

Forecasting ridership for a new mode using binary stated choice data – methodological challenges in studying the demand for high-speed rail in Norway

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Abstract

We discuss some methodological challenges and pitfalls when binary stated choice data is used to predict the potential ridership of new alternatives. Three challenges can be distinguished: (i) the appropriate translation of group scale parameters into nest parameters; (ii) the use of binary data for a full mode choice model; (iii) the use of stated choices involving transport modes which do not currently exist.

The paper first critically examines the approach chosen in the market analysis underlying the official HSR-assessment study in Norway (Atkins 2012, Jernbaneverket 2012) and suggests more sophisticated methods, in particular joint RP/SP models with a cross-nested logit specification for a theoretically better justified forecasting procedure.

We then examine this model estimation problem using similar data, providing some new insights regarding estimation of group scale parameters and their potential use in the construction of forecasting models for new alternatives that might be correlated with existing alternatives, using revealed preference and binary stated choice data.

Introduction

A large-scale study on the feasibility and social benefits of high-speed rail (HSR) in Norway has been 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 market analysis part of the assessment study was done by British consultants Atkins (2011, 2012a, 2012b). The model coefficients and structural parameters applied for forecasting (thereafter 'forecasting model') were derived from a stated preference (SP) study of binary choices between respondents' current mode of transport (air, traditional train, car or bus) and HSR.

The variance of the error term associated with a stated choice model may differ between different groups (g_n) of individuals n sharing particular characteristics (i.e. the current mode). Given the specification of the indirect utility functions, the error variance of models between - for instance - air and HSR, could be smaller or greater than the error variance of models between traditional train and HSR. Therefore, when estimating a pooled model (of all binary SP choices), one usually specifies different group scale parameters, v_{g_n} , to account for the possibility of differences in error variances (Louviere *et al* 2000)¹. As group scale parameters will in general differ in value, the scale of the indirect utility function of HSR will depend on the user group. This is desirable for inference as it allows estimating a consistent set of model coefficients (β -parameters) for HSR.

When implementing a forecasting model one should take into account the estimated group scale parameters as they may be considered – as shown later in the paper – a measure of which transport modes are closer substitutes. Fully accounting for group scale parameters – and not omitting or restricting them – will in general complicate the implicit structure of the mode choice model. Indeed, we will show that only in special cases, the often used multinomial (MNL) and nested logit (NL) models can be derived in a straightforward manner.

Using binary choices for predicting demand for a full choice set of options has the pitfall that not all relevant scales (scale differences) can be assessed. In the aforementioned study, one does not, for example, observe how car-users react to changes in the indirect utility of air (e.g. the effect of a decrease in boarding time), so the scale of the error variance in choices between current transport modes might be unknown. Without further data, this relative scale has to be assumed implicitly. In the special case of stated preference (SP) choices that involve new potential transport modes subject to political debate (i.e. HSR), imposing restrictions on the relative scales is particularly appealing as the relative impact of the error term in SP choices is likely to be different from real-world choices among current transport modes due to the possibility of hypothetical and policy bias.

¹ We use the notion of group scale parameters as in Bierlaire (2003).

This paper pinpoints some methodological challenges, and gives suggestions for improvements when binary stated choice data are used to build forecasting models including all current modes and a hypothetical new transport mode.

Theory

Heteroscedastic logit model

We describe a standard discrete choice set up where traveller n chooses between different transport modes i belonging to a (personal specific) choice set C_n , according to the following choice rule:

$$(1) \quad U_{in} = V_{in} + \varepsilon_{in} > U_{jn} = V_{jn} + \varepsilon_{jn} \quad \text{for all } j \in C_n.$$

In standard multinomial logit models (MNL), the random terms ε_{in} are assumed to be IID-Gumbel distributed with mean zero and variance given by²: $\sigma^2 = \frac{\pi^2}{\lambda^2 6}$. With this, the MNL model choice probabilities can be shown to be given by (McFadden 1974):

$$(2) \quad P_{in} = \Pr(V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}) = \frac{e^{\lambda V_{in}}}{\sum_{j \in C_n} e^{\lambda V_{jn}}}.$$

The IID-assumption in equation (2) implies proportional substitution patterns across alternatives as the utility of any two alternatives is uncorrelated. Note that the scale factor λ cannot be estimated separately from the parameters β in the deterministic component of utility, V , so it has to be normalized (see the discussion on identifiability by Walker 2001)³.

In certain cases the analyst might wish to allow for different error variances for different subgroups in the data; for example, in our case we have that people using different modes in reality are subject to different SP experiments, asking them to choose between that mode and HSR. This can be easily treated by allowing the scale factor (which is inversely proportional to the error variance) to be not generic (as λ as in equation (2)), but to differ by subgroup; thus, allowing for different *group scale parameters*, v_{g_n} , the choice probabilities become⁴:

$$(3) \quad P_{in} = \frac{e^{v_{g_n} V_{in}}}{\sum_{j \in C_{g_n}} e^{v_{g_n} V_{jn}}} \quad \text{for all } i \in C_{g_n}$$

If we can mix the data for all groups, we would obtain a 'heteroscedastic logit' model.

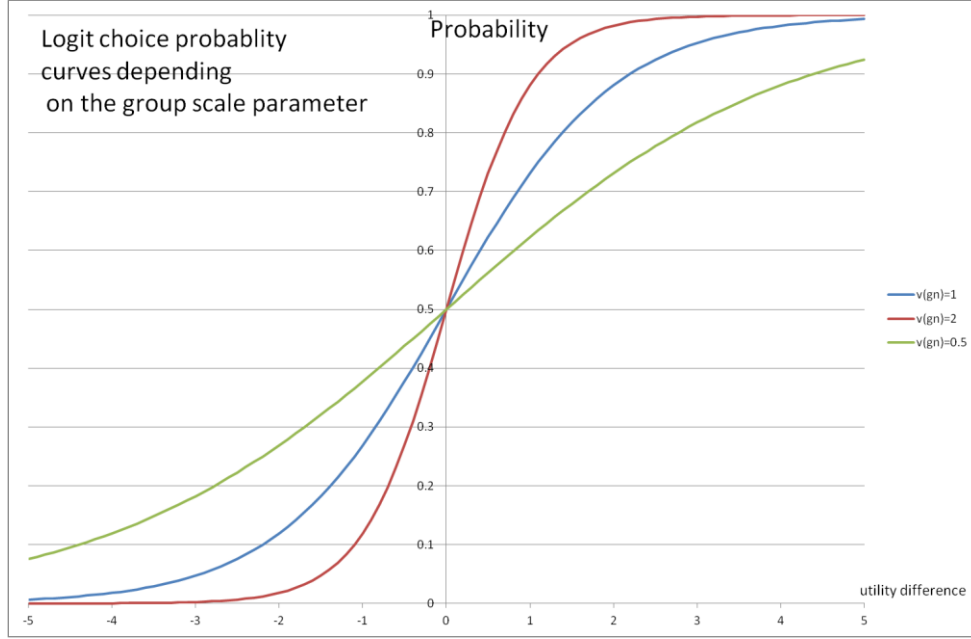
Obviously the group scale parameters affect the resulting choice probabilities as is illustrated in Figure 1.

² $\lambda > 0$ denotes the scale parameter of the Gumbel distribution.

³ For similar reasons, also the *overall scale of utility* U is arbitrary. When all utilities U_{in} in (1) are multiplied by a positive scalar μ (homogeneity parameter or 'overall scale parameter'), the choice probabilities in any discrete choice model, including MNL, do not change.

⁴ We note that not all group scale parameters can be estimated simultaneously. For identification, one group scale parameter has to be fixed (typically at the value 1).

Figure 1: Illustration of effect of group scale parameter on choice probability



If group scale parameters are different in value, the IID-assumption only applies within the subgroup but is relaxed for the whole sample. Given different but partly overlapping choice sets across groups, a model like (3) is not characterising by proportional substitution between all alternatives. In our case, HSR will have (potentially) different degree of substitution with the various current transport modes based on the estimated group scale parameters.

Due to the relationship of the group scale parameters with the error variance, it is clear that they depend on how well specified the indirect utility function V_{in} is. If V_{in} is specified in such a way that it takes into account all differences between user groups (e.g. by using personal and alternative specific parameters) the group scale parameters might approximate each other and an IID distribution assumption (from that perspective seen as the ideal and not a restriction) could be used⁵.

Nested logit and cross-nested logit models

In a *nested logit* (NL) model, alternatives are allocated into non-overlapping nests, m , that contain alternatives $i = 1, \dots, J_m$. NL models (Williams 1977; Daly and Zachary 1978) can also be derived from the family of GEV-models (McFadden 1981). Using GEV-notation, the choice probability for the NL model is given as:

$$(4) \quad P_{in} = \frac{(\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}}{\sum_{m=1}^M (\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}} * \frac{e^{\mu_m V_{in}}}{(\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})}$$

⁵ Actually, if only alternative specific parameters are used it will not be possible to estimate group scale parameters as they will not be identifiable. However, most models include at least some generic parameters.

where μ_m are scale parameters applied to alternatives in nest m . We refer to them as *nest parameters*. Similar to the group scale parameters v_{g_n} (but arising from a different perspective), the nest parameters are inversely related to the corresponding error variance. As pointed out before (footnote 3), μ is an arbitrary positive number and only the ratio $\frac{\mu}{\mu_m}$ has a behavioural interpretation. It can be shown that the correlation between two alternatives is given as:

$$(5) \quad \text{Corr}(U_i, U_j) = \left(1 - \left(\frac{\mu}{\mu_m} \right)^2 \right) d_{ij}$$

where d_{ij} is one when i and j belong to nest m and zero otherwise.

A low error variance in nest m (i.e. μ_m relatively larger than μ) implies a large correlation among utilities between the nested alternatives. For GEV-conditions to hold, we need $\mu_m \geq \mu > 0$. This implies that the utility of the nested alternatives must be positively correlated. This has to be taken into account when setting up a nested structure⁶.

The choice probability in (4) has a nice two-fold interpretation. It is the choice between nests (choice at the ‘upper level’/‘root’) times the choice between alternatives in the chosen nest (choice at the ‘lower level’).

A restriction of NL model is that nests cannot overlap, that is, each alternative can only enter one nest. A GEV-model that allows alternatives to enter into several nests, is the *cross-nested logit*, CNL (Vovsha 1997; Bierlaire 2006). Choice probabilities in the CNL model are given by (Abbe *et al.* 2007, page 797)⁷:

$$(6) \quad P_{in} = \sum_{m=1}^M \frac{(\sum_{j=1}^J \alpha_{jm} \frac{\mu_m}{\mu} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}}{\sum_{m=1}^M (\sum_{j=1}^J \alpha_{jm} \frac{\mu_m}{\mu} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}} \frac{\alpha_{jm} \frac{\mu_m}{\mu} e^{\mu_m V_{in}}}{(\sum_{j=1}^J \alpha_{jm} \frac{\mu_m}{\mu} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}}$$

Bierlaire (2006, page 293) also gives the following conditions to be met by CNL:

1. $\mu_m \geq \mu > 0$ for all $m = 1, \dots, M$
2. $\alpha_{jm} \geq 0$ for all $j = 1, \dots, J, m = 1, \dots, M$
3. $\sum_{m=1}^M \alpha_{jm} > 0$ for all $j = 1, \dots, J$.

⁶ Again, the interpretation of low error variance among related alternatives as a situation where these alternatives share a high proportion of unobservable variables is important. This has to be considered when one set ups a nested structure; one should nest alternatives that are likely to share unobservable variables, that is (with a naive specification of V) alternatives which are close substitutes. Again, when V is perfectly well-specified there should not be any correlation of error terms and IID error terms (as in the MNL-model) should be sufficient.

⁷ Equation (6) is for the resulting choice probability for the most general formulation of CNL. Other formulations are found in e.g. Ben-Akiva and Bierlaire (1999) or Wen and Koppelman (2001). BIOGEME 1.8 (and later versions) use the CNL model version as in equation (6)

Following Train (2009) we refer to the α -parameters as *allocation parameters*⁸. The NL-model is a special case of the CNL-model where all α_{jm} are zero except for the nest m the alternative is included in.

The exact correlation structure of CNL models (Abbe *et al.* 2007) is much more involved than that for the NL (equation 5)⁹. An approximation is proposed by Papola (2004) as follows:

$$(7) \quad \text{Corr}(U_i, U_j) \approx \sum_{m=1}^M \alpha_{im}^{\frac{1}{2}} \alpha_{jm}^{\frac{1}{2}} \left(1 - \left(\frac{\mu}{\mu_m} \right)^2 \right)$$

Equation (7) underlines the fact that the allocation parameters affect the correlation structure of the model. Equations (6) and (7) can be thought of as ‘weighted averages’ of (4) and (5) respectively, where averages are taken over nests and where the allocation parameters represent weights.

Relationship between group scale parameters and nest parameters

As mentioned above, group scale parameters (v_{g_n}) and nest parameters (μ_m) are both inversely proportional to their related error variances. The difference lies in which error variance one is considering. Group scale parameters relate to the error variance in choices between (non-nested) alternatives of a particular user group. Nest parameters relate to the choice between alternatives in one nest (independent of the user type). An interesting question is in which cases the two types of scale parameters might be equal or have the same behavioural implications. To answer this, we examine under which conditions the resulting choice probabilities (P_{in}) in (4) and (3) would be equivalent; that is, under which conditions a NL model can be written as (reduced to) a heteroscedastic logit model with scale parameters related to groups with (possibly) different choice sets.

One can immediately spot a similarity between the *second term* in (4) and (3), which only differ by (i) the summation in the numerator is run over all alternatives inside nest m in (4) and over all alternatives in the (personal-specific) choice set C_n in (3); (ii) the indirect utility functions are multiplied (scaled) by μ_m in (4) and by v_{g_n} in (3). So, in order that (4) equals (3), it would be required that the *first term* in (4) is equal to one for all alternatives $i \in C_n$ and zero otherwise. The latter is required as person's n choice probabilities for all alternatives outside his/her choice set must be zero. This condition ensures that the choice at the upper level

⁸ For interpretation and parameter identification, the condition $\sum_{m=1}^M \alpha_{jm} = 1$ should be imposed. When this condition is imposed, that is if the allocation parameters for a given alternative sum up (over nests) to one, the allocation parameters are readily interpreted as the portion of an alternative that enters each nest. The relationship between α_{jm} and μ_m is however not obvious. Intuitively, a high correlation of nested alternatives (high μ_m) should go along with a relative high portion of a particular alternative being associated with that nest. However, we are not aware of suggestions for possible functional relationship between α_{jm} and μ_m .

⁹ See equation (20) in Abbe *et al* (2007, page 800) for the exact formula of correlation between two alternatives in a CNL.

(choice between nests) does not violate the definition of choice sets available to different user groups.

More formally:

$$\frac{(\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}}{\sum_{m=1}^M (\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}} * \frac{e^{\mu_m V_{in}}}{(\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})} \rightarrow \frac{e^{v_{g_n} V_{in}}}{\sum_{j \in C_{g_n}} e^{v_{g_n} V_{jn}}}$$

if and only if:

- 1) $C_{g_n} = 1, \dots, J_m$
- 2) $\mu_m = v_{g_n}$

and 3) $\frac{(\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}}{\sum_{m=1}^M (\sum_{j=1}^{J_m} e^{\mu_m V_{jn}})^{\frac{\mu}{\mu_m}}} = \begin{cases} 1 & \text{for } i \in C_{g_n} \\ 0 & \text{otherwise} \end{cases}$

This implies that the estimated group scale parameters v_{g_n} could only be used (mathematically) as nest parameters if alternatives were nested according to the group-specific choice sets (condition 1) and if the choice between nests was deterministic (condition 3).

Condition 1 would only be valid if the different choice sets are non-overlapping (i.e. no transport mode could be available to several user groups). This will hardly be the case in reality. Later in the paper we discuss if and to what extent the use of a CNL model can ease the requirement of condition 1.

Condition 3 is very restrictive as a model like (3) does not include information about the 'choice' of which user group a person belongs to (which corresponds to the choice at the upper level in the "transformed" NL model). Later in the paper we discuss the possibility of including additional information/data about that type of choice (in our application of HSR, the use of revealed preference data on the choice between current transport modes).

Limitations of binary stated choice data

Type of data

In this section we describe the general type of data used in two recent studies on HSR in Norway (Atkins 2011, 2012; Flügel and Halse 2012). It is also the kind of data the (theoretical) discussion of the paper is based upon and which is used also in the estimation part.

As HSR is a new option in the Norwegian context it was considered that the propensity to choose HSR was best investigated by designing choice experiments and analyzing the choice behaviour of a relevant sample of potential travellers¹⁰.

¹⁰ Extrapolation of the classical train using existing models seems not valid given the great improvement in level-of-service and the likely perceptions of HSR as a new (and not just an upgraded) transport mode.

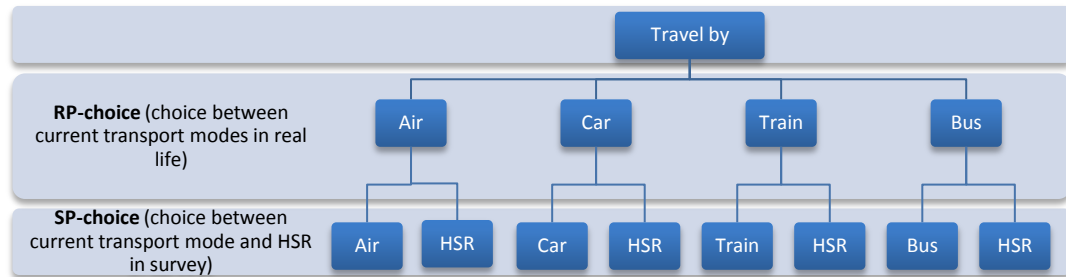
Such *stated preference* (SP) data ('SP-choices') can be used to infer the parameters of a mode choice model used to predict ridership of HSR in future scenarios.

The procedure in the two Norwegian studies was such that survey participants were first asked about their current transport mode for a certain 'reference trip' in their given origin-destination (OD). This choice, done in real life, is here referred to as the *revealed preference* choice ('RP-choice'). Given their RP-choice, respondents then received a customised web-survey including a choice experiment between their current transport mode and the hypothetical HSR option. We thus have binary choices in the SP dataset¹¹.

One should note that the SP-choices were conditioned on the RP-choices. The decision structure of the two Norwegian studies is illustrated in Figure 2. For example, current car users can not choose between air and HSR but only between car and HSR. The SP-choice discards all rejected alternatives in the RP-choice (*status quo* without HSR) implicitly assuming that these will not be relevant for that user group in a future scenario with HSR.

The reminder of this chapter discusses limitations and resulting pitfalls that this type of data brings along.

Figure 2. Decision structure in recent Norwegian HSR-studies



Limitation of binary choice data

With binary data, as above, we do not observe how, for instance, car-users change behaviour when other existing modes (air, bus and classical train) improve or decline their level-of-service (LoS). This lack of information is problematic given that the LoS of all modes is likely to change after implementation of HSR. In the special case where one would assume no changes in LoS for the current modes in the forecasting year, one might discard the possibility of transfers between current modes (assuming a deterministic RP-choice), such that HSR ridership would be the sum of the share of travellers choosing HSR in the separate binary choice settings. However, in the case of HSR in Norway, which is likely to change the competitive structure of the market and for which one needs to forecast far in the

¹¹ The use of binary choices, instead of a full choice set of all available current modes plus HSR, reduces the complexity of the choice tasks. Given 4-6 attributes by alternative, choice tasks with more than two alternatives can easily produce too much burden on respondents (Caussade *et al* 2005). The incapability of processing all the information can easily result in extensive lexicographic choice behaviour. It can also be mentioned that having binary choice tasks ease the experimental design (especially in the case of efficient designs as used by Flügel and Halse 2012).

future, such an assumption is hardly acceptable. Indeed, a full mode choice model that can explain future choice behaviour for the complete choice set is desirable and for many applications a necessity.

For such a full choice model a consistent set of β -parameters for HSR is required. As explained in the introduction, when estimating a pooled model one should then (under the hypothesis of different error variances in the different binary choices) estimate group scale parameters, which might later be used to set the implicit structure of the forecasting models.

In a full forecasting model, that in general should include all transport modes in every choice set¹², one then faces an important shortcoming of having binary choice data, namely that not all relevant scales are assessable as would be needed to fully map the implicit structure of the decision process. The binary choice data might only reveal (if generic parameters are assumed to hold) the relative scale of the choices between the current preferred transport mode and HSR compared to the other binary choices. This will, in general, not be enough information to build a forecasting model that allows for correlated alternatives (as the NL model). In particular, one does not know the relative scale parameter between nests that do not include HSR, nor does one know the relative scale at the lower levels compared to the upper level. Further assumptions about these scales are then required. We will come back to this problem with a concrete example (the model implemented by Atkins).

Limitation of stated choice data

It is likely that the estimated utility in SP-choice space is different from the utility that would be obtained using real world choices. The hypothetical context (lacking real-world consequences for the decision maker) might be a reason for some respondents to put less effort into the choice tasks. Some respondents may also hide their real preferences either by choosing 'socially preferable' alternatives (and not 'personally preferable' option as required by the theory) or by choosing in such a way that the results of the study are driven towards an outcome which is in the respondent's favour (the so-called 'policy bias'). Thus, in general one should expect different error variances in SP and real world settings.

The pitfall of this comes when parameters derived from SP-data only are used to predict behaviour in real world settings. Given that the error variance in SP-choices is, in principle, different than what is true in a real world setting, the transport mode choice may appear less or more 'deterministic' (more or less random) as they actually are in reality. As a consequence, a SP-based model could under or overestimate the market share gain (or loss) of a transport mode the LoS of which has improved (or declined). When forecasting the effect of a HSR-implementation (assuming that HSR will offer better LoS than existing modes), a SP-only model could underestimate the market penetration of HSR, if it overrates

¹² For certain OD pairs (e.g. no airport at a reasonable distance) and for a specific group of people (e.g. those without a driving license) the choice sets can be restricted, but we discard such option for the purpose of this discussion.

the impact of the random error term in the choice between current transport modes and (assumably 'better') HSR options.

One way of treating the above weaknesses of SP-only-data is to supplement it with RP-data (that reflects the real world setting) and to estimate a heteroscedastic logit model on the combined data (Ortúzar and Willumsen, 2011). One would then use a unique scale parameter for RP but might (given the various user groups in SP) estimate different group scale parameters for the SP-component of the data.

As RP-choice data among all current transport modes is available for every respondent, we will examine under which conditions the inferred scale parameter for RP might be interpreted as the scale at the upper level of a hierarchical forecasting model¹³.

Besides the hypothetical bias contained in SP, the scale parameters in combined SP-RP data models may also vary when the input data differs in nature (as in many empirical studies). The SP-experiments in the Norwegian HSR-studies were pivoted around directly reported or inferred LoS-information for the respondent's actual journeys. As it would have been cumbersome to ask for personal-specific information for all available transport modes, we only have precise data for the currently chosen transport mode. For the rejected options in the RP setting, we needed to import zonal data (i.e. average data inferred from network models based on information about the origin-destination pairs for each traveller). As average data does not accurately reflect the LoS actually perceived by the decision makers, a considerable measurement error in the RP-data component is likely.

Validity of forecasting models

Translation of estimated group scale parameters into a nested structure (without using combined RP-SP data)

In this section we discuss strategies to translate an estimate heteroscedastic logit model (allowing different error variance for current user-groups) into full a forecasting model. With 'full' we mean that every decision maker is assumed to have a choice set containing all possible (future) transport mode and not just his/her current transport mode and HSR as in SP. Such a forecasting model will not distinguish between current user groups; this seems sensible as these user groups will hardly be stable for long term-forecasts as required for HSR. For

¹³ The relative error variance in RP can only be identified when the indirect utility function applied to the SP and RP parts of the data share at least one common β -coefficient. However, the alternative specific constants (ASC) should be allowed to be specific as the average impact of the error term in the mode's utility function is likely to differ in RP and SP. See Cherchi and Ortúzar (2006; 2011) for a discussion about handling the ASC in joint RP-SP models. Even if the SP-choices included more than two alternatives, it would also be vital to test for different implicit structures in SP and RP (Yáñez *et al.* 2010). In our case, of binary stated choices in SP, the focus is however not on the correct implicit structure in estimation, but on how to use the (relative) error variance of user groups in SP and the error variance in RP (derived from the heteroscedastic logit model) to infer a proper implicit structure for a forecasting model.

example, a current bus-user (in year 2010) might not consider just bus and HSR when doing his/her transport mode choice in year 2024 (the planned year of HSR-implementation in Norway). S/he might, in the meanwhile, consider car or air as better options compared to bus.

For now we assume that only SP data (and no RP-data) is available. It is fairly obvious that we could tackle our forecasting problem by just combining the binary SP choices into a MNL model. However, that model could not take into account the potentially serious correlation between HSR and the current modes or among some of the current modes themselves. For this reason we are interested in examining the possibility of achieving a more general model, such as a NL, to treat this problem.

We have already discussed the (theoretical) conditions under which estimated group scale parameters could be directly used as nest parameters. For this purpose the nesting structure has to correspond to the available choice sets (defined by user groups). Given overlapping choice sets in reality a (standard) NL model is insufficient from a mathematical point of view. Moreover, a heteroscedastic logit model as in equation (3) does not include a respondent's 'choice' about which user group s/he belongs to (this is predefined by the researcher). Thus, a NL or CNL model that is 'reduced' to a heteroscedastic logit model must assume a deterministic choice at the upper level (see mathematical condition 3).

When different group scale parameters are estimated and we wish to see under which conditions these could be used as nest parameters in a hierarchical forecasting model, in the absence of further information (such as RP data) it is necessary to assume the relative scale at the upper level of that forecasting model.

As not all group scale parameters can be identified, it is always possible to transform them in such a way that the lowest among them is fixed to one. Then, a logical assumption would be to set the upper scale to one as well. However, this is a fairly restrictive assumption in general, as obtaining scale parameters that are lower than one is eminently possible from a mathematical point of view.

In our application of mode choice, we are concerned with the right allocation of transport modes (all current modes and HSR) into nests. Applying the above assumption, the current transport mode(s) with the lowest associated group scale parameters can be allocated into a nest with the same scale as assumed for the upper level (that is 1). Such a nest is referred to as 'degenerated nest'. Regarding HSR (which is associated with all groups), it should be nested with the current transport mode(s) associated with highest group scale parameter(s). A nested logit model (non-overlapping nest) would (under the above assumption) be sufficient when the scale parameter(s) (that are greater than 1) are not significantly different from each other. If this is not the case (i.e. if more than two group scale parameters are distinct from each other), the different degrees of correlation between HSR and the other transport modes should be taken into account with a cross nested logit specification.

For illustration, Table 1 discusses four potential cases of estimated group scale parameter values. The group scale parameter for car-users is fixed to one in these

examples (this is consistent with assuming that choice between car and HSR is the binary choice with highest error variance).

Table 1: Possible nesting structures suggested by group scale parameters

	Case 1	Case 2	Case 3	Case 4
Estimated group scale parameter	car-users $\equiv 1$; train-users ≈ 1 ; air-user ≈ 1 ;	car-users $\equiv 1$; train-users ≈ 1 ; air-user ≈ 3 ;	car-users $\equiv 1$; train-users ≈ 3 ; air-user ≈ 3 ;	car-users $\equiv 1$; train-users ≈ 2 ; air-user ≈ 3 ;
Proposed nest 1	-	car	car	car
Proposed nest 2	-	train	train, air, HSR	train, HSR
Proposed nest 3	-	air, HSR	-	air, HSR
Resulting forecasting model*	MNL	NL with two degenerated nests	NL with one degenerated nests	Cross- nested logit model

*Under the assumption that the overall scale (at the upper level) is one.

If all estimated group scale parameters were close (and insignificantly different) to one (i.e. case 1 in Table 1), a MNL would be obtained. Note that even this model might not be theoretically justified given the missing information inherent to binary choice data. In fact, the MNL model would only be valid under the assumption that the scale in choices between current modes is equal to the scale in choices between single current modes and HSR.

It is also interesting to look at the correlation structure in the estimation and forecasting model structures. Let \mathbf{x} and \mathbf{y} denote the following vectors:

$$\mathbf{x}' = \begin{pmatrix} U_{\text{car-user,car}} \\ U_{\text{train-user,train}} \\ U_{\text{air-user,air}} \\ U_{\text{car-user,HSR}} \\ U_{\text{train-user,HSR}} \\ U_{\text{air-user,HSR}} \end{pmatrix} \quad \mathbf{y}' = \begin{pmatrix} U_{\text{car}} \\ U_{\text{train}} \\ U_{\text{air}} \\ U_{\text{HSR}} \end{pmatrix}$$

Cov ($\mathbf{x}'\mathbf{x}$) is then the covariance matrix consistent with the heteroscedastic logit model, while Cov ($\mathbf{y}'\mathbf{y}$) would be the covariance structure for the proposed forecasting model.

For case 1 we would need to translate:

$$\text{Cov } (\mathbf{x}'\mathbf{x}) = \frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \text{ into } \text{Cov } (\mathbf{y}'\mathbf{y}) = \frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

This seems logical but contains - as mentioned above - an implicit assumption about the correlation between the current modes (car, air, train) which is not possible to ascertain using binary choice data.

In case 2, if the group scale parameter for air-users was estimated as significantly higher than those for the remaining groups, this would indicate that air and HSR are closer substitutes (have a lower error variance) and a NL structure with air and HSR in one nest and two degenerated nests for car and train could be proposed.

Here the following translation would apply:

$$\frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1/3 \end{pmatrix} \text{ into } \frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & (1 - 1/9) \\ 0 & 0 & (1 - 1/9) & 1 \end{pmatrix}$$

Thus, the variance in the binary choices between air and HSR for current air users is used to set the covariance between air and HSR for the full forecasting model (via equation 5). Note that this is only valid if the group scale parameters can really be interpreted as accounting for different degrees of similarity (related to unobserved attributes) regarding the transport modes; however, the group scale parameters can also be affected by the heterogeneity in preferences related to the user groups. As a proper forecasting model needs to allow for a full choice set for all decision makers (discarding the previous allocation into user groups) the size of the nested parameters might not be correctly derivable from the size of the group scale parameters. If this was not a problem, a forecasting model is easy to implement. Given the assumption of $\mu = 1$ (see discussion above), the group scale parameter estimated equal to three can be directly used as the nest parameter in the nest containing air and HSR.

In case 3, if the scale parameter for train-users is estimated as significantly greater than one and insignificantly different from the air-user scale parameter, train, air and HSR may be nested together. Similar to the second case, the following correlation structure in the forecasting model would be proposed:

$$\frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1/3 \end{pmatrix} \text{ into } \frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & (1 - 1/9) & (1 - 1/9) \\ 0 & (1 - 1/9) & 1 & (1 - 1/9) \\ 0 & (1 - 1/9) & (1 - 1/9) & 1 \end{pmatrix}$$

Finally in case 4, if the train-user scale is greater than one but significantly lower than the air-users scale, the only valid option would be to allow for HSR entering

one nest with train and another nest with air. In that case a CNL model would be required¹⁴ and the following correlation structure would be desirable:

$$\frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1/3 \end{pmatrix} \text{ into } \frac{\pi^2}{6} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & (1 - 1/4) \\ 0 & 0 & 1 & (1 - 1/9) \\ 0 & (1 - 1/4) & (1 - 1/9) & 1 \end{pmatrix}$$

It may however be difficult to find a CNL model that implies this correlation structure. In particular the choice of allocation parameters in conjunction with the nest-parameters is not obvious¹⁵.

In summary, facing distinct binary choice data, the translation of group scale parameters from estimation into nest parameters for a full forecasting model is actually invalid from a strict theoretical point of view. However, given some further assumptions, practical strategies for setting up reasonable forecasting models may be found. One of the assumptions (about the relative scale at the upper level) in a hierarchical forecasting model may be relaxed if more data is available (see suggestion below).

Approach used by Atkins 2012

The market demand study by Atkins (2011, 2012a) was also based on binary stated choices between the current transport mode and HSR. As forecasting model they applied a NL model where HSR and air were nested together ('fast mode nest'¹⁶). For the remaining alternatives (car, classical train and bus) degenerated nests were used¹⁷.

The structure of the model used by Atkins (2011; 2012) is illustrated in Figure 3. This structure corresponds well with the group scale parameters Atkins reports for a pooled estimation model. Table 2 summarises the group scale variables ('scales on data sets') reported by Atkins (2011, page 44 and 46)¹⁸.

¹⁴ Apart from a CNL model, a fully general mixed logit (ML) model (Train 2009), might be an alternative and provide an even better way to handle this issue at the expense of more complex estimation, interpretation and application.

¹⁵ It is also not obvious whether or not air and train should be nested together in case 4.

¹⁶ The interpretation of the 'fast mode nest' seems appealing at first glance as air and HSR are faster than other modes (and thus more "similar" among themselves). However, correlation applies only to unobserved variables (the error term). As travel time belongs in the systematic utility function, it does not seem obvious why HSR and air should be more correlated than other modes. Also the fact that we segment the mode choice model in work and non-work trips seems to take care of possible correlation associated with the argument that HSR and air satisfy similar types of travel demand. One might also argue that given that we control systematically for travel time and trip purpose, HSR is expected to have a higher correlation with conventional train as both modes share many unobserved variables (e.g. accessibility, comfort and environmental perception).

¹⁷ Atkins applied a typical mode choice model for the choice between HSR and air, and an incremental mode choice model for choices at the upper level. The discussion of this paper is equally valid for both types of approaches as they need the same relative scale information.

¹⁸ Appendix A1 depicts the original result outputs reported by Atkins

Figure 3. Structure of implementation model in Atkins 2011/2012

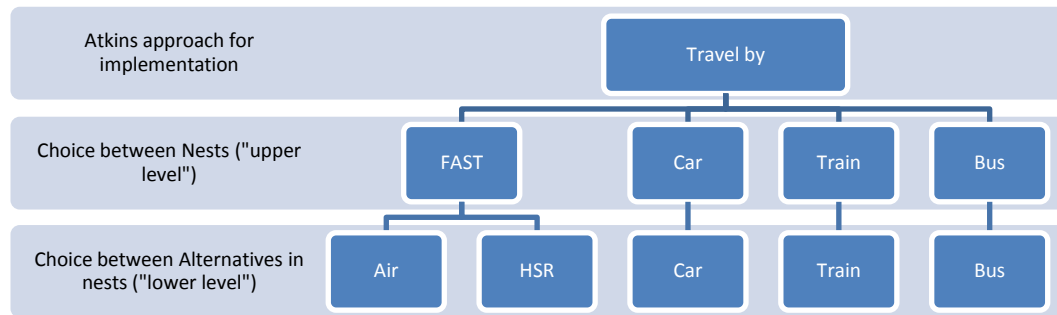


Table 2 Scale parameters reported by Atkins 2011*

Scales on datasets (equivalent to what we call 'group scale parameters')	Non-Work model		Work model	
	Value	"t-ratio"	Value	"t-ratio"
Bus-users	1	n/a	1	n/a
Train-users	1	n/a	1	n/a
Car-users	1	n/a	1	n/a
Air-users	1	n/a	1.55	9.6

*Atkins (2012a) presented an updated estimation model for OD pairs where air was not available. The parameter estimates for the 'air-available' model changed somehow; also, a significant scale parameter for air users was reported for the non-work model.

Table 2 indicates that the scale parameter applied to current air-users is significantly greater than one for the work model¹⁹. The t-statistics for the other scale parameters were not reported by Atkins (2011, pages 44 and 46) nor by Atkins (2012a, page 28), which presents their updated model. It is unclear (to us) whether they excluded these scale parameters in their final estimation run.

Given the above scale parameters, Atkins (2011) applied a NL model to work related trips²⁰. The nest parameter was 1.55 and as (implicitly) an overall scale of one was assumed, an inclusive value parameter of 0.643 (i.e. 1/1.55) was used in the calculation of ridership.

What is worth criticizing is that Atkins does not comment and discuss (after what we can see) their fundamental assumption that the scale parameter associated with the choices between nests ('fast modes', car, bus and train) equals one (i.e. the scale parameter of the SP-choices between car/HSR, train/HSR, and bus/ HSR).

¹⁹ It is unclear if the t-test relates to values of 1 (as it should) or 0.

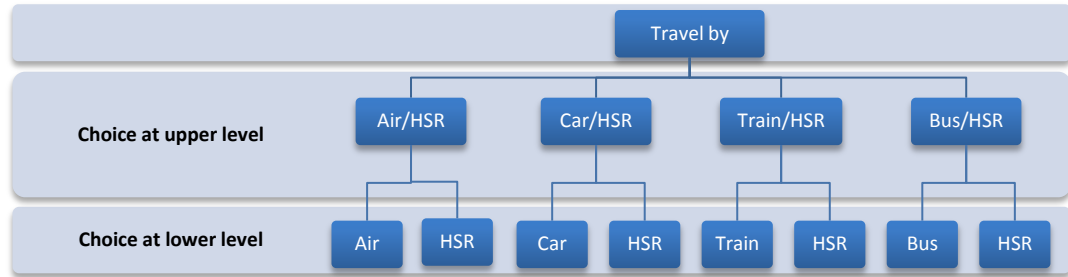
²⁰ Given the incremental approach that Atkins uses for all modes besides air and HSR, their non-work model is also framed as a NL model. However as all nest parameters are equal to one, the model is essentially a MNL.

This assumption is far from obvious and ignores the fundamental lack of information in the use of binary choices.

Suggested improvements

We propose including the RP-data on choice between current transports modes to build the full modal choice model. Arguably, the relative scale estimated in a joint SP-RP model can be a measure of the relative scale at the upper level relative to the lower level. There is a slight difference between the choice of current modes and the choice between nests, as in Figure 4 below, as the latter reflects the choice of current modes given that HSR is available later in the decision structure. Because of missing RP-data on HSR, this seems to be the best practical approach.

Figure 4. Decision structure in a proposed CNL model



Given a possibly complex pattern of estimated group scale parameters (case 4 in Table 1), we propose a more general model, namely the cross-nested logit (CNL) model. We see two ways of moving forward. One possibility is to estimate a joint RP-SP MNL model including group scale parameters and translate it into a forecasting model with implicit structure as in Figure 4. As usual the RP-scale is set to one (and would be treated as upper level scale) and we estimate the group scale parameters (in an effort to treat them as nest parameters at the lower level). If we want the resulting hierarchical forecasting model to be consistent with GEV theory, the estimated group scale parameters should be greater than one. Clearly this is not guaranteed and one might consider imposing a lower boundary (of one) for the group scale parameters. As mentioned above the translation from a heteroscedastic logit model into a CNL model may be difficult in terms of finding the correct allocation parameters.

A second, and arguably better option, is to directly estimate a CNL model on the combined RP-SP data. But again, it is not guaranteed that the nest parameters in the CNL model will have the right size (greater or equal one) so pre-estimation restrictions might be considered once more. This would enable, in theory²¹, also to estimate the allocation parameters needed by equation (6).

A CNL model consistent with the decision structure in Figure 4 allows HSR to enter each nest and the current modes enter only one nest. Thus, we set all allocation parameters for the current modes to zero except for the nest where the mode is where its allocation parameter takes the value one.

²¹ We experienced practical (numerical) problems in estimating the alpha parameters.

Empirical results on own data

Brief description of data

For the empirical part of the paper we used data from an independent SP study conducted by the Institute of Transport economics (TØI). Details can be found in the report by Flügel and Halse (2012a)²².

Respondents were recruited from a previous study about the current market situation in the main long distance corridors in Norway²³ (Denstadli and Gjerdåker 2011), here referred to as 'RP-study'. The RP-study asked air, bus, train and car users about general information regarding their reference trip (i.e. the trip they actually made when filling out the pen-and-pencil questionnaire). In the last item travellers were asked to leave their e-mail address in order to receive a web-based survey concentrating on high-speed rail. A sub sample of 893 respondents completed the online SP-study (about 33% of the invited respondents); 815 respondents were considered for the following analysis.

Each respondent made 14 choices between its current mode of transport (as observed in the RP-study) and HSR. The attributes characterizing the transport modes were total travel costs, in-vehicle travel time, travel time to station/airport ('access time'), travel time from station/airport ('egress time'), frequency (number of departures per day) and the share of the ride spent in tunnels ('tunnel share'). In the first eight choice tasks ('CE1'), the attributes of the current mode were kept fixed to the reported values, while they varied within certain percentage changes in the last six choice tasks ('CE2'). CE2 included also an opt-out option ('neither of the two alternatives'). A typical choice task (of CE2) is depicted in Figure 5.

Figure 5: Illustration of choice task ('CE2')

tøi Transportøkonomisk institutt
Stiftelsen Norsk senter for samferdselsforskning

Hvilken av de følgende reisemåtene ville du ha valgt?

	Fly	Høyhastighetstog	Ingen av disse reisealternativene
Totalkostnad:	1585 kroner	980 kroner	
Reisetid ombord (inkl. tid på flyplass):	2 timer og 15 minutter	3 timer og 50 minutter	
Reisetid til stasjon/flyplass:	50 minutter	38 minutter	
Reisetid fra stasjon/flyplass:	1 time og 10 minutter	15 minutter	
Avganger:	5 avganger i døgnet	14 avganger i døgnet	
Andel av strekning i tunnel:		30 prosent	

(Totalkostnad inkluderer kostnader til reise til og fra flyplassene eller togstasjonene.)

Forrige Neste

0% 100%

²² The paper by Flügel and Halse (2012b) also provides basic information and descriptive statistics about the study.

²³ Oslo-Trondheim, Oslo-Bergen and Stavanger-Bergen. For the SP-study, only the former two corridors were considered.

The general choice behaviour of the sample is summarised in Table 3.

Table 3: sample size of user groups and general choice behaviour

SP-sample (both Oslo-Bergen and Oslo-Trondheim)		Group size	Percent of SP choices (%)			Percent of respondents always choosing (%)		
Purpose	User group	Final sample	Current mode	HSR	Opt-out	Current mode	HSR	Switch between
Non-work travel	car	320	61.6	37.7	0.6	31.3	13.8	55.0
	air	76	34.5	64.7	0.8	1.3	31.6	67.1
	train	176	40.8	57.2	2.0	6.3	18.2	75.6
	bus	35	41.0	58.5	0.6	0.0	17.1	82.9
Work-related travel	car	46	56.7	41.7	1.6	23.9	15.2	60.9
	air	132	41.6	57.2	1.2	4.5	22.0	73.5
	train	31	44.9	54.4	0.6	9.7	19.4	71.0

Compared to a representative dataset (Denstadli and Gjerdåker 2011), we have somewhat under-sampled current air users and over-sampled current car and train-users²⁴ (note that the share of group-membership relates to the 'RP-choice' as described earlier). Notwithstanding, air-users are the largest group among respondents with a work-related trip (the actual market share for air was around 84%). For 'non-work' trips car is the largest group in SP followed by train and air (the actual market shares of car, train and air for non-work trips were, respectively, 40, 21 and 35%). As both in reality and in the SP-sample, the share of bus was very low, especially for work-related trip, this mode was discarded as an alternative in the work-model.

The choice behaviour in SP shows that current car users have a lower propensity towards HSR. In 61.6% of the choice tasks car-users chose car and not HSR (and neither the opt-out). Close to 1/3 of all car-users in the sample did not choose HSR at all (e.g. in none of the 14 choice tasks). Current public transport users are more inclined to choose HSR (at least as indicated in SP). A considerable share (17.1-31.6%) always chooses the HSR option. The choice pattern by user-group is pretty similar for work and non-work trips. But HSR is more frequently observed as the chosen alternative for work related trips as the car-user group is relatively smaller for that purpose. Finally, as the opt-out alternative was very seldom chosen it was excluded for the analysis in this paper²⁵.

²⁴ External weights were used in estimation to offset this.

²⁵ This is done for simplicity (streamlining models and output tables). In alternative models the opt-out was included by using constant terms (based on the user groups). They were estimated as strongly negative (as shares of opt-outs were low as shown in Table 3) but the inclusion of this alternative does not change the other utility functions (i.e. parameter estimates) considerably.

Heteroscedastic logit model

In this section we present SP-only models and discuss their estimation results, especially related to the group scale parameters. The specification of the standard model is similar to that used by Atkins (2011). We report and discuss here the results for non-work trips (Table 4); the results for the work-trips model are given in Appendix A2.

Looking at the first model ('IID-MNL'), where group scale parameters are not included (i.e. they are all fixed to one) we see that all variables have expected signs. The cost variable segmented by income is in right order and the interaction effect with a dummy for "do not pay for trip myself" is, as expected, positive (reduces the marginal disutility of travel costs).

Travel time was modelled as alternative-specific. For car and air the total travel time was used, while we distinguish between in-vehicle time and access/egress time for bus, train and HSR²⁶. All marginal utilities of travel time are negative. However, according to the robust t-statistic²⁷, not all marginal utilities are significantly different from zero the IID-MNL model. A dummy applied to trips under six hours (as in Atkins 2011), making a possible return trip on the same day more convenient, is as expected positive. The inverse of frequency ('headway') applied to the scheduled modes is negative, as is the share of tunnels (the latter effect is not significant in 'IID-MNL').

The second model ('heterosc. logit') estimates group scale parameters for air, train and bus-users. As one sees (Table 4), the group scale parameter for car users was normalised (i.e. set to one) and all the other group scale parameters were estimated significantly greater than one.

That the lowest group scale parameter is related with car-users is intuitive for several reasons. First, in the car sample the most 'extreme' choice behaviour is observed (in Table 3 only 55% of the respondents switched their choice between car and HSR in the 14 consecutive choice tasks). Also, car as a transport mode is more distinct from HSR than the remaining modes (compared to air and train, car offers the possibility to transport heavy luggage, have a flexible routes etc.), so the observed choices may be more driven by 'unobservable' (not included) characteristics.

Interestingly, the group scale parameter for train (3.10) is greater than for air (2.01). This difference is considerable although it is not significantly different at the 5% level (but with a p-value of 0.09). According to these values, train would be a closer substitute to HSR than air.

²⁶ Obviously for car there is no access and egress time (discarding the walk to the car and the possibility of renting a car at some places where access time would be needed). For air we used total travel time instead of in-vehicle time as the latter hardly varies in the RP-data. Also, Atkins used total travel time for air (even though they did not consider RP-data in their analysis).

²⁷ The reported robust t-statistic take into account the panel-structure of the data via the PANEL section in Biogeme. Therefore, no bootstrapping or other methods to correct for the unrealistic assumption of IID error terms of the MNL model in pseudo-panel data needed to be performed.

Table 4: SP-only models, non-work related trips

Non-work Trips		IID-MNL		heterosc. logit		heterosc. logit 2		Mixed hetero. logit *	
Variable type/name	Applied utility function	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)
ASC	HSR	1.3	2.39	0.67	1.51	4.31	6.73	11.2	8.2
	Car	0	fixed	0	fixed	0	fixed	0	fixed
	Air	-0.115	-0.12	-0.185	-0.3	5.72	4.9	17.9	4.34
	Train	0.512	0.7	-0.301	-0.65	3.78	5.17	11.2	5.66
	Bus	1.33	1	0.34	0.59	3.88	5.08	10.4	6.19
Travel cost	generic	-0.00333	-8.29	-0.00213	-6.31	-0.00235	-6.14	-0.00978	-11.87
low income	generic	-0.00265	-7.69	-0.00169	-5.49	-0.00182	-5.4	-0.00666	-6.95
mid. income	generic	-0.00248	-7.96	-0.0015	-5.09	-0.00166	-5.56	-0.0067	-10.7
high income	generic	-0.0103	-4.32	-0.00661	-4.98	-0.00757	-5.03	-0.0193	-1.95
missing income	generic	0.00165	2.92	0.00115	3.25	0.00122	2.86	0.00368	1.96
Interaction: not pay trip	generic								
Travel time	HSR	-0.00531	-5.08	-0.00341	-5.29	-0.00409	-5.21	-0.0158	-9.73
In-vehicle	Train	-0.00283	-1.68	-0.00033	-0.46	-0.00043	-0.54	-0.00681	-3.35
	Buss	-0.00367	-1.32	-0.00135	-1.47	-0.00157	-1.49	-0.01	-4.52
Total time	Air	-0.0033	-0.97	-0.00235	-1.28	-0.00305	-1.94	-0.0206	-2.68
	Car	-0.00129	-1.22	-0.00125	-1.45	-0.0019	-1.79	-0.00554	-3.86
Access + egress time	HSR, Train, Bus	-0.00214	-1.13	-0.00273	-2.34	-0.00281	-2.49	-0.00986	-4.29
Dummy (<6h)	generic	0.49	2.87	0.283	2.62	0.26	2.42	0.492	2.67
Headway	generic (not car)	-1.08	-2.86	-0.444	-2.55	-0.525	-2.45	-2.55	-4.76
Tunnel share	generic (not air)	-0.00267	-0.54	-0.00286	-1.09	-0.00344	-1.32	-0.0204	-3.87
Importance scores						1.13	7.54	2.2	6.49
Flexibility	Car								
Comfort	Air					-0.619	-2.53	-2.3	-2.37
Reliability	Train					-0.158	-1.92	-0.929	-2.89
Variance of pers. spec. error term	HSR							3.93	12.11
Group scale parameters		Value	Rob. T-stat (1)	Value	Rob. T-stat (1)	Value	Rob. T-stat (1)	Value	Rob. T-stat (1)
Car-users		1	fixed	1	fixed	1	fixed	1	fixed
Air-users		1	fixed	2.01	2.03	1.92	2.2	0.772	-1.32
Train-users		1	fixed	3.1	3.61	2.86	3.56	1.35	2.44
Bus-users		1	fixed	3.96	2.66	3.52	2.48	1.88	2.77
No. of parameters		18		21		24		25	
No. of observations		8402		8402		8402		8402	
No. of respondents		607		607		607		607	
Null-LL		-5822.44		-5822.44		-5822.44		-5822.44	
Final-LL		-4640.69		-4522.51		-4146.59		-2791.84	
Adjusted rho-squared		0.2		0.22		0.284		0.516	

*1000 Halton draws were applied.

As pointed out before, correlation between modes is not affected by observed similarities of transport modes (similar prices and total travel time in air and HSR) but, rather, by unobservable similarities (similar comfort and perceived security in traditional train and HSR).

Bus-users are associated with the highest group scale parameter. This result seems odd at first glance. A prospective explanation is that the bus-user group is a fairly homogenous group of people (mostly students). This might make the impact of the error term relatively lower for this group and yield a high group scale

parameter because of the inverse relationship to the error variance. As pointed out before (and discussed again later in the paper) this might be problematic if one wants to directly use these group scale parameters as a nest parameters in a nest bus/HSR say, as such a nest (applied in a forecasting model) should account for similarities between modes (and not within the user groups).

Including group scale parameters does increase the model goodness-of-fit. A likelihood ratio test (Ortúzar and Willumsen, 2011, page 279) clearly rejects the IID-MNL, to be the true model (LR=236.4; $\chi^2_{95\%,3} = 7.8$).

The estimated group scale parameters are not in line with the results obtained by Atkins 2011 (Table 2) which reported scale parameters equal to one for all user groups in the non-work related model. However, the specification of the indirect utility is not exactly the same.

In an extended version of the standard heteroscedastic model ('heterosc. logit 2') we included personal specific scores of items, in an attempt to catch latent variables such as flexibility, comfort and reliability²⁸. All scores have expected sign and decent t-statistics, and the general goodness-of-fit of the model increases substantially. Thus, the impact of the unobservable variables (i.e. error term) diminishes. This makes also the group scale parameters to change slightly in value, something which underlines the fact that these parameters depend on the specification of the indirect utility function. The scores are not included in later models as there is no information about them (and their development over time) at the population level (or at the level of the extended RP-data).

Finally, we included a personal specific error term (normally distributed) in the utility function of HSR in a 'mixed heterosc. logit model'. This error term should catch much of the unobserved propensity towards HSR. This model, which takes explicit care of the panel effect in the SP data (the unobserved propensity towards HSR is based on all 14 SP-choices of a respondent), is clearly superior in goodness-of-fit to the former ones. Also, most of the formerly insignificant variables (like access/egress time) are significant in this last model (however, this function might be impracticable for forecasting purposes). We also see that the group scale parameters change substantially in value. Thus, controlling for unobserved heterogeneity makes car appearing to be a closer substitute to HSR than air.

²⁸ Flexibility was included in the utility function of car as it is likely that car is chosen at the expense of HSR when respondents value the possibility to adjust departure time and route, and to have a car available at destination, highly. In relation to comfort, we hypothesised that people who appreciate the possibility to read, sleep and move around are more likely to choose HSR; however, as this variable only entered the choices between HSR and air, we included it in the latter and expected a negative sign (as HSR is assumed to offer better comfort than air). Finally, as current trains are perceived as rather unreliable, we included the score on the items related to reliability in the utility function of the train.

Joint RP-SP models

In this section we combine the SP data with RP data on the choice of current transport mode. The RP data includes all travellers in the RP study (within the defined corridors) independent of whether they left an e-mail address and were included in the SP study. Based on the - in many cases rough - information on the travelled OD pair, we imported LoS zonal data from the Norwegian national transport model. These LoS-data are average values for the relevant zone pairs (and are, in some instances, not updated) such that the RP data must be considered rather imprecise.

For the non-work model, we added to the 8,402 SP choices (from 607 respondents), 8,450 RP choices from 8,450 individuals (including those on the SP sample) yielding 16,852 observations for the joint RP-SP model.

We included separate ASC for the RP and SP alternatives and used common coefficients for the SP and RP data LoS variables²⁹. We applied the set of β -variables as in the first two models because personal specific 'importance scores' were not available for most of the RP data.

Table 5 gives the estimation results for three models with different restrictions on the estimated scale parameters³⁰. For the most general model (RPSP2) we also run a mixed MNL version³¹.

In the first model ('RPSP1'), the group scale parameters in RP are fixed at one and a common scale parameter for all the SP choices (without taking into account user groups) was estimated as 0.557 (significantly different from one). We conclude that the error variance of the RP-choices (based on zonal data for all current modes) is lower than the error variance in the binary stated choices. This is interesting and contrary to initial expectations. Also the diverse personal specific propensity towards HSR (as seen in Table 3 and indicated in the huge gain in LL in the ML model on SP data) is likely to be a reason for the relative high error variance in SP. The high scale parameter estimated for the RP-data component already indicates that it will be hard to use this scale as the upper level scale in a hierarchical forecasting model.

In the second model ('RPSP2') we estimate all group scale parameters from SP without restrictions. This model might be used to derive a (hierarchical) forecasting model as suggested earlier.

²⁹ Based on pretests this was actually shown to be a rather restrictive assumption. However, having different β coefficients for the same LoS variable introduces the problem of which value use in forecasting. In most practical applications the issue is resolved easily as the SP-based variables tend to be much better. We have not explored this issue here.

³⁰ Notably, the sign of IVT for bus was estimates as positive (while it was negative for the SP-only data); this is clearly caused by the requirement to be common (and the imprecise nature of the RP LoS data); in a practical application we would take this variable out of the "common" set.

³¹ As the Panel command in BIOGEME does not allow for having different user groups for identical person-ID variables, we split the person ID in SP and RP. This is the reason why Biogeme reports 9,057 and not 8,450 persons.

Table 5: Combined RP-SP models, non-work

Non-work Trips		RPSP1		RPSP2		RPSP2 (mixed)		RPSP3	
Variable type/name	Applied utility	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)
SP ASC	HSR	2.75	4.33	2.13	3.55	2.62	7.61	1.63	3.98
	Car	0	fixed	0	fixed	0	fixed	0	fixed
	Air	0.884	1.21	0.534	0.77	1.18	2.51	0.97	1.76
	Train	-0.408	-0.84	-0.428	-0.89	0.0244	0.07	0.157	0.43
	Bus	-4.36	-5.73	-3.56	-3.88	-3.73	-5.56	-2.85	-2.13
RP ASC	Car	0	fixed	0	fixed	0	fixed	0	fixed
	Air	2.95	5.07	2.56	4.82	3.06	9.18	1.94	3.87
	Train	-0.267	-0.75	-0.525	-1.46	-0.187	-0.77	-0.391	-1.16
	Bus	-6.50	-10.42	-5.83	-7.65	-6.05	-10.21	-5.44	-4.56
Travel cost	generic	-0.00530	-11.37	-0.00518	11.81	-0.00522	-13.71	-0.0031	-9.6
low income	generic	-0.00450	-10.67	-0.00436	-10.91	-0.00384	-9.41	-0.0025	-8.24
mid. income	generic	-0.00432	-10.58	-0.00407	-10.24	-0.00383	-13.74	-0.0024	-8.1
high income	generic	-0.00436	-27.13	-0.00431	-26.42	-0.00438	-29.17	-0.0035	-21.92
missing income	generic	0.00205	3.24	0.00216	3.65	0.000695	1.52	0.0014	3.35
not pay trip	generic								
Travel time In-vehicle	HSR	-0.0108	-5.50	-0.00961	-6.88	-0.00923	-9.85	-0.0056	-7.06
	Train	-0.00258	-3.20	-0.00223	-2.72	-0.00284	-4.97	-0.0013	-1.78
	Bus	0.00616	6.62	0.00485	3.95	0.00545	5.48	0.0050	2.48
Total time	Air	-0.0110	-6.69	-0.0104	-6.40	-0.0118	-13.38	-0.0076	-4.73
	Car	-0.00377	-3.36	-0.00408	-3.95	-0.00406	-7.26	-0.0021	-2.38
Access + egress time	HSR, Train, Bus	-0.0106	-17.54	-0.0110	-18.28	-0.0111	-22.20	-0.0076	-9.84
Dummy (<6h)	generic	0.192	1.54	0.269	2.31	0.127	1.80	0.193	2.01
Headway	generic (not Car)	-0.753	-3.26	-0.741	-3.40	-1.07	-5.18	-0.609	-3.15
Tunnel share	generic (not Air)	-0.00508	-0.58	-0.00826	-1.26	-0.0131	-5.06	-0.0043	-1.16
Variance of HSR error						2.25	11.96		
Group scale parameters		Value	Rob. T-stat (1)	Value	Value	Rob. T-stat (1)	Rob. T-stat (1)	Value	Rob. T-stat (1)
Car-users (SP)				0.378	-10.38	1.89	5.82	1	fixed
Air-users (SP)				0.727	-1.63	1.51	1.55	1.18	0.63
Train-users (SP)				1.22	1.48	2.48	6.38	2.05	3.83
Bus-users (SP)				1.10	0.29	1.81	2.01	1.26	0.35
SP-choice (generic)		0.557	-6.67						
RP-choices		1	fixed	1	fixed	1	fixed	1	fixed
No. of est. parameters		22		25		25		24	
No. of observations		16852		16852		16852		16852	
No. of respondents		8450 (9057)		8450 (9057)		8450 (9057)		8450 (9057)	
Null-LL		-16868.364		-16868.364		-16868.364		-16868.364	
Final-LL		-11085.925		-10965.676		-8953.482		-11111.635	
Adjusted rho-squared		0.341		0.348		0.447		0.340	

Unfortunately, the scale for the RP component is estimated to be lower than the scales for car and air-users. While this does not degrade the validity of the estimation model, it is problematic in respect to the proposed forecasting approach. The RP-choices cannot be used as the scale at the upper level, as the group scale parameter for car-users and air-users would imply a wrong inclusive value parameter for the car and air alternative.

In model RPSP3 we impose the restriction that the RP-scale equals the group scale parameter of the car-users group. This restriction guarantees that the nested parameters would obey the GEV-requirements. As the goodness-of-fit reduces substantially, the estimation model is inferior to the previous one (LR = 291.9; $\chi^2_{95\%,1} = 3.8$). Notwithstanding, it might be the only model usable for the purpose of a valid hierarchical forecasting model.

Table 5 shows also results for a ML version of model RPSP2, including the same personal specific error term in the HSR utility function as before (that is only in SP). In this model all group scale parameters in SP are greater than the scale in RP such that all nest parameters in a derived (cross) nested logit model would be of correct size. The parameters in this model might also be used for a valid forecasting model, however the forecasting framework should allow for the inclusion of the additional random term (e.g. by simulation) as it has obviously a strong effect on the scale parameters and therefore on the implicit structure in the forecasting model.

Cross-nested logit models

As proposed earlier we also estimated CNL models that allow the HSR to be nested with each of the four current modes. The model structure is depicted in Figure 4, and shows that the current modes enter only one nest. Thus, we set all allocations parameters for the current modes to zero except for the nest they belong to, where the allocation parameter takes the value one³².

We intended to estimate the allocation parameters from the data. However, serious numerical and (empirical) identification problems occurred. Thus, in Table 6 we only present CNL models for non-work related trips where the allocation parameters are fixed to predefined values (results for work trips are given in Appendix A2). In the first two we constrain the allocation parameters for HSR to be 0.25 for each nest; model 'CNL_RPSP_1a' imposes the extra restriction that the estimated nest parameters are one or greater (as required by theory) while the second ('...b') allows the nest parameters to take any positive number.

In a second set of two models we let single allocation parameters respond to the actual market shares. Although there is no theoretical reason for that it seems an intuitive approach. Again we would have liked to estimate these parameters as well but failed to obtain reasonable results in this version of the paper.

³² This is a somewhat restrictive structure as it might be that, for example, train and bus are correlated in the RP-data. Up to now we have not explored the possible correlation structures among existing modes as inferred from the RP-data (see discussion later).

Table 6 CNL modes, non-work

Non-work Trips		CNL_RPSP_1a		CNL_RPSP_1b		CNL_RPSP_2a		CNL_RPSP_2b	
Variable type/name	Applied to utility	Value	T-stat (0)*	Value	Rob. T-stat (0)	Value	T-stat (0)*	Value	Rob. T-stat (0)
SP ASC	HSR	1.82	9.87	2.36	4.02	1.86	10.03	2.34	4.05
	Car	0	fixed	0	fixed	0	fixed	0	fixed
	Air	1.05	4.99	0.887	1.28	1.06	5.06	0.797	1.16
	Train	-0.101	-0.51	-0.249	-0.53	-0.0775	-0.38	-0.358	-0.77
	Bus	-2.77	-6.01	-3.03	-3.66	-3.18	-7.61	-3.51	-5.18
RP ASC	Car	0	fixed	0	fixed	0	fixed	0	fixed
	Air	2.16	9.82	2.6	4.76	2.17	9.80	2.64	4.90
	Train	-0.313	-1.67	-0.54	-1.48	-0.273	-1.44	-0.536	-1.48
	Bus	-5.24	-9.13	-5.49	-6.4	-5.72	-12.23	-5.91	-9.26
Travel cost	generic	-0.00336	-28.3	-0.0051	-12.28	-0.00340	-28.24	-0.00521	-12.43
low income	generic	-0.00278	-23.2	-0.00431	-12.25	-0.00281	-23.13	-0.00439	-12.20
mid. income	generic	-0.00272	-21.89	-0.00402	-11.27	-0.00274	21.83	-0.00409	-11.32
high income	generic	-0.00359	-34.21	-0.0043	-28.29	-0.00361	-34.13	-0.00433	-28.17
missing income	generic	0.00142	8.46	0.00203	3.58	0.00146	8.51	0.00209	3.61
not pay trip	generic								
Travel time	HSR	-0.00608	-10.38	-0.00911	-7.3	-0.00631	-10.45	-0.00949	-7.45
	Train	-0.00144	-3.33	-0.00201	-2.49	-0.00156	-3.48	-0.00206	-2.55
	Bus	0.00469	5.02	0.00439	3.14	0.00549	7.38	0.00506	5.33
In-vehicle									
Total time	Air	-0.00813	-13.68	-0.0104	-6.22	-0.00813	-13.62	-0.0105	-6.29
	Car	-0.0022	-6.58	-0.00391	-3.64	-0.00224	-6.65	-0.00396	-3.73
Access + egress time	HSR, Train, Bus	-0.00789	-23.67	-0.0109	-17.53	-0.00793	-23.66	-0.0110	-17.51
Dummy (<6h)	generic	0.216	3.91	0.299	2.53	0.203	3.64	0.286	2.43
Headway	generic (not Car)	-0.62	-4.62	-0.717	-3.37	-0.648	-4.66	-0.725	-3.32
Tunnel share	generic (not Air)	-0.00427	-2.39	-0.00877	-1.41	-0.00397	-2.17	-0.00872	-1.35
Nest-parameters		Value	T-stat (1)	Value	T-stat (1)	Value	T-stat (1)	Value	T-stat (1)
Car/HSR		1(at the boundary)	0	0.302	-16.64	1(at the boundary)	0.00	0.323	-14.58
Air/HSR		1.04	0.36	0.598	-2.35	1.05	0.51	0.620	-2.25
Train/HSR		3.07	4.94	3.23	3.76	2.84	4.22	1.83	2.00
Bus/HSR		1.98	1.05	1.83	0.78	1.53	0.24	1.91	0.94
Allocation parameters for HSR		Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)
Car/HSR		0.25	fixed	0.25	fixed	0.41	fixed	0.41	fixed
Air/HSR		0.25	fixed	0.25	fixed	0.35	fixed	0.35	fixed
Train/HSR		0.25	fixed	0.25	fixed	0.21	fixed	0.21	fixed
Bus/HSR		0.25	fixed	0.25	fixed	0.03	fixed	0.03	fixed
No. of parameters		25		25		25		25	
No. of observations		16852		16852		16852		16852	
No. of respondents		8450 (9057)		8450 (9057)		8450 (9057)		8450 (9057)	
Null-LL		-16868.364		-16868.364		-16868.364		-16868.364	
Final-LL		-11131.865		-10959.315		-11139.473		10960.815	
Adjusted rho-squared		0.339		0.349		0.338		0.349	

*Robust t-stats not reported by Biogeme probably because some variables are estimated at the imposed (lower) boundary

In the first model, the nest parameter for nest 'car/HSR' is estimated at the lower boundary of 1. The Final-LL is worse than in all the combined RP-SP models in Table 5, even than in 'RPSP3' where we imposed a similar restriction for the car-user scale.

In the second model we see that the true estimated value of the 'car/HSR' nest parameter is lower than one. This violates the condition discussed in the theoretical part of the paper. This CNL version is, therefore, not valid. It simply seems that the data (and/or the chosen specification of V) does not support the proposed hierarchical structure. Nevertheless, it is interesting to compare the estimated nest parameter with the group scale parameters of model 'RPSP2' (Table 5). We can see that scales related to car and air, are lower than 1 (i.e. the overall scale in 'CNL_RPSP_1b' which relates to the scale of the RP choices in 'RPSP2'). The scale parameters related to bus and train are greater than 1 (also in correspondence with the group scale parameters in the bespoke MNL model). The actual values of the two sets of scale parameters are however different. Both models ('RPSP2b' and 'CNL_RPSP_1b') yield about the same final log-likelihood.

The CNL models where the allocation parameters are fixed at the current market shares are similar to the models where the allocation parameters are fixed to 0.25 each, but the model goodness-of-fit is slightly lower in this latter set of models.

Summary and further research

The paper is concerned with the use of models estimated with binary stated choice data (derived from pivoted choice experiments including only two alternatives: the current transport mode and a new transport mode) for the establishment of a forecasting model that includes all future transport modes. When using binary stated choice data, it seems good practise to join the responses from different users groups (current car, air, train and bus users) to estimate a joint model that includes group scale parameters (heteroscedastic logit model) allowing to treat the potentially different error variance in the separate binary choice experiments.

Atkins (2011, 2012a) translated such estimated group scale parameters directly into nest parameters used in a forecasting nested logit model to predict the market shares of all future transport modes in Norway (including high-speed rail). Our paper shows that this procedure has serious methodological shortcomings.

In particular, binary stated choice data alone does not provide the necessary (relative) scale of SP-choices (compared to RP-choices) and the scale in choices between current modes needed for a full forecasting model with consistent implicit structure. The use of combined SP-RP data (which is well understood in the literature) is considered highly important for such purposes. This paper suggests (in addition) the use/estimation of cross-nested logit models in order to release the possibly restrictive assumption of non-overlapping nests for the hierarchical forecasting model.

In the empirical part of the paper the suggested approaches are tried out on data similar to the data used by Atkins (2011), but with the inclusion of additional RP data. The RP-scale was estimated to be greater than (most of) the group scale parameters in SP making it impossible to translate the estimation model into a valid hierarchical structure where the estimated RP-scale was intended to serve as the scale at the upper level. In correspondence, some of the nest parameters in the estimated cross-nested logit models were estimated to be lower than 1, violating their GEV-requirements. Models imposing restrictions (to make models theoretically justified) were estimated as well. These models, however, are clearly inferior from the models goodness-of-fit point of view.

One of the main reasons for the lower error variance in RP-choices was shown to be the great inter-personal differences in the propensity towards the HSR-option. Controlling for (unobserved) taste variation towards HSR in mixed logit models showed that the error variance in SP is considerably reduced (yielding higher scale parameters) and that in such models the RP-scale is indeed smaller than the SP-scale. However, the forecasting model based on mixed logit results needs to simulate the additional error term and this might not be compatible with existing model systems.

Somewhat related to this discussion, the group scale parameters based on user groups in SP might be affected by the different degree of heterogeneity of decision makers within the user groups. This is an important caveat when interpreting group scale parameters. For example, the group scale parameter for current bus users was found to be the largest in value. This is likely to be related to a relative low degree of heterogeneity among decision makers (as mentioned, students make up for a high share of bus-users) and not to similarities among transport modes. Indeed, as bus and HSR seem not to be very similar transport modes (both with respect to observed and unobserved attributes) nesting them together 'feels wrong'. Therefore, specification of the indirect utility should try to explain inter-personal differences such that the group scale parameters may really account for different error variances related transport modes. This is required for hierarchical forecasting models that discard the existence of user groups (i.e. that assume the same full choice set for all individuals).

From the theoretical discussion and from empirical results in this paper it was also shown that the specification of indirect utility (V) does influence the estimation of scale parameters. Further estimation runs improving the specification of the utility functions in SP might make it possible to obtain desirable relative sizes of the scale/nest parameters. In this connection also the use of SP and RP specific coefficients (besides ASC) should be tested.

Another strategy which was not discussed in this paper, would be to estimate (test for) the implicit nesting structure in the RP-data only, and to use estimation results on the group scale parameters in SP to allocate HSR to the pre-existing nest(s) obtained in RP. The implicit assumption with this approach would be that the correlation structure between current modes would not change after the implementation of HSR.

Given the shortcoming of binary choices discussed in the paper it is indispensable to consider alternative approaches for the experimental design in SP-studies. It seems desirable to include (at least some) choice tasks where the respondent is faced with all transport modes. As pointed out before (footnote 10) designing choice experiments including many alternatives can make it difficult for respondents to process all information and to make thoughtful decisions.

Good practise is found in the study reported by Yáñez *et al.* (2010) where each SP-respondent received four transport modes. One of these modes was the current mode and one the HSR and in addition two other transport modes were added in the choice experiments on a random basis. In this case it seems possible to estimate the implicit structure of the complete choice model.

It seems also interesting and important to do more research on the estimation and use of cross-nested logit models. The interpretation of allocation parameters and their connection to the nest parameters seems unclear and estimating the allocation parameters freely for our data yield serious numerical and (empirical) identification problems.

Finally, an important element missing in the current paper are investigations on the effect of ridership based on the different models. Further research in this direction will be conducted.

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Appendix A1 Reported parameters in reports by Atkins (2011/2012)

Figure A1: Extract of reported estimation results in Atkins 2011(work- model)

Table 4.6: Choice model jointly estimated on data from SP1 and SP2 (work purposes)			
Term	Description	Coefficients	t-ratio
SP1 + SP2 - Jointly estimated terms			
Cost (kroner)	HH income below 800,000 NOK	-0.00081	-8.3
	HH income 800,000 - 1,199,999 NOK	-0.000679	-7.4
	HH income more than 1,199,999 NOK	-0.000567	-5.6
	HH income not known	-0.000669	-6.2
Log Cost (kroner)	All respondents	-0.0592	-3.6
SP1 - Mode Choice			
In-vehicle time (mins)	Car	-0.000529	-0.8
	Air (door to door travel time)	-0.00348	-2.6
	Bus	-0.00266	-2.8
	Train	-0.00501	-7.8
	HSR	-0.00373	-9.0
	+ Employer pays for travel	-0.00209	-5.1
Access and Egress time (mins)	Do not apply for air or car	-0.00636	-13.0
Waiting time (mins)	Do not apply for air or car	-0.00518	-2.7
Tunnel perception	% of HSR time in tunnels (i.e. 25% = 0.25 * coefficient)	-0.152	-3.0
1 / Frequency (services per day)	All PT modes	-0.749	-10.0
Interchanges	All PT modes (number of interchanges)	-0.303	-11.0
Return in one day	If return journey time < 6 hours	0.26	2.9
Constants	Car, if current trip is made in one day	0.556	2.1
	Air, if traveller has no luggage	0.194	3.2
	Air, if travelling in a group of 3 or more	-0.242	-3.1
	HSR, if individual perceives rail as "very poor" or does not know	-0.338	-4.3
	HSR, if traveller is female	-0.0928	-1.4
	HSR, if indicate would "probably" or "definitely" not use with tunnels	-0.34	-3.2
	No trip, if respondent pays	0.781	3.8
	No trip, if day trip	0.544	2.6
	HSR, if currently travelling by car	1.01	5.0
	HSR, if currently travelling by air	1.18	4.0
Alternative specific constants	HSR, if currently travelling by bus	0.45	1.8
	HSR, if currently travelling by train	0.0624	0.4
	No trip, if bus user	-4.52	-11.0
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Contract 5, Subjects 2 and 3 Expected Revenue and Passenger Choices			
44			
	No trip, if train user	-4.82	-13.0
	No trip, if air user	-4.58	-11.0
	No trip, if car user	-4.24	-9.8
Scales on datasets	Bus	1	n/a
	Train	1	n/a
	Car	1	n/a
	Air	1.55	9.6

Source: Atkins 2011, page 43/44

Figure A2: Extract of reported estimation results in Atkins 2011(non-work model)

Table 4.7: Choice model jointly estimated on data from SP1 and SP2 (non-work purposes)			
Term	Description	Coefficients	t-ratio
SP1 + SP2 - Jointly estimated terms			
Cost (kroner)	HH income below 200,000 NOK	-0.00163	-6.4
	HH income 200,000 NOK or more	-0.00137	-11.0
	HH income not known	-0.00169	-7.1
	All respondents	-0.174	-4.8
SP1 - Mode Choice			
In-vehicle time (mins)	Car	-0.000753	-4.1
	Air (door to door travel time)	-0.00316	-5.3
	Bus	-0.00338	-4.5
	Train	-0.00481	-9.4
	HSR	-0.0033	-7.9
Access and Egress time (mins)	Do not apply for air or car	-0.00762	-10.0
Waiting time (mins)	Do not apply for air or car	-0.00859	-4.2
Tunnel perception	% of HSR time in tunnels (i.e. 25% = 0.25 * coefficient)	-0.154	-2.9
1 / Frequency (services per day)	All PT modes	-0.563	-6.4
Interchanges	All PT modes (number of interchanges)	-0.265	-9.2
Return in one day	If return journey time < 6 hours	0.248	3.2
Constants	Car, if current trip is made in one day	0.568	2.5
	Car, if current trip is made less frequently than once a year	-0.252	-1.6
	Car, if individual is retired	0.503	2.7
	Car, if purpose is "holiday"	0.359	2.6
	HSR, if respondent uses rail less than once per year	-0.251	-2.5
	HSR, if indicate would "probably" or "definitely" not use with tunnels	-0.642	-5.7
	No trip, if day trip	0.685	1.9
	HSR, if currently travelling by car	1.02	6.1
	HSR, if currently travelling by air	0.816	4.4
	HSR, if currently travelling by bus	0.000161	0.0
Alternative specific constants	HSR, if currently travelling by train	0.04	0.3
	No trip, if bus user	-5.26	-11.0
	No trip, if train user	-5.56	-12.0
	No trip, if air user	-6.1	-12.0
Scales on datasets	No trip, if car user	-4.9	-11.0
	Bus	1	n/a
	Train	1	n/a
	Car	1	n/a
	Air	1	n/a

Source: Atkins 2011, page 46

Figure A3: Coefficients in mode choice mode by Atkins 2012a (updated model)

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Table 4. Estimation results

	Description	Air Available Coefficients		Air Un-available Coefficients	
		Work	Non-Work	Work	Non-Work
Cost (NOK)	HH income below 800,000 NOK	-0.000947	n/a	-0.000611	n/a
	HH income 800,000 - 1,199,999 NOK	-0.000891	n/a	-0.000575	n/a
	HH income more than 1,199,999 NOK	-0.000719	n/a	-0.000464	n/a
	HH income below 200,000 NOK	n/a	-0.0017	n/a	-0.00115
	HH income 200,000 NOK or more	n/a	-0.00114	n/a	-0.00077
Log Cost (NOK)	All respondents	-0.904	-1.51	-0.583	-1.02
In-vehicle time (mins)	Car	-0.00447	-0.0013	-0.00288	-0.000882
	Air (door to door travel time)	-0.00795	-0.00711	-0.00513	-0.0048
	Bus	-0.00812	-0.00616	-0.00523	-0.00417
	Train	-0.01058	-0.00692	-0.00682	-0.00468
	HSR	-0.00905	-0.00548	-0.00584	-0.0037
Access and Egress time (mins)	Bus, Train, Air and HSR	-0.0108	-0.0104	-0.00694	-0.00702
Waiting time (mins)	Bus, Train, Air and HSR	-0.0109	-0.00748	-0.00706	-0.00506
Tunnel perception	(% of HSR time in tunnels)	-0.228	-0.172	-0.147	-0.116
Frequency (services per day)	All PT modes	-1.19	-0.8170	-0.7680	-0.553
Interchanges	All PT modes (number of interchanges)	-0.497	-0.396	-0.321	-0.267
Return in one day	If return journey time < 6 hours	0.339	0.378	0.219	0.256
Alternative specific constants	HSR (compared to car)	n/a	n/a		
	HSR (compared to air)	1.09	0.201	0.113	-0.481
	HSR (compared to bus)	n/a	n/a	n/a	n/a
	HSR (compared to train)	n/a	n/a	n/a	n/a
Implied structural parameters	Bus	1	1	1	1
	Train	1	1	1	1
	Car	1	1	1	1
	Air	0.645	0.676	n/a	n/a

Source: Atkins 2012a, page 28

Appendix A2: Model for Work related trips

For work-related trips, bus is discarded as a relevant travel alternative. The specification of the indirect utility function is as in the work-related trips (instead of 6 hours we use 4 hours for the dummy applied short total travel times). In the combined RP-RP model, we add to the 2,888 SP-choices, 2,289 RP-choices from 2289 individuals yielding 5,177 observations.

The results from the work-model are comparable to the non-work models when comes to groups scale parameters and nest parameters. Also the effects of the mixed hetero. logit models are similar (massive improvement in LL, lower RP-scale parameter)

Table A1: SP-only models, work related trips

work Trips		IID-MNL		heterosc. logit		heterosc. logit 2		Mixed logit *	hetero.
Variable type/name	applied utility function	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)
Alternative specific constants	HSR	-0.718	-0.49	-1.69	-1.89	-0.277	-0.18	6.76	1.81
	car	0	fixed	0	fixed	0	fixed	0	fixed
	air	-1.93	-1.26	-2.15	-2.34	-0.0975	-0.06	7.18	1.74
	train	-3.49	-1.87	-2.71	-2.57	-0.652	-0.39	8.75	1.29
Travel cost	generic	-0.00312	-3.80	-0.00141	-2.32	-0.00157	-2.32	-0.00848	-4.15
low income	generic	-0.00265	-3.58	-0.000970	-1.71	-0.00107	-1.73	-0.00543	-3.68
mid. income	generic	-0.00156	-2.26	-0.000542	-1.38	-0.000599	-1.39	-0.00342	-2.75
high income	generic	-0.00133	-0.79	-0.000657	-1.10	-0.000594	-0.96	-0.00133	-0.70
missing income info.	generic	0.000706	1.03	0.000251	0.84	0.000284	0.86	0.00139	1.18
Interaction: not pay trip	generic								
Travel time	HSR	-0.00970	-4.24	-0.00360	-1.95	-0.00370	-1.96	-0.0218	-4.79
In-vehicel	train	0.000757	0.22	0.000210	0.17	0.000315	0.21	-0.0126	-2.27
air	air	-0.00703	-2.72	-0.00258	-1.61	-0.00217	-1.51	-0.0107	-2.32
Total time	car	-0.00959	-3.09	-0.00677	-2.99	-0.00647	-2.76	-0.0118	-4.25
Access + egress time	HSR, train	-0.00824	-3.10	-0.00321	-1.70	-0.00296	-1.68	-0.00960	-2.10
Dummy (<4h)	generic	0.324	1.56	0.111	1.18	0.142	1.35	0.360	1.38
Headway	generic (not car)	-2.27	-2.69	-0.886	-1.77	-0.946	-1.80	-5.87	-4.20
Importance scores									
flexibility	car					0.394	1.01	1.37	1.48
comfort	air					-0.195	-1.70	-0.952	-2.35
reliability	train					-0.181	-0.77	-0.841	-0.64
Variance of pers. spec. error term	HSR							2.85	5.64
Group Scale parameters		Value	Rob. T-stat (1)	Value	Rob. T-stat (1)	Value	Rob. T-stat (1)	Value	Rob. T-stat (1)
car-users		1	fixed	1	fixed	1	fixed	1	fixed
air-users		1	fixed	2.95	1.34	2.75	1.33	1.06	0.32
train-users		1	fixed	3.08	1.42	2.86	1.41	0.927	-0.35
# est. parameters		15		17		20		21	
# observations		2888		2888		2888		2888	
# respondents		209		209		209		209	
Null-LL		-2002.256		-2002.256		-2002.256		-2002.256	
Final-LL		-1632.196		-1617.409		-1587.674		-1167.604	
Adj.rho-squ		0.177		0.184		0.197		0.406	

* 1000 Halton draws applied

Table A2: Combined RP-SP models, non-work

work Trips		RPSP1		RPSP2		RPSP2 (mix.MNL)		RPSP3	
Variable type/name	applied utility function	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)	Value	Rob. T-stat (0)
Alternative specific constants SP	HSR	0.592	0.65	0.885	0.66	2.48	3.11	0.284	0.28
	car	0	fixed	0	fixed			0	fixed
	air	-0.170	-0.19	-0.125	-0.10	1.98	2.58	-0.349	-0.33
	train	0.257	0.32	0.458	0.40	1.80	2.13	0.435	0.44
Alternative specific constants RP	car	0	fixed	0	fixed			0	fixed
	air	-0.316	-0.36	-0.295	-0.25	1.49	2.15	-0.652	-0.64
	train	-1.17	-1.49	-1.40	-1.40	-0.174	-0.27	-1.47	-1.59
Travel cost low income	generic	-0.00306	-5.27	-0.00443	-5.37	-0.00473	-7.08	-0.00344	-5.33
mid. income	generic	-0.00269	-5.11	-0.00361	-5.14	-0.00343	-5.77	-0.00302	-5.06
high income	generic	-0.0019	-4.12	-0.00254	-3.75	-0.00251	-4.43	-0.00214	-3.82
missing income info.	generic	-0.00191	-6.36	-0.00259	-8.14	-0.00251	-9.36	-0.00225	-7.77
Interaction: not pay trip	generic	0.00105	2.40	0.00143	2.45	0.00126	2.36	0.00123	2.43
Travel time In-vehicel	HSR	-0.00883	-4.74	-0.0115	-3.84	-0.0125	-6.25	-0.00928	-4.20
	train	-0.00551	-4.06	-0.00724	-4.85	-0.00765	-5.80	-0.00732	-4.91
Total time	air	-0.00809	-4.38	-0.0104	-5.57	-0.0129	-9.46	-0.00944	-5.37
	car	-0.00594	-3.12	-0.00756	-3.55	-0.00515	-4.51	-0.00736	-4.25
Access + egress time	HSR, train	-0.00745	-5.41	-0.0101	-1.68	-0.00895	-9.72	-0.00881	-3.87
Dummy (<4h)	generic	0.387	2.67	0.500	2.67	0.235	1.84	0.390	2.30
Headway	generic (not car)	-1.93	-3.00	-2.65	-3.39	-2.98	-5.97	-2.18	-3.22
Group Scale parameters		Value	Rob. T-stat (1)	Value	Rob. T-stat (1)	Rob. T-stat (1)	Rob. T-stat (1)	Value	Rob. T-stat (1)
car-users		1	fixed	0.415	-3.54	1.74	2.37	1	fixed
air-users		1	fixed	0.827	-1.29	1.81	3.89	0.992	-0.05
train-users		1	fixed	0.808	-0.94	1.63	2.36	0.942	-0.23
RP-sample		1.33	1.63	1	fixed	1	fixed	1	fixed
# est. parameters		18		20		21		19	
# observations		5177		5177		5177		5177	
# respondents		2498		2498		2498		2498	
Null-LL		-3955.574		-3955.574		-3955.574		-3955.574	
Final-LL		-2888.428		-2881.103		-2432.831		-2893.366	
Adj.rho-squ		0.265		0.267		0.380		0.264	

Table A3: CNL modes, work-related trips

work Trips		CNL_RPSP_1a		CNL_RPSP_1b		CNL_RPSP_2a		CNL_RPSP_2b	
Variable type/name	applied utility function	Value	T-stat (0)*	Value	Rob. T-stat (0)	Value	T-stat (0)*	Value	Rob. T-stat (0)
Alternative specific constants SP	HSR	0.269	0.48	1.02	0.72	0.269	0.48	1.24	0.80
	car	0	fixed	0	fixed	0	fixed	0	fixed
	air	-0.346	-0.63	0.0410	0.03	-0.346	-0.63	0.264	0.18
	train	0.427	0.67	0.630	0.51	0.427	0.67	0.892	0.67
Alternative specific constants RP	car	0	fixed	0	fixed	0	fixed	0	fixed
	air	-0.650	-1.17	-0.294	-0.25	-0.650	-1.17	-0.332	-0.29
	train	-1.50	-2.50	-1.39	-1.41	-1.50	-2.50	-1.41	-1.44
Travel cost low income	generic	-0.00341	-9.09	-0.00444	-5.51	-0.00341	-9.09	-0.00443	-5.43
mid. income	generic	-0.00299	-8.78	-0.00363	-5.28	-0.00299	-8.78	-0.00360	-5.23
high income	generic	-0.00212	-6.94	-0.00259	-3.86	-0.00212	-6.94	-0.00254	-3.83
missing income info.	generic	-0.00224	-11.03	-0.00260	-8.28	-0.00224	-11.03	-0.00259	-8.31
Interaction: not pay trip	generic	0.00121	4.09	0.00145	2.49	0.00121	4.09	0.00143	2.48
Travel time	HSR	-0.00918	-6.90	-0.0114	-3.94	-0.00918	-6.90	-0.0112	-3.91
	In-vehicel	-0.00721	-6.08	-0.00727	-4.89	-0.00721	-6.08	-0.00727	-4.92
	air	-0.00940	-10.43	-0.0104	-5.53	-0.00940	-10.43	-0.0103	-5.56
	Total time	-0.00733	-6.92	-0.00759	-3.60	-0.00733	-6.92	-0.00762	-3.65
Access + egress time	HSR, train	-0.00877	-11.62	-0.0101	-9.05	-0.00877	-11.62	-0.0101	-9.06
Dummy (<4h)	generic	0.386	4.39	0.511	2.72	0.386	4.39	0.505	2.71
Headway	generic (not car)	-2.16	-6.17	-2.66	-3.39	-2.16	-6.17	-2.64	-3.41
Nest parameters		Value	T-stat (1)	Value	Rob. T-stat (1)	Value	T-stat (1)	Value	Rob. T-stat (1)
car/HSR		1	0.00	0.331	-5.71	1	0.00	0.260	-8.80
air/HSR		1	0.00	0.726	-1.74	1	0.00	0.819	-1.33
train/HSR		1	2.72	1.95	-1.31	1	2.72	0.584	-1.77
Allocation parameter for HSR		Value	T-stat (0)	Value	Rob. T-stat (0)	Value	T-stat (0)	Value	Rob. T-stat (0)
car/HSR		1/3	fixed	1/3	fixed	0.076	fixed	0.076	fixed
air/HSR		1/3	fixed	1/3	fixed	0.837	fixed	0.837	fixed
train/HSR		1/3	fixed	1/3	fixed	0.087	fixed	0.087	fixed
# est. parameters		20		20		20		20	
# observations		5177		5177		5177		5177	
# respondents		2498		2498		2498		2498	
Null-LL		-3955.574		-3955.574		-3955.574		-3955.574	
Final-LL		-2893.415		-2880.080		-2893.415		-2880.212	
Adj.rho-squ		0.263		0.267		0.263		0.267	

* robust T-stats not reported by Biogeme probably because some variables are estimated at the constrained boundary