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Task Title: Provision of Travel Trends Analysis and Forecasting Model Research

Analysis and Developer Report

develop a tool that allows estimation of trip rates up to

Plan Design Enable

Highways Agency/DfT
Framework for Transport Related Technical and Engineering Advice and Research Lot 2

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Submitted by:

Atkins

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Contents

Section **Page**

1. Introduction

1.1 Context

1.1.1.1 The Department for Transport (DfT) commissioned a research study to investigate recent travel trends and identify the main drivers of these trends. Whilst trends in various travel demand measures are of interest, the main focus of the study was trip rates.

1.1.1.2 The research was expected to result in the development of a forecasting model to forecast trip rates following the identification of the main drivers and estimation of their partial effects.

1.1.1.3 The study was therefore undertaken in three main stages which are reported here. The objective of the first stage of the study was to conduct a literature review of research into recent travel trends and identify possible drivers of travel trends.

1.1.1.4 The objective of the second stage of the study was to develop a forecasting model which uses the statistical relationships identified from the analysis conducted in the first stage and estimate their likely impact on future trip rates via their impact on the forecasting parameters within NTEM.

1.1.1.5 The third stage of the study was planned to match the segmentation from the output trip rates and other NTEM parameters from the forecasting models to the NTEM input segmentation structure, enabling the forecasting output to be used within NTEM.

1.2 Structure of the Note

1.2.1.1 The remainder of this report is structured as follows:

- Chapter 2 provides a summary of the literature reviewed and sets out a list of potential drivers of trip rates;
- Chapter 3 describes the key study hypotheses, the data used to develop the study dataset, and the approach taken to model trip rates;
- Chapter 4 explains the key findings from the analysis, and discusses the possible explanations behind these;
- Chapter 5 describes the trip rate forecasting tool, developed based on findings from the analysis;
- Chapter 6 provides a summary of the main findings and recommends further areas of study;
- Appendix 1 shows the estimated negative binomial models;
- Appendix 2 shows the estimated zero-inflated models for the segments where these models were preferred to the standard negative binomial models; and
- Appendix 3 shows a correspondence between Census categories of household composition and car ownership, and household type and age categories in the trip rate models, used to prepare the base year population data for the tool.

2. Literature Review Summary

2.1 Overview

2.1.1.1 The purpose of this chapter is to summarise the nature of changes in travel behaviour that have been observed.

2.1.1.2 Given the overall study purpose, we focused first on changes in trip rates that have been observed over time; and secondly on trends in other travel demand indicators. Finally we discuss cross-sectional variations in travel demand. In Section 2.3 we discuss the factors proposed in the literature that may have caused the observed trends.

2.2 Observed Trends

2.2.1 Time-series Changes

Trends in GB trip rates

2.2.1.1 Recent analysis of GB National Travel Survey (NTS) data suggests that average trip rates have decreased between 1988 and 2010 for the majority of trip purposes (i.e. commuting, shopping, visiting friends and family, and personal business) whilst average trip rates for holiday / day trips have increased and education trip rates do not show any clear trend (DfT, 2014a: DfT, 2014d). Analysis of trip rates by mode and distance band has suggested that changes in walking trips and short trips have made a significant contribution to the overall observed trends in trip rates:

- the analysis of NTS data undertaken by DfT (DfT, 2014b) shows that for commuting trips, only trips less than 5 miles have decreased whilst trips greater than 5 miles do not show any clear trend;
- in the case of shopping trips, the effect of the decline in shorter trips on overall observed trends in trip rates is even more clear where trips less than 1 mile are the only category of trips that have dropped consistently since 1988; and
- for visiting trips, all distance bands show a similar deceasing trend; however, there has been a significant shift from shorter trips to longer trips (5 miles or greater).

2.2.1.2 In terms of modes of travel, walking, car driver, and car passenger account for the vast majority of trips made across all purposes (DfT, 2014a; DfT, 2014b). For commuting trips, car trips (accounting for the majority of trips) have clearly decreased whilst rail / underground have slightly increased and bus trip rates remained constant, during 1998-2010. For both shopping and visiting trips, the vast majority of trips are car and walking, both of which have decreased consistently since 1998. For shopping trips, walk trips decreased more than car trips.

2.2.1.3 In the analysis undertaken by DfT (DfT, 2014b), significant variations in trends in trip rates were also observed between area types.

- For commuting trips, whilst trip rates have decreased consistently for all area types, urban areas with population between 25,000-100,000 show the greatest reduction followed by rural areas.
- The greatest reduction in the average number of shopping trip rates during 1998-2010 has been observed in London. The trip rates in other areas have increased or remained relatively flat during 1988-1998 and then constantly decreased from 1998.
- Similarly, whilst average trip rates for visiting trips have decreased significantly across all area types, London shows the biggest decrease.

2.2.1.4 Analysis of trends by age and sex during 1998-2010 has shown that, for commuting trips, trip rates for the 65+ age group has increased slightly whilst trip rates for other age groups have decreased (16-29 age group show the largest decrease) (DfT, 2014a; DfT, 2014b). The analysis also shows that commuting trip rates for females have stayed roughly the same. For shopping trips, the middle age group (16-64) shows the sharpest decrease whilst the 65+ age group does not follow any clear trend. In the case of visiting friends and family trip rates, whilst all age groups show a decreasing trend, the 16-29 age group has had the greatest rate of decrease in trip rates.

2.2.1.5 As noted earlier, education trip rates have remained relatively flat during 1988-2010 (DfT, 2014a). However, analysis of trends for education trips by working status has suggested that trip rates respectively for full-time employees and students (i.e. full time or part time student who is not in paid work) have increased and decreased (DfT, 2014b).

Trends in other travel demand indicators

2.2.1.6 Recent research into shifting car and train travel trends in the UK ("On the Move" report) has found a number of interesting and important trends in various aspects of demand and travel behaviour (Le Vine and Jones, 2012). Whilst it was found that the average car driving mileage per head of population has not changed much during 1995-2007, substantial differences in trends by sex were identified (with mileage increasing for females and decreasing for males). It was also found that car and rail travel in London is significantly different from the rest of the country. The proportion of car travel and rail travel in London has been lower and higher, respectively, than that in the rest of the country in all years. In terms of trends over time, private car mileage has increased in all areas of travel except London where there has been a reduction while rail growth has been similar across all areas.

2.2.1.7 The "On the Move" report found that about 60% of the substantial growth in rail travel in Great Britain is the result of more people starting to travel by rail rather than existing users travelling more (Le Vine and Jones, 2012). It was also found that business rail mileage has had highest substantial growth (nearly tripling) during 1995-2007.

2.2.1.8 A recent study undertaken by DfT underlines different aspects of observed trends in road travel in Great Britain (DfT, 2015). Whilst there has been substantial growth in traffic over the last 60 years, the study highlights that the rate of growth has been slowing in the last decade, and falling during the recent economic recession. This implies that the overall level of traffic in 2013 was just 0.4% higher than that in 2003. This study finds significantly different trends across different parts of the road network, different vehicle types, and different population groups (segmented by age and sex).

2.2.1.9 Car usage patterns in Greater London, and particularly Inner London, have been found to be substantially different from that in the rest of the UK (Le Vine and Jones, 2012). Both London residents and those who live outside but commute to work within London at least two times a week for commuting/business purpose have a significantly lower car usage compared with the residents in the rest of the UK. While some of this effect could be linked to the reduction in company car usage, the linkage of this effect to other factors such as investments in other modes is unknown (Le Vine and Jones, 2012).

2.2.2 Cross-sectional Variation

2.2.2.1 Understanding the sources of observed variability in various travel demand factors, in particular trip rates, is the key to distinguishing existing trends and forecasting any future trends. For example, understanding the relationship between various demographic and socio-economic factors and trip generation provides insights into population segments that tend to have significantly different trip rates.

2.2.2.2 Findings from several trip generation studies show that the following three groups of factors include the main sources of observed heterogeneity in trip rates:

- individual characteristics;

- household characteristics; and
- geographical / spatial factors.

2.2.2.3 Amongst individual characteristics, age, sex, ethnicity, marital status, employment status, individual income, and driving licence holding status are variables that have been found to explain observed variability in trip rates.

2.2.2.4 Depending on the trip purpose, the household factors which have been found to be associated with trip rates include household size, number of workers in the household, number of children in the household, household income, car ownership, housing type, and home ownership status.

2.2.2.5 Apart from individual and household characteristics, a number of spatial factors have been shown to explain observed variation in trip rates. Examples of these include length of residency at current location, distance from different land-uses, land-use characteristics, area type (urban, rural, etc.), and accessibility measures (DfT, 2014b; Jahanshahi et al., 2009; Daly and Miller, 2006; Daly, 1997).

2.3 Changes in Potential Drivers of Change

2.3.1 Overview

2.3.1.1 A number of studies have investigated trends in various individual, household, behavioural, and geographical factors that could potentially explain the cross-sectional variation in trip rates and other travel demand measures. These are summarised below.

2.3.1.2 It should be noted that whilst this section brings together the key findings in the literature in terms of changes in potential drivers, the conclusions on the nature of changes and their likely contributions on observed travel trends will be given in the next chapter.

2.3.1.3 It should also be noted that the research reviewed identified a number of other changes in travel behaviour that are not within the scope of this study on trip rates, therefore not included in this section, but which nonetheless may merit further investigation.

2.3.2 Economic activity and income

2.3.2.1 A research study undertaken by DfT using 1988-2010 NTS data showed that in general, there was limited variation in trends between individuals in different work status categories (DfT, 2014a). Analysis of trends by age showed that within the 65+ age group, there has been a significant increase, from 75% in 1988 to 90% in 2010, in the proportion of individuals who are retired/permanently sick. There was also a slight increase in the proportion of full-time workers in this age group.

2.3.2.2 Analysis of trends by sex has shown that the proportion of women who are full-time employees and NEET (not in employment, education or training) has increased and decreased, respectively (DfT, 2014a).

2.3.2.3 Comparison of 2001 and 2011 Census data has revealed that there has been a dramatic increase in the proportion of part-time employment (i.e. less than 30 hours a week) and self-employment over the decade. This suggests a shift from full-time employment and economic inactivity into limited hours and less secure forms of employment (Headicar, 2014). This, however, implies more participation in the workforce as levels of economic inactivity have decreased.

2.3.2.4 The spatial analysis of Census data has shown that the level of economic inactivity in 2011 was lower than that in 2001 across all areas in England. The lowest levels of inactivity and relatively high levels of full-time employment have been found in 'London Periphery' and the outer parts of South East England (Headicar, 2014).

2.3.2.5 According to the NTS data over 1988-2010, patterns of observed changes in household income and individual income have both been similar (DfT, 2014a). On average, income rose initially and then started decreasing from 2008 onwards.

2.3.2.6 It is now well-established that patterns of income by demographic groups within Great Britain have been changing in recent years, with older/female groups experiencing faster growth in real income than younger/male groups. This appears to have coincided with distributional shifts, with average incomes rising faster than median incomes (i.e. increasing inequality) in the 1990s/2000s. This is seen within the NTS sample (in which gross personal income, including any benefits received, is measured as a single quantity), and corroborated by the Annual Survey of Hours and Earnings and the Survey of Personal Incomes.

2.3.3 Car ownership / usage and driving licence holding

2.3.3.1 In the analysis of NTS data undertaken by DfT (DfT, 2014a), the trend in car ownership was found to have changed where the proportion of individuals in households with no cars as well as those in households with one car has decreased, while the proportion of individuals in households with two or more cars has increased over 1988-2010. It should be noted that these trends have largely stopped since 2007, most likely due to the recession (Le Vine and Jones, 2012).

2.3.3.2 Consistently, the proportion of people with a full driving licence has increased from 47% in 1988 to 58% in 2010 (DfT, 2014a). The “On the move” report notes that between 1995-2007, the proportion of males who are drivers has remained stable (except for a fall among the 20-29 age group) while there has been an increase in the proportion of female population becoming drivers, and links this to the observed growth in women’s driving levels (Le Vine and Jones, 2012). It is noted that for women, it was shown that driving licence holding had increased across all age groups except for those in the 20-29 age group.

2.3.3.3 Many of the observed changes in overall car usage have been linked to the observed trends in company car ownership and usage. According to the NTS data, company car ownership per person fell by 20% between 1995/7 and 2005/7 (Le Vine and Jones, 2012). Analysis of trends by type of employment has shown a significant reduction of about 60% in company car ownership among men classified as “professionals” and a smaller drop of about 25% among those classified as “employer/managers”. These are likely to reflect changes in taxation and company travel policies over this period.

2.3.3.4 Analysis of data also suggests a transfer of some mileage from company cars to private cars among the “employer/manager” group (Le Vine and Jones, 2012). This is, however, not the case for the “professional” group, responsible for the largest drop in company car use, where mileage in both company cars and private cars have dropped.

2.3.3.5 The “On the Move” report partly links the substantial growth in business rail mileage to a partial shift of business travel from company car to rail for men.

2.3.4 Demographic changes

2.3.4.1 There is evidence in the literature on differences in travel trends between different population groups. Annual car mileage has increased more for females and older age groups, and the decline in distance travelled by car has predominantly been seen amongst the young people and men (DfT, 2015).

2.3.4.2 Consistently, the “On the Move” report highlights the substantial reduction in car driver mileage among men in their 20s and links this to a reduction in the number of male drivers in this age group (Le Vine and Jones, 2012). It raises the uncertainty in the extent to which this change will persist as this group ages.

2.3.4.3 The literature has shown substantial population increases in cities, as well as young people being more likely to live in urban areas (Dunkerley et al., 2014). However, there have been few discussions on the reasons behind these changes and their likely effects on observed trends in car usage remains unclear.

2.3.4.4 An analysis of changes in the spatial distribution and composition of the population in England based on Census data has suggested that differences in the demographic composition of different area types has contributed to a widening gap in per capita car mileage rates (Headicar, 2014).

2.3.4.5 Analysis of NTS data over 1988-2010 has shown no clear trend in age distribution of individuals as well as relative proportion of males and females (DfT, 2014a). Whilst the data show some variation from year to year in the proportion of people in different area, no clear trend can be identified.

2.3.4.6 Analysis of drivers of demand in London, undertaken by Transport for London (TfL), indicated that whilst in longer term (since 1960) London's population has concentrated more on younger age bands, London's age profile has changed very little between 2001 and 2011 (TfL, 2014a). However, substantial changes in travel behaviour of Londoners of different ages have taken place. This has suggested that a change in the age distribution amongst the population has not been a major driver of the observed changes in travel patterns.

2.3.5 Working from home

2.3.5.1 The proportion of people working from home has more than doubled during 1998-2008, from 3% in 1998 to 6.6% in 2008, based on time-series analysis of NTS data (DfT, 2014a). Consistently, comparison of 2001 and 2011 Census data has shown that the proportion of workers categorised as "working mainly at or from home" has increased by 1.4 percentage points to 10.6% in 2011 (Headicar, 2014). The differences in reported results based on NTS and Census are mainly due to differences in the definition of working from home and slight differences in the questions asked in each survey.

2.3.5.2 Analysis of Census data has also revealed that a much higher proportion of people working mainly at or from home (almost twice the rest) live in the lower density and more rural areas (Headicar, 2014). While the profile of this group of workers across the Census area types has remained almost the same between 2001 and 2011, growth amongst areas with higher proportions has been higher suggesting a trend towards greater spatial differentiation

2.3.6 Internet use and information technology

2.3.6.1 Analysis of the Government's Office of National Statistics (ONS) data on internet use during 2006-2013 shows a significant increase in the proportion of adults who accessed the internet daily, from 35% in 2006 to 73% in 2013 (DfT, 2014a). Similarly, significant rises have been observed in internet banking and internet shopping over 2006-2013.

2.3.6.2 There have been a number of studies investigating the relationship between information technology and the level of trip making; however, the findings from these studies are inconsistent and sometimes conflicting.

2.3.6.3 In a recent literature review undertaken to understand the effects of different factors on observed car traffic trends in Great Britain, no evidence was found regarding the effect of information technology, e-commerce and social media on car travel despite substantial changes in internet technology in recent years (Rohr and Fox, 2014).

2.3.7 Migration

2.3.7.1 The "On the Move" report revealed interesting findings on the relationship between country of birth and car usage in Great Britain, based on the analysis of 2010 NTS data (Le Vine and Jones, 2012). The analysis results showed that people born outside the UK tend to use cars less, especially those in the 20-39 age group which account for the highest proportion of migrants in the UK.

2.3.7.2 London continues to see net outflows of migration to the rest of the UK, but at a lower level than previously (TfL, 2014a). At the same time, there has been arrival of migrants from the EU; these in many cases are linked to low levels of car use.

2.3.7.3 Analysis of 2001 and 2011 Census data on spatial concentration of immigrants in England revealed that the majority of people born in non-EU countries are in London with a lower proportion in "centres with industry[1]" (Headicar, 2014). Surprisingly, the 'Industrial Hinterlands' and 'Manufacturing Towns' were found to have very low proportions of this group (less than 3%). The distribution of EU immigrants; however, showed a very different pattern where they are spread much more evenly between different areas with only a significantly higher proportion within London. No substantial change in the distribution of immigrants was observed between 2001 and 2011.

2.3.8 Summary

2.3.8.1 Following the collected evidence from the literature, summarised in the previous section, Table 2-1 provides an initial list of possible drivers of observed trends in trip rates.

Table 2-1: Possible Drivers of Trends in Trip Rates

Subject Area	Possible Drivers
Economic factors	- Fuel prices
	- GDP
	- Income
	- Taxation
	- Employment level by employment type
Demographic factors	- Ageing population
	- Immigration / migration
	- Changes in household structure
	- Changes in age distribution by area types
Technology	- Online shopping
	- Telecommuting
	- Social Media
Land-use / locational factors	- Level of urbanisation
	- Changes in accessibility
Car ownership and usage	- Company car ownership and usage
	- Changes in car usage by age / sex
	- Changes in car ownership and usage by area type
	- Taxation policies
Other factors	

2.3.8.2 Some of the trends listed in Table 2-1 are historical trends which are unlikely to continue in the future (e.g. company car usage) whilst the others are trends that have started relatively recently and are likely to continue in the future (e.g. online shopping). While we have considered both groups of factors in the analysis, the latter group has been the focus of the study as they are the key factors that are likely significantly to affect forecasting.

[1] Including places such as Bradford, Manchester, Birmingham and Leicester

3. Analysis Approach and Data

3.1 Study hypotheses

3.1.1 Possible Drivers of Observed and Future Trends

3.1.1.1 As introduced in Chapter 1, the study objective was to expand the existing knowledge on trends in trip rates and their drivers.

3.1.1.2 In particular, the recent analysis of trends in trip rates based on 1998-2010 NTS data, undertaken by DfT, provides useful information on appropriate segmentation and the list of explanatory variables which help explain the variation in trip rates (DfT, 2014a; DfT, 2014b; DfT, 2014c; DfT, 2014d).

3.1.1.3 In this study, trip rate is defined as the average number of outbound trips (trip started from home) made per person during the week. On average, the data suggest that non-home-based trips only account for 10% of all trips made during 2002-2012 and the tendency to make non home based trips did not change over this period.

3.1.1.4 Our aim was to make use of additional sources of data to investigate the influence of those possible drivers, summarised in Table 2-1, which are identified by the existing evidence to influence trip rates but their partial effects have not been quantified properly.

3.1.1.5 We considered the merits of investigating particular drivers applying judgement on the:

- extent to which trip rates are likely be affected by particular explanatory factors, based on our experience and the findings of the literature review;
- quality of information that is accessible, both cross-sectionally and for an extended time series to allow structured statistical analysis;
- likelihood that the explanatory factor will continue to change and thus influence future trip rates; and
- extent to which existing studies have quantified the influence of particular factors.

3.1.1.6 Overall we sought to focus on the areas where we judged there to be the greatest likelihood of reaching robust conclusions that would significantly affect forecast trip rates, within the study timescales. With reference to Table 2-1, we concluded that:

- existing car ownership and trip rate models reflect employment status and household income (through affecting car ownership) and the underpinning research has considered car fuel costs; nevertheless the recent trends appear to reflect variations in the distribution of income and the source of disposable income that is not currently represented and may be expected to change further in the future; furthermore, while the NTS does not include detailed questions on income structure, there is an opportunity to link data from the Expenditure and Food Survey (EFS) / Living Costs and Food survey (LCF) survey to provide a basis for structured analysis;
- demographic segmentation was considered in research undertaken by the DfT (DfT, 2014a; DfT, 2014d), and we intended to build on this research to provide a framework to test the causes of variations in behaviour evidenced for particular segments; the research indicated differences in behaviour by nationality or place of birth which, if migration trends continue, may be of particular importance and we identified the possibility of integrating Census data to complement NTS data and investigate this further;

- technology has and continues to provide increased opportunities to interact and undertake activities without incurring travel and this is likely to influence future trip rates; NTS data have since 2002 included questions on online shopping and we will seek to exploit this information; while there may be other influences such as working at home or for leisure activities, we have not identified a data source adequate for the purposes of this study; we have also observed that new technologies, such as driverless cars might influence future travel, but the lack of historic data precludes the structured statistical investigation planned for this study;
- the ward level NTS data that was made available for this study were not sufficiently detailed to explore variations in accessibility; while there are variations in trip rates between different urban areas we were doubtful that the data sets we were able to exploit for statistical analysis would yield significant findings and therefore attached a low priority to this area of investigation; we would however note that trip rates forecast by the DfT's national model are often applied at local level in detailed planning and there would nevertheless be merit in investigating these variations further;
- the literature demonstrated that reductions in company car ownership have resulted in a reduction in car use; nevertheless we assume that these have resulted from changes in taxation policy over the past two decades and there might be much more limited change in the future; for the purposes of this study therefore we decided to represent the effects of car ownership on trip rates, but not to investigate further the factors that influence car ownership itself; and
- the other area of which we took particular note is the trend reflecting the reduction in trips and whether there has been any changes in the extent to which these trips are reported (or under reported) in the NTS over time.

3.1.1.7 Accordingly four key areas were identified to be the main focus of this study. These are income, migration, technology, and possible change in under reporting of trips. These are described further in the following sections.

3.1.2 The Role of Income

3.1.2.1 What has yet to be documented is whether hypothesised differences in income after housing expenditure provide further explanatory power regarding trends in personal mobility. There are reasons to believe that after-housing-expenditure income may have trended differently than aggregate income; these reasons include structural shifts in the housing market (e.g. structural price increases in property values, the growth of buy-to-let and the private rental market, etc.) that have affected younger and older age groups differently.

3.1.2.2 Other linked reasons for changes in mobility patterns include the differential costs of motor insurance as well as learning to drive, which disproportionately accrue to younger age groups. It may also be of interest to investigate patterns of residual income after other expenditure such as food and utilities, though we did not analyse food/utilities/etc. expenditure in this this study.

3.1.3 Technology and Internet

3.1.3.1 Existing evidence consistently shows an increase in the level of internet use and online shopping in the past few years and these trends are expected to continue. This is also true for the proportion of people who work from home, either part or full time.

3.1.3.2 There have been a number of studies investigating the relationship between information technology and the level of trip making; however, the findings from these studies are inconsistent and sometimes conflicting. Geographical and cultural factors seem to play a role in the relationship between internet use and level of trip making.

3.1.3.3 Clearly, an increase in the number of individuals who work from home regularly is linked to a reduction in the number of commuting trips made. Similarly, it could be hypothesised that buying goods online is a substitute for a trip to a shop and it could also be hypothesised that using online social networks and online gaming substitute social travel to some extent.

3.1.3.4 It is noted that some complexity is involved in examining the above hypotheses due to the possibility that the extra time saved as a result of replacing some out-of-home activities by these in-home activities (use of internet) could lead to schedule other activities; and hence, more travel.

3.1.3.5 Within the UK, there is lack of evidence on the partial influence of different aspects of information technology on personal trip rates for different trip purposes. Understanding this relationship is the key to forecast trip rates and other travel demand measures as there have been substantial changes in people's tendency and attitude to use internet for various reasons in recent years and these trends are expected to continue in the future.

3.1.4 Migration

3.1.4.1 The NTS now collects information regarding migration-status (via a question that asks NTS respondents to self-report their country of birth), but these data were collected for the first time in 2010. Therefore, using only NTS data it is possible to estimate cross-sectional differences in trip rates between people born in the UK versus those born in other countries.

3.1.4.2 It is not possible to analyse the time-trend in these patterns. This is of interest as cross-sectional analyses using the NTS (e.g. Le Vine and Polak 2014) show large differences in mobility-related outcomes on the basis of this country-of-birth data point, even after accounting for confounding factors (e.g. income, place-of-residence, age, etc.)

3.1.4.3 We have therefore considered the possibility of time-trends in mobility outcomes being coincident with time-trends in migration patterns.

3.1.5 Trends in Walking Trips and Short Trips

3.1.5.1 Analysis of trip rates by mode and distance band has suggested that changes in walking trips and short trips have made a significant contribution to the overall observed trends in trip rates. In the case of short trips, this is particularly the case for commuting and shopping trip purposes.

3.1.5.2 These observations are primarily based on time-series analysis of NTS data. A question that could be raised here is to what extent these trends are genuine and not a consequence of non-response or reporting issues within the data.

3.1.5.3 The hypothesis that is therefore made here is whether the respondents in the NTS sample have developed a tendency, through time, towards reporting their trips less frequently. We have attempted to investigate this as far as availability of data has allowed.

3.1.6 Key research questions

3.1.6.1 In summary, the following specific research questions were identified and addressed:

- How the existing NTEM segmentation could be extended to include more factors, providing greater forecasting accuracy?
- Does income after housing expenditures provide statistical salience in explaining trip rates beyond gross income, both cross-sectionally and trends over time?
- What is the effect of migration on trip rates and to what extent changes in migration can explain observed trends in trip rates?
- What is the effect of online shopping and internet use on trip rates and to what extent changes in these factors can explain observed trends in trip rates?

3.1.6.2 We investigated the above questions, separately for each trip purpose, through a disaggregate analysis of a cross-sectional time-series data. The study dataset and the statistical approach are described in Sections 3.2 and 3.3, respectively.

3.2 Study Data

3.2.1 Data Requirements

3.2.1.1 In order to examine the list of hypotheses described in the previous section, time-series information on various aspects of travel behaviour and demand, including trip rates, as well as information on potential drivers of change was required.

3.2.1.2 At the same time, the study data should include cross-sectional information on various aspects of travel patterns and potential drivers of these. Therefore, the dataset should ideally include a repeated cross-sectional travel survey, including data ideally covering 10-15 years or longer to allow undertaking a detailed analysis of trends.

3.2.1.3 The unit of observations should be individuals to allow a detailed disaggregate analysis of travel behaviour measures and their association with individual and household characteristics.

3.2.1.4 The dataset should include a travel diary, recording detailed information on all the journeys made by each individual within the households in the sample, for a distinct period of time (i.e. one day, one week, etc.). Therefore, a hierarchical travel survey dataset including household, individual, and journey level variables was required.

3.2.1.5 It was noted in the previous sections that a number of locational factors are found to be associated with various travel choices and there are regional differences between various travel trends. Therefore, the study dataset should include spatially-distributed data together with geographical information (e.g. geographical location of the household) in a reasonably detailed level to allow calculation of locational factors.

3.2.1.6 Migration, technology (internet use), and income after housing costs were identified in Section 3.1.1 as the key areas of focus in the study. The study data should therefore include detailed information on these variables.

3.2.2 Final Study Dataset

3.2.2.1 On this basis of the above, the NTS data were selected as the primary data source to develop the study dataset as it contains the characteristics listed above. We used the NTS data between 2002 and 2012, dictated by the availability of explanatory variables of interest for the entire duration.

3.2.2.2 The NTS includes information on household access to the internet (since 2009), online shopping by type of product (since 2002), and the frequency of online shopping (since 2002). We have used this information to define technology-related explanatory variables and directly included them in the trip rate regression models.

3.2.2.3 To investigate the influence of migration on trip rates, the relevant information in the 2001 and 2011 Census data was linked to the NTS data based on ward geographies. This is explained further in the following paragraphs.

3.2.2.4 The 2001 and 2011 Census data both contain information on Country of Birth. In 2011, an additional question on Year of Arrival to the UK was added. However, this information is not available for 2001 and hence it was not possible to look at trends for Year of Arrival. We used the following sources of data, which provide the resident population by their country of birth at the ward level from ONS Neighbourhood statistics website[1] (Table UV08) and "Country of Birth,

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[1] https://neighbourhood.statistics.gov.uk/

2011" information (Table KS204EW). These tables provide a detailed classification of countries of birth.

3.2.2.5 There was a significant change in ward definitions (i.e. boundaries) between 2001 and 2011. 2001 Census data are presented using CAS 2003 Wards and 2011 Census data are presented using 2011 Wards. NTS data uses 2011 Ward definitions and therefore we estimated trends using 2011 Ward definitions. We downloaded the shape files for 2011 Wards and CAS 2003 Wards boundaries from ONS Geoportal[1]. We overlaid the two sets of wards and calculated the percentage of 2001 ward areas that fall in 2011 ward areas. We used these percentages to estimate the 2001 Country of Birth population variables for 2011 Wards. In the final set of data, each 2011 Ward has the required information from both years 2001 and 2011. This dataset was then merged with the NTS data using 2011 Ward codes.

3.2.2.6 We used the following sources of data to gather time-series information on various aspects of income: Expenditure and Food Survey (EFS): 2001:-2006 and Living Costs and Food Survey (LCF): 2006-present. This is explained further in the following paragraphs.

3.2.2.7 LCF is collected continuously by the Office for National Statistics (ONS) and is traditionally used to track aggregate household expenditure patterns as well as to monitor price inflation over time. For this study, we used rental and mortgage costs collected at the household level.

3.2.2.8 The relevant LCF and EFS datasets were downloaded from the UK Data Service and merged for years 2001-2012 at the household level. Using the merged dataset, we calculated the average rental and mortgage costs for different age groups at household level (using the age of the household reference person grouped into 6 categories) and 11 categories of Government Office Regions (GORs) over the years. The categories of housing payments that are differentiated in the LCF and EFS are complex (e.g. to do with Council Tax, housing benefit); the relevant ONS team was contacted to make sure the variable definitions we use are consistent with ONS definitions.

3.2.2.9 The final set of data on average rental and mortgage costs for different HRP age groups, GOR and year were then merged with the NTS dataset. In the resulting dataset, each individual in NTS has an average housing cost variable based on tenure type, age of HRP, GOR, and year.

3.2.2.10 For estimating the individual income after housing expenditure in NTS, we have allocated a share of housing costs to each individual in the household proportionally based on their share of income from total household income, and used this together with individual gross income to estimate individual income after housing expenditure.

3.2.2.11 As mentioned earlier, the unit of observations in the final dataset should be individuals to allow a disaggregate analysis of trip rate. For each person record in the NTS data, the relevant household variables were added from the household dataset and the total number of weekly trips by purpose were calculated and added from the trip dataset. The final study dataset therefore included records of individuals linked with their household characteristics and the number of trips they made, by purpose, during the travel diary week. The total number of records was about 210,000 covering NTS data between 2002 and 2012.

3.2.3 Description of the Data

Trip Rates

3.2.3.1 Figure 3-1 shows trends in average trip rates per week by purpose between 2002 and 2012. Trip rates are calculated as the average number of outbound trips (trip started from home) made during the travel diary week, weighted using NTS household and trips weights to account for various biases in the sample.

[1] https://geoportal.statistics.gov.uk/geoportal/catalog/main/home.page

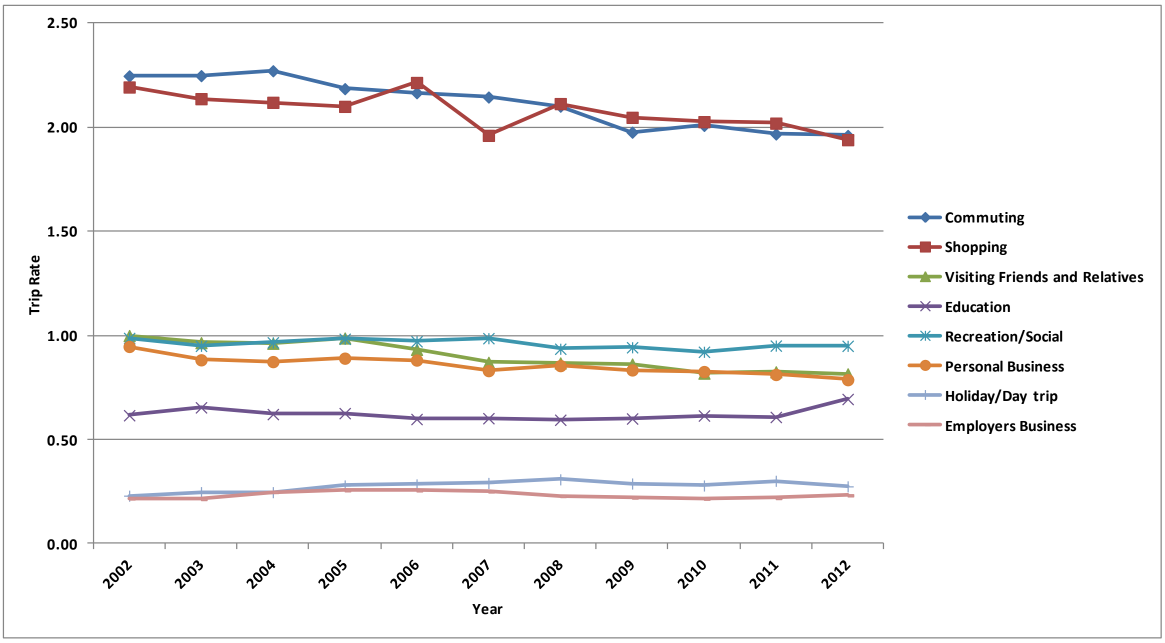

Figure 3-1 – Observed Trends in Weekly Trip Rates (NTS 2002-2012)

3.2.3.2 As the results show, across all trip purposes, commuting and shopping trips have the highest trip rates, both of which have decreased by over 10% between 2002 and 2012. The other trip purposes that show a clear decline over this time period are personal business and visiting friends and relatives. Other trip purposes do not follow a clear trend except holiday trips which have increased.

Migration Trends

3.2.3.3 Figure 3-2 and Figure 3-3 show the proportion of residents with a country of birth other than UK in 2001 and 2011, respectively, calculated using Census information.

3.2.3.4 The results suggest that the majority of migrants live in London and other urban areas. The comparison of the two figures shows a clear increase in the proportion of migrants between 2001 and 2011. On average, the proportion of migrants living in England and Wales has increased by about 40% over this period.

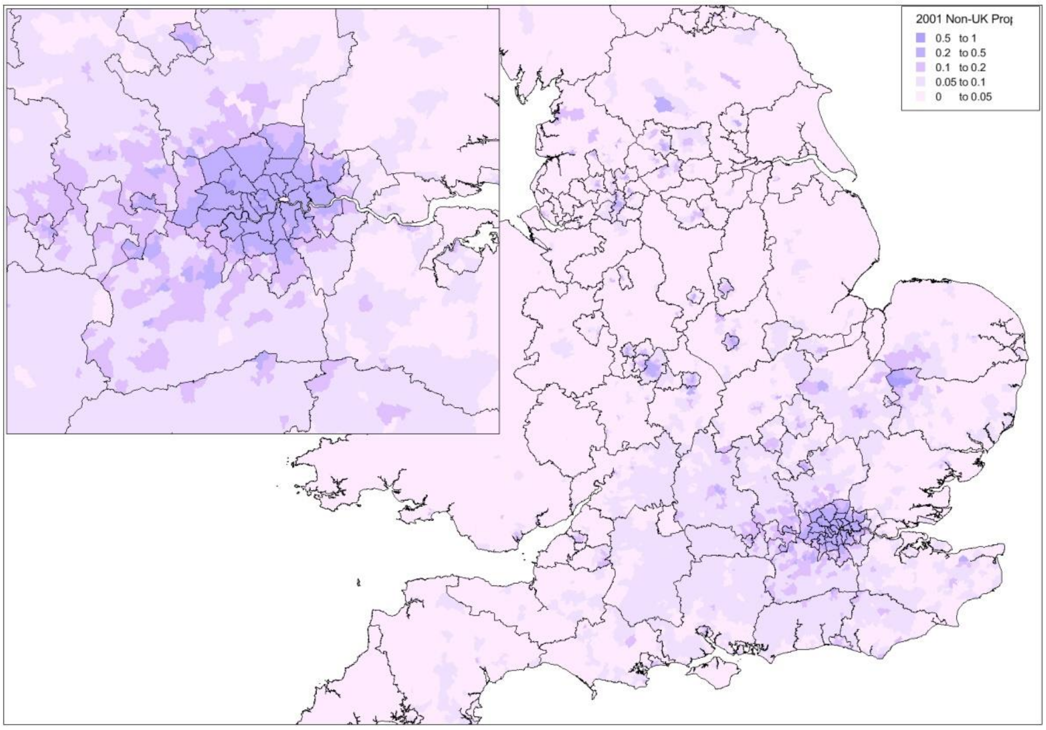

Figure 3-2 – Proportion of Non-UK Residents (Source: 2001 Census)

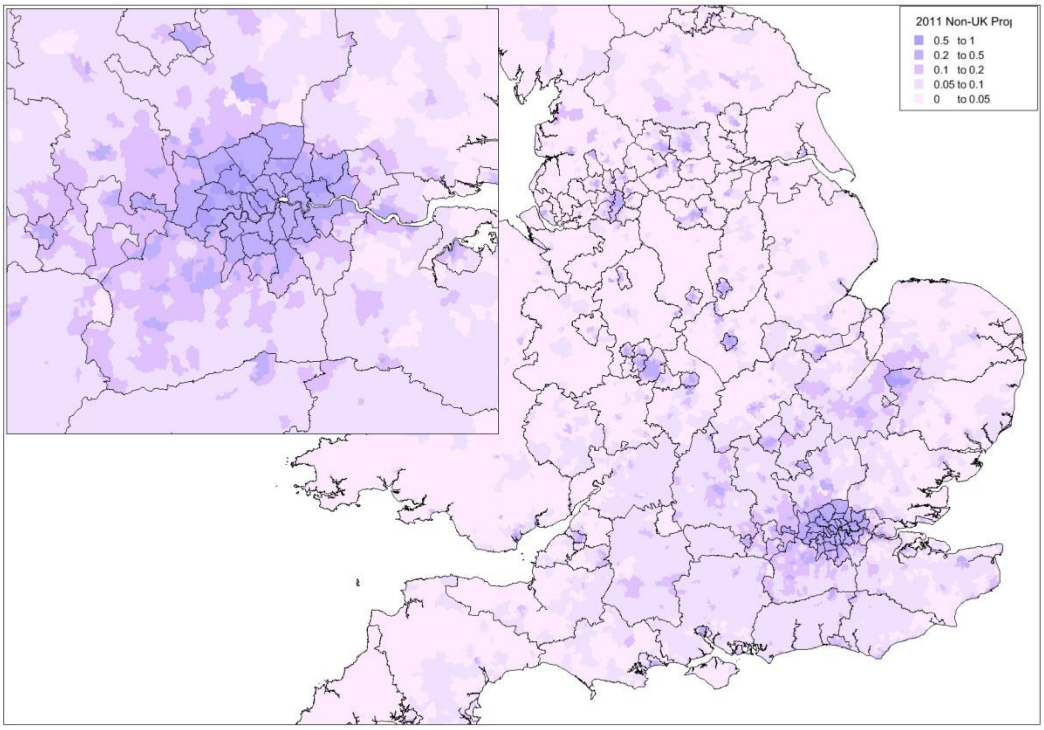

Figure 3-3 – Proportion of Non-UK Residents (Source: 2011 Census)

Housing Expenditures

3.2.3.5 Figure 3-4 and Figure 3-5 show trends in weekly expenditure, in real prices, by area and age, respectively. These are calculated based on data from LCF survey. The figures show an overall increase in housing expenditure across all ages and areas. The rate of increase seems to be higher in London compared to other areas. Across different age groups, younger households seem to have experienced a slightly stronger rate of increase in housing expenditures.

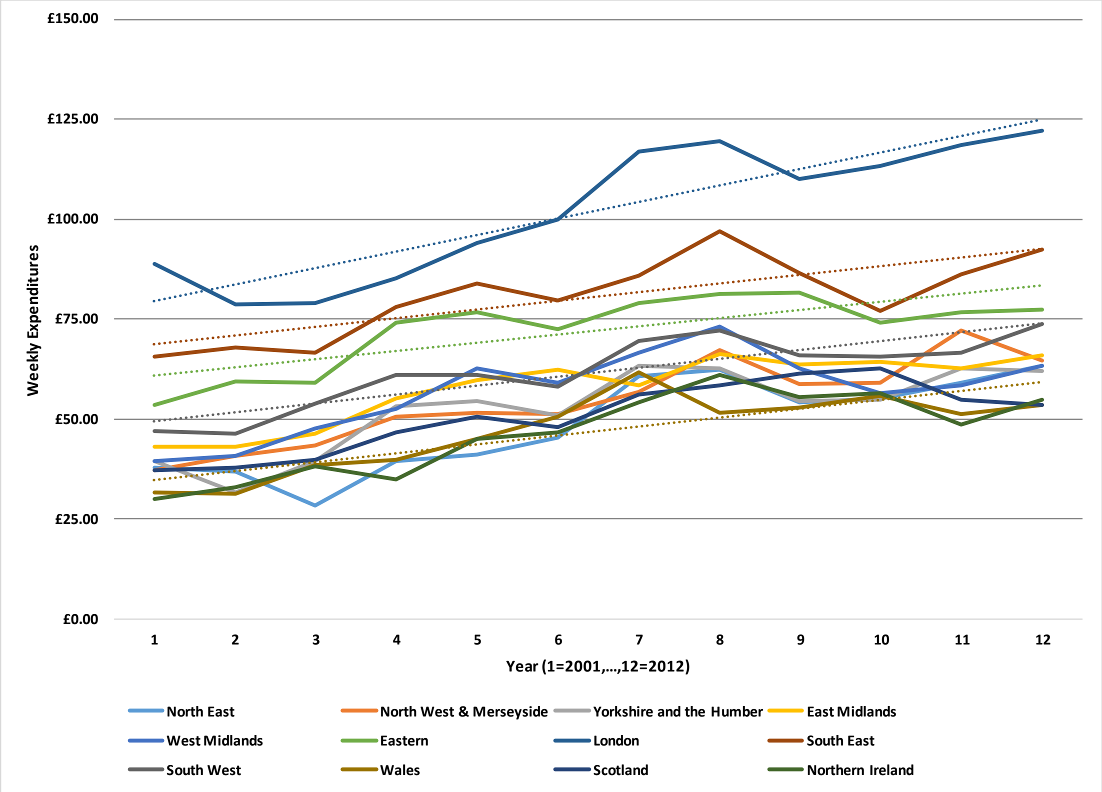

Figure 3-4 – Trends in Weekly Expenditure on Housing by Government Office Regions (Source: LCF 2001-2012)

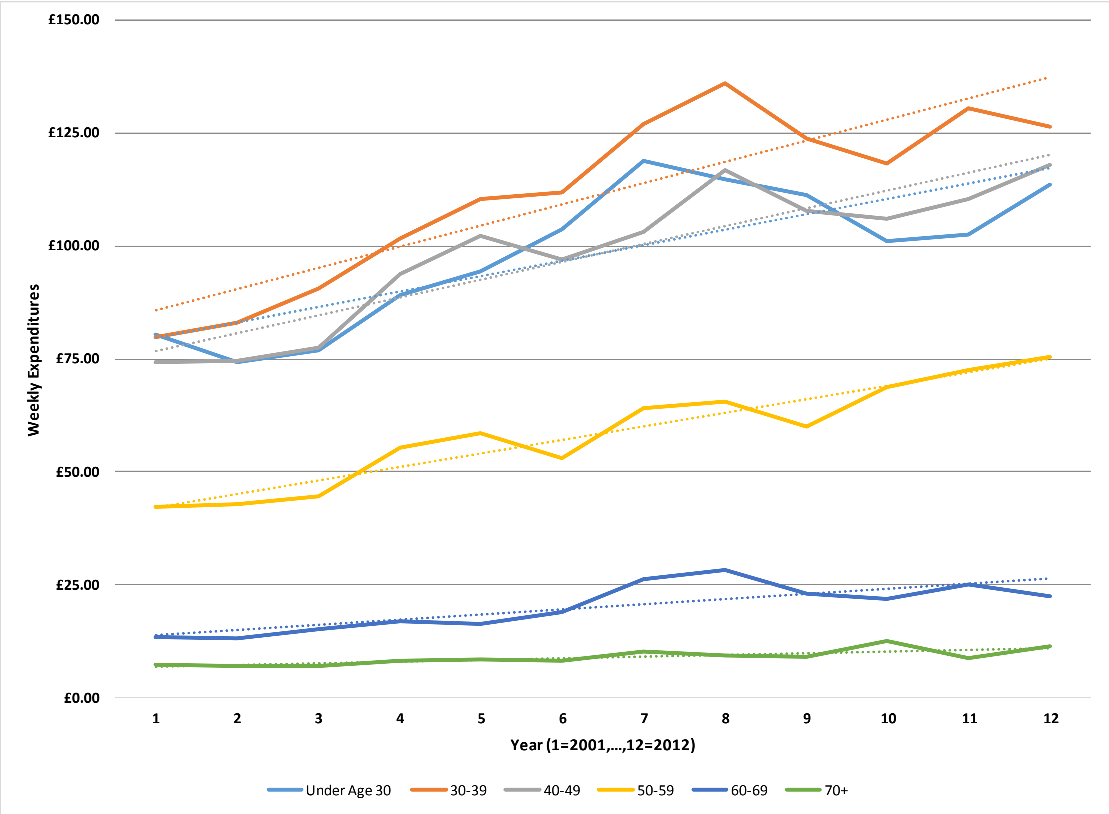

Figure 3-5 – Trends in Weekly Expenditure on Housing by Age (Source: LCF 2001-2012)

Internet Use

3.2.3.6 As mentioned earlier, the 2002-2012 NTS data include information on frequency of household online shopping (with the exception of 2005, 2006, and 2007 data). We have used this variable in our analysis to examine the effect of online shopping (also used as a proxy for internet use) on trip rates. For this analysis, the records of data for which this variable was not available were excluded from the analysis.

3.2.3.7 Figure 3-6 shows the trends in the proportion of households who order products online or by phone, separately for different types of products. The results show that online shopping has increased across all products between 2002 and 2012.

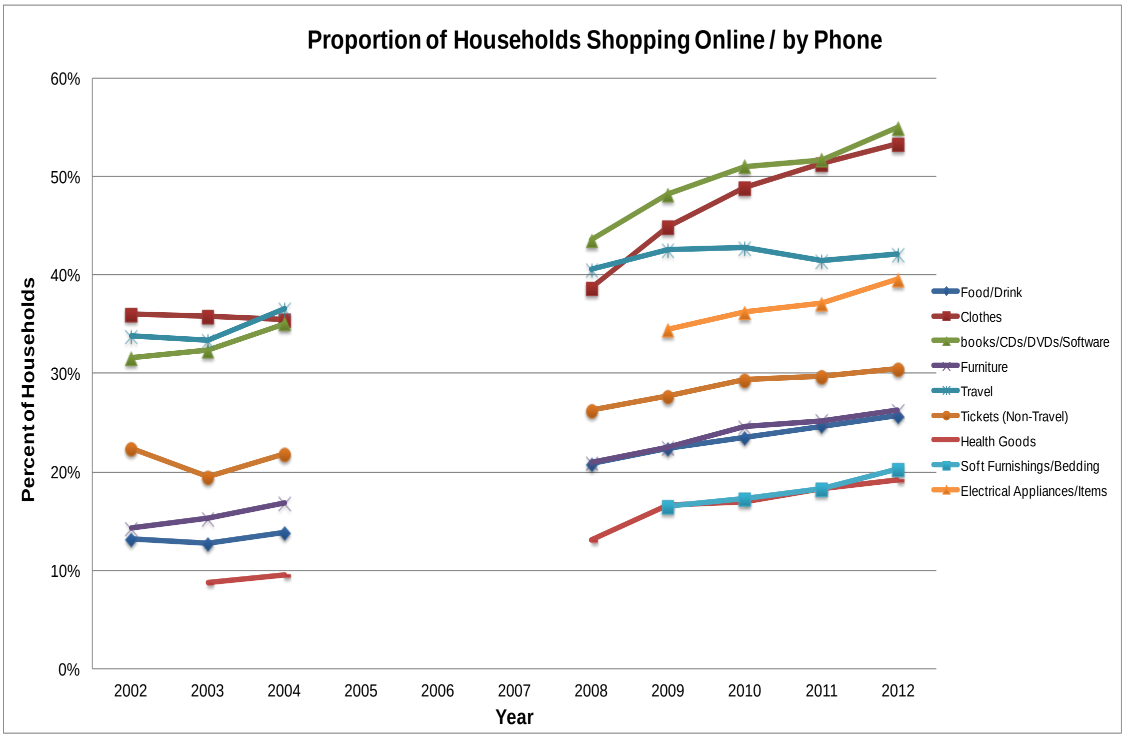

Figure 3-6 – Trends in Online or Phone Shopping by Type of Product (Source: NTS 2002-2012)

3.3 Modelling Approach

3.3.1 Choice of Statistical Models

3.3.1.1 The recent modelling of trends in trip rates based on 1998-2010 NTS data, undertaken by DfT, was used as the basis of analysis (DfT, 2014a; DfT, 2014b; DfT, 2014c; DfT, 2014d). In the DfT analysis, Poisson and negative binomial regression models were used to estimate trip rates as a function of independent explanatory variables.

3.3.1.2 The approach used by DfT was developed further in this study, making use of new additional sources of data, to examine the effects of potential drivers. These were included as explanatory variables in the regression models to estimate their partial effects on trip rates.

3.3.1.3 In the analysis undertaken by DfT, Poisson and negative binomial regression models (and zero-inflated extensions of these) were used to model trip rates (DfT, 2014c). Poisson and negative binomial models are models from the family of Generalised Linear Models where the distribution of residuals is assumed to be Poisson or negative binomial (allowing for over-dispersion). They are therefore suitable model forms to use when the dependent variable is integer in nature (count data). The detailed specifications of these models are described in the relevant DfT report (DfT, 2014c).

3.3.1.4 We have applied the same model forms used by DfT for different data segments and trip purposes. We used the statistical package R to estimate parameters of the trip rate regression models.

3.3.1.5 The zero-inflated versions of these models are sometimes shown to result in better predictions when there are many zero counts in the data. These models have two parts: a zero model using a binary distribution (to estimate the probability of making a trip) and a count model using either a Poisson or negative binomial distribution (to estimate number of trips made conditional on making a trip).

3.3.1.6 We have also estimated these models for the segments of data where DfT have found zero-inflated models to have a better performance than the ordinary negative binomial models, and compared their performance. The main disadvantages of the zero-inflated models are the added complexity in the estimation of parameters and the interpretation of the effects of different variables in the model.

3.3.2 Choice of Dependent Variable

3.3.2.1 The dependent variable should be the number of trips made by each individual (each record of data) for each trip purpose; these were calculated from the travel diary data.

3.3.2.2 In choosing the dependent variable, we encountered an issue that is a by-product of the current procedure used by the NTS team for dealing with what is assumed to be under-reporting of trip frequencies in second and subsequent days the NTS diary. This procedure uses empirically-derived response-day specific weights within NTS travel diary data to uplift reported trip rates on second and subsequent response days, in line with those observed on the first day.

3.3.2.3 Although this procedure has the virtue of simplicity it has a number of significant draw backs for this work. One of these is that the resulting imputed trip frequencies for days 2 to 7 are in general non-integer. This in turn presents problems given that, in line with the DfT's preliminary analysis, we are seeking to model trip frequencies as count (i.e., integer) data.

3.3.2.4 The approach to this problem adopted by the DfT in its preliminary analysis was to simply round non-integer trip frequencies to the nearest integer. This is effectively equivalent to de facto using different under-reporting weights than those originally derived. Moreover, these effective weights will in principle be person-specific, since the rounding will depend on the original observed trip frequency.

3.3.2.5 If we assume that the weighting (and hence non-integer) NTS trip frequencies are correct, a further problem arises. Application of count data models in general requires integer dependent variables. If we rounded the weighted NTS data to the nearest integer, in the manner of the Department's preliminary analysis, it was unclear to us how any parameters derived from such models would relate to the properties of the (assumed correct) weighted NTS data. There is evidence from analysis of other data sets that rounding of dependent variables can lead to biases (especially in the covariance structure) of regression parameters. In certain circumstances these biases can be avoided or corrected but these can be complex and, as far as we were able to ascertain, have not been previously investigated for the specific processes and model forms we are using in this study.

3.3.2.6 We therefore decided to proceed with our analysis using a two stage process, which we agreed with DfT and the NTS team. First we excluded the day 2-7 weighting from the NTS data to undertake the regression analysis to estimate the effects of different factors (effectively using un-weighted data) and thus avoid the problems generated by this weighting.

3.3.2.7 Since the data as used for this analysis will understate trip rates, we then make adjustments to the aggregate segment average trip rates to reproduce the net effect of the day 2-7 correction factors in the original data when we use the estimated models for forecasting trip rates, as explained in Section 5.3.3.4.

3.3.3 Explanatory Variables

3.3.3.1 The regression modelling undertaken by DfT uses the following variables, currently used within NTEM, to define population segments:

- Age / work status (child, full-time[1], part-time[2], student[1], NEET[2], 65+)

[1] Aged 16 or over working more than 30 hours a week
[2] Aged 16 or over working less than 30 hours a week

- Household type (1 adult 0 cars, 1 adult 1+ cars, 2 adults 0 cars, 2 adults 1 car, 2 adults 2+ cars, 3+ adults 0 cars, 3+ adults 1 car, 3+ adults 2+ cars)
- Sex (male, female)

3.3.3.2 In addition to these, DfT has used time (year) as an explanatory variable to model time trends.

3.3.3.3 Following the review of literature and further analysis of data, we added the following explanatory variables to the regression models, taking into account the future forecasting requirements of the trip rate models:

- Age (16-29, 30-44, 45-64, 65-74, 75+)
- Area Type (inner London, outer London, metropolitan, small/medium/small-medium/large urban, rural)
- Children (below 16 years) in the household (binary variable)
- Driving licence availability (binary variable)

3.3.3.4 Two measures of individual income[3] were prepared and added to the models, separately, as continuous variables: gross income (reported income within NTS) and residual income after housing costs (estimated as described in Section 3.2.2.6).

3.3.3.5 Within NTS, income is only given in bands. The income variables were therefore made pseudo continuous by using mid-point value in the income band for each individual. To be consistent with the approach taken by DfT in their analysis of trip rates (DfT, 2014a), the income bands higher than £50,000 were assigned the value of £60,000. These were then deflated using the ONS consumer price index (CPI) to reflect income in 2002 prices.

3.3.3.6 The migration variable used in the regression models was the proportion of residents in each ward who are not born in the UK; hence reflecting the probability of being born abroad for each individual. This was to investigate the change in trip rates of the individuals living in wards which have been subject to a higher degree of migration.

3.3.3.7 The migration data were only available from Census for 2001 and 2011. These were interpolated and extrapolated to provide estimate of number of residents by country of birth for each ward for the years when data were not available.

3.3.3.8 The following variables, directly available in NTS, were used to represent the effect of online shopping and internet use:

- online shopping (binary variable); and
- frequency of online shopping (at least once a week, less often than once a week, never).

3.3.3.9 It should be noted that the online shopping variables were missing for three years (2005, 2006, and 2007). The regression models that include these variables are therefore estimated using a subset of data that exclude these years.

3.3.4 Model Estimation Procedure

3.3.4.1 Regression models were developed to estimate trip rates for the following distinct home based trip purposes:

- commuting;

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[1] Full time or part time student who is not in paid work
[2] Not in employment, education, or training
[3] Initial testing demonstrated a significantly better fit using individual rather than household income

- employers’ business;
- education;
- shopping;
- personal business;
- recreation / social;
- visiting friends & relatives; and
- holiday / day trips.

3.3.4.2 For most purposes, each age/work status group (i.e. child, full-time, part-time, student, NEET, 65+) showed different patterns. For example, there was often a bigger difference in trip rates between males and females in the 65+ group and almost no difference in the child group. Therefore, regression models were fitted to each group individually, i.e. each purpose had six different regression models, one for each age/work status group, resulting in a total number of 48 regression models to be estimated. The following approach was used to estimate a “final” model for each category.

3.3.4.3 In the first stage of model estimation process, a step-wise search algorithm was used for each category to find the model that represents the best segmentation for that category. This search algorithm is described below in details:

1. Re-estimate models estimated by DfT, using the extended NTS data. These models include the following explanatory variables.
   a. household type (1 adult, 0 car, 1 adult, 1+ cars, 2 adults, 0 car, 2 adults, 1 car, 2 adults, 2+ cars, 3+ adults, 0 car, 3+ adults, 1 car, 3+ adults, 2+ cars)
   b. sex (male, female)
   c. year
2. Run 5 regression models; in each of these 5 models add in one of these variables:
   a. Place-of-residence (the 7 area type categories as binary indicators, with ‘London’ fixed at zero as the reference case)
   b. Presence of children age 15 or younger in the household (binary: yes/no)
   c. Full-Car-Driving-licence-holding-status (binary: yes/no)
   d. Age (4 categories as defined in Paragraph 3.3.3.3)
   e. Gross individual income (continuous, in GBP, 2002 prices)
3. If none of these 5 variables are found to be statistically significant, then leave the DfT’s specification unchanged.
4. If at least one of these 5 variables is statistically significant, then retain the one for which the improvement in Akaike Information Criterion AIC is largest.
5. Then run 4 regression models, which each include the ‘retained’ variable (from Step #3) as well as one of the other 4 candidate variables (from Step #1).
6. If none of these 4 variables are found to be statistically significant, then the specification-search stops, with only the 1 ‘retained’ variable included.
7. If at least one of these 4 variables is statistically significant, then retain the one for which the improvement in AIC is largest (as well as the variable retained in Step #3).
8. Repeat steps #4 through #6, each time adding in the most impactful (as characterized by the AIC criterion) additional variable, until either all 5 variables are retained, or the point is reached that none are statistically significant (e.g. the criterion of Step #2 above).

3.3.4.4 In the next stage, the above search algorithm was repeated, replacing gross individual income with residual income after housing expenditures. The final models from these two stages were then compared, using the values of AIC, to understand which measure of income provides a better explanatory power to the trip rate models; the better model was selected.

3.3.4.5 The migration variable was then added to this model in the next stage. It was retained if it was statistically significant and improved the performance of the model, measured using the value of AIC, otherwise it was discarded.

3.3.4.6 Finally, the selected model from the previous stage was re-estimated using a subset of data for which internet data were available, and the two online shopping variables were added to this model individually, resulting in 3 alternative models. Amongst these, the model with a better performance (lower value of AIC) was selected as the best model. If none of the online shopping variables improved the model performance the best model from previous stage, which was estimated using all years of data, was selected as the best model.

3.3.4.7 The above process resulted in a “best” trip rate regression model for each of the 48 categories (i.e. different combinations of trip purposes and age / work status). These models were used to investigate the effects of different factors on trip rates; these are explained in the next stage.

3.3.4.8 As mentioned earlier, while negative binomial or Poisson models were estimated for all categories of trips, zero-inflated models were also estimated for those categories that contained a large number of zero trips where zero-inflated models were found to provide more accurate estimates in the DfT analysis (DfT, 2014c).

3.3.4.9 Vuong’s non-nested test is a statistical hypothesis test used to compare two models fit to the same data that do not nest[1]. We used Vuong’s test to compare model fits between standard negative binomial models and zero-inflated models for the model categories where zero-inflated models were preferred in the previous models estimated by DfT which included limited number of explanatory variables.

3.3.4.10 Table 3-1 shows the selected model form for each category. In the majority of cases, negative binomial models were found to be preferred over their zero-inflated alternatives. This is mainly due to the extra complexity of the zero-inflated models and large number of parameters to be estimated (as a result of adding more explanatory variables), which is penalised by the Vuong test.

Table 3-1: Trip Rate Models: Preferred Model Forms

Trip Purpose	Full-time	Part-time	NEET	Student	65+	Child
Commuting	ZIP	ZINB	ZINB	ZINB	ZINB	NB
Employers’ Business	NB	ZINB	NB	NB	NB	NB
Education	NB	NB	NB	ZINB	NB	NB
Shopping	NB	NB	NB	NB	NB	NB
Personal Business	NB	NB	NB	NB	NB	NB
Recreation / Social	NB	NB	NB	NB	NB	NB
Visiting Friends & Relatives	NB	NB	NB	NB	NB	NB
Holiday / Day Trip	NB	NB	NB	NB	NB	NB

NB: Negative Binomial
ZIP: Zero-Inflated Poisson
ZINB: Zero-Inflated Negative Binomial

[1] http://artax.karlin.mff.cuni.cz/r-help/library/pscl/html/vuong.html

4. Main Findings

4.1 Introduction

4.1.1.1 This section summarises the estimated effects of different variables on trip rates and discusses the key findings. All the estimated effects are 'partial' effects, where the effect is the result of a change in the value of the variable, holding all other factors constant.

4.1.1.2 Table 4-1 shows average trip rates across all trip purposes and model segments, as well as proportion of each segment in the study dataset. The highest trip rates belong to full time and part time commuting trips, student and child education trips, and shopping trips (across all model segments). On the other hand trip rates by employers' business and holiday trips, as well as commuting trips by non-workers, and education trips by full time and 65+ groups are relatively close to zero, as expected. There are also a few segments where no trips are expected to be made (e.g. commuting or business trips for NEET and child groups) whilst the results show small values of trip rates. These are mainly the outcome of the way trip data are recorded in NTS. It might be that, for example, some individuals in NEET category take a few hours of work within the week for which some commuting or business trips are recorded. The results also suggest that full time employees and students are the largest and smallest segments of the population, respectively.

Table 4-1: Average Trip Rates (Un-weighted) by Model Segments (Data: NTS 2002-2012)

	Full-time	Part-time	NEET	Student	65+	Child
Proportions in the Data (%)	36%	11%	14%	4%	16%	19%
Trip Purpose	**Average HB (from home) trip rates per week**					
Commuting	3.53	2.42	0.26	0.46	0.23	0.12
Employers' Business	0.39	0.29	0.04	0.05	0.05	0.01
Education	0.27	1.33	0.96	2.52	0.07	2.81
Shopping	1.42	2.02	2.57	1.19	2.46	1.31
Personal Business	0.53	0.74	1.08	0.53	1.27	0.61
Recreation / Social	0.90	0.99	0.87	1.16	0.96	0.96
Visiting Friends & Relatives	0.75	0.97	1.19	1.00	0.77	1.11
Holiday / Day Trip	0.25	0.32	0.30	0.19	0.29	0.30

4.1.1.3 The main objective of this section is to estimate the partial effects of different factors on trip rates based on the Poisson or negative binomial models estimated using the methods described in Chapter 3. Whilst zero-inflated models were found to perform slightly better for a few model segments (see Table 3-1), there is additional complexity interpreting the significantly more complex zero inflated models and the analysis here is sufficient at this stage to interpret the main findings of our analysis.

4.1.1.4 Appendix 1 and Appendix 2 include the estimation results of negative binomial models and zero-inflated models (where applicable), respectively, for various categories of trip rates.

4.2 Extended Segmentation

4.2.1 Age

4.2.1.1 Evidence from the literature as well as explanatory analysis of data suggested that age was an important factor in explaining variations in trip rates; it was therefore added to the regression models as an explanatory variables.

4.2.1.2 Four categories of age were defined, as explained in Section 3.3.3.3; however, it should be noted that depending on the model segment, age variable in each trip rate model includes only two categories. Trip rate models for the 65+ segment include 65-74 and 75+ age groups, whilst models for other segments (excluding child segment) include 16-29 and 30-64 age groups.

4.2.1.3 It should be noted that the age groups were chosen taking into account possible changes in demographics in future, and hence influencing future trip rates, as well as the need to reduce model complexity by minimising the number of categories for each variable.

4.2.1.4 The estimated coefficients of age variables for different trip rate models are reported in detail in Appendix 3 and Appendix 4. Table 4-2 summarises the effect of age on trip rates for different categories, in terms of their relative effect on trip rates, where other explanatory factors are controlled for. The model coefficients have been used to estimate the percent difference in trip rates of those in “alternative” age groups compared to those in “reference” age groups. The reference age groups for 65+ model segment and other model segments are 16-29 and 65-74, respectively.

4.2.1.5 Therefore, for example, full time people in 30-64 age group have 3% lower commuting trip rates compared to those in 16-29 age group. Similarly, for example, those in the 65+ category who are older than 75 have 16% lower shopping trip rates than those aged between 65 and 74. It should be noted that in Table 4-2, results are not shown for those segments where percent changes are large and subject to misinterpretation due to trip rates being close to zero (see Table 4-1) and where the estimated effects are not statistically significant.

Table 4-2: Estimated Relative Effects of Membership in Different Age Groups on Un-weighted Trip Rates (Reference Age Groups: 16-29 and 65-74)

Model Category	Age Group	Commuting	Employers' Business	Education	Shopping	Personal Business	Recreation / Social	Visiting Friends & Relatives	Holiday / Day Trip
Full-time	***30-44***	-3%	34%	na	18%	29%	-23%	-25%	12%
	45-64	-5%	60%	na	33%	61%	-28%	-32%	23%
Part-time	***30-44***	10%	52%	16%	30%	38%	-14%	-26%	29%
	45-64	14%	69%	-71%	43%	71%	-20%	-25%	20%
NEET	***30-44***	-29%	3%	54%	17%	19%	-16%	-25%	14%
	45-64	-44%	-9%	-72%	30%	31%	-15%	-32%	22%
Student	***30-44***	NS	na	NS	33%	46%	-41%	-27%	NS
	45-64	NS	na	NS	29%	143%	-28%	-27%	NS
Over 65	***75+***	na	na	na	-16%	-5%	-23%	-30%	na

NS: the effect is not statistically significant at 95% confidence level
na: not shown because percent changes are large and subject to misinterpretation due to trip rates being close to zero

4.2.1.6 As the results show, the effects of age vary across different segments and trip purposes. For 65+ group, there is a consistently lower propensity for making trips among people older than 75, perhaps reflecting reduced mobility. For other categories, individuals younger than 30 tend to have higher social, recreational, and visiting trips but lower shopping and personal business trips compared to those aged between 30-65. No effect could be estimated for education trip rates of students due to lack of large enough sample size in 30-64 age groups.

4.2.2 Area Type

4.2.2.1 As explained in Paragraph 3.3.3.3, 7 categories of area type were defined and included in the trip rate models. These distinguish between London, other Metropolitan build-up areas, small, medium, and large urban areas, and rural areas. Evidence from the literature has shown large variations in trip rates by area. The estimated coefficients for the area variables, reported in detail for all models in Appendix 3, provide similar conclusions (as described in the next paragraph).

4.2.2.2 In general, the modelling results show that, after controlling for factors including age, income, licence holding, and the presence of children, living in London is associated with lower trip rates. This is particularly the case for discretionary purposes such as shopping, personal business and visiting friends and relatives. This is followed by rural areas where trip rates tend to be lower than those in urban and build-up areas. The reasons for this marked 'London effect' are likely to complex and involve the interaction of a range of social, demographic, economic and transport system supply considerations.

4.2.2.3 There is little variation in trip rates between area types for commuting and employers' business trips. The only exception is commuting trips for full-time employees where trip rates are higher in urban and built-up areas. One possible hypothesis explaining this could be that more professionals live in what are defined as rural areas, professionals are much more likely than the population generally to work at or from home (either regularly or occasionally) and that professionals who live in rural areas are more likely to do so than their urban counterparts; hence commuting less.

4.2.2.4 For the purposes of this study we have focused our analysis on the area types recorded in NTS. We observed in developing the models some interactions between area type models and other variables which could be associated with more detailed local variations in trip rates associated with other more local, social or demographic factors. There may be benefits in further analysis, particularly if insight on trip making is sought at a local rather than national scale.

4.2.3 Driving Licence

4.2.3.1 Whether an individual holds a full driving licence was another explanatory variable that was included in the trip rate models, represented as a binary variable. Table 4-3 summarises the estimated effect of holding a driving licence on trip rates in terms of percent changes, when other factors are controlled for. The values of the estimated model coefficients are reported in Appendix 3. Results are not shown for those segments where percent changes are large and subject to misinterpretation due to trip rates being close to zero (see Table 4-1) and where the estimated effects are not statistically significant.

Table 4-3: Percent Change in Un-weighted Trip Rates as a Result of Holding a Driving Licence

Trip Purpose	Full-time	Part-time	NEET	Student	65+
Commuting	3%	NS	na	na	na
Employers' Business	49%	48%	na	na	na
Education	17%	19%	40%	-12%	na
Shopping	28%	30%	16%	38%	21%
Personal Business	28%	34%	22%	33%	35%
Recreation / Social	29%	25%	30%	36%	43%
Visiting Friends & Relatives	31%	34%	10%	NS	30%
Holiday / Day Trip	60%	53%	57%	45%	42%

NS: the effect is not statistically significant at 95% confidence level
na: not shown because percent changes are large and subject to misinterpretation due to trip rates being close to zero .

4.2.3.2 As expected, the results show a positive association between trip rates and driving licence holding for the majority of segments; the sole exception being education trips made by students, where holding a full driving licence is associated with a lower trip rate. However, these results should be interpreted with caution due to the potential for parameter estimates to be affected by endogeneity bias due to licence holding and trip rates being co-determined.

4.2.4 Children in the Household

4.2.4.1 A further explanatory variable added to the trip rate models was the presence of children in the household, represented as a binary variable. The estimated effect of presence of children in the household on trip rates are shown in Table 4-4, with the full results on estimated coefficients in Appendix 1.

Table 4-4: Estimated Effects of Having Children in the Household on Un-weighted Trip Rates

Trip Purpose	Full-time	Part-time	NEET	Student	65+
Commuting	-13%	-20%	na	na	na
Employers' Business	-11%	-41%	na	na	na
Education	na	-	-	18%	na
Shopping	15%	12%	11%	NS	-28%
Personal Business	NS	-12%	-23%	NS	NS
Recreation / Social	-11%	-11%	-25%	-16%	-38%
Visiting Friends & Relatives	-4%	NS	NS	NS	NS
Holiday / Day Trip	NS	-23%	-14%	NS	NS

NS: the effect is not statistically significant at 95% confidence level
na: not shown because percent changes are large and subject to misinterpretation due to trip rates being close to zero .

4.2.4.2 Similarly, results are not shown for those segments where percent changes are large and subject to misinterpretation due to trip rates being close to zero (see Table 4-1) and where the estimated effects are not statistically significant. The results are not also shown for education trip rates for part time and NEET segments as limited variation in the data does not allow estimating effects that are statistically reliable.

4.2.4.3 Where the effect is statistically significant, having children in the household is associated with lower trip rates for the majority of trip purposes and segments; the sole exception are shopping trips where people living in household with children tend to have higher trip rates (except those in 65+ model segment).This could be explained by the fact that more shopping is required for children and also more in-home activity could be associated with children, therefore there will be less time to make other discretionary trips. The reduction in commuting trip rates associated with having children might be due to occasional children illness or other necessary support they might need from the parents.

4.2.4.4 It should be noted that the impact of children on personal trip rates is likely to be influenced by the structure of household organisation and task allocation including sex roles. These are complex issues that we have not attempted to explore in the current study but which merit attention in future research.

4.3 Income Effects

4.3.1 Gross Personal Income vs. Income after Housing Costs

4.3.1.1 As explained in Section 3.2.2, two different variables of income (i.e. gross individual income and individual income after housing costs) were added to the trip rate models separately and their effect on model performance (improvement in the log-likelihood measured through the change in the value of AIC), was compared. Table 4-5 shows, for each combination of trip purpose and model segment, the absolute change in the value of AIC as a result of replacing gross income with income after housing costs. It should be reminded that AIC is a measure of the relative quality of a statistical model for a given set of data. The model with a lower AIC has a better fit to the data and a unit reduction (improvement) in AIC results in a model with a significantly better performance.

Table 4-5: Absolute Change in the AIC Value as a result of Replacing Gross Income Variable with Income after Housing Costs Variable

Trip Purpose	Full-time	Part-time	NEET	Student	65+
Commuting	-11	-3	-4	3	11
Employers' Business	NS	NS	NS	2	NS
Education	NS	-20	NS	NS	NS
Shopping	NS	-1	-1	NS	NS
Personal Business	NS	-5	NS	NS	-3
Recreation / Social	28	-1	-21	NS	-9
Visiting Friends & Relatives	-4	5	-2	-1	3
Holiday / Day Trip	-2	-1	-4	NS	-1

NS: the change in the value of log-likelihood as a result of replacing gross income with income after housing costs is not statistically significant

4.3.1.2 In Table 4-5, the negative values show an improvement in the model fit as a result of using income after housing costs. As can be seen from the results, income after housing costs provides better statistical performance for the majority of the models (18 for 'income after housing costs' versus 6 for 'gross personal income'). The biggest improvements to the model fit were found for full time commuting, part time education, and recreation / social trips for NEET category.

4.3.1.3 For employers' business trips, income after housing was not found to have any influence. This is sensible as income is associated with type of work and housing costs are irrelevant to employers' needs. There are two particular instances where the use of residual income after housing costs rather than individual income significantly worsened the model fit (recreation/social travel by full time employees and commuting by individuals aged 65+). In the former it may be that there is substitution between 'free' activities and 'paid' activities that influences the relationship of trip rates with income; in the latter it may be that the availability of pensions and the associated reasons to continue in employment similarly imply more complex relationships between income and trip rates.

4.3.2 Estimated Effects of Income

4.3.2.1 Table 4-6 shows the partial effects of income, estimated based on the value of coefficients for income variables, when the effects of other variables are controlled for (see Appendix 1 for full model estimation results). All the estimated effects are based on models that include the "preferred" income variable, shown in Table 4-5.

Table 4-6: Partial Effects of Income - % Change in Un-weighted Trip Rates by 10k Increase in Income

Trip Purpose	Full-time	Part-time	NEET	Student	65+
Commuting	-3%	-4%	na	na	na
Employers' Business	7%	12%	na	na	na
Education	na	-15%	-	NS	na
Shopping	NS	2%	2%	NS	NS
Personal Business	NS	3%	NS	NS	3%
Recreation / Social	7%	8%	12%	NS	8%
Visiting Friends & Relatives	-8%	-4%	-4%	NS	-6%
Holiday / Day Trip	10%	6%	7%	NS	6%

NS: the effect is not statistically significant at 95% confidence level
na: not shown because percent changes are large and subject to misinterpretation due to trip rates being close to zero .

4.3.2.2 The general pattern of the results suggests that higher income is associated with higher levels of trip making for recreational and holiday purposes, which the suggestion that this may be at the expense of trip making for the purpose of visiting friends and relatives.

4.3.2.3 Evidence from the LCF suggests discretionary income (e.g. income available for spending after the essentials such as housing expenditure are taken account of) has changed over time in a different manner compared to gross income. However, income as measured by the NTS does not capture such affects and as a result in the current analysis we have been forced to approximate discretionary income at an aggregate rather than disaggregate level. Notwithstanding these approximations, the analysis presented above suggests that such measures of discretionary income offer improved explanatory power in models of travel demand. This points to a need to reconsider this aspect of the NTS data collection protocols.

4.3.2.4 We should also note that the particular measure of discretionary income we have used in this analysis is rather simplistic, being based on the simple netting out of (spatially averaged) housing costs. However other interpretations of discretionary income are of course possible including those that would include elements of transport-related expenditure (e.g., essential trips for medical care), so this is an area that could benefit from further research.

4.4 Effects of Migration

4.4.1.1 Estimated Effects on Trip Rates

4.4.1.2 Table 4-7 shows the partial effects of migration, estimated based on the value of coefficients for migration variables, when the effects of other variables are controlled for (see Appendix 3 for full model estimation results).

Table 4-7: Partial Effects of Migration - % Change in Un-weighted Trip Rates by 10% Increase in Non-UK Residents

Trip Purpose	Full-time	Part-time	NEET	Student	65+
Commuting	NS	-2%	na	na	na
Employers' Business	NS	9%	na	na	na
Education	na	8%	-	NS	na
Shopping	NS	-3%	-4%	4%	-2%
Personal Business	3%	2%	2%	NS	4%
Recreation / Social	-5%	-2%	-7%	-5%	NS
Visiting Friends & Relatives	-4%	-8%	-6%	-12%	3%
Holiday / Day Trip	-8%	NS	-13%	-17%	-11%

NS: the effect is not statistically significant at 95% confidence level
na: not shown because percent changes are large and subject to misinterpretation due to trip rates being close to zero.

4.4.1.3 The results indicate that classification as a migrant is associated with a significantly lower level of trip making for the purposes of recreational/social, visiting friends and relatives, and holiday/day trips. These results are consistent with the hypothesis that migrants are relatively disconnected from their social network. There is also evidence of higher trip rates by migrants for personal business. However, we must also bear in mind that the NTS only records journeys that begin and end in GB. Thus, some of these socially-related trips might potentially be being made by migrants but not recorded entirely by the NTS (i.e. only trips to / from the airport are recorded in NTS), since they are not wholly within GB. This is likely to be a particular consideration for recent migrants from the EU.

4.4.1.4 Our results indicate that those classified as migrants have distinctively different patterns of travel behaviour compared to the indigenous population. Given recent and likely future levels of inbound migration to the UK, this result has potentially important policy implications. However, once again, limitations in the information available in the NTS mean that we should proceed with caution in drawing conclusions at this stage. For example, since the NTS does not collect information on the year of arrival in the UK it is difficult to establish to what degree these differences are transitional/temporary or persistent in nature. This is yet another area in which better data would be beneficial.

4.5 Effects of Internet Use for Shopping

4.5.1 Estimated Effects on Trip Rates

4.5.1.1 Table 4-8 and Table 4-9 show the partial effects of internet use, estimated based on the value of coefficients for online shopping variables, when the effects of other variables are controlled for (see Appendix 3 for full model estimation results). The results in Table 4-8 show the effects on trip rates if individuals shop online, while the results in Table 4-9 show the effects of frequency of internet use for shopping, shown as the percent change in trip rates if shop online less frequently compared to using internet for shopping more frequently.

Table 4-8: Partial Effects of Internet Use for Shopping - % Change in Un-weighted Trip Rates if Shop Online

Trip Purpose	Full-time	Part-time	NEET	Student	65+
Commuting	-2%	-9%	na	na	na
Employers' Business	NS	NS	na	na	na
Education	na	NS	13%	NS	na
Shopping	11%	15%	6%	NS	NS
Personal Business	16%	16%	NS	NS	11%
Recreation / Social	32%	35%	34%	37%	22%
Visiting Friends & Relatives	NS	NS	NS	NS	NS
Holiday / Day Trip	30%	36%	30%	NS	NS

NS: the effect is not statistically significant at 95% confidence level
na: not shown because percent changes are large and subject to misinterpretation due to trip rates being close to zero.

Table 4-9: Partial Effects of Internet Use for Shopping - % Change in Un-weighted Trip Rates if Shop Online More Frequently Than Once a Week Compared to Shopping Online Less Frequently

Trip Purpose	Full-time	Part-time	NEET	Student	65+
Commuting	-6%	-11%	na	na	na
Employers' Business	NS	NS	na	na	na
Education	na	19%	NS	NS	na
Shopping	-6%	NS	-11%	NS	-23%
Personal Business	NS	9%	NS	NS	-12%
Recreation / Social	NS	NS	NS	NS	-26%
Visiting Friends & Relatives	-8%	-10%	-18%	NS	NS
Holiday / Day Trip	NS	NS	NS	NS	NS

NS: the effect is not statistically significant at 95% confidence level
na: not shown because percent changes are large and subject to misinterpretation due to trip rates being close to zero.

4.5.1.2 The results indicate that internet use for shopping is in general associated with substantially higher levels of non-work related trip making, especially for recreational and holiday purposes and correspondingly lower levels of commuting. Whilst use of the internet for shopping is not directly related to these purposes it is reasonable to assume that attitudes and use of the internet for reasons associated with these purposes may be correlated, and if so this would imply that use of the internet may be best viewed as an enabler, providing individuals with information facilitating more travel for discretionary purposes as well as providing opportunity to work from home.

4.5.1.3 The results on the effects of how frequently the internet is used for shopping (Table 4-9) are interesting. When the effects are statistically significant, in most of the cases trip rates tend to be lower for those who do online shopping more frequently (at least once a week).

4.5.1.4 Although striking, these findings should, we believe, be interpreted with some caution especially for future forecasts. Whilst online shopping has grown rapidly in recent years, it is still a minority behaviour and accordingly these findings reflect the particular features of the sub-population group of early adopters, and might not generalise straightforwardly to the general population. Further, the capabilities of internet technology is changing very rapidly and likewise also the business models and user experience of online shopping (and wider internet-enabled activities) is also subject to rapid development. As a result, this is an area in which it is especially difficult to draw reliable conclusions for the future from observations of past data.

4.6 Trends in Trip Rates

4.6.1 Trends Explained by Explanatory Variables

4.6.1.1 Amongst various trip purposes, observed trends shown in Figure 3-1 suggest that trip rates have declined between 2002 and 2012 for commuting, shopping, personal business, and visiting friends and relatives trip purposes.

4.6.1.2 In order to be able to model changes in trip rates over time, DfT included a continuous variable "year" in the trip rate regression models. The coefficient of this variable reflects the average changes in trip rates over time, not explained by other explanatory variables in the model.

4.6.1.3 An objective of this study was to identify factors that could explain part or all of the observed trends in trip rates, and to identify to what extent they can do so. Comparison of the coefficient of variable "year" between the models estimated by DfT and the final models estimated in this study provides insights into this. The reduction in the value of the estimated coefficients of "year" variables as a result of adding the extra explanatory variables show the changes in trip rates over time that are explained by changes in the explanatory variables.

4.6.1.4 In order to estimate the partial contribution by the explanatory variables used in the model, estimated coefficients of "year" variables in the models were used to estimate changes in trip rate over time that are not explained by other explanatory variables in the model. These were then compared between models estimated in different stages of model estimation, which included different explanatory variables. The results are summarised in Table 4-10 for four trip purposes that show a significant decline over the 11 years studied.

Table 4-10: The Proportion of Trends in Un-weighted Trip Rates Which are Explained by Model Variables

Trip Purpose	Trip Rates			% of Change Explained by Other Explanatory Variables	
	2002	2012	Change	Model with Added Segmentation	Final Model
Commuting[1]	3.56	3.05	-0.51 (-14%)	2%	13%
Shopping	2.01	1.80	-0.21 (-11%)	4%	7%
Visiting Friends & Relatives	0.96	0.76	-0.20 (-21%)	1%	11%
Personal Business	0.90	0.77	-0.13 (-15%)	0%	0%

[1]: Commuting trip rates show trip rates for full-time and part-time workers only

4.6.1.5 In this table, the reduction in trip rates between 2002 and 2012 are shown (as absolute numbers and percentages) as well as the proportion of this reduction which is explained by the explanatory variables in two models: the models with added segmentations (i.e. existing NTEM segmentation plus age, area, children in the household, and driving licence) and the final models which also include income, migration and internet use variables.

4.6.1.6 As the results show, the majority of observed trends in trip rates remain unexplained by the explanatory variables in the models. This is particularly the case for personal business trips where the variables in the models do not explain any of the observed changes in trip rates over time (i.e. the coefficient of "year" variable remains unaffected by adding extra explanatory variables).

4.6.1.7 For other trip purposes, between 7% and 13% of the observed trends are explained by additional segmentation and the added variables. It should be noted that for commuting and visiting trip purposes, the majority of these are explained by migration and internet use variables. Income variables do not seem to explain any of the observed changes in trip rates over the 11 years.

4.6.1.8 It should be noted that the nature of cross-sectional variations is very different from time-series changes. Cross-sectional variations[1] reflect differences in trip rates between different categories whilst time-series changes[2] are the outcome of changes in underlying casual factors over time, some of which might not even vary cross-sectionally (and vice-versa). Therefore, for example, whilst trip rates show significant variations by income, income might not explain changes over time in trip rates if the distribution of income does not change significantly.

4.6.1.9 Whilst some of the variables used in the regression models do not explain the observed trends for the period of study, they significantly contribute to the cross-sectional variation in trip rates. They could therefore substantially improve the accuracy of forecasts if distribution of these variables changes in future. For example, if population structure changes in future, using trip rate models estimated in this study for forecasting can materially improve NTEM forecasts.

4.6.2 Possible Effects of Response Bias and Survey Method

4.6.2.1 Following the result reflected in Table 4-10 and as mentioned in Section 3.1.5, a question that is raised is to what extent the observed changes in trip rates over time that are not explained by added variables in the models are in fact the consequence of behavioural changes over time (i.e. “real” changes) and not an indirect result of potential data collection issues and / or response bias.

4.6.2.2 There is a wide range of evidence in the literature suggesting that response bias exists to various degrees in travel diaries and these could significantly influence mobility outcomes derived from the survey. For example, it has been argued that those most likely to respond to home-based surveys such as the NTS are those individuals who spend the most time at home (Jahanshahi, et al., 2009).

4.6.2.3 In a study into non-response bias in the 2001 London Area Transport Survey (LATS), carried out by Polak (2002) for Transport for London, the following findings were reported:

> *“The nature of the non-response mechanism is in general such as to reduce the representation of high mobility households in the final sample. Simple tests using the sample data collected in the pilot survey suggest that the biases in the estimation of mobility that are introduced in this way can be highly significant. …*
>
> *This significance is twofold. First, since highly mobile households are less likely to participate in the main survey than less mobile ones, estimates of mobility based on data from the main survey will be biased downwards. Second, ex-post treatments such as re-weighting that are based solely on demographics are unlikely to adequately account for these effects.”*

4.6.2.4 Although this study was not based on NTS, the findings could be applicable to NTS given the similarities between LATS and NTS. In 2013, an experiment was conducted by DfT to examine whether there is any difference in reported short walks in day 1 of the travel diary week instead of day 7 (DfT, 2014e). It was concluded that, in general, trips in day 7 are under reported by about 10% and short walks on day 7 are under reported by about 36%.

4.6.2.5 A detailed investigation of NTS response bias was not within the scope of this study; while the response rate for NTS declined from nearly 80% in 1991 to just over 60% in 2001, the overall response rate has remained at this level with no material change over the period we have analysed. We undertook some explanatory analysis to investigate if there is any indication of change in the way trips are reported over time.

[1] See for example WebTAG M2 Section C3.4, Table C1 which summarises cross-sectional income elasticities between 0.15 and 0.36 depending on purpose.
[2] WebTAG databook applies an elasticity of 1.0 to GDP per capita to estimate future values of time

4.6.2.6 We focused on commuting trips where we expect consistent interview quality and very low risk of under reporting. We then sought to exclude possible contributing factors that might result in no trips being reported by selecting full time employees only (to exclude effects related to part time and un-employment). We then calculated the proportion of people who have not reported any commuting trips during the travel diary week and analysed the changes in these proportions over time. The estimated proportions (and 95% confidence intervals) of people recording no commuting, and with no commuting or business trips, are shown in Figure 4-1 and Figure 4-2, respectively.

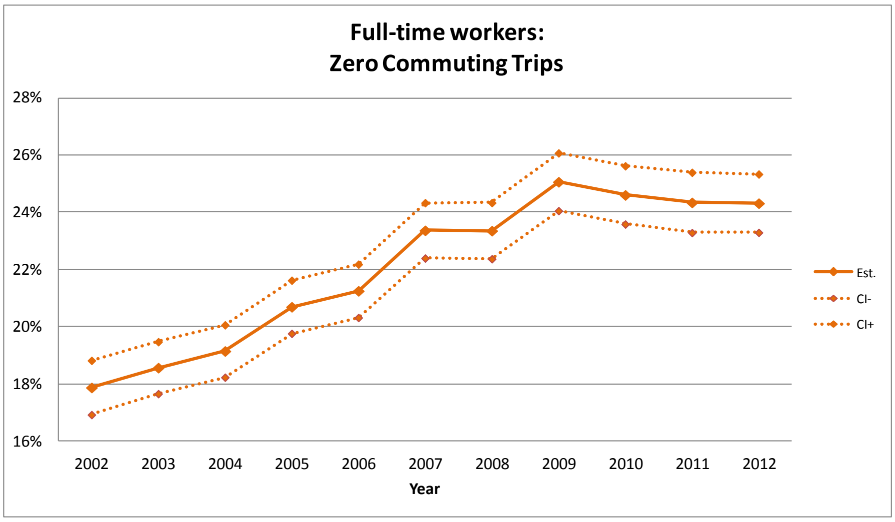

Figure 4-1 – Changes in the Proportion of People with Zero Commuting Trips: Full Time Employees

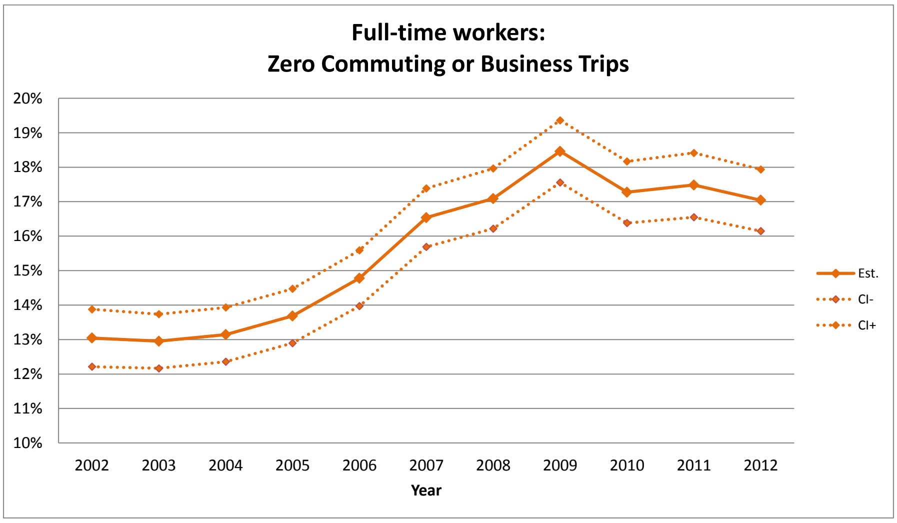

Figure 4-2 – Changes in the Proportion of People with Zero Commuting and Business Trips: Full Time Employees

4.6.2.7 The results show a significant increase in the proportion of full-time workers with no commuting trips over time, from 18% in 2002 to about 24% in 2012. A similar pattern is observed when business trips are included as well (Figure 4-2). The existing evidence suggests a growth in the number of self-employed people in the past decade. We therefore repeated the above analysis, excluding self-employed people from the data. The results, shown in Figure 4-3, still show a significant increase over time.

Figure 4-3 – Changes in the Proportion of People with Zero Commuting and Business Trips: Full Time Employees excluding self-employed

4.6.2.8 There could be various reasons for people in full time employment not to make any commuting trips during the week. These include annual leave, sick leave, maternity / paternity leave, training, working from home, etc. while we are not aware of complete statistics, our judgement suggests that non-attendance at work is likely to be broadly 15% due to various leaves, and this is consistent with the NTS responses. However, we did not find any indication of changes in these over time that could explain the observed pattern.

4.6.2.9 A review of legislation changes suggests that increases in parental leave entitlement may have explained up to 10% of the observed pattern, however, this appears to be slightly outweighed by evidence on reduced average sick leave.

4.6.2.10 Another factor that could explain these trends is a potential rise in homeworking. Whilst NTS data shows that proportion of people working from home has more than doubled during 1998-2008 (DfT, 2014a), analysis of data during 2002-2012 did not suggest such a trend. This result is based on the analysis of the binary responses that the respondents gave to the question of whether it is possible to work from home. The question was reworded and the ranges of possible responses were changed in 2009; which could partly explain the difference in the outcome of the two analyses mentioned above.

4.6.2.11 Other statistics also suggest a slight increase in the number of people who actually work from home. For example, ONS figures on homeworking trends[1] show that the proportion of homeworkers in the UK has increased from 11.1% in 2001 to about 13% in 2011, although this increase could only represent part of the change observed in NTS responses. There are limits to our ability to interpret these data; it could be argued that there has been an increase in flexibility to work some days at home and some in the work place, and this variability is poorly identified in existing surveys.

4.6.2.12 It therefore remains unclear to us as to what extent the trends shown in Figure 4-1, Figure 4-2, and Figure 4-3 could be explained by an increase in the proportion of people working from home. We understand that the NTS survey methodology has not changed in any way that would influence the likelihood of recording trips and do not have any evidence that would support a hypothesis that respondents have increased their tendency to forget and under report travel. Similarly the stability of the overall survey response rate over the period we have analysed might indicate that associated biases in recorded trip rates may have remained stable.

[1] http://www.prospect.org.uk/news/story/2012/March/20/ONS-figures-on-homeworking-trends

4.6.2.13 One possible explanation for these trends could be more linked trips (i.e. people doing other activities on the way to and from work). For example, if a person drops off and picks up a child on the way to/from work every day, then no commuting trips would be recorded. We, however, did not find any strong evidence on any significant change in trip chaining over time.

5. Trip Rate Forecasting Tool

5.1 Background

5.1.1 Context

5.1.1.1 The objective of the second stage of this study was to develop a tool that allows estimation of trip rates up to a horizon year of 2051 and the production of trip rate scenarios with assumptions about the input variables and the trends, using the statistical models estimated in the first stage of work, reported earlier in this document.

5.1.1.2 The tool was also intended to be used to produce base year (2011) and forecast trip rates, and trip rate scenarios for input into NTEM 7.

5.1.1.3 This chapter describes the forecasting model, preparation of the base year data, forecasting methodology, and the outcome of a series of back-casting undertaken to verify the performance of the forecasting tool.

5.1.2 Overview of the Forecasting Model

5.1.2.1 The trip rate regression models estimated based on 2002-2012 NTS data, described in Section 3.3, were used as the basis of forecasting average trip rates. The forecasting tool used to estimate future trip rates is a stand-alone model developed using Microsoft Excel and Visual Basic Applications (VBA).

5.1.2.2 Figure 5-1 provides an overview of data flow into the trip rate forecasting tool. The statistical package R was used to produce disaggregate estimates of trip rates for the base year (2011), based on estimated regression models. These are used as fixed inputs to the forecasting tool. This process, also assigns the base year population to each model segment, to be used, with assumed future changes, in forecasting aggregate trip rates, e.g. for distinct population segments.

5.1.2.3 As Figure 5-1 shows, three sets of inputs are required by the forecasting model: time trend scenarios, base year population split by trip rate model segments, and a series of forecasting assumptions.

5.1.2.4 Time trend scenarios define changes in trip rates over time, which are not explained by the explanatory variables in the regression models. During 2002-2012, these are quantified by the estimated coefficients of variable “Year” in the regression models. Assumptions are needed on how these unexplained trends continue in future, and different scenarios can be defined to reflect various assumptions. The “Forecasting Tool User Guide” provides more details on the format and requirements of the time trend scenarios.

5.1.2.5 The process of estimating base year population by model segments from various data sources is described in detail later in Section 5.2.

5.1.2.6 As Figure 5-1 shows, a series of assumptions are also required to forecast trip rates. These are factors that determine changes in the distribution of population between model segments, relative to the base year population, and are used to aggregate trip rates across various population segmentations. A detailed description of these factors is given in the “Forecasting Tool User Guide”.

5.1.2.7 The “Forecasting Tool User Guide” provides more details on the inputs to the tool, forecasting assumptions, processing, and outputs from the tool. It should therefore be used to prepare forecasting inputs and run the forecasting tool.

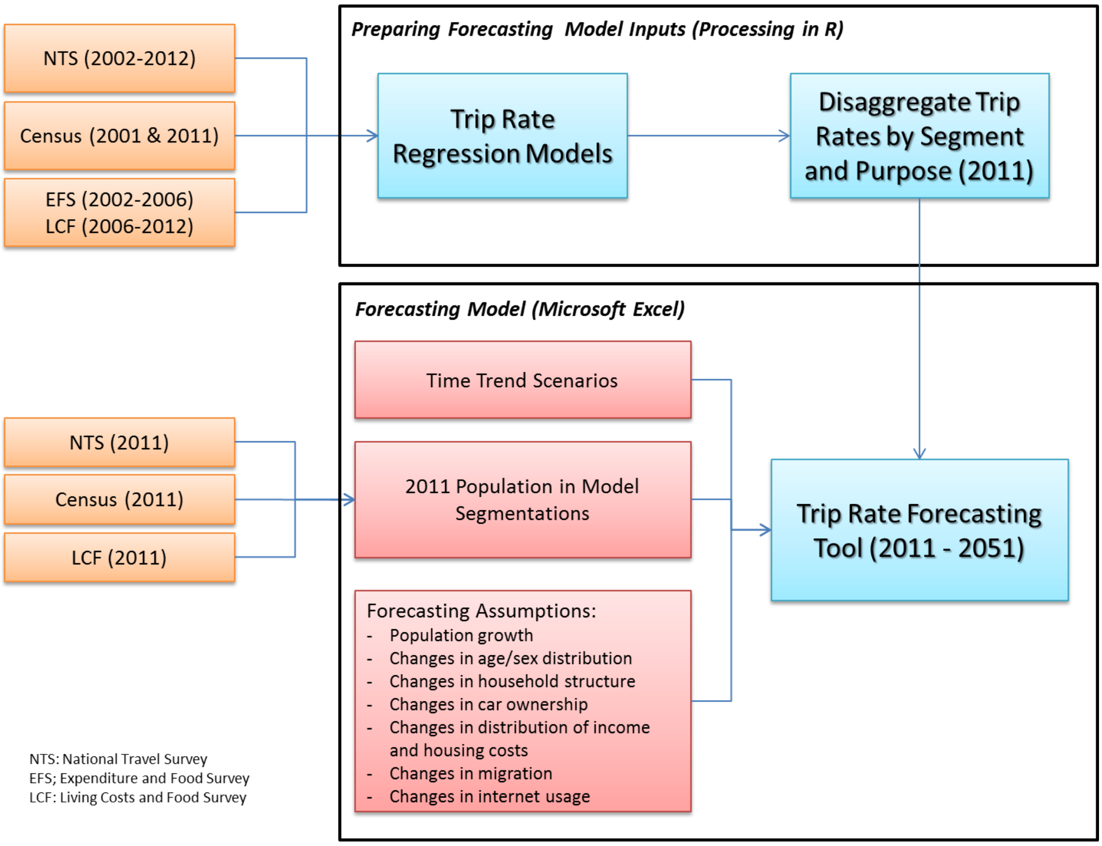

Figure 5-1 – Overview of the Trip Rate Forecasting Process

5.2 Base Year Population Data

5.2.1 Segmentation Requirements

5.2.1.1 Table 5-1 shows the list of explanatory variables used in the trip rate regression models. Different possible combinations of these variables define segmentations of the forecasting tool, each of which will have a distinct average trip rate estimated by the trip rate regression models.

Table 5-1: Segmentation of the Trip Rate Forecasting Tool

Variable Group	Variable Name	Variable Type	Variable Categories / Definitions	Comments
Person Type	Age / work status	Categorical	Full time	Aged 16 or over working more than 30 hours a week
			Part time	Aged 16 or over working less than 30 hours a week
			Student	Full time or part time student who is not in paid work
			NEET	Not in employment, education, or training
			65+	Aged 65 or over
			Child	Aged under 16
	Household Type	Categorical	1 adult, 0 car	Household type is defined as a combination of number of adults and household car ownership
			1 adult, 1+ cars	
			2 adults, 0 car	
			2 adults, 1 car	
			2 adults, 2+ cars	
			3+ adults, 0 car	
			3+ adults, 1 car	
			3+ adults, 2+ cars	
	Sex	Categorical	Male	
			Female	
	Age	Categorical	16 to 29	
			30 to 44	
			45 to 64	
			65 to 74	
			75+	
	Children in the household	Categorical	0 children	
			1+ children	
	Full driving licence	Categorical	Yes	
			No	
	Household online shopping frequency	Categorical	At least once a week	Includes online shopping for all types of products
			Less often than once a week	
			Never	
Income	Individual income	Continuous	Annual income, £	In 2010 prices
	Housing costs	Continuous	Annual housing costs, £	In 2010 prices
Traveller residential location	Area type	Categorical	Inner London	
			Outer London	
			Metropolitan built-up	
			Large urban	Over 250k population
			Medium urban	25k to 250k population
			Small/medium urban	10k to 25k population
			Small urban	3k to 10k population
			Rural	
	Non-UK residents	Continuous	Proportion of residents born outside the UK	Calculated in Census 2011 Ward level
Forecast year	Year	Continuous	Forecasting year	

5.2.1.2 In order to forecast trip rates for various combinations of these segments, and any aggregation of these, detailed population data is required for each segment. This is sourced from the 2011 Census data disaggregated using factors derived from various sources of data; this process is detailed in the next section.

5.2.2 Estimation of Population in Model Segments

5.2.2.1 Figure 5-2 provides an overview of the sources of data used and the process developed to disaggregate Census population by trip rate model segments, for the base year. The following individual steps were taken to prepare an estimate of population in segmentations shown in Table 5-1.

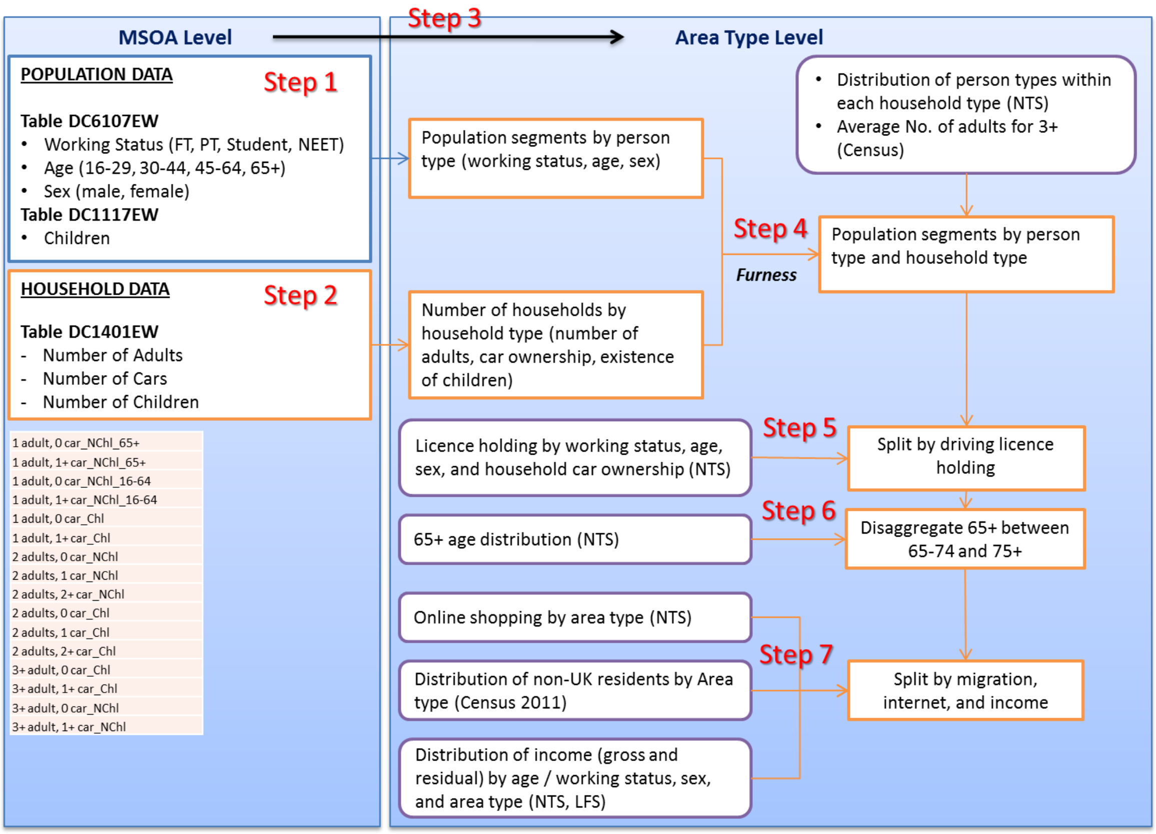

Figure 5-2 – Process of Disaggregating Base Year Population by Model Segments

Step 1 – Population by working status, age, and sex (MSOA Level)

5.2.2.2 Economic activity by sex and age is available at MSOA level from 2011 Census (Table DC6107EW). This information was used to estimate the number of people by working status, age, and sex categories used in the trip rate models.

5.2.2.3 However, this table does not provide any information about the age split for 65+ and the number of children (under 16). Sex by single year of age is separately available at MSOA level from Census (Table DC1117EW). This information was used to obtain total number of children (under 16) in each MSOA. Refined segmentation for 65+ is discussed in Paragraph 5.2.2.13.

5.2.2.4 Table 5-2 shows the relationship between Census economic activity definitions and working status categories used by the trip rate models.

Table 5-2: Correspondence between Census Economic Activities and Trip Rate Working Status Categories

2011 Census Category	Trip Rate Model Category
Employee Full-time	Full-time
Employee Part-time	Part-time
Self-Employed Full-time	Full-time
Self-Employed Part-time	Part-time
Unemployed	NEET
Economically Inactive Retired	NEET
Economically Inactive Student	Student
Economically Inactive Home	NEET
Economically Inactive Disabled	NEET
Economically Inactive Other	NEET

Step 2 – Households by household type and car ownership (MSOA Level)

5.2.2.5 Household composition by car availability information is available from 2011 Census at MSOA level (Table 1401EW). The household information includes number of adults in the household, whether children exist in the household, and age groups of the adults living in the household (16-64 or 65+).

5.2.2.6 The above information was used to create correspondence between Census categories of household composition and car ownership, and household type and age categories in the trip rate models. A total of 45 household composition categories available from Census were grouped into the following 16 household categories (the correspondence between Census categories and these is given in Appendix 3):

- 1 adult, 0 car - without Children – age 65+
- 1 adult, 1+ car - without Children – age 65+
- 1 adult, 0 car - without Children – age 16-64
- 1 adult, 1+ car - without Children – age 16-64
- 2 adults, 0 car - without Children
- 2 adults, 1 car - without Children
- 2 adults, 2+ car - without Children
- 2 adults, 0 car - with Children
- 2 adults, 1 car - with Children
- 2 adults, 2+ car - with Children
- 3+ adult, 0 car - without Children
- 3+ adult, 1+ car - without Children
- 1 adult, 0 car - with Children
- 1 adult, 1+ car - with Children
- 3+ adult, 0 car - with Children
- 3+ adult, 1+ car - with Children

Step 3 – Aggregate population and household segments into area types

5.2.2.7 The population and household segmentations obtained in steps 1 and 2, respectively, were aggregated from MSOA level into the 8 area type categories used in the trip rate models (see Table 5-1). These area types are defined in the NTS and correspond to ONS local authority districts, used to develop the correspondence between MSOAs and the area types.

Step 4 – Merge person and household segmentations

5.2.2.8 In order to merge person and household segmentations obtained in steps 1 and 2 for each area type, NTS data (2011 survey year) was used to estimate the distribution of person types (defined by working status, sex, and age group) who live in each of the 16 household categories listed in Paragraph 5.2.2.6 above.

5.2.2.9 These proportions were used, separately for each area type, to estimate number of individuals from various person types living in each household category. For households with 3+ adults, an average household size was calculated by comparing total number of individuals living in these households and total number of 3+ adult households.

5.2.2.10 A matrix balancing procedure (Furness method) was then used to adjust number of people in each person type and household category so that the total estimated number of individuals in each person type and household category matched total figures observed from the Census for each category. It is noted that this process was undertaken separately for each area type.

Step 5 – Split by driving licence holding

5.2.2.11 The proportion of adults who have driving licence was estimated from the NTS data (2011 survey year). These were estimated separately by working status, sex, age, and household car ownership categories; these are the factors that significantly influence the probability of adults holding full driving licence.

5.2.2.12 The above estimates were used to split population into two further categories, defined by full driving licence holding status.

Step 6 – Split 65+ segment by two age groups

5.2.2.13 As shown in Table 5-1, adults over 65 need to be disaggregated between 65-74 and over 75+ age groups. It was mentioned in Paragraph 5.2.2.3 that the Census information by economic activity and age (Table DC6107EW) did not include any further age split for the 65+ age group.

5.2.2.14 NTS data were used to estimate proportion of over 65 adults in these age categories by working status and age; these estimates were used to allocate total individuals over 65 into the two age groups required by the trip rate models.

Step 7 – Split by Income, migration, and internet usage categories

5.2.2.15 The proportion of households in different online shopping categories was estimated from the NTS, separately for each area type. These were used to split the population by online shopping categories shown in Table 5-1.

5.2.2.16 The proportion of residents born outside the UK is available from Census 2011. These were used to estimate distribution of residents by migration categories, separately for each area type, and used to split the population by migration categories.

5.2.2.17 Income distribution was calculated from the NTS, separately by working status / age categories, sex, and area type. Within the forecasting tool, these were used to allocate base year population into various income groups.

5.3 Trip Rate Forecasting Process

5.3.1 Overview

5.3.1.1 The forecasting tool allows users to apply various factors and weights to the base year population in order to forecast the changes in base year trip rates and population, and subsequently estimate:

- disaggregate trip rates – i.e. trip rates and population proportions for every traveller segment, purpose, area type, and for every segment;
- aggregate trip rates – i.e. trip rates and population estimates for aggregate traveller segments, by trip purpose and area type; and
- trip rates in the format required as an input to NTEM7.

5.3.1.2 Figure 5-3 provides an overview of the overall structure of the tool. More details are given in the "Forecasting Tool User Guide".

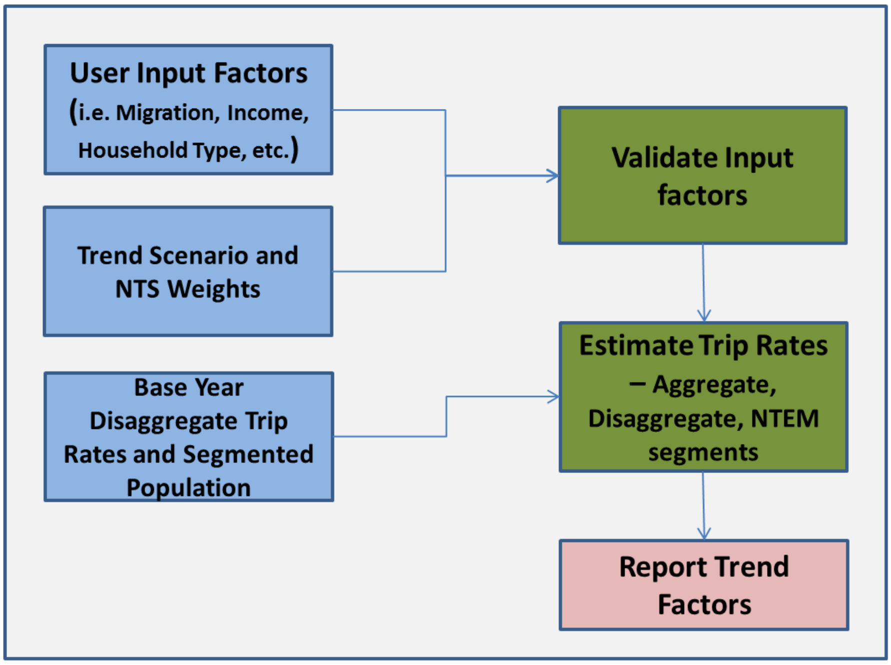

Figure 5-3 – Overall Structure of the Forecasting Tool

5.3.2 Forecasting Scenarios

5.3.2.1 Different scenarios can be defined, which will then be used to forecast trip rates. Forecasting scenarios can be defined by a combination of the following:

- different assumptions on input factors within the tool (e.g. population growth, income distribution, migration, etc.); and
- various trend scenarios, (explained in Section 5.1.2.4, and in greater detail in the "Forecasting Tool User Guide").

5.3.2.2 Once a particular scenario has been defined, the user can proceed to apply the model to estimate trip rates for the chosen scenario and selected forecast year.

5.3.3 Forecasting Methodology

5.3.3.1 The regression models described in Section 3.3 and reported in Appendices 1 and 2 are used to estimate disaggregate trip rates for all possible combinations of categories reflected in Table 5-1.

5.3.3.2 Aggregate trip rates for a given year, area type A, purpose Q, and traveller segment T (i.e. full-time, part-time, NEET, student, 65+, child) are estimated as the average of the trip rates for all person type categories (see Table 5-1) living in area type A (disaggregate trip rates), weighted by the numbers of travellers in each person type category living in area type A – i.e.:

$$\text{Aggregate Trip Rate} = \frac{\sum_i^n P_i T_i}{\sum_i^n P_i},$$

where n is the number of person types living in area type A, and Pi and Ti are, respectively, the estimated population and trip rate for the person type category i in the given year.

5.3.3.3 As mentioned earlier, the inputs contain the disaggregate trip rates for all person type categories defined by various combination of the following factors:

- age;
- sex;
- driving licence holding status;
- household type;
- existence of children in the household;
- household online shopping frequency;
- income (gross or residual); and
- born in the UK or being born abroad.

5.3.3.4 It should be noted that disaggregate trip rates are estimated by the regression models as inputs to the tool, excluding response day response weights (Section 3.3.2). Weights are applied to account for underreporting of trips in the NTS data. The weights are calculated directly from the NTS. For each purpose, an average weight across all survey years (2002-2012) is used to weight forecast trip rates. These were derived comparing NTS trip rates with and without the response day specific weights.

5.3.3.5 The population growth factors, which are amongst the user inputs for a given forecast year, are used to estimate population for unique population segments defined by traveller segment, age, sex, driving licence holding, and presence of children in the household. For a given forecast year, the migration, income and online shopping factors are used to split the forecast population as follows:

$$P_{jy} = M \times O \times I \times P_y$$

where P_{jy} is the forecast population for unique population segment j and forecast year y (estimated by applying growth factors to the base year population), and M, O, and I are migration, online shopping and income factors, respectively.

5.3.3.6 Base year trip rates are used together with response day weights and time trend factors to forecast trip rates. For a given trend factor F (refer to user guide) and response day weight W_B corresponding to year y, the trip rate for a given traveller, T_Y, is estimated as follows:

$$T_y = T_B \times (1+F) \times W_B \; ,$$

where T_B is the base year trip rate (excluding response day weight) derived from the regression model.

5.4 Interpretation of Model Forecasts and Uncertainty

5.4.1 Overview

5.4.1.1 There are three main sources of uncertainty in the model forecasts; these are listed below:

1. model estimation errors;
2. uncertainty in forecasting input assumptions; and
3. trip rate trends not accounted for by model inputs (explanatory variables).

5.4.2 Model Estimation Errors

5.4.2.1 Model estimation errors are directly given as a standard output of the tool, in the form of estimated standard errors and 95% confidence intervals for forecast trip rates.

5.4.2.2 Standard errors for aggregate trip rates reported by the tool are obtained by aggregating standard errors from regression models used for base year estimates. The aggregation process is as follows.

5.4.2.3 Aggregate trip rate Ta for a segment a is computed as:

$$T_a = \alpha_1 T_1 + \alpha_2 T_2 + \ldots + \alpha_n T_n \; ,$$

where α_i is the proportion of the segment's population in sub-segment i and T_i is the estimated trip rate for that sub-segment. Assuming that trip rate estimates are independent, the error variance of trip rate estimates for a given segment is equal to the sum of the variances of trip rates for each sub segment.

5.4.2.4 Consequently, the weighted aggregate error variance of the segment can be computed as

$$\mathrm{Var}(T_a) = \alpha_1^2 \mathrm{Var}(T_1) + \alpha_2^2 \mathrm{Var}(T_2) + \ldots + \alpha_n^n \mathrm{Var}(T_n) \; ,$$

where α_i is the aforementioned population proportion. Given that the standard error of an estimate may be defined as the square root of the estimated error variance of the quantity,

$$SE(t) \equiv \sqrt{\mathrm{Var}(t)} \; .$$

the standard error for the segment a is computed as:

$$SE(T_a) = \sqrt{\alpha_1^2 SE(T_1)^2 + \ldots + \alpha_n^2 SE(T_n)^2} \; ,$$

where $SE(T_i)$ is the error variance for sub segment i obtained by applying NTS weight and time trend factors to the base year variance as shown in Paragraph 5.3.3.6.

5.4.3 Uncertainty in Input Assumptions and Time Trend Factors

5.4.3.1 Other sources of uncertainty relate to the uncertainty in the forecasting input assumptions (i.e. population growth, income distribution, migration changes, etc.), as well as uncertainty in the assumed changes in trip rates over time which are not explained by the input factors.

5.4.3.2 As explained in Section 5.3.2, various forecasting scenarios could be defined by the user to cover a range of assumptions based on changes in the above two factors. It is therefore recommended that a scenario-based approach is used where a range of inputs and trend scenarios could be tested.

5.5 Back-casting

5.5.1 Back-casting

5.5.1.1 The developed forecasting tool was used to back-cast trip rates by purpose between 1995 and 2012; these were then compared with observed trip rates from the NTS, in order to verify the forecasting process. The results are shown by trip purpose in Figure 5-4 to Figure 5-11, comparing the projections of the tool with average trip rates tabulated directly from NTS data.

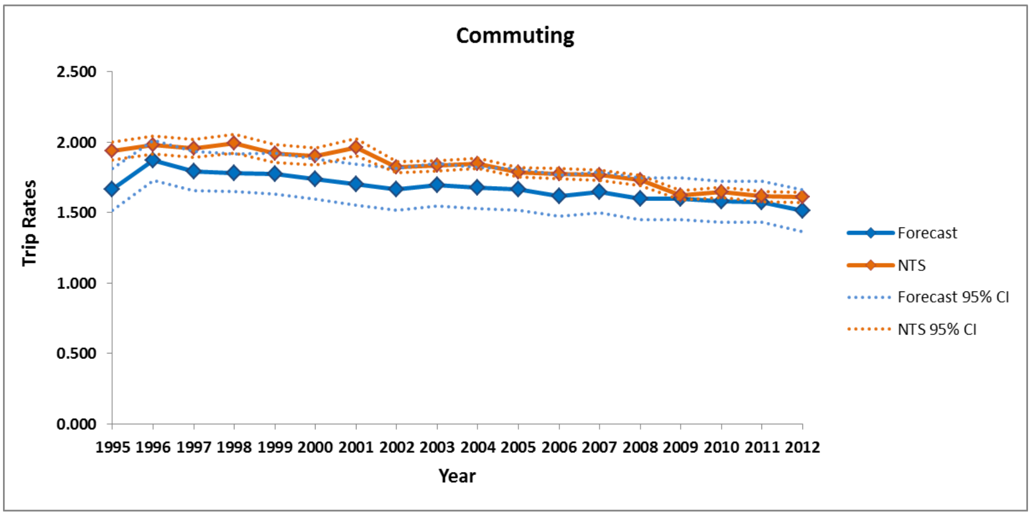

Figure 5-4 – Back-casting Results: Commuting Trip Rates

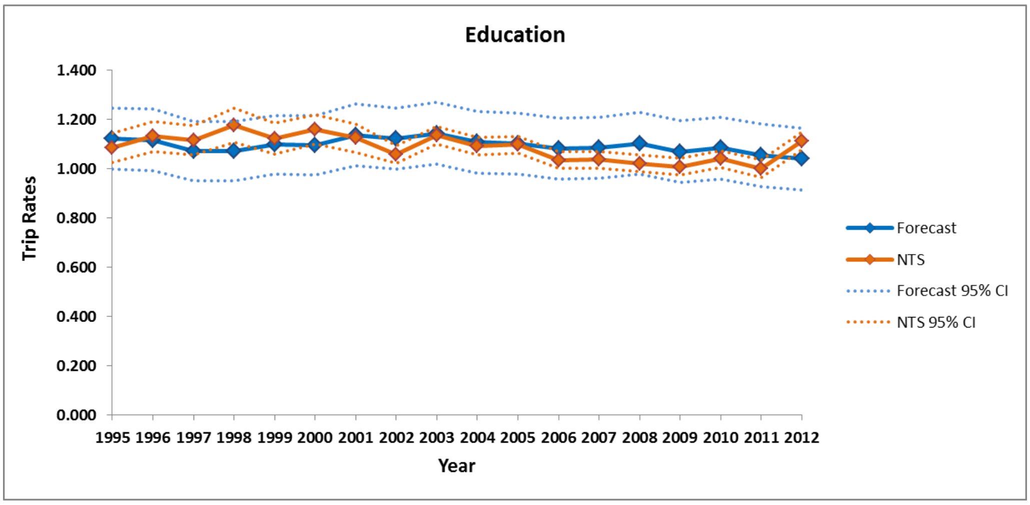

Figure 5-5 – Back-casting Results: Education Trip Rates

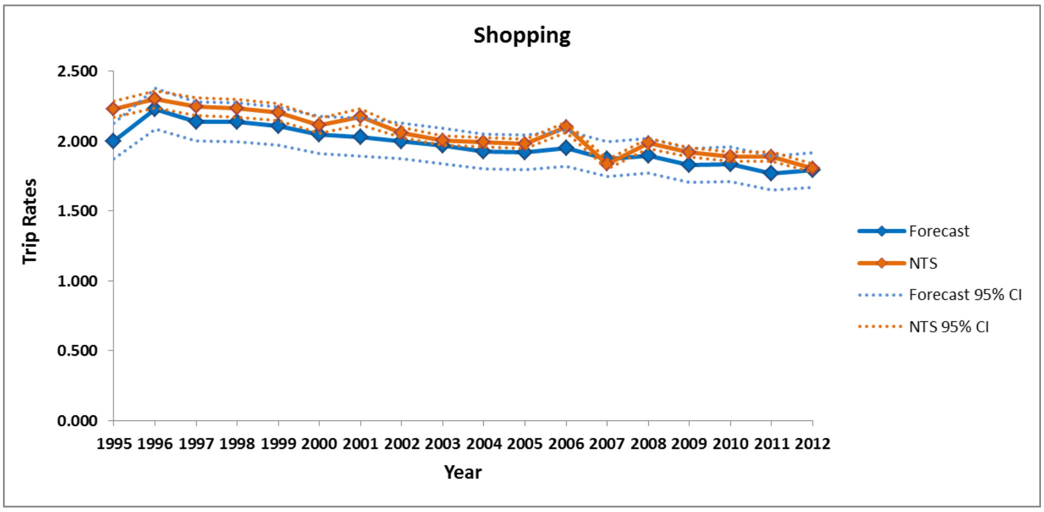

Figure 5-6 – Back-casting Results: Shopping Trip Rates

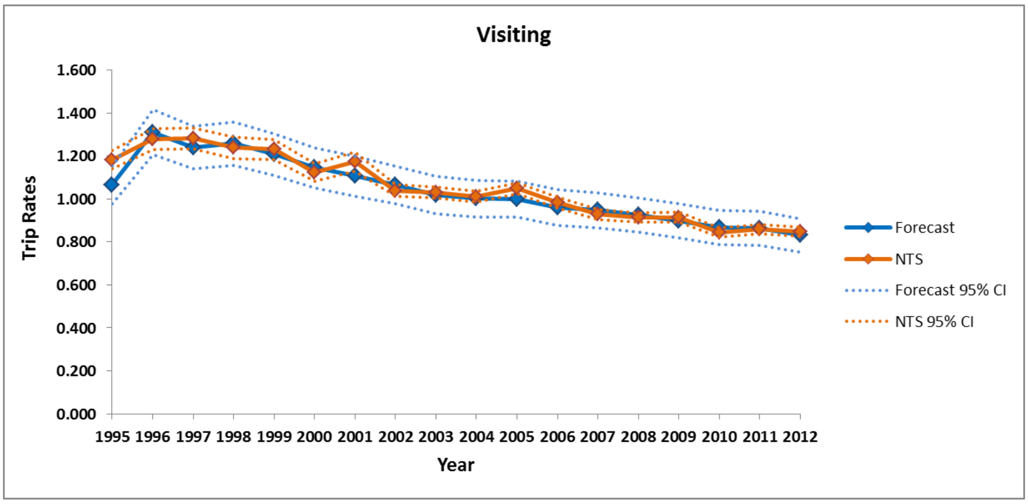

Figure 5-7 – Back-casting Results: Visiting Trip Rates

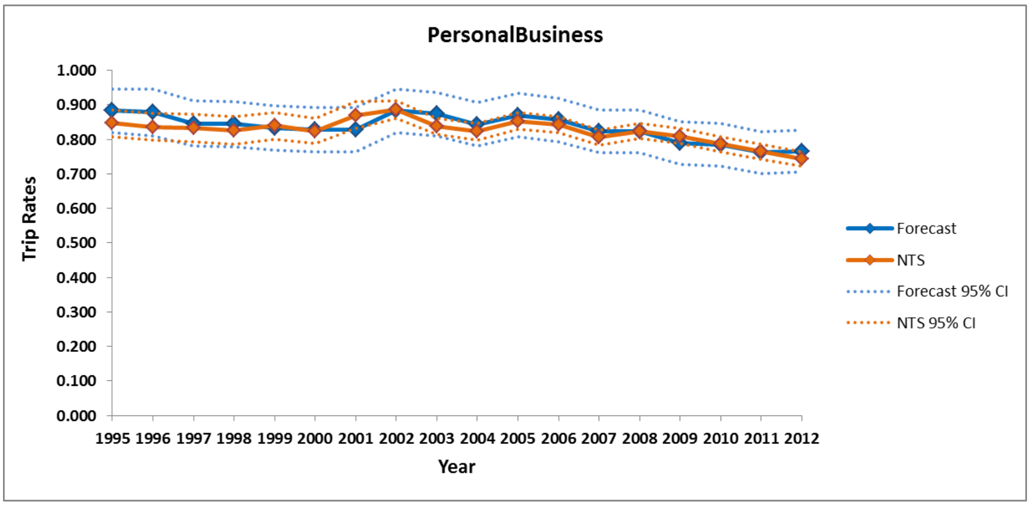

Figure 5-8 – Back-casting Results: Personal Business Trip Rates

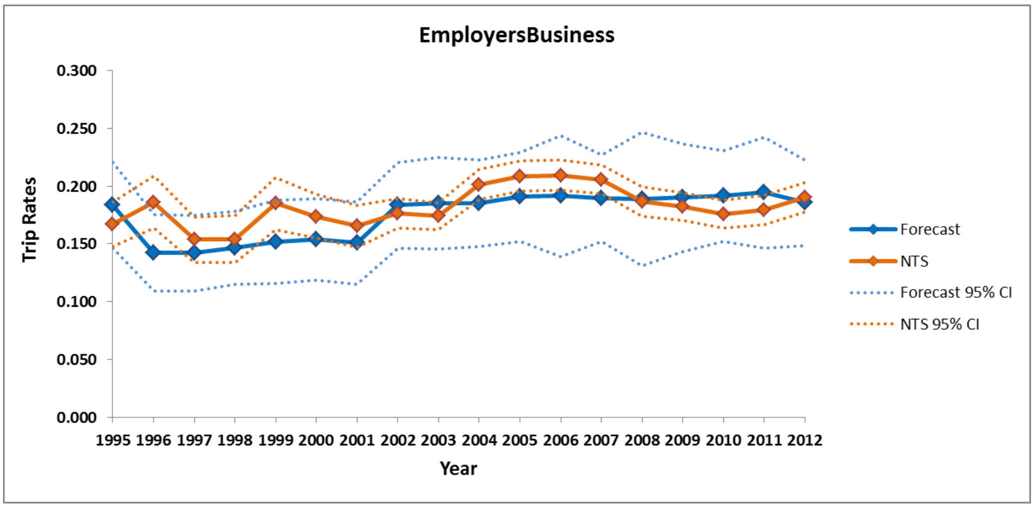

Figure 5-9 – Back-casting Results: Employers' Business Trip Rates

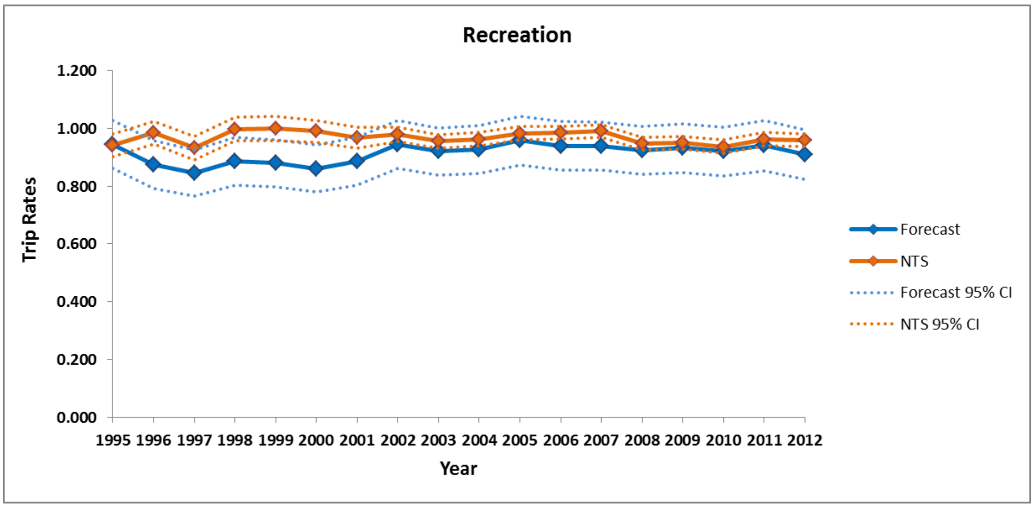

Figure 5-10 – Back-casting Results: Recreational Trip Rates

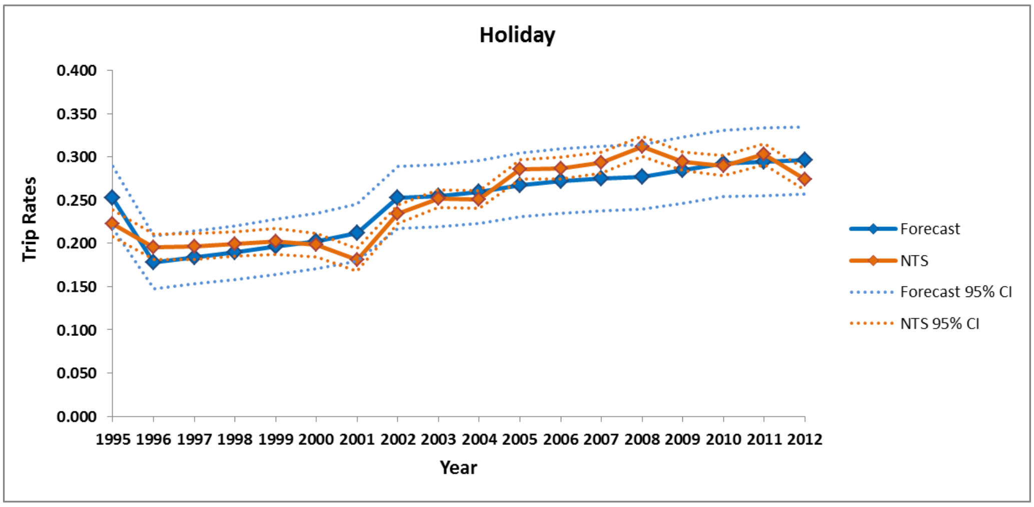

Figure 5-11 – Back-casting Results: Holiday/Day Trip Rates

5.5.1.2 A combination of 2001 and 2011 Census data, ONS population estimates, and NTS data were used to prepare population splits by model segment, and other inputs to the forecasting tool for these back-casting tests (refer to the Forecasting Tool User Guide for a detailed description of inputs). As can be seen from the results, in general, there is a good fit between estimates from the trip rate forecasting model and those based on the NTS data.

5.5.1.3 The differences in the two estimates are largely explained by the assumptions used to estimate the average trip rates for the historic population. For example, in the case of commuting trips, the proportion of full-time workers in the NTS sample is higher than that in the Census data (36% compared to 31%) in 2001. This gives a greater weight to trip rates for full time employees in the NTS data, and since full time employees have higher commuting trip rates, the higher average trip rate. This is demonstrated further in Figure 5-12 which shows that the forecasting tool provides trip rate estimates that are close to the NTS estimates, when compared separately for full-time and part-time employees.

5.5.1.4 It should also be noted that the NTS data used for the back-casting tests prior to 2002 (1995-2001) were not consistent with the 2002-2012 dataset in terms of availability of variables, definition of variables, and the categories used. This was also the case for data on housing costs and migration. Accordingly, certain assumptions had to be made for the back-casting inputs for the period between 1995 and 2001. The likely outcome of this has been a greater difference in the underlying distribution of population in model segments between the NTS data and input assumptions to the forecasting tool, resulting in a potentially greater level of discrepancy between back-cast trip rates and estimates from the NTS between 1995 and 2001. This should be taken into account when comparisons shown in in Figure 5-4 to Figure 5-11 are assessed.

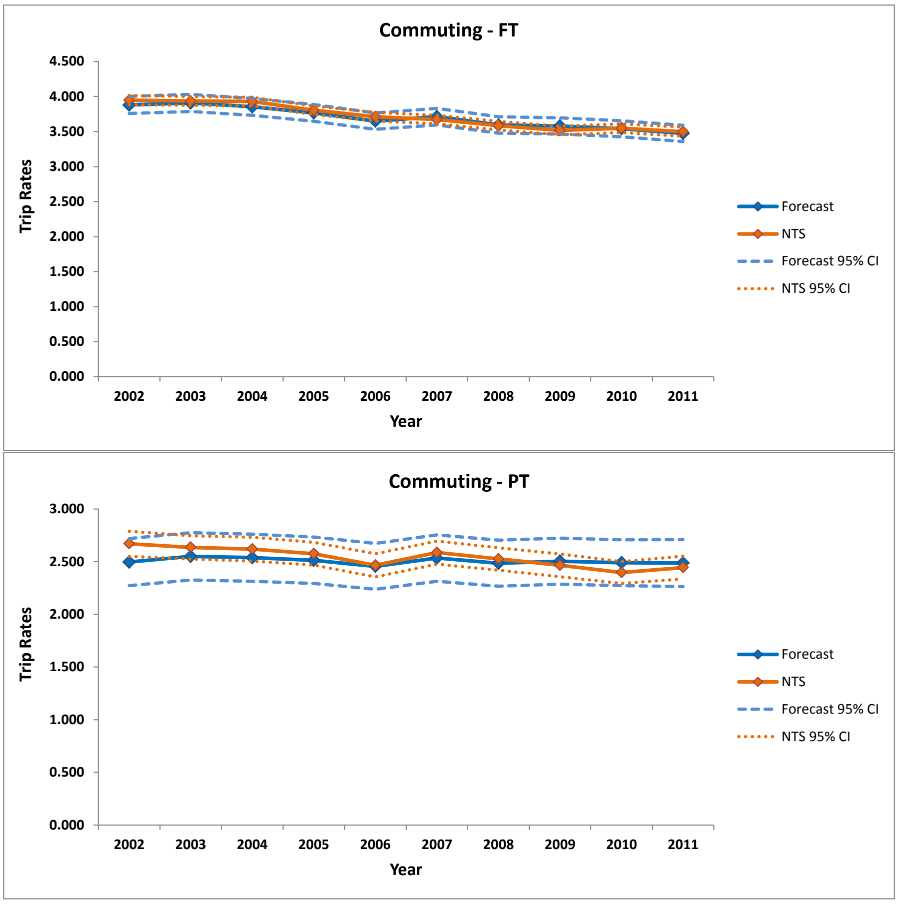

Figure 5-12 – Back-casting Results: Commuting Trip Rates for Full-time and Part-time Employees

6. Summary, Conclusions, and Recommendations

6.1 Summary and Conclusions

6.1.1.1 The following research questions were addressed in this study:

- How the existing NTEM segmentation could be extended to include more factors, providing greater forecasting accuracy?
- Does income after housing expenditure provide statistical salience in explaining trip rates beyond gross income?
- What is the effect of migration on trip rates and to what extent changes in migration can explain observed trends in trip rates?
- What is the effect of online shopping and internet use on trip rates and to what extent changes in these factors can explain observed trends in trip rates?

6.1.1.2 The recent modelling of trends in trip rates based on 1998-2010 NTS data, undertaken by DfT, was used as the basis of this analysis. This analysis was developed further, making use of new additional sources of data, to examine the effects of other possible drivers. These were included as explanatory variables in the regression models to estimate their partial effects on trip rates.

6.1.1.3 National Travel Survey data between 2002 and 2012 were selected as the primary data source to develop the study dataset. To investigate the effect of migration, relevant information from the 2001 and 2011 Census data were linked to the NTS data based on ward geographies. Personal income after housing expenditure was estimated for each record, using estimates of average housing costs based on Living Costs and Food Survey, linked to the NTS data.

6.1.1.4 Negative binomial regression models (and zero-inflated version of these models) were used to estimate trip rates. Separate models were estimated for each trip purpose, and for each age / work status group within each purpose.

6.1.1.5 The estimated effects of age on trip rates were found to be different across different segments and trip purposes. For the 65+ group, there was consistently lower propensity for making trips among people older than 75. For other categories, individuals younger than 30 were found to have higher social, recreational, and visiting trips but lower shopping and personal business trips compared to those aged between 30 and 65.

6.1.1.6 Modelling results showed that, on average, individuals living in London tend to have a lower trip rates. This was particularly the case for non-discretionary trips. This is followed by rural areas where trip rates were found to be lower than those in urban areas and build-up areas. The results also showed a positive correlation between trip rates and driving licence holding for the majority of segments.

6.1.1.7 It was found that having children in the household is associated with lower trip rates for the majority of trip purposes and segments; the only exception are shopping trips where people living in household with children tend to have higher trip rates.

6.1.1.8 It was found that income after housing costs provides better statistical performance for the majority of the estimated models. Findings on the effects of income suggest that higher income is associated with higher levels of trip making for recreational and holiday purposes, which the suggestion that this may be at the expense of trip making for the purpose of visiting friends and relatives.

6.1.1.9 It was found that migrants tend to make fewer recreational/social, visiting friends and relatives, and holiday/day trips. These results are consistent with the hypothesis that migrants are disconnected from their social network. Given recent and likely future levels of inbound migration to the UK, this result has potentially important policy implications.

6.1.1.10 Internet use for shopping in general was found to be associated with substantially higher levels of non-work related trip making, especially for recreational and holiday purposes and correspondingly lower levels of commuting. When the effects are statistically significant, in most of the cases trip rates tend to be lower for those who do online shopping more frequently (at least once a week).

6.1.1.11 For commuting, shopping, and visiting trip purposes, it was found that only between 7% and 13% of the observed trends are explained by the explanatory variables added to the existing trip rate models estimated by the DfT; the majority of which are explained by migration and internet use variables. Income variables do not seem to explain any of the observed changes in trip rates. The majority of observed trends in trip rates therefore appear not to be caused by the changes in migration, demographic structure of the population, aggregate changes in settlement patterns between London, major cities and rural areas, or access to the internet, and remain unexplained by the explanatory variables in the models.

6.1.1.12 In general, this study established a richer understanding of factors influencing trip rates and explained more about the cross-sectional variations in trip rates observed in the UK. Additionally, the forecasting tool provides the capability to explore the impact of alternative assumptions about future trends in trip rates.

6.2 Areas of Further Research

6.2.1.1 This research has highlighted a number of areas in which further research would be desirable. These areas fall into three broad groups related to substantive issues, methodological issues, data and forecasting guidance.

6.2.1.2 The substantive issues include further investigation into:

- The causes of the 'London effect', in particular the influence of density of development and the quantity *and quality* of transport supply.
- The influence of changes in the structure of household organisation and task allocation between individuals.
- The most appropriate definition of discretionary income and the influence of the source of income (e.g., earned vs unearned) on the transport expenditure and mobility.
- The mobility of migrants and in particular the influence of cultural and religious factors and the dynamics of migrants' adaptation over time.
- The influence of new internet-based services and business models on personal mobility and more broadly the interaction between physical and virtual behaviours.

6.2.1.3 Addressing each of these questions will require suitable data, much of which are currently not collected in the NTS. Further research would be required to investigate how the current data envelope can most usefully and efficiently be increased both through extending the scope of the NTS and the use of complementary data sources (such as the Census and LCF, as used in this study). This will require new research into formal methods of optimal data fusion as well as consideration of the most appropriate questions in individual surveys.

6.2.1.4 The challenge of developing improved methods for data fusion is one of a number of methodological challenges that have been presented by this research. Amongst the other issues highlighted are:

- The need for a study of possible improvements in dealing with non-response bias in the NTS, in particular, methods that can be flexibly integrated into a range of subsequent modelling work.
- The need to apply more sophisticated methods of both diagnosing and dealing with the problems of endogeneity, which are pervasive in the analysis of travel demand.
- The need for better methods of causal inference, including a better understanding of what causal mechanisms can and cannot be inferred from repeated cross-sectional data (such as the annual waves of the NTS) and when and how enrichment of repeated cross-sectional data with longitudinal can render most value.

6.2.1.5 For the purposes of this study we have focused our analysis on the area types recorded in NTS. We observed, in developing the models, some interactions between area type models and other variables which could be associated with more detailed local variations in trip rates associated with other more local, social or demographic factors. There may be benefits in further analysis, particularly if insight on trip making is sought at a local rather than national scale.

6.2.1.6 In preparing the study dataset, we have made some assumptions in calculating values of some of the explanatory variables (e.g. income after housing costs, migration, etc.). Whilst our assumptions could be justified as reasonable starting points, it is plausible that other ways of dealing with some of these explanatory variables could (or could not) provide better results. For example, individual income after housing costs could be calculated alternatively by dividing individual income after housing costs by the number of economically active individuals rather than proportionally according to the distribution of individual income within the household. More work is required to investigate these.

6.2.1.7 In addition to these, more research would help to understand whether the observed trends in trip rates are real changes in travel behaviour or in part consequences of potential data collection issues and / or response bias. Comparisons of trends with other independent sources of data could provide useful insights on this. For example, evidence from the London Travel Demand Survey (LTDS) shows that aggregate trip rates in London have largely stayed constant over time (TfL, 2014b).

6.2.1.8 Finally, a potential area of further work relates to forecasting where uncertainties in forecast trip rates can be investigated using the forecasting tool provided. Understanding the scale of these uncertainties could help better to articulate the uncertainty in the national travel demand forecasts.

6.2.1.9 The scope of this research was limited to trip rates. More qualitative research undertaken by the ITC and discussed with the steering group indicated that there may also be trends affecting modal and distributional travel behaviours that vary between different social and age groups. Identification and quantification of such trends could similarly improve travel demand forecasting.

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Appendix 1 –Trip Rate Regression Models: Negative Binomial

Table A1-1: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Commuting Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	1.457	45.046	0.921	9.891	-1.843	-8.367	0.444	2.178	-0.753	-2.758	-3.306	-11.787
1 adult 1+ cars	-0.070	-2.859	-0.226	-3.791	0.696	3.538	0.402	2.958	-0.230	-0.609	0.412	2.332
2 adults 0 car	0.104	4.102	0.099	1.618	0.849	4.985	0.014	0.091	0.110	0.474	0.148	0.756
2 adults 1 car	0.067	2.961	0.026	0.518	1.497	9.908	0.820	7.057	0.394	1.727	1.876	13.023
2 adults 2+ cars	-0.064	-2.779	-0.227	-4.419	0.895	5.238	0.213	1.560	0.659	2.267	0.777	5.341
3+ adults 0 car	0.102	3.540	0.233	3.616	1.577	8.157	0.264	0.807	0.179	0.826	-0.697	-1.893
3+ adults 1 car	0.144	5.974	0.180	3.289	2.204	13.284	1.687	10.640	0.061	0.288	1.465	8.298
3+ adults 2+ cars	0.057	2.484	0.092	1.799	1.849	11.076	1.206	7.851	0.550	2.692	1.357	8.376
Female	-0.076	-10.396	0.016	0.698	-0.723	-9.549	-0.869	-14.241	0.069	0.921		
Age 30 to 44	-0.025	-2.582	0.122	4.526	-0.068	-0.625						
Age 45 to 64	-0.034	-3.593	0.190	7.503	-0.629	-5.921						
Age +75							-0.720	-11.498				
Area: Outer London	0.027	1.400	-0.064	-1.183			-0.667	-3.481			0.372	1.769
Area: Metropolitan built-up	0.094	5.419	0.035	0.612			-0.256	-1.528			0.506	2.373
Area: Large urban	0.076	4.307	0.001	0.017			-0.291	-1.718			0.810	3.785
Area: Medium urban	0.114	6.911	0.021	0.376			-0.155	-0.958			0.864	4.073
Area: Small/medium urban	0.112	5.771	0.012	0.181			-0.254	-1.442			0.635	2.732
Area: Small urban	0.063	3.098	-0.019	-0.286			-0.600	-3.265			0.680	2.833
Area: Rural	0.013	0.705	-0.091	-1.455			-0.620	-3.674			0.592	2.600
Full driving licence	0.027	2.275			1.092	11.938	0.949	10.681	0.504	6.031		
Children in the household	-0.142	-17.849	-0.193	-8.943	-0.402	-4.486						
Gross income (2002 prices)									18.242	2.256		
Income after housing exp (2002 prices)	-3.135	-11.687	-5.673	-5.386	-14.146	-3.052						
Online shopping: Less often than once a week	0.056	5.133	0.102	3.576								
Online shopping: Never	0.075	5.408	0.193	5.345								
Online shopping (binary)					0.021	0.249						
Over65 WorkingStatus: PT							0.082	0.618				
Over65 WorkingStatus: NEET							-3.470	-30.414				
Non-UK resident (proportions)			-0.267	-2.234							-2.713	-6.895
Year (survey year – 1992)	-0.014	-14.430	-0.007	-2.775	-0.047	-4.692			-0.042	-3.554	-0.030	-3.307
Model Statistics												
Observations	50,114		14,829		20,950		37,234		6,651		39,097	
Null deviance	73,224		18,336		5,157		12,650		3,391		7,134	
Residual deviance	71,581		17,718		4,451		6,586		3,271		6,385	
AIC	252,588		62,556		17,565		21,254		11,620		21,534	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A1-2: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Employers' Business Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	-1.778	-20.673	-1.853	-10.621	-2.596	-17.274	-1.744	-4.678	-3.676	-27.064	-4.629	-20.907
1 adult 1+ cars	0.271	3.099	0.066	0.339			0.674	2.674				
2 adults 0 car	-0.107	-1.130	-0.128	-0.640			-0.407	-1.183				
2 adults 1 car	-0.019	-0.229	-0.097	-0.578			0.445	1.969				
2 adults 2+ cars	0.399	4.865	0.076	0.442			0.949	3.854				
3+ adults 0 car	0.225	2.126	0.286	1.363			-2.250	-1.355				
3+ adults 1 car	0.011	0.127	0.221	1.244			1.273	4.123				
3+ adults 2+ cars	0.249	3.041	0.126	0.751			1.417	5.131				
Female	-0.217	-8.557	-0.327	-4.568	-0.742	-6.998	-0.351	-3.139				
Age 30 to 44	0.296	8.540	0.508	5.725					0.869	2.192		
Age 45 to 64	0.469	14.090	0.638	7.763					0.306	0.372		
Age +75							-0.842	-6.946				
Area: Metropolitan built-up	-0.189	-4.181			-0.545	-2.942					-0.863	-2.676
Area: Large urban	-0.138	-3.033			-0.407	-2.071					-0.249	-0.801
Area: Medium urban	-0.171	-4.181			-0.394	-2.313					0.345	1.311
Area: Small/medium urban	-0.126	-2.345			-0.289	-1.266					0.476	1.424
Area: Small urban	-0.062	-1.093			-0.145	-0.596					0.748	2.126
Area: Rural	0.049	1.063			0.084	0.430					0.605	2.041
Full driving licence	0.400	9.172	0.423	5.341			1.049	5.868	0.731	3.280		
Children	-0.072	-2.638	-0.471	-6.952								
Gross income (2002 prices)	6.121	7.314	9.412	3.239					63.735	3.158		
Income after housing exp (2002 prices)							13.151	2.958				
Over65 WorkingStatus: PT							-0.022	-0.100				
Over65 WorkingStatus: NEET							-2.771	-14.339				
Non-UK resident (proportions)			1.068	4.155								
Year (survey year – 1992)							-0.043	-2.674				
Model Statistics												
Observations	70,592		20,577		30,134		37,253		6,651		42,687	
Null deviance	32,950		6,724		2,053		3,947		556		960	
Residual deviance	31,779		6,410		1,989		2,264		518		923	
AIC	106,174		22,791		7,370		7,076		2,055		3,815	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A1-3: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Education Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	-2.743	-22.075	0.511	3.623	-0.602	-4.287	-5.086	-14.703	1.001	9.811	1.053	21.822
1 adult 1+ cars	0.324	2.459			0.077	0.540	1.613	9.490	0.405	2.932	0.102	2.328
2 adults 0 car	0.377	2.616			0.000	-0.002	0.477	2.399	0.079	0.928	-0.107	-2.332
2 adults 1 car	0.850	6.982			0.329	3.280	1.641	11.435	-0.021	-0.246	0.010	0.293
2 adults 2+ cars	0.901	7.484			0.272	2.293	1.687	9.601	-0.132	-1.145	0.034	0.945
3+ adults 0 car	-0.339	-1.955			-0.271	-1.934	0.977	2.337	0.158	1.977	0.121	1.847
3+ adults 1 car	0.579	4.328			0.110	0.936	1.974	7.923	0.037	0.471	0.060	1.256
3+ adults 2+ cars	0.673	5.508			0.267	2.264	1.847	8.049	0.059	0.769	0.122	2.831
Female	0.447	11.680	0.408	7.508	0.646	11.011						
Age 30 to 44	1.066	20.891	0.109	1.894	0.433	5.390			0.016	0.252		
Age 45 to 64	0.416	8.059	-1.279	-22.104	-1.269	-16.887			-0.570	-4.198		
Age +75							-1.256	-13.456				
Area: Metropolitan built-up			0.197	2.448			0.644	3.535	0.116	2.694		
Area: Large urban			0.077	0.953			0.458	2.447	0.092	1.968		
Area: Medium urban			0.025	0.342			0.455	2.672	0.115	2.674		
Area: Small/medium urban			0.001	0.013			0.398	1.963	0.012	0.165		
Area: Small urban			-0.055	-0.543			0.392	1.876	-0.047	-0.651		
Area: Rural			-0.051	-0.620			-0.072	-0.385	0.037	0.628		
Full driving licence			0.351	6.895	0.484	6.828			-0.116	-3.501		
Children in the household									0.167	5.597		
Income after housing exp (2002 prices)	-6.839	-4.979	-9.934	-4.030								
Online shopping: less often than once a week			-0.266	-4.234	-0.194	-1.990						
Online shopping: never			-0.546	-6.632	-0.268	-2.518						
Online shopping (binary)											0.058	2.491
Over65 WorkingStatus: PT							0.934	2.735				
Over65 WorkingStatus: NEET							1.113	3.774				
Non-UK resident (proportions)					0.877	4.176						
Year (survey year – 1992)			-0.015	-2.466					-0.015	-3.464	-0.007	-3.084
Model Statistics												
Observations	70,592		15,668		19,761		37,253		6,651		30,620	
Null deviance	17,777		11,048		8,661		3,650		8,964		31,303	
Residual deviance	16,785		10,019		7,549		3,138		8,844		31,249	
AIC	67,782		41,097		34,226		11,886		32,655		127,055	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A1-4: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Shopping Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	-0.147	-3.160	0.156	2.060	0.750	12.276	0.203	2.927	0.001	0.010	0.465	8.010
1 adult 1+ cars	-0.068	-1.820	-0.130	-2.245	-0.116	-3.062	0.027	0.996	0.113	0.656	-0.206	-4.812
2 adults 0 car	-0.040	-1.006	-0.002	-0.030	-0.043	-1.435	0.033	1.335	0.055	0.522	-0.057	-1.285
2 adults 1 car	-0.031	-0.891	-0.100	-2.013	-0.086	-3.197	0.133	6.366	-0.151	-1.428	-0.011	-0.314
2 adults 2+ cars	-0.169	-4.848	-0.179	-3.485	-0.108	-3.356	0.029	1.015	-0.180	-1.290	-0.107	-3.077
3+ adults 0 car	-0.149	-3.221	-0.117	-1.792	-0.262	-6.821	-0.024	-0.370	-0.157	-1.571	-0.200	-3.091
3+ adults 1 car	-0.135	-3.627	-0.167	-3.108	-0.243	-7.528	-0.056	-1.376	-0.255	-2.642	-0.210	-4.460
3+ adults 2+ cars	-0.247	-7.057	-0.256	-5.030	-0.238	-7.380	0.005	0.145	-0.389	-4.100	-0.328	-7.683
Female	0.242	22.313	0.199	8.644	0.109	6.734	-0.159	-11.446	0.367	9.940		
Age: 30 to 44	0.162	10.797	0.264	10.050	0.154	6.677			0.288	3.778		
Age: 45 to 64	0.284	19.583	0.359	14.390	0.264	11.546			0.251	1.685		
Age: +75							-0.182	-13.561				
Area: Metropolitan built-up	0.275	13.668	0.195	4.660	0.097	3.014	0.083	3.259	0.327	4.888	0.173	4.637
Area: Large urban	0.257	12.417	0.197	4.784	0.118	3.475	0.022	0.836	0.293	4.079	0.162	4.181
Area: Medium urban	0.321	17.462	0.216	5.387	0.103	3.200	0.036	1.540	0.281	3.790	0.190	5.158
Area: Small/medium urban	0.289	12.270	0.235	4.916	0.108	2.679	0.023	0.818	0.512	4.827	0.254	5.607
Area: Small urban	0.221	8.660	0.205	4.033	-0.002	-0.044	-0.015	-0.514	0.197	1.746	0.124	2.499
Area: Rural	0.152	7.068	0.015	0.333	-0.086	-2.200	-0.134	-5.092	-0.001	-0.012	0.048	1.087
Full driving licence	0.248	13.336	0.262	10.820	0.144	7.447	0.184	9.826	0.320	7.635		
Children in the household	0.174	14.649	0.157	7.616	0.157	8.230	-0.358	-5.909				
Online shopping: less often than once a week	0.046	2.794			0.093	3.363	0.212	5.800				
Online shopping: never	-0.068	-3.231			0.021	0.700	0.188	5.061				
Online shopping (binary)			0.147	5.831							0.069	2.997
Over65 WorkingStatus: PT							0.317	5.776				
Over65 WorkingStatus: NEET							0.594	12.665				
Non-UK resident (proportions)			-0.215	-1.891	-0.331	-3.858			0.394	2.029	-0.237	-2.347
Year (survey year – 1992)	-0.011	-7.594	-0.016	-6.747	-0.012	-5.711	-0.006	-3.109	-0.015	-2.526	-0.018	-7.539
Model Statistics												
Observations	50,129		14,834		19,761		27,072		6,099		28,116	
Null deviance	58,893		17,683		22,548		28,215		7,061		27,494	
Residual deviance	56,905		16,584		21,843		26,922		6,699		27,161	
AIC	176,980		57,091		82,430		97,892		21,018		85,274	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A1-5: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Personal Business Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	-1.215	-14.732	-0.295	-2.619	0.180	3.361	-0.366	-5.007	-0.374	-2.636	-0.583	-6.782
1 adult 1+ cars	0.078	1.188	0.008	0.083			0.133	3.971			0.113	1.548
2 adults 0 car	-0.191	-2.699	-0.027	-0.275			-0.118	-3.725			0.119	1.572
2 adults 1 car	-0.009	-0.145	-0.047	-0.588			0.036	1.395			0.275	4.629
2 adults 2+ cars	0.011	0.173	-0.018	-0.221			0.097	2.774			0.395	6.654
3+ adults 0 car	-0.201	-2.464	-0.295	-2.700			-0.237	-2.881			-0.078	-0.702
3+ adults 1 car	-0.174	-2.644	-0.074	-0.851			-0.199	-3.866			-0.133	-1.637
3+ adults 2+ cars	0.034	0.551	-0.078	-0.959			-0.073	-1.617			0.166	2.324
Female	0.165	8.839	0.015	0.409	-0.102	-5.136			0.197	3.755		
Age 30 to 44	0.258	10.037	0.322	7.626	0.175	5.881			0.378	3.633		
Age 45 to 64	0.474	18.799	0.537	13.822	0.272	9.429			0.888	4.461		
Age +75							-0.062	-3.674				
Area: Metropolitan built-up	0.204	4.824							-0.192	-2.393	-0.067	-1.343
Area: Large urban	0.114	2.711							0.031	0.362	-0.142	-2.686
Area: Medium urban	0.127	3.144							-0.213	-2.680	-0.178	-3.847
Area: Small/medium urban	0.094	1.875							0.001	0.004	-0.287	-4.683
Area: Small urban	0.181	3.413							0.070	0.546	-0.158	-2.366
Area: Rural	0.203	4.354							-0.245	-2.279	-0.252	-4.518
Full driving licence	0.242	7.331	0.327	8.344	0.267	13.281	0.287	12.727	0.271	4.722		
Children in the household					-0.215	-8.875						
Income after housing exp (2002 prices)							3.588	4.304				
Online shopping: less often than once a week			-0.114	-2.717								
Online shopping: never			-0.263	-4.751								
Online shopping (binary)	0.162	6.134									0.146	3.796
Over65 WorkingStatus: PT							0.417	6.137				
Over65 WorkingStatus: NEET							0.639	10.917				
Non-UK resident (proportions)	0.516	4.460			0.206	2.786	0.448	5.692				
Year (survey year – 1992)	-0.020	-7.816	-0.030	-7.805	-0.024	-8.032	-0.017	-6.763	-0.027	-3.269	-0.010	-2.569
Model Statistics												
Observations	45,674		16,199		27,281		33,822		6,651		29,542	
Null deviance	37,088		14,445		26,274		31,235		5,085		18,503	
Residual deviance	36,254		13,869		25,536		30,462		4,966		18,328	
AIC	95,921		38,373		77,316		94,580		14,422		56,227	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A1-6: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Recreation / Social Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	0.242	3.553	-0.243	-3.406	0.288	2.747	-0.749	-7.424	0.179	1.700	-0.097	-1.528
1 adult 1+ cars	0.066	1.308	0.094	1.183	0.079	1.227	0.200	4.444			0.316	6.172
2 adults 0 car	-0.265	-4.832	-0.194	-2.312	-0.243	-4.465	-0.351	-7.774			-0.239	-4.073
2 adults 1 car	-0.163	-3.445	-0.004	-0.053	-0.004	-0.081	-0.052	-1.453			0.275	6.397
2 adults 2+ cars	-0.081	-1.686	0.149	2.127	0.299	5.457	0.205	4.391			0.597	14.020
3+ adults 0 car	-0.137	-2.222	-0.101	-1.153	-0.203	-3.006	-0.781	-5.930			-0.039	-0.479
3+ adults 1 car	-0.226	-4.407	-0.137	-1.833	-0.213	-3.766	-0.297	-4.120			0.064	1.116
3+ adults 2+ cars	-0.042	-0.891	0.134	1.950	0.054	0.984	-0.234	-3.640			0.519	10.507
Female	-0.069	-4.666	-0.190	-6.519	-0.144	-5.241	-0.084	-3.496				
Age: 30 to 44	-0.265	-13.613	-0.158	-4.479	-0.172	-4.310			-0.527	-5.519		
Age: 45 to 64	-0.334	-17.501	-0.220	-6.640	-0.158	-4.071			-0.323	-1.692		
Age:+75							-0.263	-11.473				
Area: Metropolitan built-up	0.008	0.260			-0.152	-2.690					-0.206	-4.821
Area: Large urban	-0.021	-0.646			-0.067	-1.148					-0.088	-2.046
Area: Medium urban	-0.042	-1.362			-0.116	-2.081					-0.115	-2.789
Area: Small/medium urban	-0.090	-2.314			-0.035	-0.500					-0.119	-2.357
Area: Small urban	-0.034	-0.830			-0.179	-2.371					-0.233	-4.257
Area: Rural	-0.134	-3.698			-0.172	-2.602					-0.165	-3.440
Full driving licence	0.261	10.337	0.222	6.854	0.263	7.827	0.347	10.671	0.316	6.852		
Children in household	-0.124	-7.678	-0.143	-5.145	-0.288	-8.701	-0.476	-4.350	-0.180	-4.045		
Income after housing exp (2002 prices)	6.297	12.196	9.173	7.537	11.927	8.209	7.388	6.631				
Online shopping: less often than once a week	-0.019	-0.883			-0.012	-0.265	0.171	2.872			-0.054	-2.045
Online shopping: never	-0.302	-10.637			-0.306	-6.040	-0.051	-0.831			-0.460	-13.012
Online shopping (binary)			0.309	8.705					0.324	5.533		
Over65 WorkingStatus: PT							0.373	4.321				
Over65 WorkingStatus: NEET							0.512	6.890				
Non-UK resident (proportions)	-0.544	-5.989			-0.620	-4.125			-0.481	-3.309	-0.949	-8.159
Year (survey year – 1992)	-0.011	-5.522			-0.007	-2.032			-0.016	-2.615		
Model Statistics												
Observations	45,672		16,199		19,761		27,072		4,464		28,113	
Null deviance	47,073		16,420		17,569		22,857		5,167		26,558	
Residual deviance	45,841		15,916		16,566		21,392		4,998		25,170	
AIC	129,450		45,421		48,896		63,356		15,219		71,533	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A1-7: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Visiting Friends & Relatives Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	-0.054	-0.723	0.492	4.721	0.646	7.341	-0.894	-8.687	0.655	4.093	0.430	5.801
1 adult 1+ cars	0.485	8.886	0.210	2.496	0.299	5.468	0.526	12.746	0.246	1.254	0.070	1.474
2 adults 0 cars												
2 adults 1 car	0.096	1.864	-0.158	-2.144	0.007	0.184	0.081	2.470	0.069	0.578	-0.186	-4.748
2 adults 2+ cars	0.094	1.798	-0.184	-2.433	-0.016	-0.333	0.170	3.894	0.139	0.895	-0.234	-5.966
3+ adults 0 cars												
3+ adults 1 car	0.003	0.054	-0.202	-2.563	-0.270	-5.640	-0.132	-2.068	-0.176	-1.604	-0.333	-6.204
3+ adults 2+ cars	0.044	0.848	-0.227	-3.047	-0.119	-2.509	-0.146	-2.511	-0.180	-1.678	-0.389	-8.047
Female	0.144	9.218	0.110	3.350					0.227	5.637		
Age: 30 to 44	-0.294	-14.234	-0.301	-8.078	-0.290	-8.806			-0.314	-3.428		
Age: 45 to 64	-0.382	-18.868	-0.284	-8.199	-0.382	-12.617			-0.310	-1.726		
Age: +75							-0.361	-16.981				
Area: Metropolitan built-up	0.191	5.368			0.106	2.192	0.192	3.902	0.051	0.684	0.310	7.141
Area: Large urban	0.111	3.126			0.109	2.161	0.135	2.745	0.042	0.529	0.236	5.240
Area: Medium urban	0.150	4.398			0.108	2.232	0.093	1.942	0.011	0.133	0.255	5.943
Area: Small/medium urban	0.193	4.654			0.020	0.333	0.192	3.468	0.196	1.703	0.274	5.216
Area: Small urban	0.047	1.041			0.059	0.903	0.056	0.955	0.163	1.376	0.240	4.218
Area: Rural	-0.039	-0.987			-0.060	-1.034	-0.083	-1.565	-0.325	-3.055	0.087	1.716
Full driving licence	0.267	9.995	0.287	8.124	0.104	3.663	0.277	9.745				
Children in the household	-0.066	-3.817										
Gross income (2002 prices)			-4.554	-3.215			-4.181	-3.828				
Income after housing exp (2002 prices)	-8.126	-13.505			-3.285	-2.349						
Online shopping: less often than once a week	0.078	3.277	0.098	2.475	0.179	4.336					0.088	3.079
Online shopping: never	0.057	1.879	0.036	0.709	0.119	2.649					-0.038	-1.052
Over65 WorkingStatus: PT							0.575	6.800				
Over65 WorkingStatus: NEET							0.670	9.054				
Non-UK resident (proportions)	-0.615	-6.228	-0.994	-8.071	-0.671	-5.242	0.361	2.555	-1.341	-6.119	-0.646	-5.487
Year (survey year – 1992)	-0.019	-8.666	-0.026	-7.251	-0.021	-6.741	-0.014	-4.254	-0.026	-4.059	-0.023	-8.384
Model Statistics												
Observations	45,672		14,834		19,761		33,822		6,099		28,113	
Null deviance	45,218		14,669		19,295		27,427		6,535		25,694	
Residual deviance	43,115		14,194		18,745		25,709		6,290		25,133	
AIC	116,543		40,904		58,621		71,855		19,295		76,903	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A1-8: Estimated Parameters of Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Holiday / day Trips

Variables	Full Time		Part Time		NEET		Over65		Student		Child	
	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.	Est.	Z val.
Constant	-2.433	-19.701	-2.757	-16.503	-2.632	-21.606	-1.985	-17.202	-1.672	-10.396	-1.855	-16.264
1 adult 1+ cars	0.139	1.477	0.612	4.297	0.682	6.826	0.758	11.131			0.568	7.288
2 adults 0 car	-0.175	-1.643	-0.247	-1.485	-0.123	-1.227	-0.018	-0.242			-0.192	-2.029
2 adults 1 car	0.235	2.664	0.450	3.489	0.642	8.065	0.586	10.504			0.472	6.958
2 adults 2+ cars	0.285	3.196	0.625	4.764	0.953	10.930	0.850	12.358			0.729	10.856
3+ adults 0 car	-0.260	-2.053	-0.410	-2.186	-0.310	-2.316	-0.989	-3.744			-0.459	-3.025
3+ adults 1 car	-0.129	-1.337	-0.036	-0.251	0.481	5.205	0.134	1.248			0.123	1.357
3+ adults 2+ cars	0.044	0.494	0.303	2.324	0.780	8.864	0.334	3.662			0.394	5.036
Female	0.057	2.317	0.141	2.729	0.084	2.045	-0.183	-5.297	0.336	4.819		
Age: 30-44	0.117	3.503	0.253	4.134	0.134	2.109						
Age: 45-64	0.209	6.264	0.184	3.200	0.197	3.214						
Age: +75							-0.315	-9.444				
Area: Metropolitan built-up	-0.042	-0.729	0.044	0.526					-0.123	-0.894	-0.070	-1.059
Area: Large urban	0.200	3.615	0.263	3.251					0.117	0.824	0.205	3.157
Area: Medium urban	0.040	0.732	0.269	3.623					-0.124	-0.835	0.016	0.249
Area: Small/medium urban	0.090	1.371	0.297	3.343					0.180	0.913	0.116	1.532
Area: Small urban	0.192	2.814	0.331	3.542					0.537	2.808	0.148	1.836
Area: Rural	0.176	2.883	0.397	4.970					0.054	0.302	0.163	2.259
Full driving licence	0.440	9.303	0.388	6.773	0.433	8.496	0.355	7.443	0.443	6.089		
Children in the household			-0.283	-5.997	-0.129	-2.569						
Income after housing exp (2002 prices)	7.080	8.572	5.562	2.804	6.450	3.067	5.534	3.504				
Online shopping: less often than once a week	-0.110	-3.241									-0.078	-2.055
Online shopping: never	-0.368	-7.775									-0.270	-5.141
Online shopping (binary)			0.292	4.769	0.268	5.786						
Over65 WorkingStatus: PT							0.169	1.464				
Over65 WorkingStatus: NEET							0.280	2.851				
Non-UK resident (proportions)	-0.915	-5.739			-1.551	-8.958	-0.996	-5.767	-2.319	-5.940	-0.743	-4.170
Year (survey year – 1992)	0.023	6.898	0.014	2.804	0.021	3.894					0.016	3.998
Model Statistics												
Observations	45,672		16,199		19,764		33,822		6,099		28,113	
Null deviance	27,577		10,203		11,452		16,691		3,343		17,814	
Residual deviance	26,386		9,494		10,187		15,329		3,166		17,068	
AIC	60,800		23,164		25,426		39,000		7,142		36,707	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Appendix 2 –Trip Rate Regression Models: Zero-Inflated Models

Table A2-1: Estimated Parameters of Zero-Inflated Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates for Commuting Trips

Variables	Full Time		Part Time		NEET		Over65		Student	
	Est.	Z val.	Est.	Z val.			Est.	Z val.	Est.	Z val.
Count Model										
Constant	1.606	72.386	1.292	20.451	1.011	5.698	1.631	16.903	0.748	13.157
1 adult 1+ cars	-0.081	-4.804	-0.278	-6.017	-0.190	-0.857	-0.132	-1.313		
2 adults 0 car	0.058	3.387	-0.018	-0.383	0.104	0.491	0.104	0.824		
2 adults 1 car	0.025	1.662	-0.092	-2.400	0.122	0.651	-0.039	-0.418		
2 adults 2+ cars	-0.074	-4.721	-0.298	-7.649	-0.284	-1.414	-0.320	-3.293		
3+ adults 0 car	0.048	2.456	0.055	1.158	0.408	1.886	-0.022	-0.101		
3+ adults 1 car	0.065	4.005	0.041	0.996	0.386	2.043	0.158	1.325		
3+ adults 2+ cars	0.004	0.237	-0.085	-2.225	0.037	0.195	0.051	0.479		
Female	-0.079	-15.783	-0.053	-2.977	-0.288	-4.999	-0.333	-7.683	-0.137	-2.334
Age 30 to 44	-0.003	-0.392	0.168	8.085						
Age 45 to 64	0.027	4.235	0.263	13.825						
Outer London	0.013	0.970	-0.081	-2.010						
Area: Metropolitan built-up	0.061	5.120	0.037	1.017						
Area: Large urban	0.053	4.334	0.023	0.640						
Area: Medium urban	0.078	6.797	0.017	0.497						
Area: Small/medium urban	0.080	5.994	0.028	0.720						
Area: Small urban	0.063	4.490	0.021	0.489						
Area: Rural	0.054	4.289	-0.043	-1.129						
Full driving licence	0.019	2.368			0.252	3.126			0.130	2.200
Children	-0.064	-11.506	-0.092	-5.611	-0.174	-2.977				
Gross income (2002 prices)									13.665	2.475
Income after housing exp (2002 prices)	-3.579	-18.491	-5.355	-6.127	-8.640	-2.813				
Over65 WorkingStatus: PT							-0.222	-4.556		
Over65 WorkingStatus: NEET							-0.495	-9.616		
Non-UK resident (proportions)										
Year (survey year – 1992)	-0.005	-8.165	-0.005	-2.797						
Zero Model										
Constant	-1.857	-18.436	-0.667	-5.063	3.199	14.596	0.324	1.486	1.524	5.783
1 adult 1+ cars	-0.065	-0.879	-0.136	-1.079	-0.883	-4.135	-0.512	-3.183	0.280	0.757
2 adults 0 car	-0.212	-2.628	-0.353	-2.648	-0.702	-3.385	-0.243	-1.373	-0.285	-1.232
2 adults 1 car	-0.200	-2.918	-0.369	-3.444	-1.471	-8.221	-0.894	-6.513	-0.637	-2.873
2 adults 2+ cars	-0.068	-0.999	-0.190	-1.765	-1.150	-5.973	-0.626	-3.965	-0.738	-2.771
3+ adults 0 car	-0.238	-2.562	-0.574	-3.898	-1.153	-5.335	-0.724	-2.161	-0.228	-1.047
3+ adults 1 car	-0.398	-5.174	-0.461	-3.887	-1.923	-10.501	-1.506	-8.177	-0.298	-1.410
3+ adults 2+ cars	-0.260	-3.765	-0.612	-5.574	-1.870	-10.122	-1.298	-7.424	-1.014	-5.005

Female	0.000	0.000	-0.279	-5.226	0.429	7.146	0.278	3.921	-0.363	-5.025
Age 30 to 44	0.122	3.789	0.152	2.352	0.357	4.181				
Age 45 to 64	0.300	9.610	0.289	4.725	0.616	8.022				
Outer London	-0.067	-1.096					0.361	1.687		
Area: Metropolitan built-up	-0.160	-2.881					0.007	0.037		
Area: Large urban	-0.115	-2.030					0.100	0.518		
Area: Medium urban	-0.182	-3.446					-0.110	-0.598		
Area: Small/medium urban	-0.155	-2.496					0.051	0.254		
Area: Small urban	-0.003	-0.050					0.372	1.774		
Area: Rural	0.159	2.812					0.659	3.420		
Full driving licence					-1.009	-12.428	-0.588	-5.936	-0.561	-7.293
Children	0.367	14.864	0.380	7.479						
Gross income (2002 prices)									-2.413	-0.340
Income after housing exp (2002 prices)	-1.867	-2.243								
Over65 WorkingStatus: PT							-0.173	-1.522		
Over65 WorkingStatus: NEET							3.736	37.301		
Non-UK resident (proportions)			0.684	3.718						
Year (survey year – 1992)	0.043	13.461			0.028	3.550			0.052	4.821
Model Statistics										
Observations	48,351		14,834		30,134		33,825			
Log Likelihood	-114,800		-30,270		-8,478		-9,073		-5,638	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Table A2-2: Estimated Parameters of Zero-Inflated Negative Binomial Models – Dependent Variable: Un-weighted Trip Rates

Variables	Employer's Business Part Time Est.	Employer's Business Part Time Z val.	Education Student Est.	Education Student Z val.
Count Models				
Constant	0.482	4.186	1.492	27.088
1 adult 1+ cars			0.034	0.501
2 adults 0 car			-0.081	-1.743
2 adults 1 car			-0.128	-2.738
2 adults 2+ cars			-0.152	-2.331
3+ adults 0 car			-0.050	-1.145
3+ adults 1 car			-0.136	-3.187
3+ adults 2+ cars			-0.138	-3.293
Female				
Age 30 to 44	0.166	1.728	0.164	4.962
Age 45 to 64	0.333	3.820	-0.232	-2.543
Age +75				
Outer London				
Area: Metropolitan built-up			0.037	1.611
Area: Large urban			0.055	2.183
Area: Medium urban			0.112	4.856
Area: Small/medium urban			0.083	2.188
Area: Small urban			0.003	0.072
Area: Rural			0.015	0.477
Full driving licence	-0.321	-3.818		
Children	-0.165	-2.339	0.113	7.294
Gross income (2002 prices)	-16.481	-6.690		
Income after housing exp (2002 prices)				
Over65 WorkingStatus: PT				
Over65 WorkingStatus: NEET				
Non-UK resident (proportions)				
Year (survey year – 1992)			-0.008	-3.206
Zero Model				
Constant	1.891	10.036	-0.520	-2.974
1 adult 1+ cars	0.178	0.939	-0.896	-3.584
2 adults 0 car	0.487	2.379	-0.368	-2.573
2 adults 1 car	0.285	1.739	-0.232	-1.641
2 adults 2+ cars	0.005	0.031	-0.040	-0.214
3+ adults 0 car	0.073	0.350	-0.516	-3.837
3+ adults 1 car	0.125	0.706	-0.404	-3.118
3+ adults 2+ cars	0.034	0.209	-0.478	-3.764
Female	0.494	6.908		
Age 30 to 44	-0.323	-3.059	0.361	3.414
Age 45 to 64	-0.245	-2.561	0.704	3.286
Outer London				
Area: Metropolitan built-up			-0.222	-2.879
Area: Large urban			-0.094	-1.136
Area: Medium urban			-0.005	-0.069
Area: Small/medium urban			0.174	1.450
Area: Small urban			0.138	1.106
Area: Rural			-0.077	-0.732
Full driving licence	-0.879	-9.389	0.238	4.160
Children	0.506	6.477	-0.158	-2.943
Gross income (2002 prices)	-45.120	-8.127		
Income after housing exp (2002 prices)				
Over65 WorkingStatus: PT				
Over65 WorkingStatus: NEET				
Non-UK resident (proportions)	-1.258	-4.781		
Year (survey year – 1992)			0.022	2.852
Model Statistics				
Observations	20,577		6,651	
Log Likelihood	-11,160		-15,330	

Reference categories: 1 adult & no car, male, age 16 to 29 (full time, part time, NEET, and student), age 65 to 74 (65+), Area: London, online shopping: at least once a week

Appendix 3 – Correspondence between Census Categories and Trip Rate Model Categories for Household Types

Table A3-1: Correspondence between Census Categories and Trip Rate Model Categories of Household Types

Census Category	Trip Rate Model Household Category
One person household: Aged 65 and over, No cars or vans in household	1 adult, 0 car (Children.No)_65+
One person household: Aged 65 and over, 1 car or van in household	1 adult, 1+ car (Children.No)_65+
One person household: Aged 65 and over, 2 or more cars or vans in household	1 adult, 1+ car (Children.No)_65+
One person household: Other, No cars or vans in household	1 adult, 0 car (Children.No)_16-64
One person household: Other, 1 car or van in household	1 adult, 1+ car (Children.No)_16-64
One person household: Other, 2 or more cars or vans in household	1 adult, 1+ car (Children.No)_16-64
One family only: All aged 65 and over, No cars or vans in household	2 adults, 0 car (Children.No)
One family only: All aged 65 and over, 1 car or van in household	2 adults, 1 car (Children.No)
One family only: All aged 65 and over, 2 or more cars or vans in household	2 adults, 2+ car (Children.No)
One family only: Married or same-sex civil partnership couple: No children, No cars or vans in household	2 adults, 0 car (Children.No)
One family only: Married or same-sex civil partnership couple: No children, 1 car or van in household	2 adults, 1 car (Children.No)
One family only: Married or same-sex civil partnership couple: No children, 2 or more cars or vans in household	2 adults, 2+ car (Children.No)
One family only: Married or same-sex civil partnership couple: Dependent children, No cars or vans in household	2 adults, 0 car (Children.Yes)
One family only: Married or same-sex civil partnership couple: Dependent children, 1 car or van in household	2 adults, 1 car (Children.Yes)
One family only: Married or same-sex civil partnership couple: Dependent children, 2 or more cars or vans in household	2 adults, 2+ car (Children.Yes)
One family only: Married or same-sex civil partnership couple: All children non-dependent, No cars or vans in household	2 adults, 0 car (Children.No)
One family only: Married or same-sex civil partnership couple: All children non-dependent, 1 car or van in household	2 adults, 1 car (Children.No)
One family only: Married or same-sex civil partnership couple: All children non-dependent, 2 or more cars or vans in household	2 adults, 2+ car (Children.No)
One family only: Cohabiting couple: No children, No cars or vans in household	2 adults, 0 car (Children.No)
One family only: Cohabiting couple: No children, 1 car or van in household	2 adults, 1 car (Children.No)
One family only: Cohabiting couple: No children, 2 or more cars or vans in household	2 adults, 2+ car (Children.No)
One family only: Cohabiting couple: Dependent children, No cars or vans in household	2 adults, 0 car (Children.Yes)
One family only: Cohabiting couple: Dependent children, 1 car or van in household	2 adults, 1 car (Children.Yes)
One family only: Cohabiting couple: Dependent children, 2 or more cars or vans in household	2 adults, 2+ car (Children.Yes)
One family only: Cohabiting couple: All children non-dependent, No cars or vans in household	3+ adult, 0 car (Children.No)
One family only: Cohabiting couple: All children non-dependent, 1 car or van in household	3+ adult, 1+ car (Children.No)
One family only: Cohabiting couple: All children non-dependent, 2 or more cars or vans in household	3+ adult, 1+ car (Children.No)
One family only: Lone parent: Dependent children, No cars or vans in household	1 adult, 0 car (Children.Yes)
One family only: Lone parent: Dependent children, 1 car or van in household	1 adult, 1+ car (Children.Yes)
One family only: Lone parent: Dependent children, 2 or more cars or vans in household	1 adult, 1+ car (Children.Yes)
One family only: Lone parent: All children non-dependent, No cars or vans in household	3+ adult, 0 car (Children.No)
One family only: Lone parent: All children non-dependent, 1 car or van in household	3+ adult, 1+ car (Children.No)
One family only: Lone parent: All children non-dependent, 2 or more cars or vans in household	3+ adult, 1+ car (Children.No)
Other household types: With dependent children, No cars or vans in household	3+ adult, 0 car (Children.Yes)
Other household types: With dependent children, 1 car or van in household	3+ adult, 1+ car (Children.Yes)
Other household types: With dependent children, 2 or more cars or vans in household	3+ adult, 1+ car (Children.Yes)
Other household types: All full-time students, No cars or vans in household	3+ adult, 0 car (Children.No)
Other household types: All full-time students, 1 car or van in household	3+ adult, 1+ car (Children.No)
Other household types: All full-time students, 2 or more cars or vans in household	3+ adult, 1+ car (Children.No)
Other household types: All aged 65 and over, No cars or vans in household	3+ adult, 0 car (Children.No)
Other household types: All aged 65 and over, 1 car or van in household	3+ adult, 1+ car (Children.No)
Other household types: All aged 65 and over, 2 or more cars or vans in household	3+ adult, 1+ car (Children.No)
Other household types: Other, No cars or vans in household	3+ adult, 0 car (Children.No)
Other household types: Other, 1 car or van in household	3+ adult, 1+ car (Children.No)
Other household types: Other, 2 or more cars or vans in household	3+ adult, 1+ car (Children.No)