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by

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ABSTRACT

This paper evaluates gains in efficiency produced by the use of efficient designs to analyze stated choice (SC) data. Based on a standard experiment used in a previous research, we compare the efficiency of this design with that of the efficient design obtained according to the minimization of the D-error, considering different modelling strategies. The experiment was conducted in the context of the choice between the plane and the new high speed train in the route Madrid-Barcelona. As the levels assigned to some attributes in the stated choice exercise were customized to each respondent experience, pivoting the information provided by preliminary revealed preference questions around the reference alternative (the plane, in this case), a different efficient design was created for every respondent in the sample. Results of the analysis demonstrate that substantial gains in the significance level of the parameter estimates could have been attained if the efficient design had been used to analyze SC data.
Keywords: Stated Choice Data, Efficient Designs, Discrete Choice Models

1. INTRODUCTION

During decades, the use of orthogonal designs, obtained as a fraction of the full factorial design preserving the orthogonality among the attribute vectors, was considered common practice in the construction of stated choice experiments. The majority of these designs were extracted from existing catalogues or specialized software that provided the corresponding combinations of the attribute levels in every choice situation (e.g. Kocur et al, 1982; Hahn y Shapiro, 1966; Bradley, 1988; SDG, 1990 among others) leaving decisions such as the number and the value of the attributes and levels included in the experiment to the analyst.
More recently, researchers have raised questions about the relevance of the orthogonality in the construction of stated choice experiments, claiming that this property is normally lost once the attribute values are assigned to the orthogonal codes of the experimental design (Rose and Bliemer, 2004). Hence, the construction of fractional experiments based on efficiency criteria like the minimization of the asymptotic standard error of the parameter estimates is becoming a more attractive idea. Although there exist different methods to obtain efficient designs, the most popular are those that minimize the D-error, that is defined in terms of the asymptotic variance-covariance (VC) matrix, which depends, in turn, on the second derivatives of the log-likelihood function. Thus the difficulty entailed in the computation of the D-error varies with the complexity of the choice model to be estimated. At this point, as much of the previous research have been done using classical designs, the question arise to which extent the use of non-efficient designs reduces the efficiency of the experiment or the accuracy in the estimates. In other words, it would be interesting to assess the loss of efficiency due to the use of non-efficient designs and to which extent the sample size could have been reduced by using an efficient design in order to guarantee the same level of significance in the estimates obtained with a non-efficient design.
In this paper we compare the efficiency of the experimental design used in a previous research with the efficient design obtained according to the minimization of the D-error, in the case of a Multinomial Logit (MNL) and a Mixed Logit (ML) model. In the previous experiment, we faced respondents to the choice between the plane and the new high speed train in the route Madrid-Barcelona. As the levels assigned to some attributes in the stated choice exercise were customized to each respondent experience, pivoting the information provided by preliminary revealed preference questions around the reference alternative (the plane, in this case), a different efficient design was created for every respondent in the sample. The comparison of the D-error for these two designs allowed us to conclude that, for this particular case with a sample of around 300 individuals, we could have obtained substantial savings in the sample size (ranging from 5% to 24%) if models were estimated with efficient design data; which is equivalent to say that, maintaining the same sample size, we could have improved the level of significance of the parameter estimates.

2. CRITICAL ISSUES IN THE CONSTRUCTION OF STATED CHOICE EXPERIMENTAL DESIGNS

The main purpose of every experimental design is to determine the independent effect of different attributes upon certain observed outcomes that, in the particular case of SC experiments, are represented by choices made by the sample respondents that undertake the experiment (Rose and Bliemer, 2009). A typical SC experiment consists in a sample of individuals that complete different choice tasks in which they are asked to select the most preferred alternative among a finite set of options. Alternatives are defined in terms of the different values, or levels, that the attributes can take. Technically, the experimental design consists in the disposition of the levels of the attributes, on a certain way, in the design matrix *X*, whose columns and rows are normally associated to the attributes of the alternatives and to the choice situations, respectively (see, e.g. Bliemer and Rose, 2006; and Rose and Bliemer, 2008)[1]. The way the attribute levels are arranged in the design matrix determines the ability of the experiment to measure the independent effect of every attribute and to obtain statistically significant parameter estimates. Many different design types can be considered by the analyst. The simplest one to construct is the so-called *full factorial design*, consisting of all possible combinations of the attribute levels, yielding all possible different choice situations. Although this design guaranties that main and all interaction effects can be estimated and has many other desirable properties, it is not useful in practice as the number of choice situations may become typically too high. Therefore, most researchers rely on *fractional factorial designs,* consisting in the selection of a subset of choice situations from the *full factorial design*.

The principle of orthogonality has been considered, in the past, the paradigm in the construction of fractional factorial experimental designs. In an orthogonal design all the columns of the design matrix are perpendicular vectors. In other words, the product of the design matrix by its transpose is a diagonal matrix. Thus, the attributes in an orthogonal design are treated as statistically independent variables, being possible to estimate the influence of each attribute upon the observed outcomes. Rose and Bliemer (2009), point out that orthogonality is purely a statistical property that is related to the correlation structure between the attributes of the design and not a behavioural property imposed upon the experiment. Therefore, an orthogonal design, by construction would not be theoretically appropriate in cases where attributes were cognitively correlated in the minds of the respondents (e.g. price and service quality attributes).

In the case of linear models (such as linear regression models), the orthogonality of the design is considered an especially important property. The *VC* matrix of a linear regression model is represented by the expression:

$$VC = \sigma^2 \left[X'X \right]^{-1} \tag{1}$$

Where σ^2 is the model variance and *X* is the design matrix. It is relatively simple to demonstrate that the diagonal elements of *VC* (that is, the variances of the parameter estimates) are minimized and that the off-diagonal elements (covariances) are zero when *X* is an orthogonal matrix. Therefore, for linear models, apart from the absence of

[1] Rose and Bliemer (2009) point out other typical representations of the design matrix used by other researchers that associate multiple rows of the design matrix to an individual choice situation (see, e.g. Huber and Zwerina, 1996; Sándor and Wedel, 2001, 2002; Carlsson and Martinsson, 2002; Kanninen, 2002; Kessels et al., 2006).

multicollinearity (i.e. uncorrelated parameter estimates), the analyst will have the guaranty that the model will optimize the significance level of the parameter estimates, producing the highest t-ratios at a given sample size.

Unfortunately, these properties are not transferred to non-linear models, such as discrete choice models, and orthogonality does not ensure the minimization of the standard errors of the parameter estimates. This is the main reason why many researchers during the past decade have questioned the use of orthogonal designs to analyse SC data providing different strategies to generate statistically efficient designs (see e.g. Huber and Zwerina, 1996; Kanninen, 2002; and Sándor and Wedel, 2002).

A choice among a set of alternatives requires the application of a decision rule. Discrete choice models are based on the utility maximization behavioural rule, which lies under the scheme of the rational choice, and normally implies a compensatory decision process, i.e. individuals made trade-offs among attributes in determining the alternative with the highest utility. Since the analyst does not have full information about the utility of the decision maker *n* for the alternative *j* in the choice situation *s,* U_{nsj}, it is modelled as the sum of two components: a deterministic or observable utility V_{nsj}, and a random term ε_{nsj} representing the portion of utility unknown to the analyst. Thus, the true utility to the decision maker is represented by the random variable $U_{nsj} = V_{nsj} + \varepsilon_{nsj}$; and therefore, the analyst, under the assumption of utility maximization, is only able to model the choice probability of the different alternatives.

The observed component of the utility is typically assumed to be a linear relationship of observed attribute levels of each alternative, *X*, and their corresponding weights represented by a set of unknown parameters β. The random component, can adopt different forms depending on the type of model considered. Thus, in the case of the widely used MNL model, the unobserved random component ε_{nsj} are assumed to be a vector of variables iid extreme value type I distributed. Then the probability that respondent *n* chooses alternative *j* in choice situation *s* is given by the well know formula (see McFadden, 1974):

$$P_{nsj} = \frac{\exp(V_{nsj})}{\sum_{i \in J_{ns}} \exp(V_{nsi})} \tag{2}$$

Where J_{ns} is the set of alternatives presented to respondent *n* in the choice situation *s.* Unknown parameters β are estimated from data, SC data in our case, by maximizing the likelihood function *L* given by the following expression:

$$L = \prod_{n=1}^{N} \prod_{s \in S_n} \prod_{j \in J_{ns}} (P_{nsj})^{y_{nsj}} \tag{3}$$

Where *N* denotes the total number of respondents, S_n is the set of choice situations faced by respondent *n, and* y_{nsj} is equal to one if respondent *n* chooses alternative *j* in choice situation *s*, and zero otherwise. Equation (3) is transformed into a simpler expression by taking the natural logarithm (log-likelihood), yielding the same optimal solution without loss of generality:

$$\log L = \sum_{n=1}^{N} \sum_{s \in S} \sum_{j \in J_{ns}} y_{nsj} \log P_{nsj} \tag{4}$$

As the error terms in the MNL model are independent variables, all the observations are treated as independent, obviating the possible correlation among choices of the same respondent in the different choice sets. Despite this fact pose an important question about the appropriateness of the MNL model to deal with panel data, there is still much research work done using this model to analyze SC data.

In case of a ML model, we assume that some of the parameters are random[2], following a certain probability distribution. In that case, simulation is required and the expected likelihood function in the following expression is maximized in order to estimate the distribution of the parameters.

$$E(L) = E\left(\prod_{n=1}^{N}\prod_{s\in S_n}\prod_{j\in J_{ns}}(P_{nsj})^{y_{nsj}}\right) = \prod_{n=1}^{N}E\left(\prod_{s\in S_n}\prod_{j\in J_{ns}}(P_{nsj})^{y_{nsj}}\right) \tag{5}$$

In which the second term holds since we assume that all respondents make their decisions independent of each other, but taking into account the dependency among the choice probabilities for a single respondent in multiple choice situations. This formulation is known as the panel Mixed Logit model (Bliemer and Rose, 2009). The expectation in (5) is taken over the random β values, which make the probabilities P_{nsj} random as well. As in the case of the MNL model, expression (5) is also simplified by considering the log-likelihood:

$$\log E(L) = \sum_{n=1}^{N}\log E\left(\prod_{s\in S_n}\prod_{j\in J_{ns}}(P_{nsj})^{y_{nsj}}\right) \tag{6}$$

Behind the construction of statistically efficient designs there exists a trade-off between: i) obtaining the maximum amount of information about the parameters of the attributes from each choice task; and ii) reducing the cognitive effort that the respondent may experience during the entire experiment through a reduction in the number of choices required. Thus, efficiency measures for SC experiments focus on the minimization of sample size required to obtain asymptotically efficient and reliable parameter estimates; or alternatively, minimize the standard error of the parameter estimates for a fixed number of choice observations. The most commonly used efficiency measure within the literature is the D-error that is computed by taking the determinant of the asymptotic VC matrix and applying a scaling factor in order to take the number of parameters into account. Thus, for one single respondent, the D-error of the experimental design represented by the design matrix X is defined as:

$$D-\text{error} = (\det\Omega_1)^{1/K} \tag{7}$$

Where Ω_1 is the asymptotic VC matrix for one single respondent facing s choice situations in the experiment, and K is the total number of parameters to estimate. The D-error measures the inefficiency of the design in the sense that the lower the D-error the more efficient the design is. A design with the lowest D-error is called D-optimal. Bliemer and Rose (2006) point out that it is very difficult, in practice, to find the design with the lowest D-error, therefore we should use instead a design with sufficiently low D-error, called the D-efficient design.

For linear models, Ω_1 is defined in terms of the design matrix as in Equation (1), and it is relatively straightforward to demonstrate that the D-error is minimized when X is an orthogonal matrix. Therefore, the orthogonal design is optimal, i.e., it is the one with the lowest D-error. The former argument does not hold for non linear models and the derivation of the asymptotic VC matrix entails certain complexity. The asymptotic VC matrix is defined as the inverse of the Fisher information matrix I_1 (see, e.g. Train, 2003), where the latter, is equal to minus the expected Hessian (i.e., the matrix of the second derivatives) of the log-

[2] Note that this is true for the two equivalent formulations for this model, error component and random parameters used in practice (Train 2003)

likelihood function. Therefore, in general, we will say that Ω_1 varies with the model to be estimated and is represented in terms of the design matrix *X*, the outcomes of the survey *Y*, and the parameter values β :

$$\Omega_1(X,Y,\beta) = I_1(X,Y,\beta)^{-1} = \left(-E\left(\frac{\partial^2 \log L(X,Y,\beta)}{\partial\beta\partial\beta'} \right) \right)^{-1} \quad (8)$$

Since β are unknown in advance, prior information $\tilde{\beta}$ must be used to approximate the true values of the parameters.

The computation of the D-error can also be extended to a sample of *N* respondents, simply by computing the Fisher information matrix as minus the sum of the expected Hessian for every single respondent.

For the MNL model, the vector of outcomes drops out when computing the second derivatives of the log-likelihood function (McFadden, 1974), simplifying the analytical computation of the asymptotic VC matrix. In other cases, such as the panel ML model, Monte Carlo simulation is performed in order to simulate the outcomes of the survey. Bliemer and Rose (2009) and Bliemer et al. (2008) provide the analytical derivation of the asymptotic VC matrix for the panel ML model and for the Nested Logit (NL) model respectively.

Depending on the amount of information available on the prior parameters different D-error measures can be defined:

i. When no information is available, the parameters are set to zero ($\tilde{\beta} = 0$) and the efficiency measure is called D_z-error (see e.g. Huber and Zwerina, 1996).
ii. When some information is available by an accurate guess $\tilde{\beta}$ of the true parameters (priors), the efficiency measure is called D_p-error (see e.g. Carlson and Martinsson, 2002; and Huber and Zwerina, 1996).
iii. When information is available but with uncertainty, we use a Bayesian approach assuming some random priors that follow a probability distribution yielding the D_b-error measure which is represented by the expected value of the D-error according to the priors distribution (See e.g. Sándor and Wedel, 2001).

Different strategies can be use to generate efficient designs. The N-gene program is the most recent and specialized software for generating experimental designs (especially efficient designs) that are used in stated choice experiments (See ChoiceMetrics, 2009 for a detailed reference about the program).

To gain realism and accuracy in the outcomes of the experiment, it is common practice to customize the levels of the attributes to respondent's current experience. Thus, alternatives presented in the choice sets are different for each respondent and are defined pivoting attribute level values around the reference alternative, considering relative or absolute deviations. As the efficiency of the design depends on the attribute values, in an ideal situation, a specific design should be created for every single respondent. As this could be difficult to implement in practice, Rose et al. (2008) suggest different strategies to cope with this problem. The best way is to collect the data in a two stage process. In the first stage, collect the data for the reference alternative, and in the second stage optimise a design for each individual based on their reference levels. This could be done on the fly[3] if the design generator is linked to the questionnaire, but this requires specialized software to conduct the survey. Another way is to generate the design for different segments based on segment

[3] This could involve substantial processing time for certain models such as the panel ML.

averages assumed as reference levels, and to assign respondents to these segments based on how close they are in terms of the real levels. Although the latter would produce sub-optimal results, from a practical stand point, it represents the best strategy if the appropriate means are not available. As the D-error (as well as the standard error of the estimates) is expected to decrease with the sample size, the use of an efficient vs. a non-efficient design represents a compromise between model accuracy and expending extra money in additional surveys.

3. THE DATA SET

In this paper we use an existing data set consisting in choices made by 297 respondents that provided information about their travel preferences in nine different choice situations, yielding a total of 2673 sample observations. These data are part of a research project financed by the Spanish Ministry of Transport with the main purpose of analyzing potential demand for new high speed rail (HSR) services in the corridor Madrid-Barcelona (see Román et al, 2010 for more details about the project). SC data were collected during the second term of the year 2004, avoiding vacation periods (Easter and local holidays). At this time, the HSR was already operating between Madrid and Zaragoza (the main intermediate city along the corridor), but rail services between Madrid and Barcelona were still provided by conventional trains. Thus, a specific stated choice (SC) experiment was included in the questionnaire of plane travellers that were faced to the choice between the plane and the new HSR alternative in different hypothetical choice situations.

The attributes included in the experiment represent typical level-of-service variables like *travel time* (t_v), *access and egress time* (t_a), *travel cost* (c_v) and *frequency* (f)[4]. We also include the latent variables *reliability* (r) and *comfort* (C). This set of variables helped us to define the global quality of the alternatives in each choice situation.

Main features of the experimental design

A main effects fractional factorial design consisting of six attributes (four defined at three levels and two at two levels) and nine scenarios for each alternative was created using the WINMINT software[5]. The Table 1 presents the combination of attribute levels in the experimental design using the orthogonal coding (Louviere et al. 2000). Attribute levels are balanced except in the case of the *frequency* and *comfort;* and the design is non orthogonal. In this case, it is easy to check that the design matrix A does not satisfy the property: $A'A$=Diagonal matrix.

[4] This variable was introduced in the survey as the service headway, i.e. the time between two consecutive services, but was then specified in the model as the service frequency; that is, the number of services per hour.

[5] This is a standard software, developed by *Rand Europe* http://www.hpgholding.nl/ (the former Hague Consulting Group (HCG)), which was frequently used to conduct SC experiments at the time this data set was gathered.

Table I – Attributes and levels' codes in the experimental design. Orthogonal codes.

Scenario	**PLANE** (Levels' codes)					
	c_v	**t_v**	**t_a**	**r**	**f**	**C**
1	-1	-1	-1	-1	-1	-1
2	-1	0	0	+1	-1	+1
3	-1	+1	+1	0	-1	-1
4	0	-1	0	0	+1	-1
5	0	0	+1	-1	+1	+1
6	0	+1	-1	+1	+1	-1
7	+1	-1	+1	+1	-1	-1
8	+1	0	-1	0	-1	+1
9	+1	+1	0	-1	-1	-1

Scenario	**HSR** (Levels' codes)					
	c_v	**t_v**	**t_a**	**r**	**f**	**C**
1	-1	-1	-1	-1	-1	1
2	-1	0	0	+1	-1	1
3	-1	+1	+1	0	-1	1
4	0	-1	0	0	1	1
5	0	0	+1	-1	1	1
6	0	+1	-1	+1	1	1
7	+1	-1	+1	+1	-1	1
8	+1	0	-1	0	-1	1
9	+1	+1	0	-1	-1	1

Choice sets formation

Choice sets in WINMINT were created according to the following recursive process:

1. The program makes a permutation of the levels of the attributes. For example if the permutation of the Figure 1 is considered for the travel cost, the *level -1* is turned into the *level +1*, the *level 0* is turned into the *level -1*; and the *level +1* is turned into the *level 0.* Hence, after the permutation, the combination of levels for the travel cost in the nine scenarios would be: *+1, +1, +1, -1, -1, -1, 0, 0, 0*

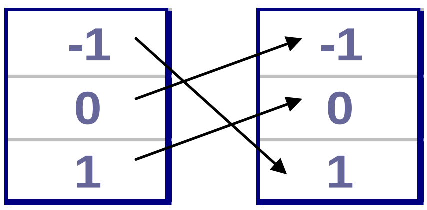


Figure 1 – Permutation of levels

2. The program selects at random scenarios for the two alternatives creating different choice sets. For example if the scenario 3 is selected for the plane and the scenario 8 is selected for the HST, the choice set of Table 2 is created.

Table 2 – Example of choice set.

CHOICE SET 1							
Scenario	**c_v**	**t_v**	**t_a**	**r**	**F**	**C**	**Alternative**
3	-1	+1	+1	0	-1	-1	**PLANE**
8	+1	0	-1	0	-1	1	**HST**

3. The program creates nine different choice sets for the same individual.
4. The program stars with a new individual at step 1.

Attributes and levels

Level codes in the experiment were associated to plausible values of the corresponding attributes. To gain realism, the levels assigned to some attributes in the SC exercise were customized to each respondent experience pivoting the information provided by some questions included in the questionnaire about the reference alternative (the plane, in this case). Thus, the levels of *travel cost* and *access time* were defined in terms of the values experienced by the sample respondents; and plausible percentage variations according to the available information about future fares and access time for the HSR were also considered. The service *frequency* was also customized to the departure time declared by the respondent. This information is presented in Table 3.

Table 3 – Attributes and levels

Attributes	Levels	Mode			
		Plane		HSR	
Travel cost (c_v)	-1	c_v*1.10		c_v	
	0	c_v		c_v*0.90	
	+1	c_v*0.90		c_v*0.80	
Travel time (t_v)	-1	1h 20 min		2h 45 min	
	0	1h 10 min		2h 30 min	
	+1	1h		2h 15 min	
Access + Egress time (t_a)	-1	t_a*1.20		t_a	
	0	t_a		t_a*0.90	
	+1	t_a*0.80		t_a*0.80	
Frequency (Headway) (f)		*Departure before 9:00*	*Departure after 9:00*	*Departure before 9:00*	*Departure after 9:00*
	-1	Every 30 min	Every 60 min	Every 60 min	Every 90 min
	+1	Every 15 min	Every 30 min	Every 30 min	Every 60 min
Reliability (r)	-1	30 min delay (Inside the plane)		10 min delay	
	0	15 min delay (in the boarding gate)		5 min delay	
	+1	Departure on time		Departure on time	
Comfort (C)	-1	Low: Small leg room Narrow seats			
	+1	High: Ample leg room Wide seats		High: Ample leg room Wide seats	

c_v=Travel cost in plane
t_a=Access+Egress time in plane

Figure 2, presents an example of a choice task in the form presented in the survey to the respondent.

Plane	**HSR**
Travel cost: 99 € **Travel time:** 1 h **Access+Egress time:** 36 min **Reliability:** 15 min delay **Service Frequency:** every 30 min **Comfort:** low (small leg room)	**Travel cost:** 72 € **Travel time:** 2h 30 min **Access+Egress time:** 45 min **Reliability:** 5 min delay **Service Frequency:** every 60 min **Comfort:** high (ample leg room)

Actual Travel cost: 90€
Actual Access time: 45 min
Departure before 9:00

Which alternative do you prefer for a trip like this one?
☐ **Plane** ☐ **HSR**

Figure 2 – Example of a choice task presented to the respondent

Model estimation

Two different model specifications were considered for this data set based on the utility maximization behavioural rule: a Multinomial Logit model (MNL) and an error component panel Mixed Logit model (ECPML) with fixed parameters but accounting for correlation among the responses provided by the same respondent[6]. In both cases a linear-in-the-parameter specification was considered for the observed utility. Parameter estimates will be used as prior information in the computation of the D-error for the analysis in the next section. Estimation results are presented in Table 4. All parameter estimates resulted significant at the 95% confidence level, with the only exception of the *frequency* in the MNL model and the *frequency* and the *comfort* in the ECPML model. It is worth to point out that the error component *sigma* in the ECPML model resulted with a high significance, indicating the existence of strong correlation among the choices of the same respondent in the experiment. This highlights the importance of using the appropriate modelling strategy when dealing with SC data.
Parameter estimates, provide very reliable prior information for the analysis carried out in the next section for the construction of efficient designs.

[6] For this purpose we added to the error term a random component sigma following the normal distribution with zero mean

Table 4 – Estimation results

	MNL			ECPML		
Parameter	**Estimate**	**Std. error**	**t-test**	**Estimate**	**Std. error**	**t-test**
Travel Cost	-0.03073	0.003	-9.1	-0.08870	0.007	-12.2
Travel Time	-0.00778	0.001	-7.4	-0.01820	0.003	-6.9
Access Time	-0.01128	0.003	-4.0	-0.02490	0.005	-5.2
Reliability	-0.01608	0.003	-5.2	-0.03960	0.005	-7.6
Frequency	0.07087	0.067	1.1	0.20000	0.119	1.7
Comfort	0.16840	0.082	2.0	0.14800	0.140	1.1
Sigma	-	-	-	3.37000	0.235	14.4
l*(0)	-1863.873			-1863.873		
l*(θ)	-1792.827			-1181.523		

4. COMPARISON OF THE ORIGINAL DESIGN WITH THE EFFICIENT DESIGN

In this section we contrast the efficiency of the original design with the efficient design for the two models estimated. For this purpose, we evaluate the original design through the computation of the D_p-error for every single respondent separately, considering the design matrix provided by our former experiment in each particular case. This information was compared with the D_p-error obtained in the case an efficient design was used instead. As we had already pointed out, prior parameters were taken from model estimates in the former section. In the case of the MNL model, a special code in Matlab was created to compute the D_p-error of the actual and efficient designs respectively. For the ECPML model case, where Monte Carlo simulation is required to simulate the outcomes of the experiment, the N-gene software (ChoiceMetrics, 2009) was used instead. In this case the, the efficient design was obtained after 100 iterations. With a regular computer, it took a computation time of five hours to run the program for 20 individuals once at a time.

Figure 3, shows the comparison of the D_p-error of the actual design (horizontal axis) with the D_p-error of the efficient design (vertical axis) for the individuals in the sample. All the observations lay below the diagonal, indicating the consistency of the analysis; that is, the efficient design exhibits lower D_p-error than the actual; and for a given model, the further from the diagonal is an observation, the more inefficient is the information provided by the actual design (represented by yellow dots in the graph). Although observations corresponding to the ECPML model are more distant from the diagonal than observations of the MNL model, this fact does not directly confer higher gains of efficiency to the ECPML model, as this effect could be confounded with the differences in scale that exist when computing the D_p-error for the two models.

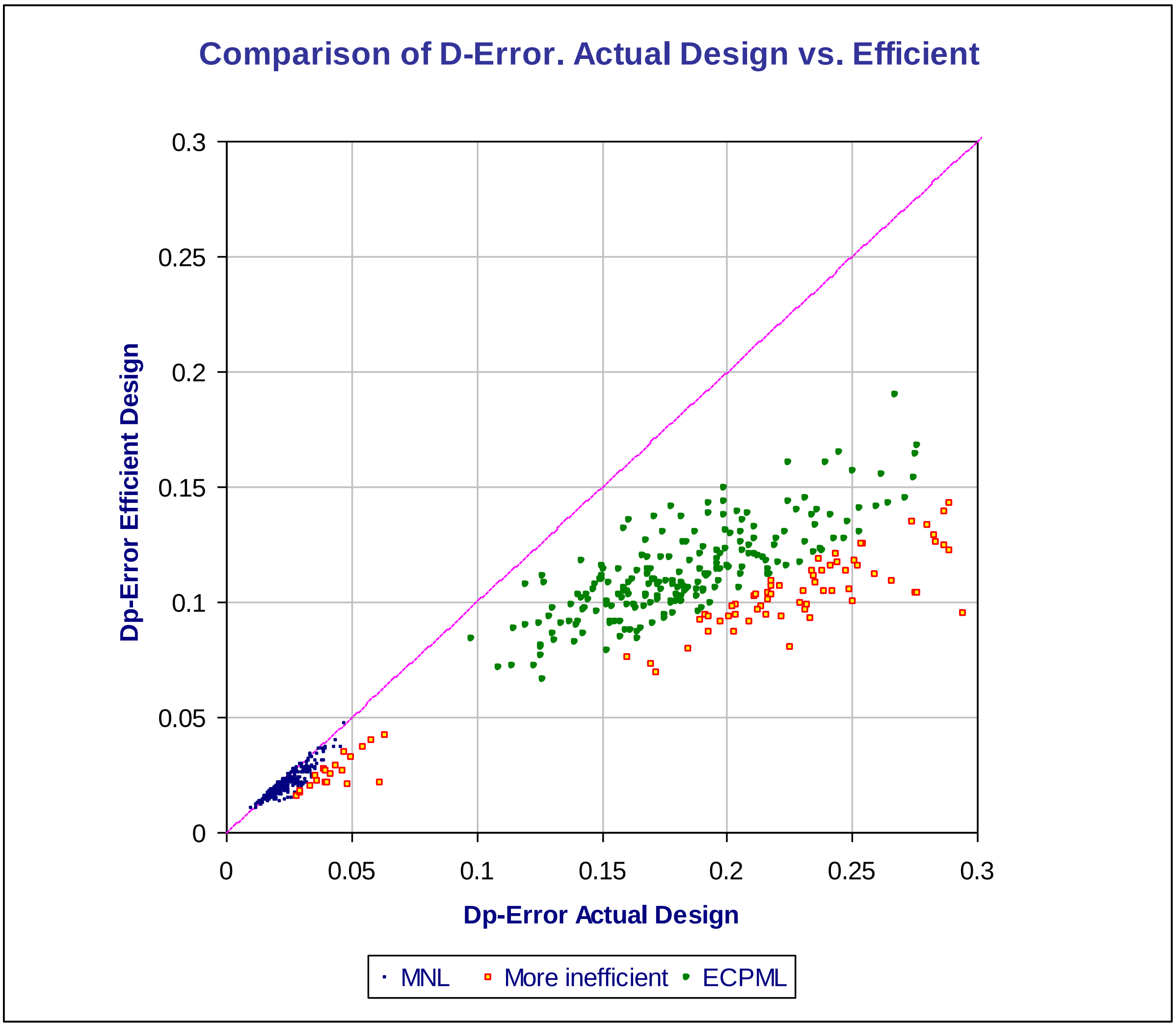


Figure 3 – Comparison of the actual design vs, the efficient for MNL and ECPML models

In Figure 4 we compare in relative terms the gains in efficiency for the two models defined in terms of the percentage reduction in the D_p-error by using the efficient design. Hence, for the MNL model, gains in efficiency are less than 20% for 200 individuals whilst, for the ECPML model, gains in efficiency are higher than 30% for 248 observations. Therefore, the impact of the efficient design upon the reliability of the estimates is much more positive for the ECPML model than for the MNL model. This could be an important argument in favour of using efficient designs, if we take into account that panel ML models represent the appropriate modelling strategy when dealing with SC data. Considering that the number of iterations used to compute the D_p-error of the efficient design in this exercise is relatively low, gains in efficiency could be substantially higher if we increased the number of iterations.

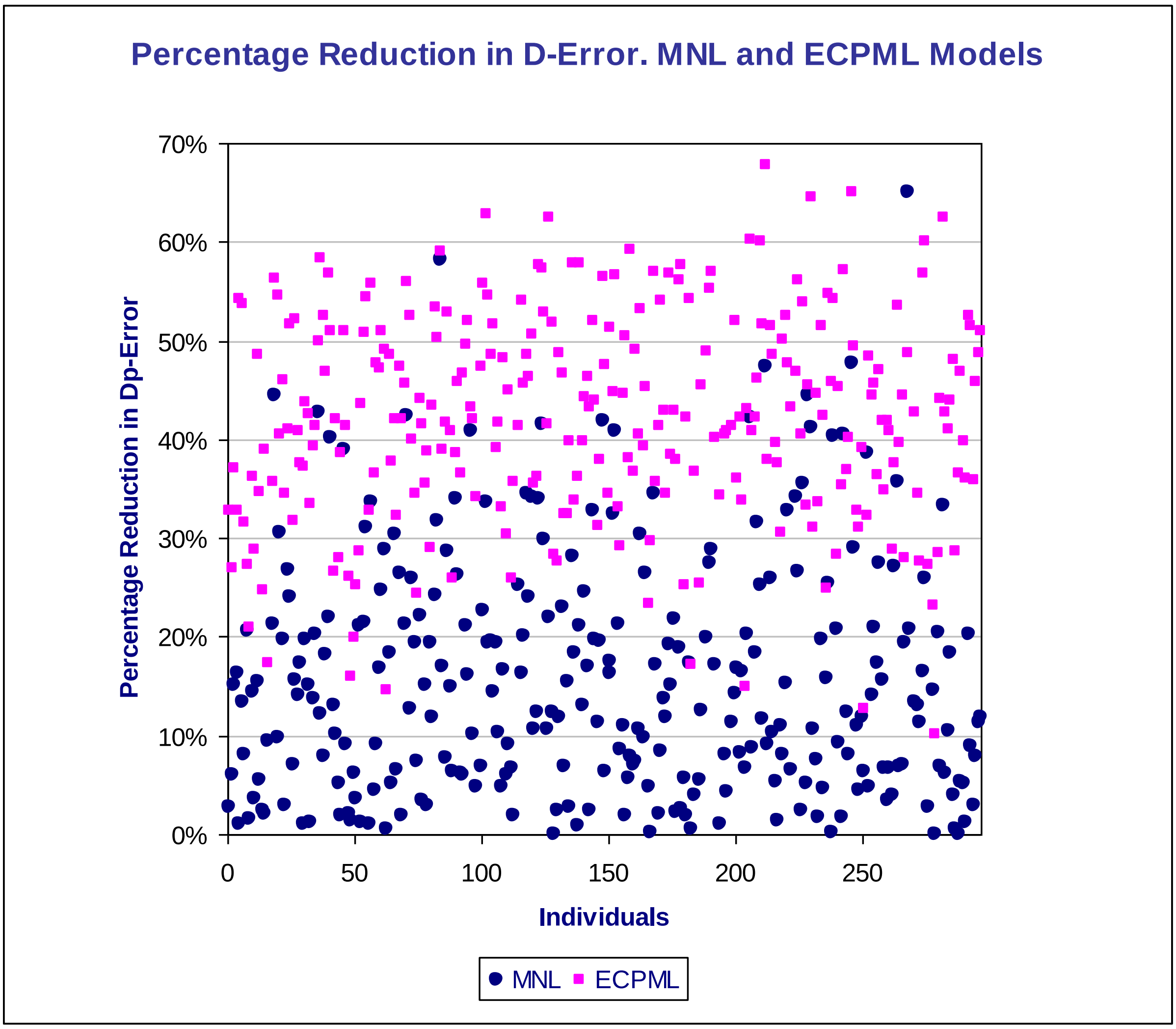


Figure 4 – Percentage reduction in D_p-error for the MNL and the ECPML models

In order to interpret efficiency gains in terms sample size savings, instead of obtaining the D_p-error for every single respondent, we analyze how the accumulate D_p-error, for the actual and efficient designs, diminishes with the sample size. This analysis is represented in the graphs of Figure 5 for the MNL model case. Although it is difficult to distinguish, due to the scale of the graph, the graphic of the efficient design lies bellow the graphic of the actual design for any given sample size. In the right hand side graph we observe that the efficient design would attain the actual level of accuracy (i.e. that of the actual design) with a sample size saving of 16 observations.

A similar analysis has been carried out for the standard error of the parameter estimates. These results are presented in Table 5. We observe that the highest percentage reduction (8.03%) in the standard error, for the actual sample size when using the efficient design, is produced for the *travel cost* parameter. However, the highest sample size savings (68 observations) for the actual level of accuracy are produced for the *access time* parameter.

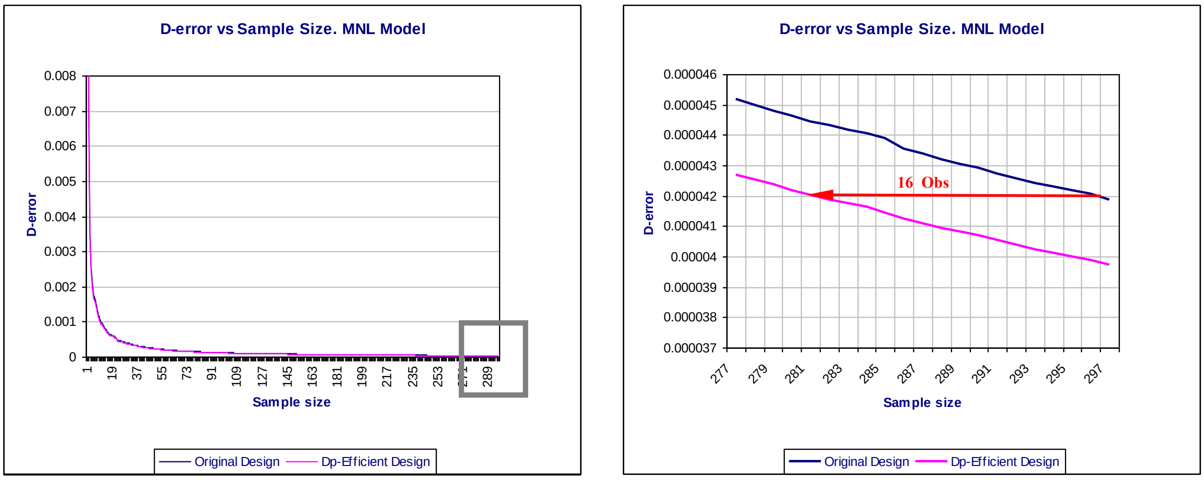


Figure 5 – D_p-error versus sample size. MNL model

Table 5 – Minimum sample size required for the efficient design. MNL model

PARAMETER MNL	Minimum Sample Size (with the efficient design)	Sample Savings	% Reduction in SE or D_p-error (with the efficient design)
Travel Cost	270	27	-8.03%
Travel Time	275	22	-2.99%
Access Time	229	68	-8.00%
Reliability	289	8	-1.15%
Frequency	280	17	-2.03%
Comfort	281	16	-2.71%
D_p-Error	**281**	**16**	**-5.10%**

If we adjust a tendency line, of the potential type, to the accumulate D_p-error (see the green line in Figure 6), and extrapolate for additional observations, we observe that the original design would require 320 observations to attain the level of accuracy of the efficient design for the actual sample size.

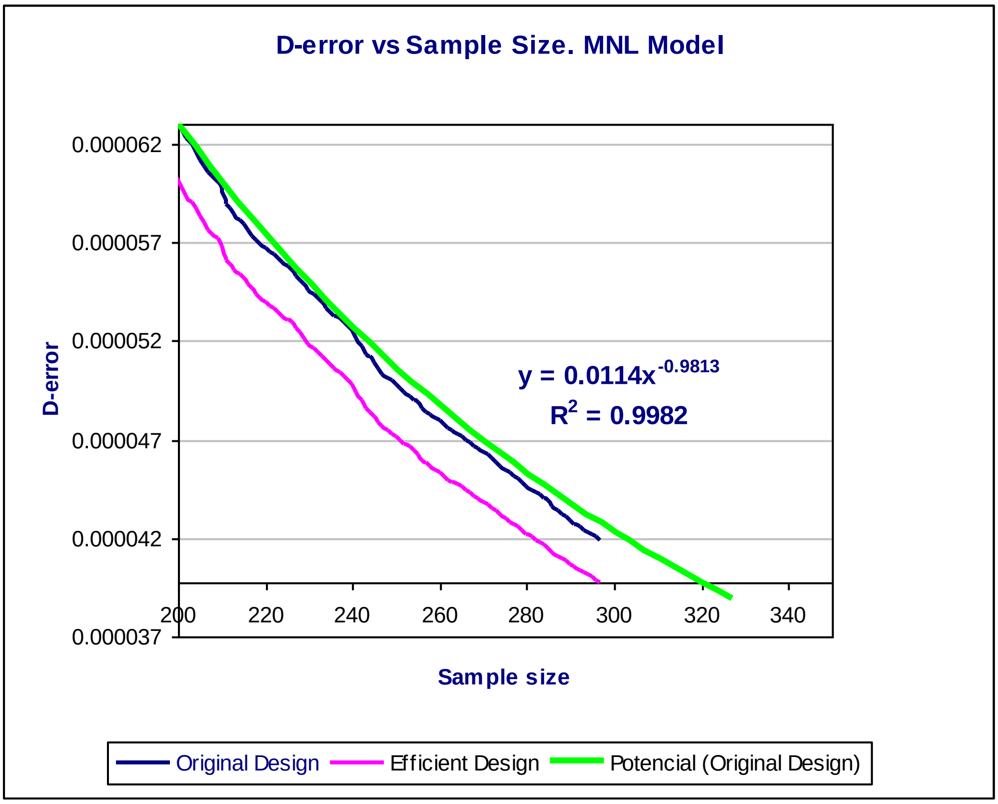
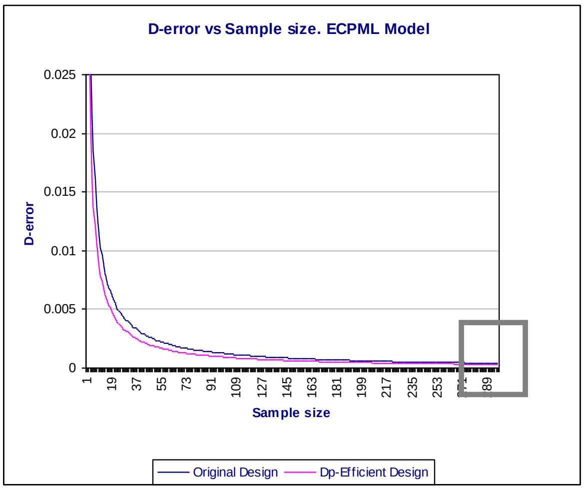


Figure 6 – Sample size required with the original design. MNL model

The same analysis is conducted for the ECPML model (see Figure 7). In this case, 70 observations less would be required in order to attain the actual level of accuracy. Regarding standard errors, we obtain substantially better results. The highest percentage reduction (21.23%) in the standard error, for the actual sample size when using the efficient design, is again produced for the *travel cost* parameter; and the highest sample size savings (124 observations) for the actual level of accuracy are produced, as well, for the *access time* parameter (see Table 6).

The tendency line adjusted to the accumulate D_p-error (see the green line in Figure 8) extrapolated for additional observations indicates that the original design would require 394 observations to attain the level of accuracy of the efficient design for the actual sample size.



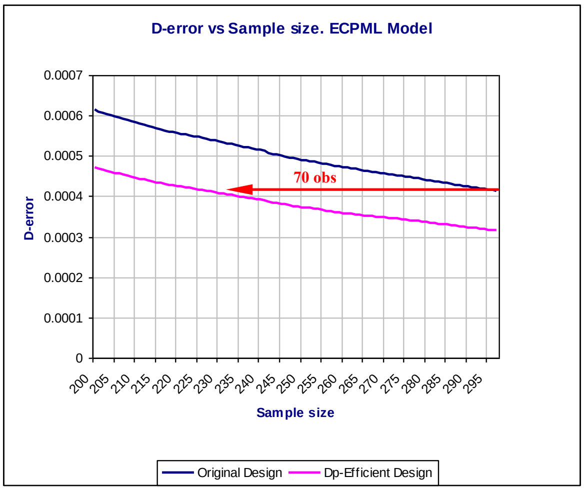


Figure 7 – D_p-error versus sample size. ECPML model

Table 6 – Minimum sample size required for the efficient design. ECPML model

PARAMETER ECPML	Minimum Sample Size (with the efficient design)	Sample Savings	% Reduction in SE or D_p-error (with the efficient design)
Travel Cost	198	99	-21.32%
Travel Time	218	79	-14.27%
Access Time	173	124	-20.92%
Reliability	215	82	-14.59%
Frequency	208	89	-18.03%
Comfort	226	71	-12.96%
D_p-Error	**227**	**70**	**-23.79%**

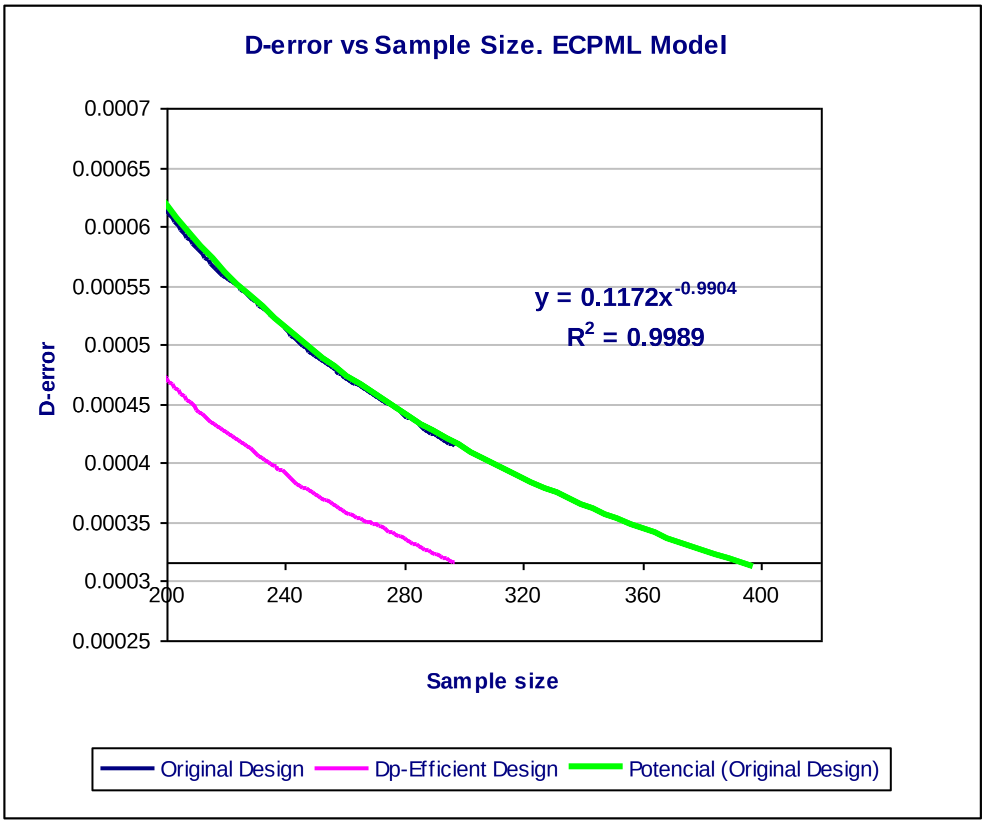


Figure 8 – Sample size required with the original design. ECPML model

5. CONCLUSIONS

SC data have become an essential tool to analyze consumers demand in many different contexts. Their use is especially important when the objective is to study the preference for alternatives that are not yet available in the marketplace. However, the construction of appropriate experimental designs has been object of discussion by researchers during many decades. The ability of the experiment to obtain significant parameter estimates has been the focus of attention in the more recent years, placing the interest on the construction of efficient designs based on the minimization of the D-error.

In this paper we quantify the efficiency gains produced by the efficient design using real data, in the context of mode choice between the plane and the new high speed rail in the route Madrid-Barcelona. To this end, we evaluate the original design computing the D_p-error. This value is compared with the D_p-error obtained for the efficient design generated with the aid of the specialized software N-gene. The use real SC data allowed us to obtain very reliable prior parameters from model estimates as necessary input for the analysis. As in the original design, the different choice tasks were created pivoting attribute levels from the reference alternative, the comparison of the D_p-error for every single respondent was required.

The analysis was carried out for two different choice models. In the first case, the general MNL model was used. The analysis demonstrates that the efficient design would produce moderate savings in the sample size (up to 5%) and fair reductions in the estimates' standard errors (less than 8%). In the second case, a panel ML model was used. This model accounts for the correlation amongst the choices of the same respondent in the different choice situations, being more appropriate to replicate choice behaviour. Substantial savings in the sample size (up to 24%) are obtained in this case, yielding also considerable reductions in the parameters' standard errors, ranging from 12% to 22%.

Finally, we would like to highlight the importance of considering the appropriate modelling strategy, as this reinforce the benefits of using efficient designs to analyze SC data.

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