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EXTENSIONS OF THE TRADITIONAL MODELS OF NON-MARKET VALUATION FOR PUBLIC GOODS TO A COLLECTIVE FRAMEWORK

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To My Family

'It is our collective and individual responsibility
to protect and nurture the global family,
to support its weaker members and
to preserve and tend to the environment
in which we all live.'

- Dalai Lama

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Table of Contents

INTRODUCTION

Whenever events or a proposed change in policy affect quality or availability of environmental resources and public goods, either explicit or implicit cost-benefit analyses must often be undertaken. It has been recognised that the value of these goods is not explicitly determined through market transactions and the absence of markets makes it extremely difficult to establish a monetary value for access to these goods. Economists answered this challenge by developing methods of nonmarket valuation for public goods. Methods for valuing environmental goods have been categorized as indirect and direct.

Direct methods, as the Contingent Valuation Method (CVM), ask consumers what they would be willing to pay (WTP) or accept (WTA) for a change in an environmental amenity. They are examples of stated preference techniques that establish hypothetical markets for public goods. Direct methods have the main advantage that they allow the measurement of non-use values but they are commonly criticised because of the hypothetical nature of the question (i.e. 'hypothetical bias') and the fact that the actual behavior is not observed. Researchers have identified also other problems and biases, such as strategic bias[1], information bias[2], and starting point bias[3] (see detailed discussion of the problems in Cummings et al., 1986 and Mitchell and Carson, 1989).

[1] For example if respondents believe they will have to pay for the good then respondents may not be willing to reveal their true WTP and their responses may be unrealistically low.
[2] Valuation may depend on how the information about the good, its provision and financing is provided, who makes the interview or what other information the respondents have about a particular good.
[3] It is possible that when follow-up questions are used, respondents may 'anchor' the value they place on the policy on the bid amounts proposed to them in the initial and/or subsequent payment questions.

To investigate the validity of direct methods, researchers have compared the WTP estimates derived by applying the CVM with the WTP estimates based on indirect methods of valuation (Bishop and Heberlin, 1979; Bishop et al., 1983; Seller et al. 1985; Cameron, 1992; Adamowicz et al., 1994; Carson et al., 1996; Azevedo et al., 2003). Indirect methods, such as the Travel Cost Method (TCM), use actual choices made by consumers. These constitute revealed preferences over goods. The basic premise of the TCM is that the time and the travel cost expenses that people incur to visit a site represent the price of access to the site. The WTP to visit a site is estimated based on the number of trips that people make at different travel costs. The TCM avoids the criticism of being based on hypothetical behavior but it has other problems such as how to handle multiple-day trips, how to value time costs, how to choose the functional form of the demand for trips and how to incorporate temporal uncertainty (Cameron, 1992).

This list can be extended but we argue that one of the main limitations is that the TCM focuses on defining a household to have the same utility level as a single individual. It assumes that a household acts as an elementary decision making unit where all resources are pooled and household decisions are made by a single decision maker. In particular, travel cost information is limiting in that it can reveal consumer preferences for non-market goods only capturing family behavior, while instead the WTP is an individual based measure. The correspondence between WTP estimates from the CVM and the TCM is maintained only in the case when considering a sample of singles.

Over the past two decades there has been a growing recognition that this approach to the household is inadequate, especially when analyzing decisions made at the household level. (McConnell, 1999; Smith and Van Houtven, 1998 and 2004; Dosman and Adamowicz, 2006). If models do not incorporate the preferences of all decision makers in the household they will not capture the decision-making structure and the bargaining between household members.

Contingent Valuation Method is hypothetical but it expresses an individual WTP. CVM information provides insights into the probable behavior of respondents that is individual, personal. In order to make CVM and TCM comparable, what should be considered in the Travel Cost Method is not the 'preferences' of a given household, but rather the preferences of the individuals that compose it.

We propose therefore that meaningful comparisons between TCM and CVM must be undertaken at the individual level. Consequently, in contrast with the existing non-market resource valuation literature, our framework does not assume the existence of a unique household utility function. Following the basic ideas of the collective approach to household behavior by Chiappori (1988, 1992), we assume that each individual is characterized by her/his own utility function.

Several are the contributions of this research to the non-market valuation literature. In Chapter 1 we deal with the distinction between individual and households in recreational demands model; we overview the literature on the collective nature of household decisions; we present the traditional recreational demand model and we develop a collective recreational demand model that allows identification of individual welfare measures such as consumer surplus for each household member by following Browning et al. (2006). This model identifies the individual consumer surplus and the allocation of resources within a household by a consumption technology function and by using information about the consumption of individuals living alone as if they were living in a household. The consumption technology function summarizes all of the technological economies of scale and scope that result from living together. In this chapter we test for differences in recreational demands between husbands and wives by using cross sectional data from a recreational survey.

In Chapter 2 we develop a 'Collective Travel Cost Method' (CTCM). We extend the traditional travel cost method to the collective framework proposed by Chiappori (1988, 1992). Knowledge of the travel cost to the recreational site of each household member allows us to identify the sharing rule between household members and to estimate the CTCM. In particular we estimate a Collective Almost Ideal Demand System that takes into account the role of each member's preferences for consumption choices and how resources are allocated within the household. We show how this method can be applied in order to find individual WTP to access a natural park for spouses using revealed preference data. The development and estimation of the CTCM allows: (1) to test whether the WTP estimated by the traditional unitary TCM is significantly different from the WTP estimated by the CTCM; (2) to test whether two spouses have equal or different WTP to access the recreational site, and (3) to make TCM and CVM estimates about WTP comparable at the individual level.

No research exists that estimates the individual WTP for each household member by using only revealed preferences data or that applies a Travel Cost Method to a collective framework.

Finally, Chapter 3 deals with one of the most common issues of the Contingent Valuation Method: the starting point bias or 'anchoring' problem. Respondents may 'anchor' the value they place on the policy on the bid amounts proposed to them in the initial and/or subsequent payment questions. We examine starting point bias in Contingent Valuation surveys with dichotomous choice payment questions and follow-ups, and double-bounded models of the WTP responses. We investigate (1) the seriousness of the biases for the location and scale parameters of WTP in the presence of starting point bias; (2) whether or not these biases depend on the distribution of WTP and on the bids used; and (3) how well a commonly used diagnostic for starting point bias—a test of the null that bid set dummies entered in the right-hand side of the WTP model are jointly equal to zero—performs under various circumstances. Because starting point bias cannot be separately identified in any reliable manner from biases caused by model specification, we use Monte Carlo simulation approaches to address this issue. We find that starting point bias is not so much a problem in creating biased WTP estimates while bid design and proper specification of the WTP distribution are important in determining unbiased WTP estimates. We also find that bid set dummies, which are used by many researchers to detect starting point bias, have only very modest power in detecting starting point bias. Bid set dummies tend to soak up misspecifications in the distribution assumed by the researcher for the latent WTP, rather than capturing the presence of starting point bias.

We conclude with suggestion for future research. The Annex describes the survey data used in Chapters 1 and 2.

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CHAPTER 1

Individual Versus Household in Recreational Demand Models

1.1 Introduction

Cost-benefit analysis has to be often undertaken when a change in policy affects the quality or the availability of environmental resources. It has been recognised that the value of these goods is not explicitly determined through market transactions and it is difficult to establish a monetary value for their access because of the absence of markets.

Economists have answered this challenge by developing alternative methods of valuing non-market goods. The Travel Cost Method (TCM) by Clawson and Knetsch (1966) aggregates visitors to a recreational site into their zones of origin and it explains the change in visitors rates from each zone by the travel cost, the income, the socio-demographic characteristics of visitors and the characteristics of the alternative sites. More research has provided extensions to the original Travel Cost Method. Research shows efficiency gains in estimating recreational demand models using the observations of individuals themselves rather than traditional zone averages (e.g. Brown and Nawas, 1973; Willis and Garrod, 1991).

We argue that these models treat the term 'household' and 'individual' as synonyms. A household is defined by Becker (1965) as a 'small factory.' It consists of individuals motivated sometimes by self-interest, other times by altruism and often by both, or as if they agree on the best way to combine capital goods, time and home production activities. Traditional recreational models focused on defining a household as having the same utility level as a single individual, implying that intra-household resource allocation is irrelevant, or that it can be addressed within a dictatorial decision process.

In particular, the traditional Travel Cost Method is limiting in that it can reveal consumer preferences for non-market goods by only capturing family behavior. It assumes that a household acts as an elementary decision making unit. This approach is referred to as ‘unitary.’ However, a household consisting of several members does not necessarily behave as a single agent and individuals have utility, not households (Browning, Chiappori and Lewbel, 2006).

In the recreational framework, consider, for example, the case of a married couple going to visit a natural park together and the case of an individual living alone who goes to visit the natural area. The main question to ask should be, ‘how much is an individual living alone willing to pay to attain the same indifference curve over goods as an individual attains, for those goods, as a member of the household?’

The utility of this study can be derived from the observation that within households choices are affected by the presence of other household members. In addition, usually only the household’s total purchases are observed in recreational surveys and not their distribution and use among members. Thus we have to identify the individual’s preferences and since the distribution of resources within the household is not usually recorded, it has to be identified from the aggregate household demand. In order to identify the individual preferences we can use either information on exclusive goods consumption by individuals living in the same households (Chiappori 1988’s approach), or information about the consumption of individuals living alone as if they were living in the family (Browning, Chiappori and Lewbel, 2006’s approach). Note that from this point we will refer to them as BCL.

Still, a comprehensive study of a collective model applied to recreational demand models does not exist. This study proposes a novel approach to estimating a collective recreational demand model that accounts for intra-household resource allocation. The technique is based on an analogy borrowed from the literature of collective household behavior and, in particular, on the BCL' model. Thanks to the BCL model, combining data from households and from people living alone and by a consumption technology function, we can completely identify the sharing rule that expresses the bargaining power between household members and the consumer surplus for each household member. The consumption technology function summarizes all of the technological economies of scale and scope that result from living together.

Finally, we test for differences in recreational demands between husbands and wives by using cross sectional data from a recreational survey. We find that husbands and wives have significantly different recreational demands. This implies that observations for husbands and wives may not be treated as identical as in the traditional recreational demand model (unless one spouse is the dictator). We also found that in absolute value the consumer surplus estimate derived from the traditional unitary recreational model appears to overestimate the consumer surplus of husbands and underestimate the consumer surplus of wives, and that wives have significantly higher consumer surplus than husbands for access at the West Garda Regional Forest.

The rest of this chapter is organized as follows: Section 1.2 presents an overview of the literature on individual versus household in non-market valuation and the collective nature of household decisions. Section 1.3 outlines the BCL model's basic structure; it presents the traditional recreational demand model and it derives our extension of the BCL model to the recreational demand model. Section 1.4 provides some evidence of significant differences in recreational demand and consumer surplus between husbands and wives. The last section summarizes and discusses the welfare implications of the framework for collective household model with suggestions for future research.

1.2 Literature Review

It is by now accepted that the distinction between individual and household in recreational models matters. In the context of Contingent Valuation, Quiggin (1998) considers whether the Willingness-To-Pay (WTP) for the benefit generated by a public good should be elicited on an individual or a household level. He finds that there may be some differences between individual and household WTP when household members are mutually altruistic. Munro (2005) shows that the household and the individual WTP are equal if and only if the household pools income.

Other authors (e.g. Haab and McConnell, 2002; Bockstael and McConnell, 2006) recognize that they ignore the distinction between household and individual in their work. In particular Bockstael and McConnell (2006) note that 'the distinction between the individual and the household is a difficult one for which there is, to date, no adequate treatment. In the original paper on household production, Becker treated the household as the decision making unit, suggesting that intra-household allocations of consumption and production activities would be made 'optimally' (p.512). In the forty years since that paper, little progress has been made in explaining this intra-household allocation process or in reconciling the distinction between the household as decision maker and the individual members as consumers. We continue to use the terms individual and household interchangeably, but recognize that embedded in their distinction are potentially important considerations' (p. 8, Chapter 4).

Smith (1988) compares five methods for estimating travel cost recreation demand models with microdata and argues that a component of research strategy should involve 'systematic effort at understanding how individuals make their recreation choices and whether these are adequately described by any of these models' (p.35).

In the framework of revealed preferences, the only papers that we could find specifically addressing these issues are McConnell (1999), Smith and Van Houtven (1998, 2004) and Dosman and Adamowicz (2006).

McConnell (1999) states that the fact that many studies do not distinguish between individual and household makes the empirical estimates ambiguous. Further, 'economists need to think carefully about the individual versus the household in designing surveys and in measuring welfare' (p. 466). He attempts to address this issue by developing a recreational model based on two individuals (spouses) sharing income, household production and earning different wages. The limit in this approach is that the basic structure of the model is the unitary model that assumes income pooling, that a household has a single utility function and that there is not bargaining and intra-household allocation of resources between household members.

Dosman and Adamowicz (2006) examine the choice of two spouses for a vacation site. They investigate intra-household bargaining using stated and revealed preference data. They overcome the problem that individual preferences for the site are not observed by using stated preference methods. They ask each partner to make choices in a stated preference experiment and they use these choices to develop estimates of the spouses' preference parameters. Then they construct a bargaining model where the household utility is defined as the weighted average utility of partners' preferences. Since the household decision about the vacation site is observed, they estimate the bargaining parameter as the value that provides the best fit between the actual household choice and the weighted utility. They find that the probability that the household will choose the husband's favorite vacation site is decreasing as the husband's income is increasing. While the wife's power for the vacation site decision is increasing as the partner's income is increasing. An explanation of this result is that the opportunity cost of time for the husband is higher and he spends less time in planning the vacation.

Smith and Van Houtven (1998, 2004) focus on the collective model by Chiappori (1988, 1992). They extend Chiappori's model for recovering Hicksian welfare measures. They describe how it affects non-market valuation of price and quality changes but they do not provide any empirical application.

Chiappori (1988) proposes the first collective model, which is a static labor supply model. This model assumes that the objective function of the household is the weighted sum of the utility functions for each member's preferences. The weights represent the bargaining power of the household members in the intrahousehold allocation process. The rule that determines the sharing of total expenditure on private goods within the household is defined as 'sharing rule'. The bargaining power is affected by exogenous variables, such as wages and non-labor income, and by other variables called 'distribution factors' (Browning et al., 1994), which influence the decision process without affecting either the utility function or the budget constraint.

Examples of distribution factors are tax laws that differ according to marital status and divorce law. Changes in these variables may effect outside opportunities of the household members and may have consequences in their bargaining power within the household. An increase in an individual's non-labor income may shift bargaining power from one individual to the other and this affects the allocation of household consumption and labor supply (see Vermeulen, 2002 and Browning, Chiappori and Lechene, 2006 for a detailed overview of collective models).

In Chiappori's model and consequently in Smith and Van Houtven (1998, 2004)'s approach the sharing rule is identified up to a constant and it is estimated by using information on two exclusive goods privately consumed. Smith and Van Houtven consider the case of a two-member household where each individual consumes two private goods and in addition each person consumes one of these goods exclusively, for example sport fishing and swimming in the ocean. Finally, both members consume a third private good. They analyze the case where one member engages in a specific recreational activity affected by a change in environmental quality, and the other member does not. The authors do not investigate the case where both household members are affected by the change in environmental quality. They point out that it is still possible to recover individual preferences but that the problem is more complicated.

Browning, Chiappori and Lewbel (2006) propose an alternative approach that does not use consumption of exclusive goods but household's consumption aggregate data of singles and couples. BCL show how to completely identify joint consumption and the allocation of resources within a household by a consumption technology function and the sharing rule. 'The idea of the consumption technology function is that features of household consumption such as economies of scale or scope, joint use of resources, etc., can be defined as a technology that describes the set of options for the joint consumption of goods that are available to household members' (BCL, p.5). BCL's framework is similar to Becker (1965) model, except that instead of using market goods to produce commodities that contribute to utility, the household produces the equivalent of a greater quantity of market goods via sharing (BCL).

BCL emphasize that they assume that individual's preferences for goods do not change when they marry but that this does not mean that once married individuals consume the same bundles as singles because of the economies of scales and scope in consumption in a couple. This assumption also does not exclude that individuals can get utility from marriage. What it implies is that the indifference curves of single men or women living alone are the same as the indifference curves associated with the utility functions of the individuals in a couple (BCL). If this assumption holds, then the demand functions of household members can be estimated directly by observing the consumption behavior of single men and women. However, BCL also show how to overcome the assumption that tastes do not change. First, they identify the demand functions for singles, then they parameterize how preferences change because of marriage and finally, they use couple's data to estimate the parameters of the change in preferences, the consumption technology and the sharing rule.

1.3 Models

1.3.1 The Benchmark Model: Browning, Chiappori and Lewbel (2006)'s Model

In this section we present BCL (2006)'s model of household behavior as the benchmark model that we use to develop a collective recreational demand model. BCL consider two cases: when the individual is living alone ('single') and when the individual is a household member ('couple'). This allows them to use the demand data of people living alone to identify individual preferences and to use household data to identify the consumption technology and the sharing rule.

When the individual i is living alone the optimisation problem is

$$Max\ U^i(\mathbf{z^i}) \text{ subject to } y^i = \mathbf{pz}^{\mathrm{i}} \qquad (1.1)$$

where the utility function U^i is monotonically increasing, continuously twice differentiable and strictly quasi-concave; y^i is the exogenous income of individual i; $\mathbf{p}$ is the vector of prices of the goods $\mathbf{z}^{\mathrm{i}}$. The solution is the vector of Marshallian demands $\mathbf{z}^{\mathrm{i}}{}_{\mathbf{m}}(\mathbf{p}\,/\,y^i)$. The corresponding indirect utility function is defined as

$$V^{\boldsymbol{i}}(\mathbf{p}\,/\,y^i) = U^i(\mathbf{z^i_m}\,(\mathbf{p}\,/\,y^i)) \qquad (1.2)$$

Then, BCL consider the case where individual i is member of a household that consists of a couple living together ($i = f$ or m). The couple's utility maximization problem is

$$Max\ U[U^f(\mathbf{x^f}),\ U^m(\mathbf{x^m}),\ \mathbf{p}\,/\,y] \text{ subject to } \mathbf{x} = (\mathbf{x^f} + \mathbf{x^m}),\ \mathbf{z} = F(\mathbf{x}),\ \mathbf{p'z} \leq y \qquad (1.3)$$

where **z** is the vector of inputs that the couple purchases; **x**, $\mathbf{x^f}$ and $\mathbf{x^m}$ are the quantities of the goods **z** respectively consumed by the household and privately by each household member; **p** is the vector of market prices; y is the household total income and F is the consumption technology function. The transformation from **z** to **x** embodied by the function F is intended to summarize all of the technological economies of scale and scope that result from living together. Consider the example of BCL (p. 10): 'Let good j be automobile use, measured by distance travelled (or some consumed good that is proportional to distance, perhaps gasoline). If x_j^f and x_j^m are the distances travelled by car by each household member, then the total distance the car travels is $z_j = (x_j^f + x_j^m) / (1 + r)$ where r is the fraction of distance that the couple rides together. This yields a consumption technology function for automobile use of $z = x / (1 + r)$.'

Note that this framework is similar to a Becker (1965) type household production model but with the following main difference: the production function combines the inputs and generates the output, while the consumption technology function transforms the output **x**, that is what the individuals consume, into the inputs **z** that are purchased by the individuals. Thus $F(x)$ can be interpreted as an inverse production function[4].

Further, note that U is a twice differentiable utility function that can be interpreted as 'a social welfare function for the household', in which each household member has different bargaining power. In BCL the bargaining function U depends

[4] As BCL note, we can have more complicated consumption technologies. For example, 'the fraction of time r that the couple shares the car could depend on the total usage, resulting in F being a nonlinear function of x_j. There could also be economies (or diseconomies) of scope as well as scale in the consumption technology, e.g., the shared travel time percentage r could be related to expenditures on vacations, resulting in $F(x)$ being a function of other elements of x in addition to x_j' (p. 11).

on the relative incomes of the household members, and each household member's utility U^i also depends on demographic characteristics. Following Chiappori (1988, 1992), the utility function U can be written as the weighted sum of the utility functions for each member's preferences

$$U[U^f(\mathbf{x^f}), U^m(\mathbf{x^m}), \mathbf{p} / y] = \mu(\mathbf{p} / y)\, U^f(\mathbf{x^f}) + U^m(\mathbf{x^m}), \qquad (1.4)$$

where the weight μ represents the bargaining power of the household members in the intrahousehold allocation process. Individual m receives a weight of one and individual f a weight of μ in determining the intrahousehold decisions. The larger μ is the larger the bargaining power of member f and therefore the larger the quantities $\mathbf{x^f}$ consumed by member f with respect to the quantities consumed by member m. As BCL note, one limit using μ is that it will depend 'on the arbitrary cardinalizations of functions U^f and U^m'. The interesting contribution of BCL that distinguishes their work from Chiappori (1988, 1992) is the introduction of 'the sharing rule' φ, which 'does not depend upon any cardinalization.' The sharing rule describes the allocation of resources among household members. BCL specify the sharing rule as a function of distributional variables **d** that affect the bargaining power, such as the wife's share of total gross income, the difference in age between husband and wife, or the log household total expenditure deflated by a Stone price index. Note that instead the approach followed by Chiappori (1988, 1992) identifies the sharing rule up to a constant.

The BCL's model for φ follows the logistic form

$$\varphi = exp(\mathbf{d}'\gamma) / [1 + exp(\mathbf{d}'\gamma)] \qquad \text{with } 0 \leq \varphi \leq 1 \qquad (1.5)$$

where **d** is a vector of distributional variables and ϕ is a vector of parameters.

The household's behavior is equivalent to allocating the fraction of shadow income $\varphi^{\mathbf{f}} = \varphi$ to member *f*, and the fraction of shadow income $\varphi^{\mathbf{m}} = (1 - \varphi)$ to member *m*.

Each member *i* maximizes their own utility function $U^i(\mathbf{x^i})$ subject to the budget constraint $\varphi^i = \boldsymbol{\pi}'\boldsymbol{x}^i$. The maximization problem for each household member is

$$\text{Max } U^i(\mathbf{x^i}) \text{ subject to } \varphi^i = \boldsymbol{\pi}'\mathbf{x^i} \qquad (1.6)$$

where $\boldsymbol{\pi}$ is the shadow price vector for the individual *i*'s private good $\mathbf{x^i}$ and η^i is the individual *i*'s shadow income. BCL show that by homogeneity the price vector $\boldsymbol{\pi}$ can be normalized such that $\boldsymbol{\pi}'\mathbf{x} = 1$, $\varphi = \varphi^{\mathbf{f}} = \boldsymbol{\pi}'\mathbf{x^f}$ and $\varphi^{\mathbf{m}} = (1 - \varphi)$. The sharing rule is the fraction of the household's shadow income that is allocated to member *f*. Note that the household purchases the vector $\mathbf{z} = F(\mathbf{x^f} + \mathbf{x^m})$.

For simplicity BCL assume a Barten type technology function[5], defined as $\mathbf{z} = \mathbf{Rx}$, equivalent to the linear technology $\mathbf{z} = \mathbf{Rx} + \mathbf{a}$ when the matrix **R** is diagonal and **a** is a vector of zeros. In this case the constraint $\mathbf{p'z} = y$ becomes $\mathbf{p}'(\mathbf{Rx}) = y$. Since $\boldsymbol{\pi}'\mathbf{x} = 1$, the shadow prices for this technology are

$$\pi = \mathbf{R'p} / y\,, \qquad (1.7)$$

where the couple faces market price **p** and total income *y*.

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[5] Barten type technology function (1964) is a special case of Gorman's (1976) general linear technology model $z = Rx + a$, with R diagonal and a zero (see also Muellbauer, 1977; Perali, 2003).

The second welfare theorem implies that the individual, facing price π and income η^i, will choose the bundle $\mathbf{x}^{\mathbf{i}}$. The solution to the utility maximization problem is a set of Marshallian demands equal to

$$\mathbf{x}_{\mathbf{m}}^{\mathbf{i}}(\boldsymbol{\pi}(\mathbf{p}/y)/\varphi(\mathbf{p}/y)) = \mathbf{x}_{\mathbf{m}}{}^{\mathbf{i}}\left(\frac{\mathbf{R'p}}{y}\frac{1}{\varphi(\mathbf{p}/y)}\right) \;, \qquad (1.8)$$

which yields the indirect utility function $V^i\ (\pi\ /\ \varphi)$[6].

Then, since $\boldsymbol{\pi} = \mathbf{R'p}\ /\ y$, the household actually purchases the vector $\mathbf{z}$ that becomes

$$\mathbf{z} \;=\; \mathbf{Rx_m}{}^{\mathbf{f}}\left(\frac{\mathbf{R'p}}{y}\frac{1}{\varphi(\mathbf{p}/y)}\right) + \mathbf{Rx_m}{}^{\mathbf{m}}\left(\frac{\mathbf{R'p}}{y}\frac{1}{1-\varphi(\mathbf{p}/y)}\right) \qquad (1.9)$$

The relationship between the weight μ and the sharing rule φ can be written as

$$\mu = -\frac{\left(\partial V^f\left(\boldsymbol{\pi}/\varphi\right)/\partial\varphi\right)}{\left(\partial V^m\left(\boldsymbol{\pi}/1-\varphi\right)/\partial\varphi\right)} \qquad (1.10)$$

where V^i is the indirect utility function of member i (see BCL p. 13 for a formal proof).

Note that one advantage of BCL model respect Chiappori (1988, 1992)'s model is that using data from households and from singles living alone, the sharing rule is completly identified. BCL empirically estimate simultaneously a joint system consisting of a vector of budget shares for singles and a vector of budget shares for couples. They can do so because all the parameters in the singles model appear in the

[6] Note that *π(.)* and φ*(.)* are functions and p/y is their argument.

couples model. They use the demand data of people living alone to identify individual preferences, thereby leaving the job of identifying the consumption technology and the sharing rule to household data.

1.3.2 Traditional Recreational Demand Model

In the traditional literature of recreational demand the terms 'individual' and 'household' are used interchangeably. Traditional analysis models the household as it was a single individual. The allocation of the resources among its members is ignored.

Following Bockstael and McConnell (2006), individuals maximize utility U which is a function of the number of trips (n) taken to a site[7], environmental quality at the site (q) and a composite commodity (b). The number of trips is produced using inputs **s** such as gasoline, food and lodging. First, note that the number of trips is a weak complement with the environmental quality: q does not affect the individual's utility if she does not go to the site ($n = 0$); second, note that some of the goods that compose the vector **s** are exclusive for the individual (for example sunscreen lotion for women and fishing equipment for men) and others are consumed and shared between members of the trip (for example gasoline and food), but for the moment, following the traditional literature, we assume that each individual that shares these goods consumes the same amount of them.

Then, consider the time constraint that limits the amount of time that can be spent on leisure activities. As Bockstael and McConnell (2006) emphasize, not considering the time cost term in the demand function would produce a biased

[7] For simplicity we consider trips on a single site.

estimated cost coefficient that leads to an underestimate of the consumer surplus for access to the site. Then, the individual's optimisation problem is

$$Max\ U(n, b; q) \text{ subject to } y + wL \geq \mathbf{ps} + b\ ,\ T \geq L + t\,n \text{ and } g(n, \mathbf{s}) = 0 \qquad (1.11)$$

where y is exogenous non-wage income, w is the after-tax wage rate, L is the total number of hours spent working, p is the vector of prices of the inputs **s**, T is the total available time to the individual, t is the time cost of access to the recreational site, b is the price of the composite commodity normalized to 1 and $g(n, \mathbf{s})$ is the household production technology. As Bockstael and McConnell note, $g(n, \mathbf{s})$ implies a cost function that is the solution of the cost minimization problem

$$C(n, p) = min_s\{\mathbf{ps} \mid g(n, \mathbf{s}) = 0\} \qquad (1.12)$$

and if the cost function is linear in n than the marginal cost per trip equals the average cost per trip $c(\mathbf{p})$. The maximization problem becomes

$$Max\ U(n, b; q) \text{ subject to } y + wL \geq c(\mathbf{p})n + b \text{ and } T \geq L + t\,n\ . \qquad (1.13)$$

Since we assume that the individual can choose how to allocate his time between work (L) and leisure (t) the two constraints can be combined into one:

$$Max\ U(n, b; q) \text{ subject to } [y + wT - n(c(\mathbf{p}) + wt) - b] \geq 0\ , \qquad (1.14)$$

which leads to the Marshallian demand $n_m(c, q, w, T, y)$.

In the traditional Travel Cost Method (TCM) the value of the site, which can be interpreted as the Willingness-To-Pay of the individual to access to the site, is derived by calculating the individual's consumer surplus (CS). The individual's consumer surplus is the area behind the Marshallian demand for trips to the site

$$CS = \int_{c_0}^{ç} n_m(c,\ q_0, w, T, y)\, dc\ , \qquad (1.15)$$

where c_0 is the observed level of constant marginal cost to produce trips n and $ç$ is the choke price of the trip: $n_m(ç) = 0$.

Further, to be useful for policy purposes, the estimated consumer surplus can be aggregated across the population of recreational users. The total economic value of the site can be estimated as the sum of the consumer surplus of each individual going to the site:

$$CS = \sum_{i}^{K} \int_{c_{0,i}}^{ç_i} n_{im}(c_i,\ q_0, w_i, T, y_i)\, dc \qquad (1.16)$$

where K is the total number of site users.

1.3.3 Collective Recreational Demand Model

In this section, we develop a collective recreational demand model applying the collective model of household behavior of BCL (2006) to the traditional recreational demand model described in the previous section.

Since we are considering individuals living together their individual choice is conditioned by the presence of the other members. This is a more complicated case than BCL's case. We have to consider not only the consumption technology function but also the household production function. The consumption technology function transforms what the individuals privately consume (for example number of trips taken to a site by member *m* and *f*) into the inputs that the couple is observed purchasing (for example number of trips taken to a site by the household). The household production function combines inputs, such as food and gasoline, to generate the output 'trips'.

Another issue is related to the time cost of the recreational trip. 'Time' raises two problems[8]. First, it is easier to pool money than to pool time in a household. For instance, the husband could spend his wife's money if he wants, but it is much harder for him to spend his wife's time to go to a recreational site[9]. Second, the time costs are not shared in the same way as money costs. Suppose a couple takes some joint recreational trips. The money costs are shared, for example the couple benefits from the same gasoline purchase. However the time costs are not shared in the same way. If both husband and wife take the trip, then both husband and wife's time costs must be charged. This problem makes the recreational demand model different from the BCL's model.

First, we analyze the case of individuals living alone, and then the case of individuals living together. In fact, BCL use the demand data of people living alone to identify the Marshallian demand functions $\mathbf{x^i_m}$ arising from the utility functions U^i, and the household data to estimate the household's demand functions **z,** the consumption technology F and the sharing rule $\boldsymbol{\varphi}$.[10]

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[8] The author thanks Nancy Bockstael for having pointed out these problems.
[9] Note that pooling time is possible when household members reallocate household tasks. For example, the husband has more time for fishing if the wife cleans and cooks the fish.
[10] BCL's model assumes that marriage does not induce preference changes. They justify this assumption claiming that 'it may be reasonable to assume that, at least for some goods, the dollar effect of a change in tastes is small.' In the recreational case we could assume that preferences of singles are not significantly different from those of married people if there are not children in the household.

1.3.3.1 Individuals Living Alone

We apply the traditional recreational demand model described in Section 1.3.2 because we consider individuals living alone, thus, there is not intra-household allocation of resources and no shared travel costs or problems with pooling time.

The utility optimisation problem of individual i is similar to that of the traditional recreational demand model, however there are two differences. The first difference is in the notation. Each variable and the utility function of individual i are characterized by the superscript i: if $i = f$ we refer to a woman; if $i = m$ to a man. The second difference consists of replacing the implicit production function $g(n^i, \mathbf{s}^i) = 0$ with $n^i = B(\mathbf{s}^i)$, where B is the transformation (production) function from inputs into the production of trips.

It is made explicit that the exogenous income (y^i), the number of trips to a recreational site (n^i), the composite commodity (b^i), the time costs of access to the recreational site (t^i), the after-tax wage rate w^i, the total number of hours spent working (L^i) and the vector of inputs used ($\mathbf{s^i}$) refer to the site's user i and not to the household as a single decision making unit.

Following the methodology presented in Section 1.3.2, we can derive the individual recreational demands for the recreational site, $n^f{}_m(c^f, q, w^f, T, y^f)$ and $n^m{}_m(c^m, q, w^m, T, y^m)$, where c^i is the constant cost per trip derived assuming marginal cost equal to average cost, and thus, we can obtain the usual welfare measures of the traditional recreational demand literature (compensating variation and consumer surplus). Note that in this case, these measures refer to the welfare of an individual that lives alone.

1.3.3.2 Individuals Living Together

Now, consider the case of two individuals living together, (i = m and f), who can take trips separately as well as jointly.[11]

As we pointed out at the beginning of Section 1.3.3, in this case travel costs will be shared if the two individuals take a trip jointly while the time costs are not shared. We deal with this problem expanding BCL's model by including time constraints on each individual in the household's maximization problem. We evaluate time at different wage rates because we assume that the household members have different jobs. Further, as in the traditional recreational demand model, the household production technology is such that trips are produced using inputs **s** (for example gasoline and lodging), and we assume that the travel cost function is linear in the number of trips. This implies that the marginal travel cost per trip equals the average travel cost per trip $c(\mathbf{p})$.

The household's optimisation problem becomes

$$Max\ U[U^f(n^f, b; q), U^m(n^m, b; q)] = \mu\, U^f(n^f, b; q) + U^m(n^m, b; q), \qquad (1.17)$$

subject to

$$N = n^f + n^m, \qquad (1.18)$$

$$Z = F(N), \qquad (1.19)$$

$$y + w^f L^f + w^m L^m \geq c(\mathbf{p})Z + b, \qquad (1.20)$$

$$T \geq L^f + t^f n^f \qquad (1.21)$$

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[11] We anticipate here that the behavior of a group is assumed equal to the behavior of a family, recognizing that important considerations are embedded in this distinction.

$$T \geq L^m + t^m n^m \qquad (1.22)$$

where the weight μ represents the bargaining power of the household members in the intra-household allocation process: individual m receives a weight of one, and individual f receives a weight of μ in determining the intra-household decisions; U is a twice differentiable utility function 'interpreted as a social welfare function for the household'; U^i is the utility of member i[12]; **p** is the vector of prices for the inputs **s**; y the household total income; b is the price of the composite commodity normalized to 1; t^f and $t^{\mathbf{m}}$ are the time costs of each household member; L^f and $L^{\mathbf{m}}$ are the total number of hours spent working by individuals f and m; w^f and w^m are the after-tax wage rate of each household member; Z is the number of trips the couple is taking to a site accounting for the fact that some trips are taken jointly; n^f and $n^{\mathbf{m}}$ are the number of trips taken by each household member; N is the total number of trips taken by both household members; F is the consumption technology function that summarizes the economies of scale that arise from traveling together and sharing[13].

We allow the two time constraints for the two household members to be collapsed in the budget constraint.

The household's optimisation problem becomes

$$Max\ U[U^f(n^f, b; q), U^m(n^m, b; q)] = \mu\, U^f(n^f, b; q) + U^m(n^m, b; q), \qquad (1.23)$$

subject to

[12] We assume that the utility functions of children are jointed with the utility of the household member f, living for future research the investigation of a model that relaxes this assumption.
[13] The consumption technology may also capture some kinds of taste that result from traveling together rather than traveling alone.

$N = n^f + n^m$,

$Z = F(N)$,

$y + (w^f + w^m)T \geq c(\mathbf{p})Z + (w^f t^f n^f + w^m t^m n^m) + b.$ (1.24)

Note that empirically we observe the total household income and not the individual income. The household's behavior is equivalent to allocating the fraction of shadow (not observed) income $\varphi^f = \varphi$ to member *f*, and the fraction $\varphi^m = 1 - \varphi$ to member *m*, where φ is defined in equation (1.5). Each household member *i* maximizes their own utility function U^i subject to the budget constraint $\varphi^i = \boldsymbol{\pi}^i n^i$, where $\boldsymbol{\pi}^i$ is the shadow price vector for the own number of trips n^i and φ^i is the individual *i*'s shadow income.

The household purchases trips $Z = F(n^f + n^m)$ and for simplicity BCL assume a Barten type technology function, defined as $Z = RN$, where $N = n^f + n^m$.[14]

The budget constraint (1.24) becomes

$$n^f[c(\mathbf{p})R + w^f t^f] + n^m[c(\mathbf{p})R + w^m t^m] + b = y + T(w^f + w^m) \qquad (1.25),$$

which yields to the shadow prices of individual *i*'s trips

$$\pi^m_m = \frac{c(\mathbf{p})R + w^m t^m}{y + T(w^f + w^m)} \qquad (1.26)$$

and

$$\pi^f_m = \frac{c(\mathbf{p})R + w^m t^m}{y + T(w^f + w^m)}, \qquad (1.27)$$

[14] *R* can be thought as a scale factor when trips are taken jointly.

where the couple faces constant cost per trip $c(\mathbf{p})$ and total income y. Note that the shadow prices of individual i's trips depend on the time costs of both individuals, not only on the time cost of individual i.

By the second welfare theorem, the solution to the utility maximization problem is a set of Marshallian demands equal to $n^i_m\ (\boldsymbol{\pi}^i / \varphi^i)$ and the indirect utility function is $V^i\ (\boldsymbol{\pi}^i / \varphi^i)$, which depend on the shadow prices and the sharing rule. This implies that the recreational demand of individual i depends not only on individual i's time cost but also on the time cost of the other household member.

Then Z becomes

$$\begin{aligned} Z \;=\; & Rn^m_m\left(\frac{c(\mathbf{p})+w^m t^m}{y+T(w^f+w^m)}\frac{1}{\varphi}\right)+ \\ & Rn^f_m\left(\frac{c(\mathbf{p})+w^f t^f}{y+T(w^f+w^m)}\frac{1}{1-\varphi}\right) \end{aligned} \qquad (1.28)$$

Note that the knowledge of the sharing rule φ permits the derivation of individual indirect utility and cost functions that can be used to perform both interpersonal and inter-household comparisons.

Finally, following the traditional recreational literature and applying equation (1.15) we can calculate the consumer surplus for each household member and for the household, taking into account the intra-household allocation of resources and that each individual has their own preferences.

1.4 Some Empirical Analysis

1.4.1 Study Site and Data Gathering

The sample is drawn from an onsite survey conducted by the Department of Economics of the University of Verona on the West side of Garda Lake in the Northeast of Italy from June to October 1997. This survey was part of an integrated analysis on the multi-functionality of the West Garda Regional Forest in order to define cooperative policies between institutions, local operators and visitors.[15]

This area was picked because the trips taken would mostly be single-destination, single-purpose trips, which is a necessary assumption of the Travel Cost Method (TCM) (Freeman, 1993). It was also felt that, due to Garda Lake's popularity with tourists from throughout the country and abroad, there would be sufficient variation in distance travelled, time and trip cost.

Each respondent was asked to recall the number of annual trips made to the West Garda Regional Forest and the number of trips to other natural areas during the year. In order to double check the declared costs, visitors were asked to specify their place of residence, the distance travelled between the natural area and their residence, the journey time and for those who were on vacation, the distance from the forest to their vacation lodging.

Moreover, the following data were collected for each individual: means of transportation used, number of passengers per means of transportation, how many family members and how many shared the expense of the trip; if stops were made at other places before going to the natural area; how many days the trip lasted;

[15] For a detailed description of the survey see the Annex.

individual and family transportation expenditure to go to the forest; individual and family expenditure in food, lodging and free time activities during the trip; occupation and weekly number of hours of work. We used this information to construct the variable 'travel cost', which comprehends the opportunity cost of time spent traveling to the natural area.[16]

In order to estimate the expenditure on alternative sites, the visitor was asked about the distance from the residence, the number of visits to each site, the quality of the area and the purpose of the trip.

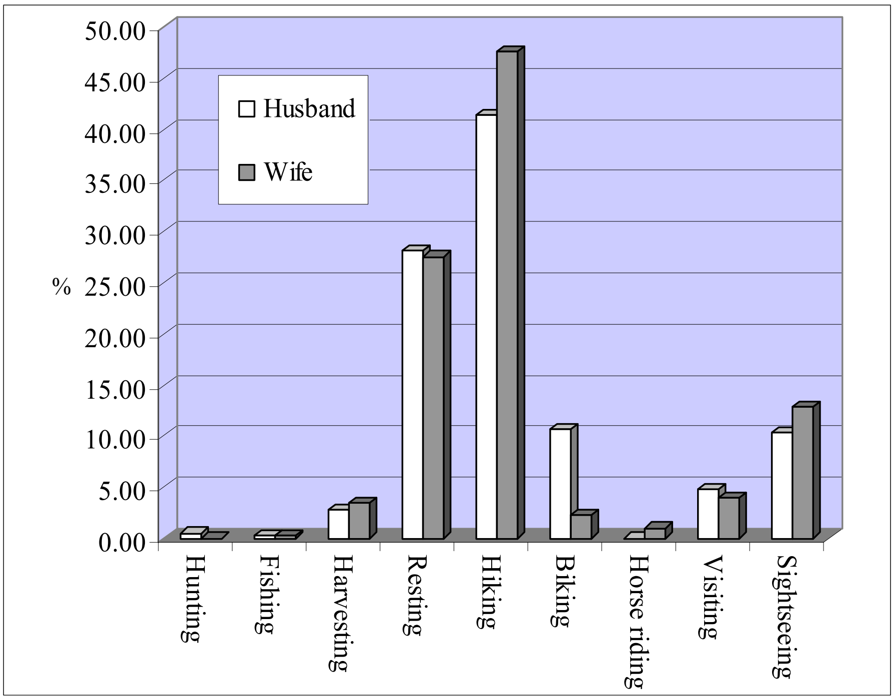
This survey also has an advantage in allowing us to know if the visitors are married, and then if the visitor is the husband or the wife.[17]

The visitor was also asked how she allocated her time during the visit between naturalistic (for example going sightseeing), harvesting (for example harvesting flowers, mushrooms, hunting and fishing) and recreational activities (for example mountain biking, horse riding, hiking, picnicking, visiting historic places), and how she would have wished to spend her time between these activities. Figure 1.1 shows the percentage of on site time spent in different activities for husbands and wives. Husbands bike and visit more than wives do, but they hike and sightsee less than wives do.

[16] Several studies apply and compare different values to estimate the opportunity cost of time (for example Cesario, 1976; McConnell and Strand, 1981; Johnson, 1983; Smith et al., 1983; Chavas et al., 1989; Bockstael et al., 1990; McKean et al., 1996). In this study we evaluate travel time at one third of the wage rate (Cesario, 1976).

[17] Note that only one respondent was interviewed in each household so 'husband' and 'wife' are not in the same couple.

Figure 1.1 – Percentage of on Site Time Spent in Different Activities



1.4.2 Empirical Model and Results

In this study we do not estimate the collective recreational demand model developed in Section 1.3.3 but first we test the null hypothesis that, after controlling for income and other socio-economic characteristics, the recreational demand of husbands is not statistically different from the recreational demand of wives. Testing for this hypothesis allows us to motivate future research in the estimation of the collective recreational demand model. If the recreational demand of husbands and wives are the same then husband and wife responses may be treated identically, as in the traditional unitary recreational demand model. Second, we test the null hypothesis of no difference in consumer surplus between husbands and wives, and third we test that the consumer surplus estimated using the traditional recreational demand model is not statistically different from the consumer surplus estimates of husbands and wives.[18]

In order to test these hypotheses we consider the sample of husbands and wives (225 observations) and we estimate an unrestricted Poisson model where we allow the parameters of the model to vary by gender. Table 1.1 defines the variables used in the Poisson model and Table 1.2 presents summary statistics for husbands and wives.

Table 1.1 - Definition of the Variables in the Poisson Model

Variable	Definition
trips	Annual number of visits to the natural area
ln_income	Log(annual income/1000) in euros
tc	Travel cost per car in euros
ln_tc1	Log(annual travel cost per car for visits to 1st alternative site) in euros
ln_tc2	Log(annual travel cost per car for visits to 2nd alternative site) in euros
edu	Number of years of education
age	Age
Obs.	Number of Observations

[18] It would have been also interesting to compare the recreational demand and the consumer surplus of single men and women with those of husbands and wives with and without children but unfortunately the small sample size does not allow us this kind of estimation. We suggest implementing this comparison as future research.

Table 1.2 - Descriptive Statistics for Selected Variables in the Poisson Model

	Pooled sample		Husbands		Wives	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
trips	7.098	12.064	8.317	14.240	5.128	6.926
ln_income	3.091	0.495	3.115	0.497	3.052	0.492
tc	3.927	7.196	4.276	7.334	3.364	6.973
ln_tc1	2.137	2.048	2.126	2.051	2.154	2.054
ln_tc2	0.915	1.700	0.932	1.714	0.889	1.685
edu	12.342	4.241	12.647	4.283	11.849	4.149
age	44.418	11.330	45.237	11.704	43.093	10.630
Obs.	225		139		86	

Let **X** be the vector of independent variables: the logarithm of the individual *i*'s monthly net income from the previous year (*ln_income*), the travel cost per car to visit the natural area (*tc*), the logarithm of the annual travel cost per car to visit two alternative sites that are different from the West Garda Regional Forest (*ln_tc1*, *ln_tc2*), education (*edu*), and age (*age*).

We allow for differences in recreational demand between husbands and wives by interacting the **X** vector with the dummy variable for sex (*sex* = 1 if male, 0 if female).

The general form for the recreational demand for the natural area becomes

$$trips^* = E(trips_i) = \exp(\mathbf{X}'\boldsymbol{\alpha} + \mathbf{X}'\boldsymbol{\beta} \cdot sex) \qquad (1.29)$$

where $trips_i$ is the annual number of visits to the natural area by individual $i = \{1, ..., K\}$ and $trips^*$ is the expected number of trips.

The α parameters correspond to the coefficients for the **X** variables for wives. The β parameters represent the difference between husbands and wives.

If the null hypothesis of no significant differences between husbands and wives is not rejected then the unrestricted model (model A in Table 1.3) becomes the same as the restricted traditional Poisson model (model B in Table 1.3). To test this hypothesis we specify the null as H_0: $\boldsymbol{\beta} = \mathbf{0}$ (i.e. 'husbands' = 'wives') and the alternative as H_1: at least one coefficient of the vector of parameters $\boldsymbol{\beta}$ is significantly different from zero.

Table 1.3 shows the parameter estimates for the unrestricted and restricted model. As expected the number of visits to the natural area decreases if the travel cost (*tc*) increases (*tc* has a negative sign and is significant at the 1% statistical level) and if income increases then the number of trips increases (*ln_income* has a positive sign and is significant at the 1% statistical level). However that the coefficient on education (*edu*) is negative is opposite of our expectations.

We use the unrestricted model to perform a Wald test of the null hypothesis H_0: $\boldsymbol{\beta} = \mathbf{0}$ of no differences between husbands and wives. We reject the null at the 1% significant level[19]. We also perform the likelihood ratio test using the unrestricted and restricted models and we again reject the null hypotheses of no difference in the recreational demand between husbands and wives at the 1% significant level.[20] Rejection of the null hypothesis suggests that observations for husbands and wives

[19] The χ^2 statistic is 195.01 for H_0: $\boldsymbol{\beta} = \mathbf{0}$ (p-value 0.000). The critical value of the χ^2 statistic with 6 degrees of freedom is 16.81 at the 1% confidence level.

[20] The χ^2 statistic is 203.34 (p-value 0.000). The critical value of the χ^2 statistic with 6 degrees of freedom is 16.81 at the 1% confidence level.

may not be treated as identical as in the traditional recreational demand model (unless one spouse is the dictator).

Table 1.3 – Poisson Estimates of Restricted and Unrestricted Models

	Model A (Restricted)			Model B (Unrestricted)		
Variable	Coef.	Std. Err.		Coef.	Std. Err.	
				α parameters		
constant	0.751	0.213	***	0.933	0.218	***
ln_income	0.491	0.060	***	0.569	0.095	***
tc	-0.010	0.001	***	-0.003	0.001	***
ln_tc1	0.073	0.015	***	0.024	0.028	
ln_tc2	-0.014	0.016		0.089	0.031	***
edu	-0.017	0.007	**	-0.064	0.013	***
age	0.003	0.002		-0.007	0.004	
				β parameters		
ln_income*sex				-0.059	0.098	
tc*sex				-0.013	0.001	***
ln_tc1*sex				0.068	0.033	**
ln_tc2*sex				-0.143	0.037	***
edu*sex				0.056	0.015	***
age*sex				0.009	0.005	**
Log likelihood	-1464.111			-1362.4418		
Sample Size	225			225		

*** Significance at the 1% level; ** Significance at the 5% level;
* Significance at the 10% level.

Finally, we want to test the null hypotheses of (i) no significant difference in the consumer surplus estimates of husbands and wives, and (ii) of no significant difference between the consumer surplus estimates of husbands and wives and the consumer surplus obtained using the traditional restricted model (i.e. model A).

The unrestricted Poisson model just described can be used to calculate the consumer surplus of husbands and wives by taking the area under the expected demand function (1.29). For the exponential demand function (1.29), the choke price, at which the demand of trips is zero, is infinite (Habb and McConnell, 2002, p. 167). Let us consider the simple demand specification *trips** = $exp(\delta_0 + \delta_1 tc)$, the consumer surplus for access to the forest is

$$CS = \int_{tc^0}^{\infty} \exp(\delta_0 + \delta_1 tc)dtc = -\frac{trips_0^*}{\delta_1} \quad \text{when} \quad \delta_1 < 0 \qquad (1.30)$$

where $trips_0^* = \exp(\delta_0 + \delta_1 tc_0)$ is the expected number of trips at the current travel cost tc_0 and δ_1 is the coefficient on tc_0. Then, the consumer surplus per trip can be calculated as -1 / δ_1 (Creel and Loomis, 1990).

We obtain the mean consumer surplus per trip estimates for husbands and wives by substituting the estimated coefficients from the unrestricted model from Table 1.3.[21] These results, along with their standard errors estimated by bootstrapping for 1000 replications, are shown in Table 1.4.[22]

Table 1.4 – Mean Consumer Surplus (CS)

Variable	Obs.	Mean	Std. Err.	Std. Dev.	95% Conf. Interval	
Traditional CS	225	6.280	0.196	2.945	5.893	6.667
Husbands' CS	139	4.503	0.223	2.634	4.061	4.945
Wives' CS	86	16.058	0.641	5.944	14.784	17.333

[21] From Table 1.3 (model B) we have that wives' δ_1 corresponds to α_{tc}, = -0.003, while husbands' $\delta_1 = \alpha_{tc} + \beta_{tc}$ = -0.003 + (-0.013) = - 0.016.

[22] Note that the CS figures in Table 1.4 have been divided by the number of passengers in the car and by the number of days of the visit at the site, so they refer to the CS per day of trip and per passenger.

In absolute value, the consumer surplus estimate derived from the restricted traditional model appears to overestimate the consumer surplus of husbands and underestimate the consumer surplus of wives. The difference is statistically significant at the 1% level.[23] We also reject the null hypothesis of no difference in consumer surplus between husbands and wives at the 1% level[24]: wives have significantly higher consumer surplus than husbands for access at the West Garda Regional Forest.

1.5 Conclusions and Discussion

The main contribution of this study to the recreational models literature is conceptual: we demonstrate that a utility theoretic framework derived from the collective model proposed by Browning, Chiappori and Lewbel (2006) can be used to formulate a collective recreational demand model. This model allows the researcher to find the consumer surplus for each household member and for the household. It takes into account the intra-household allocation of resources and that each individual has their own preferences by using information about consumption of singles and couples and by a consumption technology function, which summarizes the economies of scale and scope that result from living together.

First, we considered the case of an individual living alone. In this case, we do not have intra-household resource allocation and the household expenditure in leisure and consumption goods is equal to that of the single individual. In order to find the consumer surplus measure we can apply the traditional recreational demand model.

[23] p-value = 0.000.
[24] p-value = 0.000.

Then, we considered the case with intra-household allocation of resources. This situation refers, for example, to couples that go to visit a recreational site. If the quality of the site changes household members might be willing to pay for the change in the site's quality because it also affects the other member's recreational activities and not only their own. They can recognize that the degradation of the site can cause a reallocation of income in the household. This can affect the change in exogenous income necessary to return the individual to the utility level that he or she experienced before the change. This yields different values for the change in quality of the area, compared to the values derived by using the traditional recreational model.

The traditional recreational demand model assumes that a household acts as a single decision unit, even if it consists of different individuals. The traditional recreational model does not make any distinctions about the value of the site for different household members. The amount a household member would pay or be paid to be as well off with or without the quality change does not take into account the allocation of resources in the family, the differences in preferences or the differences in the opportunity cost of time of the household members. Individuals in a household can value a change in quality differently, depending on their opportunity cost of time, how the household income is allocated in the household, how much they like a particular site and how they use it. The collective recreational demand model developed in this study allows the derivation of consumer surplus measure for each household member taking into account the intra-household allocation of resources and that each individual has their own preferences. We also showed that the recreational demand of individual *i* depends not only on individual *i*'s time cost but also on the time cost of the other household members.

With the collective recreational demand model, the policy maker can use each household member's consumer surplus in order to know how to regulate the access of a recreational site, how much to compensate different individuals in case of degradation of a natural environment and how to target programs to individuals in certain recreational activities groups rather than to households.

We included children's welfare by assuming that there is one altruistic member that takes into account the household members' well-being. Following BCL, we assumed that the utility function of the woman and all the associated demand functions refer to the joint utility function of a woman and her children. It is not simple to relax this assumption, however. Children consume the same kind of goods as their parents. For example, the expenditure on food includes the wife's consumption, the husband's consumption and the child's consumption. Usually it is not possible to distinguish these components in the data.

We also focused on the behavior of a family and we did not account for the behavior of groups where individuals from different households choose to take a trip together. Relaxing this assumption will be the subject of forthcoming research applying the model by Chiappori and Ekeland (2006) about group behavior.

At this point one could ask if the distinction between the traditional and the collective recreational demand model is merely an academic curiosity, or if differences in how resources are distributed within households reflect appreciable differences in the welfare measures.

In this study, we made a first step in this direction. We tested the null hypothesis that, after controlling for income and other socio-economic characteristics, the recreational demand of husbands is not statistically different from the recreational demand of wives. If the recreational demand of husbands and wives are the same then husband and wife responses may be treated identically, as in the traditional recreational demand model. We rejected the null hypothesis at the 1% statistical level. There are statistical differences in the recreational demand functions of husbands and wives. This implies that observations for husbands and wives may not be treated as identical as in the traditional recreational demand model (unless one spouse is the dictator). We also found that, in absolute value, the consumer surplus estimate derived from the traditional model appears to overestimate the consumer surplus of husbands and underestimate the consumer surplus of wives, and that wives have significantly higher consumer surplus than husbands for access at the West Garda Regional Forest.

Even if these findings are referring to spouses not living in the same household, they imply that the collective setting is a plausible next step to take in the analysis of recreational demand model.

It is left for future research the estimation of the collective model developed in this study in order to obtain the consumer surplus estimates of husband and wife from the same couple and the sharing rule. For an empirical application we need data about individuals living alone and together. This should allow us to use the demand data of people living alone to identify individual preferences, thereby leaving household data the job of identifying the consumption technology and the sharing rule. This will also be the subject of forthcoming research.

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CHAPTER 2

Extension of the Traditional Travel Cost Method to a Collective Framework: An Empirical Application

2.1 Introduction

As we saw in the previous chapter the collective setting is a plausible next step to take in the analysis of recreational demand model. The traditional Travel Cost Method is limiting in that it can reveal consumer preferences for non-market goods by only capturing family behavior. It assumes that a household acts as an elementary decision making unit where all resources are pooled.

Bockstael and McConnell (2006) note that ‘In the original paper on household production, Becker treated the household as the decision making unit, suggesting that intra-household allocations of consumption and production activities would be made ‘optimally’ (p.512). In the forty years since that paper, little progress has been made in explaining this intra-household allocation process or in reconciling the distinction between the household as decision maker and the individual members as consumers.’ (p. 8, Chapter 4).

McConnell (1999) attempts to address this issue by developing a recreational model based on two individuals (spouses) sharing income, household production and earning different wages. The limit in this approach is that the basic structure of the model is the unitary model that assumes income pooling, that a household has a single utility function and that there is not bargaining and intra-household allocation of resources between household members.

Smith and Van Houtven (1998, 2004) describe the implications of the collective model of household behavior for methods used to estimate the economic value of non-market goods but they do not present any empirical application and they do not estimate any welfare measures.

Dosman and Adamowicz (2006) examine the choice of two spouses for a vacation site. They investigate intra-household bargaining using stated and revealed preference data. They ask each partner to make choices in a stated preference experiment and they use these choices to develop estimates of the spouses' preference parameters. Then they construct a bargaining model where the household utility is defined as the weighted average utility of partners' preferences.

To the best of our knowledge, no papers exist that estimate the individual Willingness-To-Pay (WTP) for access to a recreational site for each household member by using only revealed preferences data or that apply a Travel Cost Method to a collective framework.

In the previous chapter we made a step in this direction by developing a collective recreational demand model that uses information about the travel cost of singles and couples and by a consumption technology function, which summarizes the economies of scale and scope that result from living together. We also showed that the recreational demand and the consumer surplus estimate of husbands is statistically different from the recreational demand and the consumer surplus estimate of wives. However, because of the small sample size in the number of singles we could not apply the collective recreational demand model developed in that chapter.

Two are the main contributions of this chapter to the recreational models literature: first, we show how to apply the collective model theory originally proposed by Chiappori (1988, 1992) in a recreational setting by using revealed preference data from a travel cost survey; second, we show how to identify and estimate individual welfare measures, such as the equivalent variation (EV), to infer the WTP to access a natural park of each household member. We define the implemented method as ‘Collective Travel Cost Method’ (CTCM).

We adopt the identification strategy developed by Menon and Perali (2006). The minimal requirement information for the identification of the sharing rule within the household is to observe at least one assignable good.

In the ‘Collective Travel Cost Method’ knowledge of the travel cost to the recreational site of each household member allows us to identify the sharing rule and to apply the CTCM to a recreational framework. In particular, we estimate a collective Almost Ideal Demand System that takes into account the role of each member’s preferences for trips to a recreational site and how resources are allocated within the household.

Finally, the development and estimation of the CTCM allows: (1) to test if the WTP to access a recreational site estimated by the traditional unitary TCM is significantly different from the WTP estimated by the CTCM; (2) to test whether two spouses have equal or different WTP to access a recreational site, and (3) if the individual WTP estimated by the CTCM is significantly different from the WTP derived by applying the Contingent Valuation Method (CVM) on the same sample of individuals.

We find, (1) that the WTP obtained by applying the traditional TCM is significantly different from the WTP obtained by applying the CTCM; (2) that two spouses have significantly different WTP and (3) that the CTCM allows to estimate respondent's WTP closer to the CVM WTP than the traditional TCM.

The chapter is organized as follows: Section 2.2 describes the basic structure of the Collective Travel Cost Method and describes the identification strategy of the sharing rule. Section 2.3 describes the empirical model used: the Collective Almost Ideal Demand System. Section 2.4 describes the data and the results. The last section concludes with suggestions for future research.

2.2 Collective Travel Cost Method and Sharing Rule Identification

In this section, first we develop a 'Collective Travel Cost Method' (CTCM) by applying the collective model of household behavior of Chiappori (1988, 1992) then we describe the identification strategy of the sharing rule between household members developed by Menon and Perali (2006). We define it as 'Collective Travel Cost Method' (CTCM) since we use the individual expenditure to visit a recreational site (i.e. 'the annual travel cost') as necessary variables for the identification of the sharing rule.

We consider a household consisting of two members, individual r ('the respondent' of on-site survey, for example) and individual s ('the spouse'). However, we can interpret one of the utility of the two members as a joint utility function for all but one member of the household. For example, as we will see in our empirical application, one utility can represent the utility of the respondent to the survey and the other utility represent the joint utility of all the family members of the respondent (e.g. the spouse with the children).

Let the superscripts refer to household members and subscripts to goods. Each household's member i ($i = r, s$) consumes assignable private goods $\mathbf{x^i} = \left(x_1^i, ..., x_N^i\right)$ at price $\mathbf{p^i}$ and composite goods $\mathbf{Q^i}$ ($\mathbf{Q} = \mathbf{Q^r} + \mathbf{Q^s}$). For simplicity, assume $\mathbf{Q^i}$'s price is normalized to unity.

Let $U^i(\mathbf{x^i}, \mathbf{Q})$ be the egoistic direct utility function of individual i.

<u>Assumption A1</u>: Each individual has a monotonically increasing, continuous twice differentiable and strictly quasi concave utility function[25] $U^i(\mathbf{x^i}, \mathbf{Q})$ over a bundle of N goods $\mathbf{x^i}$.[26]

<u>Assumption A2</u>: Given the budget constraint the household makes Pareto efficient decisions, i.e. the household choice of $\mathbf{x^r}$ and $\mathbf{x^s}$ maximizes the weighted sum of the individual utilities subject to the budget constraint:

$$\begin{aligned} &\max_{\mathbf{x}^r, \mathbf{x}^s} W = \mu U^r(\mathbf{x}^r, \mathbf{Q}) + (1-\mu) U^s(\mathbf{x}^s, \mathbf{Q}) \\ &\textit{subject to} \quad \mathbf{p}^r \mathbf{x}^r + \mathbf{p}^s \mathbf{x}^s + \mathbf{Q} = Y \end{aligned} \qquad (2.1)$$

where $\mathbf{p^i}$ is the vector of market prices for the goods consumed $\mathbf{x^i}$; Y represents the total household income, which is exogenous, and μ represents the Pareto weight with: $\mu \in [0,1]$. The Pareto weight can be seen as a measure of individual r's bargaining power in the decision process. The larger the value of μ is, the greater is the weight that individual r's preferences receive. If $\mu = 1$ then the household behaves as though

[25] Individual utility are represented by egoistic preferences but it is not necessary to recover individual behavior. We could use a caring utility function $\tilde{u}^i = \tilde{U}^i\left[U^1\left(\mathbf{x^1}\right), U^2\left(\mathbf{x}^2\right)\right]$ without altering the conclusion of the model (Chiappori, 1992).

[26] For notational simplicity, we have suppressed the demographic variables that we will include in the empirical application.

individual r has the bargaining power in the family, whereas if $\mu = 0$ then it is as though individual s is the effective dictator. μ is assumed continuously differentiable in its arguments and it depends on a set of exogenous variables $\mathbf{z}$ that can affect the bargaining power in the household and the intra-household allocation of resources (Browning et al., 1994). If the variables $\mathbf{z}$ affect the balance of power μ without affecting preferences and the budget constraints, then these variables are defined as 'distributional factors'. Examples of distribution factors are non-labor income (Thomas, 1990), individual wages (Browning et al., 1994), spouses' wealth at marriage (Thomas et al., 1997), the targeting of specific benefits to particular members (Duflo, 2000), sex ration and divorce legislation (Chiappori et al., 2002).[27]

In equation (2.1) W can be interpreted as 'a social welfare function for the household,' in which each household member has different bargaining power, or alternatively as some specific bargaining model (e.g. Nash bargaining). The assumption that the household outcomes are Pareto efficient does not exclude the situation of household experiencing marriage dissolution. The distributional factors can affect the threat points in the marriage and household members can be viewed as players of repeated games with symmetric information, and therefore efficiency is a reasonable assumption.

The household's behavior can be represented by a two-stage budget decomposition. Partners first divide household income Y between them according to some predetermined but unknown sharing rule ϕ. Then, once income has been allocated, each member chooses her optimal consumption bundle by maximizing his/her utility subject to the budget constraint based on their respective share of

[27] See Chiappori and Ekeland (2006) for a general discussion.

household income. The additive separable objective function in (1) implies that an equivalent statement for each household member's objective function can be written as follows

$$\max U^i(\mathbf{x^i}, \mathbf{Q^i}) \text{ subject to } \mathbf{p^i x^i} + \mathbf{Q^i} = \phi^i \qquad (2.2)$$

where ϕ^i is the fraction of shadow income allocated to member i, $\phi^1 + \phi^2 = Y$.

Under assumption A2 of Pareto efficiency, solutions to the individual problem (2.2) must be equal to those obtained solving the household problem (2.1).

Unfortunately, in practice we cannot observe these two artificial stages. We observe the individual and household choices $\mathbf{x^i}$ and **Q.** Menon and Perali (2006) show that this information is enough for identifying the sharing rule without the need of using distributional factors as Chiappori et al. (2002) do and without the computational burden of the identification strategy of Chiappori (1988, 1992) that requires the calculation of second derivatives. They show that their identification strategy brings to comparable estimates of the parameters of the sharing rule to these alternatives approaches. We follow Menon and Perali (2006) because in the recreational field it is not always easy to find distributional factors and because of their computational simplicity in the identification of the sharing rule.

2.2.1 Sharing Rule Identification

The identification strategy developed by Menon and Perali (2006) is based on a technique commonly used in the literature to include demographic or other exogenous effects into demand systems (Pollack and Wales 1981; Lewbel 1985) and to estimate household technologies (Bollino et al. 2000). While in this literature demographic variables interact with prices or income, in their case the unobservable sharing rule interacts with individual total expenditure *a la* Barten (Barten 1964; Perali 2003).

The minimal information required to identify of the sharing rule is to observe at least one assignable good or two exclusive goods. We define a good exclusive when it can be consumed only by one individual and not the other (e.g. female and male clothing). We define a good assignable if we know how much is consumed separately by each individual (that is $\mathbf{x^r}$ and $\mathbf{x^s}$ are observed). In the Collective Travel Cost Method knowledge of the travel cost to a recreational site of individual *r* (the respondent) and *s* (the spouse) allows us to identify the sharing rule. Since the usage of the car is shared when they ride together, the travel cost can be considered an assignable good.

The individual total expenditure in most cases is not observed. However, we can approximate it as $y^i = x^i + \left(\frac{Y-x}{2}\right)$, where x^i is individual *i*'s assignable expenditure, *Y* is income, *x* is the assignable household expenditure $\left(x = x^r + x^s\right)$, and $\left(Y - x\right)$ represents the non-assignable household expenditure, which is divided by the total number of household members by assuming a uniform distribution between household members. In the recreational case the individual *i*'s assignable expenditure is derived by multiplying the individual's travel cost by his/her annual number of trips to the recreational site.

<u>Assumption A3</u>: Let the sharing rule of individual *i* be a continuous function of exogenous variables **z** and individual total expenditure y^i:

$$\phi^i\left(\mathbf{z}, y^i\right) = y^i m^i(\mathbf{z}) \qquad (2.3)$$

where $i = r, s$; $m^i(\mathbf{z})$ is a scaling function such that $0 \leq m^i(\mathbf{z}) \leq \frac{\phi^i}{y^i}$ and $\mathbf{z}$ can include wages, prices, non-labor income or other variables that can affect the intrahousehold allocation of resources or the bargaining between household members. In logarithm form the sharing rule becomes

$$\ln \phi^i\left(\mathbf{z}, y^i\right) = \ln y^i + \ln m^i(\mathbf{z}) \qquad (2.4)$$

where we define $\ln m^i(\mathbf{z}) = \sum_{h=1}^{H} \gamma_h z_h$. This specification tells us that the sharing rule can be interpreted as a shadow income post-intrahousehold allocation. The function $m(\mathbf{z})$ describes the size and direction of the allocation of resources between household member. It also tells us that the amount of resources allocated to individual i is different from the amount that we observed the individual spending (y^r). For example the expenditure for a trip of individual r depends on observed costs such as gasoline and the time cost of the individual r going to the site, but it may also depend on the time cost of the other household member that may stay home to take care of the children. Further note that $m(\mathbf{z})$ is not constrained between [0,1] because it interacts with the individual total expenditure y^i.

The objective of the identification strategy is to recover the partial effects of the sharing rule with respect to the exogenous variables $\mathbf{z}$. Menon and Perali (2006) show that the partial effects can be estimated directly from the structural functional form of demand equations. This approach has two main advantages: the first one is that it is computationally simpler than a reduced form approach, such as the one implemented by Chiappori et al. (2002), and the second one that it can be applied into estimations of complete demand systems, such as the one described and applied in the next sections.

In this section we present the identification of the partial effects of the sharing rule by using the structural specification of the recreational demand for trips to a natural park of household members *r* and *s*. Consider the following structural forms:

$$N^r = \alpha_0 + \alpha_1 d^r + \alpha_2 \ln p^r_{tc} + \alpha_3 \left(\ln y^r + \gamma_1 \ln p^r_{tc} + \gamma_2 \ln p^s_{tc} + \gamma_z z \right) \qquad (2.5)$$

$$N^s = \beta_0 + \beta_1 d^s + \beta_2 p^s_{tc} + \beta_3 \left(\ln y^s - \gamma_1 \ln p^r_{tc} - \gamma_2 \ln p^s_{tc} - \gamma_z z \right) \qquad (2.6)$$

with $\ln \phi^i = (\ln y^i + \ln m^i); \ln m^r = \left(\gamma_1 \ln p^r_{tc} + \gamma_2 \ln p^s_{tc} + \gamma_z z \right)$ and $\ln m^s = -\ln m^r$:

where N^r and N^s correspond to the annual number of trips to a recreational site of individuals *r* and *s*; d^r and d^s are demographic characteristics of each individual; p^r_{tc} and p^s_{tc} represent individuals *r* and *s*' travel costs; z are exogenous characteristics that can affect the intrahousehold allocation of resources (such as the number of children in the household or the presence of a disable), and y^r and y^s correspond to the total individual expenditure.

Define

$$(2.7a)\quad A=\frac{\partial N^r}{\partial x^r}=\alpha_4; \qquad (2.7e)\quad E=\frac{\partial N^s}{\partial x^s}=\beta_4;$$

$$(2.7b)\quad B=\frac{\partial N^r}{\partial p^r_{tc}}=\alpha_2+\alpha_4\gamma_1; \qquad (2.7f)\quad F=\frac{\partial N^s}{\partial p^r_{tc}}=-\beta_4\gamma_1;$$

and

$$(2.7c)\quad C=\frac{\partial N^r}{\partial p^s_{tc}}=\alpha_4\gamma_2; \qquad (2.7g)\quad G=\frac{\partial N^s}{\partial p^s_{tc}}=\beta_2+\beta_4\gamma_2;$$

$$(2.7d)\quad D=\frac{\partial N^r}{\partial z}=\alpha_4\gamma_3; \qquad (2.7h)\quad H=\frac{\partial N^s}{\partial z}=\beta_4\gamma_3;$$

It follows that the parameters of the sharing rule and of the travel cost variables are identified as long as the partial derivatives of the recreational demand with respect to the individuals' total expenditure (i.e. $A = \alpha_4$, $B = \beta_4$) are known:

$$\begin{aligned}\phi^r_{p^r_{tc}} &= \gamma_1 = -F/E\\ \phi^r_{p^s_{tc}} &= \gamma_2 = C/A\\ \phi^r_z &= \gamma_3 = D/A = -H/E\end{aligned} \quad \text{and} \quad \begin{aligned}\alpha^2 &= B + AF/E\\ \beta^2 &= G + CE/A\end{aligned}.$$

Once the parameters are identified, the value of the site, which can be interpreted as the Willingness-To-Pay of the individual to access to the site, is derived by calculating the individual's consumer surplus (CS). The individual's consumer surplus is the area behind the individual's recreational demand for trips to the site and above the observed level of constant marginal travel cost p^i_{tc} to produce trips N^i. By assuming a Poisson distribution, the consumer surplus (*CS*) of each individual becomes

$$(2.8) \quad CS^r = -\frac{N^r}{\alpha_2 + \alpha_4 \gamma_1} \quad \text{and} \quad CS^s = -\frac{N^s}{\beta_2 - \beta_4 \gamma_2} \quad (2.9).$$

2.3 A Collective Almost Ideal Demand System for Non-market Valuation

In our empirical application we assume that household members have preferences given by the Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980). In this section we extend the AIDS demand system to a collective framework by including the sharing rule between household members. The knowledge of the sharing rule allows the estimation of the individual indirect utility function and the individual expenditure functions, which can be used to find individual's welfare measures such us the compensating variation and the equivalent variation.

We estimate the AIDS demand system because it has numerous advantages: it gives an arbitrary first-order approximation to any demand system; it satisfies the axioms of choice; it does not impose any *priori* restriction on the elasticities; it has a functional form which is consistent with known household-budget data; it is simple to estimate, largely avoiding the need for non-linear estimation; and it can be used to test the restrictions of homogeneity and symmetry through linear restrictions on fixed parameters (Deaton and Muellbauer, 1980).

We choose the complete demand system specification to the single demand equations described in the previous section because the estimation only of single demand equation ignores interactions between demands of commodities and this may give us a wrong picture. By incorporating the budget constraint into the analysis, the complete system approach instead forces recognition of the fact that an increase in expenditure on one consumption category must be balanced by decreases in the expenditure on others.

Moreover, the complete system approach permits the separation of demographic effects from own and cross price effects as well as income effects. We propose the Barten-Gorman translating method, which translates the budget line through the fixed cost element, as a general method for incorporating demographic variables into complete systems of demand equations (Pollak and Wales, 1978). If we focus on visitor's expenditure, we can identify at least three variables significantly affecting patterns of spending: income, prices and socio-demographic characteristic of the visitor. A demand system which incorporates demographic variables helps to examine these effects at the same time.

<u>Assumption A4</u>: Individuals (i = r, s) have demand functions given by the integrable AIDS demand system.

<u>Assumption A5</u>: The Translog price aggregator $A^i(\mathbf{p})$ and the Gorman scaling demographic term Δ^i are equal across household members, that is $A^r(\mathbf{p}) = A^s(\mathbf{p}) = \frac{1}{2}A(\mathbf{p})$ and $\Delta^r = \Delta^s = \frac{1}{2}\Delta$.

<u>Proposition P1</u>: Let Assumptions A1, A2, A3, A4 and A5 hold. If individual r and s' expenditures in at least one assignable good or two exclusive goods are observed then the sharing rule ϕ^i, the individual indirect utilities $V^i\left(\mathbf{p},\phi^i\right)$ and the individual expenditures functions $E^i\left(\mathbf{p},U^i\right)$ are identified.

As showed in the previous section, for non-market valuation of a recreational site the travel cost to the site of individual r (the respondent) and s (the spouse) can be considered assignable and it can allows us to identify the sharing rule.

Let individual i's indirect utility function be

$$V^i\left(\mathbf{p},\phi^i\right)=\frac{\left[\ln\left(y^{*i}\right)-\frac{1}{2}A(\mathbf{p})\right]}{B^i(\mathbf{p})} \qquad (2.10)$$

where

- $\mathbf{p}$ is the price vector of goods *k-th*;

- $\ln y^{*i}=\ln\phi^i-\frac{1}{2}\Delta$, with $\Delta=\sum_{k=1}^{N}t_k(d)\ln(p_k)$ and $t_k(d)=\sum_{h=1}^{H}\tau_{kh}d_h$ be a scaling demographic function with d socio-demographic variables, and p_k the price of good k;

- $\ln\phi^i\left(\mathbf{z},y^i\right)=\ln y^i+\ln m^i(\mathbf{z})$ by Assumption 3 and equation (2.4) with $\ln m^i(\mathbf{z})=\sum_{h=1}^{H}\gamma_h z_h$; y^i individual i's total expenditure; $\mathbf{z}$ exogenous variables that affect the distribution of resources within the household;

- $A(\mathbf{p})=\alpha_0+\sum_{k=1}^{N}\alpha_k\ln(p_k)+\frac{1}{2}\sum_{k=1}^{N}\sum_{j=1}^{N}\gamma_{kj}^1\ln(p_k)\ln(p_j)$, and $B^i(\mathbf{p})=\Pi_k\, p_k^{\beta_k^i}$.

By applying the duality relationship $E^i\left(\mathbf{p},V^i(\mathbf{p},\phi^i)\right)=y^i$ we obtain the associated log-expenditure function for individual i:

$$\ln E^i\left(\mathbf{p},U^i\right)=\frac{1}{2}A(\mathbf{p})+U^iB^i(\mathbf{p})+\ln m^i\left(z\right)+\frac{1}{2}\Delta \qquad (2.11)$$

where $U^iB^i(\mathbf{p})=\ln\phi^i-\frac{1}{2}A(\mathbf{p})-\frac{1}{2}\Delta$.

By assuming that the household expenditure function is weakly separable the corresponding log-household expenditure function becomes

$$\ln E(\mathbf{p},U) = A(\mathbf{p}) + U^r B^r(\mathbf{p}) + U^s B^s(\mathbf{p}) + \Delta \qquad (2.12).$$

Roy's identity yields the collective system of share equations

$$w_k = \alpha_k + t_k(d\ ) + \sum_{j=1}^{N} \gamma_{kj} \ln(p_j) + \beta_k^r \left[\ln\left(y^{*r}\right) - A(\mathbf{p})\right] + \beta_i^s \left[\ln\left(y^{*s}\right) - A(\mathbf{p})\right] (2.13).$$

The theoretical restrictions are homogeneity: $\sum_{j=1}^{N} \gamma_{kj} = 0;\ \sum_{h=1}^{H} \tau_{kh} = 0;$ adding-up: $\sum_{k}^{N} \alpha_k = 1;\ \sum_{k}^{N} \beta_k = 0;\ \sum_{k}^{N} \gamma_{kj} = 0;$ and symmetry: $\gamma_{kj} = \gamma_{jk}$.

For non-market valuation this demand system includes the annual individual shares of household income that individual *r* and *s* spent for the recreational site. The vector of prices **p** includes the travel costs of individual *r* and *s* to the recreational site (p_{tc}^r and p_{tc}^s).

Once estimated this demand system we take the exponential of (2.11) to estimate the expenditure functions for individuals *r* and *s*. This allows us to find individual welfare measures such as the compensating variation (CV) and the equivalent variation (EV).

Let $p_{tc}^{i,1}$ be the choke price, which is the travel cost that drives at zero individual *i*'s demand for trips to the recreational site. Let $p_{tc}^{i,0}$ be the observed travel cost and $\mathbf{p}_{-1}^{0}$ the observed prices of all the other goods in the complete demand system with the exception of the travel cost. Let $U^{i,0}$ be the utility level of individual *i* at the observed travel cost $p_{tc}^{i,0}$, and $U^{i,1}$ the utility level of individual *i* at the choke price $p_{tc}^{i,1}$; $A(p_{tc}^{i,1},\mathbf{p}_{-1}^{0})$ and $B(p_{tc}^{i,1},\mathbf{p}_{-1}^{0})$ are defined as $A(\boldsymbol{p})$ and $B^{i}(\boldsymbol{p})$ above with the only difference that they are evaluated at the choke price $p_{tc}^{i,1}$. We have that the compensating variation (CV) and the equivalent variation (EV) can be written as

$$CV^{i}=E^{i}\left(p_{tc}^{i,1},\mathbf{p}_{-1}^{0},U^{i,0}\right)-E^{i}\left(p_{tc}^{i,0},\mathbf{p}_{-1}^{0},U^{i,0}\right) \tag{2.14}$$

$$EV^{i}=E^{i}\left(p_{tc}^{i,1},\mathbf{p}_{-1}^{0},U^{i,1}\right)-E^{i}\left(p_{tc}^{i,0},\mathbf{p}_{-1}^{0},U^{i,1}\right) \tag{2.15}$$

where

$$E^{i}\left(p_{tc}^{i,1},\mathbf{p}_{-1}^{0},U^{i,0}\right)=\exp\left[\tfrac{1}{2}A(p_{tc}^{i,1},\mathbf{p}_{-1}^{0})+U^{i,0}B^{i}(p_{tc}^{i,1},\mathbf{p}_{-1}^{0})+\ln m^{i}\left(z\right)+\tfrac{1}{2}\Delta\right] \tag{2.16}$$

$$E^{i}\left(p_{tc}^{i,0},\mathbf{p}_{-1}^{0},U^{i,0}\right)=\exp\left[\tfrac{1}{2}A(p_{tc}^{i,0},\mathbf{p}_{-1}^{0})+U^{i,0}B^{i}(p_{tc}^{i,0},\mathbf{p}_{-1}^{0})+\ln m^{i}\left(z\right)+\tfrac{1}{2}\Delta\right] \tag{2.17}$$

$$E^{i}\left(p_{tc}^{i,1},\mathbf{p}_{-1}^{0},U^{i,1}\right)=\exp\left[\tfrac{1}{2}A(p_{tc}^{i,1},\mathbf{p}_{-1}^{0})+U^{i,1}B^{i}(p_{tc}^{i,1},\mathbf{p}_{-1}^{0})+\ln m^{i}\left(z\right)+\tfrac{1}{2}\Delta\right] \tag{2.18}$$

$$E^{i}\left(p_{tc}^{i,0},\mathbf{p}_{-1}^{0},U^{i,1}\right)=\exp\left[\tfrac{1}{2}A(p_{tc}^{i,0},\mathbf{p}_{-1}^{0})+U^{i,1}B^{i}(p_{tc}^{i,0},\mathbf{p}_{-1}^{0})+\ln m^{i}\left(z\right)+\tfrac{1}{2}\Delta\right] \tag{2.19}$$

The policy maker can use the individual *i*'s equivalent variation in order to know individual *i*'s Willingness-To-Pay to access a recreational site. This information can then be used to regulate the access at the area or for example to target programs to individuals in certain recreational activities groups rather than to households.

2.4 Empirical Application

2.4.1 Study Site and Data Gathering

The sample is drawn from an onsite survey conducted by the Department of Economics of the University of Verona on the West side of Garda Lake in the Northeast of Italy from June to October 1997. This survey was part of an integrated analysis on the multi-functionality of the West Garda Regional Forest in order to define cooperative policies between institutions, local operators and visitors. [28] This area was picked because it was also felt that, due to Garda Lake's popularity with tourists from throughout the country and abroad, there would be sufficient variation in distance travelled, time and trip cost.

The respondent was asked to recall the number of annual trips made to the West Garda Regional Forest and the number of trips to other natural areas during the year. In order to double check the declared costs, visitors were asked to specify their place of residence, the distance travelled between the natural area and their residence, the journey time and for those who were on vacation, the distance from the forest to their vacation lodging.

Moreover, the following data were collected for the respondent: means of transportation used, number of passengers per means of transportation, how many family members and how many shared the expense of the trip; if stops were made at other places before going to the natural area; how many days the trip lasted, occupation, weekly number of hours of work, number of children less than 12 years

[28] For a detailed description of the survey see the Annex.

old in the household, household income and monthly household expenditure in food and leisure. In order to estimate the expenditure on alternative sites, the visitor was asked about the distance from the residence, the number of visits to each site, the quality of the area and the purpose of the trip.

The survey was not conducted with the purpose to estimate a collective travel cost model and neither to compare the Willingness-To-Pay of two spouses. This implies that we do not have any socio-demographic information for the spouse of the respondent. But since each respondent was asked to recall how much he or she spent for the trip and how much his family spent for the trip in terms of food, lodging and transport this allows us to compute the respondent's travel cost and his/her family members' travel cost.[29] The knowledge of assignable expenditure represents the minimal requirement for applying the Collective Travel Cost Method, identifying the sharing rule and individual welfare measures. We select only married people and the total sample size becomes of 225 observations.

2.4.2 Parameter Estimates and Analysis

According to the idea of complete demand system visitors of the West Garda Regional Forest proceed to allocate total income among the broad groups food, leisure and other goods. They also decide how to distribute the expenditure for leisure in trips to West Garda Regional Forest, trips to other sites and other leisure.

[29] Several studies apply and compare different values to estimate the opportunity cost of time (for example Cesario, 1976; McConnell and Strand, 1981; Johnson, 1983; Smith et al., 1983; Chavas et al., 1989; Bockstael et al., 1990; McKean et al., 1996). In this study we evaluate travel time at one third of the respondent' wage rate (Cesario, 1976) and we assume that respondent and spouse have the same wage rate.

In our empirical application $i = r$ refers to the respondent and $i = s$ to the group 'other family members', that is the spouse with children. The expenditure for leisure in trips to West Garda Regional Forest is divided into the amount that the respondent declared to have spent for him/her self and into the amount that his/her family members spent in trips to the West Garda Regional Forest[30].

The vector of budget shares **w** consists of the shares of total household income that the respondent and the other families members spent into trips to the West Garda Regional Forest (respectively, *Garda_trips_r* and *Garda_trips_s*), and of the shares of total household income that the household spent in food (*Food_hh*), in trips to other recreational sites (*Other_trips_hh*), in other leisure (*Other_leisure_hh*) and in other goods (*Other_goods_hh*).

The shares of each good are specified as a system of equations according to the Collective Almost Ideal Demand System described in equation (2.13) of Section 2.3.

Table 2.1 and 2.2 present the descriptive statistics for the selected variables.

[30] In order to find the annual expenditure for leisure in trips to West Garda Regional Forest we multiply the travel cost of one visit by the annual total number of trips to the natural area. In the case of the spouse we simulate the annual total number of trips by predicting the probability that the respondent travels alone, with and without family members and by multiplying this probability by the total number of trips.

Table 2.1 - Definition of the Variables in the Collective AIDS Demand System

Variable	Description
Shares	
Food_hh	Household annual expenditure share in food
Garda_trips_r	Respondent annual expenditure in trips to West Garda Regional Forest park
Ggarda_trips_s	Spouse annual expenditure share in trips to West Garda Regional Forest
Other_trips_hh	Household annual expenditure share in other recreational trips
Other_leisure_hh	Household annual expenditure share in other leisure
Other_goods_hh	Household annual expenditure share in other goods
Prices in Euros	
income	Household annual income
ln*p*(food_hh)	Log(household annual expenditure in food)
ln*p*(trips_r)	Log(respondent annual expenditure in trips to West Garda Regional Forest)
ln*p*(trips_s)	Log(spouse annual expenditure in trips to West Garda Regional Forest)
ln*p*(other_trips_hh)	Log(household annual expenditure in trips to other recreational sites)
ln*p*(other_leisure_hh)	Log(household annual expenditure in other leisure)
ln*p*(othergoods_hh)	Log(household annual expenditure in other goods)
Demographic variables	
sex_r	=1 if respondent is male; 0 if female
age_r	Respondent's age / 10
education_r	Respondent's number of years of school /10
famsize	Number of household members
children_d	= 1 if there are children < 12 years old in the household
nationality_r	= 1 if respondent is Italian
visit duration_r	Number of days of visit to West Garda Regional Forest
Sharing Rule's regressors	
num_children	Number of children in the household
log(wage_r)	Log(respondent's wage)
huntfish*nofam	Interaction term: huntfish = 1 if respondent is hunter or fisherman; nofam = 1 if respondent travels without family members

Table 2.2 - Descriptive Statistics for Variables in the Collective AIDS Demand System

Variable	Mean	Std. Dev.	Min.	Max.
Shares				
Food_hh	0.2602	0.1485	0.0321	0.7692
Garda_trips_r	0.0105	0.0182	0.0002	0.1751
Garda_trips_s	0.0024	0.0082	0.0000	0.1039
Other_trips_hh	0.0027	0.0041	0.0000	0.0231
Other_leisure_hh	0.0915	0.0715	0.0010	0.4689
Other_goods_hh	0.6328	0.1814	0.0476	0.9464
Expenditures and Prices in Euros				
income	25208.33	13526.17	7436.98	67490.59
ln*p*(food_hh)	8.4964	0.4623	7.2402	9.6482
ln*p*(trips_r)	3.5872	1.1810	0.0324	6.8009
ln*p*(trips_s)	3.1334	0.8982	0.9487	6.4838
ln*p*(other_trips_hh)	3.1157	1.1194	0.1865	6.0610
ln*p*(other_leisure_hh)	7.2969	0.8403	3.7213	9.7615
ln*p*(othergoods_hh)	9.4809	0.8215	6.4293	10.9347
Demographic variables				
sex_r	0.6178	0.4870	0	1
age_r	4.4418	1.1330	2.2	7.7
education_r	1.2342	0.4241	0.5	2.1
famsize	3.2489	1.0692	2	7
children_d	0.3333	0.4725	0	1
nationality_r	0.7822	0.4137	0	1
visit duration_r	5.6133	10.0772	1	90
Sharing Rule's regressors				
num_children	0.5067	0.8405	0	4
log(wage_r)	2.5213	0.5115	1.3541	4.0622
huntfish*nofam	0.0578	0.2338	0	1
Number of observations = 225				

The independent variables included in the collective AIDS model are the logarithm of the prices of the goods, if the respondent is male and if he or she is Italian, respondent's age and number of years of education, the number of family members, if there are dependent children less than 12 years old and how long the visit to the West Garda Regional Forest lasts. We use the logarithm of the expenditure as an approximation of the price for each good.

Zero observed shares such as the household share expenditure for other recreational sites or the other family members' share expenditure in trips to the West Garda Regional Forest are corrected by the Heckman two-stage estimation procedure described in the Appendix[31]. If only nonzero visit observations are used in the parameter estimation, ordinary least square procedures would yield inconsistent estimates from selectivity bias.[32]

Table 2.3 shows the estimated parameters. The signs are consistent with the underlying theory. In general the price parameters are significant and the respondent's demographic variables significantly affect the expenditure shares of trips to the West Garda Regional Forest with the exception of respondent's age and education: for example the presence of children or the fact that the respondent is male has a positive statistically significant effect (respectively at the 5 and 1% level) on the individual expenditure share of trips, *ceteris paribus.*

[31] In order to apply this procedure we create dummies variables equal to zero when the expenditures are zero and equal to one otherwise. As instruments we use the distance from the place of residence, the total number of hours that the respondent would have wished to spend at the recreational site, the total number of hours that the respondent would have wished to spend in hunting, fishing or harvesting flowers and mushroom; and the total number of hours that the respondent spent at the site mountain biking, horse riding, hiking, picnicking and visiting historic places.

[32] Full Information Maximum likelihood estimates for the collective AIDS demand model were obtained using the maximum likelihood routine in the computer package Gauss and after having dropped one of the six share equations, namely, the expenditure share of other leisure. Barten (1969) shows that the results are invariant to the equation deleted. The coefficients of the deleted equation are easily calculated, since they are linear combination of the parameters of the share equations included.

Table 2.3 – Estimates of the Collective AIDS Demand System

		Dependent Variable: Expenditure share of																	
Independent Variable		Food_hh			Garda_trips_r			Other_goods_hh			Garda_trips_s			Other_trips_hh			Other_leisure_hh		
		Param.		Std.Err.	Param.		Std.Err.	Param.		Std.Err.	Param.		Std.Err.	Param.		Std.Err.	Param.		Std.Err.
Constant	α_k	0.2745	***	0.0664	0.0477		0.0314	0.4138	***	0.0710	0.0075		0.0291	0.0267	***	0.0101	0.2298	***	0.0061
Prices																			
ln$p$(food_hh)	γ_{kj}	0.1780	***	0.0071	-0.0017		0.0023	-0.1513	***	0.0044	0.0001		0.0021	-0.0019	**	0.0009	-0.0232		0.0584
ln$p$(trips_r)					0.0037	**	0.0314	-0.0013		0.0017	0.0000		0.0010	0.0010	**	0.0004	-0.0017		0.0032
ln$p$(othergoods_hh)								0.1962	***	0.0039	-0.0032	**	0.0015	-0.0019	***	0.0006	-0.0385	***	0.0016
ln$p$(trips_s)											0.0038	***	0.0011	-0.0003		0.0004	-0.0004		0.0025
ln$p$(other_trips_hh)														0.0032	***	0.0004	-0.0001		0.0013
ln$p$(other_leisure_hh)																	0.0639	***	0.0027
	β_k^r	-0.0163		0.0108	0.0205	***	0.0050	-0.0093		0.0100	0.0103	**	0.0046	0.0028	*	0.0016	-0.0080	***	0.0005
	β_k^r	-0.0140	*	0.0081	0.0029		0.0053	0.0088		0.0101	-0.0018		0.0043	0.0003		0.0013	0.0038		0.0110
Demographics																			
sex_r	τ_{kh}	0.0035		0.0049	0.0063	***	0.0019	-0.0075		0.0049	0.0040	*	0.0023	-0.0002		0.0008	-0.0061		0.0074
age_r		-0.0030		0.0023	0.0000		0.0008	0.0019		0.0023	0.0004		0.0011	-0.0002		0.0004	0.0009		0.0052
education_r		-0.0043		0.0063	0.0003		0.0022	0.0071		0.0061	-0.0008		0.0031	0.0008		0.0010	-0.0031		0.0024
famsize		0.0027		0.0074	0.0150	***	0.0033	-0.0191	**	0.0095	0.0107	***	0.0033	0.0026	*	0.0014	-0.0119	*	0.0067
children_d		-0.0003		0.0084	0.0106	**	0.0043	-0.0082		0.0106	0.0147	***	0.0042	0.0015		0.0014	-0.0183	***	0.0079
nationality_r		0.0051		0.0078	0.0009		0.0030	-0.0048		0.0079	0.0039	*	0.0035	0.0018		0.0013	-0.0069		0.0086
visit length_r		-0.0029		0.0025	0.0061	***	0.0009	-0.0048	**	0.0025	0.0011		0.0013	-0.0008		0.0005	0.0013		0.0074

* Statistically significant at the 10% level; ** 5% level; *** 1% level; Number of observations = 225

Table 2.4 reports the income, demographic and compensated price elasticities computed at the mean of budget shares by using numerical procedures. The signs are as expected: positive for the income elasticities and negative for the own-price elasticities. The trips to the West Garda Regional Forest represent the most responsive goods to income and price changes while food the most necessary and less elastic good. The number of children and the family size has a positive impact on the trips to the recreational area and a negative impact on food. This is consistent with what found in other studies (e.g. Koc and Alpay, 2003; Arias et al. 2003).

Respondent's number of trips to the West Garda Regional Forest is in a complementary-type relationship with the other family members' number of trips to the West Garda Regional Forest but it is a substitute for food and other goods. The duration of the visit to the natural area has a negative effect on the trips to the other recreational sites. The number of years of education of the respondent has a positive effect on his/her expenditure in trips to the natural area but a negative impact on the other family members' expenditure in trips to the same natural area.

Table 2.4 – Income, Demographic and Compensated Price Elasticities

(at Mean Budget Shares)

Income Elasticities						
	Food_hh	Garda_trips_r	Other_goods_hh	Garda_trips_s	Other_trips_hh	Other_leisure_hh
Income	0.9422	1.6824	1.0039	1.4675	1.2264	0.997

Compensated Own and Cross Price Elasticities						
	Prices					
Good k	Food_hh	Garda_trips_r	Other_goods_hh	Garda_trips_s	Other_trips_hh	Other_leisure_hh
Food_hh	-0.0451	0.0160	0.0808	0.0094	-0.0009	0.0004
Garda_trips_r	0.0090	-0.8506	-0.1388	-0.0525	0.0552	-0.1053
Other_goods_hh	0.0186	0.0114	-0.0542	0.0003	0.0021	0.0266
Garda_trips_s	0.1338	-0.1291	-0.7020	-0.3176	-0.0718	-0.0777
Other_trips_hh	-0.1618	0.1547	0.0296	-0.0711	-0.3685	0.0422
Other_leisure_hh	-0.0025	-0.0015	0.2171	0.0015	0.0045	-0.1754

Demographic Elasticties						
	Good k					
Demographic variables	Food_hh	Garda_trips_r	Other_goods_hh	Garda_trips_s	Other_trips_hh	Other_leisure_hh
sex_r	0.0077	0.5698	-0.0119	0.8507	0.0007	-0.0738
age_r	-0.0118	0.0040	0.0029	0.0812	-0.0428	0.0103
education_r	-0.0156	0.0085	0.0112	-0.1720	0.1539	-0.0356
famsize	-0.0072	1.3971	-0.0303	2.2902	0.6040	-0.1434
children_d	-0.0161	1.0221	-0.0131	3.0170	0.3697	-0.2146
nationality_r	0.0160	0.1275	-0.0077	0.8053	0.3816	-0.0808
visit duration_r	-0.0158	0.5262	-0.0077	0.2635	-0.1333	0.0142

2.4.3 The Sharing Rule

As Table 2.5 shows, we use as factors **z** that can affect the distribution of resources within the household the number of children (*num_children*), the respondent's wage (*log(wage_r)*) and an interaction term that captures if the respondent is hunter or fisherman and travels without family member (*huntfish*nofam*). The respondent's wage is significant at the 5% statistical level and it positively affects the sharing rule: respondents with higher wages tend to allocate more resources to themselves than to the other family members. The number of children affects negatively the sharing rule at the 1% significant level. Figure 2.1 shows the relative sharing rule (that is the sharing rule divided by total household income, ϕ^r/Y) by the number of children. As the number of children increases the share of resources allocated to the respondent decreases. This is consistent with our expectations since in our sample the spouse is also representative of the preferences of the children.

Table 2.5 - Sharing Rule Parameter Estimates

	Parameter		Std. Error
num_children	-0.4395	***	0.1384
log(wage_r)	0.6065	**	0.2826
huntfish*nofam	0.1671		0.2477

** Statistically significant at the 5% level;
*** Statistically significant at the 1% level;
Number of observations = 225

Figure 2.1 – Relative Sharing Rule by Number of Children

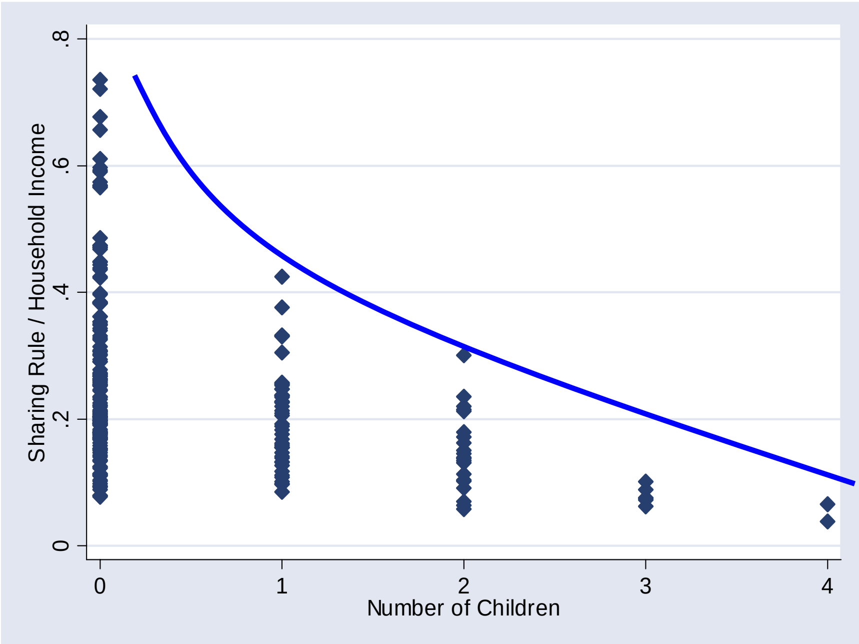
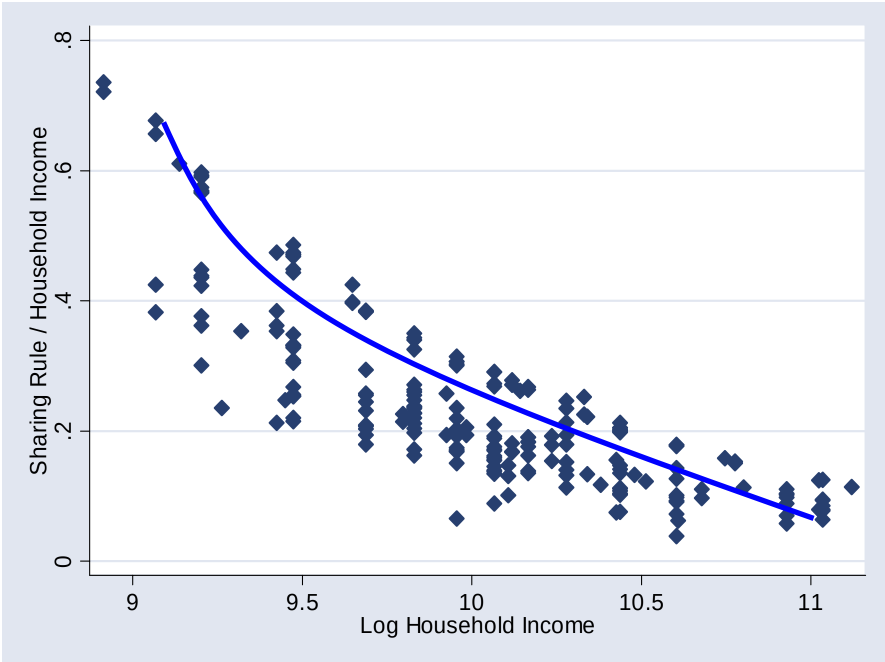


Figure 2.2 represents another interesting result. It shows how the estimated relative sharing rule varies in relation to total household income. As we can see, there is a clear decreasing relationship: if the household income increases the amount of resources allocated to the respondent decreases or, in other words, respondents of households with lower levels of total income have a lower propensity to transfer resources to the other family members.

Figure 2.2 – Relative Sharing Rule by Total Household Income



2.4.4 Welfare Comparisons and Individual Willingness-To-Pay (WTP)

The estimated collective AIDS demand system allows us to derive the individual expenditure functions for the respondent and the other family members by substituting the estimated parameters of Table 2.3 into equations (2.16)-(2.19)[33]. Once we have estimated the respondent and the other family members' expenditures in order to find the equivalent variation we can apply equation (2.15), which gives us the individual Willingness-To-Pay to access the West Garda Regional Forest. We define it *CTCM_WTP* since it derives from the application of the Collective Travel Cost Method[34].

[33] The price $p_{tc}^{i,1}$, which drives the number of trips at zero, has been calculated by using numerical procedures.
[34] Note that the WTP figures that follow have been divided by the annual number of trips, so they refer to the WTP per one trip to the West Garda Regional Forest.

Then we want to test: (1) whether the respondent's mean WTP per one trip to the recreational site estimated by the traditional unitary TCM (*TCM_WTP*) is significantly different from the respondent's mean WTP obtained by applying the CTCM (*CTCM_ WTP)*; (2) whether two spouses have equal or different mean WTP to access the recreational site, and (3) whether the respondent's mean WTP estimated by the Travel Cost Method is significantly different from the mean WTP derived by applying the Contingent Valuation Method (*CVM_WTP*) on the same sample of individuals. Does the CTCM disentangle the bundle between stated and revealed preference Willingness-To-Pay?

With regards to Test (1) Table 2.6 shows that the traditional TCM and the collective TCM give significantly different mean WTP estimates (at the 1% statistical level). In particular the traditional TCM, which does not consider the intra-household allocation of resources and it assumed that all the resources are pooled, overstates the mean WTP of the respondent.

Table 2.6 – Test (1): Is the Mean Willingness-To-Pay (WTP) Figure from the Traditional Travel Cost Method (TCM) Equal to the Mean WTP from the Collective TCM?

Test (1)
Ho: mean(TCM_WTP_r) = mean(CTCM_WTP_r)

		Mean	Std.Err.	Std. Dev.	95% Conf. Interval	
TCM_WTP_r	Respondent's WTP (traditional TCM)	6.5103	0.1985	2.9780	6.1191	6.9015
CTCM_WTP_r	Respondent's WTP (Collective TCM)	4.9369	0.4324	6.4857	4.0849	5.7890
p-value	*0.0017*					
Number of observations = 225						

With regard to Test (2), the null hypothesis of no difference in WTP between two partners, that is the respondent and his/her spouse, is rejected at the 1% statistical level (Table 2.7). In order to test this hypothesis we selected households with only two family members. We find that the the respondent's WTP is higher than the WTP of the spouse. This finding seems imply that the respondent cannot be considered as the representative individual in the household (i.e. his/her WTP does not represent the WTP of the other household members) as the traditional TCM instead assumes.

Table 2.7 – Test (2): Is the Respondent' Mean Willingness-To-Pay (WTP) Equal to the Spouse's Mean WTP?

Test (2) Ho: mean(CTCM_WTP_r) = mean(CTCM_WTP_s)						
		Mean	Std.Err.	Std. Dev.	95% Conf. Interval	
CTCM_WTP_r	Respondent's WTP (Collective TCM)	13.3901	0.6877	5.7128	12.0177	14.7625
CTCM_WTP_s	Spouse's WTP (Collective TCM)	8.2947	0.2821	2.3436	7.7317	8.8577
p-value	*0.0000*					
Number of observations = 69						

Finally, with regard to Test (3) we want to compare the WTP estimate from the Travel Cost Method with the WTP estimate from the Contingent Valuation Method. These two techniques are both estimating the Willingness-To-Pay for access to a recreational site but they differ in their approach. The CVM uses stated preference data (or hypothetical data) while TCM uses revealed preference data (or actual data). In order to find the WTP from the CVM we applied the discrete choice

CVM question format by Cooper et al. (2006) called ‘Fair-One-and-One-Half-Bound’ (FOOHB). In the Contingent Valuation survey a hypothetical market scenario is described to each respondent. Then respondents are asked whether they would be willing to pay for an entrance ticket and they are allowed to choose whether they want to start the questioning process with the low bid or the high bid. In other words, in order to make the survey ‘fair’ the starting price for the bidding process is chosen by the respondent and not by the interviewer.

Both TCM and CVM have limitations and advantages. Consequently to investigate their validity the comparison of the welfare estimates from both techniques has received considerable attention in the literature (see for example Bishop et al. 1983; Sellar et al. 1985; Carson et al. 1996).

In general, the WTP estimates from these two approaches are statistically different, as also Table 2.8 shows: the WTP from the traditional TCM is statistically different form the CVM WTP at the 1% level. In Table 2.9 we show that this difference is reduced once we use the Collective Travel Cost Method. Indeed, the WTP from the CTCM is now statistically different from the CVM WTP at the 5% level.

Table 2.8 – Test (3a): Is the Respondent's Mean Willingness-To-Pay (WTP) from the Traditional TCM Equal to the Respondent's Mean WTP from the Contingent Valuation Method (CVM)?

Test (3a) Ho: mean(TCM_WTP_r) = mean(CVM_WTP_r)						
		Mean	Std.Err.	Std. Dev.	95% Conf. Interval	
TCM_ WTP _r	Respondent's WTP (Traditional TCM)	6.5103	0.1985	2.9780	6.1191	6.9015
CVM_ WTP_r	Respondent's WTP (Contingent Valuation)	3.8477	0.0046	0.0683	3.8387	3.8567
p-value	*0.0000*					

Number of observations = 225

Table 2.9 – Test (3b): Is the respondent's mean Willingness-To-Pay (WTP) from the Collective TCM equal to the respondent's WTP from the Contingent Valuation Method (CVM)?

Test (3b) Ho: mean(CTCM_WTP_r) = mean(CVM_WTP_r)						
		Mean	Std.Err.	Std. Dev.	95% Conf. Interval	
CTCM_ WTP _r	Respondent's WTP (Collective TCM)	4.9369	0.4324	6.4857	4.0849	5.7890
CVM_ WTP_r	Respondent's WTP (Contingent Valuation)	3.8477	0.0046	0.0683	3.8387	3.8567
p-value	*0.0125*					

Number of observations = 225

2.5 Conclusions

This chapter is intended primarily to show how to estimate welfare measure for individuals living in a couple by applying the collective model by Chiappori (1988, 1992) to a recreational setting through revealed preference data from a travel cost survey. In particular, by using the individual travel cost of the respondent and his/her household members we have estimated a collective AIDS demand system that takes into account the intra-household resource allocation. This allowed us to estimate the Willingness-To-Pay of the respondent and his/her spouse to access the West Garda Regional Forest in Italy. We defined the implemented method as 'Collective Travel Cost Method' (CTCM).

We found that the traditional TCM overestimates the WTP of the respondent estimated by the CTCM and that the difference is statistically significant at the 1% level. Then we found that respondent and his/her spouse have different WTP to access the recreational site. This seems implying that the actual practice of picking an adult at random from the household as representative of the other family member preferences could not be justified and that differences in how resources are distributed within households reflect appreciable differences in the welfare measures.

Finally, we compare the respondent's mean WTP from the TCM with the respondent's mean WTP from a Contingent Valuation survey on the same sample of individuals. In line with the literature, we find that the two methods yield to statistically different results but the difference is smaller by using the CTCM rather than the traditional TCM.

In conclusion, this chapter showed that the Collective Travel Cost Method developed in this study can be implemented to yield individual welfare estimates potentially very useful for policy analysis but the need for more appropriately designed surveys must be emphasized. In the future, nonmarket valuation researchers should aspire to apply the Collective Travel Cost Method with improved data that include more observations and information about the number of trips and the demographic characteristics of the respondent's spouse. By designing *ad hoc* questionnaires analysts may be able to provide policy makers with more efficient and accurate estimates of the value o public goods for each household member.

From a theoretical perspective, two assumptions should be relaxed in the future: first, the assumption that the utility function of the spouse refers to the joint utility function of the spouse and his/her children; and second that the model does not take into account the behavior of groups where individuals from different households choose to take a trip together. Relaxing these assumptions will be the subject of forthcoming research.

Appendix: Generalized Heckman procedure

The generalized Heckman procedure consists of transforming the censored equations into uncensored equations by using the appropriate correction. Following Arias et al. (2003), we consider the unconditional mean:

$$E[y_i \mid x_{it}] = E[y_i \mid y_i > 0]\Phi\left(\frac{f_i(x_i,\beta_i)}{\sigma_i}\right) =$$
$$= f_i(x_i,\beta_i)\Phi\left(\frac{f_i(x_i,\beta_i)}{\sigma_i}\right) + \sigma_i\phi\left(\frac{f_i(x_i,\beta_i)}{\sigma_i}\right)$$

where, φ and Φ are respectively the probability density function and the cumulative density function of a standard normal distribution, y_i is the endogenous variable corresponding to the *i-th* equation in the censored system, x_i is a vector of explanatory variables, β_i is a vector of parameters. Using the expression for the unconditional expected value of each endogenous variable we consider the following system of uncensored equations:

$$y_i = f_i(x_i,\beta_i)\Phi\left(\frac{f_i(x_i,\beta_i)}{\sigma_i}\right) + \sigma_i\phi\left(\frac{f_i(x_i,\beta_i)}{\sigma_i}\right) + \xi_i$$

where $\xi_{it} = y_{it} - E[y_i \mid x_{it}]$. This system can be estimated by limited maximum likelihood assuming that

$$\xi \sim MVN(0,\Omega)$$

where, ξ is a random vector whose *i-th* element is ξ_i. An important detail stressed by Arias et al. (2003) is that this is a straightforward maximum likelihood estimation since the latter system does not contain any censored equation.

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CHAPTER 3

Detecting Starting Point Bias in Dichotomous-Choice Contingent Valuation Surveys

3.1 Introduction

Many recent high-quality Contingent Valuation surveys elicit information about Willingness-To-Pay (WTP) by asking dichotomous-choice (DC) questions.[35] Respondents are asked whether or not they would buy the good if its cost was \$X, or whether they would vote in favor or against the proposed public program in a referendum on a ballot if implementing it costs \$X to the household, usually in the form of higher taxes. In this way, the respondent's exact WTP amount is not directly observed, and all we do know is whether it is greater than the bid amount ('yes') or less than the bid amount ('no').

To refine information about WTP, it is possible to ask a dichotomous choice follow-up question (Hanemann et al., 1991). Specifically, respondents who answer 'yes' ('no') to the initial payment question are asked whether they would be willing to pay if the cost was \$Y, where Y>X (Y<X). The responses to the initial and follow-up questions are combined to form narrower intervals around the respondent's WTP, improving the efficiency of the estimates of WTP (Hanemann et al., 1991). Implicit in this approach—commonly dubbed 'double-bounded' (DB)—is the assumption that an

[35] Contingent valuation is a frequently used approach for placing a value on goods that are not traded in markets. Prominent examples of these goods include improvements in environmental quality, other public goods, ecosystem health, and risks to human health. In a Contingent Valuation study, individuals are asked to report information about their Willingness-To-Pay to obtain (or to avoid the loss of) the good to be valued. The good is specified in a hypothetical scenario, and no actual transaction takes place.

individual's responses to the initial and follow-up dichotomous-choice payment question are driven by *the same* WTP amount, which remains unobserved. WTP amounts are drawn from a distribution over the population and vary across individuals.

Although many Contingent Valuation (CV) practitioners continue to implement surveys with dichotomous choice questions and follow-ups, and to fit double-bounded models, over the last decade researchers have examined this approach's potential for undesirable response effects (see Section 3.2).

In this chapter, we focus on one such effect, namely starting point bias. It is possible that when follow-up questions are used, respondents may 'anchor' the value they place on the policy on the bid amounts proposed to them in the initial and/or subsequent payment questions. The latter problem is usually termed 'starting-point bias' and a possible mechanism for it within a dichotomous-choice format is proposed by Herriges and Shogren (1996).[36] Specifically, Herriges and Shogren formulate a model where the WTP amount driving the response to the follow-up payment question is a weighted average of the first latent WTP and the initial bids. Variants on Herriges and Shogren include Aprahamian et al. (2004), who treat the anchoring parameter as a random coefficient drawn from a specified distribution, and Lechner et al. (2003), who assume that even the first WTP amount of the respondent is influenced by the initial bid. Most recently, the Herriges and Shogren mechanism has been combined with yea-saying by Chien et al. (2005), who represent the latter using

[36] Starting point bias was suspected to affect responses to iterative bidding CV payment questions, which were first introduced by Randall et al. (1974). Boyle et al. (1985), for example, include the initial bid amount in the right-hand side of their WTP equation, where the dependent variable is the final WTP amount announced by the respondent. A significant coefficient on the initial bid variable is interpreted as evidence of starting point bias.

an additional error term that follows the half-normal distribution and is folded with the regular econometric error into a compound distribution.[37]

In empirical work, it is common to test for the presence of starting point bias by (i) including in the right-hand side of the double-bounded model dummy variables for the bid set assigned to the respondent, and then (ii) testing the null hypothesis that the coefficients on these dummies are jointly equal to zero (Whittington et al., 1990; Green and Tunstall, 1991; Cameron and Quiggin, 1994, and most recently Chien et al., 2005).

In this chapter, we examine four related issues pertaining to starting point bias. First, how serious are the biases of the location and scale parameters of WTP if starting point bias is present but ignored in the statistical model of the WTP responses? Second, what is the performance (measured in terms of nominal size and power) of the above mentioned diagnostic of starting point bias, namely the test on the coefficients on the bid set dummies? Third, how are the bias of the estimates and the performance of the diagnostic test affected when the distribution of WTP is misspecified? Fourth, how important is the bid design in all of the above?

To elaborate on the third question, we suspect that in some cases what has been interpreted by the researcher as evidence of anchoring to the initial bids is simply an artifact due to misspecification of the econometric model and/or the poor choice of distribution of WTP. In the case of the diagnostic test based on the use of bid set dummies, we suspect that the coefficients on these dummies may act as available free parameters, and absorb the effects of misspecifications of the

[37] See Johnson et al. (1994) for details about the half-normal distribution.

econometric model or of the distribution of WTP, even though no starting point bias is present.

Because starting point bias cannot be separately identified in any reliable manner from biases caused by model specification, we use simulation approaches to address this issue. Hence, we conduct a series of Monte Carlo simulations to answer these questions. We generate the latent WTP amounts from various distributions using two alternative starting point bias mechanisms, and model the responses using double-bounded models, which ignore starting point bias.

Our simulations suggest that the effect of ignoring starting point bias is complex, and depends on the true distribution of WTP and on the WTP statistic being estimated (mean WTP or the variance of WTP). We find that bid set dummies, which are used by many researchers to detect starting point bias, have only very modest power in detecting starting point bias. We find that the coefficients on these dummies tend to soak up misspecifications in the distribution assumed by the researcher for the latent WTP, so that the diagnostic test rejects the null too frequently, falsely pointing to starting point bias when the real problem is a poor distributional assumption.

The remainder of the chapter is organized as follows. Section 3.2 discusses undesirable response effects that are possible when follow-up questions are used. In Section 3.3 we present the starting point bias mechanism developed by Herriges and Shogren (1996) and a plausible variant on this model. In Section 3.4, we present a commonly used test for the presence of starting point bias. We present the simulation study design in Section 3.5, and its results in Section 3.6. Section 3.7 concludes.

3.2 Possible Response Biases in Double-Bounded Models

Cameron and Quiggin (1994) relax the assumption that the response to the initial and follow-up payments are driven by the same amount. They estimate alternative models that assume distinct, but correlated, WTP amounts for each DC payment question. To detect the presence of starting point bias they include dummy variables for the initial bids, concluding that constraining the distributional parameters to be identical and the correlation to be unity exacerbates starting point effects.

Alberini et al. (1997) apply a random effects model to DB Contingent Valuation data allowing for differing mean WTP across the initial and follow-up questions because respondents may become 'confused about how much they will have to pay or what they will actually get' (p. 311) as the survey proceeds. They reason that follow-up questions may induce respondents to effectively substitute the program or policy described in the scenario with another program or policy package that has different characteristics, and to form a new, systematically different WTP value that reflects the attributes of the new program. Using data from the San Joaquin Valley wetlands study (Hanemann et al., 1991), the study on the Kakadu Conservation Zone in Australia (Carson et al., 1994) and the Alaska survey to estimate the loss of passive-use values for Prince William sound resulting from the Exxon-Valdez oil spill of 1989 (Carson et al., 1992), they find that follow-up questions resulted in a systematic downward shift in median WTP in the Alaska study, while in the other studies the structural shift is negative but not statistically significant at the conventional levels.

DeShazo (2002) considers alternative mental models—such as prospect theory (Kahneman and Tversky, 1979, and Tversky and Kahneman, 1991), which implies forming a reference point—and starting point bias, and predicts the probability of 'yes'/'no' responses to the follow-up questions implied by these models. For example, prospect theory implies that the probability of a respondent answering 'yes' to a follow-up question from an ascending sequence is less than the probability of a respondent answering 'yes' to the same value presented in an initial valuation question. By contrast, if anchoring occurs, respondents who are assigned the ascending sequence will anchor on the lower value, while respondents who are assigned the descending sequence will anchor on the higher value. (By ascending sequence, we mean a follow-up dollar amount that is greater than the initial bid because the respondent answered 'yes' to the first payment question. The term 'descending sequence' refers to the opposite situation.)

Carson et al. (2000) examine response effects that result in violations of the assumption that the responses to all payment questions are driven by the same WTP amount. Respondents, Carson et al. argue, may (i) take the second price as the expected price but consider the cost of the program to be somewhat uncertain, (ii) take a weighted average between the two prices, (iii) adjust the quantity of the good to match the change in price,[38] or (iv) enter in a bargaining mode. Burton et al. (2003) use experiments to empirically discriminate between hypotheses (i) and (ii).

[38] Evidence from focus groups suggests that people that answer 'yes' to the initial payment question expect the government to be capable of providing the public program at the cost stated to them in the initial question. Higher cost amounts, therefore, are sometimes interpreted to imply government waste. Likewise, people who initially answered 'no' may suspect that in the follow-up question the public program being valued is a scaled down version of the initially described program.

3.3 Models of Starting Point Bias

Dichotomous-choice Contingent Valuation assumes that the 'yes' or 'no' responses to the payment questions are determined by comparing the respondent's stated WTP amount with the bids assigned to him. In DC CV surveys with a DC follow-up question, the responses to the payment questions are used to construct an interval around each respondent's unobserved WTP amount. Assuming, for example, that respondent *i*'s WTP is normally distributed with mean $\mathbf{x}_i\boldsymbol{\beta}$ and variance σ^2, this respondent's contribution to the likelihood function is:

$$\Phi\left(\frac{WTP_i^U - \mathbf{x}_i\boldsymbol{\beta}}{\sigma}\right) - \Phi\left(\frac{WTP_i^L - \mathbf{x}_i\boldsymbol{\beta}}{\sigma}\right), \qquad (3.1)$$

where WTP_i^L and WTP_i^U are the lower and upper bound, respectively, of the interval around the respondent's unobserved true WTP amount.

The log likelihood function is

$$\log L = \sum_i \ln\left[\Phi\left(\frac{WTP_i^U - \mathbf{x}_i\boldsymbol{\beta}}{\sigma}\right) - \Phi\left(\frac{WTP_i^L - \mathbf{x}_i\boldsymbol{\beta}}{\sigma}\right)\right] \qquad (3.2)$$

and the parameters are estimated by the method of maximum likelihood.[39]

If starting point bias is present, the bid amounts may influence the response to a payment question in two ways: (i) by affecting underlying WTP directly if respondents use the bid information to update their true WTP, and (ii) through the comparison between WTP (which is already affected by the bid) and the bid.

[39] This log likelihood function is easily amended to accommodate for other distributions. See, for example, Alberini, et al. (2006).

Herriges and Shogren (1996) propose the following mechanism for starting point bias. Assume that when first faced with a dichotomous-choice question, an individual compares the initial bid, B_1, with his WTP amount, WTP_{1i}. The latter is a draw from the population distribution of WTP, and the answer to the payment question is 'yes' ('in favor') if WTP_{1i} exceeds B_1, and 'no' ('against') otherwise.

Now suppose that the individual is asked a dichotomous-choice follow-up question where he is queried about B_2. Herriges and Shogren argue that the initial bid may provide a 'focal point or anchor for the uncertain respondent.'[40] This may happen when the uncertain respondent interprets the bid amount as an approximation of the good's true value, thus anchoring his or her WTP on the proposed bid to update priors in light of society's or experts' beliefs. They further propose that the response to the second payment question is driven by a different amount, WTP_{2i}, which is a weighted average of WTP_{1i} and the initial bid, B_1. Formally,

$$WTP_{1i} = \mu + \varepsilon_i , \qquad (3.3)$$

where μ is mean WTP and ε is (normally distributed) error term with variance σ^2, and

$$WTP_{2i} = WTP_{1i}(1-\gamma) + \gamma \cdot B_1 , \qquad (3.4)$$

where $0 \leq \gamma \leq 1$ is the weight placed on the initial bid. (Clearly, this notation assumes that mean WTP is the same for all respondents. This common mean replaces the individual-specific expectation $\mathbf{x}_i\boldsymbol{\beta}$ used in equations (3.1) and (3.2).)

[40] Accordingly, in this chapter the terms 'starting point bias' and 'anchoring' are used interchangeably.

If γ=0, there is no anchoring, and $WTP_{2i} = WTP_{1i}$, as is routinely assumed in double-bounded models. If γ=1, no memory of the original WTP amount is retained in the follow-up question, and WTP_{2i} is equal to the first bid amount.

Conventional double-bounded models of WTP assume that the responses to both the initial and the follow-up payment questions are driven by the same underlying WTP amount, and are thus misspecified in this situation. Herriges and Shogren show that the anchoring mechanism described by equations (3.3) and (3.4) effectively widens the boundaries placed on WTP by the follow-up question. The greater the weight γ, the wider these boundaries, and the less information about the original WTP is contained in response to the follow-up payment question. In addition, with this anchoring mechanism the WTP amount driving the response to the follow-up payment question has, by construction, a smaller variance than the original WTP, WTP_1.

If one fits a conventional double-bounded model in this situation, are the estimated coefficients biased, and, if so, how severely? Herriges and Shogren conduct simulations, showing that in the presence of starting point bias the estimates of mean WTP, μ, are unbiased, but σ, the standard deviation of WTP, is systematically underestimated.[41] They point out that 'The starting point bias squeezes the distribution tightly around the mean, but does not bias the estimated mean WTP' (Herriges and Shogren, 1996, p. 121).

Their first claim follows from the fact that multiplying WTP_1 by (1-γ) shrinks the variance, a reduction that cannot be offset by the addition of B_1. (If WTP follows

[41] By contrast, in the presence of omitted starting point bias the one-way up and the one-way down approaches produce biased estimates of both mean WTP and the standard deviation of WTP.

the normal or any other distribution defined between $-\infty$, or 0 and ∞, the bids will usually cover a much smaller range.) Their second claim rests on the fact that in their study (i) the distribution of WTP is symmetric, and (ii) the average of the bid amounts is about equal to mean WTP. Their anchoring mechanism implies that individuals simply compute a weighted average of WTP_1 and B_1, so if the average initial bid is roughly equal to mean WTP_1, mean WTP_2 is roughly equal to mean WTP_1, and so is the weighted average of these two means, which the double-bounded estimator tends to.

Based on these considerations, we would expect conventional double-bounded models to produce biased estimates of WTP if the average of the initial bids is different from mean WTP. We would also expect them to underestimate the variance of WTP, since they will tend to capture an average of the variances of WTP_1 and WTP_2, and the latter is less than the former. Because the variance of WTP enters in the computation of the standard errors around the estimate of mean WTP, this has potentially important implications for statistical inference about WTP and its use in policy contexts.

In this chapter, we generate data following the Herriges and Shogren mechanism, but we estimate double-bounded models (which ignore the presence of anchoring), and examine the consequences of doing so on the estimates of mean WTP and variance of WTP. Our work differs from earlier studies in that (i) when using the Herriges-Shogren approach, we consider WTP distributions other than the normal, (ii) we examine the effects of using different bid sets, and (iii) we check the size and power of a commonly used diagnostic test for anchoring.

In addition, (iv), we study (ii) and (iii) after introducing an amendment to the Herriges and Shogren that, in our opinion, reflects a realistic response effect induced by the follow-up payment question. We reason that while respondents might treat the initial bid as providing information about the value of the policy—as suggested by Herriges and Shogren—the follow-up question may end up confusing them. In practice, this is one possible representation for the uncertainty about the cost of the program effect discussed in Carson et al. (2000). We therefore amend equation (3.4) to obtain

$$WTP_{2i} = WTP_{1i}(1-\gamma) + \gamma \cdot B_1 + e_i\,, \qquad (3.5)$$

where the error term e_i captures the possible uncertainty/confusion associated with the follow-up question.

3.4 Detecting Starting Point Bias

Whittington et al. (1991), Green and Tunstall (1991), Cameron and Quiggin (1994) and Chien et al. (2005) include bid set dummies among the regressors of the double-bounded model to capture starting point effects.[42] This approach is an extension to dichotomous-data model of an approach previously used with WTP responses on a continuous scale elicited through open-ended questions (Boyle et al.,1985).

Letting δ be the vector of coefficients on the bid set dummies, one tests the null hypothesis that δ=0 (no anchoring) against the alternative that at least one of the

[42] By bid set dummies, we mean a set of dummies where the first takes on a value of one if the respondent was assigned to the first bid set used in the survey and 0 otherwise, etc.

elements in δ is different from 0. Rejection of the null is interpreted as evidence of starting point bias. Because the parameters of the model are estimated using the method of maximum likelihood, any one of the three classical tests—the Wald, likelihood ratio, or score test—can be used. Under relatively mild regularity assumptions, under the null the three statistics are each distributed as a chi square with m=dim(δ) degrees of freedom, and are thus asymptotically equivalent.

In this chapter, we use the Wald statistic, which is calculated as

$$w = \hat{\boldsymbol{\delta}}'\mathbf{V}^{-1}\hat{\boldsymbol{\delta}}, \qquad (3.6)$$

where $\hat{\boldsymbol{\delta}}$ is the vector of coefficients on the bid set dummies estimated from the augmented double-bounded model, and **V** is the block of the information matrix for all parameters corresponding to the coefficients on the bid set dummies. **V** is, therefore, an m×m matrix. As mentioned, for large sample size and under the null, the test statistic w is distributed as a chi square with m degrees of freedom. Failure to reject the null implies that there is no evidence of anchoring on the bid amounts.

3.5 Study Design

To answer our research questions, we conducted a series of Monte Carlo simulations. We ran a total of four sets of simulations. Each simulation set is comprised of 15 experiments (5 values of $\gamma \times 3$ bid designs).[43] In each experiment, the number of replications is 1000 and in each replication the sample size is 1000. Our study design is summarized in Table 3.1.

[43] In simulation set II, we have a total of 30 experiments, because we also change the variance of one of the error terms in the model. See Table 3.1.

Table 3.1 - Summary of the Simulation Experiment Design

(A) Simulation set	(B) True WTP distribution	(C) Parameters of true WTP distribution	(D) Anchoring mechanism	(E) Bid sets
I	Normal	μ=10 σ=10	Herriges and Shogren with γ=0 (no anchoring), 0.3, 0.5, 0.7, 0.9	--base --upper tail --lower tail
II	Normal	μ=10 σ_1=10 σ_2=3 or 20	Anchoring + error term with γ=0 (no anchoring), 0.3, 0.5, 0.7, 0.9	--base --upper tail --lower tail
III	Weibull	Scale parameter σ=10 Shape parameter θ=1	Herriges and Shogren with γ=0 (no anchoring), 0.3, 0.5, 0.7, 0.9	--base --upper tail --lower tail
IV	Lognormal	μ=1.956012 (mean of log WTP) σ=0.693147 (standard deviation of log WTP)	Herriges and Shogren with γ=0 (no anchoring), 0.3, 0.5, 0.7, 0.9	--base --upper tail --lower tail

We generate draws from the assumed distribution, shown in column (B) of Table 3.1. Each draw is assigned at random to one of the possible bid sets (reported in Table 3.3), and binary indicators corresponding to 'yes' or 'no' responses to the payment questions are created by comparing the draw with its assigned bid value and appropriate follow-up bid amount.

All simulations fit normal likelihood function, but we assume different distributions (normal, Weibull, and lognormal) for true WTP in different simulation sets. Simulation sets I, III and IV adopt the Herriges-Shogren anchoring mechanism (equations (3.1) and (3.4)). By contrast, in simulation set II we use our amendment to the Herriges-Shogren model (equation (3.5)), but assume that true distribution is normal, so that we can compare the results of these runs with those of simulation set I. In simulation set II, we assume that ε and e are uncorrelated; however, it is easily shown that WTP_1 and WTP_2 are correlated, since they both contain ε. In sum, WTP_1 and WTP_2 are jointly normally distributed.

Simulation set II is repeated under two alternative values for σ_2, where $\sigma_2^2 = Var(e)$, namely 3 and 20, where the latter signifies a situation where respondent confusion is more pronounced.

To make all simulation sets comparable as we vary the distribution of WTP, we choose the parameters of the distribution of WTP so that its expected value (mean WTP) is 10 and its variance 100.[44]

We use a total of three bid sets. Each is comprised of 5 initial bid amounts and their corresponding high and low follow-up bids. As before, it is important that the bid amounts be comparable across different WTP distributions, so we choose our bid sets to correspond to specified percentiles of the distribution of WTP, as shown in Table 3.2. (This means that the actual bid amounts differ across simulation sets to mirror the different distributions we assume for WTP. We remind the reader that the percentile is 1 minus the probability of answering 'yes' to that bid amount.)

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[44] If Y denotes a Weibull random variate, its cdf is $1-\exp\left[-(y/\sigma)^{\theta}\right]$, its mean is $\sigma \cdot \Gamma(1/\theta+1)$, and its median is $\sigma[-\ln 0.5]^{1/\theta}$. If Y is a lognormal, the density is $\frac{1}{\sigma y\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\left(\frac{\ln y-\mu}{\sigma}\right)^2\right\}$, mean is $\exp(0.5\sigma^2+\mu)$ and median is exp(μ).

Table 3.2 - Percentiles Corresponding to the Bid Amounts in the Simulations

Design	Percentile				
Base Design	0.184	0.310	0.500	0.580	0.692
Upper Tail Design	0.184	0.310	0.500	0.692	0.933
Lower Tail Design	0.184	0.242	0.274	0.310	0.382

Table 3.3 - Initial Bid Amounts

Distribution	Bid Design	1st Initial Bid	2nd Initial Bid	3rd Initial Bid	4th Initial Bid	5th Initial Bid
Normal	*Base*	1	5	10	12	15
	Upper tail	1	5	10	15	25
	Lower tail	1	3	4	5	7
Weibull	*Base*	2.034	3.689	6.931	8.657	11.759
	Upper tail	2.034	3.689	6.931	11.759	27.059
	Lower tail	2.034	2.770	3.206	3.689	4.814
Lognormal	*Base*	3.342	4.663	7.071	8.352	10.722
	Upper tail	3.342	4.663	7.071	10.723	24.652
	Lower tail	3.342	3.948	4.291	4.663	5.508

The artificial draws from the WTP distribution are evenly divided among the five possible bid sets. In the base bid set, the initial bid values cover the 18th-69th percentile. The bid set labeled 'upper tail' covers the 18th to 93th percentiles, while the bid set labeled 'lower tail' is skewed towards the lower tail of the distribution of WTP and fails to cover the right tail of the distribution of WTP. When the distribution of WTP is a normal, the average of the initial bids for the base, upper tail, and lower tail designs is 8.6, 11.2 and 4, respectively.

Earlier research (Alberini, 1995; Kanninen, 1991, and Cooper, 1993) shows that when the distribution of WTP is symmetric, an unbalanced bid design (i.e., one that places more bids and/or respondents on side of the distribution, or farther away from the mean) tends to result in inefficient, but unbiased, estimates of mean WTP.[45] However, with right-skewed distributions of WTP the estimate of mean WTP depends crucially on 'nailing down' the upper tail of distribution, a task that can be accomplished only by querying respondents about their Willingness-To-Pay relatively large bid amounts. At such large bid amounts, a large fraction of the respondents are expected to answer 'no' to the payment question.[46] These considerations suggest that with right-skewed distributions we would expect the 'upper tail' design to perform best, and the 'lower tail' design to result in less efficient, and potentially unstable, estimates of mean WTP. The follow-up amounts are double or half of the initial amount.

We use a total five values for γ, the anchoring parameter: 0, which means that there is no anchoring, then 0.3, 0.5, 0.7, and 0.9, which imply levels of anchoring ranging from mild to severe. For each artificial data generation, we fit two double-bounded interval-data likelihood functions, both of which assume that WTP is a normal variate. The first is the regular double-bounded model (with no individual characteristics), which is used to establish the seriousness of the biases (if any) of the estimates of mean and variance WTP. In the second double-bounded model, the likelihood function is amended to include dummies for the bid set.[47] Since there are a

[45] Efficiency goals with respect to estimating mean WTP are sometimes in conflict with doing a good job estimating the variance of WTP: a compromise can be reached when choosing the bid amounts, for example, by adopting the d-optimality design criterion (Kanninen, 1991).
[46] This is again a situation where statistical estimation needs may be in conflict with a realistic scenario. If the bid amount is perceived to be unrealistically large for the good described in the questionnaire, the respondent may question the credibility of the exercise and provide unreliable responses.
[47] For example, in simulation set I, when the base bid design is used, the bid set dummies are A1=1 if the initial bid is 1, and 0 otherwise; A2=1 if the initial bid assigned to this observation is 5, and 0 otherwise, etc.

total of five bid sets, we include four bid set dummies, and we compute the Wald statistics for the null that the coefficients on the bid dummies are all equal to zero.

3.6 Results

We use two criteria to examine the performance of double-bounded models in the presence of starting point bias. The first is the relative bias of mean WTP, and the second is the relative bias of the standard deviation of WTP, σ(WTP). The relative bias is the bias divided by the true value of the WTP statistic. Regarding the diagnostic test, i.e., the Wald test of the null that the coefficients of the bid dummies are jointly equal to zero, we examine the percentage of times that the test rejects the null hypothesis for a given significance level. Clearly, if γ=0, this percentage is the empirical size of the test, i.e., the frequency with which the null is falsely rejected. If γ is different from zero, this percentage is the empirical power of the test. We expect the power of the test to increase with γ. We do not have any prior expectation of the empirical size of the test when there is no starting point bias and the true WTP distribution is not normal (but the likelihood function assumes that it is).

3.6.1 Bias of the Welfare Estimates

Table 3.4 displays the relative bias of mean WTP for the three bid designs and the four simulation sets.

Panel (a) refers to the situation where true WTP is normal and one fits the double-bounded model that assumes a normal distribution (and ignores the presence of starting point bias). When there is no starting point bias (i.e., γ=0), this is the correct model, and the estimates of mean WTP are virtually unbiased. The relative bias—which is computed as the average mean WTP over the replications minus the true mean WTP, and then divided by the true mean WTP—is only -0.20 to -0.18%. With the base bid design, the bias of mean WTP does not change much, even when anchoring is more pronounced (-1.50% for γ=0.3 to -7% for γ=0.9).

The upper tail design does not fare as well, but the biases resulting from this design never exceed 15% of the true mean WTP. It is interesting that—against our expectations—the bias is non-monotonic in γ. The lower tail design is the worst of the three. Even a moderate degree of anchoring produces a bias of -16%, and extreme anchoring (γ=0.9) results in an underestimate of mean WTP by at least 50%.

Panel (b) displays the results when we use our amendment to the Herriges-Shogren model when the variance of the error term in the follow-up question is small. Clearly, the results are very similar to those of panel (a) because the variance of the additional error term is too small to offset the variance shrinkage due to the anchoring on the first bid. As shown in panel (c), the biases are of similar magnitude (but slightly smaller) when the variance of the additional error term is larger.

Panel (d) shows that assuming the wrong distribution results in biased estimates of mean WTP. What's interesting is that the bias of mean WTP varies with the bid design used, but for a given bid design does *not* vary with the severity of the anchoring. This is a somewhat surprising result. As we expected, the design that fares the best is the upper tail design, which underestimates mean WTP by about 16%. This design barely outperforms the base design, which on average underestimates mean WTP by 19%. The worst is the lower tail design, which underestimates mean WTP by about 30%. Panel (e) shows similar effects of fitting a normal double-bounded model to lognormal WTP data in the presence of varying degrees of anchoring.

Table 3.5 presents similar summary statistics of the simulations for the standard deviation of WTP, σ(WTP). Panel (a) shows that the double-bounded model underestimates true σ(WTP), an effect that becomes more pronounced as anchoring becomes stronger. As before, the best behaved design is the base design. The one that results in the most severe biases is the lower tail design, which underestimates true σ(WTP) by up to 76% for $\gamma=0.9$. Panel (b) shows similar biases when only a small error term is added to the anchoring mechanism. As shown in panel (c), the biases are reduced somewhat when the variance of the error term in equation (3.5) is larger, thus partially offsetting the shrinkage of WTP due to the anchoring.

Panels (d) and (e) confirm that when the wrong distribution is used, and anchoring is present but ignored, the estimates of σ(WTP) are biased. As before, the biases depend on the bid design, but for a given bid design they do *not* depend on the severity of the anchoring. The biases can be very pronounced: in our examples, the true σ(WTP) may be underestimated by over 50%.

Table 3.4 – Percent Bias Mean WTP

	Anchoring Level (γ)	Base Bid Design	Upper Tail Bid Design	Lower Tail Bid Design
a)	0	-0.20	-0.10	0.18
True WTP: Normal Distribution	0.3	-1.50	6.54	-16.20
Likelihood Function: Normal	0.5	-1.72	12.85	-27.22
(Simulation Set I - Herriges-Shogren's Model)	0.7	-1.74	14.89	-39.30
	0.9	-7.00	7.98	-49.70
b)	0	-0.02	-0.12	-0.15
True WTP: Normal Distribution	0.3	-2.03	5.22	-17.23
Likelihood Function: Normal	0.5	-3.23	10.21	-27.30
Sigma 2 = 3	0.7	-4.49	12.08	-37.57
(Simulation Set II)	0.9	-7.80	7.60	-46.73
c)	0	-0.02	-0.12	-0.15
True WTP: Normal Distribution	0.3	0.69	3.13	-27.60
Likelihood Function: Normal	0.5	-0.50	3.84	-30.66
Sigma 2 = 20	0.7	-1.73	4.20	-33.57
(Simulation Set II)	0.9	-2.96	4.80	-36.02
d)	0	-19.03	-16.64	-30.73
True WTP: Weibull Distribution	0.3	-18.99	-16.71	-30.62
Likelihood Function: Normal	0.5	-18.78	-16.68	-30.74
(Simulation Set III)	0.7	-19.94	-16.72	-30.83
	0.9	-19.12	-16.86	-30.67
e)	0	-17.32	-15.45	-24.68
True WTP: Weibull Distribution	0.3	-17.31	-15.49	-24.60
Likelihood Function: Normal	0.5	-17.40	-15.43	-24.71
(Simulation Set IV)	0.7	-17.43	-15.50	-24.67
	0.9	-17.44	-15.62	-24.64

Table 3.5 – Percent Bias Std. Dev. WTP

	Anchoring Level (γ)	**Base Bid Design**	**Upper Tail Bid Design**	**Lower Tail Bid Design**
a)	0	0.01	-0.01	0.31
True WTP: Normal Distribution	0.3	-24.20	-17.81	-27.37
Likelihood Function: Normal	0.5	-38.78	-28.13	-45.68
(Simulation Set I - Herriges-Shogren's Model)	0.7	-49.65	-36.52	-64.62
	0.9	-51.60	-38.68	-76.79
b)	0	0.05	-0.01	0.04
True WTP: Normal Distribution	0.3	-20.80	-15.81	-27.78
Likelihood Function: Normal	0.5	-34.32	-25.06	-43.36
Sigma 2 = 3	0.7	-44.11	-31.88	-57.91
(Simulation Set II)	0.9	-48.10	-35.13	-68.92
c)	0	0.05	-0.01	0.04
True WTP: Normal Distribution	0.3	2.30	1.51	-38.77
Likelihood Function: Normal	0.5	-2.70	-2.65	-42.58
Sigma 2 = 20	0.7	-7.57	-6.40	-46.08
(Simulation Set II)	0.9	-11.84	-9.59	-49.22
d)	0	-13.57	-6.19	-45.64
True WTP: Weibull Distribution	0.3	-13.82	-6.24	-45.52
Likelihood Function: Normal	0.5	-13.45	-6.04	-45.46
(Simulation Set III)	0.7	-13.55	-6.10	-45.62
	0.9	-13.68	-6.67	-45.57
e)	0	-35.32	-26.24	-56.50
True WTP: Weibull Distribution	0.3	-35.28	-26.61	-56.54
Likelihood Function: Normal	0.5	-35.18	-26.42	-56.53
(Simulation Set IV)	0.7	-35.50	-26.55	-56.54
	0.9	-35.32	-26.69	-56.41

3.6.2 Diagnostic test

Table 3.6 summarizes the relative frequencies of rejection of the null hypothesis that the bid set dummies are jointly equal to zero for all experiments and simulations sets. The table was constructed assuming that the significance level (or nominal size of the test) is α=0.05.

Table 3.6 shows clearly that in simulation set I, where the correct distribution (the normal) is assumed for WTP, and no anchoring is present (γ=0), the percentage of rejections of the null is similar to the nominal size of the test, although it slightly exceeds it if the upper tail bid design is used. We had expected the relative frequency of rejections to increase with γ, but this expectation is not borne out in the results: rejections occur in 5-6 percent of the replications, regardless of the value of γ, and do not appear to depend in any predictable way on the bid design. We believe that this is due to the fact that the estimate of μ adjusts accordingly. We did not detect any particular patterns in the estimated coefficients on the bid dummies.

The results are similar when we introduce an error term to capture respondent confusion, as we do in simulation set II. Changing the variance of this term does not change much the percentage of rejections.

In simulation set III, the true distribution is a Weibull, but we fit a normal double-bounded model and ignore anchoring. If anchoring is absent (γ=0), the relative frequency of the rejections does vary with the bid design used, and ranges from 11 to 26%. This means that the diagnostic test must be picking up the effect of a poor distributional assumption. We note three interesting findings at this point. First, the most frequent rejections occur with the bid design that tracks the upper tail of the distribution. Second, the percentage of rejections is insensitive to the value of γ, the anchoring parameter, in the sense that they do not exhibit a clear trend as γ increases. Third, the power of the test when γ is greater than zero is rather modest, as it never exceeds 24%.

Results for the lognormal distribution (simulation set IV) are qualitatively similar to those for the Weibull. When γ =0, the empirical size of the Wald test slightly exceeds the nominal size of the test for all designs, especially the upper tail and lower tail designs. In these cases, the empirical frequency of rejection of the null is 7-15 percent against a nominal size of 5 percent. Little change is seen when γ increases for a given bid design. We conclude that in this simulation set the Wald test exhibited limited power in picking up either anchoring or the poor distributional assumption.

Table 3.6. Empirical Size and Power of the Test of Starting Point Bias

DGP	**Anchoring Present?**	**DB Log Likelihood**	**Percent Rejection of Null Wald Test (Base Bid Set)**	**Percent Rejection of Null Wald Test (Upper Tail Bid Set)**	**Percent Rejection of Null Wald Test (Lower Tail Bid Set)**
Normal (Simulation Set I)	**No**	Normal	5.50	4.70	7.51
	Yes, $\gamma = 0.3$		**6.00**	**5.80**	**5.53**
	Yes, $\gamma = 0.5$		**5.90**	**6.70**	**5.68**
	Yes, $\gamma = 0.7$		**3.40**	**6.90**	**4.47**
	Yes, $\gamma = 0.9$		**4.70**	**6.40**	**5.82**
Normal **($\sigma_2 = 3$)** (Simulation Set II)	**No**	Normal	5.11	7.26	6.06
	Yes, $\gamma = 0.3$		**6.30**	**7.66**	**3.31**
	Yes, $\gamma = 0.5$		**4.02**	**2.47**	**6.20**
	Yes, $\gamma = 0.7$		**7.80**	**3.69**	**5.56**
	Yes, $\gamma = 0.9$		**6.69**	**6.45**	**4.66**
Normal **($\sigma_2 = 20$)** (Simulation Set II)	**No**	Normal	5.11	7.26	6.06
	Yes, $\gamma = 0.3$		**5.70**	**6.27**	**5.74**
	Yes, $\gamma = 0.5$		**5.20**	**5.27**	**6.38**
	Yes, $\gamma = 0.7$		**5.50**	**5.90**	**4.21**
	Yes, $\gamma = 0.9$		**5.80**	**4.97**	**6.29**
Weibull (Simulation Set III)	**No**	Normal	**10.88**	**26.04**	**13.65**
	Yes, $\gamma = 0.3$		13.29	21.80	12.78
	Yes, $\gamma = 0.5$		12.98	23.01	13.01
	Yes, $\gamma = 0.7$		12.18	23.57	14.13
	Yes, $\gamma = 0.9$		13.31	21.92	12.77
Lognormal (Simulation Set IV)	**No**	Normal	**7.06**	**12.84**	**14.44**
	Yes, $\gamma = 0.3$		7.43	12.23	13.02
	Yes, $\gamma = 0.5$		5.30	11.58	14.45
	Yes, $\gamma = 0.7$		8.17	10.97	16.30
	Yes, $\gamma = 0.9$		5.78	15.37	15.82

3.7 Conclusions

In this chapter, we have focused on starting point bias (anchoring) in the dichotomous choice Contingent Valuation surveys with a dichotomous choice follow-up question. We have considered a mechanism that generates anchoring first developed by Herriges and Shogren and frequently adopted in the literature, and have examined the effect of ignoring starting point bias and fitting double-bounded models.

Our results suggest that normally distributed double-bounded models *may* produce biased estimates of mean WTP and the standard deviation of WTP when anchoring is present, that these biases are more severe the stronger the anchoring is, and that the severity of the biases varies with the bid design used. A well-balanced, symmetric bid design may result in very modest biases even when the anchoring mechanism is very strong.

When the true WTP is not a normal variate, but a normal double-bounded model is estimated, the biases do *not* vary with the severity of the anchoring, and seem to depend primarily on the misspecification of the distribution. As before, the biases do depend on the bid design.

We also investigated the empirical size and power of a commonly used test for detecting the presence of starting point bias. This test consists of including bid set dummies in the right-hand side of the double-bounded model, and of testing the null that all bid set coefficients are equal to zero. We used a Wald test to test this hypothesis, but the other two classical tests (the likelihood ratio and score test) can be used interchangeably, since they are asymptotically equivalent to the Wald test.

We found that when the true distribution of WTP is a normal and the econometric model of the responses to the payment questions is a normal double-bounded, the test has very little power against the alternative even when the anchoring parameter is very high. When the true distribution of WTP is a Weibull or a lognormal, but one fits a normal double-bounded model, depending on the bid design used, one may tend to reject the null hypothesis of no anchoring too frequently when anchoring is not present. The power of the Wald test is modest, and does not change much with the anchoring parameter γ.

Based on our findings, we caution researchers that the consequences of starting point biases are complex and depend on the underlying distribution of WTP. We also caution them that simple to implement diagnostic tests, such as the inclusion of bid set dummies in the right-hand side of double-bounded models of WTP, may be misleading. We have found that tests of the null that the coefficients on these dummies are equal to zero may fail to reject the null when they should, or may tend to reject it even if no starting point bias is present, simply because the researcher did not use the correct distribution of WTP or the correct random utility model (RUM) in writing out the double-bounded models.

Unfortunately, it is difficult to come up with alternative approaches for detecting and correcting for anchoring unless the correct distribution of WTP or the correct RUM model are assumed, and one is prepared to make specific assumptions about the form of the anchoring. Semi-parametric, semi-nonparametric, and nonparametric models (reviewed in Cooper, 2002), which alleviate the need for making assumptions regarding the distribution and/or the functional form of the RUM, cannot separately identify response biases from other forms of bias.

In principle, one can compare the relative frequency of 'yes' or 'no' responses to the same bid amount in groups of respondents that were assigned different bid sets.

If the probability of a yes to \$X as a starting bid is statistically the same as a probability of a yes to \$X in the follow-ups (after converting the follow-up probability from a conditional to an unconditional probability), then the null hypothesis that there is no response bias cannot be rejected. However, even if bias is present, this approach cannot identify its form nor know which bound is associated with the most severe bias in the responses: all we can surmise when using such an approach is that the responses to the bid values are not consistent across the bounds.

In sum, unless one is prepared to make assumptions about the form of the bias, it cannot be corrected for. As we have suggested, without additional information beyond the responses to the bids themselves, econometric approaches to identifying and correcting for response bias do not appear to be fruitful. An alternative may be to use follow-up questions specifically pertaining to the respondent's views on being asked follow-up questions. Another approach that we deem worth investigating is to openly tell respondents in advance that there will be multiple bids to respond to, and that multiple bid response questions will be asked simply to get a more precise assessment of Willingness-To-Pay. We believe that this is a potentially promising area for future research.

Appendix

Double-Bounded Models of WTP with Starting Point Bias

A1. Model of the Responses Corresponding to Equations (3.3) and (3.4)

<u>Assumption:</u> $\varepsilon_1 \sim N\left(0, \sigma_1^2\right)$

Let

WTP_1: WTP to the first bid;

WTP_2: WTP to the follow-up bid;

B_1 = first bid;

B_2 = follow-up bid;

μ = mean WTP;

σ_1 = standard deviation of the first WTP variable;

γ = gamma parameter indicating the anchoring;

$$WTP_1 = W^* = \mu + \varepsilon_1$$

$$WTP_2 = \tilde{W}^* = WTP_1(1-\gamma) + \gamma B_1 \qquad \text{(A.1)}$$

γ = 0: no anchoring: $WTP_2 = WTP_1$;

γ = 1: $WTP_2 = B_1$

$$\begin{aligned} W &= 1 \ \textit{if} \ W^* \geq B_1 \\ &= 0 \ \textit{if} \ W^* < B_1 \end{aligned}$$

$$\begin{aligned} \tilde{W} &= 1 \ \textit{if} \ \tilde{W}^* \geq B_2 \\ &= 0 \ \textit{if} \ \tilde{W}^* < B_2 \end{aligned}$$

From (A.1) WTP_2 becomes

$$WTP_2 = \tilde{W}* = (1-\gamma)\mu + (1-\gamma)\varepsilon_1 + \gamma B_1$$

We denote the corresponding response probabilities as

$$P(No, No) = P(WTP_1 \leq B_1; WTP_2 < B_2)$$

$$= P\left[(\mu+\varepsilon_1 \leq B_1);\ ((1-\gamma)\mu+(1-\gamma)\varepsilon_1+\gamma B_1)<B_2\right]$$

$$= P\left[\frac{\varepsilon_1}{\sigma_1} \leq \frac{(B_1-\mu)}{\sigma_1};\ \frac{\varepsilon_1}{\sigma_1} < \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

$$= P\left[\frac{\varepsilon_1}{\sigma_1} < \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

$$= \Phi\left[\frac{\varepsilon_1}{\sigma_1} < \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

since $\left[\frac{\varepsilon_1}{\sigma_1} < \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1} < \frac{(B_1-\mu)}{\sigma_1}\right]$;

$$P(Yes, No) = P(WTP_1 \geq B_1; WTP_2 < B_2)$$

$$= P\left[\frac{\varepsilon_1}{\sigma_1} \geq \frac{(B_1-\mu)}{\sigma_1};\ \frac{\varepsilon_1}{\sigma_1} < \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

$$= \Phi\left[\frac{B_2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right] - \Phi\left[\frac{B_1-\mu}{\sigma_1}\right]$$

$$P(No, Yes) = P(WTP_1 \leq B_1; WTP_2 > B_2)$$

$$= P\left[\frac{\varepsilon_1}{\sigma_1} \leq \frac{(B_1 - \mu)}{\sigma_1}; \frac{\varepsilon_1}{\sigma_1} > \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

$$= \Phi\left[\frac{B_1 - \mu}{\sigma_1}\right] - \Phi\left[\frac{B_2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

$$P(Yes, Yes) = P(WTP_1 \geq B_1; WTP_2 > B_2)$$

$$= P\left[\frac{\varepsilon_1}{\sigma_1} \geq \frac{(B_1 - \mu)}{\sigma_1}; \frac{\varepsilon_1}{\sigma_1} > \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

$$= P\left[\frac{\varepsilon_1}{\sigma_1} > \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1}\right]$$

$$= \Phi\left[\frac{\gamma B_1}{(1-\gamma)\sigma_1} - \frac{B2}{(1-\gamma)\sigma_1} + \frac{\mu}{\sigma_1} - \right]$$

$$\text{since} \left[\frac{(B_1 - \mu)}{\sigma_1} < \frac{B2}{(1-\gamma)\sigma_1} - \frac{\mu}{\sigma_1} - \frac{\gamma B_1}{(1-\gamma)\sigma_1} < \frac{\varepsilon_1}{\sigma_1}\right]$$

Let d_{nn} = 1 if the starting bid is B_1, $B_1 > B_2$ and the response is (No, No), and 0 otherwise; let d_{yn} = 1 if the starting bid is B_1, $B_1 < B_2$ and the response is (Yes, No); let d_{ny} = 1 if the starting bid is B_1, $B_1 > B_2$ and the response is (No, Yes), and 0 otherwise; and let d_{yy} = 1 if the starting bid is B_1, $B_1 < B_2$ and the response is (Yes, Yes).

The log-likelihood function becomes

$$\log L = \sum\left[d_{yy} \log P(Yes, Yes) + d_{yn} \log P(Yes, No) + d_{ny} \log P(No, Yes) + d_{nn} \log P(No, No)\right]$$

A2. Model of the Responses Corresponding to Equations (3.3) and (3.5)

<u>Assumption</u>: $\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{pmatrix}\right]$

Let

WTP_1: WTP to the first bid;

WTP_2: WTP to the follow-up bid;

B_1 = first bid;

B_2 = follow-up bid;

μ = mean WTP;

σ_1 = standard deviation of the first WTP variable;

σ_2 = standard deviation of the error term that gets added to the function of WTP and first bid in the generation of WTP_2

γ = gamma parameter indicating the anchoring;

ω = standard deviation of new error term of WTP_2 with anchoring;

ω_{12} = covariance between new error term of WTP_2 with anchoring and the error term of WTP_1;

σ_{12} = covariance between error term WTP_1 and error term that gets added to the function of WTP and first bid in the generation of WTP_2;

ρ = correlation term between new error term of WTP_2 with anchoring and the error term of WTP_1;

$$WTP_1 = W^* = \mu + \varepsilon_1$$

$$WTP_2 = \tilde{W}^* = W^*(1-\gamma) + \gamma B_1 + \varepsilon_2 \qquad \text{(A.2)}$$

$\gamma = 0$: no anchoring: $WTP_2 = W^* + \varepsilon_2$;

$\gamma = 1$: $WTP_2 = B_1 + \varepsilon_2$;

$$\begin{aligned} W &= 1 \ \ if \ \ W^* \geq B_1 \\ &= 0 \ \ if \ \ W^* < B_1 \end{aligned}$$

$$\begin{aligned} \tilde{W} &= 1 \ \ if \ \ \tilde{W}^* \geq B_2 \\ &= 0 \ \ if \ \ \tilde{W}^* < B_2 \end{aligned}$$

From (A.2) WTP_2 becomes

$$\begin{aligned} \tilde{W}^* &= (1-\gamma)(\mu + \varepsilon_1) + \gamma B_1 + \varepsilon_2 \\ &= (1-\gamma)\mu + \gamma B_1 + \left[\varepsilon_2 + \varepsilon_1 (1-\gamma)\right] \end{aligned}$$

where $\left[\varepsilon_2 + \varepsilon_1(1-\gamma)\right]$ is the new error term

$$\begin{pmatrix} \varepsilon_1 \\ \left[\varepsilon_2 + \varepsilon_1(1-\gamma)\right] \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \omega_{12} \\ \omega_{21} & \omega^2 \end{pmatrix}\right]$$

$$\omega^2 = V\left[\varepsilon_2 + \varepsilon_1(1-\gamma)\right] = \sigma_2^2 + (1-\gamma)^2 \sigma_1^2 + 2(1-\gamma)\sigma_{12}$$

$$Cov(\varepsilon_1, \left[\varepsilon_2 + \varepsilon_1(1-\gamma)\right]) = \omega_{12} = \sigma_{12} + (1-\gamma)\sigma_1^2$$

$$\rho = \omega_{12} / \sigma_1 \omega .$$

We denote the corresponding response probabilities as

$$P(No, No) = P(WTP_1 \le B_1, WTP_2 < B_2)$$

$$= P\Big[(\mu+\varepsilon_1 \le B_1);\ (\mu(1-\gamma)+\gamma B_1+\big[\varepsilon_2+\varepsilon_1(1-\gamma)\big])<B_2\Big]$$

$$= P\left[\frac{\varepsilon_1}{\sigma_1} \le \frac{(B_1-\mu)}{\sigma_1};\ \frac{\big[\varepsilon_2+\varepsilon_1(1-\gamma)\big]}{\omega} < \frac{(B_2-\mu(1-\gamma)-\gamma B_1)}{\omega}\right]$$

$$= \int_{-\infty}^{\frac{(B_2-\mu(1-\gamma)-\gamma B_1)}{\omega}} \int_{-\infty}^{\frac{(B_1-\mu)}{\sigma_1}} \varphi(z_1, z_2, \rho)\, dz_1 dz_2$$

$$= \Phi\left[\frac{(B_1-\mu)}{\sigma_1}, \frac{(B_2-\mu(1-\gamma)-\gamma B_1)}{\omega}, \rho\right]$$

which is the cdf of a bivariate normal.

$$P(Yes, No) = P(., No) - P(No, No)$$

$$= P(WTP_2 < B_2) - P(No, No)$$

$$= \Phi\left[\frac{(B_2-\mu(1-\gamma)-\gamma B_1)}{\omega}\right] - P(No, No)$$

$$P(No, Yes) = P(No, .) - P(No, No)$$

$$= P(WTP_1 < B_1) - P(No, No)$$

$$= \Phi\left[\frac{(B_1-\mu)}{\omega_1}\right] - P(No, No)$$

$$P(Yes, Yes) = 1 - P(No, No) - P(Yes, No) - P(No, Yes)$$

$$= 1 - P(No, No) - \Phi\left[\frac{(B_1-\mu)}{\sigma_1}\right] + P(No, No) - \Phi\left[\frac{(B_2-\mu(1-\gamma)-\gamma B_1)}{\omega}\right] + P(No, No)$$

$$= 1 - \Phi\left[\frac{(B_1-\mu)}{\sigma_1}\right] - \Phi\left[\frac{(B_2-\mu(1-\gamma)-\gamma B_1)}{\omega}\right] + P(No, No)$$

Let d_{nn} = 1 if the starting bid is B_1, $B_1 > B_2$ and the response is (No, No), and 0 otherwise; let d_{yn} = 1 if the starting bid is B_1, $B_1 < B_2$ and the response is (Yes, No); let d_{ny} = 1 if the starting bid is B_1, $B_1 > B_2$ and the response is (No, Yes), and 0 otherwise; and let d_{yy} = 1 if the starting bid is B_1, $B_1 < B_2$ and the response is (Yes, Yes).

The log-likelihood function becomes

$$\log L = \sum \left[d_{yy} \log P(Yes,Yes) + d_{yn} \log P(Yes,No) + d_{ny} \log P(No,Yes) + d_{nn} \log P(No,No) \right]$$

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CONCLUSIONS AND FUTURE RESEARCH

It has long been recognized that information about consumer preferences for nonmarket environmental resources or public goods can be revealed indirectly through travel decisions or can be elicited directly through Contingent Valuation techniques. The same set of preferences should be driving both travel behavior and Contingent Valuation responses. However, the nonmarket valuation literature shows that the Travel Cost Method and the Contingent Valuation Method yield to different WTP estimates. We argue that the TCM can reveal consumer preferences for non-market goods only by capturing family behavior while instead the WTP is an individual based measure.

The main goal of this research has been to show how to extend the traditional Travel Cost Method to a collective framework in order to estimate WTP for each household member by using only revealed preference data. This allowed us to make TCM and CVM estimates about Willingness-To-Pay comparable at the individual level.

In Chapter 1 we developed a recreational demand model that uses information on singles to derive the recreational demand of individuals living in a couple. We showed that the recreational demand of individual *i* depends not only on individual *i*'s time cost but also on the time cost of the other household members, and that husbands and wives have significantly different recreational demands. This implies that observations for husbands and wives may not be treated as identical as in the traditional recreational demand model (unless one spouse is the dictator) and that the collective setting is a plausible next step to take in the analysis of recreational demand model.

In Chapter 2 by using the individual travel cost of the respondent and his/her household members we estimated a collective Almost Ideal Demand System that takes into account the intra-household resource allocation. This allowed us to estimate the WTP of the respondent and his/her spouse to access a natural park. We defined the implemented method as the ‘Collective Travel Cost Method’ (CTCM). We found that the traditional unitary TCM overestimates the WTP of the respondent estimated by the CTCM and that the difference is statistically significant at the 1% level. Then we found that respondent and his/her spouse have different WTP to access the recreational site. This implies that the actual practice of picking an adult at random from the household as representative of the other family members’ preferences could not be justified.

Finally, we compared the respondent’s mean WTP from the TCM with the respondent’s mean WTP from a Contingent Valuation survey on the same sample of individuals. In line with the literature, we found that the two methods yield to statistically different results but the difference is smaller by using the CTCM rather than the traditional unitary TCM.

In conclusion, this research showed that the Collective Travel Cost Method developed in this study can be implemented to yield individual welfare estimates potentially very useful for policy analysis in order to find the best management strategy for a natural area. We can asses the impact of policy changes on each household member and derive a measure of the incidence of a policy change on members within the household.

Theoretically in the future the collective recreational demand model of Chapter 1 and the CTCM of Chapter 2 should be extended (i) by including corner solutions in the recreational demand; (ii) by considering the presence of children: indeed one of the limitations of these models is that they include children's welfare by assuming that there is one altruistic household member that takes into account household members' well-being; (iii) by addressing the issue of dynamics: household decisions are a dynamic process that involves a tradeoff between partners and different decisions overtime; (iv) by accounting for behavior of groups where individuals from different households choose to take a trip together and not only for the behavior of a family.

Empirically in the future, new data sets should be assembled in an effort to fully apply the CTCM of Chapter 2 and to apply the recreational demand model of Chapter 1. The main caveat of this research is the small sample size and the fact that the survey used to apply the CTCM was not designed for this purpose but for estimating the traditional TCM. In the future the sample should include singles and couples with and without children. The survey should ask about the age of the children to better understand the effect of the children on the decision outcome. Then more detailed data about the spouse of the respondent should be collected. In particular questions about the age, the education, the employment status, the hourly wage, the weekly number of hours of work, the number of trips, the travel costs and the type of trips (if alone, if always with the other spouse, if with friends) of the spouse should be asked.

By designing *ad hoc* questionnaires analysts may be able to provide policy makers with more efficient and accurate estimates of the value of environmental resources or public goods for each household member. Given accelerating concern over environmental issues, research in this vein can be expected to become increasingly important. This research agenda has only begun and will require significant effort on the part of environmental economists to identify the conditions under which improved welfare estimates can be obtained through such methods.

ANNEX

West Garda Regional Forest Survey: A Platform for Policy Analysis

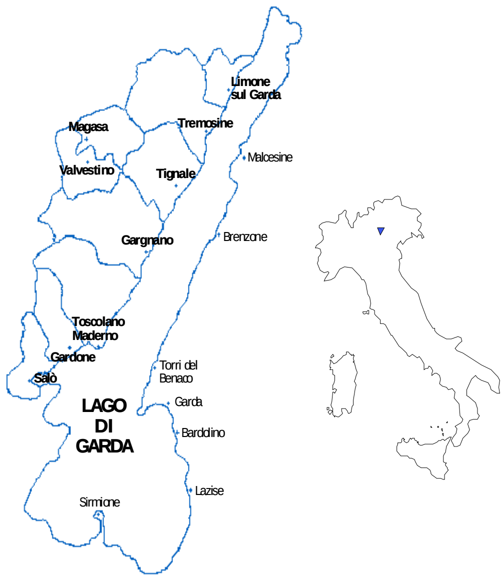
Overview

The West Garda Regional Forest survey was conducted by the Department of Economics of the University of Verona in the north-east of Italy, on the west side of Garda Lake, in June-October 1997. This survey is a primary source of information on the recreational demand, resource use and economic value of the natural, productive, protective and tourist functions of a public forest or park. It provides information about resident and non-resident visitors' preferences and individual consumption. It considers not only the household's total expenditures, but also the distribution and use among members. Such a survey can be used as an example to define policies that allow for interactions among institutions, local economic agents and the park's users, while accounting for implications of those policies on the local economy.

Study Site

The High Garda Natural Park extends over an area of 38 000 hectares (Figure A1) in Lombardy region, in Brescia province. Moving from south to north over the west part of the lake, this area covers nine town councils: Salò, Gardone Riviera, Toscolano-Maderno, Gargnano, Tignale, Tremosine, Limone sul Garda, Valvestino and Magasa. The Regional Forestry Agency of Lombardy region (ERSAF) is responsible for the management of the park side belonging to the region, called West Garda Regional Forest. This area extends over 11 064 hectares and represents the object of this survey.

Figure A1 - West Garda Regional Forest in Italy



Data Collection

The survey was in the form of on-site[48] interviews of random visitors found in the area of the West Garda Regional Forest. The questionnaire was anonymous and included ninety-seven questions. Respondents spent between twenty and thirty minutes answering all of the questions and, on average, ten people were interviewed per day.

[48] Visitors were interviewed in the following places: Passo Spino (27.98 per cent of the respondents), Valvestino (17.17 per cent), Tignale (30 per cent), Tremosine (12.47 per cent), Tremalzo (4.16 per cent) and others locations (8 per cent). There were 400 respondents, but after skimming, the actual sample consists of 361 observations.

Survey Analysis

The survey provides information about:

I. the visit to the natural area;

II. the quality of the natural area;

III. the travel cost estimation;

IV. the economic valuation:

  IV.1 the economic valuation of the natural area;

  IV.2 the economic valuation of the natural area's functions;

V. visitors' socio-demographic characteristics.

I. Characteristics of the Visit to the Natural Area

On average 52 per cent of visitors come from Brescia province, 28 per cent of the respondents come from other provinces (for example Milan, Verona, Trento) and 20 per cent consist of foreign tourists, of which 16 per cent are German (Figure A2). Twenty per cent of the respondents live in an owned vacation house, 20 per cent live in a friend's house, 18 per cent in a hotel and 17 per cent rent a house (Figure A3).

Figure A2 – Respondent's Nationality

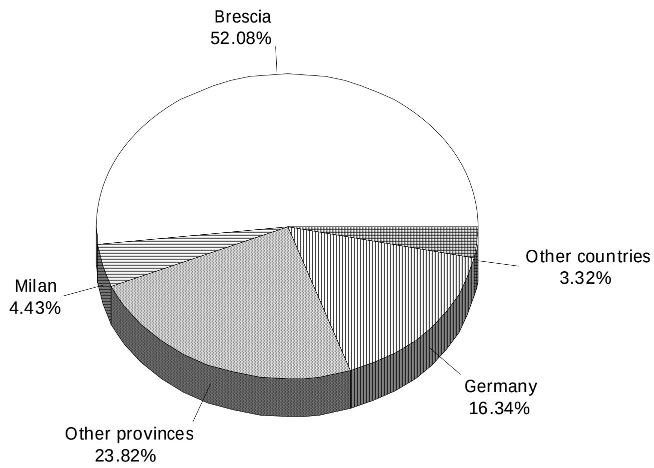
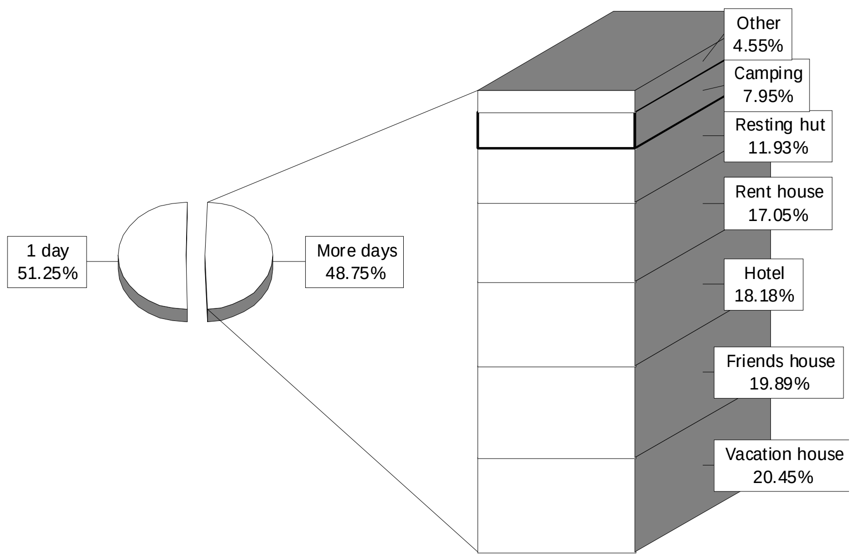


Figure A3 – Respondent's Lodge



II. Quality of the Natural Area

West Garda Regional Forest is not a crowded area as Figure A4 shows. Only 25 per cent of the sample thinks that the area is crowded, 57 per cent of the respondents think that the level of crowding is low and 18 per cent think that the area is not crowded. The quality of the area is sufficient for 42 per cent of the sample, but 46 per cent of respondents think that it is good and 5 per cent think it is very good (Figure A5).

Figure A4 – Crowding Level

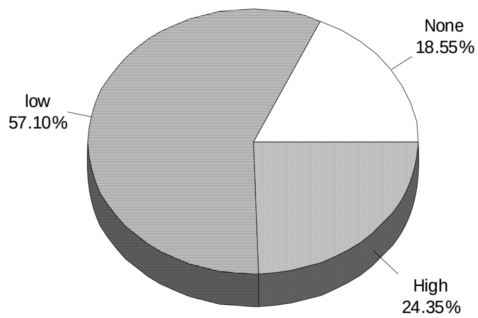


Figure A5 – Quality of the Area

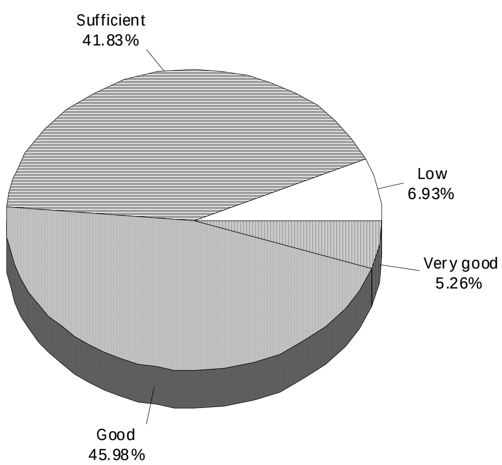
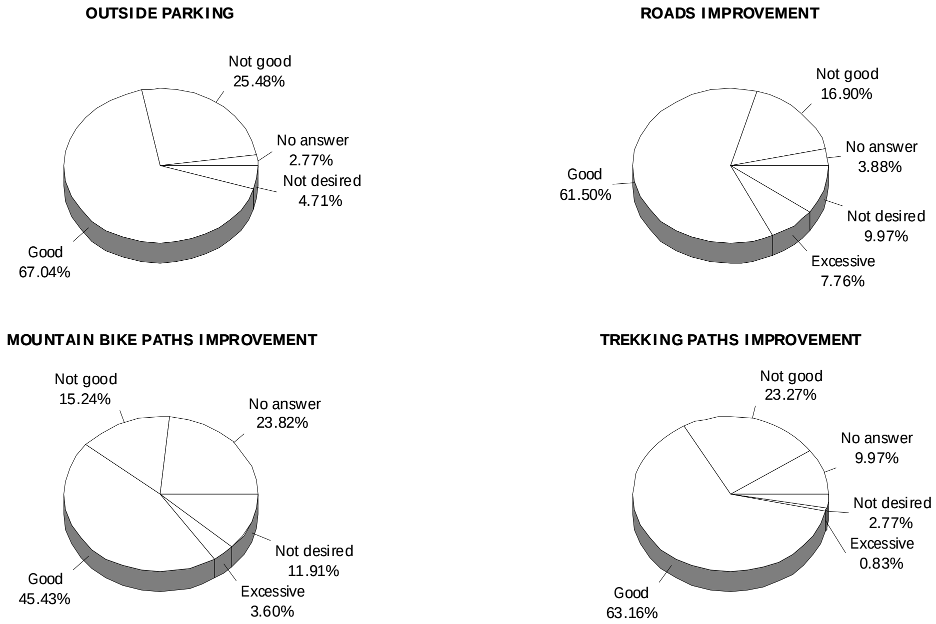


Figure A6, A7 and A8 investigate the quality of the natural area facilities. Regarding the accessibility to the area, 67 per cent of the respondents think that the outside parking is enough, though 25 per cent think that an adequate parking facility is missing. The roads inside the natural area are good for 61.5 per cent of the sample, however, 17 per cent think that the area needs more and 10 per cent do not want any infrastructures. About half of the respondents think that mountain bike paths and trekking paths are good, but 11 per cent of respondents do not want any mountain bike paths at all. If we consider picnic areas, we have 52 per cent of respondents that think they are good and 35 per cent that think they have to be improved. Concerning fishing areas, we have contradicting opinions: 42 per cent are not interested in fishing facilities, 27 per cent do not want these areas, 13 per cent of respondents consider them low quality and only 17 per cent think that they are good.

We can see conflicting opinions about the trash areas: 50 per cent of the sample considers them good and 40 per cent believe that the natural area needs more of them.

Figure A6 – Quality of the Area Facilities



Other questions were asked about the quality of guides or naturalistic teaching programs: 23 per cent of respondents are not interested, 14 per cent do not want them and if 28 per cent think that they are good 35 per cent think that they need to be improved. The quality of road and educational signs in the natural area are considered good by 47 per cent of the sample, but low by 45 per cent. The per centage of respondents not interested in a security service is 22 per cent, while 42 per cent think that this service is good and 28 per cent feel that it has to be improved. Another question was about what respondents think about the fauna and flora variety of the area. While 88 per cent of the sample think that the flora is good and only 4 per cent think that the flora quality is low, 65 per cent had a positive opinion about the fauna and 23 per cent had negative views. In general, respondents think that the West Garda Regional Forest's quality is good.

Figure A7 – Quality of the Area Facilities

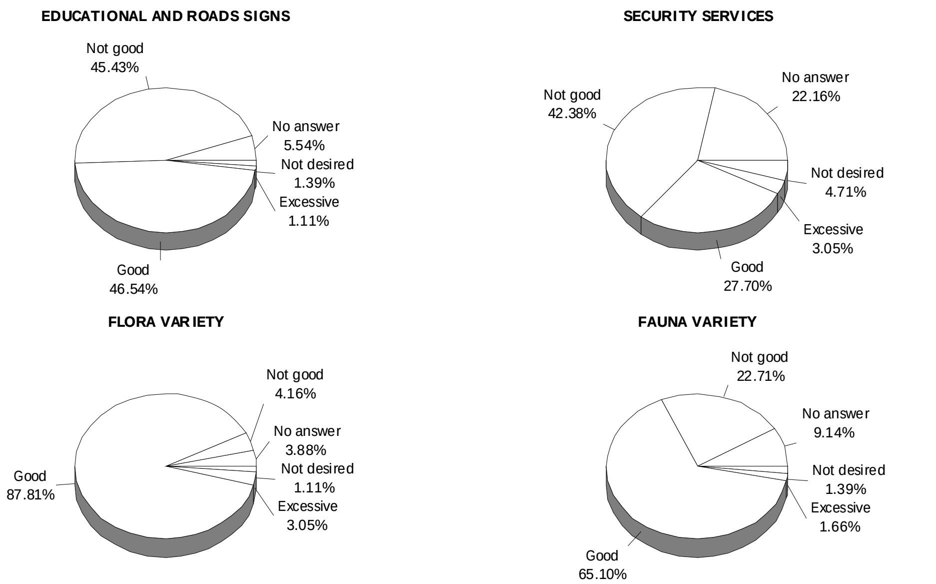
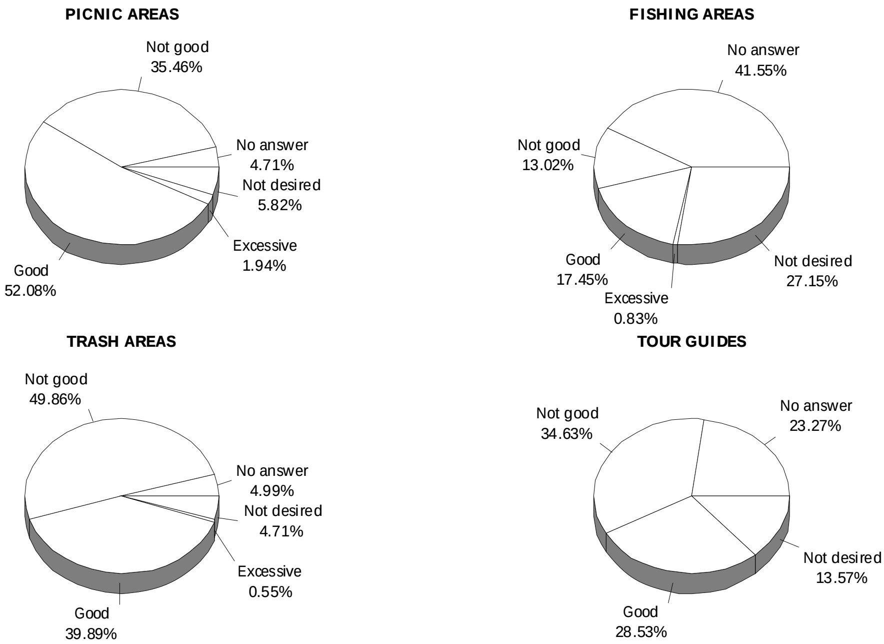


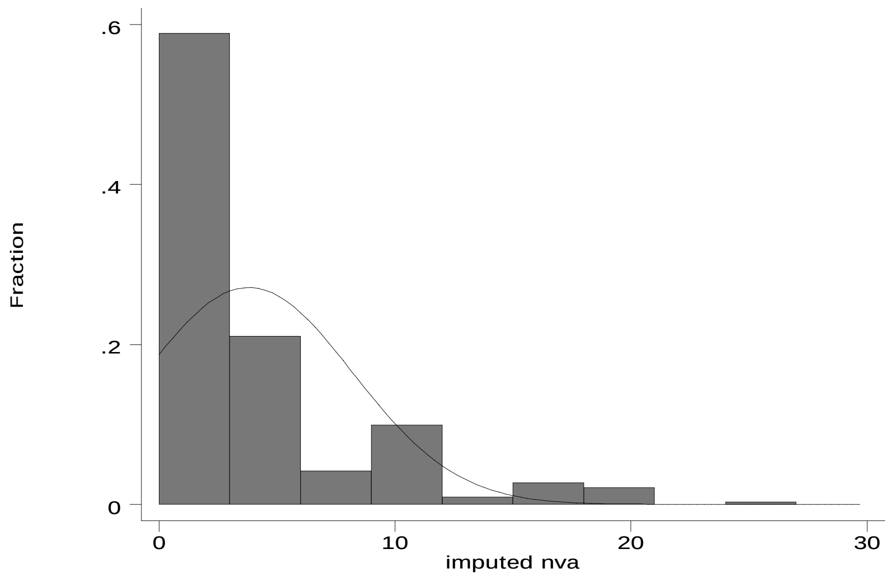
Figure A8 – Quality of the Area Facilities



III. Travel Cost Estimation

This section provides the researcher with all the information she needs for travel cost estimation (Figures A9, A10 and A11). It investigates what the respondent's mean of transportation is; how many hours visitor traveled to go to the West Garda Regional Forest and to go to alternative sites; how many people traveled with her, how many were family members and how many shared the expense of the trip; if she stopped in other places before to come to the natural area; how many days the trip lasts; individual and family transportation expenditures for getting to the forest; individual and family expenditures in food, sleeping, free time activities during the trip and what is the maximum cost to go to the natural area. The respondent was asked to recall the number of annual trips made to West Garda Regional Forest and the number of trips to other natural areas in order to distinguish between visitors with a single-destination from those with multiple destinations.

Figure A9 – Respondent's Number of Trips (nva) to the West Garda Regional Forest



In order to double check the declared costs, the visitor was asked to specify their place of residence, the distance between the natural area and their residence, travel time and for those that were on vacation, the distance from the forest to the vacation lodging. In order to estimate the expenditure for the alternative sites, the visitor was asked about the distance from their residence, number of visits for each site, quality of the area and the purpose of the trip for each alternative site.

The average number of visits per year to the West Garda Regional Forest is 6.79, the average number of days per trip is 5.78, but visitors from Brescia province like more one day trips.

Figure A10 – Number of Days per Visit

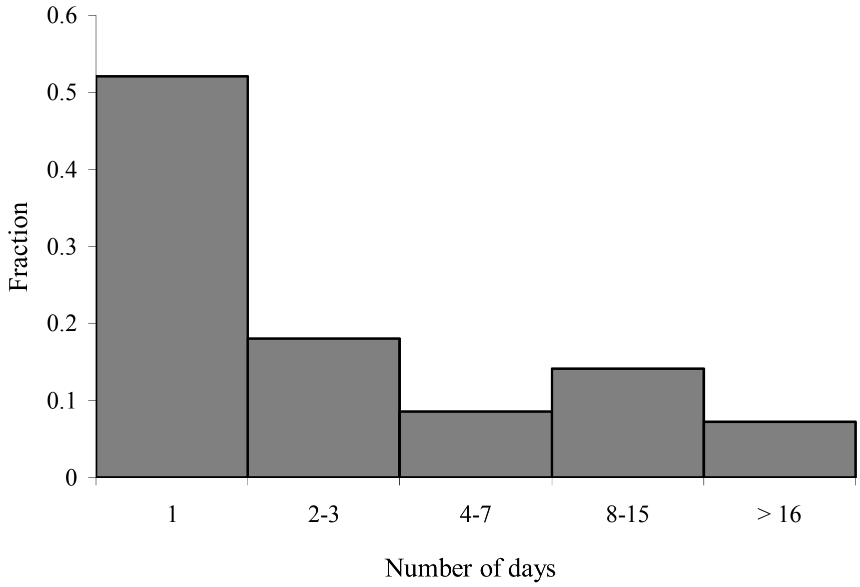
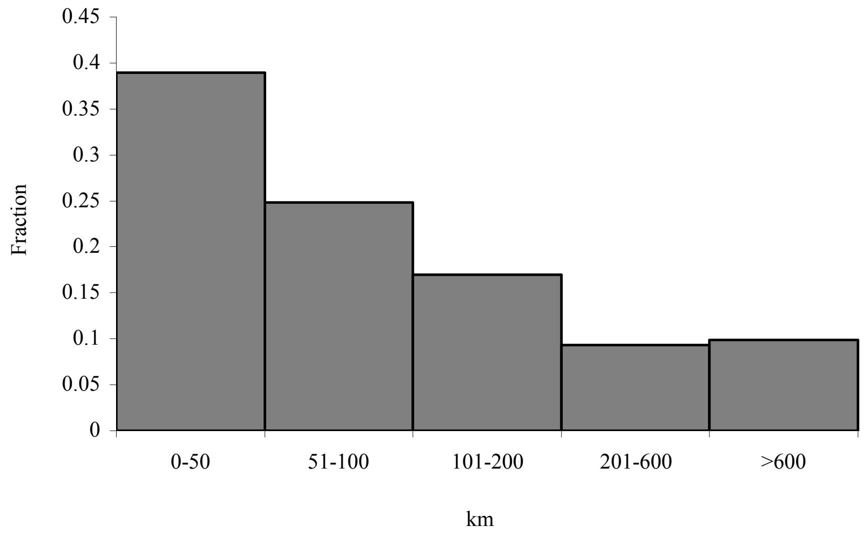


Figure A11 – Distance from Place of Residence (km)



IV. Economic Valuation

This section is divided into two subsections, one about the value of the natural area and the other about the value of its functions.

IV.1 Economic Valuation of the Natural Area

Access to the forest is currently free. Respondents were asked whether they would be willing to pay an entrance ticket in order to improve the quality of the management and preservation of the area as well as their Willingness-To-Pay an annual subscription fee, which finances projects to improve the recreational activities. The survey was prepared following the guidelines by the NOAA[49] panel. In order not to

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49 Here we give a partial list of guidelines by the NOAA (National Oceanic and Atmospheric Administration) Panel (for a complete discussion about the NOAA guidelines see Arrow et al., 1993):

1) face to face interviews with pre-test for interviewer effects in order to minimize non-response rates;

incur bias, in the introduction of the survey it is emphasized that the objective is to improve the area and that the prices are hypothetic.

Before asking the Willingness-To-Pay a ticket, it is asked to give an opinion about the area: if it is crowed and if the number of visitors should be regulated. The average respondent thinks that the level of crowding is low and only 11 per cent of respondents think that the number of visitors has to be regulated. Visitors prefer regulating motored viability and that parking is outside the natural area. The average respondent is willing to pay an annual tax to preserve the natural area of about 20 euro.

IV.2 Economic Valuation of the Natural Area's Functions

A question about time use during the visit between functions offered by the area is made before asking Willingness-To-Pay a fee to improve the recreational activities of the area. On average, visitors spend about six hours in the natural area. The activities are divided into three categories: recreational, harvest and naturalistic (Figure A12 and A13).

Visitors spend about five hours in recreational activities such as trekking and picnicking. 80 per cent of respondents do these activities respectively for an hour and a half and two and a half hours. Other available activities are horse riding, mountain biking or visiting historic places. Respondents spend only fifteen minutes doing

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2) conservative design, when aspects of the survey design and analysis of the responses are ambiguous;
c) elicit Willingness-To-Pay rather than Willingness-To-Accept;
d) dichotomous choice referendum format;
e) incorporate follow-up questions investigating the specific reasons why the respondent answered 'yes' or 'no' to the payment questions;
f) remind the respondent of substitute commodities;
g) remind the respondent of budget constraint.

harvest activities such as hunting and fishing and about thirty-five minutes harvesting mushrooms and flowers. More time (about forty-five minutes) is spent in observing the landscape, flora and fauna.

Figure A12 - Average Time of the Effective and Desired Recreational Activities (min)

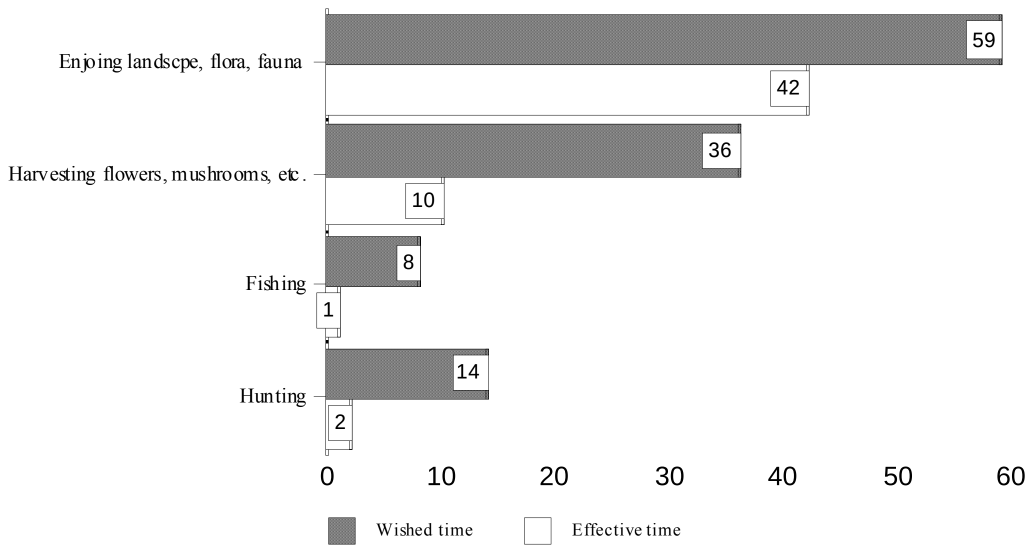
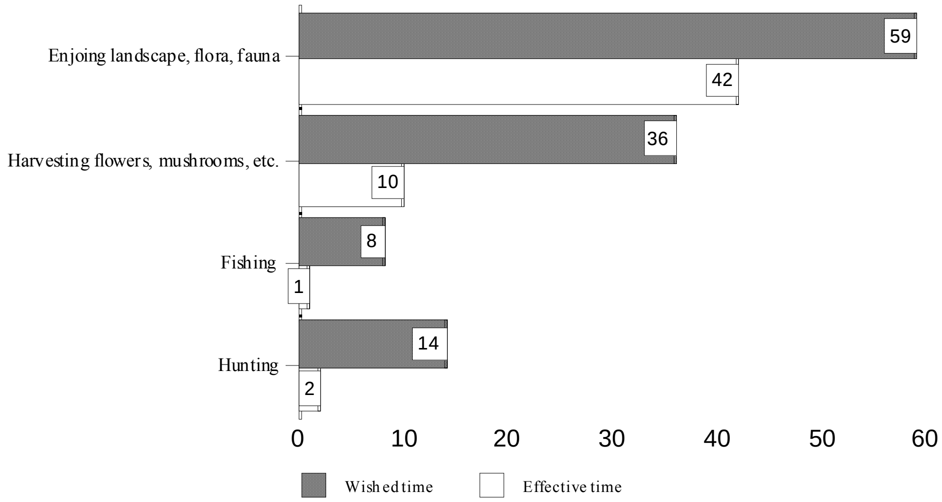


Figure A13 - Average Time of the Effective and Desired Harvest and Naturalistic Activities (min)



V. Socio-economic Characteristics of the West Garda Regional Forest's Visitors

The average visitor is 39 years old, with a secondary education (about 13 years, Figure A14) and middle-high income (around 1807.6 euro, Figure A16). Figure A15 show the job sector of respondents: 46 per cent works in service sector, 18 per cent in secondary sector, 2 per cent in primary sector and 34 per cent do not work (students, housewife, unemployed, retired). The expenditure in leisure is high since average visitor spends 10 per cent of her monthly income on leisure (about 185 euro) and 25 per cent on food (426 euro).

Figure A14 – Respondent's Education

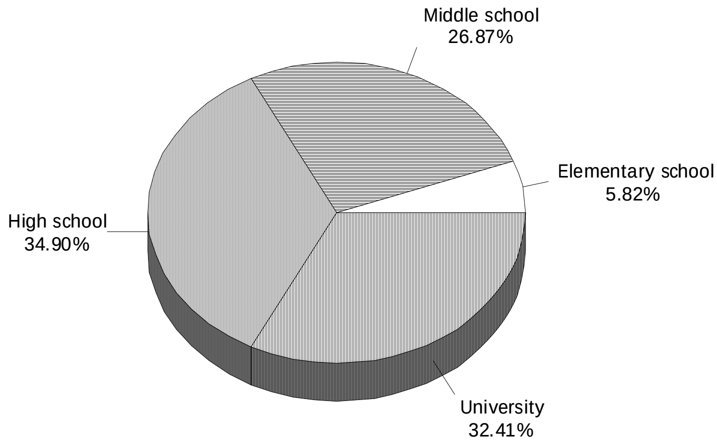


Figure A15 – Respondent's Job Sector

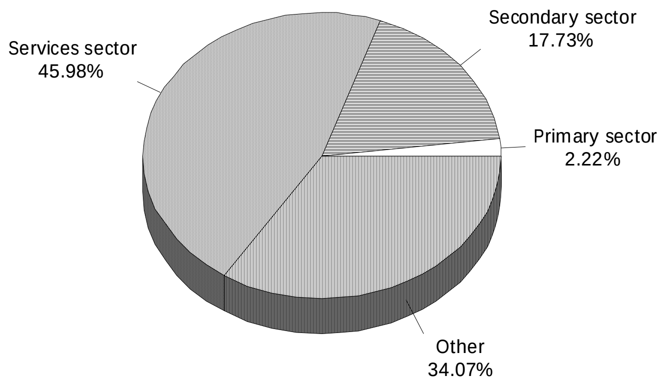
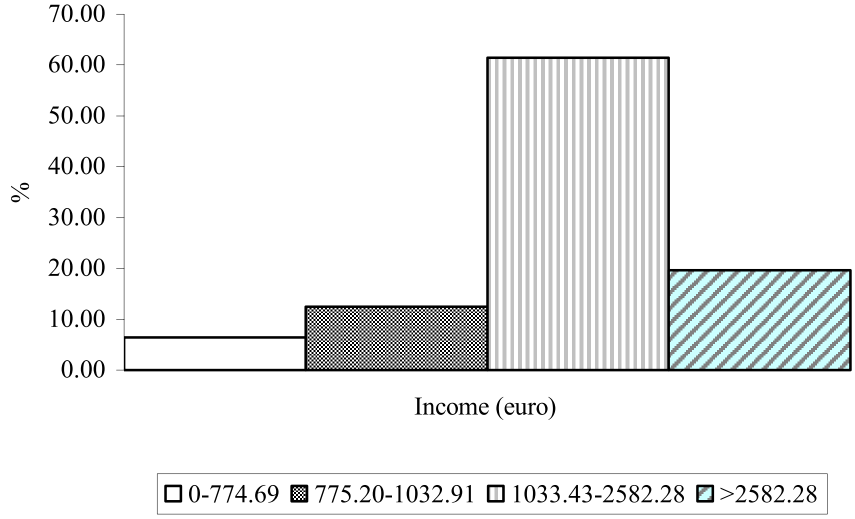


Figure A16 – Respondent's Monthly Income



References

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