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Whose house is on fire? Identifying socio-demographic and housing characteristics driving differences in the UK household CO_2 emissions

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Abstract

Achieving the goals outlined in the Paris agreement requires significant reductions in national carbon emissions. To fairly distribute the burden of mitigation, a detailed understanding of the social realities of emitters is needed.This sector-specific and sub-regional study was carried out to examine housing energy emissions in the UK and to obtain detailed information about the socioeconomic profiles of emitters. To account for the embedded nature of individuals in social groups and the social context, we applied the conceptual approach of socio-metabolic class theory. This theory posits that carbon emissions and the level of human agency are unequally distributed within the society. As a first attempt, the theory is operationalised using CO_2 emission quartiles as central units of descriptive analysis. We find significant differences between these classes, and particularly in terms of cohabitation type, home ownership, and social vulnerability factors. Complementary results from a multivariate regression analysis indicate that the main determinants of housing carbon emissions are living space, household size, and the use of heating oil. We conclude by describing the contribution of our findings to socio-metabolic class theory, outlining future directions for research at the intersection of social class and ecology, and policy implications related to a low-carbon transition.

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1. Introduction

Scenarios that limit global warming to 1.5 °C describe strong transformations of the energy system, which require the decarbonisation of energy production as well as a significant reduction in energy consumption. Current research reveals that, despite population growth, global energy use in 2050 could be reduced to levels seen in the 1960s 'through drastic changes to contemporary human society and the global economy', providing an optimistic outlook [1]. Countries and regions around the world display large levels of inequality, as do European citizens, both in terms of their contributions to climate change and their ability to mitigate and adapt. Reductions in greenhouse gas emissions from high-emitting individuals are needed to avoid the Planetary Boundary (PB) [2] climate change from being pushed still further into unprecedented territory. Different emission patterns are directly related to income [3] and affected by the place of abode, type of occupation, and possessions. Thus, these patterns are related to social class and status [4]. For instance, the top ten percent of (consumer) expenditure groups account for more than one-third of individual global GHG emissions [5]. In the European Union, emissions cuts that have been made since 1990 have been achieved principally by lower- and middle-income EU citizens, while the total emissions from the richest ten percent of the population have actually grown [6].

However, the dominant global human-environment interaction modeling approaches [7, 8] use world-region and national CO_2 emission averages; thus, they neglect the existing classes. In addition, the factors of the inequality and agency of different citizen groups in lowering their CO_2 emissions are masked. Agency refers to the ability of an individual to shape their life circumstances, future choices, and action plans [4]. Understanding different levels of agency in conjunction with emission hot spots, where high amounts of human-induced emissions occur, is fundamental to identifying levers of low-carbon transitions and to deriving effective policy solutions.

The European Green Deal is a set of policy initiatives intended to transform the EU into a fair and prosperous society with a resource-efficient and competitive economy that reaches net-zero emissions of greenhouse gases by 2050 [9, 10]. As a consequence of Brexit, the UK has withdrawn from EU agreements; however, it is obliged to adhere to the commitments it made under the Paris Agreement and to develop its own national strategy. The Climate Change Committee, an independent non-departmental public body, recommends that the UK demonstrate 'a world-leading' level of commitment and has proposed a Sixth Carbon Budget. This requires a reduction in UK greenhouse gas emissions of 78 percent by 2035 as compared to 1990 and a 63 percent reduction as compared to 2019 [11]. The "Ten Point Plan for a Green Industrial Revolution"[12] should accelerate movements toward a net-zero society, placing a focus, inter alia, on greener buildings and green public transport. These policy plans target diverse areas, ranging from energy production and supply to households and individual behavior and consumption patterns. In the UK, Moll et al. [13] estimate that 70 to 80 percent of national energy use is generated by household activities. Nonetheless, the discourse tends to be dominated by attempts to green existing structures by using technological innovations rather than by challenging different realities of life and encouraging people to transform their lifestyles by reducing their energy and resource consumption.

Previous research carried out in industrialised countries highlights the strong within-country differences regarding lifestyle CO_2 emissions. For instance, in Germany, the energy consumption in the lowest- and highest-emitting households can differ by a factor of ten [14]. Inequalities in household emissions, however, are overlooked by most existing approaches used to model human-environment interactions, including Integrated Assessment Models (IAMs). These tend to be based on the simplifying assumption that the consumption of natural resources and waste emissions is evenly distributed across the human population or within specific regions. National level indicators such as the GDP are applied to represent global inequalities between countries. A straightforward improvement over the use of national averages would be to consider household level indicators. However, the inclusion of a large number of households per country would increase the complexity of such models, challenging the capacity of modern computers. Furthermore, the interactions among different households are difficult to model.

Social class theory divides societies based on different attributes into groups to shed light on constellations of actors with common interests, whereby their interaction may result in societal conflicts (for a most recent application, see [15]). Insights from class theory could provide a framework of intermediate complexity that allows researchers to take a more refined approach than that of national averages, but that is not as complex as the approach of considering each household individually.

In this study, we propose a first step towards an operationalisation of the concept of 'socio-metabolic classes' by Otto et al. [4] and use it to describe energy and resource use patterns in the UK housing sector. Furthermore, we analyze determinants of household carbon emission (heating and electricity). Using a cross-section (wave 9) of the UK 'Understanding Society' household panel study, we identified distinct carbon emission quartiles and associated demographic, socioeconomic, and household characteristics to obtain 'household emission profiles'. In this study, we asked the following three questions: Is the method of quartile analysis a suitable method to operationalise socio-metabolic classes? Can this method be used to derive emission profiles? What are the drivers of carbon emissions in the housing sector in the UK?

The paper is structured as follows: Section 2 positions this study within the umbrella framework of the Planetary Boundaries and Earth System Targets. We review the literature on social metabolism theory, placing an emphasis on research on strong disparities in individual and household CO_2 emissions. We then introduce the theoretical foundation of this work, namely, the socio-metabolic class theory. In section 3, the 'Understanding Society' data set and the methods underlying the quantitative analysis are introduced. This includes a detailed regression model that was applied to identify important drivers of household emission, which we address in section 4. Section 5 introduces the analytical tool of emission quartiles, which we used to operationalise socio-metabolic classes, as well as household emission profiles. Finally, section 6 describes the limitations of the methodological procedure and future research implications as well as the relation of our work to the Planetary Boundaries.

2. Conceptualizing inequalities in human energy use

2.1. Carbon budgets, allocation approaches, equity and fairness

The widely used Planetary Boundaries (PB) framework and its latest reincarnation [16] as the Earth System targets [17] were developed to define a safe (and just) operating space for humanity [18, 2]. To be operational, however, this must be 'apportioned and assigned to the actor or activity that is being studied (i.e. downscaling)', for example, to the level of 'countries, companies, industry sectors, persons or products' [19]. Thus, PBs are translated into fair shares of Earth's safe operating space on a national level [20]. This translation increases their applicability and, therefore, the policy relevance [21]. Equity considerations are included when deriving national carbon budgets [22], for example, and attempts are made to fairly assign the remaining resource budgets but without reference to a globally accepted principle [21]. Different allocation approaches can be found [23, 24, 25, 26]. Equal per capita shares (apportioning the remaining permissible carbon budget according to population) are particularly significant regarding this work [21]. The equal national per capita allocation of the remaining global carbon budget sets a limit for future individual emissions, limiting the emissions scope of individuals. In the context of climate justice and historical emissions, however, 'the developing world should receive higher per capita emission rights than the developed world (...) which is justified by the fact that the latter already owns a larger share of benefits associated with emission generating activities because of its past record of industrialisation' [27]. In the EU, per capita CO_2 emissions should range prospectively between -3.9 and 1.4 t CO_2/cap/yr based on emission reduction targets of the Paris Agreement [21], including negative emissions. This work demonstrates that this boundary is exceeded by the housing emissions alone in the UK.

However, nations consist of emitting individuals who make different energy and resource-use decisions to meet their needs. These individuals can be divided into groups that have competing interests based on their resource-use patterns. Several studies have pointed out the large current carbon inequalities [3, 28, 29, 5, 30]. The factors responsible for these inequalities must be clearly understood to resolve them and to make necessary policy adjustments.

2.2. Distinct emission patterns and socio-metabolic class theory

Distinct CO_2 emission patterns are related to lifestyles and frequently associated with income disparities. An Oxfam study [6] concludes that, in 2015, the richest ten percent of the population was accountable for more than 50 percent of individual CO_2 emissions globally. Rich and super-rich households are characterized by extremely high levels of household emissions, estimated at about 130 tCO_2 [28], which differ greatly from the global average of 4.5 tCO_2 per capita (in 2018) [31]. In the EU, the richest 10 percent segment was responsible for over a quarter (27 percent) of emissions, the same amount as the poorest half of the EU population [29]. Another study considering sub-national data found that the EU within-country differences in per capita GHG and land-based biodiversity footprints could reach factors of 3.0 to 3.5 [32], showing fairly smaller, but noteworthy differences. However, the reported inequality is thus quite low because the regional comparison does not consider sufficiently different relevant aspects like income levels or household types. Although EU-wide emissions have decreased in recent decades [33] (e.g. due to efficiency gains), the decrease has only been recorded among poorer citizens [29]. Importantly, many national and global assessments that refer to the Planetary Boundaries report that a good life within the limits of the planet can only be achieved by reducing the affluence of the rich countries [34, 35], an action that is evidently aligned with restricting over-consumption in Northern countries [16, 36].

Previous scientific studies have filtered out high-emitting individuals or households, analyzing them primarily on the basis of socio-demographic factors such as income [37, 38, 39, 40, 41, 42, 43, 5], age, gender, education [37, 39, 44, 45, 46], household size [37, 47, 39, 44, 48, 49], urban rural typology [50, 51, 46, 48, 42, 52], or climatic conditions [48, 42, 53, 52]. Recently, the perspective has been widened by investigating the effects of time-use and urban form [54], health status [55], well-being [56], happiness [57], and more routine forms of behavior [58, 59].

Above all, the influence of income on housing emissions has been heavily discussed. On the one hand, the total energy or carbon footprint per capita grows as a function of income [46, 60]. Especially luxury consumption (energy-intensive consumption categories) has a high income elasticity [3]. On the other hand, direct home energy emissions are only weakly correlated with income [61, 39, 62], which led Oswald et al. [3] to the conclusion that housing energy is a basic good that is income-inelastic.

To understand social processes and conflicts, it is helpful to group individuals of societies into social classes. Most social differentiation theories apply either the Marxist or the Weberian approach, which differentiate classes on the basis of inequalities in ownership and income [4]. Schuster and Otto [14] applied Pierre Bourdieu's capital theory to identify ecological impacts in terms of per capita emissions. To provide a theoretical background for our research question, we applied socio-metabolic class theory described by Otto et al. [4] to disentangle ecological inequalities and responsibilities. In this study, we define classes based on emissions, i.e. on a dimension of environmental impacts. Social metabolism refers to energy and material flows in human societies and to how societies exchange energy and materials with the environment [63, 64]. Individuals and social groups, including households, regions, and countries, consume energy and materials in highly unequal ways [65]. To reflect these differences, Otto et al. [4] suggested dividing societies into six socio-metabolic classes based on individuals' metabolic profiles, which are related to how they use resources and energy to maintain their lifestyles, rather than on their wealth, work condition, or social status [64]. In this paper, the classes are defined as the socio-metabolic underclass, energy-poor class, lower class, middle class, upper class and super-rich class. Additionally, a level of human agency is assigned to the classes to delineate ways to reduce their ecological impact. Since the super-rich class is not recorded in the data set, and the socio-metabolic underclass cannot be expected to be found in industrialised nations, we focused on the remaining four classes. We operationalised these by assigning households to four emission quartiles. The advantages and limitations of this approach are described in sections 3.4 and 6. Based on this operationalisation, we described household emission profiles which summarize the socio-demographic and housing characteristics of the socio-metabolic classes. In this study, we focused specifically on the emissions from the housing sector.

Our results lead us to question how much citizens can influence their own emissions or whether the observed differences are due to structural factors. Considering the previously mentioned fair allocation of the remaining resource budgets and the goal to reduce the excessive shares that individual consumption contributes to national emissions, the proposed classification and analysis can help stakeholders to develop targeted policies.

3. Data and Methods

3.1. UKHLS data set

The UK Household Longitudinal Study (UKHLS) is a large and representative multi-topic survey that covers a range of social, economic, and behavioral factors at the individual and household levels in all four UK countries. Both the sample size and the number of exploitable variables are remarkable, opening up many possibilities for research - and even more so if housing CO_2 emissions are added to the data set, which can easily be done with the open source code provided with this article (see Code Availability Statement). The present study was designed as an initial attempt to operationalise socio-metabolic classes. Therefore, we analyzed commonly studied household characteristics, including locality, demographic characteristics, socio-economic characteristics, and family background of the households. A recently taken cross-section of the data set, namely, the sampling Wave 9 (2017-19) with a sample size of 20,047 households was selected. The complex survey design required the application of the cross-sectional sampling weights provided for UKHLS to estimate standard errors correctly. Each sample was given a carefully constructed weighting factor based on its characteristics, ensuring that the weighted statistics of the data set would be representative of the population at the national level. These weights must be taken into account for all descriptive and inferential statistics and when conducting an analysis of a subset of the data (e.g., on all residents of Northern Ireland).

3.2. Estimating housing CO_2 emissions based on expenditure data

CO_2 footprints may be either based on production emissions, which are allocated to the nation (or household) that produces them, or on consumption emissions, which are allocated to the entity that consumes a product or service, wherever these emissions arise along the supply chain in the world [66]. Here, we study emissions associated with household energy consumption, some of which are directly produced (burning of heating fuels) and some of which arise elsewhere (electricity consumption).

CO_2 emissions due to energy consumption are not reported directly in the survey; thus, they must be estimated. Figure 1 outlines our approach for estimating CO_2 emissions, which is inspired by Buchs and Schnepf [39] and Buchs et al. [67]. We

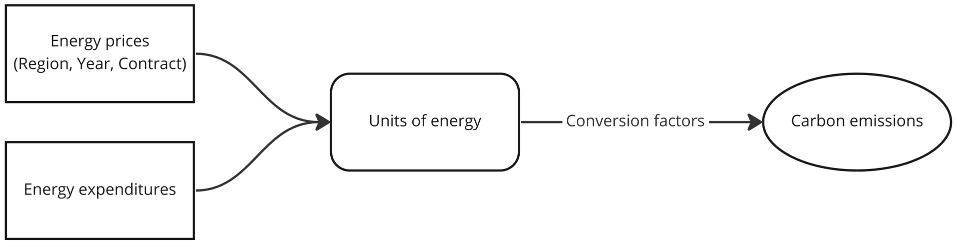

Figure 1: Schematic view of how the CO_2 emissions were estimated: The household expenditures were divided by specific energy prices to compute how much units of energy were consumed. These units were multiplied by conversion factors from official sources to obtain the household CO_2 emissions.

first converted the energy expenditure into units of consumption using price data for each energy source and for each survey year, government region, and payment method. The resulting units of energy in kWh for gas and electricity and litres for oil were subsequently converted into kg CO_2 of emission by applying an energy source-specific conversion factor. Applied fuel prices and CO_2 conversion factors are provided by the UK's Department of Energy and Climate Change (DECC)[1]. Gas prices for Northern Ireland (NI) are available from the Annual Transparency Report of Northern Ireland's Utility Regulator (UREGNI) [68].

We applied national average conversion factors to transform consumption metrics into CO_2 emissions. The approach can be developed further by considering more energy-related variables that were not available for this study due to data limitations. These variables could include information about the use of renewable energy, insulation, type of house, and consumption practices or routines [69]. For example, if a household purchases renewable energy, its electricity-based emissions should be considered as zero. This is a shortcoming of the data set and will be addressed in parts in the upcoming sampling wave 10.

One unique aspect of the data set is that electricity and gas expenditure are combined for households that purchase gas and electricity from the same supplier (i.e., the "dual-fuel deal"). For these households, a direct conversion of expenditure to units of consumption was not feasible, since the ratio of electricity to gas expenditure is unknown. To incorporate these samples into our analysis, we impute the ratio with predictive mean matching, taking into account the pre-computed electricity-to-

[1]These tables give average prices at the national level. Large differences between the exact prices each household pays are to be expected, depending on the exact contract and energy supplier of each household, but such information is not included in the data set.

gas ratio of households with separate bills and a range of other variables, such as the household income and use of heating oil[2]. Notably, more than half (≈53.9 per cent) of the studied households used dual fuel; thus, the imputation was carried out for a large fraction of the data set. A comparison between our analytical results and the results obtained from a simple mean imputation of the electricity-to-gas ratio (conditioned on the use of heating oil) did not reveal substantive differences, indicating that the results are robust with respect to the imputation method. This outcome is not surprising, because the variance in the electricity-to-gas ratio is small compared to the variance in the electricity and gas expenditures (cf. Fig. A.4 in the Appendix). Thus, while individual households may end up with very different total CO_2 emissions, the distribution of emissions in the sample population apparently does not change much[3].

UKHLS contains samples with missing variables. Missing information for the survey year, government region, or payment method of a household made it difficult to select energy prices from the respective price tables. Therefore, a mean imputation was applied, substituting the mean prices other households paid in the same government region, in the same year, or with the same payment method. In total, the energy prices of 524 households were imputed in that way.

While the original data set is representative for the UK, we restricted our analysis to a suitable subset for which all required variables were available. It was necessary to exclude households that had incomplete energy expenditure data or that relied on other fuels such as wood, was inevitable, since in these cases the CO_2 emissions could not be reliably estimated. Furthermore, we disregarded all households in the top and bottom half percentiles of the estimated carbon emissions (top 99.5% and bottom 0.5%, respectively) to regularize the data, thereby removing households that had either no or implausibly large carbon emissions (which may be due to misreporting).

The remaining (survey-weighted) subset contains 15,345 out of 20,047 households (13,109 out of 16,808 regarding survey weights). Summary statistics for the used and dropped subsets in comparison to the complete population are found in the Appendix A.5.

[2]For detailed information, see the source code. For the imputation the R package `mice`[70] was used.

[3]Omitting these households from the analysis as done in [67] would introduce other types of inaccuracies, because the groups of households with and without the dual-fuel deal differ significantly (e.g., with respect to mean household income). For more detailed information about households with the dual fuel deal, please see Appendix A.3.

3.3. Statistical methods applied

We fitted (generalised) linear models with model-robust, design-based standard errors using the `svyglm` function [71]. By assuming a Gaussian error distribution and an identity link function, this approach corresponds to ordinary least squares regression for survey data. We cautiously applied a shift and log-transformation to the variable net monthly household income to consider skewed data. By checking for multicollinearity by using the variance inflation factor (VIF), we assessed how much the variance of an estimated regression coefficient increased when the predictors were correlated [72].

Equivalised income was computed by applying a conversion factor according to a modified OECD scale. This assigns a weight of 1 to the first adult (person 14 years of age or older) in the household, a weight of 0.5 to each additional adult, and a weight of 0.3 to each child (person 0-13 years of age). It is a measure of household income that takes into account the differences in a household's size and composition; thus, it is equivalised or made equivalent for all household sizes and compositions.

Descriptive and inferential statistics at the household level were computed with the package `survey` [71] for the programming language `R` [73], which takes the complex survey design into account.

3.4. Operationalizing socio-metabolic classes and household emission profiles

Socio-metabolic class theory describes six classes that differ in terms of their CO_2 emissions and their agency. Of these classes, the underclass is not expected to be present in post-industrialised countries like the UK, and the super-rich class is not recorded in the data set. We focused on the remaining four socio-metabolic classes and operationalised them by assigning households to emission quartiles. The quartile analysis method [74] is a method used to form four groups for a data set. Between the minimum and maximum values of the data set, the quartiles divide a set of observations into four sections, each representing 25% of the observations. Carbon emission quartiles are based on estimated household energy-use carbon emissions. These can be understood as clusters of households with similar patterns of resource and energy use. Thus, our data set is partitioned into four equally sized groups with increasing emissions, and each group corresponds to a socio-metabolic class. Figure 2 shows how we operationalised the socio-metabolic classes and outlines some important attributes of the corresponding emission profiles, which are described in detail in the following sections. The differences between the middle and higher class are less pronounced; therefore, we highlight the distinctions between the lower and top class to emphasize key patterns of CO_2 emissions.

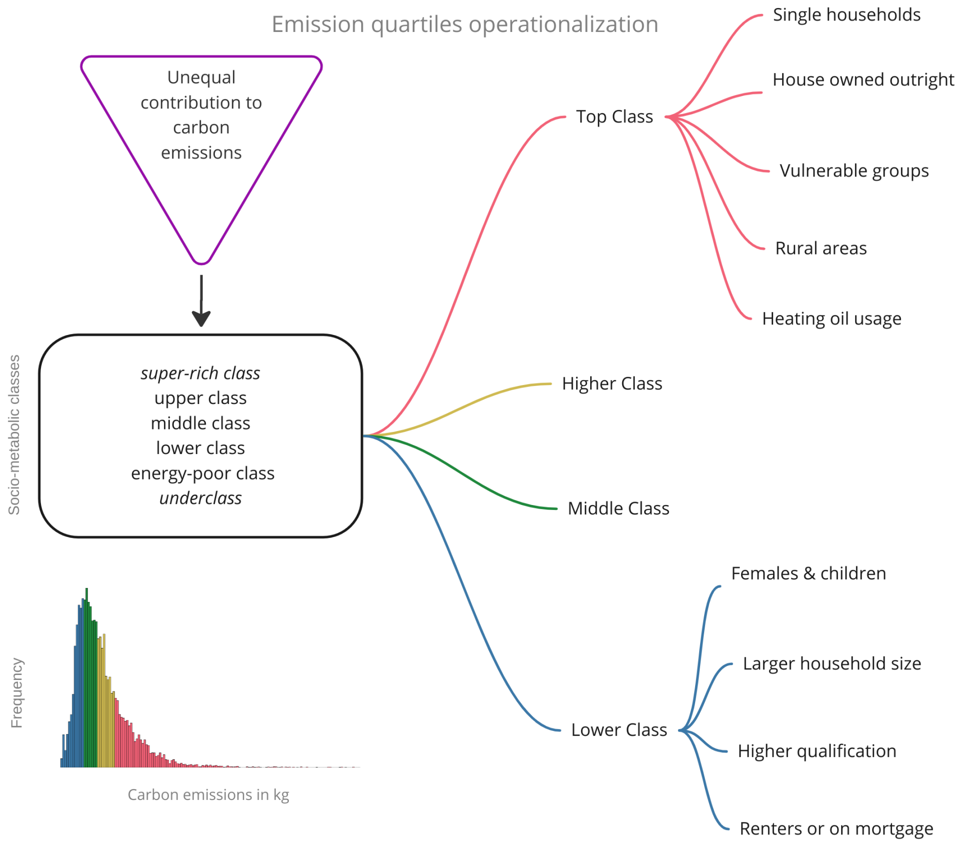

Figure 2: Overview of the research approach: The six socio-metabolic classes with unequal CO_2 emissions are operationalised as CO_2 emission quartiles. Their characteristics can be summarized in a corresponding emission profile (examples of the lower and top class shown). The quartile range of emissions that belong to the classes is plotted in the corresponding color.

Clustering-based approaches [75, 14] are a practical alternative method that can be used to capture differences between groups. However, the relative cluster size and even the number of clusters depends on both the algorithm and the specific data set these approaches are applied to. Emission-based quartiles are defined regardless of a specific data set. This ensures that the selected approach taken to operationalise socio-metabolic classes can easily be transferred between cross-sections of a panel study and distinct data sets, which may differ in terms of methodology or sampling region. The approach developed to operationalise these socio-metabolic classes in this study is a simple initial attempt; limitations of this approach are addressed in the discussion in Section 6.

We refer to the quartiles as lower, medium, high, and top emission quartiles. The basic group characteristics are described in section 5. These then serve as a basis for summarizing their main socio-demographic and housing attributes in so-called 'household emission profiles', see Section 5.2. To account for the large influence of household size (number of persons) on household emissions, we defined the emission quartiles in two different ways, i.e. based on the total household emissions or on average per capita emissions in a household. The emission profiles resulting from these competing definitions align for some variables and differ for others, providing complementary perspectives of the social circumstances of emitters. Whether the household or the per capita level accounting is preferred depends on the research question and on normative considerations of equity and justice

3.5. Variables studied as potential determinants of carbon emissions

The explanatory variables for the emission profiles, linear models, and descriptive statistics were selected on the basis of an extensive literature review. First, we examine traditional socio-demographic factors of households that have been found to have an important impact on CO_2 emissions, such as gender and education. We further investigated household size and composition. Additionally, we included important determinants in the context of time use, namely, the number of people unemployed in a household, pensioners, and members with long-standing illnesses or disabilities. At the second level, we considered housing characteristics, i.e. rented or owned, region, urban/rural, and heating technology. These determinants are considered to be significantly associated with carbon emissions in the literature. The inclusion of other variables linked to heating and electricity would be desirable, e.g. the use of and access to green energy, but are not provided in the used data set. Prospectively, the UKHLS data sets will allow researchers to conduct more detailed studies, for example, by addressing the relationship between carbon footprints and well-being, climatic conditions, or urban form measures. Such research is enabled by our preliminary work of computing emissions and providing CO_2 emission data.

3.6. Effect sizes

In Section 5.2 we compute within-quartile proportions of binary outcomes. To get an account of how much these proportions differ between quartiles, we report the *odds ratio* as a measure of effect size. For an outcome occurring with probability p the odds are defined as

$$odds := \frac{p}{1-p}, \tag{1}$$

where $1-p$ is the probability that the outcome does not occur.

Now assume the outcome is observed for two groups A and B, with probabilities p_A and p_B respectively. Then their odds ratio is

$$OR(p_A, p_B) := \frac{\frac{p_A}{1-p_A}}{\frac{p_B}{1-p_B}} = \frac{p_A(1-p_B)}{p_B(1-p_A)}. \quad (2)$$

We use the odds ratio to quantify how much the proportion of cases with a given attribute within a quartile deviates from the same proportion in the total population. We choose group A to include all cases within a quartile and group B to include all other cases in the data set. In Tables 5 and A.6 we report within quartile proportions, the standard error of the proportions estimate, and the odds ratio as effect size. The exact definition, of which OR indicates a large effect, depends on the context of the study and different cutoffs have been proposed in the literature. Sullivan and Feinn [76] classify OR values of 1.5, 2 and 3 as 'small', 'medium' and 'large' effects (see also [77]). We follow their convention and employ the following notation: $^{+}$ for $OR > 1.5$, $^{++}$ for $OR > 2$, $^{+++}$ for $OR > 3$ as well as $^{-}$ for $OR < 2/3$, $^{--}$ for $OR < 1/2$ and $^{---}$ for $OR < 1/3$. For a more comprehensive discussion of other measures of effect size, see Ferguson [78] and Lakens [79].

3.7. Multivariate regression analysis

Conducting a multivariate regression analysis enables us to understand associations between an independent variable and a dependent variable, accounting for the (linear) influence of other independent variables. To identify differences in emission patterns, we developed six different linear models (Table 1).

The dependent variable in the models (1) to (3) is household CO_2 emissions, which is the object of interest for socio-metabolic analyses. To assess the carbon footprint of individual members of the households more precisely, models (4) to (6) are provided, which use the per capita CO_2 emissions of each household member as the response variable[4]. To support these complementary points of view, the models (1) & (4), (2) & (5) as well as (3) & (6) use the same explanatory variables.

Models (1) & (4) include a large number of predictors that are commonly employed in the literature or are thought to be relevant regarding the CO_2 emissions. These are: household net income (log-transformed to account for skewed data), ownership status of accommodation, academic qualification of any household member, government region, and rural setting. We also included the number of persons in the household (household size) with an additional dummy variable for single households[5],

[4] We computed per capita emissions by dividing household CO_2 by the number of persons in the household.

[5] The dummy variable accounts for a possible nonlinear change in the per capita emissions from one- to two- or more-person households.

Table 1: Regression Results

	Dependent variable:					
	Household CO_2 in kg			Per Capita CO_2 in kg		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Income	479***	328***		216***	70**	
	(68)	(56)		(41)	(33)	
Accommodation owned outright	180***			136***		
	(59)			(44)		
Owned on mortgage	−39			−62		
	(60)			(42)		
Shared ownership	−288***			−204**		
	(111)			(80)		
Rented	−76			−96**		
	(58)			(42)		
Academic degree	−71*			−75***		
	(42)			(25)		
Other higher degree	−44			−28		
	(46)			(27)		
Upper secondary education	−49			−24		
	(42)			(24)		
Lower secondary education	103**			54*		
	(50)			(31)		
Other qualification	41			6		
	(58)			(42)		
No qualification	8			−21		
	(50)			(40)		
North West	142***			81***		
	(46)			(29)		
Yorkshire and the Humber	−23			−26		
	(48)			(30)		
East Midlands	90			75*		
	(65)			(40)		
West Midlands	116*			59		
	(61)			(37)		
East of England	−36			−22		
	(60)			(35)		
London	66			36		
	(58)			(39)		
South East	−81			−67**		
	(50)			(32)		
South West	−259***			−188***		
	(53)			(32)		
Wales	34			2		
	(59)			(40)		
Scotland	337***			151***		
	(55)			(36)		
Northern Ireland	−361***			−107		
	(120)			(78)		
Rural region	80*			50*		
	(47)			(29)		
Number of persons	284***	199***	221***	−451***	−406***	−401***
	(45)	(32)	(29)	(23)	(17)	(16)
Single household	−44	−229***	−333***	1,024***	993***	971***
	(81)	(61)	(61)	(44)	(41)	(41)
Number of children	−58			124***		
	(47)			(19)		
Number of lone parents	233**			−15		
	(114)			(45)		
Number of couples	−35			−55		
	(75)			(35)		
Number of pensioners	35			45**		
	(39)			(21)		
Number of unemployed	141***			77***		
	(36)			(17)		
Number of female adults	11			54**		
	(38)			(25)		
Number with long-standing illness or disability	77***			58***		
	(26)			(14)		
One or more not born in UK	−36			−25		
	(59)			(33)		
Number of bedrooms	462***	502***	529***	303***	335***	340***
	(24)	(23)	(23)	(16)	(16)	(15)
Number of other rooms	288***	307***	330***	125***	141***	145***
	(25)	(24)	(25)	(13)	(14)	(14)
Heating Oil	3,322***	3,218***	3,209***	1,786***	1,771***	1,769***
	(143)	(119)	(120)	(89)	(75)	(76)
Central heating	−150***			−105***		
	(55)			(36)		
Constant	−2,551***	−1,145***	1,393***	−149	909***	1,448***
	(536)	(425)	(95)	(324)	(245)	(55)
Observations	15,158	15,336	15,336	15,158	15,336	15,336
R^2	0.352	0.333	0.330	0.441	0.423	0.422
adjusted R^2	0.339	0.332	0.328	0.429	0.421	0.421

Note: *p<0.1; **p<0.05; ***p<0.01

Estimated with OLS with inverse-probability weighting. Design-based standard errors in brackets. The dependent variables (annual household and per capita CO_2 emissions) are estimated from expenditure data. Per capita emissions are household emissions divided by household size.

numbers of children, lone parents, couples, pensioners, unemployed individuals, female adults, persons with a long-standing illness or disability, migration background (if a person in the household was born outside of UK), number of bedrooms and other rooms, and use of heating oil or central heating.

To identify a reduced set of covariates that have (almost) the same explanatory power, we constructed models (2) & (5) and (3) & (6). In a step-wise process, all insignificant predictors were first removed from the initial models. Second, further predictors that only marginally affected the explanatory power of the model as measured by the adjusted R^2 value were also removed. This process is illustrated by the removal of the variable income in the models (3) & (6). The reduced models have almost the same explanatory power without employing any socio-demographic variables such as gender, education, or even income which was identified as a driver of emissions for other sectors in previous studies. According to models (3) & (6), we conclude that the most important determinants of energy-based carbon emissions are household size, number of rooms (as a proxy for living space), and the use of heating oil.

Omitted variable bias occurs when additional predictors, i.e. those that are not included in a model, influence the outcome variable as well as one or more of the included predictors. Consequently, their effect may be (mis-)attributed to the included variables. To address this issue, models (1) to (3) include many variables that potentially influence emissions. During the model reduction process, we knowingly excluded significant predictors; thus, we introduced some omitted variable bias. This can be observed with respect to the covariate "single household" in models (1), (2) and (3). However, between the per capita emission models (4), (5) and (6), the model coefficients do not vary greatly. This is a necessary condition for the absence of large bias and supports the interpretation of the remaining predictors in model (6) as key determinants of housing energy emissions. Below, we provide a clear illustration of housing CO_2 emissions.

4. Determinants of energy use-based carbon emissions in the housing sector

4.1. Wealth, income and house ownership

As described in Chapter 2.2, previous research noted that income can drive carbon emission [80, 81]. Otto et al. [4] assumed an outstanding emitting class based on high amounts of wealth, namely, the super-rich. We also tested household net income as an independent variable and found that housing-based carbon emissions weakly depend on it in linear models (Section 3.7) and in the defined emission quartiles (Section 5).

Equivalised income is a measure of household income that takes into account differences in household composition (see Section 3.3). Its application was motivated by the observation that households with two or more persons benefit from synergies like the common use of household equipment or heating (see e.g. [82]). As a result, those households spend a smaller fraction of their income on some basic goods, such as heating and electricity. Thus, equivalised income is a more appropriate measure when comparing how rich in income different households are. In Figure 3, Table 3 and Table 4 net household, per capita and equivalised income are shown.

Sometimes the OECD scale is used to equivalise carbon emissions as well [83]. This would assign a proportionally higher carbon footprint to households with many members. However, such an increase in accounted emissions would not be consistent with actual emissions. Since we would like to identify drivers of actual emissions, we decided against an equivalisation of emissions.

In our data set, households with an equivalised net monthly income above £6,000 emitted on average 5.50t CO_2, while households below that limit emitted only 3.94t CO_2. According to official data, these households belong to the top 3 per cent of earners in the UK (2016/2017) [84]. Compared to other emission sectors such as mobility, where differences on the order of nearly 20 are to be expected [39, 28], this gap is small. Like previous researchers, we agree that 'home energy emissions are more regressively distributed than transport or total emissions' [39].

Referring to the results in Buchs and Schnepf [39], we investigated the mean CO_2 emission for each income decile 'to compare the proportional change for CO_2 emissions and hence to judge whether emissions [...] are more or less responsive to changes in income' (Figure 3). At the household level, we used deciles based on equivalised income and household net income and found a weak, linear trend for both, indicating that household CO_2 emissions increase steadily with the income level (left panel). For per capita CO_2 emissions, the income deciles are based on equivalised income and per capita income. For the latter, a similar trend as for the total household CO_2 emissions could be observed. Interestingly, no such trend is seen for equivalised income and per capita CO_2 emissions. While the emissions from the top decile remain markedly above average, all other deciles deviate only slightly from the average. The bottom equivalised income decile even shows the second highest per capita emissions. This suggests that the influence of increased financial resources on per capita emissions for the basic goods of electricity and heating is negligible .

Affluence has multiple dimensions. Therefore, to complement the analysis of income, we studied the relation between house ownership and CO_2 emissions. Aside from the variables referring to the household composition, Table 2 shows the mean values of household and per capita CO_2 emissions, as well as the equivalised income

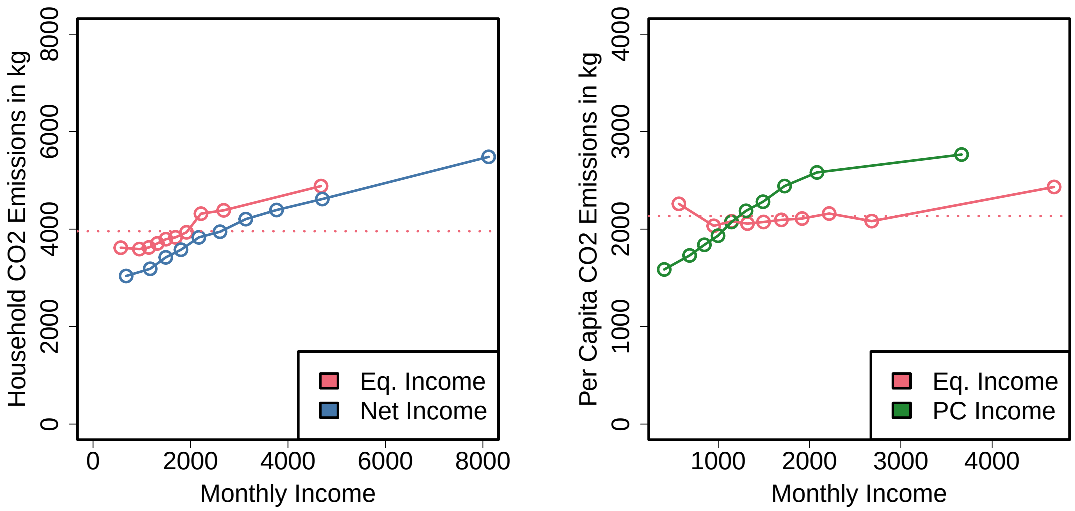

Figure 3: Average household and per capita CO_2 emissions per income deciles. The deciles are computed with respect to net household, per capita (PC) and equivalised income. The lines are a linear interpolation of the mean values (circles) per decile. The dotted lines represent the survey mean.

in households with a different ownership status. Households that own their accommodation or live rent-free have significantly higher levels of household emission and emit on average about one tonne CO_2 more per year than tenants.

4.2. Household size and composition

When considering household size and per capita emissions, a different picture emerges. In this case, households who own their accommodation outright have the highest footprints. At the household level, the average carbon footprint of households which have a mortgage on their house is similar to those who own their accommodation outright; however, they have considerably smaller per capita footprints, since their average household size is larger and includes more children. On the other hand, people who own their accommodations outright are predominantly pensioners who do not live with children. Our results show that the ownership, future ownership, or tenancy affects household carbon emissions due to the associated amount of living space per person. These differences are arguably due to age group-related lifestyle choices.

CO_2 emissions caused by additional persons living in a household steadily decrease as the household size increases. Regression results show that adding an additional

	HH CO_2	PC CO_2	eq. income	# persons	# kids	# pensioners	rooms p.p.
Owned outright	4278 (34)	2639 (24)	1918 (30)	1.85 (0.01)	0.07 (0.01)	1.02 (0.01)	3.15 (0.02)
Owned on mortgage	4292 (38)	1799 (21)	2247 (43)	2.86 (0.02)	0.72 (0.02)	0.10 (0.01)	2.20 (0.02)
Shared ownership	3065 (166)	1559 (120)	1640 (74)	2.47 (0.18)	0.59 (0.11)	0.18 (0.05)	1.76 (0.12)
Rented	3350 (37)	1892 (26)	1427 (15)	2.23 (0.03)	0.57 (0.02)	0.32 (0.01)	2.03 (0.02)
Rent-free	4180 (280)	2601 (231)	1316 (73)	2.12 (0.21)	0.42 (0.11)	0.50 (0.09)	2.63 (0.18)

Table 2: Mean values (standard deviations) of household (HH) and per capita (PC) annual CO_2 emissions in kg, equivalised annual household income in £, household size, number of kids, number of pensioners, and rooms per person with respect to ownership status of accommodation.

household member (above two-person households) generates just 0.2 to 0.3 tonnes more in emissions, which could be considered as the marginal carbon cost of living together. An economy-of-scale effect is observed.

On average, single pensioner households emit about half a tonne CO_2 more than single-person households, where the individuals are under the pensionable age. CO_2 emissions also increase when the households contain more people without a paid job or with longstanding illnesses or disabilities (Table 1). The latter was also stated by Ivanova and Middlemiss [85] who show that disabled households have higher consumption patterns than other households in terms of energy use at home (gas and electricity). Pensioners, unemployed people, and individuals with illnesses/disabilities are more likely to spend time at home, for example, because they do not work outside the home. The number of female adults is a (weak but) significant predictor in per capita regression models, indicating a need for further research on their daily lives, for example, in relation to care work provided. It would also be desirable to conduct a more comprehensive footprint analysis to consider energy use-based emissions outside the home, e.g. at the workplace, to elucidate responsibilities (employer versus employee). Unfortunately, household data are limited to on-site data; due to the scope of this data set, it was not possible to comprehensively account for all emissions generated (e.g. at work, while travelling, and during leisure activities).

4.3. Regional differences and urban-rural typology

Average household and per capita CO_2 emissions differ between the 12 regions in the UK (Table A.7 in the Appendix). For the North West, South West, Scotland, and Northern Ireland, regression coefficients differ significantly from the average of all regions. Causes may include distinct available energy infrastructure or the modernity of areas. Most households in Northern Ireland utilise central heating with oil (68 per cent) and only 24 per cent use gas [86]. In the UK, only 5 per cent use oil and 85 per cent use gas (ibid). Our data set analysis reveals that 66 per cent of households in Northern Ireland utilise heating oil as opposed to only 2.7 per cent of households in the rest of UK. The strong influence of heating oil on CO_2 emissions is clearly visible in the corresponding regression coefficient which is by far the largest of any factor variable. On average, more affluent regions do not necessarily generate higher emissions. The analysis of the urban and rural settings revealed less than expected. The regression coefficient for rural settings is only weakly significant ($p < 0.1$).

5. Emission quartiles and household emission profiles

5.1. Overview of household characteristics in the quartiles

The differences between household carbon emissions in the UK are striking. The annual average CO_2 emissions for household energy use in our data set are 3.96t CO_2, with a minimum of 0.27t CO_2 and a maximum of 16.2t CO_2. Some households consume 60 times more than others, concerning only the housing sector, i.e. emissions generated from heating and electricity.

In this section, we describe the social realities of emitters within the emission quartiles, based on either the total household emissions or on the average per capita emissions from a household (cf. Section 3.4). Table 3 and Table 4 display basic characteristics of households belonging to each of the emission quartiles, namely, the mean values of household and per capita CO_2 emissions, net and equivalised monthly household incomes, household size, number of bedrooms and other rooms (per household and per person, respectively), and the percentage of single households and households with oil heating within a quartile. Both household and per capita CO_2 emissions increase from quartile to quartile, reaching a value up to five times higher in the top quartile than in the lower quartile.

To account for the strong influence of household size, we provide summary statistics for per capita (PC) emission quartiles in Table 4. In particular, household size increases and the share of single households decreases from quartile to quartile for the household quartiles. However, for the per capita quartiles, the household size decreases and the share of single households increases. The opposing trends for these variables result in striking differences between the top quartiles.

Equivalised income, that adjusts household income to account for the different financial requirements of different household types [87], displays an increasing trend for both types of quartiles, but the overall variation is small ($\approx 30\%$), and no significant difference between the high and top quartiles is detected at the per capita level.

We used the number of rooms per household and per person, respectively, as proxies for living space. The strong association between more living space and higher

CO_2 emissions indicates that a high transformative potential exists in households rich in living space, regardless of their economic status.

	lower	middle	high	top
Household CO_2 in kg	1752 (14)	3140 (6)	4192 (7)	6742 (37)
Per capita CO_2 in kg	1350 (15)	1949 (20)	2200 (25)	3038 (36)
Net income in £	2193 (67)	2540 (33)	3033 (46)	3912 (77)
Equivalised income in £	1662 (45)	1705 (20)	1830 (27)	2162 (40)
Number of persons	1.65 (0.02)	2.11 (0.03)	2.48 (0.02)	2.87 (0.03)
% of single households	0.61 (0.01)	0.37 (0.01)	0.23 (0.01)	0.15 (0.01)
Number of bedrooms	2.14 (0.02)	2.62 (0.02)	2.97 (0.02)	3.33 (0.02)
Number of other rooms	1.38 (0.01)	1.59 (0.02)	1.84 (0.02)	2.15 (0.02)
% using heating oil	0.00 (0.00)	0.01 (0.00)	0.02 (0.00)	0.13 (0.01)

Table 3: At the household level, household size (persons and rooms) and equivalised net income naturally increase. The numbers stated as well as in Table 4 are means (standard deviations) of important variables for emission quartiles.

	lower	middle	high	top
Household CO_2 in kg	2759 (34)	3726 (34)	4101 (39)	5242 (46)
Per capita CO_2 in kg	826 (5)	1487 (4)	2207 (5)	4018 (27)
Per capita income in £	1141 (33)	1295 (15)	1520 (27)	1701 (26)
Equivalised income in £	1734 (43)	1809 (20)	1914 (37)	1902 (31)
Number of persons	3.36 (0.04)	2.53 (0.02)	1.87 (0.02)	1.34 (0.01)
% of single households	0.12 (0.01)	0.17 (0.01)	0.36 (0.01)	0.71 (0.01)
Bedrooms per person	0.96 (0.01)	1.23 (0.01)	1.62 (0.01)	2.24 (0.02)
Other rooms per person	0.60 (0.01)	0.77 (0.01)	1.05 (0.01)	1.47 (0.02)
% using heating oil	0.01 (0.00)	0.02 (0.00)	0.03 (0.00)	0.11 (0.01)

Table 4: On the per capita level high emissions are associated with a high proportion of single households, thus smaller living arrangements but more living space.

5.2. Deriving household emission profiles

To operationalise socio-metabolic classes, we grouped the UK housing sector into emission quartiles, then derived household emission profiles from these. These profiles may inform targeted policy decisions to reduce CO_2 emissions (Figure 2 and Section 3.4).

Tables 5 (based on per capita emission) and A.6 in the Appendix (based on household emissions) describe the households belonging to each emission quartile in detail and how the quartiles differ. The percentage of households belonging to a certain quartile is listed for each of the variables previously analyzed as potential predictors of carbon emissions (cf. Sections 3.5 & 3.7). Quartiles that deviate by a large margin from the population average are also indicated (cf. Section 3.6). Ordinal variables, e.g. the number of children in a household, were converted to binary variables ('no children', 'one or more children'). Continuous variables could not be transformed in this way; hence, we report their mean values per quartile in tables 5 and A.6. Large differences were observed for many variables between the quartiles based on the household and per capita emissions.

By jointly examining the attributes with high (or low) prevalence in a given quartile, either with respect to absolute shares or to their relative deviation from the population mean, we arrived at an understanding of the social circumstances associated with carbon emissions. Our findings for the top and lower per capita emission quartiles are reported below.

For the top quartile, a higher-than-average probability exists that household members have no professional qualifications and that they do not include female adults or members born outside the UK. Households in the top quartile frequently have one or more household member who is unemployed or pensioned. The average household size is small, and most (71 per cent) are single households. In addition, these households are unlikely to include children; the proportion with children (2.9 per cent) is much lower than the population mean (nearly 24.5 per cent). Furthermore, the members own their accommodation outright more frequently than on average and are less likely to rent or to hold a mortgage. In fact, the households with the highest emissions are more than two times more likely to include members that own their accommodations than rent them. In addition, households in the top quartile are more likely to be found in rural areas or in Northern Ireland. At eleven per cent, the use of heating oil is much more prevalent in the top quartile than in the entire population. These households have slightly higher equivalised income, although the overall variation of equivalised income between per capita quartiles is small.

We find the opposite results in the lower emission group, and Table 5 provides a detailed overview. These households are less likely to include pensioners or unemployed people but are more likely to include at least one female adult and at least one household member with a professional qualification. The average household size is large (3.36); only a few of these households are single households, and more than half of them include children. As many as 85 per cent either hold a mortgage or rent their accommodation, and less than one per cent utilise heating oil.

These household properties should be seen as an initial attempt at deriving household emission profiles from consumption data. The insights gained increase our understanding of the characteristics of emitting groups and how they can be distinguished.

Per Capita Quartiles	lower	middle	high	top	pop.
Academic degree	35.7 (1.0)	34.5 (1.0)	28.6 (0.9)	25.1 (0.9)	31.0 (0.5)
Other higher degree	15.6 (0.8)	15.0 (0.7)	13.8 (0.7)	14.0 (0.7)	14.6 (0.4)
Upper secondary education	22.5 (0.9)	21.5 (0.9)	19.9 (0.8)	16.2 (0.8)	20.0 (0.4)
Lower secondary education	15.0 (0.8)	15.2 (0.7)	16.5 (0.8)	16.6 (0.8)	15.8 (0.4)
Other qualification	4.5 (0.5)$^{--}$	6.5 (0.5)	8.5 (0.6)	11.4 (0.7)$^{+}$	7.7 (0.3)
No qualification	4.3 (0.5)$^{--}$	5.5 (0.5)$^{--}$	12.2 (0.7)	16.4 (0.8)$^{++}$	9.6 (0.3)
Missing ‘qualification‘	2.3 (0.3)$^{++}$	1.8 (0.3)$^{+}$	0.5 (0.1)$^{---}$	0.3 (0.1)$^{---}$	1.2 (0.1)
One or more persons not born in UK	14.2 (0.7)$^{+}$	11.1 (0.7)	7.2 (0.5)	5.5 (0.4)$^{--}$	9.5 (0.3)
Single household	11.9 (0.8)$^{---}$	16.8 (0.9)$^{---}$	36.3 (1.0)	71.0 (0.9)$^{+++}$	34.0 (0.5)
No female adults	10.1 (0.7)$^{--}$	13.3 (0.8)$^{-}$	20.8 (0.9)	30.2 (1.0)$^{++}$	18.6 (0.4)
One or more children	56.2 (1.0)$^{+++}$	28.7 (1.0)	10.1 (0.6)$^{---}$	2.9 (0.3)$^{---}$	24.5 (0.4)
One or more lone parents	10.9 (0.7)$^{++}$	8.1 (0.6)$^{+}$	3.9 (0.4)$^{-}$	1.6 (0.3)$^{---}$	6.1 (0.3)
One or more couples	72.0 (1.0)$^{++}$	66.3 (1.1)$^{+}$	52.9 (1.0)	24.1 (0.8)$^{---}$	53.8 (0.5)
One or more unemployed	48.5 (1.1)$^{-}$	54.0 (1.1)	64.7 (1.0)	67.7 (1.0)$^{+}$	58.7 (0.5)
One or more pensioners	14.4 (0.7)$^{---}$	29.5 (0.9)$^{-}$	47.7 (1.0)$^{+}$	55.8 (1.1)$^{++}$	36.8 (0.5)
One or more with long-standing illness or disability	48.5 (1.1)	53.8 (1.1)	56.9 (1.0)	56.8 (1.1)	54.0 (0.5)
Accommodation owned outright	13.9 (0.6)$^{---}$	30.6 (0.9)	45.9 (1.0)$^{+}$	52.0 (1.1)$^{++}$	35.6 (0.5)
Owned on mortgage	39.8 (1.0)$^{+}$	33.6 (0.9)	23.5 (0.8)	19.1 (0.8)$^{--}$	29.0 (0.4)
Shared ownership	1.1 (0.2)$^{+}$	1.4 (0.3)$^{++}$	0.4 (0.1)$^{--}$	0.4 (0.1)$^{--}$	0.8 (0.1)
Rented	44.8 (1.1)$^{+}$	33.7 (1.1)	29.6 (1.0)	27.6 (1.0)	33.9 (0.6)
Rent free	0.4 (0.1)$^{-}$	0.7 (0.2)	0.6 (0.1)	0.9 (0.2)$^{+}$	0.7 (0.1)
Rural area	16.2 (0.8)	18.7 (0.9)	20.6 (0.9)	27.1 (1.0)$^{+}$	20.7 (0.5)
North East	5.1 (0.4)	4.4 (0.4)	4.6 (0.4)	5.1 (0.4)	4.8 (0.2)
North West	10.1 (0.7)	11.6 (0.7)	12.6 (0.7)	12.4 (0.8)	11.7 (0.4)
Yorkshire and the Humber	9.5 (0.6)	10.0 (0.7)	9.6 (0.7)	8.2 (0.6)	9.3 (0.4)
East Midlands	7.2 (0.6)	7.7 (0.5)	7.2 (0.5)	8.0 (0.6)	7.6 (0.3)
West Midlands	8.6 (0.6)	9.0 (0.6)	8.3 (0.6)	8.6 (0.6)	8.7 (0.3)
East of England	10.5 (0.7)	9.6 (0.7)	9.3 (0.6)	9.1 (0.6)	9.6 (0.4)
London	13.7 (0.8)$^{+}$	10.2 (0.7)	9.7 (0.7)	8.0 (0.6)	10.4 (0.4)
South East	13.7 (0.8)	13.6 (0.7)	13.1 (0.7)	13.2 (0.7)	13.4 (0.4)
South West	9.8 (0.6)	8.4 (0.6)	8.5 (0.5)	7.0 (0.5)	8.4 (0.3)
Wales	3.8 (0.3)	4.8 (0.3)	5.0 (0.4)	5.3 (0.4)	4.7 (0.2)
Scotland	6.6 (0.5)$^{-}$	8.9 (0.6)	9.8 (0.6)	10.4 (0.6)	9.0 (0.3)
Northern Ireland	1.2 (0.2)$^{--}$	1.7 (0.2)$^{-}$	2.2 (0.2)	4.5 (0.3)$^{++}$	2.4 (0.1)
Heating oil	0.7 (0.1)$^{---}$	1.8 (0.3)$^{--}$	3.4 (0.3)	10.9 (0.6)$^{+++}$	4.2 (0.2)
Central heating	11.7 (0.7)	9.9 (0.6)	9.1 (0.6)	9.0 (0.6)	9.9 (0.3)

Table 5: Estimated mean (and standard error) of household and housing related attributes within per capita emission quartiles and the total population (pop.). As a measure of effect size an odds ratio of 1.5, 2 and 3 is designated with $^{+}$, $^{++}$ and $^{+++}$ and an odds ratio of 2/3, 1/2 and 1/3 is designated with $^{-}$, $^{--}$ and $^{---}$ (cf. Section 3.6).

6. Discussion and Conclusion

This study was carried out to increase our understanding of the social context of CO_2 emitters in the UK housing sector. A comprehensive multivariate regression analysis was performed, and oil heating, living space, and household size were identified as the main drivers of housing CO_2 emissions. Income and house ownership, which are indicators of wealth, are significant predictors in the regression models; however, their explanatory power is small. Thus, our findings match results of previous studies which conclude that housing energy is a basic good that is inelastic to income [39, 61, 62, 3].

As a starting point for further research, we operationalised the concept of socio-metabolic classes by conducting a quartile analysis of CO_2 emissions. The average per capita emissions from households in the lowest and highest quartiles differ by a factor of five, underlining stark within-country carbon inequalities which have been emphasized by previous authors [6]. We identified socio-demographic characteristics of the classes which can be summarized as distinct *emission profiles*: Households in the top emission quartile are more likely to be single households, the members generally own their accommodation, and a higher than average share of these households includes individuals who belong to vulnerable groups, e.g. pensioners or people with disabilities or illnesses. Like Wiedenhofer et al. [54], our findings highlight the need to further investigate time-use patterns and the social realities of high-need households [67, 55]. However, large data gaps exist that impair more exact assessments. As an example, if we examine only household emissions, neglecting emissions from the work place, we find that unemployed persons have much larger CO_2 footprints. In addition, more data are needed to conduct more detailed analyses by including enhanced energy-related variables (e.g. the use of renewable energy), data for super-rich households, or emissions that occur in other sectors like mobility or consumption.

Limitations of the operationalisation of socio-metabolic classes. To operationalise the socio-metabolic class theory, we initially chose a method that could be easily applied to data sets of diverse range (e.g. varied sectors of emissions) and origin (e.g. different countries/regions). However, the approach taken in this study differs from the theoretical basis. Otto et al. [4] defined socio-metabolic classes dually on the basis of agency and carbon emissions, and increasing trends for both were found. This study operationalised the theory on the basis of carbon emissions only, i.e. without measuring and incorporating the level of human agency; thus, in this context, further methodological development is needed. If agency is treated as a dependent variable that emerges due to certain socio-demographic characteristics of the emission groups, our findings do not provide a clear picture of its distribution. On the one hand, house owners, who are typically wealthier and thus have more agency, are most abundant in the top emitting class. On the other hand, people who are unemployed, pensioned, have a longstanding illnesses or disability, or do not have a professional qualification are more commonly found in the top quartile as well. These groups can be perceived as more vulnerable and as having a lower level of agency. This result leads us to ask whether it is possible to assign a particular agency level to the emission groups at all. Our results shift the question from 'who emits the most' to 'who needs the most', changing the narrative to actual needs and the energy required to support a decent life [88].

Our operationalisation was based on emissions in the housing sector rather than total emissions due to the lack of comprehensive consumption information. Finally, we applied a nation-wide perspective instead of a global one due to the need to downscale the Planetary Boundaries framework to national scales.

Future research directions. The UKHLS is a panel study that allows us to observe trends over periods of years, i.e. to study the effects of social, political, or environmental changes on emission patterns and profiles. In this study, we focused on one yearly cross-section of the data to obtain a detailed understanding of emissions profiles at one point in time. We assume that socio-metabolic classes are mostly stable over time and exist regardless of the individuals that compose them. If and how they change could be studied by leveraging the longitudinal aspect of the data set.

With regard to the decarbonisation of the energy system, the term 'carbon tunnel vision' [89] was coined recently, drawing attention towards the environmental impacts of oil and gas extraction. In a similar vein, to avoid tunnel vision regarding environmental inequalities, the scope of socio-metabolic classes might be broadened by incorporating further ecological markers related to the Planetary Boundaries, e.g. a phosphorus, nitrogen, or water footprint.

Additionally, looking beyond the social-metabolic class theory, other ways of conceptualising social class may help determine how carbon emissions are embedded in social constellations. For example, Lindner et al. [90] operationalised Reckwitz's class theory [15], which diagnoses a split middle class in post-industrial societies. The authors measured the ecological impact of those classes and provided important insights into the effects of economic and cultural capital on emission patterns. However, the long-term goal of operationalising socio-metabolic classes is to improve Earth System Modeling [4], which combines world-region and national CO_2 emission averages with a more complex and realistic picture of emission patterns and social differentiation within nations. Our study contributes to our understanding of environmental inequalities; therefore, the findings may improve our ability to model distinct emission patterns.

Planetary Boundaries and policy implications. Regarding the guiding framework, our methods and results contribute to the application of the Planetary Boundaries, the just-Earth System Targets, and the related downscaling attempts in two ways: First, by focusing on a (historically) strongly emitting country, i.e. the UK, and its national contribution to increasing GHG emissions and, second, by revealing excessive CO_2 emissions from a majority of households in only one sector, as well as remarkable inequalities within the country that significantly complicate compliance with the planetary boundary on climate change [18].

Our findings contribute to our understanding of emission inequalities and the variables driving these differences, supporting the design of more targeted policy interventions. For households to reduce their emissions, we consider the following options as valuable: Switch to renewable energy providers, reduce the size of living space, and invest in more energy-efficient technological equipment. The latter is certainly easier for high-income households, especially when they own their accommodation, as they have more financial resources and planning security. Ivanova et al. [91] estimated the mitigation potentials of retrofitting and renovations as having medians of 1.6 and 0.9 tCO_2 per capita, revealing high potentials to reduce CO_2 emissions. Regarding the living space, Cohen [92] stated that the globally 'sustainable' amount of living space per person in a 'safe and just' corridor may only be 14 to 20 sqm. In the UK, Foye [93] found that moving to a larger accommodation had no positive impact on subjective well-being. Please note that emissions in other sectors (transportation and secondary consumption) are constituted differently (see [3]). Nevertheless, our work shows that subtle aspects of the sectors require sector-specific political sensitivity. For example, Owen and Barrett [62] also addressed this issue by analysing how the low-carbon policy could be implemented differently in the UK to prevent low-income households from having to pay disproportionately higher costs.

We complement the fact that "our house is on fire" stated by Greta Thunberg (World Economic Forum 2019 in Davos, Switzerland), and propose an approach that allows researchers to disentangle emissions generated within our societies to specific social groups, lifestyles, and infrastructures. We analysed emissions from the housing sector, but similar research could also be carried out in other sectors, including the transportation, food and non-food consumption sectors, if data were available.

Data availability

The Understanding Society data sets (Waves 1-10) are available at `https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=6614`.

Code availability

The `R` code used for the analysis and plots in this paper are available at `https://github.com/lindnemi/understandingemissionprofiles` [94]. We used multiple functions from `R`'s rich package ecosystem [70, 71, 95, 96, 97, 98, 99, 100].

Competing interests

The authors declare that they have no competing interests.

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Appendix A.

Appendix A.1. Total household emission-based quartiles

Household Quartiles	lower	middle	high	top	pop.
Academic degree	27.1 (1.0)	28.0 (0.9)	30.5 (0.9)	38.2 (0.9)$^{+}$	31.0 (0.5)
Other higher degree	11.8 (0.7)	15.0 (0.7)	16.0 (0.7)	15.6 (0.7)	14.6 (0.4)
Upper secondary education	18.3 (0.8)	20.6 (0.9)	22.4 (0.8)	18.8 (0.8)	20.0 (0.4)
Lower secondary education	17.0 (0.9)	16.2 (0.7)	15.4 (0.8)	14.8 (0.7)	15.8 (0.4)
Other qualification	10.5 (0.7)$^{+}$	8.0 (0.6)	7.1 (0.6)	5.4 (0.5)$^{-}$	7.7 (0.3)
No qualification	14.2 (0.8)$^{+}$	10.8 (0.7)	7.4 (0.5)	6.1 (0.5)$^{-}$	9.6 (0.3)
Missing ‘qualification‘	1.1 (0.3)	1.4 (0.3)	1.2 (0.2)	1.1 (0.2)	1.2 (0.1)
One or more persons not born in UK	8.7 (0.6)	8.9 (0.6)	9.0 (0.5)	11.4 (0.6)	9.5 (0.3)
Single household	60.6 (1.1)$^{+++}$	36.9 (1.0)	23.2 (0.9)$^{-}$	15.3 (0.7)$^{---}$	34.0 (0.5)
No female adults	30.7 (1.1)$^{++}$	19.7 (0.8)	13.0 (0.7)$^{-}$	11.0 (0.6)$^{--}$	18.6 (0.4)
One or more children	13.9 (0.7)$^{--}$	22.9 (0.9)	28.2 (0.9)	32.9 (0.9)$^{+}$	24.5 (0.4)
One or more lone parents	4.5 (0.5)$^{-}$	6.9 (0.6)	6.4 (0.5)	6.7 (0.6)	6.1 (0.3)
One or more couples	29.8 (0.9)$^{---}$	49.5 (1.1)	63.7 (1.0)$^{+}$	72.2 (0.9)$^{++}$	53.8 (0.5)
One or more unemployed	54.3 (1.1)	58.5 (1.0)	59.0 (1.0)	63.0 (0.9)	58.7 (0.5)
One or more pensioners	36.5 (1.1)	38.8 (1.0)	36.5 (1.0)	35.6 (0.9)	36.8 (0.5)
One or more with long-standing illness or disability	53.1 (1.1)	53.8 (1.1)	54.4 (1.0)	54.7 (1.0)	54.0 (0.5)
Accommodation owned outright	25.1 (0.9)$^{-}$	36.5 (0.9)	40.4 (1.0)	40.6 (0.9)	35.6 (0.5)
Owned on mortgage	21.5 (0.9)$^{-}$	27.2 (0.9)	31.7 (0.9)	35.6 (0.9)$^{+}$	29.0 (0.4)
Shared ownership	1.3 (0.3)$^{+}$	1.0 (0.2)	0.7 (0.2)	0.2 (0.1)$^{---}$	0.8 (0.1)
Rented	51.5 (1.1)$^{++}$	34.7 (1.0)	26.7 (1.0)$^{-}$	22.8 (0.9)$^{--}$	33.9 (0.6)
Rent free	0.6 (0.2)	0.6 (0.2)	0.5 (0.1)	0.9 (0.2)	0.7 (0.1)
Rural area	15.9 (0.8)$^{-}$	18.0 (0.9)	20.2 (0.9)	28.6 (0.9)$^{+}$	20.7 (0.5)
North East	5.0 (0.5)	5.1 (0.5)	5.4 (0.5)	3.7 (0.4)	4.8 (0.2)
North West	9.8 (0.7)	12.3 (0.7)	13.2 (0.7)	11.4 (0.6)	11.7 (0.4)
Yorkshire and the Humber	9.1 (0.7)	9.9 (0.6)	10.6 (0.7)	7.6 (0.5)	9.3 (0.4)
East Midlands	6.0 (0.5)	7.9 (0.6)	8.8 (0.6)	7.5 (0.5)	7.6 (0.3)
West Midlands	7.3 (0.6)	8.4 (0.6)	9.9 (0.6)	9.0 (0.6)	8.7 (0.3)
East of England	9.9 (0.7)	8.9 (0.5)	9.2 (0.6)	10.5 (0.7)	9.6 (0.4)
London	14.0 (0.9)$^{+}$	9.2 (0.7)	8.7 (0.7)	9.7 (0.6)	10.4 (0.4)
South East	14.8 (0.8)	13.6 (0.7)	12.1 (0.7)	13.1 (0.7)	13.4 (0.4)
South West	10.2 (0.7)	9.1 (0.6)	7.5 (0.5)	7.0 (0.5)	8.4 (0.3)
Wales	4.0 (0.3)	5.0 (0.3)	4.6 (0.4)	5.2 (0.4)	4.7 (0.2)
Scotland	8.6 (0.6)	9.4 (0.6)	8.1 (0.5)	9.7 (0.6)	9.0 (0.3)
Northern Ireland	1.2 (0.2)$^{--}$	1.2 (0.1)$^{--}$	1.7 (0.2)$^{-}$	5.4 (0.3)$^{+++}$	2.4 (0.1)
Heating oil	0.4 (0.1)$^{---}$	0.8 (0.1)$^{---}$	2.1 (0.3)$^{--}$	13.4 (0.6)$^{+++}$	4.2 (0.2)
Central heating	11.0 (0.7)	9.3 (0.6)	9.7 (0.6)	9.7 (0.5)	9.9 (0.3)

Table A.6: Estimated mean (and standard error) of household and housing related attributes within household emission quartiles and the total population (pop.). As a measure of effect size an odds ratio of 1.5, 2 and 3 is designated with $^{+}$, $^{++}$ and $^{+++}$ and an odds ratio of 2/3, 1/2 and 1/3 is designated with $^{-}$, $^{--}$ and $^{---}$ (cf. Section 3.6).

Appendix A.2. Regional differences

	HH CO_2 in kg	PC CO_2 in kg	income in £	% oil heating
North East	3665 (83)	2126 (57)	1563.18 (32.54)	1.07 (0.44)
North West	3999 (56)	2179 (44)	1748.85 (30.59)	0.91 (0.25)
Yorkshire and the Humber	3728 (58)	2018 (40)	1654.97 (37.34)	1.00 (0.30)
East Midlands	4058 (72)	2166 (51)	1750.00 (36.42)	2.30 (0.59)
West Midlands	4084 (72)	2116 (47)	1770.08 (46.74)	2.05 (0.40)
East of England	4047 (84)	2115 (53)	1881.18 (54.27)	5.98 (0.72)
London	3740 (75)	1939 (46)	2231.56 (75.81)	0.02 (0.02)
South East	3900 (64)	2113 (40)	2101.38 (89.36)	2.64 (0.54)
South West	3717 (71)	1962 (39)	1837.54 (42.89)	4.40 (0.79)
Wales	4079 (76)	2254 (51)	1662.58 (32.33)	5.99 (1.12)
Scotland	4034 (74)	2290 (46)	1730.26 (33.12)	4.59 (0.77)
Northern Ireland	5667 (120)	3194 (96)	1522.81 (40.24)	65.84 (2.32)

Table A.7: Mean values (standard deviations) of household (HH) and per capita (PC) annual CO_2 emissions in kg, equivalised annual household income in £, and utilisation of heating oil for each government region.

Appendix A.3. Detailed information about households with the dual fuel deal

Table A.8 summarises relevant variables for households with the dual fuel deal or with separate bills for gas and electricity. For the imputation, only the further subset of households that reported expenditures for both electricity and gas was used.

	eq. income	# pax	# kids	# bedrooms	% oil heating
Separate Bills	1705 (33)	2.25 (0.03)	0.44 (0.02)	2.68 (0.02)	2.36 (0.21)
Dual Fuel	1988 (20)	2.37 (0.02)	0.44 (0.01)	2.99 (0.01)	0.20 (0.05)

Table A.8: Comparison of relevant characteristics of households with and without dual fuel deal, excluding households using ‘other fuels’.

The mean equivalised monthly household income is £1840, but households that pay for their gas and electricity with one bill have higher average incomes (£1988) than those who pay for these with separate bills (£1705). In the UK, accepting a dual fuel deal, i.e. purchasing gas and electricity from the same supplier, results in cheaper energy bills in many cases [101]. It appears, therefore, as though poorer households pay higher prices than their richer counterparts. This could be related to a time factor or information constraints in low-income households. In addition, poorer households pay higher energy prices, because they use more expensive methods of payment. In the data set, the electricity and gas prices for households in the bottom and top income deciles differ by approximately two per cent, since poorer households are less likely to use direct debit payment.[6]

Appendix A.4. Ratio of electricity to gas expenditure

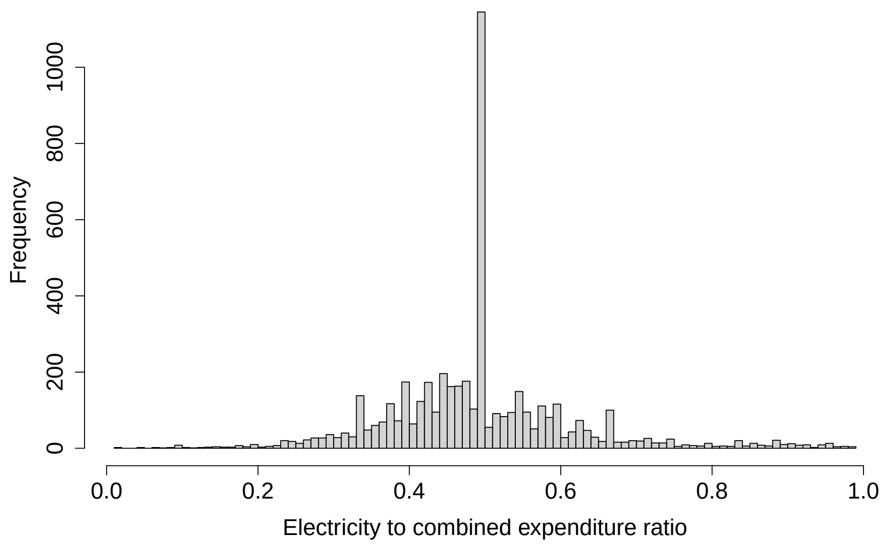

Figure A.4: Histogram of the ratio of electricity expenditure to combined gas and electricity expenditures for households with separate bills. These are the data used for the imputation.

Appendix A.5. Summary statistics of subset used for analysis

Summary statistics for some of the most important determinants of household energy carbon emissions for the subset used as compared to the dropped households (Table A.9). Most notably, the subset we used for the analysis differs from the complete data set regarding the use of heating oil. Since oil heating typically generates high carbon emissions, we may have underestimated the mean emissions for the whole population, and in particular for the top emitting quartile, to some degree. Since the total number of households using heating oil in the whole population is rather low (6.55 %), however, we expected the overall deviations to be small. All

[6] If only households with split bills are considered, for which non-imputed consumption data are available, the difference between the top and bottom deciles increases to almost four per cent.

other differences observed for the studied variables are small. Hence, the reduced data set may be considered as highly valuable for analysis. The pre-processing steps can be reproduced with the publicly available source code.

	eq. income	# pax	# bedrooms	% oil heating
Dropout	1955 (28)	2.25 (0.03)	2.98 (0.03)	15.04 (0.61)
Used Subset	1840 (18)	2.28 (0.01)	2.77 (0.01)	4.18 (0.19)
Complete Survey	1865 (15)	2.27 (0.01)	2.81 (0.01)	6.55 (0.21)

Table A.9: Mean (standard deviation) of important variables for the subset of dropped households, the subset of used households, and the whole data set.