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THE PROSPECTS FOR LONGER DISTANCE DOMESTIC COACH, RAIL, AIR AND CAR TRAVEL IN BRITAIN

Report to the

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TABLE OF CONTENTS

SUMMARY 1
1 Introduction 10
2 The Forecasting Model 13
  2.1 Model specification 13
  2.2 Input data 15
3 Long Distance Travel in GB 17
  3.1 Travel by mode 17
  3.2 Travel by journey purpose 22
  3.3 Travel by distance band 24
4 Estimation of Elasticities Based on Existing Data 25
  4.1 Estimation of elasticities from aggregate time-series data 25
  4.2 Estimation of the effects of socio-economic, demographic and geographic factors 27
  4.3 Estimation of NTS models using geo-demographic data (ACORN) 33
  4.4 Income elasticities used in the forecasting model 35
5 Estimation of Elasticities Based on New Survey Data 36
  5.1 Long distance travel survey 36
  5.2 Comparison of ITS survey with the NTS 36
  5.3 Estimation of diversion factors 40
  5.4 Elasticities based on transfer cost and transfer time 44
  5.5 Choice modelling 45
  5.6 Choice of cost and time elasticities for the forecasting model 48
6 Input Assumptions and Scenario Specification 51
  6.1 Elasticity assumptions 51
  6.2 Projections of the population: socio-demographics and geography 51
  6.3 Projections of the economy 52
  6.4 Transport costs 53
  6.5 The Base Case 55
  6.6 Alternative scenarios 55
7 Projections of Long Distance Travel 57
  7.1 The Base Case 57
  7.2 The impact of different scenarios 59
  7.3 Sensitivity testing 62
8 Model Evaluation and Limitations 64
  8.1 Assumptions 64
  8.2 Backcasting 65
References 68

Appendix A: Long distance travel – NTS estimates A-2
Appendix B: Estimates of GDP elasticities from aggregate NTS data A-3
Appendix C: Estimates of NTS models A-5
Appendix B: Estimates of NTS models using ACORN classifications A-30
Appendix B: ITS long distance travel survey A-34

SUMMARY

Background

This paper presents the results of a study, carried out for the Independent Transport Commission, to investigate the prospects for longer distance travel in Great Britain by car, rail, coach and air. The study is based on a forecasting model which incorporates the effects of economic and demographic factors, policy measures and developments in transport supply. The timescale considered is to the year 2030.

The motives for the study are twofold. First, long distance travel makes up a substantial proportion of total travel. Although trips of 50 miles or more one-way make up less than 2% of all journeys made by British residents in Great Britain, they account for about 1/3 of the distance travelled. In addition, both long distance travel and average trip length have increased over the past decades. It is apparent that long distance travel and how it develops in the future will have important implications for the environment and for congestion. The second motive is that existing knowledge of long distance travel in Britain is limited. This study contributes to understanding of this important travel segment.

The background for this work was developed in a scoping study (Dargay and Wardman, 2008), which examined the long distance travel market and proposed an elasticity-based framework for the forecasting model. From a review of the evidence on elasticities in existing aggregate and disaggregate studies, it was concluded that existing empirical evidence was limited and outdated, so that an essential element of the project would be to obtain new elasticity estimates.

The Forecasting Model

The main objective of this study is to provide projections of long distance travel by mode over the coming decades, given various assumptions about economic growth, changing demographics, transport supply, prices and policies. The intention is to produce aggregate national forecasts based on an aggregate model, rather than geographically-specific forecasts. The absence of geographic detail limits the ability of the model to examine the impacts of geographically-specific developments in transport supply such as a high-speed rail line or local congestion charging. Instead, only more general, national policies and developments can be analysed. The main advantage of an aggregate model in comparison to a more detailed geographically-defined model, however, lies in its simplicity and transparency. It is also relatively easy to run, so that different scenarios can be examined.

Long distance travel is defined as trips of 50 miles or more one-way. The model is also limited to journeys made by British residents in Great Britain, so that travel by British residents abroad and travel by foreign residents in GB are excluded. These definitions were chosen for compatibility with the National Travel Survey (NTS) which forms the basis of much of the analysis and modelling.

The forecasting model developed for the study is based on a system of demand equations, in which demand in terms of passenger miles by mode is determined by a number of demand drivers, chiefly economic and demographic factors and travel costs and travel time. The influence of these demand drivers are expressed in the form of elasticities. The model is dynamically specified so that the effect on demand of changes in the demand drivers occurs over a period of years, such 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 dynamic adjustment is motivated by factors such as the persistence of habit, uncertainty and imperfect information regarding alternatives and prices and costs of adjustment. Such dynamic adjustment is supported by empirical evidence on the difference between short- and long-run elasticities and allows projections of demand to be made at specific points in time.

To allow for differences in the demand relationships depending on the purpose of the journey, each of the four modes is broken down into five journey purposes: business, commuting, leisure day trips, visiting friends and relatives (VFR) and holiday. Since competition between modes is not the same for all distances, the demand for car, rail and coach is further divided into two distance bands: 50 to less than 150 miles, and 150 miles and greater, while air is only considered a relevant mode for trips of 150 miles or more. The forecasting model is thus specified as a system of 35 demand equations. All elasticities vary by purpose and distance band as well as by mode. Substitution between modes is captured through cross-elasticities for travel costs and time. There is, however, no substitution between journey purposes or distance bands.

Calibration of the model requires base values for demand and the demand drivers and the elasticities determining the relationships between these. The demand values are per capita annual long distance miles travelled by mode, journey purpose and distance band approximated from the NTS, while annual data for the demand drivers - income, travel costs and relevant socio-demographic variables - were collated mainly from the Office of National Statistics and the Department for Transport. The elasticities used in the model were derived from estimates based on the NTS, national aggregate time series data and a survey of long distance travel specially carried out for the study.

Long Distance Travel

Data on long distance travel in GB are rather limited and there is no survey carried out specifically for long distance travel. The most useful dataset is the NTS, which provides information on all travel in Great Britain by British households, including long distance trips. In this study, we use data from the surveys for the years 1995 to 2006. Data from more recent surveys are unfortunately not yet available.

The NTS collects data on long distance journeys in the 7-day travel diary and also retrospectively for the previous 3 weeks (1 week in 2006) in order to increase the number of observations. However, because of the inconsistency caused by the reduction in the retrospective period in 2006, it was decided to use only the diary data for the analysis. On the basis of these data, during the period 2002-2006, each individual in Britain made on average 20.5 long distance journeys per year, travelling 2114 miles. The average trip length one-way was 103 miles. For the individual modes, average trip length was 98 miles by car, 110 by rail, 122 by coach and 406 by air.

During the same period, long distance journeys accounted for only 2% of all trips, but made up about 1/3 of all miles travelled. By mode, long distance journeys accounted for 29% of car miles, 68% of coach miles and 54% of rail miles. In terms of trips, the figures are 3% for car and 15% for rail and coach. All air travel is long distance. Along with air, coach and rail are clearly predominantly long distance modes, whereas car is mainly used for shorter distance trips.

Although less than 1/3 of the total distance travelled by car is for trips of 50 miles or more, car is the predominant mode for long distance travel, making up on average 77% of the total distance travelled, followed by rail (11%), coach (6%) and finally air (4%), with other modes accounting for the remainder. This can be compared with the mode shares of total miles travelled: car (81%), rail (6%), coach (3%), air (1%), with other modes (including walk) making up 8%.

The per-capita estimates of long distance travel on an annual basis are multiplied by the population of GB for the respective year to obtain estimates of total long distance travel in Great Britain by British residents. Over the period 1996 to 2005, long distance travel accounts for between 114 and 124 billion miles per annum.

The estimates indicate that long distance travel in terms of miles increased by about 0.9% per annum between 1996 and 2005. This can be compared to a 0.6% annual growth rate for trips of less than 50 miles. Thus, based on the NTS, long distance travel increased more rapidly than short distance travel over the period as a whole. However, the increase is long distance travel has not been constant over the period. Up until 2002, the long distance travel increased by about 1.3% per annum, but has since levelled off, with total miles in 2005 about the same as in 2002. Whether this is a temporary stagnation, a result of sampling variability or the beginning of a longer-term trend is impossible to discern from the data. Analysis of more recent NTS data may provide some answers.

The levelling off of long distance travel since 2002 is primarily explained by a reduction in car travel, while rail travel increased at a higher rate than previously. There is, however, some discrepancy between the NTS data and other data sources, particularly the traffic count data published in Transport Statistics Great Britain. Although the traffic counts indicate a decline in growth for all car, van and taxi passenger kilometres (both short and long distance), there is no absolute reduction as suggested by the NTS estimates. Since these data are not strictly comparable, we cannot conclude that long distance car travel has not declined, but it does suggest that one should be careful about drawing conclusions concerning saturation based on the NTS data. Clearly, further study is required on this issue.

Regarding journey purpose, visiting friends and relatives (VFR) accounts for the greatest share of long distance travel (28%) and commuting for the smallest (10%), while leisure and holiday make up 21% each and business, 20%. Although there is some variation in shares over the period, there are no discernible trends, with perhaps the exceptions of a decline in the share of commuting and an increase in the share for holiday.

Car is the dominant mode for long distance travel for all purposes: for the 2002-2006 period, it accounted for on average from 75% of business and holiday mileage to 84% of VFR. The rail share is highest for commuting (23%) and lowest for leisure and holiday travel (9% each), while coach's share is greatest for leisure and holiday (12% and 11%) and smallest for business and commuting (2% each). Air's share is greatest for business travel (10% of distance) and holiday (4%).

Of total long distance mileage by car nearly 30% is for VFR and only 9% for commuting, while business, holiday and leisure make up around 20% each. VFR also dominates rail travel (28%), with other purposes each accounting for between 16% and 22%. Coach is predominantly used for holiday (42%) and leisure (38%) travel, and seldom used for commuting (3%) and business (5%), while air is mainly used for business (55%) and holiday (25%).

The modes used for long distance travel differ by journey distance. Although car dominates both distance bands (50 - 149 miles and 150 miles or more), its share is far higher for the *shorter* long distance trips. For journeys between 50 and 149 miles, car accounts for 84% of mileage, rail for 11% and coach for 5%, while for journeys over 150 miles, the comparable shares are 68%, 14% and 8%, with air accounting for 10%.

The Impact of Socio-economic and Demographic Factors

The influence of socio-economic and demographic factors on long distance travel was examined using models based on the NTS data for the years 1995 to 2006. The income elasticities derived from the NTS models indicate that air is most income-elastic, followed by rail, car and finally coach. This is the case for most journey purposes and distance bands. Regarding journey purpose, most notable is that the income elasticities for rail for business and commuting are much higher than for holiday, leisure and VFR. In addition, longer distance journeys have higher income elasticities than shorter distance journeys.

Other factors shown to be important for long distance travel are gender, age and household type. These will be relevant for future travel demand, since the proportions of women, the over-60s and single-person households are expected to increase over the coming decades. The elasticities estimated on the basis of the NTS are interpreted as medium-run elasticities, 2/3rds of the long-run values.

The NTS data were used to investigate long distance travel by geo-demographic classification (ACORN), providing a novel insight into the social make up of long distance travellers. The category with the lowest travel is "Council Estate Residents, Greatest Hardship". "Prosperous Professionals", travel most, on average travel 24 miles per week more than the lowest group. Other categories with high long distance mileage (17 miles per week more than the lowest group) are "Wealth Achievers", "Affluent Greys in Rural Communities", "Prosperous Pensioners in Retirement Areas" "Affluent Executives in Family Areas", "Affluent Urbanites", "Better-off Executives in Inner-city Areas", and surprisingly, "People in Multi-Ethnic, Low Income Areas". Interestingly, those in "High Unemployment Council Estates" travel as much as the Comfortable Middle Age in Home Owning Areas" and "White Collar Workers in Better-off Multi-ethnic Areas". Also rather surprisingly, those in "Better-off Homes on Council Estates" travel comparatively little, and less than those on "Council Estates with High Unemployment". These differences in long distance travel between household categories are after controlling for income differences.

The Impact of Travel Costs and Travel Time

Elasticities of demand with respect to travel costs and travel time are essential components of the forecasting model. Ideally, both own- and cross-elasticities should be differentiated by journey purpose and distance band. Such elasticities cannot be based on the NTS since it does not contain the necessary cost and time information, and other data sources are limited. For this purpose, a new 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. Own-elasticities with respect to journey cost and journey time were estimated from transfer price and time questions. These values were used as relativities to determine journey cost and time elasticities by mode, purpose and distance band from elasticities obtained from aggregate data. Economic theory concerning the relationships between elasticities was used to assure consistency. The elasticities obtained provide an up-to-date set of journey cost and time elasticities for long distance travel by mode, journey purpose and distance band not available from other sources and thus represent a useful contribution to the literature on this subject.

Forecasts of Long Distance Travel – The Base Case

The model is used to forecast long distance travel by mode and journey purpose annually for a Base Case and a number of different scenarios. The Base Case uses population and demographic projections for the Principal Case produced by the Office of National Statistics. Population is expected to reach 68.8 million by 2030, an increase of 14% from 2009. 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 a growing share of 1-adult households.

GDP forecasts are obtained from HM Treasury publications, which are based on the average of a number of independent forecasts. The Base Case uses HMT's Forecasts for the UK Economy produced in April 2009, which reflect the reduced growth of the recent economic recession. The annual growth rates for the years 2009 to 2011 are -3.7%, 0.3% and 2.2%, respectively. For 2012 to 2030 an historic growth rate of 2.5% per annum is assumed. This implies an increase in GDP of 58% in real terms between 2009 and 2030.

Fuel prices are determined largely by crude oil prices and taxation. Crude oil price projections are taken from the scenarios produced by The Department of Energy and Climate Change (DECC): $84 in 2010, rising to $102 in 2015, and to $120 in 2020 and thereafter. The US$-Sterling exchange rate is assumed constant at $1.60/£ over the forecast period. Projections of petrol and diesel prices and air fares based on these assumptions were provided by DfT.

Petrol and diesel prices are projected to increase by 27% in real terms over the period. This also takes into account the increased taxation of 2p/litre in 2009, and 1p/litre in real terms in 2010 – 2013 announced in the 2009 Budget. With car fuel efficiency improvements of 1% per year between 2009 and 2030 (an improvement of 23%), per mile fuel costs increase 4% by 2030. Finally, assuming non-fuel car costs remain constant in real terms, total motoring costs increase only marginally (about 0.5% to 2030).

Growth rates in air 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 CO_2 emissions. The DfT have provided air fare forecasts based on the oil price assumptions and the exchange rate of $1.60/£ as used for our motor fuel price projections, which indicate a decline in domestic air fares decline by 12.5% between 2009 and 2030.

Regarding the other modes, coach fares increase by 3% between 2009 and 2030 (based on increased fuel costs), while rail fares increase by 28% (RPI+1% per annum).

The Base Case also assumes an average increase in journey time on the road network from 2003 of 3% by 2015 and of 6% by 2025 as in the Central Forecast in DfT (2008), and of 0.3% per annum thereafter, an increase 7.5% from 2009 to 2030. Otherwise there are no capacity constraints on the rail or air networks and no travel time changes.

Given the assumptions above, total long distance travel measured in person miles per year 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.

The Base Case projections reflect the impact of the current recession on long distance travel. These can be compared with forecasts based on the more optimistic GDP projections made before the downturn. The revised projections result in GDP being 8.1% lower in 2030 than it is using the earlier projections. The implication of this reduction in GDP growth is that long distance travel is 1.4% lower in 2009 than it would have been otherwise. It is 5% lower in 2013 and remains 7% lower in 2030. By 2030, long distance car travel is reduced by 6%, rail by 11%, coach by 1% and air by 17%.

Forecasts for Different Scenarios

In addition to the Base Case forecast, the model is used to investigate the impact of various scenarios regarding policy measures and supply-side factors. The scenarios examined are: constant rail fares, a national road charging scheme, constant car fuel efficiency, high car fuel efficiency, an increase of total motoring costs of 1% per annum, low car travel growth, an increase in Air Passenger Duty of £10 and a reduction of air fares by 25%.

Constant real rail fares, as opposed to an increase of 1% per annum in the Base Case, result in a substantial increase in rail travel in 2030, 24 billion person miles, 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.

For the road user charging scenario, a charge of 5 pence/km for business and commuting and 2p/km for other travel are assumed to reflect the differences in congestion at the time of day the different types of travel are normally carried out. This charge reduces car travel by 2.2% in 2030 compared to 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.

Assumptions regarding car fuel efficiency improvements are also important for projections of long distance travel. We consider two cases in addition to the Base Case (efficiency improvement of 23% over the period): no improvement over the period and that assumed by DfT of 92% for petrol cars and 43% for diesel cars (high fuel efficiency). With no improvements in fuel efficiency car travel is 4.4% lower in 2030 than in the Base Case and total travel is 2.8% lower. With high fuel efficiency, car travel is 4.7% higher than in the Base Case and total travel is 3% higher. The decrease in car travel in the low efficiency case is reflected in an increase in all other modes and particularly rail, while the increase in car travel in the high efficiency case is reflected in a similar decline in the other modes.

An increase in total motoring costs of 1% per year in real terms from 2010 (23% by 2030) results in a fall in car travel by 10.5 billion person miles (8.8%) compared to the Base Case in 2030. Some of this is a switch to other modes, chiefly rail, but the greatest part, 8.8 billion passenger miles, is a reduction in total travel by 5.6%.

The final two scenarios examine different assumptions concerning air fares. An increase in APD of £10 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 in the Base Case without this reduction. About half of this is a switch from car and rail, while half is generated.

The different scenarios result in increases in total long distance travel from 2005 to 2030 of between 26% (1% per annum increase in motoring costs) and 38% (high car fuel efficiency). Car travel also increases least (19%) with and most (36%) in these two scenarios. Since car makes up the predominant share of total travel, a given percentage change in car travel has a far greater impact on total travel than comparable percentage changes in the other modes.

The growth in rail travel is greatest when constant rail fares are assumed (60%) and is also relatively strong in the scenario with road user charging (48%). Lowest growth for rail (31%) 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 most substantial growth in air travel (154%) and the increase in APD in the lowest (101%). Growth in coach travel is greatest in the scenario with increased motoring costs (30%) as these are assumed not to impact upon 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 (17%), since rail becomes more competitive.

Projected growth is greatest for air in all scenarios (over 100%), generally followed by rail. Growth in rail travel is much higher than for car, the only exception being in the scenario with high car fuel efficiency. In most instances, coach travel is projected to increase less than car travel. The most obvious exception is in the scenario with a 1% per annum increase in total motoring costs.

There are only marginal differences in the projections of travel for different journey purposes across scenarios. 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 (an increase of 1.5% compared to the Base Case). In most other scenarios, the largest impact is on holiday travel.

Sensitivity Tests

The sensitivity of the forecasts to some of the assumptions made in the Base Case is also examined. The first relates to GDP growth. 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%). The reduction in GDP growth results in total travel being 12% lower in 2030 than in the Base Case. The impact is greatest for air and rail, which are 35% and 26% lower, respectively, in 2030 than in than in the Base Case, while car is only 9% lower and coach actually increases by 1%. These differences are explained by differences in income elasticity across 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. The low GDP growth also results in lower congestion on the roads, which favours car and coach travel relative to other modes.

The second sensitivity test concerns the income elasticities. A low elasticity case is examined, in which the elasticities are assumed to be 33% lower than those in Base Case. 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, a sensitivity test is examined 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). Car travel is thus not related to income growth, but determined solely by population, other demographic factors and travel costs and travel time. The projection for car travel in 2030 is reduced by 16.6 billion person miles to 101.9, and that for total travel is reduced by the same amount 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 reduces the projections of long distance travel substantially. 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.

The final test examines the impact of a reduction in population growth to ½ the assumed values in the Base Case from 14% to 7% between 2009 and 2030. 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 overall long distance travel by 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.

Limitations

The forecasts of long distance travel produced in this study are based on a number of assumptions, and their accuracy rests on the validity of these assumptions. The most important of these are the projections of the drivers of long distance travel and the elasticities which determine the impact these have. We have seen in the results for the different scenarios and sensitivity tests that the projections of long distance travel are highly dependent on the assumptions regarding future income and travel costs. These are clearly in themselves extremely difficult to forecast. Although we have suggested a Base Case, given the uncertainty in the future values of the underlying demand drivers, it would perhaps be more prudent to consider the range of forecasts produced and the differences between them rather than take the Base Case as the most likely forecast of long distance travel.

We have also shown that the forecasts are dependent on the elasticities assumed. There are a number of different opinions of what these elasticities may be, and the empirical evidence – where it exists – is not always in agreement. The elasticities used in the study are mutually consistent and based on sound empirical evidence using recent data for Great Britain. At this point, we feel that they are the best available.

A real advantage of the model is its transparency. The elasticities as well as the assumptions concerning demand drivers are clearly specified and can be easily changed to explore other hypothetical scenarios and elasticities.

1 Introduction

This paper reports the results of a study undertaken in order to forecast longer distance domestic travel by coach, air, rail and car in Great Britain. It is based on a forecasting model which allows the examination 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 most detailed information on long distance travel in Great Britain is provided by the National Travel Survey (NTS), which forms the basis of much of the analysis and modelling in this 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. As with all journeys in the NTS, long distance journeys are comprised of stages by different modes. For example, a 100 mile journey may include a 10 mile car trip from home to a rail station, an 85 mile rail trip and a 5 mile taxi ride from the destination rail station to the final destination. Although each of these three stages is reported separately in the NTS, journeys are defined in terms of the main mode used, so the journey described is considered as a 100 mile journey by rail. We also use the “main-mode” definition.

The NTS data have been analysed for the survey years 1995 to 2006. Before 1995, weights are not available so the data cannot be made comparable to the later years. The 2007/08 survey is currently being validated by the DfT and has not been available for use in this study.

The relevance of long distance travel within Great Britain is apparent from the NTS data: although trips of 50 miles or more account for only 2% of all trips, they are responsible for a third of the total distance travelled.

The characteristics of long distance travel were examined in a scoping study (Dargay and Wardman, 2008). On the basis of this analysis, it was decided to break down long distance travel into five journey purposes: business, commuting, leisure day trips, visiting friends and relatives (VFR) and holiday. Following the NTS, the model covers travel only within Great Britain by British residents.

Since competition between modes is not the same for all distances, demand is divided 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.

The forecasting model is a dynamic, elasticity driven system of 35 demand equations for the four modes by five purposes and two distance bands[1]. 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 own- and 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.

[1] There are 35 equations since the shorter distance band does not include air.

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 accuracy of the forecasts will depend on the accuracy of these values and the underlying input data.

In the absence of other data on long distance travel, 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 (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).

The ability of the model to provide accurate forecasts will depend on the accuracy of the parameter values, or elasticities, which drive the model. Although there is some existing information on aggregate elasticities for most of the modes, there are few estimates relating solely to long distance travel, and there is even less empirical evidence on elasticities for different journey purposes and distances. In the scoping study it was stressed that existing information on elasticities is insufficient or outdated and that an essential stage in the model development would be the determination of these elasticities.

The elasticities used in the model are based on new empirical evidence obtained from a wide range of data sources. In addition to empirical estimation, elasticities are derived using economic theory regarding the relationships amongst elasticities, the use of diversion factors to derive cross-elasticities from own-elasticities, and the use of other empirical information regarding the relativities among various elasticities.

In the context of this project, cost and income elasticities have been estimated on the basis of aggregate time-series data, the impact of socio-economic, demographic and geographic factors on models based on the NTS and disaggregate time and cost elasticities using the survey of long distance travel carried out for the project. Since there is no existing survey specifically devoted to, and designed for, long distance travel in Britain, one of the contributions of this project has been to carry out such a survey.

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 the elasticities to serve as parameters 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 DfT.

A Base Case is defined in order to produce projections of annual long distance travel to 2030. 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.

A sensitivity analysis is carried out to explore the impacts of different assumptions regarding economic and population growth and income elasticities.

The model is evaluated using backcasting techniques. Basically, this involves measuring how well the model explains present and past data. Overall, the forecast error is quite acceptable, but, unsurprisingly, the model is less-successful in explaining modes/purposes with small market shares and a high degree of variability.

The structure of the report is as follows. Chapter 2 provides a description of the forecasting model and the input data and parameters required. Long distance travel in GB is examined in Section 3, primarily on the basis of NTS data. Elasticity estimation is discussed in Sections 4 and 5, and new empirical evidence is presented based on existing data and on the survey carried out for the project. The input assumptions are summarised in Section 6, and the Base Case and alternative scenarios are defined. The projections of long distance travel are presented and discussed in Section 7. The evaluation of the model by backcasting techniques and the limitations of the study and forecasting methodology conclude the paper.

2 The Forecasting Model

This section presents the specification of the forecasting model and identifies the input values required for calibration of the model.

2.1 Model specification

The model is defined as a system of 35 equations: 5 journey purposes by 2 distance bands by 4 modes[2]. 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 miles per capita by mode (*m* = car, rail, coach and air), purpose (*p* = business, commuting, leisure, VFR and holiday) and distance band (*d* = 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:

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

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 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 different socio-economic characteristics (η) also vary by mode, purpose and distance band.

The system of equations can be interpreted as 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.

[2] 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.

if complete adjustment to changes in these factors occurs within the time interval specified for the forecasts (in this case, one year) or if the 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 longer[3].

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:

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

where $0 \le \theta < 1$ 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:

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

where *m* and *i* = 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

[3] See, for example, Dargay and Hanly (2002), Dargay (2007a), Dargay (2007b), Jevons *etal*. (2005).

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.

2.2 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.

2.2.1 Demand values

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 approximated from the National Travel Survey (NTS) data for the years 1995 to 2006. The NTS data and the methods used for construction of the base values are detailed in Section 3.

2.2.2 Exogenous variables

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 variables included in the database are listed in Table 1.

Table 1: Variables included in the aggregate annual time-series database

GDP
GB Population
Number of households in GB
Household size
Household disposable income
Privately owned cars
Domestic airfares – business and leisure, separately
Motoring cost index
Rail fare index
Bus fare index
Motor fuel price index
Retail price index
Revenue per pkm for non-local bus
Average traffic speed

2.2.3 Elasticities

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 (4x5 = 20), and between car, coach and rail by 5 purposes for distance band less than 150 miles (3x5 = 15);
- 90 cross-cost elasticities between each of the four modes (12 elasticities) by 5 purposes for distance band 150 miles or more (12x5 = 60), and between car, coach and rail by 5 purposes for distance band less than 150 miles (6x5 = 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 (4x5 = 20), and between car, coach and rail by 5 purposes for distance band less than 150 miles (3x5 = 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 (12x5 = 60), and between car, coach and rail by 5 purposes for distance band less than 150 miles (6x5 = 30);
- 35 elasticities with respect to income for each of the 4 modes by 5 purposes for distance band 150 miles or more (4x5 = 20), and between car, coach and rail by 5 purposes for distance band less than 150 miles (3x5 = 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.

3 Long Distance Travel in GB

There is no single data source or specific survey for long distance travel in Great Britain. However, the National Travel Survey provides information on all travel in GB by British households, including long distance trips. The NTS thus serves as an important data source for this study. The NTS is used primarily to determine base values for long distance travel by mode, purpose and distance band and as a basis for the estimation the effects of socio-economic and demographic factors on long distance travel. It is also used to examine the development of long distance travel over time and as an empirical basis on which to validate the model by backcasting techniques.

In our study, we use data from the surveys for the years 1995 to 2006. The NTS is based on a sample of private households in Great Britain, using a stratified multi-stage random probability approach. The journeys reported are trips by British residents within Great Britain. Each member of the household keeps a seven-day travel diary, with adults reporting for younger children and others unable to provide information on their own behalf. Data collected include information on the households, individuals, vehicles, journeys and stages of journeys made during the travel week. Information on long distance journeys, defined as trips of 50 miles of more (one way), is collected for a 4-week period (2-week in 2006), the 1-week diary period and retrospectively for the previous 3 weeks (1 week in 2006).

The NTS includes a number of weights which are intended to improve the accuracy and representativeness of the data. Household weights adjust for non-response bias. Since our analysis is based solely on information on households in the diary sample, the diary sample household weights (W2) are used. Journey weights adjust for the drop-off in the number of trips recorded by respondents during the course of the travel week (W5). Long distance journeys weights (W4) adjust for drop-off in the number of long distance journeys reported over the reporting period and for under-reporting of journeys reported retrospectively in comparison with those reported during the diary week.

3.1 Travel by mode

A comparison of estimates of long distance travel based solely on the travel diary with estimates also including the retrospective interview data is shown in Table 2. The annual average long distance travel per person is obtained by dividing the weighted number of trips and journey distance by the number of individuals weighted with the diary sample household weights (W2) and by assuming 52.14 weeks per year. For the "diary only" estimates, the recorded journeys are for a 1-week period, while for the "diary + retrospective" the journeys are for a 4-week period (2-week in 2006).

The table shows average annual long distance travel per person for the years 2002-2006 in miles, numbers of trips and average trip length by mode and totally[4]. On the basis of all the data (diary + retrospective), during this period each individual in Britain made on average 20.2 long distance journeys per year, travelling 2251 miles. This accounted for about 32% of their total annual distance travelled within Britain. The average trip length was 111 miles (1

[4] In this table and in all analysis of NTS data, we omit travel by modes other than the 4 modes (which accounts for around 1.5% of distance travelled) and travel for purposes not easily categorized into the 5 purposes (which accounts for 4% of distance travelled).

way). Using only the diary data, the number of trips is slightly higher (20.5), but total distance travelled is estimated to be 6% lower, at 2114 miles. The average trip length is also 7% lower, suggesting that respondents tend to record longer journeys in the retrospective part of the survey than in the travel diaries. This may simply have to do with memory: respondents are more likely to recall *longer* long distance journeys than *shorter* ones and so will be more likely to report them. However, we note that although the average journey length is shorter for the diary week for car, rail and coach (by 8%, 6% and 5%, respectively), it is 6% greater for air.

Both estimates agree that the average trip length was greatest by air and shortest by car, and slightly longer by coach than by rail.

Table 2: Average annual long distance travel per capita, mean 2002-2006 NTS

	Car	Rail	Coach	Air	Total
Diary + retrospective					
miles	1804	248	118	81	2251
trips	17.0	2.1	0.9	0.2	20.2
average trip length, miles	106	117	129	383	111
Diary only					
miles	1654	252	132	75	2114
trips	16.9	2.3	1.1	0.2	20.5
average trip length, miles	98	110	122	406	103

Comparison of travel diary information on long distance journeys with journeys of all distances for the years 2002-2006 indicates that although long distance journeys account for only about 2% of trips, they make up about 31% of all miles travelled. By mode, long distance journeys account for 29% of car miles, 68% of coach miles, 54% of rail miles and 100% of air miles. In terms of trips, the figures are 3% for car, 15% for rail and coach and 100% for air. Coach, rail and air are clearly predominantly long distance modes, whereas car is mainly used for shorter distance trips.

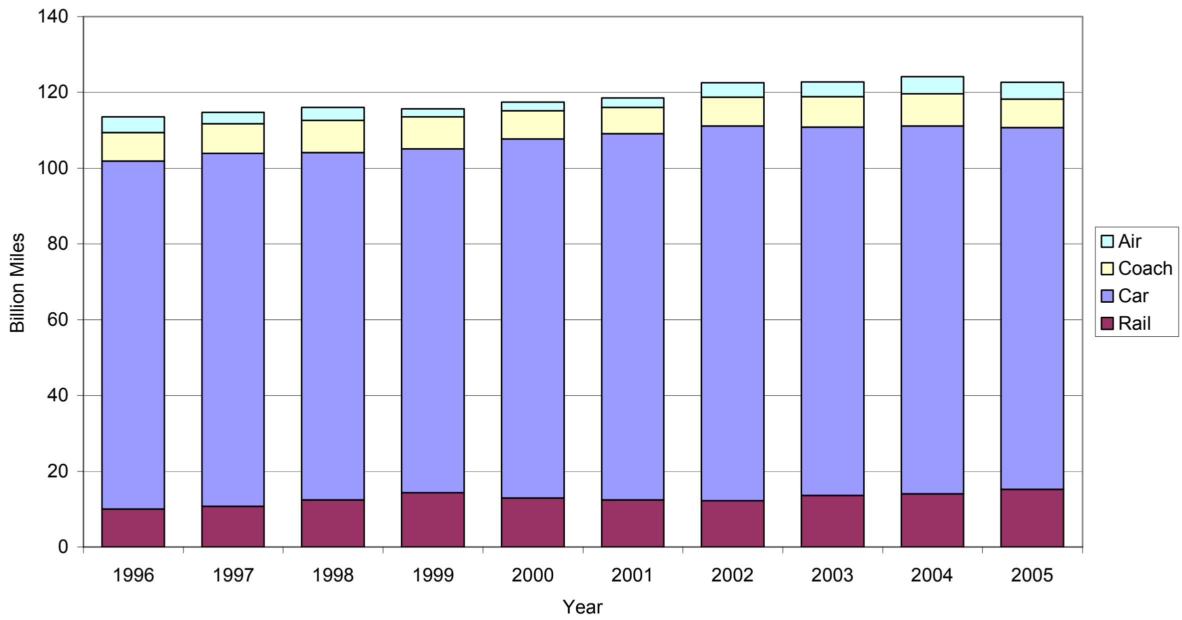
Despite that fact that only about a third of the total distance travelled by car is for trips of 50 miles or more, car is the predominant mode for long distance travel, making up on average 77% of the total distance travelled, followed by rail (11%), coach (6%) and finally air (4%), with other modes accounting for the remainder. This can be compared with the modes shares of total miles travelled: car (81%), rail (6%), coach (3%), air (1%), with other modes (including walk) making up 8%.

To obtain estimates of total miles travelled annually for long distance trips in Great Britain by British residents, the estimated average per person rates are multiplied by the population of GB in the corresponding year. Since there is substantial year-to-year variation in the data for long distance journeys, which may be related to sampling error rather than to actual changes in travel patterns, NTS publications group the data into periods of 3 years in order to improve reliability by increasing sample size. We follow this procedure, but instead use a 3-year moving average, so that 1996 is taken as the mean of the years 1995, 1996 and 1997 etc., thus loosing individual observations for the first and last year of the available period (1995 and 2006).

Initially, our intention was to use both the diary and retrospective data to create a time-series for long distance travel. However, in doing so, a significant reduction in long distance travel between 2005 and 2006 by 10 billion miles was noted. It was found that this was likely to be explained by the reduction in the length of the retrospective travel period in the 2006 survey (from 4 to 2 weeks). As noted above, the retrospective data tends to over-represent *longer distance* long distance journeys. By reducing the length of the retrospective period in 2006, this over-representation of longer trips is reduced in comparison to earlier years, thus resulting in an apparent fall in long distance travel in 2006.[5] For this reason it was decided to base comparisons over time purely on the long distance travel reported in the travel diaries.

The resulting estimates of total travel by mode are shown in Figure 1. These data indicate that long distance travel accounts for between 114 and 124 billion miles per annum over the period. This is about ¼ of the total passenger miles reported in Transport Statistics Great Britain (TSGB), which also include shorter distance trips, other modes and purposes, journeys not made by households and journeys made in GB by non-residents (in 2005, the estimated long distance journeys accounted for 23% of car, van and taxi miles[6], 50% of non-local bus and coach miles[7], 47% of rail miles and 71% of air miles[8] reported in TSGB).

Figure 1: Long distance travel by mode by British residents in GB, 3-year moving average for median year shown, estimates based on the 1995-2006 NTS



[5] A comparison of the estimates based on both diary and retrospective data with those based on diary data alone is shown in Appendix A.

[6] Apart from a large number of short distance journeys included in the figures from TSGB, they also include car journeys not made by households, taxi journeys and van journeys used for commercial purposes which are not included in the NTS.

[7] Public Transport Bulletin 2008.

[8] TSGB air passenger data also include journeys to Northern Ireland which are not included in the NTS. These journeys account for about 1/3 of all air passengers in the UK.

From the estimates shown in Figure 1, long distance travel in terms of miles has increased by about 0.9% per annum over the 10-year period[9]. This can be compared to all travel by all modes reported in the NTS, which shows a lower average annual growth rate of 0.7%. Based on the NTS, long distance travel increased more rapidly than total travel over this period, and thus also more rapidly than short distance travel (<50 miles), which grew by 0.6%. These figures can be compared with the 1.1% annual growth for all travel by the four modes based on TSGB, whilst holding in mind that TSGB includes journeys not covered by the NTS: those not made by households, those made by non-residents and air journeys to Northern Ireland.

Two periods can be identified in the above figure. Growth in long distance travel was more-or-less continual up until 2002, at about 1.3% per annum. From 2002 long distance travel appears to level off, with total miles in 2005 about the same as in 2002. The development is rather different for short distance travel, suggesting that long distance travel increased more rapidly than short distance from 1996 to 2002, but less rapidly thereafter.

NTS data for the years 2007 and 2008, not available in time for this study, indicate that per capita distance travelled by all modes (and distances) declined continually from 2005.[10] A similar decline is noted for car travel, while rail travel shows continued growth. Whether this is also the case for long distance travel remains to be examined. One must, however, be cautious about drawing conclusions from short-term NTS changes since much of the variation from year to year is due to sampling variability.

The variability over time in long distance travel in Figure 1 is even more apparent for the individual modes. Car travel reaches a maximum in 2002, and declines thereafter, so it is 3.5% lower in 2005. Coach and air reach a maximum in 2004, while the maximum for rail occurs in 2005. It is thus the reduction in car travel which is behind the levelling off of total long distance travel noted in the figure. Over the period as a whole, the average annual growth for car is only 0.4%. This is just less than half the 0.9% per annum growth for all car, van and taxi passenger kilometres[11] for the same period reported in TSGB. In addition, although TSGB shows a reduction in growth after 2002, there is no absolute reduction as indicated by the NTS.

According to our NTS estimates, rail has shown the most rapid growth, on average 5% per annum. This, however, is somewhat greater than the 3.3% annual growth for all rail passenger kilometres reported in TSGB and 4% per annum for journeys of 50 miles or more estimated on the basis of LENNON[12] data.

The greatest discrepancy between the NTS and TSGB estimates is for air. We note a growth in air travel of 0.6% annually over the period, compared with 5% reported in TSGB. This difference is likely due to the small number of air journeys in the NTS and the large sampling errors, but the inclusion of trips to Northern Ireland in the TSGB figures may also contribute

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9 The average annual percentage change is calculated using the figures for 1996 and 2005. Because of the volatility in the annual figures, the annual percentage change varies from year to year and depends on the start and end years used.

10 Transport Statistics Bulletin: National Travel Survey 2008, August 2009.

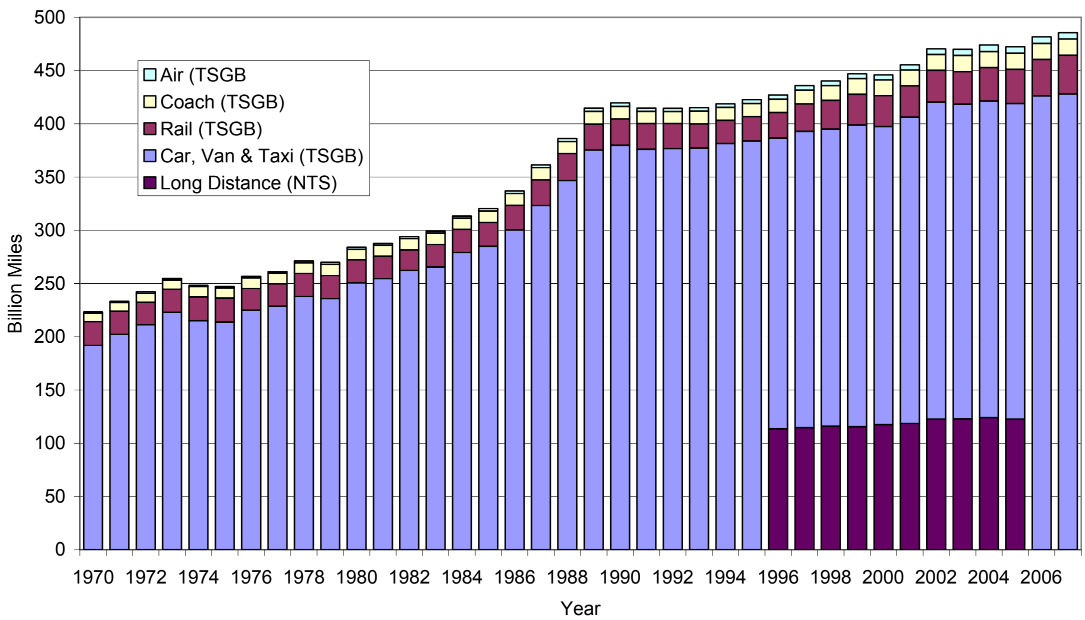
11 TSGB does not report car separately from van and taxi.

12 LENNON (formerly CAPRI) is the rail industry's central ticketing system. It provides information on passenger kilometres, journey data, and ticket sales by origin and destination pairs.

to the discrepancy. Finally, coach shows no discernible growth over the period, whereas passenger kilometres for non-local buses and coaches in GB increased by 2% annually over the same period. [13]

Figure 2 compares the estimates of long distance travel from the NTS from Figure 1 with the development of total travel by car (including van and taxi), coach, rail and air from TSGB. As noted above, the TSGB data show a higher rate of growth for 1996 to 2005 than the NTS long distance estimates. They also confirm the levelling off between 2002 and 2005, but show a renewed increase in 2006 and 2007. Again, it must be held in mind that, in addition to short distance trips, the TSGB figures also include mileage of non-households and non-residents. This particularly impacts on the figures for the group car, van and taxi. Nevertheless, there is no reason to suppose that including these trips would have a significant effect on trends over time.

Figure 2: Total passenger miles by mode (1970 – 2007), TSGB, and total long distance miles (1996 – 2005), NTS



The growth in long distance travel based on the NTS estimates appears rather low. This is particularly the case since 2002. It should be noted that there was a change in contractor for the survey in 2002 from ONS to NatCen and different coding procedures were used. It is possible that this could have had an impact on the data.

A comparison of total travel for the years 1996 to 2008 based on the NTS and data from other sources[14] indicates that there is a strong correlation for public transport modes, but less of a correlation for private modes. The NTS, in agreement with other sources, indicates a significant increase in total miles travelled by bus in London, surface rail and London

[13] Public Transport Bulletin 2008.

[14] National Travel Survey 2008 Technical Report, July 2009.

Underground, but no apparent trend in other local bus services. Regarding car, on the other hand, the Road Traffic Census data indicate that total distance travelled by cars and taxis has steadily increased over the period (albeit with a slight fall in 2008) while the NTS indicates a fall over the period as a whole. Other modes are not considered. However, since car is such a dominant mode, estimates of total travel are highly dependent on the quality of data on car travel. This is clearly also the case for long distance travel.

Although the NTS data (Figure 1) seem to suggest a levelling-off in long distance travel during the first 5 years of the century, this is primarily dependent on a decline in car travel. Given the discrepancy in estimates of car travel between the NTS and traffic counts, one should be careful about drawing conclusions concerning saturation based on these data. Clearly, further study is required on this issue.

The estimates in Figure 1 have been used to obtain implied GDP elasticities. The results are reported in Appendix B, along with plots of distance versus GDP for each mode and totally. A constant elasticity model was estimated using simple regression of the log of distance travelled on the log of real GDP. The implied GDP elasticities are shown in Table 3. The elasticities for car and total travel are far lower than those reported in the literature[15] for all travel (short and long distance together), as is the elasticity for air. On the other hand, the elasticities for rail and coach are within consensus ranges.

Table 3: Implied GDP elasticities based on aggregate NTS data 1995-2006

Mode	Elasticity
Car	0.25
Rail	1.18
Coach	0.00
Air	1.01
Total	0.35

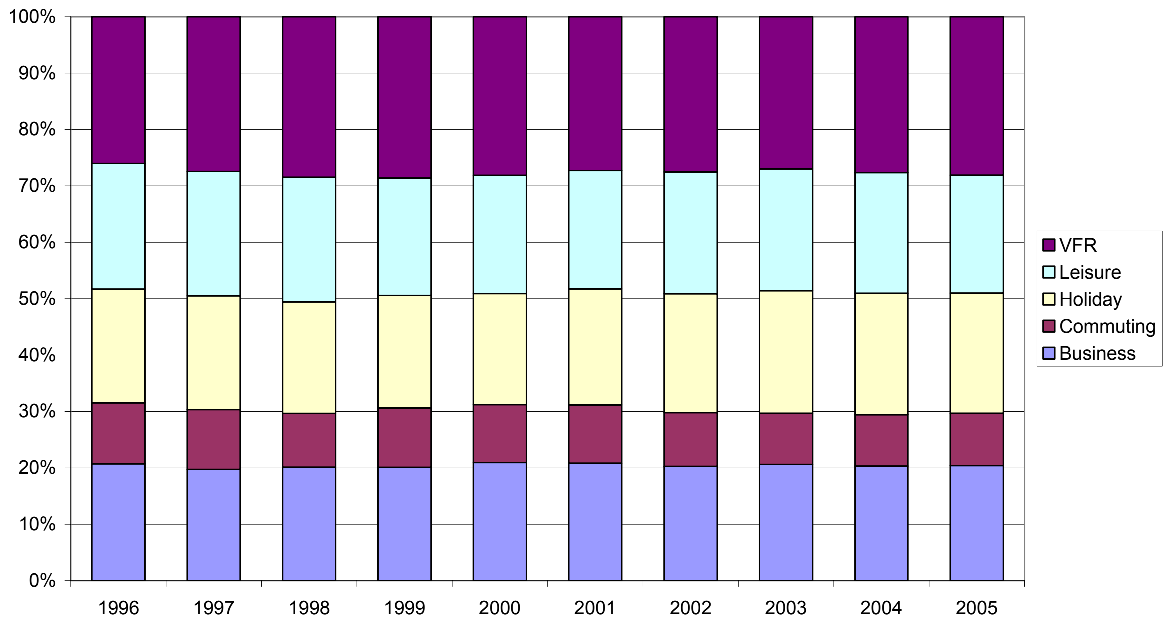
3.2 Travel by journey purpose

The breakdown of long distance travel by purpose is illustrated in Figure 3. Visiting friends and relatives (VFR) accounts for the greatest share (28%) and commuting for the smallest (10%), while leisure and holiday make up 21% each and business, 20%. Although there is some variation in shares over the period, there are no discernible trends, except perhaps a decline in the share of commuting[16] and an increase in the share for holiday.

[15] Owing to the small number of observations available, only a simple static model was estimated so that one cannot interpret the elasticities as short or long run.

[16] Using the diary plus retrospective data shows a substantial decline in commuting combined with an increase in employers' business from 2003. This was found to be a coding error in the NTS retrospective data, which cannot currently be resolved by the DfT.

Figure 3: Long distance travel by purpose, percentage of total miles, 3-year moving average for median year shown, estimates based on 1995-2006 NTS



As shown in Table 4, car is the dominant mode for long distance travel for all purposes: for the 2002-2006 period, it accounted for on average from 75% of business and holiday mileage to 84% of VFR. The share of rail is greatest for commuting (23%) and lowest for leisure and holiday travel (9% each), while coach's share is greatest for leisure and holiday (12% and 11%) and smallest for business and commuting (2% each). Air's share is greatest for business travel (10% of distance) and holiday (4%).

Table 4: Long distance travel, mode shares (%) of distance travelled by journey purpose, 2002-2006 NTS

	Car	Rail	Coach	Air
Business	75	13	2	10
Commuting	74	23	2	1
Holiday	75	9	12	4
Leisure	79	9	11	1
VFR	84	12	3	1

Shares do not sum to 100 due to rounding.

Journey purpose by mode is shown in Table 5. Of total long distance mileage by car nearly 1/3 is for VFR and only 10% for commuting, while business, holiday and leisure make up around 20% each. VFR also dominates rail travel (28%), with other purposes each accounting for between 16% and 22%. Coach is predominantly used for holiday (42%) and leisure (38%) travel, and seldom used for commuting (3%) and business (5%), while air is mainly used for business (55%) and holiday (25%).

Table 5: Long distance travel, journey purpose shares (%) of distance travelled by mode, 2002-2006 NTS

	Car	Rail	Coach	Air
Business	20	22	5	55
Commuting	9	18	3	3
Holiday	21	16	42	25
Leisure	21	16	38	6
VFR	30	28	12	11

Shares do not sum to 100 due to rounding.

3.3 Travel by distance band

The mode shares differ by journey distance. As shown in Table 6, although car dominates both distance bands, its share is far higher for trips less than 150 miles than it is for trips over 150 miles. For *longer* long distance trips, the shares for all other modes are higher than for *shorter* long distance trips.

For journeys between 50 and 149 miles, car accounts for 84% of mileage, rail for 11% and coach for 5%, while for journeys over 150 miles, the comparable shares are 68%, 14% and 8%, with air accounting for 10%.

Table 6: Long distance travel, mode shares (%) of distance travelled by distance band, 2002-2006 NTS

	Car	Rail	Coach	Air
< 150 miles	84	11	5	0
150+ miles	68	14	8	10

Clearly, miles travelled by the different modes also have different distributions by distance band. As seen in Table 7, only 1/3 of long distance car mileage is for trips 150 miles or more, while essentially all air travel falls in this distance band. Rail and coach travel are split more evenly between the two bands, with coach travel having a nearly equal distribution.

Table 7: Long distance travel, distance band shares (%) of distance travelled by mode, 2002-2006 NTS

	Car	Rail	Coach	Air
< 150 miles	68	57	51	0
150+ miles	32	43	49	100

4 Estimation of Elasticities Based on Existing Data

From a review of the evidence on elasticities in existing aggregate and disaggregate studies carried out in the scoping study, we concluded that although there is a wealth of estimates, few are totally relevant to long distance travel. This is particularly the case with the aggregate models reviewed. Rail is an exception, but even here there is little empirical evidence on elasticities other than those relating to journey time, fare, headway, GDP and population. There are virtually no studies which distinguish elasticities by distance and purpose and provide estimates of both own- and cross-elasticities with respect to cost and time.

Since much of the existing empirical evidence is lacking or outdated, we concluded that an important element of the project, and one that is indispensable for producing robust forecasts, was to obtain new estimates of elasticities. This was achieved through the estimation of models using existing data and a special survey of long distance travel. In this Section elasticity estimates based on existing data are reported. These are income and cost elasticities based on aggregate data and disaggregate elasticities with respect to income and socio-demographic factors based on the NTS.

4.1 Estimation of elasticities from aggregate time-series data

To start 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.[17] The dependent variable in all models is passenger kilometres (or miles) by the given mode. Prices are defined as the motoring cost index and the rail fare index from ONS, revenue per kilometre for non-local bus and coach from the DfT and domestic air fares from DfT. Income was defined as real GDP.

From the aggregate models, we were only able to obtain reliable and realistic estimates for own-cost and income elasticities. This difficultly in obtaining 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 prices[18].

The short- and long-run elasticities are reported in Table 8. The estimated elasticities are generally in line with previous evidence[19]. 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

[17] 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 etal (2002) for a description of these models.

[18] Dargay etal. (2002).

[19] See Dargay and Wardman (2008) and Oum etal (1992).

of car travel is about -0.33, which agrees well with other studies[20]. 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 evidence[21].

Table 8: 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

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 range[22]. Regarding the income elasticity, 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 2005[23] 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 9. 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 8. The results also suggest that, for long distance journeys, both the cost and income elasticities are greater for journeys greater 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 9: 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

[20] Goodwin etal (2004) and Graham and Glaister (2004).

[21] Dargay etal (2002).

[22] See Dargay etal (2006) for a review of the literature.

[23] 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.

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.

4.2 Estimation of the effects of socio-economic, demographic and geographic factors

In order to determine the effects of socio-economic, demographic and geographic factors on long distance travel, models were estimated using the 1995-2006 National Travel Surveys. The models were estimated at the individual level for all respondents completing the travel diary, which for the 12 years gives a sample of 147,826 individuals. The journeys are weighted to adjust for drop-off in the number of journeys reported over the reporting period. Because of the problems with the retrospective data on long distance journeys discussed earlier, only long distance journeys reported during the diary week are used for the analysis.

The estimated models express the distance travelled for long distance journeys by individual *i,* D_i , in terms of K socio-economic, demographic and geographic characteristics, X_{ki}, and a time trend, t:

$$D_t = \alpha + \sum_{k=1}^{K} \beta_k X_{ki} + \gamma t + \varepsilon_i \qquad (4)$$

where α is a constant intercept term, β_k are the coefficients of the K factors, γ is the parameter relating to the time trend and ε_i is a random error term.

The socio-economic, demographic and geographic factors included in the models are shown in Table 10. The estimates obtained from the econometric models will help determine which variables are most important to include in the forecasting model.

Table 10: Socio-economic, demographic and geographic factors in the NTS models

Household income (gross)
Gender
Age
Employment status
Government Office Region of residence
Size of municipality
Number of adults in household
Whether there are children in the household
Whether main driver of a company car
Type of residence
Length of residence

Separate models were estimated for total travel, travel by each of four modes (car, rail, coach and air), travel by five purposes (business, commuting, leisure, holiday and VFR) and two journey lengths (<150 miles and 150+ miles one way), as well as the 40 mode-purpose-distance combinations. The models were estimated by weighted least squares using the diary sample household weights (W2) provided by the NTS to correct for non-response bias. In all cases, the estimated coefficients of the majority of the variables in Table 10 are highly significant and of the expected signs. The goodness of fit is typical of models estimated on the basis of individual repeated cross-section data (adjusted R^2 between 0.1 and 0.2).

The estimates for all the models are presented in Appendix C. A typical example is shown in Table 11, which is for long distance journeys of less than 150 miles by all modes. The definitions of the variables included in the model are shown in Table C.1 in Appendix C. The table shows the estimated coefficients, standard errors, t-statistics and the elasticities calculated at the mean values of the dependent and independent variables[24]. The estimation procedure omits any variables which are not significant at the 0.10 level.

As expected, the income variable is highly significant. Long distance travel (between 50 and 150 miles, in this case) increases with income, with an estimated income elasticity of 0.42 calculated at the mean distance and income for trips in this category. The time trend is not significant, so there is no trend over time not explained by the other explanatory variables in this trip category.

With the exception of income and the time trend, the variables included in the models are categorical so that the coefficients are interpreted in relation to an excluded, or base, category (male, age 60+, not employed, main driver of company car, under 1 year residence at current address, South East, metropolitan area, 2-adult household, children in household, semi-detached house)[25]. Omitted variables in each group are not statistically different from the reference category. The elasticities for the categorical variables give the percentage change in miles travelled when the proportion of the category in the total population increases by 1%. For example, the elasticity for Age059 of 0.04 means that if the proportion of population under 60 increases by 1%, miles travelled will increase by 0.04%.

The results show that long distance travel (for journeys less than 150 miles) is lower for women than for men, greater for those under 60 than for those over 60, greater for the employed and students than for the unemployed/retired and lower for those who do not have company cars than it is for those that do.

Length of residence at current address is also shown to have a significant effect on travel, with travel generally declining the longer an individual lives at the same address. Regarding regional variations, individuals living in the two excluded regions – the South East and Eastern England – are not significantly different from each other when it comes to this category of long distance travel, while those in the South West and East Midlands (positive coefficients) travel *more* and those in the remaining regions (negative coefficients) travel *less* than those in the South East and Eastern regions. Long-distance travel also increases as the size of the conurbation decreases, and is, as expected, greatest for those living in rural areas.

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[24] Given the linear function used, the elasticities are not constant but are dependent on the values of D and X in equation (1). Those reported in the tables are calculated at the mean values of these variables, so the elasticity for variable k $= \beta_k \overline{X}_k / \overline{D}$.

[25] Choice of reference category is immaterial because the coefficients can be transformed to any other reference category.

Regarding household composition, long distance travel is greater for individuals in 1-adult households than it is for those in 2-adult households and it is lowest for those in households with 3 or more adults. Travel is also lower for those living in households with children, than for those in households without. Finally, long distance travel is greater for individuals living in detached houses, even once income and conurbation size are controlled for.

Table 11: Estimated model for journeys 50 to 150 miles by all modes, 1995-2006 NTS

	Estimated coefficient	Std. Error	t-statistic	Elasticity
Constant	98.54	1.68	58.7	
Household Income	0.0007	0.00	29.2	0.42
Female	-8.54	0.42	-20.2	-0.17
Age059	1.27	0.71	1.8	0.04
Employed	11.15	0.52	21.6	0.21
Student	8.39	1.25	6.7	0.01
NoCompanyCar	-89.18	1.34	-66.8	-3.37
Residence0	4.65	0.92	5.1	0.01
Residence12	3.64	0.87	4.2	0.01
Residence23	2.98	0.89	3.4	0.01
Residence35	1.27	0.76	1.7	0.01
Residence10p	-2.02	0.62	-3.3	-0.02
ResidenceEver	-2.89	0.72	-4.0	-0.02
NorthEast	-11.08	1.09	-10.2	-0.02
NorthWest	-7.35	0.76	-9.7	-0.03
Yorkshire	-5.01	0.84	-6.0	-0.02
EastMidlands	1.41	0.89	1.6	0.00
WestMidlands	-3.30	0.82	-4.0	-0.01
London	-9.92	0.76	-13.0	-0.05
SouthWest	1.94	0.84	2.3	0.01
Wales	-8.35	1.03	-8.1	-0.02
Scotland	-10.29	0.85	-12.1	-0.04
Pop3K25K	4.19	0.58	7.2	0.03
Rural	6.52	0.72	9.0	0.03
Adults1	3.49	0.63	5.6	0.02
Adults3p	-5.76	0.54	-10.7	-0.06
Children0	7.06	0.53	13.4	0.15
Detached	7.91	0.58	13.7	0.07
Terrace	-1.10	0.53	-2.1	-0.01
PurposeFlat	-4.32	0.81	-5.4	-0.02
AccomOther	-5.02	2.94	-1.7	0.00

Note: see Table C.1 in Appendix C for the variable definitions.

The main objective of the NTS modelling is to obtain estimates, for use in the forecasting model, of the influence of socio-economic factors on various types of long distance travel.

The income elasticities[26] derived from the NTS models are shown in Table 12. 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 these as medium-run elasticities[27]. Indeed, we see that for all long distance travel (last row) the income elasticities for each mode are generally between the short- and long-run elasticities obtained from the time-series analysis above in Table 8. Also encouraging is the agreement in the magnitude ranking of the modal elasticities based on the two types of data: air is most income-elastic, followed by rail, car and finally coach. This is the case for most journey purposes and distance bands. Notable is the substantial difference in income elasticities for rail for business/commuting as opposed to holiday/leisure/VFR. In addition, we see that the income elasticity for coach travel is very low, and zero for the majority of purpose-distance bands, suggesting coach travel to be an inferior mode in comparison to car, rail and air.

Regarding journey distance, we find that longer distance journeys are more income elastic than shorter journeys, which is in agreement with the evidence obtained for rail in Table 9. In general the elasticities are of the order of magnitude found in other studies[28].

Table 12: Income elasticities (medium term) for long distance travel estimated from the NTS and real average household income (1995 – 2006) in 2000 prices

Purpose	Distance (miles)	Car	Rail	Coach	Air	Household income (thousand 2000£)
Business	<150	0.34	1.39	0.00	*	24.2
	150+	0.54	1.51	0.00	1.53	
Commuting	<150	0.31	1.34	0.00	*	23.7
	150+	0.50	1.57	0.00	*	
Holiday	<150	0.38	0.64	0.00	*	19.1
	150+	0.61	0.56	0.00	1.31	
Leisure	<150	0.31	0.50	0.00	*	19.0
	150+	0.47	0.43	0.28	1.26	
VFR	<150	0.53	0.25	0.00	*	19.6
	150+	0.70	0.42	0.31	1.63	
All	All	0.46	0.83	0.10	1.44	20.7
Household income (thousand 2000£)		20.8	21.7	14.9	25.9	

* air is not considered for travel under 150 miles as there are too few observations

Also shown in the table are the mean incomes for individuals making each type of long distance trip, weighted by their travel distances. As expected, coach users have the lowest incomes and air travellers the highest; they differ by a factor of 1.7. Car and rail users have similar incomes, with those of rail travellers being slightly higher. Regarding journey

[26] The income elasticities relate to gross income. The affects of wealth or access to credit are not included as there is no information on these in the NTS. This is not a problem since we are not concerned with forecasting the effects of changes in wealth/credit and their omission is unlikely to bias the income elasticity estimates.

[27] See Goodwin etal (2006).

[28] See, for example, PDFH, Balcombe (2004) and Dargay and Wardman (2008).

purpose, business and commuting travellers have higher incomes than the average for other purposes. It can also be mentioned, that with regards to journey distance (not shown in the table), incomes are slightly higher for longer distance trips than for shorter distance trips (for all modes and purposes together 21.1 compared to 20.4.

Given the apparent decline in growth in long distance travel noted in Figure 1, the sensitivity of the elasticity estimates to the time period used in the estimation was examined. This was done by estimating the model for the two periods separately (1995 to 2001 and 2002 to 2006). The resulting income elasticities are shown in Table 13 and compared with those estimated on the basis of the full 1995 to 2006 sample. The elasticities are presented for each mode, purpose and distance band rather than for all combinations of these as in the previous table. Firstly, it can be noted that the elasticities estimated for the whole sample (1995 to 2006) are in between the elasticities for the two sub-periods in all cases. This is as would be expected.

The greater of the elasticities for the two sub-samples is shown in bold. Regarding mode, the elasticities for car and coach are higher for the most recent period, while the opposite is the case for rail and air. This is contrary to what one would expect given the evidence that growth in car and coach is slowing down, whereas growth in rail and air travel is continuing at relatively high rates. Considering journey purpose and distance, in all cases the elasticities for the latter period are greater than for the earlier period.

Table 13: Income elasticities (medium term) estimated for different sample periods, NTS

	Sample period		
	1995 to 2001	2002 to 2006	1995 to 2006
Mode			
Car	0.36	**0.49**	0.46
Rail	**1.04**	0.74	0.83
Coach	0.00	**0.15**	0.10
Air	**1.76**	1.38	1.44
Purpose			
Business	0.56	**0.63**	0.62
Commuting	0.45	**0.64**	0.57
Holiday	0.44	**0.51**	0.50
Leisure	0.28	**0.36**	0.33
VFR	0.55	**0.58**	0.56
Distance			
<150 miles	0.34	**0.45**	0.42
150 + miles	0.66	**0.67**	0.67

Although these estimates generally suggest that the elasticities are increasing over time, we must be cautious in this interpretation. Given that the number of individuals in each year is far greater than the number of years in the data sample, the elasticities will largely reflect differences in travel and income between individuals rather than differences over time. It is well-documented[29] that elasticities based on cross-section data show a good deal of variability over time which generally cannot be explained. This questions the existence of a unique

[29] See Penyala etal (1994) for example.

equilibrium which is implicitly assumed in cross-section models, or at least the possibility of estimating it on the basis of cross-section data. It is thus preferable to base elasticity estimation on dynamic models, or if this cannot be done (as is the case with the repeated cross-section data in the NTS), to use as many cross-sections as possible. For this reason, the estimates based on the entire period shown in Table 12 will be used in the forecasting model[30].

Estimates of the impacts of demographic factors on long distance travel which are relevant to the forecasting model are shown in Table 14. Empty cells denote that the estimated value is not statistically different from zero.

The elasticities shown in the table give the percentage change in demand resulting from a 1% change in the proportion of the population with the given attribute, i.e. the proportion of women, the over 60s, single adult households and the employed. For example, the elasticity of -0.46 for business travel under 150 miles by car for women means that if the proportion of women in the population increases by 1% then travel for this mode, purpose and distance band will fall by 0.46%.

The sign of the elasticity indicates whether individuals with the given attribute travel more (+) or less (-) individuals without the attribute. It is apparent that women travel less than men with few exceptions: holiday by car (only 150+ miles) and leisure by rail (less than 150 miles) and coach (150+ miles). The over 60s travel more by coach and less by car than those under 60, while persons in 1-adult households generally travel more than those in households with more adults. The employed travel more than others, and as expected, particularly for business and commuting. These differences will be relevant for future travel demand, since the proportions of women, the over-60s and single-person households are expected to increase over the coming decades, while the proportion employed is likely to decline owing to the ageing of the population.

Although other variables were used in the NTS models (see Appendix C), 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[31]. For example, the elasticities relating to geographic characteristics (region and size of conurbation) are generally very small and according to population projections, only small changes in population distribution are expected.

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[30] As mentioned earlier, we assume that the estimated elasticities represent medium-term values. A sensitivity analysis is carried out assuming these to be long-term elasticities.

[31] The model could be extended to include other factors.

Table 14: Elasticities (medium term) with respect to demographic factors estimated from the NTS (blank cells denote elasticity not significantly different from zero)

Purpose	Distance (miles)	Attribute	Car	Rail	Coach	Air
Business	< 150	Women	-0.46	-0.35	-0.32	*
		Age 60+			-0.21	*
		1 Adult	0.04	0.14	0.26	*
		Employed	0.53	0.52	0.75	*
Business	150 +	Women	-0.47	-0.20	-0.57	-0.44
		Age 60+				
		1 Adult	0.04	0.10	0.22	0.10
		Employed	0.49	0.51	1.03	0.45
Commuting	< 150	Women	-0.56	-0.40	-0.91	*
		Age 60+				*
		1 Adult		0.13	1.01	*
		Employed	0.61	0.64		*
Commuting	150 +	Women	-0.48	-0.54		
		Age 60+				
		1 Adult	0.10			
		Employed	0.64	0.55	1.19	0.95
Holiday	< 150	Women	0.04			*
		Age 60+			0.17	*
		1 Adult	-0.04	0.09		*
		Employed		0.18		*
Holiday	150 +	Women				
		Age 60+		0.13	0.30	
		1 Adult		0.06		
		Employed	0.07	0.15		
Leisure	< 150	Women	-0.10	0.08		*
		Age 60+	-0.05	-0.08	0.24	*
		1 Adult	-0.01		0.07	*
		Employed	0.08	-0.12		*
Leisure	150 +	Women	-0.17	-0.31	0.20	
		Age 60+	-0.08			
		1 Adult		0.20		0.17
		Employed	0.20	0.29		0.56
VFR	< 150	Women				*
		Age 60+	-0.03			*
		1 Adult	0.03	0.08		*
		Employed				*
VFR	150 +	Women				
		Age 60+	-0.06	-0.11		
		1 Adult	0.05	0.09	0.26	0.18
		Employed	0.06		-0.25	

* air is not considered for travel under 150 miles

4.3 Estimation of NTS models using geo-demographic data (ACORN)

The NTS also provides a classification of households based on geo-demographic data known as ACORN (A Classification of Regional Neighbourhoods). The data are derived from census information and classify every UK street as one of a number of different categories. Although ACORN data cannot be used for the forecasting model, since there are no projections of the various categories into the future, they can provide a novel insight into the social make up of long distance travellers.

Two ACORN categorizations have been used: small, based on 6 categories and medium, based on 17 categories[32]. We are limited to using the years 1997 to 2004 for the analysis since ACORN data were not available for the remaining years.

Only a model for total long distance travel by all modes is estimated. The model is also estimated omitting the ACORN variable for comparison. This is shown in Table D.3 in Appendix D. The results using the small ACORN classification are shown in Table D.4 and the results using the medium ACORN classification are shown in Table D.5. First, we note that the income elasticity declines from 0.48 to 0.45 when the ACORN variables are included. This is not surprising since the ACORN categories are partially describe income-related characteristics.

We begin with the results for the medium ACORN classification as the categories are more clearly defined. These are shown in Table 15, in terms of the extra miles per week travelled per capita by each group compared to the group with the lowest travel, "Council Estate Residents, Greatest Hardship". The ACORN category with greatest long distance travel is "Prosperous Professionals", who on average travel 24 miles a week more than the lowest group.

Table 15: Estimated additional miles travelled per week compared to the base (in bold) for medium ACORN classification, NTS 1997-2004

Number	Definition	Miles per week
1	Wealthy Achievers, Suburban Areas	17
2	Affluent Greys, Rural Communities	17
3	Prosperous Pensioners, Retirement Areas	17
4	Affluent Executives, Family Areas	17
5	Well off Workers, Family Areas	9
6	Affluent Urbanities, Town & City Areas	17
7	Prosperous Professionals, Met Areas	24
8	Better-off executives, Inner City Areas	17
9	Comfortable Middle Age, Mature Home Owning Areas	12
10	Skilled Workers, Home Owning Areas	5
11	New Home Owners, Mature Communities	9
12	White Collar Workers, Better Off Multi-Ethnic Areas	12
13	Older People, Less prosperous Areas	7
14	Council Estate Residents, Better Off Homes	3
15	Council Estate Residents, High Unemployment	12
16	**Council Estate Residents, Greatest Hardship**	**0**
17	People in Multi-Ethnic, Low Income Areas	17

The next greatest incremental travel, 17 miles, is noted for a number of ACORN categories which are not found to be statistically different in terms of mileage: "Wealthy Achievers", "Affluent Greys in Rural Communities", "Prosperous Pensioners in Retirement Areas" "Affluent Executives in Family Areas", "Affluent Urbanites", "Better-off Executives in Inner-city Areas", and surprisingly, "People in Multi-Ethnic, Low Income Areas". Interestingly, those in "High Unemployment Council Estates" travel as much as the Comfortable Middle

[32] See Tables D.1 and D.2 in Appendix D.

Age in Home Owning Areas" and "White Collar Workers in Better-off Multi-ethnic Areas". Also rather surprisingly, those in "Better-off Homes on Council Estates" travel comparatively little, and less than those on "Council Estates with High Unemployment".

The results for the small ACORN classification are shown in Table 16. The numbers of the corresponding medium ACORN groups are also shown. These are given as the increment in weekly travel compared to the group who travel the least, "Striving". We see that those defined as "Rising" travel most, followed by "Thriving", and then by "Expanding". There is no significant difference in travel between the "Settling" and "Aspiring", both of which travel relatively little. These results generally support those from the medium ACORN classification, but conceal some important distinctions between groups.

Table 16: Estimated additional miles travelled per week compared to the base (in bold) for small ACORN classification, NTS 1997-2004

	Medium ACORN categories	Miles per week
Thriving	1 – 3	12
Expanding	4 – 5	7
Rising	6 – 8	14
Settling	9 – 10	4
Aspiring	11 – 12	4
Striving	**13 – 17**	**0**

4.4 Income elasticities used in the forecasting model

The elasticities relating to socio-economic and demographic factors are based on the NTS model estimates in Table 12 and Table 14, assuming these to be medium-term elasticities (2/3rds of the long-run values). Because of the importance of the income elasticities in the forecasting model and for ease of comparison with other sources, the long-run income elasticities are given in Table 17.

Table 17: 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

5 Estimation of Elasticities Based on New Survey Data

Elasticities of demand with respect to travel costs and travel time are essential components of the forecasting model. Ideally, both own- and cross-elasticities should be differentiated by journey purpose and distance band. Existing empirical evidence is limited, and in many instances, is contradictory or outdated. As noted in Section 4.1, obtaining market journey time and cross-elasticities on the basis of aggregate time series data has not been possible. Such elasticities cannot be based on the NTS since it does not contain the necessary cost and time information, and other data sources are limited. For this reason, new data collection was undertaken to derive these elasticities.

5.1 Long distance travel survey

For the purpose of elasticity estimation and to complement the NTS data, the Institute for Transport Studies carried out a survey of long-distance car, rail, coach and air travellers (hereafter designated as the ITSS). The survey was piloted in September 2008 and carried out in the autumn and augmented with additional air travellers in December – January[33]. The questionnaire is attached in Appendix E. Car drivers were surveyed at Welcome Break Motorway Service Areas at Leicester Forest East, London Gateway and Sheffield Woodall (on the M1) and Membury (M4). Rail users were surveyed onboard trains: Virgin trains out of Crewe between Lancaster, Llandudno and Wolverhampton; National Express on the East Coast Main Line out of Newcastle between Doncaster and Edinburgh; and Crosscountry out of Birmingham between Newport, Bristol and Sheffield.[34] Coach travellers were surveyed at London Victoria, Birmingham and Leeds Coach Stations. Air passengers were surveyed at Newcastle, Gatwick, Heathrow, Manchester and Aberdeen Airports, the last three with the assistance of the CAA. The number of valid responses by mode is shown in Table 18.

Table 18: ITS survey responses

Mode	Responses
Car	1006
Train	1115
Coach	917
Air	1050
TOTAL	4092

5.2 Comparison of ITS survey with the NTS

Since the ITS survey (ITSS) was carried out with the intention of analysing the characteristics of long distance travel and long distance travellers by mode, a similar sample size was chosen for each. Clearly the modal split is not representative of long distance travel in GB and the

[33] Questionnaires were distributed on weekdays, weekends and during the day and evenings, but the actual times were not recorded on each questionnaire.

[34] The choice of on-board survey locations for rail unfortunately excludes shorter long distance rail journeys to and from London. The possible effect of this on the estimated elasticities based on the data is discussed in the following sections.

individuals sampled not representative of the population, nor comparable with the NTS. We can, however, compare the characteristics of the individuals by mode with the NTS, but the comparison must be based on individuals in the NTS who report at least one long distance journey by the given mode, since the ITSS only interviews individuals who are making a long distance trip. The comparisons in Table 19 below are based on NTS data for 2006, using only individuals over the age of 16 and weighted with the diary sample weights W2. Since individuals who make more trips are more likely to be sampled in the ITSS, the NTS data are weighted by the number of long distance trips made by the individual.

The agreement in the two surveys differs for the various characteristics. Regarding gender, in comparison to the NTS, the ITS survey has a lower share of men for rail, air and car, but both surveys agree that men are responsible for a greater proportion of car and air journeys, while women predominate for coach journeys. Only for rail are the shares reversed.

Table 19: Comparison of ITSS with NTS – individual characteristics, % of sample

	Car		Train		Coach		Air	
	ITSS	NTS	ITSS	NTS	ITSS	NTS	ITSS	NTS
Gender								
Male	58.5	63.7	48.0	60.0	44.2	42.8	56.6	65.4
Female	41.5	36.3	52.0	40.0	55.8	57.2	43.4	34.6
Cars								
no cars	3.2	2.3	18.2	18.9	34.8	18.9	9.0	13.5
1 car	33.1	33.2	37.4	34.2	37.9	46.2	38.3	36.3
2 cars	47.4	51.4	33.8	37.9	20.8	24.3	41.0	45.4
3+ cars	16.3	13.0	10.6	9.0	6.5	10.6	11.7	4.8
Area type								
Metropolitan	21.0	35.5	29.7	42.8	32.4	35.0	24.7	40.8
Medium	47.3	48.8	45.8	42.1	50.2	48.3	45.1	49.6
Rural	31.7	15.7	24.5	15.0	17.3	16.7	30.2	9.6
Employment								
Full time	59.5	68.9	57.8	67.6	33.1	34.5	72.2	81.1
Part time	12.3	12.2	11.2	9.6	9.9	12.3	11.8	10.5
Unemployed	1.5	0.9	2.7	1.8	4.4	1.9	1.0	0.0
Retired/sick	19.7	12.2	13.3	8.6	26.6	38.1	9.1	2.2
Student	3.8	1.8	13.2	8.2	24.1	6.5	5.0	0.0
Home	3.2	4.0	1.9	4.2	1.9	6.7	1.0	6.2
Individual Income								
under £19,999	34.0	45.1	39.6	41.3	69.6	79.5	23.4	28.1
£20,000 to £39,999	36.1	37.0	34.7	32.4	24.0	19.2	32.7	39.4
£40,000 or more	29.9	17.8	25.7	26.3	6.4	1.3	43.9	32.5
Household Income								
under £19,999	13.7	17.0	19.8	15.0	46.3	44.9	10.6	10.7
£20,000 to £39,999	28.3	29.8	24.5	22.8	28.6	28.0	21.9	13.6
£40,000 or more	58.0	53.2	55.7	62.2	25.1	27.1	67.6	75.7

Car ownership differs in the two surveys, with the ITSS sample indicating a greater number of household cars compared to the NTS for travellers by all modes with the exception of coach. Given the 2 years between the two surveys, an increase in car ownership is not surprising.

However, nearly 35% of coach users in the ITSS do not have a car compared to only 20% in the NTS. This discrepancy may partially be explained by the fact that long distance coach travel in the NTS includes a large proportion of private hire bus travel, whereas the ITSS contains mainly scheduled express coach services, which attract a younger market less likely to own cars.

The next factor, area type, relates to the size of the municipality of residence, with Medium defined as a population of 3,000 to 250,000, Metropolitan above this and Rural below. The ITSS has much larger proportion of individuals living in rural areas and a much smaller proportion in large metropolitan areas than the NTS for all modes, with coach showing the greatest degree of similarity between the surveys. One reason why the figures for coach agree reasonably well may be that coaches generally serve larger cities and users were surveyed at coach stations in large cities, so the sample is likely to be reasonably representative of the urban/rural split of coach users. The reason for the discrepancies in the other modes is unclear. It may be due to the choice of survey locations. For example, as mentioned earlier, the locations of the on-board train surveys will have omitted shorter long distance journeys around London, thus resulting in an under-representation of London, and hence metropolitan-area, residents. However, this should not be the case for car and air, so the discrepancies are not fully explained by sampling method.

The breakdown by employment status is very similar in the two surveys. A notable difference is the high share of students and lower share of pensioners for coach in the ITSS. This is likely a result of the small proportion of private hire bus (which tends to be used by pensioners) and the large proportion of scheduled express services (which tends to be used by students), as noted earlier.

The final two factors considered are individual and household income. Both of these are higher in the ITSS than in the NTS. This is partly explained by increasing incomes over the intervening two years. However the general trends are in agreement: both individual and household incomes are highest amongst air travellers and lowest for coach users, with car and rail showing a similar income distribution.

Individual weights by mode can be created using these data to make the ITSS data more comparable to the NTS, which we assume is representative of the population making long-distance journeys.

We can also compare the ITSS with the NTS in terms of journey characteristics. Table 20 shows the breakdown of journeys[35] by the 4 modes, 5 journey purposes and 2 distance bands we use in the forecasting model. The NTS data are weighted as described earlier. This is done by mode since our sampling procedure of collecting similar sized samples for all four modes means that car journeys are under-represented compared to the NTS and all other modes over-represented, particularly the least used modes, coach and air.

Regarding journey purpose, the share for business appears to be underestimated in the ITS survey for rail and air, but not for car, whilst the share for commuting is underestimated both for car and rail. This seems to suggest that business travellers and commuters were less-willing to partake in the survey. Leisure trips by car, rail and coach are also underestimated in

[35] Note that these are shares of trips, not distance travelled as in the tables in Section 3.

the ITSS, while the share for VFR is much greater in the ITSS than the NTS. The large discrepancy between the NTS and the ITSS for leisure trips by coach (46% vs. 17%) is partially due to our survey locations, which tended to capture scheduled express coach services, rather than private hire bus which is often used for day excursions[36]. VFR is over-represented in the ITSS for all modes, and particularly for coach.

Table 20: Long distance travel, purpose and distance band shares (%) of journeys by mode, NTS and ITSS

Mode – Purpose - Distance	NTS	ITSS
Car		
Business	20	21
Commuting	13	5
Holiday	14	17
Leisure	24	15
VFR	29	41
Less than 150 miles	85	37
150 miles or more	15	63
Rail		
Business	16	31
Commuting	26	5
Holiday	13	15
Leisure	21	16
VFR	24	33
Less than 150 miles	80	35
150 miles or more	20	65
Coach		
Business	6	8
Commuting	3	5
Holiday	33	23
Leisure	46	17
VFR	12	46
Less than 150 miles	73	55
150 miles or more	27	45
Air		
Business	47	38
Commuting	1	3
Holiday	38	15
Leisure	3	12
VFR	10	32
Less than 150 miles	0	6
150 miles or more	100	94

In terms of distance, we note that car and rail journeys of less than 150 miles are substantially under-represented in the ITSS: 37% of car journeys in the ITSS are less than 150 miles, compared to in 85% the ITSS, while the corresponding figures for rail are 35% and 80%. A similar, but less marked, tendency is noted for coach travel, with the proportion of journeys

[36] Some of these, however, will have been surveyed at motorway service areas.

less than 150 miles being 55% and 73% in the ITSS and NTS, respectively. The under-representation of commuting and leisure trips noted above may be explained by the under-representation of trips less than 150 miles, since both leisure and commuting trips tend to be shorter than long distance trips for other purposes.

The under-representation of shorter distance car journeys in the ITSS is explained by the choice of interview locations. It is less likely that travellers making shorter distance trips will be using the motorway, or if so, that they will break their trip by stopping at a motorway service area. For rail, the lower proportion of journeys of less than 150 miles may be explained by the omission of shorter long distance trips around London mentioned earlier, while for coach the choice of survey locations does not capture private hire bus used for shorter day excursions.

The accuracy of any estimates (of diversion factors, elasticities, etc.) based on the survey will, of course, be dependent on the quality of the data and the representativeness of the sample. However, differences in trip characteristics between the ITSS and the NTS noted above will have little bearing on these estimates, since they are based on each mode-purpose-distance band separately. However, we note that the under-representation of shorter distance trips (and shorter distance trips to/from London) may have some effect on the estimates for journeys less than 150 miles, but we do not have sufficient information to judge the magnitude of the effect or to correct for it.

5.3 Estimation of diversion factors

The diversion factor[37] 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.

$$v_{ji} = \frac{\partial D_i}{\partial D_j} \tag{5}$$

The diversion factors can be 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:

$$\varepsilon_{ij} = \left|\varepsilon_{jj}\right| \frac{s_j}{s_i} v_{ji} \tag{6}$$

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.

[37] See Wardman and Toner (2003).

Questions on intended behaviour in the ITSS were used to derive the diversion factors. 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 proportion of individuals giving each response and the implied diversion factors for cost and time are shown in Table 21 and Table 22. The diversion factors are simply the proportion of individuals using a given mode who say they would switch to another specified mode. For example, the diversion factor from car to rail for business travellers travelling under 150 miles of 0.37 implies that 37% of car users would switch to rail, if car became more costly.

The values are quite reasonable and in agreement with other evidence. The diversion factors for cost and time are similar, with the greatest difference noted for coach. Diversion to car, rail and coach is greater for journeys less than 150 miles than it is for longer journeys, where diversion to air becomes significant, particularly from rail. Diversion factors from air are not estimated for journeys less than 150 miles, as these are very marginal. For all journeys, diversion to rail and car is a similar order of magnitude, while diversion to coach is marginal.

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 percentages of individuals giving this response are shown in the final column of the tables. The responses are consistent: car and air travellers are most likely to consider other modes unsuitable, while coach users are least likely to do so.

Business travellers are most likely to consider themselves unable to switch modes, while holiday travellers making journeys 150 miles or more are least likely to be bound to their current mode. For most non-work journey purposes, car users are more likely to consider the car indispensable for journeys less than 150 miles, than for longer journeys.

The percentages shown in the table 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.

Table 21: Diversion factors and other responses to transfer price question in the ITSS, proportion of responses

			Car	Rail	Coach	Air	Go somewhere else	Not travel	Must use current mode
Business									
	<150	Car	0.00	0.37	0.02	0.00	0.02	0.05	0.53
		Rail	0.57	0.00	0.07	0.00	0.04	0.10	0.23
		Coach	0.23	0.64	0.00	0.00	0.00	0.05	0.09
	150+	Car	0.00	0.32	0.02	0.07	0.01	0.04	0.54
		Rail	0.42	0.00	0.04	0.29	0.01	0.06	0.18
		Coach	0.29	0.38	0.00	0.10	0.00	0.10	0.14
		Air	0.16	0.37	0.00	0.00	0.00	0.06	0.41
Commuting									
	<150	Car	0.00	0.71	0.00	0.00	0.00	0.00	0.29
		Rail	0.50	0.00	0.14	0.00	0.05	0.05	0.27
		Coach	0.21	0.67	0.00	0.00	0.00	0.00	0.13
	150+	Car	0.00	0.60	0.08	0.00	0.00	0.04	0.28
		Rail	0.30	0.00	0.09	0.30	0.04	0.00	0.26
		Coach	0.22	0.33	0.00	0.00	0.00	0.22	0.22
		Air	0.35	0.45	0.00	0.00	0.00	0.05	0.15
Leisure									
	<150	Car	0.00	0.40	0.04	0.00	0.05	0.07	0.44
		Rail	0.61	0.00	0.14	0.00	0.08	0.03	0.14
		Coach	0.27	0.52	0.00	0.00	0.00	0.07	0.15
	150+	Car	0.00	0.46	0.06	0.03	0.01	0.14	0.30
		Rail	0.42	0.00	0.12	0.20	0.04	0.11	0.11
		Coach	0.33	0.40	0.00	0.08	0.06	0.06	0.06
		Air	0.30	0.44	0.03	0.00	0.01	0.06	0.15
Holiday									
	<150	Car	0.00	0.31	0.17	0.00	0.13	0.15	0.25
		Rail	0.62	0.00	0.19	0.00	0.04	0.08	0.08
		Coach	0.48	0.26	0.00	0.00	0.14	0.06	0.06
	150+	Car	0.00	0.36	0.09	0.05	0.15	0.11	0.23
		Rail	0.31	0.00	0.04	0.31	0.13	0.13	0.08
		Coach	0.39	0.27	0.00	0.03	0.07	0.10	0.14
		Air	0.17	0.51	0.03	0.00	0.03	0.11	0.15
VFR									
	<150	Car	0.00	0.39	0.10	0.00	0.01	0.13	0.37
		Rail	0.53	0.00	0.29	0.00	0.00	0.06	0.11
		Coach	0.21	0.64	0.00	0.00	0.00	0.08	0.07
	150+	Car	0.00	0.50	0.04	0.04	0.01	0.10	0.30
		Rail	0.43	0.00	0.12	0.26	0.02	0.06	0.12
		Coach	0.23	0.54	0.00	0.08	0.01	0.07	0.08
		Air	0.45	0.28	0.03	0.00	0.00	0.06	0.17

Table 22: Diversion factors and other responses to transfer time question in the ITSS, proportion of responses

			Car	Train	Coach	Air	Go somewhere else	Not travel	Must use current mode
Business									
	<150	Car	0.00	0.34	0.02	0.00	0.01	0.10	0.52
		Rail	0.58	0.00	0.05	0.00	0.02	0.08	0.27
		Coach	0.18	0.55	0.00	0.00	0.05	0.00	0.23
	150+	Car	0.00	0.40	0.00	0.06	0.01	0.01	0.52
		Rail	0.35	0.00	0.04	0.31	0.01	0.04	0.25
		Coach	0.12	0.35	0.00	0.12	0.06	0.18	0.18
		Air	0.13	0.29	0.01	0.00	0.00	0.04	0.53
Commuting									
	<150	Car	0.00	0.60	0.00	0.00	0.00	0.00	0.40
		Rail	0.58	0.00	0.05	0.00	0.05	0.11	0.21
		Coach	0.14	0.76	0.00	0.00	0.00	0.10	0.00
	150+	Car	0.00	0.38	0.08	0.04	0.00	0.04	0.46
		Rail	0.40	0.00	0.10	0.30	0.05	0.00	0.15
		Coach	0.29	0.43	0.00	0.00	0.00	0.00	0.29
		Air	0.21	0.29	0.00	0.00	0.00	0.08	0.42
Leisure									
	<150	Car	0.00	0.44	0.04	0.00	0.05	0.09	0.38
		Rail	0.61	0.00	0.08	0.00	0.12	0.04	0.14
		Coach	0.35	0.44	0.00	0.00	0.02	0.06	0.13
	150+	Car	0.00	0.48	0.06	0.06	0.05	0.06	0.29
		Rail	0.32	0.00	0.05	0.24	0.04	0.09	0.24
		Coach	0.24	0.38	0.00	0.02	0.09	0.09	0.18
		Air	0.18	0.32	0.04	0.00	0.05	0.07	0.34
Holiday									
	<150	Car	0.00	0.27	0.10	0.00	0.10	0.13	0.40
		Rail	0.48	0.00	0.24	0.00	0.00	0.08	0.20
		Coach	0.49	0.33	0.00	0.00	0.00	0.06	0.12
	150+	Car	0.00	0.32	0.08	0.06	0.15	0.09	0.30
		Rail	0.23	0.00	0.05	0.39	0.09	0.10	0.14
		Coach	0.27	0.26	0.00	0.12	0.05	0.07	0.22
		Air	0.17	0.40	0.02	0.00	0.02	0.09	0.29
VFR									
	<150	Car	0.00	0.32	0.09	0.00	0.00	0.09	0.50
		Rail	0.58	0.00	0.27	0.00	0.00	0.04	0.11
		Coach	0.18	0.53	0.00	0.00	0.01	0.10	0.18
	150+	Car	0.00	0.47	0.06	0.05	0.00	0.07	0.35
		Rail	0.38	0.00	0.11	0.23	0.04	0.08	0.16
		Coach	0.18	0.55	0.00	0.05	0.02	0.06	0.15
		Air	0.36	0.26	0.01	0.00	0.00	0.09	0.28

5.4 Elasticities based on transfer cost and transfer time

The responses to the 'transfer cost' and 'transfer time' questions presented in the previous section can be used to obtain estimates of own-cost and -time elasticities. Although the absolute levels of elasticities estimated by this technique may be questionable, the relativities implied can nevertheless be used to derive unknown elasticities from known ones.

The responses to the transfer cost and time questions were used to construct a demand curve from which to calculate journey cost and journey time elasticities. 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 resulting cost- and time-elasticities are shown in Table 23. To have a reasonable sample size for the estimation, we only consider two purposes: business and other. The average journey time and average cost for each mode-distance-purpose combination is also shown in the table. We see that business journeys generally cost more than others although they are not necessarily longer in terms of time. As expected, coach journeys are the least expensive and air journeys the most costly, while car trips cost less than rail trips.

The estimated cost and time elasticities are of a reasonable order of magnitude, and of the order of magnitude reported in the literature. We find that air is most price-sensitive, followed by rail, then coach and finally car. Coach and rail travellers are more sensitive to changes in journey time than car users are, but air travellers are least sensitive. Otherwise, there is little consistent difference in elasticities between the two journey purposes or distance bands. The differences between business and other trips are not consistent. Generally, the elasticities are very similar for the two purposes or business is slightly less cost sensitive, as would be expected. The opposite, however, is the case for car, with business trips being more elastic.

The value of time, λ, can be calculated from the cost and time elasticities according to:

$$\lambda = \frac{T}{C}\frac{\varepsilon^{C}}{\varepsilon^{T}} \qquad (7)$$

where T and C are the average journey time and journey cost and ε^T and ε^C are the journey time and journey cost elasticities. The implied values of time, shown in the final column of the table, are in line with other evidence[38], although the values for leisure trips are rather high. As expected, the value of time is greater for business trips than it is for leisure trips, while it is greatest for air travellers and lowest for coach users.

[38] See Wardman (2009).

Table 23: Own elasticities with respect to travel cost and journey time based on transfer cost and time and implied Value of Time (2008 prices), ITSS

Mode	Distance (miles)	Purpose	Mean journey time (mins)	Mean cost (£)	Cost elasticity	Journey time elasticity	Implied value of time p/min
car	<150	business	257	35	-0.43	-1.71	55
		other	266	24	-0.32	-1.57	44
	150 +	business	407	49	-0.55	-1.86	41
		other	473	35	-0.47	-2.00	32
rail	<150	business	230	45	-0.83	-2.17	52
		other	265	28	-0.79	-1.80	25
	150 +	business	490	82	-0.79	-2.22	47
		other	436	55	-0.87	-2.15	31
coach	<150	business	267	24	-0.70	-1.90	25
		other	341	20	-0.74	-2.18	17
	150 +	business	453	27	-0.62	-1.72	16
		other	601	35	-0.71	-2.44	20
air	<150	business	210	245	*	*	*
		other	240	112	*	*	*
	150 +	business	308	205	-0.98	-0.89	60
		other	271	128	-1.00	-0.86	40

* air is not considered for journeys less than 150 miles.

5.5 Choice modelling

As mentioned earlier, the ITS Survey was conducted primarily to obtain estimates of diversion factors from which to deduce cross elasticities. Another purpose of the survey was to collect transfer price and transfer time data, which denote respectively the cost and time increases that would induce a change in behaviour. Whilst not necessarily a reliable guide to behaviour in absolute, they can be expected to provide a more accurate guide to relative elasticities and therefore serve a useful purpose in enabling decomposition of overall elasticities into market segment specific elasticities.

As part of the survey, respondents were also asked to provide details of the times and costs of the modes available to them. Of the 4092 returned questionnaires, only 1101 provide sufficient information for modelling purposes. This consists of time and cost information for their current mode and at least one available alternative. Whilst it is typical that a large number of respondents in self-completion questionnaires do not provide full details of the times and costs of alternative modes, this level of attrition is atypically high. However, as the survey relates only to long distance journeys which are generally not made regularly, it is perhaps not surprising that individuals are not as aware of the costs and travel times by modes they are not using.

Given that above caveat, we took the opportunity to model the data. Initially, standard multinomial logit models were estimated. However, these constrain the cross-elasticities to be the same, the infamous independence of irrelevant alternatives property, and this was deemed undesirable given that a key contribution of these choice models was to provide such cross-elasticity estimates. The usual means of overcoming this problem is to estimate hierarchical or nested logit models. We found that the best fitting model was to combine car and air in one nest and rail and coach in another.

We also examined the extent to which the time and cost coefficients varied across the journey purposes of business, commuting, visiting friends and relative, holiday and leisure. This was done by means of incremental terms, allowing a coefficient for a specific purpose to vary from the arbitrarily selected base purpose category. We also allowed the time and cost coefficients to vary with distance.

The models were estimated in units of round trip time and cost, although distance is one way. The only significant effects discerned for purpose were, as would be expected, that the cost coefficient was lower for business travel, since the employer will pay, and it was larger for visiting friends and relatives.

No significant effect was obtained from distance on journey time. However, we specified a function for the cost coefficient of:

$$U = \alpha C + \beta D^{\lambda} C \qquad (8)$$

We found that the best fitting model was for a λ of 0.7. Given that β was found to be positive while α has the usual negative sign, this means that the sensitivity to cost falls with distance.

The model results are reported in Table 24. The Rho-squared goodness of fit measure is respectable for choice models. Whilst the t ratios of the coefficient estimates are low relative to more common SP models, the sample size is much smaller than typically contained in SP models. Nonetheless, the model has the attraction of being based on what people actually do rather than what they say they will do.

The alternative specific constants (ASCs) denote a preference for a mode relative to the base mode of car. Whilst these are all relatively large terms, indicating all modes are preferred to car, our sample is not representative of the overall population of travellers. Standard procedures have been used to adjust these constants in line with the actual market shares by mode as apparent in the NTS data prior to forecasting. This adjustment has been done by purpose and whether distance is more or less than 150 miles. However, since the models themselves will not be used for forecasting, ASCs are not important.

The time coefficient was allowed to vary by mode. Whilst not all the coefficients are statistically significant, a single time coefficient by mode is certainly significant, so we maintained differences by mode since the relative variations seem sensible. Time spent in car is found to be least unpleasant, followed by train and coach. The highest disutility of travel time is found for air, and presumably this reflects a ‘fear’ factor. Note these reflect variations in the value of time by mode, not by mode user.

The distance effect does not have a large impact on the value of time, and will not of itself have a large impact on the elasticities implied by this model. For a distance of 200 miles, and for purposes other than business and visiting friends and relatives, the value of time for car is 3.30 pence per minute, which is rather low. However, it rises to 7.27 pence per minute for rail, to 11.80 pence per minute for coach and to 17.20 pence per minute for air. In general the implied values of time are much lower than those calculated from the transfer cost and time questions reported in Table 23 and also lower than those reported elsewhere.[39] Of greater interest, given the purpose of the study, are the implied elasticities.

Table 24: Estimation results for Hierarchical Logit Mode Choice model based on ITSS

ASC-Car	Base
ASC-Train	4.107 (2.9)
ASC-Coach	6.575 (3.6)
ASC-Air	5.538 (3.2)
Car Time	-0.0015 (1.3)
Train Time	-0.0032 (2.1)
Coach Time	-0.0052 (3.1)
Air Time	-0.0078 (2.1)
Cost	-0.0566 (3.0)
+ Cost Business	0.0224 (2.0)
+ Cost VFR	-0.0166 (1.7)
+Miles$^{0.7}$	0.0003 (2.3)
Scale Car&Air	0.51 (4.6)
Scale Rail&Coach	0.64 (4.4)
Rho Squared	0.162

Note: Costs in pounds and times in minutes. t ratios in parentheses

Table 25 and Table 26 report the own elasticities for cost and time implied by the models. These were derived using sample enumeration. It must be recalled, however, that mode choice models only capture competition between modes and do not allow overall demand to increase or fall in response to changes in travel costs and time, so that the elasticities obtained will underestimate the market demand elasticities which are required for forecasting purposes. We note that the cost elasticities are lower for employer's business in line with the incremental effect on cost.

Table 25: Own cost elasticities from Hierarchical Logit model, ITSS

		Business	Leisure	Holiday	VFR	Commuting	All	Total both distances
<150 miles	Car	-0.057	-0.280	0.000	-0.082	-0.100	-0.087	
	Rail	-0.313	-1.913	0.000	-0.304	-0.724	-0.456	
	Coach	0.000	0.000	0.000	-0.273	0.000	-0.179	
150+ miles	Car	-0.026	-0.061	-0.031	-0.094	-0.082	-0.069	-0.069
	Rail	-0.326	-0.495	-0.561	-0.719	-0.477	-0.566	-0.557
	Coach	-0.280	-0.256	-0.276	-0.354	0.000	-0.304	-0.290
	Air	-0.194	-0.797	-0.296	-1.065	-1.050	-0.640	-0.607

[39] See Wardman (2009).

Table 26: Own time elasticities from Hierarchical Logit model, ITSS

		Business	Leisure	Holiday	VFR	Commuting	All	Total both distances
<150 miles	Car	0.000	0.000	0.000	-0.041	0.000	-0.017	
	Rail	-0.313	-1.913	0.000	-0.304	0.000	-0.340	
	Coach	0.000	0.000	0.000	-0.273	0.000	-0.179	
150+ miles	Car	-0.046	-0.035	-0.031	-0.035	-0.055	-0.037	-0.036
	Rail	-0.468	-0.423	-0.447	-0.482	-0.477	-0.466	-0.445
	Coach	-1.167	-0.652	-0.704	-0.846	-1.000	-0.822	-0.751
	Air	-0.696	-0.797	-0.600	-0.763	-0.512	-0.710	-0.677

The main contribution of choice models is the information they provide on switching between modes and thus on cross-elasticities. However, it was felt that values of the cross-elasticities obtained were rather questionable, and given the small samples on which they were based, it was decided that they should not be used in determining the cost and time elasticities to be used in the forecasting model. They are thus not reported here.

5.6 Choice of cost and time elasticities for the forecasting model

The estimates of aggregate elasticities, diversion factors and relativities discussed in the previous sections, together with the results of the transfer cost/time analysis have been used in conjunction with information from the NTS and the ITSS to determine the elasticities for the forecasting model. A final set of cost and time elasticities are presented in Table 27. In addition to the relationship between diversion factors and cross-elasticities in equation (6), we have also made use of economic demand theory, and in particular, Slutsky symmetry between opposite cross-price elasticities:

$$\varepsilon_{ij} = \frac{c_j}{c_i}\varepsilon_{ji} \qquad (9)$$

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 :

$$\varepsilon_{ij}^T = \lambda \frac{T_j}{C_j}\varepsilon_{ij}^C \qquad (10)$$

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 8, 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 8 suggests a much lower elasticity. Based on other evidence[40], 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 (Table 21) 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 9).
- The cross-elasticities are calculated using the diversion factors (Table 21), the relationship between cross-elasticities and diversion factors and Slutsky symmetry (equation 9).
- The own- and cross-elasticities with respect to journey time are calculated from equation 10 using the cost elasticities and the value of time estimates shown in the table. This method ensures consistency between the cost and time elasticities[41].

Since the own-elasticities are based on long-run values, and other elasticities derived from these, all elasticities are assumed to represent long-run values. Since the ITS survey was only used to determine relativities amongst elasticities, the observation that the ITSS sample is not representative of the long-distance travel as reported in the NTS (or of actual long distance travel) should not bias the results significantly. Limited sensitivity analysis was carried out by weighting the diversion factors by area of residence, but this was shown to have very little effect on the resulting elasticities.

[40] See Dargay etal (2006)

[41] Alternatively, we could have begun from the journey time elasticities, but aggregate estimates could not be obtained from the available data (see Section 3.1) and the existing literature is rather limited.

Table 27: 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
			Car	Rail	Coach	Air	Car	Rail	Coach	Air	p/min
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

6 Input Assumptions and Scenario Specification

In this section, the assumptions underlying the base projections are discussed, followed by a summary of the specific scenarios which will be examined.

6.1 Elasticity assumptions

The elasticities relating to socio-economic and demographic factors are based on the NTS modelling. The long-run income elasticities are shown in Table 17. The others are given in Table 14, assuming these to be medium-term elasticities (2/3rds of the long-run values). The long-run elasticities with respect to journey cost and journey time are those presented in Table 27. All 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.

6.2 Projections of the population: socio-demographics and geography

Projections of the population and its socio-economic and demographic characteristics are important inputs to the forecasting model. We make use of national projections provided by the Office of National Statistics (ONS), the Government Actuary's Department (GAD) and the General Register Office of Scotland. These are listed below:

- Population by age and gender to 2031;
- The number of households, average household size, the number of 1-person households and the employment age population to 2031.

Principal projections as well as a number of variants (high/low with regards to migration/life expectancy/fertility) are given in the statistical sources, which can be used for sensitivity testing. The principal projections are used in the forecasting model. These are shown in Table 28, along with the average annual growth rates. 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.

Table 28: Socio-demographic projections

	1996	2005	2010	2020	2030	Average annual % change	
						1996-2010	2010-2030
Population (mill.)	56.5	58.5	60.5	64.8	68.8	0.49	0.64
% Women	51.4	51.0	50.8	50.5	50.4	-0.08	-0.04
% 60 years +	20.7	21.2	22.6	24.6	27.9	0.62	1.07
% 1-adult hhs	14.2	16.8	17.9	20.1	21.8	1.70	0.98
% Working age	62.2	62.2	61.9	62.1	61.3	-0.04	-0.05
Households (mill.)	23.0	24.8	26.2	29.2	31.8	0.92	0.98

A substantial growth in the proportion of the population 60 years of age and older is apparent. However, only a small decline in the proportion of the population of working age is expected since the retirement age is expected to increase[42].

6.3 Projections of the economy

Projections of income are based on GDP[43] forecasts from HM Treasury[44] and the 2009 Budget Report shown in Table 29. The first row shows the forecasts for 2009 and 2010 from HMT's 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). Both of these are based on the averages of a number of independent forecasts. The second row gives the GDP forecasts for 2009 – 2011 from HM Treasury Budget Report 2009. Clearly, these are more optimistic than the independent forecasts shown in the first row, whilst both of these represent a substantial reduction in growth from the forecasts presented a year ago in HMT (February 2008), which were 2.0% and 2.6% for 2009 and 2010, respectively. In the longer term (from 2012) we assume an average growth rate of 2.5% per annum, based on historic average rates.

Table 29: Real GDP forecasts, annual % change

	2009	2010	2011	2012 to 2030*
HMT (April 2009)	-3.7	0.3	2.2	*2.5*
2009 Budget Report	-3.5	1.25	3.6	*2.5*
HMT (February 2008)	2.0	2.6	2.6	*2.5*

* historic average

The effect of the downturn in the economy on long-term GDP projections is illustrated in Figure 4. The dashed line shows real GDP development to 2030 based on the forecasts of February 2008 for years 2009-11 and the growth rates shown in Table 29 for subsequent years. GDP is forecast to grow by 72% by 2030. The solid line is GDP based on the revised forecasts (April 2009) for 2009-11 and the same growth rates as previously for subsequent years. GDP is forecast to grow by only 58% by 2030. Thus in 2030 GDP will be 8.1% lower than originally forecast. Assuming an income elasticity for domestic long distance travel of 1.0, the reduction in GDP growth over the next two years implies, *ceteris paribus*, that long-distance travel would be 8.1% lower in 2030 than would have been the case otherwise.

For the long distance travel projections, the central GDP growth assumptions will be the HMT (April 2009) forecasts shown in the table. These are less optimistic than the forecasts in the 2009 Budget Report, but over the longer term, the difference is marginal. To investigate the impact of the recession, the forecasts will be compared with those based on the GDP assumptions in HMT (February 2008).

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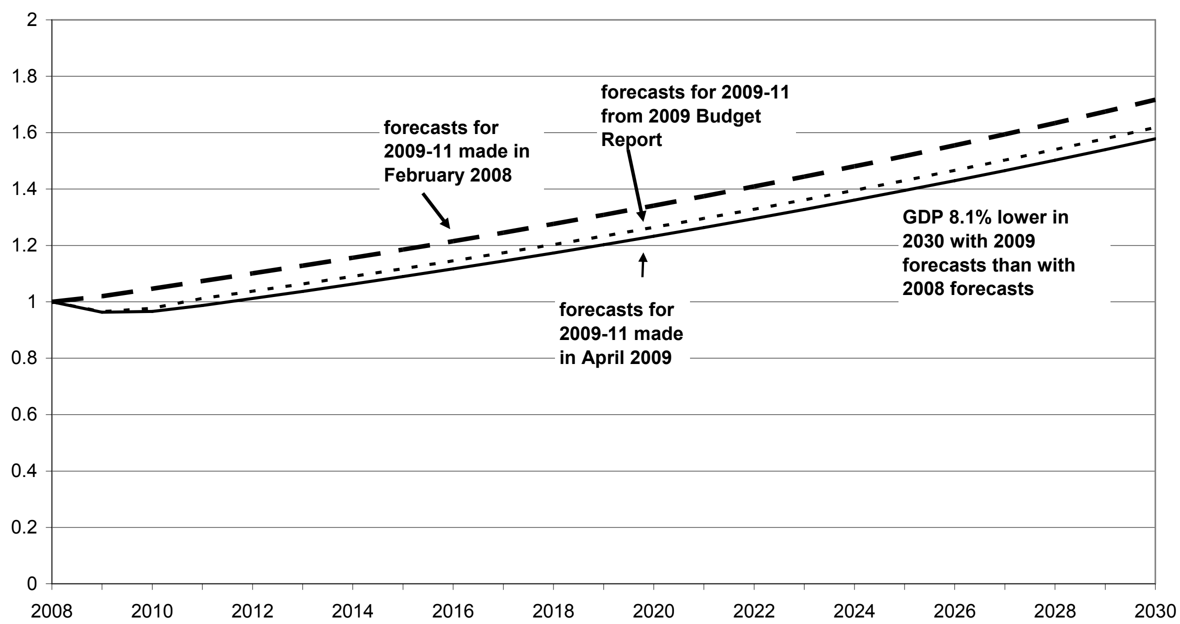
[42] Between 2010 and 2020 the state pension age will be equalised to 65 years for both sexes and between 2024 and 2046 it will increase to 68 years in three stages.

[43] 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.

[44] Projections are only available for the UK. These are assumed to be the same for GB.

Income enters the forecasting model in per household terms and based on the projections of the number of households, GDP per household will increase by around 1.5% per year from 2012.

Figure 4: Real GDP forecasts



6.4 Transport costs

- Fuel prices

Fuel prices are determined largely by crude oil prices and taxation. Crude oil price projections are taken from the scenarios produced by The Department of Energy and Climate Change (DECC), which are shown in Table 30.

Table 30: Crude oil price assumptions, 2008 US$/bbl, DECC (2009), 2008 price: $102/bbl

Scenario	2010	2015	2020	2025	2030
1	50	58	60	60	60
2	70	75	80	85	90
3	84	102	120	120	120
4	103	142	150	150	150

Since crude oil is priced in US dollars, an assumption will also be 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.

Forecasts of the prices of petrol and diesel (including duty and VAT) based on the above crude oil price scenarios and US$ exchange rate have been obtained from the DfT[45]. 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 between 16% (Scenario 1) and 33% (Scenario 4). Over the same period, vehicle fuel efficiency (km/l) is assumed to increase by 92% for petrol cars (from 13.1 km/l to 25.0 km/l) and by 43% for diesel cars (from 16.0 to 22.8 km/l). This improvement in fuel efficiency assumes that the two EU new car fuel efficiency targets are met, i.e., 130g CO_2 in 2013 and 95g CO_2 in 2020. Taking this into account, fuel costs per km (or mile) are forecast to decline from by 40% for petrol cars and 19% for diesel cars (Scenario 1) to by 30% for petrol cars and 7% for diesel cars (Scenario 4) over the period.

- Motoring costs

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 over the forecast period. This is not based on DfT projections, but is a reasonable assumption given current policy[46].

- Air fares

Projections of air fares are obtained from DfT[47] and are calculated as described in their UK Air Passenger Demand and CO_2 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 CO_2 emissions. The DfT have provided air fare forecasts based on the oil price assumptions in Table 30 and the exchange rate of $1.60/£ as used for our motor fuel price projections. As shown in Table 31, under these assumptions domestic air fares are expected to fall by between 9% and 18% over the next 20 years, depending on the crude oil price.

Table 31: Domestic air fare projections, oil price scenario as in Table 30, $1.60/£ exchange rate, 2004 prices (Source: DfT)

Scenario	% change 2009 - 2020	% change 2009 - 2030
1	-15	-18
2	-15	-16
3	-8	-13
4	-3	-9

[45] These were kindly provided by Taro Hallworth, DfT.

[46] Although car purchase costs have declined considerably over the past decades, this is unlikely to continue due to the costs of efficiency improvements and alternative fuel technologies.

[47] These were kindly provided by Alison du Sautoy, Scott Wilson.

- Coach fares

As with motoring costs, these are 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.

- Rail fares

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

6.5 The Base Case

The assumptions used for the Base Case are outlined below:

- GDP growth from HMT (April 2009) as Table 29, 2.5% per annum from 2012 (58% between 2009 and 2030).
- Crude oil price of $84 in 2010, rising to $102 in 2015, and to $120 in 2020 and thereafter as DECC Scenario 3.
- US$-Sterling exchange rate: constant at $1.60 over the period as assumed by DECC.
- Petrol and diesel prices increase by 27% in real terms over the period as calculated by DfT on the basis of DECC Scenario 3
- 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. Assuming non-fuel costs remain constant in real terms, total motoring costs increase only marginally (about 0.5% over the entire period).
- Average increase in journey time on the road network 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.
- No capacity constraints on the rail or air networks and no travel time changes.
- Rail fares to increase 1% per annum in real terms over the period.
- Coach fares increase by 3% between 2009 and 2030.
- Air fares to decline by 12.5% between 2009 and 2030 from DfT's projections based on DECC Scenario 3.
- ONS 2006-based Principal Case projections for population, the number of households, the proportion of women, the share of the population aged 60 and over and the proportion of 1-adult households as shown in Table 28. Population is assumed to increase 14% between 2009 and 2030.

6.6 Alternative scenarios

The objective of the model is to investigate the impact of various policy measures and supply-side factors on long distance travel. These are incorporated into the model by considering their effects on the exogenous variables included, primarily travel costs and travel time, by determining how they will affect the average traveller. This is done on the basis of NTS data, the ITS Survey and other data collected in the project, as well as through discussion with various experts, both academic and in the transport industry. The following discusses the specific scenarios which are considered.

- Constant real rail fares over the period

In the Base Case, it was assumed that all rail fares increase by 1% per annum in real terms over the forecast period. This can be seen as an upper estimate. In this scenario, we assume that real rail fares remain at their 2009 level until 2030.

- National road charging scheme

We assume an average charge of 5p/km (in 2008 prices) for business and commuting and 2p/km for all other purposes, because of differences in congestion in the peak and off-peak. All other motoring costs are assumed to remain as in the Base Case. This results in an increase in total motoring costs of 21% (business and commuting) and 8% (other) between 2009 and 2030. We also assume that the introduction of road user charging will reduce congestion so that the assumed increase in journey times in the Base Case is reduced by one half.

- Tax on air travel

An increase in the APD of £10 is added to the Base Case air fares. This results in an increase in air fares of 1% over the period.

- Double the reduction in air fares

Air fares to decline by 25% over the period.

- Different car fuel efficiency assumptions

In the Base Case, an improvement in car fuel efficiency of 1% per year between 2009 and 2030 (23% over the period) is assumed. Two alternatives are examined: no improvement over the period and that assumed by DfT of 92% for petrol cars and 43% for diesel cars (High car fuel efficiency). Using DECC Scenario 3 fuel prices, the former results in an increase in motoring costs of 10% over the period and the latter an decrease of 10%.

- Motoring cost increase by 1% per annum over the period

We assume an increase in total motoring costs of 1% per year, which arises from increases in any of the components of motoring costs: fuel, road tax, purchase costs, etc.

7 Projections of Long Distance Travel

A dynamic, elasticity-driven forecasting model has been developed in Excel based on the model described in Section 2 and the cost, time and socio-economic and demographic elasticities presented in Sections 4 and 5. The resulting forecasts for long distance travel based on the various assumptions described in Section 6 are presented below. Although point estimates are given for each year, it must be stressed that, as is the case with any forecasts, these points should be seen as lying within ranges of possibilities.

7.1 The Base Case

The assumptions used in the Base Case and described in the previous section are summarised in Table 32 below.

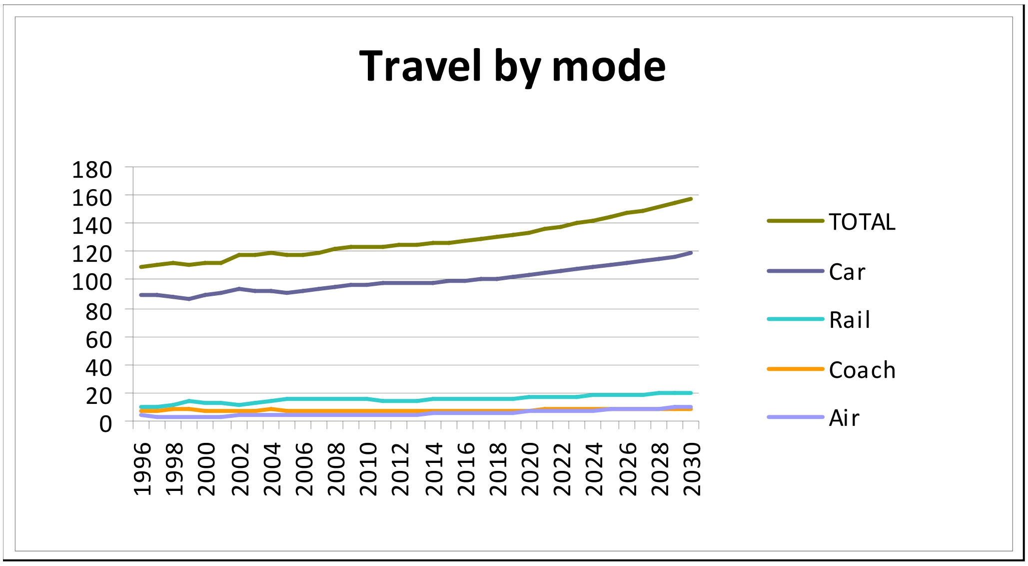
Table 32: Base Case assumptions

	% change 2009 - 2030	Source/assumptions
GDP	58%	HMT (April 2009)
Population	14%	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

The projections for the Base Case are shown in Figure 5. 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).

To estimate the impact of the current recession on long distance travel, Table 33 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), shown earlier in Table 29. Recall that 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 5: Base Case projections for long distance travel, billions of person miles



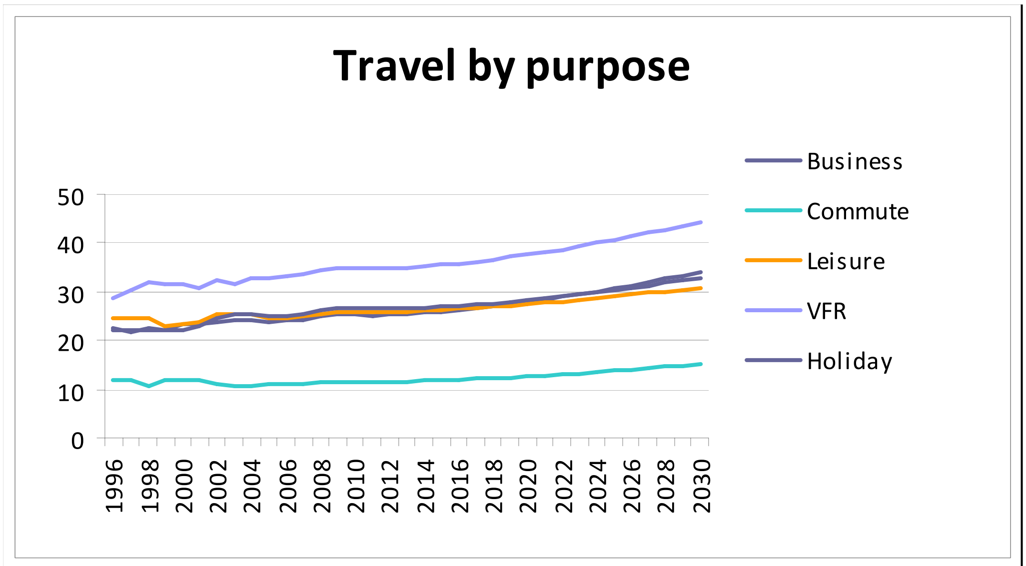
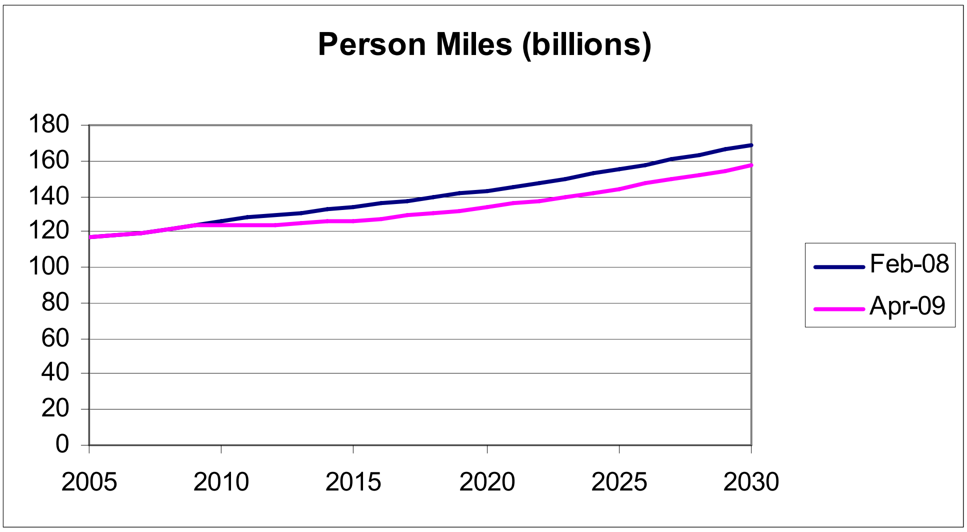


Table 33: Long distance travel forecasts for 2030, billion person miles, based on different GDP forecasts

GDP forecast	Car	Rail	Coach	Air	Total
HMT (April 2009)	118.5	20.1	8.6	9.9	157.1
HMT (Feb 2008)	125.9	22.7	8.7	11.9	169.2
% change from 08	-6%	-11%	-1%	-17%	-7%

The effect of the downturn on total long distance travel is further illustrated in Figure 6. Travel is reduced by 1.4% in 2009, is 5% lower in 2013 and remains 7% lower in 2030.

Figure 6: Effect of the recession on long distance travel, based on GDP forecasts of February 2008 and April 2009.



7.2 The impact of different scenarios

The assumptions made in the scenarios under consideration are summarised in Table 34. 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 34: 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 Journey time +3% (+6%)	5p/km business & commuting 2p/km all other purposes
Increase in APD	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 35 (in billions of person miles) and
Table 36 (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 billions 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.

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 35: 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

Table 36: 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 37. 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 37: 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 38. 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 38: 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

7.3 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 39. 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.[48]

Table 39: 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 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.

A sensitivity test was also carried out using the projections of the working age population from Table 28 and the elasticities relating to employment from Table 14. The forecasts are not very different from the Base Case and thus are not reported here. Although the population is expected to age substantially, the planned increase in the pension age will mean that the proportion of the population of working age will not decline significantly by 2030, so it will have a negligible impact on travel.

[48] 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.

8 Model Evaluation and Limitations

As is the case with any model, the accuracy of the forecasts produced by the model developed in this study depends upon a range of factors. These are primarily: the external drivers included in the model, the parameters determining the effects of external factors on travel demand and the base values from which the forecasts are made. In this section, the importance of these assumptions for the forecasts is discussed and the model is evaluated using backcasting techniques.

8.1 Assumptions

Regarding demand drivers, our model includes the most important factors known to influence travel demand – income, travel costs and travel time. We have also included socio-demographic factors shown in our analysis of NTS data to have a bearing on long-distance travel. We were limited to those factors for which projections into the future exist and have excluded those for which no significant changes are foreseen. By definition, a model is a simplification, but we feel the main driving factors have been included.

Our forecasts are also clearly highly dependent on the accuracy of the projections for the external drivers. We have seen that the projections are sensitive particularly to assumptions concerning future income growth. This is not at all surprising, as there is little doubt that rising income has been, and will continue to be, the primary impetus for growth in travel. The socio-demographic projections used are based on national sources and are the best available. Any changes in population growth will, of course, impact on our projections. As population growth might be lower than assumed, owing to reduced immigration resulting from the economic downturn, the travel forecasts might be considered to be upper values.

The parameters defining the relationships in the model – the elasticities – play an important role in determining the forecasts. Considerable effort has been put into the estimation of these elasticities using a variety of data sources: NTS data, aggregate time-series data and a survey of long distance travel carried out for the project. The elasticities are of reasonable orders of magnitude and are in the ranges suggested by other empirical evidence. Of course, there is always some degree of uncertainty in estimated values. However, although we feel that the values used in the model represent the most reliable information currently available, further sensitivity testing would be useful.

The base values for travel demand by mode, purpose and distance band are based on the NTS. We have seen that there might be some question in the development of long distance travel over time obtained from the NTS, but as the model doesn't rely on these changes to forecast future demand, this is not a significant problem. The base values are taken as an average of the 3 most recent years' data (2004-2006). Although they may contain sampling errors, these data are the only information available. Any errors in these data, however, will only affect the absolute level of our forecasts, but not growth rates over time, nor differences in demand amongst scenarios.

As witnessed in the previous section, the model is projecting a significant increase in travel to 2030. This may seem questionable given the relatively low growth noted from the NTS. Table

40 shows the average annual growth rates implied by the Base Case projections compared to the growth rates from the NTS and TSGB. We see that the Base Case implies that total long distance travel will grow more rapidly in the future than that implied by the NTS for the period 1996 to 2005. The growth rate is nearer to, but still greater than, that in TSGB for all travel by these modes (both long and short distance) for the same period.

The reason for this discrepancy lies mainly with car travel. The projected growth rate is over twice that noted in the NTS, and also higher than for all distances by car and taxi from TSGB. However, it is not unlikely that long distance car travel has increased more rapidly than shorter distance travel and that it will continue to do so. The NTS data do suggest a fall in car travel for all distances between 1996 and 2005, but an increase in car travel for trips over 50 miles. This question requires further examination and analysis of the more recent NTS data may shed some light upon this.

Regarding the other modes, the Base Case implies a lower growth rate for rail than either the NTS or TSGB. The low projections for rail travel are likely explained by the assumed increase in rail fares in comparison to motoring costs used in the Base Case. For air, projected growth is much higher than in the NTS, but lower than that noted in TSGB. The latter is more likely to be accurate as it is based on aviation statistics whilst the NTS sample for air trips is rather small. For coach the projected increase is greater than shown in the NTS but smaller than TSGB estimates. Given the small proportion of coach trips in the NTS, the growth rate estimates are questionable.

Table 40: Average annual growth rates, Base Case, NTS and TSGB

	Car	Rail	Coach	Air	Total
Base Case 2005 to 2030	1.1	1.2	0.9	3.3	1.2
NTS 1996 to 2005	0.4	4.7	0.03	0.6	0.9
TSGB 1996 to 2005	0.9*	3.3	2.0**	5.0	1.1

* car and taxi; ** non-local coaches and buses, Public Transport Bulletin 2008

8.2 Backcasting

The performance of the model can be evaluated by backcasting, which shows how well it explains the existing data. To do this we use the estimates of long-distance travel for the years 1996 to 2005 by mode, purpose and distance obtained on the basis of the NTS, which were discussed in Section 3 and illustrated by mode in Figure 1. The model takes 1996 as the base (start) value and produces forecasts for the years 1997 to 2005 based on historic values of the explanatory variables. The ability of the model to explain the data, or the model's accuracy, can be measured by the Mean Absolute Percent Error (MAPE). This is calculated as the average of the absolute values of the percent error for each year, with the percent error equal to (actual value – forecast value)/actual value.

The MAPEs are shown in Table 41. From the first row we see that the MAPE for total long distance travel is quite low, 1.8%, suggesting a very good accuracy. The MAPE is also small for car, but very high for air (23.3%), while those for rail and coach are 7.8% and 6.5%. By purpose, the model performs better, with MAPEs between 2.2 and 3.3% for all purposes but commuting, which is quite a bit higher at 6.6%. We note that the forecast errors are greatest for the mode and purpose which have the smallest shares of total travel.

Also shown in the table is the coefficient of variation (the standard deviation divided by the mean) of the actual values of the travel observations over the 10 year period. This gives a comparable measure of variation in the observations of travel for each mode/purpose. A high coefficient of variation indicates a high degree of variability in the data. It is apparent that the model's ability to explain the data is inversely related to the coefficient of variation, i.e., the more variability in the data the more difficult it is to explain and the greater the MAPE. The high variability in the air data reflects its small share and the inaccuracy in its measurement in the NTS due to the small number of air trips recorded. It is not surprising that the model performs so poorly in explaining this measure of air travel. Similar observations can be made with respect to rail and coach travel.

Given the nature of the data, it is not so surprising that the backcast errors are so high, and it is encouraging that total long distance travel and car travel are predicted so well.

Table 41: Backcasting results

	MAPE	Coefficient of variation
All	1.8	0.020
Car	2.8	0.020
Rail	7.8	0.120
Coach	6.5	0.072
Air	23.3	0.233
Business	3.3	0.026
Commuting	6.6	0.053
Leisure	3.3	0.031
VFR	2.7	0.034
Holiday	2.2	0.056

The percentage forecast errors for each year are shown in Table 42. Since these are calculated as (actual value – forecast value)/actual value, positive values indicate that the forecasts are below the actual values (an underestimation) and negative values indicate that the forecasts are above the actual values (an overestimation). There is a good deal of volatility and there appear to be no obvious trends over time. The forecasts for the latest year (2005) are the most inaccurate for car, coach and total travel, while the largest errors for rail and air are for 1999.

Most notable is that in the most recent years, the model is overestimating total travel and car travel and underestimating rail travel. Whether this is an anomaly of the NTS data or a weakness on the part of the model requires further investigation. One suggestion is to compare the rail backcasting results with data from the rail industry (LENNON data). A further test would entail comparing the model forecasts for 2006 to 2008 with the latest NTS data when they become available.

The large errors are perhaps not surprising given the fact that the NTS data are more suited for discerning long-term trends in travel behaviour, rather than for measuring the year-to-year changes we are forecasting. It can be noted, that over the period as a whole, the forecasted growth rates are higher for total travel, car and air and lower for rail than the growth rates suggested by the NTS and thus more in agreement with other sources.[49] In particular, the forecast growth rate for air is very much higher than suggested by the NTS.

Table 42: Forecast errors in %: (actual – forecast)/actual

	Car	Rail	Coach	Air	Total	Business	Com-muting	Leisure	VFR	Holiday
1997	0.8	5.2	3.8	-44.1	0.2	-4.8	-1.9	-0.6	5.2	0.3
1998	-2.4	13.4	9.5	1.5	0.3	0.2	-12.0	0.5	5.6	-1.6
1999	-4.0	17.1	2.0	-59.7	-2.1	-4.0	5.3	-8.6	1.0	-1.9
2000	0.7	-2.6	-7.4	-26.1	-0.7	2.0	-2.6	-1.7	-0.3	-2.4
2001	-1.1	0.7	-9.3	-27.3	-2.0	-2.6	-3.4	-3.0	-3.2	1.8
2002	0.0	1.1	5.6	14.8	0.9	-2.4	-8.5	3.0	2.6	4.2
2003	-4.5	11.9	4.3	-17.4	-2.5	-2.5	-11.7	-2.1	-3.7	2.3
2004	-4.2	6.0	6.4	0.6	-2.2	-4.7	-6.2	-2.8	0.4	-0.7
2005	-7.2	12.5	-10.6	-17.9	-5.3	-6.3	-7.8	-7.4	-2.7	-4.5

[49] See Section 3.1.

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