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Analysis

Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions

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ABSTRACT

Does the association between household characteristics and household CO_2 emissions differ for areas such as home energy, transport and indirect emissions? This question is policy relevant because distributional implications of mitigation policies may vary depending on the area of emissions that is targeted if specific types of households are likely to have higher emissions in some areas than in others. So far, this issue has not been examined in depth in the literature on household CO_2 emissions. Using a representative UK expenditure survey, this paper compares how household characteristics like income, household size, education, gender, worklessness and rural or urban location differ in their association with all three areas as well as total emissions. We find that these associations vary considerably across emission domains. In particular, whilst all types of emissions rise with income, low income, workless and elderly households are more likely to have high emissions from home energy than from other domains, suggesting that they may be less affected by carbon taxes on transport or total emissions. This demonstrates that fairness implications related to mitigation policies need to be examined for separate emission domains.

1. Introduction

Since households contribute substantially to the UK's total emissions – around 74% according to Baiocchi et al.'s (2010) estimate, including indirect emissions – a reduction of household emissions is essential for meeting the UK's carbon reduction targets. Additional climate change mitigation policies (in the following "mitigation policies") will thus be needed to reduce household emissions. To examine potential fairness implications of these policies, we need to analyse the distribution of emissions across household groups.

Two points are particularly relevant here: first, if factors other

than income thus need to be considered in distributional analysis of emissions. However, some characteristics such as income and education or income and rural/urban location are related to each other. Whilst bivariate analysis may find that each of these characteristics is associated with emissions, multivariate analysis is required to determine whether or not characteristics such as education or rural location remain associated with emissions after income is controlled for. So far, only few studies employ multivariate analysis to control for relationships between different factors, but examples are studies by Baiocchi et al. (2010), Gough et al. (2011) and DEFRA (2008) for the UK context and by Weber and Matthews (2008) and Lenzen et al. (2006) for other countries. However, these studies differ regarding the types of emissions studied and their conclusions on how various household characteristics relate to emissions.

Second, from a policy perspective it is relevant to examine whether the association between emissions and household characteristics varies for different types of emissions. For example, do emissions in different areas increase at the same rate with income or household size? Is rural location more important for transport or for home energy emissions? So far there is no study available that compares the role of

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generalise claims regarding the (un-)fairness of mitigation policies, currently made for individual areas of emissions (e.g. Barnes, 2003; DEFRA, 2008; Dresner and Ekins, 2006; Grainger and Kolstad, 2010; Starkey, 2008).

To address this gap in the literature, this paper compares the role of household characteristics for home energy, transport, indirect and total household CO_2 emissions. Household characteristics include amongst others income, household size, age, worklessness, gender, education and rural/urban location. Whilst an analysis of distributional implications of mitigation policies goes beyond the scope of this paper, we will outline possible policy implications in Sections 5 and 6.

Our analysis is based on a representative expenditure survey in the UK, the Living Costs and Food Survey (LCF) and its predecessor

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the Expenditure and Food Survey (EFS), merged over the years 2006 to 2009. We combine expenditure data with other data sources to estimate household CO_2 emissions as discussed in Section 3. The analysis comprises two steps. First, unconditional associations between various household characteristics and different areas of CO_2 emissions are examined; second, conditional associations are analysed, applying multivariate OLS regression. This provides us with an indication of the types of households that might be particularly affected by mitigation policies targeting specific areas of emissions. Section 2 provides a more detailed overview of existing research in this area. Section 3 describes the data, data limitations and methods of analysis. Results are presented in Section 4 and discussed in Section 5. Section 6 concludes.

2. Previous Research

The extent to which socio-economic factors other than income and household size are associated with household CO_2 emissions and whether associations vary across emission domains remains contested in the literature. Whilst some authors have claimed that characteristics other than income and household size are not relevant for household emissions (e.g. Wier et al., 2001: 267), several multivariate studies found that characteristics such as employment status, education, rural/urban location, household composition and age remained to be associated with emissions once income and household size were controlled for (Baiocchi et al., 2010; DEFRA, 2008; Gough et al., 2011; Lenzen et al., 2006). Based on this evidence, we expect characteristics other than income and household size to be relevant for household emissions. However, the way in which these factors are associated with emissions and whether associations vary by emission domain is still an open question.

The role of income is widely discussed in the literature. All studies on this topic conclude that emissions in all different areas rise with income (e.g. Baiocchi et al., 2010; Brand and Boardman, 2008; DEFRA, 2008; Druckman and Jackson, 2008; Fahmy et al., 2011; Gough et al., 2011; Weber and Matthews, 2008). Several studies on non-UK countries also compare the distribution of CO_2 emissions or energy requirements over income groups for different domains (but without controlling for other factors). All of these studies find that home energy emissions are more regressively distributed than transport or total emissions (e.g. for the US or Spain Duarte et al., 2010: 181; Herendeen et al., 1981; O'Neill and Chen, 2002: 69). Only Gough et al.'s (2011: 50–3) study compares the role of income for different areas of greenhouse gas (GHG) emissions using multivariate analysis. Whilst income remains significant for each area of emissions, the coefficients are almost identical (Gough et al., 2011: Tables A2.3 and A2.7), suggesting that different levels of regressivity disappear once other factors are controlled for. This paper will examine whether this also holds in this study on CO_2 emissions.

Previous literature has also shown that household size and composition (e.g. the presence of children) are important factors for household emissions and that there are economies of scale once individuals share household resources (DEFRA, 2008: 5; Druckman and Jackson, 2008: 3184; Gough et al., 2011: 13–4). Using bivariate analysis, O'Neill and Chen (2002: 67–8) showed that per capita domestic energy requirements in the US drop much more with increasing household size than energy requirements related to transport. This indicates that economies of scale are larger for home energy than for transport emissions which would be highly relevant for the design of mitigation policies, particularly if they include per capita rebates or allowances. However, multivariate results regarding the presence of children are mixed so far: having a child was positively associated with direct CO_2 emissions in DEFRA's (2008: 82) study but negatively with total emissions in Baiocchi et al. (2010: 64). We thus hypothesise that household size has a larger 'effect' on transport than on home energy emissions in multivariate analysis and that the presence of children matters more for direct than for indirect and total emissions.

Findings regarding age also remain inconclusive: DEFRA's (2008: 82) study found that direct CO_2 emissions increased with age in multivariate analysis whilst Wier et al. (2001: 267) concluded from bivariate analysis that age had little effect on CO_2 emissions from home energy. Other bivariate studies showed that the relationship between age and transport emissions takes on an inverse u-shape (O'Neill and Chen, 2002: 65). Since older people may be less likely to travel and more likely to spend time at home, requiring energy for heating, we hypothesise that an inverse u-shaped relationship between age and transport emissions holds in multivariate analysis whilst the same may not apply for home energy emissions.

Several multivariate studies have included employment status: Gough et al. (2011) found unemployment to be negatively associated with GHG emissions in different areas, confirmed by DEFRA (2008: 82) for direct CO_2 emissions whilst Meier and Rehdanz (2010) found a positive relationship between unemployment and space heating expenditure. Since being out of work may increase the time spent at home, we expect emissions from home energy to be higher and emissions from transport to be lower for people out of work compared to those in employment.

Some studies have also included education in multivariate studies on emissions, again with differing results. Baiocchi et al. (2010: 61, 64) found that education and total emissions are positively correlated but that high education 'reduces' emissions once other factors are controlled for, supporting the hypothesis that awareness of environmental problems rises with high education and contributes to low carbon practices. However, Brand and Preston (2010: 16) found that those who attended university or full time education (which could be seen as a proxy for high education) had significantly higher transport emissions that those who did not. Lenzen et al. (2006: 192) found a negative association between emissions and high education for Australia but a positive association for Brazil and India, arguing that high education is a privilege of the rich in the latter and thus related to high emissions. Based on existing evidence for the UK, we expect education to be positively associated with transport emissions, but not with other types of emissions.

It is generally assumed that living in a rural location is associated with higher emissions due to greater car dependency and more isolated dwellings than in cities (e.g. DEFRA, 2008). However, since in the UK incomes in rural locations are, on average, significantly higher than those elsewhere,[1] the question arises whether rural location remains to be associated with emissions once income is controlled for and whether the association is stronger for transport or home energy emissions. Brand and Preston (2010) did not find location to be significant in OLS regressions on transport CO_2 emissions in the UK whilst DEFRA (2008: 82) found that those living in rural places had significantly higher direct (home energy and motor fuel) CO_2 emissions than those living elsewhere. This suggests that rural location is no longer associated with higher transport emissions once income is controlled for whilst the association with home energy emissions (which make up the largest share in the DEFRA study) may remain significant — an assumption we will test.

Neither Baiocchi et al. (2010), Gough et al. (2011), Lenzen et al. (2006), nor Weber and Matthews (2008) included gender in their multivariate analysis. DEFRA (2008) found that female headed households had higher direct CO_2 emissions than male headed households whilst Brand and Preston (2010) did not find a significant difference between men and women's transport CO_2 emissions. Since our study is based on household data we can only distinguish between 'female' and 'male headed' households, depending on the gender of

[1] Based on the LCF/EFS 2006–9, equivalised weekly household income was £367.0 in rural areas (standard error 6.1) and £331.6 (standard error 4.3) elsewhere which is significantly different at the 1% level.

the reference person.[2] Since in our dataset female headed households are more likely than male headed households to be single retired and lone parent households who may spend more time at home, we would expect them to have higher home energy and equal or lower transport emissions than other households.

Overall, this review demonstrates that whilst a small number of multivariate studies exist on the relationship between emissions or energy requirements and socio-economic background, they have generated conflicting results and have so far not systematically compared these relationships across different domains of CO_2 emissions. Furthermore, authors like Starkey (2008, 2012) have recently stressed that household characteristics other than income may be highly relevant for household emissions and thus for fairness implications of mitigation policies. Whether or not this is the case can be examined using multivariate analysis that controls for the role of income and other factors, the approach chosen in this paper to address this question.

3. Data and Methods

3.1. Data

For the UK, there is currently no representative dataset available that combines household level CO_2 emissions and household characteristics. Research on the association between emissions and household characteristics thus relies on other data sources to estimate household emissions. In this paper, we convert rich information on households' expenditure into CO_2 estimates. The UK Living Costs and Food Survey (LCF) 2008 and 2009 and its predecessor, the Expenditure and Food Survey (EFS) 2006 and 2007 provide us with household expenditure data and a range of household characteristics. The merged dataset has a total household sample size of 24,446. We convert households' expenditure into CO_2 emission estimates using the following methods.

For home energy, we first convert expenditure to units of consumption using price data. Tables 2.2.3 and 2.3.3 of the Quarterly Energy Prices statistics by the Department of Energy and Climate Change provide annual domestic electricity and gas prices per kWh for three payment methods and each electricity/gas region which can be matched to information in the EFS/LCF. DECC Table 4.1.1 provides monthly prices for heating oil whilst prices for bottled gas, coal and wood are sourced from the Sutherland tables.[3]

For transport CO_2 emissions we estimate litres of motor fuel (petrol and diesel) consumed using AA statistics[4] on monthly motor fuel prices for each government region. For public transport we estimate kilometres travelled per pound expenditure employing information on average annual passenger miles for train, tube, bus and coach journeys from travel surveys for Great Britain[5] and Northern Ireland[6]. Flight emissions are based on estimating flight kilometres by merging information from the EFS/LCF survey on the number of person flights per household within the UK, Europe and outside Europe with average flight distances to these destinations based on the National Travel Survey and the International Passenger Survey.

CO_2 conversion factors (DECC, DEFRA, 2011) provided for different fuels and modes of transport are then applied to units of home energy and litres of motor fuels consumed, as well as to kilometres travelled by mode of transport to estimate CO_2 emissions for each household.

To estimate indirect emissions we use the Resources and Energy Analysis Programme (REAP) database which provides estimates of total UK household CO_2 emissions for 57 consumption categories in 2006, based on input–output analysis (Paul et al., 2010). This information can be matched with the EFS/LCF because both define consumption categories using the United Nation's *Classification of Individual Consumption according to Purpose* typology to generate 'CO_2 per pound expenditure factors' for 49 consumption categories (alternative methods are employed for the remaining eight categories as described above). These factors are then applied to households' expenditure (inflation corrected for 2007–2009, using Consumer Price Index data provided by the Office for National Statistics for each of the 49 consumption categories as this is more precise than using a single index) to estimate emissions.[7] For further details on estimation methods see Büchs and Schnepf (2013).

3.2. Data Limitations

Estimating emissions based on household expenditure is limited in several ways. The first set of limitations relates to the insight that expenditure does not necessarily equate to consumption — on which emissions are based. For example, an expensive loaf of bread might have a similar or even lower carbon content than a cheaper one whilst higher expenditure automatically translates into a higher emission figure in studies that convert expenditure data — a problem we can call the 'product quality problem'. Since richer households may tend to purchase higher quality and thus more expensive goods and services, this might lead to an overestimation of their emissions. Girod and De Haan (2010) have analysed this issue in a recent study and concluded that about half of the increase in expenditure for high income households is due to purchasing more expensive products rather than more products. However, they conceded that rich households' increase in emissions is not necessarily overestimated by that same proportion because the exact carbon content of luxury goods and services could not be compared to cheaper ones. Overall, we have to assume that we will slightly overestimate rich households' emissions but can be confident, based on Girod and De Haan's study, that emissions are rising with income.

Furthermore, expenditure may not correctly reflect consumption due to the 'infrequency of purchase problem' which is widely discussed in studies on household expenditure (e.g. Baker et al., 1989; Deaton and Irish, 1984). Purchases may be infrequent if households consume from stocks, leave longer periods before they replace items such as furniture or cars or simply do not engage in certain activities regularly enough that they are captured by brief periods of expenditure diaries. We can demonstrate this problem in relation to private flights as the EFS/LCF collects both expenditure on flights from the two week diary and the number of flights in the last year through the survey. Only 1.3% of all households have an expenditure on flights within two weeks but 41.0% of households record at least one flight during the last year. Whilst expenditure is correct for the two-week period, it would substantially underestimate the proportion of households having had a flight when this is totalled up to a year. Since flight emissions are an important source of CO_2 emissions, we use the number of flights per year instead of expenditure data to estimate flight emissions.

The infrequency of purchase problem affects those expenditures collected through the two week-diaries, including motor fuels, public transport and electricity and gas prepayments. Does the infrequency of purchase problem influence our analysis? All previous studies

[2] This is defined as the person who is financially responsible for the accommodation or, if equally shared, the higher earner.

[3] See http://www.sutherlandtables.co.uk/, last accessed 23 February 2013.

[4] See http://www.theaa.com/motoring_advice/fuel/fuel-price-archive.html, last accessed 23 February 2013.

[5] See https://www.gov.uk/government/statistical-data-sets/nts03-modal-comparisons, table NTS0305, last accessed 23 February 2013.

[6] See http://www.drdni.gov.uk/stats-catagories-travel_survey.htm, NI Travel Survey In-Depth Report 2007–9, Table 3.1, last accessed 23 February 2013.

[7] Based on these conversion methods, our mean annual total estimate of household CO_2 emissions in the UK between 2006 and 2009 is 513 million tonnes. This compares to an average of 527 million tonnes for the same period as estimated by DECC (2012: Table 1), 505 million tonnes in 2000 as stated by Baiocchi et al. (2010: 57) and 560 million tonnes in 2004 as estimated by Druckman and Jackson (2009: 2072).

using expenditure data for estimating CO_2 emissions implicitly or explicitly (DEFRA, 2008: 13) assume that mean CO_2 estimates derived from random expenditure surveys will be unbiased. Zero expenditures for infrequently purchased items should be compensated by recorded purchases as those who do buy these items during the diary period may not fully consume them within two weeks. There is no obvious reason to believe that this assumption does not hold for our data, particularly due to the large sample size used in this study. However, measures of dispersion such as standard deviation and variance are likely to be overestimated. Given that we conduct OLS regressions and experience the measurement error in the dependent variable, we need to be aware that standard errors of coefficients are likely to be inflated. Table 1 below provides the per cent of households in the sample that have "zero" emissions due to zero expenditures for sub-categories of emissions.

Finally, issues arise in relation to the methods of converting expenditure to emissions. For example, input–output data are applied to estimate indirect emissions at the household level. Input–output datasets only provide emission estimates for broad consumption categories, make simplifying assumptions about the energy intensity of production abroad and are affected by lags in data availability. These limitations are discussed in more depth elsewhere (e.g. Baiocchi et al., 2010; Druckman and Jackson, 2009; Minx et al., 2009). However, due to a lack of alternatives, input–output data are widely used in studies on household emissions (e.g. Baiocchi et al., 2010; Druckman and Jackson, 2009; Herendeen et al., 1981; Lenzen et al., 2006).

3.3. Methods of Analysis

Associations between household characteristics and emissions are examined in two steps. First, we examine bivariate relationships to gain an insight into the ways in which emissions are distributed across different household groups. Whilst bivariate analysis is indispensable for estimating, for instance, mean emissions for specific social groups, it cannot account for relationships between several household characteristics. For example, income and education and income and rural/urban location are associated in our sample: highly educated and rural households have significantly higher disposable and equivalised household incomes than their counterparts.

To examine whether or not education and rural location account for any of the variation in household emissions in addition to income, multivariate OLS regression is therefore required as it models the association between individual predictor variables holding all other variables constant. CO_2 household emissions for the four emission domains are the dependent variables. Emissions are log transformed to model a linear relationship between emissions and independent variables.

The following independent variables are included: disposable household income, again log transformed to model a linear relationship with emissions and providing elasticities; due to the inverse u-shaped relationship between age and emissions and the way age is coded in the EFS/LCF, age is represented by three variables: 'age', giving the household reference person's age, squared age divided by 100 to account for the inverse u-shaped relationship, and a dummy variable 'age top coded' with 1 for those aged 80 and above since the EFS/LCF top-codes age at this level; four dummy variables for each additional adult and three dummy variables for each additional child in the household with one adult and zero children being reference categories (e.g. adult2 is coded 1 for households with two or more adults and 0 otherwise, adult3 is coded 1 for households with 3 or more adults and zero otherwise); a variable for gender which is coded 1 if the household reference person is female and zero otherwise; three dummy variables for education where 'education16+' is coded 1 if at least one member of the household attended full time education for 16 or more years, 'education 12–15' which is coded one if at least one member of the household was in full time education for 12 to 15 years, 'education missing' which is coded 1 if information on education is missing. Households in which none of the members attended full time education for more than 11 years represent the reference category. The variable 'workless' is coded 1 if at least one household member is of working age but nobody in the household is in employment or self-employed; ethnicity is coded 1 for households with 'non-white' reference persons; the variable 'rural' is coded 1 for households in rural locations, defined as areas with populations under 10,000 people and 'rural missing' is coded 1 if information on location is missing (mainly for Northern Ireland).

Table 1
Mean and median annual household CO_2 emissions in tonnes; per cent of total emissions; and per cent of households not having emissions by emission area.

	Median tonne	Mean tonne	Standard error mean tonne	Per cent of total mean CO_2 emissions	Per cent of households without emissions
Home energy total of which	4.48	5.11	0.03	25.3	5.7
Gas	2.35	2.49	0.02	12.3	22.8
Electricity	1.84	2.09	0.01	10.4	8.1
Other home energy	0.00	0.53	0.03	2.6	93.2
Transport total of which	2.97	4.40	0.04	21.8	15.2
Motor fuels	1.60	2.38	0.03	11.8	36.4
Flights	0.00	1.13	0.02	5.6	59.0
Public transport	0.00	0.89	0.02	4.4	50.2
Indirect total of which	8.69	10.67	0.08	52.9	0.0
Indirect home energy and motor fuel emissions	2.23	2.60	0.02	12.9	9.0
Food	1.33	1.53	0.01	7.6	0.7
Catering/hotels	0.69	1.11	0.01	5.5	11.6
Cars & repairs	0.05	0.40	0.01	2.0	39.5
Recreation	0.33	0.77	0.03	3.8	3.7
Clothing	0.23	0.66	0.01	3.3	32.6
Furniture, appliances, tools	0.13	0.67	0.01	3.3	32.1
Personal care	0.17	0.38	0.01	1.9	12.3
Other indirect	1.53	2.54	0.03	12.6	0.0
Total	17.13	20.18	0.13	100.0	0.0

Note: Households without emissions are included in the calculation for all emission areas. Standard error for mean tonne takes complex survey design (weighting and clustering) into account. Sample size is 24,446 households.

Table 2
Households' annual mean CO_2 emissions by household size and emission area.

		Total CO_2	Home energy	Indirect emissions	Transport (all)	Transport (non-zero CO_2)
Households without children	1 adult	10.9 (0.11)	3.6 (0.04)	5.5 (0.07)	1.8 (0.03)	2.6 (0.04)
	2 adults	21.4 (0.18)	5.3 (0.05)	11.2 (0.12)	4.9 (0.06)	5.4 (0.06)
	3 adults	27.3 (0.42)	6.2 (0.12)	14.5 (0.25)	6.6 (0.16)	6.9 (0.16)
	4 adults	33.9 (0.84)	6.9 (0.20)	18.1 (0.51)	8.9 (0.34)	9.0 (0.34)
Two adult households	1 child	24.5 (0.36)	5.7 (0.10)	13.4 (0.22)	5.5 (0.13)	5.8 (0.13)
	2 children	28.0 (0.36)	6.3 (0.09)	15.3 (0.22)	6.3 (0.13)	6.6 (0.13)
	3 children	29.0 (0.87)	6.7 (0.19)	15.8 (0.56)	6.4 (0.30)	6.9 (0.32)

Note: Standard errors taking complex survey design (weighting and clustering) into account are reported in parentheses. Zero emissions are included in all but the last column.

We calculated variance inflation factors (vif) for the independent variables to check for multicollinearity. Whilst the age and age squared terms are naturally highly correlated and thus violate assumptions about multicollinearity, this is usually not considered a problem if both terms are significant in the model. None of the other variables had a vif higher than 2.35, far below the recommended upper threshold of 10. We also report adjusted R^2 to account for the number of independent variables in the models.

To exclude outliers that can lead to biased regression results, the 1% of households with the highest and lowest emissions and income as well as those with post-regression residuals >|3| are excluded. We also exclude around 6% of households with zero or negative home energy expenditure in all models to be able to compare the same sample of households (sample size 21,876). For transport emissions, we exclude all households without emissions due to zero expenditure (sample size 18,942).

4. Results

4.1. The Association between CO_2 Emissions and Household Characteristics

4.1.1. CO_2 Emissions in the UK by Emission Area

Table 1 shows mean and median household CO_2 emissions in our pooled sample, together with the per cent that individual categories contribute to overall CO_2 emissions and the per cent of households 'without' emissions due to zero expenditure. Median UK total household emissions are 17.1 tonnes of CO_2 emission per year whilst the mean is as high as 20.2 tonnes, demonstrating a positively skewed distribution. Home energy contributes 5.1 tonnes or 25.3% to total emissions. 4.4 tonnes or 21.8% of total household emissions originate from transport, including flight emissions that contribute as much as 5.6% on average to households' total emissions (equating to only 0.6 private flights per person per year or 1.3 flights per household). The remainder of total emissions, 10.7 tonnes or 52.9%, consists of indirect emissions incorporated in other goods and services.[8]

4.1.2. CO_2 Emissions and Household Size

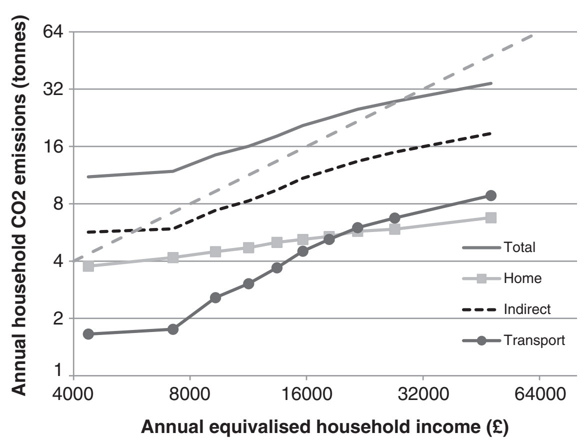
Table 2 presents average CO_2 emissions for different household sizes: the first four rows present results for single, two, three and four adult households (all without children and adults defined to be 18 years or older); the last three rows refer to two adult households with one, two or three children. The results demonstrate that household size and composition play different roles for different emission domains. On average, two adult households have almost three times higher transport CO_2 emissions than single adult households (4.9 compared to 1.8 tonnes CO_2). Indirect emissions double for a two adult compared to a single adult household. In contrast, CO_2 emissions for home energy increase by less than half when we compare one to two-adult households. This indicates that economies of scale are most relevant for this area of emissions but less so for transport and indirect emissions. Since 32% of single adult households have 'zero' transport emissions (compared to just 10% of two, 4% of three and 1% of four adult households (all without children)), we also compared transport emissions for households with non-zero emissions. This shows that non-zero transport emissions still double for two adult households compared to single adult households (last column of Table 2).

Whilst two adult households with one child have significantly higher total, indirect and home energy emissions than their childless counterparts, emissions only increase by 8.0 (home energy), 12.2 (transport, including zero emissions), 14.5 (total) and 19.6 (indirect) per cent (this difference is not significant for transport emissions).

4.1.3. CO_2 Emissions and Income

Graph 1 plots mean household CO_2 emissions against equivalised household income deciles (using the modified OECD scale) by emission area using log scales. This makes it easier to compare the proportional change for CO_2 emissions and hence to judge whether emissions in different areas are more or less responsive to changes in income. The slashed "elasticity" line on the diagram represents a 1% increase in CO_2 emissions for a 1% increase in income. Any parallel line would reflect this 1% increase. If the data points rise more steeply than the 1% line, emissions are classified to be progressive in economic terms, if the line rises less steeply they are regressively distributed.

If we disregard the 10% of households with lowest and highest annual equivalised household income, the transport data series is nearly parallel to the elasticity line, indicating that transport CO_2 emissions are almost neutrally distributed, rising proportionally with income. In contrast, the line is much flatter for home energy, demonstrating that CO_2 emissions are most regressively distributed in this area. Indirect and total emissions show a regressive increase with income but less so than for home energy.



Graph 1. Annual equivalised household income and household CO_2 emissions by emission area (log-log scale). Note: The graph plots mean household CO_2 emissions by mean income at each income decile on log scales. The dashed "elasticity" line shows a 1% increase in household CO_2 emissions if income increases by 1%. Sample size: 24,446 households.

[8] This category includes emissions arising in the production of heating and motor fuels (12.9%) as well as 'other' indirect categories (12.6%) such as medical care, hospital and communication services and cosmetics.

These results are confirmed when we conduct OLS regression using log of CO_2 emissions as dependent and log of annual equivalised household income as only explanatory variable, providing us with income elasticities. Regression results show that a 1% increase in equivalised income relates to a 0.3% increase of home energy CO_2 emissions, 0.7 for indirect, 0.9 for transport and 0.6 for total emissions.[9]

4.1.4. CO_2 Emissions and Other Household Characteristics

From a policy perspective it is important to ask whether household characteristics other than income may also be associated with emissions since this would have implications for distributional effects from mitigation policies. To examine this question, bivariate associations are examined in a first step. Table 3 provides the percentage of households within different groups having low (equal or below the 25th percentile of emissions) or high CO_2 emissions (equal or above the 75th percentile of emissions) by emission area. If household characteristics were not related to CO_2 emissions, all cells in Table 3 would show a percentage of 25.

Table 3 demonstrates that education plays an important role for high emissions. Only 14% of households in which no household member participated in full time education for more than 11 years are in the highest total emissions quartile, compared to 44% of households in which at least one member took part in full time education for 16 or more years. The results also show that rural households and households with children more likely belong to the highest emission quartile than urban households and households without children. Conversely, households with younger or older reference persons, workless households, households with female reference persons and ethnic minority households are less likely to be in the highest emission quartile. Chi squared tests confirmed that all these household characteristics, apart from ethnicity, are significantly associated with emissions in all four areas at the 1% level.

The results in this table also illustrate that the high likelihood to have high emissions for households with high incomes, high education and with children is mainly driven by high indirect and high transport emissions. Conversely, households with older reference persons, workless households and female headed households are much more likely to have high home energy emissions relative to other types of emissions.

4.2. Conditional Impact of Household Characteristics on CO_2 Emissions

The previous section showed that a range of factors other than income are significantly associated with emissions and that associations vary for different types of emissions. As discussed above, multivariate regression is required to examine how factors such as household size, high education and rural location are associated with emissions once all other factors are held constant. Regression results are reported in Table 4.

As expected, income continues to play an important role for emissions in the full model, particularly for transport emissions: a 1% increase in income still relates to a 0.60% increase of transport emissions, 0.48% of indirect, 0.43% of total, but only 0.19% of home energy emissions.

Even after controlling for income, high education remains significant and positively related to emissions. The education coefficient is highest for transport emissions: households in which at least one person has been in full time education for 16 years or more have on average 17% higher emissions (exp(0.154)) than the control group. This compares to an increase by 11% for indirect, 11% for total, but just 2% for home energy emissions.

Another interesting factor to examine is rural location. Our results show that living in a rural place is still significantly associated with higher emissions even after controlling for income for all three emission areas. The effect is strongest for transport emissions which are 16% higher for rural than for urban households. Table A1 in the Appendix shows the three types of transport emissions separately, indicating that most of the ‘effect’ of rural location on transport emissions derives from motor fuel emissions: rural households have on average as much as 22% higher motor fuel emissions than urban households. In contrast, rural location is not significant for public transport emissions whilst for flight emissions, we find a 5% negative ‘effect’ (significant at $p < 0.1$).[10]

Whilst female headed households have lower transport emissions (the latter being due to lower motor fuel emissions, see Table A1 in the Appendix), they have higher home energy, indirect and total CO_2 emissions than male headed households. Workless households also have higher home energy but lower transport emissions than other households. However, if they do use transport, they have higher public transport emissions than households in employment (Table A1).

The results for the role of age are more complex to interpret because we use three age variables in the model as explained above. Turning points and slope of increase differ for the three emission areas. The conditional transport and indirect emission curves have a deeper inversed u-shape than the home energy curve. For home energy, the turning point lies at around 74 years, whilst the decrease in indirect emissions is estimated to start at around 51 and for transport at around 50 years of age. This indicates that older people are generally less likely to have high total and transport emissions (given the early turning point), whilst their home energy demand stays high up to old age.

Whilst we controlled for ethnicity, no significant differences were found apart from indirect emissions which are significantly lower for households with a ‘non-white’ household head.

5. Discussion

Our results demonstrate that many new and policy relevant insights can be gained if associations between household CO_2 emissions and socio-economic factors are compared across emission domains. Multivariate analysis showed that associations considerably differ across domains. This is relevant for debates about possible fairness implications of mitigation policies as it helps to identify the different ways in which various household groups contribute to emissions. Fairness claims are often made either on the basis of responsibility for emissions (the “polluter pays principle”), the capacity to bear mitigation costs, and potential additional “needs” for emissions that do not arise from someone's own choice but from “structural” circumstances (Baer, 2013; Druckman and Jackson, 2010; Hyams, 2009; Starkey, 2008). Identifying additional emission “needs” has played an important role in questioning the fairness of per capita allocations of tradable emission permits (or rebates from carbon taxes) (Hyams, 2009; Starkey, 2008) but is also important for discussions on carbon taxes as it may indicate unfair tax burdens.[11]

Given that fairness claims are usually expressed in a general way or in relation to just one area of emissions (e.g. Barnes, 2003; DEFRA, 2008; Dresner and Ekins, 2006; Grainger and Kolstad, 2010; Starkey, 2008), insights can be gained by comparing different emission domains. Whilst a discussion about what constitutes emission “needs”, rather than “wants” or “expensive tastes”, goes beyond this paper (but see Hyams,

[9] Households without transport emissions are excluded from the transport regression model, while they are included in Graph 1. This is one explanation why we do not find a coefficient closer to 1.

[10] Table A2 in the Appendix presents a model which controls for the type of dwelling given that they are likely to differ between urban and rural areas. Households living in detached houses have on average 28% higher home energy emissions than households living in purpose built flats and households with oil central heating have on average 13% higher domestic energy emissions than those with main gas central heating (both conditional on the number of bedrooms per dwelling). Once type of dwelling and heating is controlled for, rural households' home energy emissions are no longer significantly different to those in urban areas. This indicates that the higher proportion of detached houses and less access to main gas in rural areas accounts for a significant part of the difference in rural and urban home energy emissions.

[11] For an overview of these different mitigation policies see Büchs et al. (2011).

Table 3
Percentage of households having high or low CO_2 emissions by household characteristics and emission area.

	Low CO_2	High CO_2	Low indirect	High indirect	Low home energy	High home energy	Low transport	High transport
Low income	53.4	6.7	54.0	6.5	39.6	17.0	51.5	7.2
High income	4.4	51.0	4.6	51.2	15.3	34.9	7.0	48.6
Children in hh	12.4	37.3	10.4	38.6	17.2	34.9	16.2	32.6
No children hh	30.2	19.9	31.0	19.4	28.3	20.9	28.7	21.9
Age ≤ 35	22.2	21.1	19.4	23.0	32.9	16.0	21.0	25.8
Age 36 to 64	17.1	33.8	16.8	33.5	20.9	30.9	17.2	32.3
Age ≥ 65	43.7	9.5	46.6	8.7	27.6	19.5	44.4	9.0
Education ≥ 16	9.0	43.9	8.7	43.9	19.0	32.5	8.9	42.9
Education ≤ 11	35.5	13.5	35.8	13.2	30.7	19.1	35.2	15.0
Rural area	19.2	32.9	20.3	31.5	22.4	32.0	19.9	30.4
Urban area	26.8	22.4	26.5	22.9	25.6	22.3	26.5	23.5
Workless hh	50.8	8.1	49.8	8.2	42.2	17.8	48.8	9.1
In employment	21.4	27.4	21.5	27.4	22.6	26.0	21.6	27.3
Female head	34.4	16.8	34.3	17.0	28.9	20.8	34.7	17.1
Male head	19.1	30.2	19.1	30.0	22.5	27.6	18.9	30.0
Not white	26.6	22.8	28.9	19.1	27.3	25.9	22.7	26.8
White	24.9	25.2	24.7	25.5	24.8	24.9	25.2	24.8
Detached	8.7	45.8	10.2	43.9	10.9	43.5	13.6	39.6
Semi-detached	19.7	25.5	20.3	25.1	18.1	26.3	21.4	26.0
Terraced	27.3	17.8	26.4	19.3	25.8	19.6	28.1	19.6
Flat converted	44.0	13.5	42.5	14.8	48.0	8.5	32.0	17.3
Flat purpose	53.3	7.3	51.4	8.0	54.4	7.0	43.3	12.2

Note: Households with low emissions are those at or below the 25th percentile of the emission distribution, whilst households with high emissions are those at or above the 75th percentile. Low income households have equivalised household income equal or below the 25th percentile, high income households are situated at or above the 75th percentile of the equivalised income distribution. Sample size: 24,446 households.

2009; Starkey, 2008), we identify characteristics as indicating potential additional "needs" for emissions if a household group's emissions are significantly higher but their income significantly lower than their comparator group as it indicates reduced capacity to bear mitigation costs. Groups with significantly lower income (based on multivariate regression analysis using the dataset for this paper, see Table A3) include households with reference persons aged 50 and over, as well as single adult, workless and female headed households.

Regarding income we find that even after controlling for other factors, transport emissions rise more steeply with income than all other types of emissions, and least so for home energy emissions. This contrasts to Gough et al.'s (2011) study which did not find significant differences in the association between income and different types of emissions, perhaps because their study used equivalised income in addition to controlling for household size whilst our regressions use disposable income. Whilst taxes on transport or motor fuel emissions are often perceived as unfair because they hit the poorest more (Hammar and Jagers, 2007), this needs to be put in perspective as they are likely to be much less regressive than carbon taxes on domestic energy.

In contrast to Baiocchi et al.'s (2010: 62–3) study we found that high education was still positively associated with all areas of emissions (apart from home energy), and particularly with transport emissions. This suggests that increasing education levels alone is unlikely to tackle household CO_2 emissions. It also suggests that people with high education may engage in higher consumption and travel as part of their identity as suggested in qualitative research (Hurth, 2010). Since households with highly educated members also have significantly higher incomes, one can argue that they bear higher responsibility than their counterparts for shouldering the costs of mitigating climate change.

Our study largely confirmed previous findings regarding associations between emissions and household size: whilst larger households have higher emissions, per capita emissions shrink with rising household size due to economies of scale. However, this is mostly the case for home energy but less so for all other areas of emissions (in particular transport), indicating that larger households would not necessarily 'gain' from tradable per capita permit schemes, contrary to what has been argued elsewhere (Starkey, 2012: 16).

Our study adds new insights regarding the presence of children (Baiocchi et al., 2010; DEFRA, 2008): whilst the first child 'reduces' transport emissions, it 'increases' emissions in all other areas, particularly home energy. This indicates that having children, particularly when they are still young, may reduce mobility but increase needs for heating, washing and the consumption of other goods.[12] Households with children are thus likely to be additionally burdened by carbon taxes on home energy and total emissions and may require further compensation, particularly if they are on low incomes. They might also 'lose' from schemes that allocate equal emission allowances to each adult, requiring additional allowances for children in these emission domains.

Furthermore, the results provide additional evidence that mitigation policies that target transport emissions are fairer than those that target home energy emissions when we focus on older, workless or female-headed households: even after controlling for income, household size and other factors, these types of households have significantly higher home energy emissions than their counterparts. This is likely to be related to them spending larger amounts of time at home and thus have greater "needs" for heating. In addition, older people may be more likely to "feel the cold" and thus require warmer indoor temperatures. Since all of these groups also have significantly lower income than their counterparts, one could argue that they would be unjustly burdened by taxes on home energy emissions. Conversely, these types of households have significantly lower transport emissions compared to their counterparts, even after controlling for other factors. This is likely to be related to reduced mobility or capacity to pay for travel. It is thus likely that they would be less burdened by taxes on transport emissions or would 'gain' more from equal per capita permit or rebate schemes in this area.

Findings also demonstrate that rural location is associated with higher emissions in all areas, even after controlling for income. The

[12] If we had included other GHG emissions, indirect emissions may have been even higher for households with children, given the inelastic demand for food.

Table 4
OLS regression results of the natural logarithm of CO_2 emission in tonnes by emission area.

	Total CO_2 emissions	Home energy emissions	Indirect emissions	Transport emissions
Ln income	0.432***	0.187***	0.481***	0.598***
	(0.00733)	(0.00869)	(0.00792)	(0.0163)
Adult2	0.267***	0.203***	0.278***	0.322***
	(0.00849)	(0.0109)	(0.00898)	(0.0198)
Adult3	0.111***	0.108***	0.115***	0.105***
	(0.00999)	(0.0135)	(0.0111)	(0.0216)
Adult4	0.0736***	0.0542**	0.0694***	0.104***
	(0.0199)	(0.0247)	(0.0223)	(0.0396)
Adult5 +	0.110***	0.168***	0.113**	0.0423
	(0.0411)	(0.0508)	(0.0474)	(0.0837)
Child1	0.0966***	0.168***	0.126***	−0.0637***
	(0.00905)	(0.0122)	(0.00982)	(0.0198)
Child2	0.0727***	0.0867***	0.0794***	0.0521**
	(0.0108)	(0.0140)	(0.0117)	(0.0246)
Child3 +	0.0605***	0.110***	0.0537***	0.00224
	(0.0153)	(0.0202)	(0.0161)	(0.0348)
Age	0.0203***	0.0216***	0.0166***	0.0327***
	(0.00153)	(0.00199)	(0.00168)	(0.00371)
$Age^2/100$	−0.0188***	−0.0149***	−0.0160***	−0.0335***
	(0.00154)	(0.00200)	(0.00168)	(0.00381)
Age top coded (80 +)	−0.0877***	0.0331	−0.138***	−0.198***
	(0.0164)	(0.0210)	(0.0176)	(0.0442)
Female headed households	0.0256***	0.0524***	0.0324***	−0.0881***
	(0.00668)	(0.00848)	(0.00734)	(0.0151)
Education 12–15	0.0734***	0.0306***	0.0825***	0.0972***
	(0.00780)	(0.00997)	(0.00830)	(0.0176)
Education 16 +	0.0996***	0.0190*	0.103***	0.154***
	(0.00879)	(0.0115)	(0.00965)	(0.0197)
Missing education	−0.0390***	−0.0217	−0.0427***	−0.0906***
	(0.0139)	(0.0172)	(0.0145)	(0.0327)
Workless households		0.0531***	−0.0143	−0.169***
		(0.0145)	(0.0127)	(0.0298)
Not ‘white’	−0.00918	−0.0104	−0.162***	0.0720**
	(0.0119)	(0.0165)	(0.0152)	(0.0294)
	(0.0140)			
Rural location	0.0880***	0.0585***	0.0693***	0.150***
	(0.00804)	(0.0110)	(0.00884)	(0.0149)
Missing rural	0.178***	0.207***	0.158***	0.0954***
	(0.0121)	(0.0203)	(0.0116)	(0.0222)
Constant	−0.578***	−0.575***	−1.468***	−3.472***
	(0.0484)	(0.0615)	(0.0531)	(0.112)
Observations	21,892	21,892	21,892	18,729
R-squared	0.584	0.196	0.592	0.353
Adj. R-squared	0.583	0.195	0.591	0.352

Note: Results are weighted and standard errors presented in parentheses take clustering within primary sampling units into account. Highest and lowest percentiles of income and emission households were excluded from the analysis, as well as households with zero home energy and transport emissions.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

association between rural location and transport emissions is higher than the one for home energy emissions, in fact, rural location is no longer significant for home energy emissions once dwelling and heating type are controlled for, indicating that the greater occurrence of detached houses and oil central heating in rural places accounts for much of the variation in emissions. It still indicates that households in rural places are likely to be burdened more by carbon taxes in all areas than their urban counterparts. Whether or not living in a rural place can be considered as an “expensive taste” or whether it comes down to “brute luck” (Dworkin, 1981a,b; Starkey, 2008) is still a contested matter. Since households in rural places and those living in detached houses or those having oil central heating all have significantly higher incomes than their counterparts, we'd be inclined to argue that higher mitigation burdens are less troublesome from a fairness perspective than for some other areas that we discussed above. However, poor rural households will still be hit hard by taxes on transport emissions and complementary policies such as greater investments in public transport or insulation schemes in rural areas may further reduce rural emissions.

Section 2 discussed a range of data limitations related to this study. Based on this discussion, we expect that our study slightly overestimates emissions by high income households and that standard errors in the regression analysis are likely to be inflated because of the infrequency of purchase problem. Due to a lack of alternative datasets, we are not able to compare our results to ‘true’ estimates of household CO_2 emissions and their distribution (like all other expenditure-based studies on household emissions) but we analyse in more detail how different methods of estimation affect distributional analysis within the bounds facing research in this area (Büchs and Schnepf, 2013). Due to the way the LCF/EFS is organised, we were also unable to examine these associations at the individual level, which would be particularly relevant for studies on potential distributional implications of per capita emission permit schemes. Further investments to improve data quality are thus required to take research in this area forward.

6. Conclusion

This paper addressed a gap in the literature by comparing the association between household characteristics and carbon dioxide emission across four emission areas: home energy, indirect emissions, transport and total CO_2 emissions. Our results show that many household characteristics still remain significant once income and household size are controlled for. This means that distributional implications of mitigation policies that aim to create financial dis/incentives are likely to differ not only across income groups but also along other household characteristics. Furthermore, these associations vary across emission domains, a topic highly relevant from a policy perspective: policies targeting a specific emission area or total emissions will affect household groups in different ways. More specifically, we found that whilst carbon taxes on home energy emissions are not only likely to be much more regressive than taxes on transport (or total) emissions, they would also put unfair burdens on low income households with greater home energy requirements, including households with children and those with older reference persons as well as single, workless and female headed households (after controlling for other factors). These kinds of households may also still ‘lose’ out from schemes that allocate equal per capita allowances for home energy emissions. The opposite applies to schemes that target transport emissions which are more likely to put the main burdens on those that contribute most to these kinds of emissions but also have greater resources to bear mitigation costs. However, further research on distributional implications is required to confirm these hypotheses.

These findings also imply that claims regarding the fairness (or otherwise) of mitigation policies need to distinguish not only between different policy instruments (e.g. taxes vs. per capita trading schemes) but also between different areas of emissions. This is highly relevant because only if it is known where unfair burdens are likely to originate can effective complementary policies be formulated. Complementary policies may include financial compensations or further infrastructure investments to facilitate greater use of public transport and improve the thermal efficiency of the housing stock.

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Appendix A

Table A1
OLS regression of the natural logarithm of transport CO_2 emissions in tonnes by type of transport.

	Motor fuel emissions	Public transport emissions	Flight emissions
Ln income	0.308***	0.525***	0.308***
	(0.0141)	(0.0297)	(0.0269)
Adult2	0.150***	0.170***	0.411***
	(0.0167)	(0.0350)	(0.0317)
Adult3	0.136***	−0.0778*	−0.0284
	(0.0213)	(0.0440)	(0.0409)
Adult4	0.142***	0.110	−0.0871
	(0.0378)	(0.0815)	(0.0768)
Adult5+	0.0937	−0.155	0.149
	(0.0974)	(0.164)	(0.151)
Child1	0.00485	−0.167***	0.0427
	(0.0191)	(0.0380)	(0.0361)
Child2	0.00853	−0.0164	0.139***
	(0.0223)	(0.0469)	(0.0471)
Child3+	0.0973***	−0.0611	0.0130
	(0.0301)	(0.0687)	(0.0699)
Age	0.0192***	−0.00899	0.0127**
	(0.00313)	(0.00639)	(0.00635)
Age2/100	−0.0231***	0.0114*	−0.0103
	(0.00317)	(0.00654)	(0.00648)
Age top coded (80+)	−0.0230	−0.150*	−0.216**
	(0.0341)	(0.0770)	(0.0848)
Female headed households	−0.0701***	0.0437	−0.0370
	(0.0136)	(0.0293)	(0.0251)
Education 12–15	0.0421***	−0.0847**	0.00568
	(0.0154)	(0.0350)	(0.0313)
Education 16+	0.0645***	−0.0669*	0.109***
	(0.0174)	(0.0382)	(0.0339)
Missing education	−0.0726***	−0.0305	−0.0526
	(0.0256)	(0.0604)	(0.0632)
Workless households	−0.0526**	0.150***	0.158***
	(0.0250)	(0.0473)	(0.0549)
Not 'white'	−0.0612**	0.165***	0.604***
	(0.0298)	(0.0487)	(0.0408)
Rural location	0.196***	0.00976	−0.0515*
	(0.0141)	(0.0356)	(0.0292)
Missing rural	0.195***	−0.0221	−0.448***
	(0.0204)	(0.0433)	(0.0436)
Constant	−1.411***	−3.305***	−2.282***
	(0.0957)	(0.207)	(0.192)
Observations	14,736	10,478	9,028
R-squared	0.212	0.073	0.130
Adj. R-squared	0.211	0.071	0.128

Note to Table 4 applies in the same way.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table A2
OLS regression of the natural logarithm of total and home energy CO_2 emissions in tonnes, extended model.

	Total CO_2 emissions	Home energy emissions
Ln income	0.358***	0.103***
	(0.00722)	(0.00853)
Female headed households	0.0304***	0.0539***
	(0.00633)	(0.00809)
Education 12–15	0.0500***	0.00792
	(0.00741)	(0.00954)
Education 16+	0.0697***	−0.00992
	(0.00840)	(0.0109)
Missing education	−0.0350***	−0.0155
	(0.0125)	(0.0158)
Workless households	−0.00715	0.0474***
	(0.0112)	(0.0142)
Not 'white'	−0.0362***	0.0328**
	(0.0128)	(0.0151)
Rural location	0.0435***	0.00120
	(0.00778)	(0.0103)
Missing rural	0.0366***	0.0348
	(0.0177)	(0.0304)
Own outright	0.122***	0.0498***
	(0.00921)	(0.0118)
Own with mortgage	0.0998***	0.0451***
	(0.00835)	(0.0112)
Missing own	0.113***	0.184***
	(0.0234)	(0.0315)
Detached house	0.154***	0.244***
	(0.0134)	(0.0169)
Semi-detached house	0.0782***	0.171***
	(0.0119)	(0.0152)
Terraced house	0.0365***	0.132***
	(0.0115)	(0.0146)
Converted flat	0.0356	0.0687***
	(0.0217)	(0.0248)
Central heating electricity	−0.159***	−0.193***
	(0.0126)	(0.0159)
Central heating oil	0.109***	0.120***
	(0.0169)	(0.0300)
Other heating	−0.116***	−0.133***
	(0.0136)	(0.0192)
Number bedroom	0.0670***	0.108***
	(0.00416)	(0.00537)
Constant	−0.0943**	−0.103*
	(0.0476)	(0.0614)
Observations	21,892	21,892
R-squared	0.626	0.275
Adj. R-squared	0.625	0.274

Note to Table 4 applies in the same way. Results presented are conditional on age and household size. 'Own outright' means that the household owns the property without mortgage, 'missing own' denotes that information is not available, the control household is renting the property. The control household for type of dwelling is a household in a purpose built flat and the control household for the heating variables has central gas heating.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table A3
OLS regression of log disposable household income.

Variables	(1) ln income	(2) ln income	(3) ln income
Adult2	0.761***	0.541***	0.503***
	(0.00963)	(0.00860)	(0.00863)
Adult3	0.264***	0.199***	0.203***
	(0.0134)	(0.0116)	(0.0114)
Adult4	0.192***	0.119***	0.111***
	(0.0250)	(0.0225)	(0.0221)
Adult5+	0.162***	0.198***	0.196***
	(0.0464)	(0.0426)	(0.0415)
Child1	0.0922***	−0.00927	−0.0229**
	(0.0119)	(0.0106)	(0.0104)
Child2	0.130***	0.0809***	0.0634***
	(0.0149)	(0.0120)	(0.0117)
Child3+	−0.0781***	0.0548***	0.0560***
	(0.0196)	(0.0161)	(0.0156)
Age		0.0464***	0.0415***
		(0.00163)	(0.00162)
Age2/100		−0.0518***	−0.0485***
		(0.00163)	(0.00161)
Age top coded (80+)		0.131***	0.128***
		(0.0155)	(0.0153)
Female headed households		−0.0717***	−0.0647***
		(0.00737)	(0.00731)
Education 12–15		0.185***	0.163***
		(0.00851)	(0.00839)
Education 16+		0.445***	0.412***
		(0.0101)	(0.0102)
Missing education		0.124***	0.120***
		(0.0132)	(0.0132)

Table A3 (*continued*)

Variables	(1) ln income	(2) ln income	(3) ln income
Workless households		−0.695***	−0.683***
		(0.0123)	(0.0121)
Not 'white'		−0.233***	−0.194***
		(0.0157)	(0.0154)
Rural location		0.0478***	0.0103
		(0.00935)	(0.00941)
Missing rural		−0.100***	−0.126***
		(0.0105)	(0.0168)
Detached			0.261***
			(0.0129)
Detached house			0.0968***
			(0.0112)
Semi-detached house			0.0419***
			(0.0112)
Terraced house			−0.00825
			(0.0247)
Converted flat			−0.0322**
			(0.0137)
Central heating electricity			−0.0187
			(0.0171)
Central heating oil			−0.0960***
			(0.0136)
Constant	5.431***	4.697***	4.813***
	(0.00864)	(0.0397)	(0.0398)
Observations	23,966	23,966	23,966
R-squared	0.358	0.583	0.599

Note: Results are weighted and standard errors presented in parentheses take clustering within primary sampling units into account. Highest and lowest percentiles of the income distribution are excluded.

*** $p < 0.01$.

** $p < 0.05$.

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