Estimating and evaluating spatial and longitudinal consumption-based emissions of UK households

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Front Matter

Declaration

The candidate confirms that this work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and other authors to this work is explicitly indicated below. The candidate confirms that appropriate credit is given within the thesis where the reference has been made to the work of others.

The work in **Chapter 2** of this thesis is published in *Economic Systems Research* as:

Kilian, L., Owen, A., Newing, A., and Ivanova D. (2022). Microdata selection for estimating household consumption-based emissions. *Economic Systems Research*, DOI: 10.1080/09535314.2022.2034139.

The research question was developed by all authors. The analysis was done by me, with feedback from the co-authors. Emission estimated were produced by me, based on code produced by Anne Owen. This code was adjusted to different datasets by me, and I adapted units for some emission estimates. I also changed the unit of measurement from regions to neighbourhoods. The further analysis was done by me. I produced all the figures and tables in the article. I wrote the manuscript, which was improved by suggestions and comments from all the co-authors, the anonymous reviewers, and editors of Economic Systems Research.

The work in **Chapter 3** of this thesis is published in *Sustainability* as:

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The conceptualisation for this paper was done by all authors. The analysis and write-up were done by me, with feedback and comments for improvement from the co-authors. I produced the emission estimates generated for this research by adapting code from Anne Owen. These estimates were the further analysed by me. I produced the figures and tables in the article and adjusted these based on feedback from the co-authors. I wrote the original draft for the manuscript, which was improved by suggestions and comments from all co-authors. The manuscript was also adjusted in accordance with feedback from the anonymous reviewers and editors of Sustainability.

The work in **Chapter 4** of this thesis is ready to be submitted:

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The research questions for this paper were developed jointly by all authors. The analysis and write-up were done by me, with feedback from the co-authors. I adapted code from Anne Owen to calculate emission estimates. Further longitudinal analysis was done by me, with suggestions and comments from the co-authors. I produced the figures and tables in the article. I wrote the original draft for the manuscript, which was improved by suggestions and comments from all co-authors.

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In loving memory, I dedicate this thesis to my mum, my grandpa, and my grandma.

Thesis Abstract

Urgent and radical actions are needed to limit global warming to 1.5 degrees Celsius. To assess what this action may look like from a demand-side perspective, consumption-based greenhouse gas emissions are needed. Moreover, as local policy makers are increasingly involved in climate change mitigation efforts, it is necessary to understand policy impacts, as well as spatial emission patterns. With a focus on UK households, this thesis contributes to this need in three ways. Firstly, it provides a method of estimating neighbourhood level emissions as robustly as possible and using open data. Furthermore, this work provides a discussion on how uncertainty from microdata can be reduced in other international contexts to estimate neighbourhood level emissions. Moreover, such a method can provide a more replicable way of estimating emissions for both researchers and policy makers.

Secondly, it provides a spatial analysis of transport emissions, one of the highest emission categories with much reduction potential at a local policy level. As transport infrastructure varies strongly throughout the UK, this research focuses on London. This analysis bridges the gap between consumption-based emissions research and geographical analysis, providing novel insight into spatial patterns of the links between emissions and social factors. Furthermore, this work highlights the need to incorporate spatial statistics in spatialised emission analyses, due to the spatial heterogeneity of these patterns. In addition, this work enables an assessment of where different policies may be most effective in reducing emissions and increasing social equity, making it a timely contribution to the consumption-based emissions literature.

Thirdly, this research looks at consumption-based greenhouse gas emissions of UK households longitudinally. Particular attention is paid to changes in emissions, which occurred after the 2007/08 economic crisis and the 2020 COVID-19 lockdowns. While these events increased inequality and should not be seen as a means to reduce emissions, they can provide insight into how emissions are impacted by income reductions, economic uncertainty, and mobility restrictions. This analysis, therefore, shines light on how emissions of different age and income groups are impacted by these shocks to showcase how future policy can reduce emissions without further increasing social inequalities. Moreover, this work provides insight into where rebound effects occur and how targeted policy can be used to reduce emissions more effectively. We conclude that, while all groups need to meet emissions substantially to meet climate goals, different policies are needed for different social cohorts. Such a targeted approach could ensure effective emission reductions, while increasing social equity.

In addition to this empirical work, general limitations and conclusions are discussed. These limitations cover data quality and access issues, as well as methodological limitations. It is concluded that, consumption-based accounting can be a useful tool in highlighting how emissions can be reduced and redistributed through changed consumption, to achieve emission reductions and increase social equity. Although consumption-based emissions are only one piece of the puzzle, calls and the need for demand-side mitigation are increasing. This thesis contributes to this discussion by further highlighting the need for demand side mitigation, and, thus, presents a timely method of analysis, as well as a spatial and longitudinal overview of consumption-based emissions of UK households.

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List of Abbreviations

AIC	Akaike Information Criterion
BAME	Black, Asian, and Minority Ethnic
BEIS	Department for Business, Energy & Industrial Strategy
CCC	Climate Change Committee (formerly Committee on Climate Change)
CMA	Competition & Markets Authority
CO_2e	Carbon Dioxide Equivalent
COICOP	Classification of Individual Consumption by Purpose
DEAL	Doughnut Economics Action Lab
Defra	Department for Environment, Food & Rural Affairs
DWP	Department for Work & Pensions
DZ	Data Zones (Scotland)
EIA, U.S.	United States Energy Information Administration
GBP / £	Great British Pound
GHG	Greenhouse Gas
GWR	Geographically Weighted Regression
HRP	Household Reference Person
IG	Intermediate Geography (Scotland)
IO	Input-Output
IPCC	Intergovernmental Panel on Climate Change
LAD	Local Authority District
LCFS	Living Costs and Food Survey
LCFS	Living Costs and Food Survey
LGA	Local Government Association
LM	Linear Regression Model
LSOA	Lower Super Output Area (England & Wales)
M	Mean
MAUP	Modifiable Areal Unit Problem
MIOT	Monetary Input-Output Table
MRIO	Multi-Regional Input-Output
MSOA	Middle Super Output Area (England & Wales)
NAEI	National Atmospheric Emissions Inventory
NISRA	Northern Ireland Statistics and Research Agency
OA	Output Area
OAC	Output Area Classification
OECD	Organisation for Economic Co-operation and Development
OFGEM	Office of Gas and Electricity Markets
ONS	Office for National Statistics
PIOT	Physical Input-Output Table
PTAL	Public Transport Access Level

RMSE	Root Mean Squared Error
RQ	Research Question
SA	Small Area (Northern Ireland)
SD	Standard Deviation
SOA	Super Output Area (Northern Ireland)
SPH	Single Person Household
SRIO	Single-Region Input-Output
UK	United Kingdom
UKMRIO	UK’s Multi-Regional Input-Output Model
UN	United Nations
UN: DESA	United Nations Department of Economic and Social Affairs

Chapter 1. Introduction and Overview

1.1. Background

Reducing global greenhouse gas (GHG) emissions is both necessary and urgent. Reaching net-zero GHG emissions by 2050 is necessary to limit global warming to 1.5 degrees Celsius compared to pre-industrial levels (CCC, 2019; IPCC, 2022a; Masson-Delmotte et al., 2018). While climate targets for different countries are typically set in mind of emissions from the production of goods and services within a territory, the consumption of a country's residents also affects global and domestic emissions. Indeed, despite many countries reporting higher consumption- than production-based GHG emissions, frameworks to measure and mitigate production-based emissions continue to be better understood. Consumption-based approaches attribute the direct and indirect emissions that occur throughout the global supply chain to final demand, and a production-based approach attributes emissions based on where goods and services are produced. While both have their merit and are often regarded as complementary in the literature, this thesis focuses on consumption-based emissions.

This thesis contributes to consumption-based emissions research in multifold ways. First, this thesis uses data and methods that are consistent with national accounts, something that lack of data often does not allow for, but which can add robustness to the results (Tukker et al., 2018). The development of a UK model which is consistent with national accounts now allows for this kind of analysis and is used throughout this thesis. Second, much of the research estimating subnational household footprints of neighbourhoods in the UK relies on commercial data (e.g. Baiocchi et al., 2010; Minx et al., 2013). In contrast, this comes up with a robust and validated approach to use open data for this kind of analysis. This can allow for more replicable and transparent research, as well as allow policy makers to more easily track emission estimates and progress directly. Third, this research offers a geographic perspective which is often missing from consumption-based emissions research. As such, spatial methods are used to analyse emissions data and gain novel insights into the spatial nature of relationships between emissions and social factors. Finally, the impacts of the COVID-19 pandemic and the resulting lockdowns are only beginning to be studied. To this, this thesis adds a household emissions perspective to assess what emission reduction policy can learn from the lockdowns to be more effective and socially just.

The UK is a good point of analysis for showcasing the importance of looking at emissions from a consumption perspective. This has various reasons. First, the UK is a net-importer of

GHG emissions (Defra, 2020). Second, over two thirds of household consumption-based emissions are indirect (Chitnis et al., 2012), meaning that they occurred along the global supply chain. Third, an analysis of the UK's consumption-based emissions can complement existing climate aims, such as reducing emissions from production by 78% by 2035 (BEIS et al., 2021) and to net-zero by 2050 (CCC, 2019). Moreover, in the UK, consumption by private households can be attributed approximately 70% of consumption-based emissions in the UK (Defra, 2022). Understanding how UK household consumption contributes to global emissions is therefore critical to reducing emissions effectively. In addition, being able to estimate emissions subnationally can further aid the development of targeted and local policy efforts.

To achieve sustainable lifestyles within planetary boundaries, the global per capita consumption-based footprint needs to reduce to 2.5–3.2 tCO_2e by 2030 and to 0.7–1.4 tCO_2e by 2050 (Akenji et al., 2019; Koide et al., 2021). In contrast to this, the UK's 2019 per capita consumption-based footprint of private households is greater than 9 tCO_2e/capita (Defra, 2020). Consequently, a reduction of around 8% each year is needed in the UK to meet these climate goals. This current assessment of consumption-based GHG emissions of UK households can enable a more detailed understanding of how these emissions can be reduced.

The structure of this thesis follows the alternative format as outlined by the Faculty of Environment at the University of Leeds. This means that the main body of this thesis consists of three journal articles. To date, Chapter 2 (Kilian et al., 2022a) and Chapter 3 (Kilian et al., 2022b) are published in peer-reviewed journals, and Chapter 4 is formatted to be ready for submission. The research aims and objectives of the PhD as well as of the individual papers are described below. These are followed by a literature review, the three main text chapters, and a general discussion. This thesis explores GHG emissions, which are reported as carbon equivalents (CO_2e) and, thus, uses the terms GHG emissions and carbon emissions interchangeably.

1.2. Research Aims and Objectives

This PhD thesis aims to explore UK household and neighbourhood footprints for use in UK policy making. The overarching aim of this PhD is to assess UK household GHG emissions spatially and longitudinally at a product-level, to assess how social factors are linked to consumption-based emissions, and how this can aid consumption-based emission reduction policy. To address this, the following research questions (RQ) are asked:

RQ1. How robust are estimates of consumption-based GHG emissions of neighbourhoods?

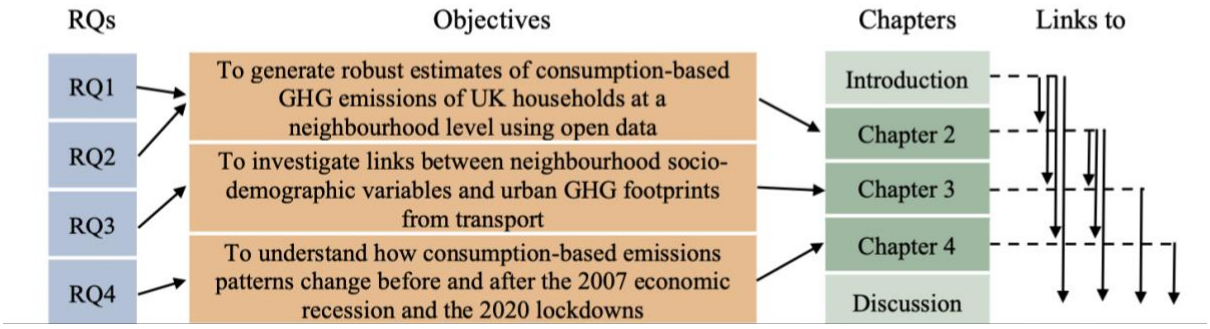
RQ2. Can open data be used to estimate consumption-based GHG emissions of neighbourhoods?

RQ3. What are the neighbourhood level differences in consumption-based emissions and the relationships between social factors and consumption-based GHG emissions?

RQ4. How do longitudinal changes in consumption impact GHG consumption-based emissions for different household types?

These RQs can be summarised into multiple objectives, which are addressed by the empirical chapters of this thesis. These chapter specific objectives are outlined below and the structure of the thesis is visualised in Figure 1.1.

Figure 1.1. Thesis structure outlining links between RQs, objectives, review and empirical chapters.



**Notes: Review chapters have lighter green shading, empirical chapters have darker green shading.

1.2.1. To Generate Robust Estimates of Consumption-based GHG Emissions of UK Households at a Neighbourhood Level Using Open Data

This thesis aims to generate sub-national estimates of household GHG emissions across the UK at a product-level. To estimate household footprints at the sub-national level, datasets on local household expenditure are needed to disaggregate the UK total. To ensure robustness of these estimates, this research compares different household expenditure datasets, including two openly available datasets. These datasets are compared in their ability to provide the most accurate estimate possible of spatial household GHG emissions across the UK. The robustness of the different emission estimates is evaluated, with the aim of generating robust estimates from the open datasets.

This research helps to assess which levels of spatial and product aggregation are most appropriate to ensure robustness of estimates. The thesis aim is to generate estimates below neighbourhood level, with minimum levels of aggregation necessary for products and services, across the whole UK. Neighbourhoods used are below-municipal census geographies (see section 2.3.1.3 and Appendix B for more detail on UK geographies). Two neighbourhood sizes are compared: smaller neighbourhoods with populations of 400-3,000 people and larger neighbourhoods with populations of 950-15,000 people (NISRA, 2013a; ONS, n.d.; Scotland's Census, 2013). Moreover, this part of the thesis aims to generate a transparent and replicable method of calculating sub-national footprints, to increase the current understanding of GHG emissions and allow tracking of these in the future. Simultaneously, this research aim provides recommendations for how aggregation over different variables can ensure robustness, while providing detailed and useful outputs.

1.2.2. To Investigate Links between Neighbourhood Socio-demographic Variables and Urban GHG Footprints from Transport

This thesis aims to assess spatial variations in neighbourhood GHG emissions, as well as their links to socio-demographic factors. Bridging the gap between industrial ecology and geographical analysis, this research employs methods from spatial statistics to investigate the relationships between emissions and social and spatial factors. As transport is one of the highest emitting sectors in the UK and as some aspects of UK transport policy are administered locally, transport is chosen as a point of analysis. This kind of analysis can reveal where such relationships are heterogeneous and homogeneous. Spatial methods and components are often overlooked by consumption-based emissions research. The aim of this research is, therefore, to address this gap and investigate where such spatial variations occur. London is chosen as a case study, as it has the most extensive public transport system in the UK and is, in population size, more comparable to other international metropolitan areas.

1.2.3. To Understand how Consumption-based Emissions Patterns Change before and after the 2007 Economic Recession and the 2020 Lockdowns

A longitudinal analysis can provide insight into complexities of consumption patterns and into not only *how much*, but also *which products and services* are consumed by UK households. Similarly, understanding how income reductions change the basket of goods, and consequently the footprints of different household types can be critical. Importantly, by looking at emissions in a time-period with two major income and consumption changes – the economic recession in 2007, and the COVID-19 pandemic in 2020 – this research aims to highlight the differences in reaction to income reductions and COVID-19-related behaviour policies of different household types. The former reveals how emissions change with income reductions, while the latter shows how emissions change with income uncertainty and government mandated lifestyle changes.

This can reveal where emissions decrease because of these changes and where they remain stable or increase. As the time period studied in this research covers a unique time period, with heavy restrictions on mobility, these results can give important and novel insight into the effects on emissions. Moreover, this research can inform policy by showcasing the importance different households place on different goods and services even after income reductions, uncertainty, and lifestyle changes.

1.3. An Introduction to Consumption-Based Emissions

1.3.1. Territorial, Production-Based and Consumption-Based Emissions

Emissions are typically recorded as being production-based, territorial or consumption-based, all of which measure different types of emissions and thus present different emission estimates (Owen et al., 2020). Territorial emissions refer to GHG emitted by industry, agriculture, domestic use, and transport within a country's territory (Franzen and Mader, 2018). Production-based emissions refer to the emissions related to the production of goods and services owned by a country and its citizens. A country's consumption-based emissions, on the other hand, are emissions that occur throughout the supply chain due to the production of products and services which are consumed within a country (see Table 1.1). This includes indirect emissions from the production of goods and services globally, and direct emissions from burning fuel at home or to drive. Moreover, consumption-based accounts also include emissions from international shipping and aviation, so-called bunker fuels (Franzen and Mader, 2018; Kander et al., 2015). In addition, single-country territorial accounts may overlook effects of outsourcing. Due to differences in manufacturing processes between countries, outsourcing may increase global emissions. For instance, Liu et al. (2016) show that carbon emissions embodied in Chinese exports are higher than those in German or Japanese exports, as the Chinese energy sector is coal-based. On the other hand, Kander et al. (2015) highlight that disregarding production-based accounts can overlook efforts to reduce emissions embedded in exports. This type of research underlines the complexity of emissions attribution and the need for a global climate strategy, which incorporates both production- and consumption-based accounts.

To such a nuanced understanding of GHG emissions, consumption-based accounting can offer three key contributions. First, it is not as susceptible to the impacts of outsourcing as production-based emissions, and can, in fact, highlight how emissions change with such outsourcing. Second, understanding consumption-based emissions can provide insight into the effects of demand-side approaches to reducing emissions. Third, it can quantify carbon inequalities both within and between territories (see Figure 1.2), to showcase where emissions can be reduced, and where they need to be redistributed to improve social equality and equity.

Table 1.1. What is included the UK's production-based, territorial, and consumption-based emissions?; adapted from (Owen, 2021).

				UK's Emissions		
	Owned by	Based in	Consumed by	Production-based	Territorial	Consumption-based
Industry	UK	UK territory	UK	✓	✓	✓
			RoW	✓	✓	
		RoW territory	UK	✓		✓
			RoW	✓		
	RoW	UK territory	UK		✓	✓
			RoW		✓	
		RoW territory	UK			✓
			RoW			
Citizens' direct emissions		UK territory	UK	✓	✓	✓
			RoW		✓	
		RoW territory	UK	✓		✓
			RoW			
Bunker shipping & aviation	UK		UK	✓		✓
			RoW	✓		
	RoW		UK			✓
			RoW			
Land use, land change, forestry					✓	

** Note: RoW refers to Rest of World

In light of the UK's consumption-based emissions being higher than production-based emissions (Defra, 2020; Millward-Hopkins et al., 2017; Sudmant et al., 2018), understanding how and where the UK's consumption contributes to global emissions becomes invaluable for effective climate mitigation. While production- and consumption-based emissions were more similar in the 1970s, over the last decade the UK's production-based footprint is estimated to have been only 55-66% of the consumption-based footprint (Eora Global MRIO, 2021).

On a subnational level, the use of consumption-based inventories can be useful for measuring the effectiveness of behaviour change policy. Whilst consumption-based inventories have for long been outside of the focus of subnational climate change policy (Peters, 2008; Turner et al., 2011), local policy makers in the UK are showing an increasing interest in consumption-based emissions in recent years (Owen, 2021; Owen and Barrett, 2020a; Owen and Kilian, 2020). This comes from aims to reduce consumption-based emissions. London Local Authority Districts (LADs), for example, aim to reduce consumption-based emissions of

London residents by two-thirds by 2030, with a particular focus on food, electronics, textiles, and aviation (Gilby, 2021). This is only possible with subnational estimates available regularly to track progress and understand where and how emissions can be reduced most effectively.

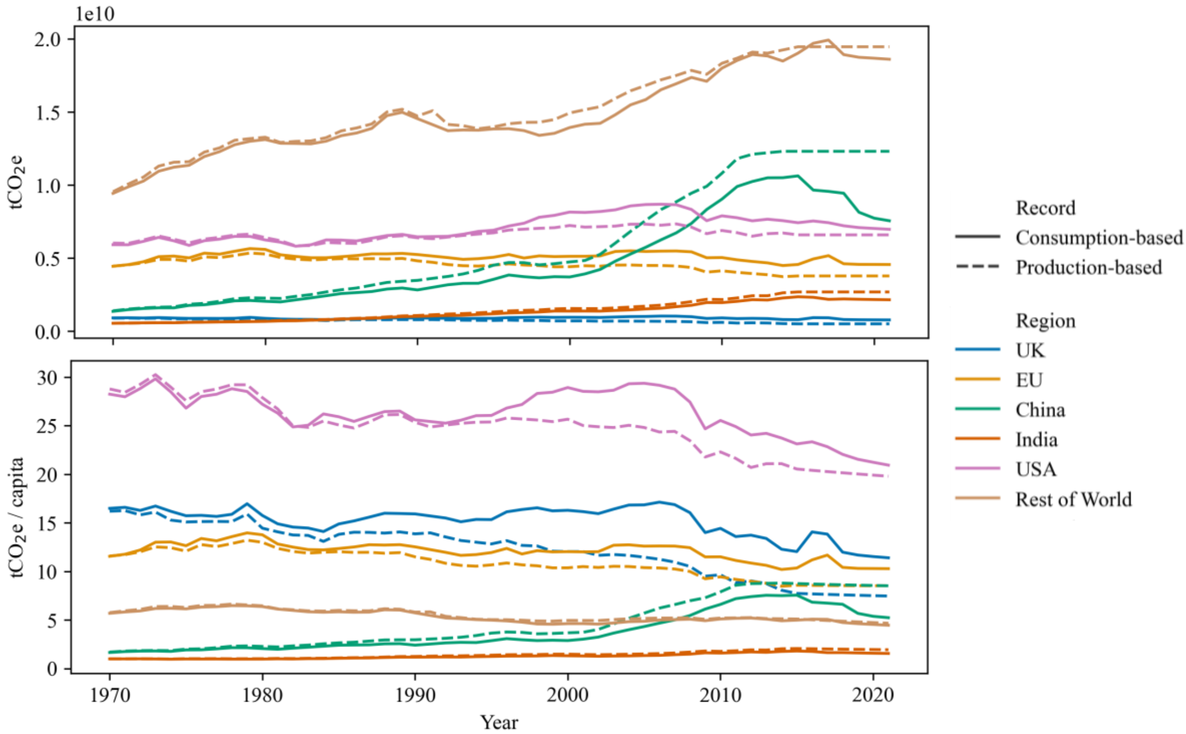


Figure 1.2. Total (top) and per capita (bottom) consumption- vs. production-based emissions over time.

**Note: Data via EORA (Eora Global MRIO, 2021; Kanemoto et al., 2016)

1.3.2. Environmental Accounting and Input-Output Analysis

Environmental accounting combines environmental and economic data to understand resource use and environmental impacts of countries, corporations, or consumers (UN: Statistics Division, 2003). Environmental accounting can use a combination of physical and monetary flow data to be done at various levels, including global, national, or corporate level (Lamberton, 2005; Parker, 2014). At these different levels environmental impacts can be assessed with regards to the global supply chain, within-country-, and within company-flows. Moreover, environmental accounting has several branches, including sustainability cost, which refers to the hypothetical cost for an organisation to remove their impact, natural capital inventory accounting, which traces stocks of natural resources and other natural capital over time, and input-output (IO) analysis, an analysis of material flows across territories and industries (Gray, 1992; 1993; Lamberton, 2005). A more detailed description of these and other environmental accounting methods is provided by Lamberton (2005). The method from environmental accounting used throughout this thesis is IO analysis.

IO analysis stems from economics and was first conceived by Wassily Leontief (1936) and can show how industrial output responds to changes in demand. These models originate in economics, but have been applied to environmental pressure data since the 1960's (Førsund, 1985; Leontief and Ford, 1970). By linking global economic IO data with environmental pressure data and conducting a so-called environmentally extended IO analysis, embodied energy and emission can be estimated (Hertwich and Peters, 2009; Proops et al., 1993; Tukker and Dietzenbacher, 2013; Wiedmann and Lenzen, 2018). With an increased need to address human-caused climate change and increased computing power, IO analysis became an increasingly popular tool among environmental researchers (Wiedmann and Lenzen, 2018). Today, IO analysis is integrated into the UN's central framework of systems of environmental-economic accounting (UN et al., 2014). More detail on the history and future of IO analysis can be found in the literature (Dietzenbacher et al., 2013; Rose and Miernyk, 1989; Tukker and Dietzenbacher, 2013; Wiedmann and Lenzen, 2018).

To conduct IO analysis, IO data are needed. Such datasets contain financial flow data across industries and final demand, and can contain data for single regions or multiple regions. While single region IO tables have been around for multiple decades, global multi-regional IO (MRIO) databases have only been around since the 2010s, as data quality, availability, and access improved (Tukker and Dietzenbacher, 2013). An environmentally-extended global MRIO framework provides the opportunity to estimate emissions for final products and services which occurred throughout the global supply chain (Forssell and Polenske, 1998; Leontief and Ford, 1970; Miller and Blair, 2009; Minx et al., 2009). Since the development of environmentally extended IO and global MRIO, it has been applied internationally and across resources (see Hoekstra, 2010), including carbon emissions (e.g. Hertwich and Peters, 2009; Su and Ang, 2010; Feng et al., 2021), energy footprints (e.g. Vringer and Blok, 1995; Lenzen et al., 2004; Baynes et al., 2011; Anderson et al., 2015), land and water use (e.g. Guan and Hubacek, 2007; Ivanova et al., 2016), and deforestation (Hoang and Kanemoto, 2021).

1.4. How Are Social and Spatial Factors Linked to Consumption-Based Emissions?

1.4.1. The Role of Social Factors and Inequalities in Consumption-Based Emissions

Carbon footprints are often linked to various demographic variables. For instance, higher carbon emissions are consistently linked to higher incomes (Lee et al., 2021; López et al., 2019;

Moran et al., 2018; Niamir et al., 2020; Otto et al., 2019; Vringer and Blok, 1995). Indeed, affluence, which is a compound measure of wealth that includes income, is widely considered to be a main driver of environmental destruction (Wiedmann et al., 2020). Moreover, a recent paper finds that shrinking household sizes contribute notably to increases in global emissions (Ivanova and Büchs, 2022). Higher emissions are often also associated with degree of rurality/urbanity, levels of car ownership, and percentage of the population with a higher degree (Baiocchi et al., 2010; Czepkiewicz et al., 2018; Jones and Kammen, 2014; Minx et al., 2013; Ottelin et al., 2014; Shigetomi et al., 2021). As these factors – particularly car ownership and education – are also strongly linked to incomes, however, there is debate around the extent to which these relationships are causal (Wier et al., 2001). More recent research also find effects of age (Zheng et al., 2022) and gender (Toro et al., 2019), which stem largely from product-level consumption pattern differences due to differences in not only lifestyles, but also needs (see also Druckman and Jackson, 2009; Ivanova and Middlemiss, 2021).

Moreover, Baiocchi et al. (2010) find that carbon emissions, particularly those related to transport, increase with income, while Büchs and Schnepf (2013) reveal differences in socio-demographic associations across different GHG emissions. Similarly, Lenzen et al. (2004) highlight that products and services, for which energy is used, vary between demographic groups: Sydney households' energy footprints linked to mobility increase with age and decrease with degree of urbanity, as people living in less central, higher income areas have increased access to trains. Moreover, while population and settlement density in urban areas often leads to lower housing and land transport emissions, air travel emissions are often higher in urban areas (Czepkiewicz et al., 2018; Ottelin et al., 2014). Interestingly, although pro-environmental attitudes appear to impact household behaviours, they do not impact flight emissions (Alcock et al., 2017). Finally, Druckman and Jackson (2008) find differences in energy requirements across dwelling types and increases in total per capita energy requirements with increasing degree of urbanism. Consequently, these studies underline the impact spatial and socio-demographic factors can have on footprints, through factors including local infrastructure, dependency on private transport, and home insulation.

Consumption-based emissions research can also highlight carbon inequalities, climate injustices and the need for not just reduction, but redistribution of resources. Globally, as developed countries continue to outsource production to low- or middle-income countries, production-based GHG emissions are stabilising in developed countries but continue to grow in developing countries (Wood et al., 2019b) – Böhm (2015) calls this 'carbon colonialism'.

Against a background of the poorest 50% of the global population having only an approximately 10% share of global GHG emissions, while the richest 10% have a share of approximately 50% (Chancel, 2022; Oxfam, 2015), and the ones emitting least being most vulnerable to the effects of climate change (Barnett, 2020), tackling climate change mitigation solely from a production-based perspective overlooks social inequalities. Indeed, some argue that consumption-based accounting may be a fairer approach to distributing global emissions than a production-based one (Baker, 2018; Peters, 2008). While a consumption-based approach is not a one-fit-for-all solution to these geo-political issues – which often have historical and structural causes and are deeply entangled with a range of other social justice issues – it adds a perspective that can account for some of the inequalities embodied in our current approaches to climate change mitigation (see Connolly et al., 2022; Hubacek et al., 2017; Ivanova and Middlemiss, 2021; Millward-Hopkins and Oswald, 2021; Owen et al., 2022).

Similarly, this type of research can highlight subnational inequalities. For instance, in 2012 in China, the richest 5% of the population comprised 19% of the consumption-based footprint (Wiedenhofer et al., 2017). In the UK in 2004, research finds that emissions at a Local Authority level range from 10.21 tCO_2e/capita to 15.51 tCO_2e/capita, with some of the highest and lowest footprints being measured within London (Minx et al., 2013), likely linked to high levels of income inequality. Recent research also highlights the interaction between urban-rural classification and income across various countries in the Global South, where rural low-income households have lower emissions than urban low-income households, but rural high-income households have higher emissions than urban high-income households (Connolly et al., 2022). Finally, research across European Union countries indicates that despite having higher energy needs, people with disabilities tend to have lower footprints, highlighting a need to redistribute energy use (Ivanova and Middlemiss, 2021).

These findings call for the need not only to reduce, but also to redistribute resource use. Oswald et al. (2021) suggest that equitable and inequitable distributions of energy are structurally different. They argue that an equitable distribution of energy would substantially reduce the number of people living in energy poverty and shift energy use away from transport and luxury goods and services to subsistence and necessities. In line with this, consumption patterns are shown to differ between the lowest and highest earners by goods and services, such that high income households have proportionally much higher indirect and transport emissions than low income households (Baltruszewicz et al., 2021b; Connolly et al., 2022; Otto et al., 2019). For instance, it is estimated that only 20% of the global population have access to air travel, one of the most carbon intensive consumer goods and services (Negroni, 2016). This global trend is mirrored in the UK: although in the UK air travel participation of low income households is increasing, domestically carbon inequality from air travel also remains high (Büchs and Mattioli, 2021). Moreover, research indicates that reducing household expenditure inequalities and redistributing these expenditures to public services could substantially decrease emissions (Millward-Hopkins and Oswald, 2021). Research from India also shows that eradicating extreme poverty can be done while meeting climate goals, but that the richest households, who have disproportionality high emissions, need to be targeted (Lee et al., 2021). A consumption-based approach can thus shine a light on the links between social inequality and emissions, and highlight changes needed to live within planetary boundaries, while reducing social inequalities.

How different socio-demographic groups are impacted by the COVID-19 pandemic lockdowns and consequent austerity politics presents a further important area of research, as this can shine further light on links between emission reduction, and social inequalities. Chapter 4 of this thesis investigates these relationships to assess what researchers and policy makers can learn to make emission reduction efforts both effective and equitable.

1.4.2. Comparing Emissions Over Time

Analysing emissions longitudinally can serve two key purposes: historical inequalities and contributions to climate change can be analysed, and emission changes can be tracked. Between 1850-2011, almost 80% of historical territorial carbon emissions are attributed to the Global North (Center for Global Development, n.d.). From 1850-2021, the UK[1] is reported to have been responsible for 3% of total historical territorial emissions (Evans, 2021), despite – according to 2019 figures – making up less than 1% of the global population (ONS, 2021a; UN: DESA, 2019). Similarly, the EU-28 countries are estimated to be responsible for 23% of cumulative territorial carbon emissions between 1850-2015, and the US for 26% (Hickel, 2020). The historical emissions – from the 1850s until 2010 – of the top investor- and state-owned entities are also substantial, such that the top 20 highest emitters are responsible for 30% of historical emissions (Heede, 2014). Given that the total carbon budget must be limited to reach climate goals (Akenji et al., 2019; Masson-Delmotte et al., 2018; Rogelj et al., 2019; Rogelj and Foster, 2019), such historical analysis points to clear inequalities and raises

[1] This figure refers to territorial emissions from Great Britain and Northern Ireland only.

questions of justice and responsibility (e.g. Alcaraz et al., 2018; Böhm, 2015; Evans, 2021; Heede, 2014; McKinnon, 2015; Okereke and Coventry, 2016).

In addition, studying emissions over time can also be a useful tool to track emission changes over time. This includes both recording emissions from previous years to assess trends (Defra, 2022; Fitzgerald et al., 2018; Hickel et al., 2022a; Steinberger and Roberts, 2010), and being able to make projections for the future (Friedlingstein et al., 2014; Grubler et al., 2018; Millward-Hopkins et al., 2020; Victor, 2012). Such a longitudinal analysis can allow, for example, quantification of the impacts the of the 2020 lockdowns on emission estimates of different households. Longitudinal analysis can therefore be a valuable tool to address questions of responsibility, progress, and impact.

1.4.3. The Importance of Geography

The importance of considering geography is multifaceted, conceptually, practically, and methodologically. Conceptually, spatial differences are able to capture inequalities and place specificity. Although there is debate whether spatial inequalities merely represent a spatial overview of social injustices (Bouzarovski and Simcock, 2017; Chatterton, 2010; Garvey et al., 2022; Pirie, 1983; Soja, 2016, 2010), applying a spatial justice framework can be helpful in highlighting and evaluating emission inequalities.

Spatial differences in energy use and carbon emissions are reported in the literature both within and between countries (Clarke-Sather et al., 2011; Experian, 2004; Ivanova et al., 2017; Lenzen et al., 2004; Minx et al., 2013). Similarly, differences between countries in social drivers of energy needs are reported (Lenzen et al., 2006). Due to unique contexts including climate, history, culture, and existing infrastructure, these drivers can differ. This emphasises the place-specificity of this type of research. Moreover, spatial inequalities of resource use are documented in the UK, such that different product types have different levels of inequality (Druckman and Jackson, 2008b). Similarly, in a critical review on low-carbon transitions, Garvey et al. (2022) call for the need for spatially targeted policy interventions. By appreciating the diversity of economic vulnerabilities which coexist in regions, the authors argue, such an approach has the potential to be both more effective and more just. Consequently, a spatial approach allows for the incorporation of spatial issues and inequalities, which allow for more place-specific interventions.

In practice, space also matters. As policy is inherently spatial and can be implemented and drafted at various geographical levels, considering how different geographies are impacted by policy is important. As they find vastly different consumption patterns and consumption-based emissions between urban, rural, and suburban areas, Jones and Kammen (2014) argue that climate change mitigation needs to be place and population specific, underlining the usefulness of including a geographically disaggregated analysis of consumption-based emissions. Similarly, finding large inequalities between cities in China's pearl river basin, Qian et al. (2022) suggest that a region and sector specific emission reduction policy may be fairer than an inter-province one. In addition, geographic boundaries allow researchers to estimate, for instance, the impact of cities. Using such strategies, existing research is able to calculate the consumption-based emissions of various cities that are imbodied in imports (Feng et al., 2014; Meng et al., 2018; Mi et al., 2019). Lastly, as local actors are increasingly involved in climate change mitigation efforts (e.g. LGA, n.d.; C40, 2019; DEAL et al., 2020), understanding spatial differences and geographical contexts matters for designing effective local policy. Local climate policy can include local transport and infrastructure planning, localised behaviour change campaigns, or housing strategies, like increasing insulation.

In the UK context, local governments are involved in climate change mitigation in various ways. For instance, many local governments are declaring climate emergencies (LGA, n.d.), municipalities in London have additional targets, such as reducing emissions by two thirds by 2030 (Gilby, 2021), moreover, London LADs (London Councils, n.d.) and Mayor of London (2018) aim to increase active transport, increase the number of bus services, and expand infrastructure for electric vehicles. Finally, some UK cities are tracking consumption-based footprint emissions over time at different geographic scales (Owen, 2021; Owen and Barrett, 2020a; Owen and Kilian, 2020). Having geographical emission estimates can help locate where certain policies may be most effective.

Methodologically, when analysing geographic data quantitatively, spatial methods should be used. Spatial data are typically spatially dependent, meaning that areas in closer geographic proximity are more likely to be more similar than two areas that are further away from one another (Fotheringham, 2011; Miller, 2004). This phenomenon is summarised by Tobler's First Law of Geography: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970:236). Neglecting to use spatial methods ignores such dependencies and consequently can overlook spatial variations (Comber et al., 2022). Given their aforementioned uneven geographical distribution, emission data are inherently spatial. As the relationships between emissions and its predictors are shown to be spatially heterogeneous (S. Wang et al., 2019; Y. Wang et al., 2019; Xu and Lin, 2017), the geographic perspective of emissions data should not be ignored. Despite this, consumption-based emissions research often sits outside of the discipline of geography and thus geographic methods are not frequently used in emission data analysis.

It is also useful to highlight the importance of not just geography, but the neighbourhood level. Galster (2001) points to the difficulty of urban social scientists to explicitly define the neighbourhood both in terms of its meaning as well as its boundaries. The author puts forward a notion of the neighbourhood as a social construct, which is a "bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses" (Galster, 2001:2112). Other scholars point to differences between humanistic, instrumental and phenomenological approaches of defining the neighbourhood (Kallus and Law-Yone, 2000). Respectively, these approaches consider the neighbourhood as a manifestation of human activity, a unit for urban planning, and a phenomenon describing everyday flows (Kallus and Law-Yone, 2000). In the more recent literature, the definition of the neighbourhood remains fluid (Baffoe et al., 2020). In this thesis, the neighbourhood is used as a geographic unit of quantitative analysis. Particularly, this thesis employs statistical geographic units as neighbourhoods. While these may not reflect everyday, or functional understandings of where neighbourhood boundaries are, they are useful for statistical purposes, as they are defined by socio-demographic similarity of residents (ONS, 2016a). Moreover, these statistical units are nested within LADs, making them a useful tool for policy makers, as administrative boundaries overlap with statistical ones. Finally, using this statistical definition of a neighbourhood allows for increased data access, as geographic UK data are typically reported in the units used throughout this thesis.

1.5. Challenges and Opportunities for Climate Policy

As the usefulness of consumption-based emissions to inform local policy and carbon inequality have been discussed, this section focusses on some of the challenges effective and fair climate policy faces.

1.5.1. Incorporating Consumption-Based Carbon Footprints in Policy

Existing policies to reduce emissions often centre on technological shifts (CMA, 2021; HM Treasury, 2021; IPCC, 2014). This is despite warnings that major societal, economic and cultural changes are needed to reduce global emissions sufficiently (Brand et al., 2019; Haberl et al., 2020; Wiedmann et al., 2020). However, the number of peer-reviewed research articles published on reducing emissions have increased substantially in recent years (Creutzig et al., 2021a; Heinonen et al., 2020). Indeed, such research shows that GHG emissions can be decreased substantially by decreasing demand (Barrett et al., 2022; Creutzig et al., 2021a; Girod et al., 2014; Shigetomi et al., 2021). Some of these shifts include, for example, avoiding flying and living car-free (Ivanova et al., 2020), or following a vegan diet (Garvey et al., 2021). Moreover, consumption-based emissions can be effectively reduced through local policies (Creutzig et al., 2016, 2015, 2012). However, such policy may face various challenges. Moreover, a recent review of policy implication also highlights policy implications which are unique to the consumption-based carbon emissions literature (Ottelin et al., 2019). The authors, for instance, claim that while climate change literature and consumption-based emissions literature both promote carbon pricing approaches and travel behaviour change, consumption-based emissions approaches also discuss responsibility of emissions, rebound effects, sustainable consumption patterns, and population-specific policies. This showcases the important contribution consumption-based emissions literature can bring to practice.

First, existing research also reports that reductions in one area may be paired with increased overall emissions, as people may have more money for more carbon-intensive goods and services (Druckman et al., 2011). For example, Duarte et al. (2016) find that shifting to a more plant-based diet, which includes many vegetables, results in a rebound effect due to the additional savings from eating a cheaper diet. As a solution to this, the authors therefore propose that behaviour change policy should be paired with environmental education.

Second, as already discussed, social inequities, such as differences in incomes and access to services are strongly linked to emissions (Baiocchi et al., 2010; Büchs and Schnepf, 2013a; Druckman and Jackson, 2008a; Ivanova et al., 2018; Ivanova and Wood, 2020; Millward-Hopkins and Oswald, 2021; Minx et al., 2013; Sudmant et al., 2018). A policy which does not consider such contexts risks replicating inequalities and inequities or could even disproportionately affect those most marginalised or with the lowest emissions (e.g. Büchs et al., 2021). Differences in consumption patterns between socio-demographic groups, as well as the differences in impacts of climate change interventions on such groups must therefore be considered. For instance, fuel poverty can be the result of a number of factors, including ‘low income, high cost’, the main focus of the UK government (Secretary of State for Energy and Climate Change, 2014), but also poverty, high energy and living costs, income inequality, energy market failures, and austerity politics (Chester, 2014; Middlemiss and Gillard, 2015; Moore, 2012). Understanding the context in which patterns of consumption occur, therefore, is vital to creating a socially just climate policy. In line with this, Druckman and Jackson (2009) argue for targeting specific climate mitigation policies at different types of households, with a particular focus on those emitting the most.

1.5.2. Evidence from Tax-Based Approaches

Although commonly regarded as an incentive to reduce emissions, cost- and tax-based emission reduction strategies are complex. This is highlighted by Barrett and Owen (2018), who find that while the UK's Energy Company Obligation scheme to reduce emissions by providing energy efficiency measures to low-income households reduces energy costs for these households, it is funded by an additional charge to households and businesses, which disproportionately affects low-income households. Where more affluent households are charged 0.16% of their income, less affluent households – which already have the lowest emissions – pay around 9 times more relative to their income (Barrett and Owen, 2018).

Moreover, research shows that carbon taxes are not as effective as often assumed, and can only work when low carbon alternatives are widely available at sufficiently lower prices (Büchs et al., 2021; Dirix et al., 2015; Haites, 2018; Kiss and Popovics, 2021). However, introducing a carbon tax to transport may distribute this tax more fairly than a household energy carbon tax (Büchs and Schnepf, 2013a), and taxing flights may be one of the more effective and least regressive options (Büchs and Mattioli, 2022). Other suggestions include an increased focus on the super-rich (Otto et al., 2019), or those with the highest carbon footprints (Druckman and Jackson, 2009). Finally, Büchs et al. (2021) propose expanding green infrastructure related to housing and motoring emissions and pairing this with so-called green vouchers to reduce emissions as well as fuel and transport poverty. To reduce and redistribute emissions, therefore, social justice and existing structures and vulnerabilities must be taken into account. Combining emission estimates at with more product and service detail with socio-demographic information, may help further understand where emissions can best be reduced, without increasing existing social inequalities.

1.5.3. Wellbeing and Sufficiency

In addition to social structures, climate policy needs to consider wellbeing. Research suggests that achieving high-wellbeing within planetary boundaries is possible (Millward-Hopkins et al., 2020). Indeed, after a certain threshold, the improvements in well-being for energy used begin to plateau (Martínez and Ebenhack, 2008; Steinberger et al., 2012; Steinberger and Roberts, 2010). Some lower-level demand-side mitigation efforts are even shown to increase wellbeing (Creutzig et al., 2021b). Decreased commuting, for example, is not only linked to decreased transport emissions (Brand et al., 2013) but also to higher subjective wellbeing (Creutzig et al., 2021b). Similarly, increased active and public transport can decrease emissions, motor vehicle crashes, and noise, all the while increasingly offering possibilities to increase greenspace and promoting improved physical health (Brand et al., 2021; Khreis et al., 2017; Nieuwenhuijsen, 2020). This means that an approach focussed on sufficiency, has the potential to meet both positive social outcomes, as well as emissions within planetary boundaries (O'Neill et al., 2018).

Much literature assessing the global reduction and redistribution of energy to achieve carbon emissions within planetary boundaries calls for such a sufficiency framework, where technological advances, such as high-quality, well-insulated housing, is paired with radically reduced consumption, and an increased focus on public goods and services, such as public transport (Millward-Hopkins et al., 2020; Oswald et al., 2021). Millward-Hopkins et al. (2020) also note that such a level of sufficiency provides a high standard of living, with access to heating and cooling where needed, transport, education, health, and reduced work hours. However, the authors also highlight the challenges to such a model, which requires systematic changes at a global level to increase social equity and increased inclusivity (see also Aiken, 2012).

Moreover, the focus of research on degrowth is increasing (e.g. Brand et al., 2019; Haberl et al., 2020; Lenzen et al., 2022; Parrique et al., 2019; Wiedmann et al., 2020). Degrowth scholars argue that a 'greening' of the economy cannot sufficiently reduce emissions without a radical reduction of production and consumption to meet climate goals. Instead, they propose shifting the current focus on GDP to measures of social wellbeing and environmental welfare (Hickel et al., 2022b; Hickel and Kallis, 2020; Hoekstra, 2019; Kallis et al., 2018; Raworth, 2017; Wiedmann et al., 2020).

In practice, however, sufficiency frameworks and degrowth are challenged by the aims of states and governments to achieve economic growth (Haberl et al., 2020; Hickel, 2021; Hickel and Kallis, 2020; Parrique et al., 2019). Despite suggestions to replace GDP with measures of wellbeing and sustainability (Hoekstra, 2019; Kallis et al., 2018; Kreinin and Aigner, 2022), and warnings that technological changes alone cannot reduce emissions sufficiently in the time needed (Brand et al., 2019; Haberl et al., 2020; Parrique et al., 2019; Wiedmann et al., 2020), governments and intergovernmental organization typically centre technological shifts as solutions to reduce emissions (CMA, 2021; HM Treasury, 2021; IPCC, 2014).

1.5.4. Overcoming Lock-Ins

Finally, carbon lock-ins can present a major challenge to policy makers (Brand-Correa et al., 2020; Jackson and Papathanasopoulou, 2008; Seto et al., 2016). Carbon lock-ins refer to the self-perpetuating dependency of existing infrastructure, social, political, and economic structures on high-carbon energy systems (Unruh, 2002, 2000). For instance, Mattioli et al. (2020) show that the entanglement between the automotive industry, car-related infrastructure, political-economic relations, public transport provision, and socio-cultural factors create a lock-in, which hinders moving to more sustainable systems. The authors propose that a move away from car-dependency, therefore, needs to consider all factors simultaneously. Similarly, exploring how policy makers can promote more sustainable consumption patterns, Shove (2014) illustrates the importance of understanding behaviours within the socio-cultural, economic, and infrastructural contexts in which they occur. To effectively change behaviours, she argues, requires a shift from a focus on individuals' behaviours to creating the conditions which make more sustainable behaviours possible. This, in turn, necessitates a radical change in conventions, expectations, common practices and standards, and markets; in other words, systemic change which considers socio-cultural factors, infrastructure, as well as political and economic structures is needed (Shove, 2014). To address the possibility of policy intervention in the high carbon lock-in domains of mobility and housing, Ivanova et al. (2018) suggest that increased population density, reduced travel distances, reduced car ownership, reduced air travel, smaller dwelling sizes, and more recently constructed or refurbished dwellings, and income should be key considerations for climate change mitigation policy. In line with this, research from Helsinki Metropolitan Area finds that policy targeting the energy efficiency of buildings and an increased switch from private to public transport, through the instalment of public transport zones, pedestrian zones, and the increased promotion of active transport, contributed to a 7% reduction in transport emissions and to a 15% reduction in housing emissions (Ottelin et al., 2018). These findings show that while decreasing emissions in high lock-in domains requires a multifaceted approach, reductions are possible. However, as shown by these examples, such an approach needs to consider socio-cultural norms, infrastructure and political and economic structures.

1.6. Data and Methods

In this section, data and methods used throughout this thesis are summarised. Detailed methods and data used for each of the papers that constitute the research chapters of this thesis are described within the relevant chapters.

1.6.1. Environmentally Extended Input-Output Analysis

To calculate subnational estimates of emissions two pieces of data are needed: product-based multipliers estimating the emissions per unit spend, and subnational household expenditure microdata. To estimate such multipliers, first, total indirect consumption-based emissions need to be calculated using an environmentally-extended MRIO analysis.

MRIO tables are generated from single-region IO tables (SRIO); the structure of an MRIO table is displayed in Figure 1.3 (see Miller and Blair, 2009; Owen, 2017; Wood et al., 2019). The transaction matrix (**Z**) is coloured grey and captures and shows how output from one sector is being used as input into another sector. For example, the agricultural sectors may produce flax, which is then sold to the textile industry to produce linen. Sales to final demand are represented by **y** and contain all final sales from different sectors to end consumers including households, and governments. In addition, vector **x** contains total outputs for each sector, the sum of which should match the sum to the total input, and vector **f** contains emissions data by sectors.

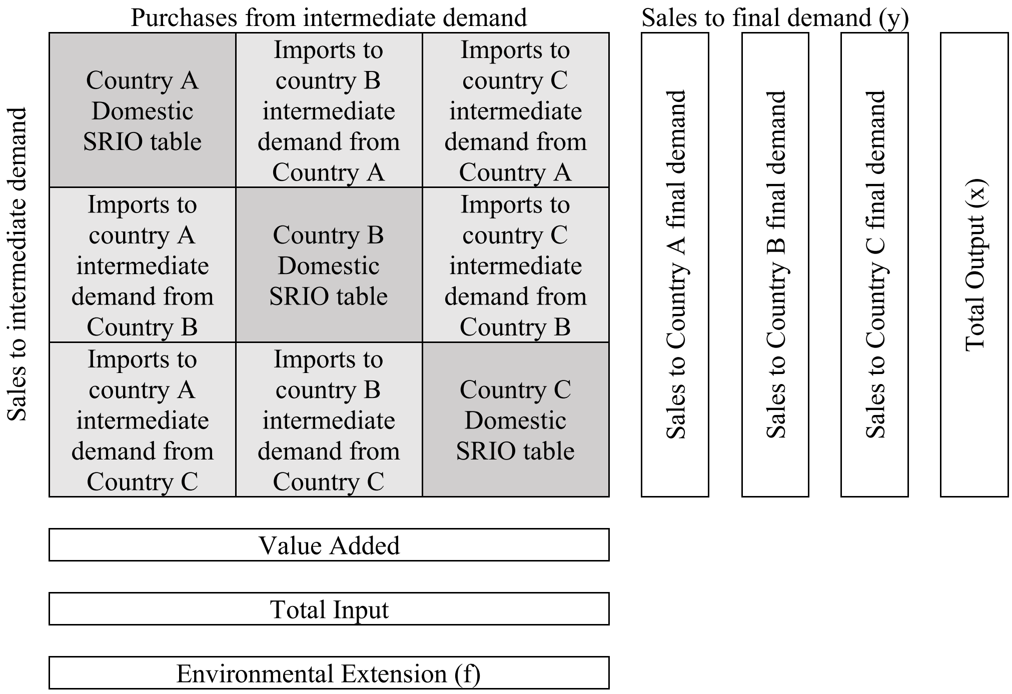


Figure 1.3. MRIO data structure; adapted from Owen (2017).

To calculate indirect consumption-based emissions, the fundamental Leontief equation is used (see Miller and Blair, 2009),

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}$$

This indicates the inter-industry requirements of each sector to deliver a unit of output ($\mathbf{x}$) to final demand ($\mathbf{y}$). Here, $\mathbf{I}$ is the identity matrix with the same dimensions as the Transaction Matrix ($\mathbf{Z}$) (see Figure 1.3), and $\mathbf{A}$ is the technical coefficient matrix, $\mathbf{A} = \mathbf{Z}\mathbf{x}^{-1}$. The element $(\mathbf{I} - \mathbf{A})^{-1}$ is known as the Leontief inverse (further identified as $\mathbf{L}$) and indicates the total inputs required for producing one unit of output for each of the sectors (see also Owen et al., 2014). Thereafter, a region's indirect consumption-based emissions (E) can then be calculated,

$$E = \mathbf{sLy}$$

Where $\mathbf{s}$ is a vector showing direct industry emission coefficients ($\mathbf{s} = \mathbf{f}\hat{\mathbf{x}}^{-1}$, where $\mathbf{f}$ is the environmental extension), and $\mathbf{y}$ is a vector showing sales to final demand. To estimate indirect emissions by product ($\mathbf{e}_p$), the final demand vector must be diagonalized,

$$\mathbf{e}_p = \mathbf{sL}\hat{\mathbf{y}}$$

Direct household emissions are then added to the according product to estimate total household consumption-based emissions. In the current UK model, total direct emissions from transport and total direct emissions from home heating and cooking are added to indirect emissions from motoring oils, and home gas used, respectively. In case of the UK, direct emissions associated with consumer expenditure are published annually by the Office for National Statistics (ONS) and are openly available (ONS, 2019a). Information on direct emissions mainly comes from the National Atmospheric Emissions Inventory (NAEI). More information on how these are calculated can be found in section 1.6.3.

1.6.2. Subnational Footprinting

Subnational footprinting can be done by splitting total national emission estimates, or by using subnational IO tables. Subnational IO models document flows of resources between different parts of one country. They can therefore allow for an analysis of differences in imported and exported emissions between subnational areas (e.g. Aniello et al., 2019; Davidson et al., 2022; Kronenberg and Többen, 2011; Mi et al., 2019; Vasconcellos and Caiado Couto, 2021; Zheng et al., 2019). Moreover, such models can be used to investigate, for instance, city-level emissions through using only IO tables (Wiedmann et al., 2021). Resources such as the IELab's Global MRIO database (Lenzen et al., 2017) increasingly allow for such analyses.

In the UK, however, subnational IO tables are currently only available for Scotland, and for Northern Ireland (Davidson et al., 2022), but not for England and Wales or any lower level geographies. As a result, to estimate subnational emissions, expenditure datasets are used to disaggregate the national total. This is done under the assumptions that expenditure is relative to products and services consumed. After total direct and indirect household consumption-based emissions are calculated (see 1.6.1), total household emissions are divided by total household spend to estimate household emissions per unit spend (here in $tCO_2e/£$). These can then be multiplied by data from household expenditure surveys to estimate subnational household emissions. Compared to using subnational IO tables, this approach cannot provide an overview over interregional trade, but is often more accessible with regards to the data available.

To minimise uncertainty from inconsistencies between the household surveys and MRIO data (see Min and Rao, 2017), this research uses bridging tables. These tables are provided by the ONS and allow for conversion of the reported sectors into Classification of Individual Consumption by Purpose (COICOP) classifications (UN: Statistics Division, 2019). Similarly, household surveys used in this thesis follow the COICOP structure. Hence, the expenditure categories from all datasets are complete and map onto each other.

The COICOP structure contains four nested levels of product aggregation, reaching from the most aggregated COICOP 1 level, to the most disaggregated COICOP 4 level. For example, bread expenditure appears under COICOP 1 level 'Food and non-alcoholic beverages', under COICOP 2 level 'Food', under COICOP 3 level 'Cereals and cereal products', and under COICOP 4 level 'bread and bakery products' (UN: Statistics Division, 2019).

To get a more detailed understanding of emissions, these are typically broken down into per household or per capita emissions. As households with multiple members can share some resources, they need less income per person than single occupant households. This is also an important consideration to make when investigating consumption-based emissions, as differences in household sizes and compositions also linked to consumption-based emissions (Ivanova and Büchs, 2022, 2020). To control for this effect, equivalisation is often used, meaning that household composition is taken into consideration in order to compare households more meaningfully (Gough et al., 2011).

For the analysis carried out in this thesis, various measurements of emissions are used, including non-equivalised per population emissions (Chapter 2), total neighbourhood emissions (Chapter 3), and equivalised single person household emissions (Chapter 4). Where needed to compare between cohort with different average household composition, as is done in Chapter 4, equalisation is used. Chapter 2, however, compares non-equivalised per population emissions for the same neighbourhoods calculated using different microdata. This means that as neighbourhood populations are the same for the datapoints being directly compared, equivalisation is not necessary. Similarly, Chapter 3 uses total neighbourhood emissions, rather than per capita emissions to avoid spurious correlations from statistically analysing dependent and independent variables which are derived from common ancestor variables (Pearson, 1897; Ward, 2013). As a result, equivalisation does not apply to the main analysis conducted in this chapter.

1.6.3. The UKMRIO Model

The MRIO database used to calculate emissions in this research uses the UKMRIO model (Defra, 2020; ONS, 2019a, 2020a). It is constructed annually by the University of Leeds, following methods outlined by Tukker et al. (2018) and Edens et al. (2015) to ensure consistency with National Accounts (see Owen and Barrett (2020) for more detail). It is an Official Statistic, which is based primarily on data provided by the ONS, with additional data on the UK's trade coming from other MRIO databases, such as EXIOBASE (Owen et al., 2018a). The UKMRIO reports the greenhouse gases carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF_6) and nitrogen trifluoride (NF_3). All greenhouse gases reported in the UKMRIO are converted into carbon dioxide equivalents (CO_2e).

In the UKMRIO, data is structured into Supply (**S**) and Use (**U**) tables, splitting products and services into 106 sectors (ONS, 2018a; Owen et al., 2018a, 2017). The use tables display the sum of domestic transaction and intermediate imports, meaning that they are combined tables. Similarly, the final demand table captures the sum of domestic and imported final products and services. To separate intermediate imports from domestic use, the ONS releases tables containing only domestic use and final demand every 5 years (Owen et al., 2017).

Due to this difference in structure, to estimate emissions from the UKMRIO, first, the transaction matrix (**Z**) is created from **S** and **U**,

$$
\mathrm{Z} = \begin{pmatrix} 0 & \cdots & 0 & \mathrm{U}^{1,n+1} & \cdots & \mathrm{U}^{1,2n} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \mathrm{U}^{n,n+1} & \cdots & \mathrm{U}^{n,2n} \\ \mathrm{S}^{n+1,1} & \cdots & \mathrm{S}^{n+1,n} & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{S}^{2n,1} & \cdots & \mathrm{S}^{2n,n} & 0 & \cdots & 0 \end{pmatrix}
$$

Second, the UKMRIO contains a product-level final demand matrix (**Y**), which needs to be adapted to the **Z**, to ensure it matches the different structure of **Z**,

$$
\mathbf{Y}_{\boldsymbol{big}} = \begin{pmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \\ \mathbf{Y}^{n+1,1} & \cdots & \mathbf{Y}^{n+1,2n} \\ \vdots & \ddots & \vdots \\ \mathbf{Y}^{2n,1} & \cdots & \mathbf{Y}^{2n,2n} \end{pmatrix}
$$

Finally, **x** is generated,

$$
\mathbf{x} = \begin{pmatrix} \sum_{\boldsymbol{k}}^{\mathbf{1}} \mathbf{Z}^{1,n} \\ \vdots \\ \sum_{\boldsymbol{k}}^{\mathbf{1}} \mathbf{Z}^{k,n} \end{pmatrix} + \begin{pmatrix} \sum_{\boldsymbol{k}}^{\mathbf{1}} \mathbf{Y}_{big}{}^{1,n} \\ \vdots \\ \sum_{\boldsymbol{k}}^{\mathbf{1}} \mathbf{Y}_{big}{}^{k,n} \end{pmatrix}
$$

Thereafter, the analysis follows the steps outlined in section 1.6.1, to calculate indirect emission by product and service categories for the UK. In short,

$$
\mathbf{e} = \mathbf{f}\hat{\mathbf{x}}^{-1} \times (\mathbf{I} - \mathbf{Z}\mathbf{x}^{-\mathbf{1}})^{-1} \times \widehat{\begin{pmatrix} \sum_{\boldsymbol{k}}^{\mathbf{1}} \mathbf{Y}_{\mathrm{big}}{}^{1,n} \\ \vdots \\ \sum_{\boldsymbol{k}}^{\mathbf{1}} \mathbf{Y}_{\mathrm{big}}{}^{k,n} \end{pmatrix}}
$$

Once indirect emissions are calculated, direct emissions linked to household activities are added to the indirect emissions to estimate total consumption-based emissions. The ONS (2019a) reports direct emissions linked to consumer expenditure on travel and non-travel. Total direct emissions linked to household expenditure is openly available and used throughout this thesis. Here, non-travel emissions are added to indirect emissions from home gas use, whereas travel emissions are added to indirect emissions from petrol, fuel, and other motoring oils. These categories are chosen as they best represent the direct emission categories as described by the ONS (2019a) and NAEI (Tsagatakis et al., 2022).

In the UK, direct emissions linked to household expenditure are estimated using a variety of data sources (Defra, 2023; Tsagatakis et al., 2022). Conversion factors for energy use to

GHG emissions for gas, oil, and solid fuel use come from BEIS via the Digest of UK Energy Statistics (DESNZ and BEIS, 2022). These are then combined with various other datasets to estimate energy use and emissions. Direct emissions from domestic gas consumption, for example, use additional data from gas meters at a spatially granular level ranging from postcode level to a 1km-by-1km grid resolution. Direct emissions from domestic oil and solid fuel consumption, on the other hand, match spatially localised information on central heating and housing data from the census with addresses, as well as with data on average household energy consumption estimates across the UK regions and the Met Office's climate regions. Using this approach, domestic oil and solid fuel consumption are modelled at a 1km-by-1km grid and at the smallest census geography. Tsagatakis et al. (2022) describe this process in further detail.

Direct emissions from the use of motor vehicles, similarly, are estimated using a variety of datasets. Data on fuel consumption and emissions factors are combined with detailed and spatialised information on vehicle fleets, such as vehicle ages and types, as well as with traffic data from the UK's Department for Transport. This includes vehicle kilometres, as well as secured data on vehicle registration plate recognition, allowing for added validity of the estimates. Emission factors used to estimate such direct emissions are empirically derived and come from the EMEP/EEA Emission Inventory Guidebook and are consistent with databases from the European Environment Agency. Among other factors, engine capacity and vehicle mass are considered (see Tsagatakis et al. (2022) for further detail).

Despite this spatialisation, direct emissions are published by the ONS (2019a) as the UK total. In the current work, therefore, the aggregate total direct emissions from households are added to the total indirect emissions from households. These total emissions are then divided by total household spends at a product-level, to estimate carbon multipliers (tCO2e/£), which can be multiplied by average spends of household types or to consumption-based emissions of these household types. Limitations in their disaggregation therefore mirror those in the disaggregation of indirect emissions (see section 1.7.2).

The work in this thesis makes use of the above equations to estimate emissions in Chapter 2, Chapter 3, and Chapter 4.

1.6.4. The Living Costs and Food Survey

To disaggregate UK emissions subnationally, microdata on household consumption are needed. The microdata dataset used throughout this thesis is the Living Costs and Food Survey (LCFS). This is an annual survey recording full expenditure from 4,000-6,000 private UK households (ONS, 2017a). Table 1.2 provides more detail on the number of surveys available from 2001-2019. Household expenditure is recorded for all household members for all purchases of goods and services at current prices. Household expenditure is recorded for two weeks for everyday items and for up to 12 months for infrequently purchased items, such as flights and cars. In addition to expenditure, the LCFS contains physical units for certain products, such as number of flights taken or number of rooms available in the household's accommodation, as well as geographic and sociodemographic information. To ensure that household expenditure from the LCFS matches that from the UKMRIO database, throughout this thesis, spend totals from the LCFS are adjusted to spend totals in the UKMRIO for each COICOP 4 category.

Table 1.2. Number of surveys and time spanned for each LCFS from 2001-2019.

Year	Time period covered	Number of households surveyed
2001	April 2001 - March 2002	7473
2002	April 2002 - March 2003	6927
2003	April 2003 - March 2004	7048
2004	April 2004 - March 2005	6797
2005	April 2005 - March 2006	6785
2006	April 2006 - March 2007	6645
2007	April 2007 - March 2008	6136
2008	April 2008 - March 2009	5843
2009	April 2009 - March 2010	5822
2010	April 2010 - March 2011	5263
2011	April 2011 - March 2012	5691
2012	April 2012 - March 2013	5593
2013	April 2013 - March 2014	5144
2014	April 2014 - March 2015	5133
2015	April 2015 - March 2016	4912
2016	April 2016 - March 2017	5041
2017	April 2017 - March 2018	5407
2018	April 2018 - March 2019	5473
2019	April 2019 - March 2020	5438

The LCFS uses a multi-stage stratified sample in Great Britain and a systematic random sample in Northern Ireland, with quotas for household types and geographic areas to ensure a nationally representative sample (ONS, 2017a). Despite this representativeness, answers which are unique and could thus lead to data disclosure, are changed, or sometimes excluded. This means that the highest incomes are typically capped, limiting the ability to research the top earning households in the UK. However, all other private households with an address may be included (ONS, 2017a). In addition, the LCFS contains a weight variable, which estimates the total number of households that are represented by one observation. Consequently, the data can be used as an estimation of total UK household expenditure.

The LCFS is the most comprehensive public expenditure survey in the UK and sets the basis for much expenditure microdata available (e.g. ONS, 2020b, 2019b; Singleton, 2016). The LCFS is openly available via the UK Data Service, although the data are safeguarded. In this thesis, LCFS data from 2001-2019 are used.

1.6.5. The Output Area Classification

The Output Area Classification (OAC) is the UK's ONS's openly available geodemographic classification. It uses bottom-up clustering approaches, to group Output Areas (OAs), the smallest census area geography, by socio-demographic similarities (Gale et al., 2016). The UK census is a population-wide survey conducted every 10 years. It provides an overview of the socio-demographic characteristics of the population and is published for various geographic units. Census geographies are geographies designed for statistical purposes, rather than political or administrative ones (ONS, 2016a). Nonetheless, these are nested within administrative geographies, such as LADs. OAs are the smallest census geography, with populations of up to 700 people. Other census geographies include Lower Super Output Areas (LSOAs) and Middle Super Output Areas (MSOAs)[2]. These have populations of up to 3,000 and up to 15,000 people, respectively. An overview of UK geographies and how they are used in this thesis can be found in section 2.3.1.3 and Appendix B.

Sociodemographic data used in the OAC also come from the census and include variables such as age, ethnicity, dwelling type, and employment (Gale, 2014; Gale et al., 2016). The 2011 OAC groups OAs into 3 levels of nested groups, where the top level has 8 classifications, the middle level contains 26 classifications and the most detailed level contains 76 classification. Expenditure profiles are attached to these classifications, which are updated every 2-3 years based on expenditure from the LCFS. The OAC classification itself is only updated every 10 years, with each new census. It is therefore assumed that neighbourhood classifications remain stable for 10 years.

In the UK, geodemographic classifications are established for small areas under the assumption that areas with similar sociodemographic characteristics have similar spending habits (Webber and Burrows, 2018). Geodemographic profiles are multivariate categories, which are based on the assumption that people living in closer geographic proximity are more

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[2] LSOAs and MSOAs are names used for English and Welsh geographies. In Scotland and Northern Ireland, census geographies differ slightly, but equivalents for LSOAs and MSOAs (by population) are established in section 2.3.1.3.

likely to be similar in terms of sociodemographic identities, beliefs, values, and behaviours; though whether this relationship has a directional causality is unclear (Rothman, 2019). Research indeed shows that consumer behaviours are more comparable within neighbourhoods than within age and income groups (Webber, 2004). In other words, therefore, geodemographic profiles represent clusters of people and households with similar traits, which are organised by geographical area. Although organisation occurs by where people live, classifications are typically constructed at national level, meaning that similarities between neighbourhoods by factors such as settlement type can be observed. Despite small areas containing a diversity of households, Webber and Burrows (2018) argue that unified neighbourhood classification can be achieved, by basing classification not on a person's personal characteristics, but on whom else is most likely to live in the same neighbourhood as them. UK geodemographic classifications include commercial products such as Acorn, Cameo, and Mosaic, as well as the OAC. Although geodemographic classifications are mainly used in commercial settings, they also find applications in research (Webber and Burrows, 2018), including in the fields of transport, retail, migration, and urban policy (Singleton and Spielman, 2014). Additionally, they can be used to estimate consumption-based emissions subnationally. Acorn, for instance, is used by Baiocchi et al. (2010) to investigate impacts of social factors on CO_2 emissions, while Minx et al. (2013) use the Mosaic classifications to link sociodemographic variables to household carbon footprints. In Chapter 2 and Chapter 3 of this thesis, the OAC is used to create local expenditure profiles.

Nonetheless, despite geodemographic classifications finding frequent use in commercial marketing, as well as governmental targeting of specific services, policy, and in the allocation of public funds (Webber, 2004), various critiques have been offered. First, though unsupervised clustering techniques are used to establish neighbourhoods, researcher bias cannot be eliminated as the data which are used to build the clusters may contain biases (Jacobsen, 2019). As a result, neighbourhood classification may unintentionally perpetuate biases which are present in the data. Second, Rothman (2019) argues, categorising neighbourhoods may result in 'redlining' – or, put differently, create a systematic lack of access to governmental and commercial services based on postcode (see also Burrows and Ellison, 2005). In other words, therefore, although geodemographic classifications are based on clusters which emerge from data, they are not free of bias and limitations.

1.7. Limitations of Subnational Footprinting

In this section general limitations from disaggregating national footprints are outlined.

1.7.1. MRIO Uncertainties

MRIO analyses are strongly dependent on the quality and quantity of data available. Since the 2000's, projects such as the EU-funded EXIOPOL[3] have increased MRIO data availability (Tukker et al., 2013, 2009; Wiedmann, 2009). However, MRIO databases differ drastically in their level of sector aggregation, country coverage and aggregation, which environmental indicators are included, availability of time series data, and how they deal with uncertainties (Hoekstra, 2010; Owen, 2017; Tukker and Dietzenbacher, 2013). Nonetheless, the combination of improved data availability and the development of environmental extensions increasingly allow for estimates of environmental pressure data from a consumption perspective.

Different databases have different strengths and weaknesses related to sector aggregation, availability of time series data, and inclusion of uncertainty estimates (Hoekstra, 2010; Tukker and Dietzenbacher, 2013). Lenzen et al. (2004) summarise the sources of these as follows

a. Errors in sampling and reporting of source data
b. Assumptions around factor multipliers between domestic and competing foreign industries being the same
c. Assumptions around foreign industry homogeneity
d. Assumptions that monetary flow is a good proxy for physical flow[4]
e. Aggregation by industry leading to the aggregation of various products/services as well as various producers/service providers. Here consumption-based accounts also have to reallocate emissions from technologies to industries, as well as from imports to industries, leading to further uncertainty (Peters, 2008).
f. Limiting products' lifecycles from production to consumer, and thus neglecting the full lifecycle of a product

To assess the level of uncertainty introduced by these, studies have estimated error by investigating the source data as well as the MRIO datasets. Karstensen et al. (2015), for instance, estimate uncertainty in source data using a Monte Carlo analysis. The authors find that uncertainties in economic data are low at national level, but higher at sectoral level. Moreover, they report a range of ±10-27% uncertainty in emissions, in both national and

[3] A database containing multi-regional Supply and Use tables with environmental extensions.

[4] The debate around the ability of expenditure to capture volume of product/service is described further in section 4.3.2

sectoral accounts. Notably, these emission uncertainties affect consumption- and production-based emissions equally. However, their study assumes an independent sample, an approach criticized by Rodrigues et al. (2018), who argue that sectors are heavily dependent. They provide the example of electricity emissions in country A decreasing while electricity emissions from country B are increasing, due to outsourcing of production. Neglecting this dependency, the authors write, biases the uncertainty analysis. Using a depended sampling approach, they find that uncertainty ranges from 5-10% in OECD and from 10-20% in non-OECD countries, at country level, with higher levels of uncertainty at sectoral level. Research also provides evidence that the uncertainty in estimates are lower in larger regions, such as the European Union (Wood et al., 2019b).

Further studies comparing global MRIO databases suggest that uncertainty in emissions data is a main cause of variance in results produced using different datasets (Owen et al., 2014; Tukker et al., 2018). When comparing five major MRIO databases, Abd Rahman et al. (2021) report that broader aggregates are similar, but that individual sector-level data can be more different between the datasets. However, Moran and Wood (2014) find that, despite differences in estimates, patterns of change over time are comparable between global MRIO models. Thus, while differences in industry carbon emissions data may lead to variations in results, general trends in outputs are comparable across the databases. While some of these differences can be explained by methodological differences (Heinonen et al., 2020; Owen et al., 2016; Peters et al., 2012), robustness may be increased by using a Single-country National Accounts Consistent footprint, where an existing global MRIO database is adjusted to national data on environmental footprints (Tukker et al., 2018). The UKMRIO used in the current research uses this methodology, as outlined by Tukker et al. (2018), to increase robustness and reduce uncertainty. Finally, research on the UKMRIO, though dated, shows that the UKMRIO is a robust framework for assessing consumption-based emissions, with higher uncertainties at sectorial level (Lenzen et al., 2010; Wiedmann et al., 2008). Wiedmann et al. (2008) use a Monte Carlo simulation to estimate the uncertainty in the UKMRIO model from existing and known uncertainties in the input-output data, the UK’s carbon emissions data, GTAP data used to inform trade between other regions, inflation data used, international data on carbon emissions and trade data. The authors and find that two thirds of the variation in results lies within +/- 1 standard error, which is estimated to be within 3.3%-5.5% of total consumption-based emissions between 1992-2004. Similarly, 95% of the variation is estimated to be within +/- 2 standard errors from the mean (within 6.6-11%). In other words, there is an almost 95%

certainty that total consumption-based emission estimates are within 10% of the mean calculated using the UKMRIO model.

1.7.2. Splitting National Emissions Using Microdata

A second area of uncertainty arises from using country-level MRIO tables to estimate emissions subnationally. Where subnational input-output models are not available, as is the case for this research, expenditure datasets are often used under the assumptions that expenditure is relative to products and services consumed. This poses various limitations. First, error is introduced when linking MRIO data to household expenditure survey data, which arises from the inconsistencies between the two datasets as well as from the aggregation of different sectors when matching national accounts with household surveys (Min and Rao, 2017). As the UKMRIO model contains a bridging table, however, this error is minimised in this research. Second, uncertainty is introduced when using expenditure as a proxy for volume consumed. For a national dataset this has limitations with regards to regional price variations, as well as being unable to distinguish between households consuming larger quantities and households consuming fewer but more expensive goods and services.

Subnational estimates of environmental pressure data using Input-Output models are typically generated with household expenditure data (e.g. Minx et al., 2013; Steen-Olsen et al., 2016; Pothen and Tovar Reaños, 2018). Even research which supplements some expenditure data with physical measurements (e.g. Vita et al., 2019) can rely heavily on expenditure data, due to the unavailability of other measures of consumption (such as number of items consumed, calories consumed, or miles travelled). Girod and de Haan (2009; 2010), on the other hand, criticise this approach for being unable to distinguish between 'green consumers' – those who make more ecological choices and buy products which are more expensive, but more sustainable – and those consuming a lot. An example of this is increased purchase of organic produce. Using monetary expenditure data, thus, may lead to an overestimation of emissions. Using only physical data, on the other hand, may result in an underestimation of emissions (Vringer and Blok, 1997 *in* Girod and de Haan, 2009). In their research, therefore, Girod and de Haan (2010) use a hybrid approach (see Kok et al. 2006), where they combine expenditure with physical data to calculate functionality. The authors estimate that approximately 50% of increased spending of high-income Swiss household can be linked to higher purchase prices, while the other 50% is linked to increased consumption. Particularly where emissions are high and prices fluctuate, functional data may be most useful. For instance, flights have both high emissions and high price per mile differences between airline companies. Thus, adjusting flight expenditure data with functional units may be particularly valuable (Büchs and Schnepf, 2013b). Despite the introduction of uncertainties from using only monetary data to split footprints sub-nationally, lack of data availability often does not allow for functional unit use.

Using monetary units may result in an underestimation of footprints of households with low expenditure and in an overestimation of footprint of households with high expenditure. The total UK footprint, however, is not affected by this. While this introduces uncertainty in the estimates, trends in consumption are still measurable. In other words, research using only expenditure is still able to capture where ranges in emissions are high within certain product or service sectors, indicating areas of consumption where behaviour change policy may be the most impactful. With regards to greener choices, these findings will represent consumption of average products and services. This means that when only a minority of consumers purchase higher quality products, current estimates may misrepresent these. However, when average consumption patterns shift to higher quality, footprints for affected products or services should reduce in current findings. While this generalises consumption patterns, and may miss certain local movements, it may still be useful for national policy intervention, as nation-wide trends are still captured. Moreover, sub-national policy makers may still be able to use trend data to make local decisions. As the emissions for products are averaged in this research, they provide an indication of what the average person consumes. Finally, the wider availability of financial transaction data, is a key advantage for using it in this type of research. While the limitations need to be noted, this type of data still provides many benefits to this research and can make subnational footprinting possible in many contexts. Indeed, recent research using big transaction data further highlights how transaction data can contribute to footprinting thanks to its wider availability and potentially large sample sizes (Trendl et al., 2022).

Regional price differences may also affect results. Where prices differ by regions, expenditure may be higher in a region, even though consumption volume is the same as elsewhere. For instance, renting a two-bedroom apartment in London is much more expensive than renting a property of the same size in Bradford. Using expenditure to split housing emissions may misrepresent footprints. The impact this has on findings, however, is strongly dependent on the type of products or service. Findings from Germany indicate that regional differences are much higher for housing than for other product and service types – the contrast is particularly apparent in an urban-rural and East-West comparison (Weinand and von Auer, 2020). In the UK, housing prices also differ regionally and have different convergence levels in the North and South (Blaseio and Jones, 2019; Cook, 2003; Drake, 1995; Kyriazakou and

Panagiotidis, 2018). Despite this not affecting all consumption categories equally, this limitation can be mitigated by using average rent prices or dwelling size and/or dwelling type as a corrector for housing.

1.7.3. Geographic Uncertainties

One common problem in spatial research is the Modifiable Areal Unit Problem (MAUP). This problem is first written about by Gehlke and Biehl (1934) and describes how where spatial boundaries are drawn influences results. Often spatial boundaries can be drawn in different ways, altering the description of the areas within them (Wong, 2011). Research demonstrates that individual and ecological correlation coefficients can range from -1 to 1 across different levels of aggregation in Sunderland, highlighting the potential differences between individual observations and aggregations (Openshaw, 1984). Nonetheless, the authors highlight that these differences become smaller with smaller levels of aggregation. In addition, Flowerdew (2011) argues that the boundaries chosen by Openshaw (1984) are for the purpose of demonstrating the extremes, rather than ones which would be set under policy-making or other empirical situations. In a paper looking at the MAUP effect on 2001 English census data, Flowerdew (2011) shows that, when assessing correlations of commonly researched census variables – including ethnicity, employment status, and dwelling type – between OAs, wards and districts (see section 2.3.1.3 and Appendix B for detail on UK geographic units), correlations at different geographical scales are mostly comparable. Nonetheless, some variables show effects of the MAUP across these geographies, where correlation coefficients vary strongly. Thus, the author concludes, although the MAUP effect is often low for English census data and geographies, it can occur.

Despite the MAUP being a common issue in spatial research, is minimised in this thesis. The MAUP only occurs where geographies are not related to the variables measured within them. As the English, Welsh, and Northern Irish OA structure depends on the homogeneity of socio-demographic variables within them, their boundaries are heavily linked to the variables used in the current study. In Scotland, on the other hand, OAs depend only on geography (ONS, n.d.). As a result, current findings may differ from previous findings using other geographic scales, but the current study itself should not be affected by the MAUP outside of Scotland, as boundaries consider socio-demographic charateristics outside of Scotland.

Leaning onto this, one limitation with geographic research that applies to this thesis is the ecological fallacy. The term ecological fallacy describes the false assumption that group findings and characteristics apply to individuals or individual households (Piantadosi et al., 1988). For instance, inferences about individual households within a neighbourhood cannot be made from neighbourhood level findings. Although the concept of ecological fallacy applies to all groupings, not just geographic ones, it is a common limitation of research that groups persons and households by geographic units (Openshaw, 1984). Thus, although the research in this thesis outlines trends that occur between geographies, inferences about the individuals living in this neighbourhood, rather than the neighbourhood unit as a whole, cannot be made.

1.8. Thesis Structure and Alternative Format

The Faculty of Environment at the University of Leeds offers the submission of PhD theses in the so-called 'alternative format'. This means that the empirical chapters of this thesis (Chapter 2, Chapter 3, and Chapter 4) consist of first-author, peer-reviewed journal articles at various stages of the submission and publication process. It is required for one of these papers to be accepted for publication, for one paper to be accepted for resubmission, and for one paper to be ready for submission. Both Chapter 2 and Chapter 3 are published as Kilian et al. (2022a) and Kilian et al. (2022b), respectively, and Chapter 4 is in a format and at a standard ready to be submitted for peer-review. Thus, this thesis meets the conditions for the alternative format. In addition to this, Chapter 1 provides and introduction and literature review, while Chapter 5 provides a discussion and conclusion to the thesis. For further details on this format please refer to the Faculty of Environment's guide on the alternative style thesis (University of Leeds: Faculty of Environment, 2020).

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Chapter 2. Microdata Selection for Estimating Household Consumption-based Emissions

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2.1. Abstract

To estimate household emissions from a consumption-perspective, national accounts are typically disaggregated to a sub-national level using household expenditure data. While limitations around using expenditure data are frequently discussed, differences in emission estimates generated from seemingly comparable expenditure microdata are not well-known. We compare UK neighbourhood greenhouse gas emission estimates derived from three such microdatasets: the Output Area Classification, the Living Costs and Food Survey, and a dataset produced by the credit reference agency TransUnion. Findings indicate moderate similarity between emission estimates from all datasets, even at detailed product and spatial levels; importantly, similarity increases for higher-emission products. Nevertheless, levels of similarity vary by products and geographies, highlighting the impact microdata selection can have on emission estimates. We focus our discussion on how uncertainty from microdata selection can be reduced in other UK and international contexts by selecting data based on the data generation process, the level of disaggregation needed, physical unit availability and research implications.

Keywords: consumption-based footprints, household consumption, carbon footprint, greenhouse gas emissions, consumer expenditure data, environmentally extended multiregional input-output analysis

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2.2. Introduction

To meet international and national climate change reduction targets in a socially just manner, it is important for governments to be able to understand and predict greenhouse gas (GHG) emissions and their distributional inequalities. In light of existing research highlighting the need for consumption change beyond technological advances of increased energy efficiency to live within planetary boundaries (Haberl et al., 2020; Parrique et al., 2019; Wiedmann et al., 2020), a consumption-based approach can be a tool to uncover the role of governments in climate change mitigation. While attributing emissions to final consumption should be complementary to other approaches, which focus more heavily on the role of corporate responsibility (e.g. Heede, 2014), supply chains' impacts on emissions (e.g. Owen et al., 2018), and production-based emissions (e.g. Sudmant et al., 2018; Liang et al., 2018), consumption-based accounting can point to the ways in which policy can target consumption behaviour change (Girod et al., 2014), showcase the effect of infrastructure (Lenzen et al., 2004), and highlight the need to redistribute emissions, energy and resource access to alleviate poverty (Hubacek et al., 2017; see also Spangenberg, 2017).

From a consumption perspective, households make up the end user with the highest emissions – although emissions from other consumption, such as that of governments and investments, should not be overlooked (Hertwich, 2011). To estimate household consumption-based emissions sub-nationally, expenditure and consumption microdata are frequently used. While previous research addresses some limitations emerging from using expenditure as a proxy for volume consumed (Girod and de Haan, 2010), and from inconsistencies between household surveys and national consumption-based accounts (Min and Rao, 2017), uncertainties around how seemingly comparable microdatasets can impact emission estimates are not yet well-understood. We aim to address this research gap by evaluating the extent to which choice of seemingly comparable consumption microdata can influence emission estimates and make recommendations about how increased robustness can be achieved.

Differential impacts from consumption can be broken down in various ways, such as into consumption patterns, scenarios based on policy recommendations, by socio-demographic groups, and spatially. All of these can be useful in providing different perspectives on carbon inequalities and contribute to understanding how climate change mitigation efforts may be most effective. For example, existing research investigates the carbon emissions of both actual diets and dietary recommendations (Garvey et al., 2021; Hendrie et al., 2014). Similarly, research investigating footprints of people in different income groups highlight the need to not only reduce, but redistribute resources and to target luxury consumption (Büchs and Mattioli, 2021; Millward-Hopkins and Oswald, 2021; Wiedenhofer et al., 2017). Spatially, existing research highlights the importance of place in international (e.g. Ivanova et al., 2017) as well as sub-national (e.g. Clarke-Sather et al., 2011; Jones & Kammen, 2014) contexts. Jones and Kammen (2014), for example, find higher emissions in US suburbs than urban cores and therefore conclude that climate change mitigation efforts need to be place and population specific, underlining the importance of including a downscaled analysis of space when investigating consumption-based emissions. In line with this, Lenzen et al. (2006) point to differences between countries, not just in energy needs, but also in social drivers of energy needs. These can vary drastically due to countries' unique situations regarding factors such as climate, history, culture, and existing infrastructure, highlighting that place-specific understandings of energy need and carbon emissions are vital for reducing emissions. Moreover, UK-based research finds stark inner-city differences in London (Minx et al., 2013; Owen, 2021). However, as that research is at a local governmental area, or LAD, level, inner-city differences outside of London and localised details of footprints cannot be investigated. Consequently, to enable a detailed understanding of spatial carbon inequality, a sub-district analysis is needed. In addition, a product-level disaggregation allows for a greater understanding of the context in which spatially specific patterns of consumption occur. For instance, Australian research suggests that higher income neighbourhoods may have better access to public transport links, reducing private transport emissions and thus emphasising the impact of local infrastructure and access to services on consumption-based emissions (Lenzen et al., 2004). Local, product-level consumption-based emissions can aid local strategies, by providing a spatial overview of sub-national carbon and energy inequalities, and a point for analysis of local and national governmental mitigation efforts. Such efforts might include local transport and infrastructure planning, localised behaviours change campaigns, or housing strategies. Indeed, recent years have seen an increased involvement of local actors in tackling climate change, including global (e.g. C40 Cities, 2020) and local city-level initiatives (DEAL et al., 2020). In the UK, local governments are increasingly making declarations of climate emergencies (LGA, n.d.), with London Councils targeting a reduction in emissions of two thirds by 2030 (Gilby, 2021), and cities like London and Bristol have begun tracking neighbourhood footprint trajectories (Owen, 2021; Owen and Barrett, 2020a; Owen and Kilian, 2020).

To investigate consumption-based emissions sub-nationally, microdata on consumption are needed to disaggregate national accounts. As microdata are not available for every neighbourhood, however, data modelling and different data generation processes increase uncertainty in emission estimates. Using the UK's 2016 consumption-based emissions as a case study, we explore how differences in microdata can shape neighbourhood emission estimates and make recommendations about which factors to consider when selecting microdata. The UK makes for a compelling case study for various reasons, most importantly it is a net-importer of GHG emissions (Defra, 2020a). In addition, the UK reports annual consumption-based emissions accounts as a National Statistic (Defra, 2020a) and has a national framework to measure consumption-based emissions (the UK Multiregional Input-Output Model (UKMRIO)), as well as a variety of public and private microdatasets which allow for a detailed breakdown of national emissions. Whilst data availability and access arrangements vary globally, the UK example highlights how the use of different microdata could result in different policy conclusions and reveals where additional care should be taken when selecting microdata.

While uncertainties across different expenditure microdata are under-explored in the consumption-based accounting literature, methodological limitations, as well as uncertainties from input-output data are well-documented. Different input-output databases can vary drastically with regards to sector aggregation, availability of time series data, and inclusion of uncertainty estimates (Hoekstra, 2010; Owen, 2017; Tukker and Dietzenbacher, 2013), causing them to have different strengths and weaknesses. Moreover, consumption-based inventories carry higher levels of uncertainty than production-based accounts, as these are in closer proximity to statistical sources (Peters, 2008). Lenzen et al. (2004) summarise the sources of these as erroneous sampling, sector aggregation, limiting products' lifecycles from production to consumer, and assumptions around factor multipliers between domestic and competing foreign industries being the same, foreign industry homogeneity, and monetary flow being a good proxy for physical flow. To quantify the uncertainties, studies have investigated both source and multi-regional input-output (MRIO) data. Uncertainties of MRIO databases are estimated to be higher at sectoral than at national level (Karstensen et al., 2015; Rodrigues et al., 2018). Additionally, these can vary by territory, with uncertainties ranging from 5-10% in OECD and from 10-20% in non-OECD countries, at country level (Rodrigues et al., 2018b), and uncertainties being lower in larger regions, such as the European Union (Wood et al., 2019b). Despite differences in estimates, Moran and Wood (2014) find that patterns of change over time are comparable between global MRIO models. Thus, while differences in industry carbon emissions data may lead to variations in results, trends in outputs are comparable across the databases. Using a single-country National Accounts consistent footprint, where an existing global MRIO database is adjusted to national data on environmental footprints, may increase robustness (Tukker et al., 2018). The UKMRIO used in the current research uses this methodology outlined by Tukker et al. (2018) to reduce uncertainty. Finally, research on the UKMRIO, though dated, suggests that the UKMRIO is a robust framework for assessing consumption-based emissions, with higher uncertainties at sectorial level (Lenzen et al., 2010; Wiedmann et al., 2008).

A second area of uncertainty is related to splitting national into sub-national emissions. Sub-national estimates of environmental pressure data can be estimated in different ways when using Input-Output models, including with consumption and expenditure data and spatially-specific MRIO databases (see Ploszaj et al., 2015; Sun, et al., 2019). Here we focus on those sub-national emission estimates generated with household expenditure data, as these are often the most accessible and a frequently used way of disaggregating national accounts (e.g. Minx et al., 2013; Steen-Olsen et al., 2016; Pothen and Tovar Reaños, 2018). Here, various limitations arise. Firstly, error is introduced due to inconsistencies between household surveys and national accounts as well as aggregation of different sectors when matching national accounts with household surveys. Min and Rao (2017) estimate this error to be at around 20% for India and Brazil. Secondly, disaggregating national consumption-based accounts using spend data can be problematic where the same products vary in price. For example, cheap supermarket bread does not necessarily have lower consumption-based emissions than an expensive artisan loaf. To reduce this uncertainty, some research uses other measures of consumption. For instance, existing research from Australia (Hendrie et al., 2014) and the US (Goldstein et al., 2017) uses physical data from nutrition surveys to estimate food emissions. Data on other consumption measures, such as on household energy consumption (e.g. EIA, n.d.; BEIS, 2020a, 2020b) and transport (see Jones & Kammen, 2014) are also available in some countries, although not all can be disaggregated spatially. Despite this, depending on the country and context, even research which replaces some expenditure data with physical measurements, such as weight, (e.g. Vita et al., 2019) often relies heavily on expenditure data, due to the unavailability of other measures of consumption. Girod and de Haan (2010) estimate that approximately 50% of increased spending of high-income Swiss household can be linked to higher purchase prices, while the other 50% is linked to increased consumption. However, while this may lead to an underestimation of low footprints and an overestimation of high footprints, overall trends remain measurable. Nonetheless, despite this additional uncertainty, lack of data availability often does not allow for functional unit use. In addition to these commonly reported uncertainties, this research aims to assess to what extent choice of seemingly comparable consumption microdata can influence emission estimates and to make recommendations about how increased robustness can be achieved.

To review microdata differences, we compare household GHG emission estimates generated from three UK household expenditure datasets, at a product and neighbourhood level following data validation guidelines from Eurostat (Zio et al., 2016). Two of the datasets we compare are considered open data, one of which is publicly available. With most nations having a 2020 census cycle (UN: Statistics Division, 2021) – including the upcoming publication of new UK census data in 2021 –, an increased interest of local government bodies to track sub-Local Authority emissions (Owen and Barrett, 2020a; Owen and Kilian, 2020), increased use of open data, and city-government calls for climate emergencies, it is important to validate emissions generated using different microdata, and to assess their usefulness for different purposes. We provide an overview of the robustness of product-level consumption-based emissions at a neighbourhood level, to give recommendations about various levels of product and spatial-aggregation which can also be employed outside of the UK context, and to provide an openly available method for local governments to track emissions over time.

Finally, in order to facilitate an accessible and replicable method which can be reproduced by local governmental bodies, a move to open data is beneficial. Despite growing demands for increased reproducibility across the social sciences (Brunsdon, 2016; Tay et al., 2016), consumer data is often commercially created, resulting in much research on consumption-based emissions using commercial expenditure datasets (e.g. Baiocchi et al., 2010; Minx et al., 2013). Not only does this mean that data are less accessible to other researchers and policy makers by being behind a pay-wall, but also that data generation processes are often not fully transparent. In line with arguments presented by Pfenninger et al. (2017) we include two openly available datasets within this research. Although open data are not strictly necessary for this type of research, they can provide more transparency and a more replicable method.

In the following section we describe the methods used to both generate the various neighbourhood and product-level emission estimates as well as how we assess their similarity. This is followed by our findings, and a discussion of the findings, in which make internationally-applicable recommendations about microdata selection based on the data generation process, the level of disaggregation needed, physical unit availability and research implications.

2.3. Materials and Method

2.3.1. Data and Access

This research uses a combination of geographic data, census data, expenditure data, and input-output data to estimate consumption-based neighbourhood emissions using three seemingly comparable household expenditure microdatasets. These estimates are then analysed to assess how different microdata influence emission estimates.

2.3.1.1. Neighbourhood-level Household Expenditure Microdata

The expenditure microdatasets used to disaggregate UK national emission estimates to a neighbourhood level are the Living Costs and Food Survey (LCFS), Output Area Classification (OAC), and a rarely used commercial consumer expenditure dataset by TransUnion. Expenditure from all datasets is from the year 2016, using 2016 prices, as it is the most recent year for which all three datasets are available.

The LCFS is an openly available annual expenditure survey recording detailed spends from 4,000-6,000 private households across the UK (ONS, 2017a). Expenditure is recorded for two weeks for everyday items and for up to 12 months for infrequently purchased items. To ensure representativeness, the LCFS uses a multi-stage stratified sample in Great Britain and a systematic random sample in Northern Ireland (ONS, 2017a). Moreover, the LCFS has quotas for household types and geographic areas to ensure a nationally representative sample (ONS, 2017a). The LCFS used in the current analysis is from the year 2016/17 and can be accessed through the UK Data Service (ONS and Defra, 2020). In 2016/17 5,041 households were surveyed. In addition to expenditure, the LCFS contains physical units for certain products, such as number of flights taken.

Expenditure in the OAC and TransUnion is modelled from the LCFS, highlighting the central role the LCFS plays in measuring household expenditure in the UK. Many other UK household expenditure datasets, including publicly available household expenditure datasets (e.g. ONS, 2020), are derived from the LCFS, as it is a comprehensive, annual national statistic. As a result, this research compares a variety of end-products derived from the LCFS, which, despite similarities in the primary data generation process, have varying strengths and limitations as a result of secondary modelling differences.

The OAC is the UK's publicly available geo-demographic classification, whose current version is created from 2011 census data (Gale et al., 2016). It clusters Output Areas (OAs), the smallest census area geography, by socio-demographic similarities and thus represents a summary of multivariate categories. Classifications incorporate information from 60 census variables, including ones on age, ethnicity, dwelling type, and employment (Gale, 2014; Gale et al., 2016). Each OA is thereafter assigned a classification. The OAC is available at 3 different levels: supergroup (8 classifications), group (26 classifications), and subgroup (76 classification)[5]. Here the 'group' level is chosen, as this provides a good balance of product and spatial detail[6]. Supergroups include classifications such as 'suburbanities', which is made up of the two group level classifications 'suburban achievers' and 'semi-detached suburbia'. Classifications for all supergroup, group, and subgroup levels can be found in (Gale et al., 2016). OAC expenditure profiles are updated every 2-3 years based on expenditure from the LCFS, with the one used in the current research being for the years 2015-2017; the classification process occurs only every 10 years.

Lastly, the TransUnion dataset, while based on the LCFS, considers the mix of housing types in each OA for its estimates of consumer spending. This makes the TransUnion dataset more spatially-detailed than the OAC, and our regional LCFS expenditure profiles. While this dataset does not have a fully transparent modelling process, due to its commercial nature, the spatial detail and rare access to these data in academic research make this dataset a valuable and novel resource for this research. The three expenditure datasets are chosen for their respective strengths and limitations (Table 2.1), which can provide a thorough comparison of their respective emissions estimates, as well as data availability. All datasets contain all household spends and follow the structure of Classification of Individual Consumption by Purpose (COICOP) (UN: Statistics Division, 2019), which means that the expenditure categories from all datasets are complete and map onto each other[7]. The OAC and TransUnion data are structured by COICOP 3 categories, which include detailed spends such as 'Milk', 'Bus and Coach Fares', and 'Women's Outdoor Apparel'. The LCFS also contains expenditure at a more detailed COICOP 4 level for many products and services.

The LCFS is the most comprehensive consumption and expenditure survey in the UK and thus sets the basis for much expenditure microdata available. Despite the three datasets all being derived from the LCFS being a potential limitation in this study, the three datasets are fundamentally different in the way they are modelled to represent the whole UK, rather than just the survey participants. The OAC assigns expenditure based on demographic similarity, the TransUnion dataset is a commercial product which uses localised information on household

[5] OAC classification levels are nested, such that each supergroup is divided into groups, which can further be divided into subgroups (see Appendix A for details).

[6] The supergroup and group categories are at a COICOP 3 level, while the subgroup profiles contain COICOP 1 level expenditure.

[7] Where expenditure categories do not match between datasets compared, further uncertainties arise. Moreover, if expenditure categories are missing in one or more datasets, further microdata may be needed to estimate missing (see Lenzen et al. 2006).

types, and while the LCFS modelling we did here relies on the OAC it also includes geographic information from regions and thus disaggregates expenditure in a way that incorporates more spatial detail than the OAC does. These differences allow us to see how the different modelling processes impact our emission estimates. Indeed, being derived from the same base product may make differences more striking and provide insight into how the modelling processes can shape emission estimates.

Table 2.1. Strengths and limitations summarised.

	LCFS Regional Profiles	OAC	TransUnion
Data Type and Structure	Individual household surveys	UK-wide geodemographic classification, modelled from LCFS	Postcode means, modelled from LCFS
Access	Open	Public	Commercial
Physical Unit Data	For some products/services	From Census	No
Product Detail	High	Dependent on classification level	High
Robustness to Outliers	Medium	High	N/A
Spatial Detail	High	Medium	High
Transparency	High	High	Low

** Notes: Robustness to Outliers cannot be determined for TransUnion as the exact modelling process is unknown. OAC product detail is high at group and supergroup levels

2.3.1.2. Multiregional Input-Output Data

To calculate the GHG emissions associated with the consumption-patterns of UK neighbourhoods we need a set of product-based conversion factors that can be used to convert household activity into emissions. Conversion factors need to take into account both the direct emissions associated with burning fuel to heat homes and drive cars and the indirect emissions associated with the full production supply-chain of the goods and services bought by the household. In addition, the factors should include both emissions from domestic production and those emissions released abroad which are used in the production of imports.

MRIO databases have been used by environmental economists due to their ability to make the link between the environmental impacts associated with production techniques and the consumers of products. The Leontief input-output model is constructed from observed economic data and shows the interrelationships between industries that consume goods (inputs) from other industries in the process of making their own products (outputs) (Miller and Blair, 2009). The fundamental Leontief equation, $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}$, indicates the inter-industry requirements of each sector to deliver a unit of output ($\mathbf{x}$) to final demand ($\mathbf{y}$)[8]. Since the 1960s, the input-output framework has been extended to account for increases in the pollution associated with industrial production due to a change in final demand. Consider, $\mathbf{F} = \mathbf{eLy}$ where $\mathbf{F}$ is the GHG emissions in matrix form. $\mathbf{F}$ is calculated by pre-multiplying $\mathbf{L}$ by $\mathbf{e}$, emissions per unit of output, and post-multiplying by final demand $\mathbf{y}$. The vector $\mathbf{eL}$ is a product-based full-supply chain conversion factor for indirect emissions. In addition to inter-industry requirements, an MRIO framework is also able to account for imported goods and differences in emission intensities which occur throughout the supply-chain across different regions.

We use the UKMRIO to calculate the conversion factors for the year 2016 at current prices: GHG per unit spend (£) by COICOP product (Defra, 2020a; ONS, 2020a, 2019a). The UKMRIO is a national statistic constructed annually by the University of Leeds following methodology outlined by Tukker et al. (2018) and Edens et al. (2015). Greenhouse gases reported in the UKMRIO are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF_6) and nitrogen trifluoride (NF_3), these are converted into their carbon equivalent and are reported as tCO_2e. A more detailed description of the UKMRIO can be found in Owen & Barrett (2020b). A unique feature of the UK Supply and Use Tables used to construct the UKMRIO is the disaggregation of the column of household final demand into COICOP categories providing a COICOP to SIC bridging table. Thus, it is straightforward to calculate the GHG emissions associated with household spend by COICOP product. After direct emissions from burning fuel to heat homes and drive cars are added to the relevant COICOP products[9], emissions by COICOP can be divided by total household spends reported in the LCFS to produce a COICOP product-based full-supply chain conversion factor for both direct and indirect emissions.

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[8] $\mathbf{I}$ is the identity matrix, and $\mathbf{A}$ is the technical coefficient matrix, which shows the inter-industry requirements. $(\mathbf{I} - \mathbf{A})^{-1}$ is known as the Leontief inverse (further identified as $\mathbf{L}$). It indicates the inter-industry requirements of the i^{th} sector to deliver a unit of output to final demand

[9] Direct emissions from heating homes are added to gas emissions, while direct emissions from motorvehicle use are added to emissions from petrol, gas, and other motoring oils.

2.3.1.3. *Geographic, Census, and Other Data*

Geographic and census data used in this research are all publicly available. To estimate neighbourhood emissions, we use data from the 2011 census for OA populations, geography lookup tables, and geographical boundaries (National Records of Scotland, 2013; NISRA, 2013b; ONS, 2013), and from the ONS (2017) for the 2016 mid-year populations. In addition, as physical use proxy data (see section 2.4.3) we use levels of car ownership from the 2011 census, and gas and electricity consumption data from the Department for Business, Energy and Industrial Strategy (BEIS, 2020b, 2020a).

This research aggregates emissions to small neighbourhoods (Lower Super Output Area (LSOA)) and medium neighbourhoods (Middle Super Output Area (MSOA)), the second and third smallest census geographies in England and Wales, respectively (see Table 2.2).

Table 2.2. Summary of UK neighbourhood geographies used in this research.

	Description and Demographics		Naming throughout the UK		
	Population	Number of Units in the UK	England and Wales	Scotland	Northern Ireland
Smallest Census Geography	50 – 700	232,296	Output Area	Output Area	Small Area
Small Neighbourhood	500 – 3,000	42,619	Lower Super Output Area	Data Zone	Super Output Area
Medium Neighbourhood	2,000 – 15,000	9,062	Middle Super Output Area	Intermediate Geography	Ward[10]

Geographies vary slightly by the different countries in the UK. Equivalents from Northern Ireland and Scotland are chosen based on area populations. For easier reading, this paper refers to the English and Welsh names (OA, LSOA and MSOA), even where equivalents from Scotland and Northern Ireland are used. More details are provided in Appendix B.

2.3.1.4. *Data Pre-Processing*

Product-level expenditures from the expenditure microdatasets are adjusted to household final demand figures reported in the UKMRIO, to ensure that all expenditure reported in the UKMRIO is accounted for. Secondly, using a physical measure of accommodation, such as number of rooms may be better than a financial measure, as rents can vary drastically by region,

[10] A ward is a geographic area at a more aggregated scale than an MSOA level. Wards mainly reflect electoral wards (ONS, n.d.). This is chosen as it is the Northern Irish geography most like MSOAs by population.

even when housing size is controlled for (ONS, 2020c; von Auer, 2012). Therefore, number of rooms is used as a physical proxy for both the LCFS and OAC, the two datasets containing this measure. In addition, the LCFS allows for the adjustment of expenditure data on flights through physical units, as information on the number of domestic and international flights taken is provided[11].

Moreover, households paying by direct debit or monthly instalments pay approximately 80 GBP less per year for gas and electricity, due to using different payment methods (OFGEM, 2014). Payment type is also often linked to income and house ownership, with low-income households and renters being more likely to have pre-paid utilities. As payment method information is available for gas and electricity consumption in the LCFS and can be matched to the OAC through the census (National Records of Scotland, 2013; NISRA, 2013b; ONS, 2013), expenditure for electricity and gas use is adjusted for the OAC and LCFS.

Spatially, the LCFS includes information on regions[12] and OAC. To disaggregate beyond regional level, we group weekly expenditure data from the LCFS by OAC and regional information. This allows us to create regional expenditure profiles, which we can associate with specific geographic location, whereas the OAC expenditure profiles relate only to OAC group, but not spatial location. This is done using all three levels of the OAC, such that the highest level of disaggregation is possible, while ensuring that each grouping contains a minimum of 10 observations; this provides groups small enough to attain high spatial detail, while being large enough to maintain a mean that in most cases is not dominated by one observation. Moreover, later aggregation to higher geographies further increases group sizes and thereby helps further reduce susceptibility to outliers. More details can be found in Appendix C.

Aggregation to a minimum of 10 surveys results in 283 expenditure groups with regional information. Of the 5,041 surveys, 9 could not be grouped due to missing OAC values. A further 237 could not be included in the regional profiles because no group with more than 10 observations could be made below national level. These are mainly for OACs not common in a region, and as OAs are aggregated to higher geographies after footprint calculation, results will not be significantly affected by this. Separately, footprints are also calculated based only

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[11] Conversion factors then become tCO_2e / room and tCO_2e / flight purchased, respectively.
[12] The UK consists of 12 regions, 9 of these are in England; Northern Ireland, Scotland, and Wales, consist of one region each.

on a LCFS-aggregation by OAC supergroups, which are attached to OAs in instances where the UK's OAs do not match any of the region-specific profiles generated.

Population estimates attached to each expenditure dataset are adjusted to the 2016 mid-year population estimates, such that proportions of populations within a certain expenditure category are kept the same as they are in the expenditure datasets, but the total population is adjusted to the mid-year estimates. This controls for slight population differences between the datasets and allows for better comparison of emission estimates.

2.3.2. Analysis

An environmentally-extended input-output analysis is employed to estimate household GHG emissions using all three household expenditure datasets. Neighbourhood GHG emissions are calculated using the highest product and service level available for each survey. Thereafter, findings are aggregated to LSOA and MSOA levels and compared at COICOP 2 and COICOP 3 levels. To prevent a spurious correlations by using multiple variables which are derived from common ancestors (Pearson, 1897; Ward, 2013), per capita tCO_2e rather than total population emission estimates are used for each MSOA and LSOA in our analysis.

To validate our emission estimates we follow guidelines from the Eurostat ESSnet ValiDat Foundation (Zio et al., 2016). As these guidelines also include error location for big data analysis, we follow only the validation levels applicable to the current research. These include checking for consistency within the dataset, consistency to other similar datasets (which is the main aspect of this paper), and, where possible, we compare our emission estimates to physical use data or proxies from other data providers.

To compare various aspects of the data we use multiple statistical comparisons. As data are non-normally distributed we employ a Friedman test[13] to assess whether the results from the three datasets are statistically derived from different distributions (Friedman, 1937). In addition, to assess covariance we run a Spearman's ρ correlation analysis. As large sample sizes can inflate statistical significance testing, we focus on effect size for both tests. As is common in statistical analysis, we interpret effect size from the Friedman test (Kendall's W value) to be small if it is below 0.3, and the correlation coefficient to indicate at least a weak correlation if it is 0.3 or above. Both tests assign ranks and as a result can only be used to understand

[13] The Friedman test is a non-parametric equivalent to a repeated measures analysis of variance.

distributions and covariances, but not magnitudes of similarities and differences. To understand dataset differences and similarities between actual emission values we therefore also calculate and compare the root mean squared errors (RMSEs) of the three dataset comparisons. RMSEs are in the unit of measurement and thus need to be interpreted in relation to emission estimates.

2.4. Results

2.4.1. Total per Capita Consumption Emissions of UK Neighbourhoods

The mean household consumption emissions for the UK are 9.36 tCO_2e per capita for the year 2016. At both MSOA and LSOA levels, 80% of total per capita emissions range from 7 to 12 tCO_2e, in all three disaggregation methods. While distributions of emissions from the LCFS and TransUnion datasets are similar with one peak, the OAC results have a multimodal distribution at neighbourhood levels (Figure 2.1).

This is stronger at LSOA than at MSOA level, likely pointing towards the limited number of categorised expenditure profiles in the OAC, as well as to some profiles being much more common than others; for instance, groups falling within the ‘Suburbanites’ and ‘Hard-pressed living’ supergroups make up approximately 40% of OAs.

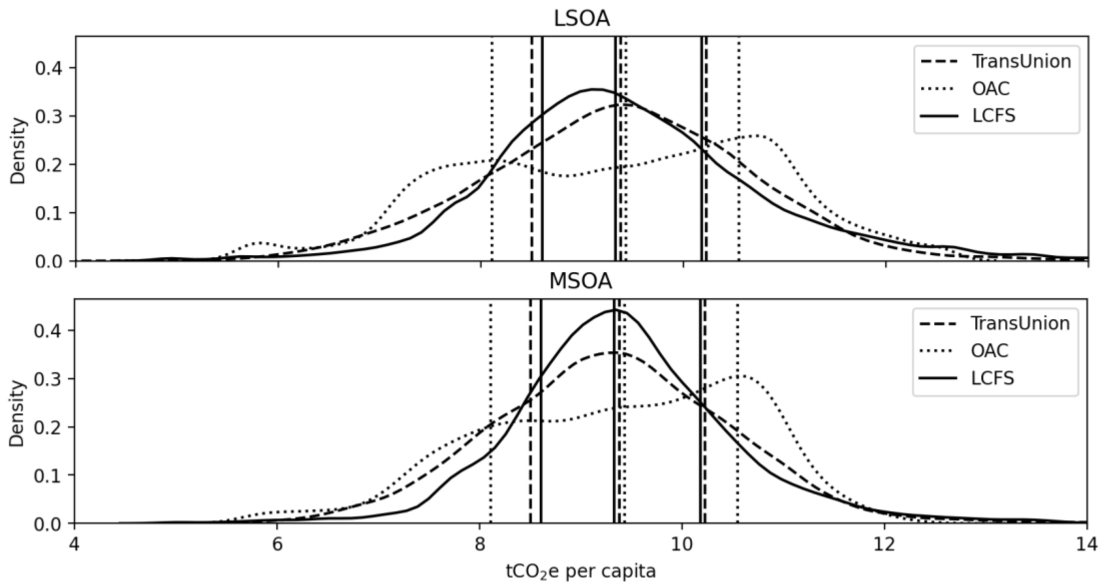

Figure 2.1. Distributions of per capita footprints of UK LSOAs and MSOAs. Vertical lines show the 25th, 50th, and 75th percentiles.

Some differences are also evident spatially. The spatial distributions of MSOA per capita GHG emissions are shown in Figure 2.2. The OAC footprints are high in rural areas without much variance as only 3 of the 26 profiles are linked to rural areas, whereas the TransUnion and LCFS emissions appear to have more nuanced variances over space. The OAC may therefore be less precise in rural than in urban areas. Moreover, the OAC results do not show possible regional differences, as the OAC is a UK-wide classification, regional variances may therefore get overlooked. These include possible lower emissions in Northern Ireland and Wales, which we find with the other two datasets. Finally, the LCFS assigns rural parts of Scotland higher emissions than the other two datasets, however, as populations are small, footprints for the total population in Scotland are among the lowest in the UK.

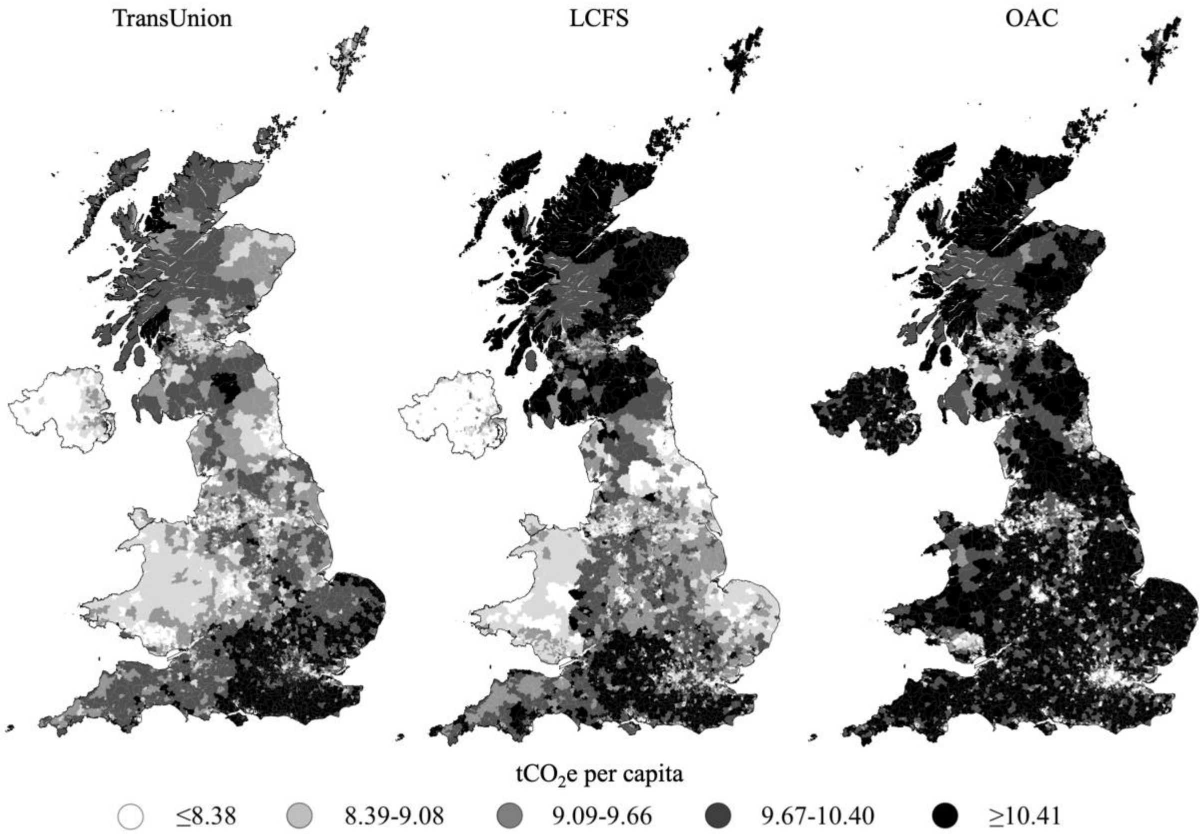

Figure 2.2. UK MSOA per capita GHG emission quintiles.

A statistical comparison of the datasets is undertaken, where distributions, correlation coefficients and RMSEs are analysed. A Friedman test finds negligible effect sizes of Kendall's W = 0.01 for both MSOAs and LSOAs, indicating that the difference between distributions is only very weak. Similarly, at both geographic levels data have Spearman's ρ correlation coefficients of 0.44 or stronger, indicating at least moderately strong correlations between emission estimates from all datasets (see Table 2.3). RMSE results show mean errors of 10-

17% of the UK mean per capita emissions. Emission estimates from TransUnion and the LCFS appear to be most strongly correlated and have the lowest error. This is reflective of the higher levels of spatial detail in the LCFS and TransUnion datasets and indicates that the LCFS may a better open data option than the OAC at disaggregating total emissions spatially, to a neighbourhood level.

Table 2.3. Statistical results for total emissions.

Geography	Kendall's W (Friedman test)	Spearman's ρ			RMSE		
		OAC & TransUnion	OAC & LCFS	TransUnion & LCFS	OAC & TransUnion	OAC & LCFS	TransUnion & LCFS
MSOA	0.01	0.47	0.44	0.62	1.29	1.34	0.95
LSOA	0.01	0.53	0.46	0.53	1.39	1.56	1.25

2.4.2. Product-level Findings

In the UK, household consumption-based emissions are highest for emissions related to transport, followed by housing and food and drinks (see Figure 2.3). These product and service categories can be further disaggregated, such as into COICOP 2 and COICOP 3 product and service categories. This section focuses on UK neighbourhood emission estimates produced by the three microdatasets for these more disaggregated product and service. A full list of COICOP 1, 2, and 3 categories can be found in Appendix D.

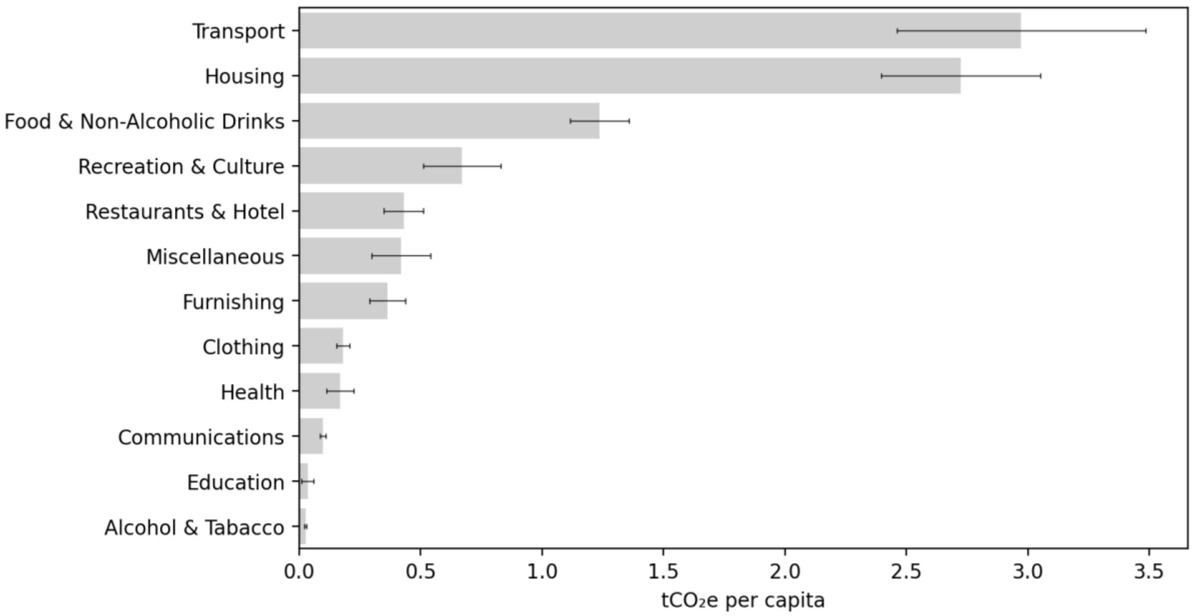

Figure 2.3. Mean UK per capita GHG emissions by COICOP 1 categories from all datasets

** Notes: Error bars show the standard deviation from MSOA-level results across all three datasets.

Distributions, covariance, and error are also analysed at COICOP 2 and 3 product/service levels. We consider a product/service category to 'pass' the Friedman validation test if it has Kendall's W < 0.3 and to 'pass' the correlation validation test if it has Spearman's $\rho \geq 0.3$. As shown in Table 2.4, we find that product/service categories that pass all tests only make up around half of the UK consumption-based household footprint. For most geographic and product levels rates for number of products are a little lower, suggesting that higher-emitting products and services more often have more similar distributions and higher covariance than lower-emitting ones. Notably, results from individual tests are higher than those considering all tests. This shows that differences between the datasets occur down to a product level, or in other words, that dataset differences are not consistent across product/service categories.

Table 2.4. Percentages of total tCO_2e / capita from products and number of products passing the Friedman (Kendall's W < 0.3) and correlation (Spearman's $\rho \geq 0.3$) validation tests.

		Total tCO_2e / capita (%)					Number of products (%)				
				Passed correlation test					Passed correlation test		
COICOP	Geography	Passed all tests	Passed Friedman test	LCFS & TU	OAC & LCFS	OAC & TU	Passed all tests	Passed Friedman test	LCFS & TU	OAC & LCFS	OAC & TU
2	MSOA	51.98	100.00	53.30	68.82	60.17	56.41	100.0	64.10	74.36	82.05
	LSOA	63.30	100.00	64.50	66.88	73.48	53.85	100.0	58.97	66.67	87.18
3	MSOA	51.10	85.17	66.74	78.31	74.25	44.78	90.30	55.97	79.10	68.66
	LSOA	46.08	85.42	60.68	75.32	74.59	38.81	91.04	46.27	70.90	68.66

** Notes: The UK has a footprint of 9.36 tCO2e / capita. The COICOP 2 classification contains 39 product and service categories, the COICOP 3 classification contains 134 product and service categories.

Moreover, correlation results from the LCFS and TransUnion comparison are lower than those from other comparisons, contradicting the total emission comparisons and hinting at the impact different microdata generation processes can have on product-level emission estimates. Finally, higher level aggregation almost always increases total pass rates, showing convergence to the mean with decreased detail. Exempt from this are COICOP 2 level difference between MSOA and LSOA; here it may be that aggregation to an MSOA level merged LSOAs with high levels of dataset similarity with LSOAs with low levels of similarities between datasets. These exceptions are likely data-specific and dependent on individual outliers rather than systematic emission estimate generation processes.

Results for individual product/service categories are shown in Figure 2.4. This highlights various important characteristics of the results. Firstly, there is significant overlap in the distribution and covariance tests between LSOAs and MSOAs at both product levels, indicating

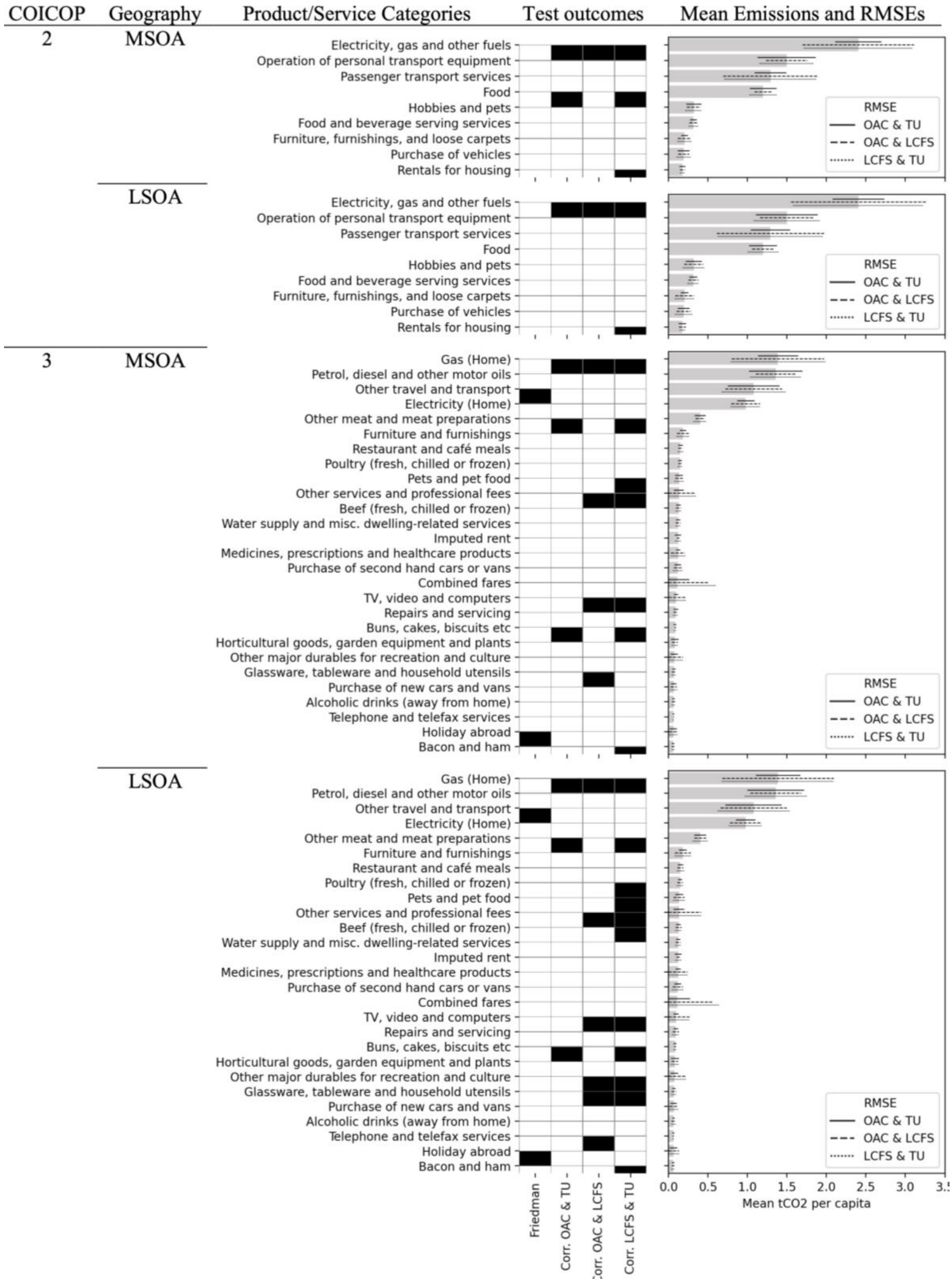

Figure 2.4. Detailed selected results from Friedman test and correlations (black cells indicate a failed test), and mean emissions and RMSEs. Results are displayed for highest-emitting products contributing to over 80% of consumption-based emissions; this constitutes 23% of COICOP 2 and 21% of COICOP 3 products/services.

that dataset differences are more consistent across geographic disaggregation than product-level disaggregation. Secondly, most product/service categories which did not pass all tests, failed more than one test. This suggests that some products may be more dissimilar than others and that by using physical data for such products uncertainty may be reduced. Thirdly, per capita footprints are logarithmically distributed between products, with only very few product and service categories having high per capita emissions. This indicates that there are a few products and services for which estimating accurate emissions is more important. Indeed, the product and service categories with the highest per capita footprints (COICOP 2: 'Electricity, gas and other fuels'; COICOP 3: 'Gas (Home)') failed all correlation tests across both geographies. Given that gas pricing in the UK can vary according to payment type and time of day this finding is not surprising and emphasises the need for a physical unit measure rather than expenditure to disaggregate household gas emissions sub-nationally. Interestingly, however, 'Electricity (Home)' alone, passes all tests, indicating that microdata are more similar for electricity than for gas expenditure. While this does not indicate that a physical unit measure may not be better, it does show that monetary data from the three microdatasets disaggregated the footprints similarly across neighbourhoods.

Finally, despite having a small RMSE between all three datasets pairings, 'food' and 'other meat and meat preparations' – the highest food-related COICOP 3 category – fail the correlations tests involving the TransUnion in most product- and neighbourhood-level combinations. This indicates that the OAC and LCFS report more similar food expenditure than the TransUnion data. Although we cannot be certain why the TransUnion data are different, as their data generation process is not fully available, it is possible that this difference is due to the LCFS and OAC establishing mean expenditure over regions and the whole UK. It may be, therefore, that price differences from purchasing different kinds of food products that fall within the same COICOP category have a higher convergence to the mean for the LCFS and OAC. Reversely, price differences may impact emissions more strongly when using the TransUnion data to disaggregate national accounts.

Moreover, knowledge about the various data generation and modelling processes may further inform why differences occur and which dataset may be most suitable for which type of analysis. Finally, RMSEs are mainly proportional to mean emissions and comparable across dataset pairings. Again, products linked to home gas use have disproportionally high errors, mirroring findings from the correlation analysis. Notably, errors are also higher for pairings including the LCFS for the COICOP 2 category 'Passenger transport services'. This category includes emissions from flights, which are likely more accurate for the LCFS than the other two datasets, as number of flights was used to disaggregate emissions instead of flight expenditure.

2.4.3. Physical Proxy-data Comparisons

To evaluate which dataset best represents physical units, we also compare the different emission estimates to physical use proxies. We use simple linear regression models to assess which estimates can best predict physical use proxies. Physical use proxy data are available for three high-emission COICOP 3 categories at a neighbourhood level in the UK: 'Electricity', 'Gas', and 'Petrol, diesel and motoring oils'. For gas and electricity we use consumption data available via BEIS (BEIS, 2020b, 2020a), which is available for England, Wales, and Scotland at both MSOA and LSOA levels for 2016. As a proxy for 'Petrol, diesel and motoring oils', we use 2011 statistics of amount of car ownership[14] from the census, which are available for the whole UK. Model validation is done by splitting the data into an 80% train and a 20% test set and indicates no concern of overfitting.

Results indicate that the OAC and LCFS can best predict 'Electricity' and 'Gas' use respectively, although fits for all models are poor (Table 2.5). RMSEs are at around 18-26% of mean values for both gas and electricity, but at a lower 7-15% for car ownership. Levels of car ownership are also better predicted by our emission estimates, with good model fits for the OAC data, and moderate model fits from the LCFS. The TransUnion data performs poorly on all variable predictions. It should be noted that high levels of car ownership do not *per se* mean that emissions should be higher, as car use emissions can be linked to other factors such as infrastructure, place, and public transport links. Despite this, lower car ownership levels should also come with decreased emissions. Thus, while high levels car ownership may not be a good proxy for emissions, we expect low levels of car ownership to be paired with low emissions. As shown in Figure 2.5, both the LCFS and the OAC show low emissions from car use, in neighbourhoods with low car ownership. The TransUnion data, on the other hand, assigns similar levels of emissions from motoring oils across neighbourhoods with different levels of car ownership. As census variables, including car ownership, are used to generate the OAC expenditure profiles, the OAC may best capture distributions of emissions related to these

[14] We use rates of household which have at least one car or van to measure car ownership.

variables. This is followed by the LCFS as used here, where OAC data are incorporated to model expenditure across the UK.

Table 2.5. Prediction model summaries.

Product/ Service	Dataset	MSOA				LSOA			
		AIC	RMSE	R^2 (train)	R^2 (test)	AIC	RMSE	R^2 (train)	R^2 (test)
Electricity	OAC	**107,328**	**683.35**	**0.19**	**0.19**	**542,315**	**806.31**	**0.13**	**0.14**
	TransUnion	108,610	755.34	0.02	0.01	546,726	866.01	0.01	0.01
	LCFS	108,708	759.98	0.00	0.00	546,943	868.68	0.00	0.00
Gas	OAC	124,561	2643.57	0.08	0.09	628,035	3304.35	0.05	0.11
	TransUnion	125,092	2758.14	0.01	0.01	629,552	3470.67	0.01	0.01
	LCFS	**123,146**	**2374.76**	**0.26**	**0.27**	**624,500**	**3054.26**	**0.15**	**0.24**
Petrol, diesel and motoring oils	OAC	**47,226**	**7.16**	**0.79**	**0.77**	**239,853**	**8.29**	**0.74**	**0.75**
	TransUnion	56,114	13.16	0.25	0.24	274,922	14.12	0.27	0.26
	LCFS	51,630	9.97	0.60	0.56	264,566	11.92	0.46	0.47

** Notes: R^2 model fit is shown for both the training (80% of dataset randomly selected) and testing sets (20% of dataset randomly selected). The best model fits for each product/service are highlighted in boldface. Mean values are around 3,800 kWh for electricity and 13,500 kWh for gas, for reference for RMSE interpretation.

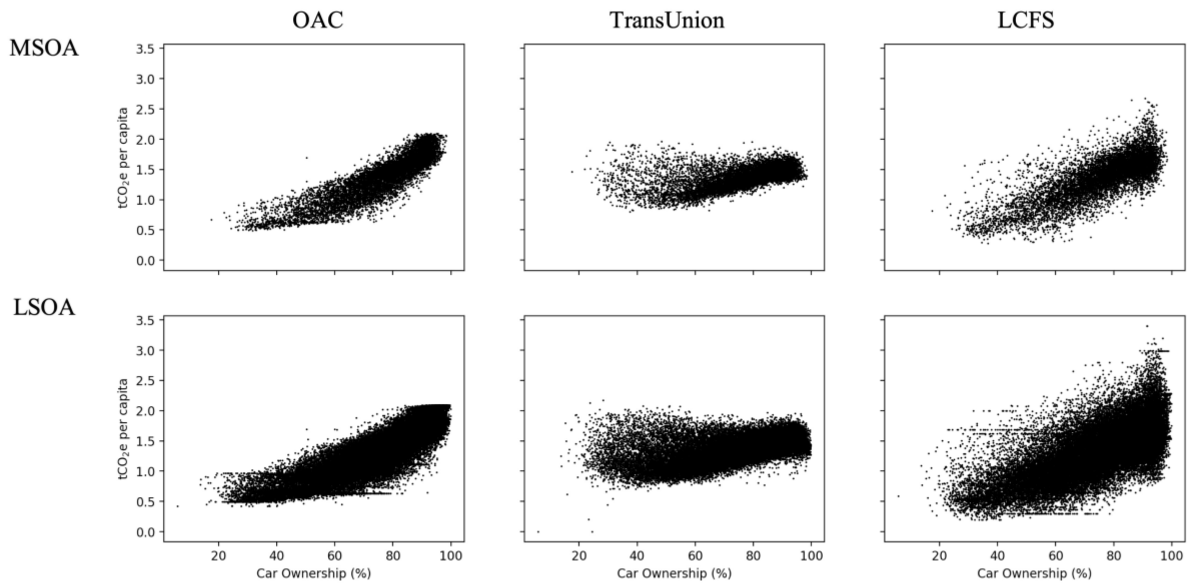

Figure 2.5. Scatterplots showing levels of car ownership vs emissions from ‘Petrol, diesel and motoring oils’.

2.4.4. Local Authority District Level Analysis

For policy purposes it is important to understand the dataset variance at an LAD level, whose boundaries are defined by local government districts, as this is where policy decisions can be made. An analysis of LSOA and MSOA footprints is therefore done within LAD boundaries to assess the similarity of neighbourhood emission within a local administrative boundary. Hence, instead of correlating product and neighbourhood emission estimates from the three datasets at a national level, as done in the previous section, here we correlate these product and neighbourhood emission estimates for some UK LADs and summarise the results as the proportions of LADs with a Kendall's W value of lower than 0.3 or correlation coefficients of $\rho \geq 0.3$ for the various product and neighbourhood levels.

The LADs analysed here are Antrim and Newtownabbey, Blaenau Gwent, Sevenoaks, and the cities of Bristol, Manchester, and Glasgow. In addition, results from the London Region are assessed. These LADs and regions are chosen for their geographic and demographic diversity; findings are shown in Table 2.6. Analysing these at a neighbourhood and product level highlights the spatial variation between emission estimates as well as the importance of looking at a product level. Rates of emissions from products which passed all validation tests are low.

Table 2.6. Mean emissions of LADs and percentages of total tCO_2e/capita from products passing the Friedman (Kendall's W < 0.3) and correlation (Spearman's $\rho \geq 0.3$) validation tests within various LAD boundaries.

Local Authority District	COICOP	Geography	Mean tCO_2e / capita	Percentage of total tCO_2e / capita emissions (%)				
				Passed all tests	Passed Friedman test	Passed correlation test		
						LCFS & TU	OAC & LCFS	OAC & TU
Antrim and Newtown-abbey (N. Ireland)	2	MSOA	9.20	21.20	27.01	58.43	64.22	71.42
		LSOA	9.20	22.08	30.02	28.86	31.10	71.07
	3	MSOA	9.20	21.25	29.69	43.00	57.27	67.66
		LSOA	9.20	21.30	44.02	42.36	40.47	66.92
Blaenau Gwent (Wales)	2	MSOA	8.60	0.00	18.32	32.22	64.70	15.72
		LSOA	8.60	0.71	27.96	46.40	51.57	44.91
	3	MSOA	8.60	0.00	29.99	37.87	50.38	14.73
		LSOA	8.60	0.14	42.10	46.84	35.87	33.17
Bristol (England)	2	MSOA	8.97	25.04	46.92	60.40	64.11	36.09
		LSOA	8.97	23.53	79.93	56.68	59.92	36.09
	3	MSOA	8.97	12.25	26.25	50.34	73.49	40.21
		LSOA	8.97	13.41	64.22	60.61	71.59	41.47
Glasgow (Scotland)	2	MSOA	8.89	18.42	22.32	60.21	92.02	58.40
		LSOA	8.89	19.75	60.30	54.66	89.33	58.40
	3	MSOA	8.89	7.84	31.69	55.33	70.07	68.80
		LSOA	8.89	10.29	55.65	51.57	66.81	67.62
London Region (England)	2	MSOA	9.72	5.32	34.82	77.94	68.85	72.52
		LSOA	9.72	6.89	36.19	52.28	69.85	71.99
	3	MSOA	9.72	7.99	39.19	58.77	62.35	60.15
		LSOA	9.72	10.29	43.38	51.17	61.08	69.26
Manchester (England)	2	MSOA	7.79	5.07	26.60	21.74	53.47	62.64
		LSOA	7.79	6.11	28.49	21.74	50.77	62.46
	3	MSOA	7.79	16.71	34.73	36.20	59.66	66.74
		LSOA	7.79	17.83	40.93	35.14	56.86	65.26
Sevenoaks (England)	2	MSOA	10.33	25.55	33.27	63.54	72.51	73.49
		LSOA	10.33	46.13	54.11	68.26	73.53	75.94
	3	MSOA	10.33	26.16	37.13	56.61	73.68	69.05
		LSOA	10.33	35.86	49.88	60.41	73.67	73.84

** Notes: Darker grey indicates higher percentage.

Despite this, correlation tests show high similarity across the datasets in covariance, with approximately 75% of neighbourhood and product level correlation results indicating that the majority of their footprint come from product/service categories with Spearman's $\rho \geq 0.3$. The Friedman distribution analysis performs worse; however, this may also be impacted by the small number of neighbourhoods in each LAD. Blaenau Gwent, for instance, contains only 47 LSOAs, which make up only 9 MSOAs. Indeed, it is notable that LSOAs, of which there are more in each LAD than MSOAs, have higher pass rates than MSOAs in the Friedman test, indicating that the small number of neighbourhoods may impact the results. These findings point to the importance of understanding uncertainties in the data which derive from microdata. Thus, findings from the LAD level analysis suggest that a LAD level overview of neighbourhood emissions can be more severely impacted by the microdata generation process than a national analysis.

2.5. Discussion

While findings indicate an overall robustness, similarities between estimates from different datasets are smaller for some specific products and services, including emissions related to household gas consumption. These differences are perhaps more surprising than the similarities, as all datasets are derived from the LCFS. Where the similarities highlight the robustness of estimates across various data modelling techniques, the differences highlight some important considerations to make when using microdata for a neighbourhood and product level disaggregation of consumption-based emissions. These differences emphasise the importance of understanding the microdata, their generation and modelling processes, as well as their strengths and limitation. For instance, petrol, diesel and motoring oil emissions showed different results between datasets, particularly between the emissions generated from the TransUnion and the OAC datasets. A policy maker aiming to reduce these emissions might make different decisions depending on which estimates they have. It is therefore crucial to understand the microdata before using them to draw conclusions about emission estimates and to be aware of where errors can occur. In addition, where multiple datasets are available, a few important questions must be asked prior to selection, to ensure the most appropriate dataset for the research question is chosen.

While the recommendations below are derived from the UK example, they highlight questions to consider not only inside, but also outside of the UK. The UK may have some of the most detailed datasets globally, as well as a variety of microdata available from different sources, however the following considerations go beyond the UK context. While access to consumption and expenditure microdata is far from universal, many countries, particularly those with the highest consumption-based GHG emissions, have geodemographic classifications[15] and/or official household expenditure surveys[16]. Data access depends, as in the UK, on the level of data security, whether use is for research or commercial purposes, and the level of disaggregation wanted, where some datasets may be more easily accessible if aggregated by geographic or other household characteristics. Moreover, differences in the data generation methods in different countries, such as the exclusion of one-person student households in Japan (Statistics Bureau of Japan, n.d.), require further contextual understanding of the relative expenditure microdata, and may allow for different levels of spatial and product-level disaggregation than possible in the UK example. To attain a neighbourhood level detail, expenditure data may have to be combined with socio- or geodemographic characteristics as done in the LCFS example in the current research. While the current research can provide a model of how this can be done, how and if this can be implemented varies strongly depending on the data available, and the implications this has on the data. Having access to a publicly available geodemographic classification allows us to disaggregate the regional LCFS reliably. This may not be possible where such a reliable classification of different neighbourhood types may not exist. Finally, the ability to perform such an analysis depends greatly on the availability of MRIO data for specific territories, while global databases exist, countries may be aggregated into greater regions depending on the MRIO data used. Nevertheless, while not all recommendations may be applicable to every context, the UK case study reveals questions of considerations for any microdata dataset used, which can be applied internationally.

2.5.1. How Much is Known about the Data Generation Process?

The most important question to consider when either choosing or using microdata to disaggregate national accounts is ‘how much is known about how the data are generated and/or modelled?’. The importance of this becomes clear when assessing where, how, and why differences emerge across the three emission estimates. While the TransUnion dataset produces more similar total emissions to the LCFS at a national level, on an urban neighbourhood and

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[15] Examples of these include the Australian geoSmart Segments (RDA Research, n.d.) and the US American Tapestry Segmentation (Esri, n.d.)

[16] Examples of these include the US American Consumer Expenditure Survey (U.S. Bureau of Labor Statistics, n.d.), the Australian Household Expenditure Survey (Australian Bureau of Statistics, n.d.), the German Einkommens- und Verbrauchsstichprobe (*English: Sample of Income and Expenditure*) (Statistisches Bundesamt, n.d.), and the Japanese Family Income and Expenditure Survey (Statistics Bureau of Japan, n.d.)

product level, its estimates are more strongly correlated to the OAC estimates. Despite this pointing to the strengths of some of the estimates, which are comparable across a variety of differently modelled expenditure data used to estimate them, limitations of using the TransUnion data become apparent, as the data generation process is not transparent, not allowing for the assessment of the results in relation to their data generation processes. In the LCFS and OAC results, the interpretation of why differences emerge are clearer, allowing for an open discussion of strengths, limitations, and uncertainties. For instance, the multimodal distribution of total OAC emissions can be attributed to the way in which OAs are clustered into 26 different groups, whereas the larger range in LCFS emissions is likely linked to being more susceptible to outliers, due to expenditure profiles being based on smaller samples than the ones in the OAC.

Uncertainty from the microdata used feeds directly into uncertainties of emission estimates. Being aware of how the data are generated allows for a better understanding of where uncertainties are, as well as where they come from. Particularly when results are used to inform climate change intervention, it is important to understand how, where and why precision of emission estimates varies. In the UK example, the data generation and modelling processes are transparent in the openly available datasets, but not in the commercially-created one. While this may indicate that using open data may be beneficial in the UK, the same may not apply in other countries where open data is not available or equivalent to commercial alternatives. Some commercial datasets may provide more information on their data generation processes than others. It should be stressed, therefore, that while in this study the lack of transparency is linked to the commercial nature of one of the datasets, this is specific to the datasets in question. Additionally, where open data are not equivalent in the level of detail to a commercial product, the uncertainty in the data generation process must be weighed against the absence of detail in other datasets. Nonetheless, in all these cases an open discussion of the limitations introduced either by the data generation process or by the lack of transparency about it contributes to a better understanding of possible errors and uncertainties in emission estimates.

2.5.2. What Level of Disaggregation does the Research Question Require?

Findings from this research show that, overall, the majority of emissions come from products and services with comparable emission estimates across the different datasets. Importantly, similarity is even slightly higher for products and services with higher emissions, as these are most likely to be targeted by sustainability interventions. Nonetheless, higher levels of aggregation at both a product and neighbourhood level are associated with increased similarity between the different estimates. Despite some of these differences being small, they indicate the importance of disaggregating intentionally, when this is needed to answer a specific research question, to maintain the highest level of robustness possible. If a research question does not require a small neighbourhood scale at a COICOP 3 product level, then this level of disaggregation should not be used, as it can introduce additional uncertainty.

Higher levels of disaggregation may also require different datasets. For instance, the LCFS contains COICOP 4 level categories, whereas the other two datasets have mostly COICOP 3 level expenditure categories. Geographic precision also matters. Using the LCFS the way it is used here to look at OA rather than LSOAs or MSOAs may result in outliers not being controlled for, as some groups contain as few as 10 observations. Choosing a dataset needs to be done in terms of which level is possible and necessary, while also considering increased uncertainty that may arise from higher levels of product-level and spatial disaggregation.

2.5.3. Is Expenditure Recorded Nationally or Sub-nationally?

The way in which expenditure is modelled matters for the interpretation of results. While neither a national nor a sub-national approach is necessarily better, they each have different sources of uncertainty, which one must be aware of. On one hand, a national clustering approach on non-expenditure features, such as the OAC or other national geodemographic classification systems (e.g. Esri, n.d.; RDA Research, n.d.), reduce the uncertainty in emissions estimates coming from regional price differences. Instead, the average price of a specific product or service is assigned, effectively reducing the error from assigning 10% higher emissions to household A than to household B, simply because all food is 10% more expensive in region A than in region B. Nonetheless, depending on the country these price differences may be low for the majority of products and services (Weinand and von Auer, 2020), and do not drastically impact total emissions outside of high-emission categories.

On the other hand, a sub-national approach, such as the LCFS and the TransUnion datasets, can provide spatial detail that goes beyond the make-up of nationally classified household types. Indeed, in the current research, the OAC provides more different results to the other two datasets in Northern Ireland and Wales, suggesting that regional differences may have been overlooked. While a national approach can be helpful in negating regional price differences, it may also overlook regional variation in expenditure. As a result, if the area in question is socio-demographically different from the majority of other areas – for example in the UK Northern Ireland, Wales, and Scotland each have their own governments, in addition to being part of the wider UK structure, and MSOAs in Northern Ireland and Scotland have smaller populations than in England and Wales – not considering regional variation may be a source of uncertainty.

When using sub-national expenditure profiles, regional price differences can be adjusted for using regional price indices, or physical unit data (see section 2.5.4), to reduce uncertainty, especially for high emission categories. Where this is not done, one should consider the impact of regional price differences as a source of error in ones' interpretations. Here, looking at how much prices differ within the country in question can be helpful. In contrast, when using national expenditure profiles, one should be aware that spatial variation in emissions is derived from the different combinations of national expenditure profiles in a neighbourhood, city or region, which may overlook some regional specificity.

2.5.4. Are Physical Units Available?

The type of microdata chosen should be informed by which emissions need to be studied. The way in which physical use data can feed into this type of analysis is twofold. First, in cases where expenditure is not representative of quantity consumed, either due to regional or areal price variations – often this includes rent (ONS, 2020c; von Auer, 2012) – or because prices vary drastically across days, times of day, payment method, etc., including flights (e.g. Boruah et al., 2019) and, in the UK, household gas and electricity use (OFGEM, 2014). Physical use data may be directly available at a household level, such as in the LCFS in the UK, or at an aggregated level, including through the census. Swiss data rich in physical use information has shown at various instances how uncertainties around price differences can be decreased with physical use data, to highlight, not only the uncertainties in expenditure, but also how consuming more sustainable, but higher-priced products can be accounted for in a consumption-based footprints estimation (Girod and de Haan, 2009; 2010; Girod et al., 2014). Where such rich data are not available, area-level information may be attained by using physical proxies through the census.

In this research, we are unable to compare neighbourhood emissions from food which are calculated from expenditure to physical proxies, due to lack of data availability. As this is a high-emission category with pricing differences across different products and brands which fall within the same expenditure categories, using physical data for this category could also be important. Although we find moderate similarity of food footprints across datasets, with the OAC and LCFS being most comparable, limitations from using expenditure data to measure volume of food consumed cannot be accounted for in the current research.

Secondly, the way in which expenditure data are modelled may reflect physical use data. We find that levels of car ownership are most similar to petrol emissions estimated using the OAC. As car ownership is one of the variables used to model the 2011 OAC (Gale et al., 2016), OAC expenditure profiles reflect levels of car ownership more than expenditure profiles not modelled on this variable. While we need to select proxies of physical use carefully, the inclusion of physical use data in modelling processes may be advantageous. For instance, higher levels of car ownership may not necessarily be linked to higher emissions, but lower levels of car ownership should be coupled with lower emissions from car use. Thus, although we need to be aware of such limitations, using an expenditure profile which has either a direct measure of physical use, or is modelled on a physical use proxy may be advantageous to using expenditure profiles more closely linked to income. This is particularly important for product and service categories with high emissions, which depend on factors other than income, such as public transport availability, and ones that are not well-reflected by expenditure.

Lastly, although findings indicate higher levels of similarity between neighbourhood footprints of products and services associated with higher emissions, emissions associated with gas consumed in the home, such as for heating and cooking, cannot be validated, as they show no correlations or even negative correlations between the different estimates. It is suggested here, to estimate these emissions using physical unit data, such as data from smart meters, or to combine expenditure or fuel poverty data with proxy data containing information on the energy efficiency of a home (see Ivanova and Wood, 2020). This points towards the high level of uncertainty when using expenditure data to disaggregate national emissions for high-emission product and service categories where price fluctuations are strong. Consequently, where physical use data are not available, these emissions cannot be evaluated sub-nationally and expenditure should not be used as a proxy.

2.5.5. What are the Implications of the Research?

Finally, the intended implications and practical application of the research may inform the choice of microdata. Firstly, this concerns the use of open versus non-open data. In cases where estimates are generated for an external party to track spatially-detailed emissions, for instance, it may be beneficial to use longitudinally-available open data, which could allow for easier replication of the method in the future. Even where open data are not completely equivalent to non-open sources, considering the trade-off between additional uncertainty and accessibility can be useful. This may not always decide in the favour of open data, however it should be a consideration made.

Secondly, our LAD-level analysis indicates that at this smaller scale emission estimates become less consistent across different microdata used to estimate them. This points to the importance of using such estimates for spatial trends, rather than for the analysis of specific neighbourhoods. While results from the correlation results indicate a moderate level of robustness, only a small fraction of total emissions comes from products which passed all validation tests. Consequently, emission estimates from different microdata are less correlated and have more varied distributions at an LAD level than at a national level. This points to the importance to use a hybrid approach for high emission categories, particularly when assessing neighbourhoods within municipalities rather than assessing national neighbourhood trends.

2.6. Conclusions

Understanding local trends of greenhouse gas emissions which can be linked to household consumption in countries and cities with high consumption-based footprints can allow for local approaches to climate change intervention. This can have a positive impact on national and global emission reduction efforts. In order to do this effectively, however, we need to understand the microdata used to estimate these emissions. Our findings suggest that different microdata generate mostly similar total greenhouse gas emission estimates at a neighbourhood level, also showing that open data can be used to generate detailed emission estimates. Encouragingly, products and services with higher per capita footprints appear to be more similar across datasets. Nonetheless, when disaggregated to achieve high levels of spatial detail and product detail, the importance of understanding the uncertainties in the microdata used to disaggregate national emissions cannot be overstated. This research shows that different microdata have different sources of uncertainty. We show that differences between emissions generated from different datasets can yield dramatically different policy implications. Thus, the importance of selecting a dataset which is appropriate for the research question in question, as well as the extent of the limitations linked to the microdata and the use of expenditure data as a proxy for quantities of products and services consumed must be understood for meaningful interpretation of spatially detailed and product level household emission estimates. The selection of microdata and the choice of levels of disaggregation must consider limitations and uncertainties from the data generation process, including whether datasets represent localised or national expenditure trends, the level of disaggregation necessary to address a research or policy question, the target audience of the emission estimates, and finally, whether physical unit data is necessary to disaggregate emissions of a specific product or service.

2.7. Notes

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Chapter 3. Exploring Transport Consumption-Based Emissions: Spatial Patterns, Social Factors, Well-Being, and Policy Implications

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3.1. Abstract

Recent years have seen an increased interest in demand-side mitigation of greenhouse gas emissions. Despite the oftentimes spatial nature of emissions research, links to social factors and infrastructure are often not analysed geographically. To reach substantial and lasting emission reductions without further disadvantaging vulnerable populations, the design of effective mitigation policies on the local level requires considerations of spatial and social inequalities as well as the context of well-being. Consequently, we explore spatial variations in the links between consumption-based transport emissions with infrastructural factors, such as workplace distance and public transport density, and with risk-factors of transport poverty, including income, age, ethnicity, mobility constraints in London. We find that linear models report significant spatial autocorrelation at $p \leq 0.01$ in their model residuals, indicating spatial dependency. Using geographically weighted regression models improves model fits by an adjusted R^2 value of 9–70% compared to linear models. Here, modelling flight emissions generally sees the lowest improvements, while those models modelling emissions from cars and vans see the highest improvements in model fit. We conclude that using geographically weighted regression to assess the links between social factors and emissions offers insights which global, linear models overlook. Moreover, this type of analysis enables an assessment of where, spatially, different types of policy interventions may be most effective in reducing not only emissions, but transport poverty risks. Patterns of spatial heterogeneity and policy implications of this research are discussed.

Keywords: transport footprints; geographically weighted regression; consumption-based accounting; greenhouse gas emissions; social factors

3.2. Introduction

The increased involvement of local actors in climate change mitigation has meant an increased focus on local strategies (C40, 2019; Cedemia, 2020; DEAL et al., 2020; London Councils, 2020; London Councils and Glanville, 2020). Determining how local consumption contributes to global and national emissions is therefore important for effective, socially just greenhouse gas (GHG) reduction and resource inequality management (Baker, 2018; Bruckner et al., 2022; Hubacek et al., 2017; Peters et al., 2015). With transport being one of the highest emitting sectors (Cohen et al., 2005; Ivanova et al., 2018; Jackson and Papathanasopoulou, 2008; Wiedenhofer et al., 2017) and some aspects of UK road transport (including road building, infrastructure projects, congestion charging and creating low emissions zones) and airport planning being administered locally, a spatial analysis of transport can aid local climate policy makers.

Reducing transport emissions faces various challenges. Differences in incomes and access to services link emissions to social inequalities (Baiocchi et al., 2010; Büchs and Schnepf, 2013a; Druckman and Jackson, 2008a; Hubacek et al., 2017; Ivanova et al., 2018; Ivanova and Wood, 2020; Lenzen et al., 2004; Millward-Hopkins and Oswald, 2021; Minx et al., 2013; Sudmant et al., 2018), which a focus on behaviour change can overlook. For instance, UK-based research links increased transport poverty to rural communities, lower incomes, Black, Asian, and Minority Ethnic (BAME) households, households with children, people with disabilities, and women (Simcock et al., 2021, 2020). Reducing and redistributing transport emissions must, therefore, also take existing inequalities and vulnerabilities into account. Furthermore, high transport emissions are driven by lock-ins (Brand-Correa et al., 2020; Jackson and Papathanasopoulou, 2008; Seto et al., 2016). Mattioli et al. (2020) argue that the entanglement between the automotive industry, car-related infrastructure, political-economic relations, public transport provision, and socio-cultural factors create a lock-in and that moving away from car dependency requires consideration of all factors.

Similarly, although air travel participation of low-income households is increasing, carbon inequality remains high (Alcock et al., 2017; Büchs and Mattioli, 2021; Ottelin et al., 2014; Otto et al., 2019). Moreover, prioritisation of economic growth, increased reliance on flights (Wood et al., 2012), disagreements about how international aviation emissions are assigned in footprint calculations, and a focus on individual responsibility (Higham et al., 2019; Higham and Font, 2020) results in increased flight emissions over time and side-lines systemic changes needed for emission reductions. With policy strategies of different cities to reduce aviation emissions differing widely (Elofsson et al., 2018), the extent to which local policy can and does reduce aviation emissions is highly varied and often limited.

Despite evidence suggesting that energy efficiency advancements can only reduce emissions sufficiently if combined with major societal, economic, and cultural changes (Brand et al., 2019; Haberl et al., 2020; Wiedmann et al., 2020), transport decarbonisation discussions and policies often centre technological shifts (CMA, 2021; HM Treasury, 2021; IPCC, 2014). Nonetheless, recent years have seen a steep increase in research published on reducing emissions through decreasing demand (Creutzig et al., 2021a), such as avoiding flying and living car-free (Ivanova et al., 2020). Moreover, research suggests that transport emissions can be effectively reduced through local policies (Creutzig et al., 2016, 2015, 2012). In line with this, the UK's Climate Change Committee (CCC, 2021) aims to encourage increased use of public and active transport by 2030, through investment in local infrastructure. A spatial analysis of neighbourhood footprints can offer a perspective on how such infrastructure affects transport emissions.

Climate policy also needs to consider energy justice and well-being. Creutzig et al. (2021b) suggest that demand-side mitigation can positively impact different aspects of well-being. For instance, decreased commuting is linked to decreased land transport emissions (Brand et al., 2013) and increased subjective well-being (Creutzig et al., 2021b). Active and public transport can decrease emissions, motor vehicle crashes, and noise, while increasing greenspace can promote physical activity (Brand et al., 2021; Khreis et al., 2017; Nieuwenhuijsen, 2020). Moreover, understanding emissions through energy (Hall, 2013; Jenkins et al., 2016) and transport (Gössling, 2016; Verlinghieri and Schwanen, 2020) justice lenses is necessary: Energy and transport access are impacted by factors such as income, age, and disability (Ivanova and Middlemiss, 2021; Lucas et al., 2016; Schwanen, 2020; Simcock et al., 2021). Emission reduction efforts need to consider human well-being and social factors to avoid widening inequalities.

While much research looks at the links between social factors and consumption-based emissions (Baiocchi et al., 2010; Büchs and Mattioli, 2021; Büchs and Schnepf, 2013a; Czepkiewicz et al., 2018; Druckman and Jackson, 2008a; Ivanova et al., 2018; Ivanova and Wood, 2020; Lenzen et al., 2004; Mattioli and Scheiner, 2022; Millward-Hopkins and Oswald, 2021; Minx et al., 2013; Mishalani et al., 2014; Sudmant et al., 2018), the spatial aspects of consumption-based emissions are not well-studied. Although concepts of spatial justice and injustice are debated, as some argue that spatial injustices only represent social injustices

(Bouzarovski and Simcock, 2017; Chatterton, 2010; Garvey et al., 2022; Pirie, 1983; Soja, 2016, 2010), applying a spatial justice framework can be helpful in highlighting and evaluating emission inequalities. Using such a framework, Bouzarovski and Simcock (2017) are able to identify various mechanisms which produce and reproduce energy poverty and vulnerability. Space is similarly important in quantitative analysis. Geographic data are generally considered to be spatially dependent, such that areas in closer geographic proximity are more likely to be more similar (Fotheringham, 2011). Ignoring spatial dependencies falsely assumes that relationships between variables are the same in all areas (Comber et al., 2022) and can overlook inconsistencies and spatial variance. Indeed, evidence from China suggests that the relationships between emissions and its predictors are spatially heterogeneous, and that employing spatial statistics can shine light on these differences (S. Wang et al., 2019; Y. Wang et al., 2019; Xu and Lin, 2017).

To our knowledge, consumption-based transport emissions and their links with social factors have not been analysed spatially, in the UK. We focus on transport emissions as these have inherently spatial qualities, have the potential for local policy interventions, and as transport is one of the highest emitting sectors in the UK (Kilian et al., 2021; Owen, 2021; Owen and Kilian, 2020). Moreover, we assess spatial factors, such as distance to workplace and public transport network density, as well as factors which increase the risk of transport poverty (where transport poverty is defined as being caused by high cost and low public transport access), including lower incomes, BAME households, households with children, people with health or mobility difficulties (Simcock et al., 2021, 2020).

Bridging the gap between environmental economics and geographical analysis, we employ geographically weighted regression analysis, a variation of a regression analysis which embeds the spatial relationships between observations to estimate local parameters for each observation (Brunsdon et al., 1996; Fotheringham, 2011; Xu and Lin, 2017). The aim of this paper is to explore whether and how relationships between social factors and transport emissions are spatially heterogenous and assess how this may impact local policy decisions. We look at emissions from the years 2015–2016 with a particular focus on London. In this paper, we first discuss the methods and data used for our analysis, results from analysis, which we split into spatial patterns of the relationships between incomes and emissions, and other social factors and emissions, as well as provide an overview of the links between emissions and well-being. Finally, we discuss our findings in the context of other research and their policy implications.

3.3. Materials and Methods

3.3.1. Neighbourhood Emissions

To estimate neighbourhood GHG emissions, we need two pieces of data: an estimate of local expenditure and product-based intensities (in tCO_2e/£). The multipliers incorporate both indirect emissions which occur throughout the supply chain globally and direct emissions from the burning of fuel for personal transport use (e.g., private cars).

To calculate these product-based multipliers, we first need to calculate the UK's total household GHG emissions. We conduct a multi-regional input–output (MRIO) analysis with an environmental extension to calculate indirect emissions from goods and services consumed by UK households, which occurred throughout the global supply chain. MRIO databases originate from economics but have been used by environmental economists since the 1960s due to their ability to make the link between the environmental impacts associated with the production of goods and services and final demand. The Leontief input–output model reports the economic interrelationships between industries throughout the supply chain, by documenting, in monetary units, which inputs industries consume from each other to produce their own outputs (Miller and Blair, 2009). Equation (1) shows how product-level emissions ($\mathbf{p}$) can be estimated using the fundamental Leontief equation, $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\mathbf{y}$, where $\mathbf{s}$ is a vector showing direct industry emission coefficients, $\mathbf{I}$ is the identity matrix with the same dimensions as the input–output matrix ($\mathbf{Z}$), $\mathbf{A}$ is the product of $\mathbf{Z}$ and the total industry output vector, and $\mathbf{y}$ is final demand. More details of the structure of an MRIO database can be found in the literature (Miller and Blair, 2009; Wood et al., 2019b).

$$\boldsymbol{p} = \boldsymbol{s}(\boldsymbol{I} - \boldsymbol{A})^{-\mathbf{1}}\hat{\boldsymbol{y}} \tag{1}$$

The MRIO database used to calculate product-level household emissions for the UK in the current research is the UKMRIO model from the year 2015 for 307 products and services (Defra, 2020a; ONS, 2020a, 2019a). The UKMRIO is an annually reported national statistic, which is constructed by the University of Leeds and follows the recommendations from Tukker et al. (2018) and Edens et al., (2015) for calculating consumption emissions consistent with National Accounts (see Kilian et al. (2022) for more detail). All greenhouse gases reported in the UKMRIO are converted into CO_2 equivalents (CO_2e) and include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF_6) and nitrogen trifluoride (NF_3). We estimate emissions at a Classification of Individual Consumption by Purpose (COICOP) 4 level, (UN: Statistics

Division, 2019), using a UKMRIO sector to COICOP bridging table, from the UK's Office for National Statistics. After indirect emissions of UK households are calculated, direct household emissions are added to products associated with fuel burning. Direct emissions are also reported in the UKMRIO as CO_2 equivalents.

To disaggregate UK emissions subnationally, we use microdata on neighbourhood-level household expenditure. Product-level emissions estimates can be divided by total household spends for each product to produce the aforementioned carbon multipliers. The expenditure microdata used here is from the Living Costs and Food Survey (LCFS), an openly available expenditure survey recording detailed spends from 4000–6000 private households across the UK every year (ONS, 2017a). To increase our sample size, we combine data from 2015 and 2016 LCFS. Moreover, to reduce the effect of outliers on emission estimates, product-level household expenditures that are 3.5 standard deviations above or below the sample mean are windsorised. To ensure that household expenditure from the LCFS matches that from the UKMRIO database (Min and Rao, 2017), we adjust expenditure in the LCFS for each COICOP 4 product/service by the total spend reported in the UKMRIO.

To generate neighbourhood expenditure profiles, we follow the method used by Kilian et al. (2022) to calculate neighbourhood emissions in the UK using the LCFS. This means that we use the geodemographic classification of Output Areas, the smallest census geography in the England (with a population of 100–625 people (ONS, n.d.)), and regional information from the LCFS to generate sub-regional neighbourhood expenditure profiles. Applying the carbon multipliers to neighbourhood expenditure provides an estimate of household GHG consumption-based emissions by neighbourhood. This method provides emission estimates which are comparable, for the majority of the consumption-based footprint, to estimates generated from other microdata (Kilian et al., 2022a). Moreover, our selection of the method, neighbourhood size and microdata is based on suggestions by Kilian et al. (2022) to ensure that data are as robust as possible.

The neighbourhood geography used in this research is the Middle Layer Super Output Area (MSOA), the third smallest census geography in England, with populations of 5,000–15,000 people (ONS, n.d.; Figure 3.1). To match official records, we also adjust populations from the LCFS to mid-year populations (ONS, 2017b). The mean number of unique households used to create an MSOA expenditure profile is 259.38 households (SD = 89.91). The distribution of sample sizes for each MSOA is shown in Figure 3.1: This only shows the unique observations; MSOA expenditure profiles are weighted by how often household types are present in each MSOA. Moreover, the same observation may be used to estimate emissions for multiple MSOAs, where the geodemographic neighbourhood classification indicates similar neighbourhood types in multiple MSOAs.

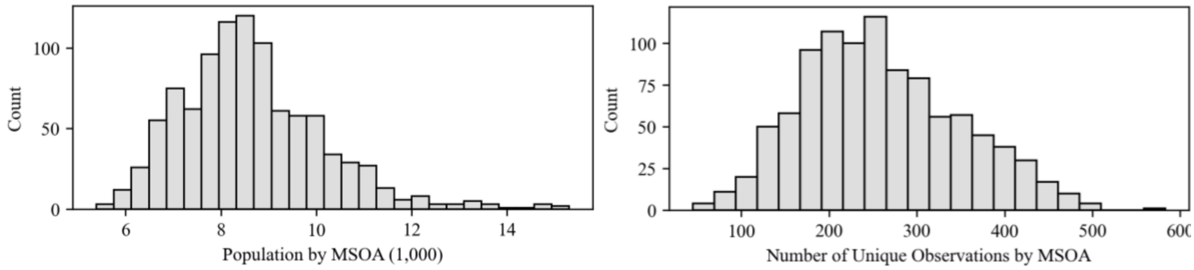

Figure 3.1. Histogram showing the population (left) and the number of unique observations (households) from LCFS (right) in each MSOA in London.

Using expenditure as a proxy for volume consumed is a source of uncertainty for this type of analysis (Girod and de Haan, 2010). We reduce this uncertainty by using data on the number of flights taken, rather than cost. We also follow Kilian et al.'s (2022) recommendations to increase emission estimate robustness, including aggregating to large neighbourhoods and combining expenditure surveys from 2 years. However, using expenditure presents an issue for public transport season tickets. Here, ticket cost is not reflective of trip numbers. However, travelcard prices change with distance from central London, so prices are adjusted to the maximum distance travelable. Therefore, while we do not know the number of journeys taken, we can assume that those traveling less frequently purchase individual tickets. In other words, we assume that those buying travel cards purchase these when buying individual tickets for journeys is more expensive than buying a travel card. Thus, we assume that those buying travel cards take more journeys than those buying individual tickets, and that, therefore, prices are indicative of distance travelled, up to the travel card price.

3.3.2. Geographic, Census and Other Data

In this section, we summarise additional datasets we use in the current research. Descriptive statistics for all variables are shown in Table 3.1.

3.3.2.1. 2011 Census

We use data from the 2011 census (ONS, 2013) for geography lookup tables, geographical boundaries, distance to workplace and the numbers of people aged 65 and over, 14 and younger, limited in their day-to-day activities due to long-term health problems and/or disabilities, and identifying as BAME. To ensure consistency between population data from the emission estimates and census, we adjust census data to the 2015 mid-year population (ONS, 2017b). Mid-year populations estimate populations for 30 June of a given year by adjusting population counts from the census with administrative data on births, deaths, and migration (ONS, 2016b).

Table 3.1. Means and standard deviations of social and spatial factors.

	Weighted by Population		MSOA Average					
	Weekly Income (1000 GBP)	Distance to Workplace (100 km)	Public Transport Density (Metric)	Pop. Aged ≥65 (%)	Pop. Aged ≤14 (%)	Pop. Identifying as BAME (%)	Pop. Limited in Day-to-Day Activities (%)	MSOA Population (1000)
Mean	0.23	0.11	2.31	11.22	18.68	39.51	14.17	8.69
Std. deviation	0.08	0.02	0.77	4.12	3.88	19.35	2.68	1.54
Minimum	0.10	0.06	0.00	2.40	5.78	3.81	6.04	5.41
Maximum	0.59	0.18	4.64	27.23	34.00	93.86	22.79	15.36

3.3.2.2. *Public Transport Density*

Data for 2015 public transport density are available via the London Datastore (Transport for London, 2017). We use the Access Index measurement from the Public Transport Access Level (PTAL) indicator, which estimates public transport network density and frequency at a small area level across London. We use a log transformation on Access Index values to better represent the PTAL categories linearly (Mayor of London and Transport for London, 2015). How this transformed variable maps onto original PTAL categories is shown in Table 3.2, more information on how these categories are defined is available at the London Datastore (Mayor of London and Transport for London, 2015). Public transport density data are spatially divided into 100 m grid squares with 159,451 cells. For each of these, the centroid is calculated and the median transport density value of all centroids that fall within one MSOA are taken to represent the public transport density of this MSOA.

Table 3.2. Transformed public transport density mapping onto original PTAL category.

Original Category	Transformed Variable Used in This Paper	
PTAL 2015	Minimum	Maximum
0 (lowest)	0.00	0.00
1a	0.01	1.24
1b	1.25	1.79
2	1.80	2.40
3	2.41	2.77
4	2.78	3.03
5	3.04	3.26
6a	3.27	3.71
6b (highest)	3.72	4.64

3.3.2.3. *Income*

The income data we use are available via the UK's Office for National Statistics (ONS, 2020d). As data are reported as household income, we adjust them to per capita income using data on household size from the 2011 census.

3.3.2.4. *Well-Being*

We use well-being data from the London Datastore (Mayor of London, 2011; Mayor of London and London Assembly, 2015). For data availability reasons, we use the 2013 data. These data are at ward level, which is an electoral geography larger than MSOAs. Ward boundaries for the data are from the year 2009. For this part of the analysis, therefore, we calculate ward-level emissions by generating the mean emissions from the MSOAs in each ward, weighted by MSOA population and the proportion of each MSOA's area in each ward. As research indicates that findings can depend on the definition of well-being used (Lamb and Steinberger, 2017), we analyse both a well-being index score and subjective well-being. The well-being index captures life expectancy, childhood obesity, incapacity benefit claimant rate, unemployment rate, crime rate, rate of deliberate fires, GCSE point scores, unauthorised pupil absence, children in out-of-work households, public transport accessibility, access to public open spaces, and subjective well-being (Mayor of London, 2011; Mayor of London and London Assembly, 2015). The subjective well-being score captures self-reported life satisfaction, worthwhileness, anxiety, and happiness, and is used here as transport choices have been linked to subjective well-being in the past (Chatterjee et al., 2020; De Vos et al., 2020; Singleton, 2019).

3.3.3. Geographically Weighted Regression

Spatial data typically exhibit spatial dependency and non-stationarity. This means that more proximal locations share more similar attributes than those further apart and that processes responsible for observed phenomena can spatially vary (Fotheringham, 2011; Oshan et al., 2019). Traditional regression modelling neglects these spatial differences. We therefore use geographically weighted regression (GWR) models, an extension of regular regression models. This can be expressed as shown in (2), where $\mathbf{y}$ is the dependent variable, $\mathbf{x_1}$ to $\mathbf{x_n}$ are independent variables, $\boldsymbol{\beta_0}$ is the intercept, $\boldsymbol{\beta_1}$ to $\boldsymbol{\beta_n}$ represent model coefficients, and $\boldsymbol{\varepsilon}$ is the random error term (Fotheringham, 2011). Here $\mathbf{i}$ refers to a location, in this research an MSOA-level neighbourhood. A distance weight is used to weigh data from nearer locations more strongly than data from more distant locations, resulting in local coefficients highlighting variable relationships around location **i** (Fotheringham, 2011). This is calculated using Euclidian distance. Moreover, we use an adaptive cross-validation approach to selecting the bandwidth, or number of neighbours included in each model. This means that we can find the optimal bandwidth, as a too small value can lead to large variance in local coefficients, while a too large bandwidth value can bias local estimates by including observations which are too far away (Fotheringham, 2011). This helps select a model which has a good model fit, without overfitting to the data. A more detailed description of GWR can be found in Fotheringham (2011). We use the R-package 'Gwmodel' (Lu et al., 2017) to estimate the GWR models and the distance matrix.

$$\boldsymbol{y_i} = \boldsymbol{\beta_{0_i}} + \boldsymbol{\beta_{1_i} x_{1_i}} + \boldsymbol{\beta_{2_i} x_2} + \cdots \boldsymbol{\beta_{n_i} x_{n_i}} + \boldsymbol{\varepsilon_i} \tag{2}$$

To assess the usefulness of GWR modelling for our data, we follow recommendations by Comber et al. (2022). We do this by running both GWR and ordinary least squared linear regression (LM) models with the same variables, and comparing the fits of the two models, as well as assessing the spatial distribution of the residuals of the LM models. If residuals of LM models exhibit significant spatial clustering, they are not considered independent, thus violate assumptions of linear regression modelling. Moreover, we can compare model fits to assess which model is better able to represent the data. This allows us to evaluate whether GWR models should be used for this type of research, and if yes, where they are most able to improve on LM models.

3.4. Results

3.4.1. Descriptive Statistics and Spatial Emission Patterns

In 2015–2016, approximately 30% of London's consumption-based household emissions come from transport. As shown in Table 3.3, when breaking transport emissions down into various modes of transport, we find that cars have the largest footprint (M = 1.11, SD = 0.39), followed by flights (M = 0.98, SD = 0.35). It should be noted that UK flight emissions are lower between 2008 and 2018 (BEIS, 2021) due to the 2007/08 economic crisis. Combined, emissions from flights and cars make up over 75% of the average Londoner's transport footprints. The lowest per capita emission, on the other hand, come from bus and combined transport, which includes emission from combined bus and mass rapid transit system tickets. Their combined footprint is only 0.11 tCO_2e/capita, or less than 5% of the total transport footprint. Detail on the aggregation of different COICOP 4 categories to the transport modes analysed in this paper can be found in Appendix E.

Table 3.3. Descriptive statistics for emissions from different transport modes in London.

	Car/Van Purchases and Motoring Oils	Flights	Rail	Bus	Combined Fares	Other Transport	Total Transport
Mean (tCO_2e/capita)	1.11	0.98	0.13	0.03	0.08	0.39	2.72
Standard deviation	0.39	0.35	0.07	0.01	0.02	0.17	0.66
Minimum (MSOA)	0.52	0.45	0.02	0.01	0.01	0.10	1.44
Maximum (MSOA)	2.26	2.40	0.47	0.06	0.16	1.29	4.47

When comparing per capita emissions of different London neighbourhoods, we find that per capita flight emissions have the largest range between London neighbourhoods (Range = 1.95 tCO_2e/capita), followed by emissions from cars (Range = 1.74 tCO_2e/capita). However, relative to magnitudes, car emissions have the smallest, albeit notable, difference where the neighbourhood with the highest emission has a per capita footprint four times that of the lowest emitting neighbourhood. For flights, it is five times as high, while for rail, bus, and combined fare emissions the highest per capita footprint is 9–21 times as high as the lowest. Thus, large carbon inequalities occur across all transport modes in London.

Spatial patterns are also evident (Figure 3.2). Car emissions are lower in Inner London and higher in Outer London. Contrastingly, higher rail and flight emissions are clustered mostly in Inner London. Higher bus emissions non-uniformly clustered, mostly around the southern half of Inner London and north-eastern parts of Outer London. This may be linked to reduced availability of suburban rail and mass rapid transport in some areas. Higher emissions from combined fares, on the other hand, are more present in Inner London, likely mirroring income patterns, as buses are cheaper than combined fares. Notably, some areas between the centre and outskirts indicate below median emissions from car, rail, and bus transport. This could point to areas with increased transport poverty, or with higher active transport.

3.4.2. Emissions and Social Factors

3.4.2.1. Spatial Variance in the Relationship between Income and Emissions

Regression analyses are conducted to explore the relationships between socio-demographic and spatial factors and consumption-based GHG emissions. For this, we run geographically weighted regression (GWR) models. A GWR produces two results: a 'global' model, which here is a London-wide regression model that does not consider spatial variation; and 'local' coefficients for each neighbourhood. Local coefficients represent the relationships between variables for the given and surrounding MSOAs. We also run ordinary least square regression (LM) models with the same parameters to be able to compare the model fits of a linear regression to a GWR.

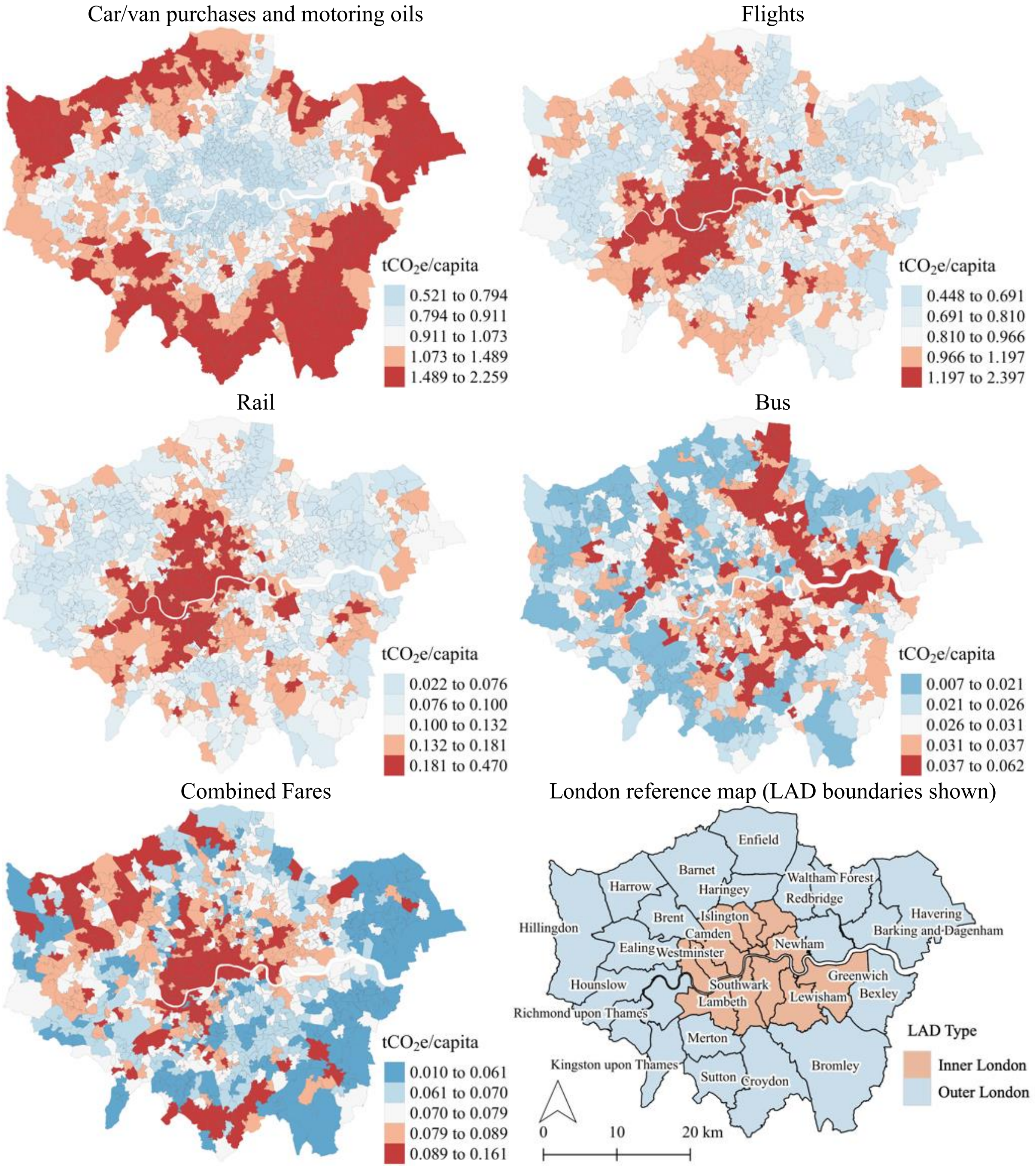

Figure 3.2. London's consumption-based transport emissions from 2015 to 2016 for different modes of transport.

Notes: Colour ranges show quintiles. Blue neighbourhoods have below median, white neighbourhoods have close to median, red neighbourhoods have above median per capita emissions for a given transport mode.

First, we run one GWR and one LM model for each mode of transport, where we use income to predict consumption-based GHG emissions. This analysis allows us to explore spatial differences in the relationship between income and emissions. To prevent a spurious correlations by using multiple variables which are derived from common ancestors (Pearson, 1897; Ward, 2013), we use total MSOA emissions and incomes, but control for MSOA populations in our models.

First, we compare the LM models to the GWR models, following suggestions by Comber et al., (2022) by looking at the spatial distribution of LM residuals and model fits. The residuals of all LM models show significant spatial autocorrelation, as indicated by the Moran's *I* statistic and significance testing; Moran's $I \geq 0.50$ ($p < 0.01$). A Moran's *I* value of -1 indicates an even distribution, 0 indicates a random distribution, 1 indicates complete clustering. Thus, residuals of the LM models are significantly clustered and the use of a GWR model is advised. Next, we compare model fits of the LM and GWR models. The Akaike Information Criterion (AIC) considers both the complexity of a model, as well as its goodness of fit. This can be used to compare models, where a lower score is regarded as a better model, with less risk of over- or underfitting. Adjusted R^2 is based on the R^2 statistic, which provides a value between 0 and 1, which expressed the proportion of change in the dependent variable, which is explained by the model. Here 1 means that all change in the dependent variable is explained, while 0 means that no change in the dependent variable is explained by the model. Adjusted R^2 adjusts for the number of terms in the model and is always lower than the R^2 value of a model.

Results from our analysis are shown in Table 3.4. For all dependent variables, GWR has a lower AIC and a higher adjusted R^2 value, indicating that the GWR models provide a better fit for the data than the LM models. Most notable are the model improvements for the model estimating emissions from car/van purchases and motoring oils, which explains over 70% more of the change in emissions when using a GWR rather than an LM. For combined fare and bus emissions, this is around 40%, while flight and rail emissions see an improvement of 16% and 22%, respectively. As GWR models provide a better fit, we continue to assess the GWR models in more detail.

The global, London-wide results indicate that income significantly predicts emissions from all transport modes, $p < 0.01$. As shown in the local predictor coefficient columns, however, local, neighbourhood-level income coefficients vary. Local coefficients for income are greater than 0, and thus positively linked to emissions, for over 80% of MSOAs for emissions from cars, flights, and rail transport. In line with previous research, therefore, we find that higher incomes mostly predict higher emissions in carbon-intensive transport such as flights and cars (Baiocchi et al., 2010; Brand et al., 2013; Büchs and Mattioli, 2021; Feng et al., 2021; Ivanova et al., 2018; Ivanova and Wood, 2020).

Table 3.4. Results from the GWR and LM models when using income as a predictor of emissions from different transport modes.

Dep. Variable (tCO_2e)	Residual Moran's I (LM)	AIC		Adjusted R^2		Global Coefficients (GWR)			Local Income Coeff. (GWR)			
		LM	GWR	LM	GWR	Income	Intercept	Pop.	1st Qu.	Med	3rd Qu.	>0 (%)
Cars/vans	0.79**	5139	3016	0.17	0.88	1.06**	1.55*	0.69**	0.42	1.59	4.35	83.2
Flights	0.54**	3867	2817	0.73	0.89	3.84**	−1.41**	0.26**	2.46	3.15	3.98	98.89
Rail	0.55**	842	−282	0.65	0.87	0.73**	−0.25**	−0.01	0.46	0.62	0.81	96.26
Bus	0.51**	−2069	−3089	0.31	0.72	−0.05**	0.02	0.04**	−0.11	−0.06	−0.02	17.91
C. Fares	0.56**	−761	−1877	0.38	0.77	0.07**	−0.07*	0.07**	−0.07	0.06	0.14	64.47

Notes: Single asterisk (*) indicates significance at $p < 0.05$, double asterisk (**) indicates significance at $p < 0.01$. Each line in the table shows a different model.

Despite predominantly positive associations between income and emissions from cars and flights, our results also indicate notable differences in the strength of the associations within London. The inter quartile range of local coefficients of income to predict car emissions is 3.93, more than three times the coefficient of the global model. Similarly, the inter quartile range of local coefficients of income to predict emissions from flights is almost half as large as the global coefficient—at 1.52. These findings highlight that here spatial variance in the relationship between income and different transport emissions is strong and cannot be captured well by the global models.

Furthermore, associations between income and combined fare emissions range clearly from negative to positive (see also Figure 3.3). Thus, in 64.47% of MSOAs higher incomes predict higher combined fares emissions, while in the rest of London higher incomes predict lower combined fare emissions. Thus, for combined fare emissions relying on a global model can lead to misleading conclusions for local areas.

Spatial distributions of local coefficients are visualised in Figure 3.3. These reveal that neighbourhood clusters with negative associations between income and combined fare emissions appear mostly in Outer London. In Inner London, on the other hand, we find mostly neighbourhood clusters with negative associations between income and car emissions. Moreover, neighbourhoods with strong positive associations between car emissions and income also have the strongest negative associations between income and emissions from combined transport. This indicates that local factors other than income, such as infrastructure and workplace commute, may be important. Moreover, these findings emphasise the importance of understanding local contexts and spatial differences, as the global models can fail to capture large differences in patterns between different areas of the same city.

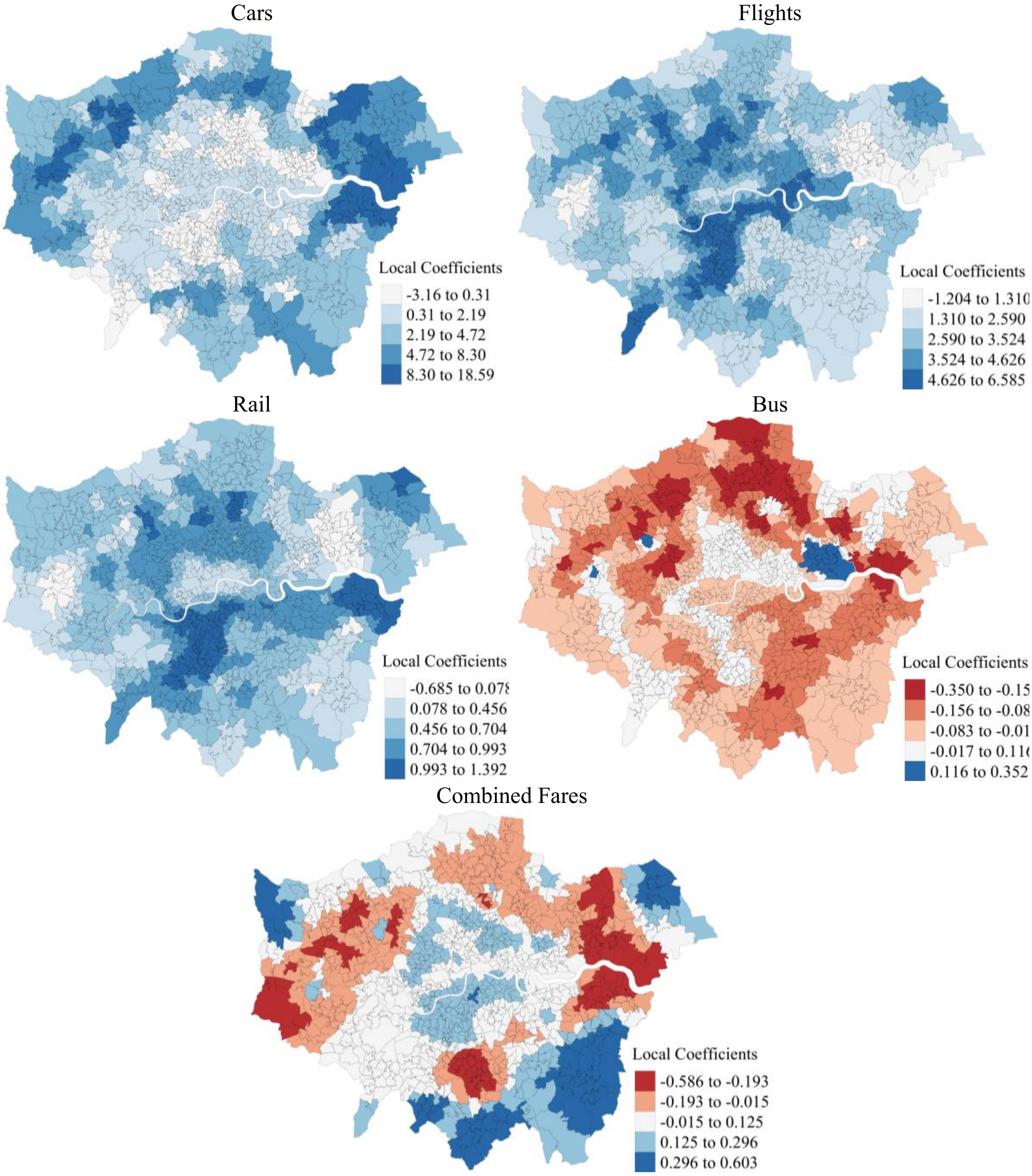

Figure 3.3. Spatial distributions of local coefficients of income when predicting bus and combined fare emissions.
Notes: Emission estimates are from the years 2015–2016. Population is controlled for.

3.4.2.2. Spatial Variance in the Relationship between Other Social Factors and Emissions

In this section, we repeat a similar analysis for other social and spatial factors. We fit GWR and LM models for using other social factors to predict emissions from different transport modes. As the link between higher incomes and higher emissions is well-established, both in previous research (Baiocchi et al., 2010; Brand et al., 2013; Büchs and Mattioli, 2021; Ivanova et al., 2018; Ivanova and Wood, 2020) and our findings in the previous section, we control for income in all models in this section. Moreover, as spurious correlations can occur when modelling multiple variables which are derived from common ancestors (Pearson, 1897; Ward, 2013), we again use total MSOA values for emissions, incomes, and other variables. As our aim is to explore the spatial variance in relationships between individual variables, and not to create a predictive model or infer causality, we run individual models for the different social factors, controlling only for population and income. This means that we model the total income from all households in one MSOA, the total emissions from all households in one MSOA, combined distance to workplace of all MSOA residents, as well as the total the numbers of people aged 65 and over, 14 and younger, limited in their day-to-day activities due to long-term health problems and/or disabilities, and identifying as BAME. To control for the effect of MSOA population, we include this as a control variable in our models. This analysis is conducted to explore spatial variance in the relationships between different social factors and emissions when controlling for income. Social factors are chosen as they are linked to increased risk of transport poverty (Simcock et al., 2021, 2020), or have previously been linked to increased emissions (Brand et al., 2013). While results from this analysis cannot infer causation, they can highlight where and how such relationships are spatially heterogeneous.

Results for the model comparison indicate that the use of GWR models rather than LM models is appropriate for all models. The spatial autocorrelation tests show significant spatial clustering of residuals for all models, Moran's $I \geq 0.37$ ($p < 0.01$). Moreover, model fits indicate, again, that the GWR has a better model fit than a LM for the same data, as indicated by lower AIC, and higher adjusted R^2 values (Table 3.5). GWR models explain 9–69% more change in the dependent variables than LM models, varying both by transport type and independent variables. Again, models predicting emissions from cars see the greatest improvements, with adjusted R^2 values increasing by 0.18–0.69, followed by models predicting bus emissions, which see increased in adjusted R^2 values of 0.32–0.42. For flight emissions, GWRs see the smallest improvements in adjusted R^2 values across all models.

Table 3.5. Model fits of GWR and LM models when using different social factors as predictors of emissions from different transport modes.

Dependent Variable (tCO_2e)	Predictor Variable	Residuals' Moran's *I* (LM)	AIC		Adjusted R^2	
			LM	GWR	LM	GWR
Car/van purchases and motoring oils	Public Transport Density	0.49**	4534	3072	0.55	0.88
	Pop. ltd in day-to-day act.	0.74**	5087	3223	0.21	0.86
	Pop. aged 65 or older	0.42**	4140	3148	0.70	0.88
	Pop. aged 14 or younger	0.77**	5123	3184	0.18	0.87
	Pop. identifying as BAME	0.69**	4856	3127	0.38	0.88
	Distance to workplace	0.51**	4577	3240	0.53	0.86
Flights	Pop. ltd in day-to-day act.	0.50**	3669	2500	0.78	0.92
	Pop. aged 65 or older	0.43**	3542	2749	0.81	0.90
	Pop. aged 14 or younger	0.53**	3733	2630	0.76	0.91
	Pop. identifying as BAME	0.44**	3764	2822	0.76	0.89
Rail	Public Transport Density	0.38**	565	−197	0.73	0.87
	Pop. ltd in day-to-day act.	0.50**	746	−168	0.68	0.86
	Pop. aged 65 or older	0.37**	538	−196	0.74	0.87
	Pop. aged 14 or younger	0.53**	766	−133	0.67	0.86
	Pop. identifying as BAME	0.49**	798	−210	0.66	0.87
	Distance to workplace	0.39**	601	−119	0.72	0.86
Bus	Public Transport Density	0.49**	−2107	−3047	0.34	0.71
	Pop. ltd in day-to-day act.	0.51**	−2076	−3029	0.32	0.71
	Pop. aged 65 or older	0.49**	−2226	−3101	0.41	0.73
	Pop. aged 14 or younger	0.51**	−2084	−3155	0.32	0.74
	Pop. identifying as BAME	0.51**	−2067	−2999	0.31	0.70
	Distance to workplace	0.50**	−2076	−3024	0.32	0.70
Combined fares	Public Transport Density	0.47**	−876	−1877	0.45	0.77
	Pop. ltd in day-to-day act.	0.52**	−856	−1752	0.43	0.75
	Pop. aged 65 or older	0.50**	−849	−1788	0.43	0.76
	Pop. aged 14 or younger	0.53**	−812	−1773	0.41	0.75
	Pop. identifying as BAME	0.37**	−1205	−1975	0.60	0.80
	Distance to workplace	0.47**	−885	−1803	0.45	0.76

Notes: Double asterisk (**) indicates significance at $p < 0.01$. Each line in the table shows a different model.

An analysis of the coefficients confirms that spatial differences in the relationships between transport emissions and social factors occur throughout London, when controlling for income. As shown in Table 3.6, the GWR analyses show, for instance, that approximately 50% of local coefficients of workplace distance are above 0 for all modes of transport, indicating high local variation. This could be due to different types of jobs and households in different areas, or differing levels of transport poverty and active transport. While our global model confirms Brand et al.'s (2013) findings that workplace distance is positively linked to car emissions, locally we find spatial heterogeneity. As Figure 3.4 shows, both negative and positive associations between workplace distance and car emissions mostly appear in Outer London. Both trends may be linked to commuting: The negative association may be explained through better public transport connections into Central London, than within Outer London; the positive association could be linked to people in these areas working mostly outside of London. Notably clusters of positive associations are near motorways (see Appendix F). It is also possible that journeys within Outer London have higher emissions than longer journeys into Inner London, due to rail networks mainly going into London. Future analyses of the impacts of the COVID-19 lockdowns on emissions may reveal the effects of increased localisation. Although we cannot assess why these local variations occur, it emphasises the importance of understanding local contexts.

Table 3.6. Geographically weighted regression coefficients when using different social factors as predictors of emissions from different transport modes. 'Predictor' refers to the variable listed in the 'Predictor Variable' column.

Dependent Variable (tCO_2e)	Predictor Variable	Global Coefficients				Local Predictor Coefficients			
		Predictor	Intercept	Pop.	Income	1st Qu.	Med	3rd Qu.	>0 (%)
Car/van purchases and motoring oils	Public Transport Density	−2.91**	6.50**	0.76**	1.63**	−1.71	−0.76	−0.17	15.08
	Pop. ltd in day-to-day act.	3.74**	0.98	0.07	1.73**	−2.35	−0.53	1.63	42.41
	Pop. aged 65 or older	7.86**	−0.81*	0.36**	−0.10	0.97	3.78	5.55	83.20
	Pop. aged 14 or younger	1.70**	1.39*	0.25*	1.65**	−2.07	−0.35	1.24	41.40
	Pop. identifying as BAME	−1.46**	−0.49	2.15**	−1.72**	−1.19	−0.49	0.20	31.88
	Distance to workplace	1.17**	0.64	−0.64**	1.51**	−0.38	0.00	0.37	49.60
Flights	Pop. ltd in day-to-day act.	−3.63**	−0.85**	0.86**	3.20**	−4.49	−2.29	−0.81	11.44
	Pop. aged 65 or older	−2.75**	−0.58*	0.38**	4.25**	−3.52	−1.80	−0.68	12.15
	Pop. aged 14 or younger	−2.34**	−1.20**	0.86**	3.04**	−3.20	−1.67	−0.36	17.51
	Pop. identifying as BAME	0.49**	−0.73*	−0.23**	4.77**	−0.37	0.02	0.37	52.23
Rail	Public Transport Density	0.24**	−0.66**	−0.01	0.68**	−0.01	0.01	0.04	63.77
	Pop. ltd in day-to-day act.	−0.56**	−0.16*	0.09**	0.63**	−0.07	0.00	0.10	50.91
	Pop. aged 65 or older	−0.58**	−0.07	0.02*	0.82**	−0.18	−0.08	−0.02	19.03
	Pop. aged 14 or younger	−0.39**	−0.21**	0.09**	0.60**	−0.02	0.05	0.12	69.33
	Pop. identifying as BAME	0.07**	−0.15*	−0.08**	0.86**	−0.03	0.00	0.02	47.47
	Distance to workplace	−0.09**	−0.17**	0.10**	0.69**	−0.01	0.00	0.02	59.41
Bus	Public Transport Density	0.02**	−0.02	0.04**	−0.05**	0.04	0.12	0.20	84.01
	Pop. ltd in day-to-day act.	−0.04**	0.02	0.05**	−0.05**	−0.66	−0.40	−0.14	12.96
	Pop. aged 65 or older	−0.10**	0.05**	0.04**	−0.03**	−0.57	−0.33	−0.06	19.33
	Pop. aged 14 or younger	0.04**	0.01	0.03**	−0.03**	−0.52	−0.31	−0.11	14.98
	Pop. identifying as BAME	0.00	0.02	0.04**	−0.05**	−0.15	−0.03	0.06	43.02
	Distance to workplace	0.00**	0.02	0.04**	−0.05**	−0.02	0.03	0.06	66.50
Combined fares	Public Transport Density	0.07**	−0.19**	0.07**	0.06**	−0.22	−0.11	0.01	26.62
	Pop. ltd in day-to-day act.	−0.25**	−0.03	0.11**	0.03**	−0.19	−0.09	0.10	36.03
	Pop. aged 65 or older	−0.15**	−0.03	0.07**	0.09**	−0.19	−0.08	0.03	30.26
	Pop. aged 14 or younger	−0.14**	−0.06	0.10**	0.02*	0.00	0.04	0.09	77.13
	Pop. identifying as BAME	0.09**	0.05*	−0.02**	0.24**	−0.02	0.01	0.03	59.41
	Distance to workplace	−0.03**	−0.05	0.10**	0.06**	−1.71	−0.76	−0.17	15.08

Notes: Single asterisk (*) indicates significance at $p < 0.05$, double asterisk (**) indicates significance at $p < 0.01$. Each line in the table shows a different model.

Rail emissions mostly increase with public transport density, when controlling for income and population. In contrast, car emissions are mostly negatively associated with public transport density. However, the spatial variation in local coefficients (Figure 3.4), shows that in Outer London, and particularly in the south, this association is stronger, indicating that here public transport density is more strongly linked to reduced car emissions. This may be due to different modes of public transport being distributed unevenly throughout London but could also be linked to local attitudes, place of work, access to services, or other factors. Regardless of the reasons behind these differences, we can see that looking at the global and local coefficients may result in different policy interventions. Whereas distance to workplace is positively associated with car emissions globally, the local coefficients indicate that a positive association between these variables is only found in half the MSOAs. This means that policies aiming to reduce car emissions from workplace travel can be targeted at specific areas, namely areas where the link is strongly positive (see Figure 3.4).

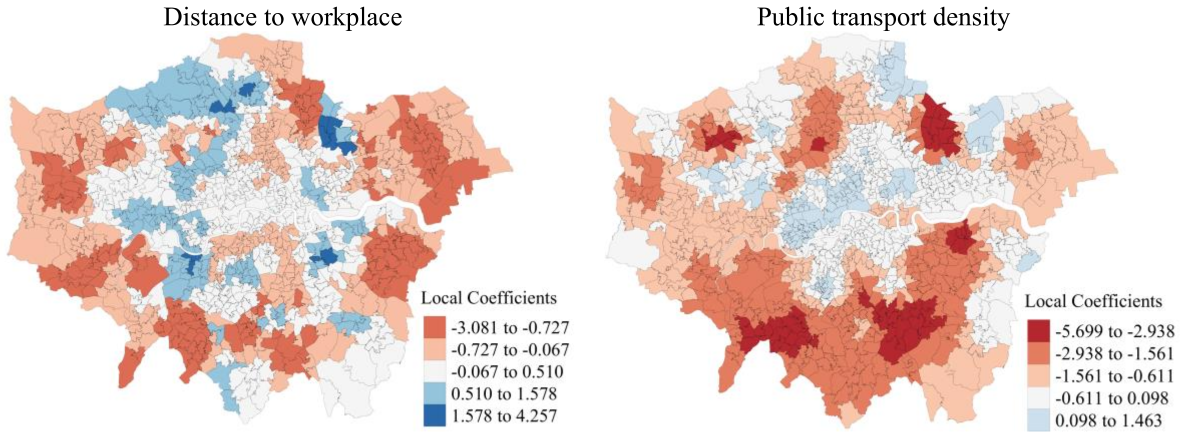

Figure 3.4. Spatial distributions of local coefficients of public transport density and distance to workplace when predicting emissions for cars/vans and motoring oils.

Notes: Emission estimates are from the years 2015–2016. Population and income are controlled for.

Spatial variation between the relationships of population characteristics and emissions, when controlling for income and population, vary by transport type. For example, increases in populations limited in day-to-day activities, aged 14 or younger and aged 65 or older associated with decreased flight emissions for over two-thirds of MSOAs. On the other hand, increases in populations aged 14 or younger are linked to increased rail emissions in over two-thirds of MSOAs. Moreover, an increased population of people limited in their day-to-day activities is linked to increased rail emissions in 52% of MSOAs, indicating that the direction of this relationship is evenly varied across London.

Next, we analyse the land transport patterns of those identified by Simcock et al. (Simcock et al., 2020) to be at increased risk of transport poverty. In the previous section, we report lower income to be mostly associated with bus emissions, where lower incomes are associated with higher bus emissions for over 80% of MSOAs (see Table 3.4), indicating that buses may be the most accessible form of motorised transport for low-income households across London. In this section (see Table 3.5), we find that stronger variance in local estimates occurs for the links between car-related emissions and larger populations of people identifying as BAME, limited in their day-to-day activities due to health problems or disabilities, or aged 14 or younger. This is shown by 50–60% of MSOAs being associated with increased emissions and the other ones are associated with decreased emissions, after controlling for income. This emphasises the need of understanding the contexts within which land transport emissions occur for effective and just climate policy. Transport choices can be deeply embedded in cultural, gender, and class structures (Aldred, 2013; Aldred and Jungnickel, 2014; Steinbach et al., 2011), and, as Shove (2014, 2012, 2010) points out, emissions and behaviours must be understood within the socio-cultural context in which they occur.

Moreover, larger populations identifying as BAME and 14 and younger are most commonly positively associated with increased emissions from combined fares when controlling for income. For larger populations limited in their day-to-day activities, this is for emissions from rail transport, although here positive associations only occur for around 50% of MSOAs. Thus, public transport may not only be less carbon intensive, but also more used in areas with larger populations at increased risk of transport poverty. Nonetheless, even after controlling for income, we find strong differences in different parts of London, indicating that local context matters and that global models overlook the variety of transport patterns. Moreover, this highlights specific neighbourhoods in which public transport may be more or less used indicating where further research or policy needs to asses reasons behind transport use and accessibility. This can help not only with targeting policy to reduce total transport emissions to specific areas, but also with assessing spatial differences in transport poverty.

Finally, for those aged 65 or older and those limited in day-to-day activities, accessibility needs may differ. For instance, the finding that car emissions are mostly negatively associated with a higher population of people limited in day-to-day activities points to transport and energy injustice, as this population should have higher transport energy needs due to decreased accessibility of public and active transport. Our results support previous findings that despite having increased energy needs, people with disabilities have lower energy footprints in the UK than those without disabilities (Ivanova and Middlemiss, 2021).

3.4.3. Emissions and Well-Being

To assess relationships between land transport emissions and well-being, we analyse well-being index scores and subjective well-being. Here, our aim is not to assess the causal links between emissions and well-being, but to see if there are neighbourhoods in London with high well-being scores but low transport emissions.

Index scores are positively correlated to car emissions, land transport emissions, and all transport emissions (Figure 3.5). Income likely mediates these relationships, as the well-being index incorporates rates of incapacity benefit claimants, unemployment, and children in out-of-work households. Promisingly, transport emissions are only weakly correlated with subjective well-being, in line with previous findings (Andersson et al., 2014; Verhofstadt et al., 2016; Wilson et al., 2013).

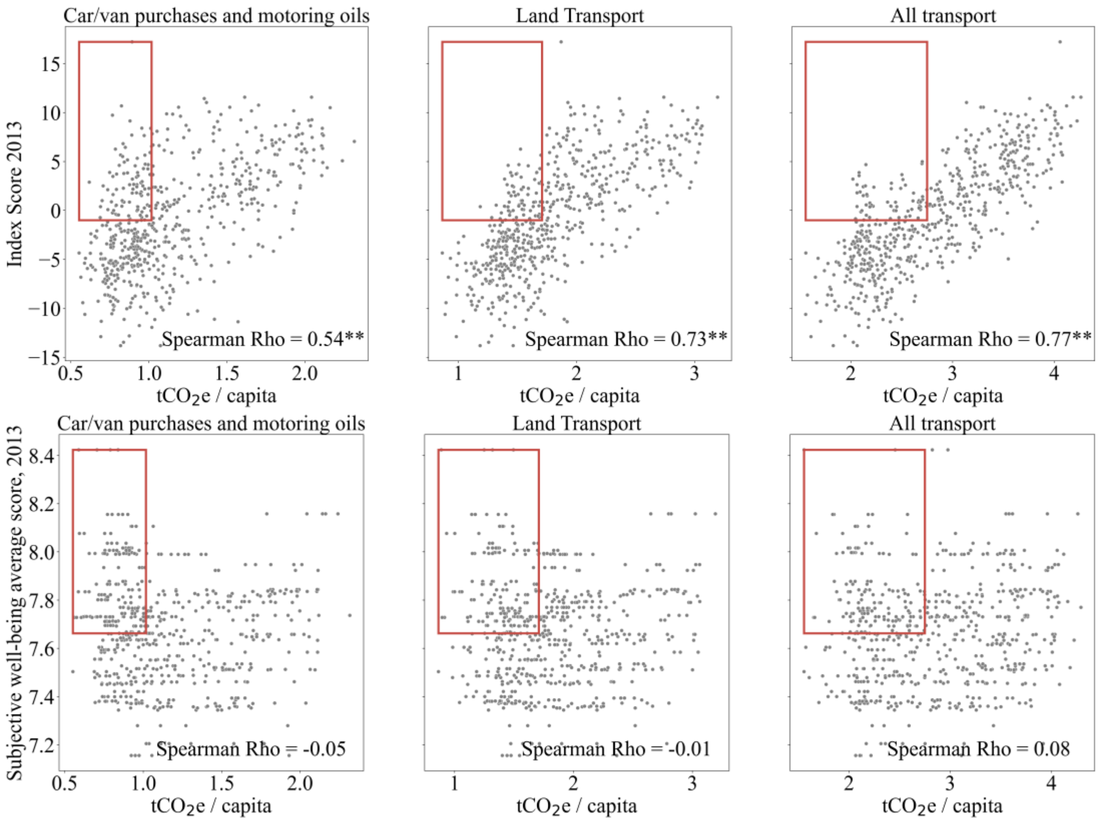

Figure 3.5. Scatterplots of London wards' well-being and emissions, shaded by population.

Notes: Pearson's *r* values show correlation coefficients. Double asterisk (**) indicates significance at $p < 0.01$. Red boxes highlight below median emissions and above median well-being.

Most importantly for this analysis, we find that 10.56% of wards have below median emissions from all transport, but a median or above median score on the well-being index (Table 3.7). For subjective well-being, this is higher at 24.80%. A spatial overview of this is provided in Appendix G.

While the relationship between well-being and emissions is complicated and this is not a causal analysis, our findings indicate that some areas in London have low land transport footprints, but high well-being. In other words, therefore, it is possible to have reduced emissions without negatively impacting well-being.

Table 3.7. Percentages of wards with below median emissions and median or above well-being.

	Car/Van Purchases and Motoring Oils	Land Transport	All Transport
Index Score 2013	17.60	11.68	10.56
Subjective well-being average score, 2013	27.84	25.60	24.80

3.5. Discussion

3.5.1. Geographically Weighted Regression as a Tool for Emissions Analysis

In this paper, we bring together methods from industrial ecology and spatial statistics to assess if and how the relationships between transport emissions and social and spatial factors show spatial variance. Although the links between social factors and consumption-based emissions are well-studied (Baiocchi et al., 2010; Büchs and Mattioli, 2021; Büchs and Schnepf, 2013a; Czepkiewicz et al., 2018; Druckman and Jackson, 2008a; Hubacek et al., 2017; Ivanova et al., 2018; Ivanova and Wood, 2020; Lenzen et al., 2004; Mattioli and Scheiner, 2022; Millward-Hopkins and Oswald, 2021; Minx et al., 2013; Mishalani et al., 2014; Sudmant et al., 2018; Zheng et al., 2022), the spatial aspects of consumption-based emissions are not well-understood. Although some existing research already highlights the benefits of using spatial models for emission analyses (Clement et al., 2021; S. Wang et al., 2019; Y. Wang et al., 2019; Xu and Lin, 2017), to our knowledge, this paper is the first to investigate spatial heterogeneity in the relationship between social factors and consumption-based emissions, highlighting the important contribution spatial statistics can make to the field of industrial ecology. In this paper, we find that geographically weighted regression models should be used in all tested instances of this paper, as our data exhibit spatial dependency. Thus, geographically weighted regression models are better able to model the relationships between consumption-based neighbourhood transport emissions from cars and vans, flights, rail, buses, and combined fare public transport with public transport density, distance to workplace, income, and populations limited in their day-to-day activities due to long-term health problems or disabilities, aged 14 or younger, aged 65 or older, and identifying as BAME.

For instance, in line with previous UK-based research which finds consumption-based GHG emissions to increase with income (Druckman and Jackson, 2008a; Minx et al., 2013), especially transport emissions (Baiocchi et al., 2010), we find mostly positive relationships between income and transport emissions across London. An exception to this is emissions from buses, which are mostly negatively associated with income. Despite this, our findings also indicate that both the direction and the strength of these relationships can vary. Our findings thus complement this previous research by showing that the association between income and transport emissions can vary across neighbourhoods, even within one city. Moreover, in contrast to previous research reporting a positive link between car emissions and distance to workplace (Brand et al., 2013), we find that this relationship is spatially heterogeneous, with some neighbourhoods in London having a positive and some a negative association.

We find differences in spatial heterogeneity of the relationships between higher populations of those more at risk of transport poverty and emissions from different transport modes, even after controlling for income. This links to previous research which points out that air and land travel emissions are not necessarily complementary for the same social groups (Alcock et al., 2017; Czepkiewicz et al., 2018; Mattioli and Scheiner, 2022). For example, our results indicate that across London, increases in populations of people identifying as BAME are less frequently linked to increased car emissions that to increased flight emissions. However, in addition to previous findings, we find that even after controlling for income the relationship between higher populations of people identifying as BAME and flight emissions varies spatially both in strength and direction, indicating that consideration of spatial factors is necessary in this analysis. Similarly, we find spatial variation in the links between increased populations of those identified by Simcock et al. (2020) to be at increased risk of transport poverty and different land transport emissions. Despite being more frequently linked to higher public transport emissions from rail, buses, and combined tickets, here too we find spatial variance across London. These findings highlight the importance of local and spatial contexts for understanding emissions. Regardless of whether this highlights the need for a spatial inequality lens or only points to other social inequalities which are unevenly distributed across space (Bouzarovski and Simcock, 2017; Chatterton, 2010; Garvey et al., 2022; Pirie, 1983; Soja, 2016, 2010), our analysis underlines nuances in the relationships between emission and social factors, which global analyses overlook.

The following section discusses our findings in more detail and in light of well-being and the policy implications they may have.

3.5.2. Policy Implications

In the UK, transport is one of the highest emitting sectors (Kilian et al., 2021; Owen, 2021; Owen and Kilian, 2020), and thus, reducing transport emissions is important for meeting climate targets. Effectively reducing consumption-based transport emissions requires focussing on the highest-emitting categories: cars and flights.

While aviation is not part of the London Councils' (2020) programmes on climate change, there is potential for local policy makers to impact aviation emissions (Elofsson et al., 2018), for instance, by influencing aviation infrastructure. Nationally, while the Committee on Climate Change (CCC, 2020) outlines demand management as flight emission reduction strategy, the UK Government focuses on growing the aviation sector and reducing emissions through future technological advancements (HM Government, 2018). This contrasts our and previous (Ivanova et al., 2020) findings that reducing aviation demand can strongly reduce emissions and that flight emissions cannot be reduced sufficiently through technological changes alone (Bows-Larkin et al., 2016; Wood et al., 2012). Moreover, although some other social drivers may play a role (Czepkiewicz et al., 2018; Mattioli and Scheiner, 2022), flight emissions are strongly income-dependent and present a main source of carbon inequality. Continued focus on aviation growth does not challenge such patterns, which have long been pointed out by the literature on carbon lock-ins (Brand-Correa et al., 2020; Mattioli et al., 2020), carbon inequality (Büchs and Mattioli, 2021; Clarke-Sather et al., 2011; Ivanova and Wood, 2020; Oswald et al., 2020), and degrowth (Haberl et al., 2020; Parrique et al., 2019; Wiedmann et al., 2020).

Although we find spatial heterogeneity in the strength of the relationships between income and flight emissions, the association is positive for over 98% of London neighbourhoods. Indeed, while a geographically weighted regression model has an improved model fit compared to a linear regression model, we find flight emission models to improve the least compared to those modelling other transport modes. We conclude from this that a global model can approximate the relationship between flight and income. Thus, a widely used income-based approach to reducing emissions from aviation, such as a distance-based tax as outlined by Larsson et al. (2019), may be most effective in reducing emissions from flights from a demand-side perspective.

Cars present a second large source of emissions and carbon inequality. Current strategies to reduce land transport emissions of the London Councils (n.d.) and the Mayor of London (2018) include making active transport more attractive, increasing the number of bus services, adding bus lanes, and building charging stations for electric vehicles. Here, efforts to increase bus services and reduce bus congestion should be prioritised, as buses may be more accessible to those at risk of transport poverty and as fast and dense public transport networks, particularly in Outer London, may be most effective in reducing car emissions. Investing in accessible, affordable, and fast public transport infrastructure in outer areas with high car emissions may be able to reduce car emissions as well as congestion. However, affordability also needs to be considered.

Considering links between emissions and socio-demographic characteristics differ at a neighbourhood level, approaches can also better incorporate local needs. As the relationship between workplace distance and car emissions is heterogeneously distributed across London, understanding what kind of journeys people use cars for and why people use cars is also essential when encouraging increased use of active and public transport. Investigating attitudes towards public transport could provide further insight into transport choices and how emissions can be reduced. Moreover, our findings suggest that increased public transport access in the southern outskirts of London may reduce emission more effectively than in the north, although this may be linked to having better or faster existing routes available. Other ways to reduce emissions from commuting include increased remote working (Creutzig et al., 2021b).

Furthermore, our analysis suggests that higher public transport emissions are more often associated with those identified by Simcock et al. (2020) to be at increased risk of transport poverty across different neighbourhoods. Higher bus emissions are linked to neighbourhoods with lower incomes, and higher combined fare emissions to larger populations of people aged 14 or younger and identifying as BAME, more often than emissions from other transport modes. Thus, increasing bus and mass rapid transit access and making public transport more affordable for those with lower incomes may also reduce transport inequality. This mirrors survey findings that cost is the key factor determining transport choices for 25% of Outer London commuters (London Councils et al., 2015). Despite this, spatial factors and inequalities need to be considered, as our analysis reveals spatial variation in all relationships between higher populations of groups more at risk of transport poverty and transport emissions.

Nonetheless, increasing transport access—and emissions—for those whose mobility is limited by long-term health problems or disabilities is necessary, who have lower energy footprints despite having higher energy needs (Ivanova and Middlemiss, 2021). Likewise, those with age-related mobility constraints may have different transport needs. Understanding reasons for lower and higher transport footprints is therefore important.

For most Londoners, however, decreased transport emissions can likely coexist with high well-being, where switching to public transport can be the key to reducing emissions. Some previous research already points to some positive impact demand-side emission mitigation efforts can have on well-being (Brand et al., 2021; Creutzig et al., 2021b; Khreis et al., 2017; Nieuwenhuijsen, 2020). Here, our research only focuses on assessing whether areas of higher well-being and lower emissions already exist within London. Promisingly, subjective well-being does not appear to be correlated to combined fare emissions, confirming previous findings (Andersson et al., 2014; Verhofstadt et al., 2016; Wilson et al., 2013), and suggesting that switching from private to public transport does not necessarily reduce subjective well-being. Additionally, while high objective well-being is often associated with high transport emissions, some neighbourhoods in London have below average emissions while maintaining high well-being scores, showing that achieving low emissions and high well-being is possible. Consequently, investing in well-connected, convenient, and affordable bus infrastructure, in addition to making combined fares more affordable, may be key to providing low-carbon transport in a socially just way.

3.5.3. International Applications

In the UK, these findings are specific to London, as neither its size nor its public transport infrastructure are comparable to other cities. However, our findings may be relevant to large cities worldwide. With one in eight people globally living in megacities with more than 10 million people in 2018 (UN: DESA, 2018), understanding urban transport emissions from reduction and redistribution perspectives is becoming increasingly important. Our research highlights, first, that understanding local contexts such as how existing infrastructure is being used and localised travel needs and access barriers for public transport can be key in moving from private to public transport, and, second, that methods from spatial statistics may be able to improve on more frequently used linear models when trying to understand the relationships between emissions and social factors. At the same time, high incomes have been linked to higher emissions transport internationally–particularly to higher emissions from private and air travel (Baiocchi et al., 2010; Brand et al., 2013; Ivanova et al., 2018; Ivanova and Wood, 2020; Oswald et al., 2020; Sudmant et al., 2018; Wiedenhofer et al., 2017). This mirrors our findings that reductions in flight and private transport emissions are needed to reduce the global greenhouse gas footprint. Reducing transport footprints, therefore, needs to be viewed not only from an emissions, but also an inequality lens.

3.5.4. Limitations

IO analysis comes with various data and analytical limitations (Girod and de Haan, 2010; Lenzen et al., 2010; Rodrigues et al., 2018), such as uncertainty from using expenditure to represent quantity. We reduce this uncertainty by using data on the number of flights taken, rather than cost. We also follow recommendations from the literature to increase emission estimate robustness (Kilian et al., 2022a), including aggregating to large neighbourhoods and combining expenditure surveys from 2 years; however, despite these considerations, we are generating population data from a household sample and thus introducing bias.

A further data uncertainty comes from using data from various years. Data from the census are taken from 2011, income data, emission data, and public transport data are from 2015, and well-being data from 2013. While this adds some uncertainty, we have ensured that emissions data are calculated for the last year that other data are available, such that the independent variables come chronologically before the dependent variables. Moreover, the UK census is only updated every 10 years, under the assumption that demographic changes within a smaller timeframe are relatively small. Finally, as we analyse data from 983 MSOAs, we assume that, even though some neighbourhoods may see demographic changes within the 2011–2015 time period, the majority of neighbourhoods remains constant and thus, trends are consistent between these time periods.

Moreover, this analysis is exploratory. While our relationships show correlations and predictive value, estimates do not infer causality. Future research investigating these relationships under a carefully controlled causal framework can better assess whether the associations and local variations we find here are correlational or causal.

Our findings may be linked to a further issue policy makers face: decreasing demand of one product may increase total footprints as people may consequently have more money for more carbon-intense activities (Druckman et al., 2011). Thus, understanding household emission patterns overall and not just for transport may be most useful in guiding campaigns and policies.

Finally, geographic research can suffer from various limitations. One common problem in spatial research is the Modifiable Areal Unit Problem (MAUP), which describes how where spatial boundaries are drawn influences results (Gehlke and Biehl, 1934). While research has shown that the MAUP effect is often low for English census data and geographies, it can occur (Flowerdew, 2011), and may therefore be a point of uncertainty in this research. Secondly, making inferences about individuals based on areal observation can result in ecological fallacies (Openshaw, 1984). Thus, the findings of this paper should be interpreted at a neighbourhood level and cannot be projected onto individuals.

3.6. Conclusions

Understanding consumption-based emissions through a geographical lens is important for understanding the links between GHG emissions and social factors. Especially for advising a socially just transport policy, recognising spatial heterogeneity between the relationships between those at risk of transport poverty and transport emissions is invaluable. In this paper, we find that geographically weighted regression models improve on linear models, when modelling the relationships between different social factors, infrastructural factors, and consumption-based transport emissions. We conclude, therefore, that greater consideration must be given to the geographical component of consumption-based emissions when assessing their links with social factors and their social drivers. Moreover, we show how our analysis can highlight specific areas where different kinds of policy interventions may be more effective. For instance, we find that links between car emissions and distance to workplace are spatially varied, indicating that policy aiming to reduce emissions from commuting may be most effective when targeting areas of high positive links between these variables. While our current analysis is exploratory, future research could investigate this under a causal inference framework, evaluating the levels of spatial heterogeneity for social drivers of emissions. In light of local actors being increasingly involved in climate change mitigation efforts, this analysis also highlights the potential local actors have in creating context-based policies. Finally, our research highlights both consistencies and inconsistencies with previous research looking at emissions and social factors. We highlight where findings are in line with previous research and can be represented by a global model, and where local, spatial statistical approaches are needed. Bringing together industrial ecology and spatial statistics, as this paper shows, can provide new insights into consumption-based emission patterns, which are overlooked by non-geographic analysis.

3.7. Notes

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Chapter 4. Achieving Emission Reductions without Furthering Social Inequality

This chapter is ready for submission.

4.1. Abstract

To meet global climate goals, such as limiting global warming to 1.5 degrees Celsius, urgent and substantial reductions of greenhouse gas emissions are needed. From a consumption-based perspective, such measures include a radical reduction of emissions from private households. Despite this urgency, attention must be paid to achieve such reductions without furthering social inequalities. To address these issues, this research looks at consumption-based greenhouse gas emissions of UK households longitudinally, with a particular focus on changes that occurred after the 2007/08 economic crisis and the 2020 COVID-19 lockdowns. Analysing these two events allows us to learn how emissions from different social cohorts are impacted by external shocks, providing a learning for policy. We find significant ($p<0.05$) differences in the relationships between income and emissions of some age and income groups, as well as substantial descriptive differences between how age and income groups are impacted at a product-level. Importantly, we also find that despite existing levels of carbon inequality, substantial emission reductions are needed for all social cohorts assessed. However, to avoid further increasing existing inequalities and to make policies more effective, we propose interventions targeted at specific social cohorts. While an income reduction may reduce emissions of high-income households, increased access to high quality housing and public services may help reduce emissions of low-income households, whose emissions are already decoupled from income. Finally, age and income-specific interventions targeting specific consumption categories may reduce the impact of rebound effects, as well as reduce emission overall.

Keywords: household footprints; climate change, social factors, COVID-19, recession, climate policy

4.2. Introduction

To limit global warming to 1.5 degrees Celsius, reaching net-zero greenhouse gas (GHG) emissions by 2050 is necessary (CCC, 2019; IPCC, 2022b; Masson-Delmotte et al., 2018). As research shows that GHG emissions can be decreased substantially by decreasing demand (Barrett et al., 2022; Girod et al., 2014; Shigetomi et al., 2021), demand-side mitigation has become an increased focus of emission research (Creutzig et al., 2021a). For private households to meet this net-zero target and live within planetary boundaries, the global average per capita consumption-based footprint needs to reduce to 2.5–3.2 tCO_2e by 2030 and to 0.7–1.4 tCO_2e by 2050 (Akenji et al., 2019; Koide et al., 2021). In contrast, the 2019 consumption-based GHG footprint of households is around 9 tCO_2e/capita (Defra, 2020). For UK households, this means compared to 2019 levels reductions of 65-72% are needed by 2030, and 85-92% by 2050. This means a reduction of around 8% each year, which, in the UK is only observed following the 2007 economic crisis and the 2020 COVID-19 lockdowns (Defra, 2020). However, the impacts on different types of households of these crises were vastly uneven. Studying these events in light of their social and environmental impacts can therefore help our understanding of how sizable emission reductions can be achieved while satisfying decent living standards and needs.

When aiming to analyse consumption changes following the economic crisis and the lockdowns, however, it is important to consider the social impacts of these events. The 2007/08 economic crisis has wide-reaching effects on UK households. Between the first quarter of 2008 and the second quarter of 2009, the UK's GDP saw a 6% decrease (ONS, 2018b). In the same timeframe unemployment increased from 5.2% to 7.8%, reaching its peak in 2011 (ONS, 2018b). Other consequences of the economic crisis include increased debt (Bunn and Rostom, 2014), decreased consumer spending (Gerstberger and Yaneva, 2013), increased income inequality, and lower median wages (Hills et al., 2013). A report on the effects of the crisis on UK households finds that economic effects differ between households: where people in their 20s are more strongly impacted by the economic crisis, pensioners and children are found to be more protected (Hills et al., 2013). Moreover, UK research reports increased impacts of the crisis and the subsequent austerity politics on minorities including non-White ethnic groups (Fisher and Nandi, 2015) and disabled people (Jones et al., 2021).

The COVID-19 pandemic, on the other hand, triggered lockdowns beginning in March 2020 across the UK, which included restrictions on social life, mandates to work and school from home where possible, the temporary closure of non-essential shops and services, and travel restrictions (Institute for Government, n.d.). Although measures differed between England, Northern Ireland, Scotland, and Wales, all countries had some lockdown procedures in place. Economically, the pandemic meant decreased incomes for some households and increased unemployment, especially for low-income households (ONS, 2021b) and non-pensioner groups (DWP, 2022). People from different age groups are also found to be impacted differently, with those aged under 30 reporting decreased income at greater rates than other age groups (ONS, 2021b) and those aged 70 or older asked to reduce social contacts even further than other age groups (Cabinet Office, 2020). The UK's Office for National Statistics (ONS, 2021c) reports changes in consumption patterns, such as a decrease in consumer spending by over 20% from the first to the second quarter of 2020, where transport, hospitality, and recreation saw some of the largest reductions (ONS, 2021c), and increased economic uncertainty (Altig et al., 2020). Finally, home-schooling and losing access to free school meals has increased job-related and financial burdens on working parents and low-income households (Parnham et al., 2020).

Although the lockdowns disrupted wellbeing and increased inequalities (Goldin and Muggah, 2020) and, therefore, do not provide a suitable blueprint for climate policy (Howarth et al., 2020), they highlight the drastic impact behaviour change can have on emissions (Stoll and Mehling, 2020). Hence, analysing patterns of consumption change can provide a lesson of where and how consumption-based emissions can be reduced and of the social consequences of such efforts. Moreover, as the recession and lockdown are very different, with the lockdowns implementing mobility restrictions, comparing these two events allows for a broader understanding of the impact of different types of policies. Recently published data in the UK allows, for the first time, for such an analysis.

Similarly, understanding how income reductions shape emissions of different household types can be critical. Social inequalities in consumption-based carbon emissions are well-established in the literature (Druckman and Jackson, 2008a; Lenzen et al., 2004; Millward-Hopkins and Oswald, 2021; Minx et al., 2013; Owen and Barrett, 2020b) and high income is frequently seen as a key driver for higher consumption-based emissions (Baiocchi et al., 2010; Büchs and Schnepf, 2013a; Hubacek et al., 2017; Ivanova et al., 2018; Ivanova and Wood, 2020; Sudmant et al., 2018). Moreover, age is shown to play an important role in consumption-based emissions due to changes in expenditure patterns (Zheng et al., 2022). Other social factors that have been linked to consumption-based emissions include urban-rural divisions (Connolly et al., 2022; Jones and Kammen, 2014; Wiedenhofer et al., 2017), proximity to public transport infrastructure (Kilian et al., 2022b; Lenzen et al., 2004), and household size (Ivanova and Büchs, 2022; Minx et al., 2013).

As various age and income groups were affected differently by both the economic crisis and the lockdowns, understanding their different consumption changes can reveal how these groups may react differently to different types of policy. Indeed, a recent review of policy implication highlights the need for consumption-based emissions approaches to discuss rebound effects, sustainable consumption patterns, and population-specific policies (Ottelin et al., 2019). Incorporating age and income structures into this research can reveal household differences of where emissions decrease with income changes and economic uncertainty and where they remain stable or increase. Such results can inform not only how emissions can be reduced by targeting different types of interventions at different groups, but also shines light on social consequences of such interventions. Attention needs to be paid that energy and carbon reduction effort should first target those with the highest emissions, and not further marginalise vulnerable groups. Despite this, climate policies often disproportionately affect lower income households (Owen et al., 2022; Owen and Barrett, 2020b). Thus, understanding the goods and services different types of households consume at different income levels is key to understanding how policy can reduce emissions of those emitting the most. In light of evidence suggesting that major societal, economic, and cultural changes are needed to reduce energy use and emissions sufficiently (Brand et al., 2019; Haberl et al., 2020; Wiedmann et al., 2020), understanding the social context within which such changes occur is vital to design effective and socially just climate policy.

In this paper we ask the following research questions:

1. What are the patterns of consumption-based emissions for different age and income groups?
2. Do links between consumption-based emissions and incomes differ for age and income groups?
3. How are patterns of consumption-based emissions of different age and income groups affected by the recession and lockdowns?
4. How can effective climate policy be achieved without furthering social inequalities?

To answer these, we analyse changes before and after the 2007/08 economic recession and before and after the 2020 lockdowns to assess how emissions change with income reductions, economic uncertainty and government mandated lifestyle changes. We use this analysis to assess how emission reductions can be achieved without furthering social inequalities.

4.3. Methods and Data

4.3.1. Household Emissions: Data and Methods

4.3.1.1. Estimating Consumption-based Emissions

We estimate household emissions using data on household expenditure, as well as product-based multipliers (in tCO_2e/£). Such multipliers incorporate both indirect and direct emissions, meaning that they account for emissions which occur throughout the supply chain as well as those from burning fuel, respectively. To calculate these multipliers, we use the UK's multi-regional input-output model (UKMRIO). This contains financial interrelationships between different industries, both domestically and globally, as well as environmental pressure data by industry for each year analysed (Defra, 2020; ONS, 2020a, 2019a). The GHGs reported in the UKMRIO include carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, sulphur hexafluoride and nitrogen trifluoride. All GHGs are converted into their carbon equivalent using UKMRIO reference data.

To calculate the multipliers, we first need to estimate the total indirect consumption-based emissions from UK households using a multi-regional input-output (MRIO) analysis. The Leontief input-output model reports the economic interrelationships between industries throughout the supply chain, by documenting monetary inputs and outputs between industries (Miller and Blair, 2009). Adding environmental extension data to this, indirect emissions (**p**) can be estimated, as shown in Equation 1. Here **s** is a vector showing direct industry emission coefficients, **I** is the identity matrix with the same dimensions as the input-output matrix (**Z**), **x** is the total industry output vector, and **y** is final demand (for more detail see Miller and Blair, 2009; Wood et al., 2019).

Equation 1.

$$\boldsymbol{p} = \boldsymbol{s}(\boldsymbol{I} - \boldsymbol{Z}\boldsymbol{x}^{-1})^{-1}\hat{\boldsymbol{y}}$$

After indirect emissions are estimated, we add direct household emissions to the products associated with fuel burning. Further detail on both MRIO analysis (Miller and Blair, 2009; Wood et al., 2019b) and on the UKMRIO model (Kilian et al., 2022a; Lenzen et al., 2010; Owen et al., 2018b) can be found in the literature.

Once total household emissions are calculated at a product-level, we can divide these emissions by the total spend of UK households for each product. This generates conversion factors in tCO_2e/£, which can then be multiplied by individual household spend to estimate emissions. For this, we use the Living Costs and Food Survey (LCFS), an annual survey recording full expenditure from 4,000-6,000 private UK households (ONS, 2017a). This means that household expenditure is recorded for all purchases of goods and services, including travel, transport, leisure expenditure, housing, utilities, health, and financial and insurance services. The LCFS also contains household weights, allowing us to estimate expenditure for all UK households.

We choose the Classification of Individual Consumption by Purpose (COICOP) 4 level (UN: Statistics Division, 2019) to classify our products and services, as both the UKMRIO and the LCFS contain bridging tables to allow for easy and consistent conversion into COICOP.

Moreover, as the LCFS contains information on the number of flights taken by each household, as well as the number of rooms available in each household's flights and rent, respectively. This is done to reduce the uncertainty introduced by using expenditure to estimate emissions for products and services with high price differences.

4.3.1.2. LCFS Demographic Variables

To provide an overview of the socio-demographic make-up of the LCFS, we summarise the LCFS from 2001-2019 in Table 4.1. Importantly, age ranges of HRPs appear to be similar to mean ages of all adults in the households for all groupings. Thus, analysing households by the age of their HRP should also give an indication of age differences overall. However, socio-demographic variables in the LCFS from 2001-2019 show slight differences in demographics between groups. For instance, households with a household reference person (HRP) in both the youngest and oldest age range have around 10% more females, on average. Households with older HRPs and those in higher income deciles have larger dwellings for fewer people. Households with HRPs under the age of 50 are more likely to have minors in the household. Similarly, households in higher income deciles are less likely to have minors and tend to have fewer people in them.

To compare household types we weigh the number of people in a household by their household composition, as suggested by Gough et al. (2011). We calculate emissions per single adult person household (SPH) by using the OECD-modified scale, which accounts for the non-proportional relationship between additional household members and income or expenditure. This assigns a weighting of 1 for the first adult, 0.5 for every other adult, and 0.3 for every child (OECD, 2011). Thus, equivalised results reported are not in tCO_2e/capita, but instead in tCO_2e/SPH. We choose this scale as it is the one used by the UK's Office for National Statistics. As differences in household sizes and compositions are shown to be linked to carbon emissions

(Ivanova and Büchs, 2022, 2020), controlling for this effect is important for comparing other variables.

Table 4.1. Demographic summary from LCFS 2001-2019.

		Number of households in Survey	Number of households in Survey (%)	Number of households in UK (%)	Mean age of HRP	Mean age adults	Mean age minors	Mean household size (not equivalised)	Mean household size (OECD mod. scale)	Mean number of adults in household (%)	Mean number of females in household (%)	Mean number of rooms in household
	All	112571	100.00	100.00	52.10	47.73	8.54	2.36	1.48	78.20	50.81	5.44
Age of HRP	<18	31	0.03	0.03	14.53	34.14	11.87	2.08	1.31	29.35	60.59	4.07
Age of HRP	18-29	9533	8.47	9.88	25.54	25.84	3.73	2.40	1.49	76.77	50.23	4.61
Age of HRP	30-49	41543	36.90	36.71	39.90	37.92	8.63	2.98	1.69	63.61	49.85	5.46
Age of HRP	50-64	30430	27.03	26.32	56.69	50.06	12.41	2.26	1.51	90.57	49.43	5.74
Age of HRP	65-74	23533	20.91	19.30	71.45	67.49	10.87	1.69	1.22	98.63	53.11	5.51
Age of HRP	75+	7501	6.66	7.75	80.17	77.75	10.53	1.37	0.99	99.62	62.67	5.13
Income Decile	Lowest	11266	10.01	9.73	52.08	47.99	8.06	2.62	1.59	72.82	51.26	5.18
Income Decile	2nd	11254	10.00	9.60	54.96	51.22	8.09	2.44	1.48	72.96	52.95	5.10
Income Decile	3rd	11254	10.00	9.68	55.32	50.86	8.22	2.41	1.48	74.41	52.37	5.17
Income Decile	4th	11253	10.00	9.80	56.21	51.02	8.51	2.30	1.42	75.96	53.15	5.12
Income Decile	5th	11252	10.00	9.88	54.87	49.40	8.61	2.35	1.46	77.88	52.26	5.27
Income Decile	6th	11262	10.00	9.95	52.60	47.46	8.76	2.42	1.51	78.25	51.18	5.40
Income Decile	7th	11254	10.00	10.10	51.09	46.13	8.98	2.41	1.52	80.25	50.29	5.51
Income Decile	8th	11253	10.00	10.32	49.78	45.04	9.01	2.40	1.53	82.05	49.23	5.67
Income Decile	9th	11243	9.99	10.41	47.68	43.89	9.04	2.34	1.50	82.62	48.20	5.86
Income Decile	Highest	11280	10.02	10.53	47.29	45.58	8.66	1.96	1.30	85.55	47.04	5.99

4.3.1.3. Longitudinal Comparison

For the longitudinal comparisons we calculate two sets of emission estimates. First, we calculate emissions using the UKMRIO and LCFS from the same year to estimate emissions for each year. Second, we calculate emission estimates using the 2007 multipliers. This year was chosen as it captures consumption directly before the financial crisis. Using multipliers from the same year allows us to isolate the impact of consumption changes on GHG emissions. This allows for a more direct comparison of consumption behaviours and the emissions these would have caused in 2007. To ensure that inflation and price changes over time do not impact our results, we adjust income and expenditure to 2007 values. We do this at a product level using the Consumer Price Inflation tables from the Office for National Statistics (ONS, 2022a). A product matching table is provided in Appendix H.

For electricity and gas use, we adjust the prices in the LCFS, by physical data on household energy consumption (BEIS, 2022). As gas and electricity produce some of the highest consumption-based footprints and can fluctuate hugely in price, using physical units to estimate total use reduces the uncertainty of our analysis.

4.3.1.4. 2020 Data

At the time of writing the LCFS and UKMRIO model for 2020 are not yet published. However, aggregated income and expenditure are available via the Office for National Statistics. To estimate 2020 emissions, we therefore use such aggregated data (ONS, 2022b). The levels of aggregation available include age of the Household Reference Person (the person answering the survey), income decile, and all households. To ensure consistency with the LCFS, we calculate the ratio of 2019 and 2020 aggregated data at a product level, and then multiply the 2019 LCFS data by this ratio. This means the data are also adjusted to 2019 prices. We then use 2019 multipliers to estimate 2020 emissions.

Income data are also available in aggregated form (ONS, 2021d). We adjust aggregated 2019 incomes by the proportional differences between the 2019 and 2020 income data available via the ONS, to minimise potential differences between the datasets. Finally, household age groups for income differ to household age groups of expenditure. We therefore use the nearest age range to infer income; a matching table is shown below (Table 4.2).

Table 4.2. Income age groups used for 2020

HRP age in 2020 data	Group assigned in analysis
0-17	<18
18-24	18-29
25-34	-
35-44	30-49
45-54	-
55-64	50-64
65-74	65-74
75-84	75+
85+	-

4.3.2. Elasticities

We calculate income elasticities of GHG emissions to assess the changes in environmental footprints linked to income changes (see Ivanova et al., 2016). This elasticity (ε) measures the percentage change of per SPH GHG emissions (f) related to one percent increase in per SPH household income (i). We calculate these elasticities using Equation 2.

Equation 2.

$$\boldsymbol{\varepsilon} = \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{i}} \times \frac{\boldsymbol{i}}{\overline{\boldsymbol{f}}}$$

Equation 2 can be transformed into a univariate regression model using natural logarithm transformation, with the two constants a and ε and an error term (u), as shown in Equation 3.

Equation 3.

$$\ln \boldsymbol{f} = \boldsymbol{a} + \boldsymbol{\varepsilon} \ln \boldsymbol{f} + \boldsymbol{u}$$

4.4. Results

4.4.1. Consumption-based Emission Patterns of UK Households

Emission estimate and income means from 2001-2019 point to differences between households (Figure 4.1). The results show large income inequality between the highest and lowest deciles, where the mean income of those in the highest income decile is more than seven times as high as the mean income of households in the lowest income decile. Similarly, emissions of the lowest decile are less than half of the emissions of the highest decile, even after household size equivalisation. Especially transport and recreational products appear to increase strongly with income. Despite these differences, when considering average consumption between 2001-2020, a single occupant household in the lowest income decile still has emissions that are 10-20 times as high[17] as the 0.7–1.4 tCO_2e/capita target set for 2050 (Akenji et al., 2019; Koide et al., 2021). While this is notably lower than the 25-50 times as high emissions the highest income decile show for SPHs, this finding shows the need to substantially reduce emissions for all household groups. Research suggests that such reductions require a combination of existing technologies, such as high-quality, well-insulated housing, radically reduced consumption, and an increased focus on public, shared goods and services (Millward-Hopkins et al., 2020; Oswald et al., 2021).

We also find age group differences. Households with HRP aged 18-29 have some of the lowest total emissions (16.45 tCO_2e/SPH), but the highest emissions from air transport (1.53 tCO_2e/SPH), compared to other age groups. Households with HRP aged 75+, on the other hand, have the lowest emissions from all transport combined (2.75 tCO_2e/SPH), but the highest emissions from electricity and gas use (6.80 tCO_2e / SPH). This indicates different consumption

[17] It should be noted that this is in tCO_2e/SPH, whereas the 0.7–1.4 target is in tCO_2e/capita.

patterns between age groups at a product level, showcasing that targeting specific products and services with emission reduction efforts may be more effective for different age groups. Moreover, this shows that environmental policies influencing prices affect various social cohort differently, hence, highlighting the importance of equity considerations.

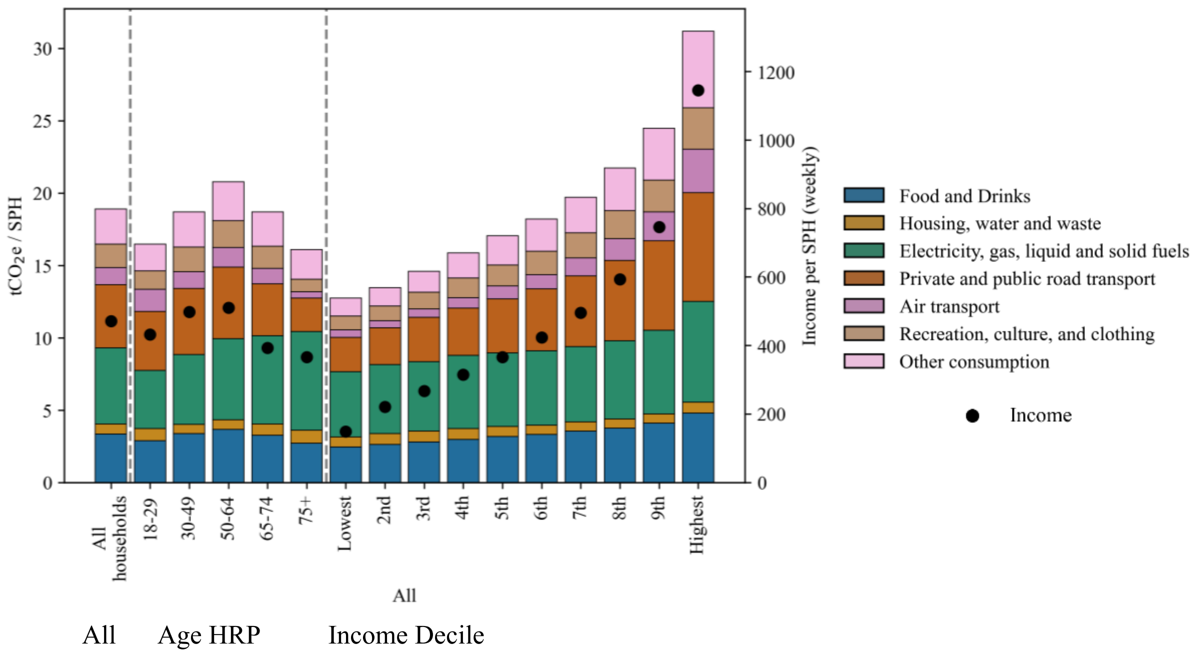

Figure 4.1. Mean emissions and incomes by household type for the year 2001-2020.

4.4.2. Income and Emissions

To further assess the extent to which emission reductions following the economic and lockdown may be linked to income, we first analyse the relationship between emissions and incomes. For this, we calculate the income elasticities of emissions. These elasticities quantify, as a percentage, the amount of change in emissions per change increase in income. Thus, an elasticity of 1 indicates that with a 1% increase in income, emissions also increase by 1%. Moreover, an elasticity of greater than 1 indicates that emissions increase at a faster rate than income, and vice versa. For this analysis we assess data from 2001-2019, as 2020 data are not yet available at a detailed enough level.

As shown in Figure 4.2, total emissions for all households have an elasticity of 0.32-0.56 across the years, however, elasticities vary widely both by product and by household type. As shown in previous research, we also find necessities such as food and drinks (Hertwich and Peters, 2009c; Ivanova et al., 2016), to be less income elastic than other manufactured products and services, like recreational goods and services and clothing. Moreover, considering all

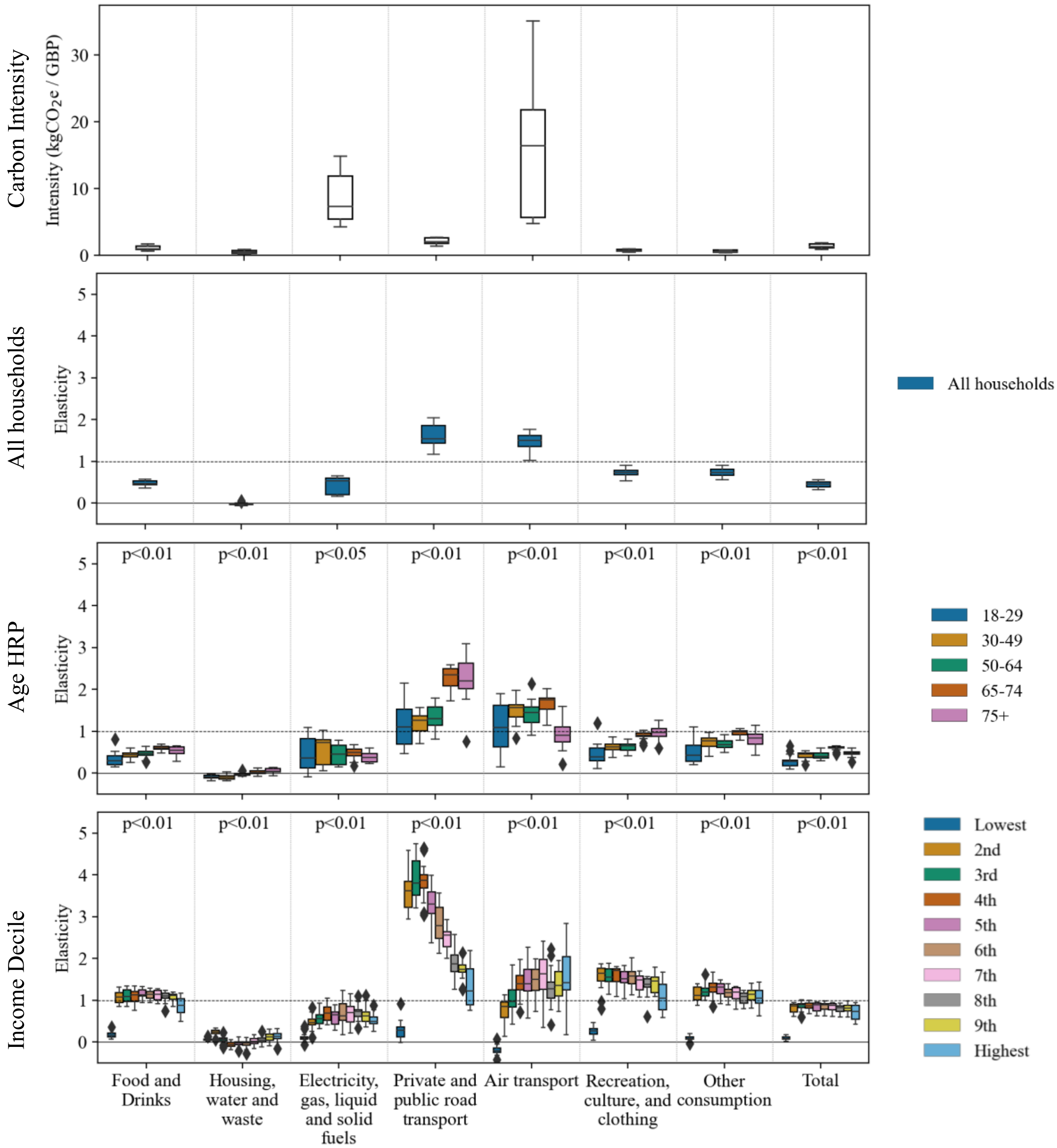

Figure 4.2. Carbon intensities for 2007 and income elasticities of emissions for 2001-2019 for all households (top), and by age of the HRP (middle), and income decile (bottom).

**Notes: Error bars show 2.5% and 97.5% confidence intervals. Dotted horizontal line indicates elasticity of 1. P-values show results from repeated measures ANOVA, comparing intensities between the groups.

households, emissions from transport are most income-elastic, while emissions from housing are least income elastic. For the average household, this suggests that reduced income would reduce consumption-based emissions from road, rail, and air transport the most, relatively, while emissions from housing remain comparatively stable even with reduced income. However, as shown below, these elasticities can vary largely by household type. Moreover, it should be noted that this is likely only the case where transport is a luxury good and does not apply to necessary transport needed in day-to-day life or for groups with already low transport footprints (see Kilian et al., 2022b; Simcock et al., 2021). Thus, transport poverty still needs to be a consideration in discussions about transport emissions.

We find large differences in elasticities between household types. Repeated measures ANOVAs reveal significant differences between the intensities of the groups, for all product types ($p<0.05$). This means that at least one of the groups is significantly different to one other group in each comparison. Thus, different households react differently to income changes, prioritising different kinds of products and services. To assess where these differences occur, pairwise comparisons are done. For this, paired sample t-tests are conducted, with a Bonferroni correction for multiple comparisons. Results are summarised in Table 4.3 and Table 4.4; more detailed results can be found in Appendix I.

Table 4.3. Significance testing from paired sample t-test results for the intensities of age groups; Bonferroni correction used for multiple comparisons.

	Air transport				Electricity, gas, liquid and solid fuels				Food and Drinks				Housing, water and waste				Other consumption				Private and public road transport				Recreation, culture, and clothing				Total			
	18-29	30-49	50-64	65-74	18-29	30-49	50-64	65-74	18-29	30-49	50-64	65-74	18-29	30-49	50-64	65-74	18-29	30-49	50-64	65-74	18-29	30-49	50-64	65-74	18-29	30-49	50-64	65-74	18-29	30-49	50-64	65-74
30-49	*								*								*								*				*			
50-64													*	*															*			
65-74	*		*						*	*	*		*	*	*		*	*	*		*	*	*		*	*	*		*	*	*	
75+		*	*	*					*	*			*	*	*	*	*		*	*	*	*	*		*	*	*		*			*

**Notes: '*' indicates significance after Bonferroni correction ($p<0.005$). Data are only displayed in shaded cells.

The highest income decile has lower elasticities for many products than some lower deciles, with statistical significances reported for many products (Table 4.4). This suggests that a reduced income for this decile would reduce emissions from this group at a slower rate than for some lower deciles. The lowest decile, on the other hand, has the lowest elasticities for all emissions, suggesting that the emissions are almost completely decoupled from income. The large difference in elasticities from the lowest decile compared to other deciles also suggests that elasticities for all households and by age group are likely skewed by households from the lowest income decile in these groups and thus, should be higher for most households in the sample.

Table 4.4. Significance testing from paired sample t-test results for the intensities of income decile; Bonferroni correction used for multiple comparisons.

Air transport

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd	*								
4th	*	*							
5th	*	*							
6th	*	*							
7th	*	*	*						
8th	*	*							
9th	*	*							
Highest	*	*							

Electricity, gas, liquid and solid fuels

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd	*								
4th	*								
5th	*								
6th	*								
7th	*								
8th	*	*							
9th	*								
Highest	*							*	*

Food and Drinks

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd	*								
4th	*								
5th	*								
6th	*								
7th	*								
8th	*								
9th	*				*		*		
Highest	*	*	*	*	*	*	*	*	*

Housing, water and waste

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd		*							
4th	*	*	*						
5th	*	*	*						
6th	*	*	*						
7th		*		*		*			
8th		*		*	*	*	*		
9th		*		*	*	*	*		
Highest				*	*	*	*	*	

Other consumption

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd	*								
4th	*	*							
5th	*								
6th	*			*					
7th	*								
8th	*		*	*	*				
9th	*			*	*				
Highest	*		*	*	*				

Private and public road transport

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd	*	*							
4th	*								
5th	*		*	*					
6th	*	*	*	*	*				
7th	*	*	*	*	*	*			
8th	*	*	*	*	*	*	*		
9th	*	*	*	*	*	*	*		
Highest	*	*	*	*	*	*	*	*	*

Recreation, culture, and clothing

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd	*								
4th	*								
5th	*								
6th	*								
7th	*		*						
8th	*	*	*	*	*	*			
9th	*								
Highest	*	*	*	*	*	*	*		*

Total

	Lowest	2nd	3rd	4th	5th	6th	7th	8th	9th
2nd	*								
3rd	*								
4th	*								
5th	*								
6th	*								
7th	*								
8th	*		*	*	*				
9th	*								
Highest	*	*	*	*	*	*	*		

**Notes: '*' indicates significance after Bonferroni correction ($p<0.001$). Data are only displayed in shaded cells.

Thus, a general income or tax-based approach to reducing emissions would be hugely regressive for the lowest income decile in particular. Following the framework of using a pairing reduced consumption with existing technologies, and an increased public goods and services (Millward-Hopkins et al., 2020; Oswald et al., 2021), we conclude that reducing emissions for the lowest income decile requires a strong focus on increasing social equity and providing access to better insulated housing, and public goods and services. This mirrors findings from Büchs et al. (2021), that universal vouchers for renewable electricity and public transport, paired with investment into greener infrastructure could not only help reduce emissions, but also decrease levels of fuel and transport poverty.

When looking at elasticities by age group, we find that households with HRPs aged 65-74 or older have more elastic emissions from private and public rail and road transport than other groups. Indeed, except compared to each other, these differences are statistically significant, $p<0.005$. Similarly, with air transport emissions, households with HRPs aged 30-49 have higher income elasticities of air travel emissions than other age groups, with significant differences to both the 18-29 and 75+ groups. Reasons for this, however, may vary. As the youngest age group has the highest air travel emissions, this also indicates that air travel emissions reduce less with reduced income for households with HRP aged 18-29. In contrast, households with HRP aged 75+ have the lowest air travel emissions, and these do not increase as drastically with increased income as in other groups.

Elasticities for private and public road and rail transport follow a similar pattern; they increase until the 3rd income decile but decrease after this. Moreover, statistically significant differences are found in almost all pairwise comparisons (p<0.001; see Table 4.4). This may be due to transport emissions initially increasing a lot with daily needs, but in higher income deciles, where such needs are covered, having a lower rate of increase relative to the increase in income. This mirrors findings from the wellbeing literature, which shows an a inverse exponential relationship between needs satisfaction and energy use (Martínez and Ebenhack, 2008; Steinberger et al., 2012; Steinberger and Roberts, 2010; Vogel et al., 2021). Similarly, we find that the relative increase of road and rail transport emissions decreases compared to the relative increase of income after a certain level of income is reached. This is not because higher income households have lower road and rail transport emissions, but because their income, after a certain threshold, increases at a faster rate than their rail and road transport use. Thus, to reduce emissions in this domain through an income approach, would require a proportionally larger reduction of income for higher than low- and middle-income households.

For air transport higher deciles show higher elasticities indicating that the rate of emissions relative to income increases with higher incomes. As this is the category with the highest carbon intensity, it is important to focus on the reduction of flights of high-income households. Indeed, UK research shows that carbon inequality from air travel also remains high (Büchs and Mattioli, 2021), while globally, it is estimated that only 20% of the population have access to air travel (Negroni, 2016). Our findings also mirror previous suggestions by Larsson et al. (2019) to reduce aviation emissions through an income-based approach, such as a distance-based flight tax.

4.4.3. Recession vs. Lockdown Differences

The average UK SPH decreased its consumption-based emissions by half between the years 2001 and 2020. Even excluding the lockdowns, between 2001 and 2019 emissions reduced by over a third per SPH (see Figure 4.3). However, it is important to isolate whether decreases in emissions are a result of energy efficiency improvements, changes in the UKMRIO model, or consumption changes. Consequently, we calculate household emissions using 2007 emission intensities (Figure 4.4). For this, expenditure from each year is adjusted at a product-level to 2007 prices.

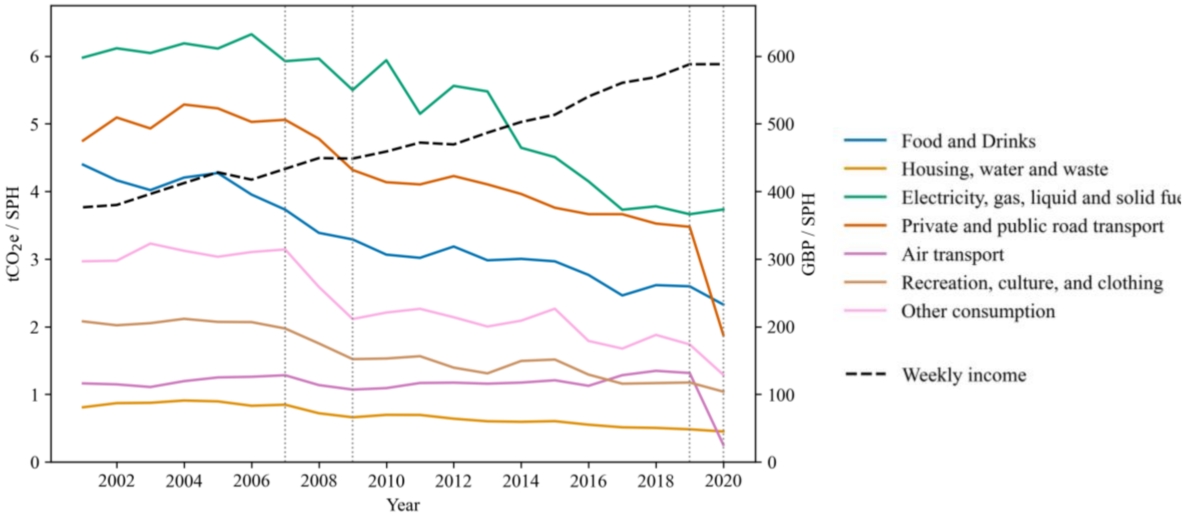

Figure 4.3. Emissions between the years 2001 and 2020 for all households.

**Notes: Dotted vertical lines show years 2007, 2009, 2019, and 2020.

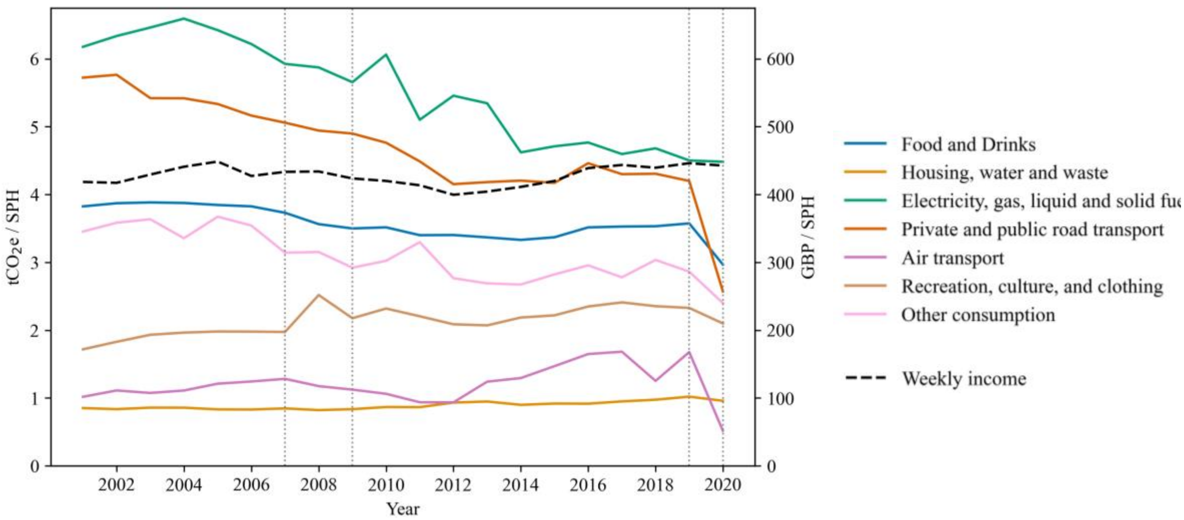

Figure 4.4. Emissions between the years 2001 and 2020 for all households, 2007 values and multipliers.

**Notes: Dotted vertical lines show years 2007, 2009, 2019, and 2020.

When 2007 multipliers and prices are used, mean emissions still decrease between 2001 and 2019, but by a smaller amount (11.65%, or 2.64 tCO_2e/capita). Thus, we conclude that some emission reductions result from changed consumption, but others are due to changes in emission intensities between 2001 and 2019. In addition, when controlling for inflation, mean incomes remain relatively stable over time. Even when controlling for changes in emission intensities, we find slight decreases in emissions from most products between 2007 and 2009. In contrast, emission reduction for most products is much more notable between 2019 and

2020, particularly when looking at transport. These patterns indicate changes in consumption in those periods, which result in reduced emissions, raising the question how these patterns differ between household types.

To evaluate the impacts of the 2007 financial crisis and the 2020 lockdowns on emissions, we compare emissions before and after these events. To ensure that we measure only the changes in consumption patterns, we assess only the emissions calculated using 2007 multipliers and prices in this analysis. Thus, the incomes and emissions presented in this section show the emissions consumption patterns from the years 2009, 2019, and 2020 would have produced in 2007. Incomes are also adjusted by inflation to 2007 values. The number described in this section therefore reflect the changes in emissions which are due to a change in consumption. Values using own year prices and multipliers can be found in Appendix J.

As shown in Table 4.5, both between 2007-2009 and 2019-2020 emissions reduced for the mean UK household, as well as for most household groups. When using 2007 multipliers, the emission reductions following the 2007 recession are only 3.88% for the average household, notably less than the annual 8% necessary to meet climate goals. In contrast, when using multipliers and prices from 2009, total reduced by almost 16% over 2 years, thus meeting the necessary reductions. We conclude that reductions in emissions following the 2007 economic crisis are in part due to consumption, and in part due to increased energy efficiency in production. To maintain similar levels of emissions reductions until emissions are at 85-92% below 2019 levels (see Akenji et al., 2019; Koide et al., 2021), much larger changes in consumption are needed (see Haberl et al., 2020; Wiedmann et al., 2020).

However, for all households and most household groups, emissions show a proportional reduction greater than the reduction in income, suggesting a reaction in consumption to the changed incomes. Findings for the 9th and 10th income deciles indicate a reduction in income of below 3%, but a reduction in total emissions of over 6%. Investigating the reduction patterns of these households in more detail may, therefore, give an indication of the types of consumption patterns needed to reduce emissions from these households near the reduction levels necessary. Notably, however, the 75+ age group shows an increase in emissions following the recession.

On the other hand, reductions from consumption changes following the COVID-19 lockdowns are 20.67%. Thus, a change in consumption was able to achieve sufficient emission reductions in 2020. However, proportional reductions differ between groups, and the highest income decile has the lowest reduction in total emissions, while the lowest income decile has the highest proportional reductions. This shows that while overall emission reduction goals are met, carbon inequality increased, indicating that this reduction comes at the cost of social equity.

Table 4.5. Percentage differences in per SPH income and total emissions between 2007-2009 and 2019-2020.

		2007-2009				2019-2020			
		Total tCO_2e/SPH		Weekly income		Total tCO_2e/SPH		Weekly income	
		Not adjusted	2007 Multiplier	Not adjusted	2007 Value	Not adjusted*	2007 Multiplier	Not adjusted	2007 Value
	All	-15.88	-3.88	3.50	-2.24	-24.08	-20.67	0.03	-0.80
Age HRP	18-29	-14.26	-2.20	0.30	-5.26	-24.72	-17.48	1.40	0.56
Age HRP	30-49	-17.02	-4.08	3.16	-2.56	-22.02	-16.61	-0.46	-1.28
Age HRP	50-64	-17.79	-6.13	3.67	-2.08	-24.90	-21.47	7.06	6.18
Age HRP	65-74	-12.22	-1.52	9.63	3.55	-24.54	-25.44	0.05	-0.78
Age HRP	75+	-5.31	3.81	4.54	-1.25	-15.99	-17.28	11.43	10.51
Income decile	Lowest	-12.18	-1.28	7.23	1.29	-31.40	-30.49	-12.68	-13.41
Income decile	2nd	-14.18	-4.22	6.65	0.74	-24.49	-21.64	-0.15	-0.97
Income decile	3rd	-18.65	-8.27	4.29	-1.49	-19.90	-20.25	0.98	0.14
Income decile	4th	-14.95	-4.02	4.61	-1.19	-24.99	-23.91	1.35	0.51
Income decile	5th	-14.48	-3.21	3.35	-2.38	-22.20	-20.03	3.30	2.45
Income decile	6th	-14.02	-2.44	2.20	-3.46	-18.69	-6.99	1.51	0.67
Income decile	7th	-15.77	-3.72	2.42	-3.25	-26.18	-24.01	0.75	-0.09
Income decile	8th	-11.31	2.28	3.27	-2.45	-29.45	-25.38	1.11	0.27
Income decile	9th	-18.06	-6.15	3.13	-2.59	-23.10	-20.04	1.14	0.30
Income decile	Highest	-20.59	-6.50	3.65	-2.10	-16.34	-13.50	-1.55	-2.37

**Notes: This shows the change in the later year's values compared to the earlier year's values as a percentage, calculated: $(Emissions_{Year\ 2} - Emissions_{Year\ 1}) / Emissions_{Year\ 1}$. Thus, negative values show a reduction, while positive values show an increase in emissions or income over time. Darker blue indicates a greater reduction, white indicates no change, dark red indicates a greater increase. (*) For 2019-2020 tCO_2e/SPH 2020 values are adjusted to 2019 and use 2019 multipliers. Differences shown come from categories where 2019 data are physical units, while 2020 data use expenditure and do not show differences in emission intensities or MRIO data changes.

The patterns of product-level details vary between the two events as well as between household groups (Table 4.6). Between the years 2007 and 2009 we find emission reductions for all consumption categories, except recreation, culture, and clothing. This 10.26% increase in recreation, culture, and clothing is particularly driven by higher income deciles, as well as by those with HRP aged 30-64. Findings from the two highest income deciles reveal high levels of reductions in emissions from transport, electricity and gas, and other consumption, some of the highest emitting categories these groups have (see Figure 4.1). Income-related policy targeted at these high-income households may, therefore, be helpful in reducing emissions in these high emission categories, which is still greater than the rebound effect of increased emissions from recreation, culture, and clothing.

Between the years 2019 and 2020, on the other hand, we find emission reductions for all consumption categories, except housing and gas and electricity. These increases, are, again driven by higher income deciles. Especially in the lockdown, we find rebound effects for high-income households, but not for low-income households. In part, this may be linked to low-income households also having seen the largest income reduction of all household groups. Thus, while overall reduced emissions may be seen as a positive, carbon inequality between income groups increased further in the lockdown.

Table 4.6. Percentage differences in per SPH income and emissions between 2007-2009 and 2019-2020; emissions and incomes are estimated using 2007 prices and multipliers.

			Food and Drinks	Housing, water, and waste	Electricity, gas, liquid, and solid fuels	Private and public road transport	Air transport	Recreation, culture, and clothing	Other consump-tion
2007-2009		All	-6.20	-1.36	-4.56	-3.17	-12.40	10.26	-7.05
	Age HRP	18-29	-14.59	8.28	-4.83	0.02	0.21	-3.21	11.09
		30-49	-5.21	-0.38	-6.70	-4.37	-12.58	18.18	-9.66
		50-64	-6.54	-4.12	-6.57	-5.28	-16.56	10.04	-11.86
		65-74	-3.25	-6.40	-1.52	10.37	-17.33	-2.13	-8.21
		75+	-3.76	-3.81	8.76	-21.66	8.68	-9.53	42.03
	Income decile	Lowest	-12.07	2.80	0.86	16.87	-18.12	-13.84	-3.04
		2nd	-6.46	-2.74	-7.55	4.97	3.49	-3.62	-9.66
		3rd	-5.08	6.47	-8.07	-17.76	-31.82	11.45	-8.75
		4th	-6.22	-4.38	-2.47	-0.50	-19.72	23.31	-20.29
		5th	-8.42	2.34	-3.75	-6.51	14.33	5.02	-2.20
		6th	-0.74	-3.29	-4.03	-5.59	-22.18	8.94	6.07
		7th	-14.63	-1.03	-1.83	-0.95	-2.05	-16.45	10.51
		8th	-4.85	-3.80	3.82	7.68	-11.83	14.40	-1.85
		9th	-4.33	-7.82	-10.67	-5.20	-14.19	23.31	-14.62
		Highest	-1.68	-2.88	-9.22	-11.57	-14.63	32.70	-14.74
2019-2020		All	-16.97	-6.03	-0.42	-38.77	-69.14	-9.84	-16.19
	Age HRP	18-29	-13.83	50.24	0.89	-42.93	-77.92	19.65	-4.07
		30-49	-16.86	-0.34	0.66	-35.05	-64.88	2.88	-4.54
		50-64	-18.96	-26.28	1.24	-40.82	-65.44	-13.93	-9.07
		65-74	-14.54	-11.06	-2.37	-35.22	-74.31	-35.08	-38.57
		75+	-5.28	-31.42	-6.69	-35.41	-76.01	-17.63	-22.12
	Income decile	Lowest	-13.20	-32.55	-26.14	-43.39	-79.37	-35.21	-16.46
		2nd	-17.23	-23.41	-17.27	-31.70	-66.37	-2.37	-21.95
		3rd	-7.40	-24.73	-6.35	-32.44	-68.95	-20.28	-26.48
		4th	-9.48	-24.15	-6.41	-37.14	-83.45	-19.47	-31.94
		5th	-13.43	14.20	-0.74	-40.77	-73.65	-18.80	-21.64
		6th	-16.93	-10.15	-1.11	-43.40	-78.32	14.13	59.36
		7th	-21.30	-13.07	0.28	-37.05	-61.99	-14.71	-32.53
		8th	-18.95	24.79	2.13	-43.06	-71.40	-19.41	-27.57
		9th	-18.43	24.80	8.24	-30.38	-64.76	-20.09	-17.34
		Highest	-21.27	19.86	34.46	-39.49	-59.20	24.96	-25.61

**Notes: This shows the change in the later year's values compared to the earlier year's values as a percentage, calculated: (Emissions$_{\text{Year 2}}$ – Emissions$_{\text{Year 1}}$) / Emissions$_{\text{Year 1}}$. This means that negative values show a reduction over time while positive values show an increase in emissions or income over time. Darker blue indicates a greater reduction, white indicates no change, dark red indicates a greater increase.

Unsurprisingly, given the travel restrictions, emissions from air transport, and road and rail transport decreased by 69.14% and 38.77% respectively from 2019 to 2020. However, we also find decreases of over 16% for emissions from food and drinks, and from other consumption. From 2007 to 2009 the greatest relative reduction is also in air transport (12.40%), but this is followed by emissions from other consumption (7.05%). Notable are also differences in where households reduce emissions. For instance, between 2007-2009 households with HRP aged 18-29 decrease emissions from food and drinks by 14.59%, while both air and land transport increase – despite having the highest income reductions. This matches the different air transport elasticities that are observed for this age group in section 4.4.2. In contrast the households with HRP aged 75+ decreased land transport by over a fifth, but increased emissions from electricity and gas by 8.76%. We conclude from this that different age groups prioritise different kinds of consumption and thus may react differently to policy.

4.5. Discussion

4.5.1. What are the Patterns of Consumption-based Emissions for Different Age and Income Groups?

Consumption-based emissions vary widely by both group and income decile. The relationship between emissions and income decile appears positive, meaning that higher income deciles have higher emissions. For instance, emissions of a SPH in the lowest income decile are less than half of the emissions of a SPH the highest income decile, reflecting previous research that emissions increase with income (Baiocchi et al., 2010; Büchs and Schnepf, 2013a; Hubacek et al., 2017; Ivanova et al., 2018; Ivanova and Wood, 2020; Sudmant et al., 2018). At a product level, emissions from all products are found to increase from the highest to lowest income deciles, with emissions from transport having a particularly strong increase. In addition, we also find differences between age groups, including basket of goods differences. Households in the 18-29 group are found to have some of the lowest total consumption-based emissions, but the highest air transport emissions. This complements findings from Alcock et al. (2017), that those aged under 66 years are significantly more likely to fly. Similarly, households in the 75+ age group, have the lowest emissions from transport, but the highest emissions from electricity and gas use. This points to clear differences in consumption patterns between households in different age groups, mirroring findings by Zheng et al. (2022) that expenditure patterns change with age.

Despite differences in emissions by household groups, when considering average consumption between 2001-2020, all household groups have higher consumption-based emissions than necessary to live within planetary boundaries (see Akenji et al., 2019; Koide et al., 2021). However, the as our finding show, the approaches needed to reduce emissions should be targeted to specific social cohorts to be both effective and socially equitable.

4.5.2. Do Links between Consumption-based Emissions and Incomes Differ for Age and Income Groups?

In line with existing findings (Hertwich and Peters, 2009c; Ivanova et al., 2016), we find increases in incomes to be more strongly associated with increases in emissions from luxury purchases rather than necessities when considering all UK households. However, our research shows that the association between income and consumption-based emissions from different products and services vary by household group, with many of these differences being statistically significant. For instance, emissions from the lowest income decile are much less strongly linked to changes in incomes than for all higher deciles across most products and services. Indeed, we find emissions from the lowest income decile to be almost completely decoupled from income. In contrast, for the highest decile we find that proportionally greater reductions in income may be needed to reduce emissions by the same percentage than some of the lower income deciles, indicating a need for targeted interventions for both effectiveness and fairness. In other words, these findings suggests that general income or tax-based approach to reducing emissions would be hugely regressive for the lowest income decile and not effective for the highest income decile.

By age groups, we find that income is more strongly linked to transport emissions from the 65-74 and 75+ age groups than other age groups. Moreover, our findings show that households in the 30-49 age group have a stronger relationship between income and air travel emissions, especially when compared to the youngest and oldest age groups. This means that change in income are expected to affect changes in air emissions most strongly for 30-49 year olds.

We conclude, therefore, that links between income and emissions vary not only by product but also by age and income of a household. Thus, changes in income are expected to have varying impacts on emission patterns of difference social cohorts.

4.5.3. How are Patterns of Consumption-based Emissions of Different Age and Income Groups Affected by the Recession and Lockdowns?

We find that, emission reductions between 2007 and 2009 are only in a small part due to changes in consumption and in large part due to increases in energy efficiency or changes in the UKMRIO model. In contrast, the reductions between 2019 and 2020 indicate sufficiently reduced consumption necessary to meet climate goals (see Akenji et al., 2019; Koide et al., 2021). However, it is important to keep in mind that the emission reductions in 2020 come at the price of decreased wellbeing and increased inequalities (Goldin and Muggah, 2020). Assessing the differences between the recession and lockdowns can, however, provide an indication of consumption-emission pattern differences and social inequalities.

Our findings indicate that proportionally for all households combined, emissions changes from a change in consumption decrease at a higher rate than incomes, for both 2007–2009 and 2019–2020. This points to an effect of income-reductions and economic uncertainty on emissions. Moreover, we find that between 2007–2009 the highest income households have the largest proportional reductions, mainly from decreases in high emission products and services including transport, and electricity and gas. This is in line with strong link between income and/or affluence and emissions reported in the literature (Baiocchi et al., 2010; Büchs and Schnepf, 2013a; Hubacek et al., 2017; Ivanova et al., 2018; Ivanova and Wood, 2020; Sudmant et al., 2018; Wiedmann et al., 2020). However, our finding adds that emission reductions in high-carbon products and services may be possible, with income reductions and economic uncertainty.

On the other hand, from 2019–2020, the lowest income decile saw the greatest proportional reduction in total emissions. Thus, although total emission reductions mirror those needed to meet climate goals, carbon inequality increased in 2020. For example, the lockdowns saw strong reductions in emissions from gas and electricity from lower income households, paired with strong increases in emissions from gas and electricity from higher income households. This centres the need for social equity and fuel poverty in discussions on emission reductions and highlights, once more, that the lockdowns cannot be a blueprint for climate policy (Howarth et al., 2020). Our findings indicate that lower income households reduced emissions based on necessity, while higher income households saw higher rebound effects.

In line with this, we find specific rebound effects for specific groups. Emissions from recreation, culture and clothing increase for many household types following both events. As these products and services tend to be less carbon intensive than activities that were reduced, like transport, we find an overall reduction of emissions. Furthermore, despite reductions in incomes, young adults appear not to reduce transport emissions following the 2007 economic crisis. Similarly, households with adults aged 65 and older, show lower reductions or even increases in emissions from electricity and gas. One reason electricity and gas emissions may be higher for adults aged 65 and older is the higher room to person ratio these households have. An income- or tax-based policy to reduce emissions may therefore not reduce emissions of some high-intensity activities of some household groups. This reflects the vastly different lifestyles of different age groups and suggest that behaviour change campaigns may be more effective when targeting different age groups with different changes. It may be helpful, therefore, to pair general emission reduction efforts with environmental education targeted at particular age groups, as suggested by Duarte et al. (2016).

Finally, the lockdowns also resulted in reduced emissions from food and drinks. Likely, this is due to reduced spending on restaurant meals (ONS, 2021c), which can contribute strongly to food emissions (Kanemoto et al., 2019). Although further analysis of food-related emissions is needed, our findings suggest that we can learn from food and drink consumption during the lockdowns to reduce household emissions from food and drinks.

4.5.4. How can Emission Reductions be Achieved without Furthering Social Inequalities?

While the current analysis focuses on the UK, age and income-related patterns of emissions are reported throughout the literature internationally (Baiocchi et al., 2010; Connolly et al., 2022; Hubacek et al., 2017; Ivanova et al., 2018; Ivanova and Wood, 2020; Wiedmann et al., 2020; Zheng et al., 2019). Thus, the findings from the research as well as the policy recommendations are applicable beyond the UK context.

Our findings suggest that an income-reduction policy targeting, specifically and exclusively, the highest income households may be able to reduce emissions for some of the highest emission categories. A universal income-reduction or tax-based policy, on the other hand, would hit lower income households harder, and likely result in increased levels of fuel and transport poverty. Büchs et al. (2021) suggest that combining universal vouchers for renewable electricity and public transport with investment into greener infrastructure can reduce emissions and reduce fuel and transport poverty. Our findings support this, by showing that for the lowest income decile incomes and emissions are already fully decoupled. Reducing emissions of households in the lowest income decile, while necessary, should therefore be done by increasing access to good quality basic needs, like insulated housing and reliable public transport (see also Millward-Hopkins et al., 2020; Oswald et al., 2021). Similarly, Duarte et al.

(2016) argue that an increased shift from private to public transport is the most environmentally efficient policy tested in their scenarios.

Findings from the 2020 lockdowns further highlight the need to consider social equity. While emissions reduced by over a fifth between 2019 and 2020, and thus sufficiently meet the 8% reduction target, proportional emission reductions of the lowest income decile are almost twice as high as that of the highest income decile. This is mirrored by the lowest income decile seeing the highest reduction in income, and points to the need to consider social equity as an integral part of any climate change mitigation policy (Büchs et al., 2021). As higher paid jobs more frequently had opportunities for telecommuting (Goldin and Muggah, 2020), this finding is not surprising. Thus, while overall reduced emissions may be seen as a positive, carbon inequality between income groups increased further in the lockdown. Despite this, we can learn from emission reduction patterns to design policy which is effective and socially just. For instance, in line with this, our findings support existing evidence that telecommuting (Creutzig et al., 2021b), where possible, or a 4-day work week (Fitzgerald et al., 2018; Kallis et al., 2013; King and van den Bergh, 2017) can contribute to decreased emissions, but that limiting mobility overall is regressive for lower income households.

To reduce emissions effectively, attention needs to be paid to rebound effects. Existing research warns that reductions in one area may result in increased overall emissions, as people may have more money for more carbon-intensive goods and services (Druckman et al., 2011; Duarte et al., 2016). While analysing the emission reductions following the 2007 economic crisis and the 2020 lockdowns may not reveal rebound effects fully, as incomes are reduced in both events, we still find patterns of higher emissions for some products. For instance, emissions from recreation, culture and clothing increase for many household types following both events. As these products and services tend to be less carbon intensive than activities that were reduced, like transport, we find an overall reduction of emissions. Moreover, we observe age group-specific rebound effects, where younger age groups appear to prioritise emissions from flights, while older age groups appear to prioritise emissions from gas and electricity use. Interventions targeting the particular consumption patterns of different age groups may therefore be more effective than a general campaign. Moreover, as Duarte et al. (2016) suggest, providing environmental education may help reduce some of these rebound effects. Alternatively, Howarth et al. (2020) propose that increased citizen engagement could permit behaviour changes to become more accepted and widely practiced, leading to long-term reductions of consumption-based emissions.

4.5.5. Limitations

As is common for consumption-based emissions research, this study has various limitations. For instance, using expenditure data as a proxy for volume consumed, can lead to uncertainty in the emission estimates (Girod and de Haan, 2010, 2009). Despite this, due to lack of physical data for both MRIOs and subnational microdata, much research relies on financial data to estimate subnational consumption-based emissions (e.g. Minx et al., 2013; Steen-Olsen et al., 2016; Pothen and Tovar Reaños, 2018). Moreover, while using household expenditure data to disaggregate national emissions accounts may lead to an underestimation of emissions from low-expenditure households and an overestimation of emissions from high-expenditure households, overall emissions trends remain stable. Moreover, aggregation to household groups minimises the effect of outliers.

Secondly, this research relies on aggregated data for 2020, rather than the raw survey result, for data availability reasons. While this poses a limitation to the current research, the impact of this is minimised by, first, using methods of household group aggregation that are the same as the 2020 data, by, second, using expenditure data for 2020 that is also based on the LCFS, and by, third, adjusting the estimates from 2019 by the proportional difference in the aggregated 2019 and 2020 data.

In addition, using the OECD-modifier scale may introduce uncertainty. While the scale is widely used, for example by the UK's Office for National Statistics, and considered reliable, it is typically used or total income or expenditure. However, in this study we use it for individual products. It is possible, that not all products or services should be equivalised using the same weighting. Despite this, however, equivalisation is necessary to compare social cohorts as is done here, and the OECD-modified scale is best scale available for household equivalisation, and also used in other UK statistics.

Finally, as noted in both the method and findings sections, this research reports emissions by SPH, as well as using 2007 values of emission intensities. This allows for comparison between groups, as well as between years. However, this also means that while estimates reflect emission trend and can be analysed in relation to one another, they to not represent actual emission estimates for the different groups, as per capita emissions, or years.

4.6. Conclusions

To achieve climate goals, such as limiting global warming to 1.5 degrees Celsius, the average UK household needs to reduce their consumption-based footprint by around 8%

annually (see Akenji et al., 2019; Defra, 2020; Koide et al., 2021). Investigating changes in consumption-based emissions following both the 2007 economic crisis and the 2020 lockdowns allows us to learn about the impacts certain types of policies might have on GHG emissions of households. Importantly, we find that all household types studied here need to reduce their total consumption-based emissions to meet climate targets. However, some household types need to reduce more than others, and strategies to achieve climate targets need to differ between social cohorts to not further increase inequality. While our findings highlight that the 2020 lockdowns had a greater impact on changing consumption and reducing emissions than the 2007 economic crisis, social impacts must be considered. As different household groups have different consumption patterns as well as different access to resources, targeting policies towards specific household groups may be more effective than universal policies or campaigns. For instance, our findings show that a universal income-reduction or tax-based policy would, while reducing emissions, increase social inequalities. However, a tax targeting specifically the highest income households, paired with increased access to better insulated housing and public goods and services for all may not only reduce emissions, but also inequalities.

Moreover, we advocate for looking at total, as well as product-level emissions, as rebound effects occur. While policies such as increased telecommuting or a 4-day work week may reduce emissions from commuting, they can increase emissions in other domains, like home gas and electricity use. While we find overall emissions to still be reduced, the reductions in transport are offset.

Finally, we find that further research into consumption patterns of food and drinks during the lockdowns may illuminate how food emissions can be reduced.

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Chapter 5. Discussion and Conclusion

This chapter begins by briefly summarising the findings from empirical chapters in light of this thesis' research questions, followed by a discussion of overarching themes – including methodological contributions, the links between social factors and product-level emissions, and policy implications. Moreover, international applications, the limitations and future directions of this research, and finally some concluding remarks are discussed. This chapter, therefore, summarises the novel contributions of this research and how these sit within the wider network of consumption-based emissions and sustainability research.

5.1. Summary of Findings

In Chapter 1 of this thesis, 4 RQs are posed (see section 1.2). This section briefly summarises the results from Chapter 2, Chapter 3, and Chapter 4 in light of the RQs, to showcase how these are answered by the empirical chapters. The structure of the thesis follows these research questions in the form of data quality and validity, spatial analysis, longitudinal analysis. Thus, this section mainly summarises the findings from the individual chapters. The subsequent sections offer a reflection of the findings in light of the overarching objectives.

5.1.1. How Robust are Estimates of Consumption-based GHG Emissions of Neighbourhoods? (RQ1)

The level of robustness of the findings is found to vary with level of product- and neighbourhood-disaggregation, as well as with the unit of analysis. When assessing all UK neighbourhoods, most levels of product- and neighbourhood-disaggregation produce estimates which are comparable for the majority of the footprint. At an LAD level, these figures are lower. Chapter 2 addresses this question in detail, with a focus on microdata selection in the UK context. Emission estimates of UK neighbourhoods are generated from three different microdatasets. These estimates are compared in terms of their distributions, correlations, and the RMSE is used to quantify the differences between these datasets (see section 2.4). Differences between datasets differ by geography and product-level chosen, as well as by the study area.

To address this, various methods of increasing robustness as well as improving awareness of where uncertainties arise are discussed (see section 2.5). These include consideration of the data generation process of the microdata selected for disaggregation, what unit consumption and expenditure are recorded, if physical units are available or used to model the microdata, and the research questions in light of the level of disaggregation necessary as well as the implication of the findings. While these findings are derived from a UK case-study, recommendations for microdata use to estimate emissions subnationally can be applied in other contexts.

Findings from this chapter are used to inform microdata selection throughout this thesis. They are particularly relevant for the research conducted in Chapter 3, as spatial disaggregation of emissions is also done here. Moreover, although not spatially disaggregated, Chapter 4 makes use of the recommendations made in Chapter 2 to disaggregate data subnationally and understand the limitations of the dataset used.

5.1.2. Can Open Data be Used to Estimate Consumption-based GHG Emissions of Neighbourhoods? (RQ2)

This thesis finds that open data can be used to estimate neighbourhood emissions. The use of open data to estimate household consumption-based emissions for neighbourhoods is assessed in detail in Chapter 2, and applied in Chapter 3. Moreover, Chapter 4 uses open data as well, although for household groups, rather than neighbourhoods.

Indeed, using open data to estimate consumption-based GHG emissions of neighbourhoods may not only be possible, but also advantageous (see section 2.4 and section 2.5). This is due to increased replicability as well as an increased knowledge of the data generation process. Where expenditure and/or consumption microdata are available at a product-level, as they are in the UK, using open data offers insights into the data generation process of microdata, that commercial data often fails to offer. This means that using open data for this type of analysis can provide an overview of the limitations and uncertainties of the research, as data collection and processes are transparent. Hence, open data is continued to be used in Chapter 3 and Chapter 4.

Nonetheless, availability of open data does not necessarily facilitate the analysis of individual neighbourhoods. As the use of open data requires creating expenditure profiles from regional, geodemographic, or national data, results cannot be used to measure the progress of individual neighbourhoods. Thus, open data can be used to analyse spatial patterns at a national or regional level, but should not be used to assess emission changes of specific neighbourhoods.

5.1.3. What are the Neighbourhood Level Differences in Consumption-based Emissions and the Relationships between Social Factors and Consumption-based GHG Emissions? (RQ3)

Spatial patterns of consumption-based GHG emissions across the UK are shown in Chapter 2 (Figure 2.2). These show that while neighbourhood emission estimates can vary between methods used to estimate them. Overarching spatial patterns become apparent. For instance, emissions appear to be higher in the south of England than the north of England, and higher in rural than urban areas. In addition, spatial trends show large variations even within cities, most notably in London.

In light of transport being one of the highest emitting sectors in the UK and as some aspects of UK transport policy are administered locally, an analysis of transport at the local level is particularly relevant. Thus, spatial patterns of transport emissions (see Figure 3.2) and their links with social factors (see Table 3.4, Table 3.5, Table 3.6, Table 3.7, Figure 3.3, Figure 3.4, and Figure 3.5) are analysed further in Chapter 3. A spatial autocorrelation analysis on residuals of a linear analysis reveals a significant spatial impact on the data. Consequently, when using geographically weighted regression models rather than linear regression models, model fit improves by up to 70% for the different modes of transport. This shows that relationships between consumption-based GHG emissions and social factors vary across neighbourhoods, both in strength and in direction.

5.1.4. How do Longitudinal Changes in Consumption Impact GHG Consumption-based Emissions for Different Household Types? (RQ4)

Around 12% of emission reductions between 2001 and 2019 are due to changes in emission intensities of different products (see Chapter 4). Focussing on the effects of the 2007 economic crisis and the 2020 COVID-19 further highlights how emissions can change between years, as a result of external events, but also how these changes are different between these two events. Differences in how emissions change over time are found between household groups. For instance, younger households show higher rebound effects for flights, whereas older households show higher rebound effects for gas and electricity. Moreover, longitudinal comparisons show that between 2019 and 2020, the lowest income group saw the proportionally largest reductions in emissions, despite having the lowest emissions to begin with. The impact that longitudinal changes in consumption have on GHG emissions therefore depend on household types.

5.2. Contributions to the Knowledge Base

This research is designed to both estimate and analyse consumption-based GHG emissions of UK households. The contributions of this thesis thus sit within both the estimation of subnational footprints as well as their analysis.

5.2.1. Methodological Contributions

Methodologically, this thesis makes four key and novel contributions to the knowledge base: improving the validity of neighbourhood-level footprinting through microdata selection processes, estimating neighbourhood-level footprints that are consistent with national accounts, bridging the gap between industrial ecology and spatial analysis, and promoting the use of open data. Each of these are discussed below in more detail.

5.2.1.1. Improving Validity of Neighbourhood Level Footprinting through Microdata Selection Processes

Chapter 2 of this thesis focuses heavily on the validity of microdata that are used to generate subnational emission estimates. While much research has addressed differences and uncertainties in IO analysis and models (Abd Rahman et al., 2021; Heinonen et al., 2020; Hoekstra, 2010; Karstensen et al., 2015; Lenzen et al., 2010, 2004; Moran and Wood, 2014; Owen et al., 2014; Owen, 2017; Owen et al., 2017, 2016; Peters, 2008; Peters et al., 2012; Rodrigues et al., 2018; Tukker and Dietzenbacher, 2013; Wiedmann et al., 2008; Wood et al., 2019b, 2019a), and some the differences between using physical use or expenditure data (Girod and de Haan, 2010, 2009; Vringer and Blok, 1997), this thesis is the first to compare emission estimates from seemingly comparable expenditure microdata. While, using physical units instead of expenditure has benefits (Girod and de Haan, 2010, 2009; Vringer and Blok, 1997), much research relies on expenditure data to disaggregate national emissions due to lack of physical unit data (e.g. Minx et al., 2013; Steen-Olsen et al., 2016; Pothen and Tovar Reaños, 2018). As a result, this research makes an important contribution by offering a framework under which to assess expenditure microdata.

5.2.1.2. Consistency with National Accounts

In addition, this thesis generates household consumption-based emissions at the neighbourhood and household group level, which are consistent with national accounts. This can add robustness to the results (Tukker et al., 2018) and therefore supply more reliable emission estimates.

5.2.1.3. Bringing Together Industrial Ecology and Spatial Methods

This research is at the forefront of the analysis of neighbourhood consumption-based emissions, by considering spatial analysis methods. Existing research showcases the need for spatial models in emission analyses (Clement et al., 2021; S. Wang et al., 2019; Y. Wang et al., 2019; Xu and Lin, 2017). Moreover, many consumption-based emission estimates have spatial component and assess links with social factors (e.g. Baiocchi et al., 2010; Minx et al., 2013), spatial heterogeneity in the relationship between emissions and social factors have not been investigated. This gap is bridged in Chapter 3, which showcases how spatial statistics methods can and should be applied to consumption-based emissions analysis.

5.2.1.4. Promoting the Use of Open Data

This research offers a method to generate sub-regional emission estimates from open data. Despite growing demands for increased reproducibility across the social sciences (Brunsdon, 2016; Tay et al., 2016), much of the research estimating subnational household footprints in the UK relies on commercial data (e.g. Baiocchi et al., 2010; Minx et al., 2013) and is therefore more difficult to reproduce. In addition to making reproducibility more difficult as data access is limited by funding, the use of commercial data means that data generation processes may be less transparent, hindering an assessment of limitations. In contrast, Chapter 2 describes a robust and validated approach to use open data to estimate subregional footprints. Pfenninger et al. (2017) argue that data and methods should be openly available to allowing for more reproducibility, transparency, and traceability, to reduce the need for duplication, and to enable more research-based policy outcomes. Thus, using open data and openly available method to estimate consumption-based emissions for neighbourhoods can allow for more replicable and transparent method to generate emission estimates, for both researchers and policy makers. To further increase access, neighbourhood-level emissions data for 2016 from this thesis is published via the UK Data Service repository (Kilian et al., 2021). Emissions estimates for the years 2007–2019 are in the process of being published.

5.2.2. Social Factors and Emissions: A Spatial and Temporal Perspective

In addition to the methodological contributions, this thesis provides a detailed perspective on the links between social factors and emissions across both time and space. This includes a spatially heterogeneous perspective on the links between transport emissions and social factors, as well as an investigation of how emission of different household types change over time, with a particular focus on the 2007 economic crisis and the COVID-19 pandemic.

As mentioned in section 5.2.2, this thesis offers a novel spatial approach to analysing household consumption-based emissions and social factors. Understanding the links between social factors and consumption-based emissions through such a geographical lens is important not only methodologically, but also practically. As efforts to reduce emissions should also aim to decrease social inequalities, a spatially detailed approach can indicate where specific policies may be most effective to reduce both emissions and transport poverty. While the research in Chapter 3 of this thesis is exploratory, it highlights the important contribution a spatial perspective can make in understanding heterogeneity. For example, where previous research finds that longer distance to workplaces are linked to higher car emissions (Brand et al., 2013), findings reported in Chapter 3 show that this relationship can be spatially heterogenous. Context-based, and place-specific understandings of social factors and emissions are therefore important to reduce consumption-based emissions.

In addition to a novel spatial perspective, emissions are assessed longitudinally in Chapter 4. Here, emissions from different household types are compared with a particular focus on the 2007 economic crisis and the COVID-19 pandemic. In this chapter, various aspects to consumption-based emission changes are investigated. This includes where households reduce emissions, if these reductions disproportionally affect specific household types, and an assessment of rebound effects. Moreover, this chapter presents a novel view of the impacts of the COVID-19 pandemic on household emissions, which is only enabled by the recent publication of household expenditure data from 2020 (ONS, 2022b). Thus, the analysis in Chapter 4 adds a novel perspective of what happens to consumption-based emissions in severe disruptions to incomes and lifestyles to the knowledge base. In addition, this chapter adds a discussion of what policy can learn from this to make climate change mitigation more effective and socially just.

5.2.3. Context-targeted Interventions

Findings from this research call for the need to context-specific interventions. For instance, Chapter 3 finds spatial differences in the relationships between social and infrastructural factors and transport emissions. This echoes a need for place-specific policy interventions, which consider which emissions need to be reduced in which area. While existing research discusses the need of place-specific innervations in light of rurality or urbanity (Baiocchi et al., 2010; Heinonen et al., 2013; Jones and Kammen, 2014; Ottelin et al., 2015), this thesis adds a neighbourhood level perspective, which highlights spatial heterogeneity even within one urban area.

In addition, findings from Chapter 4 show the need for considering age and income for policy. Rebound effects differ by age group, and the lowest income decile in the UK has already decoupled consumption-based emissions from incomes. To reduce emissions of UK households through financial incentives, for example through a general carbon tax, would therefore further affect the ability of the lowest-income households to meet basic needs, while the highest income-households would be least affected. Thus, while financial incentives may be effective at reducing emissions (Khanna et al., 2021), doing this without understanding social contexts can increase social inequality (Büchs et al., 2021). To reduce emissions from the lowest-income group, therefore, this research proposes increased access to better quality housing and to public goods and services (see also Millward-Hopkins et al., 2020; Oswald et al., 2021). To reduce emissions form high-income households, overall consumption needs to decrease. Similarly, findings for age groups show that reducing consumption for specific products and services can aid emission reduction efforts. Younger age groups have higher rebound effects on air travel, while older age groups have higher rebound effects on home energy and gas. The literature suggests that providing environmental education or increasing citizen engagement in climate change mitigation could reduce rebound effects (Duarte et al., 2016; Howarth et al., 2020). The current research adds to this discussion that aiming behaviour change initiatives to reduce consumption for specific products at specific age and income groups may further reduce rebound effects. Thus, understanding the spatial and social contexts within which consumption and consequent emissions occur is essential for effective and socially just climate policy.

5.3. Project Impacts

This PhD project and thesis were undertaken as part of the Data Analytics and Society Centre for Doctoral Training, which is funded by the Economic and Social Research Council. Although this project is not directly associated with a project partner, some of the outputs from this project are made in association with various stakeholder or industry partners. For example, I wrote a report on neighbourhood-level consumption-based emissions for Arup. Arup is a multinational professional services consultancy with specialism in the built environment. Among other projects, they estimate consumption-based emissions for local governments. Their interest in this project is on improving methods to estimate subnational consumption-based emissions.

In addition, as part of this project I have written (see Appendix K) and co-written (Owen and Kilian, 2020) reports for Bristol City Council, as well as provided detailed data on Bristol's consumption-based emissions for Bristol City Council. This helps Bristol City Council understand and visualise their residents' emissions at a spatially-detailed level, track them over time, and compare them to the UK average. However, despite Bristol City Council's interest in consumption-based emissions data, these data have not yet been used to inform policy directly. Working with LADs to make consumption-based emission targets, rather than just monitoring emissions over time, may be an impactful way to use the type of data generated in this project. Recent increased interest in consumption-based emissions data by LADs may lead to an inclusion of such targets in the near future. Indeed, other stakeholder, including C40 Cities Climate Leadership Group, a group of 97 cities around the world, are also increasingly incorporating consumption-based accounts into understandings of a city's emissions (e.g. C40, 2022). For instance, the publication of Chapter 2 has led me to consult on a project on consumption-based emissions for London and New York run by C40 (2022), which aims to provide the cities with data indicators to measure the impacts of actions on consumption-based emissions.

The research presented in this thesis has been disseminated widely within the academy and, where possible, research outputs have been made publicly available. This includes the two open access papers that are direct outputs from this thesis (Kilian et al., 2022a, 2022b), and a data collection of consumption-based neighbourhood footprints (Kilian et al., 2021). The papers which make up two chapters of this PhD thesis are published in the peer-reviewed journals *Economic Systems Research* (impact factor 2.08) and *Sustainability* (impact factor 3.89). These journals were chosen due to their relevance to the topic of this thesis, as well as their wide and international readership. To date, the article presented in Chapter 2 has had over 4,600 views, while the one presented in Chapter 3 has been viewed more than 700 times. Moreover, the data collection has been downloaded more than 50 times. This showcases the interest in the articles, as well as the datasets and highlights the timeliness of the topic of this PhD thesis.

Work from this PhD was also accepted for presentation at various UK and international conferences, showcasing interest in the research conducted as part of this thesis. This includes conferences on a wider range of topics, such as the one organised by the American Association of Geographers, as well as more specialised conferences, like the one run by the International Input-Output Association. This highlights the wide range of interest in the work presented in this thesis, both from within the Input-Output research community, as well as from the broader discipline of Geography. Moreover, it showcases the international interest in this work. In addition, in November 2022 I was awarded first place in the Research Design & Methods category in the Outstanding Postgraduate Paper Competition organised by the RGS-IBG Energy Geographies Research Group for a shorter version of the paper presented in Chapter 3. Following this, I was invited to present a webinar on the findings from Chapter 3 as part of the webinar series from the Energy Geographies Research Group of the Royal Geographical Society.

The work from this PhD leans on and complements existing work coming out of the University of Leeds and other institutions. Situated within a network of research on consumption-based emissions undertaken at the University of Leeds (e.g. Baltruszewicz et al., 2021a; Büchs and Mattioli, 2021; Ivanova and Middlemiss, 2021; Millward-Hopkins and Oswald, 2021; Owen, 2021), this thesis offers a novel spatial and longitudinal analysis of household emissions in the UK. For instance, being situated at the University of Leeds has allowed me to use data that are consistent with national accounts, which can add robustness to the results (Tukker et al., 2018). Moreover, the research in this thesis is able to lean on existing methods to assess impacts of the COVID-19 pandemic and the resulting lockdowns on different on the emissions of household types. Finally, sitting within human geography, data science, and sustainability offers this thesis a novel geographic perspective on consumption-based household emissions in the UK. This allows for both the expansion of existing municipality level estimates of household emissions (Minx et al., 2013) to a UK-wide approach to estimate emissions at a neighbourhood level, as well as an analysis of these emissions through a spatial lens.

5.4. Limitations and Challenges

This section discusses the limitations and challenges that are specific to this thesis. Methodological limitations are also discussed in the relevant chapters, but summarised here. In addition, challenges around data access are outlined in section 5.4.2. The focus is on the specific limitations of this research, data access and data quality. For general methodological and data limitations, concerning MRIO uncertainties, the UKMRIO, and limitations and biases related to geographic data and analyses please refer to section 1.7.

5.4.1. Data Quality

Some of the key limitations of this research concern the quality of the data available. Both the microdata used, as well as the MRIO data used have benefits and limitations.

MRIO databases have different strengths and weaknesses related to sector aggregation, availability of time series data, and inclusion of uncertainty estimates (Hoekstra, 2010; Tukker and Dietzenbacher, 2013). Moreover, uncertainties can vary by country. For instance, Rodrigues et al. (2018), find that uncertainty ranges from 5-10% in OECD and from 10-20% in non-OECD countries, at country level.

To increase robustness, a global MRIO database can be adjusted to single-country national data on environmental footprints (Tukker et al., 2018). The UKMRIO model, which is used throughout this thesis, uses such an approach. Indeed, the UKMRIO is a robust framework for assessing consumption-based emissions, although uncertainties increase at sectorial level (Lenzen et al., 2010; Wiedmann et al., 2008). Nonetheless, general uncertainties and limitation linked to MRIO modelling apply to the UKMRIO, resulting in this being a limitation of the work presented in this thesis. More detail on these differences can be found in section 1.7.1.

Chapter 2 describes some of the limitations of different microdatasets in more detail, these include relying primarily on financial data as a proxy for physical volume (Girod and de Haan, 2010). This means that if one household purchases a loaf of bread for £1.00, and another household purchases the same loaf of bread for £1.50, the latter household will be assigned a 50% higher footprint for the same purchase as the former. Effectively, higher emissions may reflect overestimation of some products, while lower emissions may be underestimated. However, while this adds uncertainty to the estimates, the trends of which households have higher and lower emissions remain stable. Moreover, to mitigate this further, where physical unit data were available, this research made used of such data. Most importantly this includes data on the number of flights taken.

In addition, the sampling of the microdata presents several limitations. Firstly, the surveys are self-reported and are thus subject to self-report biases. However, the survey design does minimise other issues, such as missing data from misremembering, as the data are collected in a diary format. Secondly, despite the LCFS taking steps to ensure a nationally representative sample, the highest income households are systematically changed in the survey due to data disclosure risks (ONS, 2017a). Thus, the highest income households, who likely have the highest emissions (Lee et al., 2021; López et al., 2019; Moran et al., 2018; Niamir et al., 2020; Otto et al., 2019; Vringer and Blok, 1995) cannot be studied separately. Additional data is therefore needed to study the environmental impact of those households in the UK.

Sampling also matters for scalability. In this research emissions are estimated for the entire UK. This means that the LCFS sample of 4,000-6,000 households annually is scaled up to 24.5-28 million household in the timeframe studied (ONS, 2022c). However, the uncertainty from this is reduced due to the sampling method of the LCFS. The Office for National Statistics ensures representativeness of the LCFS by using a multi-stage stratified sample in Great Britain and a systematic random sample in Northern Ireland with quotas for household types and geographic areas (ONS, 2017a). Moreover, the LCFS contains a weight indicating the number of households in the UK, which are comparable to a given household based on geographic and socio-demographic similarity. Hence, the LCFS is designed to be scalable to the UK.

Data quality limitations also apply to the use of other data in this research. In Chapter 2 and Chapter 3 of this thesis, other sociodemographic data from the census and other data sources are used. One key limitation of the comparisons done is that the data are from different years. While care was taken to ensure that the years match as closely as possible, and that dependent variables (emissions) are from a later point in time than independent variables (socio-demographic characteristics) a lack of more data means that data are collected at different points in time. Moreover, census data and the OAC geodemographic classifications only being updated every 10 years mean that changes within neighbourhoods that occur within this timeframe cannot be detected.

Finally, data differences between the four countries in the UK are a limitation of this research. For example, as shown in section 2.3.1.3 and in Appendix B, definitions of census geographies can vary between the countries. Although the census is conducted UK-wide, this can also present a problem when aiming to include more physical data. Domestic gas and electricity use data, for instance, is available for England, Wales, and Scotland at a neighbourhood level, but not for Northern Ireland (BEIS, 2020b, 2020a). Thus, the differences in geographical definitions and data availability between the UK countries presents a challenge for current and future research.

5.4.2. Data Access

Data access presented a further challenge for this research. The LCFS exists in two versions: the anonymised version used throughout this thesis, and an address-level version which requires safeguarded access for data protection reasons. The initial plan for this thesis was to also incorporate address-level version of this dataset, as it contains greater geographic specificity as well as additional variables, such as flight destinations. Particularly for the work conducted in Chapter 2 of this thesis, having this greater level of detail would have provided additional opportunities for data validation. However, obtaining access to these data presented two barriers: long application processing times and working from home requirements. Despite submitting an application to access these data early during my PhD research, I only heard back around the time of the nation-wide lockdowns. After the pandemic hit during the first year of my PhD research, it was no longer possible to access the facilities at the University of Leeds that would allow for the processing of these data. Subsequently, I withdrew my application and worked only with the anonymised version of the LCFS. While the anonymised version has several advantages with regards to reproducibility of the research, future access to the non-anonymised LCFS can be an additional resource for data validation of small-scale neighbourhood expenditure and emissions, and the subnational distribution of flight emissions.

The second data access challenge presented itself around the LCFS from the year 2020. In previous years the LCFS was published in June/July, meaning that the expected publication date for the 2020 LCFS was July 2022. However, due to data disclosure concerns and subsequent delays with the publication, the data only became available in November 2022, and could thus not be included in Chapter 4 of this research. While I was able to use more aggregated household expenditure data derived from the LCFS, which had already been published, not having had timely access to the LCFS presents a limitation in this research. In the future, rerunning the analysis in Chapter 4 with access to individual survey results could negate this uncertainty.

5.5. Moving Forward

5.5.1. Household vs. Neighbourhood Level

It is useful to reflect on the benefits and limitations of using household unit and neighbourhood level data. Both have advantages and disadvantages related to methodological limitations, availability of other data, and their usefulness for policy. These are discussed in this section, to assess which roles these different units of analysis may play in future consumption-based emissions research. In this research household emissions are grouped either by neighbourhoods (Chapter 2 and Chapter 3) or by socio-demographic characteristics (Chapter 4). As the geographic classification in England, Wales, and Northern Ireland, for the smallest geographies, is based on socio-demographic similarities (ONS, n.d.) an analysis of UK neighbourhoods combines these strategies to a certain extent. Nonetheless, the more aggregated geographies are, the more diverse they become in terms of their socio-demographic makeup. Thus, the different applications of different types of grouping or even individual household unit analysis must be considered.

Using geography as a unit of aggregation is useful for policy and to assess spatial inequalities. Despite debate whether the notion of spatial inequalities is unique or only summarises other social inequalities (Bouzarovski and Simcock, 2017; Chatterton, 2010; Garvey et al., 2022; Pirie, 1983; Soja, 2016, 2010), a spatial overview and analysis of emissions can be helpful in investigating emission inequalities. Spatial differences in emissions even within countries are reported in the literature (Connolly et al., 2022; Lenzen et al., 2004; Minx et al., 2013; Wiedenhofer et al., 2017), as well as in the current research, emphasising the importance of place in this type of research.

In Chapter 2 and Chapter 3 of this research, I also find spatial differences in emission patterns as well as the links between emissions and social factors. Thus, using geographic disaggregation can be useful to assess spatial patterns, inequalities, and differences, and to design place-specific policy. For policy, using spatial units rather than individual households can also be important. With local actors, such as Local Authorities, being increasingly involved in climate change mitigation efforts (e.g. LGA, n.d.; C40, 2019; DEAL et al., 2020), having spatialised estimates of emissions can be invaluable for local policy interventions. Moreover, as shown in Chapter 3, understanding local contexts for effective emission reduction is important, due to the high levels of spatial heterogeneity in emissions and their relationships with social factors.

Despite this, looking at emissions from only a spatial perspective can result in overlooking differences between types of households. As shown in Chapter 4, household type level analysis reveals income and age group specific consumption and rebound effects. Moreover, the income analysis shows how different income elasticities of emissions are of the lowest compared to other income deciles. This highlights how this type of information gets lost when aggregating households in any other way. Grouping households by different socio-demographic characteristics, can therefore reveal insight that a purely geographic aggregation misses. Other research further highlights the need to disaggregate both by geography (e.g. Jones and Kammen, 2014), as well as by socio-demographic groups (e.g. Ivanova and Middlemiss, 2021).

Finally, both household type and neighbourhood level aggregation come with different benefits and limitations. On one hand, neighbourhood level analyses are limited by ecological fallacy. On the other hand, wider availability of other data at neighbourhood levels can remove uncertainty and provide new lenses of analysis. The UK census, for instance, is reported by geographies, meaning that detailed level information about all residents in the UK is available for geographic areas. In addition, domestic energy use data in the UK is available for neighbourhoods (BEIS, 2020a, 2020b). The wider availability of openly available data for geographic areas mean that physical use data can be used more widely to estimate emissions subnationally, as well as that more opportunities for different types of analysis are possible.

5.5.2. Data Sources

The findings from this thesis that neighbourhood-level consumption-based emissions in the UK can be estimated using open data. This is in line with a call for increased use of open data, where possible, in the social sciences (Pfenninger et al., 2017). In addition to this, consumption-based emissions research is seeing further changes from a data perspective and may see further changes in the future.

Firstly, recent UK research explores the opportunity to use novel big data sources from financial transactions of private bank accounts to disaggregate emissions subnationally (Trendl et al., 2022). Incorporating such data sources into consumption-based emissions estimations has several advantages, including larger sample sizes, not relying on self-reported data, and availability of such data in countries and regions where detailed household survey data may not be available. While these data sources also come with novel limitations, such as not knowing whether they represent full spendings, Trendl et al. (2022) find similarity between emissions estimates from large-scale transaction data and from the LCFS. Future research should explore further opportunities to use such data sources, to enable subnational emission estimates where survey data may not be available and to provide larger sample-sizes for increased scalability.

Secondly, input-output data itself may change. Similarly to limitations around using monetary data to disaggregate emissions subnationally, using physical units rather than monetary flow data within the IO table itself comes with various benefits and limitations (Giljum and Hubacek, 2004; Hubacek and Giljum, 2003; Suh, 2004; Weisz and Duchin, 2006). Unlike monetary IO tables (MIOTs), which capture flows in financial units, physical IO tables (PIOTs) capture the flows in the IO table in physical product quantities, volumes of natural resource extraction, amount of waste, emissions, and stock exchange (Hoekstra and van den Bergh, 2006). While PIOTs may reduce some of the uncertainty from MIOT, where they are available at all they often do not include the same scope for longitudinal analysis as MIOTs (Giljum and Hubacek, 2004; Wiedmann et al., 2006). Even in the 2020's data remain mismatched and incomplete and contain high levels of uncertainty (Wieland et al., 2022). Despite these challenges, researchers have been able to generate PIOTs or in some instances hybrid-unit IO models and use them to estimate emissions and other resource use (Hubacek and Giljum, 2003; Lindner and Guan, 2014; Singh et al., 2017). With the recent publication of the first global PIOT covering 10 years and 32 regions (Wieland et al., 2022), and the development of data sharing hubs (Vunnava et al., 2022), it is likely that consumption-based emissions research will continue to move towards the increased incorporation of physical units in the next years.

Thirdly, input-output analysts are increasingly creating subnational IO models (see Lenzen et al., 2017). Such models are useful, as they allow evaluate the flows of resources between regions of one country. For instance, they can highlight differences in imported and exported emissions between subnational areas (e.g. Aniello et al., 2019; Davidson et al., 2022; Kronenberg and Többen, 2011; Mi et al., 2019; Vasconcellos and Caiado Couto, 2021; Zheng et al., 2019). Whereas the research in this thesis relies on household survey data to disaggregate national accounts, other research, where subnational IO models are available, is able to utilise these. In the UK, IO tables or SUTs currently exist for the whole UK, for Scotland, and for Northern Ireland (Davidson et al., 2022). However, Davidson et al. (2022) put forward a framework for generating additional IO tables for England and Wales. Provided the data differences between the four countries (see section 5.4.1) and regional differences, using such country-level IO data, once they are available, can be a tool to further explore emission differences between the UK countries and to better allow for the use of additional data when estimating neighbourhood emissions.

5.5.3. Beyond the UK Context

Much research on consumption-based emissions both at national and at subnational emissions has been done outside of the UK. For instance, to address the lack of in-depth analysis on consumption-based emissions in developing countries, Connolly et al. (2022) provide and analyse subnational consumption-based emission estimates for 90 developing countries. Kanemoto et al. (2016) on the other hand combine MRIO data with atmospheric emissions data to spatialise consumption-based emissions of countries beyond the national level. In other words, the authors provide a method to gain more geographical detail on where emissions that are consumed in a given country come from. While much of this thesis focusses on the UK, consumption-based emissions research has been applied in many other regions, countries and contexts, emphasising the importance of this field for better understanding emission patterns and informing climate change mitigation efforts. While summarising the breadth and depth of these projects is beyond the scope of this thesis, some of this international research is highlighted throughout this thesis (especially in Chapter 1, section 2.2, section 3.2, and section 4.2).

International research also highlights the advantages and shortcomings of the UK context in light of data availability and methods. For instance, to disaggregate national accounts some non-UK based research is able to use physical measurement to estimate emissions from food (Goldstein et al., 2017; Hendrie et al., 2014). Similarly, many countries are able to use subnational IO tables, which allow for an assessment of resource flows between different regions or even municipalities within the same country. This is discussed in greater detail in section 5.5.2 and essentially highlights the advances of consumption-based accounting research globally. These data differences highlight the impact data availability has on the type of research possible within environmental accounting. While the LCFS and UKMRIO model are detailed data sources which allow for an analysis of subnational emissions in the UK which are in line with national accounts, in other contexts, due to the availability of other data, other types of research are possible.

Finally, although this thesis uses UK data, some of the findings and methods are applicable internationally. For instance, Chapter 2 provides a framework for microdata selection which can be employed beyond the UK context. Section 2.2 further describes how this framework can be applied internationally. Furthermore, the work presented in Chapter 3 of this thesis highlights the value of using geographic methods in industrial ecology research, not just in the UK, but everywhere spatial data are used. Chapter 4, in addition to this, analyses emission longitudinally, with a particular focus on the COVID-19 lockdowns and the 2007/08 economic recession. Both of these being global events means that, while the data used are from the UK, the impacts of these events are global. Thus, both the research questions, as well as the analysis and discussion can be applied internationally. Employing the learnings from this thesis outside of the UK context can therefore provide important insights into the estimation and analysis of subnational consumption-based household emissions internationally.

5.5.4. Moving towards Wellbeing and Sufficiency

The last decade has seen an increased rate of publications on degrowth scenarios as a pathway for a more ecologically sustainable future (Figure 5.1). Degrowth rejects the notion that a ‘greening’ of the economy can sufficiently reduce emissions without a radical reduction of production and consumption to meet climate goals (Brand et al., 2019; Haberl et al., 2020;

Lenzen et al., 2022; Parrique et al., 2019; Wiedmann et al., 2020). Instead, the degrowth literature suggests to move away from GDP as a central measure of a country's success to measures of social wellbeing and environmental welfare (Hickel et al., 2022b; Hickel and Kallis, 2020; Hoekstra, 2019; Kallis et al., 2018; Raworth, 2017; Wiedmann et al., 2020). This literature combines notions of environmental justice and social equity with questions of environmental sustainability (D'Alessandro et al., 2020; Lenzen et al., 2022). In other words, the focus is on resource sufficiency and wellbeing.

Degrowth stands in stark contrast to green growth, which is based on the notion of decoupling economic growth from environmental destruction (World Bank, 2012). Green growth is also central to much current environmental policy, which aims to reduce emissions while increasing GDP – mainly through technological means (CMA, 2021; HM Government, 2018; HM Treasury, 2021; IPCC, 2022a). For instance, UN's Sustainable Development Goals include global economic growth as the 8th of their 17 goals (UN: DESA, 2015).

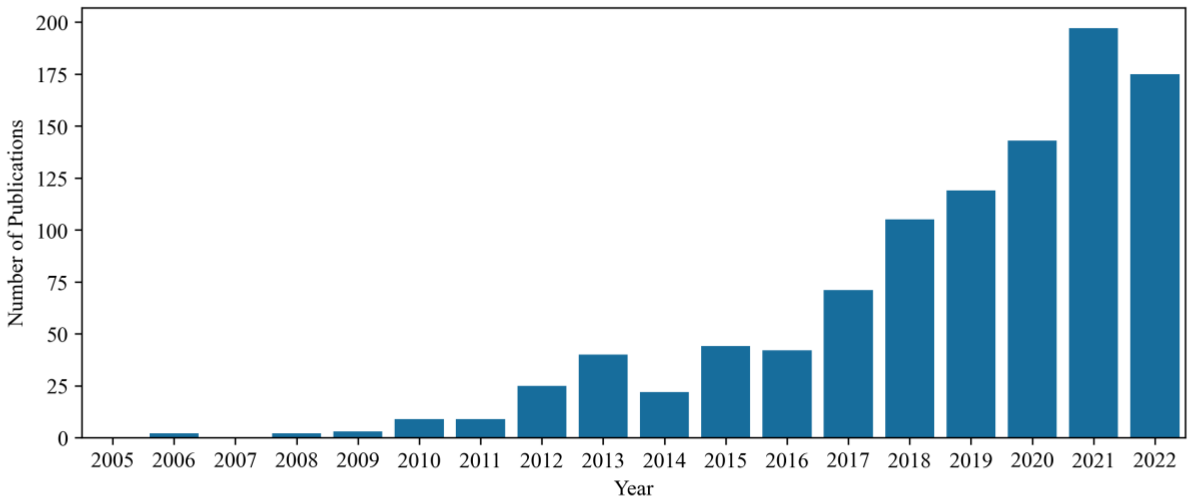

Figure 5.1. Number of publications containing 'degrowth' in their topic description on Web of Science, data from www.webofscience.com.

Research on consumption-based emissions, including the research presented in this thesis, particularly in Chapter 3 and Chapter 4, highlights the need for a redistribution of resources, and a radical reduction in consumption-based emissions, which can be achieved through a combination of reduced consumption and increased income equality. This sits in a network of recent publications on consumption-based GHG emissions and energy use, which have a strong focus on wellbeing and sufficiency (Baltruszewicz et al., 2021b; Creutzig et al., 2021b; Fanning and O'Neill, 2019; Martínez and Ebenhack, 2008; Millward-Hopkins et al., 2020; O'Neill et al., 2018; Oswald et al., 2021; Steinberger et al., 2012; Steinberger and

Roberts, 2010). This thesis and the existing literature therefore suggest that this shift toward an integration of wellbeing and sufficiency will continue in the literature in the next few years.

In practice, dependencies on economic growth remain intact. However, as Hickel et al. (2022b) point out, certain aspects of wellbeing and sufficiency are already in place in some cities or countries, including free public transport, education and healthcare, high-quality public housing, and shorter working hours. Moreover, some cities are exploring implementing the 'doughnut economics' model (Raworth, 2017), which is centred around meeting social wellbeing within planetary boundaries (DEAL, n.d.; DEAL et al., 2020). As UK cities, including London and Bristol, are showing an increased interest in tracking their consumption-based emissions (Owen, 2021; Owen and Barrett, 2020a; Owen and Kilian, 2020), it is possible that these cities will also begin adopting some degrowth principles, despite large-scale shifts away from GDP being unlikely in the near future.

5.6. Conclusion

Thus far, this chapter demonstrated how the RQs are answered in this work, discussed this work's key themes, its limitations and challenges, as well as its international applications and future directions. Adding to this, this section demonstrates how this thesis fulfils its overarching aim, before noting concluding remarks.

5.6.1. Overarching Aim

The objective of this thesis was to assess UK household GHG emissions spatially and longitudinally at a product-level, to assess how social factors are linked to consumption-based emissions, and how this can aid consumption-based emission reduction policy. This aim is achieved throughout the empirical chapters. To address this question, Chapter 2 creates spatially and product-level detailed consumption-based emission estimates for all UK neighbourhoods using various methods. This allows for an assessment of how microdata can be best selected for robust emission estimates. Thus, the research conducted in Chapter 2 is particularly linked to the first part of the overarching aim of this thesis, to assess UK household GHG emissions spatially at a product-level. Moreover, by generating the method to estimate emissions spatially and using open data, this chapter allows for the analysis of emission estimates in Chapter 3 and Chapter 4.

Chapter 3 builds on the work done in Chapter 2 of this thesis to answer the main objective of this thesis. Chapter 3 provides a spatial analysis of emission estimates and their links with social factors. Thus, the objective of *assessing UK household GHG emissions spatially and* *assessing how social factors are linked to consumption-based emissions* is achieved in Chapter 3. Finally, in the discussion, Chapter 3 explores how this spatial understanding of consumption-based emissions and their links to social factors *can aid consumption-based emissions reduction policy*, in light of local actors being increasingly involved in climate change mitigation initiative and policy making.

Lastly, Chapter 4 looks at UK household GHG emissions longitudinally at a product-level, assesses how the social factors age and income are linked to consumption-based emissions, and how this can aid consumption-based emission reduction policy. By looking at longitudinal differences of consumption-based emissions of various age and income-related social cohorts, Chapter 4 addresses the main objective of this thesis. Furthermore, this chapter provides a discussion of how emission reductions can be achieved effectively, without furthering social inequalities, based on the findings from the chapter.

As a combined piece of research, therefore, this thesis is able to achieve its aim of assessing UK household GHG emissions spatially and longitudinally at a product-level, assessing how social factors are linked to consumption-based emissions, and how this can aid consumption-based emission reduction policy throughout the empirical chapters. In addition to this Chapter 1 provides an introduction to the background and literature, while Chapter 5 provides a discussion and summary of the work presented in the thesis, embedding the empirical chapters in their context.

5.6.2. Concluding Remarks

To limit global warming to 1.5 degrees Celsius, urgent and radical actions are needed. Consumption-based accounting only provides one aspect of this and not the whole picture. However, it can be a useful tool in highlighting how emissions can be reduced through changed consumption, and where emissions need to be redistributed for increased social equity. Aiming to contribute to this discussion, this thesis provided an overview and analysis of longitudinal and spatial GHG emissions of UK households. Despite tensions existing between a focus on GDP and purely technological solutions and some of the shifts in consumption being advocated for in this thesis and by much of the consumption-based emissions research community (e.g. Keyßer and Lenzen, 2021; Lenzen et al., 2022), more local policy makers and organisations (e.g. C40, 2022; Owen, 2021) are incorporating consumption-based accounts. This thesis, therefore, adds to the calls of demand side mitigation, and presents a timely method and analysis of consumption-based emissions of UK households.

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Appendices

Appendices Chapter 2

Appendix A. Table: Output Area Classification levels and descriptions from the year 2011.

Supergroup		Group		Subgroup	
1	Rural Residents	1A	Farming Communities	1A1	Rural Workers and Families
				1A2	Established Farming Communities
				1A3	Agricultural Communities
				1A4	Older Farming Communities
		1B	Rural Tenants	1B1	Rural Life
				1B2	Rural White-Collar Workers
				1B3	Ageing Rural Flat Tenants
		1C	Ageing Rural Dwellers	1C1	Rural Employment and Retirees
				1C2	Renting Rural Retirement
				1C3	Detached Rural Retirement
2	Cosmopolitans	2A	Students Around Campus	2A1	Student Communal Living
				2A2	Student Digs
				2A3	Students and Professionals
		2B	Inner-City Students	2B1	Students and Commuters
				2B2	Multicultural Student Neighbourhoods
		2C	Comfortable Cosmopolitans	2C1	Migrant Families
				2C2	Migrant Commuters
				2C3	Professional Service Cosmopolitans
		2D	Aspiring and Affluent	2D1	Urban Cultural Mix
				2D2	Highly-Qualified Quaternary Workers
				2D3	EU White-Collar Workers
3	Ethnicity Central	3A	Ethnic Family Life	3A1	Established Renting Families
				3A2	Young Families and Students
		3B	Endeavouring Ethnic Mix	3B1	Striving Service Workers
				3B2	Bangladeshi Mixed Employment
				3B3	Multi-Ethnic Professional Service Workers
		3C	Ethnic Dynamics	3C1	Constrained Neighbourhoods
				3C2	Constrained Commuters
		3D	Aspirational Techies	3D1	New EU Tech Workers
				3D2	Established Tech Workers
				3D3	Old EU Tech Workers
4	Multicultural Metropolitans	4A	Rented Family Living	4A1	Social Renting Young Families
				4A2	Private Renting New Arrivals
				4A3	Commuters with Young Families
		4B	Challenged Asian Terraces	4B1	Asian Terraces and Flats
				4B2	Pakistani Communities
		4C	Asian Traits	4C1	Achieving Minorities
				4C2	Multicultural New Arrivals
				4C3	Inner City Ethnic Mix
5	Urbanites	5A	Urban Professionals and Families	5A1	White Professionals
				5A2	Multi-Ethnic Professionals with Families
				5A3	Families in Terraces and Flats
		5B	Ageing Urban Living	5B1	Delayed Retirement
				5B2	Communal Retirement
				5B3	Self-Sufficient Retirement
6	Suburbanites	6A	Suburban Achievers	6A1	Indian Tech Achievers
				6A2	Comfortable Suburbia
				6A3	Detached Retirement Living

				6A4	Ageing in Suburbia
		6B	Semi-Detached Suburbia	6B1	Multi-Ethnic Suburbia
				6B2	White Suburban Communities
				6B3	Semi-Detached Ageing
				6B4	Older Workers and Retirement
7	Constrained City Dwellers	7A	Challenged Diversity	7A1	Transitional Eastern European Neighbourhoods
				7A2	Hampered Aspiration
				7A3	Multi-Ethnic Hardship
		7B	Constrained Flat Dwellers	7B1	Eastern European Communities
				7B2	Deprived Neighbourhoods
				7B3	Endeavouring Flat Dwellers
		7C	White Communities	7C1	Challenged Transitionaries
				7C2	Constrained Young Families
				7C3	Outer City Hardship
		7D	Ageing City Dwellers	7D1	Ageing Communities and Families
				7D2	Retired Independent City Dwellers
				7D3	Retired Communal City Dwellers
				7D4	Retired City Hardship
8	Hard-Pressed Living	8A	Industrious Communities	8A1	Industrious Transitions
				8A2	Industrious Hardship
		8B	Challenged Terraced Workers	8B1	Deprived Blue-Collar Terraces
				8B2	Hard-Pressed Rented Terraces
		8C	Hard-Pressed Ageing Workers	8C1	Ageing Industrious Workers
				8C2	Ageing Rural Industry Workers
				8C3	Renting Hard-Pressed Workers
		8D	Migration and Churn	8D1	Young Hard-Pressed Families
				8D2	Hard-Pressed Ethnic Mix
				8D3	Hard-Pressed European Settlers

Appendix B. UK Geographies

The UK Statistics Authority divides the UK into a nested hierarchy of geographic zones for the dissemination of census and population data at various spatial scales. Output Areas (OAs) provide the highest level of geographic detail in the 2011 census, followed by Lower Super Output Areas (LSOAs), and Middle Super Output Areas (MSOAs) in England and Wales (ONS, n.d.), and by Data Zones (DZs) and Intermediate Geographies (IGs) in Scotland (Scotland's Census, 2013). In the Northern Irish census, OAs are introduced in 2001, and not redefined in 2011. The 2011 census introduces Small Areas (SAs), which combine the 5,022 OAs to 4,537 SAs and are followed by Super Output Areas (SOAs) in Northern Ireland (NISRA, 2013a). Population sizes of these areas are shown in Table Appendix 1. Municipality level geographies, in the UK, are referred to as Local Authority Districts (LADs). The UK is made up of 434 LADs, which are also contained in this nested hierarchy, such that LADs can be subdivided into unique MSOAs, LSOAs, or OAs.

OAs are built from neighbouring postcode which are within the same ward. In Scotland OAs depend only on geography, while in England, Wales, and Northern Ireland levels of socio-demographic homogeneity and levels of rural- and urbanity are also considered (ONS, n.d.).

Higher level geographies are clusters of OAs, and thus have lower levels of socio-demographic homogeneity. They are made to fit within SOAs (ONS, n.d.). Whereas Scottish DZs and IGs are roughly equivalent to English and Welsh LSOAs and MSOA, respectively, Northern Irish SOAs are comparable to LSOAs. Where MSOA level aggregation is done, therefore, this research uses ward level data for Northern Ireland as an additional, higher-level geography.

Table Appendix 1. Population ranges of 2011 UK census geographies.

Territory	Geography	Minimum	Maximum
England, Wales	OA	100	625
	LSOA	1,000	3,000
	MSOA	5,000	15,000
Northern Ireland	OA (2001 census)	100	700
	SA	100	1,500
	SOA	800	4,000
	Ward	950	9,000
Scotland	OA	50	500
	DZ	400	1,500
	IG	1,900	7,500

** Note: To round and remove extreme outliers, <1% of values are removed. Sources: ONS (n.d.), NISRA (2013b), and Scotland's Census (2013).

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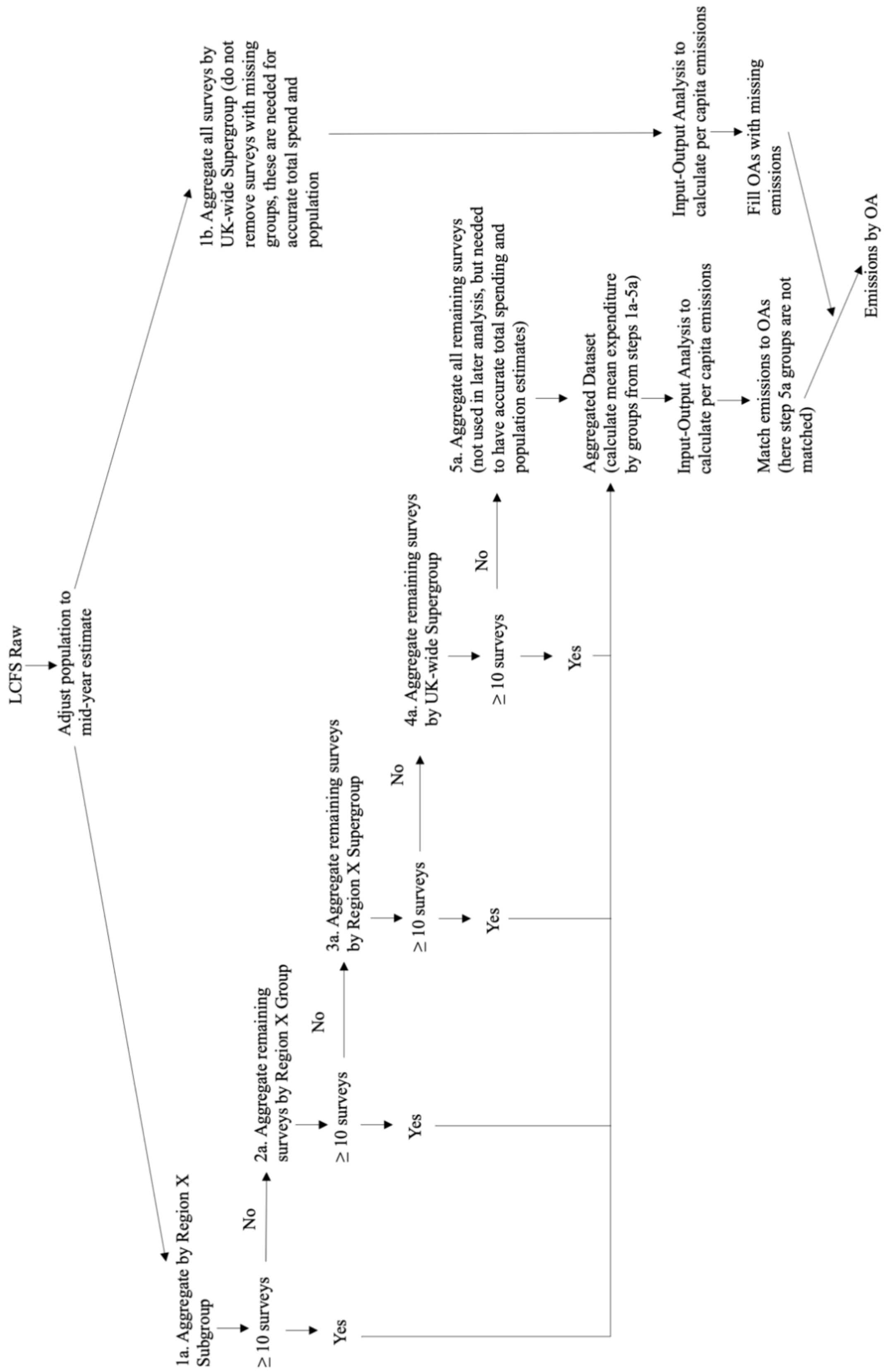
Appendix C: Figure: Aggregation of the LCFS into groups representing geographic areas.



Appendix D. Table: COICOP Codes and Descriptions

Food and non-alcoholic beverages (1)

COICOP 2		COICOP 3	
1.1	Food	1.1.1	Bread, rice, and cereals
		1.1.2	Pasta products
		1.1.3	Buns, cakes, biscuits etc
		1.1.4	Pastry (savoury)
		1.1.5	Beef (fresh, chilled, or frozen)
		1.1.6	Pork (fresh, chilled, or frozen)
		1.1.7	Lamb (fresh, chilled, or frozen)
		1.1.8	Poultry (fresh, chilled, or frozen)
		1.1.9	Bacon and ham
		1.1.10	Other meat and meat preparations
		1.1.11	Fish and fish products
		1.1.12	Milk
		1.1.13	Cheese and curd
		1.1.14	Eggs
		1.1.15	Other milk products
		1.1.16	Butter
		1.1.17	Margarine, other vegetable fats and peanut butter
		1.1.18	Cooking oils and fats
		1.1.19	Fresh fruit
		1.1.20	Other fresh, chilled, or frozen fruits
		1.1.21	Dried fruit and nuts
		1.1.22	Preserved fruit and fruit-based products
		1.1.23	Fresh vegetables
		1.1.24	Dried vegetables
		1.1.25	Other preserved or processed vegetables
		1.1.26	Potatoes
		1.1.27	Other tubers and products of tuber vegetables
		1.1.28	Sugar and sugar products
		1.1.29	Jams, marmalades
		1.1.30	Chocolate
		1.1.31	Confectionery products
		1.1.32	Edible ices and ice cream
		1.1.33	Other food products
1.2	Non-alcoholic beverages	1.2.1	Coffee
		1.2.2	Tea
		1.2.3	Cocoa and powdered chocolate
		1.2.4	Fruit and vegetable juices (inc. fruit squash)
		1.2.5	Mineral or spring waters
		1.2.6	Soft drinks (inc. fizzy and ready to drink fruit drinks)

Alcoholic beverages, tobacco, and narcotics (2)

COICOP 2		COICOP 3	
2.1	Alcoholic beverages	2.1.1	Spirits and liqueurs (brought home)
		2.1.2	Wines, fortified wines (brought home)
		2.1.3	Beer, lager, ciders and perry (brought home)
		2.1.4	Alcopops (brought home)
2.2	Tobacco and narcotics	2.2.1	Cigarettes
		2.2.2	Cigars, other tobacco products and narcotics

Clothing and footwear (3)

COICOP 2		COICOP 3	
3.1	Clothing	3.1.1	Men's outer garments

		3.1.2	Men's under garments
		3.1.3	Women's outer garments
		3.1.4	Women's under garments
		3.1.5	Boys' outer garments (5-15)
		3.1.6	Girls' outer garments (5-15)
		3.1.7	Infants' outer garments (under 5)
		3.1.8	Children's under garments (under 16)
		3.1.9	Accessories
		3.1.10	Haberdashery, clothing materials and clothing hire
		3.1.11	Dry cleaners, laundry and dyeing
3.2	Footwear	3.2	Footwear

Housing, water, electricity, gas and other fuels (4)

COICOP 2		COICOP 3	
4.1	Rentals for housing	4.1.1	Actual rentals
		4.1.2	Imputed rent
4.2	Maintenance, repair, and security of the dwelling	4.2	Maintenance, repair, and security of the dwelling
4.3	Water supply and miscellaneous services relating to the dwelling	4.3	Water supply and miscellaneous services relating to the dwelling
4.4	Electricity, gas, and other fuels	4.4.1	Electricity
		4.4.2	Gas
		4.4.3	Other fuels

Furnishings, household equipment and routine household maintenance (5)

COICOP 2		COICOP 3	
5.1	Furniture, furnishings, and loose carpets	5.1.1	Furniture and furnishings
		5.1.2	Floor coverings
5.2	Household textiles	5.2	Household textiles
5.3	Household appliances	5.3	Household appliances
5.4	Glassware, tableware, and household utensils	5.4	Glassware, tableware, and household utensils
5.5	Tools and equipment for house and garden	5.5	Tools and equipment for house and garden
5.6	Goods and services for routine household maintenance	5.6.1	Cleaning materials
		5.6.2	Household goods and hardware
		5.6.3	Domestic services, carpet cleaning, hire of furniture/furnishings

Health (6)

COICOP 2		COICOP 3	
6.1	Medicines and health products	6.1.1	Medicines, prescriptions, and healthcare products
		6.1.2	Spectacles, lenses, accessories, and repairs
6.2	Outpatient care services	6.2	Hospital services

Transport (7)

COICOP 2		COICOP 3	
7.1	Purchase of vehicles	7.1.1	Purchase of new cars and vans
		7.1.2	Purchase of second hand cars or vans
		7.1.3	Purchase of motorcycles and other vehicles
7.2	Operation of personal transport equipment	7.2.1	Spares and accessories
		7.2.2	Petrol, diesel, and other motor oils
		7.2.3	Repairs and servicing
		7.2.4	Other motoring costs
7.3	Passenger transport services	7.3.1	Rail and tube fares
		7.3.2	Bus and coach fares
		7.3.3	Combined fares

		7.3.4	Other travel and transport

Information and communication (8)

COICOP 2		COICOP 3	
8.1	Postal services	8.1	Postal services
8.2	Telephone and telefax equipment	8.2	Telephone and telefax equipment
8.3	Telephone and telefax services	8.3	Telephone and telefax services
8.4	Internet subscription fees	8.4	Internet subscription fees

Recreation, sport and culture (9)

COICOP 2		COICOP 3	
9.1	Recreational durables	9.1.1	Audio equipment and accessories, CD players
		9.1.2	TV, video, and computers
		9.1.3	Photographic, cine and optical equipment
9.2	Other major durables for recreation and culture	9.2	Other major durables for recreation and culture
9.3	Hobbies and pets	9.3.1	Games, toys, and hobbies
		9.3.2	Computer software and games
		9.3.3	Equipment for sport, camping and open-air recreation
		9.3.4	Horticultural goods, garden equipment and plants
		9.3.5	Pets and pet food
9.4	Recreational services	9.4.1	Sports admissions, subscriptions, leisure class fees
		9.4.2	Cinema, theatre, and museums
		9.4.3	TV, video, satellite rental, cable subscriptions
		9.4.4	Miscellaneous entertainments
		9.4.5	Development of film, deposit for film development
		9.4.6	Gambling payments
9.5	Newspapers, books and stationery	9.5.1	Books
		9.5.2	Diaries, address books, cards etc
		9.5.3	Diaries, address books, cards etc
		9.5.4	Newspapers
		9.5.5	Magazines and periodicals

Education services (10)

COICOP 2		COICOP 3	
10.1	Education fees	10.1	Education fees
10.2	Payments for school trips, other ad-hoc	10.2	Payments for school trips, other ad-hoc

Restaurants and accommodation services (11)

COICOP 2		COICOP 3	
11.1	Food and beverage serving services	11.1.1	Restaurant and café meals
		11.1.2	Alcoholic drinks (away from home)
		11.1.3	Take away meals eaten at home
		11.1.4	Other take-away and snack food
		11.1.5	Contract catering (food) and canteens
11.2	Accommodation services	11.2.1	Holiday in the UK
		11.2.2	Holiday abroad
		11.2.3	Room hire

Other Miscellaneous Products and Services (12)

COICOP 2		COICOP 3	
12.1	Personal care	12.1.1	Hairdressing, beauty treatment
		12.1.2	Toilet paper
		12.1.3	Toiletries and soap
		12.1.4	Baby toiletries and accessories (disposable)

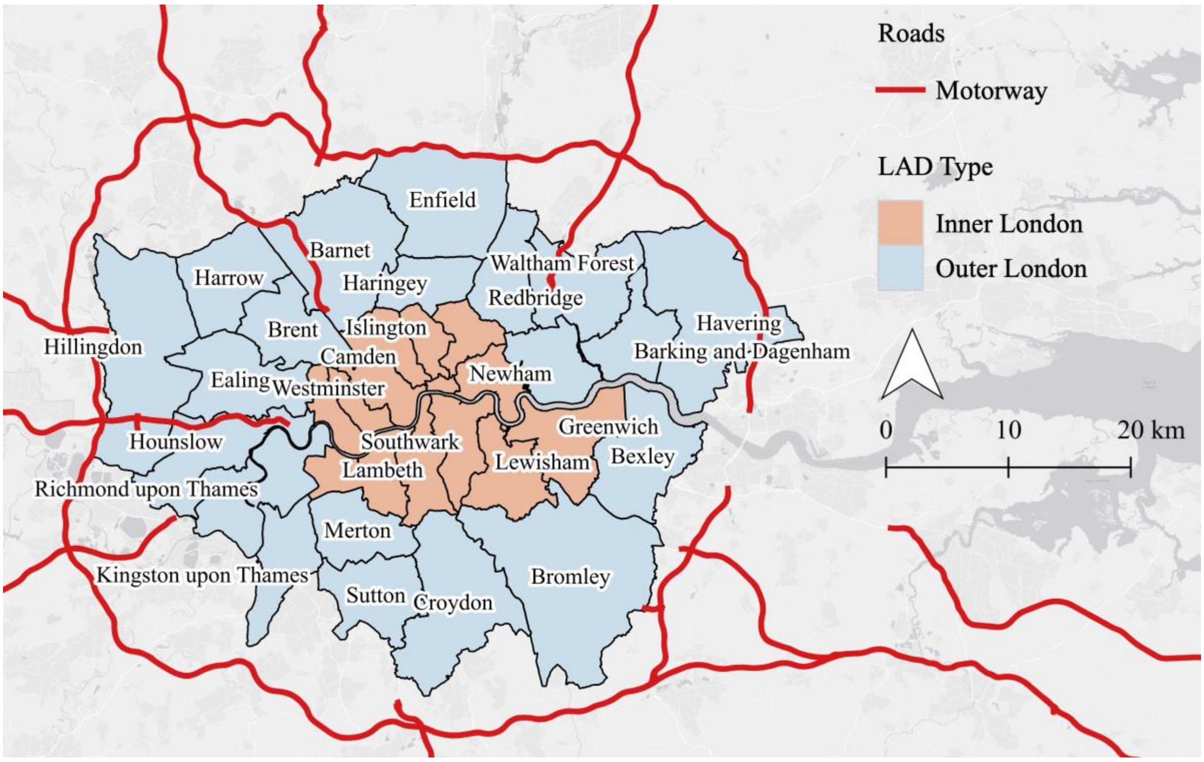
		12.1.5	Hair products, cosmetics, and related electrical appliances
12.2	Other personal effects	12.2	Personal effects
12.3	Social protection	12.3	Social protection
12.4	Insurance	12.4.1	Household insurances - structural, contents
		12.4.2	Medical insurance premiums
		12.4.3	Vehicle insurance including boat insurance
		12.4.4	Non-package holiday, other travel insurance
12.5	Other Products and Services	12.5.1	Moving house
		12.5.2	Bank, building society, post office, credit card charges
		12.5.3	Other services and professional fees

Appendices Chapter 3

Appendix E. Table: Product aggregation description from COICOP 4.

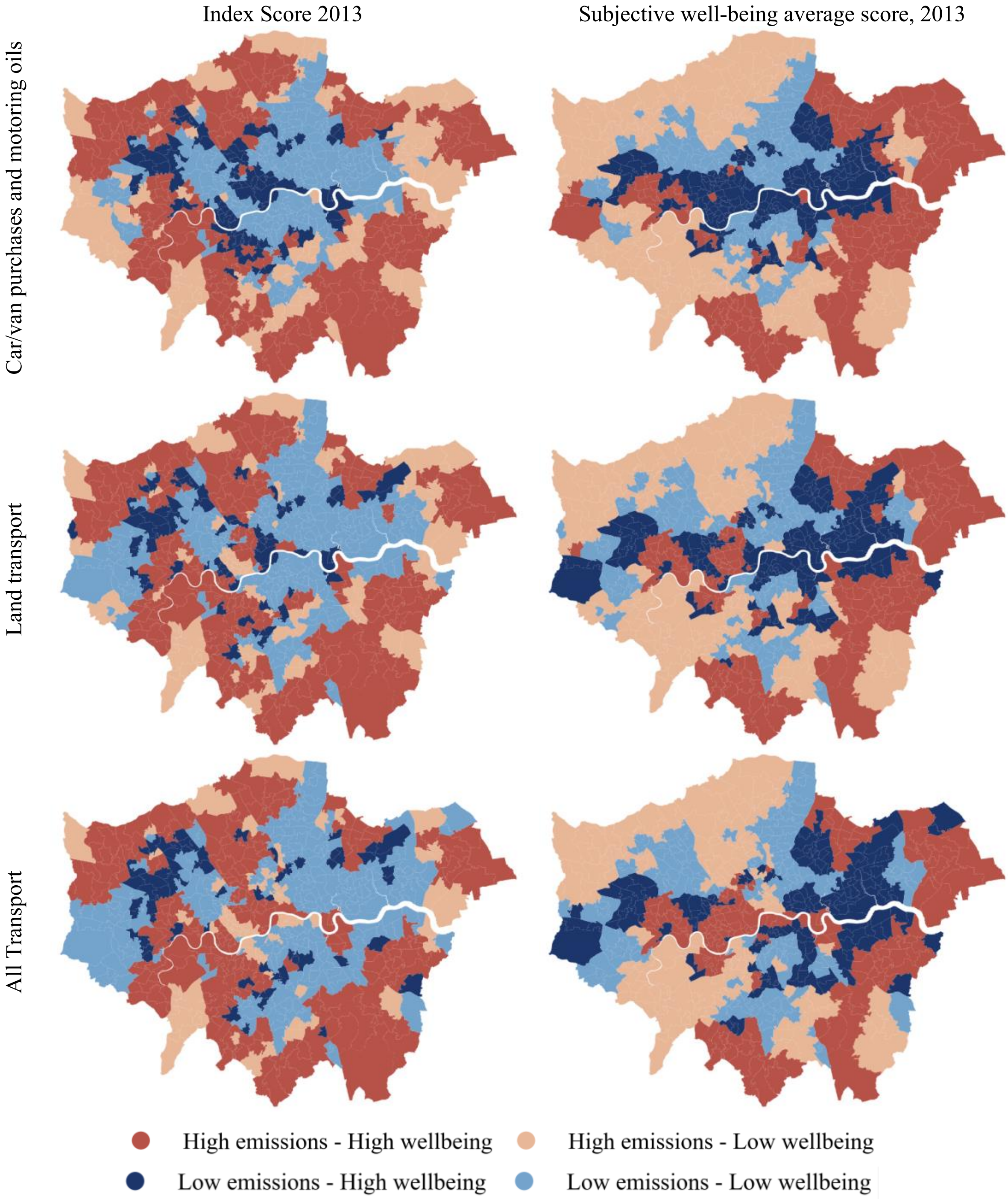
COICOP 4 Code and Description	New Category
7.1.1.1 New cars/vans outright purchase	Car/van purchases and motoring oils
7.1.1.2 New cars/vans loan/HP purchase	Car/van purchases and motoring oils
7.1.2.1 Second-hand cars/vans outright purchase	Car/van purchases and motoring oils
7.1.2.2 Second-hand cars/vans loan/HP purchase	Car/van purchases and motoring oils
7.1.3.1 Outright purchase of new or second-hand motorcycles	Car/van purchases and motoring oils
7.1.3.2 Loan/HP purchase of new or second-hand motorcycles	Car/van purchases and motoring oils
7.1.3.3 Purchase of bicycles and other vehicles	Other transport
7.2.1.1 Can/van accessories and fittings	Car/van purchases and motoring oils
7.2.1.2 Car/van spare parts	Car/van purchases and motoring oils
7.2.1.3 Motorcycle accessories and spare parts	Car/van purchases and motoring oils
7.2.1.4 Bicycle accessories and spare parts	Other transport
7.2.2.1 Petrol	Car/van purchases and motoring oils
7.2.2.2 Diesel oil	Car/van purchases and motoring oils
7.2.2.3 Other motor oils	Car/van purchases and motoring oils
7.2.3.1 Car of van repairs, servicing and other work	Other transport
7.2.3.2 Motorcycle repairs and servicing	Other transport
7.2.4.1 Motoring organisation subscription	Other transport
7.2.4.2 Garage rent other costs, car washing	Other transport
7.2.4.3 Parking fees, tolls and permits	Other transport
7.2.4.4 Driving lessons	Other transport
7.2.4.5 Anti-freeze, battery water, cleaning materials	Other transport
7.3.1.1 Rail and tube season tickets	Rail
7.3.1.2 Rail and tube other than season tickets	Rail
7.3.2.1 Bus and coach season tickets	Bus
7.3.2.2 Bus and coach other than season tickets	Bus
7.3.3.1 Combined fares other than season tickets	Combined fares
7.3.3.2 Combined fares season tickets	Combined fares
7.3.4.1 Air fares within UK	Flights
7.3.4.2 Air fares international	Flights
7.3.4.3 School travel	Other transport
7.3.4.4 Taxis and hired cars with drivers	Other transport
7.3.4.5 Other personal travel and transport services	Other transport
7.3.4.6 Hire of self drive cars, vans, bicycles	Other transport
7.3.4.7 Car leasing	Car/van purchases and motoring oils
7.3.4.8 Water travel, ferries and season tickets	Other transport

Appendix F. Figure: Map of motorways in London.



Notes: Road data come from OpenStreetMap, downloaded via https://www.geofabrik.de (accessed on 14 February 2022).

Appendix G. Figure: Maps showing spatial above and below median emission and well-being patterns.



Appendices Chapter 4

Appendix H. Table: Product-level matching of LCFS expenditures to the Consumer Price Inflation tables.

COICOP		Match For Years 2001-2014	Match For Years 2015 And Later
Code	Description	CPI COICOP 3	CPI COICOP 4
1.1.1.1	Rice	01.1.1 Bread & Cereals	01.1.1.1 Rice
1.1.1.2	Bread	01.1.1 Bread & Cereals	01.1.1.3 Bread
1.1.1.3	Other breads & cereals	01.1.1 Bread & Cereals	01.1.1.2 Flours & Other Cereals
1.1.2	Pasta products	01.1.1 Bread & Cereals	01.1.1.6 Pasta Products & Couscous
1.1.3.1	Buns, crispbread & biscuits	01.1.1 Bread & Cereals	01.1.1.4 Other Bakery Products
1.1.3.2	Cakes & puddings	01.1.1 Bread & Cereals	01.1.1.4 Other Bakery Products
1.1.4	Pastry (savoury)	01.1.1 Bread & Cereals	01.1.1.4 Other Bakery Products
1.1.5	Beef	01.1.2 Meat	01.1.2.1 Beef & Veal
1.1.6	Pork	01.1.2 Meat	01.1.2.2 Pork
1.1.7	Lamb	01.1.2 Meat	01.1.2.3 Lamb & Goat
1.1.8	Poultry	01.1.2 Meat	01.1.2.4 Poultry
1.1.9	Bacon & ham	01.1.2 Meat	01.1.2.8 Other Meat Preparations
1.1.10.1	Sausages	01.1.2 Meat	01.1.2.8 Other Meat Preparations
1.1.10.2	Offal, pate etc	01.1.2 Meat	01.1.2.6 Edible Offal
1.1.10.3	Other preserved/processed meat & meat preparations	01.1.2 Meat	01.1.2.7 Dried, Salted or Smoked Meat
1.1.10.4	Other meat	01.1.2 Meat	01.1.2.8 Other Meat Preparations
1.1.11.1	Fish	01.1.3 Fish	01.1.3.1 Fresh or Chilled Fish
1.1.11.2	Seafood, dried, smoked or salted fish	01.1.3 Fish	01.1.3.4 Frozen Seafood
1.1.11.3	Other preserved or processed fish & seafood	01.1.3 Fish	01.1.3.6 Other Preserved Processed Fish & Seafood-Based Prep
1.1.12.1	Whole milk	01.1.4 Milk, Cheese & Eggs	01.1.4.1 Whole Milk
1.1.12.2	Low fat milk	01.1.4 Milk, Cheese & Eggs	01.1.4.2 Low Fat Milk
1.1.12.3	Preserved milk	01.1.4 Milk, Cheese & Eggs	01.1.4 Milk, Cheese & Eggs
1.1.13	Cheese & curd	01.1.4 Milk, Cheese & Eggs	01.1.4.5 Cheese & Curd
1.1.14	Eggs	01.1.4 Milk, Cheese & Eggs	01.1.4.7 Eggs
1.1.15.1	Other milk products	01.1.4 Milk, Cheese & Eggs	01.1.4.6 Other Milk Products
1.1.15.2	Yoghurt	01.1.4 Milk, Cheese & Eggs	01.1.4.4 Yoghurt
1.1.16	Butter	01.1.5 Oils & Fats	01.1.5.1 Butter
1.1.17	Margarine & other vegetable fats & peanut butter	01.1.5 Oils & Fats	01.1.5.2 Margarine & Other Vegetable Fats
1.1.18.1	Olive oil	01.1.5 Oils & Fats	01.1.5.3 Olive Oil
1.1.18.2	Edible oils & other animal fats	01.1.5 Oils & Fats	01.1.5 Oils & Fats
1.1.19.1	Citrus fruits	01.1.6 Fruit	01.1.6.1 Fresh or Chilled Fruit
1.1.19.2	Bananas	01.1.6 Fruit	01.1.6.1 Fresh or Chilled Fruit
1.1.19.3	Apples	01.1.6 Fruit	01.1.6.1 Fresh or Chilled Fruit
1.1.19.4	Pears	01.1.6 Fruit	01.1.6.1 Fresh or Chilled Fruit
1.1.19.5	Stone fruits	01.1.6 Fruit	01.1.6.1 Fresh or Chilled Fruit
1.1.19.6	Berries	01.1.6 Fruit	01.1.6.1 Fresh or Chilled Fruit
1.1.20	Other fruits	01.1.6 Fruit	01.1.6.1 Fresh or Chilled Fruit
1.1.21	Dried fruit & nuts	01.1.6 Fruit	01.1.6.3 Dried Fruit & Nuts
1.1.22	Preserved fruit & fruit based products	01.1.6 Fruit	01.1.6.4 Preserved Fruit & Fruit-Based Products
1.1.23.1	Leaf & stem vegetables	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.1 Fresh or Chilled Vegetables Other Than Potatoes & Other Tubers

1.1.23.2	Cabbages	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.1 Fresh or Chilled Vegetables Other Than Potatoes & Other Tubers
1.1.23.3	Vegetables grown for their fruit	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.1 Fresh or Chilled Vegetables Other Than Potatoes & Other Tubers
1.1.23.4	Root crops, non starchy bulbs & mushrooms	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.1 Fresh or Chilled Vegetables Other Than Potatoes & Other Tubers
1.1.24	Dried vegetables	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.3 Dried Vegetables, Other Preserved or Processed Vegetables
1.1.25	Other prepared or processed vegetables	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.2 Frozen Vegetables Other Than Potatoes & Other Tubers
1.1.26	Potatoes	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.4 Potatoes
1.1.27	Other tubers & products of tuber vegetables	01.1.7 Vegetables Including Potatoes & Other Tubers	01.1.7.6 Other Tubers & Products Of Tuber Vegetables
1.1.28.1	Sugar	01.1.8 Sugar, Jam, Honey, Syrups, Chocolate & Confectionery	01.1.8.1 Sugar
1.1.28.2	Other sugar products	01.1.8 Sugar, Jam, Honey, Syrups, Chocolate & Confectionery	01.1.8.1 Sugar
1.1.29	Jams & marmalades	01.1.8 Sugar, Jam, Honey, Syrups, Chocolate & Confectionery	01.1.8.2 Jams, Marmalades & Honey
1.1.30	Chocolate	01.1.8 Sugar, Jam, Honey, Syrups, Chocolate & Confectionery	01.1.8.3 Chocolate
1.1.31	Confectionery products	01.1.8 Sugar, Jam, Honey, Syrups, Chocolate & Confectionery	01.1.8.4 Confectionery Products
1.1.32	Edible ices & ice cream	01.1.8 Sugar, Jam, Honey, Syrups, Chocolate & Confectionery	01.1.8.5 Edible Ices & Ice Cream
1.1.33.1	Sauces, condiments	01.1.9 Food Products	01.1.9.1/2 Sauces, Condiments, Salt, Spices & Culinary Herbs
1.1.33.2	Bakers yeast, dessert preparations, soups	01.1.9 Food Products	01.1.9.9 Other Food Products
1.1.33.3	Salt, spices, herbs & other food products	01.1.9 Food Products	01.1.9.9 Other Food Products
1.2.1	Coffee	01.2.1 Coffee, Tea, Cocoa	01.2.1.1 Coffee
1.2.2	Tea	01.2.1 Coffee, Tea, Cocoa	01.2.1.2 Tea
1.2.3	Cocoa & powdered chocolate	01.2.1 Coffee, Tea, Cocoa	01.2.1.3 Cocoa & Powdered Chocolate
1.2.4	Fruit & vegetable juices	01.2.2 Mineral Waters, Soft Drinks & Juices	01.2.2.3 Fruit & Vegetable Juices
1.2.5	Mineral or spring waters	01.2.2 Mineral Waters, Soft Drinks & Juices	01.2.2.1 Mineral or Spring Waters
1.2.6	Soft drinks	01.2.2 Mineral Waters, Soft Drinks & Juices	01.2.2.2 Soft Drinks
2.1.1	Spirits & liqueurs	02.1.1 Spirits	02.1.1 Spirits
2.1.2.1	Wine from grape or other fruit	02.1.2 Wine	02.1.2 Wine
2.1.2.2	Fortified wine	02.1.2 Wine	02.1.2.3 Fortified Wines
2.1.2.3	Champagne & sparkling wines	02.1.2 Wine	02.1.2 Wine
2.1.3.1	Beer & lager	02.1.3 Beer	02.1.3 Beer
2.1.3.2	Ciders & Perry	02.1.3 Beer	02.1.3 Beer
2.1.4	Alcopops	02.1 Alcoholic Beverages	02.1 Alcoholic Beverages

2.2.1	Cigarettes	02.2 Tobacco	02.2.0.1 Cigarettes
2.2.2.1	Cigars	02.2 Tobacco	02.2.0.2 Cigars
2.2.2.2	Other tobacco	02.2 Tobacco	02.2.0.3 Other Tobacco Products
3.1.1	Men's outer garments	03.1.2 Garments	03.1.2.1 Garments For Men
3.1.2	Men's under garments	03.1.2 Garments	03.1.2.1 Garments For Men
3.1.3	Women's outer garments	03.1.2 Garments	03.1.2.2 Garments For Women
3.1.4	Women's under garments	03.1.2 Garments	03.1.2.2 Garments For Women
3.1.5	Boys outer garments	03.1.2 Garments	03.1.2.3 Garments For Infants (0-2 Yrs) & Children (3-13 Yrs)
3.1.6	Girls outer garments	03.1.2 Garments	03.1.2.3 Garments For Infants (0-2 Yrs) & Children (3-13 Yrs)
3.1.7	Infants outer garments	03.1.2 Garments	03.1.2.3 Garments For Infants (0-2 Yrs) & Children (3-13 Yrs)
3.1.8	Children's under garments	03.1.2 Garments	03.1.2.3 Garments For Infants (0-2 Yrs) & Children (3-13 Yrs)
3.1.9.1	Men's accessories	03.1.3 :Other Articles Of Clothing & Accessories	03.1.3.2 Clothing Accessories
3.1.9.2	Women's accessories	03.1.3 :Other Articles Of Clothing & Accessories	03.1.3.2 Clothing Accessories
3.1.9.3	Children's accessories	03.1.3 :Other Articles Of Clothing & Accessories	03.1.3.2 Clothing Accessories
3.1.9.4	Protective head gear	03.1.3 :Other Articles Of Clothing & Accessories	03.1.3.1 Other Articles Of Clothing
3.1.10	Haberdashery, clothing materials & clothing hire	03.1.4 Cleaning, Repair & Hire Of Clothing	03.1.4 Cleaning, Repair & Hire Of Clothing
3.1.11.1	Dry cleaners & dyeing	03.1.4 Cleaning, Repair & Hire Of Clothing	03.1.4 Cleaning, Repair & Hire Of Clothing
3.1.11.2	Laundry, laundrettes	03.1.4 Cleaning, Repair & Hire Of Clothing	03.1.4 Cleaning, Repair & Hire Of Clothing
3.2.1	Footwear for men	03.2 Footwear Including Repairs	03.2.1.1 Footwear For Men
3.2.2	Footwear for women	03.2 Footwear Including Repairs	03.2.1.2 Footwear For Women
3.2.3	Footwear for children & infants	03.2 Footwear Including Repairs	03.2.1.3 Footwear For Infants & Children
3.2.4	Repair & hire of footwear	03.2 Footwear Including Repairs	03.2 Footwear Including Repairs
4.1.1	Actual rentals	04.1 Actual Rents For Housing	04.1 Actual Rents For Housing
4.1.2	Imputed rent	04.1 Actual Rents For Housing	04.1 Actual Rents For Housing
4.2.1	Central heating repairs	04.3 Regular Maintenance & Repair Of The Dwelling	04.3 Regular Maintenance & Repair Of The Dwelling
4.2.2	House maintenance	04.3 Regular Maintenance & Repair Of The Dwelling	04.3 Regular Maintenance & Repair Of The Dwelling
4.2.3	Paint, wallpaper, timber	04.3 Regular Maintenance & Repair Of The Dwelling	04.3 Regular Maintenance & Repair Of The Dwelling
4.2.4	Equipment hire, small materials	04.3 Regular Maintenance & Repair Of The Dwelling	04.3 Regular Maintenance & Repair Of The Dwelling
4.3.1	Water charges	04.4.1 Water Supply	04.4.1 Water Supply
4.3.2	Other regular housing payments incl service charge for rent	04.4 Water Supply & Misc. Services For The Dwelling	04.4 Water Supply & Misc. Services For The Dwelling
4.3.3	Refuse collection including skip hire	04.4 Water Supply & Misc. Services For The Dwelling	04.4 Water Supply & Misc. Services For The Dwelling
4.4.1	Electricity	04.5.1 Electricity	04.5.1 Electricity
4.4.2	Gas	04.5.2 Gas	04.5.2 Gas
4.4.3.1	Coal & coke	04.5.4 Solid Fuels	04.5.4 Solid Fuels
4.4.3.2	Oil for central heating	04.5.3 Liquid Fuels	04.5.3 Liquid Fuels

4.4.3.3	Paraffin, weed, peat, hot water etc	04.5 Electricity, Gas & Other Fuels	04.5 Electricity, Gas & Other Fuels
5.1.1.1	Furniture	05.1.1 Furniture & Furnishings	05.1.1.1 Household Furniture
5.1.1.2	Fancy/decorative goods	05.1.1 Furniture & Furnishings	05.1.1 Furniture & Furnishings
5.1.1.3	Garden furniture	05.1.1 Furniture & Furnishings	05.1.1.2 Garden Furniture
5.1.2.1	Soft floor coverings	05.1 Furniture, Furnishings & Carpets	05.1.2.1 Carpets & Rugs
5.1.2.2	Hard floor coverings	05.1 Furniture, Furnishings & Carpets	05.1.2.2 Other Floor Coverings
5.2.1	Bedroom textiles including duvets & pillows	05.2 Household Textiles	05.2.0.2 Bed Linen
5.2.2	Other household textiles, including cushions, towels, curtains	05.2 Household Textiles	05.2 Household Textiles
5.3.1	Gas cookers	05.3.1/2 Major Appliances & Small Electric Goods	05.3.1.3 Cookers
5.3.2	Electric cookers, combined gas/electric cookers	05.3.1/2 Major Appliances & Small Electric Goods	05.3.1.3 Cookers
5.3.3	Clothes washing machines & clothes drying machines	05.3.1/2 Major Appliances & Small Electric Goods	05.3.1.2 Clothes Washing Machines, Clothes Drying Machines & Dish Washing Machines
5.3.4	Refrigerators, freezers & fridge freezers	05.3.1/2 Major Appliances & Small Electric Goods	05.3.1.1 Refrigerators, Freezers & Fridge Freezers
5.3.5	Other major electrical appliances e.g. dish washers, microwaves, vacuum cleaners, heaters	05.3.1/2 Major Appliances & Small Electric Goods	05.3.1/2 Major Appliances & Small Electric Goods
5.3.6	Fire extinguishers	05.3.1/2 Major Appliances & Small Electric Goods	05.3.1/2 Major Appliances & Small Electric Goods
5.3.7	Small electric household appliances	05.3.1/2 Major Appliances & Small Electric Goods	05.3.1/2 Major Appliances & Small Electric Goods
5.3.8	Spare parts for appliances & repairs	05.3 Household Appliances, Fitting & Repairs	05.3 Household Appliances, Fitting & Repairs
5.3.9	Rental/hire of major hhold appliances	05.3 Household Appliances, Fitting & Repairs	05.3 Household Appliances, Fitting & Repairs
5.4.1	Glassware, china, pottery, cutlery & silverware	05.4 Glassware, Tableware & Household Utensils	05.4 Glassware, Tableware & Household Utensils
5.4.2	Kitchen & domestic utensils	05.4 Glassware, Tableware & Household Utensils	05.4.0.3 Non-Electric Kitchen Utensils & Articles
5.4.3	Repair of glassware, tableware & household utensils	05.4 Glassware, Tableware & Household Utensils	05.4 Glassware, Tableware & Household Utensils
5.4.4	Storage & other durable household articles	05.4 Glassware, Tableware & Household Utensils	05.4 Glassware, Tableware & Household Utensils
5.5.1	Electrical tools	05.5 Tools & Equipment For House & Garden	05.5 Tools & Equipment For House & Garden
5.5.2	Garden tools, equipment & accessories	05.5 Tools & Equipment For House & Garden	05.5 Tools & Equipment For House & Garden
5.5.3	Small tools	05.5 Tools & Equipment For House & Garden	05.5 Tools & Equipment For House & Garden
5.5.4	Door, electrical & other fittings	05.5 Tools & Equipment For House & Garden	05.5 Tools & Equipment For House & Garden
5.5.5	Electrical consumables	05.5 Tools & Equipment For House & Garden	05.5 Tools & Equipment For House & Garden
5.6.1.1	Detergents, washing-up liquid, washing powder	05.6.1 Non-Durable Household Goods	05.6.1 Non-Durable Household Goods

5.6.1.2	Disinfectants, polishes, other cleaning materials, some pest controls	05.6.1 Non-Durable Household Goods	05.6.1 Non-Durable Household Goods
5.6.2.1	Kitchen disposables	05.6.1 Non-Durable Household Goods	05.6.1 Non-Durable Household Goods
5.6.2.2	Household handwear & appliances, matches	05.6.1 Non-Durable Household Goods	05.6.1 Non-Durable Household Goods
5.6.2.3	Kitchen gloves, cloths etc	05.6.1 Non-Durable Household Goods	05.6.1 Non-Durable Household Goods
5.6.2.4	Pins, needles, tape measures, nails, nuts & bolts	05.6.1 Non-Durable Household Goods	05.6.1 Non-Durable Household Goods
5.6.3.1	Domestic services including cleaners, gardeners, au pairs	05.6.2 Domestic Services & Household Services	05.6.2 Domestic Services & Household Services
5.6.3.2	Carpet cleaning , ironing service & window cleaner	05.6.2 Domestic Services & Household Services	05.6.2 Domestic Services & Household Services
5.6.3.3	Hire/repair of household furniture & furnishings	05.6.2 Domestic Services & Household Services	05.6.2 Domestic Services & Household Services
6.1.1.1	NHS prescription charges & payments	06.1.1 Pharmaceutical Products	06.1.1 Pharmaceutical Products
6.1.1.2	Medicines & medical goods (not NHS)	06.1.1 Pharmaceutical Products	06.1.1 Pharmaceutical Products
6.1.1.3	Other medical products	06.1.2/3 Other Medical & Therapeutic Equipment	06.1.2/3 Other Medical & Therapeutic Equipment
6.1.1.4	Non-optical appliances & equipment	06.1.2/3 Other Medical & Therapeutic Equipment	06.1.2/3 Other Medical & Therapeutic Equipment
6.1.2.1	Purchase of spectacles, lenses, prescription sunglasses	06.1.2/3 Other Medical & Therapeutic Equipment	06.1.3.1 Corrective Eye-Glasses & Contact Lenses
6.1.2.2	Accessories/repairs to spectacles/lenses	06.1.2/3 Other Medical & Therapeutic Equipment	06.1.3.1 Corrective Eye-Glasses & Contact Lenses
6.2.1.1	NHS medical, optical, dental & medical auxiliary services	06.2.1/3 Medical Services & Paramedical Services:	06.2.1/3 Medical Services & Paramedical Services:
6.2.1.2	Private medical, optical, dental & auxiliary services	06.2.1/3 Medical Services & Paramedical Services:	06.2.1/3 Medical Services & Paramedical Services:
6.2.1.3	Other services	06.2.1/3 Medical Services & Paramedical Services:	06.2.1/3 Medical Services & Paramedical Services:
6.2.2	In-patient hospital services	06.3 Hospital Services	06.3 Hospital Services
7.1.1.1	New cars/vans outright purchase	07.1.1a New Cars	07.1.1a New Cars
7.1.1.2	New cars/vans loan/HP purchase	07.1.1a New Cars	07.1.1a New Cars
7.1.2.1	Secondhand cars/vans outright purchase	07.1.1b Second-Hand Cars	07.1.1b Second-Hand Cars
7.1.2.2	Secondhand cars/vans loan/HP purchase	07.1.1b Second-Hand Cars	07.1.1b Second-Hand Cars
7.1.3.1	Outright purchase of new or secondhand motorcycles	07.1.2/3 Motor Cycles & Bicycles	07.1.2.0 Motor Cycles
7.1.3.2	Loan/HP purchase of new or secondhand motor cycles	07.1.2/3 Motor Cycles & Bicycles	07.1.2.0 Motor Cycles
7.1.3.3	Purchase of bicycles & other vehicles	07.1.2/3 Motor Cycles & Bicycles	07.1.3.0 Bicycles
7.2.1.1	Can/van accessories & fittings	07.2.1 Spare Parts & Accessories	07.2.1 Spare Parts & Accessories
7.2.1.2	Car/van spare parts	07.2.1 Spare Parts & Accessories	07.2.1 Spare Parts & Accessories
7.2.1.3	Motorcycle accessories & spare parts	07.2.1 Spare Parts & Accessories	07.2.1 Spare Parts & Accessories

7.2.1.4	Bicycle accessories & spare parts	07.2.1 Spare Parts & Accessories	07.2.1 Spare Parts & Accessories
7.2.2.1	Petrol	07.2.2 Fuels & Lubricants	07.2.2.2 Petrol
7.2.2.2	Diesel oil	07.2.2 Fuels & Lubricants	07.2.2.1 Diesel
7.2.2.3	Other motor oils	07.2.2 Fuels & Lubricants	07.2.2 Fuels & Lubricants
7.2.3.1	Car of van repairs, servicing & other work	07.2.3 Maintenance & Repairs	07.2.3 Maintenance & Repairs
7.2.3.2	Motor cycle repairs & servicing	07.2.3 Maintenance & Repairs	07.2.3 Maintenance & Repairs
7.2.4.1	Motoring organisation subscription	07.2.4 Other Services	07.2.4 Other Services
7.2.4.2	Garage rent other costs, car washing	07.2.4 Other Services	07.2.4.1 Hire Of Garages, Parking Spaces & Personal Transport Equipment
7.2.4.3	Parking fees, tolls & permits	07.2.4 Other Services	07.2.4.2 Toll Facilities & Parking Meters
7.2.4.4	Driving lessons	07.2.4 Other Services	07.2.4.3 Driving Lessons, Test Licences & Road Worthiness Test
7.2.4.5	Anti-freeze, battery water, cleaning materials	07.2 Operation Of Personal Transport Equipment	07.2 Operation Of Personal Transport Equipment
7.3.1.1	Rail & tube season tickets	07.3.1 Passenger Transport By Railway	07.3.1 Passenger Transport By Railway
7.3.1.2	Rail & tube other than season tickets	07.3.1 Passenger Transport By Railway	07.3.1 Passenger Transport By Railway
7.3.2.1	Bus & coach season tickets	07.3.2/6 Passenger Transport By Road & Other Transport Services	07.3.2.1 Passenger Transport By Bus & Coach
7.3.2.2	Bus & coach other than season tickets	07.3.2/6 Passenger Transport By Road & Other Transport Services	07.3.2.1 Passenger Transport By Bus & Coach
7.3.3.1	Combined fares other than season tickets	07.3 Transport Services	07.3 Transport Services
7.3.3.2	Combined fares season tickets	07.3 Transport Services	07.3 Transport Services
7.3.4.1	Air fares within UK	07.3.3 Passenger Transport By Air	07.3.3 Passenger Transport By Air
7.3.4.2	Air fares international	07.3.3 Passenger Transport By Air	07.3.3 Passenger Transport By Air
7.3.4.3	School travel	07.3 Transport Services	07.3 Transport Services
7.3.4.4	Taxis & hired cars with drivers	07.3 Transport Services	07.3.2.2 Passenger Transport By Taxi & Hired Car With Driver
7.3.4.5	Other personal travel & transport services	07.3 Transport Services	07.3 Transport Services
7.3.4.6	Hire of self drive cars, vans, bicycles	07.3 Transport Services	07.3 Transport Services
7.3.4.7	Car leasing	07.3 Transport Services	07.3 Transport Services
7.3.4.8	Water travel, ferries & season tickets	07.3.4 Passenger Transport By Sea & Inland Waterway	07.3.4 Passenger Transport By Sea & Inland Waterway
8.1	Postal services	08.1 Postal Services	08.1 Postal Services
8.2.1	Telephone purchase	08.2/3: Telephone & Telefax Equipment & Services	08.2.0.1 Fixed Telephone Equipment
8.2.2	Mobile phone purchase	08.2/3: Telephone & Telefax Equipment & Services	08.2.0.2 Mobile Telephone Equipment
8.2.3	Answering machine, fax machine purchase	08.2/3: Telephone & Telefax Equipment & Services	08.2/3: Telephone & Telefax Equipment & Services
8.3.1	Telephone account	08.2/3: Telephone & Telefax Equipment & Services	08.3.0.1 Wired Telephone Services
8.3.2	Telephone coin & other payments	08.2/3: Telephone & Telefax Equipment & Services	08.3.0.1 Wired Telephone Services

8.3.3	Mobile phone account	08.2/3: Telephone & Telefax Equipment & Services	08.3.0.2 Wireless Telephone Services
8.3.4	Mobile phone other payments	08.2/3: Telephone & Telefax Equipment & Services	08.3.0.2 Wireless Telephone Services
8.4	Internet subscription fees	08.2/3: Telephone & Telefax Equipment & Services	08.3.0.3 Internet Access Provision Services
9.1.1.1	Audio equipment, CD players incl. in car	09.1.1 Reception & Reproduction Of Sound & Pictures	09.1.1.1 Equipment For The Reception, Recording & Reproduction Of Sound
9.1.1.2	Audio accessories e.g. tapes, CDs, headphones	09.1.1 Reception & Reproduction Of Sound & Pictures	09.1.1.1 Equipment For The Reception, Recording & Reproduction Of Sound
9.1.2.1	Purchase of TV & digital decoder	09.1.1 Reception & Reproduction Of Sound & Pictures	09.1.1.2 Equipment For The Reception, Recording & Reproduction Of Sound & Vision
9.1.2.2	Satellite dish purchase & installation	09.1.1 Reception & Reproduction Of Sound & Pictures	09.1.1.2 Equipment For The Reception, Recording & Reproduction Of Sound & Vision
9.1.2.3	Cable TV connection	09.1.1 Reception & Reproduction Of Sound & Pictures	09.1.1.2 Equipment For The Reception, Recording & Reproduction Of Sound & Vision
9.1.2.4	Video recorder	09.1.1 Reception & Reproduction Of Sound & Pictures	09.1.1.2 Equipment For The Reception, Recording & Reproduction Of Sound & Vision
9.1.2.5	DVD player/recorder	09.1.1 Reception & Reproduction Of Sound & Pictures	09.1.1.2 Equipment For The Reception, Recording & Reproduction Of Sound & Vision
9.1.2.6	Blank, pre-recorded video cassettes & DVDs	09.1.4 Recording Media	09.1.4.1 Pre-Recorded Recording Media
9.1.2.7	Personal computers, printers & calculators	09.1.2 Photographic, Cinematographic & Optical Equipment	09.1.2 Photographic, Cinematographic & Optical Equipment
9.1.2.8	Spare parts for TV, video, audio	09.1.3 Data Processing Equipment	09.1.3.2 Accessories For Information Processing Equipment
9.1.2.9	Repair of AV	09.1.5 Repair Of Audio-Visual Equipment & Related Products	09.1.5 Repair Of Audio-Visual Equipment & Related Products
9.1.3.1	Photographic & cine equipment	09.1.2 Photographic, Cinematographic & Optical Equipment	09.1.2 Photographic, Cinematographic & Optical Equipment
9.1.3.2	Camera films	09.1.2 Photographic, Cinematographic & Optical Equipment	09.1.2 Photographic, Cinematographic & Optical Equipment
9.1.3.3	Optical instruments, binoculars, telescopes	09.1.2 Photographic, Cinematographic & Optical Equipment	09.1.2 Photographic, Cinematographic & Optical Equipment
9.2.1	Purchase of boats, trailers & horses	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance	09.2.1.3 Boats, Outboard Motors & Fitting Out Of Boats
9.2.2	Purchase of caravans, mobile homes	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance	09.2.1.1 Camper Vans, Caravans & Trailers
9.2.3	Accessories for boats, horses, caravans & motorhomes	09.2 Other Major Durables For Recreation & Culture	09.2 Other Major Durables For Recreation & Culture
9.2.4	Musical instruments	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance	09.2.2.1 Musical Instruments

9.2.5	Major durables for indoor recreation	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance
9.2.6	Maintenance & repair or other major durables for recreation & culture	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance	09.2.3.0 Maintenance & Repair Of Other Major Durables For Recreation & Culture
9.2.7	Purchase of motor caravan - outright purchase	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance	09.2.1.1 Camper Vans, Caravans & Trailers
9.2.8	Purchase of motor caravan - loan/HP	09.2.1/2/3 Major Durables For In/Outdoor Recreation & Their Maintenance	09.2.1.1 Camper Vans, Caravans & Trailers
9.3.1	Games, toys & hobbies	09.3.1 Games Toys & Hobbies	09.3.1 Games Toys & Hobbies
9.3.2.1	Computer software & games cartridges	09.1.3 Data Processing Equipment	09.1.3.3 Software
9.3.2.2	Console computer games	09.3.1 Games Toys & Hobbies	09.3.1 Games Toys & Hobbies
9.3.3	Equipment for sport, camping & open-air recreation	09.3.2 Equipment For Sport Camping & Open-Air Recreation	09.3.2 Equipment For Sport Camping & Open-Air Recreation
9.3.4.1	BBQ & swings	09.3 Other Recreational Items & Equipment Gardens & Pets	09.3 Other Recreational Items & Equipment Gardens & Pets
9.3.4.2	Plants, flowers, seeds, fertilisers, insecticides	09.3.3 Garden Plants & Flowers	09.3.3.2 Plants & Flowers
9.3.4.3	Garden decorative	09.3.3 Garden Plants & Flowers	09.3.3.1 Garden Products
9.3.4.4	Artificial flowers, potpourri	09.3.3 Garden Plants & Flowers	09.3.3 Garden Plants & Flowers
9.3.5.1	Pet food	09.3.4/5 Pets, Related Products & Services	09.3.4/5 Pets, Related Products & Services
9.3.5.2	Pet purchase & accessories	09.3.4/5 Pets, Related Products & Services	09.3.4.1 Purchase Of Pets
9.3.5.3	Veterinary & other services for pets	09.3.4/5 Pets, Related Products & Services	09.3.5.0 Veterinary & Other Services For Pets
9.4.1.1	Spectator sports - admission charges	09.4.1 Recreational & Sporting Services	09.4.1.1 Recreational & Sporting Services - Attendance
9.4.1.2	Participant sports	09.4.1 Recreational & Sporting Services	09.4.1.2 Recreational & Sporting Services - Participation
9.4.1.3	Subscriptions to sorts & social clubs	09.4.1 Recreational & Sporting Services	09.4.1 Recreational & Sporting Services
9.4.1.4	Hire of equipment for sport	09.3.2 Equipment For Sport Camping & Open-Air Recreation	09.3.2.1 Equipment For Sport
9.4.1.5	Leisure class fees	09.4.1 Recreational & Sporting Services	09.4.1.2 Recreational & Sporting Services - Participation
9.4.2.1	Cinemas	09.4.2 Cultural Services	09.4.2.1 Cinemas, Theatres, Concerts
9.4.2.2	Live entertainment, theatre, concerts, shows	09.4.2 Cultural Services	09.4.2.1 Cinemas, Theatres, Concerts
9.4.2.3	Museums, zoological gardens, theme parks	09.4.2 Cultural Services	09.4.2.2 Museums, Libraries, Zoological Gardens
9.4.3.1	TV licences	09.4.2 Cultural Services	09.4.2.3 Television & Radio Licence Fees, Subscriptions
9.4.3.2	Satellite subscriptions	09.4.2 Cultural Services	09.4.2.4 Hire Of Equipment & Accessories For Culture
9.4.3.3	Rent for TV/Satellite/VCR	09.4.2 Cultural Services	09.4.2.4 Hire Of Equipment & Accessories For Culture

9.4.3.4	Cable subscriptions	09.4.2 Cultural Services	09.4.2.4 Hire Of Equipment & Accessories For Culture
9.4.3.5	TV slot meter payments	09.4.2 Cultural Services	09.4.2.4 Hire Of Equipment & Accessories For Culture
9.4.3.6	Video, cassette & CD hire	09.4.2 Cultural Services	09.4.2.4 Hire Of Equipment & Accessories For Culture
9.4.4.1	Admissions to clubs, dances. Discos, bingo	09.4.2 Cultural Services	09.4.2 Cultural Services
9.4.4.2	Social events & gatherings	09.4.2 Cultural Services	09.4.2 Cultural Services
9.4.4.3	Subscriptions for leisure activities	09.4.2 Cultural Services	09.4.2 Cultural Services
9.4.5	Development of film, photos	09.4.2 Cultural Services	09.4.2 Cultural Services
9.4.6.1	Football pools stakes	09.4.2 Cultural Services	09.4.2 Cultural Services
9.4.6.2	Bingo stakes	09.4.2 Cultural Services	09.4.2 Cultural Services
9.4.6.3	Lottery	09.4.2 Cultural Services	09.4.2 Cultural Services
9.4.6.4	Bookmaker, tote, other betting stakes	09.4.2 Cultural Services	09.4.2 Cultural Services
9.5.1	Books	09.5.1 Books	09.5.1 Books
9.5.2	Diaries, address books, cards etc	09.5.1 Books	09.5.1 Books
9.5.3	Cards, calendars, posters & other printed matter	09.5.1 Books	09.5.3/4 :Misc. Printed Matter Stationery & Drawing Materials
9.5.4	Newspapers	09.5.2 Newspapers & Periodicals	09.5.2.1 Newspapers
9.5.5	Magazines & periodicals	09.5.2 Newspapers & Periodicals	09.5.2.2 Magazines & Periodicals
10.1	Education	10 Education	10 Education
10.2	Educational trips	10 Education	10 Education
11.1.1	Restaurant & café meals	11.1.1 Restaurants & Cafes	11.1.1.1 Restaurants, Cafes & Dancing Establishments
11.1.2	Alcoholic beverages	11.1.1 Restaurants & Cafes	11.1.1.1 Restaurants, Cafes & Dancing Establishments
11.1.3	Takeaway meals	11.1.1 Restaurants & Cafes	11.1.1.2 Fast Food & Take Away Food Services
11.1.4.1	Hot food & cold food	11.1.1 Restaurants & Cafes	11.1.1.2 Fast Food & Take Away Food Services
11.1.4.2	Confectionery	11.1.1 Restaurants & Cafes	11.1.1.2 Fast Food & Take Away Food Services
11.1.4.3	Ice cream	11.1.1 Restaurants & Cafes	11.1.1.2 Fast Food & Take Away Food Services
11.1.4.4	Soft drink	11.1.1 Restaurants & Cafes	11.1.1.2 Fast Food & Take Away Food Services
11.1.5	Contract catering	11.1 Catering Services	11.1 Catering Services
11.1.6.1	School meals	11.1.2 Canteens	11.1.2 Canteens
11.1.6.2	Meals bought in workplace	11.1.2 Canteens	11.1.2 Canteens
11.2.1	Holiday in the UK	11.2 Accommodation Services	11.2 Accommodation Services
11.2.2	Holiday abroad	11.2 Accommodation Services	11.2 Accommodation Services
11.2.3	Room hire	11.2 Accommodation Services	11.2 Accommodation Services
12.1.1	Hairdressing, beauty treatment	12.1.1 Hairdressing & Personal Grooming Establishments	12.1.1 Hairdressing & Personal Grooming Establishments
12.1.2	Toilet paper	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.3.2 Articles For Personal Hygiene & Wellness

12.1.3.1	Toiletries	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.3.2 Articles For Personal Hygiene & Wellness
12.1.3.2	Bar of soap, liquid soap, shower gel	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.3.2 Articles For Personal Hygiene & Wellness
12.1.3.3	Toilet requisites	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.3.2 Articles For Personal Hygiene & Wellness
12.1.4	Baby toiletries & accessories	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.3.2 Articles For Personal Hygiene & Wellness
12.1.5.1	Hair products	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.3.2 Articles For Personal Hygiene & Wellness
12.1.5.2	Cosmetics & related accessories	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.3.2 Articles For Personal Hygiene & Wellness
12.1.5.3	Electrical appliances for personal care	12.1.2/3 Appliances, Articles & Products For Personal Care	12.1.2.1 Electric Appliances For Personal Care
12.2.1.1	Jewellery clocks & watches & other personal effects	12.3.1 Jewellery Clocks & Watches	12.3.1 Jewellery Clocks & Watches
12.2.1.2	Leather & travel goods	12.3.2 Other Personal Effects	12.3.2.1 Travel Goods
12.2.1.3	Sunglasses	12.3.2 Other Personal Effects	12.3.2 Other Personal Effects
12.2.2.1	Baby equipment	12.3.2 Other Personal Effects	12.3.2.2 Articles For Babies
12.2.2.2	Prams, pram accessories	12.3.2 Other Personal Effects	12.3.2.2 Articles For Babies
12.2.2.3	Repairs to personal goods	12.3.2 Other Personal Effects	12.3.2.2 Articles For Babies
12.3.1.1	Residential homes	12.4 Social Protection	12.4.0.2 Retirement Homes For Elderly Persons & Residences For Disabled Persons
12.3.1.2	Home help	12.4 Social Protection	12.4.0.3 Services To Maintain People In Their Private Homes
12.3.1.3	Nursery, creche, playschools	12.4 Social Protection	12.4.0.1 Child Care Services
12.3.1.4	Child care payments	12.4 Social Protection	12.4.0.1 Child Care Services
12.4.1.1	Structure insurance	12.5 Insurance	12.5 Insurance
12.4.1.2	Contents insurance	12.5.2 House Contents Insurance	12.5.2 House Contents Insurance
12.4.1.3	Insurance for household items	12.5 Insurance	12.5 Insurance
12.4.2	Medical insurance premiums	12.5.3/5 Health Insurance & Other Insurance	12.5.3/5 Health Insurance & Other Insurance
12.4.3.1	Vehicle insurance	12.5.4 Transport Insurance	12.5.4.1 Motor Vehicle Insurance
12.4.3.2	Boat insurance	12.5.4 Transport Insurance	12.5.4.1 Motor Vehicle Insurance
12.4.4	Non package holiday, other travel insurance	12.5.4 Transport Insurance	12.5.4.2 Travel Insurance
12.5.1.1	Moving & storage of furniture	12.7 Other Services	12.7.0.4 Other Fees & Services
12.5.1.2	Property transaction - purchase & sale	12.7 Other Services	12.7.0.1 Administrative Fees
12.5.1.3	Property transaction - sale only	12.7 Other Services	12.7.0.1 Administrative Fees
12.5.1.4	Property transaction - purchase only	12.7 Other Services	12.7.0.1 Administrative Fees

12.5.1.5	Property transaction - other payments	12.7 Other Services	12.7.0.1 Administrative Fees
12.5.2.1	Bank building society fees	12.6 Financial Services	12.6.2.1 Charges By Banks & Post Offices
12.5.2.2	Bank & post office counter charges	12.6 Financial Services	12.6.2.1 Charges By Banks & Post Offices
12.5.2.3	Credit card fees	12.6 Financial Services	12.6.2.1 Charges By Banks & Post Offices
12.5.3.1	Other professional fees	12.6 Financial Services	12.7.0.4 Other Fees & Services
12.5.3.2	Legal fees	12.7 Other Services	12.7.0.2 Legal Services & Accountancy
12.5.3.3	Funeral expenses	12.7 Other Services	12.7.0.3 Funeral Services
12.5.3.4	TU & professional organisations	12.7 Other Services	12.7.0.4 Other Fees & Services
12.5.3.5	Other payments for services	12.7 Other Services	12.7.0.4 Other Fees & Services

Appendix I. Additional results from repeated measures ANOVA and paired-sample T-tests.

Table Appendix 2. Detailed results from repeated measures ANOVAs.

	Product	F-Value	Num DF	Den DF	P-value
Age Group	Food and Drinks	25.01	4	72	5.3E-13
	Housing, water and waste	62.88	4	72	9.3E-23
	Electricity, gas, liquid and solid fuels	2.96	4	72	2.5E-02
	Private and public road transport	61.70	4	72	1.6E-22
	Air transport	17.27	4	72	5.6E-10
	Recreation, culture, and clothing	41.23	4	72	6.2E-18
	Other consumption	26.70	4	72	1.4E-13
	Total	32.33	4	72	2.0E-15
Income Decile	Food and Drinks	171.19	9	162	5.7E-78
	Housing, water and waste	43.62	9	162	7.0E-39
	Electricity, gas, liquid and solid fuels	24.00	9	162	1.0E-25
	Private and public road transport	310.06	9	162	2.9E-97
	Air transport	34.78	9	162	1.5E-33
	Recreation, culture, and clothing	119.18	9	162	1.0E-66
	Other consumption	159.59	9	162	9.3E-76
	Total	271.60	9	162	6.8E-93

Table Appendix 3. Detailed results from repeated measures ANOVAs.

	Group 1	Group 2	Air transport		Electricity, gas, liquid and solid fuels		Food and Drinks		Housing, water and waste		Other consumption		Private and public road transport		Recreation, culture, and clothing		Total	
			t-val.	p-val.	t-val.	p-val.	t-val.	p-val.	t-val.	p-val.	t-val.	p-val.	t-val.	p-val.	t-val.	p-val.	t-val.	p-val.
Age Group HRP	18-29	30-49	-3.67	0.00 *	-2.35	0.03	-3.74	0.00 *	0.03	0.98	-4.49	0.00 *	-1.22	0.24	-4.07	0.00 *	-4.50	0.00 *
	18-29	50-64	-2.56	0.02	-0.22	0.83	-3.05	0.01	-5.49	0.00 *	-3.09	0.01	-1.46	0.16	-3.13	0.01	-3.66	0.00 *
	18-29	65-74	-4.86	0.00 *	-0.43	0.67	-7.91	0.00 *	-7.84	0.00 *	-8.21	0.00 *	-9.76	0.00 *	-8.46	0.00 *	-9.45	0.00 *
	18-29	75+	0.98	0.34	0.73	0.48	-6.37	0.00 *	-11.00	0.00 *	-5.38	0.00 *	-10.16	0.00 *	-7.69	0.00 *	-5.12	0.00 *
	30-49	50-64	0.88	0.39	2.65	0.02	-0.37	0.72	-8.66	0.00 *	1.22	0.24	-0.80	0.43	-0.14	0.89	-0.30	0.76
	30-49	65-74	-2.42	0.03	2.05	0.05	-6.91	0.00 *	-12.09	0.00 *	-6.17	0.00 *	-13.68	0.00 *	-9.49	0.00 *	-9.15	0.00 *
	30-49	75+	6.24	0.00 *	2.92	0.01	-3.53	0.00 *	-11.95	0.00 *	-2.19	0.04	-9.40	0.00 *	-6.66	0.00 *	-2.22	0.04
	50-64	65-74	-3.33	0.00 *	-0.39	0.70	-6.99	0.00 *	-4.61	0.00 *	-10.49	0.00 *	-17.40	0.00 *	-13.55	0.00 *	-8.94	0.00 *
	50-64	75+	4.47	0.00 *	1.72	0.10	-3.02	0.01	-6.68	0.00 *	-3.42	0.00 *	-8.02	0.00 *	-6.70	0.00 *	-1.96	0.07
	65-74	75+	11.18	0.00 *	3.09	0.01	3.12	0.01	-3.60	0.00 *	3.40	0.00 *	0.11	0.91	-1.39	0.18	6.37	0.00 *
Income Decile	Lowest	2nd	-13.97	0.00 *	-8.51	0.00 *	-32.74	0.00 *	-13.78	0.00 *	-31.34	0.00 *	-30.90	0.00 *	-23.47	0.00 *	-33.16	0.00 *
	Lowest	3rd	-13.90	0.00 *	-9.59	0.00 *	-27.45	0.00 *	-0.02	0.99	-30.37	0.00 *	-34.80	0.00 *	-33.11	0.00 *	-39.23	0.00 *
	Lowest	4th	-20.07	0.00 *	-11.12	0.00 *	-28.66	0.00 *	7.57	0.00 *	-28.95	0.00 *	-31.86	0.00 *	-27.82	0.00 *	-35.02	0.00 *
	Lowest	5th	-15.63	0.00 *	-10.10	0.00 *	-33.02	0.00 *	4.57	0.00 *	-28.54	0.00 *	-31.56	0.00 *	-30.24	0.00 *	-33.94	0.00 *
	Lowest	6th	-18.24	0.00 *	-9.06	0.00 *	-45.81	0.00 *	4.48	0.00 *	-38.59	0.00 *	-28.65	0.00 *	-27.99	0.00 *	-35.69	0.00 *
	Lowest	7th	-15.35	0.00 *	-10.13	0.00 *	-31.88	0.00 *	2.27	0.04	-31.22	0.00 *	-31.76	0.00 *	-37.44	0.00 *	-38.60	0.00 *
	Lowest	8th	-14.54	0.00 *	-12.89	0.00 *	-28.75	0.00 *	-0.07	0.95	-33.01	0.00 *	-19.52	0.00 *	-25.85	0.00 *	-31.77	0.00 *
	Lowest	9th	-16.08	0.00 *	-12.56	0.00 *	-36.43	0.00 *	-2.18	0.04	-34.27	0.00 *	-31.24	0.00 *	-23.71	0.00 *	-34.83	0.00 *
	Lowest	Highest	-9.57	0.00 *	-11.32	0.00 *	-13.71	0.00 *	-2.54	0.02	-18.94	0.00 *	-10.44	0.00 *	-10.77	0.00 *	-17.89	0.00 *
	2nd	3rd	-2.34	0.03	-1.77	0.09	-1.20	0.25	9.67	0.00 *	-2.67	0.02	-3.89	0.00 *	-0.41	0.69	-3.53	0.00
	2nd	4th	-5.87	0.00 *	-3.12	0.01	-1.13	0.27	15.99	0.00 *	-3.89	0.00 *	-2.06	0.05	-0.72	0.48	-3.53	0.00
	2nd	5th	-6.57	0.00 *	-1.93	0.07	-2.57	0.02	13.92	0.00 *	-2.48	0.02	1.99	0.06	1.18	0.25	-2.18	0.04
	2nd	6th	-5.98	0.00 *	-2.67	0.02	-2.01	0.06	13.17	0.00 *	-0.16	0.87	7.63	0.00 *	0.40	0.69	-1.83	0.08
	2nd	7th	-6.09	0.00 *	-2.64	0.02	-2.04	0.06	9.39	0.00 *	0.46	0.65	13.12	0.00 *	2.87	0.01	-1.26	0.22
	2nd	8th	-5.87	0.00 *	-4.71	0.00 *	0.14	0.89	7.85	0.00 *	3.82	0.00	20.44	0.00 *	4.85	0.00 *	2.96	0.01
	2nd	9th	-6.55	0.00 *	-3.61	0.00	2.45	0.02	4.47	0.00 *	1.27	0.22	20.60	0.00 *	2.77	0.01	0.55	0.59
	2nd	Highest	-4.01	0.00 *	-0.71	0.49	4.55	0.00 *	3.55	0.00	2.77	0.01	17.93	0.00 *	5.77	0.00 *	3.90	0.00 *
	3rd	4th	-3.62	0.00	-2.12	0.05	-0.07	0.94	7.62	0.00 *	-0.90	0.38	1.06	0.30	-0.38	0.71	-0.36	0.73
	3rd	5th	-3.86	0.00	-0.56	0.58	-1.72	0.10	4.69	0.00 *	0.09	0.93	5.67	0.00 *	1.61	0.12	0.92	0.37
	3rd	6th	-3.61	0.00	-1.77	0.09	-0.70	0.49	5.51	0.00 *	2.07	0.05	13.30	0.00 *	1.01	0.33	1.47	0.16
	3rd	7th	-4.17	0.00 *	-1.55	0.14	-1.07	0.30	2.39	0.03	2.90	0.01	14.47	0.00 *	4.17	0.00 *	2.04	0.06
	3rd	8th	-3.05	0.01	-2.41	0.03	1.04	0.31	-0.05	0.96	6.98	0.00 *	19.83	0.00 *	6.92	0.00 *	4.65	0.00 *

3rd	9th	-3.65	0.00	-1.85	0.08	3.08	0.01	-2.66	0.02	3.71	0.00	20.86	0.00 *	3.69	0.00	3.06	0.01
3rd	Highest	-2.66	0.02	1.43	0.17	4.81	0.00 *	-2.98	0.01	4.19	0.00 *	21.54	0.00 *	6.02	0.00 *	5.78	0.00 *
4th	5th	-0.69	0.50	2.09	0.05	-1.88	0.08	-2.06	0.05	1.09	0.29	4.62	0.00 *	1.63	0.12	1.24	0.23
4th	6th	-0.36	0.73	-0.04	0.97	-0.61	0.55	-1.31	0.21	4.38	0.00 *	10.65	0.00 *	1.08	0.29	1.91	0.07
4th	7th	-1.74	0.10	0.45	0.66	-0.81	0.43	-4.54	0.00 *	3.51	0.00	11.61	0.00 *	3.77	0.00	2.24	0.04
4th	8th	-0.14	0.89	-0.23	0.82	1.28	0.22	-8.71	0.00 *	7.37	0.00 *	18.52	0.00 *	7.91	0.00 *	5.36	0.00 *
4th	9th	-1.02	0.32	0.04	0.97	2.77	0.01	-10.11	0.00 *	5.16	0.00 *	19.54	0.00 *	3.12	0.01	3.36	0.00
4th	Highest	-0.74	0.47	3.21	0.00	4.87	0.00 *	-9.81	0.00 *	4.56	0.00 *	21.34	0.00 *	6.49	0.00 *	5.04	0.00 *
5th	6th	0.37	0.72	-1.71	0.10	1.10	0.29	0.86	0.40	2.34	0.03	5.98	0.00 *	-0.64	0.53	0.58	0.57
5th	7th	-0.95	0.35	-1.83	0.08	1.30	0.21	-1.67	0.11	2.98	0.01	8.68	0.00 *	2.01	0.06	0.94	0.36
5th	8th	0.68	0.51	-2.39	0.03	2.68	0.02	-4.39	0.00 *	7.21	0.00 *	19.51	0.00 *	4.35	0.00 *	4.81	0.00 *
5th	9th	-0.19	0.85	-2.00	0.06	4.28	0.00 *	-7.22	0.00 *	3.96	0.00 *	16.02	0.00 *	2.76	0.01	2.37	0.03
5th	Highest	-0.26	0.80	2.11	0.05	7.05	0.00 *	-7.36	0.00 *	4.60	0.00 *	21.04	0.00 *	5.97	0.00 *	4.96	0.00 *
6th	7th	-1.22	0.24	0.60	0.56	-0.18	0.86	-4.03	0.00 *	0.53	0.60	5.06	0.00 *	2.69	0.01	0.67	0.51
6th	8th	0.13	0.90	-0.14	0.89	1.63	0.12	-9.47	0.00 *	3.87	0.00	10.93	0.00 *	5.11	0.00 *	3.73	0.00
6th	9th	-0.58	0.57	0.07	0.95	3.69	0.00	-10.87	0.00 *	1.54	0.14	12.33	0.00 *	2.51	0.02	1.70	0.11
6th	Highest	-0.50	0.62	2.41	0.03	5.68	0.00 *	-10.47	0.00 *	2.55	0.02	15.11	0.00 *	5.49	0.00 *	4.45	0.00 *
7th	8th	1.56	0.14	-0.62	0.54	1.84	0.08	-4.89	0.00 *	3.68	0.00	7.46	0.00 *	3.00	0.01	3.36	0.00
7th	9th	0.81	0.43	-0.48	0.64	4.64	0.00 *	-9.48	0.00 *	0.84	0.41	10.17	0.00 *	0.95	0.36	1.21	0.24
7th	Highest	0.34	0.74	2.81	0.01	5.66	0.00 *	-6.82	0.00 *	2.43	0.03	10.90	0.00 *	5.82	0.00 *	4.51	0.00 *
8th	9th	-0.79	0.44	0.34	0.74	1.55	0.14	-3.46	0.00	-2.79	0.01	1.75	0.10	-1.35	0.19	-1.91	0.07
8th	Highest	-0.65	0.52	4.26	0.00 *	5.20	0.00 *	-3.88	0.00 *	0.53	0.60	5.72	0.00 *	3.42	0.00	2.84	0.01
9th	Highest	-0.20	0.85	4.06	0.00 *	4.06	0.00 *	-1.09	0.29	1.73	0.10	4.02	0.00 *	4.07	0.00 *	3.75	0.00

Appendix J. Percentage and absolute differences in per SPH income and emissions between 2007-2009 and 2019-2020, equivalised.

Table Appendix 4. Percentage differences in per SPH income and emissions between 2007-2009 and 2019-2020; emissions and incomes are estimated using own year prices and multipliers.

Period	Group		Weekly income	Total	Food and Drinks	Housing, water and waste	Electricity, gas, liquid and solid fuels	Private and public road transport	Air transport	Recreation, culture, and clothing	Other consumption
2007-2009		All	3.50	-15.88	-11.80	-22.00	-7.19	-14.66	-16.54	-22.93	-32.73
2007-2009	Age HRP	18-29	0.30	-14.26	-21.68	-15.62	-7.50	-12.30	-2.06	-30.12	-16.58
2007-2009	Age HRP	30-49	3.16	-17.02	-12.07	-21.36	-9.25	-15.74	-16.79	-20.77	-34.52
2007-2009	Age HRP	50-64	3.67	-17.79	-11.97	-23.83	-9.16	-16.16	-21.14	-20.59	-37.36
2007-2009	Age HRP	65-74	9.63	-12.22	-5.51	-25.40	-4.27	-3.19	-22.08	-28.54	-34.98
2007-2009	Age HRP	75+	4.54	-5.31	-5.06	-23.59	5.80	-31.14	6.05	-30.12	10.90
2007-2009	Income decile	Lowest	7.23	-12.18	-15.05	-19.07	-1.95	1.81	-23.07	-36.90	-28.52
2007-2009	Income decile	2nd	6.65	-14.18	-9.05	-23.39	-10.11	-6.85	-2.45	-30.30	-36.77
2007-2009	Income decile	3rd	4.29	-18.65	-7.78	-16.19	-10.76	-27.07	-35.41	-22.09	-35.47
2007-2009	Income decile	4th	4.61	-14.95	-9.62	-24.20	-5.23	-11.57	-23.86	-14.65	-41.29
2007-2009	Income decile	5th	3.35	-14.48	-12.61	-18.98	-6.42	-16.84	8.38	-25.37	-29.74
2007-2009	Income decile	6th	2.20	-14.02	-6.43	-23.70	-6.70	-16.06	-26.55	-19.18	-25.42
2007-2009	Income decile	7th	2.42	-15.77	-20.17	-21.05	-4.51	-13.22	-6.91	-39.95	-19.03
2007-2009	Income decile	8th	3.27	-11.31	-11.03	-23.41	1.13	-5.15	-15.73	-23.37	-30.63
2007-2009	Income decile	9th	3.13	-18.06	-11.77	-26.62	-13.16	-16.65	-18.60	-9.92	-36.88
2007-2009	Income decile	Highest	3.65	-20.59	-11.85	-23.74	-11.67	-22.59	-17.52	-14.60	-37.66
2019-2020		All	0.03	-24.08	-10.40	-6.72	1.91	-45.99	-80.72	-11.51	-25.87
2019-2020	Age HRP	18-29	1.40	-24.72	-6.15	46.18	3.37	-49.16	-86.20	12.12	-8.35
2019-2020	Age HRP	30-49	-0.46	-22.02	-10.50	-1.97	3.10	-42.64	-78.07	-0.21	-20.29
2019-2020	Age HRP	50-64	7.06	-24.90	-12.28	-25.17	4.06	-49.33	-78.41	-12.37	-21.39
2019-2020	Age HRP	65-74	0.05	-24.54	-7.82	-7.20	0.52	-41.82	-83.95	-30.97	-39.72
2019-2020	Age HRP	75+	11.43	-15.99	0.43	-27.59	-3.93	-38.46	-85.01	-16.60	-25.67
2019-2020	Income decile	Lowest	-12.68	-31.40	-7.32	-30.68	-23.88	-45.98	-87.11	-45.89	-29.04
2019-2020	Income decile	2nd	-0.15	-24.49	-12.40	-22.09	-14.91	-41.16	-79.00	-0.13	-34.76
2019-2020	Income decile	3rd	0.98	-19.90	-1.71	-23.32	-3.59	-38.11	-80.61	-20.68	-27.12
2019-2020	Income decile	4th	1.35	-24.99	-4.02	-23.11	-4.03	-45.79	-89.66	-24.51	-30.56
2019-2020	Income decile	5th	3.30	-22.20	-7.22	13.60	2.09	-46.65	-83.55	-18.64	-30.52
2019-2020	Income decile	6th	1.51	-18.69	-10.12	-11.08	1.31	-47.48	-86.45	0.81	16.03
2019-2020	Income decile	7th	0.75	-26.18	-14.89	-14.28	3.30	-46.39	-76.26	-18.21	-29.13
2019-2020	Income decile	8th	1.11	-29.45	-12.05	19.94	5.13	-52.74	-82.11	-21.16	-33.62
2019-2020	Income decile	9th	1.14	-23.10	-11.34	19.71	11.63	-38.56	-78.01	-19.84	-21.10
2019-2020	Income decile	Highest	-1.55	-16.34	-13.31	12.47	39.52	-47.10	-74.50	32.83	-29.62

**Notes: This shows the change in the later year's values compared to the earlier year's values as a percentage, calculated: $(\text{Emissions}_{\text{Year 2}} - \text{Emissions}_{\text{Year 1}}) / \text{Emissions}_{\text{Year 1}}$. This means that negative values show a reduction over time while positive values show an increase in emissions or income over time. Darker blue indicates a greater reduction, white indicates no change, dark red indicates a greater increase. 2020 values are calculated using 2019 multipliers.

Table Appendix 5. Differences in per SPH income and emissions between 2007-2009 and 2019-2020; emissions and incomes are estimated using own year prices and multipliers.

Period	Group		Weekly income	Total	Food and Drinks	Housing, water and waste	Electricity, gas, liquid and solid fuels	Private and public road transport	Air transport	Recreation, culture, and clothing	Other consumption
2007-2009		All	15.15	-3.49	-0.44	-0.19	-0.43	-0.74	-0.21	-0.45	-1.03
2007-2009	Age HRP	18-29	1.19	-2.63	-0.72	-0.15	-0.33	-0.55	-0.03	-0.48	-0.38
2007-2009	Age HRP	30-49	14.99	-3.79	-0.46	-0.16	-0.52	-0.85	-0.21	-0.44	-1.15
2007-2009	Age HRP	50-64	17.06	-4.41	-0.49	-0.19	-0.59	-0.95	-0.33	-0.46	-1.40
2007-2009	Age HRP	65-74	31.36	-2.47	-0.19	-0.24	-0.28	-0.12	-0.23	-0.51	-0.90
2007-2009	Age HRP	75+	14.53	-0.93	-0.14	-0.29	0.43	-0.86	0.02	-0.30	0.22
2007-2009	Income decile	Lowest	9.52	-1.80	-0.42	-0.17	-0.09	0.05	-0.15	-0.54	-0.49
2007-2009	Income decile	2nd	12.98	-2.16	-0.25	-0.23	-0.54	-0.20	-0.01	-0.39	-0.54
2007-2009	Income decile	3rd	10.41	-3.15	-0.24	-0.15	-0.57	-1.01	-0.24	-0.32	-0.61
2007-2009	Income decile	4th	13.32	-2.75	-0.31	-0.22	-0.29	-0.43	-0.20	-0.22	-1.08
2007-2009	Income decile	5th	11.32	-2.81	-0.45	-0.16	-0.37	-0.72	0.07	-0.43	-0.76
2007-2009	Income decile	6th	8.66	-2.88	-0.23	-0.19	-0.39	-0.81	-0.29	-0.33	-0.64
2007-2009	Income decile	7th	11.11	-3.58	-0.79	-0.16	-0.26	-0.72	-0.09	-0.97	-0.59
2007-2009	Income decile	8th	17.95	-2.76	-0.46	-0.18	0.07	-0.31	-0.23	-0.54	-1.11
2007-2009	Income decile	9th	21.72	-5.15	-0.54	-0.20	-0.90	-1.21	-0.38	-0.24	-1.67
2007-2009	Income decile	Highest	37.64	-7.92	-0.66	-0.21	-0.95	-2.13	-0.61	-0.49	-2.87
2019-2020		All	0.16	-3.48	-0.27	-0.03	0.07	-1.60	-1.06	-0.14	-0.45
2019-2020	Age HRP	18-29	7.81	-3.18	-0.13	0.28	0.09	-1.60	-1.80	0.10	-0.11
2019-2020	Age HRP	30-49	-2.82	-2.95	-0.26	-0.01	0.10	-1.50	-0.99	0.00	-0.29
2019-2020	Age HRP	50-64	43.93	-3.98	-0.35	-0.11	0.16	-1.97	-1.11	-0.18	-0.42
2019-2020	Age HRP	65-74	0.25	-3.84	-0.22	-0.04	0.02	-1.32	-0.96	-0.41	-0.92
2019-2020	Age HRP	75+	53.13	-2.03	0.01	-0.16	-0.20	-0.78	-0.41	-0.13	-0.36
2019-2020	Income decile	Lowest	-22.84	-3.27	-0.15	-0.16	-0.87	-0.95	-0.58	-0.34	-0.22
2019-2020	Income decile	2nd	-0.42	-2.66	-0.25	-0.11	-0.53	-0.90	-0.49	0.00	-0.37
2019-2020	Income decile	3rd	3.33	-2.33	-0.04	-0.12	-0.13	-0.91	-0.59	-0.16	-0.37
2019-2020	Income decile	4th	5.43	-3.12	-0.10	-0.12	-0.14	-1.38	-0.79	-0.23	-0.37
2019-2020	Income decile	5th	15.33	-2.91	-0.18	0.07	0.07	-1.46	-0.80	-0.22	-0.39
2019-2020	Income decile	6th	8.11	-2.61	-0.27	-0.05	0.04	-1.70	-0.91	0.01	0.27
2019-2020	Income decile	7th	4.64	-3.96	-0.41	-0.07	0.12	-1.88	-1.00	-0.21	-0.52
2019-2020	Income decile	8th	8.16	-4.93	-0.35	0.08	0.18	-2.28	-1.45	-0.31	-0.80
2019-2020	Income decile	9th	10.34	-4.10	-0.34	0.08	0.43	-1.86	-1.64	-0.30	-0.46
2019-2020	Income decile	Highest	-20.97	-3.55	-0.46	0.07	1.75	-2.30	-2.18	0.64	-1.06

**Notes: This shows the change in the later year's values compared to the earlier year's values, calculated: $\text{Emissions}_{\text{Year 2}} - \text{Emissions}_{\text{Year 1}}$. This means that negative values show a reduction over time while positive values show an increase in emissions or income over time. Darker blue indicates a greater reduction, white indicates no change, dark red indicates a greater increase. 2020 values are calculated using 2019 multipliers.

Appendices Chapter 5

Appendix K. Report for Bristol Council and Arup

Understanding patterns of consumption-based greenhouse gas emissions in Bristol

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Introduction

To meet climate change mitigation targets, global carbon emissions must be reduced by 60% below 1990 levels by 2050 (Hoekstra and Wiedmann, 2014). In line with this goal, the UK is legally bound to reduce greenhouse gas (GHG) emissions by 80% compared to 1990 levels by 2050 (Commitee on Climate Change, 2008). Yet, despite consumption-based emissions being higher in the UK than production-based emissions (Millward-Hopkins et al., 2017; Sudmant et al., 2018), this target focusses only on those emissions created by industry in the UK, as well as territorial emissions due to transport (i.e. emissions released within the UK). Millward-Hopkins et al.'s (2017) research on CO_2 emissions in Bristol, for instance, reveals consumption-based emissions to be more than twice has high as production-based carbon emissions. However, to date frameworks to measure and mitigate carbon production-based emissions are better understood, more developed, and more embedded in policy than consumption-based emissions. As a result, investigating UK cities' consumption-based emissions is important for understanding how UK households contribute to global emissions. Moreover, in light of research highlighting that cities have some of the highest and lowest carbon footprints in the UK (Minx et al., 2013), understanding differences in consumption and carbon emission patterns between urban households is central for designing policy which effectively reduces a city's carbon footprint without widening social inequalities.

Previous research suggests that carbon footprints from UK households are positively related to income, household size, education level, and car ownership (Minx et al., 2013). However, as the authors analyse CO_2 per capita emissions at Local Authority District level, inner-city variations in consumption and emission patterns are not identified outside of London. Using Bristol as a case study, the current research expands on these previous findings and investigates spatial patterns of carbon emissions as well as links between socio-demographic variables and consumption-based carbon emissions of urban neighbourhoods.

Research Objectives

The current project aims to:

1) Explore Bristol's household carbon emissions at Lower Super Output Area (LSOA) level for the year 2016.

2) Analyse differences in consumption behaviours and associated carbon footprints between urban neighbourhoods.

3) Investigate socio- and geo-demographic patterns of:
   a) Total household CO_2 emissions.
   b) Household carbon emissions associated with food and drinks.

Method

Data Collection

The current analysis uses secondary data. The carbon footprint data is converted consumer spending data from the year 2016 – using environmentally extended Input-Output analysis (Leontief and Ford, 1970; Forssell and Polenske, 1998; Miller and Blair, 2009; Minx et al., 2009) – which comes from a household expenditure dataset from TransUnion. This dataset contains information on household carbon emissions from 263 LSOAs in Bristol, broken down into 136 categories including 40 food categories, such as 'pasta products', 'soft drinks', and 'restaurant and café meals' (for a sample of the dataset see Appendix A).

Additionally, the current analysis uses open data including from the Index of Multiple Deprivation (IMD) dataset (Department of Communities and Local Government, 2015), the 2011 UK Census (Office for National Statistics, n.d.), and open LSOA boundary data (Office for National Statistics, 2016). Variables used from these datasets are the IMD score, income deprivation score from the IMD dataset, as well as measures of full-time employment, ethnicity, religion, number of persons per bedroom, and socio-economic diversity of an area from the Census.

Analysis

The current analysis consists of both statistical and spatial components. First, emissions are clustered and visualised spatially. For this, *k*-means clustering is used; a technique in which the dataset is split into *k* clusters – where *k* is a manually chosen number of clusters – and each observation is assigned to the cluster with the nearest mean (see Hartigan and Wong, 1979). In the current analysis, this algorithm is re-iterated until no observation is changed between cluster between two iterations. As Euclidian distance is used, the data is scaled between 0 and 1 in the current analysis to avoid categories with larger emissions dominating the clustering. In the current study, *k*-means analyses are run with and without spatial restrictions. In the non-restricted analysis clusters reflect groupings based only emissions from various categories, while observations in the restricted analysis can only be in the same cluster if they – in addition to sharing emission patterns – share a border (queen neighbours) with another observation in this cluster.

Second, variables are explored in terms of their distributions, covariance with other variables, and relationships with total and food-related CO_2 emissions. As the distribution of IMD score is positively skewed, this variable is logarithmically transformed (ln) for the current analysis. Data exploration reveals high covariance between Census variables, as well as between Census variables and measures of deprivation from the IMD. Finally, regression analyses are done to evaluate the ability of socio-demographic variables in predicting food-related and total emissions.

Findings

Total Emissions

Per capita total CO_2 emissions in Bristol have a mean of 8.21 t CO_2. To analyse the data for different patterns of household emissions, *k*-means cluster analyses are performed. The number of clusters chosen for this analysis is 4, as identified using elbow method (Kodinariya and Makwana, 2013). Two cluster analyses are conducted (see Figure 1) – one with and one without spatial restriction using a queen neighbour weighting.

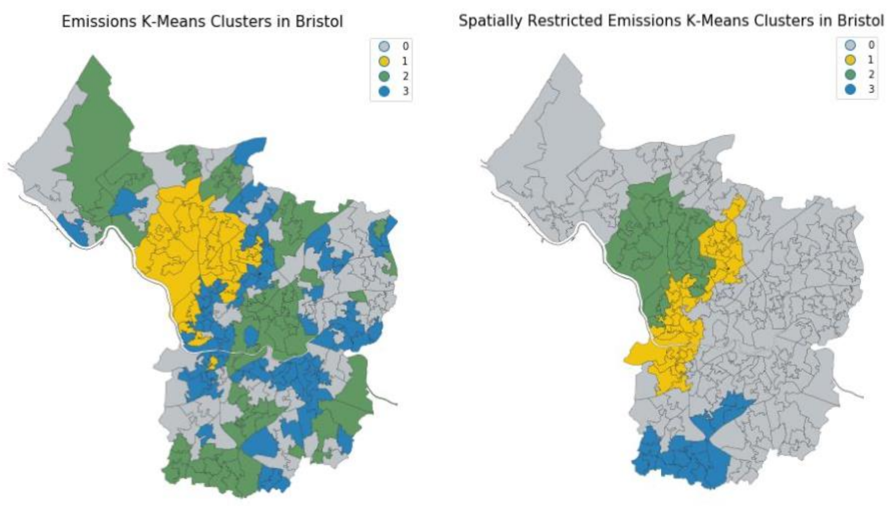
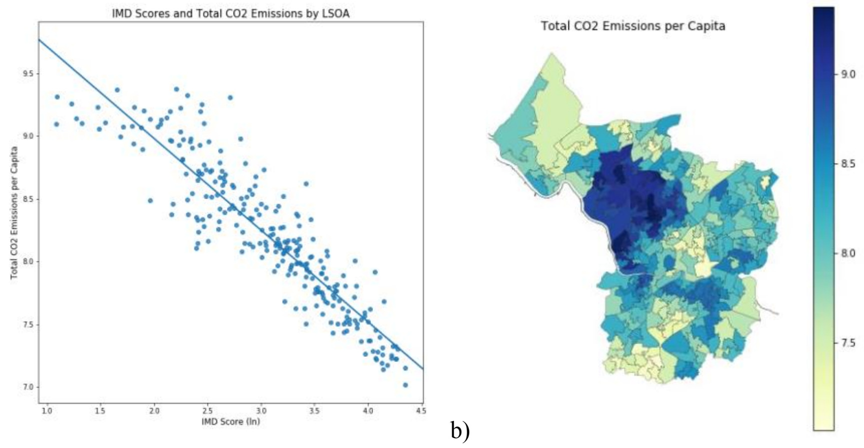


Figure 1. Emissions clusters for all CO_2 emission categories by LSOA, with and without spatial restriction.

For the non-restricted clusters, cluster means range from 9.08 t CO_2 to 7.49 t CO_2, whereas total emissions cluster means range from 9.10 t CO_2 to 7.32 t CO_2 for the spatially restricted clusters. For both (with and without spatial restriction), clusters with higher mean per capita emissions in one category also have higher mean per capita emissions in most other categories. Exceptions to this are emissions related to electricity, tobacco, gambling, and bus and coach fares. Aside from electricity, where lowest and highest cluster means differ by 0.1 t CO_2 for the spatially restricted clusters, differences between cluster means of these exception categories are small.

Moreover, the relationships between emissions and socio-demographic variables are analysed. This analysis reveals that IMD score (ln) is most strongly correlated with total emissions (Pearson's $r = -0.91$), and that levels of covariance are very high within Census variables and between Census variables and IMD scores. Figure 2 displays this relationship between IMD score and emissions and spatial distributions of emissions.



a) b)

Figure 2. a) Total CO_2 emissions (in t CO_2) vs. IMD scores (ln) by LSOA, b) the spatial distribution of total CO_2 household emissions in Bristol (in t CO_2).

Linear regression analysis reveals that IMD score (ln) is a significant predictor of total consumption-based CO_2 emissions ($R^2 = 0.837$, $p < 0.001$), such that a one unit increase in IMD score (ln) predicts a 0.059 t CO_2 decrease in per capita emissions. Even after single and repeated (50 repetitions) cross-validation, the R^2 remains high (see Table 1).

Table 1. Model fits of linear regression (IMD sc ore (ln) as a predictor of total emissions) on full dataset, a 20 -80 single cross-validation split, and a repeated (50) 20 -80 cross-validation split.

Model		R^2
Full dataset		0.837
Single cross-validation	Training Set (80%)	0.815
	Test Set (20%)	0.907
Cross-validation bootstrap mean		0.759

Food-Related Emissions

Bristol's household food-related emissions are 0.92 t CO_2 per person, excluding alcoholic drinks. Emissions across Bristol were highest for fruit and vegetables, followed by meat and fish, and dairy and eggs (see Table 2).

Table 2. Carbon emissions across Bristol by food category.

Products	Emissions in Bristol (t CO_2)
Fruit and vegetables	138,813.38
Meat and fish	133,284.12
Dairy and eggs	43,940.24
Grain products	30,618.29
Restaurant and café meals	28,391.39
Baked goods	24,688.72
Other food products	22,141.96
Drinks (non-alcoholic)	14,211.60
Cooking oils and fats	4,440.42

As for total emission patterns, food-related emissions are explored for clusters. *K*-means cluster analyses are performed with 5 clusters, as indicated by the elbow method, again with and without spatial restriction based on queen neighbour weightings. Cluster means range from 0.92 t CO_2 to 1.07 t CO_2 for clusters with not restriction, and from 0.91 t CO_2 to 1.07 t CO_2 for the spatially restricted clusters. As for total emissions, clusters with higher mean per capita emissions in one category also have higher mean per capita emissions in other categories – for restricted and non-restricted clusters. Thus, no patterns of patterns in dietary habits emerge. The results of these cluster analyses are visualised in Figure 3.

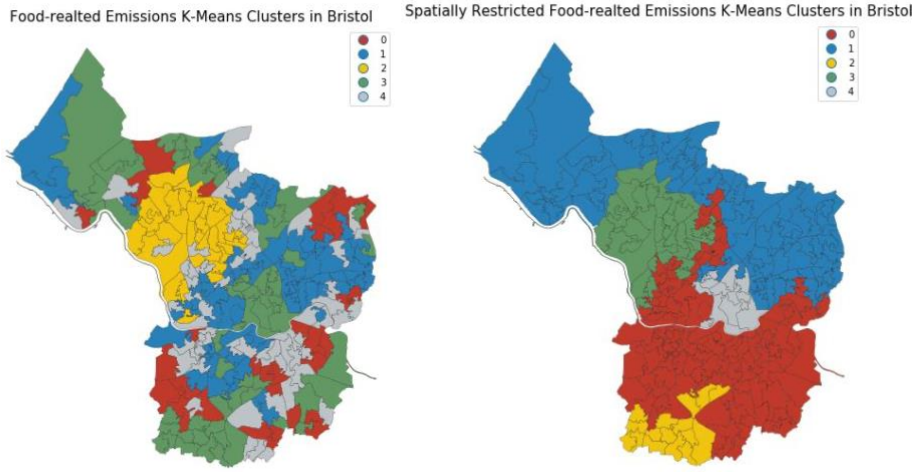
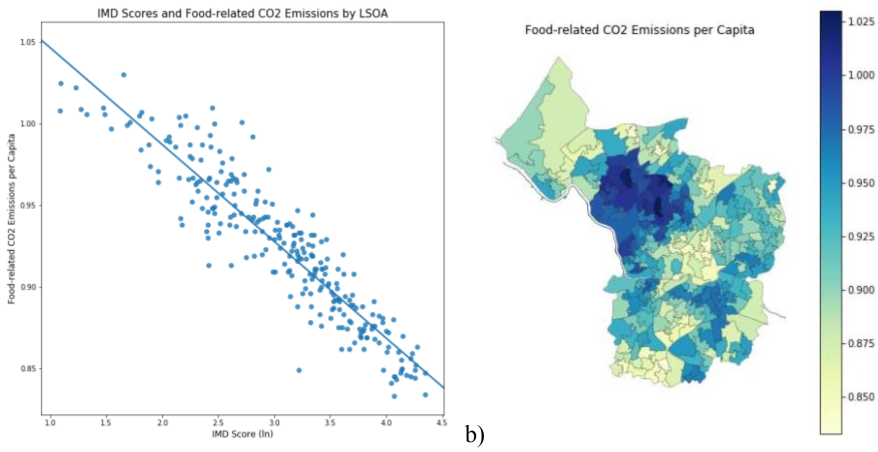


Figure 3. Emissions clusters for food -related CO_2 emission categories by LSOA, with and without spatial restriction.

Finally, spatial patterns are visualised (see Figure 4) and linear regression analyses are done to evaluate the ability of socio-demographic factors to predict food-related carbon emissions. Again, IMD score (ln) appears most strongly correlated with total emissions (Pearson's $r = -0.93$), as shown in Figure 4.



a) b)

Figure 4. a) Total food-related CO_2 emissions (in t CO_2) vs. IMD scores (ln) by LSOA, b) the spatial distribution of total food-related CO_2 household emissions in Bristol (in t CO_2).

IMD score (ln) are found to significantly predict food-related consumption-based CO_2 emissions ($R^2 = 0.858$, $p < 0.001$), where a unit increase in IMD score (ln) is linked to a 0.068 t CO_2 decrease in in per capita emissions of an LSOA. Single cross-validation and the mean R^2 of repeated cross-validation with randomly selected sub-samples reveal an R^2 above 0.73 (see Table 3).

Table 3. Model fits of linear regression (IMD sc ore (ln) as a predictor of food-related emissions) on full dataset, a 20-80 single cross-validation split, and a repeated (50) 20 -80 cross-validation split.

Model		R-squared
Full dataset		0.858
Single cross-validation	Training Set (80%)	0.846
	Test Set (20%)	0.896
Cross-validation bootstrap mean		0.738

Discussion and Conclusions

Current findings are in line with previous research indicating that higher levels of affluence are linked to increased household carbon emissions (Minx et al., 2013; Büchs and Schnepf, 2013; Hoekstra and Wiedmann, 2014; Wiedenhofer et al., 2018). The relationship between deprivation and emissions may be explained by income, as higher income levels are often linked to increased emissions (e.g. Minx et al., 2013).

One limitation of this research is its reliance on expenditure data. As a result, it is unclear whether higher emission values reflect increased consumption, consumption of more expensive products, or a combination of the two. Moreover, a comparison with Minx et al.'s (2013) findings highlights stark differences in mean emissions. While current findings suggest that the average Bristolian has a footprint of 8.21 t CO_2 for the year 2016, Minx et al. (2013) found emissions per capita from local authority areas to range from 10.21 t CO_2 to 15.51 t CO_2. While this may reflect a change over time or a difference in methodology, this contrast calls for further research into the various approaches and datasets used.

Lastly, differences in consumption-based emission patterns are revealed in the cluster analysis. Households with the highest emissions in most categories show different consumption patterns of electricity, tobacco, gambling, and bus and coach fares. Particularly an analysis of gas and electricity, and transport may provide valuable insights after further investigation, as these sectors have some of the highest consumption-based footprints.

Moreover, there is scope to expand on the current research by investigating differences between areas of low and high deprivation further. As Bristol has LSOAs in both the highest and lowest IMD deciles (Bristol City Counil, 2019b), it would be a good case study for further analysis. In addition, the availability of open data on residents' perception of climate change in Bristol (see Bristol City Counil, 2019a) allow for a future analysis into how concerns about climate change relate to emissions patterns.

In conclusion, current findings suggest that targeting areas with low levels of deprivation is most effective in reducing household carbon emissions in Bristol, as these areas have some of the largest per capita footprints. Despite certain limitations the current method holds, these findings replicate previous UK-wide research on more disaggregated geographical scale.

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