

A FORECASTING MODEL FOR LONG DISTANCE TRAVEL IN GREAT BRITAIN

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ABSTRACT

This paper summarizes the work carried out on the development of a model to forecast longer distance travel by car, rail, coach and air in Great Britain by British residents. The aim of the model is to examine the effects on long distance travel of possible future developments in transport supply as well as changes in economic, demographic and social factors and a range of policy measures. The forecasts are made to 2030.

Long distance travel is defined as trips of 50 miles or more one-way. In addition to the four modes, long distance travel is broken down into five journey purposes: business, commuting, leisure day trips, visiting friends and relatives (VFR) and holiday, and two distance bands: 50 to less than 150 miles, and 150 miles and greater. The base values for the model are taken from the National travel Survey (NTS) of Great Britain for the years 2004 to 2006.

The forecasting model is a dynamic, elasticity driven system of demand equations. Demand, in terms of person miles per capita, is related to travel costs, travel time and the socioeconomic and demographic characteristics of the population by a set of elasticities. Substitution between modes is captured through cross-elasticities for travel costs and time. The elasticities used in the model are derived from new empirical evidence based on both aggregate and disaggregate data.

A Base Case is defined to produce a 'most-likely' projection of long distance travel, annually, to 2030. The model is used to examine the impacts of a number of specific policy/supply-side scenarios. The scenarios considered include road user charging and various assumptions regarding air and rail fares, motoring costs and car fuel efficiency. In addition, the impact of different assumptions concerning economic growth on long distance travel is examined.

Keywords: long distance travel, travel demand elasticities, travel demand forecasting

INTRODUCTION

This paper summarises a study, financed by the Independent Transport Commission, which was undertaken in order to forecast longer distance domestic travel by coach, air, rail and car in Great Britain (Dargay, 2010). The motivation behind the study is that relatively little is known about long distance travel despite it being a large and growing segment of travel demand. Although trips of 50 miles or more 1-way make up only 2% of all trips by British residents within Great Britain, they account for around 1/3 of distance travelled¹.

The study is based on a forecasting model which allows the examination of the effects on long distance travel of possible future developments in transport supply, changes in economic, demographic and social factors and a range of policy measures. The forecasts are made to 2030, but the model can be extended to a longer time horizon.

The National Travel Survey (NTS) of Great Britain is an important empirical basis for the study. Long distance travel is defined as trips of 50 miles or more one-way in the NTS, and we also choose to use this definition. Travel by each of the four modes – car, rail, coach and air – is divided into five journey purposes: business, commuting, leisure day trips, visiting friends and relatives (VFR) and holiday, and each of these into two distance bands: 50 to less than 150 miles, and 150 miles and greater. Air is only considered a relevant mode for trips of 150 miles or more. Following the NTS, the model covers travel only within Great Britain by British residents.

The forecasting model is a dynamic, elasticity driven system of 35 demand equations for the four modes by five purposes and two distance bands². For each of these, demand is defined as person miles and is related to travel costs, travel time and the socioeconomic and demographic characteristics of the population by a set of elasticities. Substitution between modes is captured through cross-elasticities for travel costs and time. All elasticities vary by purpose and distance band as well as by mode. The model forecasts travel on a per capita basis and uses population projections to determine total travel.

A number of input values and parameters are required to calibrate the demand model. These are mainly the base values for demand and the exogenous variables, the elasticities determining the relationships in the model and the demand drivers we wish to analyse. The base values for the model are approximated from the NTS. Surveys for the years 1995 to 2006 were used to construct annual measures of long distance travel by mode, journey purpose and distance band.

The elasticities used in the model are based on new empirical evidence obtained from a wide range of data sources. Cost and income elasticities have been estimated on the basis of aggregate time-series data, the impact of socio-economic, demographic and geographic

¹ National Travel Survey.

² There are 35 equations since the shorter distance band does not include air.

factors on models using the NTS and disaggregate time and cost elasticities from a survey of long distance travel carried out for the project.

The survey data have been used to obtain diversion factors to determine cross-elasticities with respect to travel costs and travel time and to provide relativities between own-elasticities for different journey purposes and distances. In addition, responses to 'transfer cost' and 'transfer time' questions have been analysed to provide information to derive estimates of own-cost and own-time elasticities.

The empirical evidence obtained from the above mentioned analyses is used in conjunction with economic theory and the relationships between elasticities to determine a consistent set of parameters which is used in the forecasting model.

The model requires a reference case in order to compare various scenarios (policies, measures, etc.) which might influence long distance travel. A number of factors – the socio-demographic characteristics of the population and national economic trends – have been identified and projections have been obtained from government bodies. We have further defined a Base Case for transport costs, which is based on oil price assumptions and calculations provided by the Department for Transport.

The model is used to examine the impacts of a number of specific policy/supply-side scenarios. These are incorporated into the modelling as changes in travel costs and travel time. The scenarios considered are road user charging, an increase in Air Passenger Duty, a reduction in air fares and various assumptions regarding car fuel efficiency, motoring costs and rail fares. The impact on travel of the reduced income growth of the current economic downturn is also examined. In addition, a sensitivity analysis is carried out to explore the impacts of different assumptions regarding economic and population growth and income elasticities.

The structure of the remainder of the paper is as follows. The next section provides a description of the forecasting model and the input data and parameters required. Thereafter, the derivation of the elasticities used as parameters in the forecasting model is described and the elasticities presented. Finally, the input assumptions, the Base Case and alternative scenarios are presented and the projections of long distance travel discussed.

THE FORECASTING MODEL

Model specification

The model is defined as a system of 35 equations: 5 journey purposes by 2 distance bands by 4 modes³. We assume the existence of an equilibrium demand and a dynamic path of adjustment towards that equilibrium. The long-run equilibrium demand in terms of passenger

³ 5 purposes by 4 modes (car, rail, coach and air) for journeys 150 miles or more and 5 purposes by 3 modes (car, rail and coach) for journeys < 150 miles.

A forecasting model for long distance travel in Great Britain
DARGAY, Joyce; CLARK, Stephen; JOHNSON, Daniel; TONER, Jeremy; WARDMAN, Mark

miles per capita by mode ($m = \text{car, rail, coach and air}$), purpose ($p = \text{business, commuting, leisure, VFR and holiday}$) and distance band ($d = \text{less than 150 miles and 150 miles or more}$) is assumed to be a log-linear function of the monetary costs of the four modes, C_m , journey time by each mode, T_m , and income and other characteristics of the population, S_x :

$$D_{mpd,t}^* = \alpha_{mpd} + \sum_i \beta_{mipd} C_{i,t} + \sum_i \gamma_{mipd} T_{i,t} + \sum_x \eta_{mpdx} S_{x,t} \quad m, i = \text{car, rail, coach, air} \quad (1)$$

where all variables are in logarithmic form. Cost and time variables for all four modes (i) appear in the demand equation for each mode to allow for substitution between modes as relative cost or travel time changes. The x socioeconomic characteristics of the population, S , are the same for all modes, purposes and distance bands, while cost and time variables can differ between business and leisure travel as well as varying by mode.

The Greek letters represent long-run elasticities. The cost and time elasticities (β and γ) comprise both own- and cross-elasticities for each mode and vary by purpose and distance band. The elasticities relating to the x different socio-economic characteristics (η) also vary by mode, purpose and distance band.

The system of equations can be interpreted as a reduced form model. In the structural specification, car ownership would appear in each of the equations, as it is a determining factor of the demand for all transport modes. Car ownership, however, is not exogenous with respect to the other explanatory variables, but is determined, in principle, by all these variables, i.e., by the monetary and time costs of different modes, by income and by other socioeconomic characteristics of the population. The reduced form model is obtained by replacing car ownership with these variables. The demand model thus allows for the *direct* effects of income, costs, etc. on travel by mode, and the *indirect* effects of these factors on travel through their impact on car ownership.

Since the model will be used to forecast demand in specific time periods, we are not only interested in equilibrium demand, but also in how demand evolves over time, on an annual basis, in response to changes in external factors. In any given time period, actual demand could only be expected to be in equilibrium with respect to the prevailing costs, incomes etc. if complete adjustment to changes in these factors occurs within the time interval specified for the forecasts (in this case, one year) or if they have remained constant over a sufficiently long time for responses to have settled down.

There are numerous reasons why complete adjustment to any change may take a number of years. These include persistence of habit, uncertainty and imperfect information regarding alternatives and prices and costs of adjustment. There is also growing empirical evidence that such longer-term effects are important, which suggests that the time required for complete adjustment is on the order of 3-10 years or even longer⁴.

⁴ See, for example, Dargay and Hanly (2002), Dargay (2007a), Dargay (2007b), Jevons *et al.* (2005).

Because of this sluggish adjustment to changes in the explanatory factors, the desired long-run demand for each mode-purpose-distance combination at year t , $D_{mpd,t}^*$ is not equivalent to the *actual* travel in time t , $D_{mpd,t}$. Instead, we assume that only a proportion θ of the gap between the desired (equilibrium) demand and actual demand is closed each year. There are numerous ways of expressing this adjustment mechanism, the simplest being based on a partial adjustment model. This can be written as:

$$D_{mpd,t} - D_{mpd,t-1} = \theta(D_{mpd,t}^* - D_{mpd,t-1}) \quad (2)$$

where $0 \leq \theta < 1$ is the adjustment coefficient, which indicates the speed of adjustment to long-run equilibrium. The lower the θ , the slower the speed of adjustment and the greater the difference between the short- and long-run elasticities. For simplicity, we assume that the speed of adjustment is the same for all modes, purposes and distance bands and for all exogenous factors. This is likely to be a reasonable approximation because the possibility of switching between modes implies that response speeds cannot be treated as independent of each other.

The dynamic forecasting model, which defines demand on an annual basis, is obtained by substituting the desired long-run demand (1) into (2) and solving for $D_{mpd,t}$. This results in the following system of four mode equations for each of the 10 purpose distance bands:

$$D_{mpd,t} = \theta\alpha_{mpd} + \sum_i \theta\beta_{mipd} C_{i,t} + \sum_i \theta\gamma_{mipd} T_{i,t} + \sum_x \theta\eta_{mpdx} S_{x,t} + (1-\theta)D_{mpd,t-1} \quad (3)$$

where m and $i = \text{car, rail, coach and air}$. The coefficients (θ, β etc.) are the short-run elasticities relating to variables included in the model.

In equation (3), demand in each year is influenced by the demand in the previous year, i.e. $D_{mpd,t-1}$ as well as by the other explanatory variables. This can be interpreted in terms of habit or inertia: what individuals do in the past also affects their future behaviour. Since $D_{mpd,t-1}$ is determined by prices, income, etc. in year $t-1$, and $D_{mpd,t-k}$ is determined by prices, income etc. in year $t-k$, by repeated substitution for $D_{mpd,t-k}$, demand in any year, $D_{mpd,t}$ is implicitly a function all explanatory variables in *all* previous years.

The lag structure assumed in the above implies that the impact of the prices, income etc. declines geometrically over time, so that the effects of the most recent events (e.g., price or income changes) are the strongest while the effects of events further in the past dwindle in significance. This approach has two advantages: (a) it is consistent with empirical evidence on short- and long-run responses, and (b) forecasts are not given in terms of an eventual steady state at an unknown date in the future, but include useful policy information about how long it takes for the effects to build up.

Input data

Various input values and parameters are required to calibrate the demand model. These are mainly the base values for demand and the exogenous variables, the elasticities determining the relationships in the model and the drivers we wish to analyse.

The base values for the model are annual measures of long distance travel by mode (car, rail, coach and air), journey purpose (business, commuting, leisure, visiting friends and relatives (VFR) and holiday) and distance band (<150 miles and 150+ miles one-way). These are taken from National Travel Survey (NTS) data for the years 1995 to 2006.

Historical data (aggregate annual time series) for the exogenous variables - income, travel costs and relevant socio-demographic variables - were collated from the Office of National Statistics and the Department for Transport.

The elasticities required for the model are denoted by the Greek letters in equation (3). These include:

- 35 own-cost elasticities for each of the 4 modes by 5 purposes for distance band 150 miles or more ($4 \times 5 = 20$), and between car, coach and rail by 5 purposes for distance band less than 150 miles ($3 \times 5 = 15$);
- 90 cross-cost elasticities between each of the four modes (12 elasticities) by 5 purposes for distance band 150 miles or more ($12 \times 5 = 60$), and between car, coach and rail by 5 purposes for distance band less than 150 miles ($6 \times 5 = 30$);
- 35 own-elasticities with respect to journey time for each of the 4 modes by 5 purposes for distance band 150 miles or more ($4 \times 5 = 20$), and between car, coach and rail by 5 purposes for distance band less than 150 miles ($3 \times 5 = 15$);
- 90 cross-elasticities with respect to journey time between each of the four modes (12 elasticities) by 5 purposes for distance band 150 miles or more ($12 \times 5 = 60$), and between car, coach and rail by 5 purposes for distance band less than 150 miles ($6 \times 5 = 30$);
- 35 elasticities with respect to income for each of the 4 modes by 5 purposes for distance band 150 miles or more ($4 \times 5 = 20$), and between car, coach and rail by 5 purposes for distance band less than 150 miles ($3 \times 5 = 15$);
- 35 elasticities as above for each of the other socio-demographic factors included in the model;
- An adjustment factor describing the dynamics of adjustment and relating short- and long-term elasticities.

ESTIMATION OF ELASTICITIES

From a review of the literature on elasticities in existing aggregate and disaggregate studies⁵, it was concluded that the empirical evidence was limited and outdated, so that an essential element of the project was to obtain new elasticity estimates. This was achieved through the

⁵ This was carried out in the scoping study for this project, reported in Dargay and Wardman (2008).

estimation of models using existing data and a special survey of long distance travel. In this section, the elasticity estimates are reported.

Estimation of elasticities from aggregate time-series data

To begin with, aggregate demand models for the four modes were estimated using annual time-series data. Although existing data do not generally distinguish long distance journeys from others, any values obtained could be adjusted using relativities obtained from other sources.

The elasticities were estimated on the basis of dynamic models.⁶ The dependent variable in all models is passenger kilometres (or miles) by the given mode obtained from Transport Statistics Great Britain. Prices are defined as the motoring cost index and the rail fare index from the Office of National Statistics (ONS), revenue per kilometre for non-local bus and coach and domestic air fares from the Department for Transport (DfT). Income was defined as real GDP, taken from ONS.

From the aggregate models, we were only able to obtain reliable and realistic estimates for own-cost and income elasticities. This difficulty in obtaining journey time and cross-elasticities using aggregate models is a common problem and is a result of the difficulty of defining journey time variables on an aggregate level, the small changes in such variables over time and the multicollinearity of substitute prices⁷.

The short- and long-run elasticities are reported in Table 1. The estimated elasticities are generally in line with previous evidence⁸. Car travel is all passenger kilometres by car for both short- and long-distance trips. The cost elasticity relates to total motoring costs. Since fuel costs make up about 1/3 of total motoring costs, the implied long-run fuel price elasticity of car travel is about -0.33, which agrees well with other studies⁹. The short-run (1-year) elasticities are approximately 1/3 the long-run values, implying an adjustment coefficient of 0.7, which is also in line with other evidence¹⁰.

Table 1: Estimates of short- and long-run elasticities based on aggregate time-series data

	Own cost elasticity		Income elasticity	
	short run	long run	short run	long run
Car	-0.3	-1.0	0.3	1.0
Coach	-0.2	-0.8	0.2	0.7
Rail	-0.3	-1.0	0.4	1.3
Air	-0.1	-0.3	0.6	2.1

⁶ Both partial adjustment models and error-correction models were estimated. The results presented here are a summary of the results for the best-performing models. See e.g. Dargay et al (2002) for a description of these models.

⁷ Dargay et al. (2002).

⁸ See Dargay and Wardman (2008) and Oum et al (1992).

⁹ Goodwin et al (2004) and Graham and Glaister (2004).

¹⁰ Dargay et al (2002).

The cost elasticities for the other modes are also within the ranges reported in the literature, although that for air is well at the lower end of the range¹¹. Regarding the income elasticities, the relative magnitudes are as expected, with coach having the lowest elasticity (less than unity) and air the greatest, suggesting the luxury nature (in the economic sense) of air travel. Although the coach and air elasticities relate to long distance travel, the elasticities for car and rail are for all journeys, both short and long distance. These elasticities would need to be combined with other information if they are to be used in the forecasting model.

For rail, we also have access to annual data for individual origin-destination pairs over the period 1990 to 2005¹² which permits the estimation of elasticities for long-distance journeys separately, and for the two distance bands. The results obtained using models similar to those employed for the aggregate data are shown in Table 2. According to these results, the long-run cost elasticity is on average the same for all long distance journeys (50+ miles) as it is for all journeys (-1.0) from the previous table. The income elasticity for all long distance journeys (1.1), however, appears to be lower than for all rail journeys (1.3) in Table 1. The results also suggest that, for long distance journeys, both the cost and income elasticities are greater for journeys more than 150 miles than they are for those less than 150 miles. The estimated adjustment coefficient is again approximately 0.7 so that the short-run elasticities are about 1/3 the long-run values. It is reassuring that these results are in agreement with those in the previous table, which were estimated using aggregate time-series data.

Table 2: Estimates of long-run rail elasticities by distance band based on LENNON data

	Distance - miles		
	50-150	150+	50+
Cost	-0.9	-1.2	-1.0
Income	1.0	1.4	1.1

Aggregate data such as used in the previous analyses can provide only limited information regarding elasticities. More detailed estimates of the effects of income and costs on long-distance travel for different journey purposes and different distance bands require disaggregate data. Such data are also necessary to analyse the impact of socio-economic and demographic factors, which are lost in aggregation. In addition to this, there is the issue of confounding effects with time-series data owing to a high degree of correlation amongst explanatory variables.

Elasticities relating to socio-economic, demographic and geographic factors

The elasticities relating to income and socio-demographic factors were estimated using models based on individual data from the National Travel Survey (NTS) for the years 1995 to 2006. Separate models were estimated for each of the 35 mode/purpose/distance band

¹¹ See Balcombe et al (2004) and Dargay et al (2006) for a review of the literature.

¹² The data from 2004 are from LENNON, the rail industry's standard ticket sales database, and previous years are from CAPRI, the previous ticketing system. There are 3958 flows with a distance of 50 miles or more.

combinations.¹³ Since the elasticities are estimated from repeated cross-section data, only static models could be used, so that the interpretation of the elasticities as short- or long-run is not clear cut. Empirical evidence suggests that such elasticities fall between the short- and long-run values, so we interpret the estimates as medium-run elasticities which we assume to be 2/3rds of the long-run values¹⁴. Under this assumption, the long-run income elasticities used in the forecasting model are given in Table 3. Short-run (1-year) elasticities are assumed to be 30% of the long-run values, implying an adjustment factor of 0.7 as obtained on the basis of the aggregate time-series modelling.

Table 3: Long-run income elasticities for long distance travel used in the forecasting model

Purpose	Distance (miles)	Car	Rail	Coach	Air
Business	<150	0.51	2.09	0.00	*
	150+	0.81	2.27	0.00	2.30
Commuting	<150	0.47	2.01	0.00	*
	150+	0.75	2.36	0.00	*
Holiday	<150	0.57	0.96	0.00	*
	150+	0.92	0.84	0.00	1.97
Leisure	<150	0.47	0.75	0.00	*
	150+	0.71	0.65	0.42	1.89
VFR	<150	0.80	0.38	0.00	*
	150+	1.05	0.63	0.47	2.45
All	All	0.69	1.25	0.15	2.16

* air is not considered for travel under 150 miles

The income elasticities indicate that air is most income-elastic, followed by rail, car and finally coach. This magnitude ranking of the modal elasticities is in agreement with that obtained from aggregate time series data shown in Table 1. There is also good agreement between the two data sources on the magnitudes of the long-run elasticities for air and rail, while the aggregate models show car and coach to be more-income elastic than the disaggregate models.

Regarding journey purpose, there are no apparent trends except for rail, where the income elasticities for business and commuting are much higher than for holiday, leisure and VFR. Otherwise we find that longer journeys are more income-elastic than shorter distance journeys, which is also in agreement with the results presented for rail in Table 2.

Other factors found to be important for long distance travel are gender, age and the number of adults in the household. These are relevant for future travel demand, since the proportions of men, the over-60s and single-person households are expected to increase over the coming decades. Although other variables were used in the NTS models, these are not included in the forecasting model. The reason for this is either because the magnitude of the elasticities is very small or that projected changes in the variables over the forecasting period are marginal so that inclusion of these in the forecasting model will have but an insubstantial effect on future long distance travel demand. For example, the elasticities relating to

¹³ See Dargay and Clark (2010).

¹⁴ See Goodwin et al (2006).

geographic characteristics (region and size of conurbation) are generally very small and according to population projections, only small changes in population distribution are expected.

Cost and time elasticities

Elasticities of demand for each mode with respect to travel costs and travel time are essential components of the forecasting model. Both own- and cross-elasticities are differentiated by journey purpose and distance band. Since the required elasticities could not be estimated using existing data, a survey was undertaken to collect the data to derive these elasticities.

The survey was aimed at long distance travellers by each of the four modes. Since the intention of the survey was to analyse the characteristics of long distance travel and estimate journey cost and time elasticities by mode, a similar sample size of 1000 individuals was used for each mode. Car travellers were interviewed at motorway service areas, rail travellers on board trains, coach travellers at coach stations and air travellers at airports. At least 3 different locations were chosen for each mode.

Questions on intended behaviour were used to estimate diversion factors, from which cross-elasticities with respect to journey cost and journey time could be derived. There are two questions, one in terms of transfer price and one in terms of transfer time (cost/time increase at which individual would change behaviour). The questions were posed as follows:

About how much would your party's round trip journey cost (time) have to increase before you would switch to another main means of travel or not make this trip?

The option of *must make the journey by current mode* was also given.

The next question related to what the individual would do if the journey cost (time) increased by the amount stated:

What would you do instead?

The possible alternatives were *go by car, go by train, go by coach, go by air, go somewhere else and not make the journey*.

The diversion factor¹⁵ v_{ji} gives the proportion of the change in mode j users who divert to mode i in response to a change in one of the characteristics of mode j .

$$v_{ji} = \frac{\partial D_i}{\partial D_j} \quad (4)$$

¹⁵ See Wardman and Toner (2003).

The diversion factors are used to derive cross-elasticities. For example, the cross-elasticity of demand for mode i with respect to a given characteristic of mode j , ε_{ij} , is calculated from own-elasticity of mode j according to:

$$\varepsilon_{ij} = \left| \varepsilon_{jj} \right| \frac{s_j}{s_i} v_{ji} \quad (5)$$

where ε_{jj} is the own-elasticity of mode j with respect to that characteristic and s_i and s_j are the market shares of modes i and j . The advantage of using diversion factors is that cross-elasticities are often not possible to estimate directly, for reasons noted earlier. In addition, they ensure consistency between elasticities.

These survey questions also give information about the perceived necessity of making a trip by a particular mode by providing the individual the option of responding *must make this journey by the current mode*. The responses can be used as relativities for own-cost and own-time elasticities for different modes and distances: the higher the proportion of journeys considered necessary by a given mode or distance band, the less elastic the demand and the lower the own-elasticity.

Own-elasticities with respect to journey cost and journey time were also estimated from transfer price and time questions by using the responses to construct demand curves. The transfer cost and time values describe the individuals' willingness to pay in terms of a percentage increase in costs or time. The value of the aggregate demand function at a given percent of cost (time), p , is defined as the proportion of individuals who have a willingness to pay greater than or equal to p . The demand function is thus constructed as the cumulative distribution function of the willingness to pay for all individuals. The own-cost (time) elasticity is estimated by regression of the cumulative distribution of the willingness to pay on the percentage increases in costs (time).

The elasticities and relativities obtained from the transfer cost/time analysis were used in conjunction with the estimates of aggregate cost elasticities discussed earlier to determine the elasticities for the forecasting model. The final set of cost and time elasticities are presented in Table 4. In addition to the relationship between diversion factors and cross-elasticities in equation (5), we have also made use of economic demand theory, and in particular, Slutsky symmetry between opposite cross-price elasticities:

$$\varepsilon_{ij} = \frac{c_j}{c_i} \varepsilon_{ji} \quad (6)$$

where ε_{ij} is the cross-elasticity of mode i with respect to the cost of mode j , c_i and c_j are the cost shares of modes i and j , and ε_{ji} is the cross-elasticity of mode j with respect to the cost of mode i .

Finally, we have made use of the relationship between journey time elasticities ε^T and cost elasticities ε^C :

$$\varepsilon_{ij}^T = \lambda \frac{T_j}{C_j} \varepsilon_{ij}^C \quad (7)$$

where λ is the value of time, and T and C are the average journey time and journey cost. The Values of Time are calculated using the meta-analysis in Wardman (2004) and are also shown in the table.

The elasticities are determined as described in the following.

- The aggregate own-cost elasticity for rail is taken from the estimate (-1.0) in Table 1, since this value is well-supported by a large body of evidence.
- The aggregate own-cost elasticity for coach (-0.85) is 0.85 times the rail elasticity. This is obtained from the relativities of these elasticities obtained from the transfer cost estimates.
- The aggregate own-cost elasticity for car (-0.54) is taken as 0.54 times the rail elasticity, also based on the relativities resulting from the transfer cost estimates.
- The aggregate own-cost elasticity for air (-1.0) is assumed to be the same as for rail. Although the transfer cost relativities suggest air to be more cost sensitive than rail, the aggregate elasticity estimation in Table 1 suggests a much lower elasticity. Based on other evidence¹⁶, the value of -1.0 is assumed.
- The own-elasticities for the different journey purposes and distance bands are calculated from the above aggregate elasticities using relativities based on the proportion of individuals who say they must use the current mode for the given purpose and distance band based on the transfer cost question and the shares of each purpose and distance band of the total distance travelled by the given mode.
- For rail the estimated elasticities for the two distance bands are determined using the relativities obtained from the aggregate analysis of LENNON data by distance (Table 2).
- The cross-elasticities are calculated using the diversion factors, the relationship between cross-elasticities and diversion factors and Slutsky symmetry.
- The own- and cross-elasticities with respect to journey time are calculated from equation 7 using the cost elasticities and the value of time estimates shown in the table. This method ensures consistency between the cost and time elasticities¹⁷.

Since the own-elasticities are based on long-run values, and other elasticities derived from these, the elasticities in the table are assumed to represent long-run relationships. As in the case of income and socio-demographic factors, short-run (1-year) elasticities are assumed to be 30% of the long-run values, implying an adjustment factor of 0.7 as obtained on the basis of the aggregate time-series modelling.

¹⁶ See Dargay et al (2006)

¹⁷ Alternatively, we could have begun from the journey time elasticities, but aggregate estimates could not be obtained from the available data and the existing literature is rather limited.

A forecasting model for long distance travel in Great Britain
DARGAY, Joyce; CLARK, Stephen; JOHNSON, Daniel; TONER, Jeremy; WARDMAN, Mark

Table 4: Long-run journey cost and journey time elasticities and value of time (2008 prices)

Purpose	Distance (miles)	Mode	With respect to cost of:				With respect to journey time of:				Value of Time p/min
			Car	Rail	Coach	Air	Car	Rail	Coach	Air	
Business											
	< 150	Car	-0.34	0.04	0.00		-1.31	0.11	0.01		53
		Rail	0.21	-0.59	0.02		0.80	-1.47	0.05		49
		Coach	0.21	0.40	-0.68		0.82	0.99	-1.92		26
	150+	Car	-0.34	0.10	0.00	0.03	-1.93	0.36	0.02	0.02	69
		Rail	0.25	-0.74	0.01	0.18	1.43	-2.61	0.05	0.17	59
		Coach	0.25	0.31	-0.43	0.00	1.43	1.09	-2.27	0.00	31
		Air	0.02	0.06	0.00	-0.42	0.12	0.20	0.00	-0.40	64
Commuting											
	< 150	Car	-0.62	0.07	0.00		-0.94	0.07	0.00		21
		Rail	0.25	-0.49	0.02		0.38	-0.49	0.03		20
		Coach	0.06	0.20	-0.49		0.10	0.20	-0.57		11
	150+	Car	-0.65	0.03	0.00	0.08	-1.52	0.05	0.00	0.03	28
		Rail	0.19	-0.51	0.01	0.45	0.44	-0.75	0.02	0.18	25
		Coach	0.10	0.13	-0.28	0.00	0.24	0.18	-0.61	0.00	13
		Air	0.32	0.34	0.00	-1.15	0.74	0.49	0.00	-0.46	27
Holiday											
	< 150	Car	-0.72	0.10	0.03		-1.64	0.17	0.04		20
		Rail	0.79	-1.51	0.24		1.80	-2.64	0.41		19
		Coach	0.20	0.23	-1.02		0.45	0.41	-1.74		10
	150+	Car	-0.79	0.11	0.06	0.05	-2.79	0.19	0.12	0.03	27
		Rail	0.38	-1.68	0.44	0.48	1.36	-3.04	0.91	0.25	23
		Coach	0.17	0.36	-0.86	0.02	0.59	0.65	-1.77	0.01	12
		Air	0.08	0.21	0.01	-1.15	0.28	0.38	0.02	-0.60	25
Leisure											
	< 150	Car	-0.41	0.05	0.04		-0.90	0.08	0.07		20
		Rail	0.37	-0.85	0.09		0.81	-1.46	0.16		18
		Coach	0.47	0.13	-0.80		1.03	0.23	-1.32		10
	150+	Car	-0.61	0.10	0.05	0.02	-2.07	0.17	0.09	0.01	25
		Rail	0.23	-1.30	0.26	0.21	0.78	-2.27	0.52	0.11	22
		Coach	0.21	0.50	-0.86	0.01	0.71	0.88	-1.72	0.01	12
		Air	0.05	0.26	0.01	-1.14	0.16	0.45	0.01	-0.57	24
VFR											
	< 150	Car	-0.49	0.06	0.00		-1.10	0.10	0.01		20
		Rail	0.39	-1.02	0.12		0.87	-1.76	0.19		19
		Coach	0.13	0.56	-0.80		0.30	0.97	-1.34		10
	150+	Car	-0.60	0.15	0.01	0.03	-2.06	0.26	0.02	0.01	26
		Rail	0.28	-1.19	0.05	0.06	0.97	-2.11	0.10	0.03	22
		Coach	0.18	0.50	-0.86	0.00	0.62	0.89	-1.74	0.00	12
		Air	0.11	0.13	0.00	-0.99	0.38	0.22	0.00	-0.50	24

PROJECTIONS OF LONG DISTANCE TRAVEL

Base Case Assumptions

The assumptions used in the Base Case are summarised in Table 5 below. Projections of income are based on GDP¹⁸ forecasts from HM Treasury¹⁹ Forecasts for the UK Economy (April 2009) and for 2011 from the medium-term forecasts taken from HMT's Forecasts for the UK Economy (February 2009). In the longer term (from 2012) we assume an average growth rate of 2.5% per annum, based on historic average rates.

Projections of the population and its socio-economic and demographic characteristics are the principal projections provided by the Office of National Statistics (ONS), the Government Actuary's Department (GAD) and the General Register Office of Scotland. Population is expected to increase to 68.8 million by 2030 while the number of households is projected to increase to 31.8 million. Population growth over the next two decades is projected to be slightly higher than it was over the past 15 years. The number of households is expected to increase more rapidly than the population, as is has done over the past 15 years, so that the average household size will continue to decline. This is reflected in the percentage of 1-adult households, which is projected to continue to increase. Other changes are a slight decrease in the proportion of women and a significant increase in the proportion of those aged 60 years or more.

Table 5: Base Case assumptions

	% change 2009 - 2030	Source/assumptions
GDP	58%	HMT (April 2009)
Population	14%	ONS
% women	-0.8%	ONS
% 60 years +	25%	ONS
% 1-adult hhs	23%	ONS
Petrol prices	+27%	DECC
Car fuel efficiency	+23%	1% per year
Per km fuel prices	+4%	as above
Motoring costs	0.5%	other motoring costs constant
Coach fares	3%	other costs constant
Journey time (roads)	7.5%	DfT NTM 2008
Rail fares	+28%	RPI+1%
Air fares	-12.5%	DfT's efficiency assumptions

¹⁸ Gross household income is assumed to grow in line with GDP. This is supported by historical evidence, the two measures having a correlation coefficient greater than 0.99 over both the past 60 years and the past decade.

¹⁹ Projections are only available for the UK. These are assumed to be the same for GB.

Fuel prices are determined largely by crude oil prices and taxation. Crude oil price projections are from The Department of Energy and Climate Change (DECC), Scenario 3: \$84/bbl in 2010, rising to \$102 in 2015, and to \$120 in 2020 and thereafter. Since crude oil is priced in US dollars, an assumption is also required for the US\$-Sterling exchange rate to determine the domestic price of crude oil. Given the fall in the pound from \$2.00 in 2007 to \$1.45 in 2009, it is unclear what assumption should be made for future rates. DECC is currently using a rate of \$1.60 in its projections, which is close to the current rate, and we also use this exchange rate.

Forecasts of the prices of petrol and diesel (including duty and VAT) based on the above crude oil prices and US\$ exchange rate have been obtained from the DfT²⁰. These also take into account the increased taxation of 2p/litre in 2009, and 1p/litre in real terms in 2010 – 2013 announced in the 2009 Budget. Between 2009 and 2030, real prices are forecast to rise 27%.

We assume an increase in car fuel efficiency of 1% per year between 2009 and 2030, resulting in an improvement of 23% over the period. With the increase in prices, per mile fuel costs increase by 4% by 2030. Motoring costs are determined by fuel costs (including taxes), vehicle fuel efficiency and other (non-fuel) motoring costs. In our projections, we generally assume that other motoring costs (car purchase prices and taxes, VED, etc.) remain constant in real terms over the forecast period so that total motoring costs increase only marginally (about 0.5%) over the entire period.

Coach fares are also determined by fuel costs, improvements in vehicle fuel efficiency and non-fuel operating costs. This results in an increase of 3% in real terms 2009 to 2030.

Regarding journey time on the road network, we assume an increase from 2003 of 3% by 2015 and of 6% by 2025 as in the DfT (2008) Central Forecast, and of 0.3% per annum thereafter.

Rail fares are assumed to increase by 1% per year in real terms, according to the standard regulated fares of RPI+1%.

Projections of air fares are obtained from the DfT²¹ and are calculated as described in their UK Air Passenger Demand and CO₂ Forecasts (January 2009). Growth rates in fares are calculated on the basis of assumptions on fuel costs, fuel-efficiency improvements, non-fuel costs, taxation and other environmental charges. Fuel efficiency is assumed to increase by 1.1% per annum to 2030, while non-fuel costs are assumed to decline by 4-5% per annum to 2010, 2.4% per annum 2010 to 2015, and 1.9% pa 2015 to 2020, thereafter to remain constant. The fare forecasts also assume that fares will cover climate change costs, which are comprised of Air Passenger Duty (APD) of £4.71 increasing to £9.42 in 2007 (in 2004 prices) and a Carbon surcharge relating to CO₂ emissions. Based on the oil price and

²⁰ These were kindly provided by Taro Hallworth, DfT.

²¹ These were kindly provided by Alison du Sautoy, Scott Wilson.

exchange rate assumptions above, domestic air fares are estimated to fall by 12.5% between 2009 and 2030.

Finally, the Base Case assumes no capacity constraints on the rail or air networks and no travel time changes.

Base case projections

The projections for the Base Case are shown in Figure 1. Given the assumptions above, total long distance travel measured in person miles is forecast to increase 34% from its 2005 level by 2030. Car travel will increase 30%, rail by 35%, coach by 25% and air by 126%. By purpose, business is forecast to increase 42%, commuting by 39%, Leisure by 26%, VFR by 34% and Holiday by 31%. These growth rates can be compared with the assumed GDP growth rate of 68% over the same period (actual GDP growth 2005-2008 and 58% assumed between 2009 and 2030).

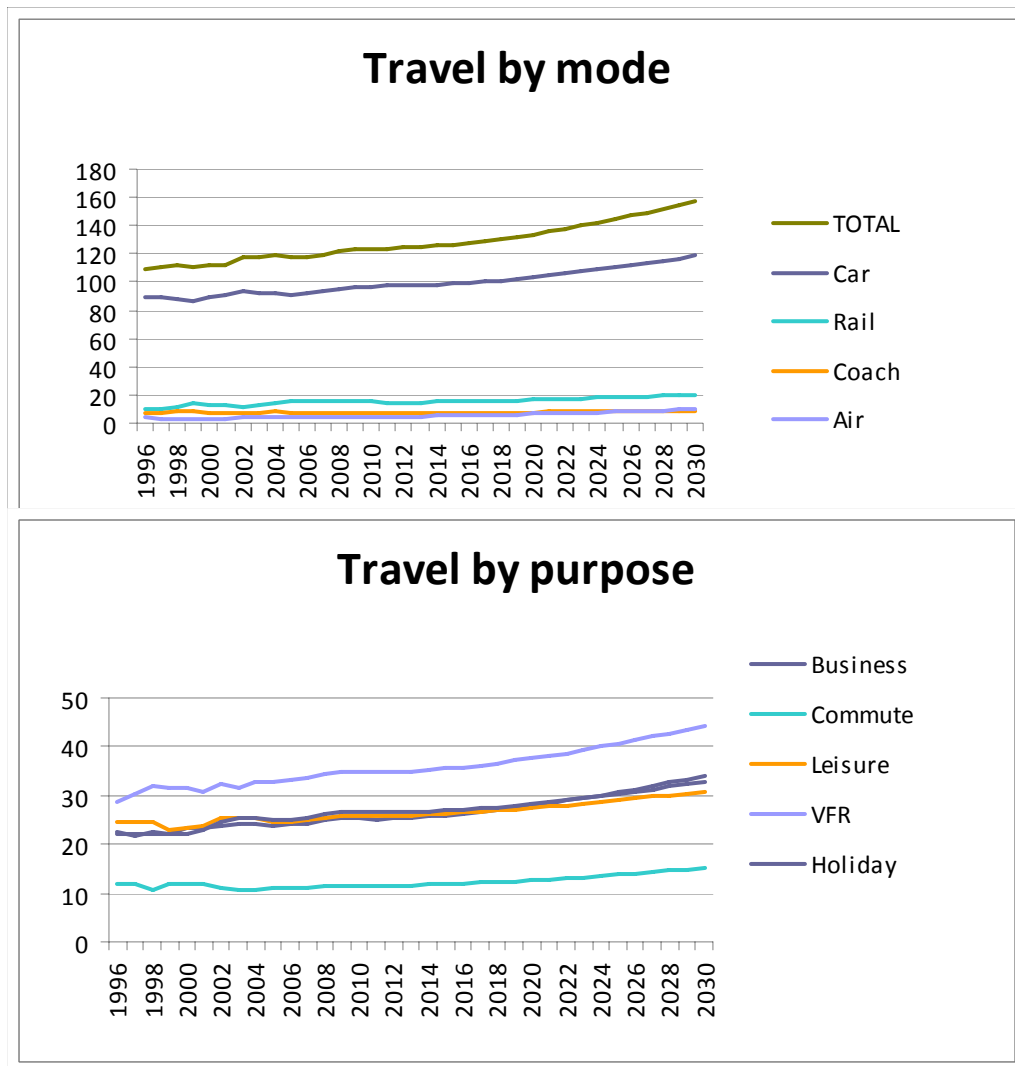


Figure 1: Base Case projections for long distance travel, billions of person miles

To estimate the impact of the current recession on long distance travel, Figure 2 compares the forecasts based on the current GDP projections (Apr-09) with those made on the basis of the GDP projections made before the downturn (Feb-08). The revised projections result in GDP being 8.1% lower in 2030 than it was in the earlier projections. The implication of this reduction in GDP growth is that long distance travel is reduced by 7% in 2030, implying an overall income elasticity of around 0.9. Regarding the individual modes, long distance car travel is reduced by 6%, rail by 11% and air by 17%.

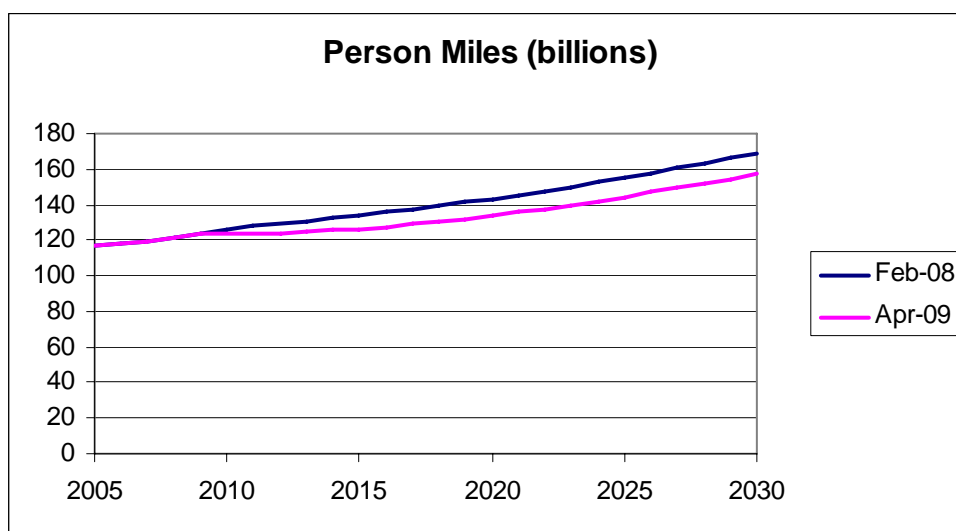


Figure 2: Effect of the recession on long distance travel, based on GDP forecasts of February 2008 and April 2009.

The impact of different scenarios

The assumptions made in the scenarios under consideration are summarised in Table 6. The assumed changes in costs, fares and journey times over the period 2009 to 2030 for each scenario are shown along with the percentage changes used in the Base Case (in parentheses).

Table 6: Assumptions made in the different scenarios, percent change 2009 to 2030 (percent change in the Base Case in parentheses)

	Impact: % change 2009 - 2030	Assumptions
Constant rail fares	Rail fare 0% (+28%)	Real rail fares at today's level
Road user charging (RUC)	Motoring cost (+0.5%) +21% business & commuting +8% other	5p/km business & commuting 2p/km all other purposes
Increase in APD	Journey time +3% (+6%) Air fares +1% (-12.5%)	£10 increase
Air fares reduced 25%	Air fares -25% (-12.5%)	DfT projections 2008
Constant car fuel efficiency	Motoring cost +10% (+0.5%)	No improvement (23% to 2030)
High car fuel efficiency	Motoring cost -10% (+0.5%)	DfT: improvement to 2030 92% petrol, cars, 43% diesel cars
Motoring costs +1% pa	Motoring cost +23% (+0.5%)	Increase in total motoring cost

The projections of long distance travel in 2030 by mode resulting from the seven scenarios are shown in Table 7 (in billions of person miles) and Table 8 (in terms of percentage change from the Base Case). In general, the impacts on total travel of the majority of the reported scenarios are minimal.

The first scenario considers constant real rail fares, as opposed to an increase of 1% per annum in the Base Case. The lower fares result in a substantial increase in rail travel in 2030, 24 billion person kilometres, compared to 20.1, or an increase of 19%. Around half the increase in rail travel is a switch from car, about 10% a switch from coach and air and 40% generated, as total travel is about 1% higher than in the Base Case.

The next scenario examines road user charging. Given the assumed road user charge of 5 pence/km for business and commuting and 2p/km for other travel, car travel is 2.2% lower in 2030 than in the Base Case, while rail travel is 10.3% higher. There also appears to be a switch to coach (which is assumed not to pay the charge, while gaining from the journey time reduction). There is also a switch from air, presumably as a result of the reduction in road congestion and travel time by car. Overall, travel is only marginally lower than without road user charging.

Different assumptions concerning air fares are examined in the next two scenarios. The increase in APD results in a decline in air travel (10.9% lower in 2030 than without the increase) as passengers switch to car and rail, but also in a small decline in long distance travel overall. A reduction in air fares of 25% results in air travel being 12.5% higher in 2030 than it would have been without this reduction. About half of this is a switch from car and rail, while half is generated.

The next two cases examine different scenarios for car fuel efficiency: no improvement over the period (Constant car fuel efficiency) and that assumed by DfT of 92% for petrol cars and 43% for diesel cars (High car fuel efficiency). These can be compared to the Base Case, where an efficiency improvement of 23% over the period is assumed. With no improvements in fuel efficiency car travel will be 4.4% lower in 2030 than in the Base Case and total travel 2.8% lower. With high fuel efficiency, car travel will be 4.7% higher than in the Base Case and total travel 3% higher.

Table 7: Travel forecasts by mode for 2030, billion person miles, based on different scenarios

Scenario	Car	Rail	Coach	Air	Total
Actual 2005	91.1	15.0	6.9	4.4	117.4
Base Case	118.5	20.1	8.6	9.9	157.1
Constant real rail fares	116.8	24.0	8.1	9.7	158.5
Road user charging (RUC)	115.9	22.2	8.8	9.8	156.6
Increase in APD	118.7	20.4	8.6	8.8	156.5
Air fares reduced 25%	118.3	19.9	8.6	11.1	157.9
Constant car fuel efficiency	113.3	20.7	8.8	10.0	152.7
High car fuel efficiency	124.0	19.6	8.4	9.9	161.9
Motoring costs increase 1% pa	108.0	21.3	9.0	10.0	148.3

The final scenario considers an increase in total motoring costs of 1% per year in real terms from 2010, or an increase of 23% by 2030. As is shown, this will result in a fall in car travel of 8.8% from the Base Case by 2030, or 10.5 billion person miles. Some of these switch to other modes, chiefly rail, but the greatest part, 8.8 billion person miles is a reduction in total travel by 5.6%.

Table 8: Travel forecasts by mode for 2030, % change in person miles from the Base Case, based on different scenarios

Scenario	Car	Rail	Coach	Air	Total
Constant real rail fares	-1.4	19.0	-5.8	-2.5	0.9
Road user charging (RUC)	-2.2	10.3	2.0	-1.5	-0.3
Increase in APD	0.2	1.3	0.1	-10.9	-0.4
Air fares reduced 25%	-0.2	-1.3	-0.1	12.5	0.5
Constant car fuel efficiency	-4.4	2.7	2.2	0.5	-2.8
High car fuel efficiency	4.7	-2.7	-2.2	-0.5	3.0
Motoring costs increase 1% pa	-8.8	5.7	4.6	1.1	-5.6

The percentage increases in travel by mode for the period 2005 to 2030 as projected by the model are shown in Table 9. Projected growth is greatest for air in all scenarios, generally followed by rail. Growth in rail travel is generally much higher than for car, the only exception being the scenario with high car fuel efficiency. In most instances, coach travel is projected to increase less than car travel. The only exceptions are for the increase in total motoring costs and the constant car fuel efficiency scenarios.

The growth in rail travel is greatest when constant rail fares are assumed and also relatively strong in the scenario with road user charging. Lowest growth for rail is noted when high car fuel efficiency is assumed since the lower motoring costs encourage a switch from rail. The reduction in air fares results in the greatest growth in air travel and the increase in APD in the least. Growth in coach travel is greatest in the scenario with increased motoring costs as these are assumed not to affect coach fares, which encourages a switch to from car to coach. Constant rail fares, on the other hand, result in the lowest growth in coach travel, since rail becomes more competitive. Car travel and total travel increase most with high car fuel efficiency and least with the 1% per annum increase in motoring costs. Since car is the predominant mode, changes in car travel have the greatest implications for total travel.

Table 9: Travel forecasts by mode, % increase in person miles 2005 - 2030, based on different scenarios

Scenario	Car	Rail	Coach	Air	Total
Base Case	30	35	25	126	34
Constant real rail fares	28	60	17	120	35
Road user charging	27	48	27	123	33
Increase in APD	30	36	25	101	33
Air fares reduced 25%	30	33	24	154	35
Constant car fuel efficiency	24	38	27	127	30
High car fuel efficiency	36	31	22	125	38
Motoring costs increase 1% pa	19	42	30	128	26

The impact of the scenarios on travel for different purposes is shown in Table 10. Road user charging has the most substantial impact on commuting (a decrease of 5.1% in 2030 compared to the Base Case), followed by constant rail fares (and increase of 1.5% compared to the Base Case). In most other scenarios, the largest impact is on holiday travel, while the low car travel growth scenario has the greatest impact on VFR (a reduction of 14.6% compared to the Base Case). In none of the scenarios, however, do the relative shares for the different travel purposes change more than marginally.

Table 10: Travel forecasts by journey purpose for 2030, billion person miles, based on different scenarios

Scenario	Business	Commute	Leisure	VFR	Holiday
Actual 2005	23.9	10.9	24.5	33.0	25.0
Base Case	34.0	15.1	30.8	44.3	32.9
Constant real rail fares	34.4	15.3	30.9	44.7	33.1
Road user charging	34.1	14.3	30.8	44.3	33.1
Increase in APD	33.9	15.1	30.7	44.2	32.6
Air fares reduced 25%	34.2	15.1	30.9	44.4	33.3
Constant car fuel efficiency	33.5	14.7	30.1	42.8	31.6
High car fuel efficiency	34.6	15.6	31.6	45.8	34.3
Motoring costs increase 1% pa	32.9	14.2	29.4	41.4	30.4

Sensitivity testing

In this section, the sensitivity of the forecasts to some of the assumptions made in the Base Case is examined. The results are reported in Table 11. The forecasts for the Base Case are repeated for comparison.

The first set of forecasts is based on lower GDP growth assumptions. Specifically, the Base Case growth rate from 2012 is halved from 2.5% per annum to 1.25%, while the growth rates for 2009-2011 are as in the Base Case. With this reduced growth, GDP is 22% lower in 2030 than in the Base Case (an increase of 27% compared to 58%). All other assumptions are as in the Base Case.

The reduction in GDP growth has a substantial effect on long distance travel. In total it is 12% lower in 2030 than in the Base Case. Owing to the different income elasticities for the different modes, they are not all affected to the same degree. The impact is greatest for air and rail, which are 35% and 26% lower, respectively, in 2030 than in the Base Case, which is predominantly explained by the high income elasticities for these modes. For rail, the effect of lower income growth is compounded with the projected rising cost of rail travel, so that demand is actually lower in 2030 than in 2005. For car, passenger mileage is only 9% lower than in the Base Case, while coach actually increases by 1%, due to its low income elasticity. The low GDP growth also results in lower congestion on the roads, which favours car and coach travel relative to other modes.

The following row shows the sensitivity of the forecasts to assumptions regarding the income elasticity. In the Base Case, it was assumed that the elasticities estimated on the basis of the

NTS data represented medium-term values, specified as 2/3s of the long-run elasticities. In the low income elasticity case, the estimates from the NTS are interpreted as long-run elasticities, and thus are 33% lower than the income elasticities assumed in the Base Case.

As shown in the table, this has a substantial impact on the projections. Total long distance travel is 5% lower in 2030 than in the Base Case. The impact is greatest for air, which is 14% lower, while coach is unaffected, owing to its low income elasticity even in the Base Case. Car is affected less than rail, with reductions of 4.5% and 7.6%, respectively, in comparison to the Base Case.

To reflect the declining growth in car travel noted in the NTS data, the a sensitivity test is carried out in which the per-household GDP elasticity for car travel is assumed to be zero for all purposes and distances instead of the estimated values (an average of 0.7 in the long run). We thus assume that income growth has no further effect on car travel, so that future car travel is determined solely by population growth, changes in other demographic factors and travel costs and travel time. The income elasticities for the other modes are as in the Base Case.

As shown in the table, the projection for car travel in 2030 is reduced to 101.9 billion person miles, and that for total travel is reduced to 140.6 billion person miles, which are 14% and 10.5% below the projections for the Base Case. Clearly, the assumption of zero income elasticity for car travel reduces substantially the projections of long distance travel by car and totally. The forecasts for the other modes are the same as in the Base Case, since the car income elasticity does not affect the demand for other modes.²²

Table 11: Sensitivity tests, travel forecasts for 2030, billion person miles

Assumptions	Car	Rail	Coach	Air	Total
Actual 2005	91.1	15.0	6.9	4.4	117.4
Base Case	118.5	20.1	8.6	9.9	157.1
GDP growth of 1.25% annually from 2012	107.9	14.9	8.7	6.4	138.0
Low Income elasticities 2/3rds of Base Case	113.1	18.6	8.6	8.5	149.0
Zero income elasticity for car travel	101.9	20.1	8.6	9.9	140.6
Population growth 50% of Base Case	115.4	20.4	8.1	10.5	154.5

The final row shows the impact of a reduction in population growth to ½ the assumed values in the Base Case from 0.64% per annum between 2010 and 2030 to 0.32% per annum. This implies an increase in population of 7% between 2009 and 2030, compared to 14% in the Base Case. Since income growth is assumed the same as in the Base Case, the reduction in population results in an increase in GDP per capita. There are thus two opposite factors at play, one leading to an increase in travel (the increase in GDP per capita) and one leading to a decrease in travel (the reduction in population). The combined effect is a reduction in

²² Car and total travel are likely to be higher than the forecasts presented since no account was taken of the effects of the reduction in congestion resulting from the lower car travel. Similarly, we would expect some switch from rail and air to car, so that the demand for these modes would likely decline.

overall long distance travel of 1.7% in comparison to the Base Case. Air travel is 6.3% higher relative to the Base Case because of its high income elasticity and coach travel is 6.1% lower owing to its low income elasticity. The effects are smaller on rail and car, since their income elasticities are between those for the other modes.

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REFERENCES

- Balcombe, R, R. Mackett, N. Paulley, J. Preston, J. Shires, H. Titheridge, M. Wardman and P. White (2004). *The demand for public transport: a practical guide*, TRL Report593.
- Dargay, J. (2010). The prospects for longer distance domestic coach, rail, air and car travel in Britain, Report to the Independent Transport Commission, http://www.trg.soton.ac.uk/itc/ldt_main.pdf (main report), and http://www.trg.soton.ac.uk/itc/ldt_apx.pdf (appendices).
- Dargay J. and S. Clark (2010). The determinants of long distance travel: an analysis based on the British National Travel Survey. 12th WCTR, July 11-15, Lisbon.
- Dargay, J. and M. Hanly (2002). The Demand for Local Bus Services in England. *Journal of Transport Economics and Policy*, 36, 1, 73-91.
- Dargay, J. (2007a). The Effect of Prices and Income on Car Travel in The UK, *Transportation Research A*, 41, pp. 949–960.
- Dargay, J. (2007b). The demand for international air travel in the UK, paper presented at the UTSG Conference at Harrogate, 3-5 January.
- Dargay, J., P. Goodwin and M. Hanly (2002). Development of an Aggregated Transport Forecasting Model (ATFM), Stage 1, Final report to the DfT, September 2002.
- Dargay, J., B. Menaz and S. Cairns (2006). Public Attitudes towards Aviation and Climate Change, Stage I: Desktop Research, report prepared for Commission for Integrated Transport, October, 2006.
- Dargay, J. and M. Wardman (2008). The prospects for longer distance domestic coach, rail, air and car travel in Britain - a scoping study, Report to the Independent Transport Commission, June.

A forecasting model for long distance travel in Great Britain

DARGAY, Joyce; CLARK, Stephen; JOHNSON, Daniel; TONER, Jeremy; WARDMAN, Mark

Department for Transport, National Travel Survey, 1995-2001 [computer file]. 2nd Edition. Colchester, Essex: UK Data Archive [distributor], February 2010. SN: 6108.

Department for Transport, National Travel Survey, 2002-2006 [computer file]. 4th Edition. Colchester, Essex: UK Data Archive [distributor], February 2010. SN: 5340.

Department for Transport (2009). UK Air Passenger Demand and CO2 Forecasts, January.

Department for Transport (2008). Road Transport Forecasts 2008: Results from the Department for Transport's National Transport Model.

Goodwin, P., J. Dargay and M. Hanly (2004). Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: a Review, *Transport Reviews*, 24, 275-292, 2004.

Graham, D. and S. Glaister (2004). Road traffic demand elasticities estimates – a review, *Transport Reviews*, 24, 261-274, 2004.

Jevons, D., A. Meaney, N. Robins, J. Dargay, J. Preston, P. Goodwin and M. Wardman (2005). How do rail passengers respond to change? European Transport Conference, Strasburg.

Oum T.H., W.G. Waters and J. S. Yong (1992). Concepts of Price Elasticities of Transport Demand and Recent Empirical Estimates: An interpretative survey, *Journal of Transport Economics and Policy*, vol.26(2), 139-154, 1992.

Wardman, M. (2004). Public Transport Values of Time. *Transport Policy* 11, pp.363-377.

Wardman, M. and T. Toner (2003). Econometric modelling of competition between train ticket types, European Transport Conference, 2003.