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A Long-Distance Travel Demand Model for Europe

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In Europe, approximately 50% of all passenger kilometres come from trips beyond 100 km according to matrices developed in the TRANSTOOLS project. This accounts for an even larger share of CO_2 emissions due to a higher modal share of air transport. Therefore long-distance trips are increasingly relevant from a political and environmental point of view. The paper presents the first tour-based long-distance travel demand model for passenger trips in and between 42 European countries. The model is part of a new European transport model developed for the European Commission, the TRANSTOOLS II model, and will serve as an important tool for transport policy analysis at a European level. The model is formulated as a nested logit model and estimated based on travel diary data with segmentation into business, private, and holiday trips. We analyse the estimation results and present elasticities for a number of different level-of-service variables. The results suggest that the perception of both travel time and cost varies with journey length in a non-linear way. For car drivers and car passengers, elasticities increase with the length of the journey, whereas the opposite is true for rail, bus, and air passengers – a fact that reflects a change in substitutability. Moreover, elasticities differ significantly by trip purpose with private trips having the highest and holiday trips the lowest elasticities.

Keywords: destination choice, discrete choice, long-distance model, mode choice, passenger demand, revealed-preference data

1. Introduction

The opportunity to travel long distances fast at a low cost combined with economic growth has made long-distance transport a basic part of people's activities. According to a recent survey (STOA 2008) more than 60% of all people find it important or very important to have access to easy and efficient transport across Europe. During the last decade (1999-2008) European air passenger traffic has increased by more than 50%. This is partly driven by an increase in average travel distances from 791 to 1050 km (Airbus 2009). Furthermore, it is expected that air transport in Europe will double in the next 15 years (Airbus 2009).

In terms of invested resources in travel demand models (in the past), there is no doubt that most resources have been applied to regional and national models, with only little attention given to

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multi-country models. As a result, models capable of analysing global factors such as climate effects or abilities to meet overall CO_2 targets have had little attention. Consequently, the substitutability among long-distance modes including air transport and high-speed rail has not been given the same attention as substitution among short-range urban modes.

To our knowledge, the model presented in this paper is the first tour-based multi-country model[3] which has been estimated on disaggregate data and subsequently implemented for policy analysis. The model is part of the TRANSTOOLS II model framework (TRANS-TOOLS 2008), which will form the basis for transport policy analysis by the European Commission with respect to climate, infrastructure, and economic development. More specifically, the model is intended to be central to the evaluation of; (i) high-speed rail initiatives in Europe and the substitution pattern between air and rail transport in general; (ii) road charging initiatives at the European level; (iii) subsidising schemes for the European Commission of large European infrastructure projects. A principle objective of the paper in that respect has been to describe the model structure and its results in a transparent way to facilitate a much needed academic debate about large scale and long-distance modelling.

In the model, we apply a generation-attraction (GA) approach, in that we consider tours (trip chains) rather than single trips (see, e.g. Adler and Ben-Akiva 1979). We discuss this approach in more detail in Section 0. In the TRANSTOOLS II model, the mode and destination choice model is linked to a frequency model by a logsum measure to account for accessibility effects in the trip generation. However, in the present paper we only consider the mode and destination choice. The reason is that the demand sensitivity in the presented model then only represents substitution effects, which can be more easily compared to other findings.

Next, in Section 1.1, the paper reviews literature on European long-distance travel demand modelling and identifies the contribution of the paper. Section 2 discusses data with emphasis on the DATELINE survey. In section 3, we discuss the model structure. Section 4 presents the estimation, while section 0 presents the elasticity results. Finally, in section 6 we offer a conclusion.

1.1 Review of European long-distance demand modelling

Most of the work on long-distance models is connected with the development of national models in Europe, state-wide models in the U.S., and intercity travel demand models. An overview of European national models is given in Lundqvist and Mattsson (2002). In terms of establishing a methodological reference point, the Dutch National model (HCG 1990) and the Swedish national model (Beser and Algers 2002) are among the best documented and most influential models.[4]

The common approach for dealing with long-distance trips in most of these models has been to make separate models for these trips, i.e. exogenous stratification. The models are typically combinations of a trip frequency or trip generation model, a destination model, and a mode choice model with the inclusion of an air alternative. Another common stratification variable is trip purpose, although experiments with endogenous stratification have been considered in Beser (2003; Chapter 2) for the Swedish national model, SAMPERS. In terms of modelling, usually a nested logit approach has been used. The model structure with a frequency at the top of the choice hierarchy and a joint mode and destination model follows the recommendations in Department of Transport (2009) although for urban models in the UK, destination is usually above mode. This is the case in a recent paper by Rohr et al. (2010), where they find evidence that the nesting structure is opposite although the estimation suggest that destination is only slightly

[3] Even though models like the Fehmarn Belt and Oresund models do include several countries we do not see these as multi-country models as their focus is to model a corridor between two countries.
[4] Attention should also be given to Fox et al. (2003) which gives an overview of the models developed by RAND Europe.

more sensitive compared to mode. In the SAMPERS long-distance model (Beser 2003; Chapter 4), the nesting structure has mode conditional on destination, which is identical to the structure found in the present paper. A case where both structures are present is presented in Börjesson (2010).

Models representing several countries, i.e. *multi-country models*, are not often seen for passenger traffic. An example, however, is the TRANS-TOOLS I model as described in (TRANS-TOOLS 2005). Although this model is the most recent and constitutes one of the more advanced models covering all of Europe, it is not very sophisticated in terms of its passenger demand model. The model, referred to as the VACLAV model, is trip-based and therefore not capable of consistently measuring the impacts of zone-based data (refer to Section 3 for a more elaborate discussion of trip-based versus tour-based modelling). Moreover, the choice of mode and the choice of destination are not estimated jointly. Another limitation is that the model is not stratified according to long- and short-distance trips. This is a problem considering the different nature of these trips (Hubert and Potier 2003). The STREAMS model (Williams 2002), STEMM (Gaudry 2002), and SCENES (SCENES 1999) can all be seen as forerunners for the TRANS-TOOLS models and generally involve a less sophisticated approach in terms of demand modelling. SCENES, the most recent of the three (completed in 2001), resembles a classic 4-stage model.

How to include journey distance is a general theme in long-distance modelling. In an analysis of mode choice of intercity passengers in Germany, Mandel et al. (1997) highlight the importance of functional form. More recently, Gaudry (2010) summarises findings with reference to non-linear responses due to high-speed rail supply. Daly (2008) opened the discussion from a theoretical point of view, with the main finding that the own-demand elasticity due to travel cost should increase with distance. In the paper all of these findings are supported in that non-linearities are confirmed and have large impact on demand response and model fit.

The main contribution of the paper to the literature of applied transport modelling is that it fills a thematic gap by being one of very few models concerned with long-distance modelling. The model represents a multi-country tour-based model where trip frequencies are connected to a joint mode and destination choice model via logsums. To this end a variety of issues particularly relevant to long-distance modelling are discussed including functional form, the balance between access/egress time and transport time, plane and rail substitution and differences in preferences for different purposes. Moreover, as the model is used by the European Commission to decide on investments in the European infrastructure, it is important simply to expose the model structure and its demand responses to facilitate an academic discussion and to go against the "black-box" tendency in many European projects.

2. Data

The construction of a large-scale multi-country model demands several sources of input data, see Axhausen et al. (2003) for an elaborate discussion of data collection issues for long-distance trips.[5] Our data consist of three elements that we present next: travel survey data, level-of-service (LoS) variables, and zone data.

2.1 The DATELINE survey

The travel survey data used come from the DATELINE survey (DG-TREN 2000). DATELINE represents a "diary type" survey in the sense that individuals were asked to provide information about their past travel history. The *past* in this context differs by purpose and is summarised in

[5] In this paper, trips above 100 km are considered as long-distance trips, i.e. tours above 200 km.

Table 1. The overall shares of trip purposes and modes among the 111,867 separate trips in DATELINE can be seen in Table 2.

Table 1. Interview periods in the DATELINE data.

Purpose	Period of record
Business	3 months
Holiday	1 year
Private	3 month
Commuters	4 weeks

Table 2. Distribution of one-way trips by purpose and by mode adjusted to a year base.

Purpose	Frequency	Percentage	Mode	Frequency	Percentage
Business	43420	29.17%	Air	22597	15.18%
Holiday	73326	49.26%	Bus	11900	7.99%
Private	27221	18.29%	Car[6]	97917	65.78%
Commuters	4882	3.28%	Train	16435	11.04%
Sum of trips	148849		Sum of trips	148849	

A cross tabulation among trip purposes and modes (weighted according to Table 1) reveals that commuters are not represented in large numbers in the data. Accordingly, these have been pooled with business trips in the model. It also exposes the dominant position of car use for all purposes. Moreover, it is seen that the air alternative is more frequently used for business and holiday trips, whereas, for private trips, air trips only account for 2.4%.

There are some specific issues concerning the DATELINE data that should be taken into consideration. Firstly, the data only cover EU27. Second, individual income data were not available. As a result, income effects are modelled by means of zone-specific gross domestic product (GDP). Thirdly, due to the revealed-preference (RP) nature of the DATELINE survey, there were problems in identifying in-vehicle-time and out-of-pocket-costs separately. As a result, we have applied country-wide value of time (VoT) measures, see section 2.3, to produce a generalised in-vehicle-cost measure.

2.2 Level-of-service data

The model is estimated for four modes: car as driver, bus, rail, and airplane. All of the modes are assigned on their respective network except for busses. The set of LoS variables across modes is shown in Table 3.

Table 3. Variation of level-of-service variables across modes.

LoS component	Description	Car/Bus	Rail	Air
Out-of-pocket costs	Monetary variable costs (fuel, tickets)	X	X	X
In-vehicle-time	Time spend in vehicle/rail/plane	X	X	X
Congestion time	The time cars are running in congestion	X		
Ferry time	Time used at ferry crossings	X	X	
Access-egress time	Access-egress time for air and rail		X	X
Frequency	Frequency of rail		X	
Headway time	Headway (frequency proxy) for air			X
Transfer time	Transfer time for air			X

[6] "Car" here includes interview persons travelling as passengers and car drivers.

The LoS variables for all modes are based on stochastic user equilibrium assignments.[7] This includes fairly advanced assignments for air as well as rail. However, busses are not assigned but given a set of pre-fixed costs and travel time variables. The same is true for the cost component for rail. This information was not available prior to the modelling exercise and was estimated in a separate analysis on the basis of a sample for rail ticket costs.

A detailed description of how the LoS data have been generated is beyond the scope of the paper as it involves; (i) a discussion of the Trans-European networks (for all involved modes), (ii) calibration of baseline matrices (adjusted according to network counts), (iii) congestion modelling and (iv) modelling of feeder-mode traffic in the air assignment to mention a few non-trivial issues. For additional details on this we refer to the background report (Rich et al. 2009).

2.3 Value-of-time and zone data

It has not been possible to properly estimate VoT measures based on the DATELINE survey. Moreover, even if it was possible, the weak coverage for large parts of Europe would force an external VoT estimate for these areas anyhow. As a result, it was decided to create a country-wise VoT table divided by trip purpose based on a sample of VoT studies. By combining a purchasing power parity index with this sample, a complete table was generated (Rich et al. 2009).

In our study, the model area includes 1441 zones with great variation in geographical size, GDP, and population. The most detailed zone structure is for Germany and Benelux, whereas Russia, Belarus, Ukraine, Turkey, Sweden, and Norway are represented by very large zones. Iceland is also included. The zone data in the model include population, hotel capacity, jobs, and GDP. All variables are based on EUROSTAT, however, for countries not covered by EUROSTAT (i.e. Russia, Belarus, and Ukraine) national statistics were used. For zones not covered by EUROSTAT and national statistics, we calculated proxies (Rich et al. 2009).

3. Model Specification

3.1 Definition of tours and trips

In the model, we apply a GA approach, in that we consider tours (trip chains) rather than single trips. This is an important improvement compared to models based on single open-ended trips such as the VACLAV model (TRANS-TOOLS 2005). This is especially true for long-distance tours, because individuals from different parts of Europe will be very heterogeneous. A trip-based modelling approach will assume that attributes are always formed in the trip departure region, irrespectively that the trip is part of a journey and should be based on the departure region of the journey (e.g. the residential zone). Consider a Swedish person travelling to Albania. Although the person would be correctly represented as a Swedish person on the way out, he would be represented as an Albanian going to Sweden on the return trip. As there are great differences in income level, car ownership, GDP, and VoT, it makes quite a difference as regard the choice of mode to consider the complete journey compared to a single trip.

Further reasons are that individuals do not make a destination choice when returning they usually return home and that individuals often use the same mode on both the out and homebound trip. In the model, we have assumed that journeys are converted into tours by attaching a main mode and a main destination. For private trips and holiday trips, we only allow home-based tours. For business journeys, however, we allow non-home based tours, with an attached main mode and main destination. For business trips there may be many trips in a chain, however, all sub-trips (not origin and final destination) are excluded. Therefore the model,

[7] The LoS data as derived from the TRANSTOOLS II is based on all traffic including freight as well as long and short distance traffic for passengers.

contrary to a number of activity-based models, may not model dependence between sub tours and main purpose. Figure 1 below illustrates two typical examples of reduced trip chains.

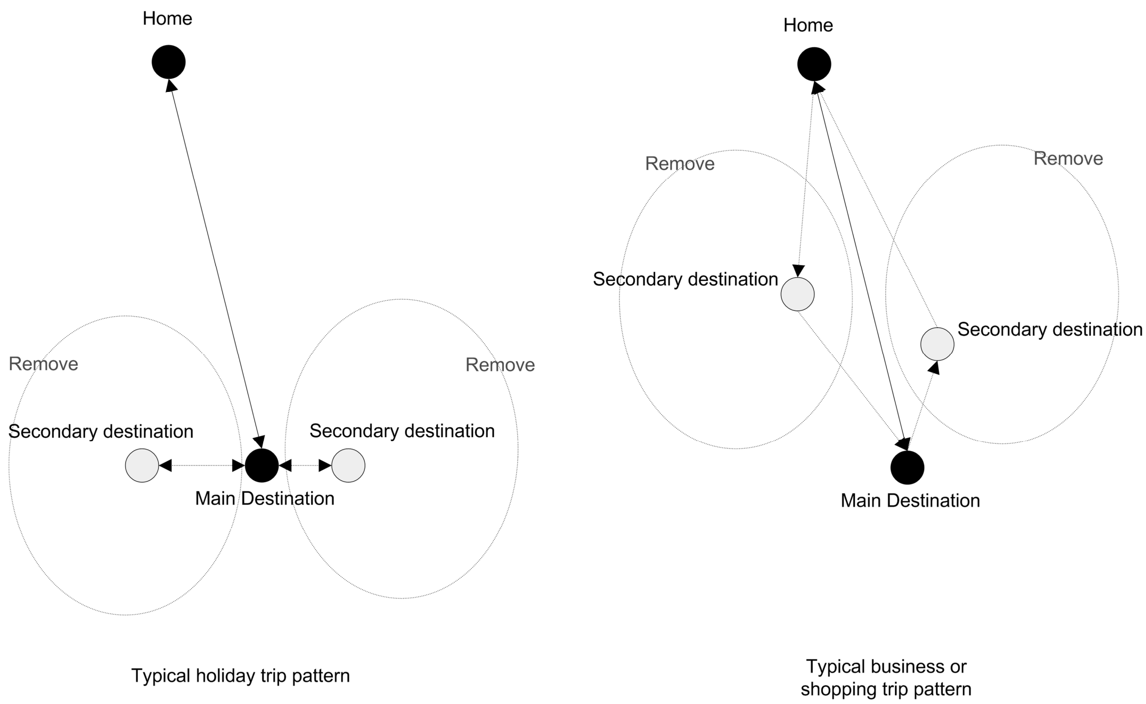

Figure 1. Illustration of how trip chains are converted to simple home-based tours.

To the left in Figure 1, a typical holiday trip pattern is illustrated. It consists of a long journey (e.g. airplane to the Canary Island) and excursions departing from the main destination. In the model only the trip to the main destination is maintained, whereas trips to the secondary destinations are left out.

To the right in Figure 1, a typical business or private trip pattern is shown. It may consist of a main destination and a number of sub-trips on the way to the main destination. However, all secondary destinations are considered as detours and excluded. As a result, only the trip from the home to the main destination is maintained. Compared to the illustration to the left, this trip chain reduction may well produce a new synthetic set of trips which was not in the original set of trips.

The consequences of the trip chain reductions may seem more critical than they are. Firstly, since the majority of the excursions are below 100 km these trips would not be included in the long-distance model anyhow. Secondly, it should be remembered that the objective of the model is to capture overall differences in preferences rather than precisely mimic the trip patterns of households. In other words, excluded trips will only have impact to the extent preferences differ. In terms of excluded mileage, the simplification of trip chains accounts for less than 7% and the impact on parameter estimates is considered to be negligible.

The modelling is done at the individual level. Each journey is seen as decided by the individual. There could be many reasons to change this into a household-based decision. But given that the only socio-economic variable used in the modelling is household car ownership, the decision unit does not influence the model estimation in the present case.

The group size is not modelled. However, it is measured indirectly in the car mode by substitution between passengers and car drivers.

3.2 Nested logit formulation

The model is indexed by n representing a specific tour, i.e. we treat the data as a cross section. The model is formulated as a nested logit model including choice of mode conditional on destination. The nesting structure with destination over mode was based on empirical testing.

The nested logit choice probabilities for observation n are given by

$$P_n(m \mid d) = \frac{e^{V_n(m|d)}}{\sum_{m'} e^{V_n(m'|d)}} \tag{1}$$

where $V_n(m|d)$ is the utility for mode m conditional on destination d. The upper-level probability for the choice of destination is given by

$$P_n(d) = \frac{e^{V_n(d)}}{\sum_{d'} e^{V_n(d')}} \tag{2}$$

The model is estimated by maximum likelihood estimation (MLE). This consists of maximising the log-likelihood function,

$$LL(\beta) = \sum_{n,d,m} y_{n,d,m} \log\left(P_n(d) P_n(m \mid d)\right) \tag{3}$$

where $y_{n,d,m}$ represents an indicator function for the choice of $\{d, m\}$ for tour n.

3.3 Utility functions

Generally, the utility functions are based on LoS variables that vary for all modes and destinations, the number of available cars, and a size variable measuring attractiveness of destinations. In the functional form, we have considered a distance-dependent parameter split (under/over 600 km Euclidian distance) and linear versus logarithmic specifications of the generalised travel cost (GTC) variable. The parameter split was applied to all models and to all time and cost components. This decision was based on an investigation of the air transport market share as a function of distance. There is very strong evidence that the hypothesis of equal parameters for long and short distances fails. The second issue regarding functional form has also turned out to be important. Utility functions have been specified as in equations (4)-(5) where q = 1(short), 2(long) represents the short/long indicator.

$$V_n(d) = Size_d + Adj_n + I_n(d) \tag{4}$$

$$\begin{aligned} V_n(m \mid d) = k_m + \sum_{q(n,d)=1}^{2} \varphi_{q,TC} f\left(GTC_{m|d,q}\right) + \varphi_{q,AE} AccEg_{m|d,q} + \varphi_{q,F} Freq_{m|d,q} \\ + \varphi_{q,FT} FerryTime_{m|d,q} + \varphi_{q,HW} HeadWayTime_{m|d,q} + \varphi_{q,TT} TransferTime \\ + \varphi_{q,m=car} CarAv_n \end{aligned} \tag{5}$$

$I_n(d)$ represents the usual logsum term that is defined as

$$I_n(d) = \mu_d \log \sum_{m|d} e^{V_n(m|d)}, \forall n \quad (6)$$

We use $\mu_d = \mu$ for all d. This ensures that cross-substitution elasticities are symmetric and that monetary units in the model count equal in all nests. In equation (5) q indicates whether the tour is short or long conditional on the destination. All φ-parameters are to be estimated. Variables are described as:

Table 4. Description of the model variables.

Variable name	**Description**
$Size_d$	The attraction variable that varies over destinations.
Adj_n	A correction term for sampling of alternatives as defined in equation (4).
k_m	Mode-specific constants
$AccEg_{m\|d,q}$	Access-egress time. This variable is only valid for the rail and air mode.
$Freq_{m\|d,q}$	Rail frequencies.
$FerryTime_{m\|d,q}$	Gross ferry time including on-board ferry time and waiting time.
$HeadWayTime_{m\|d,q}$	Headway time for the air mode.
$TransferTime_{m\|d,q}$	Transfer time for the air mode.
$CarAv_n$	Car availability based on the number of private cars in the household making tour n (recorded from DATELINE).

The definition of $GTC_{m|d,q}$ is as follows:

$$GTC_{m|d,q} = Cost_{m|d,q} + \gamma_{nm}\left(OnBoardTime_{m|d,q} + \kappa_n CongestionTime_{m|d,q}\right) \quad (7)$$

where $GTC_{m|d,q}$ define generalised variable cost, γ_{nm} is a general VoT measure for countries and modes, and κ_n is a mark-up used to further scale congestion time (a value of κ = 1.5 has been used). It should be noted that congestion time is only calculated for the road network as rail and air transport is modelled without capacity constraint in the assignment.

With respect to the functional form of $GTC_{m|d,q}$ we tested all combinations of trip purpose, distance ($q = 1,2$), and $f(\cdot)$ = linear or $f(\cdot)$ = ln(). This involved 12 models with the unambiguous result in terms of goodness-of-fit as well as model validation (in terms of elasticities) that

$$q = 1: \; f\left(GTC_{m|d,q=1}\right) = GTC_{m|d,q=1}$$
$$q = 2: \; f\left(GTC_{m|d,q=2}\right) = \log\left(GTC_{m|d,q=2}\right) \tag{8}$$

This specification means that, for longer distances, scale effects are avoided and there is proportionality between demand and travel costs. Generally, the distance effect is modelled through the GTC form and including a separate distance term would cause a multicollinearity problem and the model would not be identified. A gamma-form (linear and logarithmic included in a parallel way) was investigated but was not found to be properly identified.[8] It may be argued (Gunn 1983) that rather than do modelling in the money space, modelling should be carried out in the time space. This would imply a formulation with generalised travel time (GTT) equal to

$$GTT_{m|d,q} = OnBoardTime_{m|d,q} + \kappa_n CongestionTime_{m=1\wedge 2|d,q} + Cost_{m|d,q} / \gamma_{nm} \tag{9}$$

This formulation will tend to increase trip length relative to the current approach when forecasting as the VoT increases in real terms everything else equal. Econometrically, however, it makes no difference in the estimation process. Moreover, this only makes a difference in a linear-variable specification and not for a log-transformed specification as applied in the current model for long trips over 600 KM.

3.4 Destination attractiveness

The destination alternatives introduce a non-trivial issue with the measurement of attractions. The form of attraction variables was estimated prior to the discrete choice model. For each trip purpose, we estimated a log-linear Poisson model by regressing explanatory variables onto the enumerated trips from the DATELINE survey. The resulting form of the size variable that enters the model is given by

$$Size_d = \theta_1 \ln\left(POP_d + \theta_2 JOB_d\right) + \theta_3 \ln\left(CAP_d\right) + \theta_4 \ln\left(GDP_d\right) \tag{10}$$

where POP_d is the population of zone d, JOB_d is the number of jobs, CAP_d represent a bed-place capacity for visitors, and GDP_d is the gross domestic product.

The logarithmic specification causes the model to be unaffected by changes to the zone system (Daly 1982). In the estimation, we fixed the size parameters to unity in order to force "demand" proportional to "size" in the model.[9]

4. Estimation

4.1 Sampling of alternatives

As the model operates on a zone structure with 1441 zones, the set of destinations requires sampling of destination alternatives to reduce the computation time. An importance sampling

8 In this way, we have tested a Box-Cox representation heuristically.

9 Estimating the size parameter will usually produce a parameter below unity, indicating a limited substitution pattern in a spatial sense. This can be verified by the theory of elemental alternatives (Ben-Akiva and Lerman 1985).

strategy based on distance bands was applied. The correction term for sampling of alternatives, Adj_n, depends on n and the distance band $b(n)$ defined relatively to the origin of observation n

$$Adj_n = -\log\left(p_{n,b(n)}\right) \tag{11}$$

where $p_{n,b(n)}$ is the selection probability (Ben-Akiva and Lerman 1985). The selection probability is defined as the ratio between the number of sampled zones and the total number of zones within each distance band (relative to the origin zone). As an example, assume that we had a trip above 600 km, then we sampled destinations in 3 bands. We sampled 5 out of 20 destinations in the sampled choice set from the distance band above 1800 km. Therefore these destinations have the correction term $Adj_n = -\log(5/20)$.

As consistency as well efficiency of the nested logit estimator is not guaranteed under importance sampling, several simulation tests of the parameter sensibility due to sampling of alternatives were carried out (Rich et al. 2009). It was evidenced that the sampling bias for 20 sampled destination alternatives was well below the standard error of the model parameters.

4.2 Parameter estimates

Model parameters are estimated by MLE using SAS software. In the following, all of the parameters and goodness-of-fit measures refer to the sampled version of the model as described in section 0. As a result, the standard errors will be biased compared to the un-sampled estimation and the goodness-of-fit will be (upward) biased and indicate that the model is actually better than it is. However, parameters will not be biased (at least only biased within a narrow band corresponding to approximately 0.5-1% of their value according to sampling simulation tests). If we were to calculate corrected standard-errors, we would either need to estimate a full-scale model (which is not considered an option) or apply bootstrapping (many estimations each using repeated sampling of alternatives), which would also be very time consuming. The overall goodness-of-fit report is shown below in Table 5. For each purpose we report the null log-likelihood (LL(0)), the final log-likelihood, LL(β), and the goodness-of-fit measure $\overline{\rho}^2$. In Table 5 $\overline{\rho}^2$ is defined as $\overline{\rho}^2 = 1 - \frac{\ell(\hat{\beta}) - K}{\ell(0)}$ with K equal to the number of estimated parameters.

Table 5. Overall goodness-of-fit measures.

Trip purpose	Number of observations	LL(0)	LL(β)	$\overline{\rho}^2$
Business	6,280	-49,015	-24,089	0.509
Private	15,141	-97,254	-56,154	0.423
Holiday	36,358	-519,999	-165,337	0.682

As seen in **Error! Not a valid bookmark self-reference.** all LoS parameters have the right sign. They are significant except for rail frequency for longer trips. Note that the model includes both a linear and a logarithmic specification for the generalised cost. Generally, for a few variables, e.g. car availability, the DATELINE survey did not allow these parameters to be estimated with sufficiently accuracy. In these cases, rather than apply uncertain parameters, we have applied parameters based on other sources to reflect elasticity levels found in the international literature.

For the business model, the car availability variables were insignificant.[10] We have fixed these car-specific parameters to 0.3695 for use in the elasticity calculations in section 5.

The logsum parameter is within the unit interval, i.e. it is consistent with random utility theory. Tests of the reverse nesting structure revealed approximately identical logsum parameters, however, with a weaker model fit. The results for private and holiday travel are found in Tables 7 and 8.

Although the holiday segment represents the most observations, not all LoS variables were properly identified. For access-egress and headway time, parameters have been calibrated from other data sources. The rail frequency parameters were insignificant and set to zero. Moreover, in the estimation of generalised cost parameters, we experienced identification problems. As a result, we estimated the model under one additional constraint, $\varphi_{1,TC} = k\varphi_{2,TC}$, where k is found as a (combined) ratio between $\hat{\varphi}_1$ and $\hat{\varphi}_2$ parameters from the private and business segment.

The problems experienced with the holiday segment are not particular surprising and arise (partly) from a weak definition of "size". It is difficult to capture holiday attractiveness of a given destination by the variables included in equation (8). Eymann and Ronning (1997) analysed tourist destination choices and found that boundaries for preferred choices were determined by language borders, topographical characteristics, climate, and distance from home. In other words, the description of attractiveness in the present paper falls short of representing many of these dimensions. If attractions are weakly described, this tends to "dry out" many of the LoS effects because the travel resistance is not properly counteracted by travel attractiveness. A second reason may be that the degree of heterogeneity among holiday trips is larger than for business and private trips. An example of a source to hidden heterogeneity is the ownership of vacation homes, which is likely to be one of the most important determinants for destination choice (Hubert and Potier 2003).

4. Elasticities

In section 0, parameters were based on a sampled version of the model, elasticities presented in the following section are based on a full-scale simulation with all 1441 zones included. This avoids potential biased from the sampling as regard the evaluation of choice probabilities. In addition, car passengers (carP) have been included assuming identical LoS as for car driver (carD) but with zero monetary costs. Moreover, alternative-specific constants reflecting base-line market shares have been calibrated using the Manski-Lerman approach (Manski and Lerman 1977). Elasticities have been based on a simulation of a 25% increase for all involved variables. The results are seen in Table 8-Table 10.

It is seen that for CarD and CarP, GTC elasticities increase by distance in absolute value except for car drivers in the holiday segment. However, for the air and rail alternatives it is the other way round. This is because the size of the direct elasticity is always proportional to the term $\left(1-\Pr_{m,d}\right)$ which for these alternatives will actually decrease as a function of distance due to increasing market shares for longer trips. This tendency is similar for most other LoS attributes related to the air and rail alternatives. Moreover, as parameters for these other LoS variables are estimated using another functional form (only linear), this phenomenon seems to hold irrespectively of the functional form. Actually, the decrease in elasticities for access-egress time and rail frequencies for air and rail as a function of distance is very reasonable since these may be interpreted as "start-up" costs. The longer the trip the less relative impact of these components should be expected.

[10] This could be due to the low variation of this variable in the data.

Table 6. Parameter estimates for the business model where q=1 refers to distances below 600 km and q=2 to distances above 600 km.

Parameter	q	Estimate	Std. error	t Value	Pr > |t|
Constant - car driver		-1.5735	0.0865	-18.20	<.0001
Constant – bus		-3.5681	0.1070	-33.34	<.0001
Constant - rail		-3.1708	0.1632	-19.43	<.0001
Car availability - car driver	1,2	0.3695	0	.	.
GTC	1	-0.0026	0.0002	-16.90	<.0001
LN(GTC)	2	-0.8455	0.0160	-52.94	<.0001
Ferry time	1	-0.0023	0.0001	-16.62	<.0001
Ferry time	2	-0.0013	0.0001	-19.33	<.0001
Access-egress time	1	-0.0059	0.0002	-30.40	<.0001
Access-egress time	2	-0.0027	0.0002	-17.16	<.0001
Headway time	1	-0.0020	0.0004	-5.03	<.0001
Headway time	2	-0.0023	0.0003	-7.94	<.0001
Rail frequency	1	0.0208	0.0024	8.82	<.0001
Rail frequency	2	0.0021	0.0033	0.64	0.5251
Logsum		0.5620	0.0085	66.51	<.0001

Table 7. Parameter estimates for the private model where q=1 refers to distances below 600 km and q=2 to distances above 600 km.

Parameter	q	Estimate	Std. error	t Value	Pr > |t|
Constant - car driver		1.1585	0.1235	9.38	<.0001
Constant - bus		0.3914	0.1230	3.18	<0.0015
Constant - rail		-0.4388	0.1550	-2.83	<0.0047
Car availability - car driver	1	0.7383	0.0198	37.28	<.0001
Car availability - car driver	2	0.7344	0.0470	15.61	<.0001
GTC	1	-0.0080	0.0001	-59.63	<.0001
LN(GTC)	2	-1.7268	0.0249	-69.44	<.0001
Ferry time	1	-0.0033	0.0002	-14.91	<.0001
Ferry time	2	-0.0010	0.0001	-12.94	<.0001
Access-egress time	1	-0.0031	0.0002	-19.54	<.0001
Headway time	1	-0.0008	0.0004	-1.79	0.0739
Headway time	2	-0.0002	0.0004	-0.59	0.5584
Rail frequency	1	0.0108	0.0018	5.86	<.0001
Rail frequency	2	0.0137	0.0027	5.02	<.0001
Logsum		0.3748	0.0049	76.53	<.0001

Table 8. Parameter estimates for the holiday model where q=1 refers to distances below 600 km and q=2 to distances above 600 km

Parameter	q	Estimate	Std. error	t Value	Pr > |t|
Constant - car driver		-0.0965	0.0272	-3.55	0.0004
Constant – bus		-1.1642	0.0248	-46.95	<.0001
Constant - rail		-1.4419	0.0263	-54.83	<.0001
Car availability - car driver	1	0.7262	0.0172	42.11	<.0001
Car availability - car driver	2	0.8611	0.0168	51.24	<.0001
GTC	1	-0.0031	0.0000	-88.40	<.0001
LN(GTC)	2	-0.6402	0.0072	-88.40	<.0001
Ferry time	1	-0.0003	0.0000	-7.45	<.0001
Ferry time	2	-0.0016	0.0000	-53.54	<.0001
Access-egress time	1	-0.0019	0	.	.
Access-egress time	2	-0.0006	0	.	.
Headway time	1	-0.0024	0	.	.
Headway time	2	-0.0010	0	.	.
Logsum		0.3414	0.0028	120.71	<.0001

Table 8. Trip elasticities for the business model.

Attribute	Mode	q	Car driver	Car passenger	Bus	Rail	Air
GTC	car driver	1	-0.272	0.525	0.471	0.492	0.503
		2	-0.294	0.466	0.316	0.323	0.308
GTC	car passenger	1	0.086	-0.383	0.081	0.084	0.090
		2	0.113	-0.593	0.076	0.076	0.073
GTC	bus	1	0.054	0.058	-1.179	0.061	0.078
		2	0.066	0.069	-0.548	0.141	0.139
GTC	Rail	1	0.083	0.087	0.090	-0.804	0.128
		2	0.058	0.060	0.108	-0.581	0.112
GTC	Air	1	0.026	0.029	0.034	0.038	-1.247
		2	0.031	0.033	0.084	0.082	-0.574
Access-egress time	Rail	1	0.039	0.040	0.049	-0.385	0.051
		2	0.031	0.032	0.073	-0.309	0.063
Access-egress time	Air	1	0.028	0.031	0.035	0.036	-1.210
		2	0.039	0.041	0.110	0.104	-0.751
Frequency	Rail	1	-0.108	-0.110	-0.107	1.128	-0.159
		2	-0.039	-0.040	-0.039	0.049	-0.052
Ferry time	car driver	1	-0.015	0.051	0.077	0.068	0.113
		2	-0.223	0.108	0.175	0.166	0.167
Ferry time	car passenger	1	0.017	-0.076	0.037	0.030	0.057
		2	0.037	-0.333	0.070	0.066	0.069
Ferry time	Rail	1	0.001	0.002	0.004	-0.014	0.009
		2	0.002	0.003	0.009	-0.043	0.010
Headway time	air	1	0.013	0.015	0.019	0.016	-0.345
		2	0.031	0.034	0.107	0.097	-0.713
Transfer time	air	1	0.003	0.004	0.005	0.004	-0.089
		2	0.006	0.007	0.026	0.022	-0.165

Table 9. Trip elasticities for the private model.

Attribute	Mode	q	Car driver	Car passenger	Bus	Rail	Air
GTC	car driver	1	-0.669	0.807	0.624	0.705	0.673
		2	-0.861	0.570	0.449	0.403	0.418
GTC	car passenger	1	0.270	-0.474	0.232	0.278	0.436
		2	0.526	-0.906	0.443	0.381	0.398
GTC	bus	1	0.139	0.146	-1.570	0.221	0.340
		2	0.165	0.179	-1.076	0.309	0.303
GTC	rail	1	0.053	0.059	0.069	-1.378	0.097
		2	0.085	0.088	0.194	-1.076	0.262
GTC	air	1	0.002	0.003	0.004	0.004	-1.711
		2	0.010	0.010	0.022	0.031	-1.245
Access-egress time	rail	1	0.009	0.010	0.017	-0.280	0.021
Access-egress time	air	1	0.001	0.001	0.001	0.001	-0.769
Frequency	rail	1	-0.022	-0.023	-0.027	0.534	-0.035
		2	-0.040	-0.041	-0.086	0.532	-0.121
Ferry time	car driver	1	-0.016	0.023	0.024	0.033	0.078
		2	-0.149	0.046	0.086	0.085	0.108
Ferry time	car passenger	1	0.022	-0.054	0.066	0.072	0.288
		2	0.064	-0.177	0.154	0.156	0.196
Ferry time	rail	1	0.001	0.002	0.004	-0.029	0.013
		2	0.004	0.004	0.013	-0.056	0.024
Headway time	air	1	0.000	0.000	0.000	0.000	-0.212
		2	0.001	0.001	0.002	0.003	-0.118
Transfer time	air	1	0.000	0.000	0.000	0.000	-0.088
		2	0.000	0.000	0.001	0.001	-0.037

Table 10. Trip elasticities for the holiday model.

Attribute	Mode	q	Car driver	Car passenger	Bus	Rail	Air
GTC	car driver	1	-0.479	0.131	0.117	0.123	0.130
		2	-0.447	0.097	0.078	0.080	0.078
GTC	car passenger	1	0.065	-0.246	0.060	0.063	0.067
		2	0.088	-0.455	0.070	0.072	0.069
GTC	bus	1	0.333	0.341	-0.725	0.332	0.336
		2	0.211	0.212	-0.327	0.226	0.225
GTC	rail	1	0.127	0.132	0.121	-0.645	0.134
		2	0.091	0.091	0.095	-0.444	0.095
GTC	air	1	0.071	0.073	0.068	0.072	-0.753
		2	0.085	0.085	0.093	0.093	-0.436
Access-egress time	rail	1	0.026	0.027	0.028	-0.144	0.024
		2	0.017	0.017	0.021	-0.086	0.019
Access-egress time	air	1	0.046	0.047	0.044	0.046	-0.527
		2	0.046	0.045	0.051	0.049	-0.225
Ferry time	rail	1	-0.005	0.004	0.004	0.004	0.005
		2	-0.091	0.010	0.015	0.013	0.016
Ferry time	car passenger	1	0.004	-0.010	0.004	0.005	0.006
		2	0.010	-0.097	0.016	0.014	0.018
Ferry time	rail	1	0.002	0.003	0.002	-0.006	0.002
		2	0.003	0.003	0.010	-0.043	0.011
Headway time	air	1	0.045	0.047	0.044	0.046	-0.458
		2	0.067	0.067	0.079	0.077	-0.363
Transfer time	air	1	0.012	0.013	0.011	0.012	-0.120
		2	0.018	0.018	0.020	0.020	-0.095

Another observation is that there are significant differences among the three trip purposes, not only with respect to the size of elasticities, but also with respect to the internal weighting of distance impacts.

In-vehicle time and cost elasticities cannot be directly determined from the above tables. Let however E_{GTC} define the elasticity of the GTC, E_{Time} the travel time elasticity, and E_{Cost} the cost elasticity. It is then easy to show the two following identities: $E_{GTC} = E_{Time} + E_{Cost}$ and $\frac{\gamma \cdot Time}{Cost} = \frac{E_{Time}}{E_{Cost}}$, where γ is the VoT. Clearly, if we combine these it can be found that

$$E_{Cost} = \frac{E_{GTC}}{1 + \gamma \frac{Time}{Cost}} \tag{12}$$

$$E_{Time} = \frac{E_{GTC}}{1 + \frac{Cost}{\gamma \cdot Time}} \tag{13}$$

This exposes some of the weaknesses of using a generalised travel cost approach, namely that the split between E_{Cost} and E_{Time} is strongly dependent on the VoT. If a general country-wise VoT is used for all modes, it means that for certain expensive modes (e.g. the air alternative) the cost share of the elasticity becomes dominating. Due to this problem, some scaling of the air VoT may be necessary in order to get a more reliable balancing of the demand responses.

Table 11. Business trip elasticities for travel cost and time.

Attribute	Mode	q	Car driver	Car passenger	Bus	Rail	Air
Cost	car driver	1	-0.105	0.205	0.194	0.193	0.212
		2	-0.141	0.203	0.138	0.139	0.135
Cost	bus	1	0.023	0.024	-0.46	0.024	0.027
		2	0.026	0.027	-0.181	0.041	0.039
Cost	rail	1	0.056	0.058	0.056	-0.511	0.085
		2	0.036	0.037	0.057	-0.306	0.063
Cost	air	1	0.023	0.026	0.03	0.033	-1.072
		2	0.027	0.029	0.072	0.071	-0.474
Travel time	car driver	1	-0.168	0.317	0.277	0.298	0.292
		2	-0.154	0.274	0.187	0.192	0.181
Travel time	car passenger	1	0.086	-0.383	0.081	0.084	0.09
		2	0.113	-0.593	0.076	0.076	0.073
Travel time	Bus	1	0.035	0.039	-0.719	0.042	0.057
		2	0.045	0.047	-0.367	0.107	0.108
Travel time	Rail	1	0.032	0.034	0.039	-0.293	0.05
		2	0.026	0.027	0.058	-0.275	0.057
Travel time	Air	1	0.004	0.005	0.005	0.006	-0.175
		2	0.005	0.006	0.016	0.015	-0.101

Table 12. Trip elasticities of travel cost and time for the private model.

Attribute	Mode	q	Car driver	Car passenger	Bus	Rail	Air
Cost	car driver	1	-0.346	0.427	0.336	0.372	0.374
		2	-0.489	0.332	0.260	0.229	0.236
Cost	Bus	1	0.076	0.077	-0.732	0.088	0.105
		2	0.077	0.082	-0.427	0.100	0.103
Cost	Rail	1	0.040	0.044	0.043	-1.000	0.067
		2	0.057	0.058	0.114	-0.623	0.170
Cost	Air	1	0.002	0.003	0.003	0.004	-1.441
		2	0.008	0.009	0.019	0.026	-0.993
Travel time	car driver	1	-0.323	0.393	0.298	0.346	0.324
		2	-0.372	0.273	0.219	0.201	0.209
Travel time	car passenger	1	0.270	-0.474	0.232	0.278	0.436
		2	0.526	-0.906	0.443	0.381	0.398
Travel time	Bus	1	0.080	0.090	-0.838	0.155	0.267
		2	0.107	0.117	-0.649	0.234	0.226
Travel time	Rail	1	0.018	0.021	0.031	-0.378	0.038
		2	0.037	0.040	0.097	-0.453	0.112
Travel time	Air	1	0.000	0.001	0.001	0.001	-0.270
		2	0.002	0.002	0.005	0.007	-0.252

Table 13. Trip elasticities of travel cost and time for the holiday model.

Attribute	Mode	q	Car driver	Car passenger	Bus	Rail	Air
Cost	car driver	1	-0.251	0.071	0.063	0.066	0.070
		2	-0.236	0.054	0.044	0.045	0.044
Cost	Bus	1	0.176	0.177	-0.366	0.171	0.175
		2	0.108	0.109	-0.146	0.105	0.104
Cost	Rail	1	0.094	0.096	0.088	-0.459	0.099
		2	0.065	0.066	0.065	-0.289	0.066
Cost	Air	1	0.062	0.064	0.059	0.063	-0.656
		2	0.073	0.073	0.080	0.080	-0.356
Travel time	car driver	1	-0.228	0.065	0.058	0.061	0.064
		2	-0.211	0.049	0.039	0.040	0.039
Travel time	car passenger	1	0.065	-0.246	0.060	0.063	0.067
		2	0.088	-0.455	0.070	0.072	0.069
Travel time	Bus	1	0.170	0.177	-0.359	0.174	0.175
		2	0.116	0.115	-0.181	0.134	0.133
Travel time	Rail	1	0.038	0.040	0.037	-0.186	0.039
		2	0.031	0.031	0.036	-0.155	0.035
Travel time	Air	1	0.011	0.011	0.010	0.011	-0.097
		2	0.015	0.015	0.017	0.017	-0.080

5.1 Results compared to the literature

Compared to the literature, the size of the elasticities seems to be reasonable. However, the sample to compare with is small and caution should be taken when comparing studies with varying distance ranges. For instance, it may be argued that direct car cost elasticities around -0.489 for private trips are high compared to elasticities found in many urban studies, which are usually in the range of -0.2, -0.5. However, as shown by Daly (2008), elasticities for car will tend to increase by distance simply because the $\left(1-\Pr_{m,d}\right)$ term increases. Elasticities obtained by the SAMPERS long-distance model (Beser 2003; Chapter 4) indicate a good correspondence, although with some exceptions. Firstly, due to the imbalance between time and cost discussed above, our travel time elasticities for the air alternative are on the low side. However, for ground mode alternatives, elasticities are much in line. In meta-studies by De Jong et al. (2004) and De Jong and Gunn (2001) European elasticities are reviewed. Elasticities for car costs between -0.05 and -0.35 as reported by the Dutch model seem to be in line with our findings if the distance effect discussed by Daly (2008) is accounted for. In a meta-study on UK elasticities, Wardman and Grant-Muller (2011) largely confirm the findings for the continental models. The opposite direction of time elasticities for car drivers and passengers reflects the very simplified way car passengers are dealt with.

We also find that, whereas elasticities for car drivers and passengers tend to increase by distance, it is the opposite for the rail and air alternatives. This, however, conforms well to a meta-study conducted by Brons et al. (2002). Their analysis considered air price elasticities for three distance intervals and found a strong indication of decreasing elasticities with median elasticity in the range of -1.2 to -0.75. In another more recent analysis (Airbus 2009), air fare elasticities are quoted within the range of -0.5 and -1 with -1 referring to domestic flights and -0.5 to longer flights including intercontinental trips. This fits well with the above findings where the average (weighted) short-distance elasticity for air fares (the cost attribute) is -0.90 for the short-distance segment and -0.54 for long distances. Two recent long distance studies are described in Börjesson (2010) in a Swedish study and in Rohr et al. (2010) in a study for UK. Generally the level of elasticities when measured as a combined cost and time elasticity are comparable. However, in these studies the elasticity with respect to in-vehicle-time for car driving is 4 to 10 times higher than the elasticity for fuel cost. This cannot be verified in the present study, which to some extent may be down to the generalised cost form as discussed above.

The elasticities are lowest for holiday trips, highest for private trips, and with business trips in between. Empirically, the literature indicates that business trips will be less sensitive compared to private trips (De Jong and Gunn 2001) and Gaudry (2002), which however is in contradiction to the finding in Rohr et al. (2010). For holiday trips there is little empirical evidence that can be used as a benchmark.

Finally, the model provides sensitivity analysis for a range of LoS variables not often considered in a long-distance modelling context. These include rail frequencies, access-egress time for rail and for air, headway time, as well as transfer time. It is found that rail demand is very sensitive to rail frequencies as well as to access-egress time. Air demand is found to be very sensitive to access-egress time and less sensitive to headway time and transfer time. Generally, short-distance trips are more sensitive to these LoS components, which is logical since they may be considered as start-up costs.

6. Conclusion

More than half of all motorised passenger kilometres in Europe arise from trips above 100 km. Moreover, due to a higher share of air transport, this transport segment is responsible for the majority of transport related CO_2 emissions. The paper focuses on the long-distance transport segment. The model outlined has been developed as part of the TRANSTOOLS II model framework initiated by the European Commission and will enable assessment of European-wide transport policy. A principle objective of the paper in that respect has been to describe the model structure and its results in a transparent way to facilitate a much needed academic debate about large scale and long-distance modelling.

The model is a long-distance demand model for the choice of mode and destination. It is the first tour-based passenger demand model for Europe. It models trips over 100 km for 42 countries divided into 1441 zones. The model is segmented into three trip purposes; business, private, and holiday, and five modes; car drivers, car passengers, bus, rail, and air. A nested logit model is applied for the choice of mode conditional on destination. In the estimation, importance sampling has been used in order to reduce the choice set to a feasible size. At an upper level tour frequencies are modelled on the basis of logsum variables from the mode and destination choice model.

In the utility function, a distance-dependent split was applied for all LoS variables. Moreover, we analysed all combinations of a logarithmic and linear specification combined with the short and long distance split. This was carried out for all purposes. It was found that a linear model for shorter trips (below 600 km) and a logarithmic model for longer trips were superior in terms of goodness-of-fit. Among these, preliminary tests of Box-Cox forms were carried out. However, for the long-distance segment the Box-Cox approached the logarithmic specification.

The results from the model reveal several things. Firstly, the range of elasticities conforms well relative to other models and meta-studies. Secondly, elasticities with respect to in-vehicle cost and time (inherited in the generalised cost measure) for car drivers and passengers tend to increase with journey distance. This is consistent across all trip purposes. Thirdly, for the air and rail alternative the elasticity decreases with distance. This is consistent with empirical findings and is due to the fact that the market shares for these alternatives increase with distance. This finding is consistent for all trip purposes and holds for most other LoS variables related to the air alternative, i.e. access-egress time, transfer time, and headway time. This is very logical because these LoS components can be considered as start-up costs. Finally, it was also found that holiday tours had the lowest elasticities, private the highest, and business in between. This pattern is in line with expectations.

With increasing focus on climate effects, long-distance travel demand modelling is likely to be at the top of the applied research agenda for years to come. Although the present paper deals with some of the shortcomings of previous European multi-country models, several challenges remain: A detailed analysis of non-linearities with respect to distance, better measurement of destination attractions for holiday trips, and combined SP/RP surveys in order to better cope with identification problems in the estimation of VoT measures.

6.1 Research perspectives and future work

Recently it has been decided to upgrade the TRANSTOOLS II model to a version III. During the update the passenger model is to be updated. This includes a partly upgrade of the data foundation as well as methodological improvements. Issues to consider will be;

- Segmentation into journey durations
- A separate model for commuter trips
- An improved study on non-linearities with the possibility of including Box-Cox forms explicitly
- Party size should be considered to dealt with passengers more effectively

At a more general level the study has revealed that there is a strong need for more research in long distance trip modelling as these types of trips are very different from daily trips.

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