to be -\$136. This negative bid was obtained by regressing the π_i's on the positive bid amounts and predicting the value of the negative bid for which $\hat{\pi}(A)=1$.

In a conventional application of the non-parametric Turnbull estimator when only positive preferences are considered, the lower end of the survival curve is 0, such that $\hat{\pi}(A)=1$ when A=0. Thus, the Turnbull cdf's and pdf's are evaluated at this lower end. In the application at hand, however, $\hat{\pi}(A)=1$ when A= -\$136. Therefore, the proportions had to be adjusted to reflect the fact that only a 78.73% of the sample had positive willingness to pay.

In order to calculate the cdf's on the positive side, the sample proportion of positive bidders (78.73%) was used as starting point and the Turnbull cfd's were adjusted accordingly. These calculations are summarized in Table 3.9.

Table 3.9. Turnbull cdf and pdf's estimates with standard errors.

Bid interval	Turnbull CDF	s.e	Turnbull PDF	s.e
-136 -0	0.8526	0.0636	0.1473	0.0636
0-15	0.7873	0.0691	0.0652	0.0940
15-25	0.7515	0.0683	0.0357	0.0972
25-45	0.6976	0.0516	0.0539	0.0856
45-65	pooled	------	pooled	------
65-95	0.5693	0.0472	0.1228	0.0699
95-125	pooled	------	pooled	------
125-175	pooled	------	------	------
175-260	0.5541	0.0473	0.01518	0.0668
260-360	pooled	------	pooled	------
360-480	pooled	------	pooled	------
480+	0		0.5541	0.0473

The survival function, which represents all the points in the Turnbull cdf, is shown in Figure 3.4. When the Turnbull estimator is used, the response probability function is a step function (i.e. the pdf's are calculated as step functions of the cdf's). The "spike" corresponds simply to the proportion of people with zero willingness to pay, which in this case was equal to 6.52%.

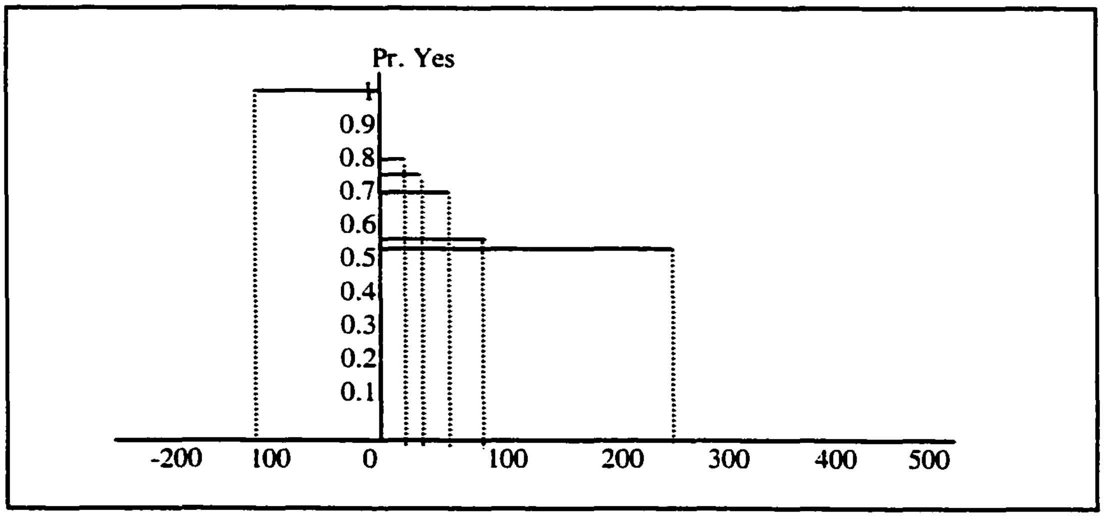

Figure 3.4. Survival function.

The expected lower bound estimate of willingness to pay and its standard error were calculated according to equations 3.12 and 3.13. The results were $E(WTP)$=\$258.81 and SE_{WTP}=22.71. The 90% confidence for the willingness to pay estimate was calculated to be [\$221, \$296] per household per year.

A lower bound willingness to pay estimate was also calculated for only positive bidders, which ignored the portion of respondents with negative willingness to pay for the program and those who were indifferent. The results from this version of the model are presented in Table 3.10.

Table 3.10. Turnbull cdf and pdf's estimates with standard errors for positive bidders.

Bid interval	Turnbull CDF	s.e	Turnbull PDF	s.e
0-15	0.9428	0.0392	0.0571	0.0392
15-25	0.9000	0.0474	0.0428	0.0615
25-45	0.8354	0.0417	0.0645	0.0572
45-65	pooled	------	pooled	------
65-95	0.6883	0.0527	0.1471	0.0672
95-125	pooled	------	pooled	------
125-175	0.6643	0.0394	0.0239	0.0659
175-260	pooled	------	pooled	------
260-360	pooled	------	pooled	------
360-480	pooled	------	pooled	------
480+	0		0.6643	0.0394

The non-parametric welfare estimate increased considerably when negative and zero responses were ignored. The expected lower bound estimate of willingness to pay and its standard error in this case were \$333.69 and \$18.46 respectively. Therefore, the 90% confidence interval was calculated to be [\$303, \$364] per household per year.

Since the 90% confidence interval for the non-parametric extended spike equal to [$221, $296] and the standard Turnbull of only positive bidders equal to [$303, $364] did not overlap, it was concluded that the mean willingness to pay estimates were significantly different from each other. These results are consistent with the parametric results in that ignoring negative preferences and indifference for the public good resulted in a significantly higher welfare measure, bias that is more serious in the parametric estimation.

Haab and McConnell (1997) suggest some caution with respect to the absolute interpretation of the lower bound willingness to pay estimate obtained fro the application of the Turnbull estimator due to its dependence on the bid vector. A different vector might lead to higher or lower estimates. In this study for example, if the highest willingness to accept bid (-$470) had been used as the lower end of the survival function, a smaller net estimate of willingness to pay would have been obtained ($209).

3.8 Conclusions

There is a class of public programs that simultaneously provide a mix of public goods and public bads. Prescribed burning of natural fuels in forests to reduce the incidence of potentially catastrophic wildfires is an example of this type of programs.

Assuming that willingness to pay was unlikely to be a large proportion of income, it was argued that willingness to accept compensation to have the program would be an appropriate proxy for negative willingness to pay, which allowed combining both type of answers in the estimation process. Based on this assumption, parametric and non-parametric versions of the extended spike model were presented, which permitted the identification of positive (e.g.WTP), negative (e.g. WTA), and zero willingness to pay. Two versions of the parametric extended spike models were estimated to account for the possibility that the negative and positive sides of the response distribution had different shapes. The extended Spike 1 allowed for different intercept parameters but a single slope coefficient, while the more flexible Spike 2 allowed for different intercept and slope coefficients at each side of the spike.

The non-parametric version of the extended spike was estimated using the non-parametric Turnbull estimator.

Statistically significant differences in public benefits were found between the parametric extended spike models, specifically the more general model Spike 2, as compared to model specifications that did not account for negative preferences. Ignoring indifference and negative values for the good produced significantly higher willingness to pay estimates.

Unlike other applications that have found "large spikes", in this paper only a small fraction of the respondents stated indifference or negative preferences for the good in question. Additionally, the non-parametric results suggest some "protest" respondents might have been included among the willingness to accept portion of respondents. It is possible that individuals refusing the highest dollar amounts offered as compensation were actually protesting some feature of the willingness to accept scenario. For example, such a large sum of money may have been interpreted as "bribery," given that previous to the willingness to accept valuation question the respondents had already stated that they would not take the prescribed fire program at no cost to them. Unfortunately, protest responses were not identified for those respondents refusing the willingness to accept amounts, and therefore there was no enough information to distinguish those "protests" respondents from those who did not receive enough compensation to support the program.

Nonetheless, the results from the non-parameteric model were consistent with the parametric results in that ignoring negative preferences yield significantly higher welfare measures, bias that was larger in the parametric estimation.

Finally, for public programs that have the potential to generate non-market public benefits but also non-market public bads, a question sequence like the one used in this contingent valuation survey combined with the models presented in this paper would allow the analyst to perform a sensitivity analysis of the benefit-cost outcome that includes negative willingness when it is known that a proportion of the population opposes the provision of the public good.

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CHAPTER IV

USING RANDOM PARAMETERS TO ACCOUNT FOR HETEROGENEOUS PREFERENCES IN CONTINGENT VALUATION OF PUBLIC GOODS

4.1 Introduction

The existence of homogeneous preferences among individuals is the prevailing assumption in modeling consumer choices in the context of random utility maximization models. However, sustaining this assumption when preferences are indeed heterogeneous may yield biased parameter estimates and, consequently, biased estimates of consumer welfare. If heterogeneity of preferences is in fact present, it has to be properly modeled if accurate choice predictions are to be obtained. In the extreme, heterogeneity toward a particular choice attribute might yield an insignificant coefficient, erroneously implying that the attribute does not matter, when in fact the distribution of preferences may be bimodal.

Heterogeneity may arise from socioeconomic differences among respondents or differences in tastes for public environmental programs. Given this individual variation, the random parameter logit model (henceforth RPL) separates the error term into an unobserved component derived from preference heterogeneity (e.g. socioeconomic and/or geographic differences and personal circumstances) and a choice-specific component. Thus, the RPL specification can represent a much broader range of choice situations allowing for a greater variability of preferences for choice specific attributes across individuals (Train, 1998; Revelt and Train, 1998; Brownstone and Train, 1999).

The use of RPL in modeling choice behavior is fairly recent. In the context of valuation of environmental goods, most research corresponds to recreational demand studies. However, little is known about the use of RPL to analyze discrete choice data from contingent valuation surveys. In this study, the RPL specification was used to analyze repeated dichotomous choice contingent valuation data, a case that has not been explicitly addressed in the literature so far. The data to show an application of the model came from a survey that valued preferences for different alternatives of management of public lands administered by the Bureau of Land management (BLM) along the Snake River in Jackson Hole, Wyoming.

The focus of this study was on testing for the existence of variation among respondents' willingness to pay for the attributes associated with each strategy for managing or disposing of open space and the impact of heterogeneous preferences on the valuation of these strategies. It also explored the nature of the individual variation, i.e. to what extent heterogeneity arises from observable individual and attitudinal variables of the respondents or unobservable differences in tastes. In order to test this, individual variables were included in interaction with the alternatives' price. Willingness to pay estimates produced by the RPL with and without interaction terms were compared with those of a standard binary logit model.

4.2 Previous studies

Within the multinomial logit framework, one option for modeling heterogeneity is to estimate the *B* coefficients as function of observable respondent's characteristics such as, for example, income and education. These individual characteristics are interacted with choice-specific attributes, which allow preferences and willingness to pay to vary according personal characteristics of the respondent.

The RPL model (also called mixed logit) generalizes the multinomial logit while allowing the taste parameters of observed variables to vary randomly in the population. Variance in the individual-specific parameters produces correlation in the stochastic portion of utility. Consequently, unlike standard multinomial logit models, RPL does not exhibit the restrictive substitution patterns implied by the independence of irrelevant alternatives (IIA) and can represent a much broader range of choice situations, allowing for a greater variability of preferences for choice-specific attributes across individuals (Train, 1998; Brownstone and Train, 1999; Train 1999a and 1999b). The specification of the utility that a respondent *n* obtains by choosing a given alternative is the same for both the multinomial logit and the RPL, and can be expressed as $U_{nj} = \beta'_n X_{nj} + \varepsilon_{nj}$. The difference is that in the RPL the β_n's vary over individuals rather than being fixed.

The use of the random parameter logit is a fairly new approach in modeling choice behavior. Nonetheless, this model has been used in a variety of applications such as recreational demand and transportation research as well as in commodity demand studies. In the context of recreational demand, Train (1998) estimated a RPL to model anglers' choice of fishing sites. Standard deviations for all the random coefficients were significant, which indicates that the parameters indeed varied across the population. Part of this variation in tastes, however, could have been explained by characteristics of the respondents, such as socio-demographic variables, which were not included in the RPL model.

McConnell and Tseng (2000) estimated a RPL to determine choice of beaches. They found that the fixed parameter attached to travel cost varied very little between the RPL and the standard logit. However, some of the random coefficients of the RPL were significantly different from the fixed coefficients of the standard logit. Breffle and Morey (2000) modeled salmon fishing participation and site choice using different model specifications. RPL explained choices significantly better than models that assumed homogeneity of tastes. Stated preference applications of the RPL include Layton (2000). He estimated a RPL using ranking data from a survey of public preferences for hazardous waste cleanup actions and found significant unobserved preference heterogeneity in the rankings, which violates the assumptions of the rank-ordered logit model. Also Morey and Rossmann (1999) used RPL to estimate benefits from different levels of preservation of marble monuments. They compared a RPL with a classic model of heterogeneity. The RPL predicted choices significantly better than the classic model, which in turn predicted better than a model of homogeneous preferences.

In addition, RPL has been used in combined revealed and stated preference studies such as Revelt and Train (1998), where they estimated a mixed logit for households' choice of appliances. The mean coefficients for the RPL were consistently larger than the fixed coefficients for the standard logit and the standard deviations of the random coefficients were still highly significant after including socio-demographic variables in interaction with price. Brownstone et al. (2000) compared a multinomial logit with a RPL using stated and revealed preference data on preferences for automobiles. The RPL performed better than the logit model in terms of goodness of fit and revealed a large heterogeneity among respondents for alternative fuel-vehicles.

This paper contributes to this literature by exploring the implications of the use of RPL in the analysis of repeated dichotomous choice contingent valuation data in terms of overall statistical performance and the magnitude of welfare estimates. This adaptation of the RPL model to dichotomous choice contingent valuation represents an important extension of RPL to one of the most widely used stated preference methods in non-market valuation.

4.3 The Random Parameter Logit Model

The specification of the RPL model can be described as follows. A respondent faces a choice among j alternatives within choice set J in each of t choice occasions. This choice is modeled using a random utility maximization (RUM) framework. The person's utility obtained from choosing alternative j on choice occasion t is the same as for a multinomial logit model and can be represented as:

$$U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt} \qquad (4.1)$$

where:

n $= 1,\dots,N$ is the number of respondents.

j = number of alternatives within choice set J.

t = number of choice occasions.

x_{njt} = M-dimensional column vector of observed variables related to alternative j and respondents n.

B_n = M-dimensional row vector of individual parameters.

ε_{njt} = extreme value error $(0,\sigma^2)$, iid over alternatives and independent of B and x.

The number of alternatives, the number of choice occasions, and the choice set can be the same or vary over respondents. In this application every respondent chose between two alternatives (j=2) in each of three survey scenarios (t=3) and these survey scenarios were the same for all respondents, as is typical in most dichotomous choice contingent valuation surveys.

In the RPL, B_n is unobserved for each individual and varies over respondents. The fact that B_n does not carry the subscript t implies that although tastes vary over respondents, they are assumed to be constant over survey scenarios. Given B_n, the conditional probability that individual n chooses alternative j in survey scenario t corresponds to:

$$L_{njt}(\beta_n) = \frac{\exp(\beta'_n X_{njt})}{\sum_i \exp(\beta'_n X_{nit})} \tag{4.2}$$

The unconditional probability shown in equation 4.3 is the integral of the conditional probability over all values of B_n, which in turn depends on the parameter θ, where P_{njt} is the choice probability for observation n and alternative j in survey scenario t, $L_{njt}(B_n)$ is the logit formula evaluated with coefficients B, and $f(B \mid \theta)$ is the density of B.

$$P_{njt}(\theta) = \int L_{njt}(B_n) f(\beta_n \mid \theta) d\beta_n \qquad (4.3)$$

The individual is assumed to know the value of her/his own coefficient B and random term ε for all the alternatives in the choice set J. The researcher on the other hand, does not observe the B_n's for each person, but knows that they vary in the population with density $f\ (B \mid \theta)$ (Train, 1999a and 1999b). B_n can be thought of as diverging from the population mean, b, by an individual stochastic component η_n that reflects the person's preferences relative to the average tastes in the population such that utility can be expressed as $U_{njt} = b' x_{njt} + \eta_n x_{njt} + \varepsilon_{njt}$. While b can be estimated, η_n cannot be observed for each individual and, consequently, there will be a non-observable part of utility represented by $\eta_n x_{njt} + \varepsilon_{njt}$ correlated among different alternatives.

Supposing for example that B_n is distributed $N(b, \Sigma)$ with η_n $N(b, \Sigma)$, when Σ is not different from zero, RPL is equivalent to conditional logit, since the variance of the random coefficients reflects the variation in individual preferences and, consequently, more variance implies more heterogeneity (McConnell and Tseng, 2000). When the variance of the B is high, a greater range for η_n can be expected and hence larger diversity in behavior will be observed. For the maximum likelihood estimation, the conditional probability of the sequence of choices made by each respondent is obtained according to equation 4.4, where $nj(n,t)$ represents the alternative chosen by person n in survey scenario t.

$$S_n(\beta_n) = \prod_t L_{nj(n,t)t}(\beta_n) \qquad (4.4)$$

The unconditional probability for the sequence in equation 4.4 is given by:

$$P_n(\theta^*) = \int S_n(\beta_n) f(\beta_n \mid \theta^*) d\beta_n \tag{4.5}$$

Since the integral in equation 4.5 does not have a close form, the probabilities have to be simulated by summing over R random draws of B, which are taken from the probability density function $f(\beta \mid \theta)$ (Morey and Rossmann, 1999; Train, 1998, 1999a and 1999b). The random draws are labeled $B^{r\backslash\theta}$, with r=1,...,R. The logit formula is calculated for each random draw and the simulated probability (SP) shown in equation 4.6 is the average of these calculations.

$$SP_n(\theta) = (1/R)\sum_{r=1,\ldots,R} S_n(B_n^{r/\theta}) \tag{4.6}$$

SP_n is an unbiased estimate of P_n whose variance decreases as R increases. The simulated log-likelihood function (SLL) shown in equation 4.7 is created from the simulated probabilities and the estimated parameters θ are those that maximize SLL (Train, 1999b).

$$SLL(\theta) = \Sigma_n \, ln(SP_n(\theta)) \tag{4.7}$$

The bias in SLL decreases as R increases, therefore a large number of draws are recommended in the estimation. In this application 500 draws were used. As suggested by Train (1999b), Halton draws rather than random draws were used, since they provide a more efficient simulation for the RPL. All estimations were conducted using GAUSS for Windows NT/95 version 3.5. The code developed by Train et al.[7] was modified in order to make it fit the estimation at hand.

In the RPL, the mean of the random parameters is estimated along with the variance and consequently the attributes with random coefficients will generate a distribution around the mean, which will reveal the existence of preference heterogeneity (Hensher, 2001). The random coefficients can be given different distributions such as normal, lognormal, triangular, or uniform. With the normal distribution, some individuals will have negative parameters and others positive, with the proportion of each group determined by the mean and standard deviation of the distribution (Train, 1998 and 1999b). The log normal distribution is useful when the coefficient is known to have the same sign for every person but, as a shortcoming, it produces a very thick tail.

As Hensher (2001) pointed out, none of the distributions has all the desirable properties and the selection of one over another is still an area of current research. Although a normal distribution of the random parameters is the most common assumption, in principle, one can choose any of the distributions that are expected to fit the estimated parameters. Of course, the choice of distribution can be guided by economic theory, since theory will often indicate if a variable can be given a sign or not.

In the application at hand, the criterion to select the distribution was that the random coefficients could take on either sign for different individuals in the population.

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[7] This code was developed by Kenneth Train, David Revelt, and Paul Ruud at University of California, Berkeley. Version is dated August 17, 1996. The adapted code is given in Appendix V.

Consequently, distributions of the B_n's were explored that support both positive and negative coefficients for a given attribute, namely the normal distribution. With the price coefficient fixed, willingness to pay follows the same distribution as the attribute's coefficient and can be easily calculated as the ratio between the mean of the random coefficient of the particular attribute and the price coefficient. The standard deviation of willingness to pay can be calculated as the ratio between the standard deviation of the random coefficient and the price coefficient (Revelt and Train, 1998).

Two different specifications of the model were estimated. The first includes only choice-specific attributes, while the second includes individual variables in interaction with the alternative's price. The conditional indirect utility expressions for these specifications are shown in equations 4.8 and 4.9 respectively. If the B's are not allowed to vary over the population, the models in equation 4.8 and 4.9 reduce to the classical multinomial logit, where heterogeneity is represented by the interaction terms. In the RPL specification instead, B_2 and B_3 in the first specification and B_5 and B_6 in the second, were allowed to vary over people while price and the interaction terms were kept fixed. Both RPL specifications were compared against the conventional binary logit model commonly used in dichotomous choice contingent valuation studies.

$$V_{njt}=B_1*p+B_2*acres+B_3*recreation \tag{4.8}$$

$$V_{njt}=(B_1+B_2*inc + B_3*vis+ B_4*wildlife)*p+B_5*acres+B_6*recreation+\varepsilon_{njt} \tag{4.9}$$

where:

p= price of the management alternative. It equals 0 for alternative A (status quo) and it takes on one of fifteen amounts from \$2 to \$295 for alternatives B, C, and D.

acres= number of acres to be kept as open space by public ownership. It takes on three different values: 0 for option A, 1,400 for alternatives B and D, and 1,600 for option C.

recreation= number of visitors allowed to float the river. It takes on three different values: 30,000 for alternatives A and D, 45,000 for option B, and 22,500 for option C.

inc= personal income.

vis= dummy variable, 1=visitor and 0 otherwise.

wildlife=attitudinal variable indicating whether wildlife habitat was a desirable use of the open space; ranges from 1 to 4, with 1= not desirable and 4=very desirable.

4.3.1 Research Hypotheses

The existence of heterogeneity was tested by determining the significance of the standard deviations of the random coefficients. If heterogeneity of preferences does not exist, the standard deviations on the acres and recreation variables would not be significantly different from zero as the null hypotheses in equation 4.10 indicate.

$$H_o\text{: } \sigma\, acres = 0 \text{ and } H_o\text{: } \sigma\, recreation = 0 \qquad (4.10)$$

4.4 Data

The data to illustrate an application of the RPL came from a survey, which aimed to quantify attitudes and economic values toward alternative ways of managing 1,600 acre of public lands administered by the Bureau of Land Management (BLM) along the Snake River in the Jackson Hole, Wyoming. This study relied upon the sub-sample of local residents, i.e. Teton County respondents.

To develop and refine the survey instrument, four focus groups were conducted: Jackson Hole residents who were visitors to the area (visitors), residents of Jackson Hole who were not visitors (local residents), Cheyenne residents (Wyoming residents), and finally Denver residents (rest of U.S). Pretesting complemented the focus groups sessions and included on site pretests of visitors and in-depth personal interviews of a sample of Cheyenne residents.

The final survey was conducted from August through December 2000. The mailing procedure followed a repeated mailing approach, with a second mailing to households that failed to return the first one. The survey booklet used included an introductory section, which described the lands, the issues before BLM and four possible management strategies (A, B, C, D) along with a map of the location of the 27 parcels of BLM public lands (1,600 acres). The introductory section was followed by a series of attitudinal questions asking the respondents to rate the desirable uses for these 27 parcels.

Alternative A was the sale of 26 of the 27 parcels of public lands (1,589 acres) to private landowners with the only restrictions on use being local zoning. Thus, the lands could be developed for houses or remain undeveloped with no public access from the levees or from the river. Mining and livestock grazing could occur if desired by the private owner. These development activities would reduce the amount and quality of wildlife and restrict some of the existing recreational activities (boat-in camping), although the number of river visitors would remain at the actual amount of 30,000.

Alternative B was to keep 19 parcels (1,400 acres) in public ownership and trade up to eight parcels to other public agencies or to private landowners. The purpose of the sale or trade would be to acquire more accessible lands or adjoining remaining BLM lands, to develop recreation facilities and manage for increased visitor use from the current number of 30,000 to 45,000 (up to 50% increase in river rafting use). However, increased recreation use would result in harmful effects to wildlife, particularly in camping areas.

Alternative C was to keep all 27 parcels (1,600 acres) in some form of public ownership and to emphasize wildlife habitat management by limiting river recreation (reduce river rafting by 25%). The number of river visitors would decrease from 30,000 to 22,500 per year.

Finally, alternative D was the most development oriented strategy and would keep 19 parcels (1,400 acres) in public ownership and sell up to eight parcels to private landowners. Although the number of river visitors would remain in 30,000 the development activities would harm wildlife habitat.

Based on the focus groups and pretesting, one of fifteen different dollar amounts was offered to each respondent ranging from $2 to $295. It was explained that the household would have to pay this amount in higher taxes in order to secure the retention and increased management of the BLM administered lands along the Snake River. The wording of the willingness to pay question was the following:

"Would your household pay $xx increase in federal income taxes each year for 20 years into a BLM Snake River Management Fund to be used only for managing these lands according to management strategy (B, C, D) instead of having BLM sell these public lands (alternative A)?" Yes ------- No-------

This dichotomous question was modeled using the conventional binary logit model. For the estimation of the RPL, a *no* response to this question was considered equivalent to choosing alternative A (status quo), whereas a *yes* response was equivalent to selecting another alternative (B, C, or D) in the particular choice occasion or survey scenario. After the valuation questions, demographics were collected on each respondent as well as information about the recreational use of the Snake River and frequency of visits.

4.5 Results

The response rate for the sub-sample of local residents from Teton County was 59%, which gave a sample size of 308 respondents. When asked for the most preferred management alternative at no cost to them, most respondents chose alternative C, which enhanced wildlife protection at the expense of a 25% reduction in recreational use. Alternative B, which increased recreational use, was the second preferred. These results are shown in Table 4.1.

As to preferences for different uses of the BLM-administered public lands, bird nesting, wildlife, fish habitat, non-motorized recreation, and open space ranked as the most desirable uses, while houses, grazing, motorized recreation, and sand gravel mining rated as the least desirable uses.

Table 4.1. Management alternative preferences.

Management Alternative	Percentage of Respondents
A	2.4%
B	25.4%
C	54.9%
D	17.4%
Total	100.0%

The variables to be included in the RPL analysis were selected by first running a series of binary logit models. Other attributes, although individually significant, were collinear when introduced along acres and recreation. Many socio-demographic variables were found significant when included individually, but they were not significant when interacted with price.

Table 4.2 shows the mean values of the variables included in the models. In order to facilitate convergence of the RPL, some of the variables had to be scaled. Number of acres was divided by 10, recreation was divided by 1,000, and income was divided by 10,000. The same scaling was used for the binary logit models.

Table 4.2. Mean values of explanatory variables.

Variable	Mean value
Price of management alternative ($)	60.5
Acres kept in public management	1,467
Number of recreators	32, 500
Income ($)	93,458
Visitor: dummy [1,0] variable	---
Wildlife: rank 1 to 4	---

4.5.1 RPL with only choice-specific attributes

The results in Table 4.3 compare the estimates produced by a binary logit versus the RPL estimates with normally distributed random parameters, including only choice or scenario-specific attributes (equation 3.8). In the binary logit model all coefficients were significant at all conventional levels and had the expected signs. In the RPL, the estimated mean coefficient of the distribution of *acres* was positive and significant.

Table 4.3. Binary logit and RPL estimates.

Attribute	Parameter	Binary Logit	RPL
Price	Mean	-0.0052[a] (0.0009)	-0.067[a] (0.02)
Acres	Mean coefficient	0.062[a] (0.011)	0.014[a] (0.003)
	St. dev. of coefficient	------	0.020[a] (0.006)
Recreation	Mean of coefficient	0.048[a] (0.011)	0.004 (0.006)
	St. dev. of coefficient	------	0.022[a] (0.002)
LL Function Value		-584.58	-504.24
WTP ($/10 acres)	Mean WTP	$11.92	$0.20
	St. dev. WTP	------	$0.29
WTP ($/1000 visitors)	Mean WTP	$9.29	------
	St. dev. WTP	------	$0.13

* Standard errors in parenthesis.
** Superscript "a" indicates the coefficient is significant at 1% level.

The standard deviation was also highly significant implying that preferences indeed vary in the population for this attribute. Thus, the null hypothesis of preference homogeneity for acres of open space was rejected. The reason for this preference heterogeneity would be that in an area such as Jackson Hole with little private land and very high housing costs, some county residents would prefer the public land be made available for development while others more environmentally inclined may prefer protection of open space. Thus, the issue of positive and negative attitudes toward the resource may be ideally tested using the RPL specification.

The mean coefficient of the distribution of *recreation* was insignificant while the estimated standard deviation was large and highly significant suggesting heterogeneity of preferences in the population. This result suggests that respondents have contrasting views about the number of recreators, such that those respondents that see it as a positive attribute nearly offset those that perceive it as negative. This is a reasonable conclusion given that some respondents may place greater value on allowing for increased recreation use, as this is the only currently unregulated and uncapped section of the Snake River. On the other hand, another segment of the population can see it as a negative feature given that more recreational use may create crowding and harm wildlife habitat. The positive coefficient yielded by the binary logit instead masks this variation suggesting that respondents see the recreational use as a distinctly positive feature. Again, the RPL is ideally suited to testing for this variation.

For both the RPL and binary logit, willingness to pay for each attribute was calculated as the ratio between the coefficient of the attribute and the price coefficient. For the binary logit, the average respondent was willing to pay \$11.92 for ten extra acres of land being kept under public management and \$9.29 for an increase in visitor use of 1,000 persons per year. For the RPL, the estimates were considerably smaller. Willingness to pay for ten extra acres of land was equal to \$0.20.

Given the price coefficient, the results from the RPL imply that willingness to pay for a ten-acre increase in land is normally distributed with mean 0.20 and standard deviation 0.020/.067=0.29. This deviation represents a significant variation in willingness to pay in the population and suggests that a proportion of the respondents have a negative coefficient on *acres*. The negative coefficient is evidence of the fact that "more conservation" is not always good for everyone. This is consistent with the assumption of a normally distributed random coefficient, which allows respondents to have both negative and positive parameters for a given attribute. The standard deviation of the willingness to pay distribution for *recreation* was equal to 0.022/0.067=0.32, but given that the mean coefficient was not significant, the interpretation of the size of the standard deviation is not all that meaningful.

4.5.2 RPL with choice-specific attributes and demographic interaction terms

Although the estimates in Table 4.3 indicate that the parameters vary in the population, they do not show to what extent this variation can be explained by individual characteristics of the respondents. The nature of this variation can be captured by interaction terms between individual characteristics of the respondent and choice-specific attributes. Table 4.4 presents the results for the model with interaction terms specified in equation 4.9 and normally distributed random parameters. *Int1* is the interaction between the price of the alternative and income of the respondent, *Int2* is the interaction between price of the alternative and visitor status of the respondent, and *Int3* is the interaction between the attitudinal variable wildlife and price of the alternative. Including these cross-products accounted for the fact that people with different incomes, different visitor status, and wildlife preferences may have different elasticities with respect to each management alternative.

Thus, in this RPL specification, willingness to pay for the attributes varied with income and visitor status as well as the respondent's most desirable use for the public lands, given that the price of the alternative entered the model in interaction with these variables. In the binary logit, all the coefficients were significant at conventional levels and they had the expected signs. In the RPL *price*, the mean coefficient on *acres*, *Int2* and *Int3* were also significant.

Table 4.4. Binary logit and RPL estimates with interaction terms of individual demographics and attitudes.

Attribute	Parameter	Binary Logit	RPL
Price	Mean	-0.066[a]	-0.092[a]
		(0.011)	(0.036)
Acres	Mean of coefficient	0.049[a]	0.010[a]
		(0.008)	(0.001)
	St. dev. of coefficient	------	0.016[a]
			(0.001)
Recreation	Mean of coefficient	0.037[a]	0.007
		(0.010)	(0.008)
	St. dev. of normal coefficient	------	0.0005
			(0.001)
Int1 (Income*price)	Mean of coefficient	0.0027[a]	0.004
		(0.0013)	(0.003)
Int2 (Visitor*price)	Mean of coefficient	0.018[a]	0.035[a]
		(0.005)	(0.012)
Int3 (Wildlife*price)	Mean of coefficient	0.105[a]	0.114[a]
		(0.026)	(0.087)
LL Function Value		-551.56	-503.78
WTP ($/10 acres)	Mean	$0.75	$0.11
	St. dev.	------	$0.18
WTP ($/1000 visitors)	Mean	$0.56	------
	St. dev.	------	------

*Standard errors in parenthesis
** Superscript "a" indicates the coefficient is significant at 1% level.

Int1 and the mean and standard deviation of *recreation* were insignificant. The estimate of the standard deviation on *acres* was still large and significant indicating that willingness to pay for this attribute varies beyond what can be explained by visitor status of the respondents or the preferred use for the open space. Thus, the null hypothesis of preference homogeneity for the acres of open space variable was also rejected in this case. The binary logit yielded much lower estimates of willingness to pay for both attributes than in the preceding logit model (Table 4.3) but still larger than those produced by the RPL. Willingness to pay for a ten-acre increase in public land was equal to \$0.75 and willingness to pay for an increase in visitor use of 1,000 persons per year was equal to \$0.56. The RPL implies that willingness to pay for ten extra acres of land being kept in public management is normally distributed with a mean equal to 0.0105/0.092= \$0.11 and standard deviation equal to 0.016/0.092=0.18. These results are close in magnitude to those in Table 4.3 for the RPL and confirm that a proportion of the population place a negative sign on the coefficient of acres and consequently, has negative willingness to pay for this attribute.

4.6 Conclusions

The use of RPL has become a popular approach in modeling choice behavior since unlike conventional logit models it has the advantage of capturing much broader substitution patterns among choice alternatives. RPL has been used in a variety of applications such as recreational demand and transportation research as well as in commodity demand studies, but little is known about its use in modeling dichotomous choice contingent valuation data.

In this analysis, the RPL model was adapted to model heterogeneous preferences for alternatives of management of open space. RPL was compared against a standard binary logit model used in conventional dichotomous choice contingent valuation analysis. Two choice-specific attributes (acres and recreation use levels) were included along with individual characteristics of the respondents and attitudinal variables to account for respondents' preferences. The RPL yielded consistently smaller estimates of the random coefficients than the binary logit estimates. Consequently, marginal willingness to pay for an increase in public land was smaller in the RPL than in the binary logit. These results confirm the existence of heterogeneity in respondents' preferences for alternatives of public land management, which is reflected in significant standard deviations of the random parameters. Standard deviation on acres remained significant after personal and attitudinal variables were included in interaction with the price of each alternative, which suggest that tastes vary beyond what these individual characteristics of the respondents can explain.

It is important to note that for most studies the results obtained depend on the application at hand. Thus, for example, some studies find small differences between willingness to pay from a conventional logit compared to a RPL, while others report large differences in willingness to pay estimates from both models. Furthermore, some studies such as that by Revelt and Train (1998) report that willingness to pay estimates from logit and RPL were different for some attributes but similar for others.

These varied results may be ascribed to the nature of the good and the attributes being valued. If people have in fact homogeneous preferences for the good, the RPL specification might not result in a significant gain with respect to the conventional logit model. If, on the other hand, the good in question generates contrasting preferences, the random parameter specification is more likely to be the proper model. In this case, the logit model can falsely conclude that a particular attribute is not statistically significant due to a large variance on the fixed coefficient. However, it might be that the attribute in question does matter, but positively for some people and negatively for others. This information on the variation in tastes and valuation can be quite useful to policy makers and public land managers who must balance welfare of a diverse population, rather than manage for the average person when making decisions.

4.7 References

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CHAPTER V

CONCLUDING REMARKS

This Dissertation has examined the issue of heterogeneous preferences in the estimation of welfare measures derived from contingent valuation studies, and has presented three different modeling approaches to jointly account for positive and negative values towards the provision of environmental public goods.

Given that some environmental policies and programs may generate a combination of non-market goods and bads, heterogeneity in values is likely to occur and, consequently, there is a rationale for the existence of winners and losers when such policies and programs are implemented. So far, nonetheless, contingent valuation studies have tended to ignore this dichotomy of preferences, arguing that provision of environmental goods should be distinctly utility increasing for everybody. Under the same premise, these studies have consistently used modeling techniques that restrict willingness to pay measures to positive values, ruling out the possibility that some people may have authentic zero and negative willingness to pay for the public good in question.

When a public policy or program may result in winners and losers, contingent valuation studies should enable respondents to explicitly express positive, zero, and negative bids and use modeling techniques that appropriately reflect this preference variation.

The series of three papers that composed this Dissertation, presented elicitation formats and associated econometric models that explicitly accounted for heterogeneity of preferences in the estimation of willingness to pay measures.

Given the difficulty of eliciting negative willingness to pay values, in the first two papers willingness to accept compensation was used as a proxy for negative willingness to pay. The first paper presented a double bounded dichotomous choice model of positive and negative preferences. In this model willingness to accept bids were coded as negative willingness to pay bids in the estimation process, which allowed the combination of negative and positive preferences for the good. The double bounded specification was used to estimate net benefits or net losses for the prescribed burning program.

In the second paper, the data structure allowed for the identification of negative, positive, and zero willingness to pay responses. The three response categories were jointly modeled using parametric and non-parametric extended spike models. Both specifications were used to calculate a net measure of willingness to pay, which took into account that a proportion of the population had negative and zero willingness to pay for the prescribed burning program.

The third paper, presented a random parameter logit model, which allowed the individual coefficients to vary over people to reflect heterogeneity. The results revealed that a proportion of the respondents had, in fact, negative coefficients and, consequently, negative willingness to pay for the attributes associated to the public good being valued.

Given the current importance of the contingent valuation method (CVM) as a technique for valuing non-market goods, it is vital that CVM studies generate reliable and unbiased welfare measures that can serve as basis for policy formulation. In order to achieve this objective, a vital issue is to properly elicit and model preference heterogeneity.

The results from all three papers presented here, showed that neglecting to account for preference variation produced consistently higher willingness to pay estimates, bias that was more serious when parametric techniques were used as compared to non-parametric approaches. In turn, this estimation bias can lead to overestimate the benefits of an environmental program or policy and it may result in a policy being implemented based on an erroneous benefit-cost analysis outcome. The bias can, however, be minimized by means of an appropriate CVM elicitation format and modeling techniques such as those presented here.

Finally, it is important to emphasize that welfare estimates can be sensitive to the survey scenario presented to the respondents as well as to the type of econometric models used. Therefore, examining a wider range of distribution functions in the estimation process is a natural extension of the studies presented here.

APPENDIX I

GAUSS CODE FOR THE DOUBLE BOUNDED WTP-WTA MODEL

```
new;
cls;
load z[775, 39] = a:\newdata.txt;
fuelred=z[.,1];
firered=z[.,2];
smokepr=z[.,3];
danger=z[.,4];
vote=z[.,5];
dep=z[.,6];
govpay=z[.,7];
govbid=z[.,8];
bi=z[.,9];
mvote=z[.,10];
rxbid=z[.,11];
mechvote=z[.,12];
herbvote=z[.,13];
seefire=z[.,14];
exsmoke=z[.,15];
bother=z[.,16];
visphys=z[.,17];
breath=z[.,18];
serious=z[.,19];
homeburn=z[.,20];
neighbor=z[.,21];
evac=z[.,22];
outcount=z[.,23];
longfla=z[.,24];
age=z[.,25];
yearnd=z[.,26];
ownrent=z[.,27];
home=z[.,28];
lotsize=z[.,29];
educ=z[.,30];
envorg=z[.,31];
hiking=z[.,32];
ethnic=z[.,33];
howmany=z[.,34];
income=z[.,35];
distance=z[.,36];
nbr=z[.,37];
mechbid=z[.,38];
berbid=z[.,39];
b = olsqr( dep , rxbid );
print "b: " b;
library cml;
```

```
#include cml.ext;
cmlset;
stval={130, -5};
@stval={130.65, -9};@
z=dep~govbid~bi~rxbid;
proc loglik(b, z);

@ log-likelihood function @

local xs1,  xs11, xs22, xs221, xs222, xs31, xs311, xs322, xs4,  xs41,
      bi, bl, bh, kids, educa, gender, nold, safe, pnn, pny, pyn, pyy,
      e1, e2, e3, e4, lnpnn, lnpny, lnpyn, lnpyy;

      e1 = (z[.,1].==1);
      e2 = (z[.,1].==2);
      e3=  (z[.,1].==3);
      e4=  (z[.,1].==4);

xs1=selif(z, e1);
xs11= ones(rows(xs1),1)~xs1[.,  2 ];
xs22=selif(z, e2);
xs221= ones(rows(xs22),1)~xs22[.,  3];
xs222= ones(rows(xs22),1)~ xs22[., 2  ];
xs31=selif(z, e3);
xs311=ones(rows(xs31),1)~xs31[.,  4  ];
xs322=ones(rows(xs31),1)~xs31[.,  3  ];
xs4= selif(z, e4);
xs41=ones(rows(xs4),1)~xs4[., 4  ];

@Probabilities@
      pnn= (1./(1+exp(-xs11*b)));
      pnn= pnn.*(1-(pnn.<0))+0.00001;
      pny=(1./(1+exp(-xs221*b)))-(1/(1+exp(-xs222*b)));
      pny= pny.*(1-(pny.< 0))+0.00001;
      pyn= (1./(1+exp(-xs311*b)))-(1/(1+exp(-xs322*b)));
      pyn= pyn.*(1-(pyn.< 0))+0.00001;
      pyy= 1-(1./(1+exp(-xs41*b)));
      pyy= pyy.*(1-(pyy.< 0))+0.00001;

lnpny=ln(pny);
lnpnn=ln(pnn);
lnpyy=ln(pyy);
lnpyn=ln(pyn);
retp( lnpny| lnpnn| lnpyy| lnpyn);

endp;

/* set maxlik parameters and output */

__title="Double-Bounded Logit Model";
_cml_algorithm= 1;

@_max_FinalHess;@
_cml_GradCheckTol=1e-4;
_cml_LineSearch=3;
_cml_Delta = .01;
_cml_GradMethod=0;
```

```
_cml_DirTol=1e-4;
_cml_CovPar=3;

{b,logl,g,vc,ret}=CMLprt(cml(z,0,&loglik,stval));

holdhessian=_cml_FinalHess;

print " holdhessian= " holdhessian;
```

APPENDIX II

CODE AND LOG-LIKELIHOOD FUNCTIONS FOR THE SIMPLE AND EXTENDED PARAMETRIC SPIKE MODELS

```
reset;
read  ; nobs = 479
      ; nvar = 7  ;file= a:/spikedata3.txt
      ; names=  VOTE,GOVPAY,GOVBID, MVOTE,BID,voteone, dep $

create; if (dep=2) e=1$
create; if (dep=3) d=1$
create; if (dep =4) f=1$
create; if (dep=1) g=1$
create; if (dep=5) h=1$
create; if (vote=0) z1=1$
create; if (mvote=1) z2=1$
create; if (mvote=0) z3=1$
$Simple spike with negatives as 0$
skip;
minimize;labels=a,c;
start= 1.3, 0.006;
fcn=- (z1*log(1/(1+exp(a)))+
       z3*log((1/(1+exp(a-c*bid)))-(1/(1+exp(a))))+
       z2*log(1/(1+exp(-a+c*bid)))); print vcov$

$Extra intercept parameter$
minimize;labels=a,c,r;
start= 1.3, 0.06, 1.5;
fcn=- (g*log(1/(1+exp(a+c*govbid)))+ h*log((1/(1+exp(a)))-
(1/(1+exp(a+c*govbid))))+ e*log((1/(1+exp(r)))-(1/(1+exp(a))))+
d*log((1/(1+exp(r-c*bid)))-(1/(1+exp(r))))+ f*log(1-(1/(1+exp(r-
c*bid))))); print vcov$

$Extra slope parameter $

minimize;labels=a,c,r,z;
start= 0.8053, 0.00288,0.49, 0.0417;
fcn=-(g*log(1/(1+exp(a+c*govbid)))+ h*log((1/(1+exp(a)))-
(1/(1+exp(a+c*govbid))))+ e*log(1/(1+exp(r))-1/(1+exp(a)))+
d*log((1/(1+exp(r-z*bid)))-(1/(1+exp(r))))+ f*log(1-(1/(1+exp(r-
z*bid))))); print vcov$
```

APPENDIX III

BINARY LOGIT, SIMPLE SPIKE, AND EXTENDED SPIKE COEFFICIENT ESTIMATES FOR THE MONTANA SUB-SAMPLE

Binary logit estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	0.7233	0.2133	3.390	0.0007
$\tilde{\beta}$	-0.0021	0.0009	-2.348	0.0189

Simple spike estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	0.8131	0.1445	5.626	0.0000
$\tilde{\beta}$	0.0051	0.0005	9.937	0.0000

Spike 1 estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	1.1194	0.1429	7.829	0.0000
$\tilde{\beta}$	0.0036	0.0003	10.633	0.0000
$\tilde{\gamma}$	0.6411	0.1267	5.058	0.0000

Spike 2 estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	1.3039	0.1628	8.005	0.0000
$\tilde{\beta}$	0.0006	0.0003	2.107	0.0351
$\tilde{\gamma}$	0.8139	0.1446	5.628	0.0000
$\tilde{\lambda}$	0.0051	0.0005	9.936	0.0000

APPENDIX IV

BINARY LOGIT, SIMPLE SPIKE, AND EXTENDED SPIKE COEFFICIENT ESTIMATES FOR THE CALIFORNIA SUB-SAMPLE

Binary logit estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	2.2319	.3113	7.169	0.0000
$\tilde{\beta}$	-0.0043	0.0011	-3.770	0.0002

Simple spike estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	1.5862	0.1786	8.881	0.0000
$\tilde{\beta}$	0.0037	0.0006	6.169	0.0000

Spike 1 estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	1.9479	0.1920	10.142	0.0000
$\tilde{\beta}$	0.0031	0.0004	7.119	0.0000
$\tilde{\gamma}$	1.4924	0.1602	9.311	0.0000

Spike 2 estimates

Variable	Coefficients	Standard Error	T-ratio	P-value
$\tilde{\alpha}$	2.0445	0.2116	9.662	0.0000
$\tilde{\beta}$	0.0013	0.0006	2.226	0.0260
$\tilde{\gamma}$	1.5875	0.1788	8.878	0.0000
$\tilde{\lambda}$	0.0037	0.0006	6.168	0.0000

APPENDIX V

RANDOM PARAMETER LOGIT CODE [8]

```
@ Space allocation for program. Do not change. @
new , 30000;
@ Output to screen? (in addition to file) @
screen on;
@ Name of the output file, reset=overwrite existing file, on=add to it @
@output file=c:\temp2\output.txt reset;@
@ Put a title for your output in the quotes below. @
print "Mix logit with 1 fixed, 1 normal, 2 uniform, and 2 triangular.";
print ;
@ 1 to check inputs for conformability and consistency, else 0. @
VERBOSE = 1;
@ Number of people. (integer) @
NP = 308;
@ Number of observations. (integer) @
NOBS = 924;
@ Maximium number of alternatives. (integer) @
NALT = 2;
@ Load or create XMAT (contain all of the explanatory variables and the@
@ censoring variable (if needed), YVEC (the dependent variable), @
@ and TIMES (giving the number of choice situations for each person.)@
@------------------------------------------------------------@

load XMAT[924,12] = a:\xmat29.txt;
load YVEC[924,1] = a:\h1yvec.txt;
load TIMES[308,1] = a:\h1times.txt;
@ Variables are now: price, acres, recreation, int1, int2, int3; 4 fixed, 2 random @
@ Number of variables in XMAT. (integer) @
NVAR = 6;
@ Give the number of explanatory variables that have fixed coefficients. @
@ (integer) @
NFC = 4;
@ NFCx1 vector to identify the variables in XMAT that have fixed @
@ coefficients. (column vector) @
IDFC = { 1, 4, 5, 6 };
```

[8] This code was adapted from the original code developed by K. Train, D. Revelt, and P. Ruud at University of California Berkeley. Original version is dated August 17, 1996.

```
@ Give the number of explanatory variables that have normally @
@ distributed coefficients. (integer) @
NNC = 2;
@ NNCx1 vector to identify the variables in XMAT that have normally @
@ distributed coefficients. (column vector) @
IDNC = { 2, 3 };
@ Give the number of explanatory variables that have uniformly @
@ distributed coefficients @
NUC = 0;
@ NUCx1 vector to identify the variables in XMAT that have uniformly @
@ distributed coefficients. (column vector) @
IDUC = { 0 };
@ Give the number of explanatory variables that have triangularly @
@ distributed coefficients @
NTC = 0;
@ NTCx1 vector to identify the variables in XMAT that have triangularly @
@ distributed coefficients. (column vector) @
IDTC = { 0 };
@ Give the number of explanatory variables that have log-normally @
@ distributed coefficients. (integer) @
NLC = 0;
@ NLCx1 vector to identify the variables in XMAT that have @
@ log-normally distributed coefficients. (column vector) @
IDLC = { 0 };
@ 1 if all people do not face all NALT alternatives, else 0. @
CENSOR = 0;
@ Identify the variable in XMAT that identifies the alternatives @
@ each person faces. (integer) @
IDCENSOR = 0;
@ If you want to weight the observation, set DOWT to 1, else 0 @
DOWT = 0;
@ If DOWT=1, load or create an NPx1 vector of weights. @
WEIGHT=0;
@ 1 to print out the diagonal elements of the Hessian, else 0. @
PRTHESS = 0;
@ 1 to rescale any variable in XMAT, else 0. @
RESCALE = 0;
@ If RESCALE = 1 create a q x 2 matrix to id which variables to @
@ rescale and by what multiplicative factor, else make RESCLMAT @
@ a dummy value. @
RSCLMAT = { 0 };
@ Starting values for the parameters. @
@ (NFC+(2*NNC)+(2*NUC)+(2*NTC)+(2*NLC)) x 1 vector of starting values. @
@ Order is NFC fixed coefficients, followed by mean and standard deviation of each @
@ of NNC normal coefficients, followed by mean and standard deviation of each of
NUC@
```

```
@ uniformly distributed coefficients, etc for the triangularly and log-normally @
@ distributed coefficients.@
B = { -0.005, 0.0023, 0.005, 0.012, 0.008, 0.02, 0.013, 0.0001};

@ 1 to constrain any parameter to its starting value, else 0. @
CZVAR = 0;
@ If CZVAR = 1, create a vector of zeros and ones of the same @
@ dimension as B identifying which parameters are to vary, else make @
@ BACTIVE = { 0 }. (column vector) @
BACTIVE = { 0 };
@ 1 to constrain any of the error components to equal each other, @
@ else 0. (integer) @
CEVAR = 0;
@ If CEVAR=1, create a matrix of ones and zeros to constrain the @
@ necessary random parameters to be equal, else make EQMAT=0. (matrix)@
EQMAT = { 0 };
@ Number of repetitions.  NREP must be >= 1. (integer) @
NREP = 500;
@ Choose random or halton draws. DRAWS=1 for random, 2 for Halton.@
DRAWS=2;
@ If DRAWS=1, set seed to use in random number generator. SEED1 must be >= 0.
(integer) @
SEED1 = 4;
@ If DRAWS=2, specify the following.@
@ HALT=1 to create Halton draws, HALT=2 to use previously created Halton draws. @
HALT=1;
@ If HALT=1, set SAVH=1 if you want to save the Halton draws that are created; 0
otherwise. @
SAVH=0;
@ HMNAME = path and name for file of halton sequences. Be sure to put double \\
where@
@ single \ appears in the path. @
@ If HALT=1 and SAVH=1, the Halton draws that are created are saved to this file.@
@ If HALT=2, the Haton draws that were previously saved to this file are loaded.@
@ Note that, if HALT=2, the sequences must meet the specs of the current model,@
@ that is, the same NREP, NOBS, number of random coefficients, and distribution for
each coefficient.@
HMNAME="c:\\temp2\\hm125.fmt";
@ Maximum number of iterations in the maximization. (integer) @
NITER = 200;
@ Tolerance for convergence. (small decimal) @
EPS = 1.e-4;
@ Identify the optimization routine: 1 Paul Ruud's routine     @
@                                   2 for Gauss's maxlik       @
OPTIM = 1;
```

```
@ Specify the optimization algorithm/hessian calculation.(integer)    @
@ Options with OPTIM=1: 1 for bhhh, 2 for numerical (newton-raphson)  @
@ Options with OPTIM=2: 1 for steepest descent, 2 for bfgs, 3 for dfp @
@     4 for numerical (newton-raphson), 5 for bhhh, 6 for prcg.       @
METHOD = 2;
@ 1 if OPTIM=1 and want to use modified iteration procedure; else 0. @
MNR = 1;
@ If OPTIM=1, set STEP to the step length the maximization routine @
@ should initially try. @
STEP = 1;
@ If OPTIM=1, then set ROBUST=1 if you want robust standard errors, or@
@ ROBUST=0 if you want regular standard errors. With OPTIM=2, this option doesn't
exist.@
ROBUST=1;
@==============================================================
========@
@@@ You should not need to change anything below this line        @@@
@==============================================================
========@
@ Create global for the number of estimated variables @
NEVAR = NFC+(NNC+NUC+NTC+NLC)*2;
@ Check inputs if VERBOSE=1 @
if ((VERBOSE /= 1) and (VERBOSE /= 0));
  print "VERBOSE must 0 or 1.";
  print "Program terminated.";
  stop;
endif;
if VERBOSE;
  pcheck;
else;
  print "The inputs have not been checked since VERBOSE=0.";
  print;
endif;

 @ Rescale the variables. @
 if RESCALE;
   j = rows(RSCLMAT);
   i = 1;
   if VERBOSE;
     if (RSCLMAT[.,1] > NVAR);
       print "RSCLMAT identifies a variable that is not in the data set.";
       print "Program terminated.";
       stop;
     endif;
     print "Rescaling Data:";
     print "       Variable     Mult. Factor";
```

```
   do while i <= j;
    RSCLMAT[i,1] RSCLMAT[i,2];
    XMAT[.,(RSCLMAT[i,1]-1)*NALT+1:RSCLMAT[i,1]*NALT] =
    XMAT[.,(RSCLMAT[i,1]-1)*NALT+1:RSCLMAT[i,1]*NALT] * RSCLMAT[i,2];
    i = i + 1;
   endo;
   print " ";
  else;
   do while i <= j;
    XMAT[.,(RSCLMAT[i,1]-1)*NALT+1:RSCLMAT[i,1]*NALT] =
    XMAT[.,(RSCLMAT[i,1]-1)*NALT+1:RSCLMAT[i,1]*NALT] * RSCLMAT[i,2];
    i = i + 1;
   endo;
  endif;
endif;

@ Print out starting values if VERBOSE = 1. @
if VERBOSE;
 print "There are " NP " respondents and " NOBS " observations.";
 print "The model has" NFC " fixed coefficients, for variables" IDFC;
 print "        and" NNC " normally distributed coefficients, for variables" IDNC;
 print "        and" NUC " uniformly distributed coefficients, for variables" IDUC;
 print "        and" NTC " triangularly distributed coefficients, for variables" IDTC;
 print "        and" NLC " log-normally distributed coefficients, for variables" IDLC;
 print;
 if CZVAR;
  print "Starting values:" ;
  print B;
  print ;
  print "Parameters that are estimated (1) or held at starting value (0):";
  print BACTIVE;
  print ;
 endif;
 if (CZVAR == 0);
  print "Starting values:";
  print B;
  print;
  print "All parameters are estimated; none is held at its starting value.";
  print;
 endif;
endif;

@ Create new B and BACTIVE with reduced lengths if @
@ user specifies equality constraints. @
if CEVAR;
 if CZVAR;
```

```
  BACTIVE = EQMAT * BACTIVE;
  BACTIVE = BACTIVE .> 0;
 endif;
 B = (EQMAT * B) ./ (EQMAT * ones((NFC+2*NNC+2*NUC+2*NTC+2*NLC),1));
 if VERBOSE and CZVAR;
  print "Some parameters are constrained to be the same.";
  print "Starting values of constrained parameters:";
  print B;
  print ;
  print "Constrained parameters that are estimated (1) or held at starting value (0):";
  print BACTIVE;
  print;
 endif;
 if VERBOSE and (CZVAR == 0);
  print "Some parameters are constrained to be the same.";
  print "Starting values of constrained parameters:";
  print B;
  print;
  print "All constrained parameters are estimated; none is held at its starting value.";
  print;
 endif;
endif;
@ Describing random terms. @
if VERBOSE;
 if DRAWS == 1;
  print "Random draws are used.";
  print "Random error terms are based on:";
  print "Seed:  " SEED1;
  print;
 elseif DRAWS == 2;
  print "Halton draws are used.";
  print;
 else;
  print "DRAWS must be 1 or 2. Program terminated.";
  stop;
 endif;
 print "Repetitions:  " NREP;
endif;
/* Number of random coefficients or 1, whichever is higher. */
NECOL = maxc( ones(1,1) | (NNC+NUC+NTC+NLC) );
if DRAWS == 2;
  /* CREATE OR LOAD HALTON SEQUENCES. */
  if HALT == 2;
   loadm hm = ^HMNAME;
   print "Loaded Halton sequences.";
  elseif HALT == 1;
```

```
@ Create the Halton sequence @
print "Creating Halton sequences ....";

 /* Provide prime number vector */
prim = { 2 3 5 7 11 13 17 19 23 29 31 37 41 43 47 53 59 61 67 71
         73 79 83 89 97 101 103 107 109 113 };
print "Halton sequences are based in primes: " prim[1,1:NECOL];
print;
/* Develop a halton matrix (hm) of size nrep x (nobs*necol); The first 'nobs'
columns provide halton numbers for first dimension of integration,
the second 'nobs' columns provide the halton numbers for the second
dimension, and so on; cdfinvn is the inverse cumulative standard normal
distribution function; PROC halton creates sequence; PROC cdfinvn takes
inverse normal: windows version of gauss has this as a command. For
non-normal distributions, use inverse of other distribution. */

h = 1;
hm = { };
do while h <= (NECOL);
   hm1 = halton(10+nrep*np,prim[h]);
   if h <= NNC or h > (NNC+NUC+NTC);  @ Normal and lognormal distributions.
@
         @ If there are no random coefs, st NECOL=1 while
NNC=NUC=NTC=NLC=0, @
         @ then, hm1 will be treated as normally distributed.@
      hm1 = cdfinvn(hm1);
      @ The inverse-normal proc produces very extreme values sometimes. This
truncates.@
       hm1=hm1.*(hm1 .le 10) + 10 .* (hm1 .gt 10);
       hm1=hm1.*(hm1 .ge -10) -10 .* (hm1 .lt -10);
   endif;
   if h > NNC and h <= (NNC+NUC);  @Uniform distribution.@
       hm1=hm1.*2 - 1;
   endif;
   if h > (NNC+NUC) and h <= (NNC+NUC+NTC); @Triangular distribution.@
       hm1= (sqrt(2.*hm1)-1).*(hm1 .<= 0.5) + (1-sqrt(2.*(1-hm1))) .* (hm1 .> 0.5);
   endif;
   hm = hm~hm1[11:rows(hm1),1];
   h=h+1;
endo;

print "Finished Halton sequences.";
if SAVH;
  save ^HMNAME = hm;
  print "Saved Halton sequences.";
endif;
```

```
  else;
    print "HALT must equal 1 or 2. Job terminated.";
    stop;
  endif;
 print "Number of rows in Halton matrix: " rows(hm);
 print "Number of columns in Halton matrix: " cols(hm);
endif;

@ END OF HALTON DRAWS @
@ IDA is a vector that identifies the variables with normal, uniform or triangular coefficients.@
@ It is used in LL, gradient and forecst procs. @
 IDA={0};
 if NNC>0; IDA=IDNC;  endif;
 if NNC==0 and NUC>0; IDA=IDUC; endif;
 if NNC>0 and NUC>0; IDA=IDA|IDUC; endif;
 if (NNC+NUC)==0 and NTC>0; IDA=IDTC; endif;
 if (NNC+NUC)>0 and NTC>0; IDA=IDA|IDTC; endif;

@ Create dependent variable permutation matrix for the gradient @
YPERM=zeros(NOBS,NALT);
i = 1;
do while i<=NOBS;
 YPERM[i,YVEC[i,1]] = 1;
 i = i + 1;
endo;
@ Initialize the STEP to twice its value for Paul Ruud's routine. @
if (OPTIM==1);
 STEP = STEP*2;
endif;
@ Set up and do maximization @
if OPTIM == 1;
 beta = domax(&ll,&gr,B,BACTIVE);
 print;
 print "Remember: Signs of standard deviations are irrelevant.";
 print "Interpret them as being positive.";
 print;
endif;

if OPTIM == 2;
 library maxlik,pgraph;
 #include maxlik.ext;
 maxset;
 _max_GradTol = EPS;
 _max_GradProc = &gr;
 _max_MaxIters = NITER;
```

```
_max_Algorithm = METHOD;
if DOWT;
  __weight = WEIGHT;
endif;
if CZVAR;
  _max_Active = BACTIVE;
endif;
{beta,f,g,cov,ret} = maxlik(XMAT,0,&ll,B);
call maxprt(beta,f,g,cov,ret);
print;
print "Remember: Signs of standard deviations are irrelevant.";
print "Interpret them as being positive.";
print;
if (CZVAR == 0);
  print "gradient(hessian-inverse)gradient is:" ((g/_max_FinalHess)'g);
else;
  g = selif(g,BACTIVE);
  print "gradient(hessian-inverse)gradient is:" ((g/_max_FinalHess)'g);
endif;
if PRTHESS;
  print "diagonal of hessian:" ((diag(_max_FinalHess))');
  print;
endif;
endif;

@ THIS IS THE END OF THE MAIN PROGRAM. @
@ PROCS ll, gr, gpnr, expand, domax, pcheck follow.@

/* LOG-LIKELIHOOD FUNCTION */
proc ll(b,x);

  @ Relies on the globals: NALT, NOBS, NP, NREP, NECOL, SEED1, CENSOR @
  @                        NFC, IDFC, NNC, NUC,NTC, IDA, NLC, IDLC @
  @                        CZVAR, BACTIVE, CEVAR, EQMAT, XMAT, DRAWS @

  local c, k, n, t, km, kmm, rd, seed2;
  local v, ev, p0, p00, err, mm;
  if CEVAR;
    b = EQMAT' * b;          @ Expand b to its original size. @
  endif;
  v = zeros(NOBS,NALT);        @ Argument to logit formula    @
  p0 = zeros(NP,1);          @ Simulated probability @
  if CENSOR;
    c = (IDCENSOR-1)*NALT;        @ Location of censor variable        @
  endif;
```

```
k = 1;
do while k <= NFC;          @ Adds variables with fixed coefficients @
  km = (IDFC[k,1]-1)*NALT;
  v = v + b[k] .* XMAT[.,(km+1):(km+NALT)];
  k = k+1;
endo;

seed2 = SEED1;
rndseed seed2;

rd = 0;
n = 1;
do while n <= NP;
  if DRAWS == 1;
     err  = rndn(NREP,NECOL);
      if NUC > 0;
           err[.,(NNC+1):(NNC+NUC)] = (rndu(NREP,NUC) .* 2) -1;
     endif;
      if NTC > 0;
          mm = rndu(NREP,NTC) ;
          err[.,(NNC+NUC+1):(NNC+NUC+NTC)] = (sqrt(2.*mm)-1).*(mm .<= 0.5)
                                   + (1-sqrt(2.*(1-mm))) .* (mm .> 0.5);
       endif;
   endif;
  if DRAWS == 2;
     err=hm[(NREP*(n-1)+1):(NREP*(n-1)+NREP),.] ;
  endif;
@ err has NREP rows and NECOL columns for each person. @

  p00 = ones(NREP,1);
  t=1;
  do while (t<=TIMES[n]);
    kmm = rd + t;
    ev = v[kmm,.];
    k = 1;
    do while k <= NNC+NUC+NTC;    @ Adds variables with normal, uniform and
tringular coefficients @
      km = (IDA[k,1]-1)*NALT;
      ev = ev + (b[NFC+(2*k)-1] + (b[NFC+(2*k)] .* err[.,k]))
          .* XMAT[kmm,(km+1):(km+NALT)];
      k = k+1;
    endo;
    k = 1;
    do while k <= NLC;       @ Adds variables with log-normal coefficients @
      km = (IDLC[k,1]-1)*NALT;
      ev = ev + exp(b[NFC+(2*(NNC+NUC+NTC))+(2*k)-1]
```

```
                +                  (b[NFC+(2*(NNC+NUC+NTC))+(2*k)]               .*
err[.,(NNC+NUC+NTC+k)]))
                .* XMAT[kmm,(km+1):(km+NALT)];
     k = k+1;
    endo;
    ev = exp(ev);
    if CENSOR;
     p00 = p00.*ev[.,YVEC[kmm,1]]./sumc((ev .* XMAT[kmm,(c+1):(c+NALT)])');
    else;
     p00 = p00.*ev[.,YVEC[kmm,1]]./(sumc(ev'));
    endif;
    t = t+1;
   endo;
   rd = rd + TIMES[n];
   p0[n,1] = meanc(p00);
   n = n + 1;
  endo;
  retp(ln(p0));
endp;

/* GRADIENT PROCEDURE */
proc gr(b,x);

  @ Relies on the globals: NALT, NOBS, NP, NREP, NECOL, SEED1, CENSOR @
  @                    NFC, IDFC, NNC, NUC, NTC, IDA, NLC, IDLC          @
  @                      CZVAR, BACTIVE, CEVAR, EQMAT, XMAT, YPERM, DRAWS
@
  local c, g, k, n, t, km, kmm, rd, seed2, y;
  local denom, der, v, ev, p0, p00, p1, err, mm;
  if CEVAR;
   b = EQMAT' * b;          @ Expand b to its original size. @
  endif;

  if CENSOR;
   c = (IDCENSOR-1)*NALT;      @ Location of censor variable    @
  endif;

  v = zeros(NOBS,NALT);       @ Argument to logit formula      @
  p0  = zeros(NP,1);          @ Simulated probability          @
  der = zeros(NP,NEVAR);      @ Jacobian matrix                @

  k = 1;
  do while k <= NFC;          @ Adds variables with fixed coefficients @
   km = (IDFC[k,1]-1)*NALT;
   v = v + b[k] .* XMAT[.,(km+1):(km+NALT)];
   k = k+1;
```

```
endo;
seed2 = SEED1;
rndseed seed2;
rd = 0;
n = 1;
do while n <= NP;
 if DRAWS == 1;
     err  = rndn(NREP,NECOL);
      if NUC > 0;
             err[.,(NNC+1):(NNC+NUC)] = (rndu(NREP,NUC) .* 2) -1;
     endif;
      if NTC > 0;
            mm = rndu(NREP,NTC) ;
            err[.,(NNC+NUC+1):(NNC+NUC+NTC)] = (sqrt(2.*mm)-1).*(mm .<= 0.5)
                                       + (1-sqrt(2.*(1-mm))) .* (mm .> 0.5);
       endif;
   endif;
   if DRAWS == 2;
     err=hm[(NREP*(n-1)+1):(NREP*(n-1)+NREP),.] ;
  endif;
@ err has NREP rows and NECOL columns for each person. @

  p00 = ones(NREP,1);
   g = zeros(NREP,NEVAR);
  t=1;
  do while (t<=TIMES[n]);
    kmm = rd + t;
    ev = v[kmm,.];
    k = 1;
    do while k <= NNC+NUC+NTC;         @ Adds variables with normal,uniform, and
triangular coefficients @
      km = (IDA[k,1]-1)*NALT;
      ev = ev + (b[NFC+(2*k)-1] + (b[NFC+(2*k)] .* err[.,k]))
           .* XMAT[kmm,(km+1):(km+NALT)];
      k = k+1;
    endo;
    k = 1;
    do while k <= NLC;       @ Adds variables with log-normal coefficients @
      km = (IDLC[k,1]-1)*NALT;
      ev = ev + exp(b[NFC+(2*(NNC+NUC+NTC))+(2*k)-1]
            + (b[NFC+(2*(NNC+NUC+NTC))+(2*k)] .* err[.,(NNC+NUC+NTC+k)]))
               .* XMAT[kmm,(km+1):(km+NALT)];
      k = k+1;
    endo;

    ev = exp(ev);
```

```
if CENSOR;
  denom = sumc((ev .* XMAT[kmm,(c+1):(c+NALT)])');
  p00   = p00 .* ev[.,YVEC[kmm,1]]./denom;
  p1    = (ev.*XMAT[kmm,(c+1):(c+NALT)])./denom;
else;
  denom = sumc(ev');
  p00   = p00 .* ev[.,YVEC[kmm,1]]./denom;
  p1    = ev./denom;
endif;
y = YPERM[kmm,.]-p1;
k = 1;
do while k<=NFC;
  km = (IDFC[k,1]-1)*NALT;
  g[.,k] = g[.,k] + sumc((XMAT[kmm,km+1:km+NALT].*y)');
  k = k + 1;
endo;

k = 1;
do while k<=NNC+NUC+NTC;
  km = (IDA[k,1]-1)*NALT;
  g[.,NFC+(2*k)-1] = g[.,NFC+(2*k)-1] +
              sumc((XMAT[kmm,km+1:km+NALT].*y)');
  g[.,NFC+(2*k)]   = g[.,NFC+(2*k)] +
              sumc((err[.,k].*XMAT[kmm,km+1:km+NALT].*y)');
  k = k + 1;
endo;

k = 1;
do while k<=NLC;
  km = (IDLC[k,1]-1)*NALT;
  g[.,NFC+2*(NNC+NUC+NTC)+(2*k)-1] = g[.,NFC+2*(NNC+NUC+NTC)+(2*k)-
1] +
               sumc((XMAT[kmm,km+1:km+NALT].*y)');
  g[.,NFC+2*(NNC+NUC+NTC)+(2*k)] = g[.,NFC+2*(NNC+NUC+NTC)+(2*k)] +

sumc((err[.,NNC+NUC+NTC+k].*XMAT[kmm,km+1:km+NALT].*y)');
  k = k + 1;
endo;

 t = t+1;
endo;

km = NFC+2*(NNC+NUC+NTC);   @ multiply correction term for log-normals @
k = 1;  do while k<=NLC;
 g[.,km+(2*k)-1:km+(2*k)] = g[.,km+(2*k)-1:km+(2*k)] .*
          exp(b[km+(2*k)-1,1]+b[km+(2*k),1].*err[.,NNC+NUC+NTC+k]);
```

```
   k = k + 1;    endo;
  p0[n,1] = meanc(p00);
  der[n,.] = (meanc(p00.*g))';
  rd = rd + TIMES[n];
  n = n + 1;
 endo;
 if CEVAR;
  der = (der./p0) * EQMAT';
 else;
  der = der./p0;
 endif;
 retp(der); endp;

/* GRADIENT FOR PAUL RUUD'S ROUTINE WHEN USING NEWTON-
RAPHSON*/
/* USE WHEN OPTIM == 1 AND METHOD == 2 */
proc gpnr(b);
 @ Relies on global: XMAT  @
 local grad;

 if DOWT;
  grad = WEIGHT .* gr(b,XMAT);
 else;
  grad = gr(b,XMAT);
 endif;

 retp(sumc(grad));
endp;

/* EXPANDS THE DIRECTION VECTOR; ALLOWS PARAMETERS TO STAY AT
STARTING   */
/* VALUES; HELPER PROCEDURE FOR &domax
        */
proc expand( x, e );
  local i,j;
  i = 0;
  j = 0;
  do while i < rows(e);
    i = i + 1;
    if e[i];
      j = j + 1;
      e[i] = x[j];
    endif;
  endo;
  if j/=rows(x); "Error in expand."; stop; endif;
  retp( e ); endp;
```

```
/* MAXIMIZATION ROUTINE COURTESY OF PAUL RUUD */
proc domax( &f, &g, b, bactive );

  @ Relies on the globals: CZVAR, EPS, METHOD, NITER, NOBS,  @
  @                    PRTHESS, XMAT, NP, NEVAR         @

  local f:proc, g:proc;
  local direc, first, grad, sgrad, hesh, ihesh, lambda;
  local nb, printer, repeat, step1, wtsq;
  local _biter, _f0, _f1, _fold, _tol;

  _tol  = 1;
  _biter = 0;
  nb = seqa(1,1,NEVAR);

  _f0 = f( b, XMAT );
  if DOWT;
    _f0 = sumc(WEIGHT.*_f0);
    wtsq = WEIGHT .^ (.5);
  else;
    _f0 = sumc(_f0);
  endif;

  format /m1 /rdt 16,8;
  print; print; print;

  do while (_tol > EPS or _tol < 0) and (_biter < NITER);
    _biter = _biter + 1;

    print
"==============================================================
===========";
    print "        Iteration: " _biter;
    print "        Function:  " _f0;

    grad = g( b, XMAT );
    if (METHOD == 1);
      if DOWT;
        grad = wtsq.*grad;
        hesh = grad'grad;
        grad = wtsq.*grad;
      else;
        hesh = grad'grad;
      endif;
    else;
      if DOWT;
```

```
   grad = WEIGHT .* grad;
  endif;
  hesh = -gradp( &gpnr, b );   @ WEIGHT done in &gpnr @
endif;
sgrad = sumc(grad);

@ Select only the variables that we want to maximize over @
if CZVAR;
  sgrad  = selif( sgrad, bactive );
  hesh   = selif( hesh, bactive );
  hesh   = selif( hesh', bactive );
endif;

if (det(hesh)==0);
  print "Singular Hessian!";
  print "Program terminated.";
  stop;
else;
  ihesh = inv(hesh);
  direc = ihesh * sgrad;
endif;
_tol    = direc'sgrad;

if CZVAR;
  direc = expand( direc, bactive);
endif;

print "        Tolerance: " _tol;
print "------------------------------------------------------------------------";

if PRTHESS;
  if CEVAR and CZVAR;
    printer = expand(sgrad./NP,bactive)~expand(diag(hesh),bactive);
    printer = nb~EQMAT'*b~EQMAT'*printer[.,1]~EQMAT'printer[.,2];
  elseif CEVAR;
    printer = nb~EQMAT'*b~(EQMAT'*sgrad./NP)~(EQMAT'*diag(hesh));
  elseif CZVAR;
    printer = nb~b~expand(sgrad./NP,bactive)~expand(diag(hesh),bactive);
  else;
    printer = nb~b~(sgrad./NP)~(diag(hesh));
  endif;
  print "                  Coefficients        Rel. Grad.          Hessian";
 else;
  if CEVAR and CZVAR;
    printer = expand(sgrad./NP,bactive);
    printer = nb~EQMAT'*b~EQMAT'*printer[.,1];
```

```
  elseif CEVAR;
    printer = nb~EQMAT'*b~(EQMAT'*sgrad./NP);
  elseif CZVAR;
    printer = nb~b~expand(sgrad./NP,bactive);
  else;
    printer = nb~b~(sgrad./NP);
  endif;

  print "                          Coefficients          Rel. Grad.";
endif;
print printer;
if (_tol >= 0) and (_tol < 1.e-6);
  break;
elseif _tol < 0;
  direc = -direc;
endif;

step1 = STEP;
lambda = .5;
repeat = 1;
first = 1;
_f1 = _f0;
steploop:
  step1 = step1 * lambda;
  _fold = _f1;
  if DOWT;
    _f1 = sumc(WEIGHT .* f(b+step1*direc,XMAT));
  else;
    _f1 = sumc( f( b+step1*direc, XMAT ) );
  endif;
print "----------------------------------------------------------------------";
  print " Step: " step1;
  print " Function: " _f1;
  if repeat;
    print " Change: " _f1-_f0;
  else;
    print " Change: " _f1-_fold;
  endif;
  if MNR;
    if (step1 < 1.e-5);
      print "Failed to find increase.";
      retp(b);
    elseif (_f1 <= _f0) and (repeat);
      first = 0;
      goto steploop;
    elseif (_f1 > _fold) and (first);
```

```
      lambda = 2;
      repeat = 0;
      goto steploop;
    endif;
  else;
    if (step1 < 1.e-5);
      print "Failed to find increase.";
      retp(b);
    elseif (_f1 <= _f0);
      goto steploop;
    endif;
  endif;

  if (repeat);
    b = b + step1*direc;
    _f0 = _f1;
  else;
    b = b + .5 * step1 * direc;
    _f0 = _fold;
  endif;

endo;
print
"==========================================================================";
print;

format /m1 /rdt 1,8;
if (_tol< EPS);
  print "Converged with tolerance:  " _tol;
  print "Function value:  " _f0;
else;
  print "Stopped with tolerance:  " _tol;
  print "Function value:  " _f1;
endif;

print;
lambda = eig(hesh);
if lambda>0;
  print "Function is concave at stopping point.";
else;
  print "WARNING:  Function is not concave at stopping point.";
endif;
print;

if ROBUST == 0 and DOWT == 1; @ Create Hessian and gradient for regular @
                  @ standard errors when have weights. @
```

```
  if CZVAR;
    grad = grad'grad;
    grad = selif(grad, BACTIVE);
    grad = selif(grad', BACTIVE);
    ihesh = ihesh*(grad)*ihesh;
  else;
    ihesh = ihesh*(grad'grad)*ihesh;
  endif;
 endif;

 if ROBUST == 1;   @Create gradient and hessian for robust standard errors. @
      if METHOD == 1;
    hesh  = - gradp( &gpnr, b );
      if CZVAR;
        grad  = selif( grad', bactive )';
        hesh  = selif( hesh, bactive );
        hesh  = selif( hesh', bactive );
     endif;
      endif;
   ihesh=inv(hesh);
   ihesh=ihesh*(grad'grad)*ihesh;

 print "Uses robust standard errors.";
 else;
 print "Uses non-robust standard errors.";
 endif;
 if CEVAR and CZVAR;
  printer = expand(sqrt(diag(ihesh)), BACTIVE);
  printer = nb~EQMAT'*b~EQMAT'*printer;
 elseif CEVAR;
  printer = nb~EQMAT'*b~(EQMAT'*sqrt(diag(ihesh)));
 elseif CZVAR;
  printer = nb~b~expand(sqrt(diag(ihesh)),BACTIVE);
 else;
  printer = nb~b~sqrt((diag(ihesh)));
 endif;

 format /m1 /rdt 16,8;
 print "     Parameters              Estimates          Standard Errors";
 print "---------------------------------------------------------------------------";
 print printer;
 retp( b );
endp;

/* This proc checks the inputs if VERBOSE=1 */
proc (0) = pcheck;
```

```
local i,j;

@ Checking XMAT @
if (rows(XMAT) /= NOBS);
  print "XMAT has" rows(XMAT) "rows";
  print "but it should have NOBS="  NOBS   "rows.";
  print "Program terminated.";
  stop;
elseif(cols(XMAT) /= (NVAR*NALT));
  print "XMAT has" cols(XMAT) "columns";
  print "but it should have NVAR*NALT= " (NVAR*NALT) "columns.";
  print "Program terminated.";
  stop;
else;
  print "XMAT has:";
  print "Rows:  " NOBS;
  print "Cols:  " NVAR*NALT ;
  print "Containing" NVAR "variables for " NALT " alternatives.";
  print;
endif;

@ Check dependent variable @
if (rows(YVEC) /= NOBS);
  print "YVEC has" rows(YVEC) "rows";
  print "but it should have NOBS="  NOBS   "rows.";
  print "Program terminated.";
  stop;
endif;
if (cols(YVEC) /= 1);
  print "YVEC should have only one column.";
  print "Program terminated.";
  stop;
endif;

@ Check TIMES @
if (rows(TIMES) /= NP);
  print "TIMES has" rows(TIMES) "rows";
  print "but it should have NP="  NP   "rows.";
  print "Program terminated.";
  stop;
endif;
if (cols(TIMES) /= 1);
  print "TIMES should have only one column.";
  print "Program terminated.";
  stop;
endif;
```

```
if (sumc(TIMES) /= NOBS);
  print "sumc of TIMES =" sumc(TIMES) "but it should equal NOBS.";
  print "Program terminated.";
  stop;
endif;

@ Check WEIGHT @
if (DOWT /=0) and (DOWT /=1);
  print "DOWT must be 0 or 1.";
  print "Program terminated.";
  stop;
endif;
if DOWT;
  if (rows(WEIGHT) /= NP);
    print "WEIGHT has" rows(WEIGHT) "rows";
    print "but it should have NP="  NP   "rows.";
    print "Program terminated.";
    stop;
  endif;
  if (cols(WEIGHT) /= 1);
    print "WEIGHT should have only one column.";
    print "Program terminated.";
    stop;
  endif;
endif;

@ Checking fixed coefficients @
if (NFC /= 0);
  if (rows(IDFC) /= NFC);
    print "IDFC has" rows(IDFC) "rows when it should have NFC=" NFC "rows.";
    print "Program terminated.";
    stop;
  endif;
  if (cols(IDFC) /= 1);
    print "Commas are needed between the elements of IDFC.";
    print "Program terminated.";
    stop;
  endif;
  if (sumc(IDFC.>NVAR)>0);
    print "IDFC identifies a variable that is not in the data set.";
    print "All elements of IDFC should be <= NVAR, which is " NVAR;
    print "Program terminated.";
    stop;
  endif;
endif;
@ Checking normal coefficients @
```

```
if (NNC /= 0);
 if (rows(IDNC) /= NNC);
  print "IDNC has" rows(IDNC) "rows when it should have NNC=" NNC "rows.";
  print "Program terminated.";
  stop;
 endif;
 if (cols(IDNC) /= 1);
  print "Commas are needed between the elements of IDNC.";
  print "Program terminated.";
  stop;
 endif;
 if (sumc(IDNC.>NVAR)>0);
  print "IDNC identifies a variable that is not in the data set.";
  print "All elements of IDNC should be <= NVAR, which is " NVAR;
  print "Program terminated.";
  stop;
 endif;
endif;

@ Check uniformly distributed coefficients @
if (NUC /= 0);
 if (rows(IDUC) /= NUC);
  print "IDUC has" rows(IDUC) "rows when it should have NUC=" NUC "rows.";
  print "Program terminated.";
  stop;
 endif;
 if (cols(IDUC) /= 1);
  print "Commas are needed between the elements of IDUC.";
  print "Program terminated.";
  stop;
 endif;
 if (1-(IDUC <= NVAR));
  print "IDUC identifies a variable that is not in the data set.";
  print "All elements of IDUC should be <= NVAR, which is " NVAR;
  print "Program terminated.";
  stop;
 endif;
endif;

@ Check traingularly distributed coefficients @
if (NTC /= 0);
 if (rows(IDTC) /= NTC);
  print "IDTC has" rows(IDTC) "rows when it should have NTC=" NTC "rows.";
  print "Program terminated.";
  stop;
 endif;
```

```
  if (cols(IDTC) /= 1);
    print "Commas are needed between the elements of IDTC.";
    print "Program terminated.";
    stop;
  endif;
  if (1-(IDTC <= NVAR));
    print "IDTC identifies a variable that is not in the data set.";
    print "All elements of IDTC should be <= NVAR, which is " NVAR;
    print "Program terminated.";
    stop;
  endif;
endif;

@ Checking log-normal coefficients @
if (NLC /= 0);
  if (rows(IDLC) /= NLC);
    print "IDLC has" rows(IDLC) "rows when it should have NLC=" NLC "rows.";
    print "Program terminated.";
    stop;
  endif;
  if (cols(IDLC) /= 1);
    print "Commas are needed between the elements of IDLC.";
    print "Program terminated.";
    stop;
  endif;
  if (sumc(IDLC.>NVAR)>0);
    print "IDLC identifies a variable that is not in the data set.";
    print "All elements of IDLC should be <= NVAR, which is " NVAR;
    print "Program terminated.";
    stop;
  endif;
endif;

@ Check CENSOR @
if ((CENSOR /= 1) and (CENSOR /= 0));
  print "CENSOR must be 0 or 1.";
  print "Program terminated.";
  stop;
endif;
if CENSOR;
  if IDCENSOR > NVAR;
    print "The censoring variable cannot be located";
    print "since you set CENSOR larger than NVAR.";
    print "Program terminated.";
    stop;
  endif;
```

```
  i = (IDCENSOR-1)*NALT;
  j = 1;
  do while j<=NOBS;
    if (XMAT[j,i+YVEC[j,1]]==0);
      print "Your censoring variable eliminates the chosen alternative";
      print "for observation " j;
      print "Program terminated.";
      stop;
    endif;
    j = j + 1;
  endo;
endif;

@ Check PRTHESS and RESCALE @
if ((PRTHESS /= 1) and (PRTHESS /= 0));
  print "PRTHESS must be 0 or 1.";
  print "Program terminated.";
  stop;
endif;
if ((RESCALE /= 1) and (RESCALE /= 0));
  print "RESCALE must be 0 or 1.";
  print "Program terminated.";
  stop;
endif;

@ Check B @
if (rows(B) /= NEVAR);
  print "Starting values B has " rows(B) "rows";
  print "when it should have NFC+2*NNC+2*NUC+2*NTC+2*NLC= " NEVAR
"rows.";
  print "Program terminated.";
  stop;
endif;
if (cols(B) /= 1);
  print "Commas needed between the elements of B.";
  print "Program terminated.";
  stop;
endif;

@ Check CZVAR @
if ((CZVAR /= 1) and (CZVAR /= 0));
  print "CZVAR must be 0 or 1.";
  print "Program terminated.";
  stop;
endif;
if CZVAR;
```

```
  if (rows(BACTIVE) /= NEVAR);
    print "BACTIVE has " rows(BACTIVE) "rows";
    print "when it should have NFC+2*NNC+2*NUC+2*NTC+2*NLC= " NEVAR
"rows.";
    print "Program terminated.";
    stop;
  endif;
  if (cols(BACTIVE) /= 1);
    print "Commas needed between the elements of BACTIVE.";
    print "Program terminated.";
    stop;
  endif;
endif;

@ Check CEVAR @
if ((CEVAR /= 1) and (CEVAR /= 0));
  print "CEVAR must be 0 or 1.";
  print "Program terminated.";
  stop;
endif;
if CEVAR;
  if (cols(EQMAT) /= NEVAR);
    print "EQMAT has " cols(EQMAT) " columns";
    print "when it should have NFC+2*NNC+2*NUC+2*NTC+2*NLC=" NEVAR "
columns.";
    print "Program terminated.";
    stop;
  endif;
  if (rows(EQMAT)>=NEVAR);
    print "EQMAT has " rows(EQMAT) " rows";
    print "when it should have strictly less than
NFC+2*NNC+2*NUC+2*NTC+2*NLC=" NEVAR;
    print "rows.";
    print "Program terminated.";
    stop;
  endif;
endif;

@ Checking NREP @
if (NREP <= 0);
  print "Error in NREP: must be positive.";
  print "Program terminated.";
  stop;
endif;

@ Check SEED1 @
```

```
if (SEED1<=0);
  print "SEED1 =" SEED1 "must be a positive integer.";
  print "Program terminated.";
  stop;
endif;

@ Check METHOD and OPTIM @
if (METHOD < 1);
  print "METHOD must be 1-6.";
  print "Program terminated.";
  stop;
endif;
if (OPTIM /= 1) and (OPTIM /= 2);
  print "OPTIM must be 1 or 2.";
  print "Program terminated.";
  stop;
endif;
if ((OPTIM == 1) and (METHOD > 2));
  print "Method "  METHOD " is not an option with OPTIM = 1.";
  print "Program terminted.";
  stop;
endif;
if ((OPTIM == 2) and (METHOD > 6));
  print "Method " METHOD " is not an option with OPTIM = 2.";
  print "Program terminated.";
  stop;
endif;

@ Check MNR @
if ((MNR /= 1) and (MNR /= 0));
  print "MNR must be 0 or 1.";
  print "Program terminated.";
  stop;
endif;

@ Check STEP @
if (STEP<=0);
  print "STEP must be greater than zero.";
  print "Program terminated.";
  stop;
endif;

@ Check ROBUST @
if ((ROBUST /= 1) and (ROBUST /= 0));
  print "ROBUST must be 0 or 1.";
  print "Program terminated.";
```

```
  stop;
 endif;

 @ Check DRAWS @
 if ((DRAWS /= 1) and (DRAWS /= 2));
  print "DRAWS must be 1 or 2.";
  print "Program terminated.";
  stop;
 endif;

 @ Check HALT @
 if ((HALT /= 1) and (HALT /= 2));
  print "HALT must be 1 or 2.";
  print "Program terminated.";
  stop;
 endif;

 print "The inputs pass all the checks and seem fine.";
 print;
 retp;
endp;

/* Halton procedure */

/*  Proc to create Halton sequences using the pattern described in Train, "Halton Sequences
for Mixed Logit." The integer n is the length of the Halton sequence that is required, and
s is the prime that is used in creating the sequence.

Given the length of the sequence n, the integer k is determined such that s^k<n<s^k+1. That is,
a sequence using s^1 up to s^k is too short, and a sequence using s^1 up to s^(k+1) is too long.
Using this fact, the proc is divided in two parts to save time and space.
The first part creates the sequence for s^1 up to s^k. The second
part creates only as much as needed of the additional sequence using s^(k+1). */

proc halton(n,s);
local phi,i,j,y,x,k;
k=floor(ln(n+1) ./ ln(s));   @We create n+1 Halton numbers including the initial zero.@
phi={0};
i=1;
do while i .le k;
 x=phi;
  j=1;
 do while j .lt s;
```

```
    y=phi+(j/s^i);
    x=x|y;
    j=j+1;
  endo;
  phi=x;
  i=i+1;
endo;

x=phi;
j=1;
do while j .lt s .and rows(x) .lt (n+1);
   y=phi+(j/s^i);
   x=x|y;
   j=j+1;
 endo;

phi=x[2:(n+1),1];  @Starting at the second element gets rid of the initial zero.@
retp(phi);
endp;

/* For the DOS version of Gauss, here is the CDFINVN
   procedure, which is incorporated directly
   in the Windows version as CDFNI */

proc (1) = cdfinvn(p);
   local p0,p1,p2,p3,p4,q0,q1,q2,q3,q4,maskgt,maskeq,sgn,y,
        xp,pn,norms,mask1,mask0,inf0,inf1;

@ constants @
   p0 = -0.322232431088;               q0 = 0.0993484626060;
   p1 = -1.0;                    q1 = 0.588581570495;
   p2 = -0.342242088547;               q2 = 0.531103462366;
   p3 = -0.0204231210245;              q3 = 0.103537752850;
   p4 = -0.453642210148*1e-4;           q4 = 0.38560700634*1e-2;

@ Main body of code @

  if not (p le 1.0 and p ge 0.0);
    errorlog("error: Probability is out of range.");
    retp(" ");
    end;
  endif;

/* Create masks for p = 0 or p = 1 */

   mask0 = (p .== 0);
```

```
    mask1 = (p .== 1);
    inf0 = missrv(miss(mask0,1),-1e+300);
    inf1 = missrv(miss(mask1,1),1e+300);

  @ Create masks for handling p > 0.5 and p >= 0.5 @

    maskgt = (p .> 0.5);
    maskeq = (p .ne 0.5);
    sgn = missrv(miss(maskgt,0),-1);

  @ Convert p > 0.5 to 1-p @
   pn = (maskgt-p).*sgn+mask1+mask0;  clear maskgt;

  @ Computation of function for p < 0.5 @
   y=sqrt(abs((-2*ln(pn))));    clear pn;

   norms = y + ((((y*p4+p3).*y+p2).*y+p1).*y+p0)./
         ((((y*q4+q3).*y+q2).*y+q1).*y+q0);  clear y;
  @ Convert results for p > 0.5 and p = 0.5 @

   norms=((norms.*sgn).*maskeq).*(1-mask0).*(1-mask1)+mask0.*inf0+mask1.*inf1;
   retp(norms);
  endp;
```