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Climate change and social justice

THE DISTRIBUTION OF HOUSEHOLD CO_2 EMISSIONS IN GREAT BRITAIN

Updated Version
Supplementary Project Paper No. 1

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This paper:

- provides a detailed look at the distribution of carbon dioxide emissions of households in Great Britain;
- demonstrates the extent to which households' annual domestic CO_2 emissions are influenced by a range of socio-demographic factors;
- shows that emissions are strongly correlated with income and that in general lower income, more vulnerable households tend to have lower than average CO_2 emissions.

The Joseph Rowntree Foundation (JRF) commissioned this paper as part of its programme on climate change and social justice, which seeks to ensure that people or places facing poverty and disadvantage are not disproportionately affected by climate change, or by policy or practice responses to it.

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Executive summary

This paper presents the findings from a quantitative study, funded by the Joseph Rowntree Foundation (JRF) and undertaken by the Centre for Sustainable Energy and the universities of Bristol and Oxford, to explore the likely social distributional impacts of UK government energy and climate change policies on domestic energy consumers.

It updates the results presented in the interim report (Fahmy *et al*., 2011) and is designed to complement the analysis presented in the main report *Fair and effective or unjust and weak? Implications of the distribution of emissions for domestic energy policy* (Thumim, *et al*., 2013), providing a more detailed look at the distribution of carbon dioxide emissions of households in Great Britain. It uses the nationally representative dataset created as part of the project to explore the distribution of household level emissions to include those from the consumption of energy in the home and personal travel by private vehicle, public transport and aviation.

The research study aimed to further the development of socially just and environmentally effective carbon reduction policies, by:

- revealing the distributional consequences of current and possible future policies to reduce carbon emissions from UK households; and
- enhancing understanding of these social aspects of climate policy within energy, climate change and social policy arenas.

Context

UK government policies to reduce CO_2 emissions do not impact UK households uniformly. The majority of these policies are funded by consumers via energy bills – that is, all customers pay towards the cost of the policy with a set amount on each unit of energy consumed. Household characteristics interact with various aspects of the design, implementation and uptake of such policies to determine the way individual households, and groups of similar households, benefit. For example the feed-in tariff (FIT) generates a revenue stream for households able to overcome the capital barriers to taking advantage of the opportunity presented by the policy; however this revenue is raised from the electricity bills of all households. Consequently the FIT can be expected to have a regressive distributional impact across UK households (see Chapter 5 of the full project report for further discussion and analysis of individual policy impacts).

The Climate Change Act 2008 created a legally binding target to reduce the UK's emissions of greenhouse gases (GHGs) to at least 80 per cent below 1990 levels by 2050. The government set out three carbon budgets for a phased reduction in emissions to the 2050 target. The Committee on Climate Change (CCC) then recommended that the government establish a fourth budget for 2023–2027 which set a limit of 1,950 MtCO2e (a cut of 50 per cent on 1990 levels). The government accepted this ambitious target in May 2011 (DECC, 2011).

These targets reflect the increasingly urgent need to reduce emissions to avoid dangerous climate change. The UK carbon reduction policy framework is likely to have to become increasingly aggressive if we are to progress toward these targets. It is therefore essential that we understand the social distributional impacts of both existing and proposed policies, so that we can feed this understanding back into the policy design process. This is a requirement if we are to implement policies which:

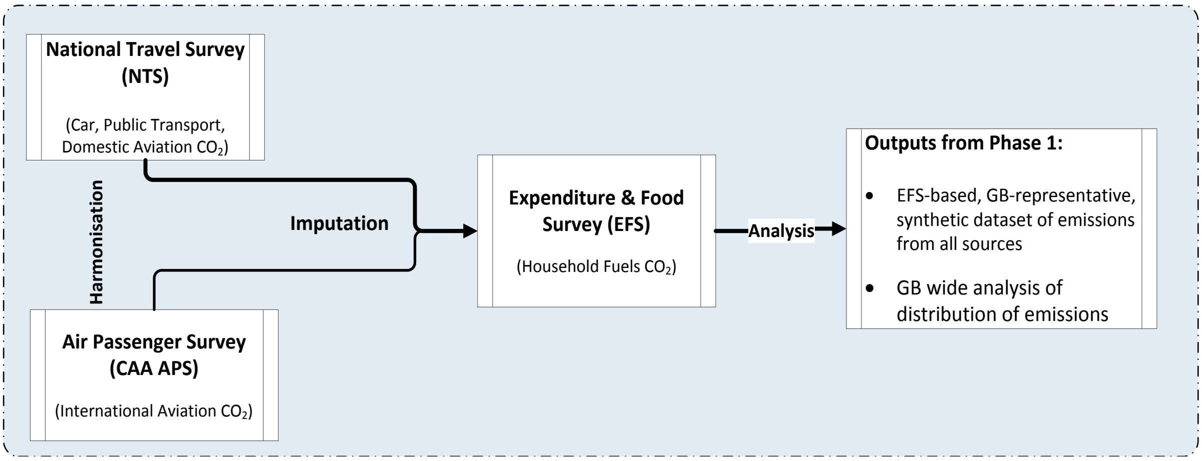
- minimise (or at the very least, avoid exacerbating) the hardship faced by vulnerable households and, where possible, improve outcomes for vulnerable households;
- are fair, and are seen to be fair: a likely precondition for successful carbon reduction policies.

Data and methods

This paper presents the results of the analysis undertaken in Phase 1 of the wider research project. This phase of the study encompasses a detailed analysis to explore the distribution of carbon emissions across households in Great Britain (Figure 1). This paper is intended to complement the results presented in the main project report, providing more detailed statistical analysis of the distribution of emissions.

The analysis presented in this paper uses the dataset developed in Phase 1 of the project. The methodology applied in creating this dataset is presented in the main project report and associated annex documents. A brief summary is provided below for context.

Figure 1: Phase 1 methodology



To explore the distribution of carbon dioxide emissions from the consumption of household fuels and all personal travel (by car, public transport, domestic and international aviation for non-business purposes) by households in Great Britain, several different data sources were required. The Expenditure and Food Survey (EFS) forms the base dataset to which data from other sources is imputed. The EFS itself is used to derive estimates of CO_2 from the consumption of household fuels (based on expenditure data in the survey). Additional data is imputed to this EFS dataset from the National Travel Survey and the Civil Aviation Authority Air Passenger Survey to provide information on emissions from personal surface travel and international aviation respectively.

The EFS includes a range of household level socio-demographic variables which provide the means for the distributional analysis. Results are presented to show the relative contribution to total household emissions by different socio-demographic descriptors, including: income deciles, household composition, age bands, number of cars in the household, settlement type, heating fuel type.

In addition, one-way analysis of variance (ANOVA) is also used to reveal any significant differences between groups as defined by: income; tenure; number of workers in the household; employment status; age; socio-economic group; settlement type; car ownership and domestic heating fuel. The results of ANOVA show the degree to which these different variables can be said to explain or predict variations in CO_2 emissions in the absence of other influencing factors.

As far as we are aware, this is the first integrated analysis of emissions from all these direct sources based entirely and directly on nationally representative survey data. The analysis provides new evidence and insight into who is responsible for emitting how much carbon dioxide, and identifies the relative contributions of different aspects (i.e. energy consumption in the home, private road travel and aviation) of household carbon emissions. Some headline results from this analysis are presented in Chapter 4 of the main project report. The full and detailed results are presented here.

Results

The analysis of the distribution of emissions from each source (domestic fuel, private transport, public transport and aviation) by different socio-demographic factors showed that emissions are strongly correlated with income: the richest 10 per cent of households in Great Britain emit three times more than the poorest 10 per cent. Despite household fuels being the largest contributor to the total household CO_2 emissions, emissions from transport show the largest variation across the income spectrum, with the highest income decile emitting seven to eight times as much as the lowest income decile for private road travel, and ten times as much for international aviation. Despite this overall trend in emissions increasing from low to high income, there remain significant variations in emissions within deciles across the income spectrum, i.e. the highest emitting poor households have comparable emissions to the mean emissions of wealthy households.

The distribution of emissions also varies significantly across many socio-demographic factors: home-owners (with mortgages) emit two to three times more from private road transport and aviation than those renting; households with a household reference person (HRP – the head of household, defined as the individual with the highest income or the older of two occupants with the same income levels) in full-time employment emit two-three times more from those sources than unemployed households. There is much less of a difference in public transport emissions between different socio-demographic factors .

In general, apart from the strong relationship with disposable income, total CO_2 emissions are higher for those with larger households (both in terms of physical size and number of occupants, particularly adults), those with more cars, the middle-age bands (35–60), those that are economically active and of a higher occupational and socio-economic class and those in more rural locations. (For total emissions, 95 per cent confidence intervals of the mean for each group are shown, to establish whether the differences in emissions can be said to statistically significant between the groups).

An analysis of variance (ANOVA) of mean total household CO_2 emissions shows the effect size and statistical significance of different predictor variables (socio-demographic variables) on each source of household level CO_2 emissions. The results of this fit well with the earlier exploratory analysis and suggest that the most important factors that show a significant difference in CO_2 emissions for all of the sources are number of cars and income, followed by the household type (composition) and size, and then other socio-demographic and economic factors.

Conclusion

There are significant differences in mean total household emissions by: income; car ownership; number of workers in the household; size of household (number of bedrooms and number of occupants); age of HRP; tenure; employment status of HRP; the main heating fuel.

These patterns support the observation that, in general, lower income, more vulnerable households tend to have lower than average CO_2 emissions. Although domestic fuel (energy consumed in the home) accounts for 60 per cent of total emissions from all sources included in this study, the majority of variation between households is in their transport-related emissions (specifically aviation and private transport). Policies which increase the cost of domestic fuels are therefore likely to be more regressive, and those which place a cost on carbon itself or target private transport emissions could be more likely to be progressive. This reflects the fact that for transport emissions there is a larger difference between emissions when comparing poorer and wealthier households.

This paper does not analyse within-group variation, and this may omit the recognition of some more vulnerable households (e.g. those on low incomes with high emissions). Further analysis needs to be undertaken to ensure that policies do not penalise this group.

Introduction

While several studies examine the distributional impacts of carbon reduction policies at an international scale, far fewer have focused on the equity of distributional impacts within countries. Of these, most consider the impact of a carbon tax on fuels, rather than the more complex range of policies that already exist or have been proposed for the UK, and few have investigated the distributional effects of such policies between households.

In recent years analysts have begun to model the potential distributional implications for households of carbon taxes, whether direct (Speck, 1999; Tiezzi 2005) or indirect (Symons *et al*., 1994; Gough *et al*., 2011). Other researchers have developed this approach to examine the potential for redistribution in mitigating the regressivity of potential carbon reduction policies in China (Brenner *et al*., 2007) and the United States (DeCanio, 2007). Work by Callan *et al* (2008) in Ireland and Dresner and Ekins (2004) in the UK are especially relevant in examining the potential distributional impacts of carbon mitigation policies. However, Dresner and Ekins' (2004) analyses are not based on housing condition data and as a result focus on the potential for *aggregate* carbon savings. In that study opportunities for modelling the distributional impacts for individual households were restricted to carbon emissions from household fuel consumption.

Druckman and Jackson (2007, 2008) use expenditure and 2001 UK census data to estimate spatially disaggregated models of carbon emissions. The synthetic estimation approach taken by Druckman and Jackson provides very useful small-area estimates of carbon emissions, although improvements in the reliability of small-area models are possible as a result of further model validation and data harmonisation. Nevertheless, few existing studies have focused specifically on mitigation opportunities at a household level in examining distributional impacts of climate change policies, nor has existing work sought to encompass the range of sources necessary to analyse a household's carbon footprint.

Gough *et al*'s (2011) innovative work is therefore especially significant in this respect. The authors use data from the Resources and Energy Analysis Programme (REAP) input-output model on the total emissions of British households, which takes a weighted average of UK emissions in different sectors, and map this to expenditure data in the UK Expenditure and Food Survey (EFS) to analyse the distribution. The analysis identifies equivalised household income as the main driver of total household emissions along with household composition and employment status. Analysis of emissions relative to income shows that lower income households and those not working have a higher ratio of emissions to income compared with higher-income, working households. This implies that any increase in the price of carbon will bear most heavily on low-income households and, within this group, on workless households.

This project seeks to build upon this earlier research by filling some key research gaps in our understanding of the way that CO_2 emissions are distributed across households in Great Britain. Unlike the study by Gough *et al*, this project applies a 'bottom-up' approach, using only household-level survey data to estimate household emissions from energy use in the home and travel by private vehicles, public transport and aviation. This paper presents some analysis of the dataset of household emissions from all these sources created as part of the project. Further modelling and analysis of the data to explore the likely social distributional consequences of UK energy and climate policiesis presented in the full project report, available as a separate document (Preston *et al*., 2013).

Data and methods

A detailed report on the methodology applied in developing the dataset used in this study is provided as a separate document (Patsios *et al., 2013*). An overview of the methods is provided here.

Creating the dataset

Deriving emissions estimates from survey data

To understand the distribution of household carbon emissions including personal travel, a dataset is needed to represent CO_2 emissions from the consumption of energy in the home, private road transport, public transport (buses, coaches, surface rail, light rail, underground, taxis and ferries), and aviation at the household level.

The information exists within, or is derivable from, a number of different survey datasets, representative of either the UK or British households (Table 1). Using data contained within each of the surveys, methods were developed to derive carbon emissions estimates. Different methods were needed for each survey, as described below.

Table 1: Summary of surveys used to derive emissions estimates

Survey	Input (raw survey data)	Output
Expenditure and Food Survey (EFS)	Expenditure on all household fuels	Annual consumption of all household fuels (kWh) and associated CO_2 emissions ($kgCO_2$) for GB households.
National Travel Survey (NTS)	Private vehicle mileage Distance travelled – public transport Distance travelled – domestic flights	Annual CO_2 emissions from all personal (non-business) travel by private vehicle, public transport and domestic aviation for GB households.
CAA Air Passenger Survey (APS)	Start airport, destination airport (international only) and flight class for all GB leisure passengers	Distance travelled and associated CO_2 emissions from (non-business) international aviation for GB households.

Expenditure and Food Survey (EFS)

The Expenditure and Food Survey (EFS)[1] uses interview and diary-based methods to collect information on a range of personal and household expenditure, including household fuels (electricity, gas and non-metered fuels). The survey also provides household-level information on method of payment (for electricity and mains gas), region, month and year of survey. A series of look-up tables (Table 2) were therefore created, containing time- and location-specific fuel price data, using DECC's energy price statistics[2] (for mains gas and electricity) and Sutherlands tables for non-metered fuels. Using these look-up tables, survey data on expenditure on each fuel was converted to consumption (kWh) and then to carbon dioxide using Defra/DECC CO_2 emissions factors[3] (Table 3).

The above process results in estimates of household emissions from energy use in the home for every case (household) in the dataset. However, due to the nature of the EFS, the distribution of expenditure – and therefore the derived energy consumption and emissions values – cannot be considered accurate. Values at the individual case (household) level in the dataset cannot be used, but mean estimates derived from sufficiently large samples of cases in the dataset can be. The Centre for Sustainable Energy (CSE) therefore devised a method using CHAID[4] – 'Chi squared automatic interaction detector' – to derive modelled values of emissions for heat and power use in the home for every case in the dataset. This modelling results in a compressed distribution, but gives a reliable estimate of baseline emissions for every household in the dataset, while maintaining the original mean value for the dataset as a whole.

Table 2: Section of look-up table for converting survey expenditure data to consumption (for mains gas by direct debit)

Gorx	Government Office Region	EFS Year	Actual Year	Year code	EFS month	Date	Fuel	Fuel	MOPn	MOP	p/kWh
1	North East	2004/05	2004	2004	4	Apr 04	2	Gas	Direct Debit	1	0.0172
3	Yorkshire & Humberside	2004/05	2004	2004	4	Apr 04	2	Gas	Direct Debit	1	0.0171
2	North West	2004/05	2004	2004	4	Apr 04	2	Gas	Direct Debit	1	0.0171

Table 3: Carbon emissions factors applied for household fuels in the EFS

EFS fuel	kg CO_2 per kWh
Electricity	0.541600
Gas (mains)	0.205150
Bottled gas	0.223570
LPG	0.229990
Coal	0.311390
Oil (for CH)	0.258570
Paraffin	0.259000
Wood	0.024563

National Travel Survey

The National Travel Survey (NTS) collects individual, household and vehicle level data, to describe travel patterns (e.g. distance travelled by mode and purpose), representative of households in Great Britain. For the purpose of this study, three different NTS datasets were used:

(1) vehicle-level data on vehicle type (including engine capacity and fuel type) and annual mileage by purpose was used to derive carbon emissions estimates for all travel by private vehicle for leisure and commuting purposes (i.e. not including business travel);

(2) journey-level data on distance travelled by mode of public transport and purpose was used to derive carbon emissions estimates for all personal (again leisure and commute) travel by public transport;
(3) the long-distance journey dataset was used to derive estimates of emissions from domestic flights.

Emissions estimates were derived in each of these surveys and then ‘aggregated’ to household level. The latest Defra/DECC CO_2 emissions factors available at the time of the study[5] were used in all the conversion calculations described above.

Civil Aviation Authority Air Passenger Survey

The Civil Aviation Authority Air Passenger Survey (CAA APS) is an annual survey (with data collected on a monthly basis) of departing passengers, covering a wide range of UK airports. The survey collects data on passenger travel (e.g. flight origin and destination) and socio-demographics. For the purpose of modelling carbon emissions from international air travel for this project, a subset of the data was purchased from CAA to include only UK passengers travelling outside of the UK for leisure purposes. Data was purchased for all airports surveyed from 1999 – 2008, for a two month randomly-selected sample.

A method was developed to calculate distance travelled (allowing for circumference of the globe and landing and take-off) from start/destination airport for each survey record (using a database of airports[6]). Distance was then converted to carbon emissions using the relevant factors (by cabin class).

Combining the surveys into one dataset

Having derived emissions estimates in each individual survey, these estimates then need to be combined into a single ‘synthetic’ dataset for analysis. While each of the surveys listed above is undertaken independently and therefore exists as a distinct dataset, they are all designed to be representative of the area they cover (in this case the UK or Great Britain) through sampling and weighting design. They also each contain some of the same socio-demographic information (for example household income, dwelling type, tenure). Using socio-demographic variables common to two or more datasets, it is possible to develop imputation models to extract (or ‘impute’) data from one survey into another. For the purpose of this study, the EFS forms the ‘base’ dataset, to which data is imputed from the NTS and CAA APS.

There are several key stages in the imputation approach:

1. Survey harmonisation: Before the imputation can be undertaken the surveys need to be ‘harmonised’. This essentially means ensuring that key concepts used in each of the surveys are defined and measured in the same way. (For example, income can be defined in a number of ways such as disposable or gross; for income to be used to impute data from one survey dataset to another, it must be defined in the same way). The full technical report on survey harmonisation process, including a list of which variables were harmonised, is available as a separate document (see Patsios *et al*., 2013).

2. The next stage in developing the dataset for analysing the distribution of emissions across households in Great Britain is to use multiple imputation techniques to impute the derived carbon emissions data from one survey to another. For each case (household), the resultant dataset comprises the original source data and a series of estimates based upon multiple imputation. Multiple

imputation is a technique for replacing missing data values with m>1 simulated versions using the Markov chain Monte Carlo method in order to derive estimates and confidence intervals which incorporate missing-data uncertainty (see Rubin, 1988; Schafer, 1999; Little & Rubin, 2002). This process involves developing predictive models where the ‘predictor’ variables include the harmonised socio-demographic variables. Each imputed variable requires its own imputation model (see Table 4). In most cases the relative efficiency of imputed estimates does not increase substantially beyond five imputations (Rubin, 1988). A pooled result (effectively the mean of the five imputations) can be derived from the five imputed values. The results presented in this paper use these pooled estimates derived by multiple imputation.

3. Finally, having imputed data to the EFS and derived pooled estimates, the results are ‘sense-checked’ and adjusted where necessary so that the imputed values correspond to the original survey sum totals (‘re-grossing’). While this issue is immaterial in terms of the distribution of emissions, it is of fundamental importance for the modelling of policy impacts.

Table 4: Variables imputed to the EFS dataset

Variables imputed from the NTS:
- CO_2 public transport – commute
- CO_2 public transport – leisure
- CO_2 private vehicle – commute
- CO_2 private vehicle – leisure
- CO_2 domestic aviation

Variables imputed from the APS:
- CO_2 international aviation (non-business)
- A variable to flag non-flying households
- Number of short haul flights to Europe in past year
- Number of long haul flights further than Europe in past year

Resulting dataset:

⇨ GB dataset of emissions from all personal travel plus the consumption of energy in the home

The ‘final’ dataset

The methodology developed and applied in this study, as outlined above, was designed with the specific aim of creating a dataset representative of household carbon emissions in Great Britain. Some key statistics describing the final dataset used in the analysis in this paper are shown below.

Table 5 shows the number of households represented in the final dataset (the ‘weighted count’); sum total of emissions across all households in the dataset (i.e. representing the population of Great Britain); and average (per household) estimates of carbon emissions.

It should be noted that no attempt has been made to reconcile the emissions estimates derived from survey data with national figures. The two differ significantly in methodological approach (‘bottom-up’ versus ‘top-down’); design purpose and population they represent.

Table 6 shows the average and range of incomes in each disposable and equivalised disposable income decile for the dataset (under-reporting of incomes is a key issue in both the EFS and EHCS survey data, as indicated by the maximum values shown). These are shown for reference, as all sections of this paper present results by different income groups.

Table 5: Household emissions estimates in imputed GB EFS dataset (2004– 07)

	Sum ($MtCO_2$)	Mean ($kgCO_2$)
Household fuels total	137	5,675
Private car total	64	2,644
Public transport total	7.3	302
Domestic aviation	0.8	33
International aviation	29	1,182
Total emissions	238	9,836
Weighted count of households ('000s)[a]	24,207	

[a] Annual survey weight adjusted to allow for multiple years in the dataset.

Table 6: Income deciles in the imputed EFS GB dataset

Income decile	Count of households (‘000s)	N %	Disposable annual income		Equivalised disposable annual income	
			Mean	Range	Mean	Range
1	2,421	10%	£5,070	£0 – £7,179	£4,241	£0 – £5,911
2	2,420	10%	£8,895	£7,180 – £10,533	£6,886	£5,912 – £7,906
3	2,421	10%	£12,158	£10,534 – £13,894	£8,892	£7,907 – £9,876
4	2,421	10%	£15,726	£13,895 – £17,685	£10,800	£9,877 – £11,752
5	2,421	10%	£19,731	£17,686 – £21,817	£12,728	£11,753 – £13,758
6	2,420	10%	£24,052	£21,818 – £26,394	£14,874	£13,759 – £16,049
7	2,421	10%	£28,926	£26,395 – £31,681	£17,371	£16,050 – £18,779
8	2,420	10%	£35,023	£31,682 – £38,841	£20,508	£18,780 – £22,498
9	2,421	10%	£44,019	£38,842 – £50,846	£25,431	£22,499 -– £29,273
10	2,420	10%	£74,060	£50,847 – £1,885,978	£43,531	£29,274 – £1,257,319
Total	*24,207*	*100%*	*£26,765*		*£16,525*	

The composition of household emissions

This section of the paper explores the distribution, across different socio-economic factors, of average household emissions by source. This includes emissions from the consumption of energy in the home (heat and power) and all non-business travel including leisure and commuting to work (but not travel while at work) by private vehicle, public transport and domestic and international aviation. The analysis shows emissions by source for different sample groups in order to address the research question '*who emits most?'*

Error bar plots are presented to show sample means along with confidence intervals to assess the extent to which differences in mean total emissions of different socio-economic groups reflect underlying differences in the wider GB population. These show the total estimated mean household emissions from all sources with an associated 95 per cent confidence interval of the population mean (see Box 1).

Box 1: Confidence intervals

Confidence intervals are derived from the standard error of the sample, defined as:

$\frac{standard\ deviation}{\sqrt{n}}$ where n = count/number of samples

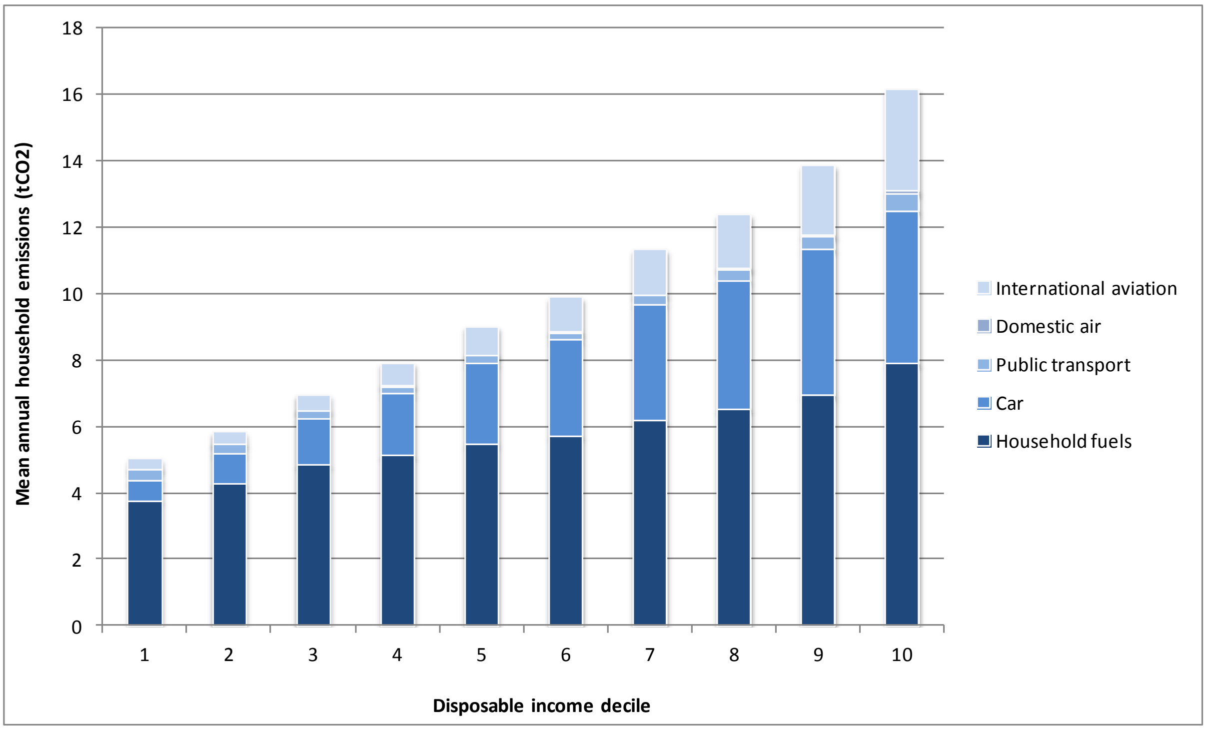
The standard error is multiplied by the *t* value, a standard number dependent on the sample size and selected confidence interval. The 95 per cent confidence interval is used here, meaning that there is a 2.5 per cent confidence margin either side of the sample mean, and the population mean can be said to be within this range with a 95 per cent confidence. In this case the population mean is that of all British households. As the sample sizes used in this analysis are very large the confidence intervals are generally very small. Where the confidence intervals for two groups do not overlap we can therefore be at least 95 per cent confident that a real difference in means also exists in the wider population.

Results

Income

Figure 2 shows the distribution of mean household CO_2 emissions from all sources, in metric tons, by net disposable household income decile. There is a clear upward trend in emissions across the income deciles from all sources, with the exception of public transport. Households within the highest disposable income decile have mean total CO_2 emissions more than three times that of households within the lowest income decile (Figure 5). Emissions from private road travel and international aviation account for a high proportion of this differential: international aviation emissions of the highest income decile are more than ten times that of the lowest income decile, while emissions from private vehicle travel are around 7–8 times as high.

Figure 2: Mean annual CO_2 emissions from all sources by household disposable income decile



Net disposable household income can, however, be considered an imprecise measure of a household's command over resources. It does not account for the size and composition of the household, yet these two factors have important implications for household emissions. There are economies of scale in multi-person households in terms of energy consumed in the home, but a higher number of adults may mean higher transport emissions (e.g. if each adult owns a car). It is therefore useful to explore the distribution of emissions by equivalised (adjusted) household income. Equivalisation adjusts income to take into account differences in household size and composition to provide a more precise estimate of a household's command over resources.

Figure 3 shows the distribution of mean household CO_2 emissions from all sources by equivalised net disposable household income decile (income has been equivalised using the OECD equivalisation scale.). This shows a slightly flatter distribution than that shown in Figure 2: average emissions of the highest income decile appear lower, and average emissions for the lowest income decile higher, for equivalised income deciles compared to the non-equivalised data. This reflects the movement of households across deciles as a result of equivalisation: larger households – who often have higher emissions – will move down the income scale as a result of equivalising incomes, while a higher proportion of single-person households will move up the income scale (see Figure 4). As with disposable income analysis, much of the variation between deciles is in relation to emissions from cars and international aviation, household fuel emissions are 1.7 times higher in decile 10 than decile 1, whereas car emissions are 4.2 times higher and international aviation emissions are 7.2 times higher (Figure 5). Public transport emissions are again the only emission source that does not increase consistently over all income deciles, but fluctuates.

Figure 3: Mean annual CO_2 emissions from all sources by equivalised household disposable income decile

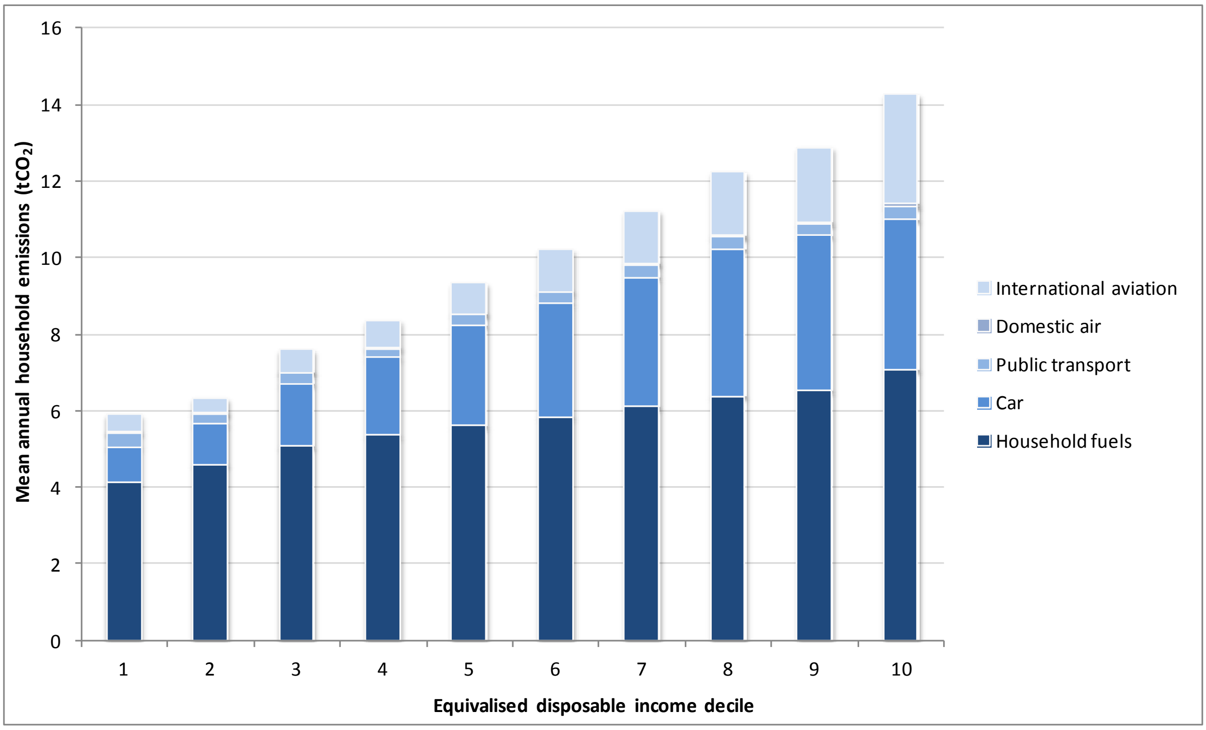


Figure 4: Proportion of single person households in each disposable and equivalised income decile

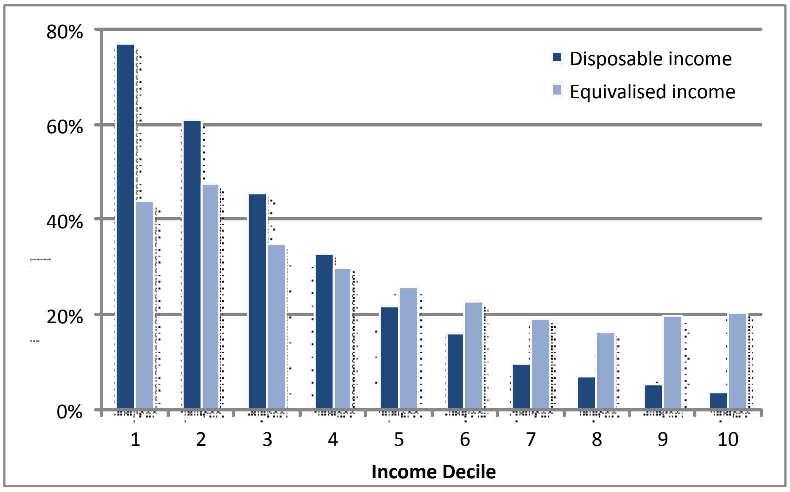


Figure 5: Proportional contribution of each income decile (disposable and disposable equivalised) to total emissions by source

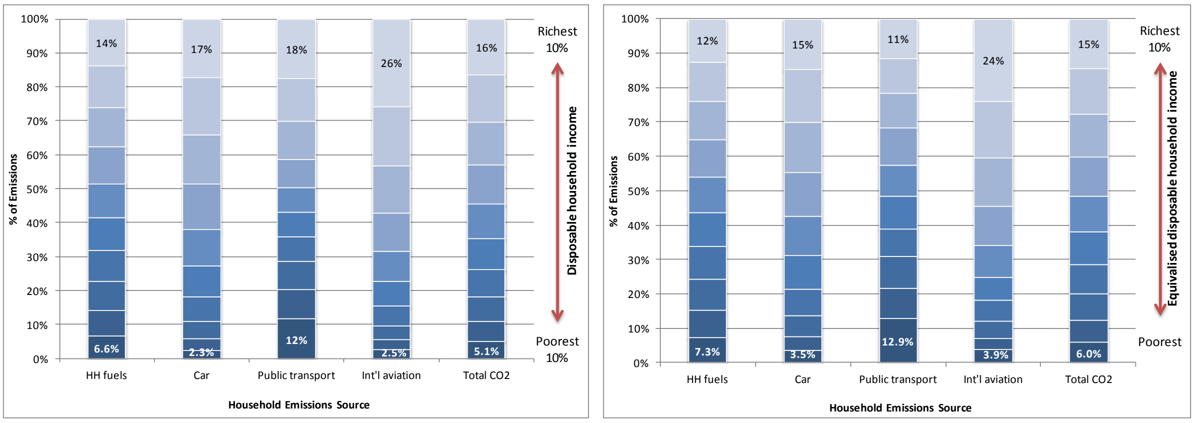


Figure 6 shows the estimated mean of total household CO_2 emissions (all sources) by equivalised income decile, in metric tons, with error bars to show the 95 per cent confidence intervals and a linear trend line. The 95 per cent confidence intervals are small and provide further evidence that social differences in mean total CO_2 emissions from all sources by equivalised income exist not only for the sample under consideration but also for the wider population of interest. The trend line allows us to observe a broadly linear relationship between household emissions and equivalised income, as found in work by Gough *et al*. (2011).

Figure 6: Mean annual total CO_2 emissions from all sources by equivalised household disposable income decile with 95% confidence intervals

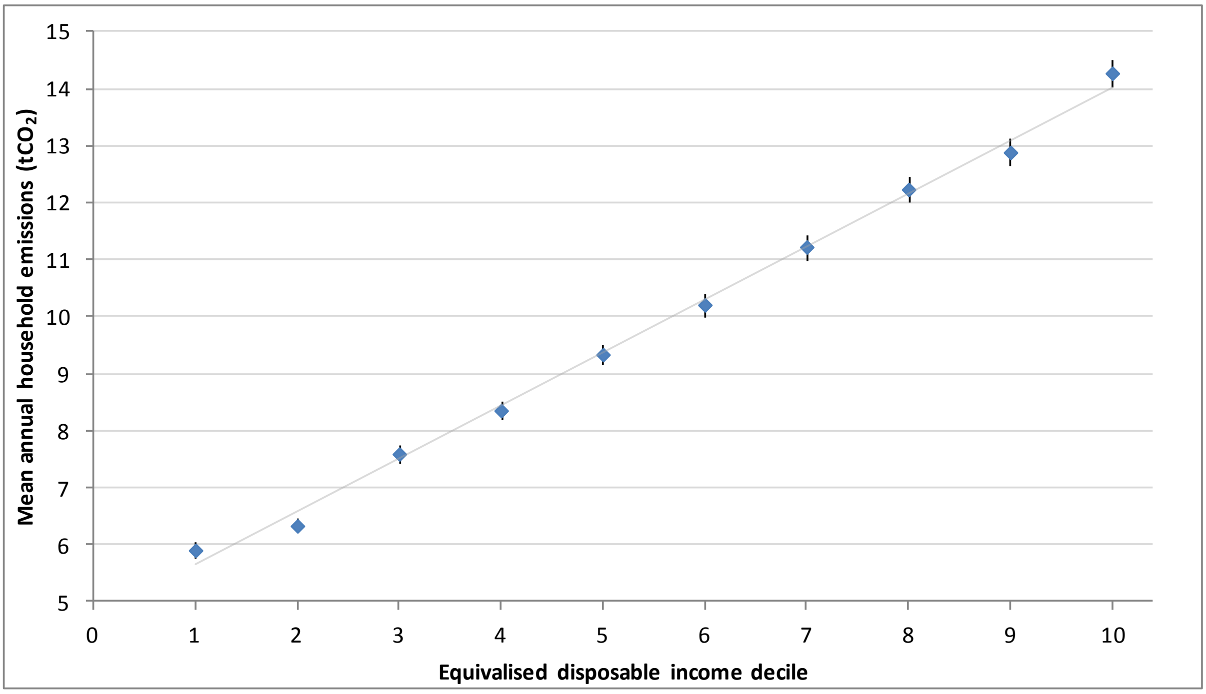
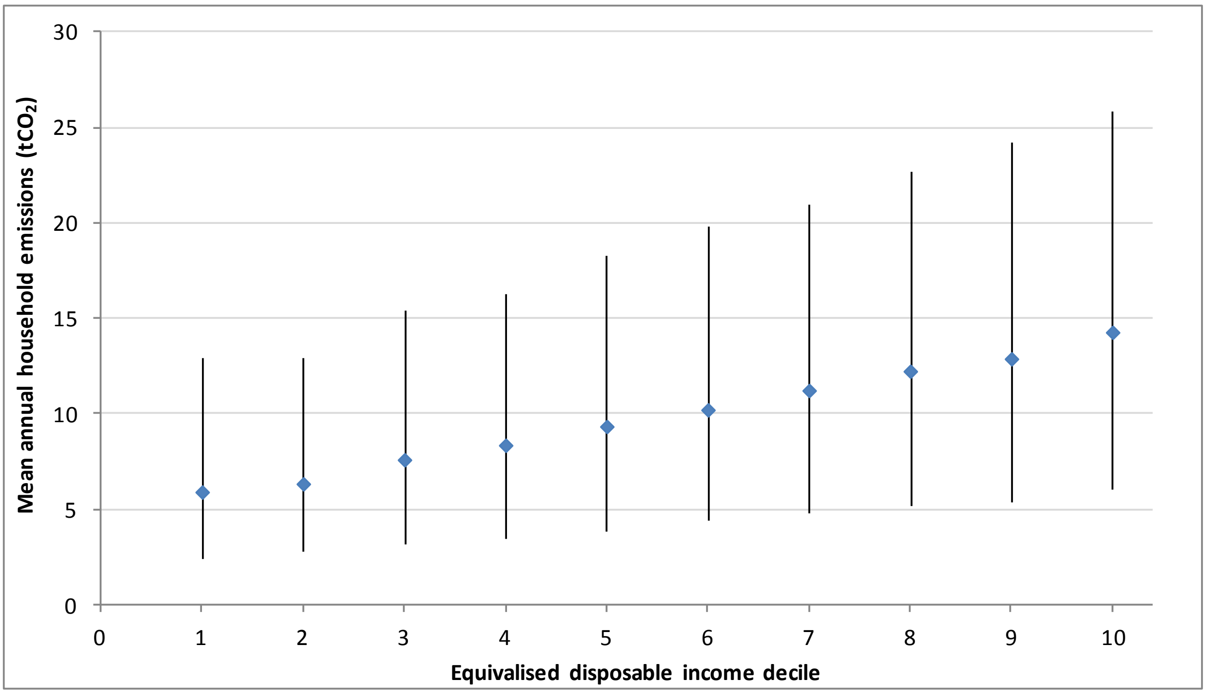


Figure 7 helps to illustrate the purpose of the confidence intervals. It again shows the mean total household CO_2 emissions by equivalised income decile, but this time the bars represent the range within which 95 per cent of the sample of households in each decile sits. The chart clearly shows that there is significant within-decile variation of emissions across the income profile. Furthermore, while we can be confident that the population means for each decile do not overlap, there will be instances of overlap of individual values within each category; or rather, the social distribution of emission at a household level is diverse. Even omitting the most extreme 5 per cent of cases from each decile (as Figure 7 does) there are still some high emitting households within decile 1 (the top end of the bar) and some low emitting households within decile 10 (the lower end of the bar). This finding is consistent with previous analysis of household energy consumption and emissions, which has shown a clear group of low-income high-consuming households (see for example White, V., Roberts, S. and Preston, I. (2010)).

Figure 7: Mean annual total CO_2 emissions from all sources by equivalised household disposable income decile with 95% range of sample



Household type

Figure 8 shows the distribution of CO_2 emissions by emissions source and household type (or composition). Single pensioner households emit the least CO_2 on average, while households with three or more adults emit the most. Between the lowest (single pensioners) and highest (three or more adults) emitters of $CO_{2,}$ the largest variation is again in emissions from cars (5.5 times higher) and international aviation (5.8 times higher), with household fuel emissions only being 1.6 times higher. The latter reflects the 'economies of scale' that apply to the consumption of energy in the home. As the bars show, emissions from household fuels do not change substantially between couple households, couples with children and multi-person (three or more adult) households (Gough *et al*., 2011).

Figure 8: Mean annual CO_2 emissions by source and household type

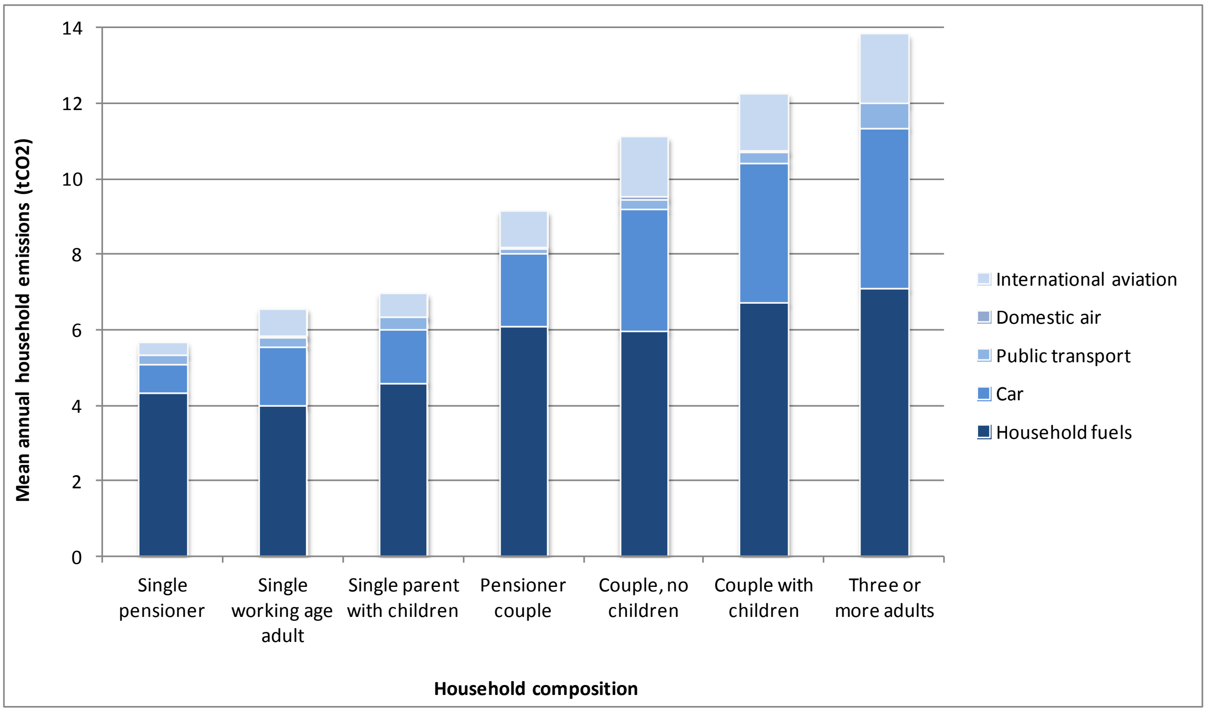
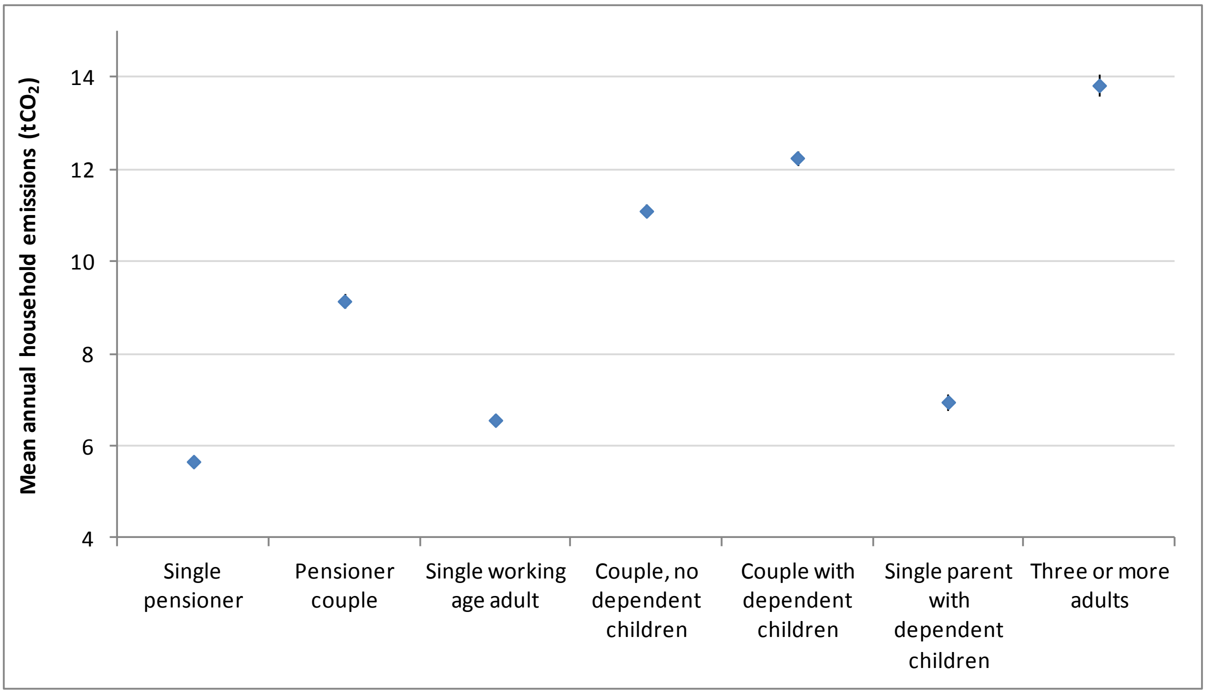


Figure 9 shows estimated marginal means and 95 per cent confidence intervals for total emissions from all sources by household type as error bars on each data point. This analysis confirms that social differences in mean total CO_2 emissions from all sources by household type exist not only for the sample under consideration but also for the wider population of interest. Variations in emissions by household type are likely to reflect variations in the size and age profile of households and associated differences in levels and patterns of consumption. However, since household type is also known to vary consistently with income and standard of living, it may also be that these differences reflect underlying differences in a household's command over resources – as we saw earlier, with the strong association between equivalised income and emissions.

Figure 9: Mean annual total CO_2 emissions from all sources by household type with 95% confidence intervals



Housing tenure

Figure10 shows the distribution of CO_2 emissions by each source, by housing tenure. This shows that householders who own their property with a mortgage have the highest total emissions, and those that rent have the lowest. Again the largest difference between these two groups is in car emissions and international aviation emissions (both 2.6 times higher in those with a mortgage than renters). This may be related to the associated incomes of these groups and, in terms of emissions from fuel consumed in the home, may be some reflection of the relative energy efficiency of property types across the tenures. For example, social housing typically has higher average energy efficiency levels than privately rented housing due to policy requirements such as the Decent Homes Programme. The combined grouping of private and socially rented properties may be masking some of these effects.

Figure 10: Mean annual CO_2 emissions from all sources by housing tenure

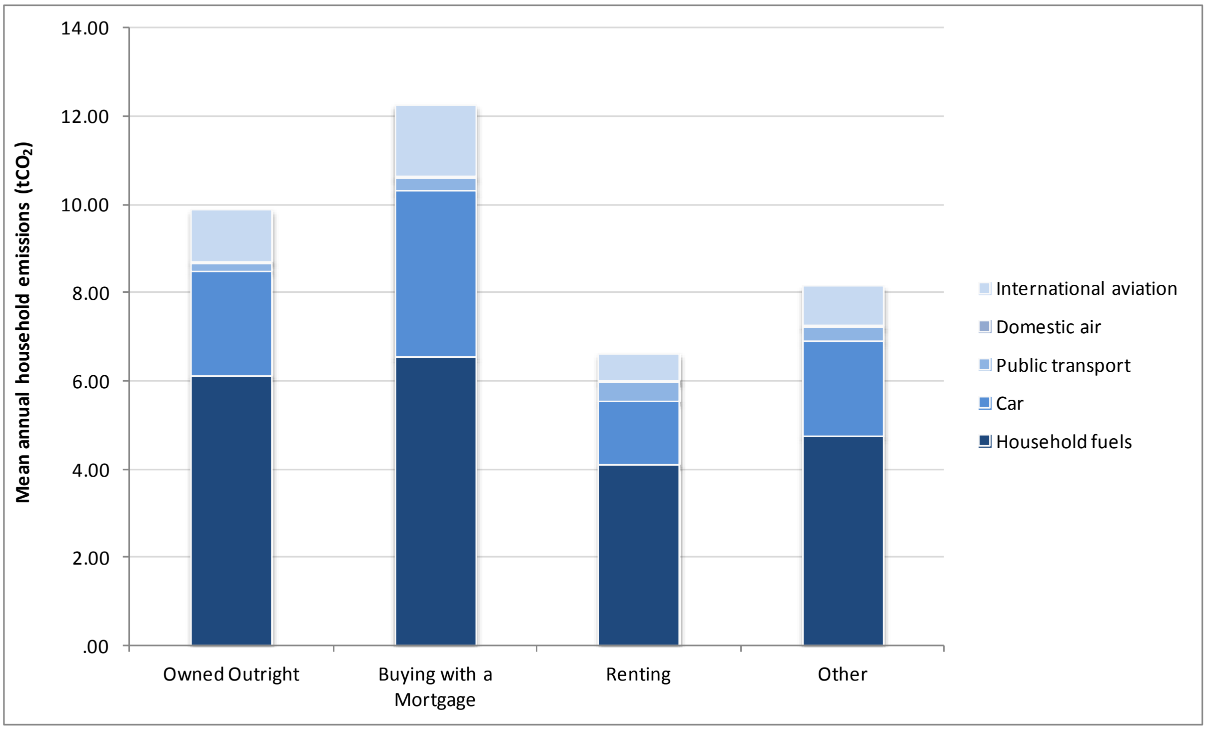
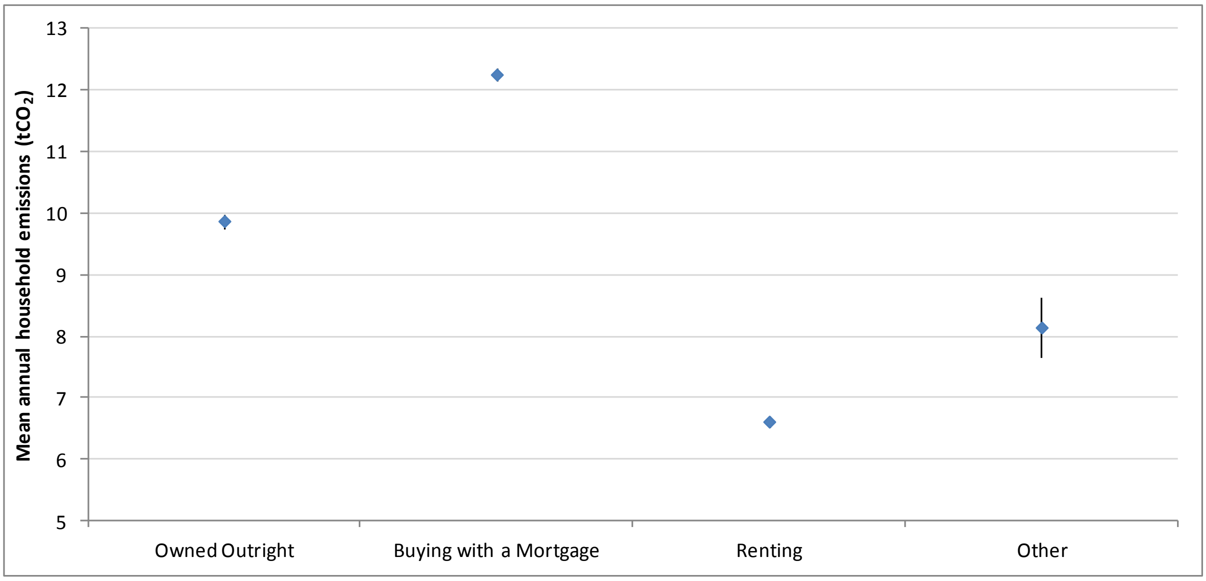


Figure 11 shows the estimated mean of total CO_2 emissions (all sources) by household tenure with the 95 per cent confidence intervals for the population means as error bars on each data point. These confirm that social differences in mean total CO_2 emissions from all sources by housing tenure exist not only for the sample under consideration but also in most cases for the wider population of interest. The 95 per cent confidence interval for 'other' tenure types is wider than for other groups due to the uncertain and varied nature of households within this group, but this group still represents a significant different total mean annual CO_2 emission from other housing tenure groups. As noted above, it is likely that such effects reflect both underlying socio-economic differences between households in their command over resources, as well as (associated) differences in the size, location and built structure of dwellings occupied on a rental basis in comparison with the owner-occupier sector. At the same time it should also be acknowledged that the private rental sector is itself highly heterogeneous in its social composition and further disaggregation would be desirable in this respect.

Figure 11: Mean annual total CO_2 emissions from all sources by household tenure with 95% confidence intervals



Number of workers in household

Number of workers is defined in the EFS (the dataset upon which this analysis is based) as anyone who is: an employee; self-employed or an employer; out of employment, seeking work within the last four weeks and available to start a job; or out of employment, waiting to start a job already obtained.

There appears a strong, positive and consistent relationship between mean total CO_2 emissions from all sources and the number of workers in the household. In comparison with households where no one is in paid work, nor actively seeking work at the time of the survey, mean total CO_2 emissions from all sources for households comprising four or more workers are approximately two-and-a-half times higher. Again, differences in mean total emissions from all sources are largely attributable to social variations in emissions from aviation and private vehicles. Compared with workless households, mean total emissions from aviation are *nearly four times* higher, and mean total emissions from private vehicles are *nearly six times* higher for households comprising four or more workers. Emissions from fuel use in the home on the other hand increases little from two workers to four or more workers in the household, again supporting the economies of scale argument of household energy consumption.

Figure 12 shows the distribution of the sample mean CO_2 emissions from all sources by the number of workers in the household. Number of workers is defined in the EFS (the dataset upon which this analysis is based) as anyone who is: an employee; self-employed or an employer; out of employment, seeking work within the last four weeks and available to start a job; or out of employment, waiting to start a job already obtained.

There appears a strong, positive and consistent relationship between mean total CO_2 emissions from all sources and the number of workers in the household. In comparison with households where no one is in paid work, or actively seeking work at the time of the survey (this encompasses households where occupants are: sick or injured; retired including those on Job Release Scheme; and those unoccupied), mean total CO_2 emissions from all sources for households comprising four or more workers are approximately two-and-a-half times higher. Again, differences in mean total emissions from all sources are largely attributable to social variations in emissions from aviation and private vehicles. Compared with workless households, mean total emissions from aviation are *nearly four times* higher, and mean total emissions from private vehicles are *nearly six times* higher for households comprising four or more workers. Emissions from fuel use in the home on the other hand increases little from two workers to four or more workers in the household, again supporting the economies of scale argument of household energy consumption.

Figure 12: Mean annual CO_2 emissions from all sources by number of workers in household

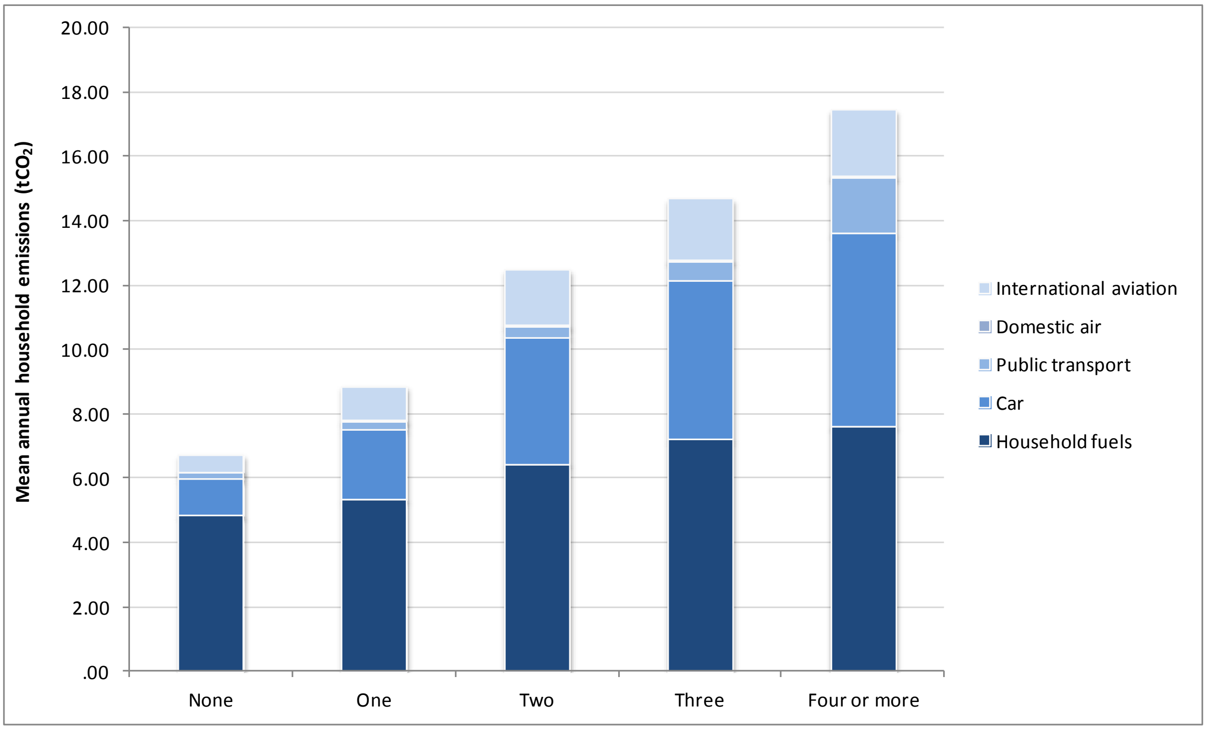
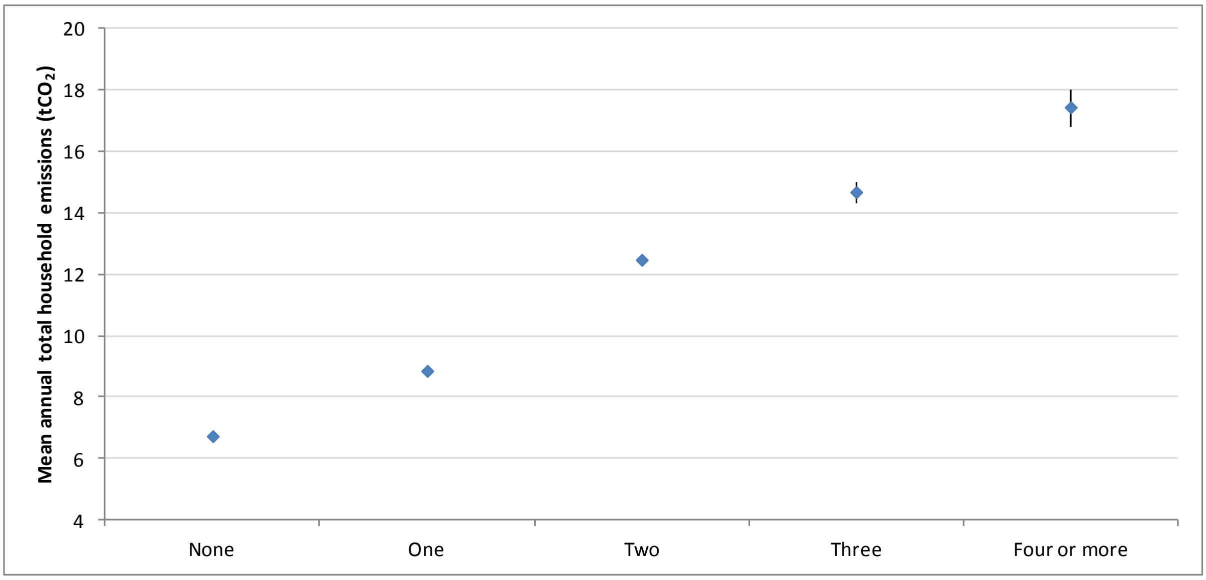


Figure 13 shows the estimated mean and 95 per cent confidence intervals for total CO_2 emissions (from all sources) by the number of workers in the household. The confidence interval is wider for the category 'four or more' due to the range of households encapsulated within this group: households from the sample within this category have between four and nine workers, resulting in a wider range of total emissions. However there were not enough occurrences within the sample to be able to further break down this group and allow for significant analysis, leading to this aggregation and increased uncertainty. Such variation is likely to be partly accounted for indirectly by differences in total household income arising from different levels of participation in paid work and associated differences in consumption patterns including, but by no means limited to, the emissions directly associated with labour market participation, for example, as a result of commuting to work.

Figure 13: Mean annual total CO_2 emissions from all sources by number of workers in the household with 95% confidence intervals



Employment status of the HRP

Figure 14 shows the mean contribution of emissions from all sources to total household emissions, broken down by the employment status of the Household Reference Person (HRP).[7] Overall those that are employed to some degree have higher emissions than those who are unemployed, retired or economically inactive (such as students, included in the 'other economically inactive category').

The group which emits the most carbon emissions are households in which the HRP is a full-time employee, while households where the HRP is unemployed (defined by the International Labour Organisation(ILO) as 'those who are currently not working but are willing and able to work for pay, currently available to work, and have actively searched for work') emit the least. Again the largest variation is in emissions due to transport: full-time employed households emit 2.8 times more CO_2 from private vehicle travel than unemployed households, and 2.4 times more from international aviation. Households where the HRP is unemployed, however, emit 2.2 times more CO_2 from public transport than the full-time employed. This may seem slightly contradictory to Figure 12, which shows that the more workers in the household the more CO_2 is emitted due to public transport. However, this is due to the way 'workers' and 'unemployed' are defined in the survey: the HRP being unemployed does not equate to there being no workers in the household, as 'workers' includes those actively seeking employment (Table 7).

Figure 14: Mean annual CO_2 emissions from all sources by employment status of the HRP

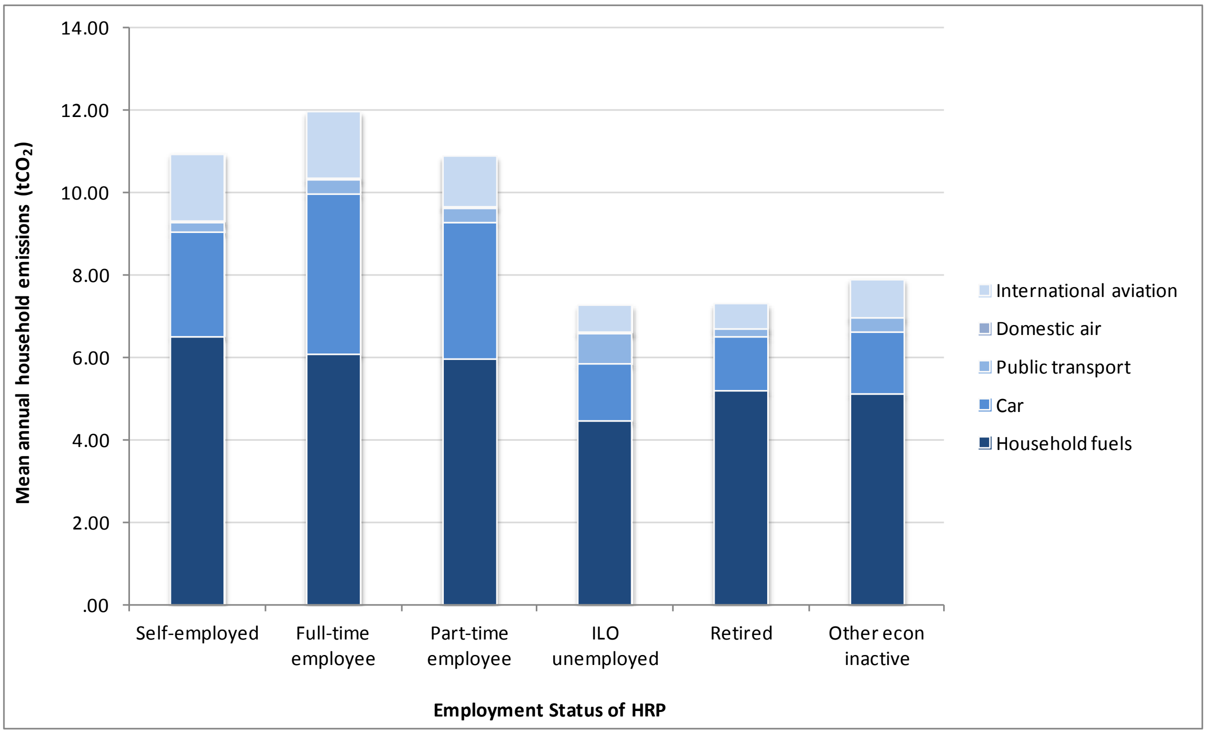
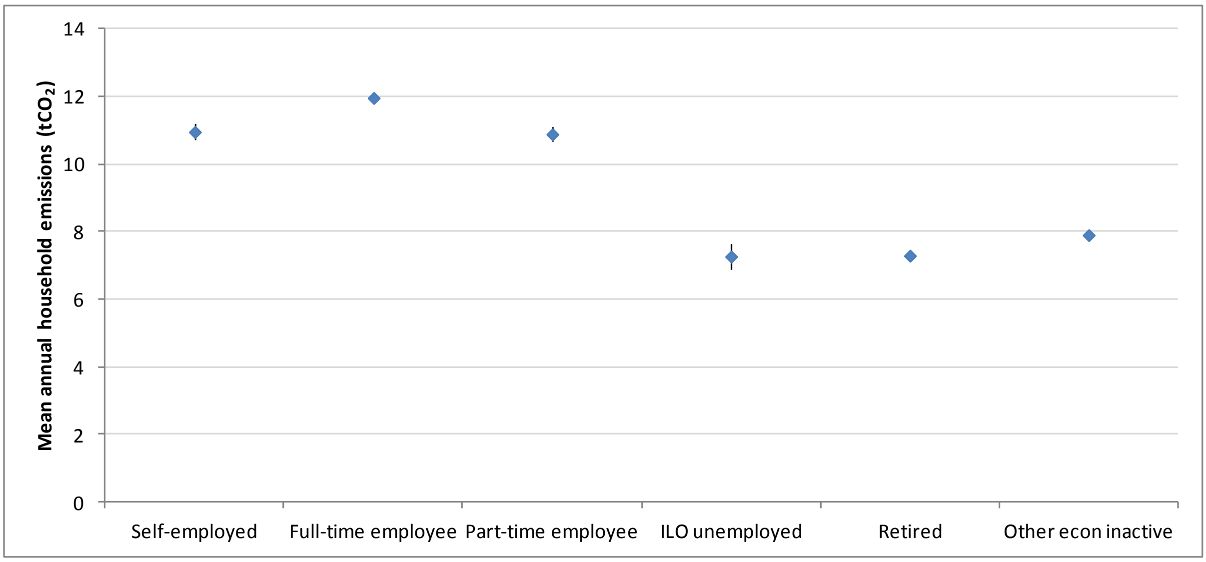


Table 7: Survey categorisation of 'workers' and employment status

	Employment status of HRP						
Number of workers	Self-employed	Full-time employee	Part-time employee	ILO unemployed	Retired	Student	Other non-working
None	0	0	0	0	5,686	145	2,053
One	675	3,146	976	332	586	64	995
Two	897	4,899	1,258	193	96	9	191
Three	213	890	256	37	10	6	57
Four or more	52	361	87	11	2	0	20

Figure 15 shows estimated means and 95 per cent confidence intervals for total emissions from all sources by the employment status of the HRP. Where the bars overlap, as they do for the self-employed and part-time employed, and for the ILO unemployed and retired, the mean estimates of household emissions for these groups cannot be confidently said to be different from the mean values for total CO_2 emissions in the whole population. Differences between the population mean emissions estimates for households where the HRP is economically active (employed) and those who are not appear significant. Part of this difference may be accounted for by the household size or income of typical households within these different groups.

Figure 15: Mean annual total CO_2 emissions from all sources by employment status of the HRP with 95% confidence intervals



Age of the HRP

Figure 16 shows how mean household carbon emissions increase and then decrease over the age bands, with a peak in the middle years (HRP aged 35–60 years). This trend in emissions across life course is likely to reflect underlying differences in income and command over resources associated with age, as well as social differences in household size and composition. Most individual sources of emissions follow this pattern, with the exception of public transport emissions which is highest in the youngest age bracket. This may reflect income, life stage and accessibility to alternatives (e.g. being unable to drive or afford a car).

Figure 16: Mean annual CO_2 emissions from all sources by age band of the HRP

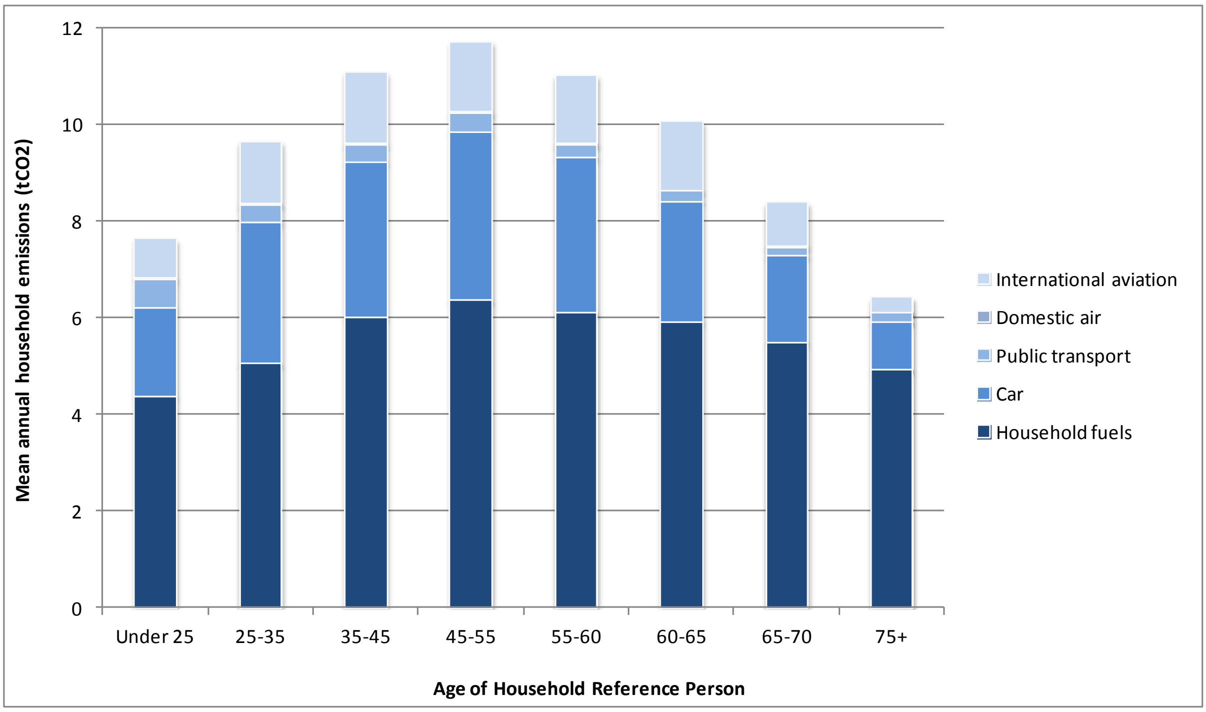
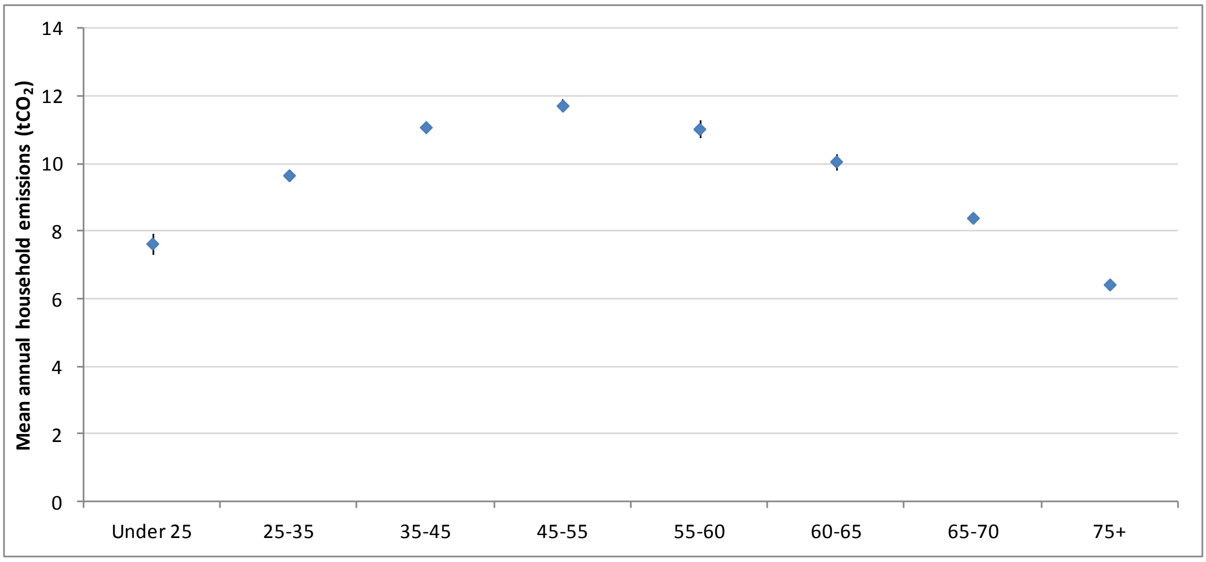


Figure 17 shows the estimated mean and 95 per cent confidence intervals of total CO_2 emissions by the banded age of the HRP. The confidence intervals overlap for households with an HRP aged 35–45 and 55–60, as do the 25–35 and 60–65 age groups, so we can be less confident that the mean emissions of these groups are statistically significantly different.

Figure 17: Mean annual total CO_2 emissions from all sources by banded age of the HRP with 95% confidence intervals



Socio-economic group of the HRP

Figure 18 shows the sample mean CO_2 emissions by all sources by socio-economic group [8] of the HRP. Total emissions (from all sources combined) are highest for those in socio-economic group A (higher managerial, administrative, professional) and lowest in group DE, which combines groups D (semi-skilled and unskilled manual workers) and E (casual labourers, pensioners, unemployed). Households of higher status groups (A and B) have higher total emissions and higher emissions from every source expect for public transport. The largest difference is in international aviation emissions, where those in group A emit 2.5 times more than those in group DE.

Figure 18: Mean annual CO_2 emissions from all sources by socio-economic group of the HRP

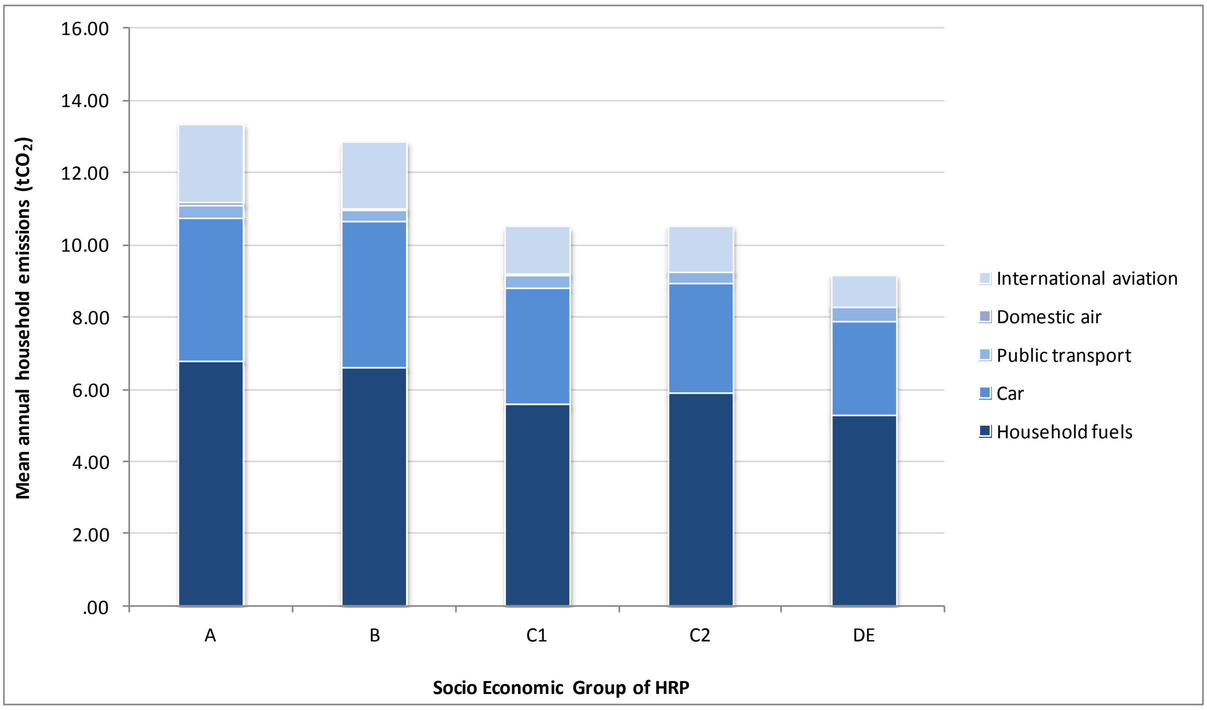
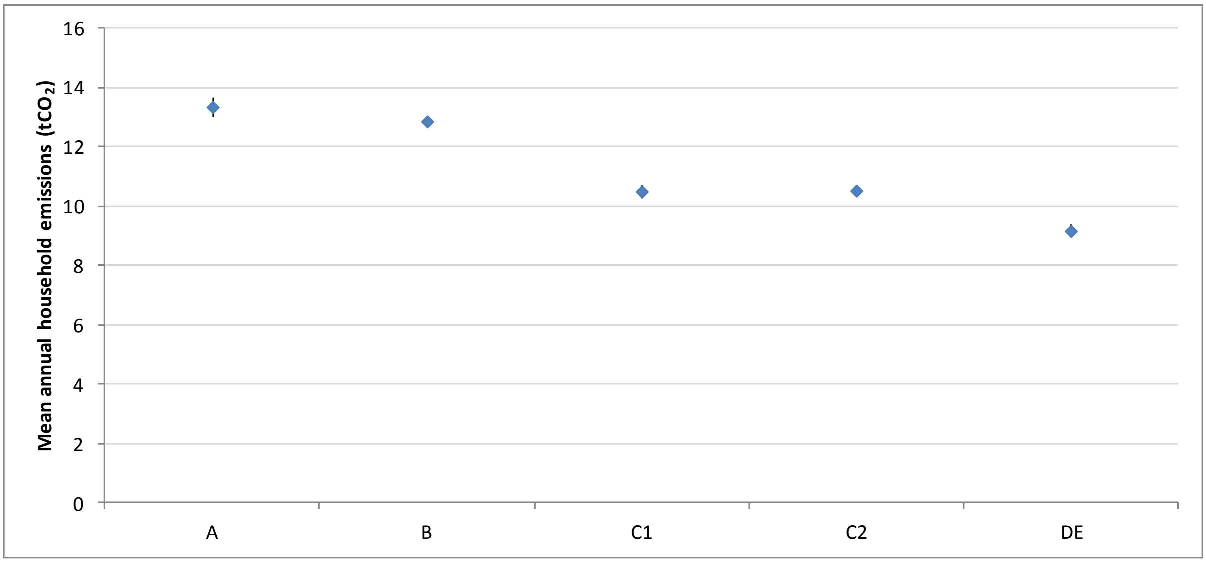


Figure 19 shows the estimated means and 95 per cent confidence intervals for total CO_2 emissions from all sources by the socio-economic group of the HRP. It shows the 95 per cent confidence intervals for the population means as error bars on each data point. The analysis confirms that social differences in mean total CO_2 emissions from all sources by socio-economic group of the HRP exist not only for the sample under consideration but also for the wider population of interest; we can be 95 per cent confident that groups A and B have higher mean total emissions than groups C1 and C2, who in turn have higher emissions than group DE. Occupational class differences in total household emissions from all sources are likely to reflect underlying inequalities in (equivalised) household incomes between occupational groups and related inequalities in command over resources and associated consumption levels.

Figure 19: Mean annual total CO_2 emissions from all sources by socio-economic group of the HRP with 95% confidence intervals



Settlement type

Figure 20 shows mean household CO_2 emissions by source and settlement types – or rather urban/rural classification. In comparison with other social variations in mean total emissions, variation by settlement type is comparatively modest. This in part reflects the fewer categories of settlement type, leading to larger sample sizes and therefore greater 'averaging' of data. Nevertheless, the analysis shows that mean total emissions from all sources are highest among households living in 'rural' areas (villages, hamlets and isolated locations). Thus, compared with households in urban areas, households in rural areas have mean total emissions which are approximately *one-fifth* higher. In contrast with other social differences in emissions, social variations in emissions by settlement type are primarily a consequence of social differences in domestic dwelling emissions. Households living in rural areas have mean total emissions from domestic fuel use which are approximately *one-quarter* higher than for households living in more urban environments. While there will be a number of factors influencing this trend (including income, property type etc) this is also likely to be a reflection of different heating systems, for example a higher proportion of rural households do not have mains gas and are therefore reliant on more carbon intensive heating fuels such as oil. Emissions from car use appear higher and public transport lower in rural areas, which may be expected due to lack of access to alternative travel options in more remote locations.

Figure 20: Mean annual CO_2 emissions from all sources by settlement type

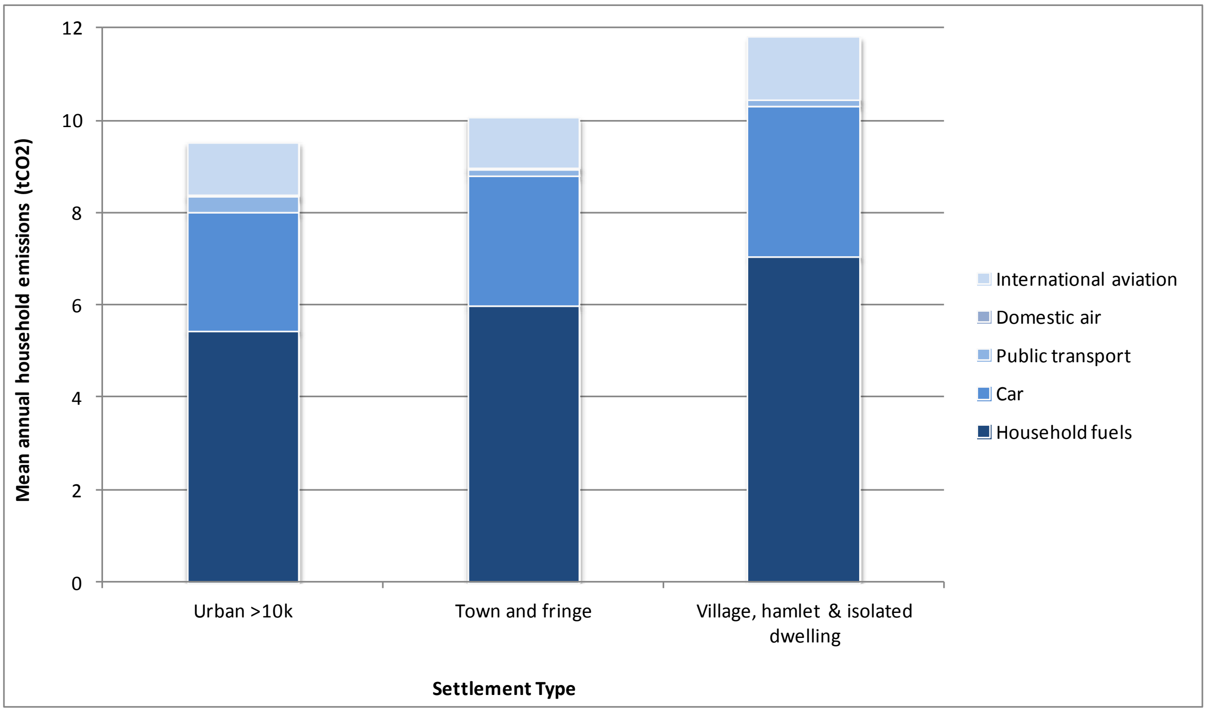
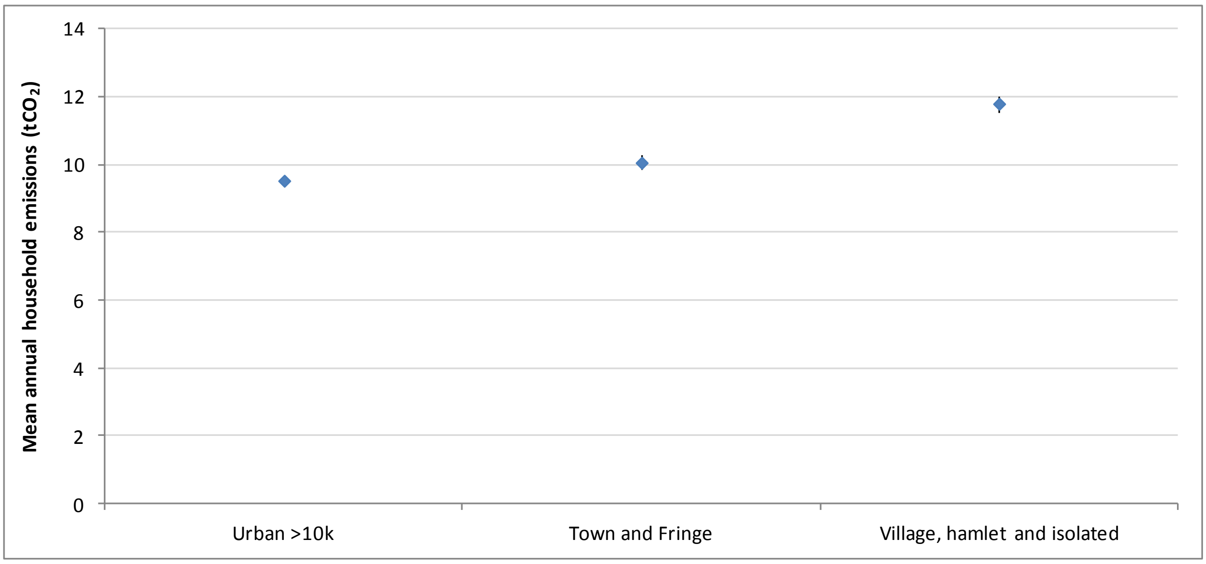


Figure 21 shows the estimated mean and 95 per cent confidence intervals of total CO_2 emissions by settlement type, in metric tons. This figure confirms that while the differences in mean household emissions between settlement types are small we can be confident that these differences exist not only for the sample under consideration but also for the wider population of interest.

Figure 21: Mean annual total CO_2 emissions from all sources by settlement type with 95% confidence intervals



Number of cars in household

Figure 22 shows mean household CO_2 emissions from all sources by the number of cars in the household. As would be expected, households with more cars emit more CO_2 from private vehicle use: average annual emissions rise from zero for those without a car to nearly 6 six tons of CO_2 per year for those with three or more cars. However, this pattern is also reflected in other emissions sources, including the consumption of energy in the home and international aviation. Households with three or more cars emit more than three times as much in total (from all sources) as those with no cars. Public transport emissions are highest for households without a car – as would be expected – and show a decline for households with one or two cars, before increasing again slightly for the final three or more vehicles category. It is likely that car ownership is to some extent a proxy for the number of working adults and income in the household.

Figure 22: Mean annual CO_2 emissions from all sources by the number of cars in the household

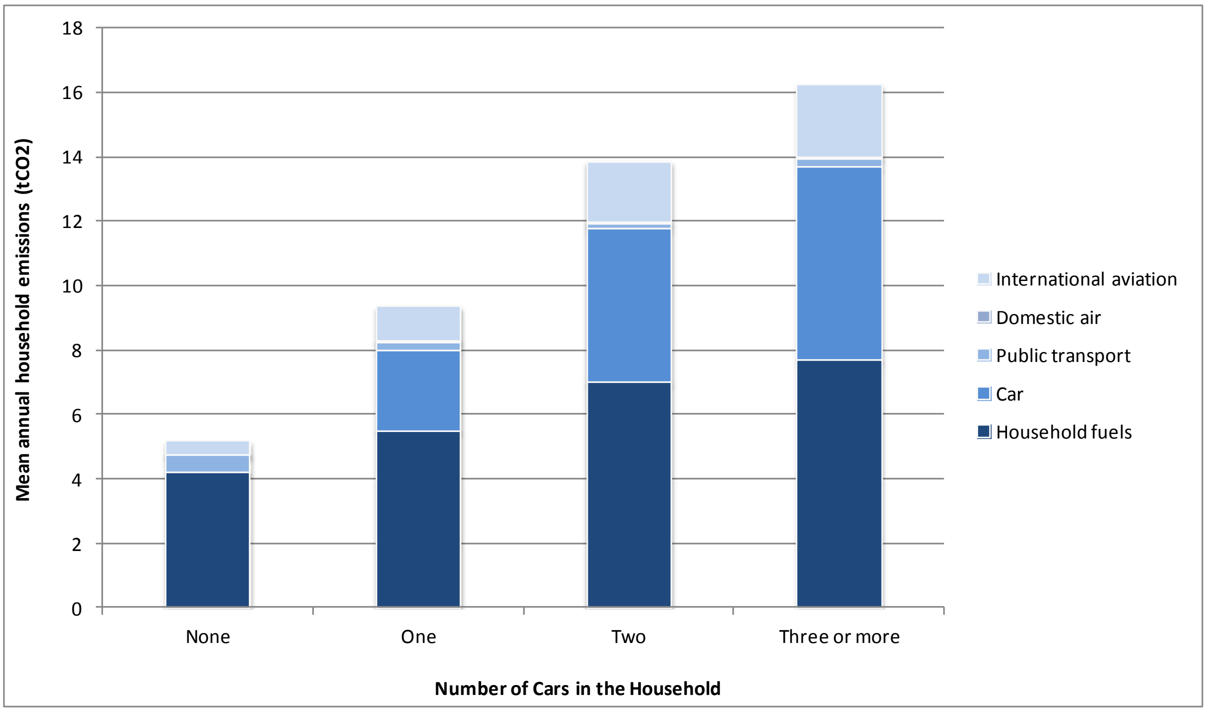
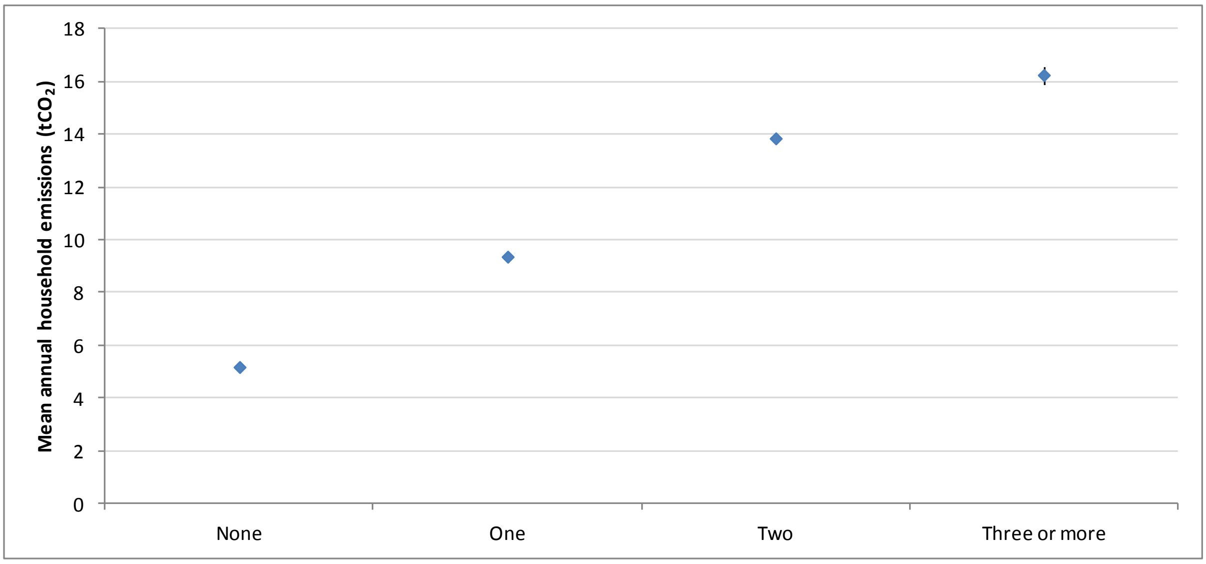


Figure 23 shows the estimated mean total CO_2 emissions and 95 per cent confidence intervals by the number of cars in the household. The 95 per cent confidence intervals are small and do not overlap, meaning that we can be 95 per cent confident that the differences in total emissions between households with different numbers of cars exist not just for the sample but for the wider population.

In the previous sections we saw that emissions from transport, especially private vehicles and international aviation, often account for a large amount of the difference of total mean emissions between groups, so it is not surprising that the number of cars in a household would lead to a large and significant difference in total household CO_2 emissions. The differences are even more marked due to car ownership reflecting other socio-economic differences and so differences in emissions from sources other than private transport also vary by car ownership.

Figure 23: Mean annual total CO_2 emissions from all sources by the number of cars in the household with 95% confidence intervals



Domestic fuel type

Figure 24 shows the distribution of the mean household CO_2 emissions from all sources in metric tons by domestic heating fuel type (referring here to the main/central heating fuel). The ‘other’ category consists of households heated by solid fuel and other gases, such as liquefied petroleum gas (LPG) (grouped together for sample size). The main difference in emissions across the categories is, unsurprisingly, from the consumption of household fuels. Households using electricity as their main heating fuel have the lowest average emissions of all categories. While the CO_2 emissions factor is higher for electricity (0.541 $kgCO_2/kWh$ – see Table 8) electrically heated households have lower overall energy consumption (in kWh) on average (due in part to the high efficiency of electricity as a heating fuel). Oil is a less efficient heating fuel, and more carbon intensive than gas, hence these households have higher average CO_2 emissions; indeed CO_2 emissions appear more than twice as high in oil-fuelled houses than electrically-fuelled houses. The breakdown of emissions by fuel type also shows how households can be characterised by the fuel used, for example electricity users emit less from other sources, possibly due to those who use this fuel typically being lower income households, and those who use oil emit very little from public transport possibly due to these households often being in more remote or rural areas (away from a mains gas connection and with poorer public transport).

Table 8: Carbon emissions factors applied for household fuels in the EFS

EFS fuel	kg CO_2 per kWh
Electricity	0.541600
Gas (mains)	0.205150

Figure 24: Mean annual CO_2 emissions from all sources by domestic heating fuel type

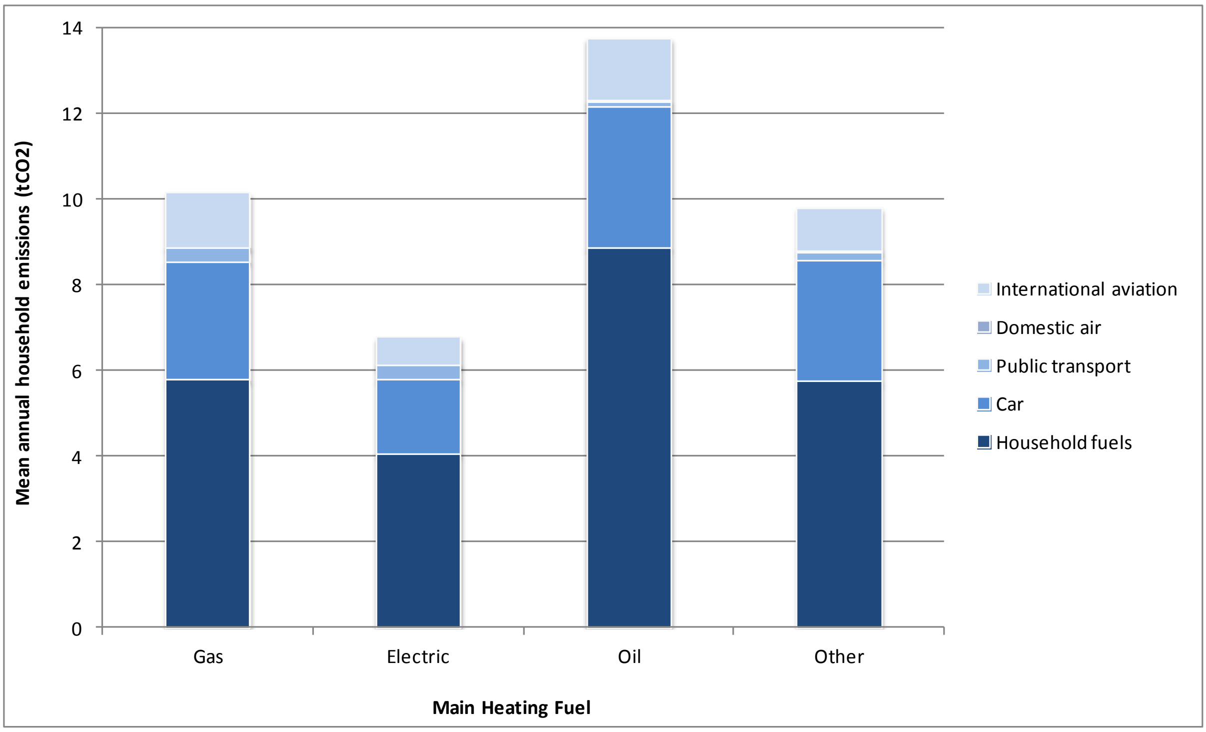
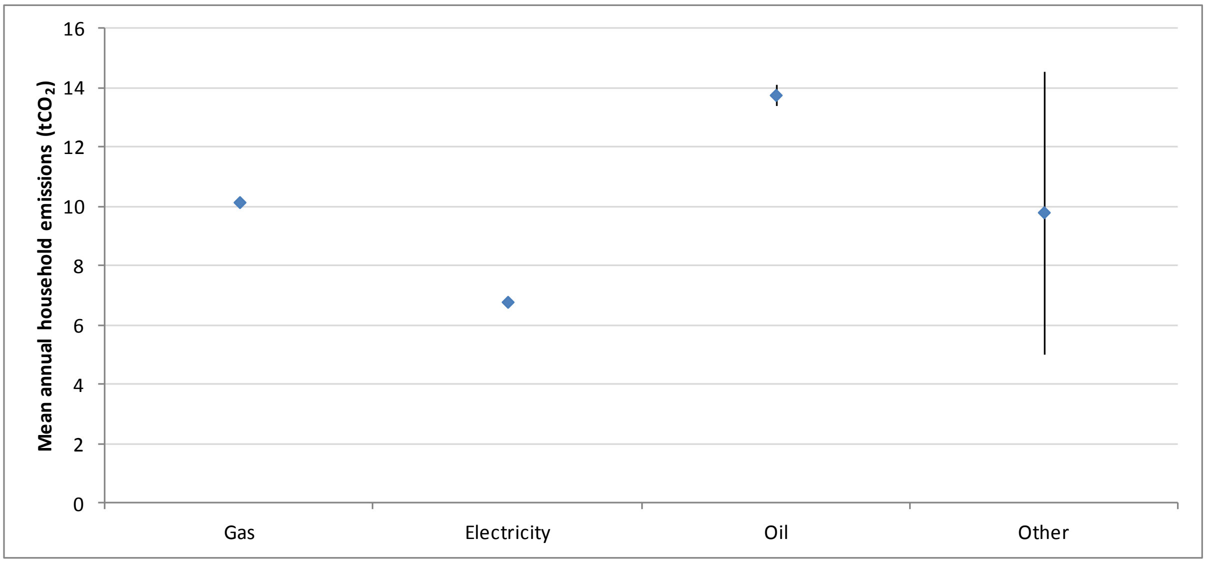


Figure 25 shows the estimated mean of total CO2 emissions by the domestic heating fuel type, in metric tons. It shows the 95 per cent confidence intervals for the population means as error bars on each data point. The 95 per cent confidence intervals do not overlap for gas, electricity and oil heated households, but the ‘other’ category has a very wide confidence interval which encompasses all other heating fuel types. This is probably due to the range of fuels included within this category, and the associated range of efficiency of these fuels meaning that the emissions associated with these fuels varies widely. Also the sample size of the ‘other’ category is less than 500, much smaller than the other groups, meaning the mean, standard deviation and standard error of the emissions are not as well constrained.

Figure 25: Mean annual total CO_2 emissions from all sources by domestic heating fuel type with 95% confidence intervals



Government office region

Figure 26 shows the distribution within the sample of mean household CO_2 emissions from all sources by government office region, along with the mean annual disposable income within these regions. The graph suggests there is little variation in average household emissions (from all sources) across different parts of Great Britain. However, the results do evidence patterns that we would expect to see. For example: households in London have the lowest emissions from car travel on average but the highest average for public transport and international aviation of all regions; Scotland has the highest average emissions for domestic aviation. There appears an interesting interaction effect with income: while the general trend in emissions across the different regions follows that of income (increase in average income equates to an increase in emissions), London is a clear anomaly here. The Underground and bus system and accessibility to airports offering international flights may be important factors here, in addition to wealth.

Figure 26: Mean annual household CO_2 emissions from all sources and mean annual disposable household income by region

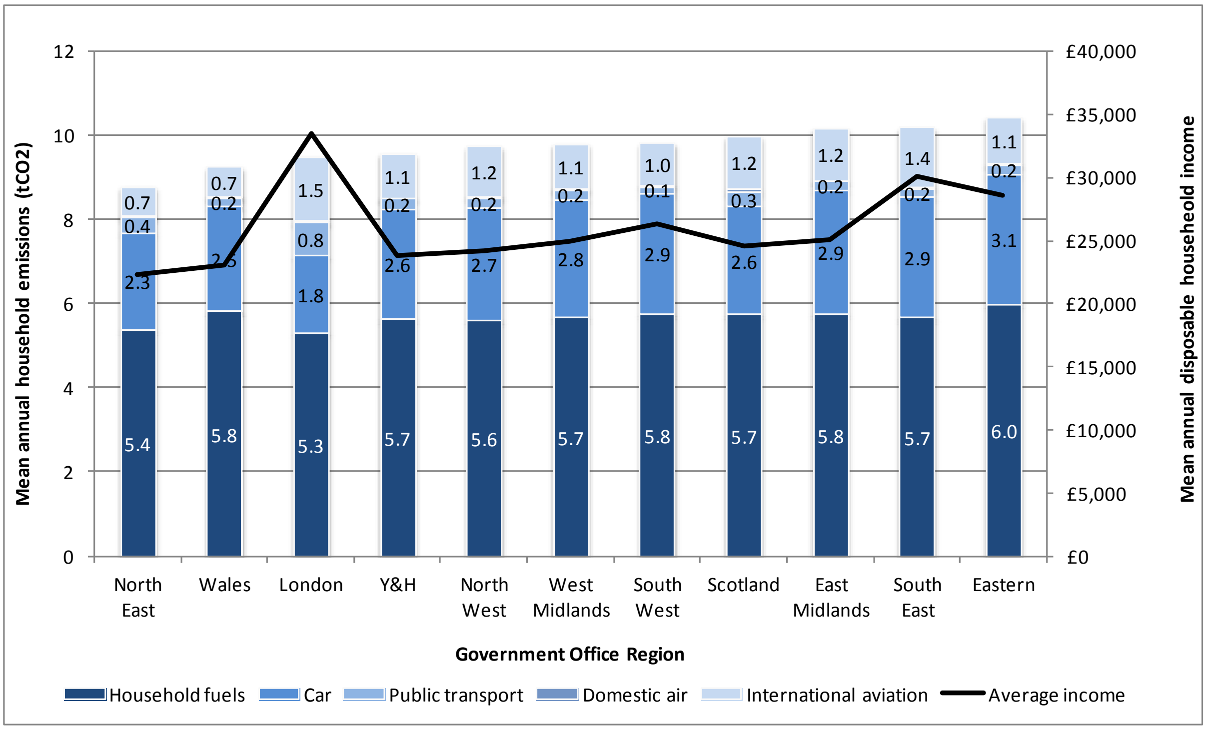
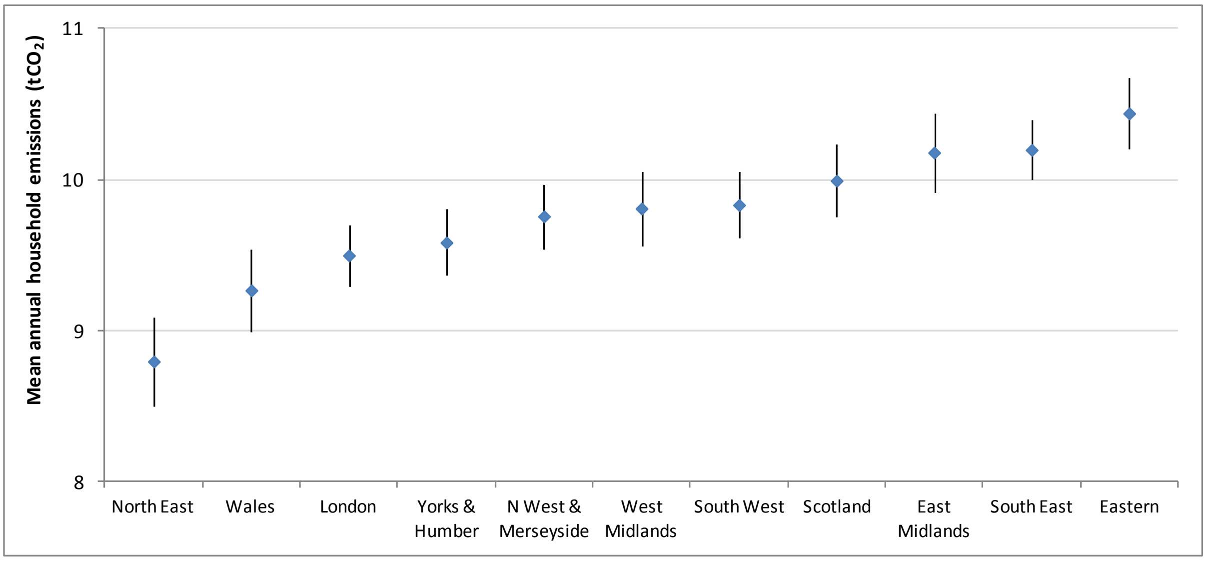


Figure 27 shows the estimated mean and 95 per cent confidence intervals of total household CO_2 emissions by government office region. Note the different scale used here. Care should be taken when interpreting this plot as differences are actually very small in magnitude (see y-axis scale). The adjusted scale makes it easier to view the overlapping 95 per cent confidence interval error bars, suggesting that average emissions do not vary significantly across regions. This suggests that government office region is not a driving factor in differences between household CO_2 emissions, although it may be an indirect factor encompassing other differences within the population, such as income or employment status.

Figure 27: Mean annual total CO_2 emissions from all sources by government office region with 95% confidence intervals



Summarising the social distribution of emissions

Table 9 summarises the pattern of association for each predictor reviewed in *Section 3 The Composition of Household Emission*s with mean annual household CO_2 emissions (by source) based on analysis of variance (ANOVA) methods. ANOVA is a statistical technique that can be used to compare the within and between group variation of the mean. In this case it can be used to analyse the variation in mean household CO_2 estimates in order to determine the extent to which variation in mean values arises as a result of differences between groups rather than differences within the groups. ANOVA also therefore provides a measure of whether the means between groups are significantly different from each other. The F statistics generated in ANOVA provides a test of the null hypothesis which states that there are no differences of means between groups within the wider population.

In this section, however, the partial eta squared value (η^2) is reported instead of the F statistic. This is derived from a one-way ANOVA methodology, defined as:

$$\eta^2 = \frac{Sum\ of\ squares\ between\ groups}{Total\ sum\ of\ squares}$$

η^2 is a measure of the effect size of the predictor variable on the dependant variable, in this case the effect of each socio-demographic characteristic (income, tenure etc.) on household CO_2 emissions (for household fuels, private transport, etc.). It gives a value between 0 and 1, and is therefore more easily interpreted than the F statistics in terms of the size of the effect. It can be broadly interpreted as the proportion of total variation in the dependent variable (mean household CO_2 emissions) attributable to the predictor variable. However as ANOVA is a uni-, rather than multi-, variate technique, it does not take into account interactions between predictor variables. Summing the η^2 values for the dependant variable may therefore lead to an answer >1.

When interpreting η^2 values it may be useful to keep in mind that, as a rule of thumb, a value of 0.01 is a small effect (has an effect but only ‘visible’ through significant analysis); 0.06 is a medium effect; and 0.14 is a large effect (an effect which is big enough, and/or consistent enough, that it may be observable 'with the naked eye') (Cohen, 1988) In Table 9 variables which have a η^2 value of greater than or equal to 0.1 are highlighted as those which have the strongest association/effect on the variation in mean household CO_2 emissions.

It should be noted that, when performing this analysis, the $\log_{10}$ values were taken for the dependant variables (CO_2 emissions by source). This was done to remove some of the positive skew evident within the data to generate a more normal distribution. In each case performing this transformation did give a distribution closer to normal, as defined by the skewness and kurtosis statistics. This allows for greater confidence in performing the analysis of variance. All effects are significant at the 95 per cent confidence level.

Table 9: Estimates of univariate effect size (η^2 values from one-way ANOVA) for selected predictor variables of mean annual CO_2 emissions from all sources. Those with an effect size >0.1 are highlighted

Predictor	Aviation	Private vehicles	Public transport	Domestic fuel	All sources
Number of cars	0.08	0.92	0.12	0.35	0.48
Disposable income (deciles)	0.15	0.29	0.02	0.40	0.44
Household type (composition)	0.07	0.20	0.04	0.38	0.33
Number of bedrooms	0.04	0.12	0.01	0.64	0.33
Number of workers	0.08	0.19	0.05	0.19	0.30
Equivalised income (deciles)	0.16	0.21	0.01	0.22	0.28
Household size	0.03	0.15	0.02	0.33	0.27
Tenure	0.05	0.18	0.04	0.35	0.25
NS-Sec of HRP	0.10	0.17	0.03	0.14	0.22
Dwelling type	0.02	0.12	0.04	0.41	0.20
Employment status of HRP	0.08	0.15	0.03	0.09	0.17
Age of HRP (banded)	0.05	0.10	0.03	0.08	0.11
Heating fuel type	0.01	0.03	0.01	0.21	0.09
Socio-economic group of HRP	0.04	0.04	0.00	0.07	0.08
Number of dependent children	0.00	0.02	0.01	0.06	0.04
Settlement type (rurality)	0.00	0.02	0.04	0.05	0.02
Government office region	0.01	0.02	0.09	0.01	0.00

Table 9 shows that for mean total household CO_2 emissions (from all sources): number of cars in the household; disposable income; household composition; number of bedrooms; number of workers in household; equivalised income; household size (number of people); tenure; occupational class of HRP; the dwelling type (detached, semi-detached, etc.); employment status of HRP; age of HRP all have a η^2 value of greater than 0.1, and so a significant effect. As described above, the ANOVA results shown here represent the variation in the dependent variable (total household CO_2 emissions) that is accounted for by variation *between* groups, rather than *within* groups, for each variable.

The analysis of each component of total household CO_2 emissions shows that for aviation (combining domestic and international) household income is the most important factor (both equivalised and disposable income). The occupational class of the HRP is the only other variable that has a value over 0.1, giving a significantly large effect. The variables that are close to a 0.1 effect are other potential proxies for household income, such as the number of workers or employment status in the household.

Several variables exhibit a significant effect (>0.1) with respect to private vehicle emissions. These include (in order from largest effect to smallest): number of cars; disposable income; equivalised income; household type; number of workers; tenure; occupational class of HRP; household size; employment status of HRP; number of bedrooms; dwelling type; age of HRP. It is no surprise that the number of cars in the household has a large effect. A number of the other variables may also bear a relationship to – and therefore be a form of proxy for – number of cars, such as income and number of workers in the household which may translate into ability to afford, and requirement for, multiple cars in the household.

Only one variable – number of cars in the household – has a significant effect on mean household public transport CO_2 emissions. Government office region has an effect size of 0.09, possibly due to London being associated with high accessibility to, and therefore high emissions from, public transport. This analysis therefore shows that public transport does vary by socio-demographic characteristics, but the effects are comparatively small.

Household CO_2 emissions from domestic fuels (energy consumed in the home) appear to be strongly associated with household size (including number of workers, number of bedrooms, number of people (‘household size’ variable), dwelling type), income and income proxies (number of cars, tenure), and heating fuel type.

In summary, the results from the ANOVA show that different sources of household CO_2 emissions are associated with different socio-demographic characteristics. The number of cars present in the household has the largest effect on total annual household CO_2 emissions. This reflects its strong correlation with emissions from private vehicles, as was shown in Section 3 (Figure 22), rising sharply from zero for households with no cars to nearly $6tCO_2$ per year for households with three or more cars.

Emissions from consumption of energy in the home appear generally more affected by household characteristics (number of bedrooms, property type, number of occupants) although income remains a key factor, while transport emissions appear generally more affected by socio-economic factors, such as a household’s command over resources (income related). This may be a reflection of the greater elasticity of travel relative to energy use in the home. The ANOVA results suggest public transport use is significantly affected only by the number of cars in the household. In the previous section, we saw how the pattern of public transport emissions is less consistent across socio-demographics (e.g. highest among lower income households, but with an increase in the top income bracket). There is likely to be a number of interrelated factors at play here, including affluence, life stage and access to public transport.

Spatial differences, such as the region or settlement type, appear to have a relatively small effect on emissions, suggesting that the socio-demographic characteristics of the household (income, occupancy, dwelling type, etc.) have a greater impact on emissions than the physical environment or climate. Again, there will be a number of interaction effects (for example income variations by region; heating fuels and rurality) which will not be captured in this univariate analysis. When such interactions are accounted for, different variables may appear as stronger predictors of household emissions.

Conclusions

The analysis presented in this paper helps to demonstrate the extent to which household's annual domestic CO_2 emissions are influenced by a range of socio-demographic factors. Two levels of analysis were applied. First error bar charts (Section 3) illustrate the distribution (pattern of relationship) of household CO_2 emissions from each source (energy consumed in the home and personal travel by private vehicle, public transport and aviation) by a number of socio-demographic factors. Section 4 then presents the results of statistical analyses (ANOVA), to examine the significance of the relationship of each factor individually with household emissions, for each source.

The results consistently show that household emissions are strongly correlated with income. In Great Britain, the richest 10 per cent of households emit some three times that of the poorest 10 per cent. The top 10 per cent of earners are responsible for 16 per cent of total household emissions including the emissions from energy use in the home and all personal travel by car, public transport and aviation. This is more than three times that of the poorest 10 per cent of households, who contribute 5 per cent to total household emissions from these sources.

The distribution of emissions is more polarised for transport emissions compared with energy consumption in the home. The highest income decile emits just over twice that of the lowest income decile for domestic household fuels. However the highest income decile emits seven to eight times that of the lowest income decile due to private transport use. International aviation shows the largest disparity between income deciles, with the highest income decile emitting some 10 times that of the lowest income decile. Emissions from public transport, however, show a flatter distribution across income deciles, with the highest income decile emitting around 1.5 times that of the lowest income decile.

In addition to income, other household characteristics associated with higher than average carbon emissions include: multi-adult (three or more adults) households and couples (with or without children); middle-aged households (aged 35–60years); households using oil to heat their home; properties which are owned outright; households containing multiple (and/or full-time) workers (and/or) those of a higher socio-economic group; and properties in rural areas.

The ANOVA results help to identify which factors have a significant effect on the variation in household CO_2 emissions from each source. In terms of domestic fuel (energy consumed in the home) household size (both in terms of physical size of the property – number of bedrooms in this case – and type and the number of occupants) has the largest effect, with income also having a strong effect. Variation in household emissions from travel by private vehicle can be mainly explained by the number of cars in the household, with 92 per cent of variation arising from between-group rather than within-group differences. Public transport CO_2 emissions are less strongly explained or affected by the socio-demographic factors examined here, with the number of cars being the only strongly significant variable, reflecting the more muted variation in public transport emissions as illustrated in Section 3. Emissions from aviation are primarily effected by income, either net disposable or equivalised income, which show 15 per cent and 16 per cent respectively of variation attributed to between-group rather than within-group variation. Income being the strongest effect factor here fits with the findings in Section 3 of a large disparity between the lowest and highest income deciles' emissions from this source.

Total household CO_2 emissions (from all sources) show strong effects from a combination of these variations, the strongest factors being the number of cars and income. This is consistent with the results for emissions from private vehicle travel. Thus while domestic fuel emissions accounts for the majority (approximately 60 per cent) of total household emissions from all sources, much of the social *variation* in household's total carbon emissions arises from private vehicle and (to a lesser extent) aviation emissions. Social variation in domestic energy consumption accounts for rather less of the total variation in household emissions. Emissions associated with public transport use are also negligible in comparison with these sources and the social patterning of emissions from this source is much less pronounced.

However these findings are based on univariate analysis and do not therefore allow for inter-correlated impacts. While the general pattern in household and transport emissions across income deciles is clear (higher income = higher emissions), certain household types and age bands have higher emissions for heat and power consumed in the home but do not also have high transport emissions. This has fundamental implications for how energy and climate policies will impact (disproportionately) on different segments of the population. For example it may be more regressive to tax domestic fuels than to tax private transport if seeking to encourage the lowering of emissions. The policy implications of energy policies on different households are explored in detail in the next phase of the wider research project.

Notes

1 In April 2001 the *Family Expenditure Survey* (FES) and *National Food Survey* (NFS) were combined to form the *Expenditure and Food Survey* (EFS), which replaced both series. From January 2008, the EFS became known as the *Living Costs and Food* (LCF) module of the *Integrated Household Survey* (IHS).

2 Average annual domestic electricity (/gas) bills for selected towns and cities in the UK and average unit costs. Available at: www.decc.gov.uk/en/content/cms/statistics/energy_stats/prices/prices.aspx#domestic (accessed 10 November 2012).

3 2010 Guidelines to Defra/DECC's GHG Conversion Factors for Company Reporting.

4 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, while maintaining a sufficient number of cases to give reliable estimates of scalar values.

5 2010 Guidelines to Defra/DECC's GHG Conversion Factors for Company Reporting. All factors were applied on a net calorific value basis where relevant.

6 Airports database was obtained from OpenFlights.org, a free flight mapping, search, statistics and sharing tool as well as the name of the open-source project to build the tool. As of October 2009, the OpenFlights airports database contained 5,497 airports spanning the globe.

7 The HRP in survey data terms is typically defined as the person who responds to household survey interview questions on behalf of the household as a whole. In the EFS – the dataset underlying this analysis – the HRP is defined as the householder with the highest income or the oldest of two or more householders with the same income.

8 Socio-economic group is derived from survey classification of HRP professions, e.g. 'higher managerial', 'lower managerial', 'semi-routine operative' etc.

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About the research

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.* This research project uses advanced modelling techniques to develop and analyse the datasets needed to support and further understanding of: the distribution of carbon emissions – from energy consumed in the home and through personal travel by car, public transport and aviation – across households in Great Britain; the impact of existing government energy and climate policies on consumer energy bills and household emissions in England; the potential for an alternative approach to reducing emissions in the domestic sector through a wide-scale retrofit of the housing stock.

The full project report and a summary of the findings are available at: http://www.jrf.org.uk/publications/carbon-emissions

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