Eliciting Consumers Preferences Using Stated Preference Discrete Choice Models: Contingent Ranking versus Choice Experiment*

Anna Merino-Castelló†

June, 2003

*This paper corresponds to Chapter 3 of my PhD Thesis. Acknowledgements: I would like to thank Jaume Puig-Junoy for his guidance and Angel López-Nicolau for his continuous support and advice. This study was supported by an unrestricted educational grant from the Merck Company Foundation, the philantrophic arm of Merck & Co Inc., Whitehouse Station, New Jersey, USA. Contact address: anna.merino@econ.upf.es.

†Departament d'Economia i Empresa, Universitat Pompeu Fabra, Ramon Trias Fargas 25-27, 08005 Barcelona, Spain. e-mail: anna.merino@upf.edu.

Abstract

The aim of this paper is twofold: firstly, to carry out a theoretical review of the most recent stated preference techniques used for eliciting consumers preferences and, secondly, to compare the empirical results of two different stated preference discrete choice approaches. They differ in the measurement scale for the dependent variable and, therefore, in the estimation method, despite both using a multinomial logit. One of the approaches uses a complete ranking of full-profiles (contingent ranking), that is, individuals must rank a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a choice set (choice experiment). From the results we realize how important the measurement scale for the dependent variable becomes and, to what extent, procedure invariance is satisfied.

Keywords: Stated preferences, contingent ranking, choice experiment.

JEL codes: D12, C42, C28, C93.

1 Introduction

In recent decades, measuring consumers' preferences for goods and services has been a significant challenge for both academics and practitioners in public and private contexts. People often want to know what other people think. Public officials want to know voters' opinion; marketing departments want to know consumers' preferences and the general public wants to know what others think about political, social, health and other issues. In this sense, individuals' valuation are used for many different purposes, including setting social policies and evaluating the acceptance of a new product in the market.

The aim of this paper is twofold: firstly, to carry out a theoretical review of the most recent stated preference techniques used for eliciting consumers preferences and, secondly, to empirically compare two stated preference approaches and discuss their main strengths and weaknesses.

Although *revealed preference* data have been traditionally used to estimate consumers' valuation for attributes, *stated preferences* hold important advantages when historical data do not suit the objective function. However, there are many methods to elicit stated preferences from individuals -contingent valuation, conjoint analysis, discrete choice methods- and recently, a great debate has emerged focusing on the pros and cons of each of them, mainly between conjoint analysis and choice methods.[1]

There is considerable confusion amongst academics and practitioners about what really constitutes the difference between each of the stated preference techniques. Nevertheless, there are substantial differences between them and a number of these divergences matter considerably in economic valuations and other applications. Although this is not the final aim of the present paper, we intend to clarify differences and similarities to understand the framework of our analysis and we could anticipate that the main differences are related to the election of the preference model, the measurement scale for the dependent variable and the estimation method (Section 2).

On the other hand, the empirical aim of this paper is to compare the results of two particular stated preference discrete choice model (SPDCM) approaches and assess the validity and reliability of each of them.[2] They

[1]There exists a great confusion about the terminology applied to stated preference techniques. Although the term contingent valuation seems to be commonly accepted by the overwhelming majority, the concepts of conjoint analysis and discrete choice methods are extremely confusing and usually receive more than one name.

[2]The term SPDCM was firstly used by J. Louviere.

differ in the measurement scale for the dependent variable and, therefore, in the estimation method, despite both using a multinomial logit (Section 3). One of the approaches uses a complete ranking of full-profiles (contingent ranking), that is, individuals must rank a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a choice set (choice experiment).[3] From the results we realize how important the measurement scale for the dependent variable becomes and, to what extent, procedure invariance is satisfied; that is, two different measurement methods used to assess the same issue should yield the same outcome. However, this is not always satisfied and inconsistency arises when these different methods yield different results. This inconsistency is called *procedure preference reversal* (Section 4).

This paper is organized as follows. Section 2 describes the most recent stated preference techniques developed in public and private fields. Section 3 revises the SPDCM approaches focusing on the contingent ranking and the choice experiment. Section 4 shows the results derived from the two approaches and finally Section 5 concludes.

2 Stated Preference Techniques

Measuring consumers preferences will allow us to quantify the individuals' economic valuation or willingness-to-pay (WTP) for public and private initiatives. In this sense, economic valuation techniques are not only valuable as a policy decision-making tool but also as a marketing research technique. In the former case, we refer to the social valuation of a public initiative such as the construction of a dam or a new environmental or health program. However, these techniques are also widely used as a marketing research tool because they allow to understand what it is about a product or service that drives customers' interest and influences their final purchase decision.

Consumers' preferences can be elicited using either revealed or stated preference data. For this purpose, and under certain circumstances, stated preference data offer some advantages over revealed preference data. One of the main differences between the two systems is the data origin and collection method; revealed preference data are obtained from the past behavior of consumers while stated preference data are collected through surveys.

[3]The terms Contingent Ranking and Choice Experiment are borrowed from the environmental literature, one of the more advanced fields in those techniques.

Over the last few years, a range of stated preference techniques have been developed for eliciting consumers preferences and measuring WTP for goods and services. All these techniques involve asking respondents to consider one or more hypothetical options and to express their preferences for them through surveys. However, aside from this general commonality, there are significant analytical differences between stated preference techniques - contingent valuation, conjoint analysis and choice modeling- although it is not always evident what constitutes such difference. This leads to great confusion about classification and each field of study -environmental, transport or health economics-, and even each author, refers to each of the techniques with different names.

What seems to be the most general and widely accepted classification of stated preference techniques is that between *contingent valuation (CV)* and what we label *multi-attribute valuation techniques (MAV);* that is, between contingent valuation and both conjoint analysis and choice modeling approaches (Figure 3.6).[4]

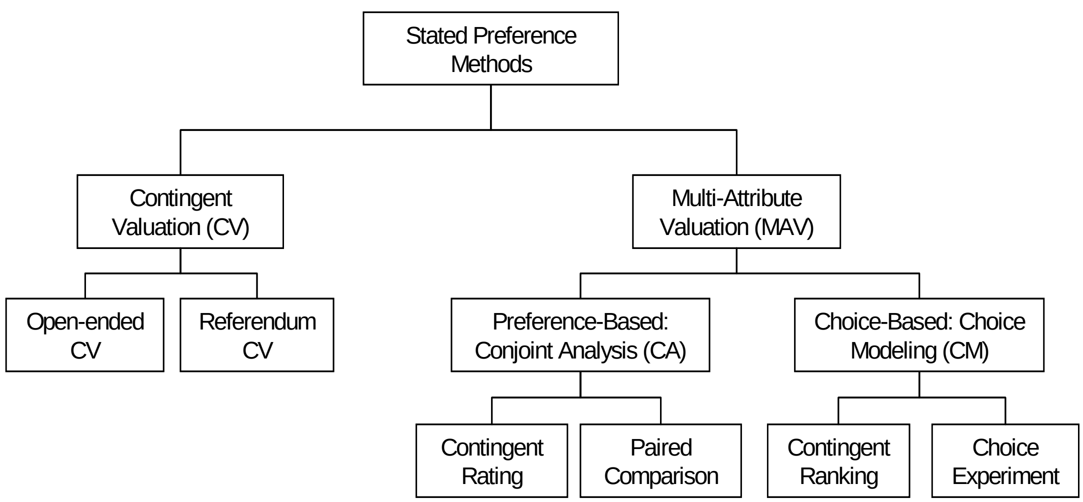

Figure 3.6. The Family of Stated Preference Methods

Contingent valuation is a direct survey approach which is able to estimate consumers' preferences. By means of an appropriately designed ques-

[4]In the most recent environmental literature, Bateman et al (2002) uses the concept of choice modelling instead of multi-attribute valuation (MAV) techniques. However, we adopt this new term in order to distinguish between preference-based and choice-based approaches.

tionnaire, a hypothetical market is described where the good or service in question can be traded. This contingent market defines the good itself, the context in which it would be provided and the way it would be financed. Respondents are then asked to express their maximum willingness to pay for, or their minimum willingness to accept, a hypothetical change in the level of provision of the good. Theoretically, contingent valuation is well rooted in welfare economics, namely in the neo-classical concept of economic value based on individual utility maximization. This assumes that stated WTP amounts are related to respondents' underlying preferences in a consistent manner (Hanley et al, 2001). This technique derives its name from the fact that the value estimates are *contingent* on a hypothetical scenario that is presented to respondents for valuing.

The choice of elicitation formats for willingness to pay questions in contingent valuation surveys has already passed through a number of distinct stages (Hanley et al, 2001). The original form of contingent valuation constitutes an open ended question, in which respondents are asked to state their willingness to pay (or accept compensation) for a specified change or improvement. The **open-ended CV** method is now rarely used because it has been found to be vulnerable to a range of biases, for example, respondents find open-ended questions too difficult to answer because they are not accustomed to paying for non-market goods and services. Respondents may have a preference for one alternative over the other but do not know their maximum willingness to pay for a good (CIE, 2001). Ordinary Least Squares regression is employed for the estimation under the open-ended CV version.

Owing to the problems of eliciting values using an open-ended question, most CV studies are now undertaken using the **referendum or dichotomous** choice elicitation. The preference data generated using this method is encoded in binary forms, as respondents are only given the option of answering yes or no, which implies the adoption of a random utility function. In this case, the coefficients values are obtained through the estimation of a binary logit model using the maximum likelihood procedure. After receiving the endorsement of the NOAA experts panel in 1993 (Arrow et al, 1993), the use of dichotomous choice questions substantially increased, particularly in US applications.[5] However, an increasing number of empirical studies revealed that dichotomous choice results seemed to be significantly larger than

[5] The National Oceanic and Atmospheric Administration (NOAA) organized a panel of experts headed by Robert Solow and Kenneth Arrow.

open-ended values, possibly due to "yeah saying" (Hanley et al, 2001).[6]

Therefore, both approaches appear to have some limitations for estimating values. Firstly, only one attribute or scenario can be presented to a sample of respondents for valuation. Secondly, it is a poor method for estimating consumer values because respondents are unlikely to provide an accurate response when presented with a hypothetical scenario. A third potential weakness of CV is that it may induce some respondents to behave strategically, particularly when public goods are involved.

Partly as a response to these problems, valuation practitioners are increasingly developing an interest in alternative stated preference formats such as *multi-attribute valuation (MAV) methods* which includes conjoint analysis and choice modeling. The main difference between contingent valuation and multi-attribute valuation is that the former analyzes one attribute of the product at a time while the latter explores more than one attribute simultaneously. This may not be a limitation for CV if the objective of the study is to estimate values for a one-dimensional attribute. However, it is an inefficient method of value estimation if multiple attributes are involved and we are interested in the values attached to each of them and trade offs between them. For this reason, contingent valuation is mainly used to contrast different policies while conjoint analysis and choice methods are more focused on marketing due to the decomposition of products into attributes.

Multi-attribute valuation techniques is a family of survey-based methodologies for modelling preferences for goods, where goods are described in terms of their attributes and the levels that these take.[7] Respondents are presented with various alternative descriptions of a good, differentiated by their attributes and levels and are asked to rank the various alternatives, to rate them or to choose their most preferred. By including price/cost as one of the attributes of the good, WTP can be indirectly ascertained from people's rankings, ratings or choices. Attribute valuation approaches allow a more direct route to the valuation of the characteristics or attributes of a good and of marginal changes in these characteristics. Contingent valuation can, of course, be used to value such changes, but the number of scenarios that can be considered is limited. There will be a presumption, therefore, that multi-

[6]The phenomenon of yeah saying appears when respondents accept to say "yes" and pay the specified amount to avoid the embarrassing position of having to say "no".

[7]The conceptual microeconomic framework for multiattribute valuation lies in Lancaster's characteristics theory of value which assumes that consumers' utilities for goods can be decomposed into utilities for composing characteristics.

attribute valuation approaches will be preferred over contingent valuation approaches in contexts where it is important to value several attributes.

Some advantages of multi-attribute valuation methods that solve the drawbacks of contingent valuation are: (i) the only way that a CV study can estimate these attributes is to design different valuation scenarios for each attribute level, however, this is very costly. Multi-attribute methods provide a natural way to do this because they look at more than two alternatives, ; (ii) since multi-attributes designs are based on the attribute theory of value, they are much easier to pool with cost models or hedonic price models than CV; (iii) multi-attribute designs can reduce the extreme multicollinearity problems because attribute levels are usually designed as orthogonal and (iv) multi-attribute methods may avoid some of the response difficulties that appear in CV (Bateman et al, 2002).

2.1 Multi-Attribute Valuation

Two different types of multi-attribute techniques have been suggested: (i) *preference-based approaches* which require the individual to rate or rank each alternative product and (ii) *choice-based approaches* which make the consumer to choose one among several alternative products. The former is a research technique in which consumers are asked to evaluate a series of hypothetical and real products, defined in terms of their features. The latter differs in that consumers are asked to view a series of competing products and select one or, in some cases, more than one. In this regard, choice-based approaches are based on a more realistic task that consumers perform every day, the task of choosing a product from among a group of competitors while preference-based approaches do not require respondents to make a commitment to select a particular option. This is one of the reasons why choice-based approaches are better than or, at least, more preferred to preference-based approaches.

Choice-based approaches originate from the economics discipline and have been widely used for valuing a diverse range of goods and services. On the contrary, preference-based approaches have their origins in the marketing literature and are mainly focused on gaining an insight into consumer preferences rather than estimating economic values (Louviere, 1988). The growing acceptance of choice-based approaches among marketing research practitioners is primarily due to the belief that obtaining preferences by having respondents choose a single preferred stimuli from among a set of stimuli is more realistic and it is thus a better method of approaching actual decision processes.

Generally speaking, preference-based approaches are labeled with the global term of **conjoint analysis** while choice-based approaches receive the name of **choice modeling**.[8] One of the main differences between them is the form of the utility function: preference-based approaches use a deterministic utility function while choice-based approaches use the random utility function where the stochastic component includes all unidentified factors that affect choices. In the deterministic case, the utility function is assumed to be related to an individual's ratings via a transformation function ϕ :

$$U_{ij} = \phi[V_{ij}(X_{ij})] \tag{1}$$

that can take the following shapes: (i) vector model (linear), (ii) ideal point model (linear plus quadratic) and (iii) part-worth function model (piecewise model). The vector model estimates the fewest parameters by assuming the potentially restrictive linear functional form, whereas the part-worth model estimates the largest number of parameters because it permits the most general functional form. The ideal point model falls between these two extremes (Green and Srinivasan, 1978, 1990).[9] These data are typically analyzed using ordinary least squares (OLS) regression techniques which implies a strong assumption about the cardinality of the ratings scale (Bateman et al, 2002).

On the contrary, choice-based approaches use the random utility function that represents the integrated behavioral theory of decision-making and choice behavior and is composed of a deterministic component V_{ij} and an stochastic one ε_{ij}:

$$U_{ij} = V_{ij}(X_{ij}) + \varepsilon_{ij} \tag{2}$$

[8] Choice Modelling is also called Stated Preference Discrete Choice Model (SPDCM).

[9] In the vector model, the preference u_j can be represented as the projection of the stimulus point x_{jp} on the vector w_p in the t-dimensional attribute space:

$$u_j = \sum_{p=1}^{P} w_p x_{jp}$$

The ideal-point model posits that the preference is negatively related to the squared weighted distance d_j^2 of the location x_{jp} of the stimuli or alternative from the individual's ideal point x_p :

$$d_j^2 = \sum_{p=1}^{P} w_p (y_{jp} - x_p)^2$$

The part-worth model permits the most general functional form: $u_j = \sum_{p=1}^{P} f_p(x_{jp})$

The Random Utility Theory (RUT) leads to families of discrete choice models that describe the behavior of individual choice probabilities in response to changes in attributes and/or factors that measure differences across individuals. The most commonly used estimation method is the maximum likelihood.

Individual preferences can be elicited by asking respondents to rank the options presented to them, to score them or to choose their most preferred. These different ways of measuring preferences correspond to different variants of conjoint analysis and choice modeling. There are four main variants according to the measurement scale for the dependent variable: *contingent rating*, *paired comparison*, *choice experiments* and *contingent rankin*g (Figure 3.7).

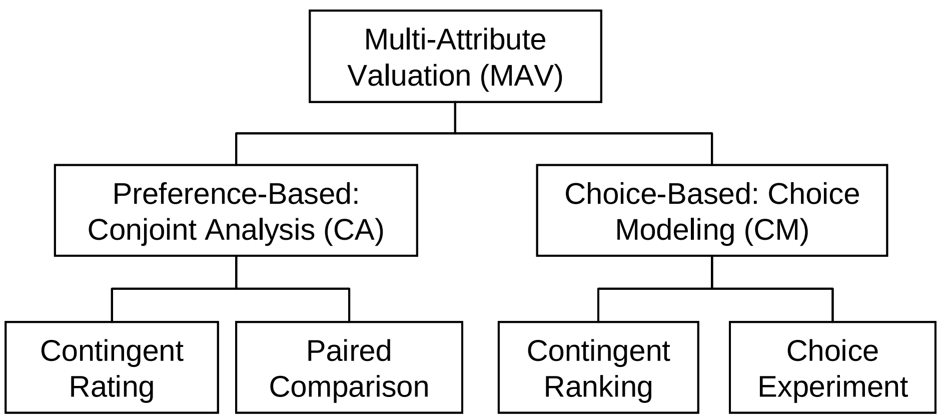

Figure 3.7. Preference-based versus Choice-based Approaches

These techniques differ in the quality of information they generate, in their degree of complexity and also in their ability to produce WTP estimates that can be shown to be consistent with the usual measures of welfare (Bateman et al, 2002).

Both *contingent rating* and *paired comparison* belong to the family of conjoint analysis, which implies the use of a deterministic utility function and ordinary least squares as the estimation procedure. However, these two variants differ in the measurement scale for the dependent variable.

In a *contingent rating* exercise, respondents are presented with a number of scenarios one at a time and are asked to rate each one individually on a semantic or numeric scale. This variant does not, therefore, involve a direct comparison of alternative choices. Ratings must be transformed into a utility scale. The indirect utility function is assumed to be related to individual's ratings via a transformation function. These data are typically analyzed using OLS regression techniques which implies a strong assumption about the cardinality of the ratings scale. These assumptions relate either to the cardinality of rating scales or to the implicit assumption of comparability of ratings across individuals: both are inconsistent with consumer theory. Hence, contingent rating exercises do not produce welfare consistent value estimates.

In a *paired comparison* exercise, respondents are asked to choose their preferred alternative out of a set of two choices and to indicate the strength of their preference in a numeric or semantic scale. This approach combines elements of choice experiment (choosing the most preferred alternative) and rating exercises (rating the strength of preference). Also in this case, the utility function is estimated using ordinary least squares.

On the other hand, *choice experiment* and *contingent ranking* belong to the family of choice modeling, which implies the use of a random utility function and the maximum likelihood as the estimation procedure.

In a *choice experiment*, respondents are presented with a series of alternatives and are asked to choose their most preferred option. A baseline alternative, corresponding to the status quo, is usually included in each choice set. Choice experiments give welfare consistent estimates for four reasons. First, they force the respondents to trade-off changes in attribute levels against the cost of making these changes. Secondly, the respondents can opt for the status quo. Thirdly, we can represent the econometric technique used in a way which is exactly parallel to the theory of rational and probabilistic choice. Fourthly, we can derive estimates of compensating and equivalent surplus. In this case, we estimate a McFadden's conditional logit model using the maximum likelihood procedure.

In a *contingent ranking* experiment, respondents are required to rank a set of alternative options from most to least preferred. Each alternative is characterized by a number of attributes, which are offered at different levels across options. Respondents are then asked to rank the options according to their preferences. In order to interpret the results in welfare economics terms, one of the options must always be in the individual's currently feasible choice set. This is because, if a status quo is not included in the choice set, respondents are effectively being forced to choose one of the alternatives presented, which they may not desire at all. Ranking data provide more statistical information than choice experiments, which leads to tighter confidence intervals around the parameter estimates. We estimate a rank ordered or an exploded logit model using the maximum likelihood procedure.

As a summary, we build a decision tree that indicates the most appropriate stated preference approach according to the sequential decisions about number of attributes, elicitation format (preference-based versus choice-based) and measurement scale (Figure 3.8). The contingent valuation variants can also be included in this decision tree as long as the o*pen ended CV* belongs to the preference-based family and the *referendum CV* belongs to the choice-based family.

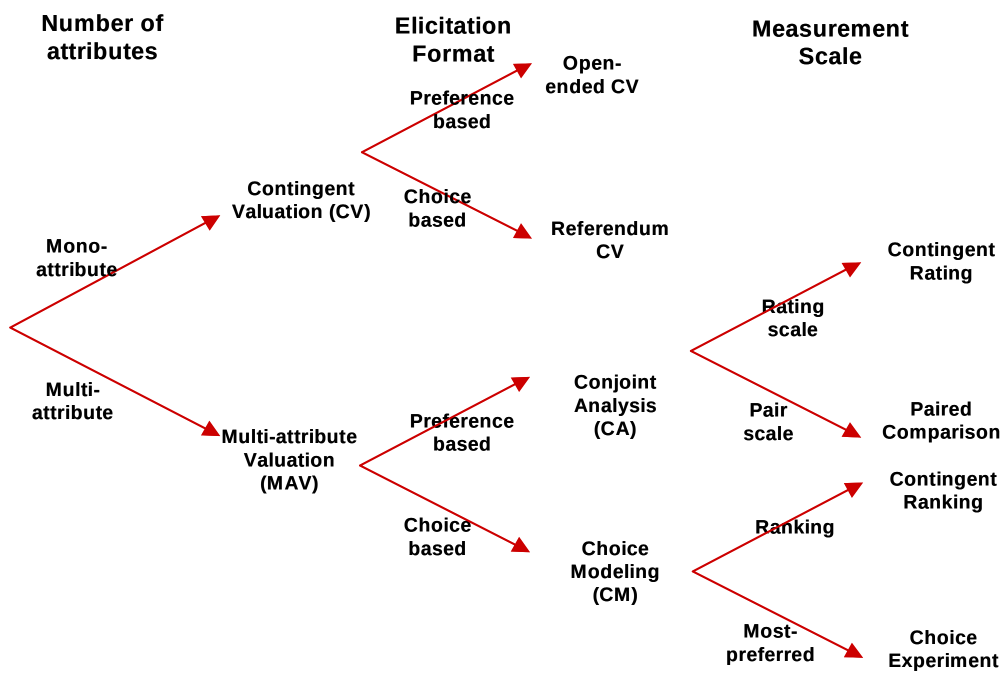

Figure 3.8. Stated Preference Method Decision Tree

The assumptions about the number of attributes, the elicitation format and the measurement scale determine the model specification and the estimation procedure for each of the variants (Table 3.19). As stated before, the specification model for the preference-based approaches is the linear regression model and the estimation procedure is the ordinary least squares (OLS). On the other hand, the specification model of the choice-based approaches is the multinomial logit model and the estimation procedure is the maximum likelihood (MLE). Due to the differences in the measurement scale, the model specification for the choice experiments is McFadden's conditional logit while the model specification for the contingent ranking is the rank ordered logit or exploded logit of Beggs et al (1981).

	Utility Model	Elicitation Format	Measurement Scale	Model Specification	Estimation Method	Welfare Consistent Estimates
Contingent Valuation (CV)	Open-ended CV: deterministic Referendum CV: stochastic	Open-ended CV: preference-based Referendum CV: choice-based	Open-ended CV: WTP in monetary units Referendum CV: yes, no	Linear Regression Model	OLS	YES
Contingent Rating	Deterministic	Preference-based	Score alternative scenarios on a scale of 1-10	Linear Regression Model	OLS	Doubtful
Paired Comparison	Deterministic	Preference-based	Score pairs of scenarios on similar scale	Linear Regression Model	OLS	Doubtful
Choice Experiments	Random Utility	Choice-based	The most-preferred between two or more alternatives	Conditional Logit Model	Maximum Likelihood	YES if non purchase option is included
Contingent Ranking	Random Utility	Choice-based	Rank a series of alternatives from most to least preferred	Rank Ordered Logit	Maximum Likelihood	YES if non purchase option is included

Table 3.19. Characteristics of Stated Preference Approaches

Contingent valuation and choice experiments can both generate results that are consistent with welfare theory. Contingent ranking can also generate welfare theory-consistent results, if do-nothing is included as an option so that the respondents are not forced to rank other options. On the other hand, contingent rating is not widely used in economic valuation mainly due to the dubious assumptions that need to be made in order to transform ratings into utilities; however, due to their simplicity, conjoint analysis variants have been frequently used in marketing fields.

2.2 Stated Preference Techniques in Health Economics

Stated preference techniques have recently been used to estimate utilities instead of the more traditional approach of revealed preferences. Actually, interest in the use of stated preference theory and methods has increased dramatically in environmental and health economics since the mid-1990's, as academics and practitioners make use of developments in transport economics and marketing. Because of its characteristics, contingent valuation has been traditionally used to obtain the monetary value of a change described as a result of a hypothetical or actual policy; on the contrary, conjoint analysis and choice modeling approaches have been traditionally used to better understand consumers' preferences and choice behavior and therefore they are more usually applied for marketing purposes.

Until a few years ago, contingent valuation techniques -open ended and referendum- have been the most common approaches employed in health economics to assess utility from various healthcare interventions or to contrast health policy initiatives. However, due to the important drawbacks of contingent valuation variants, multi-attribute valuation approaches, such as conjoint analysis and choice modeling, have been recently adopted in health economics experiments in order to obtain more detailed information about the monetary valuation of consumers for more than one attribute at a time. Contingent valuation was born in the environmental field and it was applied to health economics for the first time by Acton (1973) with the aim of putting in values the benefits of medical treatments. Some international reviews about the application of contingent valuation approaches in health economics are provided by Diener et al (1999) and Olsen and Smith (2001). In this area, we can highlight the work of O'Brien et al (1995) where the economic value of a new antidepressant is assessed or Davey et al (1998) where the authors carry out an economic valuation of the insulin lispro versus neutral insulin therapy.

The use of multi-attribute valuation (MAV) approaches constitutes an alternative way to assess utilities however, to date, the application of these methods in the area of health economics has been limited. In the USA, these approaches have been used by non-economists to examine what factors are important to patients in the provision of primary healthcare systems, to establish consumers preferences for rural primary health care facilities, to identify what factors are important to consumers in choosing a hospital and to establish consumers preferences for dental services. In the UK, it has been used by health economists to establish the monetary value of time spent on NHS waiting lists, to examine the trade-offs that individuals make between the location of clinic and waiting time in the provision of orthodontic services, to look at the value of assisted reproductive techniques and to assess preferences in the doctor-patient relationship (Ryan and Hughes, 1997). Although multi-attribute valuation methods have been widely used in several fields of economics as well as in marketing research, it has only recently become more widely used in healthcare research. Some recent studies are Ryan and Hughes (1997), Telser and Zweifel (2002), Hall et al (2002).

The majority of examples shown in Table 3.20 actually uses choice modeling approaches, or what are also called stated preference discrete choice models (SPDCM), rather than conjoint analysis approaches. In some cases, SPDCM is not appropriately labeled conjoint analysis; this is what happens in Telser and Zweifel (2002) and Ryan and Hughes (1997), where the term "conjoint analysis" is used when in fact they are using an SPDCM approach.

	Title of the paper	Journal	Approach
COTINGENT VALUATION	"Evaluating Public Programs to Save Lifes: the Case of Heart Attacks" (J.P. Acton)	Santa Monica: RAND Report (1973)	Open-ended Contingent Valuation
	"Health Care Contingent Valuation Studies: a Review and Classification of the Literature" (Diener)	Health Economics (1998)	Contingent Valuation
	"Theory versus Practice: a Review of Willigness-to-Pay in Health and Health Care" (Olsen and Smith)	Health Economics (2001)	Contingent Valuation
	"Economic Evaluation of Insulin Lipsro versus Neutral (regular) Insulin Therapy using a WTP Approach" (Davey et al)	PharmaEconomics (1998)	Open-ended Contingent Valuation
	"Assessing the Economic Value of a New Antidepressant: a WTP Approach" (O'Brien et al)	PharmaEconomics (1998)	Open-ended Contingent Valuation
MULTI-ATTRIBUTE VALUATION	"Measuring willingness-to-pay for risk reduction: an application of conjoint analysis" (Telser and Zweifel)	Health Economics (2002)	Choice modelling
	"Using conjoint analysis to assess women's preferences for miscarriage management" (Ryan and Hughes)	Health Economics (1997)	Choice modelling
	"An application of a Product Positioning Model to Pharmaceutical Products" (Green and Krieger)	Marketing Science	Conjoint analysis
	"Using Stated Preference Discrete Choice Modelling to Evaluate the Introduction of Varicella Vaccination" (Hall et al)	Health Economics (in press) 2002	Choice modelling

Table 3.20. Review of Stated Preference Experiments in Health Economics

In a recent white paper by Louviere (2000) entitled "Why Stated Preference Discrete choice modeling is NOT Conjoint Analysis (and What SPDCM is)", the author defines, compares and discusses two paradigms that are being increasingly applied in health economics and shows why one of these approaches -conjoint analysis- is generally inappropriate for economic valuation and should thus be applied with caution.

3 Choice Experiment versus Contingent Ranking

As previously explained, there are two variants of choice modeling: choice experiment and contingent ranking. They mainly differ in the measurement scale for the dependent variable, because the former implies the choice of the most preferred option relative to the other options while the latter implies a complete ranking of options from most to least preferred (true ordinal scale). In the choice experiment, respondents are usually asked to perform a sequence of such choices (true nominal scale).

The measurement scale determines the multinomial logit to be estimated, that is, choice experiment derives a *conditional logit model* (McFadden, 1973) while contingent ranking determines a *rank ordered or exploded logit* (Beggs et al, 1981; Hausman and Ruud, 1987; Chapman and Staelin, 1982). Consequently, the likelihood function in both cases is different. Both of them assume a random utility function and the only difference is that ranked data provide considerably more information than from simply the most preferred alternative.

Let's derive McFadden's conditional logit. Suppose that individual i chooses alternative j^* from a choice set C_i. If rational choice behavior is assumed, individual preference implies that $U_{ij^*} > U_{ij}$ for $j = 1, ...J$. Because the utility function is partly stochastic, the probability of this event occurring may be written as:

$$P_{ij^*} = \Pr(U_{ij^*} > U_{ij}) = \Pr(\varepsilon_{ij} - \varepsilon_{ij^*} \leq X_{ij^*}\beta_j - X_{ij}\beta_j) \qquad (3)$$

where P_{ij^*} is the probability that decision maker i chooses alternative j^*. If the stochastic error terms are assumed to be i.i.d. according to the extreme value type I distribution:

$$\Pr(\varepsilon_{ij} \leq t) = \exp[-\exp(-t)] \qquad (4)$$

one can show that the choice probabilities have the following form (McFadden, 1973):

$$P_{ij^*} = \frac{\exp(X_{ij^*}\beta_j)}{\sum_{j=1} \exp(X_{ij}\beta_j)} \tag{5}$$

This particular parametric form of the stochastic utility model is often called the multinomial (or conditional) logit model because it is the multiple choice generalization of the binary logit model. The most commonly used estimation method is the maximum likelihood. If we suppose a random sample of individuals and we observe, for each individual, the choice actually made and the values of attributes associated to each of the alternatives, the likelihood function is:

$$Li = \prod_{j=1} \frac{\exp(X_{ij^*}\beta_j)}{\sum_{j=1} \exp(X_{ij}\beta_j)} \tag{6}$$

Finally, the aggregated likelihood function is:

$$L = \prod_{i=1}\prod_{j=1} \frac{\exp(X_{ij^*}\beta_j)}{\sum_{j=1} \exp(X_{ij}\beta_j)} \tag{7}$$

Therefore, the above is the maximum likelihood function to be estimated in the case of a choice experiment where the dependent variable measures the most preferred option with respect to the remaining alternatives. If respondents make sequential or repeated choices, we assume independence between observations or elections.

For contingent ranking, we use an extension of McFadden's conditional logit regression model. In economics literature, the generalization was proposed by Beggs et al (1981) and further developed by Hausman and Ruud (1987) under the name of *rank-ordered logit model.* The model was independently formulated by marketing researchers who called it the exploded logit model (Chapman and Staelin, 1982). They developed a procedure to enhance the estimation of the parameters of the stochastic utility model by exploiting the additional information contained in the preference rank ordering of choice set alternatives. This estimation methodology can be extended if the researcher has a complete rank ordering of all alternatives in the decision makers' choice sets.

To exploit the rank ordering information, one must relate ranking behavior to choice behavior. The theoretical justification for relating ranking behavior to choice behavior is provided by a proof reported by Luce and Suppes in 1965. The Luce and Suppes *Ranking Choice Theorem* states that for any rank ordered preference we have:

$$\Pr(a, b, c, ...) = \Pr(a \mid C) \cdot \Pr(b, c, ...) \tag{8}$$

where $Pr(a, b, c, ...)$ is the probability of observing the rank order of alternative a being preferred to alternative b being preferred to alternative c and so on and $\Pr(a \mid C)$ is the probability of alternative a being chosen from the set of alternatives $C = \{a, b, c, ...\}$. This Ranking Choice Theorem enables the probability of a ranking event, $Pr(a, b, c, ...)$, to be decomposed into the product of two probabilities -the probability of a choice event $\Pr(a \mid C)$ and the probability of a subranking event $Pr(b, c, ...)$. By successively applying this Ranking Choice Theorem to the subranking events, one can derive a probability expression for the ranking event which is the product of the probabilities of $J - 1$ choice events, i.e.

$$\Pr(a, b, c, ...) = \Pr(a \mid C) \cdot \Pr(b \mid C - \{a\}) \cdot \Pr(c \mid C - \{a, b\})... \tag{9}$$

where $C - \{a\}$ is the set of alternatives excluding alternative a. The above equation is equivalent to saying that the probability of the joint ranking event of J alternatives is composed of J-1 statistically independent choice events.

If one applies the Ranking Choice Theorem to the stochastic utility model, assuming that the alternative index j is now interpreted as a serial preference index, it follows that:

$$\Pr ob(U_{i1} > U_{i2} > ... > U_{iJ}) = \prod_{j} \Pr ob(U_{ij^*} > U_{ij}, for.j = j^*, ..., J) \tag{10}$$

The left side of the equation is the joint probability that alternative 1 is preferred to alternative 2 which is preferred to alternative 3 and so on to alternative J-1 which is preferred to alternative J for decision maker i. The right side of equation may be interpreted as the statistical definition of the independence of the events $(U_{i1} > U_{ij}, j = 1, 2, ...J), (U_{i2} > U_{ij}, j = 2, 3, ...J)$ and so on.

The aim of this paper is to compare the results obtained from a sequential choice experiment with those obtained from contingent ranking, which are both consistent with economic theory if the design includes the blank card or outside option. In fact, we want to know if it is possible to replicate a contingent ranking, that is, whether two different measurement scale for the dependent variable (most preferred option versus ranked from most to least preferred) satisfy the procedure invariance or, on the contrary, any inconsistency appears.

This inconsistency, called *procedure preference reversal*, occurs when different methods for measuring a preference yield different results. A robust finding is that these reversals occur with regularity across a number of different measurement methods, yet no satisfactory explanation of this phenomenon exists. Some authors suggest that the current lack of a satisfactory explanation is due to reliance on the common assumption that alternatives are evaluated independently of each other during choice.

3.1 Experimental Design

In order to obtain efficient estimates, it is indispensable for the experiment to be designed in a way that minimizes the variances and co-variances matrix of the vector of parameters. This is a *sine qua non* condition to be able to compare the results obtained from a choice experiment (conditional logit) and a contingent ranking (rank ordered logit). For this purpose, we carry out two different experiments applied to the same sample in order to obtain two different database: one with the full ranking of alternatives from most to least preferred and the other with the most preferred options from four different choice sets.

For the *contingent ranking*, we design an experiment composed of 50 choice sets with 5 alternatives each. In this case, we obtain four orderings from each respondent $(J-1=4)$. The reasoning behind this decision is that we want ten individuals to rank the same choice set; if we assume a sample of 500 individuals $(50*10=500)$, we need a total of 50 choice sets. On the contrary, for the *choice experiment*, we design an experiment with 200 choice sets with 5 alternatives each and, in this case, we need $(n/4*10=500)$ a total of 200 choice sets. This is due to the fact that we want each respondent to select the most preferred option from four different choice sets. As a result, we also have four orderings or choices.

Another important issue is that one of the five alternatives in each choice set is always the blank card or outside option ("home remedies"). We include the outside option to get consistency with economic theory.

The cognitive process underlying each of the experiments are slightly different because, in the first case, we assume that each individual must completely rank a choice set of five alternatives from most to least preferred while in the second experiment, each respondent must choose the most preferred option from four different choice sets. Once the design matrix has been obtained, we have to analyze the existence of dominant or inferior alternatives in each choice set. The aim is to eliminate those alternatives in a choice set that are dominant because, otherwise, there could be a loss of information in the trade-off. In fact, we want utility balance criteria to be satisfied and therefore we need prior information about consumers preferences in the pharmaceutical market. Finally, we impose some additional conditions for the construction of choice sets: (i) at least one drug must be a generic version (in both contingent ranking and choice experiment cases, card or alternative one is always a generic drug and card four varies between branded and generic), (ii) at least one drug must be prescribed by the physician and (iii) at least one drug must be recommended by the pharmacist. Moreover, in each choice set, card five is always the blank card or outside option (Table 3.21).

		Contingent Ranking					Choice Experiment				
		Card 1	Card 2	Card 3	Card 4	Card 5	Card 1	Card 2	Card 3	Card 4	Card 5
Brand	Generic	100%	0%	0%	40%	0%	100%	0%	0%	51%	0%
	Clamoxyl	0%	87%	77%	26%	0%	0%	82%	68%	25%	0%
	Ardine	0%	13%	23%	34%	0%	0%	18%	32%	23%	0%
	Home remedies	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
Laboratory	Known	58%	56%	46%	40%	0%	44%	52%	53%	51%	0%
	Unknown	42%	44%	54%	60%	0%	56%	48%	47%	49%	0%
	None	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
Price	0 €	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
	1 €	47%	19%	29%	35%	0%	37%	34%	30%	35%	0%
	4 €	25%	31%	40%	30%	0%	30%	30%	38%	34%	0%
	20 €	28%	50%	32%	35%	0%	33%	36%	32%	31%	0%
Physician	Prescribed	66%	51%	46%	37%	0%	54%	51%	50%	45%	0%
	Non-prescribed	34%	49%	54%	63%	100%	46%	49%	50%	55%	100%
Pharma	Recommended	51%	62%	34%	51%	0%	46%	46%	53%	55%	0%
	Non-recommended	49%	38%	66%	49%	100%	54%	54%	47%	45%	100%

Table 3.21. Experimental Design Composition

We apply the same conditions to each of the experiments so that they are as similar as possible. If there are differences between the two methodologies, we want them to be easily identified along the measurement scale or estimation process but not in the experiment design.

We asked respondents to firstly rank the five alternatives of the choice set and then select the most preferred option from four choice sets with five alternatives each. We did it in this way because, in our opinion, it is more complicated to rank a group of five alternatives than to select just the most preferred option. We preferred respondents to undertake the most difficult task first and the less complicated ones afterwards. Obviously, there can also be a component of tiredness (or learning) but, in this experiment, it was even more important to apply both experiments to the same individuals.

4 Results

Using the choice experiment and the contingent ranking database, we estimate the objective utility function; in particular, we estimate the "main effects" model with the amoxiciline data. We do not consider interactions with socio economic and drug purchase habits because we are mainly interested in those attributes that are chosen by respondents through cards. Actually, we want to explore the consequences of two different measurement scales methods on the estimated explanatory variables that compose the utility function.

$$\begin{aligned} U_{ij} = {} & \alpha_i GENERIC_j + \mu_i ARDINE_j + \beta_i LAB_j + \gamma_i PRICE_j \\ & + \delta_i PHYSICIAN_j + \eta_i PHARMA_j + \theta_i BLANK_j + \varepsilon_{ij} \end{aligned} \tag{11}$$

Section 3.4.1 displays the estimated parameters using the choice experiment database and contrasts the consistency along the sequential choices. Section 3.4.2 compares the results of the choice experiment with those derived from the contingent ranking (Merino, 2003b) and discusses the existence of procedure preference reversal.

4.1 Conditional Logit Results

From the choice experiment database, we are able to estimate several conditional logit models taking into account the four sequential choice experiments jointly and/or separately. Actually, we can estimate the utility function for each of the choice experiments separately and analyze the choice pattern along them or we can estimate different models taking into account an additional choice experiment each time. Table 3.22 shows the cumulative choice experiments results, that is, the estimated results taking into account the first choice experiment (1), the first two choice experiments (1+2), the first three choice experiments (1+2+3), the last two choice experiments (3+4) and, finally, we estimate the model taking into account the four choice experiments (1+2+3+4).

	First choice experiment (1)	The first two choice experiments (1+2)	Third & fourth choice experiments (3+4)	The first three choice experiments (1+2+3)	Four choice experiments (1+2+3+4)
GENERIC	-0.15	-0.15	-0.35***	-0.21***	-0.27***
	(0.14)	(0.10)	(0.09)	(0.08)	(0.07)
ARDINE	-0.49***	-0.25**	-0.35**	-0.32***	-0.32***
	(0.19)	(0.12)	(0.14)	(0.10)	(0.09)
LAB	-0.62***	-0.37***	-0.19**	-0.24***	-0.28***
	(0.12)	(0.09)	(0.09)	(0.07)	(0.06)
PRICE	-0.09***	-0.08***	-0.09***	-0.09***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
PHYSICIAN	1.55***	1.50***	1.90***	1.65***	1.67***
	(0.14)	(0.09)	(0.11)	(0.08)	(0.07)
PHARMA	0.81***	0.75***	0.31***	0.63***	0.53***
	(0.12)	(0.09)	(0.09)	(0.07)	(0.06)
BLANK	0.19	0.20	0.20	0.21*	0.16
	(0.21)	(0.15)	0.15	(0.12)	(0.10)
Number of Observations	2195	4390	4380	6585	8770
Log likelihood	-548.37374	-1131.0881	-1058.4956	-1659.88	-2203.9525
Pseudo R2	0.2239	0.1996	0.2492	0.2169	0.2193

*** significant at 1%   ( ) Standard Error
** significant at 5%
* significant at 10%

Table 3.22. Cumulative Choice Experiments

Table 3.22 shows that the estimated results taking into account the four choice experiments (1+2+3+4) are all statistically significant at 1%, except for BLANK, and that the absolute value of coefficients increases as the number of sequential choice experiments grows. The pseudo R^2 is better for the last two choice experiments (3+4) than for the first two choice experiments (1+2) which suggests the existence of a **learning process.** It is important to point out that the GENERIC parameter is not significant for the first two choice experiments while PHYSICIAN and PHARMA are statistically significant at 1% from the beginning. This could be evidence that, at the first stage, individuals mainly take into account expert advice as the unique decision-making variable and that it is only after a learning process that they realize about the existence of other choice attributes. In this sense, it seems as if supplier inducement becomes more dominant than brand loyalty throughout the drug purchase process. As a curiosity we can say that, as the interviews progressed, many people first looked for the prescribed alternatives and then valued the rest of the attributes.[10]

Table 3.23 shows the estimated results for each individual choice experiment separately. In this case, the number of observations for each model is exactly the same.

	First CE (1)	Second CE (2)	Third CE (3)	Fourth CE (4)
Generic vs Clamoxyl	-0.15	-0.21	-0.28**	-0.39**
	(0.14)	(0.14)	(0.14)	(0.13)
Ardine vs Clamoxyl	-0.49***	-0.10	-0.38*	-0.26
	(0.19)	(0.17)	(0.20)	(0.21)
Unknown vs Known Laboratory	-0.62***	-0.13	0.05	-0.42***
	(0.12)	(0.12)	(0.13)	(0.12)
Price	-0.09***	-0.07***	-0.10***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
Physician Prescription	1.55***	1.45***	2.03***	1.79***
	(0.14)	(0.13)	(0.15)	(0.15)
Pharmacist Recommendation	0.81***	0.66***	0.42***	0.21*
	(0.12)	(0.12)	(0.12)	(0.12)
Blank Card	0.19	0.17	0.37*	0.08
	(0.21)	(0.21)	(0.22)	(0.21)
Number of Observations	2195	2195	2195	2185
Log likelihood	-548.37374	-575.56243	-514.81796	-536.40156
Pseudo R2	0.2239	0.1854	0.2714	0.2373

*** significant at 1% ( ) Standard Error
** significant at 5%
* significant at 10%

Table 3.23. Individual Choice Experiment Estimates

What is valuable to explore is the existence of any *structural change* along the sequential choice experiments; that is, is the choice pattern constant along the progression of the choice experiments or is there **tiredness or a learning**

[10] We have left the exercise of exploring the existence of lexicographic preferences for future research.

effect?. In order to examine this hypothesis, we undertake several likelihood ratio tests (Table 3.24):

$$LR = -2[L_{\text{restricted}} - L_{\text{unrestricted}}] \tag{12}$$

where the restricted model is one of the cumulative choice experiments (Table 3.22) and the unrestricted model is the sum of the corresponding individual choice experiments (Table 3.23). In the first test, we compare the first two choice experiments and we realize that, according to the LR test, the choice pattern is similar (H_0 accepted); the same happens with the last two choice experiments (3&4).

However, when we contrast the choice pattern along the first three models, we can not accept the null hypothesis any more (H_0 accepted). Therefore, the unrestricted model must be accepted because the three individual choice experiments are supposed to give different results. Consequently, the same happened with the four choice experiments taking into account the restricted and unresctricted models. This is evidence that there is a structural change after the first two choice experiments possibly due to a learning process or tiredness.

Restricted Model	Unrestricted Model	d.o.f.	Likelihood Ratio	Critical Value	H_0
1+2	1,2	14	14.30	23.68	Accepted
3+4	3,4	14	14.55	23.68	Accepted
1+2+3	1,2,3	21	42.25	32.67	Rejected
1+2+3+4	1,2,3,4	28	57.59	41.38	Rejected

Table 3.24. Likelihood Ratio Tests

One likely explanation for this structural change could be the fact that we estimate the different models taking into account independence across choices, that is, we estimate the models as if each choice is independent from the rest. We suppose independence between observations since choices are assumed not to be correlated. Another possibility could be to consider a kind of **Bayesian learning process** whereby individuals update their preferences with respect to experts advice and brand loyalty along the sequential choice experiments. Under this condition, we should assume that noisy terms are correlated across observations or choices. However, we have left this issue for further research.

4.2 Comparison

In this section, we want to compare the estimated results obtained from using the four choice experiments with the results derived from the full contingent ranking (Merino, 2003b). If we look at the significance level, we realize that contingent ranking parameters are all statistically significant while in the choice experiment all are significant expect for the BLANK parameter. As far as we understand, this is a consequence of the main difference between choice experiment and contingent ranking: the measurement scale for the dependent variable. Remember that contingent ranking involves the ordering of all alternatives included in the choice set while choice experiment only requires the choice of the most preferred. In the former model, the BLANK parameter is significant at 1%, which implies that respondents would have to be paid in order to switch from a chemical drug to the home remedy; in the latter model, the interpretation is that individuals always prefer a chemical compound to the outside option.

Afterwards, we carried out a *mean comparison test* in order to conclude whether the estimated coefficients could be considered equal in absolute value. The sign of the parameters is what would be expected in both models, however, the absolute value differs significantly. Confidence interval tests do not accept that the estimators of both models are equal, except for GENERIC and ARDINE parameters because they both enter in the 95% confidence interval. The rest of coefficients are statistically different (Table 3.25).

	Choice Experiment			Full Ranking		
	Coefficients	**95% Confidence Interval**		**Coefficients**	**95% Confidence Interval**	
GENERIC	-0.2656	-0.3973	-0.1339	-0.3706	-0.5094	-0.2317
ARDINE	-0.3248	-0.5069	-0.1428	-0.2549	-0.4387	-0.0711
LAB	-0.2775	-0.3963	-0.1587	-0.1049	-0.2223	0.0126
PRICE	-0.0845	-0.0937	-0.0754	-0.0385	-0.0460	-0.0310
PHYSICIAN	1.6672	1.5292	1.8052	0.9480	0.8187	1.0773
PHARMA	0.5318	0.4139	0.6496	0.2884	0.1688	0.4080
BLANK	0.1554	-0.0502	0.3611	-1.4489	-1.6691	-1.2287

Table 3.25. Four Choice Experiments versus Full Contingent Ranking

This result suggests the existence of *procedure preference reversal*, an inconsistency by which different methods for measuring a preference yield different results. A robust finding is that these reversals occur with regularity across a number of different measurement methods (rating, matching and choice methods), yet no satisfactory explanation of this phenomenon exists. However, we find inconsistency between the measurement scale used in the contingent ranking and the choice experiment, both of which are classified as choice methods. From the results we realize how important the measurement scale for the dependent variable is and the influence it exerts on the appearance of procedure preference reversal.

5 Concluding Remarks

The empirical aim of this paper is to compare the results of two different stated preference discrete choice approaches. They differ in the measurement scale for the dependent variable and, therefore, in the estimation method, despite both using a multinomial logit. One of the approaches uses a complete ranking of full profiles (**contingent ranking**), that is, individuals must rank a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a choice set (**choice experiment**). Our null hypothesis is that "*if two different measurement methods are used to quantify the same thing, they should yield the same outcome*".

Two common measurement methods, as stated in Section 2, are rating scales and choices between alternatives. A desirable property of such measurement devices is that they are consistent in outcome. With rating scales, one item is evaluated at a time and with choices methods, direct comparisons are made between items and one is chosen in preference to the other. A robust finding is that these two methods yield different outcomes. This inconsistency is called *procedure preference reversal* and no satisfactory explanation of this phenomenon exists.

In this paper, we find evidence that preference reversal also arises when comparing two choice methods: a choice experiment and a contingent ranking. In this case, the two measurement methods differ in the measurement scale for the dependent variable, as one asks for a complete rank of alternatives while the other implies the choice of the most preferred option.

Usually, this inconsistency is a violation of one of the underlying assumptions of formal choice theory, *independence of alternatives*. Actually, some authors suggest that the current lack of a satisfactory explanation is due to reliance on the common assumption that alternatives are evaluated independently of each other in choice methods.

This inconsistency poses a practical problem for the accurate measurement of people's preferences: which measure is the correct one? We have left this issue for future research, although we could point out that repeated choice exercises do not seem to be the optimal preference elicitation format since learning or tiredness effect could appear. In my opinion, it would be preferred one choice experiment applied to a larger sample rather than obtained repeated information from each individual.

References

[1] Acton J.P. (1973), "Evaluating Public Programs to Save Lives: the Case of Heart Attacks," *Santa Monica, RAND Report R-950-RC.*

[2] Arrow K., Solow R., Portney P.R., Leamer E.E., Radner R..and Schuman H. (1993), "Report of the NOAA Panel on Contingent Valuation," *Washington DC: Resources for the Future.*

[3] Bateman et al (2002), "Economic Valuation with Stated Preference Techniques: a Manual, UK Department of Transport," *Edward Elgar Publishing Inc.*

[4] Beggs S., Cardell S. and Hausman J. (1981), "Assessing the Potential Demand for Electric Cars," *Journal of Econometrics* 16, 1-19.

[5] Chapman R. and Staelin R. (1982), "Exploiting Rank Ordered Choice Set Data within the Stochastic Utility Model," *Journal of Marketing Research* 19: 288-301.

[6] CIE-Centre for International Economics (2001), "Review of Willingness-to-Pay Methodologies".

[7] Davey P., Macmillan J., Rajan N., Aristides M.and Dobson M. (1998), "Economic Valuation of Insulin Lispro versus Neutral regular Insulin Therapy using a WTP Appraoch," *PharmaEconomics* 13: 347-358.

[8] Diener A., O'Brien B and Gafni A. (1998), "Health Care Contingent Valuation Studies: a Review and Classification of the Literature," *Health Economics*, 7:313-326.

[9] Green P. and Srinivasan V. (1978), "Conjoint Analysis in Consumer Research: Issues and Outlook," *Journal of Consumer Research* 5.

[10] Green P. and Srinivasan V. (1990), "Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice," *Journal of Marketing.*

[11] Green and Krieger, "An application of a Product Positioning Model to Pharmaceutical Products," *Marketing Science.*

[12] Hall J., Kenny P., King M., Louviere J., Viney R. and Yeoh A. (2002), "Using Stated Preference Discrete Choice Modeling to Evaluate the Introduction of Varicella Vaccination," *Health Economics (in press).*

[13] Hanley N., Mourato S. and Wright R.E. (2001), "choice modeling Approaches: a Superior Alternative for Environmental Valuation?," *Journal of Economic Surveys* 15(3).

[14] Hausman J. and Ruud P. (1987), "Specifying and Testing Econometric Models for Rank-Ordered Data," *Journal of Econometrics* 34:83-104.

[15] Louviere J. (1988), "Analysing Decision Making: Metric Conjoint Analysis," *Sage Publications, Newbury Park.*

[16] Louviere J. (2000), "Why Stated Preference Discrete choice modeling is NOT Conjoint Analysis (and What SPDCM is)," *Memetrics White Paper.*

[17] McFadden D. (1973), "Conditional Logit Analysis of Qualitative Choice Behavior," in P. Zarembka, *Frontiers in Economics*, 105-142, Academic Press, New York.

[18] Merino A. (2003b), "Demand for Pharmaceutical Drugs:a Choice Modelling Experiment," *working paper Pompeu Fabra University.*

[19] Olsen J.A. and Smith R.D. (2001), "Theory versus Practice: a Review of Willingenss-to-Pay in Health and Health Care," *Health Economics* 10: 39-52.

[20] O'Brien B.J., Novosel S., Torrance G and Streiner D. (1995), "Assessing the Economic Value of a New Antidepressant: a WTP Approach," *PharmaEconomics* 8:34-45.

[21] Ryan M. and Hughes J. (1997), "Using Conjoint Analysis to Assess Women's Preferences for Miscarriage Management," *Health Economics* 6:261-273.

[22] Telser and Zweifel (2002), "Measuring Willingness-to-Pay for Risk Reduction: an Application of Conjoint Analysis," *Health Economics.*