Transportmetrica, Vol. 1, No. 3 (2005), 209-221

DOES UNIFORM DESIGN REALLY WORK IN STATED CHOICE MODELING? A SIMULATION STUDY

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Received 23 October 2004; received in revised form 24 February 2005; accepted 15 June 2005

Stated preference/choice methods have become established modeling tools for transportation studies. At the core of these methods is experimental design, which usually employs orthogonal arrays. This conventional design method, however, imposes constraints on the number of attributes and /or levels that may be included in a study, for the number of profiles it provides may be too large to handle, particularly when the number of attributes and/or levels is large and sometimes it cannot provide a reasonable number of profiles. Recently, Wang and Li (2002, *Geographical Analysis*, **34**, 350-362) introduce a new design method that may overcome the shortcomings of the conventional approach: uniform design. The number of profiles generated by uniform design is substantially less than that by orthogonal design, particularly for uneven numbers of levels. Further, uniform design can provide solutions to cases where the orthogonal design cannot. This paper presents a simulation study to analyze the statistical properties of uniform design and to compare uniform design and orthogonal design on these properties. Specifically, we study the ability to pick up the significant variables and the accuracy of parameter estimation and model prediction by uniform design and compare them with that by orthogonal design. The simulation results show that parameters estimated from uniform design are unbiased. The efficiency of the parameter estimations of uniform design is comparable to that of orthogonal design.

KEYWORDS: Uniform design, orthogonal design, experimental design, stated preference method, stated choice method

1. INTRODUCTION

Stated preference/choice methods have become a popular modeling tool for transportation studies. At the core of these methods is experimental design, which usually employs orthogonal design (or called orthogonal arrays). In order to ensure that the estimation of model parameters is unbiased and efficient, orthogonal design extracts from the profiles of the full factorial design a fraction in which the attribute arrays are orthogonal and attribute levels are balanced (i.e., levels of each attribute appear the same number of times in the fraction). Orthogonal designs are often recommended for their desirable properties, such as unbiased and efficient estimation of model parameters, the ability to estimate interaction effects and the flexibility to build separate models for individual travelers. The number of profiles generated by the orthogonal design, however, is sizable and rapidly increases with the number of attributes and/or levels. A large number of profiles imply high modeling costs and huge burden on respondents. In the extreme cases, the orthogonal design provides no solution (e.g., orthogonal design provide no solution for the case of 8 attributes, each with 6 levels) or the number of profiles can be too large to be practically handled. In such cases, modelers may have to condense the high-level attributes into low-level ones (e.g., five-level attributes are condensed into three-level attributes). In the past decades, there have been recurrent interests and persistent attempts to develop ways of handling the problem of large number of attributes. For example, Johnson (1974) suggested the ‘trade-off procedure’, which considers attributes on a pairwise basis, respondents are asked to rank the combinations of each pair of attribute levels from most preferred to least preferred.

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Louviere (1984) proposed the so-called Hierarchical Information Integration (HII) method, which group attributes into several non-overlapping sets. Each set is supposed to represent a particular construct (e.g., quality, comfort, accessibility, etc.). Separate experiments are designed and administrated to define the constructs, which are then used to develop a bridging design for concatenating the results of the separate designs and the bridging design into a fully specified utility model. This method was extended by Oppewal et al. (1994) to a so-called integrated HII approach, which includes the summary evaluative measures of all other constructs in constructing a preference or choice experiment for a particular construct. Wang et al. (2000) suggested a pairwise design method, which uses only a pair of attributes to construct a profile, assuming the values of the other attributes no change.

However, all these approaches are based on orthogonal design and applicable only to specific cases. Recently, Wang and Li (2002) introduced a new experimental design method- uniform design, which has the potential to overcome the drawbacks of orthogonal design. As for uniform designs, readers are referred to Fang et al. (2000) and Fang and Mukerjee (2000). This design method selects from the s-dimensional space ('s' refers to the number of attributes) experimental points or profiles that are uniformly (or evenly) scattered in the space. The number of profiles produced by uniform design is substantially less than that by orthogonal design. In addition, uniform design can easily handle the cases of attributes with uneven numbers of levels and provide a reasonable number of profiles. For details about the principles of uniform design, how to construct uniform design and how to apply uniform design for stated preference/choice studies, readers are referred to Wang and Li (2002).

The aforementioned advantages of uniform design (over orthogonal design) are not at no cost. Uniform design only requires that attribute levels be balanced in the profiles. Orthogonality, however, is not guaranteed. As both orthogonality and balance are usually considered important requirements for experimental design, if orthogonality is not maintained in uniform design, a number of questions regarding estimation and prediction may be raised (see, for example, Bunch and Bastell (1989), for discussion on the statistical properties of estimators). Firstly, are parameters estimated from uniform design unbiased? The unbiasedness of parameter estimation is guaranteed only for large samples (asymptotically). How about the unbiasedness of small sample? Chapman and Staelin (1982) studied the overall unbiasedness of estimators. However it couldn't preclude the possibility that subsets of the parameters could be biased. Are the parameters estimated from uniform design unbiased for small samples? Secondly, when we analyze the data, we need to test the significance of the effects. In such a case, we may make two kinds of errors: inferring the significant effects to be insignificant or the insignificant effects to be significant. How would uniform design perform in this regard? Can uniform design limit the number of errors admissible? Thirdly, are parameters estimated from uniform design close enough to the true parameters? Fourthly, will the models developed from uniform design provide predictions at acceptable accuracy level? or specifically, are the market shares predicted from uniform design close enough to the true market share? Finally, how would uniform design comparable to orthogonal design in terms of these properties? It is important to find answers to these questions before one may seriously consider uniform design for developing stated preference models.

This study thus makes an attempt to answer these questions. We study the case that uniform design is used for developing stated choice models. The case for stated preference models may be extended straightforward. We use the simulation approach to generate observation data for different scenarios. For simplicity, we only consider fixed choice set design (a profile is used to construct a choice set) and additive models, that is to say we only consider main effects in the simulation models. The reference models are from Wang and Li (2002). All the effects are alternative-specific. The next section will introduce the notations and measures that will be used. Section 3 explains the simulation procedure. The simulation results are presented and discussed in Section 4. Section 5 discusses the findings and limitations and suggests future research works.

2. NOTATIONS AND MEASURES

To answer the above questions, we need to define some measures that can assess and compare uniform design and orthogonal design. We first introduce some notations. Let N be the total number of surveys in the simulation, p the number of effects in the simulation, J the number of alternatives in each choice set and h_k the number of the times the effect β_k being significant in N surveys at the level of 0.05, for $k = 1,..., p$.

As discussed in Section 1, a good design should have strong ability to find the real significant effects or significant attributes that have an effect on the choice behavior. To measure this ability, we define the first measure: Effect Error Ratio (EER). The effect error ratio for effect β_k is defined as:

$$\mathrm{EER}_k = \begin{cases} h_k/N & \text{, when effect } k \text{ is not in the simulated model} \\ (N-h_k)/N & \text{, when effect } k \text{ is in the simulated model} \end{cases}, \text{ for } k = 1,..., p. \quad (1)$$

The effect error ratio refers to the ratio that an effect has been judged erroneously: from significant to insignificant or from insignificant to significant. A good design will not leave out the significant effects or not include the effects or attributes that have no effect on the choice behavior. Obviously, a small effect error ratio suggests that the design has strong ability to find the real significant effects.

Apart from the ability to pick the significant attributes, the design should ensure that the estimation of the unknown parameters is unbiased, especially for small samples. This is an important requirement for statistical estimator. To measure the unbiasedness, we define the second measure: Confidence Interval (CI). Let $\hat{\beta}_{kl}$ be the estimation of β_k in the lth survey. For the N surveys, we may obtain:

$$\overline{\beta}_k = \frac{1}{N}\sum_{l=1}^{N}\hat{\beta}_{kl}, \quad (2)$$

and

$$\mathrm{STD}_k = \sqrt{\sum_{l=1}^{N}(\hat{\beta}_{kl} - \overline{\beta}_k)^2/(N-1)}. \quad (3)$$

Then the 95% CI of β_k can be written as:

$$\mathrm{CI}_k = \left(\overline{\beta}_k - t_{0.975,(N-1)} \times \mathrm{STD}_k/\sqrt{N},\ \overline{\beta}_k + t_{0.975,(N-1)} \times \mathrm{STD}_k/\sqrt{N}\right), \quad (4)$$

which can be used to test whether the estimator of β_k is unbiased. If the estimator of β_k lies in 95% CI, we say that this estimator is unbiased.

The third measure we will use is Estimate Accuracy (EA). Similar to Bunch and Bastell (1989), we define the estimate accuracy of the effect β_k as the following equation:

$$\text{EA}_k = \sqrt{\frac{1}{N}\sum_{l=1}^{N}(\hat{\beta}_{kl} - \beta_k)^2}\ , \text{ for } k = 1,..., p \tag{5}$$

Estimate accuracy is a measure of efficiency. Efficiency is another important requirement for estimator. An efficient estimator is the one that has small variance. The smaller the value of EA, the more efficient the estimator is. EA is thus used to assess the efficiency of the parameter estimation from uniform design and compare to that from orthogonal design.

Apart from estimation, we are also concerned with the prediction ability. A good design should be able to predict the market shares correctly. To measure the prediction ability, we generate five choice sets for testing prediction ability. Let P_{ih} be the true choice probability for *i*th alternative in the *h*th test choice set and the $\hat{P}_{ihl}$ estimation of P_{ih} in the *l*th survey. Then the Prediction Accuracy (PA) of P_{ih} , which is the fourth measure we will use, can be calculated by the equation as follows:

$$\text{PA}_{ih} = \sqrt{\frac{1}{N}\sum_{l=1}^{N}(\hat{P}_{ihl} - P_{ih})^2}\ , \text{ for } i = 1,..., J \text{ and } h = 1,...,5\ . \tag{6}$$

The lower the value of PA, the closer the prediction of market share is to the real situation.

3. SIMULATION PROCEDURE

All our simulations are based on the case study presented in Wang and Li (2002). This case study concerns the mode choice for inter-city transportation between Hong Kong and Guangzhou. Three five-level attributes, three three-level attributes and six two-level attributes are used to characterize different transportation modes. The authors apply uniform design $U_{30}(5^3 \times 3^3 \times 2^6)$ to design profiles and thirty profiles are derived. Each of the thirty profiles is used to construct a choice set. In each choice set, there are four choice alternatives: train, bus, flight and multi-modes. That is to say, J=4. Let us denote 1 for train, 2 for bus, 3 for flight and 4 for multi-mode. Based on the utility maximization principle, we assume that the utility for the *i* alternative in the *j* choice set can be written in the following form:

$$U_{ij} = V_{ij} + \varepsilon_{ij}\ , \tag{7}$$

where V_{ij} is the linear combination of attribute effects and ε_{ij} 's are independent across alternatives and are identically distributed. We assume that ε_{ij} follows the extreme value type I distribution with the parameters 0 and 1. Thus, the multinomial logit model (MNL) may be used to model the mode choice and estimate the parameters. We generate ε_{ij} from the extreme value type I distribution with the parameters 0 and 1. In practice, we do not know which effects are significant, so we consider all attribute effects in the model. For the purpose of this study, all choices are assumed to be independent.

The simulation procedure is as follows:

Step 1: Generate ε_{ij} randomly from the extreme value type I distribution with the parameters 0 and 1, and calculate U_{ij} for $j = 1$ to n and i=1 to 4. The alternative in the jth choice set with maximum utility will be chosen. This step simulates the process that an individual makes choice for n choice sets;

Step 2: Repeat Step 1 for m times. In other words, this step simulates the process that m individuals make choice for n choice sets. After this step, a survey is completed;

Step 3: Estimate the effects by maximum likelihood method using the multinomial logit model;

Step 4: Repeat Step 1, Step 2 and Step 3 N times;

Step 5: Calculate $(\mathrm{EER}_1,\ldots,\mathrm{EER}_p)$, $(\mathrm{CI}_1,\ldots,\mathrm{CI}_p)$, $(\mathrm{EA}_1,\ldots,\mathrm{EA}_p)$ and PA_{ih} for $i = 1,...,4$ and $h = 1,...,5$.

In order to examine the properties of uniform design under different circumstances, we vary the three important factors: choice designs, the number of individuals and the choice model. Both uniform design and orthogonal design are used to generate choice profiles and choice sets so that the properties of the two design methods can be compared. The number of individuals or sample size is varied to see the performance of the design methods for small and large samples. The simulation is partitioned into three scenarios. Table 1 lists the details of the three scenarios. In the first scenario, the same uniform design $U_{30}(5^3 \times 3^3 \times 2^6)$ that was used in Wang and Li (2002) is applied to construct profiles and choice sets. The objective of this scenario is to evaluate uniform design on EER and CI, i.e., to assess whether uniform design supports unbiased estimation and evaluate the ability of uniform design to find out significant effects. In order to assess the performance of uniform design for different sample sizes, the simulation is conducted for two different sample sizes: m=100 and m=200. In the second scenario, the three five-level attributes are condensed to three-level attributes. Uniform design $U_{24}(3^6 \times 2^6)$ and orthogonal designs $OA_{36}(3^6 \times 2^6)$ are used to construct profiles and choice sets respectively. Though the number of profiles is different for the two designs, the difference is not substantial. The performance of uniform design and orthogonal design on EER, CI and EA is compared. The third scenario is designed to compare uniform design and orthogonal design in cases that the two designs generate substantially different numbers of profiles. The three five-level attributes are replaced by three four-level attributes. In this case, uniform design generates 48 profiles or choice sets (i.e., $U_{48}(4^3 \times 3^3 \times 2^6)$ is used) and orthogonal design derives 144 ones (i.e. $OA_{144}(4^3 \times 3^3 \times 2^6)$ is used). The performance of the two designs on EER, CI, EA and PA for different sample sizes as well as for different models is compared. This scenario provides a platform to conduct more comprehensive comparison between the two designs.

The choice model is changed by assuming different values of the parameters. Model 1 is similar to the model estimated in Wang and Li (2002). This model is employed to study whether uniform design supports the unbiased estimation and its ability to pick the significant or exclude insignificant effects. Model 2 is different from model 1 in the value of parameters. The parameters of model 2 have larger values. This model is used to assess if the performance of uniform design in EER and CI will change for different values of the parameters. Models 3 and 4 correspond to Scenario III, but the parameters in model 4 is about half of that of model 3. These two models are used to compare uniform design and orthogonal design on the four measures proposed in the previous section. The details about the four models are presented in Table 2.

TABLE 1: Simulation scenarios

	Design	Sample size (*m*)	Model	Measures used
Scenario I	$U_{30}(5^3 \times 3^3 \times 2^6)$	100	Model 1	EER, CI
	$U_{30}(5^3 \times 3^3 \times 2^6)$	200	Model 1	EER, CI
Scenario II	$U_{24}(3^6 \times 2^6)$	100	Model 2	EER, CI and EA
	$OA_{36}(3^6 \times 2^6)$	100	Model 2	EER, CI and EA
Scenario III	$U_{48}(4^3 3^3 2^6)$	25	Models 3,4	EER, CI, EA and PA
	$U_{48}(4^3 3^3 2^6)$	50	Models 3,4	EER, CI, EA and PA
	$OA_{144}(4^3 3^3 2^6)$	25	Models 3,4	EER, CI, EA and PA

TABLE 2: Models used for simulation

Transport mode	Train				Bus				Flight			
Variables	Model				Model				Model			
	1	2	3	4	1	2	3	4	1	2	3	4
Constant	1.3	1.3	1.3	0.65	1	1	1	0.5	-0.5	-0.5	-0.5	-0.25
Travel costs 1	-0.1	-0.55	-0.5	-0.25	-0.25	-0.5	-0.48	-0.24	-0.18	-0.65	-0.45	-0.3
Travel costs 2	0	0	0	0	-0.12	-0.45	-0.43	-0.23	-0.2	0.55	-0.41	-0.22
Travel costs 3	0	---	0	0	0	---	0	0	0.2	---	0.38	0.23
Travel costs 4	0	---	---	---	0	---	---	---	0	---	---	---
Travel times 1	-0.15	-0.5	-0.45	-0.23	-0.25	-0.55	-0.45	-0.22	0	0	0	0
Travel times 2	0	0	0	0	0	0	0	0	0	0	0	0
Border times	0	0	0	0	-0.13	-0.6	-0.5	-0.24	0	0	0	0
Comfortable	-0.25	-0.6	-0.41	-0.24	-0.3	-0.5	-0.5	-0.23	-0.25	-0.6	-0.42	-0.24

Note: 1. "---" means the effects does not appear in the MNL model.
2. The coefficients for multi-mode are all zeros.

4. SIMULATION RESULTS

In this section, we will explain and discuss the simulation results for the three scenarios. Recall that scenario 1 is used to assess uniform design in terms of EER and CI, the two indicators proposed to assess the ability of picking significant effects or isolating insignificant effects and unbiasedness, respectively. The EERs and CIs of all parameters are calculated for two cases: m=100 and m=200. Table 3 presents the results. The last two columns of Table 3 show that almost all true values of the parameters lie within their confidence interval both for m=100 and m=200. The results are virtually no different for m=100 and m=200. This fact suggests that the parameters estimated from uniform design are unbiased for different sample sizes. In terms of EER, i.e., effect error ratio, Table 3 shows that when the sample size is 100 (i.e., m=100), the average EER is about 4.8%, or the average probability of making erroneous inference is about 4.8%. In other words, on average the chance that uniform design is unable to find out the significant effects or insignificant effects is less than 5%. The EER of all but two parameters is less than 10%. The effect error ratios for real significant effects decrease significantly when the sample size increases to 200. As Table 3 indicates that all effect error ratios are less than 10% and almost all effect error ratios for real significant effects are zeros. The average EER is about 2.3%, less than half of the EER when the sample size is 100. These findings suggest that the probability of making erroneous inference by uniform design is rather low in general and this probability will be reduced along with the increase of sample size.

TABLE 3: Simulation results for scenario 1

Variables	m=100 EER$_k$	m=200 EER$_k$	True values of parameters	m=100 CI	m=200 CI
Constant train#	0	0	1.3	(1.299, 1.321)	(1.294, 1.311)
Constant bus#	0	0	1	(0.989, 1.012)	(0.990, 1.006)
Constant flight#	0	0	-0.5	(-0.530, -0.493)	(-0.524, -0.500)
Train:					
Travel costs 1#	7%	0	-0.1	(-0.104, -0.093)	(-0.103, -0.095)
Travel costs 2	2%	5%	0	(-0.007, 0.004)	(-0.006, 0.001)
Travel costs 3	9%	4%	0	(-0.003, 0.011)	(-0.002, 0.007)
Travel costs 4	5%	6%	0	(-0.002, 0.003)	(-0.001, 0.003)
Travel times 1#	21%	0	-0.15	(-0.155, -0.135)	(-0.153, -0.140)
Travel times 2	10%	2%	0	(-0.008, 0.007)	(-0.005, 0.004)
Border times	6%	4%	0	(-0.007, 0.010)	(-0.006, 0.005)
Comfortable#	0	0	-0.25	(-0.253, -0.238)	(-0.253, -0.242)
Bus:					
Travel costs 1#	0	0	-0.25	(-0.256, -0.246)	(-0.252, -0.244)
Travel costs 2#	0	0	-0.12	(-0.125, -0.117)	(-0.121, -0.115)
Travel costs 3	3%	4%	0	(-0.008, 0.003)	(-0.004, 0.004)
Travel costs 4	4%	5%	0	(-0.002, 0.002)	(0.000, 0.003)
Travel times 1#	0	0	-0.25	(-0.260, -0.238)	(-0.255, -0.239)
Travel times 2	6%	7%	0	(-0.001, 0.010)	(0.001, 0.010)
Border times#	8%	1%	-0.13	(-0.144, -0.127)	(-0.135, -0.124)
Comfortable#	0	0	-0.3	(-0.305, -0.291)	(-0.304, -0.294)
Flight:					
Travel costs 1#	10%	1%	-0.18	(-0.202, -0.180)	(-0.196, -0.179)
Travel costs 2#	1%	0	-0.2	(-0.213, -0.195)	(-0.207, -0.194)
Travel costs 3#	4%	0	0.2	(0.185, 0.206)	(0.191, 0.205)
Travel costs 4	6%	7%	0	(-0.003, 0.005)	(-0.003, 0.002)
Travel times 1	6%	5%	0	(-0.005, 0.027)	(-0.014, 0.011)
Travel times 2	6%	8%	0	(-0.005, 0.018)	(-0.002, 0.015)
Border times	4%	3%	0	(-0.004, 0.022)	(-0.003, 0.015)
Comfortable#	12%	1%	-0.25	(-0.264, -0.232)	(-0.256, -0.235)

Note: # The EER$_k$ values for real significant effects.

Recall that scenario 2 is designed to compare uniform design with orthogonal design on EER, CI and EA. We assume the same sample size (*m*=100) for both designs. Table 4 presents the simulation results. Almost all true values of the parameters are in their confidence interval for both orthogonal design and uniform design. This suggests that parameter estimation is unbiased for both designs. The effect error ratios for real significant effects are zero for both uniform and orthogonal design at the significant level 0.05. Uniform design has lower effect error ratios for some effects and orthogonal design has lower effect error ratios for other effects. It is very difficult to tell which design has obvious advantages over the other design from the point of view of EER. The average effect error ratios for orthogonal design and uniform design are 1.7% and 1.4% respectively. In other words, in terms of EER, uniform design is comparable to orthogonal design. However, orthogonal design seems outperform uniform design in terms of estimation accuracy or EA. Table 4 shows that EA is in general smaller for orthogonal design than for uniform design. Nevertheless, almost all the differences are less than 0.02, which is admissible for practical use. These differences in estimation accuracy are likely caused by the differences in the number of profiles or choice sets used by the two designs (orthogonal design uses 36 profiles, whilst uniform design uses only 24 profiles).

TABLE 4: Simulation results for scenario 2

Variables	UD EER_k	OD EER_k	UD EA_k	OD EA_k	True value of parameters	UD CI	OD CI
Constant train#	0	0	0.0707	0.0569	1.3	(1.296, 1.324)	(1.296, 1.319)
Constant bus#	0	0	0.0801	0.0625	1	(0.998, 1.029)	(0.992, 1.016)
Constant flight#	0	0	0.1054	0.0927	-0.5	(-0.526, -0.484)	(-0.531, -0.494)
Train:							
Travel costs 1#	0	0	0.0540	0.0538	-0.55	(-0.561, -0.539)	(-0.555, -0.534)
Travel costs 2	5%	2%	0.0312	0.0241	0	(-0.006, 0.006)	(-0.007, 0.002)
Travel times 1#	0	0	0.0535	0.0473	-0.5	(-0.509, -0.488)	(-0.504, -0.485)
Travel times 2	6%	1%	0.0370	0.0243	0	(-0.006, 0.009)	(-0.005, 0.004)
Border times	1%	4%	0.0450	0.0391	0	(-0.011, 0.006)	(-0.005, 0.010)
Comfortable#	0	0	0.0522	0.0376	-0.6	(-0.607, -0.586)	(-0.604, -0.589)
Bus:							
Travel costs 1#	0	0	0.0620	0.0558	-0.5	(-0.511, -0.487)	(-0.514, -0.492)
Travel costs 2#	0	0	0.0412	0.0288	-0.45	(-0.462, -0.446)	(-0.457, -0.446)
Travel times 1#	0	0	0.0660	0.0496	-0.55	(-0.557, -0.531)	(-0.550, -0.531)
Travel times 2	3%	6%	0.0351	0.0308	0	(-0.010, 0.004)	(-0.007, 0.005)
Border times#	0	0	0.0572	0.0385	-0.6	(-0.614, -0.591)	(-0.609, -0.593)
Comfortable#	0	0	0.0578	0.0408	-0.5	(-0.503, -0.480)	(-0.499, -0.483)
Flight:							
Travel costs 1#	0	0	0.0996	0.0663	-0.65	(-0.687, -0.648)	(-0.667, -0.641)
Travel costs 2#	0	0	0.0749	0.0723	0.55	(0.535, 0.565)	(0.545, 0.573)
Travel times 1	9%	5%	0.1001	0.0786	0	(-0.033, 0.006)	(-0.023, 0.008)
Travel times 2	6%	4%	0.0574	0.0432	0	(-0.018, 0.004)	(0.000, 0.017)
Border times	5%	8%	0.0816	0.0665	0	(-0.004, 0.028)	(-0.016, 0.011)
Comfortable#	0	0	0.0794	0.0663	-0.6	(-0.605, -0.574)	(-0.625, -0.599)

Note: # The EER_k values for real significant effects.

The last scenario is designed to compare uniform design and orthogonal designs in the case that the two designs generate substantially different number of profiles. Two different sample sizes (m=25 and m=50) are assumed for uniform design and one for orthogonal design (m=25). This is to test the assumption that the small number of profiles may be compensated by large sample size for estimation accuracy. Tables 5, 6, 7, and 8 present the results for EER, CI, EA, and PA, respectively. Three points of observations may be made from the results. Firstly, almost all true values of the parameters are in their confidence interval for both orthogonal design and uniform design. This fact reinforces our previous finding that both orthogonal and uniform designs are unbiased. Secondly, when the same sample size of 25 is used for both designs, the effect error ratios of orthogonal design are lower than that of uniform design. This is particularly significant for model 4 (the average EER is 7.3% for uniform design, while that for orthogonal design is 1.8%). However, when the sample size is 50 for uniform design and 25 for orthogonal design, the effect error ratios of uniform design are approximately the same as that of orthogonal design. These facts imply that, in the case that uniform design uses substantially less number of profiles than orthogonal design does, the chance of making erroneous inference is higher for uniform design than for orthogonal design. However, this shortcoming of uniform design may be overcome to a large extent by increasing sample size. Thirdly, orthogonal design obviously outperforms uniform design in estimation accuracy for both models 3 and 4 when the sample size is 25 for both designs. However, the estimation accuracy of uniform design becomes comparable to that of orthogonal design when the sample size for uniform design increases to 50. Similar observations may be made for prediction accuracy. These findings imply that in cases that uniform design uses substantially smaller number of profiles than orthogonal design does, the estimation accuracy and prediction accuracy of orthogonal design are better than that of uniform design. This is understandable because the number of profiles or choice sets used and thus the information surplus by orthogonal design is much larger than that by uniform design. Nevertheless, our findings suggest that the disadvantage of uniform design can be compensated to a large extent by increasing sample size.

TABLE 5: Simulation results for scenario 3 (EER)

Variables	Uniform design ($m_{UD}=25$)		Uniform design ($m_{UD}=50$)		Orthogonal design ($m_{OD}=25$)	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Constant train#	0	0	0	0	0	0
Constant bus#	0	0	0	0	0	0
Constant flight#	5%	26%	0	4%	0	2%
Train:						
Travel costs 1#	0	1%	0	0	0	0
Travel costs 2	2%	3%	6%	2%	5%	3%
Travel costs 3	3%	6%	5%	4%	7%	3%
Travel times 1#	0	3%	0	0	0	0
Travel times 2	3%	6%	3%	5%	4%	1%
Border times	3%	7%	0	9%	9%	6%
Comfortable#	0	4%	3%	0	0	0
Bus:						
Travel costs 1#	0	7%	0	0	0	0
Travel costs 2#	0	4%	0	0	0	0
Travel costs 3	2%	2%	7%	2%	6%	1%
Travel times 1#	0	9%	0	0	0	0
Travel times 2	4%	7%	6%	7%	3%	6%
Border times#	0	9%	0	0	0	0
Comfortable#	0	4%	0	0	0	0
Flight:						
Travel costs 1#	3%	9%	0	0	0	0
Travel costs 2#	9%	31%	0	6%	0	1%
Travel costs 3#	9%	16%	0	2%	0	2%
Travel times 1	5%	3%	5%	4%	6%	5%
Travel times 2	3%	3%	7%	6%	6%	7%
Border times	3%	5%	2%	8%	4%	6%
Comfortable#	5	10%	0	2%	0	0
Average	2.5%	7.3%	1.8%	2.5%	2.1%	1.8%

Note: # The EER_k values for real significant effects.

5. DISCUSSION AND CONCLUSION

This paper aimed at assessing the performance of uniform design and compared it with orthogonal design on four indicators: effect error ratio, unbiasedness, estimate accuracy and prediction accuracy. Monte Carlo simulations were conducted for three scenarios, which were designed to represent different cases, different sample sizes, and four models. The simulation results show that almost all true values of the parameters lie within their

TABLE 6: Simulation results for scenario 3 (CI)

Variables	Model 3				Model 4		
	True values	UD (*m*=25)	UD (*m*=50)	OD (*m*=25)	UD (*m*=25)	UD (*m*=50)	OD (*m*=25)
Constant train	1.3	(1.296, 1.339)	(1.286, 1.312)	(1.293, 1.317)	(0.639, 0.672)	(0.647, 0.669)	(0.644, 0.663)
Constant bus	1	(0.986, 1.030)	(0.986, 1.014)	(0.987, 1.011)	(0.481, 0.516)	(0.484, 0.507)	(0.497, 0.516)
Constant flight	-0.5	(-0.545, -0.492)	(-0.551, -0.507)	(-0.525, -0.490)	(-0.292, -0.253)	(-0.269, -0.242)	(-0.270, -0.243)
Train:							
Travel costs 1	-0.5	(-0.519, -0.494)	(-0.516, -0.497)	(-0.509, -0.494)	(-0.265, -0.241)	(-0.263, -0.247)	(-0.252, -0.238)
Travel costs 2	0	(-0.013, 0.010)	(-0.005, 0.014)	(-0.005, 0.009)	(-0.002, 0.022)	(-0.008, 0.009)	(-0.008, 0.006)
Travel costs 3	0	(-0.013, 0.014)	(-0.012, 0.008)	(-0.008, 0.007)	(-0.019, 0.008)	(-0.008, 0.007)	(-0.004, 0.011)
Travel times 1	-0.45	(-0.472, -0.446)	(-0.464, -0.446)	(-0.451, -0.437)	(-0.239, -0.218)	(-0.237, -0.221)	(-0.241, -0.227)
Travel times 2	0	(-0.010, 0.014)	(-0.006, 0.012)	(-0.006, 0.007)	(-0.011, 0.015)	(-0.007, 0.009)	(-0.008, 0.005)
Border times	0	(-0.019, 0.006)	(-0.011, 0.007)	(-0.017, 0.000)	(-0.026, 0.001)	(-0.015, 0.004)	(-0.002, 0.014)
Comfortable	-0.41	(-0.427, -0.404)	(-0.423, -0.402)	(-0.414, -0.399)	(-0.250, -0.223)	(-0.243, -0.225)	(-0.249, -0.236)
Bus:							
Travel costs 1	-0.48	(-0.483, -0.456)	(-0.495, -0.476)	(-0.486, -0.467)	(-0.257, -0.225)	(-0.245, -0.225)	(-0.244, -0.229)
Travel costs 2	-0.43	(-0.445, -0.421)	(-0.447, -0.430)	(-0.437, -0.420)	(-0.250, -0.223)	(-0.244, -0.225)	(-0.238, -0.225)
Travel costs 3	0	(-0.018, 0.010)	(-0.010, 0.009)	(-0.015, 0.002)	(-0.008, 0.019)	(-0.003, 0.016)	(-0.012, 0.001)
Travel times 1	-0.45	(-0.464, -0.435)	(-0.458, -0.437)	(-0.459, -0.443)	(-0.234, -0.207)	(-0.228, -0.211)	(-0.222, -0.206)
Travel times 2	0	(-0.019, 0.006)	(-0.021, -0.001)	(-0.009, 0.005)	(-0.010, 0.017)	(-0.007, 0.012)	(-0.007, 0.008)
Border times	-0.5	(-0.528, -0.497)	(-0.511, -0.492)	(-0.514, -0.498)	(-0.253, -0.225)	(-0.251, -0.230)	(-0.242, -0.227)
Comfortable	-0.5	(-0.513, -0.487)	(-0.505, -0.486)	(-0.511, -0.495)	(-0.250, -0.221)	(-0.243, -0.223)	(-0.233, -0.219)
Flight:							
Travel costs 1	-0.45	(-0.492, -0.441)	(-0.482, -0.443)	(-0.469, -0.440)	(-0.324, -0.281)	(-0.303, -0.278)	(-0.305, -0.284)
Travel costs 2	-0.41	(-0.450, -0.398)	(-0.434, -0.396)	(-0.422, -0.398)	(-0.244, -0.204)	(-0.235, -0.209)	(-0.226, -0.208)
Travel costs 3	0.38	(0.375, 0.435)	(0.371, 0.412)	(0.367, 0.396)	(0.233, 0.269)	(0.226, 0.252)	(0.227, 0.249)
Travel times 1	0	(-0.014, 0.028)	(-0.007, 0.024)	(-0.018, 0.006)	(-0.021, 0.008)	(-0.009, 0.012)	(-0.011, 0.008)
Travel times 2	0	(-0.021, 0.017)	(-0.007, 0.028)	(-0.009, 0.017)	(-0.018, 0.014)	(-0.013, 0.009)	(-0.007, 0.013)
Border times	0	(-0.016, 0.028)	(-0.016, 0.013)	(-0.019, 0.004)	(-0.015, 0.015)	(-0.008, 0.016)	(-0.003, 0.015)
Comfortable	-0.42	(-0.448, -0.401)	(-0.446, -0.410)	(-0.434, -0.405)	(-0.268, -0.236)	(-0.258, -0.235)	(-0.250, -0.230)

TABLE 7: Simulation results for scenario 3 (EA)

Variables	Model 3			Model 4		
	UD (*m*=25)	UD (*m*=50)	OD (*m*=25)	UD (*m*=25)	UD (*m*=50)	OD (*m*=25)
Constant train	0.1092	0.0649	0.0584	0.0818	0.0555	0.0479
Constant bus	0.1101	0.0702	0.0602	0.0868	0.0580	0.0468
Constant flight	0.1344	0.1121	0.0868	0.1006	0.0676	0.0666
Train:						
Travel costs 1	0.0636	0.0477	0.0394	0.0581	0.0421	0.0360
Travel costs 2	0.0564	0.0470	0.0360	0.0593	0.0415	0.0357
Travel costs 3	0.0689	0.0509	0.0379	0.0666	0.0400	0.0365
Travel times 1	0.0652	0.0463	0.0352	0.0524	0.0395	0.0350
Travel times 2	0.0611	0.0443	0.0348	0.0643	0.0414	0.0328
Border times	0.0643	0.0455	0.0427	0.0706	0.0485	0.0384
Comfortable	0.0599	0.0528	0.0365	0.0691	0.0466	0.0320
Bus:						
Travel costs 1	0.0668	0.0463	0.0464	0.0787	0.0532	0.0388
Travel costs 2	0.0597	0.0446	0.0428	0.0687	0.0494	0.0328
Travel costs 3	0.0691	0.0476	0.0430	0.0662	0.0479	0.0323
Travel times 1	0.0731	0.0535	0.0385	0.0668	0.0432	0.0398
Travel times 2	0.0609	0.0497	0.0354	0.0698	0.0496	0.0389
Border times	0.0784	0.0490	0.0390	0.0711	0.0555	0.0369
Comfortable	0.0665	0.0482	0.0404	0.0720	0.0490	0.0350
Flight:						
Travel costs 1	0.1287	0.0979	0.0729	0.1080	0.0651	0.0523
Travel costs 2	0.1323	0.0954	0.0597	0.0991	0.0648	0.0453
Travel costs 3	0.1530	0.1035	0.0715	0.0945	0.0674	0.0553
Travel times 1	0.1040	0.0770	0.0610	0.0752	0.0531	0.0476
Travel times 2	0.0955	0.0887	0.0662	0.0811	0.0547	0.0508
Border times	0.1052	0.0728	0.0571	0.0768	0.0601	0.0455
Comfortable	0.1181	0.0897	0.0718	0.0809	0.0588	0.0516

TABLE 8: Simulation results for scenario 3 (PA)

	Model 3			Model 4		
	UD (*m*=25)	UD (*m*=50)	OD (*m*=25)	UD (*m*=25)	UD (*m*=50)	OD (*m*=25)
Choice set 1:						
Train	0.0437	0.0260	0.0253	0.041928	0.0289	0.0224
Bus	0.0532	0.0327	0.0303	0.055682	0.0394	0.0297
Flight	0.0293	0.0191	0.0162	0.039194	0.0264	0.0238
Multi-mode	0.0109	0.0077	0.0063	0.017422	0.0118	0.0093
Choice set 2:						
Train	0.0538	0.0384	0.0316	0.048216	0.0343	0.0251
Bus	0.0531	0.0404	0.0321	0.050586	0.0337	0.0242
Flight	0.0151	0.0121	0.0087	0.025144	0.0172	0.0162
Multi-mode	0.0115	0.0082	0.0062	0.016069	0.0117	0.0097
Choice set 3:						
Train	0.0454	0.0364	0.0274	0.04763	0.0348	0.0283
Bus	0.0301	0.0209	0.0180	0.038783	0.0268	0.0210
Flight	0.0113	0.0079	0.0072	0.024837	0.0171	0.0103
Multi-mode	0.0293	0.0224	0.0177	0.029396	0.0194	0.0152
Choice set 4:						
Train	0.0413	0.0327	0.0246	0.037761	0.0283	0.0234
Bus	0.0520	0.0396	0.0334	0.050669	0.0360	0.0266
Flight	0.0407	0.0302	0.0226	0.040752	0.0295	0.0244
Multi-mode	0.0132	0.0089	0.0086	0.018587	0.0123	0.0102
Choice set 5:						
Train	0.0466	0.0375	0.0242	0.047446	0.0334	0.0304
Bus	0.0291	0.0173	0.0145	0.035025	0.0244	0.0178
Flight	0.0257	0.0230	0.0161	0.032801	0.0241	0.0202
Multi-mode	0.0118	0.0093	0.0063	0.015102	0.0100	0.0098

confidence interval for both orthogonal design and uniform design, suggesting that like orthogonal design, uniform design supports unbiased estimation for small samples.

In the case that the number of profiles generated by uniform design is about two thirds of that by orthogonal design, uniform design had approximately the same effect error ratios, i.e., the ability to pick significant effects is comparable for the two designs. In the case that the number of profiles generated by uniform design is three or more times less than that by orthogonal design, orthogonal design obviously outperformed uniform design in terms of effect error ratios, estimation accuracy and prediction accuracy if the sample size is the same for both designs. However, the disadvantages of uniform design could be overcome and the performance of uniform design became comparable to that of orthogonal design if the sample size for uniform design is two times that for orthogonal design.

The findings of this paper imply that the advantages of uniform design over orthogonal design in providing small number of profiles (or reducing the burdens of respondents) are at the costs of efficiency of estimation and prediction. In considering which of the two designs to use, it seems that one needs to strike a balance between the burden of respondents and the efficiency of parameter estimation. As argued by Bunch et al. (1996), apart from efficiency, minimizing the number of choice sets is another important concern in stated preference modeling. Another finding that is worthwhile to note from this study is that the efficiency of uniform design can be promoted to the level of orthogonal design by increasing sample size. One should also note that uniform design can easily handle the cases of attributes with uneven numbers of levels, which orthogonal design usually provides no solution. Based on all these facts, it may be safe to conclude that uniform design is a good alternative, if not a replacement of, orthogonal design.

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