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A comparison of contingent valuation and choice modelling with second-order interactions

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Abstract

This study compares the welfare measures estimated from two different stated choice methods, contingent valuation method and choice modelling. The welfare measures are inferred from different assumptions about the utility function definition, like allowing for second-order interactions. The application involves the estimation of non-market values from alternative afforestation programmes in the Northeast of Spain. The two techniques are found to yield equivalent estimates of welfare change for identical afforestation programmes when the fully specified utility functions are used as the basis for the calculations. When elements of the utility functions, e.g., the second-order interactions effects, are omitted from the value estimation procedure, significant differences do occur between estimates derived using the two valuation techniques.

JEL Classification: Q230; Q510
Keywords: Choice modelling; Contingent valuation; Welfare measures; Forest externalities; Second-order interactions

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Introduction

Forests produce a number of goods and services that are valued by people. In addition to timber products, forests assist in controlling soil erosion, regulating rainfall, providing habitat, sequester carbon, and are sites for recreational activities. Many of the benefits provided by forests do not have a market where values can be observed directly.

Assuming that one of the objectives of forestry management is to maximise the social value of forests, improved knowledge of the marginal benefits of extending or reducing some goods and services provided by forests could result in more efficient decisions. The full economic implications of managing forests in alternative ways, including the transformation of degraded land, can then be taken into account.

Over the last several decades economists have developed and refined a battery of methods for estimating the non-market values of goods and services, such as those associated with forest. These non-market valuation methods can be categorised as revealed and stated preference methods depending on whether they are based on existing markets or constructed hypothetical markets (Mitchell and Carson, 1989). Among the stated preference methods, the contingent valuation method (CVM) is most widely used. Other stated preference methods, notably choice modelling (CM), are increasing in popularity amongst environmental economists (Bennett and Blamey, 2001). A problem in assessing the validity of value estimates obtained from any stated preference technique is the absence of an unambiguously clear and definitive criterion by which to compare those measures. One process of assessing the validity of value estimates is convergent validity: estimates obtained from one stated preference study are compared with the results from other stated preference studies to see if they produce similar answers, or answers that vary in a predicted manner (Bateman et al., 2002).

The objective of this paper is to compare welfare measures estimated using CVM and CM, testing the convergent validity of the results derived from the two techniques where different elements of the utility functions are used as the basis for calculating welfare change estimates. The sensitivity of the welfare measures is important, especially in situations where the magnitude and direction of particular effects might alter a specific forest management decision. A key difference of this paper with respect to the preceding literature is the emphasis placed on the influence of second-order interactions in the convergence of welfare estimates. Thus, the correspondence between the values generated by the two methods can be tested both using the main effects and the two-way interactions. The empirical study focuses on two specific afforestation programmes in the same region of north-eastern Spain that have different biophysical characteristics.

The structure of the paper is as follows. In the next section, a brief outline of the CVM and CM is provided. The case study used in this project and the design of the research are described in the subsequent section. The results are presented in the penultimate section and the last section contains the conclusions and some suggestions for further research.

Contingent valuation and CM in environmental valuation

CVM is a stated preference method where respondents are asked their maximum willingness to pay (WTP) (or minimum willingness to accept in compensation) for a predetermined increase or decrease in environmental quality. In the dichotomous choice version of CVM, respondents are offered a change in the quantity or quality of a good at a given cost, and the respondent either accepts or refuses the payment of the suggested cost. CVM has been used to estimate the value of a wide variety of environmental resources. However, its use has been subject to criticism in terms of its ability to deliver reliable and accurate estimates of the WTP (Diamond and Hausman, 1994).

CM is also a stated preference valuation method that has its origin in conjoint analysis. It was initially developed in the marketing and transport literature by Louviere and Hensher (1982) and Louviere and Woodworth (1983). There has been a number of applications to estimate the value of recreational and environmental goods in recent years (e.g., Opaluch et al., 1993; Boxall et al., 1996; Adamowicz et al., 1998a; Hanley et al., 1998a; Morrison and Bennett, 2000; Christie and Azevedo, 2002).

In a CM application, respondents are presented with a series of choice sets, each containing usually three or more alternative goods. An alternative is a combination of several attributes, with each attribute taking on a value, usually called a level. For instance, an alternative could be described as h hectares of additional forest with p percentage of tree species s, costing c monetary units. One of the alternatives in each choice set describes the current or future ‘‘Business-as-Usual’’ situation, and remains constant across the choice sets. From each choice set, respondents are asked to choose their preferred alternative. The attributes used are common across all alternatives. Their levels vary from one alternative to another according to an experimental design (for a review, see Bennett and Blamey, 2001). If human-induced changes in forest ecosystems can be meaningfully represented by a set of attributes, choices made by survey respondents among sets of alternatives can provide resource managers and policy makers with valuable information about public preferences for many potential states of the environment (Holmes and Boyle, 2003).

Adamowicz et al. (1998a), Diener et al. (1998), and Hanley et al. (1998a) point out that the sensitivity of CM results to the assumptions regarding utility functional form has not been assessed adequately. Scarpa (2000) suggested that the assumptions made about how observed choices are linked to individual preferences are important when the objective is the comparison of welfare estimates.

The application of CM can provide information of the relationship between respondents' welfare and the attribute levels. An analysis of the higher-order interaction terms in this relationship can help to explain the convergence or divergence of the welfare measures obtained through different methods.

Model specification and estimation

The CVM and CM share a common theoretical framework: the random utility model (RUM) (Thurstone, 1927; McFadden, 1974). Under the RUM framework, the indirect utility function for each respondent can be expressed as

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \tag{1}$$

where U_{ij} is person *i*'s utility of choosing alternative *j*, V_{ij} is the deterministic component of utility, and ε_{ij} is a stochastic element that represents unobservable influences on individual choice.

In CM, the probability that any particular respondent prefers option *j* in the choice set to any alternative option *k*, can be expressed as the probability that the utility associated with option *j* exceeds that associated with all other options. Formally,

$$P_{ij} = P\{V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik};\ \ \forall k \in C\},$$

where *C* is the set of all possible alternatives. Assuming a Type I Extreme Value distribution for the error terms, the probability that a respondent *i* chooses alternative *j* is

$$P_{ij} = \frac{e^{\omega V_{ij}}}{\sum_{k \in C} e^{\omega V_{ik}}}.$$

This specification is known as Multinomial Logit, when it uses only attributes as regressors, or Conditional Logit, when attributes and individual characteristics are present (McFadden, 1974). ω is a scale parameter, inversely proportional to the standard deviation of the error distribution, and is typically assumed to be one (Ben-Akiva and Lerman, 1985).

In the dichotomous choice form of the CVM, there are two alternatives to the status quo in the choice set. Random utility theory can be used to represent this choice in a binary choice model where the individual must choose between an improved state, *j*, and the "Business-as-Usual", *k*. Utilising utility functions for two alternatives from (1), the probability that decision maker *i* chooses alternatives *j* or *k* are

$$P_{ij} = P(\varepsilon_{ij} - \varepsilon_{ik} < V_{ik} - V_{ij}),$$

$$P_{ik} = P(\varepsilon_{ik} - \varepsilon_{ij} < V_{ij} - V_{ik}).$$

In order to derive an explicit expression for these probabilities, an assumption is made about the distribution of the error terms. Assuming that each of the random terms is Type I Extreme Value distributed, the probability of choosing alternative *j* is given by

$$P_{ij} = \frac{1}{1 + e^{-\omega(V_{ij} - V_{ik})}}.$$

This formulation can be estimated using the binary logit model (Hanemann, 1984) where ω is a scale parameter which is often normalised to 1 and consequently ignored in notation.

There has been some discussion regarding the advantage of CM relative to CVM (Swait and Adamowicz, 2001; Bennett, 1996; Hanley et al., 1998b). CM allows for the identification of the trade-offs that individuals make between attributes. If one of the attributes is the money that a person would have to pay to secure the proposed change, it is possible to measure the marginal value of changes in each attribute. Often, this might be a more useful approach from a management or policy perspective than focusing on a single change in the provision of the whole good. By focusing on different attribute changes, CM is suited to inform the design of multidimensional policies (Hanley et al., 2001), to undertake a cost–benefit analysis of these policies (Bateman et al., 2002) or in litigation processes involving non-market goods. Furthermore, the identification of the different attributes of a damaged good is useful to design restoration projects (Adamowicz et al., 1998b; Layton and Brown, 1998). Whilst CV can also estimate the marginal values, it is relatively costly. On the other hand, a single CM application can be used to generate estimates of compensating surpluses for different attribute levels. However, there are some issues of concern related to the use of CM, including the presence of strategic behaviour in respondent choice; the assumption that the value of the whole is equal to the sum of the parts when the value of an environmental good is estimated; the design of the experiments, fatigue, learning, and complexity that still require significant research effort (Bateman et al., 2002).

Comparison between CVM and CM

Convergence tests check the validity of the results obtained through one valuation method by comparing values estimates with valuations obtained for the same environmental good using different methods of valuation. A few studies have compared welfare estimates derived from CVM and CM. The results of these studies are summarised in Table 1. Given that CM may offer some advantages over CVM, the question remains if the two methods yield estimates of compensating surpluses that are consistent.

The results reported in Table 1 provide mixed evidence of the convergent validity of the welfare measures (i.e., the two methods yield the same welfare estimate). The results are sensitive to the assumptions made regarding the specification of the form taken by individual preferences. Adamowicz et al. (1998a) found CM values to be sometimes larger and sometimes smaller than CVM values depending on the chosen specification, but the differences were not statistically significant. Foster and Mourato (2003) indicate that CM gives significantly larger or smaller values than CVM depending on the inclusiveness of the good. Convergent validity also appears to be dependent on the measure of central tendency chosen (i.e., median or mean in Lockwood and Carberry, 1998), but not on the use of in-sample studies or split-sample approaches. Moreover, as shown in the last column of Table 1, studies tend to ignore higher-order interactions, modelling only main effects.

Afforestation in Catalonia and the research design

The valuation exercise presented in this paper involves the estimation of the impact of alternative afforestation programmes on non-market forest values. The

Table 1. Comparison of welfare measures obtained by CVM and CM

Reference	Application	Format of CVM and CM questions	In-sample split-sample	CVM	CM	Statistical test of differences[a]	CE design
Boxall et al. (1996)	Impact of alternative Wildlife Management Units (WMU)	CVM referendum CM choose one from three	In-sample	US$85.59 (mean CS; DC for 1 WMU)	US$56.69 (mean CS for 1 WMU)	Not tested	Main-effects
Hanley et al. (1998a)	Conservation of environmentally sensitive areas	CVM-OE	Split-sample	£31.43 (mean OE)	£182.84 (mean CS linear model)	Not significantly different	Main-effects
		CVM-DC		£98 (mean CS; DC)	£107.55 (Mean CS Quadratic model)		
		CM choose one from three					
Hanley et al. (1998b)	Alternative forest landscapes	CVM-OE CM choose one from three	In-sample	£29.16 (mean OE for the "ideal forest")	£38.15 (sum of the marginal WTP of the forest attributes for the "ideal forest")	Not tested	Main-effects
Adamowicz et al. (1998a)	Preservation of the Caribou habitat	CV referendum CM choose one from three	In-sample	US$142.82 (median CS; DC. Linear model) US$140.86 (median CS; DC. Quadratic model)	US$91.84 (median CS. Linear model. Intercept excluded) −US$116.29 (Median CS. Linear model. Intercept included) US$217.83 (median CS. Quadratic Model. Intercept excluded) US$76.70 (Median CS Quadratic Model. Intercept included)	Not significantly different	Main-effects

Lockwood and Carberry (1998)	Remnant native vegetation conservation	CVM-DC	Split-sample	A$80.69 (mean CS; DC. New South Wales)	A$51.97 (mean CS. New South Wales)	Not significantly different	Main-effects
		CM choose one from three		A$77.35 (mean CS; DC. Northeast Victoria)	A$43.15 (mean CS. Northeast Victoria)		
				A$25.20 (median CS; DC. New South Wales)			
				A$3.71 (median CS; DC. Northeast Victoria)			
Christie and Azevedo (2002)	3 programmes to preserve and improve the quality of the lake's water	CV referendum	Split-sample	−US$658 (mean CS; DC. Plan A)	−US$2122 (Mean CS. Plan A)	Significantly different	Main-effects
		CM choose one from three		US$540 (mean CS; DC. Plan B)	US$616 (mean CS. Plan B)		
				US$821 (mean CS; DC. Plan C)	US$2921 (mean CS. Plan C)		
Foster and Mourato (2003)	Services provided by the charitable sector	CVM double bounded DC	Split-sample	US$43.4–55.9 (mean CS; DC; all charities)	All charities US$258.4 (mean CS)	Significantly different	Main-effects
		CM choose one from three		US$31.6–46.7 (mean CS; DC; housing charities only)	Housing charities only US$2.9 (mean CS)		

DC, dichotomous choice CVM; OE, open-ended CVM; CS, compensation surplus.
The CM models were computed using the conditional logit models.
[a]The tests used to check whether the results from the two methods are significantly different or not the same in all studies.

afforestation programmes under scrutiny were proposed for Catalonia, a region in the Northeast of Spain with an area of 32,100 km^2. The majority of the area has a Mediterranean climate, with winter precipitation and summer drought (Terrades and Piñol, 1996). Approximately 40% of total area of Catalonia (1.3 million ha) is occupied by forests. This percentage has been more or less stable during the last 25 years. Although the composition of the forest varies from the coastal areas to the Pyrenees and the inland plains, most are composed of Mediterranean species. The pine is the dominant species covering 50% of the forested area, followed by the holm oak with some 10% (Ministerio de Medio Ambiente, 1996). A little over three-quarters of the Catalan forest belong to private owners, the rest being in public hands, mainly municipal (DARP, 1994). The programme being proposed involves an increase in forest coverage from the current 40% of Catalonia to 50%. The additional 10% of forest area would be at the expense of marginal agricultural land.

The questionnaire designed to estimate the non-market forest values of afforestation included four parts. The first part described some positive and negative effects of the afforestation programme to the respondent. The second was the CM part. The next part was a CVM question. The final part of the questionnaire was devoted to the collection of some socio-demographic characteristics of the respondent.

Design of the CM part

The first step in implementing the CM method is the determination of the attributes to be used to describe each afforestation alternative. Discussions with experts working in forestry research, stakeholders, focus groups, and a pre-test were conducted to determine the non-market attributes associated with the forest. The attributes chosen for the analysis were some recreational activities – such as picnicking, picking mushrooms, and driving motor vehicles on forest ways – CO_2 sequestration and erosion prevention. A payment vehicle of an annual contribution that the Catalan citizens would make to a fund exclusively dedicated to the afforestation programme was also used as an attribute. Payment values were originally expressed in Spanish pesetas, although in this paper they are reported in euros. The descriptions of the attributes and their levels are shown in Table 2.

An experimental design[1] was used to structure choice sets with two afforestation alternatives (Louviere, 1988). The six attributes and their levels form a universe of $(2^3 \times 4^3) \times (2^3 \times 4^3)$ possible combinations for the afforestation alternatives. The final experimental design consisted of 64 pairs of afforestation alternatives chosen following an orthogonal fractional factorial design.

For simplicity, the vast majority of CM applications use the main effects design, assuming, explicitly, or implicitly, that interactions among attributes are not significant, i.e., the preference for the level of one attribute is independent of the level of other attributes. This has the advantage of being less demanding on the sample

[1]We are grateful to Professor Jordan Louviere for his assistance in the development of an experimental design for this application.

Table 2. Attributes and levels used in the CM exercise

Attribute	Description	Levels
Picnic	Picnicking allowed in the new forests (BAU[a] = No)	Yes No
Drive	Driving by car allowed through the new forests would be allowed (BAU = No)	Yes No
Mushrooms	Picking mushrooms allowed in the new forests (BAU = No)	Yes No
CO_2	CO_2 sequestered annually by the new forests. Equivalent to the pollution produced annually by a city of… (BAU = 0)	300,000 people 400,000 people 500,000 people 600,000 people
Erosion	Number of years that the new forest will increase the productivity of the soil (BAU = 0)	300 years 500 years 700 years 900 years
Cost	The afforestation cost per person and year (BAU = 0)	6 € 12 € 18 € 24 €

[a]BAU, business-as-usual.

size. However, this reduction comes at a cost: if relevant interactions are not included, then ignoring the non-significant interactions will produce sub-optimal results in terms of the predictions derived from the estimated model (Ortúzar et al., 2000; Hensher et al., 2005). Furthermore, as stated in Kriström and Laitila (2003, p. 309), "if the linear assumption is incorrect, the design may not allow for the test or estimation of the correct model". A goal in performing the CM experiment was to include interaction effects and to study their influence on model choice. The experimental design used in this study goes beyond the linear additive model and permits the estimation of all two-way interactions in addition to the main effects[2] (Louviere et al., 2000). Fig. 1 displays one of the resulting choice sets.

[2]An experimental design that permitted the estimation of all two-way interactions may be seen as a wise design strategy because main effects and two-way interactions account for virtually all the reliably explained variance in choices (Louviere et al., 2000).

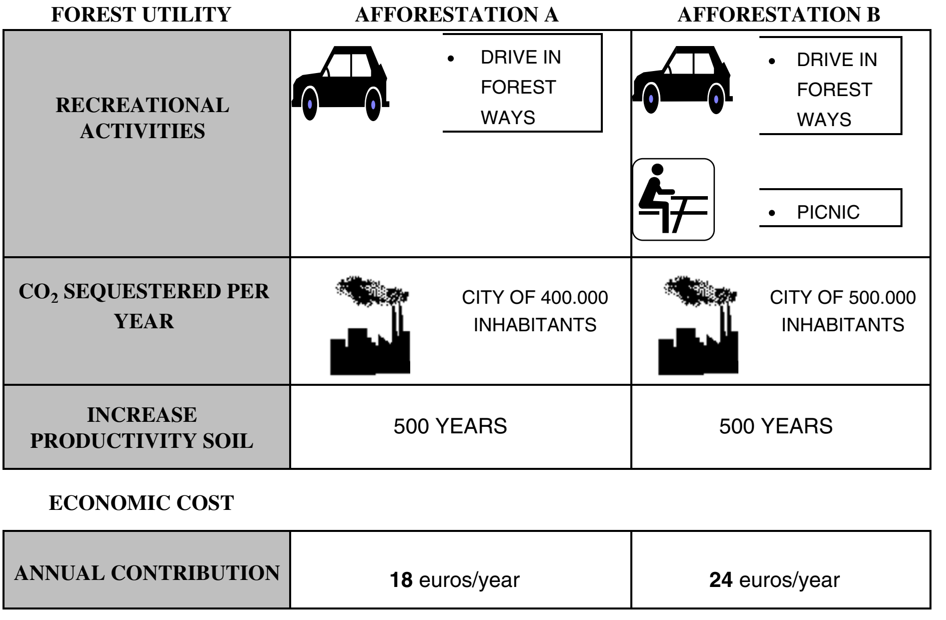

Fig. 1. Example of a pair of afforestation alternatives used in the CM exercise.

The 64 pairs were grouped into 16 blocks of four choice sets of two afforestation alternatives. Blocking was used because it was unrealistic to assume that each individual can respond to all 64 choice sets in an interview. The complexity of the choice task (as measured by the number of choice sets a respondent had to complete) was explored in the pre-test in order to decide the number of choice sets to be completed by each respondent. An issue related to task complexity is in the stability of preferences. In CM, the utility function of each individual is assumed to be stable throughout the experiment. The complexity of the exercise might cause violations of this assumption, arising from learning and fatigue effects (Hanley et al., 2002; Alpizar et al., 2003). Some evidence suggests that learning and fatigue effects occur in choice tasks. However, the degree to which such effects are present is context dependent (Swait and Adamowicz, 1997). The pre-test showed that respondents could cope with four choice sets in each questionnaire without having a significant impact on the measurement of preferences.[3] The stability of preferences to the order of the alternatives was tested following the method applied by Carlsson and Martinsson (2001) and the hypothesis of stable preferences was not rejected.[4]

[3]Furthermore, a likelihood ratio test was carried out to test the hypothesis that the parameters between different numbers of alternatives in the choice set were not statistically different. The hypothesis was rejected between the four and five alternative choice model.

[4]In the pre-tested choice experiment, half of the respondents received the choice sets in a given order (A, B, C) and the other half in another order (B, C, A). A test for stability was then performed by comparing the preferences obtained for the choices when it was given in a sequence with the preferences obtained

Table 3. Attributes and levels used in the CVM exercise

Attribute	FOREST A	FOREST B
Picnic	Yes	Yes
Drive	Yes	Yes
Mushrooms	Yes	Yes
CO_2	400,000 people	600,000 people
Erosion	500 years	900 years
Cost	6 € 12 € 18 € 36 € 48 € 72 €	6 € 12 € 18 € 36 € 48 € 72 €

The option of the "Business-as-Usual" situation (no afforestation and no payment required) was included with each pair of alternatives to form the choice sets. Hence, in each choice set, respondents were asked for their preferred choice between the "Business-as-Usual" situation and two afforestation alternatives scenarios.

Design of the contingent valuation question

A CVM question was also presented to respondents. The objective of the CVM was to estimate the maximum WTP for two specific afforestation projects: FOREST A and FOREST B. In order to facilitate the comparison between the two methods, the afforestation projects had the same basic form as those described in the CM exercise, i.e., covering an additional 10% of the surface of Catalonia, using marginal agricultural land. The quantity and quality levels of the new forests were described using the same attributes and levels as in the CM (Table 2). The two afforestation programmes involved a change from the "Business-as-Usual" situation to the afforestation programmes described in Table 3. The attribute levels of the "Business-as-Usual" were the same as in the CM. It was assumed, from the physical attribute levels, that FOREST B was preferred to FOREST A.

A dichotomous choice CVM question was employed. After describing the particular forest composition, the respondents were given the option of choosing to pay a cost (annual payment) and accepting the afforestation programme, not paying

(*footnote continued*)
when the choices were given following a different sequence. This was tested with a likelihood ratio test between the pooled model and each of the two models arising from the two sub-samples.

the cost amount and not accepting the programme (''Business-as-Usual'' option) or responding ''I don't know''. Offering a ''don't know'' option is one way of diminishing the incidence of ''yea saying'', since respondents are not forced to make a definitive choice (Arrow et al., 1993). The ''don't know'' answers were dropped from the estimations, assuming that the preferences of those responding with 'no answer' are no different from the rest of the sample.[5]

The costs (bids) were 6, 12, 18, 36, 48, and 72 €, and one amount was assigned to each questionnaire version, making a total of six versions per type of afforestation.[6]

The sample

The CM and the CVM questionnaires were administered to a sample of the Catalan population. Personal interviews were conducted in respondents' houses. The 16 versions of the CM questionnaire were assigned to sub-samples of the total sample of 1200 individuals. The sample was chosen to be representative in terms of the size of the municipality of residence, and the age and gender structure of the population. Households were selected using random walks. The CVM was presented to a sub-sample of 1000 respondents of the total sample used in the CM. This sub-sample was split into two approximately equal sub-samples also representative of the Catalan population in terms of location, gender, and age.[7] Each sub-sample was assigned a given afforestation project (FOREST A or FOREST B), and one of the six CVM questionnaire versions were randomly allocated to respondents within each sub-sample.

The interviews were undertaken in 25 locations, and administered to the population of 18 years of age or older proportionally to the population of each location. In each location, the questionnaires were distributed using random survey routes, with the sample being stratified to include 10 respondents selected in terms of gender and age in each route. Interviews were conducted during the second half of 1999.

The average response rate in the CM was 95% across all sub-samples, while in the CVM 93% of the sample responded to the FOREST A versions, and 75% responded for the FOREST B versions. The same questionnaire was used for the CVM and CM, although a larger number of individuals who did not provide any answer or said ''no'' because of a protest motive in the CVM, explains the lower response rate in the CVM. The socio-demographics of the respondents who completed the CM surveys and who completed the CVM questions with valid responses for each one of the afforestation programmes are summarised in Table 4. The age and gender of the survey sample are not statistically different from the Catalonian average. However, respondents' incomes and educational qualifications are lower than the average

[5]The results of the CVM models assuming that the ''don't know'' response is similar with ''no'' do not change significantly the results presented here. For a discussion about how could the researchers deal with the ''don't know'' answer can be found in Groothuis and Whitehead (2002).

[6]The bid vector was derived based on the distribution of WTP expressed as an open-ended answer in a pre-test, following Duffield and Patterson (1991) and Kanninen (1993).

[7]The rest of the sample (200 respondents) were asked questions irrelevant to the current study.

Table 4. Socio-demographics of the survey respondents in the CM and CVM

Variable	CM sample	CVM sample FOREST A	CVM sample FOREST B	Catalonia average
Respondent age (>18 years)				
18–29	21%	22%	24%	20%
30–44	31%	29%	28%	31%
45–64	30%	27%	30%	27%
65 or over	18%	22%	18%	22%
Gender (% male)	50%	48%	52%	49%
Education (% with primary school finished)	64%	62%	68%	82.30%
Income (average gross monthly income)	552.25	392	305	940.66
Visitation (% respondents that have gone to the forest in the last year)	57%	61%	63%	Not available
Village size (<10,000 inhabitants)	21%	14%	36%	20%

Source: Institut d'Estadística de Catalunya (2002) and Instituto Nacional de Estadística (2002).

population.[8] In the CVM, the sub-sample corresponding to FOREST A tends to be representative of the urban areas whereas for FOREST B tends to be self-selected towards rural areas.

Results

The models

The choice data collected from the CM in the surveys were analysed statistically to detect relationships between the levels of the forest attributes, the socio-demographic characteristics of the respondents and the probability of respondents choosing particular alternatives. A multinomial logit (MNL) model was initially used.

An assumption of the MNL that follows from the independence of the error terms across the different options contained in the choice set is the property of the independence of irrelevant alternatives (IIAs). This property requires that the ratio of the choice probabilities of any two alternatives does not depend on the inclusion or omission of other alternatives in the choice set. The consistency of the MNL model with respect to IIA is an infrequent outcome in the CM literature (Foster and Mourato, 2000; Hanley et al., 1998a; Rolfe et al., 2000).

[8] χ^2-Tests of independence were conducted to determine whether the CVM and CM samples had the same socio-demographics as the Catalonia population.

Violation of the IIA assumption may arise in situations where some alternatives are qualitatively similar to others or there are heterogeneous preferences among respondents (Bateman et al., 2002; Morrison et al., 1999). Violations of the IIA assumption can be checked using a test developed by Hausman and McFadden (1984). This basically involves constructing a likelihood ratio test around different versions of the model where choice alternatives are excluded. If IIA holds, then the model estimated on all choices (the full choice set) should be the same as that estimated for a sub-set of alternatives.[9] If a violation of the IIA assumption is observed, then more complex models of choice are required. Blamey et al. (1998) list some of the options available for dealing with any IIA violations detected using the Hausman and McFadden (1984) test. These include the multinomial probit model (Hausman and Wise, 1978), the nested logit (NL) model (Louviere et al., 2000), the random parameters logit model (Train, 1998), and the heterogeneous extreme value logit model (Bhat, 1995).

The Hausman and McFadden test was applied to check on the validity of the assumption of the IIA. A χ^2-value of 140.95 was found for an MNL model when "AFFORESTATION A" alternative is excluded from the choice set. Therefore, the test indicates an IIA problem.

The solution adopted was to re-specify the problem as an NL model. It involves respondents dividing the choice set into categories: individuals choose one category among given categories and then determine a specific alternative from the chosen category. The NL models can flexibly demonstrate multilevel choice structures and are appropriate when modelling a number of discrete alternatives and when similarities exist across the unobserved attributes of utility over particular choices (Louviere et al., 2000; Schwabe et al., 2001). One way to motivate the NL model in our context is by postulating that the decision between these three alternatives occurs as a sequence of two binary choices. We assumed that afforestation alternatives (A or B) are similar relative to the alternative of no afforestation. In the upper level, respondents were assumed to make a choice about whether they would support an increase in the forest area (afforestation) against continuation of the current situation ("Business-as-Usual"). In the lower level, conditional on supporting the afforestation programme, then they were assumed to choose between the two afforestation alternatives presented in each choice set.[10] With this structure, there are only two choice alternatives at each level and the notion of "irrelevant alternatives" is no longer relevant. This hierarchical structure is pictured in Fig. 2.

[9] Hausman–McFadden's specification statistic can be written as

$$\chi^2 \sim (\hat{\beta}_s - \hat{\beta}_f)' [\hat{v}_s - \hat{v}_f]^{-1} (\hat{\beta}_s - \hat{\beta}_f)$$

where $\hat{\beta}_s$ indicates the estimators based on the restricted sub-set of choices (i.e., two in our application), and $\hat{v}_s$ denote their estimated covariance matrix. $\hat{\beta}_f$ indicates the estimators based on the full set of choices (three in our application), and $\hat{v}_f$ denote their estimated covariance matrix. This statistic follows a limiting chi-squared distribution with K degrees of freedom, where k is the number of attributes.

[10] This tree structure and the variables associated to the utility functions at each level, were found to be the preferred structure (in a statistical sense) after evaluating a number of trees, and comparing the log likelihood of each tree at convergence using a likelihood ratio test.

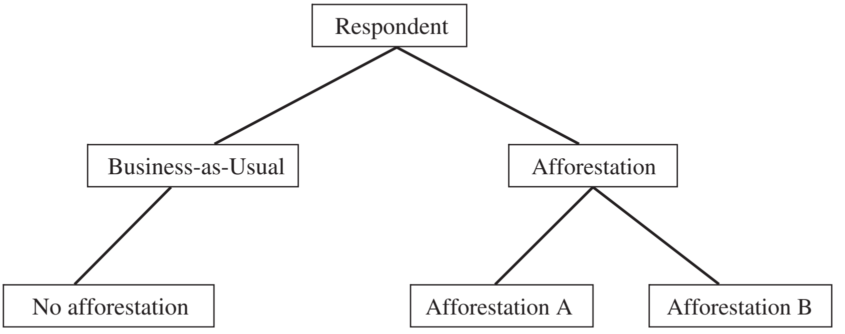

Fig. 2. Hierarchical model structure.

The utility function associated with the upper-level choice was hypothesised to be influenced by the respondent's socio-economic characteristics,[11] the interactions of choice attributes with the individual socio-demographic characteristics, and the two-way interactions between attributes. In addition to these variables, the choice between retaining the current situation or choosing the afforestation programme was assumed to be influenced by an inclusive value (IV), which represents a measure of the expected utility associated with a given nest.[12] The number of IVs is equal to the number of nests. The utility functions for the upper-level alternatives are given below.

For the upper level,

$$\begin{aligned} V_{\text{afforestation}} = {} & \beta_1\text{Age} + \beta_2\text{Age2} + \beta_3\text{Gender} + \beta_4\text{Income} + \beta_5\text{Visitation} \\ & + \beta_6\text{Rural} + \beta_7\text{Drive} \times \text{Visitation} + \beta_8\text{Drive} \times \text{Rural} + \beta_9\text{Price} \times \text{Visitation} \\ & + \beta_{10}\text{Mushroom} \times \text{Drive} + \beta_{11}\text{Mushroom} \times \text{Erosion} + \alpha_1\text{IV}_{\text{afforestation}}, \end{aligned}$$

$$V_{\text{BAU}} = \alpha_2\ \text{IV}_{\text{BAU}},$$

where $V_{\text{afforestation}}$ is the utility associated with the afforestation options and V_{BAU} the utility obtained from selecting the "Business-as-Usual" option. The IV parameter associated with the "Business-as-Usual" branch (α_2) was fixed to one.

At the lower level of the nest, the utility associated with the "Business-as-Usual" option and each afforestation alternative was assumed to be influenced by the attributes and their corresponding levels and the alternative-specific constant (ASC) associated to AFFORESTATION A. Thus, the utility for the option j is given by

$$V_j = \text{ASC}_\text{A} + \beta_{12}\text{Picnic} + \beta_{13}\text{Mushroom} + \beta_{14}\text{CO}_2 + \beta_{15}\text{Erosion} + \beta_{16}\text{Cost}.$$

[11]Since the socio-economic variables are the same for all choices, these variables are incorporated in the discrete choice models interacting with the constant. Otherwise, the variable would be the same for all choices, and its coefficient cannot be estimated (identification problem).

[12]A global sufficiency condition for the nested choice model to be consistent with random utility maximisation is that the parameter of inclusive value be in the 0–1 range (McFadden, 1981).

The results of the MNL model and the NL model are presented in Table 5. Despite the fact that the Hausman and McFadden test rejects the IIA assumption, we also report the results of the MNL, in order to compare the robustness of the models.

The signs of the parameters are consistent with a priori expectations, and all attributes are statistically significant at 95% level. The positive coefficients of picnicking, picking mushrooms, CO_2 sequestered, and erosion decrease suggest that afforestation programmes were more likely to be chosen when picnic and picking mushrooms were permitted, the amount of CO_2 sequestered was high, and erosion was postponed longer. However, afforestation programmes with higher cost contribute negatively to utility and are therefore less likely to be selected. The *Drive* attribute was found to be not statistically significant as a stand-alone variable and was not included in the model. The importance of *Drive* as an explanatory variable comes through its interaction with other attributes and the socio-demographic characteristics of the respondents. The two statistically significant second-order interactions mean that the use of cars in forests, other things being equal, tends to decrease the utility of the respondent if the motive of using the car is to pick mushrooms. Utility is also reduced due to picking mushrooms increasing the rate of erosion. The cross-products of the attributes with the socio-demographic characteristics suggest that the negative impact on utility of using cars is higher for respondents who use the forest for recreational activities and live in urban areas. The positive sign of the variable Price $\times$ Visitation means that the probability of a respondent agreeing to pay for the afforestation programme is higher in the respondents who use the forest for recreational activities.

Focusing on the socio-demographic characteristics, being female, living in a rural area, having higher income and using forest for recreation, increase significantly the probability of choosing the afforestation programme alternatives. Age was found to have a parabolic influence, where the probability of choosing the afforestation programme increases in the groups between 25 and 65 years old.

Table 5 also shows that the parameter of the IV is significantly different from 1 for the NL model; hence, the NL differs significantly from the MNL model. A comparison of the columns in Table 5 denotes that the signs of the parameters from both models are the same, although the NL values tend to be larger in absolute terms. This result is in line with those found in other studies (Hanley et al., 2002; Haaijer, 1999).

The goodness of fit of the models is based on the McFadden's pseudo-R^2 (McFadden, 1974). The explanatory power of the models is adequate according to the conditional standards.[13] The model fit comparison between the MNL and NL models is based on the Akaike's information criterion (AIC) (Akaike, 1973) and the Bayesian information criterion (BIC).[14] The NL model shows a slightly superior fit compared to

[13]A good fit is indicated by a pseudo-$R^2 > 0.2$, and a pseudo-R^2 approaching 0.4 is usually considered an exceptionally good fit (Hensher and Johnson, 1981).

[14]The AIC criterion is defined as $\text{AIC} = -2\ln L + 2n$, where n is the total number of estimated parameters in the model and the BIC criterion is defined as $\text{BIC} = -2\ln L + n\ln(O)$, where O is the number of independent observations in the conjoint choice experiment. A model with a lower BIC or AIC value is preferred to one with a higher value.

Table 5. Results of the MNL and NL model

Variable	MNL coefficient	NL coefficient
Attributes		
α (option A)	0.166***	0.172***
Picnic	0.090***	0.138***
Mushroom	0.480***	0.699***
CO_2	0.764E−6***	1.131E−6***
Erosion	0.562E−3***	0.873E−3***
Cost	−0.026***	−0.026***
Interactions with ASC		
Age	−0.012***	−0.023***
Age2	0.352E−3***	0.109E−2***
Gender	−0.3985***	−0.591***
Income	0.862E−3***	0.148E−2***
Visitation	0.351***	0.744***
Rural	0.572***	1.055***
Interactions attributes – socio-demographics		
Drive × Visitation	−0.194***	−0.193***
Drive × Rural	0.314***	0.326***
Price × Visitation	0.012***	0.011*
Interactions between attributes		
Mushroom × Drive	−0.261***	−0.282***
Mushroom × Erosion	−0.414E−3***	−0.722E−3***
Inclusive value parameter		
Afforestation (α_1)	—	0.621***
Status quo (fixed parameter)	—	1
Model statistics		
Maximum log likelihood	−4,481.962	−4,470.540
Pseudo-R^2	0.15	0.24
AIC	8997.9	8979.08
BIC	9107.2	9101.22
Observations	4,476	4,476

***Significant at 1% level and *significant at 10% level.
Variable definitions:

Age = individual's age−mean age of sample (45.64).
Age2 = age squared = $(\text{age}-45.64)^2$.
Gender = gender of the respondent (1 for male, 0 for female).
Income = income of the respondent in euros.
Visitation = use of the forest for recreation (1 if the respondent had used the forest during the last year, 0 otherwise).
Rural = village size (1 if $<10{,}000$ inhabitants, 0 if $>10{,}000$ inhabitants).

Table 6. Logit model estimation for forests A and B

Variable	FOREST A coefficient	FOREST B coefficient
Constant	0.577 ***	0.760**
Cost	−0.033***	−0.018***
Gender	−0.215E−02	−0.464**
Income	4.261E−4***	5.017E−4**
Visitation	0.581***	0.461**
Rural	1.091***	0.448*
Maximum log likelihood	−289.469	−237.815
% Of correct predictions	68	63
χ^2	64.856	22.586
Pseudo-R^2	0.1	0.06
Number of valid observations	464	371

***Significant at 1% level, **significant at 5% level, and *significant at 10% level.
Note: Age is not significant in the logit estimation.
Variable definitions:

Cost = bid amount (possible values in euros).
Gender = gender of the respondent (1 for male, 0 for female).
Income = income of the respondent in euros.
Rural = village size (1 if $<10{,}000$ inhabitants, 0 if $>10{,}000$ inhabitants).
Visitation = use of the forest for recreation (1 if the respondent had used the forest during the last year, 0 otherwise).

the MNL model, though the AIC and BIC measures are smaller in the NL model. The IV parameter estimate is consistent with random utility theory. Although moving to an NL model from an MNL model produced relatively small changes in the estimations, we opt in the rest of this paper to report only the estimations from the NL model, due to the violation of IIA present in the MNL model.

Results of the analysis of CVM responses for FOREST A and FOREST B are provided in Table 6. The two CVM models were estimated using binary logit models where the dependent variable takes the value one if the respondent accepted to pay, and zero otherwise (Hanemann, 1984; Hanemann and Kanninen, 1999). The independent variables are the monetary payment (cost) and the socio-demographic characteristics of the respondents.

The coefficient of cost is negative and significant in both models. This indicates that the probability of people agreeing to pay the proposed amount decreases as the cost increases. In both CVM models those who have more income, those who used the forest for recreation during the last year, and those who live in a rural area are more likely to pay. The χ^2 statistic indicates that each model is significant at the 0.01 level.

The CM model is superior to the CVM estimation in terms of the goodness of fit (pseudo-R^2) and increases the efficiency estimation of the parameters.[15] One possible

[15]The efficiency of the NL model and the CVM estimation is compared by examining their respective information matrices. The t-values for the β-estimates in the NL model are higher than the CVM.

reason for this is that CM choices are explained in terms of variations in multiple attributes, respondents' socio-demographic characteristics and the interactions between these variables whilst CVM responses can only be explained in terms of one attribute (cost) and the socio-economic characteristics. This result suggests that CM has a greater capacity to explain the choices made by respondents.

Welfare estimates

Since both CVM and CM are based on RUM theory, the welfare estimates associated with the afforestation programmes obtained using these methods in this study can be compared. In the CVM case, two changes were examined – the changes from the "Business-as-Usual" situation to FOREST A and from the "Business-as-Usual" situation to FOREST B. Using the welfare measures outlined by Hanemann (1984) for discrete CVM responses, the mean WTP for the FOREST A (WTPA) and FOREST B (WTPB) were estimated. The mean WTP was determined using the following expression[16]:

$$\text{mean WTP} = -\frac{\delta}{\beta},$$

where β is the value of the coefficient of the cost variable in the estimated logit equation and δ the sum of all other terms in the equation evaluated at the mean values of the explanatory variables.

In order to compare the welfare measures obtained from each method, the welfare changes for the same afforestation programmes used in the CVM were also calculated from the CM results. The levels of the attributes used in the CVM exercises were within the range of the attribute levels used in the CM.

The welfare effect of a change in the afforestation attributes can be represented as the difference between the maximum expected utility of an afforestation programme, with and without the change, divided by the estimated coefficient of the cost variable. If we assume that income effects are zero, the closed-form expression for WTP associated with a change in the quality of one alternative takes the form

$$\text{WTP} = [\text{EU}^1 - \text{EU}^0]/-\beta,$$

where β is the coefficient of the cost term and can be interpreted, in absolute value, as the marginal utility of income. EU^0 and EU^1 represent the maximum expected utility of the "Business-as-Usual" state and the alternative state, respectively.[17]

[16]The formula corresponds to the unrestricted mean WTP that implies that mean WTP can assume positive and negative values. Since it is possible that individuals would rather maintain the "Business-as-Usual" situation, the possibility of negative WTP measures in the CVM exists and the unrestricted mean WTP is appropriate. The median is not calculated separately because if the utility function is linear in parameters, as in this study, then the mean and the median of the distribution of WTP coincide (Hanemann, 1989).

[17]Expressions for computing the compensating variation associated with a change in the quality of one or more alternatives, or the elimination of an alternative are provided by Small and Rosen (1981) and Hanemann (1984), among others.

For both the CVM and CM, the attribute levels of the ‘‘Business-as-Usual’’ are set to zero. To estimate the utility of afforestation FOREST A and afforestation FOREST B, improvements were defined using the levels of the attributes outlined in each of the two CVM questions (Table 3). The socio-demographic characteristics were set at the population mean levels.

Specification of the welfare estimation process

Different model specifications of a utility function with the same parametric distribution can lead to widely different welfare estimates (Alberini and Cooper, 1995). Kling and Thomson (1996), in an analysis of the sensitivity of welfare measures to alternative nesting structures, noted the influence of the choice of variables included in the estimation of welfare measures. Similarly, the magnitude of welfare estimates can be influenced by the inclusion or omission of elements of the utility function in the estimation process. For instance, some studies that have compared welfare estimates obtained from CVM and CM have not included the socio-demographic variables and/or the ASCs in the specification of the welfare estimation process (Boxall et al., 1996; Hanley et al., 1998a b; Christie and Azevedo, 2002). The omission of the ASCs has been justified on the grounds that, even thought they may improve the model fit, they are not related to specific attributes and hence do not explain choice in terms of observable attributes (Adamowicz et al., 1997). Although some studies omit the ASCs, we have opted for including them in the different specifications. The reason is that ASCs are important in order to interpret the preferences of the individuals (Morrison et al., 2002). As defined here ASCs represent the utility of choosing the afforestation alternatives, everything else held constant. In the CVM and CM estimations, the positive sign of the constant and the ASCs indicates that respondents would prefer a change from the status quo. This result is not consistent with the more common status quo ‘‘bias’’ found in the literature, in which individuals attach some positive utility to the status quo situation (Adamowicz et al., 1998a; Samuelson and Zeckhauser, 1988).

To be able to compare the welfare estimates across stated preference methods, one ought first to control for differences due to utility specification (Scarpa, 2000). Although there are some studies that seek to compare the welfare estimates derived from CVM and CM as stated seen, there is no clear analysis, to our knowledge, of the sensitivity of CM results to the assumptions about the utility functional form and how the preference specification is important in order to obtain identical welfare estimates from different stated preference methods.

In order to examine the influence of the specification of the welfare estimation process on the convergent validity of the welfare measures derived from CM and CVM, three alternative welfare estimation specifications were investigated. Each alternative specification is based on the form of the models with the most complete utility specification. Welfare Specification A is based on the complete model. In Specification B, the welfare measures were estimated without the interactive independent variables in the CM. In Specification C, socio-demographics variables in the CVM and socio-demographics variables and interactions in the CM were

Table 7. Comparison of willingness to pay for different utility specifications

Welfare specification	FOREST A (1999 euros)	FOREST B (1999 euros)
Specification A		
CVM	37.5 (31.57, 45.97)	61.53 (47.6, 104.75)
CM	56.68 (33.18, 95.33)	63.1 (37.55, 105.83)
Specification B (interactive variables excluded)		
CVM	37.5 (31.57, 45.97)	61.53 (47.6, 104.75)
CM	76.38 (45.93, 122.73)	89.65 (54.56, 145.25)
Specification C (socio-economic and interactive variables excluded)		
CVM	17.22 (4.53, 28.51)	41.44 (15.9, 77.33)
CM	45.03 (27.98, 73.73)	58.73 (36.5, 97.06)

excluded. The welfare measures and the confidence intervals for the two afforestation programmes calculated using the CVM and the CM, under the different welfare estimation specifications, are reported in Table 7. The confidence intervals were calculated using the Krinsky and Robb (1986) bootstrapping procedure from 1000 draws. All estimates are significantly different from zero at the 5% level.

The results show that there is variation across the WTP estimates resulting from each of the different welfare estimation specifications. In all the specifications, the welfare measures obtained for the two forests are higher in the CM than in the CVM. Differences across the methods for both forests are smallest for Specification A in which the full models are used.

Tests for equivalence between methods

To substantiate these observed differences between CVM and CM welfare estimates, the following null and alternative hypotheses were tested:

H_0: $WTPA_{CVM} = WTPA_{CM}$;
H_1: $WTPA_{CVM} \neq WTPA_{CM}$

and

H_0: $WTPB_{CVM} = WTPB_{CM}$;
H_1: $WTPB_{CVM} \neq WTPB_{CM}$.

Following the convolution test proposed by Poe et al. (1997), the confidence intervals of the difference between the two random variables of interest (WTP_{CVM} and WTP_{CM}) were calculated. The null hypothesis of equality can thus be reformulated as the difference between WTP_{CVM} and WTP_{CM} being equal to zero.

The results of the hypothesis tests for the welfare measures estimated using the different welfare estimation specifications are shown in Table 8. The mean WTP

Table 8. Results of hypothesis tests for equivalence between CVM and CM

	95% confidence intervals ($WTP_{CM}-WTP_{CV}$)		Significance level ($WTP_{CM}-WTP_{CV}$)	
	FOREST A	FOREST B	FOREST A	FOREST B
Specification A	(−5.09, 58.90)	(−46.45, 47.31)	0.080	0.475
Specification B	(6.42, 85.57)	(−24.85, 84.10)	0.000	0.150
Specification C	(6.67, 59.30)	(−24.72, 64.91)	0.000	0.195

estimates derived using CM and CVM are equivalent at the 5% significance level for both FOREST A and FOREST B only when Specification A is used. The main characteristic of Specification A is the inclusion in the utility function of variables representing two-way interactions. It differs from the overwhelming majority of experiments in which individuals express preferences for attribute level combinations that make use of the main effects only. It underlines the importance of using designs that can estimate some or all two-way interactions in addition to main effects when the objective of the researcher is to understand the decision and choice processes election of the individual (Louviere et al., 2000; Cherchi et al., 2002). Although the second-order interactions only account for a relatively small portion of variance (Louviere et al., 2000), the greater amount of information from more complete factorial fractional designs allows for the estimation and the contrast of a wider array of utility specifications. This contributes to the quality of the results.

When the specification of the welfare estimate is simplified, the two techniques no longer provide consistently equivalent estimates at the 5% level for both afforestation programmes.

The above results provide a mixed picture. For FOREST A, only for Specification A do the CVM and CM yield equivalent estimates of compensating surplus. For the other specifications, the CM welfare estimates were found to be greater than those obtained from the CVM. This outcome is consistent with those found in other studies (Hanley et al., 1998a; Foster and Mourato, 2003; Christie and Azevedo, 2002).

There is a degree of consistency across the CM results for both forests using the alternative specifications for welfare estimation. In other words, no matter what specification is used, the CM estimates are not significantly different from each other. Even in the case of the CVM results where divergence across specifications is more apparent, the confidence intervals are sufficiently broad to ensure that the differences are not significant for each of the forest types.

Conclusions

A number of studies have compared welfare estimates derived from different stated preference methods and, in particular, tested whether they provided similar welfare estimates. However, how the relationship between the utility function on one side and choice attributes and individual characteristics on the other influences the welfare estimates, remains an issue in environmental valuation research. The studies that have compared CVM and CM have limited the utility function of CM to the linear or quadratic forms and the overwhelming majority of CM studies have used a design that only allows for the identification of main effects.

This paper provides a comparison of welfare measures using the contingent valuation method (CVM) and the choice modelling (CM) approach. The different welfare measures are estimated using different utility functions in order to test whether the convergence validity is sensitive to the assumptions about functional forms. It adds to most other papers the modelling of second-order interactions.

The application involved the values of alternative afforestation programmes. Non-market valuation studies can address a particular management or policy issue and contribute to specific decisions as the estimation of the economic costs or benefits of land-use changes or litigation. The sensitivity of the welfare measures is important, especially in situations where the magnitude and direction of particular effects might alter a specific decision.

First, the results show that the models estimated from both methods are significant overall, all the independent variables have the a priori expected signs and the majority are significant. This gives support to the theoretical validity of the models. However, the ability of the CM to provide a disaggregated view of values, allows for controlling a more significant proportion of the unobservable consumer utility, giving a superior estimation efficiency and a better understanding of the choices made by respondents.

The estimates of welfare change associated with two different afforestation projects were found to be positive when estimated by both CVM and CM. Variation across welfare estimates was found to result from the use of alternative specifications of the welfare estimation process. Initial observation indicated that the CM derived estimates were generally greater than those generated through the use of CVM. Statistical testing of these observations revealed that the evidence of equivalence is mixed. Only when the two-way interactions were included in the estimation of the CM utility function, the CM and CVM estimates were not statistically different for both afforestation scenarios. This result emphasises the importance of the interaction effects for understanding the process of decision and election of the individual, which is a key factor in the specification of the utility function.

Further complexity is apparent in this result because a change in the welfare estimation specification yields larger difference in the CVM estimates than in the CM estimates. The CVM results are more sensitive to the specification of the welfare estimation process. The large confidence intervals around the estimates driven by both techniques also make the drawing of firm conclusions tenuous.

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