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USING CHOICE EXPERIMENTS TO VALUE A WORLD CULTURAL HERITAGE SITE: REFLECTIONS ON THE EXPERIMENTAL DESIGN

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In the context of public amenities, whose benefits of preservation are not totally reflected by the market, the valuation of cultural heritage has given primacy to the contingent valuation method, with very few attempts being made to valuation via the discrete choice experiments technique (DCE). In the present paper, from among the various phases of the DCE conception, particular emphasis is given to the way in which the attributes levels are combined into alternatives and how they are allocated into choice sets (experimental design step). In order to configure hypothetical scenarios relating to the conservation of a World Heritage cultural landscape, this paper applies both the experimental design strategies identified in the literature review as commonly applied in DCE to value cultural items, as well as D-optimal processes, which proved to be advantageous both in terms of statistical efficiency and in the information required (number of choice sets).

JEL classification codes: C90, C18, B41, Z19, R52
Key words: discrete choice experiments, experimental design, valuation of cultural heritage

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I. Introduction

The valuation of cultural heritage items has gained relevance in recent years as a result of the growth of cultural touristic destinations, and of the public intervention in the cultural sphere in order to promote a more efficient allocation of resources. In spite of the fact that the contingent valuation method has been the predominant method for assessing the value of cultural heritage items (Navrud and Ready 2002 or Tuan and Navrud 2007), it is a rather limited technique when multi-attribute valuation is to be undertaken, or when for policy reasons the aggregate value of a given program is considered inappropriate. In such cases, the discrete choice experiments technique (DCE) has been suggested as an alternative method.[1]

DCE is based on the 'characteristics theory of value' (Lancaster 1966) and is routed on random utility theory (McFadden 1974). DCE asks respondents to select their preferred alternative from each choice set presented sequentially. Each choice set is constituted by two or more alternatives defined by the combination of the relevant attributes.

The development process of DCE embraces the following steps: 1) attribute selection and definition of their respective levels; 2) development of the alternatives and choice sets - experimental design; 3) data collection; and, 4) data analysis. Among the four steps just described, the experimental design step (i.e., the way in which the attributes levels are combined into alternatives and how they are allocated into choice sets) is one of the more complex and less understood issues.

It is worth noting that the design of choice experiments should be constructed to satisfy a number of prior considerations. These include the effects to be estimated, the dimension of the choice set (the number of options for each choice set) and the number of choice sets presented to each respondent.

In addition, empirical evidence on the complexity of the choice task and its influence on responses' validity are based on different measures of complexity and are not unanimous. For Hanley et al. (2002) and Carlsson and Martinsson (2008) designs differing on the number of choice sets did not produce a statistically

[1] DCE originated in transport and marketing research by Louviere and Hensher (1982) and Louviere and Woodworth (1983). Subsequently, the use of DCE was extended to other areas of research such as health economics and the valuation of environmental goods (e.g., Adamowicz et al. 1994; Boxall et al. 1996; Hanley et al. 1998, 2002; Alpizar et al. 2003).

significant effect on preferences. On the other hand, Dellaert et al. (1999), DeShazo and Fermo (2002) found significant effects of the design complexity on choice consistency and Hensher (2004) detected differences in welfare measures.

Nevertheless, despite the relevance of the experimental phase, actually there is not a single well developed theory, being an area in progress. Advances in experimental design theory based on a discrete choice model (discrete choice designs), particularly the conditional or multinomial logistic model, have been introduced in the literature along with the traditional criteria based on the orthogonality property, fundamental to determine independent effects in linear models. Discrete choice designs intend to satisfy a measure of statistical efficiency typically based on the D-optimal or D-efficiency criterion.[2] Various forms of constructing D-optimal designs are available to achieve this purpose and some of the work that has significantly contributed to the current state of the art is reviewed in this paper.

In this context, the literature distinguishes designs that do not consider a priori information about the value of the parameters to be estimated (e.g., Bunch et al. 1996; Street et al. 2005; Burgess and Street 2003, 2005; Burgess 2007; Street and Burgess 2007) from those that assume à priori values based on results from small pilot studies or expected information on the importance of the attributes that characterize alternatives (e.g., Huber and Zwerina 1996; Carlsson and Martinsson 2003). Also in the context of a priori assumption of information, Sándor and Wedel (2001) introduced Bayesian designs in the choice design literature, allowing the incorporation of uncertainty about the assumed values of the parameters (e.g., Kessels et al. 2006; Ferrini and Scarpa 2007; Scarpa et al. 2007; Kessels et al. 2008, 2009). Rose and Bliemer (2009) present the current state of the art of the processes for generating stated choice experiments.

Empirically, the absence of a sole theoretical guide is reflected in the implementation of a number of different strategies, varying in the degree to which they are specific to discrete choice models. This diversity of strategies has attracted growing research interest in the systematic review of the experimental design practices adopted in various fields of applied research, including studies by

[2] A design that satisfies this criterion will minimize the generalized variance of the parameter estimates (Burgess and Street 2003; Street et al. 2005; Johnson et al. 2006; Street and Burgess 2007).

Burgess and Street (2005) in marketing, transport and applied economics, and by Ferrini and Scarpa (2007) in environmental economics. In the context of DCE to value cultural items this systematic review is inexistent, constituting therefore an area that deserves research, to which the present paper contributes.

In addition to summarizing relevant information about the practice of experimental design in the cultural sphere, this paper aims to help practitioners choose the strategy of experimental design that best fits their applications and to assess the potential gains from using D-optimal designs. The objective is accomplished, using a concrete DCE application to determine the value of a program to preserve the attributes of the Alto Douro Wine Region (ADW) of Portugal (a world heritage cultural alive landscape) applying various experimental design approaches. Specifically, D-optimal designs (referred to as specific methods) are compared with the design obtained using the methods most commonly used in current applications of DCE in cultural valuation (referred to as general methods). Evidence on the performance of each strategy includes a measure of efficiency by design, the number of choice sets required, the level balance criterion (the number of times that each level attribute appears in the design) and the correlation between the estimated effects.

The paper is organized as follows. In section II, DCE and the experimental design phase's theoretical framework is explained. Section III outlines the experimental design practices used in DCE applications in the cultural realm. Section IV presents the development of the experimental design applied to the ADW world heritage site. Concluding remarks are presented in section V.

II. Theoretical framework

A. Discrete choice experiments

DCE is part of the set of choice modelling techniques included in stated preference methods. In theoretical terms, this approach has been based on the 'characteristics theory of value' (Lancaster 1966) and further developed using random utility theory (McFadden 1974).

From Lancaster's (1966: 134) perspective: 1) a good has characteristics from which the consumer derives utility; 2) generally, each good is defined by more than one attribute; and, 3) a combination of goods may exhibit different characteristics from those exhibited by individual goods.

Based on these properties, with the purpose of imitating *trade-offs* made by consumers in real markets, DCE describes the goods and services to be valued through the set of characteristics and levels they may assume. The random utility theory relies on the basic assumption that the consumers' behaviour results from a process of utility maximisation.[3] In DCE, the respondent has to choose between a set of C alternatives and he will select the alternative that provides him the highest utility. Since the researcher does not observe consumer preferences, utility is taken as having a random character.

Under random utility theory, the indirect utility function for each respondent can be expressed as:

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

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

Individual n will choose alternative i over j if:

$$V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}, \quad \forall j \in C; j \neq i \ , \tag{2}$$

As there is an error component in the specification of the utility derived, the analysis is one of a probabilistic choice. As such, the probability of individual n choosing alternative i relative to any other alternative j in C may be expressed by the following equations:

$$P_{ni} = P\,[\,(V_{ni} + \varepsilon_{ni}) > (V_{nj} + \varepsilon_{nj})\,], \ \forall j \in C \,; j \neq i \ , \tag{3}$$

$$P_{ni} = P\,[\,(V_{ni} - V_{nj}) > (\varepsilon_{nj} - \varepsilon_{ni})\,], \ \forall j \in C \,; j \neq i. \ , \tag{4}$$

[3] Louviere et al. (2000); Train (2003); and Hensher et al. (2005) contain a good description of the random utility theory.

Assuming that the error terms ε are independently and identically distributed, following a Gumbel distribution, the Conditional Logit Model (McFadden 1974) is applicable, which we refer to as MNL. The choice probability is expressed by the well-known formula:

$$P(U_{ni} > U_{nj}) = \frac{\exp(\mu V_{ni})}{\sum_{j \in C} \exp(\mu V_{nj})}, \tag{5}$$

where μ is a scale parameter of the unobserved stochastic component (typically assumed to be one).

B. Experimental design

Bearing in mind several contributions in the literature, as stated above, the design of DCE involves the following steps: attribute selection and specification of the attribute's levels; experimental design; data collection; and data analysis. In this paper, the focus of interest is the experimental design phase to estimate main effects in a generic DCE.

The experimental design includes the development of alternatives and choice sets, combining the attributes levels' into alternatives, each defining a product or program configuration. Simultaneously or sequentially two or more alternatives are allocated in choice sets from each of which respondents are asked to select their preferred option.[4]

Most of the DCE designs use Orthogonal Main Effects Plans (OMEP) in which the main effects of interest can be independently or orthogonally estimated.[5] Until recently orthogonality constituted the main criterion for generating efficient fractional factorials designs (Ferrini and Scarpa 2007). Traditionally the construction of a DCE design has been based on evidence from the experimental

[4] Progress in computational techniques now allows to create and simultaneously 'bundle' attributes into choice sets (simultaneous strategies) (Kjaer 2005). However, there are methods of constructing choice sets from an initial set of alternatives that require two separate phases (sequential strategies).

[5] These designs are used to assess the effect of an attribute on a response variable (Street and Burgess 2007). A full factorial design is formed by all possible combinations of attributes, whereas a fractional factorial design is a sub-set of the former. In order to select a specific fraction, is common to ensure that the attributes are statistically independent of one another, property displayed by an orthogonal design (Hensher et al. 2005).

design of linear models, on the assumption that it can also be applied to non linear models, such as MNL (Kuhfeld et al. 1994).

Progress in the field of statistical efficiency of experimental design has resulted in alternative methods and specific designs for discrete choice experiments.[6] In order to obtain the maximum information from each respondent and accuracy on parameter estimates, a statistical efficiency criterion needs to be satisfied, since orthogonality is no longer the main property as is the case with linear designs.

Among the diverse criteria used to define and measure the statistical efficiency of experimental design, the most commonly used is D-optimality or D-efficiency.[7] A design that satisfies this criterion will minimize the generalized variance of the parameter estimates. In this case, the determinant of the variance-covariance matrix describing the variability of the estimates will have the lower value. Considering the Fisher information matrix (C) as defined by the inverse of the variance-covariance matrix, a D-optimal design will maximize the determinant of C (Burgess and Street 2003; Street et al. 2005; Johnson et al. 2006; Street and Burgess 2007).

In the context of the D-optimality criterion, the literature provides several ways to accommodate DCE designs, some of which are reviewed below, each ones representing distinct processes of how to construct D-optimal designs to estimate main effects.

Bunch et al. (1996) developed the shifted or cyclic design, which consists in the manipulation of attributes levels' in all the available alternatives. This process begins with the allocation of original alternatives from an OMEP into distinct choice sets. Following this, according to the levels of each attribute, additional alternatives in each choice set are cyclically constructed. Thus, in the new alternative, each attribute will have the next highest level. If the level of the first alternative is the highest, it will have the lowest level in the next alternative, and so on. This procedure corresponds to the use of a generator adding a unit to each of the k attributes, creating one or more additional J alternatives.

[6] Louviere and Woodworth (1983) are referred in the literature as the first to identify the relation between the random utility model and the statistical theory of discrete choice experiments.

[7] Kessels et al. (2006) summarised other efficiency measures in addition to those based on the D criterion.

According to the approach proposed by Huber and Zwerina (1996), the selection of the designs must satisfy some desirable criteria. In the context of non linear utility specifications, they have identified the criteria of orthogonality, level balance, minimum overlap between levels, and utility balance to obtain a D-optimal design. Orthogonality implies that the levels of attributes are independent from each other; level balance requires that the levels of each attribute appear equally often in the design; minimal overlap is satisfied when an attribute level is different in each alternative of a choice set and utility balance implies alternatives with similar utility in each choice set. Having built an optimal design of neutral utility, Huber and Zwerina (1996) introduced the utility balance criterion based on the consideration of prior information regarding the values of the parameters. Huber and Zwerina (1996) and Carlsson and Martinsson (2003) have shown that the satisfaction of this criterion increases the efficiency of the design. However, other authors (e.g. Viney et al. 2005) argue that its inclusion increases the variability of the answers and, consequently, the variance of the error term. Kjaer (2005) suggests that the increase in variability may be due to an increase in complexity, leading to irrational answers or non answers.

Huber and Zwerina's criteria (1996) were formalised by Zwerina et al. (1996) adapting the computational search algorithm of Kuhfeld et al. (1994) so as to provide efficient non linear designs. Fedorov's modified algorithm, exchange, through an iterative process, the alternatives of an initial random fraction of the full factorial with the alternatives that are candidates to be included in the design until the best value of D-efficiency is achieved.[8]

More recently, Burgess and Street (2003, 2005), Street and Burgess (2004), Street et al. (2005), and Street and Burgess (2007) formalised optimal or near-optimal design strategies used to estimate main effects and interactions. These authors developed a method of constructing choice sets by adding arithmetic modulo or a generator equivalent to systematic changes in the attributes' levels. In this way it is possible "to obtain the largest number of pairs of profiles that can have different levels for attribute *q* in a choice set" (Street et al. 2005: 463). Developments of this method are presented in Appendix A.

[8] This algorithm is present in SAS software and using a macro (%ChoicEff) it is possible to obtain the D-optimal designs.

III. Experimental design practices in DCE to value cultural items

With regard to the valuation process, there is a convergence between the economics of cultural heritage and environmental economics. Both share the focus on the importance of the sustainability issue. Moreover, they also share an international dimension (Benhamou 2003) which results in a tendency to transpose valuation techniques typically applied in environmental amenity evaluation to the realm of cultural items (Navrud and Ready 2002).

However, particularities of the cultural arena, such as 1) the definition of culture and of heritage (Papandrea 1999; Noonan 2003), 2) the multiplicity of values in a given cultural item (Throsby 2001), 3) the possibility of population segments that assign a negative value to the preservation of heritage and cultural goods (Morey and Rossmann 2003; Noonan 2003), 4) the increased role of information in forming the value attributed to cultural goods (Throsby 2003; Kling et al. 2004), 5) the analysis of formation of preferences and the evolution of tastes (Peacock 1995) have all imposed new questions in non-market valuation techniques applied to cultural items.

Considering the state of the art in empirical applications, the contingent valuation method (CVM) has been used in most studies that have sought to determine the value of cultural heritage items (Navrud and Ready 2002; Tuan and Navrud 2007; Kaminski et al. 2007). In the field of arts and culture, Noonan (2002) identified 53 CVM applications for the period between 1972 and 2002 to the following topics: local/historical items (19); arts (7); museums (6); broadcasting (6); property (5); theatre (3); libraries (3); archaeological sites (2); and sport (2). While there have been some studies published in the 80's, it is in the 90's that there is a significant growth of publications. More recently Kaminski et al. (2007) reviewed valuation studies of European cultural heritage items published from 1994 to 2006. As for CVM applications, they identified 18 studies distributed by: cathedrals (3), historic areas and buildings (6), archaeological sites (2), theatres (1), museums (3), archives (2) and libraries (1).

In the cultural field, CVM has been applied to goods defined at various scales, from the local (Willis 2002; Kling et al. 2004; Salazar and Marques 2005) to the worldwide (Carson et al. 2002; Cuccia and Signorello 2002). Moreover, it has been used both to determine the value of cultural institutions (Hansen 1997; Santagata and Signorello 2000) as well as the composite of "arts" (Thompson et al. 2002). The estimated benefits refers to the value of preserving (monuments and buildings), the value of access to heritage sites and cities and the value of maintaining the current level of provision for the good “arts” and cultural institutions.

Neverthless, in the case of multi-attribute items, DCE has been proposed as an alternative to CVM (e.g., Mazzanti 2003). Distinctly from CVM, which captures the preferences expressed by monetary values, DCE obtains the individual preferences of consumers from the choices made among the options presented. The application of DCE in the cultural domain has been predominantly to estimate the use values provided by cultural institutions (Maddison and Foster 2003; Mazzanti 2003; Apostolakis and Jaffry 2005; Snowball and Willis 2006). Few studies are examples of DCE applications to monuments or groups of monuments (Morey et al. 2002) or sites (Alberini et al. 2003; Tuan and Navrud 2007). Table 1 summarizes the core of DCE-based studies of cultural items.

As indicated in Table 1, in most DCE applications valuing cultural items, choice sets are preferentially of size 2, the number of choice sets or tasks presented to each respondent varies between 2 and 10, and the number of attributes varies between 2 and 6. Relatively to the experimental design, the following development strategies are identified:

- Construction of all possible pairs of an orthogonal fractional factorial design; eliminating the dominated pairs and blocking (e.g., Mazzanti 2003; Morey et al. 2002);
- Randomly pair the alternatives of the full factorial; eliminating the dominated pairs (e.g., Alberini et al. 2003) or of a fractional factorial (e.g., Snowball and Willis 2006);
- Split into blocks the alternatives of an orthogonal fractional factorial design (e.g. Apostolakis and Jaffry 2005);
- Pair all the alternatives of the full factorial design with the status quo alternative; eliminating the dominated pairs (e.g. Maddison and Foster 2003; Tuan and Navrud 2007).

Table 1. DCE studies to value cultural items

Authors	Study object	Attributes (levels)	Tasks/ respondents (n)	Choice set size	Experimental design	Model specification
Morey et al. (2002)	100 marble monuments	2 (4 x 9)	10 (259)	2	Construction of all possible pairs of the factorial design; all dominant pairs were excluded	LM
Maddison and Foster (2003)	British Museum	2 (3 x 4)	2 (400)	1+ sq	Full factorial[a]	LM
Mazzanti (2003)	Galleria Borghese Museum, Rome	4 (2^2 x 3^2)	3 or 4 (185)	2 + sq	Smallest orthogonal main effects-plan (SPSS). Construction of all possible pairs; all dominant pairs were excluded	MNL
Alberini et al. (2003)	St. Anne's Cathedral Square vs an abstract square	4 (2 x 3^2 x 4)	5 (254)	2	Randomly pair the alternatives of the Full Factorial. All dominant pairs were excluded	MNL RPL
Apostola-kis and Jaffry (2005)	2 Greek heritage attractions	6 (3^6)	3 (253)	3	Orthogonal fractional factorial (18 alternatives) - 3 blocks (SAS- block design)	MNL
Snowball and Willis (2006)	South African National Arts Festival	6 (4^5 x 5)	3 (78)	2	Randomly pair the alternatives of an OMEP (SPSS) without reposition in 13 choice sets	MNL; HEV; RPL
Tuan and Navrud (2007)	My Son world cultural heritage site, Vietnam	4 (4 x 2^3)	7 (225 + 221)	1 + sq	Full factorial (32) excluding 4 dominated alternatives (4 blocks with 7 choice sets)	MNL RPL

Notes: sq- status quo; MNL – Multinomial Logit Model; LM- Binary Logit Model ; RPL - Random Parameters Logit Model ; MM-Mixture Model (combining RPL and Classic heterogeneity); HEV- heteroscedastic extreme value model. [a] Information reported by the authors.

The literature review shows that, in the cultural sphere, there is no application of the advances related to the theory of optimal experimental design within DCE. To compare the performance of the previous strategies and to assess the potential gains of using D-optimal designs, the next section presents experimental design strategies that are applied to configure hypothetical preservation programs to the ADW world heritage site. ADW is included in the UNESCO Cultural Landscape list since it comprises natural and man-made elements (UNESCO 2001).

The area designated by ADW embraces 13 municipalities and is located in the northeast of Portugal. Being a living and evolving cultural landscape, ADW is a complex cultural item, in which particular attributes constitute an interrelated whole (Lourenço-Gomes 2009). Additionally, due to its evolving dynamic, the maintenance of the more traditional characteristics is in constant threat by economic and development pressures. In this sense it is crucial to determine whether there is consensus in the maintenance of these more traditional attributes and the relative importance of each one.

The multi-attribute good nature and the dynamic around the preservation notion (preservation and safeguarding policies consistent with economic criteria and the living conditions of the landholders) rationalize the need for the formulation of the most valuable ADW preservation programs. In this context, DCE is expected to produce results that satisfy this desideratum better.

IV. Experimental design applications to the ADW world heritage site

Defining the relevant attributes implies selecting those that are part of the individuals' preferences and are prominent in terms of policy or program (Bateman et al. 2002; Alpizar et al. 2003). The attributes and levels to configure the hypothetical preservation programs for ADW were based on four sources, namely UNESCO's inclusion criteria, a previous study, a pilot-study, and expert interviews.

According to the criteria used for inclusion in UNESCO's list of World Cultural Heritage sites (UNESCO 2001), ADW is the result of human activities, it is an example of a traditional European wine region producing wine for over 2000 years, maintaining the traces of its evolution over time, traces that defined the way its population occupied the territory (villages, accessibility, and religion) in close relationship with the wine production.

Madureira et al. (2005), using the contingent valuation method, identify the mosaic landscape (agricultural diversity, including plots planted with and bordered by traditional crops) as the preferred characteristic of ADW. The general visitors expressed a willingness to pay for a preservation program in range 90-100€.

During a previous pilot-study, fifty visitors were asked to sort in preference order (1 to most preferred) a wide variety of attributes that are most important in ADW, ranging from the terraced vineyards supported by schist walls (a traditional technique of vineyards production), the mosaic landscape, the villages (traditional agglomerations); immaterial heritage (folk customs and practices); the monuments, viewpoints and the sacred in the landscape. The first three attributes obtained the lower rank order, being identified as the attributes that are part of the preferences of respondents. In addition, the levels of the price attribute were defined from the willingness to pay values for a preservation program obtained in the open-ended question "what is the maximum amount that you would be willing to pay for a program to preserve ADW?"

From expert interviews, including the coordinator of the ADW application to the UNESCO list, an architect, a landscape architect and an art historian, it was possible to define the politically relevant set of attributes of ADW, deserving the attention of public policy. In this sense, for example, despite the religious heritage is a key part in the characterization of ADW, all experts considered it protected by the ecclesiastical authorities, not presenting risk of disappearance or deterioration. On the other hand, the traditional agglomerations have been identified as the most jarring of the landscape and must be given more political attention. The landscape mosaic and the terraced vineyards supported by schist walls were identified as key elements of the ADW cultural landscape.

Considering the previously explained four sources, the relevant attributes to configure potential preservation programs were (Table 2): terraced vineyards supported by schist walls (A), landscape mosaic (B), traditional agglomerations (C) and annual tax payment per household (D). The three attributes related with the landscape are assumed to have only two levels: i) the attribute is protected, ensuring their presence in the landscape (level 1); ii) it is not a target of protective measures and eventually will disappear (level 0). These attributes are explained to the respondents through digitally altered photographs from an actual one of a village belonging to ADW. The price attribute, in the form of an annual tax per household, was set to levels of €20, €40 and €60 for the alternatives involving a program of preservation and €0 for the None-Option.

The designed attributes A, B, C, D are combined in a way to create alternatives that will constitute the choice sets presented to the respondents.[9] Nevertheless, the alternatives in which the three first attributes are simultaneously zero are implausible or don't make sense in the framework of the ADW program. Additionally there exists a dominance effect if an alternative, ceteris paribus, has more than one of the three first attributes at a lower price. In the resulting experimental design the choice sets implausible or dominant alternatives will be excluded or prevented. In order to select the best experimental design, alternative methods are compared to

[9] In this sense, the four attributes and their levels defines the primary data used in this research.

estimate only main effects and to support choice sets formed by two experimentally conceived alternatives.

Using the “discrete choice experiments” software (Burgess 2007), the relative D-efficiency, expressed by equation (A2), is computed and the correlation matrix of the effects to be estimated is presented. The correlation matrix is derived from the variance-covariance matrix (as defined by the inverse of the information matrix). In the process of computation, a distinction is made between two categories of methods: general methods, including those that have been used to value cultural items; and specific methods to a particular discrete choice model (namely the MNL), based on the D-optimality criterion.

Table 2. Attributes and levels of the ADW preservation program

Attributes	Levels	Code
Terraced vineyards supported by schist walls (A)	- Presence (maintain the tradition) - Absence (Expansion via modern vineyards)	1 0
Landscape mosaic with agricultural diversity, including plots planted with and bordered by traditional crops (B)	- Presence (maintain the landscape mosaic) - Absence (replace the landscape mosaic and borders around plots with modern vineyards)	1 0
Traditional agglomerations and built heritage (C)	- Presence of traditional characteristics - Absence (urban centres and villages lose their traditional character)	1 0
Price (€) Annual tax increase per household (D)	- 60 - 40 - 20 - 0 (none option)	2 1 0

A. General methods

Construction of all possible pairs of an OMEP

The design *a.1* (Table 3) presents the 12 possible choice sets resulting of the pairing of all alternatives of an OMEP, excluding the dominated or implausible pairs.[10] This design has a relative efficiency of 57.9%. The level balance criterion

[10] For this purpose, two initial OMEP were compared (from Kuhfeld 2006 and using SPSS, one of the most commonly software used), being presented the one that provided the best results (SPSS software).

is not verified by two attributes (B and C) and the effects to be estimated are correlated. As shown in Appendix B (Table A1), when there is no need to eliminate the implausible or dominated pairs, this method allows for non-correlated main effects to be estimated, even though the number of choice sets is high. However, the formulation of a specific program for a given reality generally implies that some pairs of alternatives are implausible and will not be considered.

Random pair alternatives of the full factorial

On the basis of various attempts to pair the full factorial alternatives and remove the dominated pairs, the results show that main effects are correlated and the relative efficiency is below 50%. To avoid these problems, the alternatives of the full factorial (except four non-plausible alternatives to the ADW program) were randomly paired until a solution was found where there were no choice sets to eliminate. The design *a.2* (Table 3) presents the results of this procedure.

The random pairing of the full factorial alternatives resulted in 10 choice sets with relative D-efficiency of 67.3%. Even though the estimated main effects showed some correlation, the highest correlation coefficient is 0.26 (A, B). The attributes' levels are not distributed equally and thus this design is not balanced.

Pairing the alternatives of a fractional factorial design (OMED) in option with the same differently-ordered alternatives, so as to allow plausible comparisons

The design *a.3 (*Table 3) presents the 6 choice sets that were constructed from the pairing of the alternatives of the OMEP obtained from SPSS. It is a balanced design with a relative D-efficiency of 51.7%. Since the main effects exhibited correlations, they could not be independently estimated.

Orthogonal main effects design

Similarly to method L^{MA} for symmetrical designs (Louviere et al. 2000), the 4 attributes were considered to be 8 (the first 4 correspond to the 1st option and the second 4 correspond to the 2nd option). Then, using SPSS, an OMEP was obtained. This method generates choice sets through which it is possible to estimate all main effects independently (Table A2, Appendix B). However, when the pairs with dominated or non-plausible alternatives are removed, it is no longer possible to estimate, independently, the main effects (design *a.4*, Table 3). The relative D-efficiency is 59.4%. There are two attributes without balance between levels.

B. Specific Methods

Adding generator 1111 to the alternatives of an OMED

This method corresponds to the cyclical process (Bunch et al. 1996) or to one of the Burgess and Street (2005) solutions. For choice sets with 2 alternatives, according to S_q included in equation (A1), for the 3 binary attributes $S_1 = S_2 = S_3 = 1$ and for the attribute with 3 levels $S_4 = 1$. It follows that, for the binary attributes, there has to be a systematic change in the levels via the addition of 1 to each level (in modulo 2 arithmetic). Regarding attribute D, as it has a number of levels superior to the number of alternatives in the choice set, there is also the need for a systematic change, via the addition of 1 or 2 (modulo 3).[11]

In this method, achieving a D-optimal design requires the addition of the generator 1111 or 1112 to the alternatives of an OMEP.[12] In terms of efficiency and independence of the effects to be estimated, there are no differences between generators. Balanced and orthogonal fractional designs were tested and, in all cases, the addition of a generator 1111 results in a 100% efficient design in which the main effects can be independently estimated (Table A3, Appendix B). However, the need to remove choice sets with implausible alternatives makes it impossible to satisfy this last property.

Design *b.1* in Table 3 presents the 6 choice sets that exhibited the best results in this procedure. This design is highly efficient, achieving a relative D-efficiency of 90%. The criterion of level balance is satisfied. However, attributes A, B and C are not estimated independently of each other.

[11] Note that in modulo 2 arithmetic: $0+1 \equiv 1+0 \equiv 1$; $1+1 \equiv 0$; modulo 3: $0+1 \equiv 1+0=1$; $0+2 \equiv 2+0 \equiv 1+1 \equiv 2$;$1+2 \equiv 2+1 \equiv 0$; $2+2 \equiv 1$ (Street et al. 2005: 464).

[12] In the cyclical method provided by Bunch et al. (1996), changing the attribute levels to those applying immediately above has the same effect as adding the generator 1111.

SAS software

The SAS software, through the use of its various macros, generates D-efficient designs. Previously, the restriction of exclusion of all alternatives with the three binary attributes defined simultaneously at zero level was imposed. This restriction removes the need to eliminate some choice sets, as required in the previous procedures. Specifying 6 choice sets, the relative D-efficiency was 91%. With respect to the attribute B there is no balance between the levels. The main effects are not independently estimated, the highest correlation coefficient is 0.38 (design *b.2*, Table 3).

All the designs presented in this section comply with the requirements to estimate the main effects for the preservation program of ADW.[13] However, the information required varies, and, at minimum, 6 choice sets need to be specified (processes *a.3*, *a.4*, *b.1* and *b.2*).

The need to eliminate unrealistic choice sets or choice sets with a dominance effect between alternatives explains the loss of diagonality in the information matrix (for MNL), property that ensures the independence of the estimated effects. As shown in Table 3, all processes share this problem.

With regard to D-efficiency criterion, process *b.2* has the highest performance, followed by process *b.1*, as expected. This result is due to the fact that these methods have been developed for MNL. Specifically, the cyclical method or the generator 1111 minimizes the overlap between attribute levels (bearing in mind that MNL is a model with differences between levels), while the search algorithm included in the SAS software directly satisfies this criterion. Comparing the more general processes, strategy *a.2* generates the highest efficiency value. Even though all the designs presented above have relative D-efficiencies higher than 50%, Street et al. (2005) note that many designs in the literature, mainly those based on random disposition of alternatives, have efficiencies below 50%.[14]

Relatively to the level balance, processes *a.3* and *b.1* should be highlighted, since all levels of each attribute appear equally often in the design. The worst performance with regard to this item is associated with strategy *a.2*, in which none of the attributes is balanced.

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[13] The experiments that did not conform to this basic premise were excluded from the results presented here.

[14] For each strategy various designs were tested and only the best-performing ones were included in this paper.

Table 3. Experimental designs from distinct processes

Design	Set	Option 1	Option 2	Eff (%)	Correlation matrix (MNL)					Level frequencies				
a.1	1	0 1 0 2	1 0 0 1	57.9	Main effects are correlated					Level	A	B	C	D
	2	0 1 0 2	1 0 1 2		1	0.6	0.6	-0.4	0	0	12	14	10	8
	3	0 1 0 2	0 0 1 0		0.6	1	0.6	-0.3	0.07	1	12	10	14	8
	4	1 0 0 1	0 1 1 1		0.6	0.6	1	-0.3	-0.07	2				8
	5	1 0 0 1	1 0 1 2		-0.4	-0.3	-0.3	1	0					
	6	1 0 0 1	0 0 1 0		0	0.07	-0.07	0	1					
	7	1 1 0 0	0 1 1 1											
	8	1 1 0 0	1 0 1 2											
	9	1 1 0 0	0 0 1 0											
	10	0 1 1 1	1 0 1 2											
	11	0 1 1 1	0 0 1 0											
	12	1 0 1 2	0 0 1 0											
a.2	1	1 1 1 1	1 0 0 0	67.3	Main effects are correlated					Level	A	B	C	D
	2	1 0 0 1	1 1 0 2		1	0.3	0.2	-0.2	0.2	0	9	9	9	6
	3	1 0 0 2	0 1 1 0		0.3	1	0.1	-0.2	0.2	1	11	11	11	7
	4	0 1 0 0	0 1 1 1		0.2	0.1	1	-0.2	0.07	2				7
	5	0 1 1 2	0 1 0 1		-0.2	-0.2	-0.2	1	-0.2					
	6	0 1 0 2	1 0 1 0		0.2	0.2	0.07	-0.2	1					
	7	0 0 1 0	1 0 1 1											
	8	0 0 1 1	1 0 1 2											
	9	1 1 0 1	0 0 1 2											
	10	1 1 0 0	1 1 1 2											
a.3	1	0 1 0 2	1 0 0 1	51.7	Main effects are correlated					Level	A	B	C	D
	2	1 0 0 1	1 0 1 2		1	0.6	0.6	0	0	0	6	6	6	4
	3	1 1 0 0	0 1 1 1		0.6	1	0.8	-0.4	0	1	6	6	6	4
	4	0 1 1 1	0 0 1 0		0.6	0.8	1	-0.4	0	2				4
	5	1 0 1 2	1 1 0 0		0	-0.4	-0.4	1	0					
	6	0 0 1 0	0 1 0 2		0	0	0	0	1					
a.4	1	1 0 1 1	0 1 0 2	59.4	Main effects are correlated					Level	A	B	C	D
	2	1 1 0 1	0 0 1 1		1	0.4	0.4	-0.5	0.6	0	7	6	6	2
	3	0 1 0 2	0 0 1 2		0.4	1	0.5	-0.2	0.3	1	5	6	6	4
	4	1 0 0 0	1 1 1 2		0.4	0.5	1	-0.2	0.3	2				6
	5	0 0 1 2	0 1 0 1		-0.5	-0.2	-0.2	1	-0.6					
	6	0 1 1 0	1 0 0 2		0.6	0.3	0.3	-0.6	1					
b.1	1	0 1 0 2	1 0 1 0	90	Main effects are correlated					Level	A	B	C	D
	2	1 0 0 1	0 1 1 2		1	0.5	0.5	0	0	0	6	6	6	4
	3	1 1 0 0	0 0 1 1		0.5	1	0.5	0	0	1	6	6	6	4
	4	0 1 1 1	1 0 0 2		0.5	0.5	1	0	0	2				4
	5	1 0 1 2	0 1 0 0		0	0	0	1	0					
	6	0 0 1 0	1 1 0 1		0	0	0	0	1					
b.2	1	0 1 1 0	1 0 0 2	91	Main effects are correlated					Level	A	B	C	D
	2	0 0 1 2	1 1 0 0		1	0.3	0.4	0.04	0.07	0	6	5	6	4
	3	0 1 0 2	1 0 1 1		0.3	1	0.3	0.1	0.2	1	6	7	6	4
	4	0 0 1 0	1 1 0 1		0.4	0.3	1	0.04	0.07	2				4
	5	1 1 1 2	0 1 0 1		0.04	0.1	0.04	1	0.03					
	6	0 1 1 1	1 0 0 0		0.07	0	0.07	0.03	1					

V. Conclusions

The present paper provides useful insights on the experimental design strategies adopted in the DCE valuation of cultural items. In the few DCE applications available, the recent advances put forward in the theory of experimental design to discrete choice models (construction techniques based on the D-efficiency criterion) have not been applied. Moreover, this paper focuses on experimental designs created specifically for MNL, the most commonly used model in the applications of DCE in the cultural sphere.

In order to investigate the performance of the adopted strategies (general methods) and to assess the potential gains of using D-optimal designs (specific methods), we develop the experimental design of a DCE to assess the most valuable attributes of a preservation program of ADW, a world heritage cultural landscape located in Portugal.

Among the general methods, pairing the alternatives of the full factorial proved to be the method in which both efficiency and independence among the estimated main effects was highest. Nevertheless it requires a high number of choice sets and none of the levels is balanced.

Among the specific methods or D-optimal designs, this paper compares the construction method developed in Burgess and Street (2005)— which, in this specific case, is equivalent to the cyclical method developed by Bunch et al. (1996) — and the choice sets obtained using SAS software. Both procedures proportionate a value equal or superior than 90% for D-efficiency, a higher value than the best of the general approaches. However, in both cases, the estimates of the main effects have some degree of correlation. The existence of this problem in the use of the SAS software had already been pointed out in the literature review provided by Street et al. (2005). The use of the Burgess and Street construction method (addition of the generator 1111) gives rise to correlation problems due to the exclusion of choice sets with dominated alternatives. For other situations it is possible, with this method, to obtain designs with high efficiency, independence between the effects to be estimated and with a reduced number of choice sets.

In summary, in the light of the results achieved for the concrete case of ADW, the specific designs are more efficient and require a minimum number of choice sets to estimate main effects, considering a generic or unlabelled DCE.

It is also possible to conclude that distinct design strategies for DCE have unequal properties. This is a crucial conceptual issue to estimate the desirable effects accurately, but is not often emphasised or made explicit in DCE applications. Lack of rigor in the phase of the experimental design may have more or less serious consequences in obtaining worthy utility estimates. In the worst scenario, a poor design may not allow the evaluation of all the main effects. The optimal or statistically efficient designs seek to maximize the information obtained from each respondent, minimizing the required sample size and the number of choices presented to each respondent. The researcher maximizes the information and reduces the logistic costs, and the respondents are faced with a simpler task, in the sense that they have to answer fewer questions.

Appendix

A. Optimal or near-optimal design strategies

For the general case of DCE with asymmetric attributes, the largest number of pairs of profiles that can have different levels for attribute q in a choice set (Street et al. 2005: 463) is defined by S_q:

$$S_q = \begin{cases} (m^2-1)/4 & l_q = 2,\ m\ odd \\ m^2/4 & l_q = 2,\ m\ even \\ \left[m^2-(l_q x^2+2xy+y)\right]/2 & 2 < l_q < m \\ m(m-1)/2 & l_q \geq m \end{cases}, \tag{A1}$$

where x and y are positive integers satisfying the equation $m = l_q x + y$ for $0 \leq y < l_q$; m is the number of options in each choice set; l_q are the levels of the attribute q.

In practical terms, to estimate the main effects, the method consists of: (1) considering the resulting combinations of an OMEP as the first alternatives of the choice set; (2) construct the second alternatives from the first, adding a generator to obtain the highest number of pairs with different levels for each attribute. This procedure is generalised to sets with more options and to attributes with several levels.

Having presented alternative methods of constructing D-optimal designs, the question of choosing between them arises. The computer software "Discrete

Choice Experiments" (Burgess 2007) calculates the relative efficiency (Eff D) of any set of choice sets expressed by the formula:

$$\text{Eff D} = \left(\frac{\det C}{\det C_{optimal}} \right)^{1/p}, \tag{A2}$$

where p is the number of parameters to be estimated (MNL), with $p = \sum_i (l_i - 1)$, to estimate main effects; C is the *information matrix* for the effects to be estimated; det C is the determinant of C; det $C_{optimal}$ is the maximum value of the determinant of C.

The *information matrix* is defined as $C = B \Lambda B'$, here B is the matrix of contrasts normalised for the effects to be estimated; Λ is the matrix of second derivatives of the likelihood function (MNL), it represents the extension of choice sets in which pairs of alternatives appear simultaneously.[15]

The alternatives nominate the rows and columns of Λ such that: entries in $\Lambda = -A/m^2N$, where A is te number of times that pair of alternatives occur; N is the choice sets number and m are the alternatives in each choice set. Diagonal of Λ: the values are selected so that row and column sums of Λ are 0.

The *information matrix* offers an explanation of the correlation between the parameter estimates and, therefore, should be diagonal or the closest to diagonal as possible. Consequently, the properties of a design may be checked through the properties of the information matrix and its inverse, the variance-covariance matrix (Street et al. 2007).

Regarding det $C_{optimal}$, Burgess and Street (2005) demonstrate that the maximum value of the determinant of C is (for the estimation of the main effects for the general case of any number of attributes with a variable number of levels):

$$\det C_{optimal} = \prod_{q=1}^{K} \left(\frac{2S_q}{m^2 (l_q - 1) \prod_{i=1; i \neq q}^{K} l_i} \right)^{l_q - 1} = \prod_{q=1}^{K} \left(\frac{2S_q l_q}{m^2 (l_q - 1) L} \right)^{l_q - 1}, \tag{A3}$$

where $L = \prod_{i=1}^{k} l_i$ and S_q is as defined in expression (A1).

[15] Burgess and Street (2005) and Street et al. (2005) provide detailed explanations regarding each element of D-efficiency formula.

A. Evaluation of alternative designs

Table A1. Construction of all the possible pairs

Initial Plan: Orthogonal and non balanced fractional design (SPSS) 8 alternatives

Set	Option 1	Option 2	Set	Option 1	Option 2	Relative D-efficiency and correlation matrix (MNL): General case	Relative D-efficiency and correlation matrix (MNL): Eliminating the choice sets with dominated alternatives
1	0 1 0 2	1 0 0 1	15	1 0 1 2	0 0 1 0		
2	0 1 0 2	1 1 0 0	16	0 0 0 0	0 1 0 2	62 %	57,9%
3	0 1 0 2	0 1 1 1	17	0 0 0 0	1 0 0 1	Main effects are	Main effects are
4	0 1 0 2	1 0 1 2	18	0 0 0 0	1 1 0 0	uncorrelated	correlated
5	0 1 0 2	0 0 1 0	19	0 0 0 0	0 1 1 1	Correlation matrix	
6	1 0 0 1	1 1 0 0	20	0 0 0 0	1 1 1 0	(MNL)	
7	1 0 0 1	0 1 1 1	21	0 0 0 0	1 0 1 2		
8	1 0 0 1	1 0 1 2	22	0 0 0 0	0 0 1 0	1 0 0 0 0	1 .6 .6 -.4 0
9	1 0 0 1	0 0 1 0	23	1 1 1 0	0 1 0 2	0 1 0 0 0	.6 1 .6 -.3 .07
10	1 1 0 0	0 1 1 1	24	1 1 1 0	1 0 0 1	0 0 1 0 0	.6 .6 1 -.3 -.07
11	1 1 0 0	1 0 1 2	25	1 1 1 0	1 1 0 0	0 0 0 1 .17	-.4 -.3 -.3 1 0
12	1 1 0 0	0 0 1 0	26	1 1 1 0	0 1 1 1	0 0 0 .17 1	0 .07 -.07 0 1
13	0 1 1 1	1 0 1 2	27	1 1 1 0	1 0 1 2		
14	0 1 1 1	0 0 1 0	28	1 1 1 0	0 0 1 0		

Initial Plan: Orthogonal and balanced fractional design (Kuhfeld 2006); 12 alternatives

Set	Option 1	Option 2	Set	Option 1	Option 2	Relative D-efficiency and correlation matrix (MNL): General case	Relative D-efficiency and correlation matrix (MNL): Eliminating the choice sets with dominated alternatives
1	0 1 1 1	0 1 1 2	34	0 1 0 0	1 0 1 1	61%	52,4%
2	0 1 1 1	1 0 0 2	35	0 1 0 0	1 1 0 2	Main effects are	Main effects are
3	0 1 1 1	1 0 1 0	36	1 0 1 1	1 1 0 2	uncorrelated	correlated
4	0 1 1 1	1 1 0 1	37	0 0 0 0	0 1 1 1		
5	0 1 1 1	0 0 1 2	38	0 0 0 0	0 1 1 2		
6	0 1 1 1	0 1 0 0	39	0 0 0 0	1 0 0 2	Correlation matrix	
7	0 1 1 1	1 0 1 1	40	0 0 0 0	1 0 1 0	1. 0 0 0 0	Correlation matrix
8	0 1 1 1	1 1 0 2	41	0 0 0 0	1 1 0 1	0 1. 0 0 0	1 .76 .76 -.3 .5
9	0 1 1 2	1 0 0 2	42	0 0 0 0	0 0 0 1	0 0 1. 0 0	.76 1 .76 -.2 .5
10	0 1 1 2	1 0 1 0	43	0 0 0 0	0 0 1 2	0 0 0 1. 0	.76 .76 1 -.3 .5
11	0 1 1 2	1 1 0 1	44	0 0 0 0	0 1 0 0	0 0 0 0 1.	-.3 -.3 -.3 1 -.2
12	0 1 1 2	0 0 1 2	45	0 0 0 0	1 0 1 1		.5 .5 .5 -.2 1
13	0 1 1 2	0 1 0 0	46	0 0 0 0	1 1 0 2		
14	0 1 1 2	1 0 1 1	47	0 0 0 0	1 1 1 0		
15	0 1 1 2	1 1 0 2	48	1 1 1 0	0 1 1 1		
16	1 0 0 2	1 0 1 0	49	1 1 1 0	0 1 1 2		
17	1 0 0 2	1 1 0 1	50	1 1 1 0	1 0 0 2		
18	1 0 0 2	0 0 1 2	51	1 1 1 0	1 0 1 0		
19	1 0 0 2	0 1 0 0	52	1 1 1 0	1 1 0 1		
20	1 0 0 2	1 0 1 1	53	1 1 1 0	0 0 0 1		
21	1 0 0 2	1 1 0 2	54	1 1 1 0	0 0 1 2		
22	1 0 1 0	1 1 0 1	55	1 1 1 0	0 1 0 0		
23	1 0 1 0	0 0 1 2	56	1 1 1 0	1 0 1 1		
24	1 0 1 0	0 1 0 0	57	1 1 1 0	1 1 0 2		
25	1 0 1 0	1 0 1 1	58	0 0 0 1	0 1 1 1		
26	1 0 1 0	1 1 0 2	59	0 0 0 1	0 1 1 2		
27	1 1 0 1	0 0 1 2	60	0 0 0 1	1 0 0 2		
28	1 1 0 1	0 1 0 0	61	0 0 0 1	1 0 1 0		
29	1 1 0 1	1 0 1 1	62	0 0 0 1	1 1 0 1		
30	1 1 0 1	1 1 0 2	63	0 0 0 1	0 0 1 2		
31	0 0 1 2	0 1 0 0	64	0 0 0 1	0 1 0 0		
32	0 0 1 2	1 0 1 1	65	0 0 0 1	1 0 1 1		
33	0 0 1 2	1 1 0 2	66	0 0 0 1	1 1 0 2		

Table A2. Orthogonal main effects design (2 2 2 3 2 2 2 3)

Set	Option 1	Option 2	Eff (%)	Correlation matrix (MNL)	Level frequencies				
1	1 1 1 0	1 0 0 1	62	Main effects uncorrelated					
2	1 0 1 1	0 1 0 2							
3	1 1 0 1	0 0 1 1		1 0 0 0 0	Level	A	B	C	D
4	0 1 0 2	0 0 1 2		0 1 0 0 0	0	12	14	14	12
5	1 1 1 0	0 1 1 0		0 0 1 0 0	1	16	14	14	8
6	1 0 1 2	1 0 1 0		0 0 0 1 .17	2				8
7	0 1 0 1	1 1 0 0		0 0 0 .17 1					
8	0 0 0 0	1 1 1 1							
9	1 0 0 0	1 1 1 2							
10	0 0 1 1	1 0 1 0							
11	0 0 1 2	0 1 0 1							
12	1 1 0 2	1 1 0 0							
13	0 1 1 0	1 0 0 2							
14	1 0 0 0	0 0 0 0							

Table A3. Cyclic method or Burgess and Street (2005) method

Set	Option 1	Option 2	Eff (%)	Correlation matrix (MNL)	Level frequencies				
1	0 0 0 0	1 1 1 1	100	Main effects uncorrelated	Level	A	B	C	D
2	0 1 1 1	1 0 0 2			0	12	12	12	8
3	0 1 1 2	1 0 0 0		1 0 0 0 0	1	12	12	12	8
4	1 0 0 2	0 1 1 0		0 1 0 0 0	2				8
5	1 0 1 0	0 1 0 1		0 0 1 0 0					
6	1 1 0 1	0 0 1 2		0 0 0 1 0					
7	0 0 0 1	1 1 1 2		0 0 0 0 1					
8	0 0 1 2	1 1 0 0							
9	0 1 0 0	1 0 1 1							
10	1 0 1 1	0 1 0 2							
11	1 1 0 2	0 0 1 0							
12	1 1 1 0	0 0 0 1							

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