A long-distance travel demand model for Europe

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Abstract

In Europe, more than 50% of all passenger kilometres come from trips beyond 100 km. 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 TRANSTOOL II model, and will serve as an important tool for transport policy analysis at a European level. Methodologically, the model is formulated as a nested logit model and estimated based on travel diary data with segmentation into business, private, and holiday trips. The model estimation is analysed and elasticities for a number of different level-of-service variables are presented. It is revealed that the perception of travel time and cost varies with journey length in a non-linear way. For 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.

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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) global 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). Although there has been a temporary decline in air transport as a result of the financial crisis, 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 multi-country models. As a result, models capable of analysing global and nationwide factors such as climate effects or abilities to meet overall CO_2 targets have been limited. Consequently, the substitutability among long-distance modes including air transport and high-speed rail has not been given the same attention as substitution between short-range urban modes. From a climate point of view and given the needs for analysing the economic efficiency of large-scale European infrastructure projects, this cannot be justified.

To our knowledge, the model presented in this paper is the first tour-based multi-country model which has been estimated on disaggregate data and subsequently implemented for policy analysis. The model is part of the TRANS-TOOL II model framework (TRANS-TOOL 2008), which will form the basis for transport policy analysis by the European Commision with respect to climate, infrastructure, and economic development. In the model, we apply a generation-attraction (GA) approach, in that we consider tours (trip chains) rather than single trips (Adler and Ben-Akiva 1979). This approach is especially relevant for longer trips and in particular for trips crossing country borders. The point is that there may be substantial differences among the attributes of people in different zones and countries. If a trip-based approach was used, the out and return trip would be considered separately and assigned different attributes. An example would be 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, gross domestic product (GDP), and the value of time (VoT) it makes quite a difference as regard the choice of mode to consider the complete journey compared to a single trip.

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 *distribution model* covering 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. If we were to consider income effects and induced traffic, the interpretation of the model results would be less clear.

Next, in Section 1.1, the paper reviews literature on long-distance modelling. Section 2 discusses data with emphasis on the DATELINE survey. In section 3, we discuss the model structure. Section 4 is about estimation, while section 5 presents the elasticity results. Finally, in section 6 a conclusion is offered.

1.1 Review of long-distance demand modelling

Most of the work on long-distance models is connected with the development of national models. An overview of European national models is given in Lundqvist and Mattsson (2002).[2] 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. Other models include the PETRA (Fosgerau 2002) model for Denmark. The Norwegian national model described in Lindfjord and Ramjerdi (1994) and the Italian national model described in Russo (2002) also represent state-of-the-art models based on many of the ideas put forward in the Dutch national model.

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 feature is exogenous stratification by trip purpose, although experiments with endogenous stratification have been considered in Beser (2003; Chapter 2) for the Swedish national model, SAMPERS. In terms of estimation techniques, usually a standard nested logit approach has been used. It is worth noting that the nesting structure of the SAMPERS long-distance model (Beser 2003; Chapter 4), with a nesting structure where mode is conditional on destination, is identical to the structure found in the present paper.

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

[2] Attention should also be given to Fox et al. (2003) which gives an overview of the models developed by RAND Europe.

VACLAV model, is trip-based and not capable of consistently measuring the impacts of zone-based data. 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, which 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.

The journey distance including its impact on model outputs and relationship to functional form specifications 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. Recently, Gaudry (2008) summarised some of the findings with particular reference to non-linear responses due to high-speed rail supply. Most recently, 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.

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. In our study, the model area includes 1441 zones with great variation in geographical size, GDP, and population. An illustration of the zone system is presented in Figure 1 below.

<Figure 1>

Figure 1: The TRANS-TOOLS II model area with zone borders.

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 represented but not included on the map. Our data consist of 3 elements that we present next: a travel survey, level-of-service (LoS) variables, and zone data.

2.1 The DATELINE survey

The travel diary data used is known as DATELINE (DG-TREN 2000). DATELINE represents a “diary type” survey in the sense that people were asked to provide information about their past travel history. The *past* in this context differs by purpose and is summarised in Table 1 below.

Purpose	Period of record	Weights
Business	3 months	4
Holiday	1 Year	1
Private	3 month	4
Commuters	4 weeks	10.5

Table 1: Duration of interview periods and corresponding “weights”.

The weights in Table 1 are the naïve weights that bring the survey to an annual basis and enable a comparison across trip purposes. The overall shares of trip purposes and modes can be seen in Table 2 below.

Purpose	Frequency	Percentage	Mode	Frequency	%
Business	43420	29.17%	Air	22597	15.18%
Holiday	73326	49.26%	Bus	11900	7.99%

Private	27221	18.29%	Car	97917	65.78%
Commuters	4882	3.28%	Train	16435	11.04%
Sum of trips	148849		Sum of trips	148849	

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

A cross tabulation among trip purposes and modes (weighted according to Table 1) reveals that commuters only cover 0.42% of the trips. Table 2 also exposes the dominant position of car use for all purposes. Moreover, it is clearly 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 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 VoT estimates to produce a generalised in-vehicle-cost measure. Finally, the DATELINE survey does not include many commuting trips. These have been pooled with business trips.

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.

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 the seats”	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

Table 3: Outline of level-of-service variables.

The LoS variables for all modes are based on stochastic user equilibrium assignments. 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.

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).

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. As discussed in the introduction, 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). This holds for attributes related to income, car ownership, and the VoT.

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. Figure 2 below illustrates two typical examples of reduced trip chains.

<Figure 2>

Figure 2: Illustration of how trip chains are converted to simple home-based tours.

To the left in Figure 2, 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 2, 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.

3.2 Nested logit formulation

The model is indexed by n which signifies a specific tours, i.e. even though we have a panel we estimate it like a cross section for practical reasons. 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. It signals that the error for the choice of mode is larger than the error for destination choice. This finding is consistent with Beser (2003; Chapter 4).

The nested logit choice probabilities for mode m conditional on destination d are given by

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

The logsum term is defined in the usual way by

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

The upper-level probability for the choice of destination is given by

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

with $V_n(d) = I_n(d)$. We apply a similar scaling of nests by restricting $\mu_d = \mu$ for all d.

The latter ensures that cross-substitution elasticities are symmetric and that monetary units in the model count equal in all nests. The model is estimated by maximum likelihood estimation (MLE). This consists of maximising the log-likelihood function,

(4) $$LL(\beta) = \sum_{n,d,m} y_{n,d,m} \log\left(P_n(d) P_n(m|d)\right)$$

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. 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 equation (5) where q = 1(short), 2(long) represents the short/long indicator.

$$
\begin{aligned}
&V_{m|d,q} = k_m + Size_d + Adj_{d,q} \\
(5)\ &+ \textstyle\sum_{q=1}^{2} \varphi_{q,TC} f\left(GTC_{m|d,q}\right) + \varphi_{q,AE} AccEg_{m|d,q} + \varphi_{q,F} Freq_{m|d,q} + \varphi_{q,FT} FerryTime_{m|d,q} \\
&+ \varphi_{q,HW} HeadWayTime_{m|d,q} + \varphi_{q,TT} TransferTime + \varphi_{q,CA} CarAv_n
\end{aligned}
$$

More specifically, variables are described as:

Variable name	**Description**
$Size_d$	The attraction variable that varies over destinations.
$Adj_{d,q}$	A sampling correction factor.
$f\left(GTC_{m\|d,q}\right)$	Generalised travel cost on the basis of In-Vehicle-Time and out-of-pocket costs (see below)
$AccEg_{m\|d,q}$	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).

Table 4: Description of the model variables.

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

$$
(6) \qquad GTC_{m|d,q} = Cost_{m|d,q} + \gamma_{nm}\left(OnBoardTime_{m|d,q} + \kappa_n CongestionTime_{m=1\wedge 2|d,q}\right)
$$

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).

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

(7) $$q = 1: f\left(GTC_{m|d,q=1}\right) = GTC_{m|d,q=1}$$

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

This specification means that, for longer distances, scale effects are avoided. A Box-Cox functional form was not explored, however, a gamma-form (linear and logarithmic included in a parallel way) was not properly identified.

3.4 Destination attractiveness

The destination alternatives introduce a non-trivial issues with the measurement of attractions. The correct way of estimating size variables has been described by Daly (1982), however, this approach has not been possible in the present estimation. Instead, the form of attraction variables has been estimated prior to the discrete choice model. For each trip purpose, we have estimated a log-linear Poisson model by regressing POP_d, JOB_d, CAP_d, and GDP_d onto the enumerated trips vectors from the DATELINE survey. The resulting form of the size variable that enters the model is given by

(8) $$Size_d = \theta_1 \ln(POP_d + \theta_2 JOB_d) + \theta_3 \ln(CAP_d) + \theta_4 \ln(GDP_d),$$

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

The logarithmic specification causes the model to be unaffected by the zone system (Daly 1982). In the estimation, we fix the size parameters to unity in order to force “demand” proportional to “size” in the model.[3]

4 ESTIMATION

4.1 Sampling of alternatives

The model operates on a zone structure of 1441 zones. In the present case, the destination choice modelling requires sampling of alternatives in order to reduce the memory consumption of the model during estimation. At present, the memory consumption for the largest model segment (holidays) is above 800 MB. A full-scale estimation without sampling would require in the range of 60-120 GB of swop space and would not be computationally feasible. In order to reduce the number of destination alternatives, an importance sampling strategy based on distance bands has been applied. It can be shown (Ben-Akiva and Lerman 1985) that the sample correction term $\Omega_{n,b}$ for individual n and distance band b is given by

(9) $$\Omega_{n,b} = -\log(q_{n,b}),$$

where $q_{n,b}$ is the selection probability.

[3] 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).

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 was tested (Rich et al. 2009). It was evidenced that the sample bias for 20 sampled destination alternatives was significantly 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 4.1. 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, 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 $\bar{\rho}^2$. In Table 5 $\bar{\rho}^2$ is defined as $\bar{\rho}^2 = 1 - \frac{\ell(\beta) - K}{\ell(0)}$ with K equal to the number of estimated parameters.

Trip purpose	Number of observations	LL(0)	LL(β)	$\bar{\rho}^2$
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

Table 5: Overall goodness-of-fit measures.

Parameter	DF	Estimate	Std. error	t Value	Pr > |t|
M1	1	-1.5735	0.0865	-18.20	<.0001
M2	1	-3.5681	0.1070	-33.34	<.0001
M3	1	-3.1708	0.1632	-19.43	<.0001
Size1	0	1.0000	0		
Adj	0	1.0000	0		
CarAv_1	0	0.3695	0		
CarAv_2	0	0.3695	0		
GTC_1	1	-0.0026	0.0002	-16.90	<.0001
LOG_GTC2	1	-0.8455	0.0160	-52.94	<.0001
FerryTime_1	1	-0.0023	0.0001	-16.62	<.0001
FerryTime_2	1	-0.0013	0.0001	-19.33	<.0001
AccEgTime_1	1	-0.0059	0.0002	-30.40	<.0001
AccEgTime_2	1	-0.0027	0.0002	-17.16	<.0001
HeadWayTime_1	1	-0.0020	0.0004	-5.03	<.0001
HeadWayTime_2	1	-0.0023	0.0003	-7.94	<.0001
Freq_1	1	0.0208	0.0024	8.82	<.0001
Freq_2	1	0.0021	0.0033	0.64	0.5251
Logsum	1	0.5620	0.0085	66.51	<.0001

Table 6: Parameter estimates for the business model.

As seen in Table 6 all LoS parameters have the right sign and are significant except for rail frequencies for longer trips. Note that the model includes both a linear (GTC_1) and a logarithmic (GTC_2) specification for the generalised cost. The “Adj” term represents the sampling adjustment factor described in equation (9). Moreover, for the business model, the car availability variables were insignificant. However, due to findings in the literature and forecasting abilities of the model, we have pre-fixed a set of parameters. The logsum parameter is defined by the “Logsum” parameter and fits nicely within the unit interval as required. 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.

Parameter	DF	Estimate	Std. error	t Value	Pr > |t|
M1	1	1.1585	0.1235	9.38	<.0001
M2	1	0.3914	0.1230	3.18	0.0015
M3	1	-0.4388	0.1550	-2.83	0.0047
Size2	0	1.0000	0		
Adj	0	1.0000	0		
CarAv_1	1	0.7383	0.0198	37.28	<.0001
CarAv_2	1	0.7344	0.0470	15.61	<.0001
GTC_1	1	-0.0080	0.0001	-59.63	<.0001

LOG_GTC2	1	-1.7268	0.0249	-69.44	<.0001
FerryTime_1	1	-0.0033	0.0002	-14.91	<.0001
FerryTime_2	1	-0.0010	0.0001	-12.94	<.0001
AccEgTime_1	1	-0.0031	0.0002	-19.54	<.0001
HeadWayTime_1	1	-0.0008	0.0004	-1.79	0.0739
HeadWayTime_2	1	-0.0002	0.0004	-0.59	0.5584
Freq_1	1	0.0108	0.0018	5.86	<.0001
Freq_2	1	0.0137	0.0027	5.02	<.0001
Logsum	1	0.3748	0.0049	76.53	<.0001

Table 7: Parameter estimates for the private model.

Parameter	DF	Estimate	Std. error	t Value	Pr > |t|
M1	1	-0.0965	0.0272	-3.55	0.0004
M2	1	-1.1642	0.0248	-46.95	<.0001
M3	1	-1.4419	0.0263	-54.83	<.0001
Size3	0	1.0000	0		
Adj	0	1.0000	0		
CarAv_1	1	0.7262	0.0172	42.11	<.0001
CarAv_2	1	0.8611	0.0168	51.24	<.0001
GTC_1	1	-0.0031	0.0000	-88.40	<.0001
LOG_GTC2	1	-0.6402	0.0072	-88.40	<.0001
FerryTime_1	1	-0.0003	0.0000	-7.45	<.0001
FerryTime_2	1	-0.0016	0.0000	-53.54	<.0001
AccEgTime_1	0	-0.0019	0		
AccEgTime_2	0	-0.0006	0		
HeadWayTime_1	0	-0.0024	0		
HeadWayTime_2	0	-0.0010	0		
Logsum	1	0.3414	0.0028	120.71	<.0001

Table 8: Parameter estimates for the holiday model.

Although the holiday segment represents the most observations, not all LoS variables have been properly identified. This includes access-egress time, headway time, as well as rail frequencies. For access-egress time and headway time parameters from the private model have been applied. For rail frequencies, these have simply been taken out. Moreover, in the estimation of generalised cost parameters, we experienced identification problems. As a result, we have estimate the model under one additional constraint, $\varphi_{1,TC} = k\varphi_{2,TC}$, where k is found from a combination of private and business parameters.

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).

5 Results

In the following we shall present the elasticity structure of the model. Whereas in section 4.2, parameters were based on a sampled version of the model, elasticities presented in the following section will be based on a full-scale simulation with all 1441 zones included. This is to avoid potential biased from the sampling as regard the evaluation of choice probabilities. In addition, car passengers have been included as the *carP* by assuming identical LoS as for car driver (carD) but with zero costs. Moreover, alternative 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 9 - Table 11.

Attribute	Distance	CarD	CarP	Bus	Rail	Air
GTC: CarD	Short	-0.272	0.525	0.471	0.492	0.503
	Long	-0.294	0.466	0.316	0.323	0.308

GTC: CarP	Short	0.086	-0.383	0.081	0.084	0.090
	Long	0.113	-0.593	0.076	0.076	0.073
GTC: Bus	Short	0.054	0.058	-1.179	0.061	0.078
	Long	0.066	0.069	-0.548	0.141	0.139
GTC: Rail	Short	0.083	0.087	0.090	-0.804	0.128
	Long	0.058	0.060	0.108	-0.581	0.112
GTC: Air	Short	0.026	0.029	0.034	0.038	-1.247
	Long	0.031	0.033	0.084	0.082	-0.574
AccEgr: Rail	Short	0.039	0.040	0.049	-0.385	0.051
	Long	0.031	0.032	0.073	-0.309	0.063
AccEgr: Air	Short	0.028	0.031	0.035	0.036	-1.210
	Long	0.039	0.041	0.110	0.104	-0.751
Freq: Rail	Short	-0.108	-0.110	-0.107	1.128	-0.159
	Long	-0.039	-0.040	-0.039	0.049	-0.052
FerryTime: CarD	Short	-0.015	0.051	0.077	0.068	0.113
	Long	-0.223	0.108	0.175	0.166	0.167
FerryTime: CarP	Short	0.017	-0.076	0.037	0.030	0.057
	Long	0.037	-0.333	0.070	0.066	0.069
Ferry time: Rail	Short	0.001	0.002	0.004	-0.014	0.009
	Long	0.002	0.003	0.009	-0.043	0.010
Headway: Air	Short	0.013	0.015	0.019	0.016	-0.345
	Long	0.031	0.034	0.107	0.097	-0.713
Transfer time: Air	Short	0.003	0.004	0.005	0.004	-0.089
	Long	0.006	0.007	0.026	0.022	-0.165

Table 9: Business elasticities.

Attribute	Distance	CarD	CarP	Bus	Rail	Air
GTC: CarD	Short	-0.669	0.807	0.624	0.705	0.673
	Long	-0.861	0.570	0.449	0.403	0.418
GTC: CarP	Short	0.270	-0.474	0.232	0.278	0.436
	Long	0.526	-0.906	0.443	0.381	0.398
GTC: Bus	Short	0.139	0.146	-1.570	0.221	0.340
	Long	0.165	0.179	-1.076	0.309	0.303
GTC: Rail	Short	0.053	0.059	0.069	-1.378	0.097
	Long	0.085	0.088	0.194	-1.076	0.262
GTC: Air	Short	0.002	0.003	0.004	0.004	-1.711
	Long	0.010	0.010	0.022	0.031	-1.245
AccEgr: Rail	Short	0.009	0.010	0.017	-0.280	0.021
	Long	0.004	0.004	0.007	0.007	0.007
AccEgr: Air	Short	0.001	0.001	0.001	0.001	-0.769
	Long	0.000	0.000	0.000	0.000	0.001
Freq: Rail	Short	-0.022	-0.023	-0.027	0.534	-0.035
	Long	-0.040	-0.041	-0.086	0.532	-0.121
Ferry time: CarD	Short	-0.016	0.023	0.024	0.033	0.078
	Long	-0.149	0.046	0.086	0.085	0.108
Ferry time: CarP	Short	0.022	-0.054	0.066	0.072	0.288
	Long	0.064	-0.177	0.154	0.156	0.196
Ferry time: Rail	Short	0.001	0.002	0.004	-0.029	0.013

	Long	0.004	0.004	0.013	-0.056	0.024
Headway: Air	Short	0.000	0.000	0.000	0.000	-0.212
	Long	0.001	0.001	0.002	0.003	-0.118
Transfer time: Air	Short	0.000	0.000	0.000	0.000	-0.088
	Long	0.000	0.000	0.001	0.001	-0.037

Table 10: Private elasticities.

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

Table 11: Holiday elasticities.

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 alternative it is the other way round. This is because for these alternatives, the term $(1 - \mathrm{Pr}_{m,d})$ 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 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.

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

(10) $$E_{Cost} = \frac{E_{GTC}}{1+\gamma\frac{Time}{Cost}}$$

(11) $$E_{Time} = \frac{E_{GTC}}{1+\frac{Cost}{\gamma \cdot Time}}$$

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.

Attribute	Distance	CarD	CarP	Bus	Rail	Air
Cost: CarD	Short	-0.103	0.205	0.194	0.193	0.212
	Long	-0.151	0.203	0.138	0.139	0.135
Cost: Bus	Short	0.023	0.024	-0.501	0.024	0.027

	Long	0.026	0.027	-0.193	0.041	0.039
Cost: Rail	Short	0.056	0.058	0.056	-0.537	0.085
	Long	0.036	0.037	0.057	-0.331	0.063
Cost: Air	Short	0.023	0.026	0.030	0.033	-1.114
	Long	0.027	0.029	0.072	0.071	-0.495
Time: CarD	Short	-0.165	0.317	0.277	0.298	0.292
	Long	-0.165	0.274	0.187	0.192	0.181
Time: CarP	Short	0.086	-0.383	0.081	0.084	0.090
	Long	0.113	-0.593	0.076	0.076	0.073
Time: Bus	Short	0.035	0.039	-0.783	0.042	0.057
	Long	0.045	0.047	-0.392	0.107	0.108
Time: Rail	Short	0.032	0.034	0.039	-0.308	0.050
	Long	0.026	0.027	0.058	-0.297	0.057
Time: Air	Short	0.004	0.005	0.005	0.006	-0.182
	Long	0.005	0.006	0.016	0.015	-0.105

Table 12: Business elasticities for travel cost and time.

Attribute	Distance	CarD	CarP	Bus	Rail	Air
Cost: CarD	Short	-0.351	0.427	0.336	0.372	0.374
	Long	-0.531	0.332	0.260	0.229	0.236
Cost: Bus	Short	0.076	0.077	-0.829	0.088	0.105
	Long	0.077	0.082	-0.472	0.100	0.103
Cost: Rail	Short	0.040	0.044	0.043	-1.027	0.067
	Long	0.057	0.058	0.114	-0.690	0.170
Cost: Air	Short	0.002	0.003	0.003	0.004	-1.535
	Long	0.008	0.009	0.019	0.026	-1.074
Time: CarD	Short	-0.327	0.393	0.298	0.346	0.324
	Long	-0.404	0.273	0.219	0.201	0.209
Time: CarP	Short	0.270	-0.474	0.232	0.278	0.436
	Long	0.526	-0.906	0.443	0.381	0.398
Time: Bus	Short	0.080	0.090	-0.950	0.155	0.267
	Long	0.107	0.117	-0.717	0.234	0.226
Time: Rail	Short	0.018	0.021	0.031	-0.480	0.038
	Long	0.037	0.040	0.097	-0.502	0.112
Time: Air	Short	0.000	0.001	0.001	0.001	-0.287
	Long	0.002	0.002	0.005	0.007	-0.273

Table 13: Private elasticities for travel cost and time.

Attribute	Distance	CarD	CarP	Bus	Rail	Air
Cost: CarD	Short	-0.258	0.071	0.063	0.066	0.070
	Long	-0.254	0.054	0.044	0.045	0.044
Cost: Bus	Short	0.176	0.177	-0.381	0.171	0.175
	Long	0.108	0.109	-0.155	0.105	0.104
Cost: Rail	Short	0.094	0.096	0.088	-0.474	0.099
	Long	0.065	0.066	0.065	-0.308	0.066
Cost: Air	Short	0.062	0.064	0.059	0.063	-0.670

	Long	0.073	0.073	0.080	0.080	-0.371
Time: CarD	Short	-0.234	0.065	0.058	0.061	0.064
	Long	-0.228	0.049	0.039	0.040	0.039
Time: CarP	Short	0.065	-0.246	0.060	0.063	0.067
	Long	0.088	-0.455	0.070	0.072	0.069
Time: Bus	Short	0.170	0.177	-0.373	0.174	0.175
	Long	0.116	0.115	-0.192	0.134	0.133
Time: Rail	Short	0.038	0.040	0.037	-0.192	0.039
	Long	0.031	0.031	0.036	-0.166	0.035
Time: Air	Short	0.011	0.011	0.010	0.011	-0.099
	Long	0.015	0.015	0.017	0.017	-0.083

Table 14: Holiday elasticities for travel cost and time.

Due to this problem, we have specifically for the air alternative scaled the VoT by a factor 2 in order to get a more reliable balancing of the demand responses. This can be justified by consulting Tikoudis (2008).

5.1 Results compared to the literature

Compared to the literature, the size of elasticities seems to be reasonable. However, the sample to compare with is not very big and caution should be taken when comparing these long-distance trips with trips from other studies with a different distance range. For instance, it may be argued that direct car cost elasticities around -0.53 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 $(1 - \Pr_{m,d})$ 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 costs 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.

We also find that, whereas elasticities for car drivers and passengers tend to increase by distance, it is the other way round 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. Although they did not conclude on an average value, their median elasticity was in the range of -1.2 to -0.75 and conforms fairly well to our findings. 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 -0.944 for the short-distance segment and -0.571 for long distances.

Another finding is that 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). However, for holiday trips there is rarely any 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 these 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, as a result of a higher relative CO_2 output per kilometre, due to a higher share of air transport, this transport segment is responsible for the majority of transport related CO_2 emissions. The model outlined in the present paper particularly focuses on the long-distance transport segment. The model has been developed as part of the TRANSTOOL II model framework initiated by the European Commission and will enable assessment of European-wide transport policy initiatives including taxation scenarios and infrastructure development. More specifically, the model will 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 in an European wide perspective; (iii) subsidising schemes for the European Commission of large European infrastructure projects

The model is a long-distance demand model for the choice of mode and destination. The model 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. The parameter bias due to sampling was analysed and was found to be significantly lower than the standard variation of the estimated parameters.

In the utility function, a distance-dependent split was applied for all LoS variables. Moreover, we analysed several combinations of functional forms and 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.

The results from the model reveal several things. Firstly, the range of elasticities conforms well 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 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.

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