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Accommodating perceptual conditioning in the valuation of expected travel time savings for cars and public transport

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ABSTRACT

Travel time variability (i.e., random variations in travel time) leads to a travel time distribution for a repeated trip from a fixed origin to destination (e.g., from home to work). To represent travel time variability, a series of possible travel times per alternative (departure time, route or mode) are often used in stated choice experiments. In the traditional models, the probabilities associated with different travel scenarios (e.g., arriving early, on time and late) shown in the experiments are directly used as weights. However, evidence from psychology suggests that the shown probabilities may be transformed (underweighted or overweighted) by respondents. To account for this transformation of probabilities, this study incorporates perceptual conditioning through a non-linear probability weighting function into a utility maximisation framework, within which the empirical estimate of the value of expected travel time savings is estimated. The key advantage of this framework is that the estimated willingness to pay value can be directly linked to the source of utility (i.e., the probability distribution of travel time), while taking into account the perceptual transformation of probabilities.

1. Introduction

Travel time variability leads to multiple possible travel scenarios for a trip (e.g., arriving on time, earlier or later relative to the expected arrival time), and there are probabilities associated with these scenarios. This 'probabilistic' influence of travel time variability is reflected in many stated choice (SC) experiments for travel time variability, with two typical representations for an alternative associated with travel time variability per respondent' choice set: (1) as the extent and frequency of delay relative to normal travel time (e.g., one out of five chance of a 5-min delay) and (2) a travel time distribution (e.g., a probability of 0.6 for arriving on time, 0.3 for arriving later by 10 min, and 0.1 for arriving earlier by 5 min, using three points as an example). The latter form is preferred (see Hamer, De Jong, Kroes, & Warffemius, 2005), which is commonly embedded in the models based on the Maximum Expected Utility (MEU) theory, proposed by Noland and Small (1995). MEU has become the dominant behavioural paradigm within which to analyse and value travel time variability, under which the mean-variance model and the scheduling model are two state-of-practice modelling frameworks for valuing travel time variability.

However, most travel behaviour studies have a rather simple treatment of uncertainty, that is, as a purely statistical issue (see Bonsall, 2004). For example, the standard deviation (or variance) of travel time is simply added in the utility function established on the mean-variance model as an extra attribute, along with other attributes such as the average travel time and travel cost. In these traditional modelling frameworks, the probabilities of occurrence are directly used to weight the corresponding travel outcomes. However, evidence from psychology and behavioural economics has shown that in many cases, the raw probabilities provided in the experiments were transformed by subjects, and the transformed probabilities were used as the probability or decision weights. This transformation is also referred to as 'perceptual conditioning', which has been overlooked in the traditional frameworks for travel time variability. Given this, the primary purpose of this paper is to develop a more behaviourally realistic model, within which perceptual conditioning is addressed through a non-linear probability weighting function incorporated into a utility maximisation framework. This modelling framework allows for the transformation of probabilities provided in the experiment and the estimation of the value of expected travel time savings (VETTS) which takes into account the travel time distribution due to travel time variability. The key innovation and advantage of this framework over the traditional models is that the willingness to pay (WTP) value can be directly linked to the source of utility (i.e., the probability distribution of travel time).

The remaining sections are organised as follows. The next section provides a brief literature review on two dominant

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approaches to travel time variability, identifies an important gap of these approaches, and introduces a method to address this gap. This is followed by an improved modelling framework used in this paper. Then a stated choice data, conducted in Australia in 2009 in the context of modal choice (public transport vs. car as well as public transport vs. public transport (e.g., bus vs. train)), is briefly described. This is followed by the model estimation and empirical estimates of value of expected travel time savings. We also provide an example of how to use these estimates and the associated policy implication, before summarising the conclusions.

2. Literature review

Travel time variability (i.e., random variations in travel time due to demand fluctuations, accidents, traffic signals, road construction and weather changes) has become an important research focus in the transportation literature, in particular traveller behaviour research. Within a linear utility framework, the scheduling model and the mean-variance model, typically developed empirically within the stated choice theoretic framework, are two dominant approaches to empirical measurement of the value of time variability (Arellana et al., 2012; Bates, Polak, Jones, & Cook, 2001; Small, Noland, Chu, & Lewis, 1999). The majority of recent travel time variability valuation studies (see Li, Hensher, & Rose, 2010 for a review) are established on Maximum Expected Utility (MEU), a theory proposed by Noland and Small (1995) where the attribute levels of travel time are weighted by the corresponding probabilities of occurrence, to address the fact that travel time variability leads to multiple possible travel times for a trip. Under MEU, a scheduling model is given in equation (1).

$$E(U) = \beta_{E(T)}E(T) + \beta_{ESDE}E(SDE) + \beta_{ESDL}E(SDL) + \beta_{Cost}Cost + \ldots \tag{1}$$

The expected utility $E(U)$ is a linear function of the expected trave time ($E(T)$), the expected schedule delay early ($E(SDE)$) which is the amount of time arriving *earlier* than the preferred arrival time (PAT) weighted by its corresponding probability of occurrence, the expected schedule delay late ($E(SDL)$) which is the amount of time arriving *later* than the preferred arrival time weighted by its corresponding probability of occurrence, and other attribute such as cost.

Under MEU, a mean variance model is defined in equation (2).

$$\mathrm{E}(U) = \beta_{E(T)}E(T) + \beta_{SD}SD(T) + \beta_{Cost}Cost + \ldots \tag{2}$$

where SD is the standard deviation of travel time.

In the stated choice experiment for travel time variability, a series of possible travel times for an alternative (departure time, route or mode) are used to represent travel time variability in many studies. For example, the experiment designed by Small et al. (1999) accommodates the measurement of travel time variability for cars by both the mean variance model and the scheduling model (see Fig. 1).

The design attributes in this experiment are mean travel time, travel cost, departure time shift, and standard deviation of travel time; while each alternative in the experiment is represented by the mean travel time, travel cost, and five equi-probable arrival scenarios (early, late or on time) with respect to the PAT to illustrate the existence of travel time variability. For the mean-variance model, the standard deviation of travel time is calculated as equation (3).

$$SD(T) = \sqrt{0.2\sum_{i=1}^{5}[X_i - E(X)]^2} \tag{3}$$

PLEASE CIRCLE EITHER CHOICE **A** OR CHOICE **B**	
Average Travel Time **9 minutes** You have an equal chance of arriving at any of the following times:	Average Travel Time **9 minutes** You have an equal chance of arriving at any of the following times:
7 minutes early **4 minutes early** **1 minute early** **5 minutes late** **9 minutes late**	**3 minutes early** **3 minutes early** **2 minute early** **2 minutes early** **On time**
Your cost: **$0.25**	Your cost: **$1.50**
Choice A	**Choice B**

Fig. 1. SP task from Small et al. (1999).

where X_i is five schedule delay values (i.e., the difference between the preferred arrival time and the actual arrival time) for each alternative. The example values for alternative A in Fig. 1 are −7, -4, −1, +5 and +9, and each has a probability of 0.2 (assuming equi-probable), where the negative sign indicates arriving earlier than the PAT (i.e., schedule delay early (SDE)) and the positive sign indicates a later arrival relative to the PAT (i.e., schedule delay late (SDL)), suggesting that the probability of arriving early is 0.6 and 0.4 for arriving later; and $E(X)$ is the expected value or average of schedule delay. For the scheduling model, the expected values for *SDE* and *SDL* are:

$$ESDE = \frac{(7+4+1+0+0)}{5} = 2.4 \tag{4a}$$

$$ESDL = \frac{(0+0+0+5+9)}{5} = 2.8 \tag{4b}$$

Equations (4a) and (4b) are originally provided in Small et al. (1999) for calculating *ESDE* and *ESDL*. We transform equations (4a) and (4b) into equations (4c) and (4d) which directly illustrate the essence of *Maximum Expected Utility*, i.e., the probability weighted travel time as an attribute in the utility function.

$$\begin{aligned}\text{ESDE} &= \text{the probability of early arrival*the average minutes of arriving earlier than the preferred time}\\ &= 0.6^{*}\frac{7+4+1}{3} = 2.4\end{aligned} \tag{4c}$$

$$\begin{aligned}\text{ESDL} &= \text{the probability of early arrival*the average minutes of arriving earlier than the preferred time}\\ &= 0.4^{*}\frac{5+9}{2} = 2.8\end{aligned} \tag{4d}$$

The majority of travel time variability SC experiments are similar to the approach developed by Small et al. (1999) (see Fig. 1) with some slight changes (e.g., some used vertical bars to represent travel times (e.g., Hollander, 2006), some provided 10 travel times instead of five (e.g., Bates et al., 2001), and some show the departure time explicitly to the respondents (e.g., Holland 2006)). For the probabilities of possible travel times for an alternative, either they were assumed equally distributed (i.e., if there are five travel times for an alternative, then each has a probability of 0.2) in designs such as Small et al. (1999) and Asensio and Matas (2008), or not mentioned (but assuming that travel times are equally distributed when estimating models) in experiments such as Bates et al. (2001) and Hollander (2006). The decision context covers departure time choice, route choice and modal choice. In addition to passenger cars (e.g., Small et al., 1999), public transport is also considered (e.g.,