THE IMPORTANCE OF FREQUENCY AND DESTINATION CHOICE EFFECTS IN LONG-DISTANCE TRAVEL BEHAVIOUR: WHAT CHOICE MODELS CAN TELL US

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ABSTRACT

Trips over 50 miles in length account for just 2.3% of all trips, but about a third of all distance travelled within Great Britain. Because of the small proportion of all travel they form, long-distance trips may not be adequately represented in national data bases and models. But, because they account for a substantial proportion of total distance travelled, particularly on motorways and rail, these trips are important in terms of transport policy and have a substantial impact on congestion. Moreover, detailed study of existing data indicates that travellers' behaviour in long-distance journeys differs substantially from routine journey patterns. Not only is the set of available modes different, but the profile of travellers is substantially different, with income playing an important role both in terms of the frequency of long-distance journeys as well as an increased likelihood of travelling by rail and air. Additionally, we observe different trade-offs, with significant reductions in responsiveness and increasing values of time, as journey distances increase. For these reasons, treatment of the specific properties of long-distance travel is essential for appraising the impact of new transport infrastructure aimed at this market, such as high-speed rail, highway construction and operation policies and policies directed towards domestic air travel. In a long-distance travel demand model, there is no doubt that the accurate treatment of mode choice is vital. What was not clear at the outset of this work, however, was whether it is necessary to incorporate destination choice responses explicitly or whether it is possible to represent such effects through elastic generation, which might operate differentially for different destinations.

Models of long-distance travel have therefore been developed using cross sectional National Travel Survey data in the UK to test explicitly the importance of destination and frequency effects. Models with and without destination choice both indicated that it is important to include a frequency model which responses changes in travel accessibility. Judgements about the necessity of including a destination choice component were not straightforward, on the basis of model fit only. However, when considering the resulting values of time and model elasticities, it was judged that the models with destination choice responses were better. Therefore, the key finding of this paper is that models with both frequency and destination choice components, as well as mode choice, better reflect the choices and response behaviour of long-distance travellers than mode choice only long-distance demand models.

1. INTRODUCTION

Trips over 50 miles (80.5 km.) in length account for just 2.3% of all trips, but about a third of all distance travelled within Great Britain (calculated from National Travel Survey (NTS) 2004). Many of these miles are travelled on motorways, with estimates indicating that such long-distance trips account for around 44% of traffic on the M1, 68% of traffic on the M6 and 43% of traffic on the M40. For some rail corridors, long-distance trips are even more important. For example on the West Coast Main Line from London to the north-west, 89% of all trips are longer than 50 miles (Scott Wilson et al, 2008). Almost all air trips are over 50 miles, of course.

1.1 Importance of long-distance travel for policy

Because of the small proportion of all travel they form, long-distance trips may not be adequately represented in national data bases and models. But because they account for a substantial proportion of total distance travelled, particularly on motorways and rail, these trips are important in terms of transport policy and have a substantial impact on congestion. The importance of long-distance travel derives also from the higher values of time of long-distance travellers, partly because of the large fraction of business travellers but also because values of time increase with trip length, even for a given travel purpose (see Accent and HCG, 1996; Mackie *et al.*, 2003), a feature that does not appear in UK's national model of general travel demand, although it appears to be justified empirically (Gunn and Petersen, 2007). Moreover, the specific impacts of income and accessibility on travel frequency, which are very strong in long-distance travel, are also not present in those models, while there are also several other particular features of long-distance travel that may be covered less well in general models. For these reasons, the feasibility of a specific model of long-distance travel has been considered by the UK Department for Transport for appraising the impact of new transport infrastructure aimed particularly at high-speed rail, improving or building of motorways and trunk roads, and of transport policies which will impact long-distance travel.

In such models, there is no doubt that the accurate treatment of mode choice is vital. What was not clear, however, was the importance of generation and distribution (trip length) effects for this market. The central issue for the modelling work, therefore, was to determine whether frequency changes and/or destination switching needed to be included in the model and, if so, how these choices should relate to mode choice.

For example, between London and the North West of England, rail traffic grew by 21.6% between 2004 and 2007, while air travel declined by 22.5% in the same period (Scott Wilson et al, 2008). These figures suggest that the higher-speed and more frequent rail services may have caused a mode shift. However, road traffic statistics are difficult to interpret and it is not clear whether there has been an increase in total traffic in the corridor, or whether that increase has come about through a general increase in travel or because of destination switching.

The aim of this modelling study was therefore to provide empirical evidence on the importance of frequency and destination choice modelling for long-distance travel models, by examining the relative importance of different responses in models incorporating mode, destination and frequency choice effects.

1.2 Previous work

In Great Britain, a large body of literature has looked at the demand for long-distance rail travel, for example, studies on London-based inter-city rail travel by Jones and Nichols (1983) and Owen and Phillips (1987); and more recently Great Britain-wide studies by Wardman and Whelan (2004) and Asteriou *et al.* (2005). These studies used ticket sales data to estimate fare elasticities. They are different from this study in that they are unimodal and do not examine the competition between rail and other modes (car, bus and air).

Along a separate line of research, there is also a substantial body of work examining demand for air travel in the UK. In particular, much of the recent work is related to the rise of low-cost airlines. For example, Mason (2000) carried out a stated preference study to examine the propensity of business travellers to use low-cost airlines. The study assessed the utility placed by travellers on price, airline reward schemes, flight frequency and in-flight comfort service attributes. The focus of Mason (2000) was on the competition between low-cost airlines and traditional airlines, but this is again a unimodal study in that only air travel is considered. On the other hand, Graham (2000) examined the demand for air travel and “limits to growth” from an air transport management perspective, and concluded that if UK air travel is still to experience “healthy growth rates”, it must be at the expense of the growth of some other UK travel market. Further, Segal (2004) has used descriptive statistics to examine how domestic air travel in the UK has been threatening core rail revenues.

Efforts have also been made to develop multimodal long-distance models. Many of these are intercity models. Miller (2004) critically reviewed the current state of operational practice in intercity travel demand modelling. He concluded that many of the operational intercity demand models are too aggregate “across virtually every dimension” (including trip purpose, time of day, spatial representation, socioeconomic representation, socioeconmic characterisation of travellers): he also emphasised the importance of incorporating the overall modelling system in a consistent random utility framework. Miller also called for more research, both fundamental and applied, into issues such as trip generation relationships, induced travel, factors affecting mode choice, and use of access and egress modes. The current paper addresses some of these issues.

Additionally, we note that the intercity models reviewed by Miller are typically applied to a set of reasonably well-defined corridors and a relatively small number of major cities. Thus, destination choice was not a major consideration in a typical intercity model, while the current paper intends to contribute to the literature in this regard.

Other efforts have been made to develop comprehensive modelling frameworks for long-distance travel. Morellet and colleagues (translated in Madre (1997)) developed a disaggregate long-distance travel model for France. They reported that approximately 60 per cent of the growth in the number of passenger-km for domestic trips of over 100 km in France between 1980 and 1992 could be attributed to changes in the socio-economic context (growth in income, household car ownership levels, etc.). Their view was that income growth contributed to much of the increase in private car and air traffic in France, but less in the rail sector – a point which this paper will contest with respect to Britain in Section 2. In the United States, Erhardt *et al.* (2007) developed a long-distance travel model for Ohio. Their model incorporates a rigorous behavioural framework which encompasses a number of traveller responses (including the choice of whether or not to travel, the selection of the days on which to travel, scheduling to a specific time of day, destination choice, and mode choice). Additionally, the Ohio long-distance model is integrated with a short distance model. However, the mode choice component was not able to be estimated due to lack of high quality data (the number of transit and air observations were too small). Thus, the model components, although integrated in the same framework, are not estimated simultaneously.

Our own work in long-distance corridor modelling is largely unpublished (but see Daly and Rohr 1998, Daly *et al.*, 1999, Fox and Kroes, 2001, and Kouwenhoven *et al.* 2006). These models cover long-distance corridors in a number of countries, with models representing mode and route choice and travel frequency. Destination choice was not incorporated, possibly because the models focussed on single corridors, as discussed by Miller (2004) and following the assumption made in Gunn *et al*. (1992). However, the models do incorporate either log or linear representation of cost, tests being made to determine which of these worked better.

There seems to be little published on the frequency of long-distance travel. We show in Section 2 that the characteristics of long-distance travellers are rather different from those of travellers in general, so that the findings of general travel frequency studies may be of little help in modelling long-distance travel frequency. In particular, the influence of income is very strong on long-distance travel rates.

On this point, our previous work (studies referenced above, but also Daly and Miller (2006)) suggests that the response of travel frequency to accessibility changes is stronger in the long-distance market than in the general market. For this reason we take care to test the influence of accessibility on frequency in the models developed in this study.

1.3 Structure of the paper

Section 2 describes some of the characteristics of the long-distance travel market, as compared to the market for all trips and Section 3 describes the data used for development of the models. This is followed by a description of the structure of the models. Section 5 discusses the model results, while Section 6 contains conclusions and recommendations.

2. CHARACTERISTICS OF LONG-DISTANCE TRAVELLERS

Long-distance travel has important differences relative to travel as a whole in terms of travel frequency, purpose share and mode share. In order to understand how models to predict choices for long-distance travellers might differ from those for shorter distances, with which we are more familiar, a brief analysis was undertaken of the main characteristics of long-distance travellers.

As noted above, trips over 50 miles represent just 2.3% of trips but 30.2% of the total distance travelled in Great Britain (calculated from NTS 2004). This means that household diary data on long-distance trips is sparse, which has consequences for model quality. In the 2005 NTS (all-trip) sample, individuals reportedly made an average of 17.2 trips per week, equivalent to 2.45 trips per day. By contrast, the same set of individuals made just 0.4 long distance trips per week. Furthermore half of the individuals (50.4%) in the sample made no long-distance trips at all over the four-week interview period used to collect the NTS long-distance data. It is also noteworthy that the long-distance trip response rate is lower in the three-week recall period than that in the one-week travel diary, and so bias resulting from under-reporting in the long-distance sample is an important consideration here.

When comparing the distribution of trip purposes across trips over 50 miles, we observe that there are fewer long-distance commute and education trips compared to all trips, but that the business share is far larger. Also the share of other purposes that can reasonably be classified as essential, such as shopping and personal business, is higher in the all trip data, whereas visiting friends and relatives is an important segment for long-distance travel. Furthermore, the proportion of holiday and day trips forms a much higher share of long-distance travel.

Table 1: Purpose Shares for All Trips and Long-Distance Trips (Trips over 50 miles), Source: NTS 2002-2004

Purpose	All Trips	Long-Distance Trips
Commute/education	23.4 %	13.7 %
Business	4.8 %	16.4 %
Other Essential Purposes	42.7 %	12.8 %
Visiting Friends and Relatives	14.6 %	24.0 %
Holiday	1.1 %	15.1 %
Day Trip	2.6 %	7.5 %
Other Leisure	10.8 %	10.6 %
Total	100.0 %	100.0 %

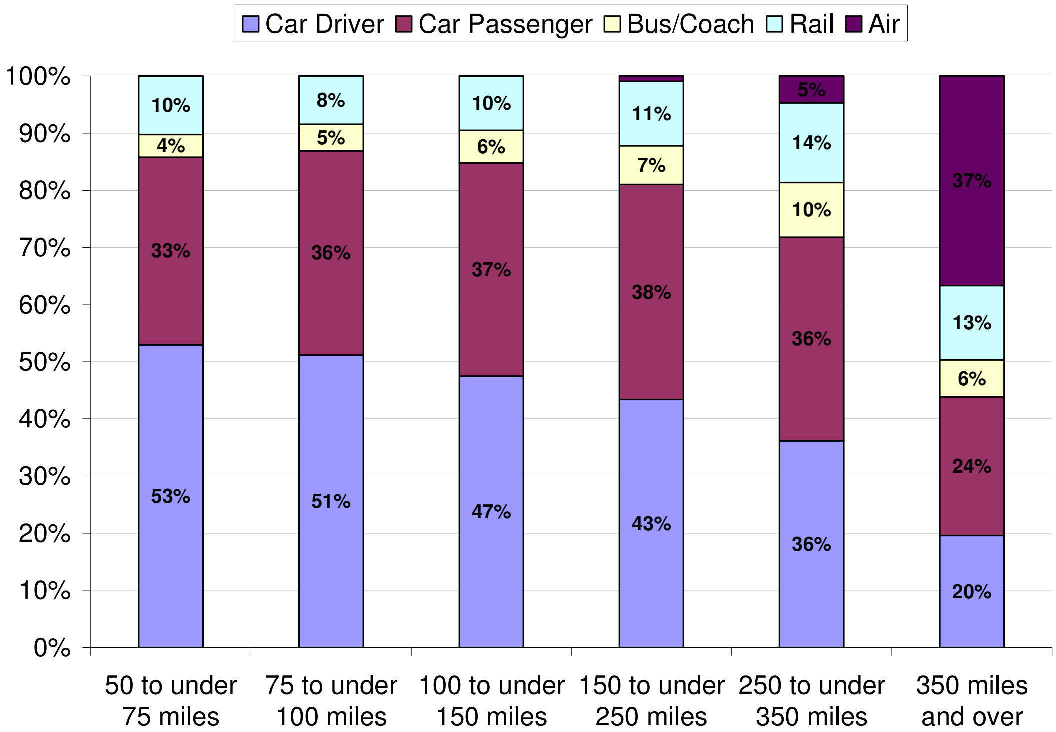
Mode shares also differ between long-distance and all travel, as shown in Table 2. Interestingly, car driver shares are similar, representing about half of the market in both cases, but there are more car passengers in the long-distance trip data, and as a result the mean car occupancy is higher at 1.68 compared to 1.54 in the all trips data. Bus usage is lower in the long-distance data as would be expected, whereas rail is significantly higher. As expected, air is negligible in the all trips data and even in the long-distance data represents less than 1% of trips.

Table 2: Mode Shares for All Trips and Long-Distance Trips (Trips over 50 miles), Source: NTS 2002-2004

Mode	All Trips	Long-Distance Trips
Car Driver	48.3 %	49.5 %
Car Passenger	26.2 %	33.7 %
Bus	10.8 %	4.9 %
Rail	1.6 %	10.0 %
Air	0.0 %	0.9 %
Other	13.1 %	0.9 %
Total	100.0 %	100.0 %

As might be expected, the mode shares vary substantially with distance, as is illustrated in Figure 1, which omits trips by ‘Other’ modes. In particular, air becomes much more important for longer trips so that it becomes the largest mode for trips of 350 miles (about 565 km) and over. It may also be seen from Figure 1 that the changes in the shares of car driver and car passenger imply an increase in car occupancy with trip length.

Figure 1: Mode Split by Distance for Long-Distance Trips, Source: NTS 2002-2005



A further distinction between long-distance and general trip making is found in the trip rates for commuting. Conditional on at least one commute trip being made, in general trip-making the average rate for commute trips is 7.60, while for long-distance commuters the rate is 1.77. Clearly the concept of 'commuting' is different between general and long-distance travel.

We also observe a clear relationship between long-distance trip making and income, with long-distance trips rates increasing exponentially with income band (see Figure 2). The long-distance trip rate in the top income quintile is 4.4 times as high as those in the bottom quintile, a feature which is not present in data on general trip-making, where the ratio of trip rates is only 1.3 (Department for Transport, 2006).

Figure 2: Trips rates by income quintile, NTS 2002-2005

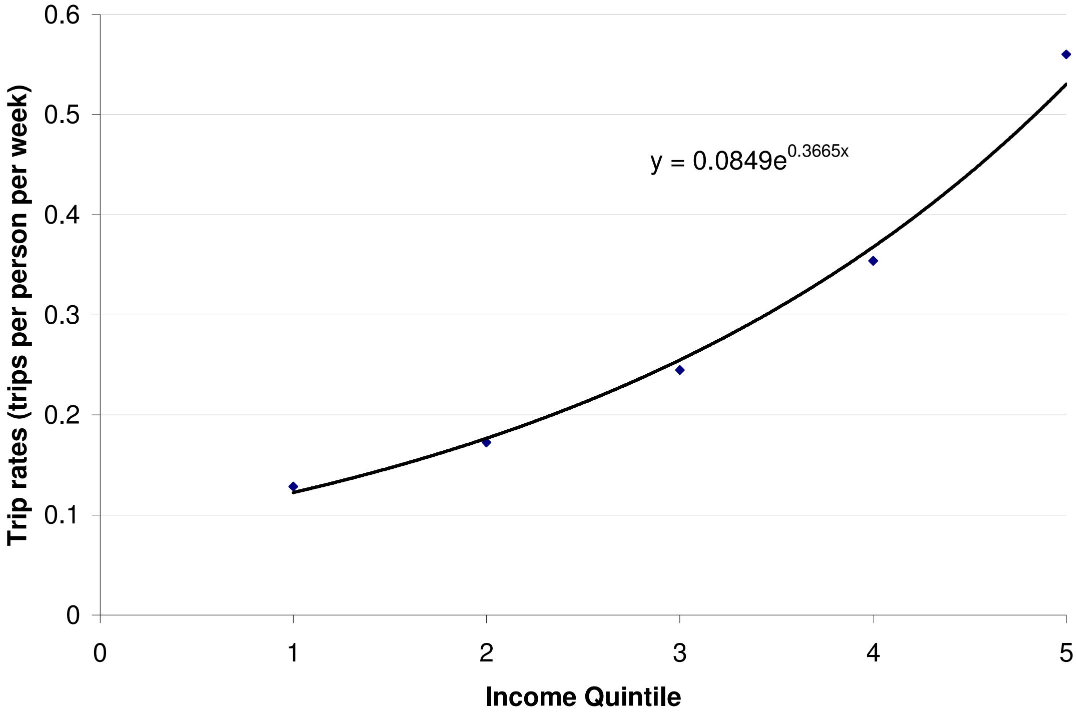
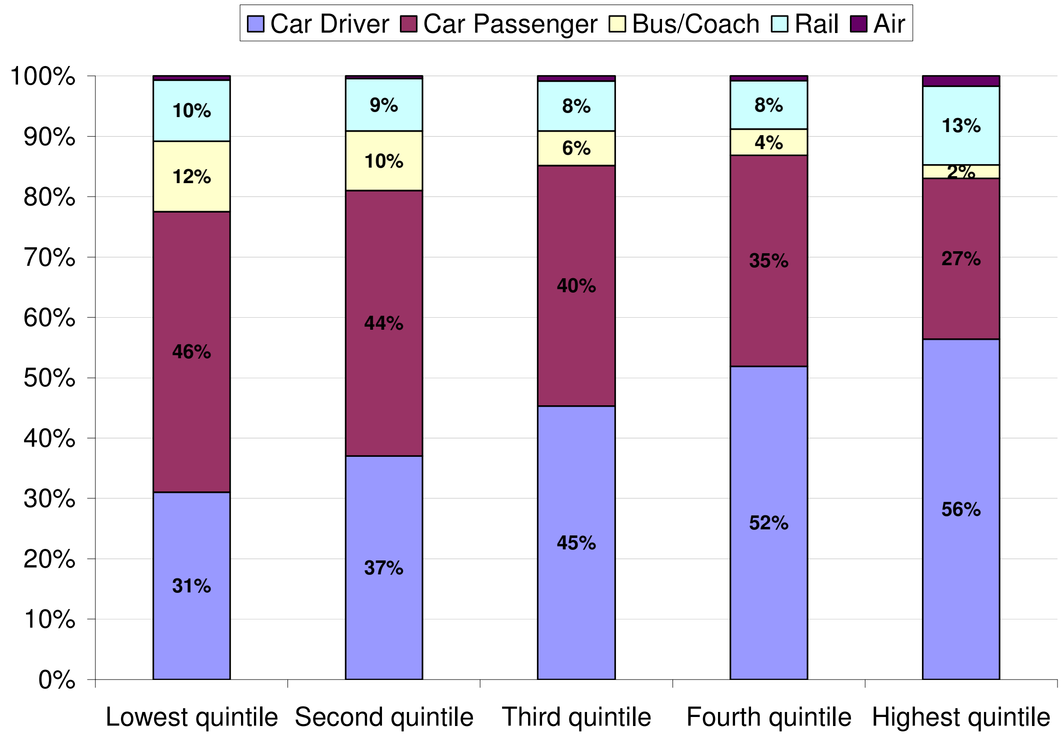


Figure 2 shows that income level is a key determinant for long-distance trip rates. Further, Figure 3 shows that mode choices are quite different for different income groups. The figure shows a clear trend that the mode share for car as a driver increases as income levels increase; but if passengers are included, car does not have the highest share for the highest income group. On the other hand, it is evident that the share for bus/coach has an inverse relationship with income level. Additionally, it is noteworthy that rail share is the highest, at 13%, for the highest income group, contrary to the traditional expectation (derived from analyses of general trip-making) that public transport is not attractive to high income travellers. Finally, for air, although its share is very small for all five income groups, it is apparent that its share is the greatest when income is the highest.

Putting together the trip rates of Figure 2 and the mode shares of Figure 3 it is clear that rail (and air) travel is much more frequent for those in the highest income quintile than for any other group.

Figure 3: Mode share by Income Quintiles, NTS 2002-2005



3. DATA

In order to develop a choice model of long-distance travel, data is necessary containing the choices made by a large sample of travellers, together with data describing the alternatives open to them. These two aspects of the data are described in the following sections.

3.1 Choice Data

The main source of data that was readily available for the estimation of the models were observations of long-distance journeys (one-way journeys greater than 50 miles) from the National Travel Survey from 2002 to 2005. The NTS long-distance journey records contain trips of 50 miles or more within mainland Great Britain[1], made by respondents over a four-week period (three weeks recall plus a one-week travel diary). Combining four years of data provides a substantial database for model estimation.

An important limitation of the NTS data made available to the study was the geographical specificity of the data, specifically that trip origin and destination information were provided at County level (Great Britain is divided into 65

1 The immediately adjacent islands are also included.

counties). In proposed phases of further work data with more geographical detail will be incorporated into the modelling.

Another limitation is that it does not collect data on party size. Although data is collected on all long-distance trips made by all individuals within a household, including children, and it is possible to link trips made by people within the same household to impute parties, this imputation is problematic for a number of reasons: (i) some respondents will make only part of their journey with other household members, (ii) essential data on date of travel are missing for over one third of the trip records, (iii) trips made together with people from other households (e.g. with business colleagues) would not be revealed by this method. Given the limitations on group size information within the NTS, we were constrained to modelling the choices of individuals, rather than travelling parties, in the modelling reported in this paper.

Despite the limitation on group size data, we modelled car driver and car passenger as a single mode because we judged that the travelling party was probably formed before the mode choice was made, while in some cases the driver may change during long-distance journeys. Consequently, if there two persons in a household who have made a car driver journey and a car passenger journey (perhaps together), the two journeys would be modelled as two separate decisions to choose to travel by car. As such, car and licence availability are not decisive in describing the possibility of car use, although we observed that higher levels of household car ownership strongly increased the probability of household members travelling by car. In order to get appropriate costs for the individual, car costs have been divided by the average group size, for each purpose segment.

A final limitation of the NTS data is that although in principle time away (duration of stay) could be imputed from travel date information, the quality of these data was quite poor, with over one third of the data having missing travel date information.

The models reflect choices for a tour: that is a return trip from home to a primary destination. In cases where the journey includes a number of destinations, a primary destination, reflecting the destination furthest from the home origin zone has been defined. The choice model predicts travel to the primary destination. This approach ensures that the error caused by not modelling non-home-based trips explicitly is minimised. The NTS trip data was therefore combined into tours for modelling.[2]

The mode choice model reflects choices between four main models of travel, air, rail, bus/coach and car (driver and passenger).[3] Models were tested for four

[2] 6.8% of the trip data were lost, after excluding non-home-based tours and non-home-based legs of part-tours. Because the most distant destination is used to define the tour, the kilometrage loss will not be so large.

[3] Travel by other modes than these four totalled 0.9% and was omitted from the modelling.

separate traveller segments: commute, business, visiting friends and relatives and other leisure travel, but it was found that better models were obtained by merging the data for visiting friends and relatives and for other leisure.

The observed mode shares for each purpose segment are presented in the following table. For all purposes, car is the dominant mode, accounting for between 75% (commute) to 85% (total other) of all journeys, although the importance of rail and air increases for longer distance journeys.

Table 3: Long-Distance Mode Shares for each Purpose Segment (NTS 2002-2005)

	Commute and Education		Business		Total Other	
	Tours	%	Tours	%	Tours	%
Air	47	1%	196	3%	244	1%
Rail	1,114	20%	970	13%	2,462	10%
Bus/Coach	225	4%	91	1%	2,008	5%
Car (Driver & Passenger)	4,257	75%	6,316	83%	27,525	84%
Total	5,643	100%	7,573	100%	32,239	100%

While the numbers of tours for some purpose-mode combinations are limited, overall this data represents a substantial base for the estimation of choice models.

3.2 Data describing the alternatives

Zone-to-zone travel service measures for each mode, for each destination, were provided by transport networks (Scott Wilson et al, 2008). It is much better to use network data, as opposed for example to service levels reported by travellers, as it is objective and can be generated for future scenarios. The supply networks were developed at district level (406 zones). Detailed networks were developed for each mode, as described below.

- The highway supply model was derived from networks developed for the MIDMAN study. The highway model reflects congestion: base year highway demand was obtained from the Department for Transport's National Transport Model (NTM). The assigned highway models were calibrated using measures consistent with those previously undertaken to validate the NTM. However, a thorough validation of the highway model has yet to be undertaken (Scott Wilson et al, 2008). Driving costs have been determined using guidance set out in the UK government's WebTAG[4].

[4] See http://www.dft.gov.uk/webtag/, WebTAG Unit 3.5.6, Section 1.3.1. This recommends using fuel costs only for commuter and other travel, while for business travel non-fuel marginal

- The rail model is also derived from the MIDMAN model (Scott Wilson et al, 2008). Measures of crowding were generated in this model, but were not found to be effective in explaining long-distance choices, perhaps because long-distance travellers are likely to be able to get a seat for most of their journey.

- The coach supply model was developed using information provided by the Department for Transport (Scott Wilson et al, 2008).

- The air model obtains airport-to-airport service levels from the SPASM model. Surface access service levels for travelling between district zones and airports are provided by the highway and rail supply models. The air model determines appropriate routes between districts via airports using either a 'minimum cost' or 'route choice' algorithm. Calibration of the base year air model has been undertaken on both airport and regional arrivals and departures (Scott Wilson et al, 2008).

Because the origin and destination information in the choice data (NTS) were only available at county level, the district level of level-of-service data were averaged for use in the demand model. A weighted averaging procedure was used, using population as weights. District pairs which were less than 50 miles apart were not included in the averaging procedure.

Population and employment data provided information on the relative attractiveness of destination zones. These attractiveness terms represent the influence of land-use changes on the distribution pattern of journeys and means that the distribution pattern of trips will change, with differential population and employment changes.

4. MODEL STRUCTURE

From the data available, it was required to estimate models that would predict the impacts from policy and exogenous changes of flows by specific modes in specific long-distance corridors. That is, it was necessary to predict the numbers of long-distance tours for each mode in total and for each corridor. The approach adopted was to represent the long-distance travel choices available to individuals. For forecasting, the forecasts given by these models are expanded by the number of relevant individuals living in each zone to obtain the total GB domestic long-distance travel market.

The models reflect the (simultaneous) choice of mode, destination and travel frequency, as is shown in Figure 4 below. To simplify the figure, destination

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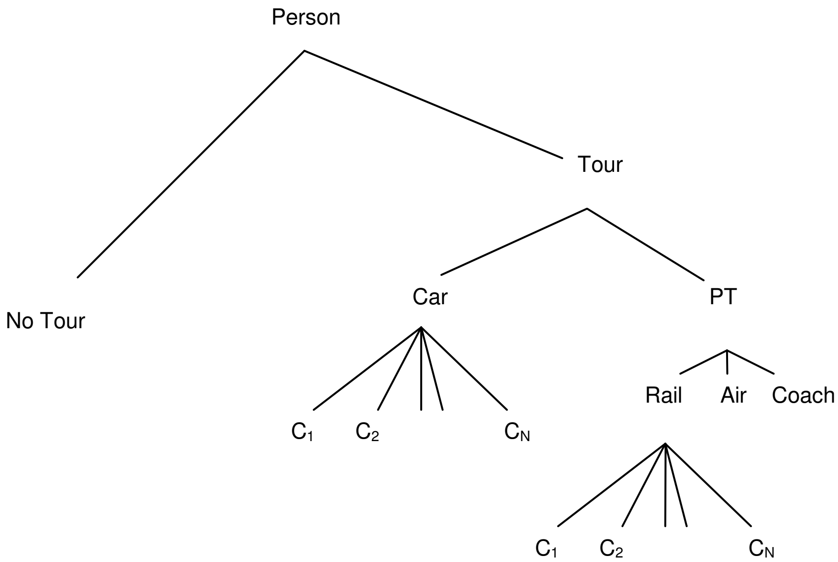
costs should also be included. These are calculated, using the WebTAG formulae, from distance and speed taken from the network model.

choice has been shown for Car and Rail only, but it is of course also applied for Air and Coach.

Alternative structures could be considered, but within the nested logit framework it is unlikely that these would give acceptable results, because of the very strong support given by the data to this structure.

A further set of models was tested in which destination choice was omitted. These models would correspond to a choice context in which the destination was considered to be fixed, i.e. a workplace, or a social visit to a specific family member, while mode and frequency of visit could vary. The results for both sets of models are reported below.

Figure 4: Frequency, Mode and Destination (FMD) Choice Structure



This model therefore represents choice among 4 modes for up to 65 destinations (eliminating those less than 50 miles away) plus the no-tour option, giving a potential total of 261 alternatives. Typically, for a given origin there would be more than 200 alternatives available, a fairly modest number by the standards of large-scale travel demand modelling, where 5,000-10,000 alternatives are commonly considered, but it is still a substantial number, requiring efficient computation.

The frequency model reflects the probability of making a long-distance tour, for a particular journey purpose, on a given weekday. It is structured as a simple binary choice: 'tour' or 'no tour'; the 'no tour' alternative includes cases where respondents made one or more trips under 50 miles, i.e. 'no tour' means "no long-distance tour". It is noteworthy that we observed only a very small number of observations (32 observations across the 4 years of NTS data) where respondents made more than one long-distance tour for the same purpose in a single day (in all cases these people made exactly two tours for the same purpose in the same day). Apart from the accessibility component measured in the mode and destination choice models, travel frequency is influenced by socio-economic variables. For convenience, these variables are specified on the 'no tour' alternative and thus reflect the increased probability of not making a journey.

In preparing the data for estimation, each tour is presented as one record and represents the choices (a) to travel, (b) to choose a mode and, for the models containing destination choice (c) to choose a destination. Given the assumption that no-one makes more than one tour for a given purpose on a given day, this represents the traveller's entire data for that day for that travel purpose. The days without a tour for the given purpose represent the choice not to travel. If a person makes n tours for the given purpose in the 28-day survey period (n = 0, 1, 2, ..) then we observe (28 – n) times that no tours were made and economy in computation is achieved by entering one no-tour record with a weight of (28–n). For the models without destination choice, these no-tour records have to be entered for each possible destination. Maximum likelihood estimates were then made under the assumption of independence of these observations.

Clearly, however, there is a problem of correlation, in that the unmeasured preferences of travellers will be very similar for all of the 28 days observed. The scale of the model made it impossible to use software specifically designed for panel data analyses, while the time available for the work did not permit the investigation of the structures of correlation that such work would require. Accordingly, the models were subjected to a Jack-knife procedure to correct the specification error arising from the correlation of unmeasured preferences.

The structure of the mode choice components of utility are discussed in detail in the following section.

In the models which incorporate destination choice, the destination component of utility also includes an attraction term, reflecting the attractiveness of a specific destination, measured as employment for commute and business travel and population for other travel purposes.

5. MODEL RESULTS

The detailed coefficient results are presented at the end of the paper. Table 8 presents results for the simultaneously estimated frequency, mode and destination choice models. Table 9 presents results for the models without destination choice, i.e. for frequency and mode choice only.

5.1 Examination of Key Model Parameters

The model estimation procedure commenced with the estimation of models with substantial detail across the level-of-service variables, moving towards models with more aggregation across the level-of-service terms to ensure that all parameters were correctly signed and significant. Specifically, the first models tested had separate in-vehicle time coefficients for rail, air, coach and car, separate out-of-vehicle time coefficients for frequency, wait time, interchanges, and access and egress, cost (both linear and logarithmic forms) and separate mode specific constants for all main modes, measured relative to car.

In all segments wrongly signed coefficients were observed for rail time and air time when these coefficients were estimated independently (for other travel, the rail time coefficient was rightly signed, but insignificant). This problem may be a result of not having party-size information or may be due to a relative lack of rail and air choice data in this phase of the modelling. The relatively poor precision of location coding – at county level – quite likely also plays a role here, as may the quality of level-of-service data. A generic in-vehicle time term was therefore used in the modelling. Future model estimation work would incorporate additional (choice-based) data collected for air and rail, as well as NTS data with more geographic detail.

In the current models, it was also not possible to identify correctly signed and significant rail out-of-vehicle terms in any segment, so these were also aggregated, with the in-vehicle time coefficients, into a generalised journey time (GJT) term, using weights taken from the Passenger Demand Forecasting Handbook (PDFH), an unpublished reference source for demand forecasting in the UK rail industry.

For all segments, we tested models with both logarithmic and linear cost parameters: the former functional form allowing for cost damping for longer distance journeys (Daly, 2008).

For commute, we were able to identify correctly signed parameters, for both cost terms, for in-vehicle time and for many out-of-vehicle components, but the resulting in-vehicle value of time was judged to be far too low, comparing our results with generally accepted values of travel time for all journeys, which should be substantially lower than the value for specifically long-distance journeys. A generalised time formulation was therefore adopted including (i) all in-vehicle time terms, plus (ii) rail out-of-vehicle times converted to in-vehicle time using PDFH guidelines, and (iii) costs converted to time units using non-working values of time as published in UK guidance (WebTAG).

In the business model, a logarithmic cost term gave the best model fit of the cost forms tested, implying a linearly increasing value of time with cost.

In the mode (and destination) component of the other travel models, we observed that many of the coefficients were wrongly signed for the visiting friends and relatives segment, and that the best models were obtained when this segment was aggregated with the 'Other Travel' segment. For this aggregated segment, both linear and logarithmic cost terms were identified in the models with frequency, mode and destination choice. Only a logarithmic cost term was identified in the models for frequency and mode choice only.

The key model parameters for both the Frequency x Mode x Destination (FMD) and Frequency x Mode (FM) models are presented in Table 4 (the brackets contain the t-statistics measured relative to a value of zero, while the parameters in the lower part of the table, without t-statistics, are derived from the parameters above). The detailed coefficient results are presented at the end of the paper.

Table 4: Key Model Parameters

Purpose	Commute		Business		Total Other	
Model	FMD	FM	FMD	FM	FMD	FM
Generalised Time (GT)	-0.0038 (-66.5)	-0.0031 (-63.9)	0 (*)	0 (*)	0 (*)	0 (*)
Generalised Journey Time (GJT)	0 (*)	0 (*)	-0.0027 (-11.6)	-0.0011 (-5.7)	-0.0025 (-30.1)	-0.0014 (-17.6)
(Linear) Cost	0 (*)	0 (*)	0 (*)	0 (*)	-6.00E-05 (-4.1)	0 (*)
Logcost	0 (*)	0 (*)	-1.14 (-13.7)	-1.41 (-18.1)	-0.751 (-19.5)	-2.24 (-49.1)
County Scale ($\lambda_{PT}/\lambda_{destination}$)	0.723 (+5.2)	0 (*)	0.789 (+9.3)	0 (*)	0.515 (+13.6)	0 (*)
PT Scale ($\lambda_{Mode}/\lambda_{PT}$)	0.366 (+5.9)	1 (*)	0.345 (+7.2)	1 (*)	1 (*)	1 (*)
Frequency Scale ($\lambda_{freq}/\lambda_{Mode}$)	0.566 (+9.0)	1 (*)	0.732 (+11.8)	0.945 (+60.1)	0.317 (+12.2)	0.564 (+75.2)
Destination-level sensitivity to time	-.0038	0	-.0027	0	-.0025	0
Mode-level sensitivity to time	-.0010	-0.0031	-.00073	-.0011	-.0013	-.0014
Frequency-level sensitivity to time	-.00057	-0.0031	-.00054	-.0010	-.00041	-.00079

In the models without destination choice (FM), the cost coefficients are larger, and the generalised time terms tend to be smaller, leading to lower values of time from these models. The resulting values of time, for the models with and without destination choice, are shown in Figure 5 and Figure 6, respectively. It is noteworthy that the values of time for long-distance commute journeys are the same in the two models because these are inputs to the models. For business travel, the values are output and increase linearly with cost, because of the logarithmic cost form. The business values for the models without destination choice are substantially lower than the values identified in the models which incorporate destination choice. For other travel, values of time are also an output. The values for other travel in the FMD models are again higher, and the values increase with cost, but not linearly so, reflecting the linear and logarithmic cost mixture. The other values for the models without destination choice are again lower, in general, and increase linearly with cost (again reflecting the logarithmic cost term identified). In general, the values of time from the models incorporating destination choice are more reasonable.

Figure 5: Values of Generalised Journey Time from the Frequency x Mode x Destination (FMD) Models

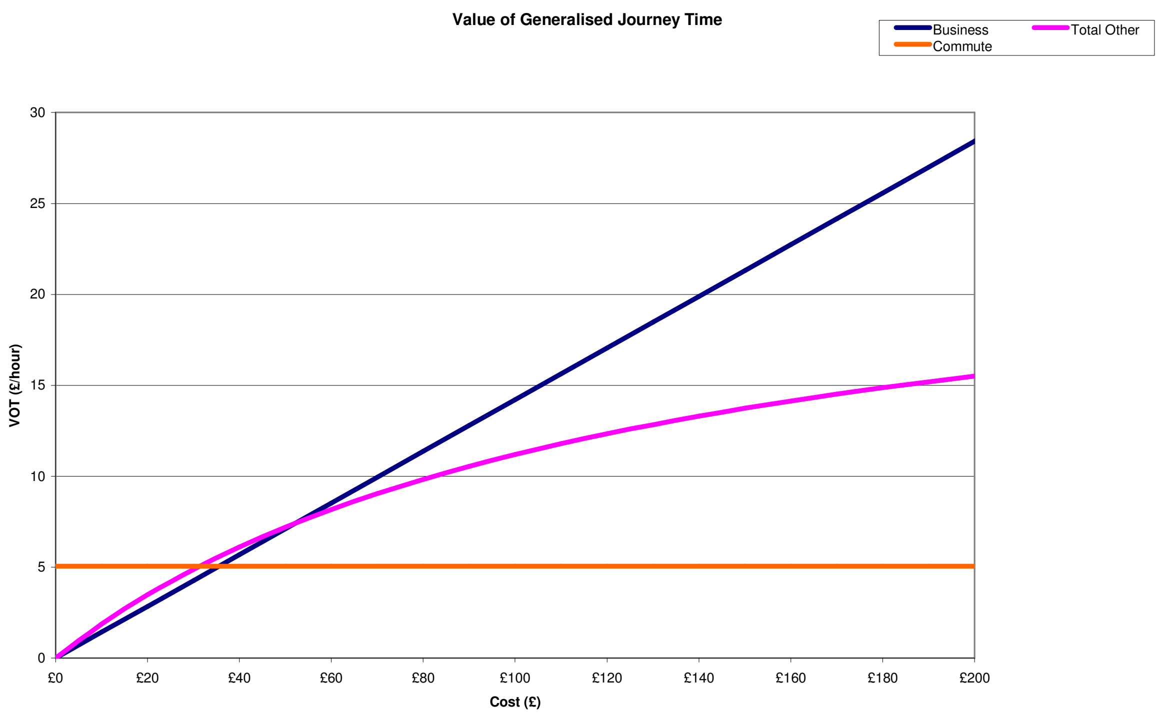
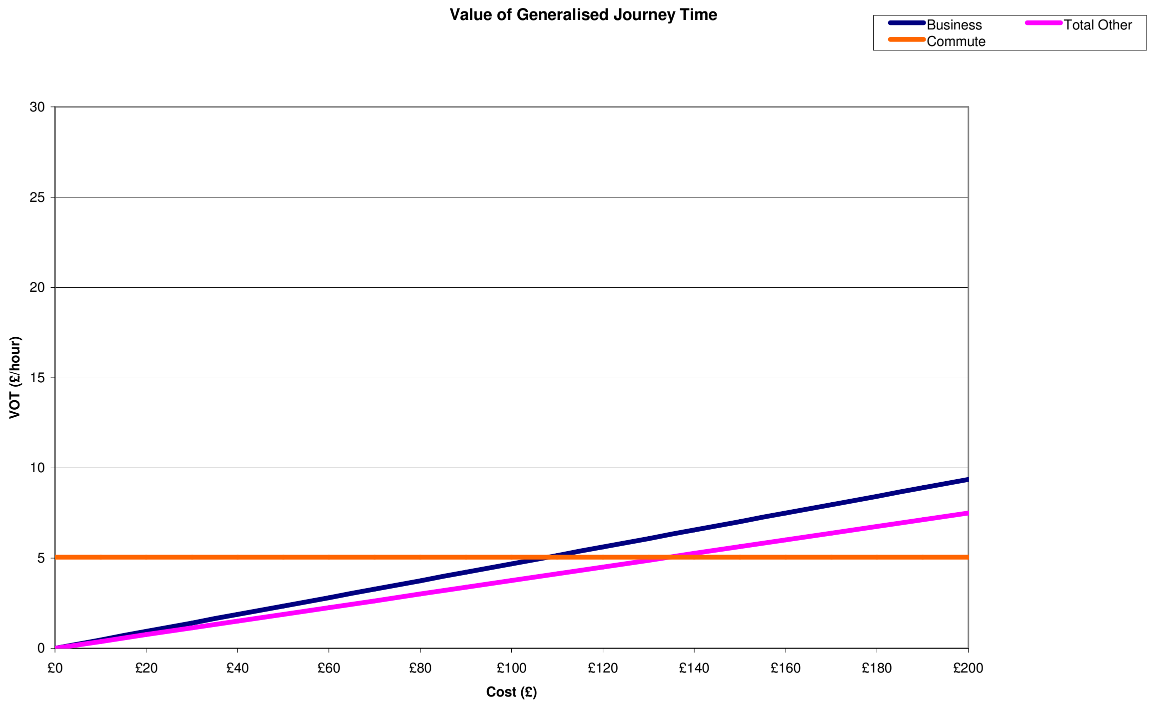
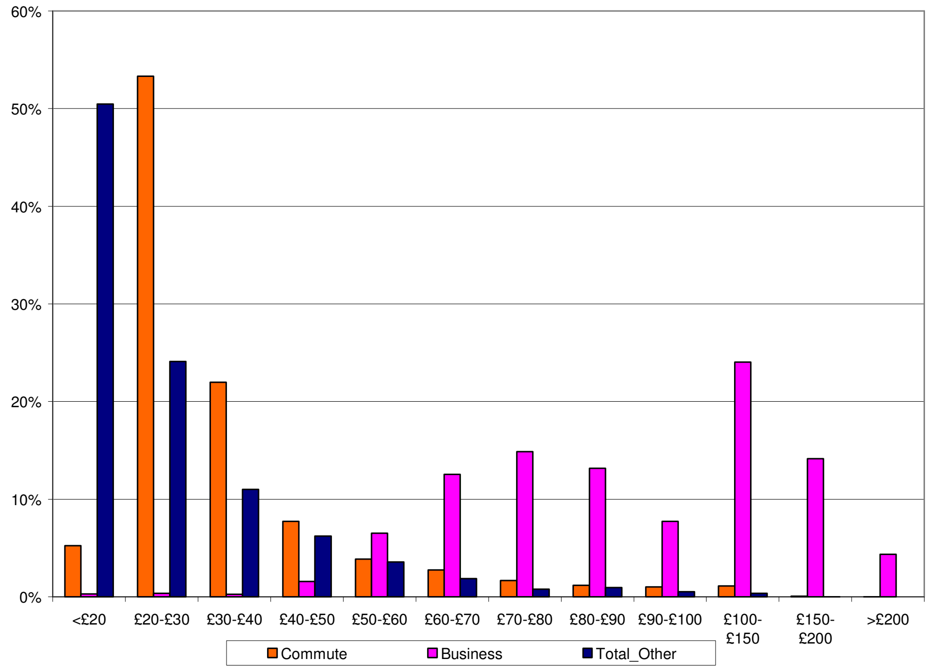


Figure 6: Values of Generalised Journey Time from the Frequency x Mode (FM) Models



The distribution of costs actually incurred by travellers is shown in Figure 7.

Figure 7: Distribution of costs incurred by travellers, by travel purpose



Given the distribution of costs, the values of time in these models can be compared with those generally accepted in the UK. Median costs for business and other travel are approximately £90 and £20 respectively. The business value of time in the FMD model at median cost appears therefore to be below the recommended values of £21.86 for driver and £15.66 for passenger (2002), values indicated by the UK government WebTAG, although the large range of values (upper and lower deciles £61 and £175 respectively) give a correspondingly large range for the value of time. For other travel, the value appears to correspond reasonably well with the recommended value (perceived cost = £4.46/hour, for 2002 in 2002 prices), which is 88% of the commuter value.

Models that fail to conform to these values by a wide margin can be rejected in favour of other models, despite possibly giving a better fit to the data, on the grounds that the standard values are well established, while the models being estimated are subject to deficiencies in the NTS and level-of-service data, as has been mentioned already. Ultimately this is a matter of judgement. Given the results obtained, it is clear that the FMD models give more acceptable values of time than the FM models, where the estimated values are too low.

In addition to these level-of-service coefficients, coefficients were also identified for access and egress time to air and air frequency (a significant term was not identified for air frequency for the Other Travel segment).

Socio-economic terms were also tested for the mode and destination component of the model, and significant terms were identified for the following groups (the bracketed mnemonics can be used to refer to Table 8 and Table 9 at the end of the paper):

- Increased likelihood of travelling by rail, for high-income (>£70k/year) travellers, across all segments (rlincgt70);
- Increased likelihood of travelling by air, for high-income (>£70k/year) travellers, for business and other travel (arincgt70);
- Increased likelihood of travelling by bus, for low-income (<£20k/year) travellers, for business (binclt20);
- Increased likelihood of long-distance commuting or education travel by bus/coach for travellers less than 17 years of age (busagelt17);
- Increased likelihood of travelling by car for long-distance trips by men, across all segments (male_car);
- Increased likelihood of travel by car, with increasing car ownership in the household (separate terms for 1 car, 2 cars and 3+ cars, relative to no cars, i.e. 0cars_car, 1car_car, 2cars_car, gt3cars_car).

Significant socio-economic variation was also identified in the frequency component of the model, specifically:

- Increased long-distance commuting and business journey rates by men (male);
- Increased long-distance commuting by those aged 30 through 49 (age3049);
- Increased long-distance journey frequency with increasing income, for all purposes (income);
- Increased long-distance journey frequency for other travel for retired persons (retired);
- Increased long-distance journey frequency for other travel for unemployed persons (unemp);
- Lower levels of long-distance trip making for other purposes for those households with children (hhwithchld);
- Lower levels of long-distance trip making for commuting and other travel for those from households with no car (nocar).

The sensitivity parameters given in the last three rows of Table 4 are obtained by extracting or multiplying together the relevant scaling parameters. These summary parameters allow comparison of the relative sensitivity of the FMD and FM models for predicting changes at all three levels of the model.

The following observations are made in terms of model structure:

- in all models, an accessibility component with a coefficient significantly different from zero is identified in long-distance journey frequency (shown as 'frequency scale' and reflecting the scale multiplying the logsum terms from either the mode and destination or mode choice only models);
- 'pt scale' terms, with coefficients significantly different from 1, reflecting higher correlation (and therefore higher cross-elasticities) between the public transport alternatives, are identified in the models incorporating destination choice for commute and business travel;
- in the models which incorporate destination choice, the destination choice component is found to be at the lowest level of the nesting structure.

On the basis of the model estimation results, it seems that the structure with destination choice is to be preferred, because destination choice appears to function properly in the structure and the values of time are more reasonable. It is difficult to formulate a formal test comparing the two structures.

5.2 Model Elasticities

Elasticity tests were undertaken for both models to output both the car cost[5] and car time elasticities. The resulting elasticities reflect first order elasticities only, i.e. without taking account of congestion feedback. They also represent long-

[5] Car costs include fuel costs, non-fuel marginal costs (i.e. distance-related maintenance and depreciation, for business only) and toll costs, although the latter apply to only a small number of journeys in the level-of-service data.

term behavioural responses, because they represent revealed preference responses, in which travellers may have adjusted other decisions (location, car ownership etc.) at the same time as their long-distance travel behaviour. Elasticities are presented both for changes in the number of tours (reflecting frequency and mode choice) and changes in kilometrage (reflecting frequency, mode and trip length changes). Because tour frequency is elastic to accessibility, total elasticities, reflecting the changes in journeys and kilometrage across all modes, are also presented.

The elasticities are calculated by the formula:

$$\eta_{mk}^{x} = \log\left(\frac{q_{mk}^{1}}{q_{mk}^{o}}\right) \bigg/ \log\left(\frac{x^{1}}{x^{0}}\right)$$

where q_{mx}^{i} is the demand for mode m, measured by $(k=1)$ the number of tours or $(k=2)$ the number of kilometres;

x^{i} indicates the variable that is changed, either time or cost;

$i=0$ refers to the base case and $i=1$ refers to a case in which the relevant variable is changed by a uniform percentage, in this case increased by 10%.

In these calculations, the demand is calculated over the estimation sample, i.e. implicitly assuming that the sample is representative of the total population. It is not likely that this assumption will cause serious distortion of the elasticity results.

Table 5: Commute Car Cost and Time Elasticities for the FMD and FM Models

Mode	Frequency x Mode x Destination (FMD)				Frequency x Mode (FM)			
	Number of Tours		Kilometrage		Number of Tours		Kilometrage	
	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity
Air	0.127	0.152	0.128	0.155	0.002	0.002	0.001	0.002
Rail	0.135	0.147	0.138	0.150	0.015	0.014	0.013	0.012
Coach	0.134	0.149	0.136	0.153	0.010	0.010	0.008	0.008
Car	-0.198	-0.220	-0.331	-0.462	-1.061	-1.207	-1.188	-1.447
Total	-0.119	-0.132	-0.221	-0.317	-0.802	-0.912	-0.911	-1.107

For the commute model, in the model incorporating destination choice (FMD), we observe a cost kilometrage elasticity of -0.46 (and that the cost kilometrage elasticity is higher than the time kilometrage elasticity). A priori, we would expect higher elasticities for long-distance travel than for all travel (Daly, 2008). We would also expect higher cost elasticities with the assumed (linear) cost formulation, which was necessary because we were not able to estimate sensible values of time (it is noteworthy that in the commute models where values of time were estimated, both log and linear cost terms were significantly identified, but these resulting in values of time that were judged to be too low). The elasticity of tour frequency is also quite large, implying substantial changes in the total number of longer-distance commute trips, in the long term, as a result of changes in car costs. Part of this change may be the result of shifts from shorter-distance commuting trips.

The tour elasticities are substantially higher in the models which do not incorporate destination choice (FM). This could be considered anomalous, as one might expect that a model with an additional behavioural response (destination choice) to be more elastic. However, another interpretation is that the possibility of changing destination allows travellers to mitigate the impact of time and cost changes, i.e. they can avoid the worst impacts of deterioration in their journeys without having to change mode or travel frequency. This mitigation then leads to lower tour elasticities.

There is of course no explicit effect of trip length change in the FM models, so that the kilometrage elasticities differ little from the tour elasticities and the difference from the FMD models is reduced.

We are aware of little published information on expected elasticities for long-distance travel. One source is a paper by de Jong and Gunn (2001), which reports elasticities from a number of models, including the Italian National Model, a model largely for long-distance tour making. The commute car cost kilometrage elasticity from the Italian National Model is -1.22, which is substantially higher than the value that we obtain from the FMD model, but is in line with the elasticities generated from the model without destination choice (FM).

For business and other travel, we observe lower car cost kilometrage elasticities in the FMD models than are observed from the commute model, and in both segments we see higher time elasticities compared to cost elasticities. It is noteworthy that for both purposes we have identified significant logarithmic cost terms (the business model contains only a logarithmic term, the other model contains both a logarithmic and linear cost term), which will damp the cost elasticity.

It is also interesting to note that there is essentially no destination shifting effect in the business model in the car cost elasticity tests, i.e. there is no difference between the tour cost elasticity and kilometrage cost elasticity. This is a because of the structure of the model, which has a logarithmic cost formulation and therefore responds uniformly for each destination when the car costs are changed by a uniform percentage. There are, however, substantial trip length changes in the time elasticity tests, which is what we would expect with a linear time term.

Again we observe much higher elasticities in the models with frequency and mode choice responses only.

Table 6: Business Car Cost and Time Elasticities for the FMD and FM Models

Mode	Frequency x Mode x Destination (FMD)				Frequency x Mode (FM)			
	Number of Tours		Kilometrage		Number of Tours		Kilometrage	
	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity
Air	0.099	0.106	0.102	0.105	0.029	0.054	0.030	0.050
Rail	0.099	0.107	0.102	0.106	0.023	0.076	0.026	0.071
Coach	0.094	0.100	0.096	0.100	0.023	0.073	0.026	0.070
Car	-0.178	-0.190	-0.373	-0.191	-0.426	-1.085	-0.519	-1.330
Total	-0.132	-0.140	-0.285	-0.136	-0.350	-0.912	-0.420	-1.068

Table 7: Other Car Cost and Time Elasticities for the FMD and FM Models

Mode	Frequency x Mode x Destination (FMD)				Frequency x Mode (FM)			
	Number of Tours		Kilometrage		Number of Tours		Kilometrage	
	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity	Time Elasticity	Cost Elasticity
Air	0.290	0.262	0.299	0.264	0.310	0.657	0.326	0.637
Rail	0.288	0.256	0.297	0.258	0.198	0.731	0.234	0.712
Coach	0.277	0.247	0.283	0.249	0.182	0.687	0.215	0.713
Car	-0.159	-0.141	-0.344	-0.185	-0.358	-1.402	-0.425	-1.376
Total	-0.092	-0.082	-0.249	-0.120	-0.273	-1.058	-0.321	-1.030

Again, we are aware of little empirical evidence on long-distance elasticities for these travel purposes, except for the Italian model elasticities reported in de Jong and Gunn (2001). The fuel cost kilometrage elasticities from the Italian model are -1.73 and -1.03, for business and other travel, respectively. Again, these elasticities are substantially higher than the values that we observe from the FMD models, with these values being more in line with the results from the FM models.

6. CONCLUSIONS AND RECOMMENDATIONS

Detailed study of existing data indicates that travellers' behaviour in long-distance journeys differs substantially from routine journey patterns. Not only is the set of available modes different, but the profile of travellers is substantially different, with income playing an important role both in terms of the frequency of long-distance journeys as well as an increased likelihood of travelling by rail and air. Additionally, we observe different trade-offs, with significant cost damping and increasing values of time, as journey distances increase. For these reasons, treatment of the specific properties of long-distance travel is essential for appraising the impact of new transport infrastructure aimed at this market, such as high-speed rail, highway construction and operation policies and policies directed towards domestic air travel.

The development of a separate model for long-distance travel, rather than trying to integrate all travel in a single model, is a question of resources. Given that the existing models are unlikely to deal adequately with long-distance travel, the development of a complete new general model which could adequately deal with long-distance policy issues would have been prohibitively expensive. A range of special issues affecting long-distance but not short-distance travel has been discussed in the paper and there is no doubt that long-distance travel has a number of special features. Among these are the elasticities, which are lower in several cases than corresponding short-distance values. Since elasticity is generally expected to increase with trip length, within a single market (Daly, 2008), this suggests that the behaviour represented by the long-distance models is different from that exhibited over shorter distances. However, these elasticities may change with further model improvements, as discussed below.

In such models, there is no doubt that the accurate treatment of mode choice is vital. What was not clear at the outset of this work, however, was whether it is necessary to incorporate destination choice explicitly or whether it is possible to represent such effects through elastic generation, which might operate differentially for different destinations.

Models of long-distance travel have therefore been developed using cross-sectional National Travel Survey data in the UK to test explicitly the importance of destination and frequency effects. Models with and without destination choice both indicated the importance of inclusion of a frequency response linked to travel accessibility. Judgements about the necessity of including a destination choice component were not straightforward, however, on the basis of model fit only. Though, when other criteria were considered, it was judged that the models with destination choice responses were better, specifically:

- the resulting values of time are unreasonably low in the models without destination choice;
- the resulting elasticities are unreasonably high in the models without destination choice, although they agree more closely with Italian results and no others are known;
- destination choice appears to operate reasonably in the models in which it is incorporated.

It is therefore concluded that the models with both frequency and destination choice components, as well as mode choice, better reflect the choices and response behaviour of long-distance travellers. This undermines the assumption of no destination shifting made by Gunn *et al*. (1992), although the application of their approach to single corridors may still be justified.

The models developed for this study have indicated the importance of segmentation in explaining choices made by long-distance travellers. Income was found to be important in explaining both travel frequency and mode choice. Additionally, age, sex, car availability, employment and household structure were found to be significant in one or both of these choices.

The quality of the models has of course been limited by the quality of the data available. Current work is seeking to improve the network data, while it is also hoped that more detailed location information on travellers long-distance choices will be provided for future modelling. The NTS data is collected with more detailed locations, but these have been withheld from this modelling work on the grounds of confidentiality. However, the main conclusions presented here are based on parameters that are significant at high levels and are very unlikely to be affected by data error.

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Table 8: Frequency x Mode x Destination Model Results

	Commute		Business		Other (VFR + Other)	
File	LD_com_v60_M61.F12		LD_bus_v50.F12		LD_tototh_v47_modified.F12	
Converged	True		True		True	
Observations	41889		41649		107334	
Final log (L)	-33540.1		-46653.8		-197278.5	
D.O.F.	20		20		21	
Rho²(0)	0.853		0.797		0.669	
Rho²(c)	0.115		0.075		0.049	
Mode x Destination Model Coefficients						
Level of Service Terms:						
Cost	0	(*)	0	(*)	-6.0e-5	(-4.1)
LogCost			-1.14	(-13.7)	-0.751	(-19.5)
GT	-0.0038	(-66.5)				
GJT			-0.0027	(-11.6)	-0.0025	(-30.1)
AirAcEgr	-0.0108	(-6.1)	-0.0127	(-11.3)	-0.0072	(-12.9)
Airfreq	0.0715	(4.6)	0.0538	(7.0)		
Alternative-specific constants:						
CarASC	0	(*)	0	(*)	0	(*)
RailASC	2.41	(3.7)	1.78	(3.4)	-0.142	(-1.3)
AirASC	0.493	(0.5)	1.45	(2.4)	-2.50	(-5.3)
CoachASC	-1.87	(-2.3)	-2.89	(-4.5)	-1.56	(-9.7)
Socio-economic terms:						
0cars_car	0	(*)			0	(*)
1car_car	3.20	(4.2)	4.96	(7.3)	3.87	(12.7)
2cars_car	6.52	(6.4)	7.08	(8.2)		
gt2cars_car					4.95	(13.4)
gt3cars_car	7.10	(6.7)	6.73	(8.0)		
male_car	2.02	(5.0)	3.19	(6.8)	0.173	(3.1)
busagelt17	4.62	(4.6)				
bagegt60					1.65	(10.8)
rlincgt70	3.17	(6.3)	2.73	(7.7)	0.899	(6.1)
arincgt70			3.09	(7.5)	1.92	(5.4)
binclt20			0.841	(2.2)		
Attraction	1.00	(*)	1.00	(*)	1.00	(*)
Frequency Model Coefficients						
Constants on No Tour alternative:						
male	-1.22	(-22.0)	-0.800	(-11.8)		
age3049	-0.469	(-15.0)				
income	-1.7e-5	(-19.4)	-2.0e-5	(-26.0)	-8.1e-6	(-21.3)
nocar	0.344	(3.3)	0	(*)	0.397	(8.5)
hhwithchld					0.308	(20.4)
retired					-0.0221	(-1.1)
unemp					-0.158	(-2.7)
NoTourASC	6.89	(24.1)	5.73	(26.5	3.38	(18.1)
Structural Parameters:						
CountySc	0.723	(5.2)	0.789	(9.3)	0.515	(13.6)
PTScale	0.366	(5.9)	0.345	(7.2)	1.00	(*)
TScale	0.566	(9.0)	0.732	(11.8)	0.317	(12.2)

Table 9: Frequency x Mode Model Results

	Commute		Business		Other (VFR + Other)	
File	LD_com_v70.F12		LD_bus_v56.F12		LD_tototh_v52.F12	
Converged	True		True		True	
Observations	2339927		2206448		4862186	
Final log (L)	-33559.5		-45884.9		-190457.8	
D.O.F.	17		18		19	
Rho²(0)	0.991		0.987		0.974	
Rho²(c)	0.197		0.135		0.089	
Mode x Destination Model Coefficients						
Level of Service Terms:						
Cost	0	(*)	0	(*)	0	(*)
LogCost			-1.41	(-18.1)	-2.24	(-49.1)
GT	-0.0031	(-63.9)				
GJT			-0.0011	(-5.7)	-0.0014	(-17.6)
AirAcEgr	-0.0083	(-5.5)	-0.0105	(-11.9)	-0.0077	(-10.9)
Airfreq	0.0288	(2.3)	0.0427	(6.5)		
Alternative-specific constants:						
CarASC	0	(*)	0	(*)	0	(*)
RailASC	0.944	(5.7)	-0.0514	(-0.4)	0.571	(12.2)
AirASC	0.0763	(0.2)	0.550	(2.0)	1.13	(5.2)
CoachASC	-2.33	(-12.3)	-4.37	(-21.7)	-0.528	(-10.5)
Socio-economic terms:						
0cars_car	0	(*)			0	(*)
1car_car	0.907	(5.7)	1.13	(11.0)	2.08	(45.0)
2cars_car	1.57	(10.0)	1.63	(15.8)		
gt2cars_car					2.44	(52.2)
gt3cars_car	1.62	(10.1)	1.48	(13.7)		
male_car	0.537	(6.8)	0.894	(12.6)	0.0454	(2.4)
busagelt17	1.48	(4.0)				
bagegt60					0.840	(17.3)
rlincgt70	0.889	(12.7)	0.690	(9.1)	0.370	(5.5)
arincgt70			1.03	(6.7)	0.847	(4.5)
binclt20			0.682	(2.5)		
Attraction	1.00	(*)	1.00	(*)	1.00	(*)
Frequency Model Coefficients						
Constants on No Tour alternative:						
male	-1.04	(-15.5)	-0.631	(-10.5)		
age3049	-0.478	(-16.8)				
income	-1.3e-5	(-16.3)	-1.8e-5	(-27.5)	-7.0e-6	(-22.4)
nocar	0.060	(0.1)	0	(*)	0.0254	(0.9)
hhwithchld					0.300	(24.1)
retired					-0.0374	(-2.3)
unemp					-0.197	(-4.1)
NoTourASC	19.6	(117.8)	8.14	(13.0)	3.71	(20.5)
Structural Parameters:						
CountySc	0	(*)	0	(*)	0	(*)
PTScale	1.00	(*)	1.00	(*)	1.00	(*)
TScale	1.00	(*)	0.945	(60.1)	0.564	(75.2)