Transport and Carbon Emissions Analysis

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The analysis presented in this paper was undertaken as part of the JRF-funded study: '*Distribution of carbon emissions in the UK: implications for domestic energy policy*'**.**

The project was carried out by a team at the Centre for Sustainable Energy, Bristol; the Townsend Centre for International Poverty Research, University of Bristol; and the Environmental Change Institute, University of Oxford. The research uses advanced modelling techniques to develop and analyse the datasets necessary to support and further understanding of: the distribution of emissions across households in Great Britain; the impact of existing and forthcoming Government policies on consumer energy bills and household emissions in England; and exploratory analysis of alternative approaches for improving the energy efficiency and sustainability of the housing stock in England. The full project report is available at: *http://www.jrf.org.uk/focus-issue/climate-change*

The main project report provides some analysis of the distribution of carbon emissions across households, including emissions resulting from travel by private vehicle, public transport and aviation. However, beyond this, the main report is limited in its analysis of travel emissions, focusing instead on the consumption of energy in the home and impacts of policy. This paper is therefore designed to complement the analysis presented in the main project report, providing more detailed discussion around emissions from personal travel. It presents some policy context in the way of introduction to the problem and then explores in some detail the distribution of travel emissions in Great Britain by accessibility to public transport and services.

1 Summary

This paper aims to explore the distribution and underlying drivers of CO_2 emissions from land based passenger transport in Great Britain. In particular the paper focuses on the accessibility of local services and public transport to households in affecting household emissions.

Using detailed National Travel Survey data, a number of suitable accessibility measures were derived. The study then applied bivariate and multivariate regression analyses to explore key associations and predictors of the three outcome variables of total, commuting and leisure travel CO_2 emissions. In addition, the CHAID[1] classification analysis provided further detail on the optimal split in the distribution of emissions between predictor variables.

Travel CO_2 emissions appear highly skewed towards wealthier households, with a relatively small proportion of households emitting most of the emissions. Emissions associated with commuting by car are least equally distributed across the income profile, with leisure travel by public transport appearing to be most equally distributed. The results of the bivariate analysis suggest that households with 'low' accessibility to services had higher car emissions (46%) and lower public transport emissions (38%) when compared to those with 'high' accessibility to services. As expected, travel emissions from commuting were inversely related to the accessibilities of local services *and* public transport, with higher overall accessibility by walking and public transport reducing CO_2 emissions from commuting. The results were similar for leisure travel emissions.

In determining the underlying reasons for people's behaviours it is important to allow for key demographic and socio-economic factors. The multivariate regression analysis therefore controls for these factors. Once they have been controlled for, household location and accessibility of services and public transport showed only a marginal effect on explaining the variation in total surface transport CO_2 emissions. The dominance of socio-economic and demographic factors was confirmed by the result that total surface transport CO_2 emissions were significantly higher in households with higher socio-economic status[2], larger household sizes and also in those with the household reference person in full-time or part-time employment. Interestingly while there was marginal evidence of lower emissions levels for households with higher services accessibility, accessibility to public transport was shown to have no significant effect on the trend for emissions distributions. The results suggest that, in isolation, improving accessibility to public transport is unlikely to reduce emissions associated with car use.

When exploring commuting and leisure travel CO_2 emissions separately, we found that the results explained more of the social variation than for total surface transport CO_2 in both cases. Interestingly the commuting model explained significantly more of the variation in emissions than the leisure

[1] CHAID ('Chi-square Automatic Interaction Detection') is a popular analytic technique for performing classification or segmentation analysis. It is an exploratory data analysis method used to study the relationship between a dependent variable and a set of predictor variables. CHAID modelling selects a set of predictors and their interactions that optimally predict the variability in the dependent measure. The resulting CHAID model is a classification tree that shows how major 'types' formed from the independent variables differentially predict a criterion or dependent variable. CHAID analysis has the advantage that it enables more detailed scrutiny of the socio-demographics of households in each category, whilst maintaining a sufficient number of cases to give reliable estimates of scalar values.

[2] Here taken to cover the socio-economic classification of the household reference person, household income and tenure

travel model. While car access had the strongest effect on leisure travel emissions, the strongest predictor of commuting emissions was employment status. Crucially for the focus of this paper, the accessibility variables have only marginal effects on the outcomes after adjusting for all other variables, with slightly *higher* mean emissions for both commuting and leisure travel in households with higher public transport accessibility and no significant correlation with services accessibility.

Finally, the CHAID analysis gave evidence on at what level of any specific predictor was most strongly associated with the variation in emissions levels. This confirmed that (in order of strength of association) car availability, employment status, socio-economic classification of the household reference person, income, household size and rail accessibility (for larger households without a car) were the strongest predictors of total emissions.

The differences that exist between the general population and subgroups within the population have far-reaching consequences for the development of transport, energy and environmental policies. Policy needs to target these high emitters by seeking out differences amongst the population, identify the causes and target these causes directly. Indicators of travel and emissions were identified, such as those characteristics indicative of higher income, being in work, middle age, small household size and higher car availability.

2 Introduction

This report provides a more detailed look at travel emissions of households in Great Britain, to accompany the main project report for the JRF-funded study: '*Distribution of carbon emissions in the UK: implications for domestic energy policy'.*

The creation of nationally representative datasets to show the distribution of household level emissions to include estimates of emissions from personal travel was a key aim of this project. This has been fulfilled and the main project report provides some analysis of the resulting dataset for Great Britain, exploring the distribution of carbon emissions across households, including emissions resulting from travel by private vehicle, public transport and aviation. However, beyond this, the main report is limited in its analysis of travel emissions, focusing instead on the consumption of energy in the home and impacts of policy.

This report therefore provides some more detailed discussion around emissions from personal travel. It presents some policy context in the way of introduction to the problem and then explores in some detail the distribution of travel emissions in Great Britain by accessibility to public transport and services.

3 The problem

At the global level, transport currently accounts for more than half the oil used and nearly 25% of energy related carbon dioxide (CO_2) emissions (IEA, 2008). From a 2005 baseline, transport energy use and related CO_2 emissions are expected to increase by more than 50% by 2030 and more than double by 2050 with the fastest growth from light-duty vehicles (i.e. passenger cars, small vans, sport utility vehicles), air travel, and road freight (ibid.). In the UK, although economy wide emissions reductions of 18% have been achieved since 1990, domestic transport emissions increased 11% from over the same period reaching 135 Million tonnes of CO_2 ($MtCO_2$) in 2007, comprising 24% of total UK domestic emissions (CCC 2009). The largest share of UK transport emissions is from road passenger cars at 86% followed by buses at 4%, rail at 2%, and domestic aviation at 2%. Importantly, this does not include an estimated 38 $MtCO_2$ from international aviation which, if accounted for, would increase the contribution of transport to total UK emissions (CCC 2009; Jackson, Choudrie et al. 2009). Therefore, without significant contribution from the transport sector, the recommended 80% reduction in emissions between 1990 and 2050 by the UK Committee on Climate Change (CCC) to cut CO_2 equivalent of Kyoto GHGs emissions is not likely to be achieved.

Transport is invariably deemed to be the most difficult and expensive sector in which to reduce energy demand and greenhouse gas emissions (Enkvist et al., 2007; HM Treasury, 2006; IPCC, 2007). The conventional transport policy response to this issue reflects this dominant techno-economic analytical paradigm and focuses on supply-side vehicle technology efficiency gains and fuel switching as the central mitigation pathway for the sector. Typically, the diffusion of advanced vehicle technologies is perceived as the central means to decarbonise transport. Since many of these technologies are not yet commercially mature, or require major infrastructure investment, this focus has reinforced the notion that the transport sector can only make a limited contribution to total CO_2 emissions reduction, particularly in the short term (HM Treasury, 2006; Koehler, 2009). In the UK for example, electrification of the passenger vehicle fleet is a key strategy and viewed as necessary to achieve the government's stated 80% reduction target (Ekins et al., 2009; CCC, 2009). The UK policy focus on vehicle technology reflects other global transport modelling exercises that depend upon between 40% to 90% market penetrations of technologies such as plug-in hybrids and full battery electric vehicles between 2030 and 2050 (IEA, 2008; McKinsey & Company, 2009; WBCSD, 2004; WEC, 2007).

4 What we know about travel patterns and carbon emissions

The growth in personal travel in the UK can be traced back to a number of factors including increasing car ownership, falling real costs of motoring, falling car occupancy levels and increasing average trip lengths, based on empirical evidence collected in the National Travel Survey (NTS). Household car availability has continued to rise in Great Britain. Income is a factor relating to the number of trips and distance travelled. In 2004, people in the highest income quintile did 28% more trips than those in the lowest income quintile and travelled nearly three times further (NTS, 2008). In particular, those in the highest income group did twice as many trips and travelled over three times further by car than those in the lowest income quintile group. Rail use is much higher in the highest income quintile, partly because commuters to London in the highest income band account for a considerable proportion of rail travel.

Different subgroups in the population, described by various socio-economic, demographic and other personal characteristics, exhibit different levels of motorised travel activity (Brand and Boardman, 2008). Travel patterns vary according to demographics, socio-economic aspects (e.g. gender, income, age, economic activity), ethnicity and culture (e.g. Banister and Banister, 1995, Carlsson-Kanyama and Linden, 1999, Stead, 1999, Cameron et al., 2003, Best and Lanzendorf, 2005). However, when accounting for the dominant factors, evidence by e.g. Timmermans et al. (2003) and Brand and Preston (2010) have shown that household location does not add significantly to explaining the variation in travel patterns amongst the population. Travel patterns and behaviour also vary according to environmental consciousness, energy costs (Fox, 1995, Nilsson and Kuller, 2000) as well as chosen lifestyles, personal preferences, worldviews and attitudes (Anable, 2005; Anable et al, 2012). The majority of the research evidence suggests the significance of the link between income and the demand for air travel (e.g. Brons et al., 2002; Korbetis et al., 2006).

5 Access to services and public transport

There is a growing evidence base, or even just a renewed appreciation of existing evidence, of the potential for behaviour to alter in ways which mean that reductions in the demand for travel activity and associated energy are both plausible and cost effective (Sloman et. al. 2010; Cairns et al., 2008; Goodwin, 2008. Also see Gross et al., 2009 for a comprehensive overview of the literature).

Achieving high levels of accessibility to shops, markets, employment, education, health services, and social and community networks is essential for health, quality of life, and social inclusion (Woodcock *et al.*, 2007). Harms are created through too much mobility and too little access. A Dutch study, including freight and passenger transport, found that strategies to achieve substantial reductions in emissions would reduce inequalities in the costs and benefits of transport, travel behaviour, and accessibility of economic and social opportunities (Geurs and van Wee, 2004).

An increase in the use of public transport, combined with a decrease in the use of private cars, can reduce traffic congestion and, more importantly, CO_2 emissions, as public transport generally causes lower CO_2 emissions per passenger kilometre than private cars. A sustainable model for transport policy also requires integration with land-use policies. These may be somewhat limited within the bounds of existing cities, but as cities grow and new cities are built, urban planners must put more emphasis on land use for sustainable transport in order to reduce congestion and CO_2 emissions. Sustainable land-use policy can direct urban development towards a form that allows public transport as well as walking and cycling to be at the core of urban mobility.

To complement the analysis presented in the main report that looks at the distribution of emissions across different household types, additional analysis – presented below - was undertaken to explore how travel emissions relate to accessibility to service and public transport.

6 Analysis of the distribution of transport emissions and access to services

The aim of this analysis was therefore:

1. To explore associations and predictive models of CO_2 emissions from non-business surface passenger transport and accessibilities of public transport and local services;
2. To identify key groups of households with potential to shift/reduce travel emissions and those with limited opportunity.

6.1 Method and Analysis

The analysis uses the harmonised dataset created for Phase 1 of this project, with additional variables from the National Travel Survey relating to accessibility.

The analysis involved two stages. First, a series of simple measures of accessibility to services (nearest doctor, post office, chemist, food shop, shopping centre and general hospital) and public transport (bus, rail) were derived for each valid case, based on raw data from the 2002-2006 National Travel Survey (NTS). Second, distributional and statistical analyses of travel emissions against access to services & access to public transport were performed. This included bivariate and multivariate analyses whilst controlling for key socio-demographics and land use variables.

6.2 Estimating the Measure of Accessibility of Services

The NTS includes a set of ordinal variables relating to bus and walking accessibility of local services:

1) Walking time to nearest doctor (h18)
2) Bus time to nearest doctor (h19)
3) Walking time to nearest post office (h20)
4) Bus time to nearest post office (h21)
5) Walking time to nearest chemist (h22)
6) Bus time to nearest chemist (h23)
7) Walking time to nearest food store (h24)
8) Bus time to nearest food store (h25)
9) Walking time to nearest shopping centre (h26)
10) Bus time to nearest shopping centre (h27)
11) Walking time to nearest general hospital (h28)
12) Bus time to nearest general hospital (h29)

Unfortunately, not all of these were collected for each year in the 2002-2006 period. In fact, data were collected only for the 2002-2004 period, following an alternating pattern between service categories, as shown in Table 1.

Table 1: Data collection of service accessibility variables in the 2002-06 NTS

Data collection						
	Doctor	**Post office**	**Chemist**	**Food store**	**Shopping centre**	**General hospital**
2002	Yes	No	Yes	Yes	No	Yes
2003	No	Yes	No	Yes	Yes	No
2004	Yes	No	Yes	Yes	No	Yes
2005	No	No	No	No	No	No
2006	No	No	No	No	No	No

In addition, the NTS includes two bus accessibility variables which were collected for all years 2002-2006:

1) Walk time to nearest bus stop (h13)
2) Frequency of bus service at nearest bus stop (h14)

The questions in the NTS household questionnaire suggest that bus times are total journey times, i.e. include travel to bus stop, waiting, on-vehicle and walk to destination times. Also, these accessibility indicators are limited to only the *single nearest* service to a respondent's residence. Whilst this is obviously a restriction, it is recognised in the literature that there is no single measure which encompasses all aspects of destination accessibility.

The following classification schemes were developed for walk and bus accessibility to local services, based on the categorisation of the NTS data for 2002-2004.

First, the walk accessibility measure is a simple function of walking time:

Table 2. Walk Accessibility Measure for Local Services

Walking time	**Doctor**	**Post office**	**Chemist**	**Food store**	**Shopping centre**	**General hospital**
Less than 6 minutes	High	High	High	High	High	High
7 – 13 minutes	High	High	High	High	High	High
14 – 26 minutes	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
27 – 43 minutes	Low	Low	Low	Low	Low	Low
More than 44 minutes	Low	Low	Low	Low	Low	Low

Secondly, the bus accessibility measure is a function of bus travel time and bus frequency at the nearest bus stop:

Table 3. Bus Accessibility Measure for Local Services

Bus travel time to doctor, post office, etc.	More frequent than once every 15 minutes	More frequent than once per half hour	More frequent than once per hour	More frequent than once per day	Less frequent than once per day
Less than 6 minutes	High	Moderate	Moderate	Low	Low
7 – 13 minutes	High	Moderate	Moderate	Low	Low
14 – 26 minutes	Moderate	Moderate	Moderate	Low	Low
27 – 43 minutes	Low	Low	Low	Low	Low
More than 44 minutes	Low	Low	Low	Low	Low

In order to combine the walk and bus accessibility measures into a measure of services accessibility (MSA), another simple mapping procedure was employed for each of the six service categories:

Table 4. Measure of Services Accessibility (for each of the six service categories)

	High Walk Accessibility	Moderate Walk Accessibility	Low Walk Accessibility
High Bus Accessibility	High	High	Moderate
Moderate Bus Accessibility	High	Moderate	Low
Low Bus Accessibility	Moderate	Low	Low

This created six new variables msa1 (nearest doctor), msa2 (nearest post office) … msa6 (nearest general hospital) with the following frequencies:

Table 5. Measures of Services Accessibility

Frequency	**MSA of nearest doctor (msa1)**	**MSA of nearest post office (msa2)**	**MSA of nearest chemist (msa3)**	**MSA of nearest food store (msa4)**	**MSA of nearest shopping centre (msa5)**	**MSA of nearest general hospital (msa6)**
High	1630	983	2036	2913	1234	728
Moderate	6720	5729	9089	17696	3084	1937
Low	7184	1534	4423	3200	3937	12860
NA/DNA	26997	34285	26983	18722	34276	27006
Total	42531	42531	42531	42531	42531	42531

The high frequencies of NA/DNA are a direct result of the irregular data collection mentioned above, as not all of the accessibility categories were collected for each year in the 2002-2006 period.

In the final step, an overall measure of services accessibility was developed in another simple mapping procedure by allocating points to each service accessibility (0 for 'High', 1 for 'Moderate', 2 for 'Low'), adding up these points and dividing them by the number of services for which HH level data were collected (not NA, DNA) to get an *average* score, and mapping average score to an Average Measure of Services Accessibility (AMSA):

Table 6. Average Measure of Services Accessibility

Average score (range)	**Average Measure of Services Accessibility**
0 – 2/3	High
2/3 – 4/3	Moderate
4/3 – 2	Low

The averaging was necessary because accessibility variables were not collected in each survey year. The average figures are thus for the period 2002-2004 and based on varying frequency of data collection shown earlier.

The subjective categorisation was developed with the dual aims of defining intuitively-appealing categories and a *reasonable* balance in the percentage of households in each of the categories. The methodology does not apply a weighting to the service categories – this may be an option for refinement in future work. Possible options include weighting by trip frequency or distance for each service destination.

Box 1. Calculating Average Measures of Services Accessibility: a worked example

AMSA EXAMPLE: a household with high (walk and bus) accessibility to doctor and chemist (0+0), moderate accessibility to food store (+1), and low accessibility to general hospital (+2) scores 3 points. This gives an average score of 0.75 (only 4 out of 6 accessibility categories were not DNA/NA here), which in this categorisation means a moderate Average Measure of Services Accessibility.

As discussed above the NTS provides the same set of service accessibility variables only for 2002 and 2004, namely accessibility of nearest doctor, chemist, general hospital and food store. The derived AMSA frequencies are shown below, suggesting a small decrease in the accessibility of these local services between 2002 and 2004:

Table 7: Combined accessibilities of nearest doctor, chemist, general hospital and food store

Year	**High**	**Moderate**	**Low**	***N***
2002	7.2%	51.5%	41.3%	7437
2004	5.0%	50.4%	44.6%	8121

6.3 Estimating the Measure of Public Transport Accessibility

The NTS includes a set of variables relating to public transport accessibility:

1) Walk time[3] to nearest bus stop (h13)

[3] In the NTS walking speed is assumed to be three miles per hour.

2) Frequency of bus service at nearest bus stop (h14)
3) Walk time to nearest train station (h15)
4) Bus time to nearest train station (h16)
5) Frequency of train service at nearest train station (h17)

In contrast to the services accessibility measures, these were collected for each year in the 2002-2006 period, thus providing cases for each of the 5 years.

These accessibility indicators are limited to only the *single closest* bus stop and train station to a respondent's residence, even if this is not the one normally used. Whilst this is a restriction, it is recognised in the literature that there is no single measure which encompasses all aspects of accessibility; even the well-known PTAL [public transport accessibility levels] system is limited in that it does not take into account the destinations served by transit.

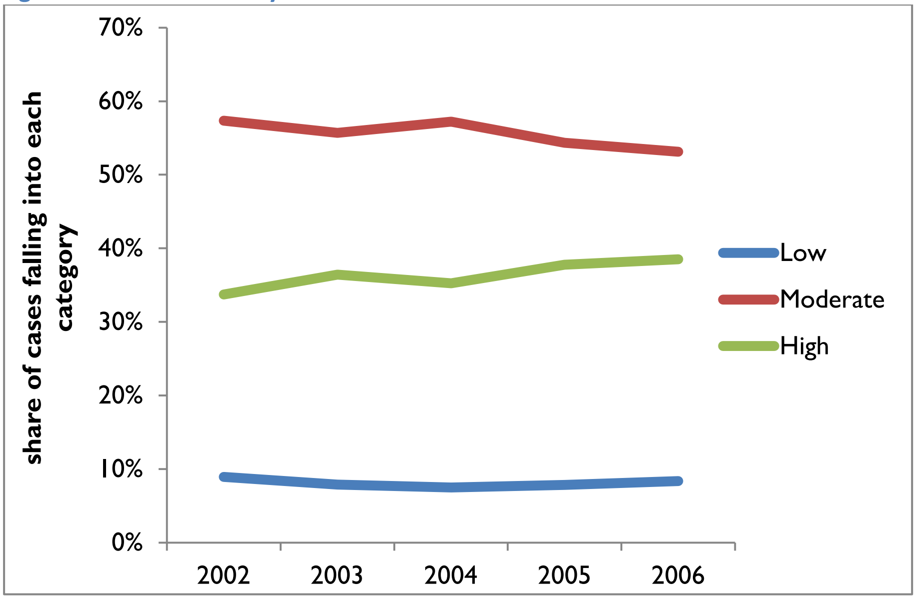
The format of the NTS dataset prevents us from using the PTAL system, therefore the following alternative classification schemes was developed for bus accessibility, based on the categorisation of the NTS data:

Table 8. Bus Accessibility Measure

	More frequent than once every 15 minutes	**More frequent than once per half hour**	**More frequent than once per hour**	**More frequent than once per day**	**Less frequent than once per day**
Less than 6 minute walk	High	Moderate	Moderate	Low	Low
7 – 13 minute walk	High	Moderate	Moderate	Low	Low
14 – 26 minute walk	Moderate	Moderate	Moderate	Low	Low
27 – 43 minute walk	Low	Low	Low	Low	Low
More than 44 minute walk	Low	Low	Low	Low	Low

Applying this mapping, the new bus accessibility measure (variable BAM) divvies up into the three categories as shown in Figure 1, suggesting a small shift from 'moderate' to 'high' bus accessibility between 2002 and 2006.

Figure 1: Bus accessibility measures derived from NTS 2002-06 data

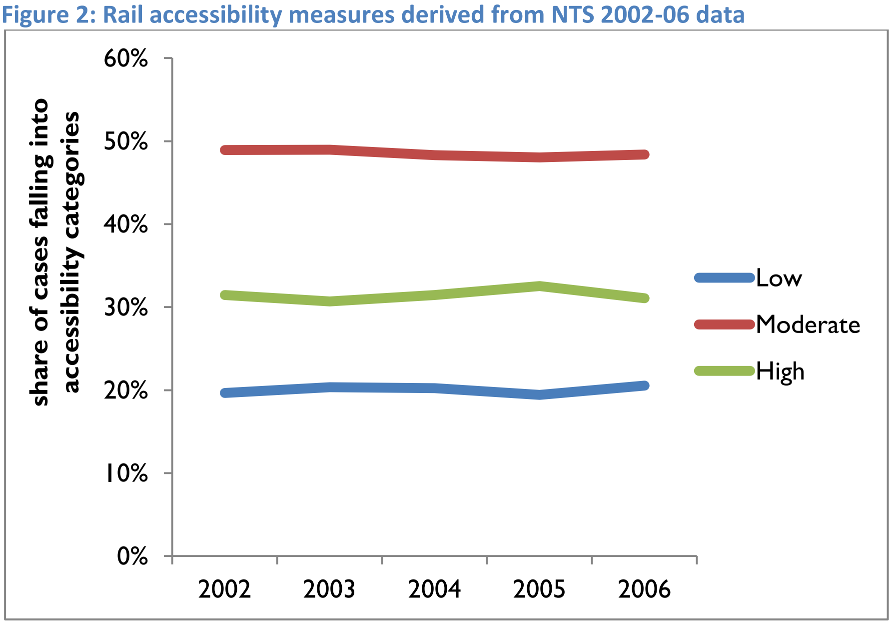


Similarly, the classification scheme for rail accessibility was developed as follows. Applying this mapping, the derived rail accessibility measure (variable RAM) splits into the three categories as shown in Figure 2, suggesting no major changes between 2002 and 2006.

Table 9. Rail Accessibility Measure

	More frequent than once per hour (throughout the day)	More frequent than once per hour (rush hours)	Less frequent than once per hour (all day)
Less than 6 minutes (walk or bus, whichever is faster)	High	High	Low
7 – 13 minutes	High	Moderate	Low
14 – 26 minutes	Moderate	Moderate	Low
27 – 43 minutes	Moderate	Low	Low
More than 44 minutes	Low	Low	Low

Figure 2: Rail accessibility measures derived from NTS 2002-06 data



In order to combine the bus and rail accessibility measures into an **overall measure of public transport accessibility**, another simple mapping procedure was employed for each possible combination:

Table 10. Public Transport Accessibility Measure

	High Rail Accessibility	Moderate Rail Accessibility	Low Rail Accessibility
High Bus Accessibility	High	High	Moderate
Moderate Bus Accessibility	High	Moderate	Low
Low Bus Accessibility	Moderate	Low	Low

The subjective categorisation was developed with the dual aims of defining intuitively-appealing categories and a reasonable balance in the percentage of households in each of the categories. The percentages of households in each category of this public transport accessibility measure are shown below, suggesting a small increase in public transport accessibility between 2002 and 2006.

Table 11: Public transport accessibility measure (PTAM), split by category over time

	PTAM (% of households)		
Year	**Low**	**Moderate**	**High**
2002	19	33	47
2003	19	33	48
2004	20	32	48
2005	18	32	50
2006	19	32	49

Note: based on unweighted NTS dataset

6.4 Distributional and statistical analysis

6.4.1 Regression Modelling

As a precursor for linear regression we used basic descriptive and bivariate analyses to explore how outcome measures of CO_2 vary by measures of accessibility, including stratifying CO_2 by mode (car, public transport) and purpose (commuting, leisure[4]).

In addition, we used linear regression to model CO_2 as a function of accessibility measures while controlling for key demographic, socio-economic, environmental and car availability variables. All bivariate significant predictors were included in the model. Because CO_2 emissions (and its subcomponents) were highly positively skewed and included a significant proportion of zeros, we transformed CO_2 to log (CO_2 + 1) as the dependent variable, adding 1 to the value before transformation to avoid generating missing values for the sample reporting zero emissions. The log-transformed outcomes were then standardised before entering into the regression.

[4] Leisure travel is defined here as the sum of all travel for non-commuting, non-business related travel. It includes travel on personal business, to visit friends and family, to/from social/entertainment activities, for shopping, and to/from schools and places of study.

The aim of the modelling was to explain any significant patterns of association and significance of stronger and less-strong effects while maximising the percentage of variation explained by the model. The log transformation resulted in a better model fit and is arguably more statistically correct. However, the interpretation of regression coefficients ("change in 'log carbon-plus-one' ") is less intuitive.

Since our purpose here was to identify the best subset of variables in predicting carbon usage (rather than testing specific hypotheses), we used a hierarchical approach to building multivariable regression models (Victora et al., 1997), starting with socio-demographic variables which we hypothesised to be further back on the causal pathway and then proceeding to environmental and accessibility variables and finally to variables relating to car access. This procedure estimates the best fitting predictive model of carbon usage based on the above statistical criteria (i.e. it provides a predictive rather than explanatory model). The three sections we have used are as follows:

1. Household demographic and socio-economic variables;
2. Environmental and accessibility variables: since socio-demographic factors may partly determine where you live, work, etc. and how far you live from local services and public transport;
3. Availability of cars: could plausibly mediate any of the above factors (people who are wealthy, live far from work and live far from the local public transport network are more likely to own a car) and likely to be close on causal pathway to CO_2 emissions

6.4.2 Collinearity check

The initial analysis of including all demographic and socio-economic variables of the harmonised dataset suggested that there were significant collinearity problems between some of the variables. For instance, 'household type' (e.g. pensioner couple, lone parent, 2 adults 2 children) showed high collinearity with the covariates 'household size' and 'number of children'. Also, the number of workers showed high collinearity with household size and HRP working status. It was therefore decided to drop the household type and number of workers variables for the models used.

6.4.3 CHAID tree classification

CHAID was used to produce a model that creates clusters of cases with a predicted value of log transformed total CO2 from land-based passenger transport. Whilst linear regression analyses identify the best subset of predictors they do not provide for rigorous assessment of what level of any specific predictor is most strongly associated with variation in the dependent measure. CHAID achieves this in a multivariate context by considering main effects alongside second and higher order interaction effects using iterative testing procedures. The resultant 'node tree' sequentially identifies the series of optimal splits in categorical predictors which give the best possible prediction of the dependent variable. The results of the linear regression analysis guide which predictor variables to enter into the CHAID model, which then selects the optimal variable parameterisation to be used in defining the nodes (or clusters). Running CHAID on the NTS and creating these nodes therefore has the advantage that it enables more detailed analysis of the resulting dataset, whilst maintaining a sufficient number of cases (set at 200 cases in the normally weighted dataset) to give a reliable prediction of the mean of the log-transformed dependent variables.

6.4.4 Weighting

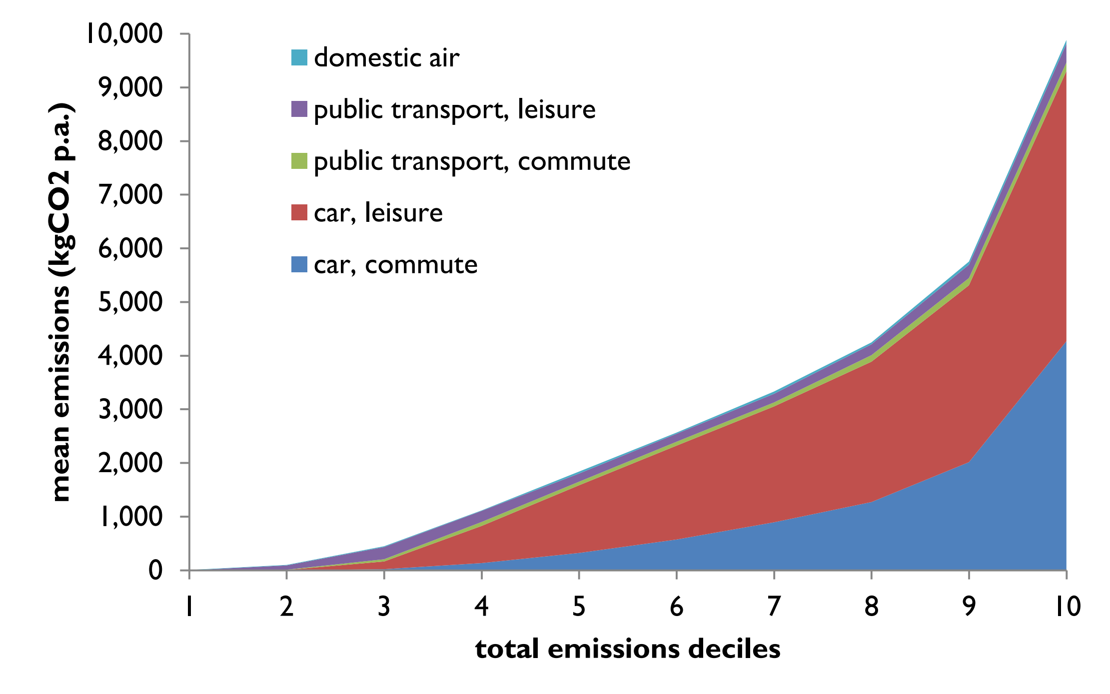
Unless mentioned otherwise, the results presented below were weighted by the NTS household interview sample weighting, W3.

6.5 Results: Descriptive analysis

6.5.1 Distribution of CO_2 emissions from all non-business travel

A small proportion of households emit most of the emissions (Figure 3). When ranked by total emissions levels, the top 10% of households are responsible for 34% of CO_2 emissions from non-business surface passenger travel, whereas households in the bottom decile emit next to nothing.

Figure 3: Distribution of household CO_2 emissions from non-business travel by car, public transport and domestic air



Note: CO_2 emissions were ranked by decile and then split by mode and purpose

Among the mode and trip purpose combinations, leisure travel by public transport is the most equal and commuting by car the least equal, as shown in Table 12.

Table 12: Emissions shares of households falling into the top and bottom emissions quintiles

	Total surface passenger travel	Car travel		Public transport travel		domestic air travel
		commuting	leisure	commuting	leisure	
bottom 20%	0.2%	0.0%	0.0%	0.5%	3.4%	5.0%
bottom 10%	0.0%	0.0%	0.0%	0.0%	0.0%	2.6%
top 10%	33.9%	45.0%	29.7%	21.6%	19.9%	23.0%
top 20%	53.6%	66.2%	49.2%	39.5%	34.0%	42.2%

When moving the analysis to how emissions levels differ between different accessibilities of local services and public transport we find that CO_2 emissions from travel by car and public transport are 46% higher and 38% lower respectively for households with a ‘low’ average measure of service accessibility (AMSA) when compared to ‘high’ AMSA (Table 13). Among the service accessibilities, public transport accessibility of the nearest chemist is the most equal and car accessibility of the nearest post office the least equal.

Table 13: Household CO_2 emissions by mode and local service accessibility

		Car		Public Transport	
		Mean CO_2 ($kgCO_2$/year)	Valid N	Mean CO_2 ($kgCO_2$/year)	Valid N
MSA1 Measure of Service Accessibility of nearest doctor	Low	2869	8116	206	8116
	Moderate	2423	7774	262	7774
	High	2181	1910	315	1910
	Total	*2600*	*17800*	*242*	*17800*
MSA2 Measure of Service Accessibility of nearest post office	Low	3328	1667	193	1667
	Moderate	2588	6379	246	6379
	High	2070	1134	316	1134
	Total	*2659*	*9180*	*245*	*9180*
MSA3 Measure of Service Accessibility of nearest chemist	Low	3161	4806	205	4806
	Moderate	2423	10627	251	10627
	High	2246	2394	281	2394
	Total	*2598*	*17827*	*243*	*17827*
MSA4 Measure of Service Accessibility of nearest food store	Low	3383	3428	182	3428
	Moderate	2533	20247	249	20247
	High	2351	3353	277	3353
	Total	*2618*	*27028*	*244*	*27028*
MSA5 Measure of Service Accessibility of nearest shopping centre	Low	3006	4261	211	4261
	Moderate	2461	3495	263	3495
	High	2105	1437	310	1437
	Total	*2658*	*9193*	*246*	*9193*
MSA6 Measure of Service Accessibility of nearest general hospital	Low	2707	14634	229	14634
	Moderate	2259	2270	267	2270
	High	1693	889	387	889
	Total	*2599*	*17792*	*242*	*17792*
AMSA Average Measure of Service Accessibility	**Low**	**3063**	**9000**	**197**	**9000**
	Moderate	**2459**	**14847**	**256**	**14847**
	High	**2101**	**3186**	**320**	**3186**
	Total	***2618***	***27032***	***244***	***27032***

Notes: The results should be viewed in conjunction with the methodology for computing services accessibility measures and data availability mentioned earlier. As described above not all service accessibility variables were collected in each of the five years 2002-06. This is the main reason why case frequencies vary across service categories.

6.5.2 Focus on commuting

Our analysis suggests an inverse relationship between the accessibilities to *local services* and *public transport* and overall CO_2 emissions from commuting.

First, we look at the effect different levels of local services accessibility has on emissions. Overall, lower accessibility to services results in higher emissions, a result that holds true for all local service accessibilities observed here (Table 14). For instance, mean emissions are 50% higher at 1.24 tCO_2/year for households with 'low' accessibility of the nearest post office than for those with 'high' accessibility (0.83 tCO_2/year). This disparity is lower at 31% for households with 'low' (over 'high') accessibility of the nearest shopping centre. In terms of the derived average measure of services accessibility (AMSA), households with 'low' AMSA show 37% higher mean emissions (1.17 tCO_2/year) than for 'high' accessibility (0.85 tCO_2/year). Nestled in between, households with 'moderate' AMSA emit 0.95 tCO_2/year, 12% higher than 'high' and 19% lower than 'low' AMSA.

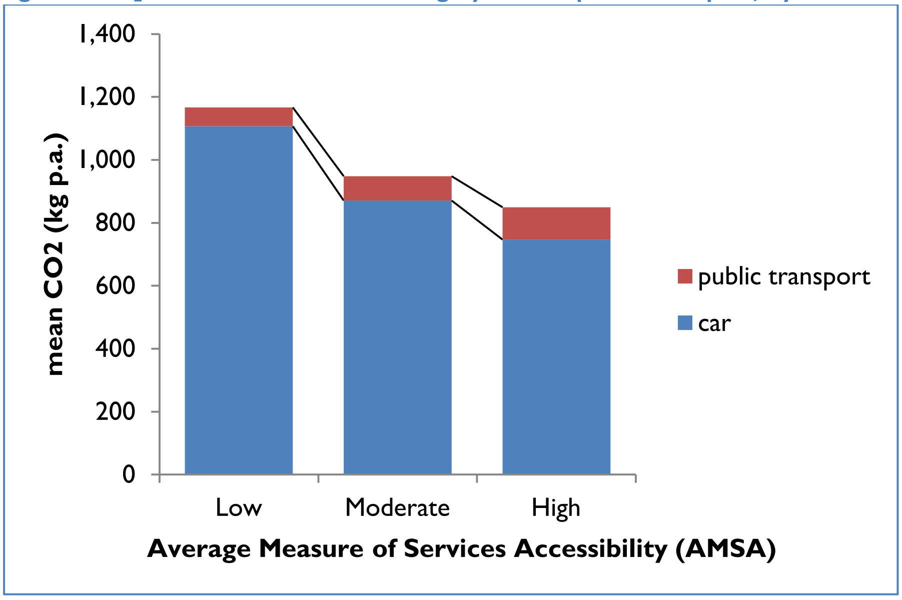
The observed differences and directions are dominated by car travel, as shown in Figure 4. While household CO_2 emissions from car travel decrease considerably with higher local services accessibility, emissions from public transport not surprisingly increase. Most importantly, however, is the result that higher overall accessibility by walking and public transport reduces CO_2 emissions from commuting overall.

Table 14: Household CO_2 emissions from commuting by service accessibility measures

Measure of service accessibility of nearest…		Surface transport commute CO_2				
		Valid N	Mean	SE of Mean	Median	SD
…doctor	Low	8116	1096.29	21.91	69.50	1974.10
	Moderate	7774	947.32	19.93	.00	1757.34
	High	1910	813.96	36.00	.00	1573.25
	Total	17800	1000.93	13.82	24.29	1843.93
…post office	Low	1667	1243.26	50.24	200.92	2051.19
	Moderate	6379	1004.96	24.02	60.11	1918.49
	High	1134	830.59	47.58	.00	1602.32
	Total	9180	1026.69	19.94	58.32	1910.91
…chemist	Low	4806	1204.12	31.21	39.72	2163.82
	Moderate	10627	940.29	16.75	26.01	1726.94
	High	2394	856.77	32.57	.00	1593.65
	Total	17827	1000.20	13.80	23.16	1843.06
…food store	Low	3428	1258.53	38.84	.00	2274.24
	Moderate	20247	986.24	12.72	55.53	1810.05
	High	3353	894.05	29.56	.00	1711.48
	Total	27028	1009.34	11.35	34.25	1866.36
…shopping centre	Low	4261	1143.44	30.37	133.31	1982.55
	Moderate	3495	948.08	31.40	28.77	1856.21
	High	1437	874.74	47.60	.00	1804.63
	Total	9193	1027.17	19.93	57.89	1911.10
…general hospital	Low	14634	1038.86	15.70	23.42	1899.62
	Moderate	2270	865.59	32.89	34.88	1567.03
	High	889	703.06	48.07	.00	1433.08
	Total	17792	999.98	13.81	24.88	1841.60
Average Measure of Service Accessibility (AMSA)	**Low**	**9000**	**1166.72**	**21.75**	**101.30**	**2063.72**
	Moderate	**14847**	**947.89**	**14.46**	**28.94**	**1761.86**
	High	**3186**	**850.01**	**30.41**	**.00**	**1716.28**
	Total	**27032**	**1009.21**	**11.35**	**34.25**	**1866.27**

Notes:
- The results should be viewed in conjunction with the methodology for computing AMSA and data availability mentioned above.
- As described earlier not all service accessibility variables were collected in each of the five years 2002-06. This is the main reason why case frequencies vary across service categories.

Figure 4: CO_2 emissions from commuting by car and public transport, by AMSA category



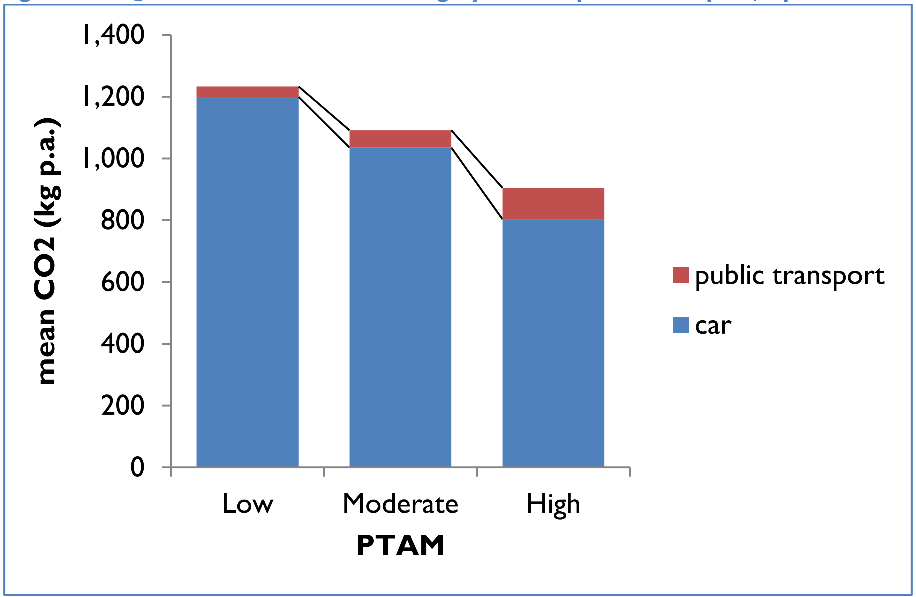
Second, a similar analysis conducted on the effects of different degrees of accessibility to *public transport services* reveals that higher accessibility results in lower CO_2 emissions from commuting, with households with high overall public transport accessibility emitting 27% less than those with low accessibility (Table 15). This difference is particularly evident for accessibility to bus services where households with high bus services accessibility emit 43% less on average at 0.82 tCO_2/year than households with low accessibility (1.43 tCO_2/year). In contrast, the effect is less pronounced for rail services accessibility, with a -16% difference between 'high' and 'low' accessibility (

Figure 5).

Table 15: Household CO_2 emissions from commuting, by public transport accessibility measures

		Surface transport commute CO_2				
		Valid N	Mean	SE of Mean	Median	SD
Bus accessibility measure	Low	3394	1425.27	40.99	.00	2387.96
	Moderate	25110	1113.21	12.32	95.11	1952.02
	High	17246	815.81	12.07	.00	1584.60
Rail accessibility measure	Low	8916	1144.24	21.76	.00	2054.67
	Moderate	21953	1021.58	12.62	43.89	1869.13
	High	14880	956.32	14.30	71.11	1744.65
Public transport accessibility measure (PTAM)	**Low**	**8338**	**1233.46**	**23.71**	**.00**	**2165.18**
	Moderate	**14661**	**1090.90**	**15.90**	**71.31**	**1925.47**
	High	**22751**	**904.63**	**11.26**	**41.28**	**1698.45**
	Total	***45750***	***1024.26***	***8.74***	***40.85***	***1869.06***

Figure 5: CO_2 emissions from commuting by car and public transport, by PTAM category



6.5.3 Focus on leisure travel

As with commuting, our analysis suggests an inverse relationship between the accessibilities of *local services* and *public transport* and overall CO_2 emissions from leisure travel.

First, lower services accessibility results in higher emissions levels from leisure travel (

). The largest difference in emissions between 'low' and 'high' service accessibility is observed for post office accessibility, with mean emissions 46% higher at 2.28 tCO_2/year for households with 'low' accessibility than for those with 'high' accessibility (1.56 tCO_2/year). This disparity is lowest at 18% for households with 'low' (over 'high') accessibility of the nearest doctor. In terms of the derived average measure of services accessibility (AMSA), households with 'low' AMSA show 33% higher mean emissions (2.09 tCO_2/year) than for 'high' accessibility (1.57 tCO_2/year). Nestled in between, households with 'moderate' AMSA emit 1.77 tCO_2/year, 12% higher than 'high' and 16% lower than 'low' AMSA.

The observed differences and directions are dominated by car travel, as shown in Table 16. While household CO_2 emissions from leisure car travel decrease considerably with higher local services accessibility, emissions from public transport go up. Most importantly, however, is the result that higher overall accessibility by walking and public transport reduces CO_2 emissions from leisure travel overall, with the effect being most prominent for the step from 'low' to 'moderate' accessibility.

Table 16: Household CO_2 emissions from leisure travel by service accessibility measures

Measure of service accessibility of nearest...		Surface transport leisure travel CO_2				
		Valid N	Mean	SE of Mean	Median	SD
...doctor	Low	8116	1978.29	23.81	1447.20	2144.81
	Moderate	7774	1737.47	22.44	1237.29	1978.71
	High	1910	1681.86	50.33	1027.38	2199.59
	Total	17800	1841.31	15.62	1368.92	2083.77
...post office	Low	1667	2278.30	58.97	1736.64	2407.87
	Moderate	6379	1829.67	25.91	1359.52	2069.21
	High	1134	1556.13	57.70	921.34	1943.15
	Total	9180	1877.35	22.23	1369.84	2130.02
...chemist	Low	4806	2161.73	33.08	1659.90	2293.28
	Moderate	10627	1733.50	19.02	1213.56	1960.49
	High	2394	1670.11	42.93	1066.06	2100.29
	Total	17827	1840.44	15.60	1362.39	2083.12
...food store	Low	3428	2306.25	40.94	1730.19	2396.71
	Moderate	20247	1795.64	14.25	1308.10	2028.18
	High	3353	1733.70	36.94	1157.76	2139.42
	Total	27028	1852.71	12.77	1369.84	2099.47
...shopping centre	Low	4261	2072.97	33.77	1568.99	2204.58
	Moderate	3495	1775.73	35.40	1267.03	2092.69
	High	1437	1540.15	50.76	922.10	1924.33
	Total	9193	1876.67	22.21	1369.84	2129.56
...general hospital	Low	14634	1897.38	17.62	1369.84	2130.90
	Moderate	2270	1659.91	39.33	1168.24	1873.93
	High	889	1376.98	56.53	831.50	1685.18
	Total	17792	1841.09	15.62	1362.99	2083.67
Average Measure of Service Accessibility (AMSA)	**Low**	**9000**	**2093.58**	**23.64**	**1553.24**	**2242.77**
	Moderate	**14847**	**1767.10**	**16.54**	**1280.67**	**2015.91**
	High	**3186**	**1571.01**	**35.35**	**941.77**	**1995.00**
	Total	**27032**	**1852.69**	**12.77**	**1369.84**	**2099.53**

Notes:
- The results should be viewed in conjunction with the methodology for computing AMSA and data availability mentioned above.
- As described earlier not all service accessibility variables were collected in each of the five NTS years of 2002-06. This is the main reason why case frequencies vary across service categories.

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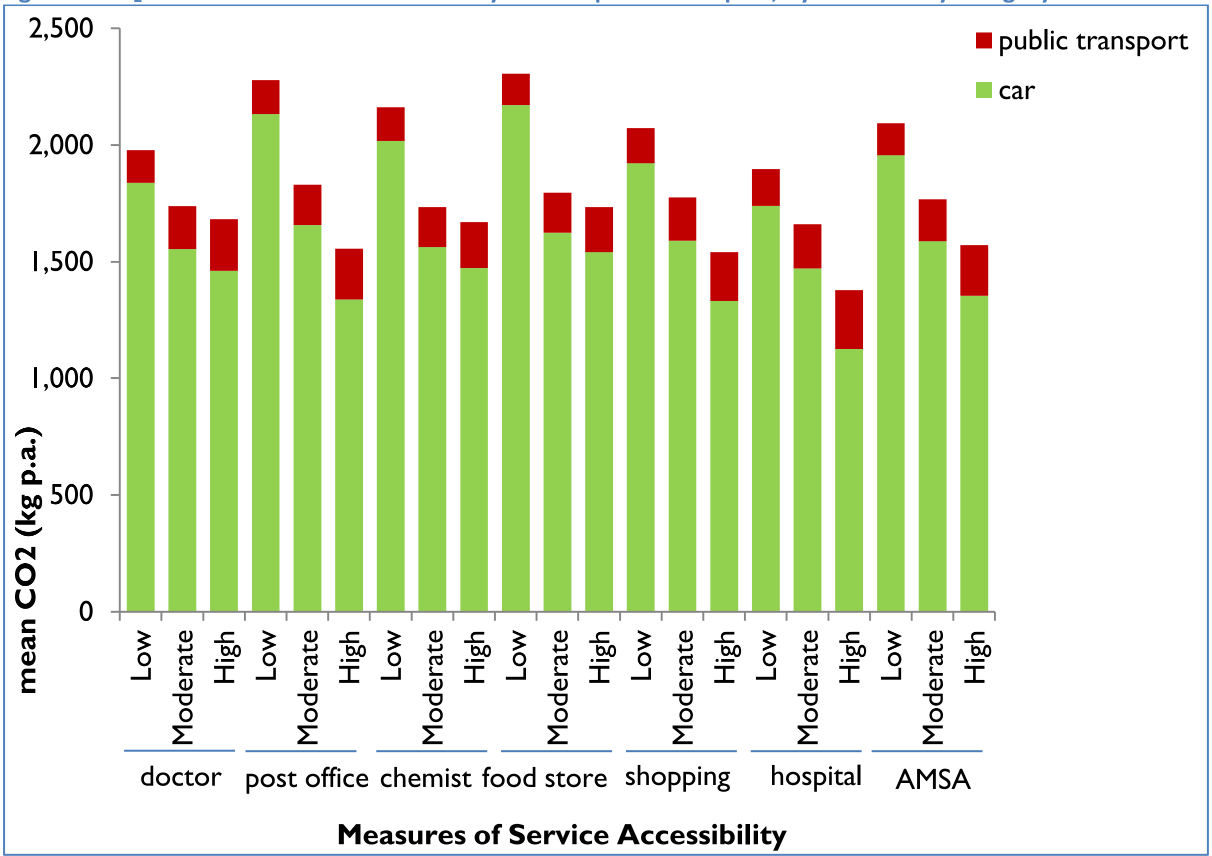
Figure 6: CO_2 emissions from leisure travel by car and public transport, by accessibility category



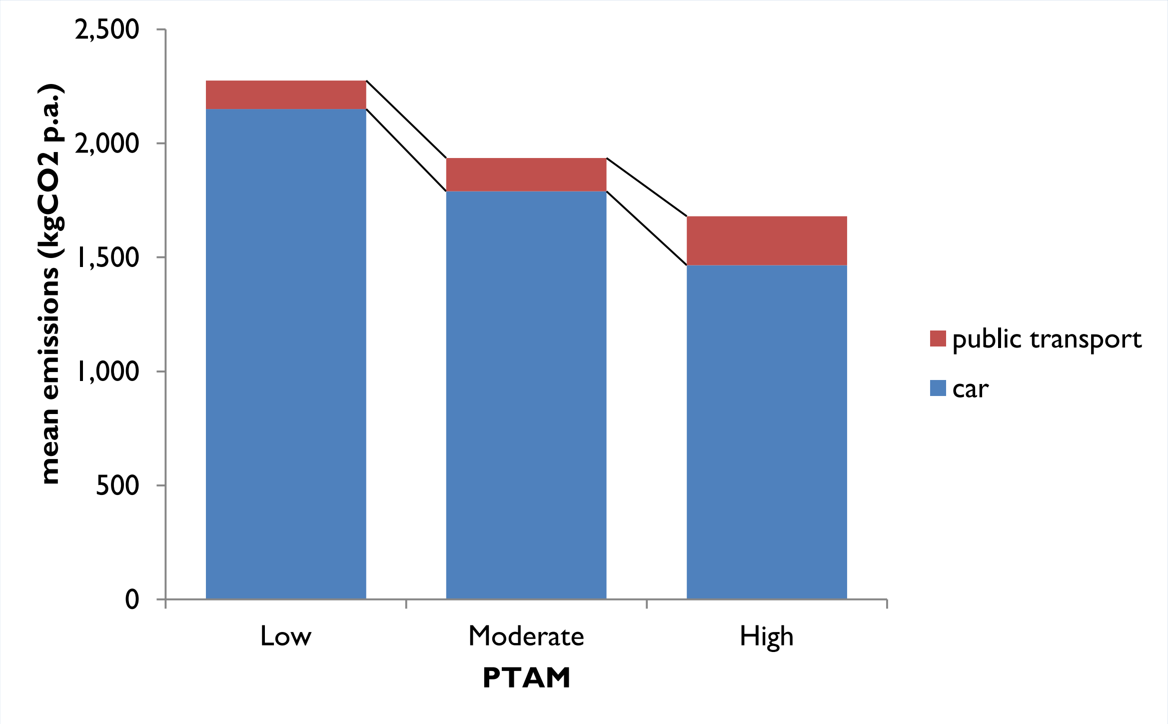
In terms of accessibility to *public transport services* the analysis suggests once again that higher accessibility results in lower CO_2 emissions from leisure travel, with households with ‘high’ overall public transport accessibility (PTAM) emitting 26% *less* than those with ‘low’ accessibility (Table 17).

This divergence is particularly evident for accessibility to bus services where households with ‘high’ bus services accessibility emit 40% less on average (1.56 tCO_2/year) than households with ‘low’ accessibility (2.62 tCO_2/year). In contrast, the effect is less pronounced for rail services accessibility, with a -17% difference between ‘high’ and ‘low’ accessibility.

Table 17: Household CO_2 emissions from leisure travel, by public transport accessibility measures

		Surface transport leisure travel CO_2				
		Valid N	Mean	SE of Mean	Median	SD
Bus accessibility measure	Low	3394	2622.97	42.76	2082.74	2491.42
	Moderate	25110	1979.59	13.29	1498.96	2106.41
	High	17246	1562.60	14.28	1013.04	1875.73
Rail accessibility measure	Low	8916	2109.47	23.58	1659.28	2226.59
	Moderate	21953	1860.18	13.71	1369.84	2030.95
	High	14880	1741.40	16.67	1198.61	2032.90
Public transport accessibility measure (PTAM)	**Low**	**8338**	**2275.45**	**25.28**	**1736.64**	**2308.16**
	Moderate	**14661**	**1935.18**	**17.06**	**1447.20**	**2065.43**
	High	**22751**	**1679.66**	**13.02**	**1157.76**	**1964.35**
	Total	***45750***	***1870.13***	***9.70***	***1369.84***	***2075.11***

Figure 7: CO_2 emissions from leisure travel by car and public transport, by PTAM category



6.6 Multivariable Analysis

This section presents the results of the hierarchical linear regression modelling of standardized log-transformed (total CO2 emissions + 1) as the dependent variable and demographic, socio-economic, environmental, accessibility and car availability as the explanatory variables.

6.6.1 Total CO_2 emissions

The regression results for total surface transport CO_2 emissions are shown in Table 18. The first three columns give the variable domain, variable name and (dummy coded) variable levels; the next two columns give the number of cases and mean CO_2 emissions for each variable level; and the last three columns give the model fit (R^2), regression coefficients (β) and 95% CI for standardised log-transformed CO_2 emissions for the three multivariate regression models (see section 2.3). Note the multivariate analyses adjust for all variables in column, thus excluding the grey shaded variables.

The results suggest the more variables are entered into the analysis, the better the model fit (R^2). While adjusting for demographic and socio-economic variables explains only 32% of the variation in emissions, adjusting also for environmental, accessibility and car availability variables explains nearly half of the variation (47%). Total CO_2 emissions are higher in households with a male HRP, those in the middle age range 25-64 and those with a white HRP after adjusting for all SEP, environmental and accessibility indicators (multivariable 2). Household size is strongly and positively related to emissions, even when adjusting for all predictor variables in the model (multivariable 3). The age effect is highest for HRP in pensionable age; however, the tolerance and variance inflation factor suggest there may be collinearity problems, particularly between age and the employment variables.

There is evidence of an independent effect of having children under 16 in all three models, with a trend towards slightly *lower* emissions and weakening the more predictors are included in the model. Note this is in contrast to total CO_2 emissions in the unadjusted analysis, where households with children under 16 years of age show *higher* mean emissions.

CO_2 emissions are significantly higher in households with higher socio-economic status (socio-economic classification of HRP, income, tenure) and also in those with the HRP in full-time or part-time employment (multivariable 1). These effects diminish somewhat but remain strong after adjusting for all SEP, environmental and accessibility variables (multivariable 2), with income and household size showing the strongest effects (beta > 0.3 or < -0.3) and household location and accessibility showing only marginal effects. In particular, while there is marginal evidence of lower emissions levels for households with higher services accessibility, we find no significant effect of the public transport accessibility variables once adjusted for the above variables.

Furthermore, most of the strong effects are attenuated towards the null (and often to below 0.1 or above -0.1, except for household size, income and employment variables) in model 3 after further adjusting for car access. Or in other words, the number of cars available to the household is a very strong predictor in all multivariable models, and adjusting for this reduces – in some cases to the null – the effects of higher SEP. This seems plausible; while income and working status were expected to be strong predictors they are further back on the causal pathway than having a car.

There is marginal evidence that households in London have slightly lower emissions than the other regions even after adjusting for other environmental and SEP characteristics. Conversely, households in rural areas have higher emissions. This may reflect better (poorer) accessibility to public transport and services in general. However, there are no great differences between regions and urban/rural location (multivariable 2), suggesting we have included the variables that explain most of the inter-regional difference in mean emission levels. Furthermore, after adjusting also for car availability (model 3), none of the environmental variables show a strong and significant effect. Interestingly, higher public transport accessibility has a significant and *positive* effect on CO_2 emissions after adjusting also for car access. However, the effect is only marginal and may be explained by non-car owning households using public transport more.

Table 18: Individual, household and environmental predictors of CO_2 emissions from land-based passenger transport (N=45,750)

					Regression coefficients (β) and 95% CI for standardised log-transformed CO_2		
Domain	**Variable**	**Level**	**N**	**Mean CO_2**	**Multi-variable 1**	**Multi-variable 2**	**Multi-variable 3**
					R^2=.323	R^2=.326	R^2=.473
Demo-graphic	Sex HRP	Male $	29209	3412	0***	0***	0
		Female	16541	1981	-.12 (-.13, -.10)	-.11 (-.13, -.09)	.00 (-.01, .02)
	Age HRP	<25 years $	1651	2023	0***	0***	0***
		25-44 years	16597	3496	.07 (.03, .11)	.07 (.03, .11)	-.07 (-.11, -.03)
		45-64 years	15709	3565	.07 (.03, .11)	.06 (.02, .11)	-.09 (-.13, -.05)
		>65 years	11794	1276	-.21 (-.26, -.15)	-.22 (-.27, -.17)	-.24 (-.29, -.19)
	Ethnicity HRP	White $	42509	2931	0***	0***	0*
		Non-white	3241	2411	-.13 (-.16, -.10)	-.08 (-.11, -.05)	-.03 (-.06, .00)
	Household Size	Single person $	12791	1204	0***	0***	0***
		2 persons	16550	2940	.45 (.43, .47)	.44 (.42, .46)	.20 (.18, .22)
		3 persons	7170	3817	.55 (.52, .58)	.54 (.51, .57)	.25 (.22, .28)
		4 or more persons	9239	4436	.62 (.59, .66)	.62 (.58, .65)	.28 (.25, .32)
	Any child under 16	No $	32111	2558	0***	0***	0***
		Yes	13639	3686	-.12 (-.15, -.09)	-.12 (-.15, -.10)	-.07 (-.10, -.05)
Socio-econ.	NS-SEC8 of HRP	Large employers, higher managerial & higher professional $	6175	4554	0***	0***	0***
		Lower managerial & professionals	11007	3669	-.03 (-.06, -.01)	-.03 (-.06, -.01)	-.04 (-.06, -.01)
		Intermediate, small employers & own account workers	8514	2820	-.13 (-.16, -.10)	-.13 (-.16, -.10)	-.10 (-.12, -.07)
		Lower supervisory & technical, semi-routine, routine	17739	2058	-.24 (-.27, -.22)	-.24 (-.27, -.22)	-.13 (-.15, -.11)
		Never worked or long term unemployed	895	917	-.39 (-.45, -.33)	-.39 (-.45, -.33)	-.19 (-.25, -.14)
		Students, not classifiable, retired	1422	1816	-.30 (-.36, -.25)	-.30 (-.35, -.24)	-.19 (-.23, -.14)
	Household income (gross p.a.)	<£10,000 $	11397	960	0***	0***	0***
		£10,000 - £19,999	10324	1989	.26 (.23, .28)	.25 (.23, .28)	.11 (.09, .13)
		£20,000 - £39,999	13848	3441	.36 (.33, .38)	.35 (.33, .38)	.14 (.12, .17)
		>£40,000	10181	5234	.39 (.36, .42)	.38 (.35, .42)	.17 (.14, .19)
	Housing tenure	Buying w/mortgage $	17615	4233	0***	0***	0***
		Own outright	14372	2452	.03 (.01, .05)	.02 (.00, .05)	.00 (-.02, .02)
		Rent, mixed & other	13763	1642	-.29 (-.31, -.27)	-.29 (-.31, -.26)	-.04 (-.06, -.02)
	Employment Status HRP	Full-time $	20703	4063	0***	0***	0***
		Part-time	2902	2558	.01 (-.03, .04)	.01 (-.03, .04)	.00 (-.03, .03)
		Self-employed	4163	3896	-.10 (-.13, -.07)	-.11 (-.14, -.08)	-.15 (-.18, -.13)
		Retired	12266	1384	-.19 (-.23, -.16)	-.19 (-.23, -.16)	-.11 (-.14, -.08)
		Other non-working	5716	1344	-.31 (-.35, -.28)	-.31 (-.34, -.28)	-.18 (-.21, -.15)
Environ-ment	Government Office Region	Northern England	11362	2689		-.04 (-.06, -.01)	.02 (.00, .04)
		Midlands and Eastern	11618	3149		-.01 (-.04, .01)	.01 (-.01, .03)
		London	5972	2157		-.13 (-.16, -.10)	.02 (.00, .05)
		South East $	6313	3514		0***	0
		South West	4056	3042		-.03 (-.06, .01)	-.02 (-.05, .01)
		Wales	2327	2897		-.05 (-.09, -.01)	-.01 (-.04, .03)
		Scotland	4101	2716		-.07 (-.10, -.04)	.01 (-.02, .04)
	Urban/rural status	Urban $	39843	2725		0***	0*
		Rural	5907	4039		.11 (.08, .14)	.03 (.01, .05)
Access-ibility	of services (AMSA)	Low $	9000	3260		0***	0
		Moderate	14847	2715		-.03 (-.05, -.02)	-.01 (-.03, .00)
		High	3186	2421		-.04 (-.07, -.01)	-.02 (-.04, .01)
	of public transport (PTAM)	Low $	8338	3509		0	0***
		Moderate	14661	3026		.01 (-.02, .03)	.04 (.02, .06)
		High	22751	2584		.00 (-.03, .02)	.07 (.05, .09)
Car avail ability	Cars	No cars $	11814	354			0***
		One car	19843	2526			1.08 (1.06, 1.10)
		Two or more cars	14094	5543			1.30 (1.28, 1.33)

Notes: *p<0.05, **p<0.01, ***p<0.001. Outcome is standardised log-transformed CO_2. Numbers add to less than 45,750 in some variables because of missing data. Multivariate analyses adjust for all variables in column. HRP = household reference person. NS-SEC = National Statistics Socio-Economic Classification. $ indicates reference level in dummy coding.

6.6.2 Emissions for commuting and leisure travel

Table 19 shows the regression results of the fully adjusted model for commuting and leisure travel emissions. The first point to note is that the commuting model explains significantly more of the variation in emissions (56%) than the leisure travel model (42%), mainly because of a better fit with SEP variables (income, tenure, employment status). While car access has the strongest effect on leisure travel emissions, the strongest (and obvious) predictor of commuting emissions is employment status (but not Socio-Economic Classification!). In particular, households with retired or non-working HRP show much lower commuting emissions, perhaps an indication that other household members also do not commute or work. As with total emissions, household size is significantly and positively related to CO_2 production, in particular for leisure travel. Conversely, both tenure and income are stronger predictors of commuting than of leisure travel emissions. There is evidence that the presence of children under 16 years of age gives lower mean emissions for commuting purposes after adjusting for all other variables. This could be explained by one of the parents staying or working at home more than in a children-free household. Finally, the gender of the HRP seems to matter only for commuting emissions, with marginally *higher* mean emissions in households with female HRPs.

Crucially for the focus of this paper, the accessibility variables have only marginal effects on the outcomes after adjusting for all other variables, with slightly *higher* mean emissions for both commuting and leisure travel in households with higher public transport accessibility and no significant correlation with services accessibility. Again, the marginal effects may be explained by non-car owning households using public transport more.

Table 19: Individual, household and environmental predictors of CO_2 emissions from land-based passenger transport for commuting and leisure travel (N=45,750)

			Regression coefficients (β) and 95% CI for standardised log-transformed CO_2	
Domain	**Variable**	**Level**	**Commuting**	**Leisure**
			R^2=.557	R^2=.415
Demo-graphic	Sex HRP	Male $	0***	0
		Female	.10 (.09, .12)	-.01 (-.03, .00)
	Age HRP	<25 years $	0***	0***
		25-44 years	.06 (.02, .09)	-.08 (-.12, -.03)
		45-64 years	.04 (.01, .08)	-.08 (-.12, -.04)
		>65 years	-.04 (-.08, .00)	-.21 (-.26, -.16)
	Ethnicity HRP	White $	0**	0***
		Non-white	.04 (.02, .07)	-.07 (-.10, -.04)
	Household Size	Single person $	0***	0***
		2 persons	.05 (.04, .07)	.21 (.18, .23)
		3 persons	.21 (.19, .24)	.25 (.22, .28)
		4 or more persons	.21 (.18, .24)	.30 (.27, .34)
	Any child under 16	No $	0***	0*
		Yes	-.16 (-.19, -.14)	-.03 (-.06, -.01)
Socio-econ.	NS-SEC8 of HRP	Large employers, higher managerial & higher professional $	0*	0***
		Lower managerial & professionals	.01 (-.01, .03)	-.05 (-.07, -.02)
		Intermediate, small employers & own account workers	.01 (-.01, .04)	-.12 (-.14, -.09)
		Lower supervisory & technical, semi-routine, routine	.00 (-.02, .02)	-.14 (-.17, -.12)
		Never worked or long term unemployed	.08 (.03, .13)	-.22 (-.27, -.16)
		Students, not classifiable, retired	-.01 (-.05, .03)	-.18 (-.23, -.14)
	Household income (gross p.a.)	<£10,000 $	0***	0***
		£10,000 - £19,999	.02 (.00, .04)	.09 (.07, .11)
		£20,000 - £39,999	.18 (.16, .20)	.11 (.08, .14)
		>£40,000	.28 (.26, .31)	.11 (.08, .14)
	Housing tenure	Buying w/mortgage $	0***	0***
		Own outright	-.17 (-.19, -.15)	.03 (.01, .06)
		Rent, mixed & other	-.13 (-.15, -.11)	-.02 (-.04, .00)
	Employment Status HRP	Full-time $	0***	0***
		Part-time	-.16 (-.19, -.14)	.06 (.02, .09)
		Self-employed	-.43 (-.46, -.41)	-.09 (-.12, -.06)
		Retired	-1.00 (-1.03, -.97)	.08 (.05, .11)
		Other non-working	-.92 (-.94, -.89)	.01 (-.02, .04)
Environ-ment	Government Office Region	Northern England	.04 (.02, .06)	.01 (-.01, .03)
		Midlands and Eastern	.01 (-.01, .03)	.00 (-.02, .03)
		London	-.05 (-.07, -.02)	.03 (.00, .05)
		South East $	0***	0*
		South West	-.01 (-.03, .02)	-.03 (-.06, .00)
		Wales	.04 (.00, .07)	-.03 (-.07, .01)
		Scotland	.04 (.01, .06)	.01 (-.02, .04)
	Urban/rural status	Urban $	0	0*
		Rural	-.01 (-.03, .01)	.02 (.00, .05)
Access-ibility	of services (AMSA)	Low $	0	0
		Moderate	.00 (-.01, .01)	-.01 (-.03, .00)
		High	-.01 (-.03, .02)	-.02 (-.05, .01)
	of public transport (PTAM)	Low $	0**	0***
		Moderate	.04 (.02, .06)	.03 (.01, .06)
		High	.03 (.01, .05)	.07 (.04, .09)
Car avail ability	Cars	No cars $	0***	0***
		One car	.32 (.31, .34)	1.12 (1.10, 1.14)
		Two or more cars	.64 (.61, .66)	1.33 (1.31, 1.36)

Notes: *p<0.05, **p<0.01, ***p<0.001. Outcome is standardised log-transformed CO_2. Numbers add to less than 45,750 in some variables because of missing data. Multivariate analyses adjust for all variables in column. HRP = household reference person. NS-SEC = National Statistics Socio-Economic Classification. $ indicates reference level in dummy coding.

6.7 CHAID tree classification for total land-based passenger transport CO_2

To identify optimal splits in the categorical predictors, the CHAID tree classification model was developed based on the results of the fully adjusted regression model (multivariable 3) above and set to a maximum of three tree levels. Of the 16 categorical predictors entered into the model only six were included in the final classification tree that comprised 45 nodes of which 29 were terminal (Table 20). The six predictors were in order of strength of association:

1. Number of cars;
2. Employment status of the HRP;
3. NS-SEC of the HRP;
4. Household gross income;
5. Household size, and;
6. Rail accessibility measure (RAM).

This largely confirms the results of the regression analysis but adds a rigorous assessment of what level of any specific predictor is most strongly associated with variation in emissions levels. When looking at the classification tree, the top categorical variable is car access.

First, while for **households without a car** at their disposal the second most important predictor was household size, it was employment status for households with one or two or more cars available to them. Interestingly, while for small (one or two persons) non-car owning households the third most important predictor was employment status, it was rail accessibility for larger (three, four or more) households without a car, with significant differences in emissions between low and moderate/high rail accessibility for this cluster.

Second, the third most important predictor for **households with one car** and where the HRP was either full-time employed, part-time employed or self-employed was his or her NS-SEC (with 2 or 3 out of 6 possible nodes selected by the model), whereas where the HRP was retired, a student or not working household emissions were more strongly associated with income.

Third, the results were similar for **households with two or more cars**, although income and household size were more important for explaining the variation in emissions than for one-car owning households (Table 20).

Table 20: Partial CHAID tree table for households with two or more cars available to them

Node	Mean	Std. Deviation	N	Percent	Predicted Mean	Parent Node	Primary Independent Variable					
							Variable	Sig.[a]	F	df1	df2	Split Values
0	6.5727	2.78376	46084	100.0%	6.5727							
3	8.2387	1.44896	14129	30.7%	8.2387	0	ncars (3 categories)	.000	17591.975	2	46081	two or more
12	8.4204	1.15470	8913	19.3%	8.4204	3	emphrp (5 categories)	.000	155.958	3	14125	full time
13	7.7550	2.01907	2003	4.3%	7.7550	3	emphrp (5 categories)	.000	155.958	3	14125	non working and other; retired
14	7.9648	1.77612	2489	5.4%	7.9648	3	emphrp (5 categories)	.000	155.958	3	14125	self employed
15	8.2827	1.06334	724	1.6%	8.2827	3	emphrp (5 categories)	.000	155.958	3	14125	part time
35	8.2970	1.13454	3503	7.6%	8.2970	12	hhgincEN (4 categories)	.000	86.731	2	8910	20-40k; <10k
36	8.5548	1.11625	4850	10.5%	8.5548	12	hhgincEN (4 categories)	.000	86.731	2	8910	>40k
37	8.0285	1.40674	560	1.2%	8.0285	12	hhgincEN (4 categories)	.000	86.731	2	8910	10-20k
38	7.9669	1.82890	1094	2.4%	7.9669	13	hhgincEN (4 categories)	.000	19.376	2	2000	20-40k; >40k
39	7.2034	2.60124	336	.7%	7.2034	13	hhgincEN (4 categories)	.000	19.376	2	2000	<10k
40	7.6739	1.90859	573	1.2%	7.6739	13	hhgincEN (4 categories)	.000	19.376	2	2000	10-20k
41	8.1031	1.66101	1527	3.3%	8.1031	14	hhsize (4 categories)	.000	24.189	1	2487	four or more; three
42	7.7452	1.92549	962	2.1%	7.7452	14	hhsize (4 categories)	.000	24.189	1	2487	one; two
43	8.3967	1.04144	409	.9%	8.3967	15	hhsize (4 categories)	.007	10.952	1	722	four or more; three
44	8.1347	1.07484	315	.7%	8.1347	15	hhsize (4 categories)	.007	10.952	1	722	one; two

Growing Method: CHAID
Dependent Variable: log(Surface Transport total CO_2 + 1)
a. Bonferroni adjusted

7 Conclusions

The results presented above reveal the extent to which households' CO_2 emissions from land based passenger transport reflect the influence of a wide range of demographic, socio-economic, environmental and accessibility characteristics. The multivariate regression modelling has unravelled some of these effects, thus providing a better understanding of the underlying drivers of social variation in households' travel CO_2 emissions. However, as the multivariate modelling explained only between 40% and 50% of the variation in the population, it may be too early at this stage to extract any firm conclusions regarding the potential distributional impacts of CO_2 mitigation policies. However, we can provide a number of observations that may potentially have an impact on CO_2 reduction policies in the transport sector.

First, the variation in households' travel carbon emissions is considerable, showing a highly and positively skewed distribution. Policy should target the high polluters, e.g. the top 10% of the population producing more than a third of land-based passenger transport CO_2 emissions. The results suggest that substantial reductions in travel CO_2 emissions could be achieved by reducing private car travel and associated energy consumption amongst those groups currently 'over-consuming' relative to the population as a whole. In particular, the data suggest that pricing policies aimed at higher car use such as road or fuel pricing are likely to be progressive. Such a strategy would also appear to be consistent with the pursuit of social equity in the distribution and utilisation of societal resources.

Second, the regression and CHAID analyses have shown that the high emitters are more likely to have higher socio-economic status, i.e. in full-time employment, on higher incomes and higher SEC status and own a house and at least one car. In contrast to the importance of car availability and socio-economic characteristics in accounting for the variation in travel CO_2 emissions, geo-spatial and accessibility variations in emissions are relatively trivial, even after controlling for household size and composition. This suggests that once households of different types have met their material and social needs, they have little legroom in reducing their travel emissions on grounds of improved accessibility to local services and public transport.

8 Discussion – policy implications

The differences that exist between the general population and subgroups within the population have far-reaching consequences for the development of transport, energy and environmental policies. Policy needs to target these high emitters by seeking out differences amongst the population, identify the causes and target these causes directly. Indicators of travel and emissions were identified, such as those characteristics indicative of higher income, being in work, middle age, small household size and higher car availability.

When controlling for these socio-economic and demographic factors, the evidence derived in the statistical and regression analyses suggests that neither environmental factors (household location, urban/rural) nor accessibility to local services and public transport have major influences on travel activity and carbon emissions. This result contributes to the literature on the linkages between travel activity, emissions generation and their underlying influences (e.g. Stead, 1999; Carlsson-Kanyama and Linden, 1999, Timmermans et al., 2003, Cameron et al., 2004; Brand and Boardman, 2008).

Residents in large urban areas may experience more difficulties in meeting any future caps on personal GHG emissions (e.g. as part of carbon cap-and-trading) – yet alternatives to the car are generally available, so the scale of any equity impacts will be lower.

This research suggests that flying has to be included in carbon mitigation policy, as a carbon tax on fuel (upstream tax), air passenger charge (downstream tax), emissions trading (upstream) or personal carbon trading (downstream). However, aviation is problematic as solutions to tackle climate change have to be international. The aviation sector is currently excluded from both fuel taxation, value added tax and emissions trading (as in the EU Emissions Trading Scheme), suggesting something must be done sooner rather than later to curb the rising demand. Higher air travel costs may prevent people from forming 'frequent flier' habits before they are 'engrained' in society. In the meantime, prices would have to go up considerably to have a restraining effect on demand, mainly because the link between prices and flying is evidently weak (Brons et al., 2002).

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