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Methodological challenges in modelling the choice of mode for a new travel alternative using binary stated choice data – The case of high speed rail in Norway

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ABSTRACT

Binary stated choices between traveller's current travel mode and a not-yet-existing mode might be used to build a forecasting model with all (current and future) travel alternatives. One challenge with this approach is the identification of the most appropriate inter-alternative error structure of the forecasting model.

By critically assessing the practise of translating estimated group scale parameters into nest parameters, we illustrate the inherent limitations of such binary choice data. To overcome some of the problems, we use information from both stated and revealed choice data and propose a model with a cross-nested logit specification, which is estimated on the pooled data set.

1. Introduction

A large-scale study on the feasibility and social benefits of high-speed rail (HSR) in Norway was recently carried out (Jernbaneverket, 2012). The estimated market potential of HSR is naturally a crucial element in this quest, as the predicted ridership has a direct effect on expected revenues, user benefits and greenhouse gas reductions. The demand forecasting model (Atkins, 2012) was based on a stated choice (SC) study where respondents faced customized surveys based on their current mode choice (revealed choice, RC). The survey included binary choice experiments (CE) between the respondents' current modes and a new HSR alternative (Fig. 1 shows a schematic illustration). A similar approach was used in an independent market study conducted by the Institute of Transport Economics, TØI (Flügel and Halse, 2012).

The main advantage of binary CE (instead of CE with a full choice set) is the simplification of the respondent's choice task. In a travel mode choice context, CE often entails a rather high degree of complexity because of the large number of attributes typically required to characterize each alternative. Lowering the overall number of attributes is likely to increase respondents' ability to choose between alternatives (Caussade et al., 2005). In a pivot design, where respondents are typically instructed to recall the last trip they made, it is quite natural to discard the rejected travel alternatives letting the respondent focus on the current travel mode and the hypothetical new alternative.

However, while it is desirable to reduce the respondent's choice set from an experimental design point of view (in our case: providing personal specific choice sets consisting of respondent's current mode and HSR), one would like to build a

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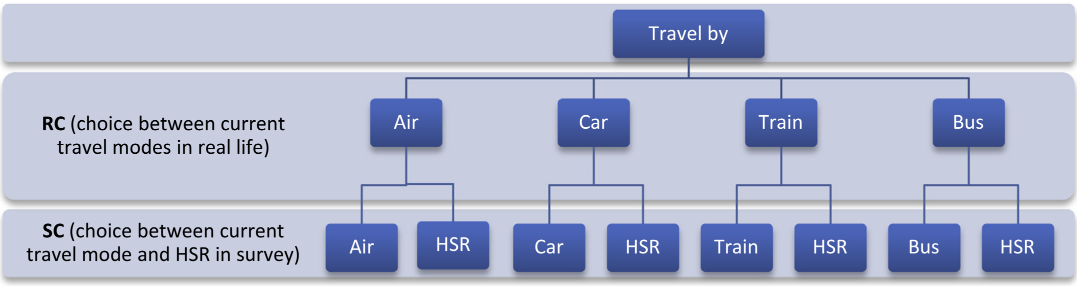

Fig. 1. Decision structure in recent Norwegian HSR-studies (RC: revealed choice; SC: stated choice).

forecasting model that allows considering the whole future choice set and which applies to all future decision makers, independent of their chosen mode at the time the CE surveys were conducted. This applies, in particular, to HSR implementation scenarios that usually involve long-term predictions. Changes in many level-of-service (LoS) variables of, potentially, all travel modes are possible not only because of the long time horizon, but also because a HSR implementation is likely to affect the competitive structure of the whole travel market. Therefore, it seems unduly restrictive to limit choice sets and to condition model parameters for choice predictions in the forecasting year (e.g. in 2024, the earliest possible year for a HSR-implementation in Norway) on current RC choices (data from year 2010 in our case). Consequently, a model with a generic choice set and utility functions, independent of the original self-selection of travellers to travel modes is necessary.

Of course, aiming for a generic forecasting model based on binary stated choices (with only one alternative, HSR, being part of every respondent's choice set) is not optimal, as it does not allow considering directly how current car users, say, react to the LoS of other current modes (air, bus and traditional train). When specifying transport specific coefficients in the utility function, one needs to assume that, for example, the current car user's marginal utility (MU) of in-vehicle-time (IVT) by car is representative of everyone's MU for IVT by car. Challenges in finding an appropriate deterministic utility function are not, however, the focus of this paper; moreover, we will assume – unless specified differently – that we can find deterministic utility functions (up to a scale parameter) that fit all *user groups* (defined on the basis current mode choice) "equally well".

For estimation, the different binary choice datasets are typically merged and a mode choice model with a common set of coefficients for HSR is estimated. In this procedure, different scale parameters (so called *group scale* parameters), that are inversely proportional to the error variances associated with each experiment, ought to be estimated to account for the fact that they might actually differ (Louviere et al., 2000).

While the group scale parameters facilitate the estimation of a common deterministic utility function based on user-specific binary choices, it is not obvious how these parameters may be carried over to a forecasting model with a full choice set. In particular, setting up a nested logit (NL) model by naively treating group scale parameters as structural (nest) parameters, as done by Atkins (2012) in the official assessment study for HSR in Norway, involves several pitfalls:

(i) The group scale parameters only reflect the relative utility scale in choices between the different binary choice tasks (i.e. HSR versus one of the current modes) but not the utility scale difference between existing travel modes. In most cases, this means that the scale at the upper level of the nesting structure and the correlation structure among current modes has to be assumed implicitly (see Sections 3.1 and 3.3); we will discuss how RC data between current modes might be utilized here (see Section 4).

(iii) The group scale parameters do not only reflect "similarity" of transport modes, (i.e. the degree to which two or more alternatives share unobserved features, which is the classical interpretation of nest parameters, see Ortúzar and Willumsen, 2011, Section 7.4.2). They might also include other error sources – in particular unobserved taste heterogeneity – that are associated with characteristics of the user groups rather than of the modes. We will discuss this in more detail in Section 3.2, and using an empirical example, we will also show that results change after accounting for unobserved taste heterogeneity with random coefficients models (Section 3.4).

(ii) In many instances a NL model might not be flexible enough to account for the correlation structure suggested by the various group scale parameters. We propose the cross-nested logit (CNL) model as a more flexible structure for this purpose.

As the paper is mostly concerned with error variance differences (utility scale differences) between various user groups, travel modes and datasets, it is important to stress that the error term is, as usual, conditioned by the specification of the deterministic part of utility (i.e. the selection of explanatory variables and their functional form). For instance, when talking about correlation (or "similarity") of travel modes, we are always relating to those parts of the utility function that are not accounted for by the explanatory variables. Indeed, correlation patterns in the error term are nothing desirable in itself and one would ideally strive for a multinomial logit (MNL) model by including all the variables that might explain correlation among travel alternatives. However, this is often not possible in practise (some variables are unobservable, others are just too expensive to collect). Thus, a question often asked to the researcher refers to the most appropriate correlation (nesting) structure in the forecasting model.