Transportation Research Part A 45 (2011) 63–79

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Experimental design influences on stated choice outputs: An empirical study in air travel choice

Michiel C.J. Bliemer [a,b,*], John M. Rose [b,1]

[a] Delft University of Technology, Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, P.O. Box 5048, 2600 GA Delft, The Netherlands
[b] The University of Sydney, Institute of Transport and Logistics Studies, Faculty of Economics and Business, NSW 2006, Australia

ARTICLE INFO

Article history:
Received 9 February 2010
Received in revised form 12 August 2010
Accepted 17 September 2010

Keywords:
Experimental design
Stated choice
Air travel
Orthogonal design
D-efficient design
Sample size

ABSTRACT

Discrete choice experiments are conducted in the transport field to obtain data for investigating travel behaviour and derived measures such as the value of travel time savings. The multinomial logit (MNL) and other more advanced discrete choice models (e.g., the mixed MNL model) have often been estimated on data from stated choice experiments and applied for planning and policy purposes. Determining efficient underlying experimental designs for these studies has become an increasingly important stream of research, in which the objective is to generate stated choice tasks that maximize the collected information, yielding more reliable parameter estimates. These theoretical advances have not been rigorously tested in practice, such that claims on whether the theoretical efficiency gains translate into practice cannot be made. Using an extensive empirical study of air travel choice behaviour, this paper presents for the first time results of different stated choice experimental design approaches, in which respective estimation results are compared. We show that D-efficient designs keep their promise in lowering standard errors in estimating, thereby requiring smaller sample sizes, ceteris paribus, compared to a more traditional orthogonal design. The parameter estimates found using an orthogonal design or an efficient design turn out to be statistically different in several cases, mainly attributed to more or less dominant alternatives existing in the orthogonal design. Furthermore, we found that small designs with a limited number of choice tasks performs just as good (or even better) than a large design. Finally, we show that theoretically predicted sample sizes using the so-called S-estimates provide a good lower bound. This paper will enable practitioners in better understanding the potential benefits of efficient designs, and enables policy makers to make decisions based on more reliable parameter estimates.
© 2010 Elsevier Ltd. All rights reserved.

1. Introduction

1.1. Choice experiments

Discrete choice experiments (DCE) have grown to become the primary source of data for obtaining estimates of behavioural importance such as consumer preferences for various transport goods and services or willingness to pay (WTP) measures for specific attributes such as travel time savings. In a discrete choice experiment, a respondent is being asked in one or multiple choice tasks to select their most preferred alternative from a given set of alternatives that are characterized by

* Corresponding author at: Delft University of Technology, Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, P.O. Box 5048, 2600 GA Delft, The Netherlands. Tel.: +31 15 2784874; fax: +31 15 2783179.
E-mail addresses: m.c.j.bliemer@tudelft.nl (M.C.J. Bliemer), john.rose@sydney.edu.au (J.M. Rose).
[1] Tel.: +61 2 93510168; fax: +61 2 93510088.

0965-8564/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.tra.2010.09.003

(hypothesized) levels of attributes. Using these choice observations, the analyst tries to capture preferences for and trade-offs between attributes (e.g., toll and travel time).

As an example, consider the very simple choice experiment depicted in Fig. 1 in which the respondent has to choose between two alternative modes of transport, namely car and train. Each alternative is characterized by only two attributes, travel time and travel cost. In the experiment we aim to find preferences for these attributes by estimating the following two utility functions in a logit model setting:

$$\begin{aligned} V_{\text{car},s} &= \beta_{\text{time}} TT_{\text{car},s} + \beta_{\text{cost}} TC_{\text{car},s}, \\ V_{\text{train},s} &= \beta_{\text{train}} + \beta_{\text{time}} TT_{\text{train},s} + \beta_{\text{cost}} TC_{\text{train},s}, \end{aligned} \tag{1}$$

where $V_{m,s}$ is the systematic utility for mode m in choice task s, $TT_{m,s}$ is the level of the travel time for mode m in choice task s, $TC_{m,s}$ is the level of the travel cost for mode m in choice task s, and β_{train}, β_{time} and β_{cost} are unknown (preference) parameters that are to be estimated. In this example we assume that all respondents face the same choice tasks, however, this could be extended to respondent specific choice tasks. If we assume that both alternatives have identically and independently extreme value type I distributed random unobserved components, the probability $P_{m,s}$ of choosing mode m in choice task s, given certain travel times and costs, is given by the following multinomial logit (MNL) model (see McFadden, 1974):

$$P_{m,s} = \frac{\exp(V_{m,s})}{\sum_{m'} \exp(V_{m',s})}. \tag{2}$$

In order to estimate β_{train}, β_{time} and β_{cost} (typically through maximum likelihood estimation), choices associated with choice tasks such as in Fig. 1 are needed. In a stated choice context, it is up to the analyst to develop such choice tasks. The set of choice tasks (which constitutes the experimental design) affects the parameter estimates and their reliability, hence constructing these experimental designs should be done carefully.

Over time, as the discrete choice modelling literature has matured, a number of econometrically more advanced models able to uncover an increasing degree of behavioural richness have been developed, typified by the rapid progression from simple MNL model, to nested logit (NL), cross-correlated NL and mixed multinomial logit (MMNL) models (see e.g., Train, 2009). At the same time, advancements in the construction of experimental designs that underlie DCE have been limited and somewhat more erratic in terms of acceptance within the wider literature. This is not to suggest however that advancements have not been made.

Unfortunately, whilst information related to which alternatives, attributes and attribute levels to use may come from secondary data sources or qualitative research such as focus groups and in-depth interviews, the precise method used to construct the underlying experimental design remain solely at the discretion of the researcher. Whilst there exist multiple possible construction methods, each of which make different assumptions during the design generation process, unlike estimation problems where a number of texts describe the advantages and disadvantages of various models (see e.g., Train, 2009), there regrettably exists little guidance as to which particular method to select when generating an experimental design for DCE type studies. A poor choice of experimental design, or one based on an inadequate or incorrect set of assumptions, may result in poor data quality. In turn, poor quality data may result in erroneous conclusions being reached, or at the very least, less reliable parameter estimates at a given sample size. At issue however, is that the advancements that have been made in relation to experimental design construction for DCEs have largely been theoretical in nature, with little empirical work demonstrating whether the theoretical advantages of the various identified design strategies actually translate into practice.

Experimental design

	car		train	
s	TT	TC	TT	TC
1	10	1.00	15	0.50
2	20	1.50	20	0.50
3	15	2.00	25	0.50
4	15	1.50	15	1.00
5	10	2.00	20	1.00
6	20	1.00	25	1.00
7	20	2.00	15	1.50
8	15	1.00	20	1.50
9	10	1.50	25	1.50

→

Choice task 1 (of 9)

	car	train
Travel time	10 min.	15 min.
Travel cost	1.00 euro	0.50 euro
Your choice:	☐	☐

Fig. 1. Example of a stated choice experiment.

Download English Version:

https://daneshyari.com/en/article/312231

Download Persian Version:

https://daneshyari.com/article/312231

Daneshyari.com