PREVALENCE, PATTERNING, AND PREDICTORS OF HEALTH- AND CLIMATE-RELEVANT LIFESTYLES IN THE UK

A cross-sectional study of travel and dietary behaviour in two national datasets

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Abstract

Background: Rising rates of chronic disease, combined with the threat of climate change, have increased the need to promote healthy, low-carbon (HLC) lifestyles globally. Nevertheless, most research in this area has focused on single behaviours in isolation, at the expense of understanding these lifestyles more broadly. This thesis aims to advance current knowledge of the patterning, prevalence, and predictors of health- and climate-relevant lifestyles in the UK, based on combinations of travel and dietary behaviour.

Methods: Two datasets, the National Diet and Nutrition Survey and UK Biobank, were used to explore this aim. Walking, cycling and public transport use were considered forms of HLC travel; lower consumption of red and processed meat (RPM), combined with higher consumption of fruit and vegetables (FV) were considered markers of a HLC diet. Study 1 examined associations between travel modes and dietary consumption. Study 2 estimated the prevalence of different health- and climate-relevant lifestyles using latent class models to identify unique patterns of travel and dietary behaviour. Study 3 explored which socio-demographic factors and types of influences were associated with each lifestyle pattern. Analyses were stratified by gender and findings were compared across both datasets.

Results: HLC travel, particularly cycling, was associated with consumption of higher FV and lower RPM. More car travel tended to cluster with higher RPM consumption, and much of the samples (47-80%) had multiple unhealthy, high-carbon (UHC) behaviours. Entirely HLC lifestyles were rare (2-5%) but a sizable minority had lifestyles that were predominantly or partially HLC. UHC lifestyles were socio-demographically diverse, but HLC lifestyles were consistently associated with higher qualifications, reduced car access, and living in urban settlements, more deprived areas, and in London.

Conclusions: HLC and UHC behaviours both cluster to some degree, which suggests that each lifestyle pattern may be driven by common influences. Socio-economic and environmental factors were the most important predictors of HLC lifestyles. These findings provide a more comprehensive understanding of health- and climate-relevant behaviours in the UK and give greater insights into the full impacts of people's lifestyles.

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Author's declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been submitted for an award at this, or any other, University. All sources are acknowledged as References.

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1 Introduction

Chapter summary: This first chapter gives an overview of this thesis and the broader research context in which it is situated (climate change and human health). After a brief introductory section, I define the aims of my project and the structure of the thesis. I then summarize the research area from which my topic originated, focusing on the parallel causes of climate change and ill health among human populations. I identify transport and agriculture (and subsequently travel and dietary behaviour) as two priority areas where there is potential for public health co-benefits from climate change mitigation, and argue that these areas should be examined together to gain a better understanding of health- and climate-relevant lifestyles in the UK context.

1.1 Background and overview of thesis

Increasing concerns about global climate change combined with rising rates of chronic disease have led to greater policy attention on behaviours and lifestyles that are beneficial for both human health and the natural environment (Watts et al., 2015a, Whitmee et al., 2015, Haines et al., 2009). From this perspective, two priority behaviours that have been identified are engaging in healthy, low-carbon travel (e.g. walking and cycling for transport) and consuming healthy, low-carbon diets (e.g. reduced consumption of animal products) (Woodcock et al., 2009, Capon et al., 2009, Friel et al., 2009, Aston et al., 2012, Lindsay et al., 2011).

In the UK, studies that have examined these behaviours in isolation have found that they are strongly patterned by socio-demographic factors, and this suggests that travel and dietary behaviours with related impacts may overlap among certain population groups and/or within specific environments (Hutchinson et al., 2014, Laverty et al., 2013, Maguire and Monsivais, 2014, Aston et al., 2013, Leahy et al., 2010). This overlap may be particularly important in light of the UK's existing commitments to reduce carbon emissions, as these dictate that behaviour change will be needed across all sectors of the economy (CCC, 2018), and there is currently very little evidence regarding how people's behaviours are patterned together across different sectors (e.g. car driving, meat consumption).

As a result, I argue that it may be useful to examine travel and dietary behaviour together, within individuals, since people's lifestyles are made up of multiple behaviours that intersect and interact in different ways. Previous research in the area of integrated health impact assessment has suggested that there may be positive interactions between healthy, low-carbon travel and dietary consumption (de Nazelle et al., 2011), but these potential links are poorly understood because existing evidence on travel and dietary behaviour in combination is lacking.

In this thesis, I aim to help fill this gap by advancing current understanding of the patterning, prevalence, and predictors of lifestyles that have joint implications for public health and carbon emissions in the UK context. Using combinations of travel and dietary behaviours, I investigate whether there are associations between different travel modes and dietary consumption, whether there are 'clusters' of healthy, low-carbon and unhealthy, high-carbon behaviours, and whether such clusters (lifestyle groups) have distinct socio-demographic profiles.

1.1.1 Thesis structure

This thesis consists of seven chapters. In Chapter 1, I give an overview of the thesis and explain why travel and dietary behaviours are important in the context of climate change and human health. In Chapter 2, I define which travel and dietary behaviours are health- and climate-relevant and describe the prevalence and socio-demographic patterning of these behaviours in the UK context. I then review existing evidence connecting travel and dietary behaviours from different theoretical perspectives, discuss gaps in current knowledge, and state my research questions (section 2.5). In Chapter 3, I give a detailed overview of my data sources, describing how each sample was collected and which measures I will use to answer my research questions. Detailed statistical methods for particular research questions are addressed separately in the relevant chapters (Chapters 4, 5 and 6).

Chapters 4 through 6 contain the empirical results of this thesis. Chapter 4 examines whether there are associations between different travel modes and dietary consumption. Chapter 5 examines whether travel and dietary behaviours cluster into distinct health- and climate-relevant lifestyle groups. Chapter 6 describes the socio-demographic profile of each lifestyle group, and examines which factors are the most important predictors of different types of health- and climate-relevant lifestyles. Chapter 7 concludes the thesis by highlighting the key findings, strengths and limitations, and opportunities for further research.

1.2 Climate change and human health: introduction to the research context

1.2.1 A brief overview of climate change

Human beings have always been inextricably linked to our environment. Traditionally this has involved our basic dependence on the natural world for our survival and wellbeing, however in the more recent era (e.g. last 150 years), this linkage has also evolved to encompass our species' ability to physically and dramatically alter the planet, so much so that the current epoch is now being referred to as 'the Anthropocene' (Lewis and Maslin, 2015, McMichael, 2014). One of the clearest ways this trend can be seen is in regards to climate change, a form of global environmental change that now fundamentally threatens many of the Earth's life supporting systems (IPCC, 2014). Indeed, there is now a strong consensus that global climate change has been caused by human activities, the most important of which are fossil fuel combustion and tropical deforestation, which both contribute to the accumulation of warming 'greenhouse' gases (GHGs) in the Earth's atmosphere (IPCC, 2013). Carbon dioxide (CO_2) is the most important of these gases, followed by methane (CH_4) and nitrous oxide (N_2O) (IPCC, 2013). Collectively, these gases are often measured in terms of CO_2 equivalents (CO_{2eq}), which describe the total climate change impact of all the different GHGs caused by an item or activity expressed in terms of the amount of CO_2 that would have the same impact[1] (Berners-Lee, 2010). This is also known as a *carbon footprint*, in which it is standard practice to use the word 'carbon' as shorthand for all other GHGs (see for example, the *Carbon Trust*[2]). As a result, throughout this thesis I will use the terms 'carbon' and 'GHGs' interchangeably; where something pertains to a specific GHG (e.g. CO_2), this will be noted explicitly.

According to the Intergovernmental Panel on Climate Change (IPCC), atmospheric CO_2 concentrations are now 40% higher than in pre-industrial times and current concentrations of CO_2, CH_4 and N_2O are unprecedented in at least the last 800,000 years (IPCC, 2013). These dramatic increases in anthropogenic emissions have been largely driven by economic and population growth since the pre-industrial era, and have resulted in increasing global temperatures such that each of the past three decades has been significantly warmer than all previous decades with recorded data (IPCC, 2013). If carbon emissions continue to rise, the impacts of climate change are predicted to become increasingly catastrophic (Costello et al., 2009). In addition to

[1] More specifically, CO_2 equivalents describe the mass of CO_2 that would have the same global warming potential as a given mixture of GHG emissions, when measured over 100 years (IPCC, 2014).

[2] https://www.carbontrust.com/resources/guides/carbon-footprinting-and-reporting/carbon-footprinting/

adverse impacts on the natural environment (e.g. melting of glaciers and ice sheets, thawing of permafrost, loss of biodiversity, sea level rise, and acidification of the oceans), climate change will also have critical effects on human health and wellbeing (Costello et al., 2009, Myers and Patz, 2009).

1.2.1.1 Health impacts of climate change

The health impacts of climate change are both direct and indirect, however the latter are predicted to be far greater (Costello et al., 2009, Myers and Patz, 2009). Direct health impacts include the effects of extreme weather and precipitation changes (e.g. heat waves, flooding, droughts, wildfires) whereas indirect impacts of climate change are those mediated by natural and social systems (e.g. increases in air pollution, vector-borne diseases, and climate-related migration and conflict) (IPCC, 2014, Patz et al., 2014). Crucially, these health impacts also reflect the reality of deep inequalities between different population groups across space and time: between the high-income countries that have caused the brunt of the emissions and the low-income countries that will largely bear the burden of impacts, and also between current generations and future generations who represent a parallel distinction (IPCC, 2014, Zehr, 2015). In recognition of these impacts, climate change has been deemed the *greatest global health threat* of the 21st century (Costello et al., 2009).

1.2.1.2 Commitments to reduce emissions

In an effort to avoid these outcomes, many governments have made ambitious commitments to reduce GHG emissions and mitigate the effects of climate change. In 2008 the UK government committed to reduce GHG emissions by 80% below 1990 levels by 2050 to help keep global temperature increases below 2°C to prevent the worst effects of climate change (CCC, 2008). Following this, in December 2015, 195 countries (including the UK) negotiated the Paris climate agreement, which commits signatories to keep temperature increases “well below” 2°C and to “pursue efforts” to limit warming to 1.5°C (CCC, 2016b). Reaching these targets means achieving ‘net zero’ emissions[3] in the second half of this century (CCC, 2016b). Importantly, this level of decarbonisation has enormous implications for all sectors of society, and on a global scale there are currently no credible plans in place to reach these goals (CCC, 2018). Indeed, according to a recent report from United Nations Environment Program (UNEP, 2017), there is an ‘alarmingly high’ emissions gap between the reductions that are

[3] Globally, net zero emissions refers to “a balance between anthropogenic emissions by sources and removals by sinks of greenhouse gases” (CCC, 2016b p. 15).

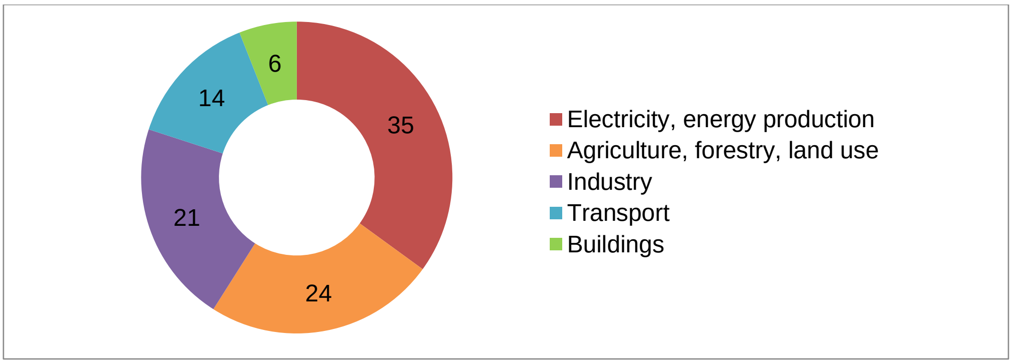
needed to meet existing targets and the national pledges made thus far (e.g. the Nationally Determined Contributions (NDCs) forming the foundation of the Paris Agreement). It is now becoming clear that if this emissions gap is not closed by 2030, it is extremely unlikely that the goal of holding global warming within the 2°C 'guardrail' can still be reached, and so "there is an urgent need for accelerated short-term action and enhanced longer-term national ambition" with regard to emissions reductions (UNEP, 2017 p. xiv).

This emissions gap also exists within the UK: though emissions have been reduced by 42% thus far (from 1990), there are currently no policies in place to achieve the decreases needed to meet further targets (CCC, 2018). Moreover, nearly all of the UK reductions to date have been in the energy sector, whereas emissions from other sectors continue to rise (CCC, 2016a). In particular, transport emissions have risen consistently over the past three years and there has been no progress in reducing agricultural emissions over the past six years (CCC, 2018). To even attempt to meet these ambitious climate commitments, emissions reductions will be needed in all sectors of the economy (CCC, 2018), and this necessitates that people's behaviours and lifestyles must change (Capstick et al., 2014).

1.2.2 Drivers of climate change with links to human health

Globally, about 35% of GHG emissions are attributable to electricity and energy production, followed by agriculture, forestry and other land use (24%), industry (21%), transport (14%) and buildings (6%) (IPCC, 2014). At the level of households and individuals, two of these sectors are of particular relevance because they also have links to human health. Transport, for example, relates to physical activity and energy expenditure, and agriculture is connected to food consumption and diet.

Figure 1.1 – Global breakdown (%) of GHG emissions (own elaboration, from IPCC, 2014)



1.2.2.1 *Transport*

Transport contributes to the production of CO_2 emissions directly through the burning of fossil fuels to support the movement of people and goods. Globally, transport-related carbon emissions have more than doubled since 1970, with 80% of this increase coming from road vehicles (IPCC, 2014). In the UK, surface transport accounts for 94% of transport emissions (CCC, 2015) and among individuals, 90% of these emissions come from car travel (Brand et al., 2013).

Car use is also damaging from a public health perspective. In addition to air pollution and road traffic crashes, society's modern dependence on personal automobiles has contributed to rising rates of obesity and other chronic diseases by reducing human movement and physical activity levels on a global scale (Faergeman, 2007, Lowe, 2014). By displacing more active modes of transportation, driving has contributed to a growing epidemic of sedentary activity[4] and made pervasive physical inactivity possible (Faergeman, 2007, Douglas et al., 2011). These health impacts have a high cost. Within the UK, for example, it has been estimated that the National Health Service (NHS) spends more than £3,000 every minute treating conditions that could be prevented by regular physical activity (Dobson, 2009), and the health care costs attributable to overweight and obesity are projected to double by 2050 to £10 billion per year (Haines et al., 2009).

1.2.2.2 *Agriculture and food production*

Similar to changes in transport, increasing wealth and changing ways of life over recent decades have resulted in dietary shifts towards foods that are more energy-dense and nutrient-poor (Lowe, 2014, Imamura et al., 2015, McMichael et al., 2007). This has been problematic because many of the most calorific foods, such as meat, dairy, and highly processed snacks, are also among the most carbon-intensive, when both production and processing are considered (Lowe, 2014, Faergeman, 2007, Garnett, 2013). Overall, food production from animal sources is the major driver of carbon emissions in the agricultural sector (Friel et al., 2009), with up to 18% of global GHG emissions attributable to livestock production alone (FAO, 2006). Notably, this is more than all global transport emissions combined (see Figure 1.1). These food-related emissions occur both directly, through the combustion of fossil fuels on farms, methane

[4] Being 'sedentary' typically refers to sitting or lying down for long periods of time, however there is a difference between being sedentary and being physically inactive. Being 'physically inactive' means not doing enough physical activity, but a person can do enough physical activity to meet recommended guidelines and still be considered sedentary if they spend a large amount of their day sitting at work, at home, for study, for travel or during their leisure time (González et al., 2017)

emissions from ruminant animals[5] and nitrous oxide emissions from fertiliser application, and indirectly, primarily due to land use change (e.g. deforestation, loss of carbon sinks) (McMichael et al., 2007, Friel et al., 2009). In addition, processes associated with the production and delivery of food to consumers, including processing, manufacturing, transportation, packaging and retail operations, also all contribute to the direct and indirect emissions of food-related GHGs (Hoolohan et al., 2013).

1.2.3 Public health co-benefits: From greatest *threat* to greatest *opportunity*

Together, these trends regarding transport and agriculture suggest that climate change and chronic disease outcomes share many of the same underlying causes: both are at least partially driven by unhealthy, high-carbon lifestyles characterised by eating too much and moving too little (Friel et al., 2011, Faergeman, 2007, Egger, 2008). As a result of these parallels, it has been argued that there is potential for positive shifts to be achieved in the areas of transport and food production that would yield co-benefits for both people and the planet (Friel et al., 2009, Haines et al., 2009, McCoy and Watts, 2014). Importantly, this has led to the emergence of a new area of research focus, which has emphasized the public health co-benefits of climate change mitigation by highlighting the fact that many of the drivers of climate change are also major drivers of chronic disease (Haines et al., 2009, Faergeman, 2007). This viewpoint has largely been advanced by those in the health field, seeking to strengthen arguments for policy action regarding climate change (Egger, 2008, Faergeman, 2007, Friel et al., 2011, Haines, 2017). The potential for public health co-benefits has also received increased prominence in the most recent report from the IPCC, which emphasized that we should see climate change in terms of its opportunities, rather than just its impacts (IPCC, 2014). In recognition of these trends, climate change mitigation has now been called the *greatest global health opportunity* of the 21st century, based on the vast number of environmental, health, and social co-benefits that have the potential to occur (Watts et al., 2015a).

[5] From a carbon perspective, the worst types of red meat are those from ruminant animals (i.e. cattle, sheep, goats, deer) because they produce methane (CH_4) as a by-product of their digestion (McMichael et al., 2007).

1.2.3.1 Evidence for co-benefits in the UK

Thus far, much of the research in the area of health and environmental co-benefits has involved modelling studies that have highlighted the potential gains that could be achieved under various theoretical shifts in travel and dietary behaviour (Haines et al., 2009, Shaw et al., 2014). For example, it has been estimated that in London there could be a 38% reduction in transport-related CO_2 emissions and 530 fewer deaths per year from physical inactivity and air pollution, if levels of walking and cycling approached those of several cities in continental Europe (e.g. Copenhagen, Amsterdam) (Woodcock et al., 2009). A subsequent study estimated that increasing active travel to this level throughout urban England and Wales could lead to savings of around £17 billion for the NHS within 20 years, due to reductions in type 2 diabetes, dementia, ischemic heart disease, cerebrovascular disease and cancer associated with increases in physical activity (Jarrett et al., 2012). Moreover, because this latter study did not include the health impacts of reducing air pollution or obesity, it is likely that these economic benefits are underestimated (Jarrett et al., 2012). Other limitations include the fact that these models did not incorporate feedback mechanisms that often occur in reality. Authors of a more recent study from New Zealand that incorporated both positive and negative feedback into their models found that policies to increase cycling in the car-dependent city of Auckland would yield public health benefits 10-25 times greater than the costs of initial policy investments (Macmillan et al., 2014).

Comparable assessments have also been conducted with regard to dietary changes. In one early study, for example, it was estimated that eating meat no more than three times a week would prevent 45,000 early deaths per year in the UK and save the NHS £1.2 billion annually (Scarborough et al., 2010). Subsequent studies have attempted to use more realistic modelling assumptions based on actual population consumption patterns. For example, a study based on 2000/2001 data from the National Diet and Nutrition Survey (NDNS) suggested that if the number of vegetarians in the UK doubled and all others adopted the dietary pattern of the lowest red and processed meat (RPM) consumers, there would be a 3-12% reduced incidence of coronary heart disease, diabetes, and colorectal cancer and a reduction of almost 28 million tonnes of CO_{2eq} (approximately 50% of agricultural emissions) (Aston et al., 2012).

Using more recent data from the NDNS (2008-2011), another study estimated that if UK adults simply adhered to WHO nutritional recommendations, GHG emissions could be reduced by 17% and that it would save nearly 7 million years of life lost prematurely (Green et al., 2015, Milner et al., 2015). In this study, further GHG reductions of up to

40% were possible by reducing animal products and processed snacks, and increasing fruit, vegetables, and cereals, however reducing emissions beyond 40% involved changes that were radically different from current consumption patterns and potentially nutritionally inadequate (Green et al., 2015).

Together, these theoretical decreases in travel and dietary emissions are substantial, but neither area is large enough on its own to meet existing climate change commitments. For example, a recent analysis has shown that to limit global warming to 2°C through emissions reductions in the food system alone, the entire planet would have to follow a vegan diet[6] (Springmann et al., 2016a). As a result, the most realistic way forward is to accept that emissions reductions will be needed across multiple sectors of the economy (CCC, 2018), and thus people's behaviours and lifestyles will likely need to change in both of these areas. This means it is crucial to begin to understand how travel and dietary behaviours overlap within individuals, and how people's behaviours are patterned together into lifestyles with different health and carbon impacts.

1.3 Chapter 1 Summary

This chapter has shown that our current lifestyles have a considerable influence on GHG emissions, though there is high mitigation potential in certain sectors that could also yield public health co-benefits (transport, agriculture). As recent reports suggest that the UK does not have sufficient policies in place to reach its existing emissions targets (CCC, 2018), there is currently a growing need to better understand ways of maximizing reductions and identifying whether there could be potential synergies between different sectors. This necessitates that we have an understanding of how multiple behaviours, in different sectors, may overlap and interact to create lifestyles with a range of different impacts. Travel and dietary behaviours may be areas where positive synergies exist, because both are related to joint health and environmental impacts, and because physical activity is often related to food consumption (de Nazelle et al., 2011). As a result, this thesis will focus on the need to understand the relationships between travel and dietary behaviours, and the extent to which these are patterned together into different types of health- and climate-relevant lifestyles.

[6] Vegans do not eat dairy products, eggs, or any other products that are derived from animals (Vegetarian Society, 2016).

2 Background: Travel and dietary behaviour

Chapter summary: The aim of this chapter is to provide an overview of travel and dietary behaviours in the UK context. In the first section, I define which elements of travel and diet have the greatest relevance for human health and carbon emissions, focusing on different travel modes and consumption of red and processed meat (RPM) and fruit and vegetables (FV). Having identified these behaviours, in the second section I review their prevalence in the UK population and identify current gaps in knowledge. Next I review the socio-demographic patterning of these behaviours in relation to the social determinants of health, and use this framework to summarize why travel modes and dietary consumption may or may not overlap based on different types of influences. Finally, I review existing evidence linking travel and dietary behaviour across different disciplines and theoretical perspectives and highlight current research gaps. These gaps are then used to shape my research questions.

2.1 Travel and diet: Which behaviours are health- and climate-relevant?

2.1.1 What is healthy, low-carbon travel?

The health and carbon implications of travel behaviour are mainly determined by the mode of travel that is used, and whether it can be considered ‘active’ or ‘passive’. Although there is no universally accepted definition, active travel (also called active transport) typically refers to modes of travel that are reliant on human physical exertion and energy expenditure in order to move from place to place. Traditionally, this has referred to walking and cycling, as these modes are most common, but it could also theoretically include such activities as skateboarding and roller-skating/roller-blading if these are used for transportation purposes. Importantly, active travel is not the same as physical activity for recreation or leisure: to be considered active travel, the key distinction is that the physical activity in question must be for *utility* purposes (e.g. getting from point A to point B), thus replacing another travel mode with greater carbon emissions (DfT, 2016a).

In addition to purely physical travel, it has also been proposed that public transport use should be considered within the realm of active travel, as there is incidental physical activity involved in virtually all public transport journeys (Flint and Cummins, 2016).

This was particularly highlighted in a systematic review of public transport use and physical activity which reported that people who used public transport typically gained an additional 8 to 33 minutes of walking time per day compared to those who travelled by car (Rissel et al., 2012).

2.1.1.1 Travel modes and health outcomes

In the UK context, walking, cycling, and public transport use have also all been associated with positive health outcomes compared with travel by car. In cross-sectional studies, all three modes have been associated with lower BMI, lower percentage body fat, and fewer diagnoses of diabetes and hypertension compared with car travel (Laverty et al., 2013, Flint et al., 2014, Flint and Cummins, 2016). In longitudinal studies, switching from car travel to walking, cycling or public transport use has been found to predict decreases in both self-reported (Martin et al., 2015) and objectively measured BMI (Flint et al., 2016). As a result, the argument can be made that walking or cycling for utility journeys and using public transport can all be considered forms of healthy, low-carbon travel because they all require some degree of physical exertion to move from place to place, and thus reduce car use, GHG emissions[7] and air pollution. Though it is also true that walking and cycling can be associated with negative health impacts related to increased exposure to air pollution and risk of road traffic injuries, studies that have comprehensively evaluated these outcomes find that they are consistently outweighed by the health benefits of physical activity in the UK and other high-income countries (Tainio et al., 2016, Jarrett et al., 2012, Woodcock et al., 2014).

When comparing all three of these modes against each other, there is also some evidence that cycling may offer greater health benefits than either walking or public transport. In a prospective analysis of 263,540 UK commuters, cycling to work was associated with a lower risk of cardiovascular disease (CVD) and CVD mortality, cancer incidence and mortality, and all-cause mortality (compared to car or PT commuting), whereas walking to work was associated with a lower risk of CVD and CVD mortality only (Celis-Morales et al., 2017). Of course, some of this variation may be explained by length of commuting journey (e.g. cyclists may be travelling farther than walkers), and indeed this study found stronger associations among those who walked and cycled for longer distances, indicating a dose-response relationship. In particular, the authors noted: “a lower risk for CVD incidence was only evident among

[7] In a study of motorized surface travel among 3474 English adults, cars were responsible for 90% of total CO_2 emissions, followed by train (4%), bus (4%), other private transport (e.g. taxi, van, motorcycle: 1.6%), and other public transport (e.g. underground, coach, ferry: 0.3%) (Brand et al., 2013).

the walking commuters who covered more than six miles a week (equivalent to two hours of weekly commuting by walking at a typical pace of three miles an hour)" (Celis-Morales et al., 2017, p. 5).

2.1.2 What is a healthy, low-carbon diet?

When considering the health and carbon implications of dietary behaviour, the main determinant is the *type* and *quantity* of the specific foods that are consumed. Given that each food's impact on the environment depends on how and where it is grown, how it is packaged and prepared, and ultimately, where it is consumed (Garnett, 2013), it is unsurprising that there is much on-going debate about which foods and what type of diet is 'best' from a sustainability perspective. According to the Food and Agriculture Organization of the United Nations (FAO), a *sustainable* diet is defined as follows:

> "Sustainable diets are diets which have a low impact on the environment, contributing to food and nutritional security as well as to a healthy life for current and future generations. Sustainable diets that contribute to the protection and respect for biodiversity and ecosystems are culturally acceptable, economically fair and accessible, adequate, secure and healthy from a nutritional viewpoint and, at the same time, optimize natural and human resources" (Burlingame and Dernini, 2012 p.7).

Importantly, this definition highlights that 'low-carbon' is only one element of sustainability since agriculture and food production can have many environmental and social impacts beyond strictly climate change. Nevertheless, from a *climate change* perspective, it is now possible to draw some relatively clear conclusions. Based on the results of several recent systematic reviews on the environmental impacts of different dietary patterns (Joyce et al., 2014, Hallström et al., 2015, Aleksandrowicz et al., 2016), whether an overall diet is low in GHGs is largely defined by the relative amount of animal products it contains, particularly with regard to red and processed meat[8] (RPM). As mentioned earlier in Section 1.2.2.2, this is because the vast majority of food-related GHGs come from livestock production due to the methane released by ruminant animals (FAO, 2006). Beef production, in particular, is a major concern because it is estimated to emit five times more GHGs than raising other types of livestock, in addition to requiring 28 times more land and 11 times more water (Eshel et al., 2014).

[8] Red meat refers to all types of mammalian muscle meat, such as beef, veal, pork, lamb, mutton, venison, horse, and goat. Processed meat refers to any meat that has been transformed through salting, curing, fermentation, smoking, or other processes to enhance flavour or improve preservation (Bates et al., 2014). In the UK, most processed meats contain pork or beef and are thus also red meats, but processed meats may also contain poultry, offal, or meat by-products such as blood. Examples of processed meat include hot dogs (frankfurters), ham, bacon, salami, sausages, corned beef, and beef jerky as well as canned meat and meat-based preparations and sauces.

Plant-sourced foods, by comparison, are a much more efficient way of producing calories because of conversion inefficiencies at each level of the food chain. Without changing the current crop mix, the amount of food grown globally today could feed an extra 4 billion people if it was not being fed to animals or used for biofuels (Cassidy et al., 2013). In terms of protein alone, beef and lamb produce 250 times more GHG emissions per gram in comparison to legumes (Tilman and Clark, 2014). Further illustrating this point, studies of the UK food system have estimated that dietary GHG emissions among meat-eaters are almost twice as high as those among vegetarians (Scarborough et al., 2014), and that eliminating meat from the diet would reduce food-related GHG emissions by 35% (compared to only 12% for cutting out all avoidable food waste, and 5% for avoiding hot-housed or air-freighted food) (Hoolohan et al., 2013). Globally, it has been estimated that reducing ruminant meat and dairy consumption will be "indispensable" for reaching the 2°C climate goal (Hedenus et al., 2014), and an illustrative modelling study from the United States has shown that the single action of substituting consumption of beans for consumption of beef (on a calorie by calorie basis) could achieve up to ¾ of the emissions reductions needed to meet the US 2020 GHG target (Harwatt et al., 2017).

2.1.2.1 Health impacts of meat consumption and vegetarian diets

Though it is well recognised that meat and meat products can be important sources of essential nutrients and vitamins (Wyness et al., 2011, SACN, 2010), there is now relatively clear evidence that *elevated* meat consumption is associated with many negative health outcomes. In the European Prospective Investigation into Cancer and Nutrition (EPIC) study, consumption of processed meat has been positively associated with mortality due to cardiovascular diseases and cancer (Rohrmann et al., 2013), and a systematic review found that consumption of processed meat and total red meat were both positively associated with all-cause mortality (Larsson and Orsini, 2014). Moreover, in 2015 the International Agency for Research on Cancer (IARC) classified processed meat as a human carcinogen, and red meat as probably carcinogenic due to positive associations with colorectal cancer (Bouvard et al., 2015). Most recently, a prospective cohort study of half a million Americans (the largest study on meat consumption and mortality to date) reported that consumption of red meat (processed and unprocessed) was associated with increased risks of all-cause mortality and death due to nine different causes, and that the associations were at least partially mediated by heme iron and nitrate/nitrite consumption[9] (Etemadi et al., 2017). This study also

[9] Both of these compounds are linked to oxidative stress in the body and help to provide a biological mechanism for the negative health outcomes associated with RPM consumption (Etemadi et al., 2017).

found that replacing red meat with white meat was associated with reduced mortality risk, even when total meat intake remained the same. In line with this evidence, even research sponsored by the UK meat industry (e.g. the British Pork Executive and the English Beef and Lamb Executive) has conceded that there is a need for high consumers of RPM to reduce their intakes for both health and environmental reasons (Wyness et al., 2011).

In accordance with the negative health impacts of excessive RPM consumption, vegetarian diets have also been found to confer protection against cardiovascular diseases, some cancers and total mortality (Scarborough et al., 2012, Soret et al., 2014), and vegan diets seem to offer additional protection for obesity, hypertension, Type 2 diabetes, and cardiovascular mortality, even in comparison to lacto-ovo-vegetarian diets[10] (Sabate and Soret, 2014). However, it is likely not just the absence of meat consumption that results in these health benefits. It is well documented that vegetarians and vegans tend to be more health conscious with regard to their overall lifestyles (Ruby, 2012, Fox and Ward, 2008a), and perhaps unsurprisingly, are found to consume more FV in comparison to omnivores in the general population (Aston et al., 2013, Scarborough et al., 2014, Cade et al., 2004, Leahy et al., 2010). This suggests that whether an overall diet is healthy cannot be simply reduced to meat consumption alone. It would, after all, be possible to be vegetarian or vegan and only eat crisps and drink sweetened carbonated beverages, however this would obviously not meet the nutritional requirements for good health. This fact was highlighted in a recent systematic review of the health benefits of low-carbon diets, where it was found that diets low in GHG emissions have the potential to be high in sugar and low in several essential micronutrients (Payne et al., 2016).

2.1.2.2 Defining dietary indicators that are health- and climate- relevant

As a result of this evidence, the argument can be made that whether a diet is healthy <u>and</u> low-carbon requires multiple dietary indicators. Most recently, eating less meat (particularly RPM) and eating more plants (especially FV) have been identified as the two most important health- and climate-relevant eating practices (Garnett et al., 2015), as these are the areas where health and environmental goals are most complementary (Figure 2.1). This is also in accordance with most nutritional guidelines: in the UK for example, adults are advised to base at least 2/3 of their diet on plant-sourced foods (including FV, starchy carbohydrates and plant proteins), specifically consuming at

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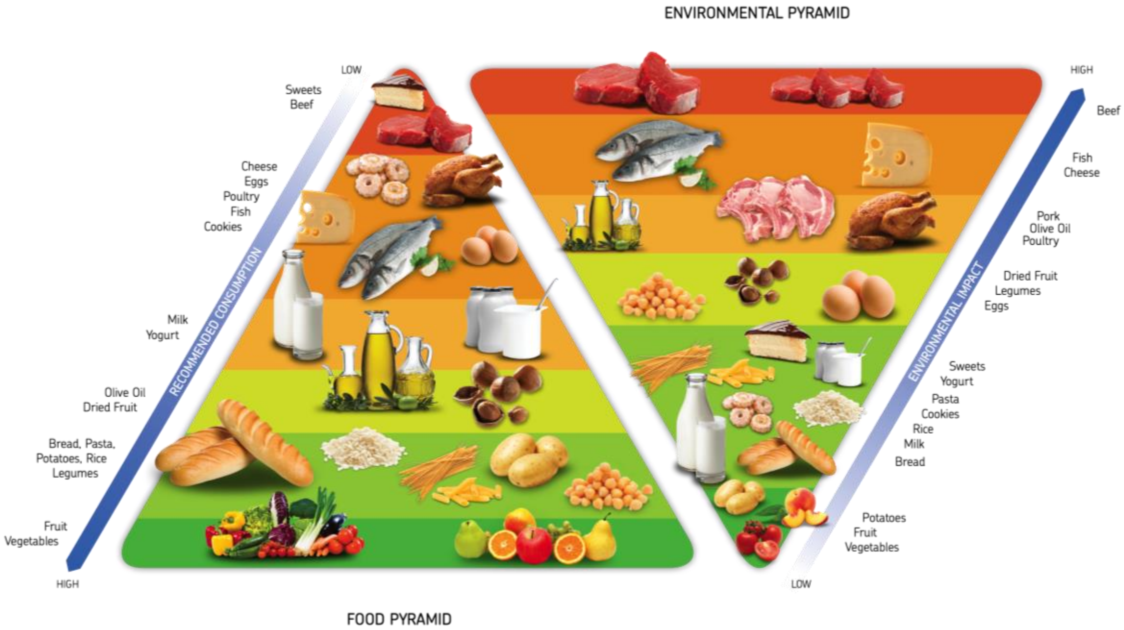
[10] Lacto-ovo-vegetarians eat both dairy products and eggs; this is the most common type of vegetarian diet (Vegetarian Society, 2016).

least five portions of FV ('5-a-day') and less than 70 grams (g) of RPM per day to prevent chronic disease outcomes (SACN, 2010, NHS, 2016). Although dairy products also come from ruminant animals and thus have high environmental impacts (though not as high as red meat) (Green et al., 2015, Berners-Lee et al., 2012), dairy consumption is generally considered healthy as it is consistently associated with beneficial health outcomes in epidemiological studies (Aune et al., 2012, Aune et al., 2013, Alvarez-Leon et al., 2006, Elwood et al., 2008, Gibson et al., 2009, Soedamah-Muthu et al., 2011, Ralston et al., 2012). In addition, consumption of fish is another area where health and environmental goals are not well aligned (Garnett et al., 2015, Clonan et al., 2012). Though public health guidelines recommend that people consume two portions of fish per week (PHE, 2016), there is currently not enough fish available globally for everyone to consume in accordance with these recommendations due to urgent concerns around biodiversity loss and ecosystem collapse (Garnett et al., 2015).

Figure 2.1 – Double Pyramid showing alignment between health and environmental benefits[11]



2.1.2.3 A note on local and organic food

Though there may be a role for eating more locally produced and organic foods as part of a *sustainable* diet (as described in section 2.1.2), there is currently little to no evidence that diets based on these foods are less GHG-intensive or beneficial to human health (Dangour et al., 2009, Edwards-Jones, 2010, Macdiarmid, 2014). Because organic foods use fewer synthetic inputs, they often have fewer environment

[11] Source: BCFN Foundation, 2015 – used with permission.

impacts per unit *area*, but not necessarily per unit *product* due to lower production yields. Depending on the product and growing conditions, this can mean that some organic products are actually more GHG-intensive than traditional products, despite their sustainable reputation (Saxe, 2014, Ravn Heerwagen et al., 2014).

Similarly, though local food consumption may help to support local economies and preserve cultural heritage, it is a fairly ineffective practice from a climate change perspective since the vast majority of diet-related GHGs are generated at the production stage rather than by food transport (Hoolohan et al., 2013). In a US study, for example, it was found that 83% of carbon emissions in the food system resulted from food production, and only 11% were attributable to transport (Weber and Matthews, 2008). Though these estimates can vary depending on individual foods and how and where they are produced and transported (Berners-Lee et al., 2012, Hoolohan et al., 2013), when considering people's diets *as a whole*, it seems clear that *which* foods are consumed and *how* they are grown or produced is more important for GHG impacts than whether foods are locally sourced[12]. Further illustrating this point, some estimates suggest that consuming foods that are exclusively local will achieve fewer GHG reductions than shifting consumption from higher-carbon foods (e.g. red meat and dairy) to lower-carbon foods (e.g. chicken, fish, eggs, or plants) for only *one day a week* (Weber and Matthews, 2008).

2.1.3 Summary of Section 2.1

In this section I have summarised the health and carbon implications of different travel and dietary behaviours in the UK context. Based on this evidence, I have argued that walking, cycling and public transport use all have the potential to offer health and carbon benefits in comparison with car travel, and that high consumption of FV and low consumption of RPM may be considered the most important markers of a healthy, low-carbon diet. In the next sections, I will critically review the evidence on measurement of these behaviours in the UK population (prevalence) and describe their socio-demographic patterning in relation to the social determinants of health.

[12] A good illustration of the role of production versus transport can be seen in a study of tomatoes in Sweden (Carlsson-Kanyama, 1998), where it was found that GHG emissions from Danish, Dutch or Swedish tomatoes were five to seven times higher per kg of tomato compared to Spanish tomatoes. This also shows how local and seasonal foods may often be in conflict—though 39% of the Spanish tomatoes' emissions were from transport, their overall emissions were still considerably lower than the tomatoes grown within or close to Sweden since the latter were all hot-housed and more intensively produced.

2.2 Prevalence of travel modes and dietary consumption in the UK context

2.2.1 Travel behaviour: Prevalence of mode use

According to data from several nationally representative surveys, most people in the UK travel by car, and only a minority of the population engages in active modes of travel (Table 2.1). For example, in the National Travel Survey[13] (NTS), 62% of all trips made in England were by car, with only 25% made on foot, 8% made by bus or train, and 2% made by cycling (DfT, 2017b). Data from the Scottish Household Survey[14] (SHS) are similar, but with a slightly higher proportion of trips made by car and by public transport (TS, 2017). Though both of these surveys represent very detailed sources of travel data, their limitations include that the SHS only captures journeys made on a single day, and the NTS only includes journeys made on routes along which motor vehicles can travel, which likely undercounts walking and cycling trips as these are often made on off-road paths (Cavoli et al., 2015).

Table 2.1 – Prevalence of travel mode use in several nationally representative studies

Source	Population (date)	Type of Journey	Car %	PT %	Walk %	Cycle %	Notes
NTS	England (2016)	All	62	8	25	2	% of all trips
SHS	Scotland (2016)	All	64	10	24	1	% of all trips
ALS	England (2015-16)	All utility	-	-	32	7	>2x in last 28 days
APS	England (2014-15)	All utility	-	-	25	2	>5x per week
Census	England/Wales (2011)	Commuting	67	18	11	3	Main mode only
UKHLS	UK (2009-11)	Commuting	69	16	12	3	Main mode only
UKHLS	UK (2009-10)	All short	-	-	43% always / very often		< 2-3 miles

NTS: National Travel Survey (DfT, 2017b)
SHS: Scottish Household Survey (TS, 2017)
ALS: Active Lives Survey (ALS, 2017)
APS: Active People Survey (DfT, 2016a)
UKHLS: UK Household Longitudinal Survey (Laverty et al., 2013, Hutchinson et al., 2014)
PT: Public transport

Indeed, other surveys, which vary in the distance and frequency of travel journeys measured, suggest that the prevalence of active travel may be higher. For example, in the UK Household Longitudinal Survey[15] (UKHLS), which measures any active travel (walking or cycling) for journeys less than 2–3 miles throughout the UK, 43% of

[13] The NTS is a continuous, population-based survey of private households in England that uses interviews and 7-day trip diaries. Typically ~7,000 households and 16,000 individuals (aged 16+) take part. The NTS defines a trip as a one-way course of travel with a single main purpose (DfT, 2016b).

[14] The SHS is a cross-sectional survey of people aged 16+ in households in Scotland. For the travel portion of the survey, participants completed a one-day travel diary that captured all of the journeys undertaken on the previous day. In 2016, the survey and travel diary had ~10,000 respondents (TS, 2017).

[15] The UKHLS is a prospective study of the socio-economic circumstances, attitudes, and behaviours of a representative sample of 40,000 UK households. This study used 35,295 individuals at wave 1 (Hutchinson et al., 2014).

participants reported that they frequently walked or cycled (21% always and 22% very often) (Hutchinson et al., 2014). This suggests that the prevalence of active travel is higher when only considering shorter trips (as would be expected), however this estimate is also limited by the fact that walking and cycling are combined, and that 'very often' is hard to interpret, as it may mean different things to different people. Prevalence estimates from the Active Lives Survey[16] (ALS) and the Active People Survey[17] (APS) also vary depending on the frequency of active travel that is measured (Table 2.1), with 32% walking and 7% cycling for transport at least twice in the past 28 days (ALS, 2017), but only 25% walking and 2% cycling for utility purposes at least five times per week (DfT, 2016a)

Together, these surveys indicate that walking is much more common than cycling in the UK, and that the prevalence of active travel is higher for shorter and occasional journeys, as active modes are often used in combination with other travel modes. In fact, estimates from the NTS indicate that 69% of English adults use multiple modes of travel on a weekly basis (Heinen and Chatterjee, 2015). Of these, most people combined walking and cycling with car travel (20.0%), or with car travel *and* public transport (17.2%) (Heinen and Chatterjee, 2015). This use of multiple travel modes within a given time period is known as multimodality, and it is an important emerging dimension of travel behaviour, as it represents a more realistic and accurate reflection of how people actually travel (Nobis, 2007). Nevertheless, multimodality is not captured in many studies, often because surveys only ask about the main mode of travel used or because they only measure one type of travel purpose. Since walking and cycling travel are less likely to be used as exclusive travel modes, surveys that do not assess multimodality may underestimate the prevalence of active travel by discounting those who use active modes in combination with car or public transport. Capturing this reality may also have implications for facilitating HLC travel, since there is some evidence that those who already use multiple travel modes may be more likely to shift their mode use than those who are 'unimodal' (Kroesen, 2014).

[16] The ALS is a 'push-to-web' survey carried out by Ipsos MORI in England. It involves postal mail outs inviting participants to complete the survey online, or by paper questionnaire. The survey is 'device-agnostic' and can be completed on mobile or desktop devices. In 2015-2016 the sample was 198,911 (age 16+) (ALS, 2017).

[17] The APS is a large annual telephone survey (n=160,000) that captures information on walking and cycling for both recreational and utility journeys among people aged 16+ in England. The APS defines *recreation* purposes as: For the pleasure or value of the activity, or enjoyment of the surroundings, whereas *utility* purposes are: Getting from A to B, which might be commuting, but would also include purposes such as shopping, going to the library, college or hospital, or visiting friends (DfT, 2016a). Based on this definition, only utility purposes would count as active travel and so these are the main focus here.

2.2.1.1 Does mode use vary by travel purpose?

Most existing data on travel mode use pertains to commuting journeys, with little evidence for other travel purposes (Mattioli and Anable, 2017). The largest source of commuting data is the Census of England and Wales, though it only reports on the single main mode of travel used. In the 2011 Census (Goodman, 2013), 67% of the population (23.7 million commuters) reported commuting by car, however the proportion commuting by public transport (18%) and cycling (3%) were higher and walking lower (11%) than for travel across all trips and travel purposes in the NTS (Table 2.1). In the UKHLS, estimates for the entirety of the UK were very similar to the Census: 69% commuted using private transport, with public transport, walking, and cycling used by 16%, 12%, and 3%, respectively (Laverty et al., 2013).

These differences between commuting trips and overall trips, however slight, reflect that fact that people may use different travel modes for different travel purposes, based on the specific characteristics of each journey. Within the NTS for example, it is estimated that 21% of shopping trips are made by walking, compared with only 11% of commuting trips (DfT, 2016b). Similarly, in the SHS, people were more likely to report using an active mode if the purpose of their journey was shopping or an appointment (28%) then if it was commuting (21.5%) (Olsen et al., 2017).

But despite these variations, there are relatively few studies that report on travel mode use across different purposes within the same individuals, which may be important for understanding multimodality. In the UK, some evidence on this comes from the iConnect2 study, a non-representative sample from three British cities (Cardiff, Kenilworth, Southampton) (Song et al., 2013). Here it was found that people were more likely to use active modes for 'discretionary' journeys than for 'obligatory' journeys[18], because the latter required longer travel distances and had more time constraints. Accordingly, when walking and cycling were compared directly, walking was found to be used more for discretionary journeys (shorter, slower) and cycling was used more for obligatory journeys (longer, faster) (Song et al., 2013). Similar results also come from a French cohort that compared mode use across different travel purposes (e.g. commuting, leisure, errands) (Menai et al., 2015). In this study, walking and cycling were also used more often for errands than for commuting, further suggesting that the prevalence of active travel is higher for non-commuting trips (Menai et al., 2015).

[18] In this study, discretionary journeys were non-compulsory travel such as shopping, personal business, and social trips, whereas obligatory journeys were commuting to work, business, and escorting children to school.

Based on this evidence, it can be argued that measuring mode use using only one travel purpose may not be an accurate representation of people's actual travel behaviour, and thus of the true impacts of their lifestyle. Since people are less likely to use active modes for commuting, only examining the journey to work will likely underestimate the true prevalence of active travel. Moreover, focusing exclusively on commuting to measure mode use may be additionally problematic because it ignores the travel of those who are unemployed, retired, or working from home, and these individuals make up a significant proportion (>40%) of the population[19]. Commuting journeys also only represent a minority of overall trips (16%) (DfT, 2016b) and personal transport carbon emissions (35%) (Brand et al., 2013). As a result, to fully understand the health and climate impacts of different types of lifestyles, there is a need for comprehensive assessment of travel mode use, across multiple types of journeys.

2.2.2 Dietary consumption: How much FV and RPM do people eat?

The most detailed estimates of UK food consumption come from the National Diet and Nutrition Survey (NDNS), a continuous cross-sectional survey based on a 4-day food diary that is used to monitor trends in nutrition and dietary intake (Bates et al., 2014). Based on recent data, it is estimated that only 27% of UK adults aged 19-64 meet the government's '5-a-day' FV recommendation, with average consumption at only four portions per day (Bates et al., 2016). According to disaggregated consumption data, vegetables are consumed in larger quantities than fruit (183 g versus 100 g per day), with cooked vegetables dishes consumed more commonly than salads and other raw vegetables (Bates et al., 2014).

Data from the NDNS also suggest that meat consumption is fairly ubiquitous, as only 2% of the UK population currently reports being vegetarian, and around 1% reports being vegan (Bates et al., 2014). These estimates are in line with more recent survey data (Vegan Society, 2016), which report that 3.25% of the British population aged 15+ are vegetarian or vegan (1.68 million people). Among meat-eaters, RPM is heavily consumed, making up 65% (71 g) of the average 109 g of daily meat intake among adults aged 19-64 (Bates et al., 2014). This estimate is just above the current government recommendation that average intakes of RPM should not exceed 70 g per day, and it is well above the amount needed to meet nutritional requirements for iron and other micronutrients (~50 g per day) (Green et al., 2015). Based on disaggregated consumption data, people aged 65+ most commonly consume processed meats like

[19] For example, in the most recent Census, 41.1 million adults aged 16–74 took part but only 57.7% commuted to work, as 14.6 million were not in employment and 2.8 million worked from home (Goodman, 2013).

‘bacon and ham’, whereas people under age 65 most commonly consume poultry (e.g. ‘chicken and turkey dishes’) (Bates et al., 2014).

2.2.2.1 Relationships between RPM and FV consumption

In addition to examining the prevalence of consumption across individuals, understanding the consumption of different food groups *within* individuals is also important as it may reveal more subtle aspects of dietary patterning, as well as what sort of foods may be subject to dietary substitution. Broadly speaking, the relationship between FV and meat consumption appears to differ depending on how meat consumption is characterised, and particularly on whether meat is consumed at all.

As mentioned previously (section 2.1.2.1), studies that dichotomise meat consumption into consumers and non-consumers typically find that vegetarians consume more FV than people who eat meat. Indeed, this finding is consistent in both national surveys (NDNS, Health Survey for England) and non-representative cohort studies (EPIC-Oxford, UK Women’s Cohort) and also when vegetarian status is defined in different ways (e.g. based on self-identification or on frequency of meat consumption) (Leahy et al., 2010, Aston et al., 2013, Scarborough et al., 2014, Cade et al., 2004). Though it may seem somewhat obvious that non-consumers of meat would eat more FV, it is important to consider that there are many other food groups that could be substituted for meat consumption (e.g. legumes, grains, dairy products). For example, in a recent study based on the UK Biobank cohort (Bradbury et al., 2017) the largest difference between RPM consumers and RPM non-consumers (poultry-eaters, fish-eaters, vegetarians and vegans) was not in consumption of FV but in consumption plant-based protein foods (e.g. legumes, vegetarian alternatives, nuts).

Amongst those who do consume meat, however, different patterns of FV consumption emerge, depending on the *quantity* or *types* of meat consumed. In terms of quantity, there does not seem to be much variation in FV consumption across different levels of meat consumption, when both RPM (Aston et al., 2013) and all types of meat are considered (Scarborough et al., 2014, Leahy et al., 2010). This suggests that when people increase or decrease their meat consumption, they do not always increase or decrease their FV consumption in a compensatory fashion. Nevertheless, there are some clear patterns in FV consumption when different types of meat (e.g. red, white, processed) are examined. In the EPIC cohort for example, studies have reported a negative relationship between consumption of FV and consumption of processed meat (Rohrmann et al., 2013, Leenders et al., 2013), and a positive relationship between consumption of FV and consumption of poultry (Rohrmann et al., 2013). Red meat, however, was more complex: women who ate the most red meat (≥160 g/day) also tended to consume more FV than average, whereas men who ate the most red meat ate more vegetables but less fruit than average (Rohrmann et al., 2013). These patterns suggest that there may be different relationships between red meat and FV compared to other types of meat, and also that dietary consumption patterns may differ slightly by gender; however, one notable limitation is that these relationships were not adjusted for overall energy intake.

Indeed, other studies that have controlled for energy intake often show inverse relationships between FV and red meat consumption, though also with slight gender differences. In a clustering study based on the 2000/2001 NDNS, both males and females had dietary patterns characterised by low consumption of fruit (not vegetables) and high consumption of red meat, however only males had a pattern characterised by high consumption of FV and low consumption of red meat (Fahey et al., 2007)[20]. Another study, comparing consumption of RPM to consumption of other sources of protein in the same NDNS 2000/2001 sample, reported that men who ate less RPM tended to eat more white meat, fish, and dairy, but fewer eggs, whereas women who ate less RPM also ate more white meat and dairy, but had no differences in fish or egg consumption (Aston et al., 2013).

Together, this evidence on dietary patterning shows that people who do not eat meat typically eat more FV, but this is not necessarily due to strict substitution as it may also reflect the fact that vegetarians tend to be more health conscious (Ruby, 2012, Fox and Ward, 2008a). In fact, based on one of the most in-depth studies of what low- and non-meat eaters actually eat, most people in these groups appeared to substitute their meat consumption with plant-based protein sources, rather than FV (Bradbury et al., 2017). Similarly, protein substitution also seems to occur amongst meat-eaters and greater amounts of FV are not necessarily consumed when total meat or RPM consumption is reduced (Leahy et al., 2010, Aston et al., 2013, Scarborough et al., 2014). Therefore, to fully understand dietary patterning from the dual perspectives of health and climate change, consumption of RPM and FV both need to be characterised—one food group cannot necessarily be inferred from the other. Some evidence also suggests that there may be gender differences in dietary patterning (Rohrmann et al., 2013, Fahey et al., 2007), but this is based on old data (e.g. 2000/2001 NDNS) and non-representative samples (e.g. EPIC cohort) that may not be generalizable to other populations.

[20] In addition to adjustment for energy intake, these patterns may differ from those in the study by Rohrmann et al. (2013) because Fahey et al. (2007) did not distinguish between consumption of red meat and consumption of processed meat, and also because only 17% of the full EPIC cohort is based on UK participants (~88,000).

2.2.3 Summary of Section 2.2

In this section I have shown that most people in the UK travel by car for most journeys, but many people also incorporate HLC modes (walking, cycling or public transport) into their overall travel behaviour for short journeys or specific travel purposes. In relation to diet, I have shown that most people do not consume enough FV and many people consume too much RPM, however relationships between FV and RPM consumption are inconsistent among meat-eaters and may vary by gender. Understanding how these behaviours are patterned together within the same individuals is important if we are to fully comprehend the overall impacts of people's lifestyles. To most accurately assess how people's lifestyles may relate to different health and carbon impacts, studies are needed which capture travel mode use across different types of journeys as well as consumption of different dietary constituents (FV and RPM). In the next section, I will review how each of these behaviours is socio-demographically patterned in the UK population, in order to summarise how different travel modes and dietary consumption may overlap in certain population groups.

2.3 Travel and dietary behaviour: socio-demographic patterning

Like many behaviours and aspects of lifestyle, travel mode use and dietary consumption are socio-demographically patterned in the UK population, as they are shaped by the general conditions and circumstances in which people live. These 'wider determinants' are conceptualised in the well-known 'rainbow' model of the social determinants of health (SDH) (Dahlgren and Whitehead, 1991). In this model, individuals are placed at the centre, and are surrounded by different 'layers' that influence their health and wellbeing. In these layers, lifestyles are shown as being related to individual characteristics (e.g. age, sex), but are also embedded in social influences, and in living and working conditions, which are in turn shaped by more general socio-economic, cultural, and environmental circumstances. This theoretical perspective is known as a socio-ecological framework (SEF), and it recognizes that the interrelationships between an individual and their environment are dynamic and reciprocal, and that many factors, at multiple levels of influence, affect people's behaviours and ways of life (Stokols, 1992, Bronfenbrenner, 1992, Sallis et al., 2008, Schneider and Stokols, 2009). Indeed, both travel and dietary behaviours are now commonly represented using this type of framework, as it best reflects the interactions between the individual, social, and environmental factors which shape their prevalence in the population (Glanz et al., 2005, Sallis et al., 2006, Kamphuis et al., 2006, Sallis and Glanz, 2009, Badland et al., 2013, Trapp et al., 2015).

In most cases, SEFs tend to be behaviour-specific, so a framework describing cycling will not necessarily be the same, or include the same layers, as a framework describing meat consumption (Sallis et al., 2008, Schneider and Stokols, 2009). However SEFs can also be used to understand how individual behaviours group together into broader lifestyles, as is the case with the SDH model. For example, a socio-ecological understanding of travel and dietary behaviour suggests that healthy, low-carbon behaviours may overlap in the same individuals due to the combined influences of individual characteristics, social circumstances, and environmental conditions. In practice, the role of these influences can be examined using the patterning of demographic, socio-economic, and area-level factors in relation to travel modes and dietary consumption.

2.3.1 Environmental patterns in the UK context

There is clear evidence that travel modes and dietary consumption are patterned differently based on where people live in the UK and the characteristics of the area.

2.3.1.1 Travel modes

For travel behaviour, one notable pattern is that people in rural areas are less likely to use active travel and more likely to travel by car. In the UKHLS for example, 46% of urban residents reported frequent walking or cycling for short journeys compared to only 33% of rural residents (Hutchinson et al., 2014), and in the National Travel Survey, 50% of rural households reported having access to two or more cars (DfT, 2016b). Beyond these simple urban / rural differences, there are also distinct regional trends, most strikingly between London and the rest of the UK. Comparing travel mode use between different parts of England, car trips are made much less frequently in London[21] than in the rest of England (urban *or* rural), and people in London are also more likely to live in households with no car (41%), compared to other urban (24%) and rural areas (10%) (DfT, 2016b). In accordance with their lower car use, residents of London also tend to make more trips by public transport (bus and rail) (DfT, 2016b) and are more likely to walk, cycle, or use public transport for their commute compared to those living in other parts of the UK (Laverty et al., 2013). For example, nine of the top 10 authorities with the highest percentage of walking (at least five times a week) were in London according to the Active People Survey (DfT, 2016a). In contrast to walking and public transport, however, cycling is patterned differently: across England rates of cycling (at least once a month) are highest in Cambridge (58%), Oxford (43%), and York (34%) (DfT, 2016a). Outside of England, commuting travel in Scotland is broadly similar to the UK average (Table 2.2), however Wales and Northern Ireland have higher levels of car commuting and lower rates of public transport and cycling (Laverty et al., 2013).

Table 2.2 – UK regional variations in travel mode use for commuting journeys

Source	Population	Car %	PT %	Walk %	Cycle %	Notes
UKHLS	UK	69	16	12	3	Commuting, main mode only
UKHLS	Scotland	68	14	15	3	Commuting, main mode only
UKHLS	Wales	78	7	13	2	Commuting, main mode only
UKHLS	N. Ireland	84	5	10	1	Commuting, main mode only

UKHLS: UK Household Longitudinal Survey (Laverty et al., 2013)
PT: Public transport

[21] Note: car trips do not include trips by taxi.

Overall, these distinct patterns in travel behaviour are generally explained as being due to notable differences in the built environment between urban and rural areas, as urban areas have greater population density and land-use mix[22]. These factors are particularly important for use of healthy, low-carbon travel modes because they affect the accessibility of different destinations and the distances people need to travel to reach them (Heath et al., 2006). Because of their higher population density, urban areas also tend to have greater provision of public transport and more facilities and infrastructure to support active travel, such as walking paths and dedicated cycling routes (e.g. off-road or on-road separated from traffic) (Panter et al., 2008, Heinen et al., 2010, Fraser and Lock, 2011, Pucher et al., 2010a). Many of these factors are now incorporated into walkability scores, which explains why more 'walkable' places also tend to have higher rates of active travel[23] (Sallis and Glanz, 2009). As a result, features of the built environment are now commonly believed to be necessary, though not sufficient, for successfully increasing active forms of travel (Giles-Corti and Donovan, 2002).

In addition to the built environment, there is also some evidence that cycling may be influenced by regional variations in culture and social norms, perhaps due to its relative rareness compared with other travel modes. For example, previous research has shown that there are distinct local cycling cultures throughout the UK (Aldred and Jungnickel, 2014, Goodman et al., 2012, Steinbach et al., 2011) and that cycling can take on different cultural meanings in different contexts, with cycling being viewed positively (e.g. Cambridge, Bristol, Hackney) or negatively (e.g. Hull) depending on class associations and local stereotypes (Aldred and Jungnickel, 2014).

[22] According to Cervero & Kockelman (1997), the built environment refers to "the physical features of the urban landscape (i.e. alterations to the natural landscape) that collectively define the public realm, which might be as modest as a sidewalk or an in-neighborhood retail shop or as large as a new town."

[23] Walkability is commonly defined by: 1) Density (e.g. the number of individuals or households within a given area), 2) Diversity (e.g. land-use mix or the variety of destinations within a given area), and 3) Design (e.g. various attributes such as street connectivity, cycling infrastructure, aesthetics, green space, etc.) (Cervero & Kockelman, 1997)

2.3.1.2 Dietary consumption

There are also regional variations in dietary consumption. In the Health Survey for England (HSE), people living in London and the south of England have been found to consume higher amounts of FV compared with other parts of England, and are also most likely to meet the '5-a-day' guideline (Roberts, 2014). Data from Scotland add to the north-south gradient: in the 2015 Scottish Health Survey, adults consumed an average of 3.1 portions of FV per day and only 20% of adults met the '5-a-day' recommendation, while 11% reported not consuming any FV at all (Brown et al., 2016)

Data from the HSE also show regional variability in meat consumption. Though there were no associations for urban / rural status, living in London and the East Midlands was associated with significantly higher odds of consuming no meat at all (compared with living in South East England), and living in the South West was associated with consuming meat less frequently (Leahy et al., 2010). By contrast, living in Yorkshire and the Humber was associated with consuming meat more frequently (Leahy et al., 2010). These data, however, are now 10 years old (2008 HSE) and include all types of meat (red meat and poultry).

Reasons for these patterns may be due to regional differences in food accessibility and culture, as well as socio-economic conditions that are regionally embedded. According to a systematic review by Kamphuis et al. (2006), the north-south gradient in FV consumption is likely related to well-known socio-economic differences between the north and south of the UK, however the fact that in one study people's consumption decreased when they moved to Scotland (from Greece) also suggests that local accessibility and cultural factors could be at play. Several studies and systematic reviews have shown that people who live nearer to supermarkets often consume more FV (Kamphuis et al., 2006, Trapp et al., 2015), whereas people living in greater proximity to fast food (takeaway) outlets tend to consume less FV (Fraser et al., 2010, Black et al., 2014). It is unlikely, however, that such differences in local proximity can explain the totality of these regional variations, and there is also little evidence for how such accessibility relates to meat consumption, if at all.

Regional differences in food cultures (e.g. rural areas having stronger links to livestock agriculture), combined with residual confounding[24] by socio-demographic factors may also be a plausible explanation for geographic variability in meat consumption. For example, Leahy et al (2010) attributed their finding of reduced meat consumption in London as being due to the fact that people there are more ethnically diverse, have more qualifications, and are younger on average than the rest of the UK, even though they adjusted for all of these factors in their study. Similarly, a recent analysis linking dietary clusters with residential geography (Output Area classification Supergroup from the 2001 Census[25]) also found regional differences in food consumption even when adjusting for socio-demographic characteristics: low meat (vegetarian) clusters were more common in greater London and in the ‘City living’ and ‘Multicultural’ Supergroups, and clusters with higher meat consumption[26] were associated with the ‘Prospering Suburbs’ and ‘Countryside’ Supergroups (Morris et al., 2016).

In addition to socio-demographic and cultural factors, these patterns may also reflect differences in the ‘foodscapes’ between different parts of the UK[27]. For example, cities and urban areas often have greater diversity in restaurants and food establishments, and some of these may feature meat less prominently than in traditional British cuisine. A prime example of this can be seen in the recent expansion of vegetarian locations of the ubiquitous UK chain Pret A Manger (Veggie Pret). Thus far, these vegetarian restaurants have all been situated in London (Pret A Manger, 2017), most likely because of the higher prevalence of vegetarians there, but these establishments (and others like them) may also make it easier for non-vegetarians in London to consume less meat, potentially creating a ‘virtuous cycle’.

[24] Residual confounding occurs when there is imperfect adjustment in a confounding variable (e.g. due to improper categorisation or measurement error) or when there are confounding variables that remain unaccounted for (Szklo and Nieto, 2007).

[25] Each Output Area is a geographical unit containing around 100 households (~250 people). Supergroup classification was based on clustering of 41 census variables, using an adapted K-means procedure (Vickers and Rees, 2007).

[26] For example, Traditional meat, chips and pudding eaters; High diversity traditional omnivores

[27] Foodscapes can be understood as “physical, organizational and sociocultural spaces in which [people] encounter meals, food and food-related issues” (Mikkelsen, 2011 p. 209).

2.3.2 Socio-economic patterns in the UK context

2.3.2.1 Travel modes

In the UK, car use has a clear social gradient in relation to household income, occupational class, and employment status. In the National Travel Survey (NTS), for example, the average number of miles travelled by car was positively associated with household income, and people working in managerial and professional jobs travelled farther by car than those in intermediate or routine occupations (DfT, 2016b). People who were employed (full-time or part-time) also made more trips by car than people who were unemployed or economically inactive. In addition to distance travelled and number of trips, household car availability (e.g. the number of cars per household) is also positively correlated with household income. In the NTS, 50% of households in the *highest* income quintile had two or more cars per household, and 50% of households in the *lowest* income quintile had no cars per household (DfT, 2016b). Household car availability is one of the strongest predictors of transport carbon emissions (Brand et al., 2013), and having no car in the household is strongly and independently associated with more frequent active travel (Hutchinson et al., 2014).

In accordance with these patterns, people who use more active modes of travel generally have lower household incomes, lower occupational class, and lack of full-time employment (Laverty et al., 2013, Hutchinson et al., 2014, Martin et al., 2015). However, conflicting associations for different active travel modes have been sometimes found in relation to education level and area-level deprivation. In the UKHLS, for example, cycle commuting and public transport use have been associated with higher qualifications (Laverty et al., 2013), however, walking and cycling for short journeys was positively associated with higher qualifications in urban areas, but negatively associated with educational attainment in rural areas (Hutchinson et al., 2014). In the 2011 Census, Goodman (2013) found that higher area-level deprivation[28] was negatively associated with car commuting and positively associated with commuting on foot and by public transport, but was only weakly associated with cycle commuting.

[28] Based on the English Indices of Multiple Deprivation (IMD), also adjusting for geographical remoteness, since urban areas also tend to be more deprived (Goodman, 2013)

These social gradients in car use primarily reflect the economic realities of car ownership: cars cost money—to buy, to drive, and to maintain—so it is logical that household car availability and average distance travelled is positively associated with household income. In addition, however, cars themselves may also be seen as status symbols (both in brand and quantity), and thus may also be used as markers of class distinction (Goodman et al., 2012).

Explanations for the different patterns observed for education may be because people with higher qualifications are often found to be more health conscious and have greater environmental concern (Howell, 2013), and thus may *choose* to use active modes of travel, even if they already own, or can afford to travel by car. Use of active travel has previously been linked to health and environmental motivations both in the UK (Thomas et al., 2016, Whitmarsh, 2009) and elsewhere (Heesch et al., 2012, Thøgersen and Ölander, 2006). Nevertheless, the distinction between urban and rural areas highlights the interactions that occur between different layers of influences in the SEF: highly educated people in rural areas may not be able to 'choose' to use low-carbon modes of travel, and in the same vein, those who live in urban areas may have 'chosen' to live there because they prefer to travel using low-carbon modes (Molin et al., 2016).

2.3.2.2 Dietary consumption

As with car use, there are also clear social gradients for consumption of FV and RPM in the UK population. Notably, however, these gradients go in opposite directions with FV being positively associated with socio-economic position (SEP) and RPM being negatively associated. For example, a study that used NDNS data (2008-2011) to examine food consumption in relation to education, equivalised household income, and occupational class found that FV consumption was positively associated with SEP across all three indicators (Maguire and Monsivais, 2014). Here the largest difference was between the most and least educated at 127.7 g (1.6 portions[29]) per day, with similar differences observed for occupational class (1.4 portions) and between the highest and lowest income groups (1.2 portions) (Maguire and Monsivais, 2014). Likewise, higher consumption of FV was also positively associated with income in the Health Survey for England (HSE) (Roberts, 2014) and a systematic review found that living in more deprived areas was associated with lower FV consumption in several UK studies (Kamphuis et al., 2006).

[29] 1 portion = 80 g of FV

An inverse social gradient was also observed for RPM consumption in the NDNS sample from 2008-2011, however the disparity between the lowest and highest SEP groups was smaller than for FV. Here the largest gradient was seen for occupational class, where participants in higher managerial and professional occupations consumed 25.5 g per day less RPM than those in routine occupations. For education level, those with no qualifications consumed 21.9 g more RPM per day than degree-educated participants, and participants in the lowest-earning households consumed 15.7 g more RPM per day than the highest-earning households (Maguire and Monsivais, 2014). Notably, however, when RPM non-consumers were examined separately, their socio-economic profiles diverged from these trends across all three indicators, suggesting that RPM non-consumers were of a *lower* SEP than RPM consumers (Maguire and Monsivais, 2014). This pattern may be related to ethnic and cultural differences, which will be discussed in the next section on demographic factors (2.3.3.2).

These socio-economic relationships are also different when total meat consumption (red meat and poultry) is examined. In the 2008 HSE, adults with any education above O level consumed meat significantly more often than those with no qualifications; however, adults who had completed higher education were also significantly more likely to consume no meat than those who had no qualifications (Leahy et al., 2010). In particular, having degree-level qualifications increased the odds of consuming no meat by 95%. For household income, it was found that adults in households earning between £100,001 and £150,000 a year consumed meat more often than those earning between £10,400 and £20,400, though there was no relationship between household income and never consuming meat (Leahy et al., 2010).

Together, this evidence suggests a complex picture between meat consumption and SEP, whereby consuming lower quantities of RPM, but higher frequencies of *all* meat, is associated with *higher* SEP, and where consuming no RPM is associated with *lower* SEP, but never consuming any meat is associated with higher educational attainment. These subtleties may reflect the fact that individuals with higher SEP consume less RPM, but more white meat overall, and that non-consumers of RPM and non-consumers of *all meat* are not necessarily the same groups of people. Comparing across the different socio-economic indicators, these gradients suggest that a range of different mechanisms (e.g. material resources, cultural practices, social norms, knowledge and skills) may play a role in dietary consumption (Maguire and Monsivais, 2014), and this is consistent with previous literature emphasizing the importance of using multiple measures of SEP to fully characterize the socio-economic patterning of diet (Turrell et al., 2003).

2.3.3 Demographic patterns in the UK context

2.3.3.1 Travel modes

Age and gender

Walking, cycling, and public transport use are usually highest among those in younger age groups, as younger people may not have acquired a driver's license or be able to afford a car. As a result, travel by car typically increases substantially between the ages of 20 to 30 (from <50% of trips to >60% of trips), remains high among those of working age, and then decreases slightly above the age of 70 (DfT, 2016b). Findings from the UKHLS also report that younger people (age 16-29) are more likely to walk, cycle, or use public transport for their commute than older age groups (Laverty et al., 2013) and data from the Active People Survey show that both walking and cycling for utility purposes declines steadily with age (DfT, 2015a).

Use of different travel modes also varies by gender. Men tend to make more trips by car (especially as driver), as well as by rail and by cycling, whereas women make more trips by bus and by walking (DfT, 2016b). After age 20, men make more trips as car driver than women across the rest of the life course, corresponding with the fact that men are more likely than women to have a driver's licence across all age groups (DfT, 2016b). Cycling travel is also a particular point of divergence, as the rate of cycling among men is at least double the rate among women, across all age groups and types of cycling journeys (DfT, 2016a). These variations also persist when specific travel purposes are examined: in the UKHLS women were significantly more likely than men to commute using public transport (adjusted[30] odds ratio (aOR)=1.22; 95%CI 1.11, 1.35) or by walking (aOR=1.78, 95%CI 1.61, 1.97), but much less likely to cycle (aOR=0.44, 95%CI 0.36, 0.52) (Laverty et al., 2013).

Explanations for these patterns have been attributed to specific gender roles and identities (Gatersleben and Appleton, 2007, Steinbach et al., 2011), women's greater fear of cycling in traffic (Garrard et al., 2008), as well as differences in the *types* of travel journeys that men and women undertake across the life course. For example, data show that women are more likely to make trips involving shopping, errands/personal business, and escorting others (particularly children to school) and many of these journeys tend to be walked (DfT, 2016b). Several qualitative studies have also shown that women may be less likely to cycle because the culture of cycling in the UK is predominately male, and may be viewed by both men and women as

[30] Adjusted for age, ethnicity, education, social class, and region of the UK.

incompatible with a ‘feminine’ gender identity (Dickinson et al., 2003, Steinbach et al., 2011, Gatersleben and Appleton, 2007).

Ethnicity

Travel mode use also varies by ethnic group, particularly for healthy, low-carbon travel modes. In the UKHLS, all ethnic groups other than White were more likely to use public transport or walking for their commute (Laverty et al., 2013), and in the Active People Survey, White British participants were least likely to walk for utility purposes, compared to all other ethnic groups (DfT, 2015a). Importantly, whilst these variations may be reflective of real differences in travel preference between ethnic groups, these studies did not account for the fact that urban areas (where walking and public transport are higher) have a higher proportion of non-White ethnic groups, though the study by Laverty et al. (2013) did adjust for whether participants lived in London or elsewhere. Nevertheless, the fact that cycling appears to be more common among White individuals, and the fact that South Asians are particularly unlikely to cycle (even within London), suggests that these patterns are not solely due to simple urban / rural differences (Steinbach et al., 2011, Laverty et al., 2013, DfT, 2016a). Within London, for example, qualitative research has shown that cycling for transport is viewed by Black and Asian individuals as “inappropriate within their communities, or simply invisible as an adult transport mode” since it is predominantly associated with transport among affluent White men (Steinbach et al., 2011, p.1129).

Household size and structure

There is relatively little evidence about household size and structure and different travel modes in the UK context as most of the data pertain to car use only. One study of household carbon emissions reported that transport emissions increased proportionally with the number of adults and children per household (Büchs and Schnepf, 2013), which suggests that larger households with children are more likely to travel by car. This finding is also in accordance with evidence from the UKHLS, which reported that having no children in the household was positively associated with more frequent walking and cycling, though not after adjusting for household car availability (Hutchinson et al., 2014).

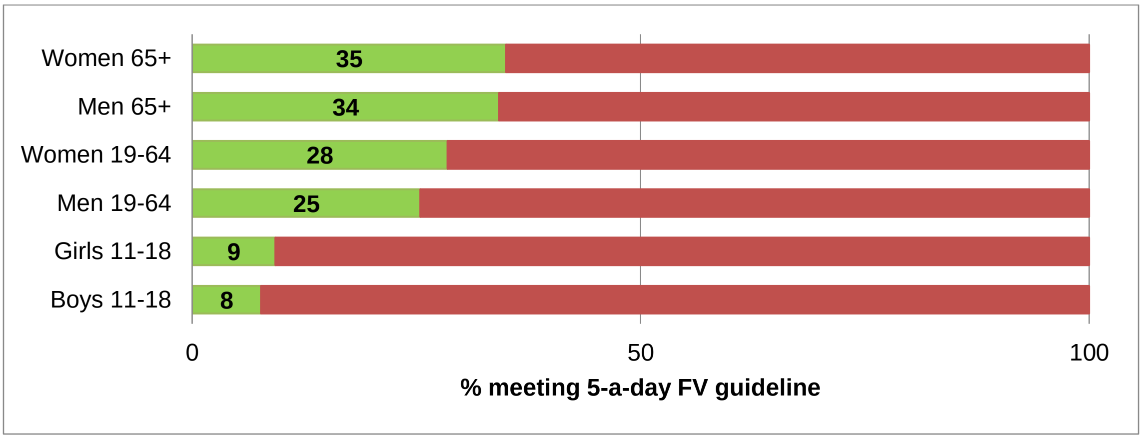
Evidence from longitudinal studies is conflicting regarding whether having a child is associated with more or less car travel. In the UKHLS, a study of life transitions and car use reported that having a child was associated with a decrease in car ownership (Clark et al., 2014), however a qualitative study of the transition to new motherhood reported that some new mothers reduced their car travel after giving birth, whereas others used having a baby as an impetus for acquiring a driver's license and purchasing a car (Burningham et al., 2014). Longitudinal evidence from the UKHLS shows that living in larger households (4+ people vs. 2 people) and increasing number of adults per household was positively associated with car ownership (Clark et al., 2014).

2.3.3.2 Dietary consumption

Age and gender

Current evidence suggests that FV consumption is higher among older age groups in the UK, which is similar to patterns observed globally (Nicklett and Kadell, 2013). This can be seen in Figure 2.2, where FV consumption increases with age, such that men and women aged 65+ were most likely to meet the 5-a-day guideline (34% and 35%, respectively). Figure 2.2 also shows that there are slight differences in FV consumption by gender, such that women (and girls) are more likely to meet the 5-a-day guideline at every age group.

Figure 2.2 – Proportion (%) meeting 5-a-day FV guideline, NDNS 2012-2014 (own elaboration)

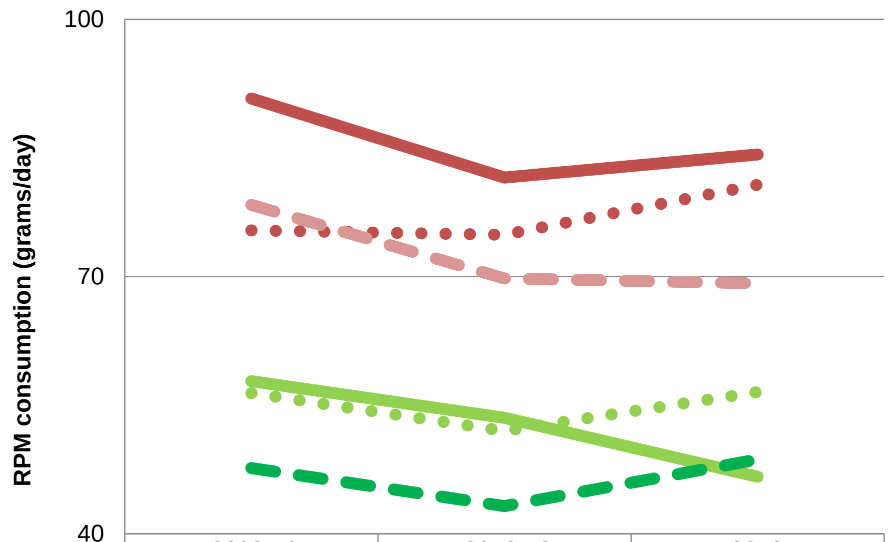


Green = meeting guideline, red = not meeting guideline

Nevertheless, this gender difference is minor compared to the difference in consumption of RPM. As can be seen in Figure 2.3, RPM consumption is much higher than the recommended 70 g per day among men aged 19+, whereas it is much lower than this among women of all age groups. As a result, it is clear that the average RPM consumption for the overall population (65 g per day in 2012-2014) is obscured by large gender discrepancy, with an average of 84 g per day consumed among men and 47 g per day consumed among women (Bates et al., 2016). It can also be seen in

Figure 2.3 that RPM consumption does not have a clear pattern in relation to age: among males, consumption is highest in the 19-64 age group, whereas among females it is highest among those aged 65+. In the HSE, consuming no meat at all was positively correlated with younger age, and women were twice as likely to never consume meat compared with men (Leahy et al., 2010).

Figure 2.3 – RPM consumption (g/day) over time by gender, NDNS 2008-2014 (own elaboration)



	2008-10	2010-12	2012-14
Men 65+	75	75	81
Men 19-64 years	91	82	84
Boys 11-18 years	78	70	69
Women 65+	56	52	57
Women 19-64 years	58	54	47**
Girls 11-18 years	48	43	49

** Indicates that consumption is significantly lower (p<0.01) in 2012-2014 compared with 2008-2010

As there is no biological reason for men to consume more RPM than women[31] these differences can be largely attributed to symbolic social meanings associated with different food groups and to RPM consumption in particular. For example, there is considerable evidence linking meat consumption (and especially RPM consumption) to images of masculinity (Ruby, 2012, Rothgerber, 2013, Roos et al., 2001, Sobal, 2005, Rogers, 2008, Ruby and Heine, 2011), which is one explanation for why men tend to consume meat more frequently and in larger quantities than women, and also why men are less likely to be vegetarian.

[31] In fact, during child-bearing years women have a higher dietary iron requirement than men due to iron lost through menstruation (Green et al., 2015, SACN, 2010).

Ethnicity

Meat consumption is also found to vary widely in relation to ethnicity in the UK context, particularly because some ethnic groups (e.g. Indians, Pakistanis) may not consume any meat, or may avoid certain kinds of meat (especially beef and pork), for religious reasons. For example, in the 2008 HSE South Asians were found to consume meat much less frequently than White individuals (OR=0.36, $p<0.001$), and were much more likely to report consuming no meat at all (OR=4.24, $p<0.001$) (Leahy et al., 2010). Regarding FV consumption, however, it is not clear whether South Asians in the UK replace the meat they do not consume with greater amounts of FV. In a review by Chowbey and Harrop (2016) some evidence shows that South Asian diets may be low in fruit, vegetables and fibre, whereas other evidence reports that "all minority ethnic groups, across both genders and all age groups, consume more FV on a daily basis than the rest of the [UK] population" (p. 2). Evidence from a study of home food availability conducted in Bradford may help to explain this contradiction, as it was found that Pakistani households had a higher frequency of fresh FV but a lower frequency of tinned, dried and frozen FV in their homes compared with White British households (Bryant et al., 2015).

In contrast to South Asians, respondents who were Black, Chinese, or of Mixed ethnicity were found to consume meat more frequently than White individuals in the HSE sample; however, reasons for these associations are unclear (Leahy et al., 2010). Findings from a large sample in the United States have also shown that meat consumption may be higher among Black, Asian, and Hispanic individuals, which the authors explain as being possibly due to meat consumption acting "as a status marker for groups that have been historically marginalized" (Gossard and York, 2003 p. 6).

Household size and structure

In the UK, studies show that living in larger households and being married are positively associated with consumption of meat and FV. In the HSE, for example, it was found that single, divorced, and cohabiting individuals consumed meat less frequently than people who were married, and that divorced and single individuals were also significantly more likely to report never consuming meat compared with those who were married (Leahy et al., 2010). Similarly, it was also found that household size was positively associated with frequency of meat consumption, among both children and adults (Leahy et al., 2010). In particular, almost 60% of adults who reported *never* consuming meat lived in small (one or two person) households (Leahy et al., 2010). These patterns may be related to economies of scale in meat purchasing, as well as the fact that larger households may be more willing to take the time and effort to prepare a meal that includes meat when there are more people with whom to share it. Alternatively, larger family size may also reflect aspects of social class and lifestyle that are not fully captured by other explanatory variables (e.g. residual confounding) (Leahy et al., 2010). At the same time, the fact that FV consumption is also higher among larger households and among married individuals (Kamphuis et al., 2006), means it is possible that both of these factors are merely markers for eating more food *in general*, as these studies did not adjust for overall energy intake. Other studies have also shown that relationships with family, friends, and neighbours, measured through social support and social ties, may be associated with increased consumption of red meat and FV (Tamers et al., 2013). Regarding children, however, evidence is equivocal: results from a systematic review of FV consumption reported that having children in the household was associated with consuming *fewer* vegetables but *greater* amounts of fruit (Kamphuis et al., 2006).

2.3.4 Summary of Section 2.3

This section has described a complex interplay of factors affecting travel and dietary behaviours in the UK context across different layers of influence, including regional environments, social and material conditions, and household demographics. Based on these population-level patterns, this evidence suggests that healthy, low-carbon travel and dietary consumption may be associated with similar environmental and demographic influences, and are most likely to overlap in urban settings (particularly London), in smaller households, and among people who are younger, non-White, female, and with higher levels of education. However, it is not clear from this evidence whether these behaviours actually intersect in the same individuals since travel modes and dietary consumption have not yet been examined together. At the same time, there is also evidence that car travel and RPM consumption follow opposite social gradients, such that higher SEP is associated with more car travel but less RPM consumption, which further complicates an already complex picture. As a result, there remains a need for greater clarity regarding how travel and dietary behaviours are patterned together among individuals in the UK.

2.4 Existing evidence of relationships between travel and dietary behaviour

Although there are currently no studies of the relationships between use of different travel modes and consumption of FV and RPM, there is some evidence from studies of other health and environmental behaviours that supports the potential for overlap between behaviours that are healthy and low-carbon. For example, studies of 'health' behaviour often examine associations between physical activity and nutrition (in relation to obesity and chronic disease), whereas studies of 'environmental' behaviour typically focus on understanding the values and attitudes that underlie various pro-environmental behaviours (e.g. active travel, recycling). This evidence comes from several different disciplines (e.g. epidemiology, environmental psychology), which use different theoretical perspectives to understand the relationships between multiple behaviours.

2.4.1 Studies of physical activity and diet in health research

2.4.1.1 Epidemiological perspective on clustering

The epidemiological perspective on multiple behaviours has already been introduced in the previous section (2.3). This perspective is largely based on the SDH model, where the observation that 'risky' health behaviours are most common in more disadvantaged population groups has been understood to mean that shared social determinants give rise to groupings of unhealthy (and healthy) behaviours (Marmot et al., 2008, Rose, 2001, Spring et al., 2012a). These groupings are often described as 'clusters' and behavioural clustering is a way to understand the propensity for certain combinations of behaviour to group together into different types of lifestyles. As a result, identifying whether behaviours are closely related is important because behaviours that share strong empirical relationships are more likely to have similar determinants (aetiologies) (Flay and Petraitis, 1994, McAloney et al., 2013).

Thus far, much of the research focus on clustering has been on identifying and understanding population subgroups with a high number of behaviours that fail to meet established health guidelines (McAloney et al., 2013). These studies often examine physical activity and FV consumption (as well as smoking status and alcohol use) and typically find that health-promoting behaviours such as greater physical activity and healthier diets cluster together in more socially advantaged population groups (Dodd et al., 2010, Poortinga, 2007, Noble et al., 2015, Buck and Frosini, 2012, Watts et al., 2015b, Graham et al., 2016). This pattern suggests that clusters of positive health behaviours may be driven by a common 'health conscious' motivation, which is shaped by shared structural factors that enable certain groups to make healthier choices and lead healthier lives.

This relationship between greater physical activity and healthy diets is also apparent in other studies that examine multiple dietary components. For example, in the Spanish cohort of the EPIC study (n=37,287), the most physically active participants consumed greater amounts of FV, fish, and dairy products compared to the least physically active group, though there were no differences in the amount of total energy consumed or overall macronutrient breakdown (Tormo et al., 2003). Similar relationships were also reported in a smaller US study (n=1,322), which found that sedentary individuals consumed smaller amounts of healthy foods (e.g. FV, whole grains) and higher amounts of RPM (Gillman et al., 2001). Though these studies show clear associations between being physically active and the quality and healthiness of one's diet, they are limited by their cross-sectional design, which means causality cannot be inferred from these relationships.

Nevertheless, there are also longitudinal studies in this area, which are more robust for assessing causality and directionality between associated behaviours (e.g. whether physical activity precedes a healthy diet, or vice versa). In the 1958 British Birth cohort, for example, participants who increased their physical activity level between the ages of 33 and 42 (1,377 males, 1,569 females) showed greater improvements in dietary quality (measured by consumption of fruit, salad, chips, sweets, biscuits, and fried food) compared to those who decreased their activity frequency (Parsons et al., 2006). Similarly, in a US intervention study which divided colorectal cancer survivors into clusters (n=595), the most "physically active" cluster reported the highest increase in consumption of FV (1.3 servings/day) over one year of follow-up (Reedy et al., 2005). Both of these studies suggest that increasing physical activity may lead to healthier dietary consumption, however they are limited by their relatively small size, possible non-representativeness, and neither study examined relationships with meat consumption.

2.4.1.2 Neurocognitive perspective linking physical activity and diet

This epidemiological evidence of longitudinal relationships between physical activity and dietary quality is also supported by early evidence and understanding in cognitive neuroscience. From this perspective, it is argued that there may be neurocognitive links between increasing physical activity and healthy diets since physical activity may act as a catalyst or ‘gateway’ behaviour by improving executive function in the brain (Loprinzi, 2015). Here, the underlying premise is that many aspects of ‘lifestyle’ are served by the same neural circuitry, which utilises shared and limited self-regulatory resources in the pre-frontal cortex (Spring et al., 2012a). Since executive function is related to both self-regulation and goal-setting behaviour, it has been argued that people who are more physically active may also have greater control over other types of activities (Loprinzi, 2015), with particularly strong relationships observed for regulation of diet and eating behaviours (Joseph et al., 2011).

Together, these epidemiological and neurocognitive perspectives explain clustering between health-promoting behaviours like physical activity and diet in two ways. First, that ‘healthy’ behaviours often cluster due to shared social determinants, and second, that engaging in physical activity may also make it easier to adopt and maintain other positive health behaviours.

2.4.1.3 Health research linking travel and dietary behaviour

Based on this evidence, a logical assumption is that physically active travel modes (e.g. walking and cycling) will also be positively associated with healthy dietary patterns (e.g. higher FV, lower RPM) (de Nazelle et al., 2011), however there are virtually no studies that have explicitly examined whether these relationships exist. For example, a recent scoping review of associations between health and environmental behaviours that reviewed over 130 studies (Hutchinson et al., 2015) identified only four that reported on relationships between active travel and dietary behaviour, though none were primarily designed for this purpose. Three of the studies were conducted among children and youth (in England, New Zealand, and Germany) and one was conducted among adults in Poland (Kwasniewska et al., 2010, Landsberg et al., 2008, Ferrar et al., 2013, Ford et al., 2007). Dietary consumption was measured in varying ways: daily calorific intake (two studies), and servings of healthy (e.g. fruit, vegetables, fish, dairy) or unhealthy foods (e.g. meat pies/sausage, soft drinks, fast food and sweets/chips) (two studies). All four studies were designed to investigate relationships between active travel and weight status.

Overall, all three studies of children and youth found no associations between active travel and diet, however, the single study of adults did report a very slightly increased daily caloric intake among male active commuters compared to non-active commuters: 2573.4 v. 2562.8 kcal/day, respectively ($p<0.05$) (Kwasniewska et al., 2010). This indicates that male active travellers may consume slightly more food overall, but does not indicate which food groups they are actually consuming, so it does not reveal much about relationships between healthy, low-carbon behaviours. Other limitations of these studies include the fact that research on children may not be relevant for understanding the travel and dietary behaviour of adults, and all four studies used combined measures of diet and active travel which may mask relationships between specific travel modes (e.g. walking, cycling) and individual food groups (e.g. FV, RPM). Relatedly, there is some evidence suggesting that positive associations may exist between commuter cycling and adopting healthy diets, though it is based on a rather limited study from the Cyclescheme organisation. As reported in their 2015 survey of nearly 10,000 UK cyclists (Cyclescheme, 2015), 48% of people who started cycling to work indicated that they had subsequently also started eating "healthier", however what these dietary changes were was not precisely defined and they were based entirely on subjective self-assessment.

In addition, there is another strand of health research that considers the influence of transportation on accessibility to healthy foods in relation to neighbourhood food environments. This research typically shows that using a car to buy food is socio-economically patterned and that this is an important factor in determining where, and how far away, people choose to shop for food (White, 2007). Put another way, in neighbourhoods with poor access to healthy foods[32], car ownership may buffer the effect between low accessibility and healthy food consumption, if people can easily drive to other places in order to shop for healthy foods. Under this line of reasoning, car access should be associated with healthier diets, however many studies have assessed this relationship based on proximity to healthy and unhealthy food establishments and not on actual dietary consumption (Burns and Inglis, 2007, Inagami et al., 2009, Black et al., 2014). One study that did examine relationships between travel modes for food shopping and FV consumption found no associations between these variables, but the study was conducted in two predominantly African American neighborhoods in Philadelphia, and thus may not be generalizable to other populations (Fuller et al., 2013).

[32] Such places may be commonly referred to as food deserts or food swamps; the former describes neighbourhoods with poor access to healthy foods (e.g. supermarkets), whereas the latter, which has gained prominence more recently, describes neighbourhoods with an overabundance of unhealthy foods (e.g. fast food and take-away establishments) (Cooksey-Stowers et al., 2017).

2.4.2 Studies of travel and dietary behaviour in environmental psychology

2.4.2.1 Behavioural 'spillover': another view on clustering

In addition to research on health behaviours, there is also some evidence linking travel and diet from the discipline of environmental psychology, most commonly in studies examining the potential for 'spillover' between different pro-environmental behaviours (Thøgersen and Ölander, 2003). Though behavioural spillover technically refers to the dynamic process of one behaviour proceeding the adoption of another (Truelove et al., 2014, Dolan and Galizzi, 2015), it is an analogous concept to behavioural clustering in the sense that a 'cluster' may represent multiple behaviours that have 'spilled-over' at a particular point in time. Indeed, most of the current evidence regarding spillover comes from cross-sectional correlations between different behaviours and the search for common 'motivational roots' (e.g. environmental values) that explain these relationships (Nash et al., 2017). Here, the theory posits that behaviours are most likely to spillover if they are perceived to be similar or linked by a common motive (consciously or unconsciously) (Truelove et al., 2014, Dolan and Galizzi, 2015).

Importantly, however, behavioural spillovers may operate in different ways, depending on the direction and outcome of the behaviours. In environmental psychology this is referred to as *positive* or *negative* spillover (Truelove et al., 2014); in health psychology it has been described as *promoting*, *permitting* or *purging* spillover (Dolan and Galizzi, 2015). From a public health perspective, a good illustration of these dynamics can be seen in relation to diet and physical activity: if someone engages in physical activity, they may be more motivated to eat healthily later on ("I ran for an hour, now let's keep up the good work" → positive, promoting spillover); alternatively, however, another possible outcome is that he/she may reward themselves for their earlier activity by consuming something unhealthy ("I ran for an hour, now I deserve a big slice of cake" → negative, permitting spillover) (Dolan and Galizzi, 2015).

In reality, both of these outcomes are likely to occur in different situations or among different people, however from a policy standpoint, the goal is obviously to encourage positive spillover to occur more often and to reduce the potential for negative spillover. Along with clustering, this growing interest in behavioural spillover reflects that fact that several disciplines are beginning to recognize the importance of looking beyond individual behaviours in isolation to take a wider view of people's overall lifestyles. In environmental psychology, spillover is seen as offering the potential of changing a whole collection of behaviours, moving from disconnected single behaviour change to more holistic *lifestyle* change (Capstick et al., 2014, Nash et al., 2017). The idea also holds promise among policy-makers, as there is considerable interest in finding ways of producing comprehensive shifts towards low-carbon lifestyles that are cost-effective and involve little regulation (Austin et al., 2011).

2.4.2.2 Associations from studies of 'environmental' behaviour

In the search for spillover among related behaviours, several studies in environmental psychology have examined associations between travel and diet, though these have not always focused on behaviours that are the most health- and climate-relevant. For example, one study of Danish residents (n=1,100) reported that buying organic food products was positively correlated with use of public transport and/or cycling and that both behaviours were associated with stronger environmental values, in addition to higher qualifications and being female (Thøgersen and Ölander, 2006). Similarly, a survey of pro-environmental behaviours amongst the UK public (n=551) reported that groupings of dietary behaviours (avoiding meat and eating organic, local, and seasonal food) and travel behaviours (walking, cycling, or using public transport for short journeys) clustered separately on different domains, but were both significantly associated with higher education levels (Whitmarsh and O'Neill, 2010). The sole longitudinal study, conducted in a Dutch sample (n=232), found that more fuel-efficient driving styles were correlated with the intention to reduce meat consumption after one year of follow-up, and that the relationship was mediated by environmental self-identity (e.g. "I see myself as an environmentally-friendly person") (Van der Werff et al., 2013).

Together, these studies demonstrate that travel and dietary behaviours that are perceived to be pro-environmental are often correlated, and that these correlations may be related to environmental values and identities, as well as with having higher qualifications. In relation to spillover, the implication is that people with stronger environmental motivations may be more likely to adopt multiple pro-environmental behaviours, but most of these studies are cross-sectional or based on self-reported behavioural intentions, and it is well-known that many people do not always act in alignment with their intentions and values (Shwom and Lorenzen, 2012). As a result, these studies do not provide much convincing evidence about actual relationships between travel and dietary behaviours, and how these may be patterned into health- and climate-relevant lifestyles in the UK context.

Nevertheless, other studies of car use and meat consumption in the UK (studied separately) have also reported that these behaviours may be related to specific social identities (Gatersleben et al., 2012, Murtagh et al., 2012, Abrahamse et al., 2009) and identity has been identified as an important route to behavioural spillover (Truelove et al., 2014). Evidence from this perspective suggests that the links between certain behaviours and specific identities may become particularly prominent if the behaviour in question is rare, as has been observed for cycling in the UK (Steinbach et al., 2011). In line with this, a qualitative study from the United States has reported a convergence between cycling and veganism in certain anarchist subgroups, as a reaction against the dominant culture of consumption characterised by excessive meat eating and car driving (Portwood-Stacer, 2012). Together, these findings suggest that healthy, low-carbon travel and dietary behaviours may be linked to certain social identities, but this evidence is very limited, as travel mode use and dietary consumption have been rarely examined together.

Building on this research are two other studies that specifically focus on associations between car use and meat consumption, but with respect to behavioural intentions. The first, a recent study which compared consumers in the Netherlands (n=527) and the United States (n=556), found that willingness to drive less was positively associated with willingness to reduce meat consumption in both the Dutch and American samples (de Boer et al., 2016). Similar data from the UK also echo these results: in the 2014 British Social Attitudes (BSA) survey (Lee and Simpson, 2016), respondents who were willing to reduce their car travel to help mitigate climate change were also more likely to report reducing their meat intake in the past year (36%) compared with those who were not willing to reduce their car travel (24%)[33].

Notably, however, most people who reported reducing their meat consumption in the BSA survey said that they were primarily motivated to change their behaviour for health reasons (58%), and other studies of organic food consumption (Magnusson et al., 2003) and active travel (Whitmarsh, 2009) have also documented that people may be more strongly motivated by improving their health than by environmental concerns. Similar findings have also been reported in a qualitative UK study that found engaging in lower-carbon lifestyles was primarily motivated by social and economic reasons (e.g. social justice, community, frugality) and not by environmental concern (Howell, 2013). Together, these studies indicate that many people engage in ‘environmental’ behaviours for non-environmental reasons, which suggests that appealing to environmental values and identities may not be the only way, or even the best way, to promote behaviours that are healthy and low-carbon.

[33] Correspondingly, respondents who were unwilling to reduce their car travel were more likely to say they had no intention of reducing their meat consumption (65%) compared with those who were willing to make changes to their travel behaviour (45%).

2.4.2.3 Limitations of evidence from environmental behaviour studies

Together, this disparate group of studies shows that pro-environmental travel and dietary behaviours are often correlated with one another and may be mutually driven by common factors like environmental identity, anti-consumption practices, or health motivations, in addition to socio-demographic characteristics (e.g. gender or education level). However, these studies also have many limitations. Particular shortcomings include the fact that many are focused on behavioural intentions and not on actual travel and dietary behaviours, and most are based on small, non-representative samples from outside the UK context. In addition, the travel and dietary behaviours that have been examined are not necessarily those with the most relevant impacts for human health and carbon emissions (e.g. eco-driving, organic food consumption). As a result, there remains a clear need for more comprehensive examination of the relationships between travel and dietary behaviour, in order to gain a better understanding of health- and climate-relevant lifestyles in the UK population.

2.4.3 Summary of Section 2.4

This section has highlighted some of the existing evidence linking travel and dietary behaviours from different disciplines and theoretical perspectives. Most of this pertains to clustering between physical activity and nutrition from studies of health behaviour, or to correlations between pro-environmental travel and dietary behaviours in environmental psychology. Together, this evidence suggests that related behaviours may share a common aetiology, whether that is shared socio-demographic factors or more proximal psychological attributes such as environmental identity or being health conscious. As highlighted in section 2.4.1.1, theories of clustering that stem from socio-ecological frameworks (like the SDH) imply that the more closely behaviours are related, the stronger the empirical relationships between them (Flay and Petraitis, 1994), and the more likely they are to share similar determinants (McAloney et al., 2013, Spring et al., 2012a). Currently, however, there is very little robust evidence of relationships between travel and dietary behaviour in the UK context, which means there are major gaps in our understanding of health- and climate-relevant lifestyles.

2.5 Current gaps, aim, and research questions

This chapter has identified an important evidence gap related to our understanding of lifestyles that have joint implications for public health and carbon emissions. Thus far, travel modes and dietary consumption have been studied primarily in isolation, and the knowledge and understanding of these behaviours remain separated from one another, both within and across disciplines. This has important implications for our understanding of people's overall lifestyles as they relate to health and environmental impacts. More specifically, it remains unclear whether travel behaviour is related to dietary consumption; whether travel and dietary behaviours cluster together into healthy, low-carbon (HLC) and unhealthy, high-carbon (UHC) lifestyles; and whether different types of lifestyles are associated with socio-demographic and environmental influences.

2.5.1 Thesis aim

As a result of these gaps, in this thesis I aim to advance current knowledge of the patterning, prevalence, and predictors of health- and climate-relevant lifestyles in the UK context, based on combinations of travel and dietary behaviour.

2.5.2 Research questions

In order to meet this aim, the thesis will be based around the investigation of four primary research questions:

1) Are there associations between use of HLC travel modes and consuming a more HLC diet (e.g. increased FV and reduced RPM)? (Chapter 4)

2) How many combinations of travel and dietary behaviour exist, and what is the prevalence of each behaviour pattern (type of lifestyle)? (Chapter 5)

3) Do travel and dietary behaviours cluster together into HLC and UHC lifestyles? (Chapter 5)

4) What is the socio-demographic profile of each behaviour pattern (type of lifestyle) and which factors and types of influences are associated with different lifestyles? (Chapter 6)

Specific contributions to knowledge are anticipated to include evidence on: the empirical relationships between travel modes and dietary consumption (if any), the number and nature of different patterns of travel and dietary behaviour, the prevalence of each lifestyle group, and which groups, socio-demographic factors, and types of influences may be most relevant for policy initiatives. Together, addressing these questions will help to enhance understanding by providing some of the first evidence on health- and climate-relevant lifestyles in the UK population, and whether there may be positive or negative interactions between travel and dietary behaviour. This evidence will help to inform the development of future policies by determining the nature of health- and climate-relevant behavioural patterns, and whether there are lifestyle groups that may be strategic targets for moves towards healthy, low-carbon behaviour.

2.6 Chapter 2 Summary

In this chapter I have defined which travel and dietary behaviours have joint implications for human health and carbon emissions (use of different travel modes, consumption of FV and RPM) (section 2.1), and I have described their prevalence in the UK context based on current evidence (section 2.2). I have explained how these behaviours are socio-demographically patterned and identified how this may lead to overlap and clustering between different behaviours based on shared determinants in the SDH model (section 2.3). Finally, I have summarized existing evidence from different disciplines and theoretical perspectives that suggest related travel and dietary behaviours may group together, and highlighted the limitations of these studies (section 2.4). Together, this has allowed to me to identify several gaps in current knowledge that will be investigated in this thesis (section 2.5).

3 Data sources: methods and measures

Chapter summary: Having identified gaps in current knowledge and articulated my research questions in Chapter 2, this chapter details the methodological approach to my thesis. In the first sections, I describe the data sources I use to examine travel and dietary behaviour in the UK context: the National Diet and Nutrition Survey and UK Biobank. In each study, I give an overview of each sample, how the data were collected, and what measures of travel, diet, and socio-demographic factors are available. I also discuss the strengths and limitations of each dataset and why it was necessary to use both of these to meet my analytical objectives. In the final section, I clarify the theoretical framework that underpins my thesis based on the data available. Details of statistical analyses are not presented here but in the specific results chapters to which they pertain (see Chapters 4, 5, and 6).

3.1 Introduction

To identify potential data sources that could be used to study relationships between travel and dietary behaviour in the UK, I began by scoping the contents of several national surveys and population-based studies to determine if there were any existing datasets with information on travel and dietary behaviour in the same individuals. Several different data sources were examined as potential candidates (e.g. UK Household Longitudinal Study, Health Survey for England, for more details see Appendix A, Table A.0.1); however, most surveys only contained information on travel behaviour and FV consumption. Ultimately, I identified only two datasets that had sufficient data on all of the behaviours I required (travel mode use, FV consumption, *and* meat consumption) in the same sample: the National Diet and Nutrition Survey (NDNS) and UK Biobank (UKB). In the next sections, I will describe each of these studies in turn, including an overview of their samples, data collection procedures, relevant measures, and strengths and limitations.

3.2 National Diet and Nutrition Survey (NDNS)

Information in this section has been synthesized from the NDNS survey documentation[34] and from the NDNS Years 1 to 4 report (Bates et al., 2014) and appendices, which are available online (PHE/FSA, 2014). Where information has come from a specific Appendix in the NDNS report, this will be noted in the text.

3.2.1 Overview

The NDNS is a continuous, cross-sectional survey of the food consumption, nutrient intake, and nutritional status of the UK population. The survey is designed to be nationally representative and is carried out in all four countries of the UK, covering adults of all ages and children aged 18 months and over living in private households. Though it has taken different forms over the years[35], the NDNS has been in its current form, known as the 'rolling programme' (RP), since 2008.

The NDNS provides the UK's only source of high quality nationally representative data on the types and quantities of foods consumed by individuals, from which estimates of nutrient intake for the population are derived. The food consumption data are also used by the UK Food Standards Agency (FSA) to assess exposure to chemicals in food, which are used to inform negotiations on setting regulatory limits for contaminants. As a result, the NDNS is a major component of the evidence base to support work by Public Health England (PHE) and other government bodies to improve the diet and nutrition of the UK population and reduce diet-related disease. The survey is jointly funded by PHE and the FSA and is conducted by a consortium of three organisations: NatCen Social Research (NatCen), MRC Human Nutrition Research and the University College London Medical School. Ethics approval for the NDNS was obtained from the Oxfordshire A Research Ethics Committee.

[34] Full citation: NatCen Social Research, MRC Human Nutrition Research and University College London. Medical School, *National Diet and Nutrition Survey Years 1-4, 2008/09-2011/12* [computer file]. *6th Edition.* Colchester, Essex: UK Data Archive [distributor], July 2014. SN: 6533 , http://dx.doi.org/10.5255/UKDA-SN-6533-5

[35] The NDNS programme began in 1992 as a series of cross-sectional surveys, each covering a different age group as a stand-alone survey (e.g. adults aged 19-64 in 2000-2001). Following a review in 2003, it was decided that future surveys should be carried out on a continuous basis across all age groups in the population in order to improve the survey's ability to track changes in diet and nutrition over time (Bates et al., 2014).

For this thesis, data from the NDNS were obtained by registering with the UK Data Service, describing the purpose of my research and downloading an anonymised dataset. The dataset was accessed in 2015, at which time data from the first four years of the NDNS RP were available (2008-2012).

3.2.2 Study design and sample recruitment

Each year, the NDNS aims to collect data from a UK representative ‘core’ sample of 500 adults (aged 19+) and 500 children (aged 1.5 to 18 years). This sample is drawn from the Postcode Address File (PAF), which contains a list of all the addresses in the UK. In order to improve cost effectiveness, household addresses on the PAF are first clustered into randomly selected Primary Sampling Units (PSUs), and a list of addresses is then randomly selected from each PSU. In addition to the core sample, further ‘country boost’ recruitment is also undertaken in Scotland, Northern Ireland and Wales in order to achieve large enough samples in these countries to enable cross-country comparisons.

After sample selection, an interviewer visited each address to determine whether it was eligible for the survey (e.g. private, residential, and occupied). If so, the interviewer enumerated the number of households at each selected address and, in cases where there were two or more, randomly selected one for the survey. After household selection, the interviewer then randomly selected one adult (or one child) from the household to take part and then obtained consent to interview[36]. Fieldwork was conducted continuously throughout each year (from February 2008 through August 2012) in order to account for seasonal variations in food consumption.

Overall for Years 1 to 4 combined, of the 21,573 addresses (core and country boost)[37] issued to interviewers, 46% were eligible for household selection (n=9,858) and 54% were ineligible. Ineligible addresses included institutions, vacant or derelict properties and addresses for the child sample that did not contain any children in the eligible age range. Household selection was carried out at 91% of eligible addresses, as only 9% refused to participate.

[36] In the case of young children, parents or guardians completed the survey on their behalf.

[37] This thesis is based on data from the core sample only (n=4,156), as the country boost sample was not included in the archived publicly available dataset at the time the data was accessed in 2015. Please note that the response rates in this section were provided by the NDNS and include the country boost sample (n=6,828).

3.2.3 Data collection

In the NDNS there are two stages of data collection: an interviewer stage (Stage 1) and a nurse visit (Stage 2). I did not use any data collected during the nurse visits (e.g. medicines, detailed anthropometry, blood and urine samples), therefore all data henceforth discussed pertains to Stage 1 only.

3.2.3.1 Overview of procedures

Among households who agreed to participate, interviewers visited up to three times. These visits typically occurred over a one-week period as the food diary was completed over four days and the final visit took place no later than three days after the last diary day.

At the first visit, participants completed the computer assisted personal interview (CAPI) and the 4-day food diary was explained by the interviewer and left with participants to complete. Height and weight measurements were also taken. At the second visit there was a brief check-in for compliance with the food diary, with the aim of collecting missing detail for foods recorded, improving recording for the remaining days and also providing encouragement to participants to continue recording. In certain circumstances, a telephone call was made in place of a home visit.

At the final visit, interviewers gave participants aged 16+ the Recent Physical Activity Questionnaire (RPAQ) for self-completion, and participants filled out the RPAQ while the interviewer reviewed their responses to the food diary. At the end of the third visit, interviewers gave each participant who took part in the CAPI and completed at least three days of the food diary (“fully productive individuals”) a token of appreciation (£30 in high street vouchers).

3.2.3.2 Instruments used

The CAPI questionnaire

The CAPI had three elements: the household interview, the main food provider (MFP)[38] interview and the individual interview. The household interview established who was the household reference person (HRP)[39] and asked questions about his or her employment to determine the socio-economic classification of the household. The MFP interview asked about shopping for food, cooking facilities, and food preparation in the household. The individual interview provided information on other socio-demographic factors (e.g. age, ethnicity), eating habits, and general health of each participant.

The food diary

Based on the day of the CAPI interview, four consecutive days were selected as the food diary recording period in order to give an even representation of diary days on all days of the week. Participants were asked to keep a record of everything they ate and drank over these four days, both in and outside the home. Interviewers followed a protocol to explain the diary, taking participants through the different sections including the instruction page, an example day, and how to record details of food, drink, and portion sizes.

On the adult diary, participants were provided with photographs of 15 frequently consumed foods as small, medium and large portion sizes, and for other foods they were asked to record portion sizes in household measures (e.g. one tablespoon of baked beans) or for packaged foods to note the weight indicated on the packet. Participants were asked to record brand names for foods wherever possible and to collect the food label information or wrappers for any unusual foods consumed to help coders identify or clarify items. For homemade dishes, participants were asked to record the individual ingredients and quantities for the whole dish along with a brief description of the cooking method and how much of the dish they had consumed. After each day, participants also noted if their intake for that day had been typical (and if not, the reason why) as well as details of any dietary supplements taken.

[38] The MFP is the person in the household with the main responsibility for shopping and preparing food. If these tasks were shared equally between two people, for example if one person did all the shopping and another person did all the cooking, then either resident could be classified as the MFP.

[39] The HRP was defined as the householder (a person in whose name the property is owned or rented) with the highest income. If there was more than one householder and they had equal income, then the eldest was selected as the HRP. Questions were asked to ascertain whether the HRP was in paid work at the time of the interview and, if not, whether they had ever had a paid job. If the HRP had ever worked, there were further questions about their current or most recent job in order to classify HRPs into the National Statistics Socio-economic Classification (NS-SEC) groupings.

After collection by the interviewer, data from the completed food diaries was processed by trained coders and editors using the DINO (Diet In Nutrients Out) database (Fitt et al., 2015), where each recorded item was assigned a food and portion code linked to the corresponding weight of the item. Composite dishes (e.g. sandwiches, curries) and homemade recipes were disaggregated into their individual components to improve the estimates of the total amount of each food group consumed, particularly for meats, fish, fruit and vegetables. Further details of how these data were processed are available in Appendix A of the NDNS report (PHE/FSA, 2014).

The RPAQ

In Year 1 of the NDNS RP a bespoke physical activity questionnaire was used, however, this was deemed to be too time-consuming for participants and was replaced by the RPAQ from Year 2 onwards[40]. The RPAQ was developed and validated by the MRC Epidemiology Unit at the University of Cambridge, and is designed to assess total energy expenditure and physical activity levels in the population (Besson et al., 2010). The RPAQ captures usual physical activity in the past four weeks across four domains: home (watching television, using a computer, climbing stairs), work (type and amount of physical activity), commuting to work (by car, public transport, cycling, and/or walking), and leisure activities (frequency of participation in 35 different activities and average time per episode). Participants completed the RPAQ while the interviewer was present (third visit), after which it was collected and sent to NatCen for manual data entry.

[40] Because of this omission, this thesis only uses data from Years 2 to 4 of the NDNS (2009-2012, n=3,025)

3.2.3.3 Individual response rates

Overall for Years 1 to 4 combined, 58% (5,730 / 9,858) of eligible households[41] were 'fully productive': at least one selected participant completed three or four dietary recording days. The overall response rate for fully productive individuals was 56% in Year 1, 57% in Year 2, 53% in Year 3 and 55% in Year 4, giving a final sample size of 6,828 fully productive individuals. Height and weight measurements were obtained for nearly all fully productive participants (height 95%, weight 94%) and 95% of those eligible (aged 16+) completed the RPAQ.

3.2.4 Survey Weighting

Population-based survey weights are available for all participants in the NDNS sample, so that the observed results are nationally representative of the UK. These weights are needed to remove any bias due to differences in the probability of households and individuals being selected to take part (selection bias) and to reduce any bias introduced through drop-out at different stages of the survey (non-response bias) (Bates et al., 2014).

Non-response weights were developed by examining the extent of non-response or drop-out at each stage of the survey, and creating a logistic regression model to identify different socio-demographic factors associated with participant non-response. At the RPAQ stage, for example, people were less likely to complete the RPAQ if they were non-white, and more likely to complete if they were older (particularly 60-69), and if they lived in the West Midlands or East of England. Those who were less likely to respond received a higher survey weight to increase their representation of the sample.

The final survey weights were thus a product of the selection weights and the non-response weights at different stages of the survey. In this thesis I used the final RPAQ weights for the full UK sample (*wtr_Y1234*), which adjust for unequal selection probabilities, non-response to the household, MFP and individual interviews, as well as non-response to the RPAQ. Full details of the NDNS RP weighting scheme is provided in Appendix B of the survey materials (PHE/FSA, 2014).

[41] As before, these response rates refer to the combined core and country boost samples (n=6,828), this thesis only includes the core sample (n=4,156).

3.2.5 Measures

3.2.5.1 Dietary consumption

RPM and FV

Derived variables representing average RPM consumption (in grams per day) and FV consumption (in portions per day) were provided in the NDNS dataset (Table 3.1). These variables were created by the survey team using the disaggregated data from the food diary as follows. Consumption of RPM was aggregated from individual meat categories (e.g. beef, burgers, lamb, offal, other red meat, pork, sausage, and processed red meat) consumed over the food diary period, and included fresh cuts, processed meats such as salami, canned meat, and meat consumed in homemade dishes and takeaways. Similarly, consumption of FV included all FV in raw, cooked, frozen or canned form, using a portion weight of 80 g. In line with '5-a-day' criteria (NHS, 2013), potatoes were not included in the calculation but fruit juice (from all sources) and pulses (including baked beans) were included up to a maximum of one portion per day each, at 150 g for fruit juice and 80 g for pulses. For analytical reasons (see Chapter 4 section 4.2.1.3) and to assess whether each participant's consumption was in line with current guidelines, I recoded both of these variables into three-level ordinal variables: <3, 3–<5, and 5+ portions/day for FV and 0, >0–70, and >70 g/day for RPM (Table 3.1).

Habitual meat consumption

In addition to the detailed consumption data from the food diary, there was also information on habitual consumption of certain foods (i.e. foods that are never consumed) collected on the CAPI questionnaire. Here, I was particularly focused on habitual meat consumption, as it is possible that people's reported consumption over the food diary recording period may be different from what they consume the rest of time. In the eating habits section of the CAPI, there were two types of questions on habitual meat consumption: questions about whether certain types of meat were ever consumed, and whether people self-identified as vegetarian or vegan. Of these, I decided to use the former (Table 3.1), as I wanted to be able to distinguish between people who never consumed any RPM from those who never consumed any type meat or fish, and also because there may be people who do not consume meat but do not necessarily identify as 'vegetarian'[42]. For these questions, participants were first asked: "Are there any types of foods that you never eat?" and if yes, were asked to identify which types of food from a series of response categories. Participants who said they never ate any "meat or meat products (not including poultry)" were classified as never consuming RPM, and participants who said they never ate any meat, poultry, or fish were classified as having a vegetarian diet (Table 3.1).

Table 3.1 – Measures of dietary consumption in the NDNS

Measure	Source	Survey question (if applicable)	Provided in dataset	Recoding	Notes
FV consumption quantity	Food diary	NA	Average portions of FV consumed per day (continuous)	<3, 3-<5, 5+ portions per day	Refers to average consumption over food diary period (3-4 days)
RPM consumption quantity	Food diary	NA	Average grams of RPM consumed per day (continuous)	None, >0-<70, >70 g per day	
Habitual meat consumption	Individual interview	Can you tell me what types of foods you never eat?	1) Meat or meat products (not including poultry): yes, no 2) Chicken or other poultry and dishes containing them: yes, no 3) Fish or seafood and fish and seafood dishes: yes, no	1) Ever consumes RPM: yes, no 2) Ever consumes meat, poultry or fish: yes, no	Refers to meat consumption on a habitual basis, beyond the food diary period

NA: not applicable
Missing values: excluded from analysis

[42] Equivalently, there may also be those who identify as vegetarian, but also consume some meat, as this has been reported in other studies (Ruby 2012, Aston et al., 2013)

3.2.5.2 Travel behaviour

Information on use of different travel modes came from the RPAQ. Here, there were two separate questions on mode(s) of travel: one for non-work journeys and one for commuting journeys (if applicable)[43]. On the non-work travel question, participants could only select the *single main mode* they used most frequently, but could select *multiple* modes and *different* frequencies for the commuting question (Table 3.2). In addition, there were also two other questions asked of commuters: how far they commuted and how often they commuted (outward journeys only).

Using the questions on travel modes, I created five different measures of travel behaviour (Table 3.2). Non-work travel mode was coded as a four-level nominal variable based on the four mutually exclusive response options on the RPAQ: car, public transport, walking or cycling. Commuting respondents who reported 'always' or 'usually' for a given travel mode were coded as commuting by that mode (and not otherwise) and multi-mode commuters were categorized according to their most 'active' mode (e.g. cycling, followed by walking, public transport, and car). In cases where respondents did not select 'always' or 'usually' for any mode but still reported commuting (n=11), participants were assigned to the mode they reported using 'occasionally' (10 to car, 1 to walking).

In addition to these measures on different types of journeys, I also created three binary measures of *combined* travel behaviour reflecting overall mode use. These were: any walking travel, any cycling travel, and any active travel (including walking or cycling) for either type of journey. Creating combined measures of walking and cycling in this way enabled me to make maximum use of the travel data that was available in the NDNS as not all participants provided a response for *both* the non-work travel and commuting travel survey items. Commuting distance and commuting frequency were also recoded based on the distributions of the data (Table 3.2).

[43] This question was only applicable to participants who answered yes to the following: "Have you been in employment, done unpaid work or attended school or college during the last 4 weeks ending yesterday?"

Table 3.2 – Measures of travel behaviour in the NDNS

Measures	Survey questions	Response categories	Recoding
Non-work travel mode Commuting travel mode (if applicable) Any walking travel Any cycling travel Any active travel	Which form of transport have you used **most often** in the last 4 weeks ending yesterday, apart from your journey to and from work?	Car/motor vehicle Walk Public transport Cycle	1) Non-work travel: car, PT, walking, cycling 2) Always/usual commute mode: car, PT, walking, cycling 3) Any walking travel: yes (non-work or always/usual commute), no 4) Any cycling travel: yes (non-work or always/usual commute), no 5) Any walking or cycling travel: yes (non-work or always/usual commute), no
	If applicable: How did you normally travel to work or school/college during the last 4 weeks ending yesterday? By car / motor vehicle By works / PT By bicycle Walking	Always, Usually, Occasionally, Never/rarely	
Commuting distance (if applicable)	What is the approximate distance from your home to your main place of work or school/college?	Miles ____ OR Kilometres ____	>0-<2 miles, 2-<10 miles, 10+ miles (Kilometres converted to miles)
Commuting frequency (if applicable)	How many times a week did you travel from home to your main place of work or school/college? Count **outward journeys only.**	Open ended	<5 times a week, 5 times a week, >5 times a week

PT: public transport, Missing values: excluded

3.2.5.3 Other variables

Socio-demographic information on participants was also collected in the CAPI questionnaire, via the household and individual interviews. In addition, there was also some limited information available on each participant's residential environment from the original sample selection procedure. Demographic, socio-economic, and environmental variables were selected for inclusion in this thesis based on theoretical or empirical relationships with travel and dietary behaviour in the UK population, as identified from the literature (see Chapter 2 section 2.3). These were: age, sex, ethnic group, household size, cohabitation status, presence of children in the household, highest qualification, occupational class, household income, region of the UK, and area-level deprivation. Further details on each of these variables and how they were handled can be found below in Table 3.3, Table 3.4, and Table 3.5.

Table 3.3 – Demographic variables in the NDNS

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Age	Individual interview	Years (continuous)	16-24, 25-39, 40-54, 55-69, 70+	
Sex	Individual interview	Male, female	NA	
Ethnic group	Household interview	1) White, non-White 2) White, Mixed, Black/Black British, Asian/Asian British, Other	NA	Binary variable used in cases of small cell counts
Household size	Household interview	Number of people (continuous)	1, 2, 3, 4, 5+	
Cohabitation status	Individual interview	1) Legal marital status: single and never married, married and living with partner, civil partnership, married and separated, divorced, widowed 2) (If not married or civil partnership) Living with someone as a couple: yes, no	Cohabiting (married, civil partnership, couple), not cohabiting	
Children in household	Household interview	Number of children (continuous)	Lives with 1+ children, lives with no children	Includes children aged 18 months to 18 years

NA: not applicable
Missing values: excluded from analysis
Individual and household interviews were part of the CAPI

Table 3.4 – Socio-economic variables in the NDNS

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Highest qualification	Individual interview	Degree or equivalent; higher education, below degree level; GCE, A level or equivalent; GCSE grades A-C or equivalent; GCSE grades D-G/ commercial qualification; foreign or other qualifications; no qualifications; still in full-time education	1) Degree or equivalent, A levels or higher education below degree, GCSE or equivalent, foreign or other qualifications, no qualifications, still in full-time education 2) Degree or equivalent, below degree level, no qualifications, still in full time education	Recoding 2) used in cases of small cell counts
Occupational class	Household interview	8-class NS-SEC: Higher managerial and professional, Lower managerial and professional, Intermediate, Small employers and own account workers, Lower supervisory and technical, Semi-routine, Routine, Never worked	3-class NS-SEC: Managerial and professional, Intermediate, Routine	Measure for the whole household based on employment status and position of the HRP 3-class NS-SEC used in cases of small cell counts
Household income	Individual interview	Equivalised household income, based on McClements equivalence score (continuous)	0-£14,999, £15,000-24,999, £25,000-34,999, £35,000-49,999, £50,000+	McClements equivalence score accounts for the number of people and composition (children and adults) in each household (Anyaegbu, 2010).

Missing values: excluded from analysis

Table 3.5 – Environmental (area-level) variables in the NDNS

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Region of the UK	Original sample selection	Wales, Scotland, Northern Ireland, North East England, North West England, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East England, South West England	London, South England, Central England, North England, Outside England	NA
Area-level deprivation	Original sample selection	English IMD score (quintiles): 0.53-8.49 (least deprived), 8.49-13.79, 13.79-21.35, 21.35-34.17, 34.17-87.80 (most deprived).	NA	Available for England residents only

IMD: Indices of Multiple Deprivation. These indices are based on seven different domains of deprivation: Income, Employment, Health and Disability, Education Skills and Training, Barriers to Housing and Services, Living Environment, and Crime. In 2010, 98% of the most deprived areas (based on lower layer super output area, LSOA) were located in urban parts of England (Lad, 2011), so higher IMD scores may be also indicative of living in a more urban environment, in the absence of other information on the local area. As a result, though this is traditionally used as a socio-economic variable, here I conceptualise it as an environmental variable in my theoretical framework since it is measured at the area-level and represents the wider conditions and contexts where people live.

In addition to socio-demographic and environmental characteristics, other factors were also examined as covariates or as predictors depending on the objective of the analysis. These variables and how they were created and recoded for my analysis are listed in Table 3.6.

Table 3.6 – Other variables in the NDNS

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Total energy intake	Food diary	Kilocalories (continuous)	NA	Derived by survey team based on total amount of food consumed as reported in the food diary, and calculated as a daily average
Overall physical activity	RPAQ	Hours (continuous)	Minutes (continuous)	Derived by survey team using the activities reported on the RPAQ and the Physical Activity Compendium (Ainsworth et al., 2000)[a]
Body mass index (BMI)	Individual interview	<18.5 (underweight), 18.5-25 (normal weight), 25-30 (overweight), 30-40 (obese), 40+ (morbidly obese)	<25 (underweight/ normal), 25+ (overweight/obese)	Derived by survey team from height and weight measures (kg/m^2)
Self-rated health	Individual interview	Very good, good, fair, bad, very bad	NA	
Activities limited by long-standing illness	Individual interview	Limited (yes), not limited (no), no long-standing illness	NA	

a) All activities covered by the RPAQ, including the type and amount of physical activity at work, were grouped into one of four categories representing the metabolic cost of each activity, expressed in metabolic equivalents (METs): sedentary (<2 METs), light (2-3.5), moderate (3.6-6), and vigorous (>6). For each participant, the number of hours per day (h/d) spent in each of the four categories was computed. Time spent in each moderate or vigorous activity (≥ 3.6 METs) was summed to provide the mean daily time (in h/d) spent in moderate or vigorous activities. For more details see Appendix V of the NDNS report (PHE/FSA, 2014).

3.2.6 Strengths and Limitations of the NDNS

Overall, there are several important strengths of the NDNS dataset. Firstly, and perhaps most importantly, is the fact that it is nationally representative of the UK population, which means that any findings with regard to travel and dietary behaviour should be externally valid and generalizable to the UK as a whole. Though it is not intended to be a travel survey, another strength of the NDNS is its travel data, as it captures information on mode use for both commuting and non-work travel journeys. This meant I did not have to focus my analysis exclusively on commuters, and that I could also characterise travel behaviour more comprehensively (e.g. across multiple purposes) among those who did commute. Finally, as it is primarily a nutrition survey, the NDNS also contains the most detailed and accurate dietary information currently available for the UK population, which means that both RPM and FV consumption are measured as precisely and robustly as possible in a population-based survey of free-living individuals[44].

This level of detail comes at a cost, however, which is that the NDNS contains a relatively small number of participants, particularly for travel behaviour, since travel data was not collected in all survey years nor in nearly half of NDNS participants (i.e. children <16). The non-work travel question was also somewhat limited since it only captured the travel mode used *most of time* and many people in the UK often use multiple modes in combination on a weekly basis (e.g. walking and car travel) (Heinen and Chatterjee, 2015). In particular, this measure is likely to underestimate walking and cycling travel, as these modes tend to be used less frequently than car or public transport. This is particularly problematic for rare groups such as cyclists, of which there were very few in the NDNS. In Years 2 to 4, for example, out of 3,025 total participants, there were only 46 who reported cycling for non-work travel journeys and only 55 who reported any commuting by bicycle (always, usually, or occasionally). Such small numbers meant that my ability to draw conclusions and conduct any subgroup analysis would be very limited for cyclists in the NDNS, so I felt it was necessary to also use a second data source where I could attempt to replicate and verify my findings in a larger sample. For this, I decided to use UK Biobank, one of the largest and most detailed studies currently on-going in the UK.

[44] For more details on the accuracy of the NDNS dietary data, see Appendix A, Section A.1 for a description of the Doubly Labelled Water sub-study used to validate self-reported energy intake.

3.3 UK Biobank (UKB)

Information in this section has been synthesized from the UKB study protocol and reference material and from the UKB Data Showcase which are available from the study website (UKB, 2018). Where information has come from other sources it will be noted and cited in the text.

3.3.1 Overview

UKB is a very large prospective cohort study, established to investigate the genetic, environmental, and lifestyle determinants of disease in mid-life and beyond (Allen et al., 2014, Sudlow et al., 2015). The study involves over 500,000 UK participants who were aged 40-69 at recruitment in 2006-2010. UKB was primarily established by the Medical Research Council and the Wellcome Trust, but has also received funding support from the Department of Health, British Heart Foundation, Diabetes UK, Northwest Regional Development Agency, Scottish Government, and Welsh Assembly Government. The study received ethics approval from the National Information Governance Board for Health and Social Care and the National Health Service North West Centre for Research Ethics Committee (Ref: 11/NW/0382).

For this thesis, access to UKB was obtained by submitting a formal application for my research topic and questions, which were then subject to multiple stages of approval. My preliminary and main applications were approved by the UKB Access Team in 2015 (Application 14840) and I received access to my requested data (through a secure, encrypted download) in early 2016.

3.3.2 Study design and sample recruitment

Between 2006 and 2010, UKB sent postal invitations to 9,238,453 individuals registered with the National Health Service (NHS) who were aged 40-69 years[45] and lived within approximately 25 miles of one of 22 assessment centres located throughout England, Wales and Scotland (Figure 3.1). Assessment centres were strategically located in order to cover a variety of different settings to provide socio-economic and ethnic heterogeneity as well as urban–rural mix.

[45] The age range for inclusion was a pragmatic compromise between participants being old enough for there to be sufficient incident health outcomes during the early years of follow-up, but still young enough for the initial assessment to occur before disease development had a major impact on exposures.

Figure 3.1 – Locations of UKB assessment centres (image © UK Biobank)

Along with their letter of invitation, potential participants received an information leaflet about the study and a provisional appointment date to attend their closest assessment centre. Individuals who agreed to participate (n=576,926) then received a confirmation letter, a pre-assessment questionnaire, and an assessment centre location map with travel directions. Upon arrival at the assessment centre, each participant completed an electronic consent form if they agreed to be part of the study, which included the use of their anonymised data and samples for any health-related research, to be re-contacted for further sub-studies, and for UKB to access their health-related records. Overall, 507,177 participants attended an assessment centre and 503,317 (5.4% of 9,238,453) consented to be part of the study. Compared with those who were invited but did not participate, participation was higher among women, older age groups, those in less socio-economically deprived areas, and those in South West England and East Scotland (Table 3.7).

Table 3.7 – Overview of participation rates in UKB (own elaboration), data from Fry et al. (2017)

Factor	Higher participation rates	Lower participation rates
Gender	Women (6.4%)	Men (5.1%)
Age	≥60 years (9.0%)	40-44 years (3.0%)
Deprivation	Least deprived areas (8.3%)	Most deprived areas (3.1%)
Region	South West England (9.6%), East Scotland (8.2%)	West Scotland (4.3%), London, West Midlands, North West England (all 4.7%)

Note: The overall participation rate (described above) was 5.4% (503,317 out of 9,238,453)

3.3.3 Data Collection

3.3.3.1 Overview of procedures

In addition to providing consent, the initial baseline assessment comprised a self-completed touchscreen questionnaire, a brief computer-assisted verbal interview, various physical and function measures (e.g. anthropometry, hand grip strength), and collection of blood, urine, and saliva samples. In total, participants spent around 2.5 hours at the baseline assessment, navigating around the different stations. Towards the end of recruitment (2009-10), the last 70,000 participants who joined UKB also completed a web-based dietary recall questionnaire as part of their baseline assessment.

After the baseline visit, large subsets of the cohort were also invited to participate in further data collection (e.g. a repeated baseline assessment, genotyping, web-based questionnaires, multimodal imaging); however all of the data used in the thesis comes from the touchscreen and web-based dietary recall questionnaires, unless noted otherwise. More details on these instruments can be found in the next section.

3.3.3.2 Instruments used

Touchscreen questionnaire

The touchscreen questionnaire was self-completed by participants at the baseline assessment centre visit. The questionnaire collected detailed information on several topics: socio-demographics, lifestyle and environment (e.g. physical activity, diet), early life factors, family history, psychosocial factors, and health and medical history. Participants were provided with additional instructions and clarifications for each question if they activated the ‘Help’ button, and the electronic data entry system incorporated logic checks to verify or reject responses that were either extreme or impossible (e.g. if a participant reported driving for more than six hours per day, he/she would be asked to confirm the response; if he/she reported driving for more than 24 hours per day, the response would be rejected). For questions that were potentially sensitive, participants had the option to select the response ‘Prefer not to answer’ and move on the next question.

Web-based dietary recall questionnaire (Oxford WebQ)

As the limited dietary data collected through the touchscreen questionnaire did not allow assessment of total energy intake or other specific nutrients, it was supplemented in UKB by a repeated 24-hour online dietary recall questionnaire, known as the Oxford WebQ. The Oxford WebQ was developed by the Cancer Epidemiology Unit at the University of Oxford for use in large-scale studies as it has similar accuracy to an interviewer-administered 24-hour recall questionnaire but is lower-cost and faster to complete (only 10-15 minutes) (Liu et al., 2011). The Oxford WebQ also automatically generates the energy and nutrient values of the reported food items (Liu et al., 2011).

As part of the Oxford WebQ, participants were asked to report which items they had eaten yesterday (i.e. during the preceding 24 hours), by completing questions about their intake of around 200 common foods and drinks, including quantities consumed. For composite dishes, participants were directed to record the ingredients individually: for example, spaghetti bolognaise would need to be entered as pasta, beef, tomato sauce. Participants were encouraged to try and complete the questionnaire even if their consumption was not typical on the previous day (though in this case they were also asked to indicate why). The questionnaire is designed to be repeated throughout the year to account for seasonal variation in dietary intake and to provide an average measure for each individual (i.e. as a marker of habitual intake).

The Oxford WebQ was administered in two ways: first as part of the baseline assessment in 2009-2010[46] (described above in section 3.3.3.1), and second, by email on four separate occasions between February 2011 and June 2012 to all participants who had provided a valid email address (n=331,013, 66% of the cohort). Participants did not receive incentives or reminders to complete the questionnaire. Overall, 211,053 participants (42% of the baseline cohort) completed the Oxford WebQ at least once,

[46] This was done at the assessment centres in Liverpool, Hounslow, Sheffield, Croydon, Birmingham, and Swansea so there are more individuals from these areas in the dietary questionnaire subsample.

and most of these (>65%) completed it multiple times. Compared to the rest of UKB participants, those who completed the Oxford WebQ were more likely to be White, female, slightly older, less deprived and more educated (Galante et al., 2016).

3.3.4 Measures

3.3.4.1 Dietary consumption

Meat consumption

On the touchscreen questionnaire, participants were asked five questions regarding their average intake of each different type of meat, with response options pertaining to frequency per week (Table 3.8). To create an overall measure of RPM consumption, I combined the four questions involving RPM (beef, lamb, pork, processed meat) into a composite index, based on the number of times each type of meat was consumed on a weekly basis. For each question, the responses were coded as follows: Never = 0, Less than once a week = 0.5, Once a week = 1, 2-4 times a week = 3, 5-6 times a week = 5.5, once or more daily = 7. This resulted in a composite index ranging from 0 to 28, where 0 indicated that participants never consumed any RPM and 28 indicated that participants consumed all four types of RPM on a daily basis. Since this index was based on the average *frequency* of RPM consumption, it measured each participant's habitual consumption rather than the quantity of RPM consumed (as measured by the guideline)[47]. Both elements of meat consumption are important to characterising dietary behaviour, as reduced RPM consumption could occur through either reduced quantity or reduced frequency (Macdiarmid et al., 2011). In addition to this composite index, these frequency questions were also used to create two binary measures of habitual meat consumption similar to the NDNS. Participants who said they never ate any beef, pork, lamb, and processed meat were classified as never consuming any RPM, and participants who said they never ate any beef, pork, lamb, processed meat, poultry and fish were classified as having a vegetarian diet (Table 3.8).

On the Oxford WebQ, participants were asked: "Did you eat any meat or poultry yesterday?" and if yes, were asked to indicate *how much* of each type of meat they had consumed on the previous day, ranging from 0 to 5+ servings. From this data, I aimed to create a measure of average quantity of RPM consumed, analogous to RPM consumption quantity in the NDNS. To create this variable I first calculated the average number of servings consumed for *each type* of RPM, across all of the questionnaires

[47] Although notably, a subsequent analysis of the UKB data has shown that these measures are correlated: those who consume RPM most frequently (>3 times per week) also consume the largest quantities per day (Bradbury et al., 2017).

that each participant completed. This included sausage, beef, pork, lamb or mutton, processed poultry, bacon, and cured meats (e.g. ham, salami).[48] Next, I added together each of these averages to create a *total* number of RPM servings consumed on average for each participant. This resulted in a measure of RPM quantity to complement the frequency measure from the touchscreen questionnaire.

Table 3.8 – Measures of meat consumption in UKB

Measures	Source	Survey Questions	Response options	Recoding (if applicable)	Notes
RPM consumption frequency Habitual meat consumption	Touchscreen	How often do you eat processed meats (such as bacon, ham, sausages, meat pies, kebabs, burgers, chicken nuggets)? How often do you eat beef? (Do not count processed meats) How often do you eat lamb/mutton? (Do not count processed meats) How often do you eat pork? (Do not count processed meats such as bacon or ham) How often do you eat chicken, turkey or other poultry? (Do not count processed meats) How often do you eat oily fish? (eg: sardines, salmon, mackerel, herring) How often do you eat other types of fish? (eg: cod, tinned tuna, haddock)	Never < Once a week Once a week 2-4 times a week 5-6 times a week Daily Do not know Prefer not to answer	1) Average servings of RPM per week (continuous) 2) Ever consumes RPM: yes, no 3) Ever consumes any meat, poultry or fish: yes, no	RPM includes processed meat, beef, lamb/mutton, pork Participants were instructed to provide an average of their intake over the last year.
RPM consumption quantity	Oxford WebQ	Did you eat any meat or poultry yesterday? If yes: Number of sausages Servings of beef Servings of pork Servings of lamb Servings of processed poultry Rashers of bacon Slices of cured meats (e.g. ham, salami)	Yes, no None, ½, 1, 2, 3, 4, 5+	Average servings of RPM per day (continuous)	If >1 questionnaire was completed, I first calculated the average number of servings for each type of RPM, and then summed these averages to get the total servings of RPM consumed overall

Missing values: excluded from analysis

[48] Participants were also asked about their consumption of liver or liver pate and other meats (e.g. duck, goose, kidney) but these were very rarely consumed and it was not clear which animal they came from so I did not include them in the calculation of RPM.

FV consumption

On the touchscreen questionnaire, participants were asked to report their FV consumption via four open-ended questions that asked about the average number of tablespoons of vegetables and pieces of fruit consumed each day[49] (Table 3.9). These responses were then recoded into standard '5-a-day' portions based on the following conversion: 3 tablespoons = 1 portion of vegetables, 1 piece of fruit = 1 portion of fruit (NHS, 2013). This resulted in a continuous overall measure of average portions of FV consumed for each participant, similar to the measure of FV portions in the NDNS. To assess whether each participant's consumption was in line with the recommended guideline, I also recoded this variable into a three-level ordinal measure: <3, 3–<5, and 5+ portions/day.

Table 3.9 – Measures of FV consumption in UKB

Measure	Source	Survey Question(s)	Response options	Recoding (if applicable)	Notes
FV consumption quantity	Touchscreen	On average how many heaped tablespoons of COOKED vegetables would you eat per DAY? (Do not include potatoes; put '0' if you do not eat any) On average how many heaped tablespoons of SALAD or RAW vegetables would you eat per DAY? (Include lettuce, tomato in sandwiches; put '0' if you do not eat any) About how many pieces of FRESH fruit would you eat per DAY? (Count one apple, one banana, 10 grapes etc as one piece; put '0' if you do not eat any) About how many pieces of DRIED fruit would you eat per DAY? (Count one prune, one dried apricot, 10 raisins as one piece; put '0' if you do not eat any)	Open ended but rejected by touchscreen if answer >50 for cooked vegetables, salad or raw vegetables and fresh fruit, and >100 for dried fruit	1) Average portions of FV consumed per day (continuous) 2) <3, 3-<5, 5+ portions	3 tablespoons = 1 portion of vegetables, 1 piece of fruit = 1 portion of fruit (NHS, 2013).

Missing values: excluded from analysis

[49] Since participants were not specifically asked about their consumption of beans and legumes and fruit juice, it is unlikely these are included in the 5-a-day estimates in UKB.

3.3.4.2 *Travel behaviour*

Information on travel behaviour was collected on the touchscreen questionnaire. As with the NDNS, there were two questions in UKB pertaining to mode use, one for general (non-work) journeys in the last four weeks and one for travel to work (commuting journeys). Both questions had the same response options (Table 3.10), and allowed people to select multiple modes in combination, however the question on commuting journeys was only applicable to those who indicated that they were currently in paid employment (or self-employed) and did not always work from home (n=265,670). In addition to mode use, there were also questions on commuting distance and frequency as well as a question about the number of hours spent driving on a typical day, which was applicable to all participants and included all types of journeys. This latter measure was informative for distinguishing between those who use cars and travel a great deal, and those who use cars but travel more seldom, and so it is a better marker of transport carbon emissions than car use alone.

Using the questions on non-work travel mode(s) and commuting travel mode(s), I categorised travel behaviour in multiple ways in order to make comparable variables to the NDNS whilst also making use of more detailed travel combinations possible in UKB. Firstly, to create an overall measure of active travel for each participant comparable to the NDNS data, I combined the responses from the two travel questions into one binary variable which included those who reported any walking or any cycling for either non-work or commuting journeys. Similar binary outcomes were also created for any walking and any cycling across the two types of journeys (Table 3.10). Secondly, to account for all possible travel combinations, I created a continuum of travel behaviour for each type of journey (non-work, commuting) which ranged from car only travel, through to exclusive cycling or cycling + walking (Figure 3.2). This continuum aimed to roughly organize the modal combinations from those producing the most carbon emissions and requiring the least physical exertion (car use only), to those producing the least emissions and the requiring the most physical exertion (cycling only or cycling + walking). This resulted in an 8-level travel variable for each type of journey based on these categories (Table 3.10).

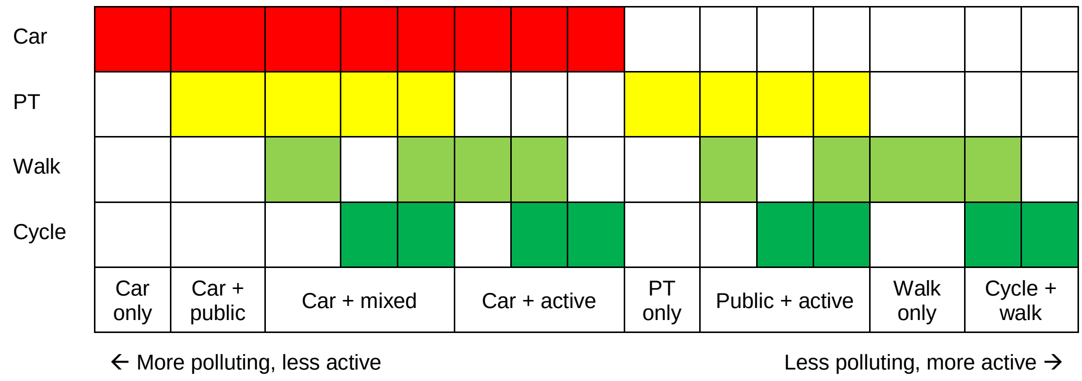
Commuting distance and commuting frequency were re-coded in the same way as in the NDNS. Finally, average time spent driving per day was also re-coded into a 5-level variable based on the distribution of the responses: None, Less than 1 hour, 1 hour, 2-3 hours, and 4+ hours (Table 3.10).

Table 3.10 – Measures of travel behaviour in UKB

Measures	Survey Questions	Response options	Recoding (if applicable)
Any active travel Any walking travel Any cycling travel Non-work travel mode Commuting travel mode (if applicable)	In the last 4 weeks, which forms of transport have you used most often to get about? (Not including any journeys to and from work; you can select more than one answer) If applicable: What types of transport do you use to get to and from work? (You can select more than one answer)	Car/motor vehicle Walk Public transport Cycle None of the above Prefer not to answer	1) Any walking or cycling travel: yes, no 2) Any walking travel: yes, no 3) Any cycling travel: yes, no 4) Non-work travel mode: car only, car + PT, car + active, car + mixed, PT only, PT + walking, walking only, cycling + walking / cycling only (see Figure 3.2) 5) Commuting mode: car only, car + PT, car + active, car + mixed, PT only, PT + walking, walking only, cycling + walking / cycling only (see Figure 3.2)
Commuting distance (if applicable)	About how many miles is it between your home and your work?	Open-ended but rejected if answer < 0 or > 9999. If answer > 70 then participant asked to confirm. Other instructions: If you have more than one 'current job' then answer this question for your MAIN job only. If you are unsure, please provide an estimate or select 'Do not know'. If you only work from home please enter 0.	>0-<2 miles, 2-<10 miles, 10+ miles
Commuting frequency (if applicable)	How many times a WEEK do you travel from home to your main work? (count outward journeys only; put 0 if you always work from home)	Open-ended but rejected if answer < 0 or > 999. If answer > 99 then participant asked to confirm. Other instructions: If the number of times varies each week, take an average over the last 4 weeks. If you only work from home please enter 0.	<5 times a week, 5 times a week, >5 times a week
Average daily driving time	In a typical DAY, how many hours do you spend driving?	Open-ended but rejected if answer < 0 or > 24. If answer > 6 then participant asked to confirm. Other instructions: If the time you spend driving varies a lot, give the average time for a 24-hour day in the last 4 weeks. Include driving a car, bus, motorcycle, boat, truck etc. Include all the driving that you do as part of work, getting to work or outside of work. If you do not drive please enter 0.	None, <1 hour, 1 hour, 2-3 hours, 4+ hours

PT: public transport
Missing data: excluded from analysis

Figure 3.2 – Continuum of travel behaviour for non-work and commuting journeys, UKB



PT: public transport

Red = modal combinations that include car use, yellow = modal combinations that include PT use, light green = modal combinations that include walking, dark green = modal combinations that include cycling

3.3.4.3 Other variables

Data on socio-demographic factors was also primarily collected via questions on the touchscreen questionnaire. From the measures available, I identified a range of relevant demographic, socio-economic, and environmental factors based on the theoretical framework described in Chapter 2 section 2.3. These were: age, sex, ethnic group, household size, cohabitation status, living with children, highest qualifications, occupational class, household income, number of cars per household, assessment centre location, population density, and Townsend deprivation score. Many of these factors were the same as in the NDNS (and were kept as similar as possible to maintain consistency and comparability between the datasets); however there was also some additional information available on each participant's residential environment and car availability. Most of these variables came directly from the questions on the touchscreen questionnaire unless otherwise noted (see Table 3.11, Table 3.12, Table 3.13).

Table 3.11 – Demographic variables in UKB

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Age (at recruitment)	Touchscreen	Years (continuous)	<45, 46-54, 55-59, 60-64, 65-69, 70+	Derived variable based on each participant's date of birth, subtracted from the day they attended the baseline assessment, truncated to whole year
Sex	Touchscreen	Male, female	NA	Acquired from the NHS central registry, and confirmed by participants on the touchscreen
Ethnic group	Touchscreen	White (British, Irish, Other), Mixed (White and Black Caribbean, White and Black African, White and Asian, other mixed), Asian or Asian British (Indian, Pakistani, Bangladeshi, other Asian), Black or Black British (Caribbean, African, other Black), Chinese, Other	White British, other White, South Asian, Black, Chinese, Mixed, Other	
Household size	Touchscreen	Number of people (continuous)	1, 2, 3, 4, 5+	Participants were asked: "Including yourself, how many people are living together in your household?" (Include those who usually live in the house such as students living away from home during term, partners in the armed forces or professions such as pilots). Responses were rejected if <1 or >100 and if >12 then asked to confirm
Household composition	Touchscreen	Lives with: husband, wife or partner, son and/or daughter (including step-children), brother and/or sister, mother and/or father, grandparent, grandchild, other related, other non-related	1) Cohabiting (lives with a husband, wife or partner), not cohabiting 2) Children in household (lives with son and/or daughter), no children 3) Lives alone, lives with son/daughter and no partner, lives with partner only, lives with partner and son/daughter, lives with others	Participants were asked: "How are the other people who live with you related to you? (You can select more than one answer)." It was not possible to know the age of the son/daughter or step-children, and given the older age of the cohort overall, some of these are likely over age 18 and thus not actually children

Missing data: excluded from analysis

Table 3.12 – Socio-economic variables in UKB

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Highest qualification	Touchscreen	College or University degree, A levels or equivalent, O levels/GCSEs or equivalent, CSEs or equivalent, NVQ or HND or HNC or equivalent, Other professional qualifications, No qualifications	NA	
Occupational class	Touchscreen and Verbal interview	Standard Occupational Classification (SOC) 2000 If participants indicated that they were currently in paid employment or self-employed on the touchscreen, data on occupation was collected by verbal interview and coded by an interviewer.	8-class NS-SEC: Higher managerial & professional, Lower managerial & professional, Intermediate, Small employers & own account workers, Lower supervisory & technical, Semi-routine, Routine, Not classified [a]	I converted each four digit SOC code into the NS-SEC classification using a derivation table obtained from the ONS website (ONS, 2016)
Household income	Touchscreen	<£18,000, £18,000 to £29,999, £30,000 to £51,999, £52,000 to £100,000, >£100,000	NA	Participants were asked to report their average total household income before tax. If participants were unsure of their annual income, weekly and monthly equivalents were also given.
Number of cars per household	Touchscreen	0, 1, 2, 3, 4+	NA	Participants were asked: How many cars or vans are owned, or available for use, by you or members of your household? (Please include company vehicles if available for private use). Do not include motorcycles

Missing data: excluded from analysis

a) Because of the large number of retired people in UKB, many people did not have a SOC code so these were categorized as 'Not classified' in the NS-SEC variable, along with those who reported being unemployed, looking after home/family, unable to work because of sickness/disability, doing unpaid/voluntary work, and being a full-time student. As it was not possible to identify people who had never worked or were long-term employed from the data available, 'Not classified' made up the 8th category of the NS-SEC variable.

GCSEs: General Certificate of Secondary Education, formerly Ordinary Levels; CSEs: vocational Certificate of Secondary Education; NVQ: National Vocational Qualifications; HND: Higher National Diploma; HNC: Higher National Certificate

Table 3.13 – Environmental (area-level) variables in UKB

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Assessment Centre	Recruitment	St Barts, Croydon, Hounslow, Oxford, Reading, Bristol, Nottingham, Birmingham, Leeds, Sheffield, Middlesbrough, Newcastle, Liverpool, Manchester, Bury, Cardiff, Swansea, Wrexham, Glasgow, Edinburgh	London, South East England, South West England, East Midlands, West Midlands, Yorkshire and the Humber, North East England, North West England, Wales, Scotland	Represented the general area of the UK in which each participant lived, as recruitment was initially based on living within 25 miles of each assessment centre[a]
Population density	Recruitment	1) England/Wales: Urban-sparse, Town and Fringe-sparse, Village-sparse, Hamlet and Isolated dwelling-sparse, Urban-less sparse, Town and Fringe-less sparse, Village-less sparse, Hamlet and Isolated Dwelling-less sparse 2) Scotland: Large Urban Area, Other Urban Area, Accessible Small Town, Remote Small Town, Very Remote Small Town, Accessible Rural, Remote Rural, Very Remote Rural	Urban, rural[b]	Derived by the study team by linking each participant's home postcode with data generated from the 2001 census from the Office of National Statistics, using the Geoconvert tool from the Census Dissemination Unit.
Townsend score	Recruitment	Score (continuous)	Quintiles	Derived by the study team immediately prior to recruitment. Each participant was assigned a score corresponding to the output area in which their postcode was located, based on the 2001 census[c]

a) Since participants were directed to attend the centre that was physically closest to their residential location, in some cases it is possible that people may have visited an assessment centre in a different region to their residence, if they lived near a regional border.

b) Rural areas included town and fringe, villages and hamlets in England and Wales and small towns and rural (remote or accessible) in Scotland.

c) Each Townsend score incorporates four different measures for an area: unemployment (% of those aged 16+ who are economically active); non-car ownership (% of all households); non-home ownership (% of all households); and household overcrowding (Townsend et al., 1988). Because most of these factors will be more prevalent in urban areas, it can be expected that more urbanized areas will have higher Townsend scores. As was described for area-level deprivation in the NDNS, I conceptualise this as an environmental variable rather than a socio-economic variable for the same reasons.

As with the NDNS, other factors were also examined as covariates or as predictors depending on the objective of the analysis. These variables and how they were created and recoded for my analysis are listed below in Table 3.14.

Table 3.14 – Other variables in UKB

Variable	Source	Provided in dataset	Recoding (if applicable)	Other Notes
Total energy intake	Oxford WebQ	Kilojoules (kJ, continuous)	Kilocalories (continuous) Conversion: 1 kcal = 4.184 kJ.	Derived by survey team based on Oxford WebQ. If this was completed more than once I calculated the average value.
Overall physical activity (PA)	Touchscreen	1) Average minutes of moderate PA per day (continuous) 2) Average minutes of vigorous PA per day (continuous)	Meets PA guideline, does not meet guideline [a]	PA guideline: 150 minutes of moderate PA or 75 minutes of vigorous PA per week
Body mass index (BMI)	Physical measures	BMI value (continuous)	<25 (underweight/ normal), 25+ (overweight/obese)	Derived by survey team from objectively measured height and weight (kg/m^2) at baseline assessment centre visit
Self-rated health	Touchscreen	Excellent, good, fair, poor	NA	
Long-standing illness, disability or infirmity	Touchscreen	Yes, no	NA	

a) Participants were asked to report if they had done both moderate and vigorous physical activity (MVPA) for 10 minutes on at least 1 day per week in the previous 4 weeks, and if so, to report the duration of each type. My intention was to total these together to create a measure of time in MVPA similar to that in the NDNS, but inspection of the data revealed that many participants seemed to have double counted their PA as both moderate and vigorous, so instead I created a binary variable to indicate of whether each participant met the recommended amount of PA: 150 minutes of moderate PA or 75 minutes of vigorous PA per week (NHS, 2015a).

3.3.5 Strengths and Limitations of UKB

There are several important strengths of the UKB dataset, particularly when compared to the NDNS. Most notably, it has an extremely large sample, which will enable me to examine population subgroups with rare behaviours (e.g. cyclists, vegetarians) with greater confidence and precision than in the NDNS. In addition, UKB has more detailed measures of some travel and dietary behaviours, as well as some supplementary socio-demographic factors not captured in the NDNS. For example, UKB has a more comprehensive assessment of non-work travel behaviour (e.g. modes are not mutually exclusive) as well as added information on average daily driving time, which has implications for both carbon emissions and health impacts (through sedentary activity). UKB also has a more comprehensive assessment of RPM consumption (frequency and quantity) and includes several additional contextual factors such as population density (urban or rural postcode) and car availability (e.g. number of vehicles per household).

Nevertheless, despite these advantages, UKB has a major limitation, which is its representativeness in comparison with the UK general population. The first and most obvious difference is the rather limited age range of the cohort, which excludes adults under age 40 and over age 70, and both of these groups may have different patterns of travel and dietary behaviour than those in midlife. UKB is also subject to a healthy volunteer effect, though this is typical of most epidemiological cohorts and particularly those with quite intensive data collection, as is the case here (Fry et al., 2017). For example, comparisons with the UK general population have shown that people in UKB are more socio-economically advantaged based on education, occupation, and deprivation index scores, and are also less likely to be obese, smoke, or drink alcohol on a daily basis (Fry et al., 2017, Hutchings et al., 2014). Correspondingly, they also have lower rates of all-cause mortality and total cancer incidence than the general population of the same age (Fry et al., 2017).

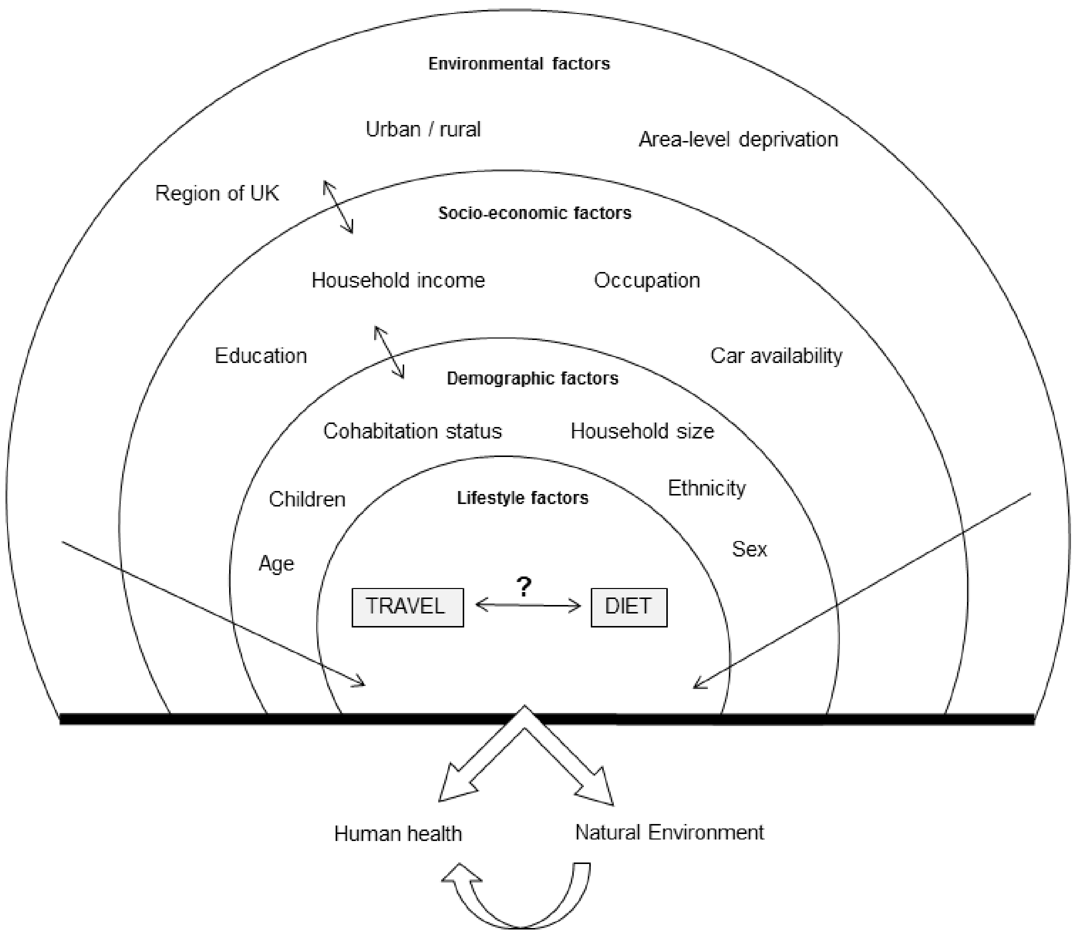
As a result, UKB alone cannot be used to provide representative prevalence estimates for the general population, but it is a useful comparison for the NDNS, since the latter sample *is* nationally representative, though very small. Notably, for a novel, exploratory piece of research such as this one, replicating and comparing my findings in more than one dataset is a particularly important consideration, as it has been argued that “no conclusions from a given set of data can be considered definitive: replication is essential to scientific progress” (Cohen et al., 2003, p.13).

3.4 Chapter 3 summary and re-capitulation of theoretical framework

In this chapter, I have described the two datasets that will be used in this thesis, focusing on how the data were collected, the measures I will be using, and the strengths and limitations of each data source. Specific details of the statistical methods used to answer each of my research questions will be described in the next three chapters: 4, 5 and 6.

Previously in Chapter 2 section 2.3, I described the patterning of travel and dietary behaviours in the UK population using a socio-ecological perspective and the SDH framework. Based on this perspective, in this chapter I have identified and described two data sources with appropriate measures of travel and diet as well as relevant socio-demographic and environmental factors that contribute to these behaviours. In Figure 3.3, I summarise these relationships and clarify the theoretical framework that underpins my thesis based on the data available in the NDNS and UKB.

Figure 3.3 – Theoretical framework for thesis based on data available (own elaboration, adapted from Dahlgren and Whitehead, 1991)



Note: urban/rural environment, car availability only in UKB

This framework is based on the SDH model discussed earlier (Dahlgren and Whitehead (1991); see section 2.3) and also draws on elements of the Health Map framework (Barton and Grant, 2006), which builds upon the SDH model by situating the 'layers' of the human environment within the wider influence(s) of the natural world. Harking back to the outset of this thesis (section 1.2), this perspective reiterates and reinforces the fact that human activities both impact upon and are influenced by the natural environment. Starting at the centre of Figure 3.3, this thesis investigates the relationships between travel and dietary behaviours in the UK, which I conceptualise as being shaped by the combined influences of demographic, socio-economic and environmental factors. In other words, *where* people live, *how* they live, and *who* they are shapes their lifestyles, and I suggest that travel and dietary behaviour may be linked by a shared aetiology across these layers of influence. Together, these behaviours are patterned into different types of lifestyles that impact on both human health and the natural environment, and the natural environment in turn affects human health (Graham and White, 2016).

Importantly, this framework does not pretend to be all-encompassing or to include all relevant contributing influences that may be represented in other socio-ecological frameworks (Sallis et al., 2008, Schneider and Stokols, 2009). I acknowledge that there are many factors that I have not be able to account for here such as specific aspects of the physical environment (built and natural), social influences like norms and identities, and personal attributes such as attitudes and values (Bopp et al., 2012, Sherwin et al., 2014, Ogilvie et al., 2012, Fraser et al., 2010, Badland et al., 2013, Fox and Ward, 2008a, Fox and Ward, 2008b, Heesch et al., 2012, Beverland, 2014, Panter and Jones, 2010). These omissions are limitations of the datasets, and not a comment on the importance of these factors in shaping travel and dietary behaviour in the UK context. In the next chapter, I begin to empirically examine the associations between travel and dietary behaviour, as well as investigate the influence of different socio-demographic factors in shaping and explaining the relationships.

4 Associations between travel modes and dietary consumption[50]

Chapter summary: This chapter investigates my first research question: whether there are associations between use of healthy, low-carbon (HLC) travel modes and consuming a more HLC diet (e.g. increased FV and reduced RPM). I examine these relationships in both datasets, but focus on RPM quantity in the NDNS and RPM frequency in UKB. Ordinal logistic regression models are used to calculate associations between different travel modes and each dietary outcome (FV, RPM), and models are adjusted for socio-demographic and lifestyle factors. After summarizing my results, I conclude the chapter by discussing my findings in relation to the literature as well as the limitations and implications of this work.

4.1 Introduction

As previously described in Chapter 2 section 2.4, there is a strong theoretical basis for associations between travel and dietary behaviour in the UK population, but little robust evidence of empirical relationships between using different travel modes and dietary consumption. At the population-level, for example, the socio-demographic patterning of these behaviours suggests that using active modes of travel and consuming HLC diets are both more common in certain types of environments and among particular subsets of the population (Laverty et al., 2013, Hutchinson et al., 2014, Maguire and Monsivais, 2014, Leahy et al., 2010), but it remains unclear whether these behaviours actually overlap within the same individuals. Though surveys and psychological research have shown that people who are willing to drive less (or drive more efficiently[51]) are also more willing to reduce their meat consumption, these correlations have been limited to behavioural intentions rather than actual travel behaviour and food consumption (Van der Werff et al., 2013, de Boer et al., 2016, Lee and Simpson, 2016).

[50] Part of this chapter was presented at the Society for Social Medicine Annual Scientific Meeting on 14 September 2016 and published as follows: Smith, M.A., Böhnke, J.R., Graham, H., White, P.C.L. and Prady, S.L., 2016. OP24 Associations between active travel and diet: An exploration of pro-health, low carbon behaviours in the National Diet and Nutrition Survey. J Epidemiol Community Health 70 (Suppl 1), A18-A18. http://dx.doi.org/10.1136/jech-2016-208064.24

[51] Also known as “eco-driving” (see Automobile Association, 2017)

At the same time, there is also consistent evidence from the UK and elsewhere of associations between increased physical activity and consuming more healthful diets (Noble et al., 2015, Poortinga, 2007, Tormo et al., 2003, Parsons et al., 2006), however it is not known whether this relationship also extends to forms of physically active *travel* or to diets that are both healthy and low-carbon (HLC). Based on this evidence, some authors have proposed that strategies to promote active travel could also offer additional population health benefits through indirect dietary outcomes, but these relationships are poorly understood and have not yet been tested empirically (de Nazelle et al., 2011).

In light of these gaps, in this chapter I examine my first research question:

- Are there associations between use of HLC travel modes and consuming a more HLC diet (e.g. increased FV and reduced RPM)?

Though I consider walking, cycling, and public transport use all to be forms of HLC travel (section 2.1.1), this chapter particularly focuses on active travel (walking and cycling for transport) due to established relationships between physical activity and dietary consumption. Since I expect these travel and dietary behaviours to share at least some socio-demographic characteristics, I adjust for important demographic, socio-economic, and environmental covariates in the analyses, as well as for overall physical activity and total energy intake. In addition to producing more accurate estimates of the associations between travel modes and dietary consumption, these adjustments will enable me to assess the degree to which these factors explain any of the relationships that are detected, which may help to identify whether certain behaviours share similar determinants.

More broadly, a better understanding of the relationships between travel and dietary behaviour may help to accelerate policy efforts to promote both health and environmental outcomes, as there may be additive or even synergistic effects of designing initiatives which focus on multiple HLC behaviours, if they are indeed found to be related (Gillman et al., 2001, de Nazelle et al., 2011). Moreover, since related behaviours may share similar aetiologies (Flay and Petraitis, 1994), identifying associations between travel modes and dietary consumption could also provide some of the first evidence that different HLC behaviours share common underlying factors in the UK population.

4.2 Methods

4.2.1 NDNS

4.2.1.1 Sample

As described in section 3.2.1, at the time of this analysis data were available from four years of the NDNS (2008-2012), though only the latter three years (2009-2012) had information on travel behaviour[52]. From this starting sample (n=3,025), 1,784 participants were eligible to complete the RPAQ (age 16+) and 94.0% (n=1,677) did so at least partially; however 68 participants did not respond to the questions on their travel mode use and were thus excluded from this study. Further sample exclusions were n=260 for missing data on one or more socio-demographic covariates[53], which left a final analytical sample of 1,349 individuals (80.4% those who completed the RPAQ) (Figure 4.1).

4.2.1.2 Measures

Travel modes and dietary consumption

In this analysis, I used several different measures of travel behaviour to explore possible variations in the relationships between travel and diet based on different travel modes (e.g. walking vs. cycling) and types of journeys (e.g. non-work vs. commuting). These measures were: any walking or cycling (hereafter referred to as any active travel; coded as yes or no), any walking (yes or no), any cycling (yes or no), non-work travel mode (car, public transport, walking, or cycling) and commuting travel mode (car, public transport, walking, or cycling). For details of how these variables were created please refer to section 3.2.5.2.

Based on the evidence in section 2.1.2, in this analysis markers of a healthy, low-carbon diet were considered to be lower consumption of red and processed meat (RPM) and higher consumption of fruit and vegetables (FV). As described previously in section 3.2.5.1, these were measured in terms of average grams per day and average portions per day, respectively.

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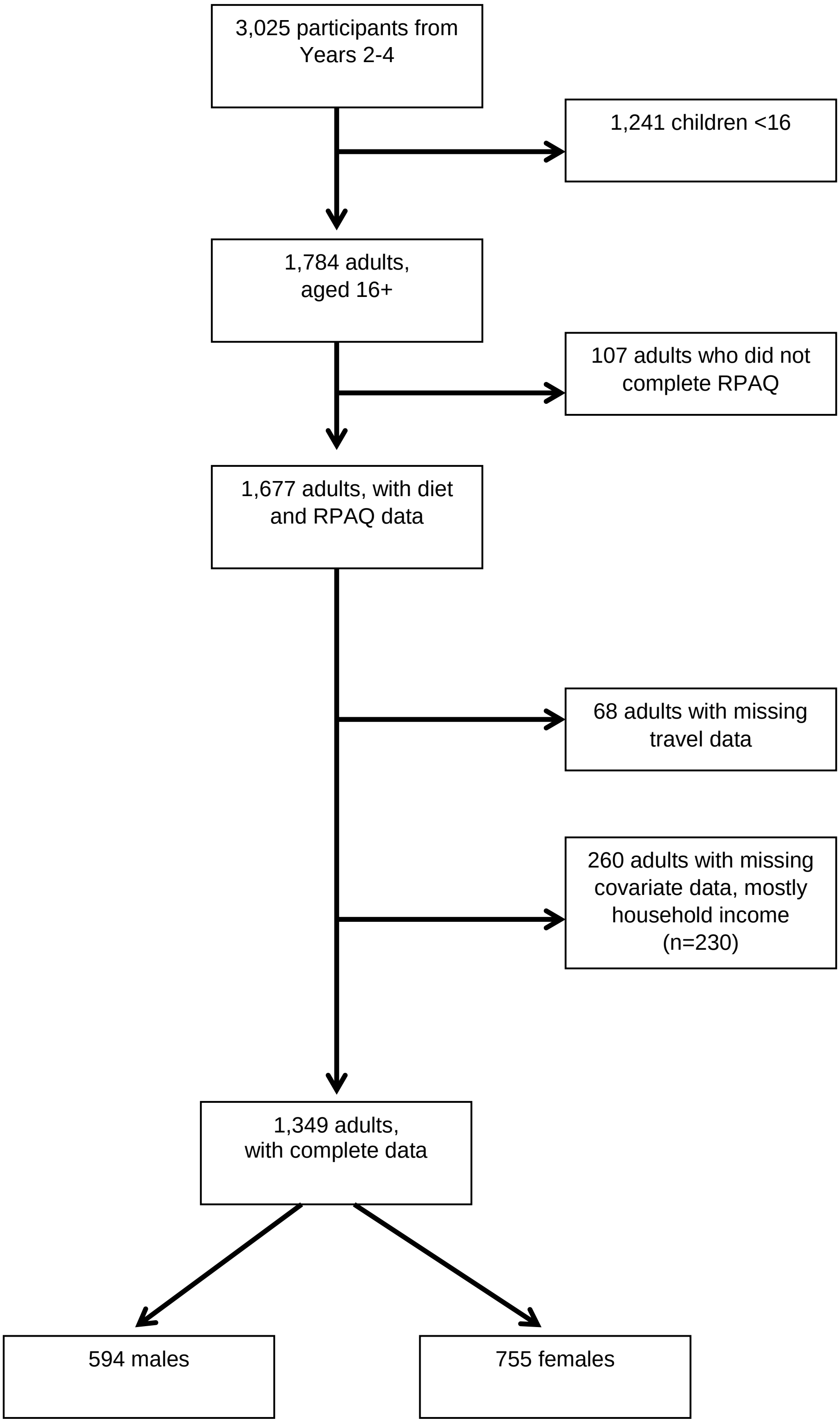
[52] All of these participants had data on dietary consumption, since those who did not complete at least three days of the food diary were excluded from the NDNS by the survey team.

[53] Most of this was for household income (n=230, 14%); further details of the implications of these exclusions can be found in section 4.4.4.2 in the Discussion.

Figure 4.1 – Flowchart of participants in the NDNS sample



NDNS: National Diet and Nutrition Survey; RPAQ: Recent Physical Activity Questionnaire

Covariates

Demographic, socio-economic, and environmental factors were included as covariates based on existing evidence of relationships with travel and dietary behaviour in the UK, as summarised previously in my theoretical framework (Chapter 3, Figure 3.3). These were: age, sex, ethnic group, household size, highest qualifications, occupational class, equivalised household income, and government office region (Maguire and Monsivais, 2014, Aston et al., 2013, Oyebode et al., 2014, Laverty et al., 2013, Hutchinson et al., 2014, DfT, 2015b, Goodman, 2013, Leahy et al., 2010). For this analysis, household size was used as a proxy for other correlated household characteristics (number of children, cohabitation status) as it has a stronger relationship with travel and dietary consumption in the literature (Clark et al., 2014, Büchs and Schnepf, 2013, Leahy et al., 2010) and there was a need to avoid over-complicating the models when using generalised ordinal regression (see section 4.2.1.3 below). Similarly, I also did not adjust for area-level deprivation (IMD quintiles) in the NDNS since this information was only available for participants in England and I did not want to reduce the sample size any further[54].

In addition to these socio-demographic factors, I also included two behavioural covariates: time spent in moderate to vigorous physical activity (MVPA) and total energy intake in kilocalories (kcal). Since it is already known that people who are more physically active tend to have healthier diets (Noble et al., 2015) and active travel is also correlated with physical activity (Hutchinson et al., 2015), adjusting for overall physical activity enabled me to assess whether there was an independent effect for active travel, and whether people actually consumed more (or less) FV and RPM and not just more (or less) food overall. In reality, both physical activity and energy intake have the potential to be both confounders and/or mediators of the relationship between active travel and dietary consumption; however, it is not possible to tease out these distinctions with cross-sectional data since all of these variables have been measured at the same point in time in the NDNS sample.

[54] 223 participants (15%) were located in Scotland, Wales or Northern Ireland.

4.2.1.3 Statistical Analysis

Associations between each measure of travel behaviour and each dietary outcome (dependent variable) were examined using multivariate regression models. Though both measures of dietary consumption were continuous variables, neither were distributed such that they met the requirements for linear regression[55], and so I decided to use ordinal logistic regression to model the trends in dietary consumption while also keeping the 'extremes' as useful categories (e.g. non-consumers of RPM, those who met or exceeded guidelines), thus enabling meaningful interpretation of the relationships with a view to national guidelines and potentially discontinuous changes.

Ordinal logistic regression (also known as the ordered logit model or the proportional odds model) is analogous to binary logistic regression but is used when a dependent variable has more than two categories and the values of each category have a sequential order (Williams, 2016). As a result, I recoded both dietary measures into ordinal variables with three levels, where the highest category for each outcome corresponded with either meeting (FV) or exceeding (RPM) the current recommended guidelines. These categories were: <3, 3–<5, and 5+ portions/day for FV and 0, >0–70, and >70 g/day for RPM (previously described in Chapter 3 section 3.2.5.1). The ordinal model assumes that the relationship between each pair of outcome groups is the same, or in other words, that the coefficients describing the relationship between the lowest outcome category and all higher categories are the same as those describing the relationship between the next lowest category and all higher categories, etc. This is called the proportional odds or parallel lines assumption (Williams, 2016), and in this case, the models assume that the odds of being in the lowest dietary consumption category compared to the two highest, are the same as the odds of being in the highest consumption category compared to the two lowest.

For each dietary outcome, I fitted a series of models with three levels of adjustment. In Model 1, I examined the bivariate association between each travel variable and each dietary outcome, adjusting only for survey year[56]. In Model 2, I added the socio-demographic covariates and in Model 3, I also introduced total energy intake and time in MVPA. All models were stratified by sex due to known gender differences in the patterning of travel behaviour and dietary consumption in the UK population (Bates et al., 2014, Laverty et al., 2013).

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[55] RPM consumption had many non-consumers; FV consumption was negatively skewed

[56] This was to account for the fact that there were some slight changes in survey procedures across different years of the study (Bates et al., 2014).

All analyses were performed in Stata/SE 14.0 (StataCorp, 2015) using the RPAQ sample weights provided with the NDNS dataset, however *n* are presented unweighted throughout. Due to the large number of covariates, I assessed whether there was multicollinearity in the models by calculating variance inflation factors and checking that these were not >10 (Stata command *regress*, option *vif*). In each ordinal model, I tested the proportional odds assumption using the Stata *oparallel* post-estimation command (Buis, 2013). This command performs five tests (a likelihood ratio test, a score test, a Wald test, a Wolfe-Gould test, and a Brant test)[57] that compare the proportional ordinal model with the fully generalised ordered logit model, which relaxes the proportional odds assumption on all explanatory variables.

In cases where the tests indicated that this assumption was not met ($p<0.05$), I re-ran each model as a generalised ordered logit or partial proportional odds model (Stata extension *gologit2*) which relaxes the proportional odds assumption for some predictor variables while maintaining it for others (Williams, 2006). This approach has the advantages of being more parsimonious and interpretable than those estimated by a non-ordinal method, such as multinomial logistic regression, and may also give added insights (e.g. discontinuous changes) into the data that would be lost by ignoring the differences and continuing to use the fully ordinal model (Williams, 2016).

In all models, adjusted odds ratios (aOR) with 95% confidence intervals (CI) are presented and a threshold of alpha = 0.05 was used to assess statistical significance.

[57] In simulation studies it has been shown that each of these tests may perform differently under different conditions (e.g. small sample sizes, size of categories in dependent variable), and since tests of the proportional odds assumption are typically “anti-conservative” it is often prudent to examine the results of more than one test (Buis and Williams, 2015).

4.2.2 UKB

4.2.2.1 Sample

Here the analysis was based on participants from the UKB baseline assessment, where data were collected between 2006 and 2010. Initially, there were 502,616 participants in the baseline sample; 7,272 were excluded for having no data on travel mode use, and 1,820 were excluded for having missing dietary data (either RPM or FV consumption). This left 493,524 participants with complete data on the main variables of interest[58]. From this an additional 81,225 participants were excluded for having missing data on one or more socio-demographic covariates[59]. This left a final analytical sample of 412,299 individuals (82% of original baseline sample), comprised of 195,131 males and 217,168 females (Figure 4.2)

4.2.2.2 Measures

Travel modes

The aim of the UKB analyses was to replicate the NDNS analyses as closely as possible, while also gleaning additional information where available. Since there was greater flexibility in the UKB measures for travel behaviour, I was thus able to use travel mode variables with more detailed combinations of subgroups than had been possible in the NDNS. These variables were:

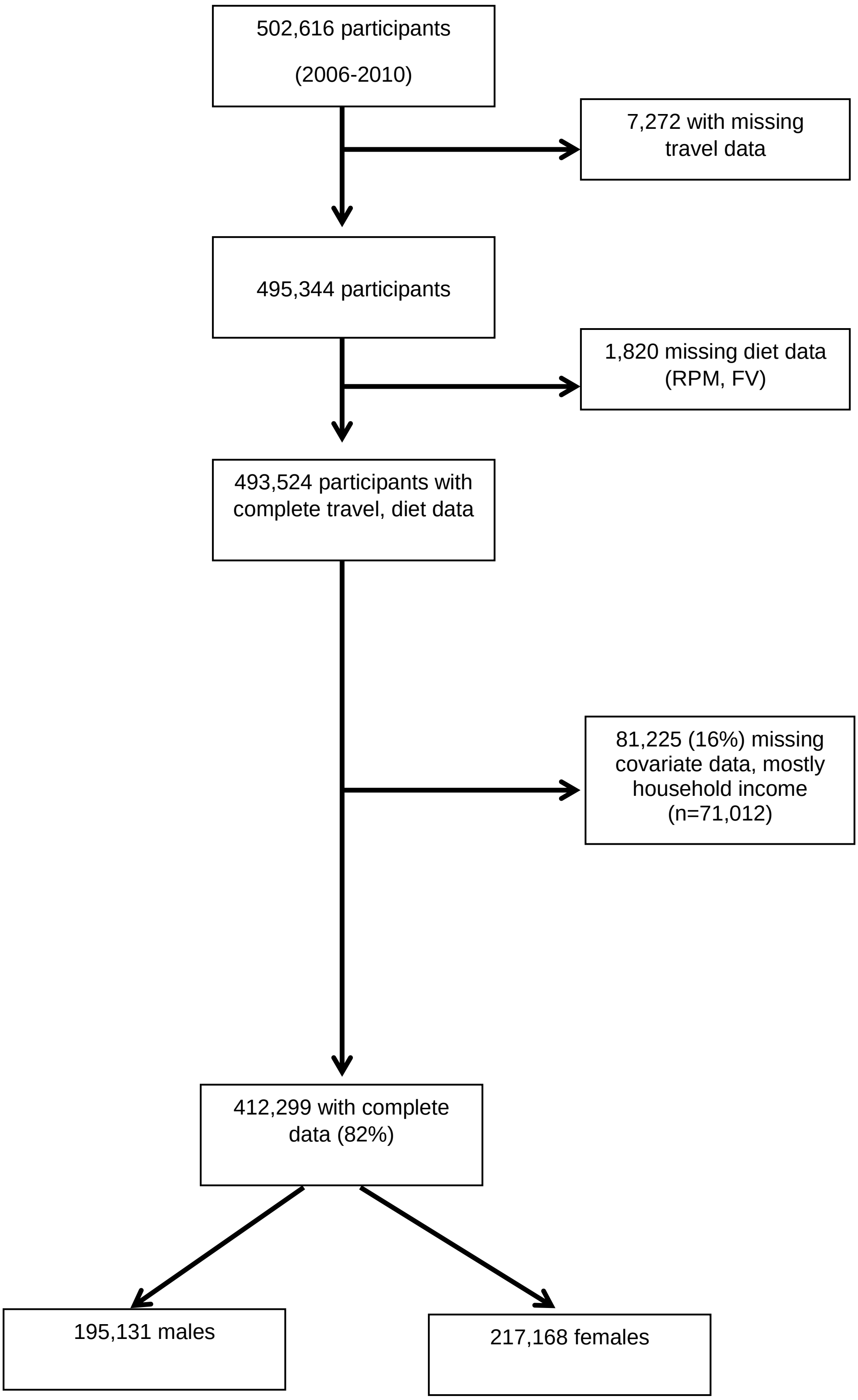
- any active travel (yes or no)
- any walking travel (yes or no)
- any cycling travel (yes or no)
- non-work travel mode (car only, car + public transport only, car + public and active transport, car + active transport only, public transport only, public + active transport, walking only, cycling only or cycling + walking)
- commuting travel mode (car only, car + public transport only, car + public and active transport, car + active transport only, public transport only, public + active transport, walking only, cycling only or cycling + walking)

Details of how these variables were created are provided in section 3.3.4.2.

[58] This sample was virtually identical to the baseline sample based on age, sex, household income, etc.

[59] Implications of these exclusions are discussed in section 4.4.4.2.

Figure 4.2 – Flowchart of participants in the UKB sample



Dietary consumption

As with the NDNS, I used consumption of FV and RPM as markers of a HLC diet in UKB. However, at the baseline assessment UKB participants were asked about the *frequency* of their RPM consumption rather than the *quantity*. Though consumption quantities are the only way to measure whether individuals are meeting recommended guidelines, consumption frequencies may offer a better approximation of people's habitual diets over time (Fahey et al., 2007), which is a crucial aspect of RPM consumption for both health and environmental impacts. As a result, one measure is not necessarily better than the other, and though the measure of RPM in UKB was not the same as in the NDNS, this variation was useful because it enabled me to investigate multiple components of RPM consumption with relevance to HLC diets.

The creation and form of both of these dietary outcomes was described previously in section 3.3.4.1. To match the outcomes in the NDNS, I recoded both FV and RPM consumption into three-level ordinal variables. FV consumption took the same form as in the NDNS (<3, 3-<5, 5+ portions of FV) whereas RPM consumption was grouped into non-consumers and consumers spilt at the median frequency: up to 3 times per week, >3 times per week[60].

Covariates

Demographic, socio-economic, and environmental factors were included as covariates using the same approach as in the NDNS analysis (see Chapter 3, Figure 3.3). These factors were generally very similar to those in the NDNS, with a few exceptions: in UKB some additional factors were available (e.g. household car availability, population density) and other factors were more comprehensive (e.g. area-level deprivation for the whole dataset versus England only). As a result, I also included number of cars per household, urban or rural residence, and Townsend score as adjustment factors in the UKB models. With regard to lifestyle factors, one major difference in UKB was that I did not have data on overall physical activity and energy intake for the whole cohort (the latter was only available in the Oxford WebQ sample), so I only adjusted for these factors in the subsample for which I had complete data (43% of 412,299; n=95,475 females, n=83,213 males).

[60] Notably, a subsequent analysis of the UKB cohort has revealed that those who consume RPM >3 times per week also consume the largest quantities of RPM (Bradbury et al., 2017), so it is likely that this frequency measure also captures the highest RPM consumers in UKB.

4.2.2.3 Statistical Analysis

To compare the UKB findings to the NDNS results the same analytical approach was used. Ordinal logistic regression models were used to examine associations between travel modes and each dietary outcome, in separate models. All models were stratified by sex and I checked the proportional odds assumption in each model. As before, I fitted a series of models for each dietary outcome with up to three-levels of adjustment, but with a few differences to the NDNS analysis. In Model 1, associations between each travel variable and each dietary outcome were unadjusted, and in Model 2 I adjusted for socio-demographic and environmental covariates. In Model 3 I also adjusted for physical activity and energy intake as explanatory factors, however this was conducted as a sensitivity analysis since these data were only available in a subsample of participants (for comparison purposes Models 1 and 2 were re-run in this subsample as well). For simplicity, this sensitivity analysis was only conducted for the any active travel variable.

In these models, I present odds ratios (OR) and adjusted odds ratios (aOR) with 95% confidence intervals (CI) and set a threshold of alpha = 0.05 for statistical significance.

4.3 Results

4.3.1 NDNS

4.3.1.1 Descriptive characteristics

After exclusions, the final sample (n=1,349) was 50.5% female and predominantly White (89.5%). Ages ranged from 16 to 92, though most participants (54.0%) were between 25 and 54 years. Overall, 25.0% of the sample had attained a degree or higher, 16.5% had household incomes over £50,000, and 35.8% lived in two person households. The full set of descriptive statistics can be seen in Table 4.1.

Car use was the most frequently reported mode for both types of journeys, at more than 60.0% of participants. Together, walking and cycling were more commonly used for non-work travel (27.1%) than for commuting (18.7%), however, only 30.0% of the sample reported walking or cycling for either type of journey (any active travel). Overall, most of this was walking, as only 4.0% of participants (n=49) reported any cycling for non-work or commuting purposes. Males were more likely than females to engage in cycling travel for non-work and commuting journeys and females were more likely than males to use public transport for non-work journeys.

Just over thirty per cent of the sample consumed an average of 5+ portions of FV per day and 40.4% exceeded the RPM consumption guideline of >70 g per day. Nearly ten per cent reported not consuming any RPM at all over the food diary period. As expected, there were considerable gender differences in RPM consumption: males were much more likely to exceed the RPM guideline (52.9% versus 28.2% among females) whereas females were much more likely to consume within the recommended amount (60.9% versus 39.3% among males). Males also had a higher average energy intake than females and also spent more time in MVPA.

Table 4.1 – Descriptive characteristics of NDNS sample, 2009-2012 (n=1,349)

	Males		Females		All	
	n	%	n	%	n	%
Total	594	49.5	755	50.5	1,349	100
Age (years) [a]						
16-24	94	13.5	139	13.9	233	13.7
25-39	137	27.0	186	25.2	323	26.0
40-54	165	28.1	213	27.9	378	28.0
55-69	129	20.0	138	18.3	267	19.0
70+	69	11.8	79	14.7	148	13.3
Ethnic group [b]						
White	550	89.7	687	89.2	1,237	89.5
Non-White	44	10.8	68	10.8	112	10.5
Qualifications						
Degree or equivalent	143	27.2	163	22.9	306	25.0
Below degree level	293	51.2	382	51.1	675	51.2
No qualifications	102	15.5	128	19.9	230	17.7
Still in full time education	56	6.1	82	6.2	138	6.1
Equivalised household income [a, c]						
0-£14,999	108	16.4	202	26.0	310	21.2
£15 000-24,999	140	26.7	172	23.9	312	25.2
£25 000-34,999	125	19.7	149	19.5	274	19.6
£35 000-49,999	108	19.4	119	15.6	227	17.5
£50,000+	113	17.9	113	15.1	226	16.5
Occupational Class (NS-SEC) [d]						
Managerial / professional occupations	280	50.7	315	41.9	595	46.3
Intermediate occupations	96	15.4	171	21.6	267	18.6
Routine / manual occupations	212	32.9	252	34.1	140	33.5
Never worked [e]	6	0.9	17	2.4	23	1.7
Household size [a]						
1	148	15.1	151	15.1	299	15.1
2	189	35.9	246	35.7	435	35.8
3	107	18.8	165	21.9	272	20.4
4	94	18.3	132	17.8	226	18.0
5+	56	12.0	61	9.5	117	10.7
Region						
London	46	11.6	66	10.9	112	11.3
South England	138	21.4	173	25.1	311	23.3
Central England	188	28.9	205	24.2	393	26.5
North England	131	22.8	179	24.6	310	23.7
Scotland / Wales / N. Ireland	91	15.3	132	15.2	223	15.2

Table 4.1 (continued)

	Males		Females		All	
	n	**%**	**n**	**%**	**n**	**%**
Non-work travel (single main mode) [f]						
Cycle	33	5.7	11	1.8	44	3.7
Walk	132	22.3	180	24.6	312	23.4
Public transport	53	8.7	101	13.2	154	11.0
Car	367	63.4	434	60.5	801	62.0
Missing	9		29		38	
Commuting travel (always/usual mode) [g]						
Cycle	17	5.4	10	2.4	27	4.0
Walk	48	11.7	85	18.1	133	14.7
Public transport	49	12.7	62	14.2	111	13.4
Car	260	70.2	270	65.4	530	68.0
Missing / not applicable	220		328		548	
Any cycling travel	35	5.9	14	2.0	49	4.0
Any walking travel	150	24.9	216	27.5	366	26.2
Any walking/cycling travel	183	30.6	229	29.4	412	30.0
FV consumption (portions/day)						
< 3	220	36.3	284	35.3	504	35.8
3 - < 5	203	33.7	254	34.4	457	34.0
5+	171	30.0	217	30.3	388	30.2
RPM consumption (g/day)						
0	38	7.7	86	10.9	124	9.3
> 0 - 70	242	39.3	451	60.9	693	50.2
> 70	314	52.9	218	28.2	532	40.4
Total energy intake in kcal/day (mean, sd)	2,059	538	1,576	445	1,815	557
MVPA in hours/day (mean, sd)	2.3	2.7	1.0	1.6	1.6	2.4

n unweighted, % weighted; MVPA: Moderate to vigorous physical activity

a) Continuous variable in models

b) Binary variable used due to small cell sizes

c) Based on McClements scale

d) NS-SEC: National Statistics Socio-economic Classification (3 categories), based on household reference person

e) Combined with routine / manual occupations due to small numbers

f) n=1,311 for non-work travel (2.6% missing), % are calculated from non-missing

g) n=801 for commuting travel (40.9% missing/not applicable), % are calculated from non-missing

4.3.1.2 Associations between travel modes and FV consumption

Table 4.2 and Table 4.3 show the results of the sex-stratified ordinal regression models between HLC travel and FV consumption among females and males, respectively. Due to the large number of variables, only associations for the travel variables are shown since this was the focus of the analysis and because the other covariates did not vary much across the different models. Full models with all covariates shown are presented in Appendix B (Table B.0.1 to Table B.0.10).

As can be seen in Table 4.2, engaging in *any* cycling travel was positively associated with FV consumption among females, though this was not the case for walking or public transport use. Though the confidence intervals were very wide due to the small number of female cyclists, these associations were particularly strong for *non-work* cycling, and were only slightly attenuated after adjustment for socio-demographic and lifestyle factors. This attenuation suggests that the association between non-work cycling and FV consumption is only partially explained by socio-demographics and overall diet and physical activity, which means that there may be other factors underlying this positive relationship. Using Model 3 as an example, women who cycled for non-work journeys were four times more likely to consume higher amounts of FV (e.g. 3+ portions/day versus <3, 5+ portions/day versus <5) compared to those who travelled by car: aOR=4.00; 95% CI 1.31, 12.19.

In contrast to cycling, walking travel was negatively associated with FV consumption among females, though this effect became non-significant after adjustment for socio-demographic factors (Model 2). In the full model (Appendix B Table B.0.2), this attenuation seemed to be largely explained by education level. In other words, women with fewer qualifications were more likely to walk for transport and also more likely to consume lower amounts of FV. No other significant associations were observed for engaging in any active travel or for commuting travel in this sample.

Most of the models in Table 4.2 were found to meet the proportional odds assumption. In cases where they did not (see 'f' superscript), this was because there was at least one variable that did not have a consistent relationship across all levels of the outcome variable. In Model 3 for example, time in MVPA was positively associated with consuming 5+ portions of FV versus <5, but not with consuming 3+ portions versus <3 (see Appendix B, Table B.0.1 to Table B.0.5)[61]. Nevertheless, the travel variables

[61] As described in section 4.1, this discontinuous relationship is what we would expect based on existing evidence: individuals with high levels of physical activity also tend to consume the most FV – both of these are indicators of very healthy lifestyles.

themselves remained proportional in all cases, so these associations are presented in the same way as the traditional ordinal models.

Table 4.2 – Ordinal logistic models between HLC travel and FV consumption among NDNS females

TRAVEL VARIABLES	Females (n=755)		
	Model 1 [a]	Model 2 [b]	Model 3 [c]
	Adjusted OR (95% CI)		
Any active travel (ref: None)	0.76 (0.53 - 1.09)	0.92 (0.65 - 1.30)	0.90 [f] (0.64 - 1.28)
Any walking (ref: None)	0.67* (0.46 - 0.96)	0.80 (0.56 - 1.14)	0.80 [f] (0.56 - 1.15)
Any cycling (ref: None)	3.27* (1.18 - 9.04)	3.18* (1.04 - 9.77)	2.69 [f] (0.96 - 7.53)
Non-work travel (ref: Car) [d]			
Public transport	0.60 (0.36 - 1.00)	0.78 (0.45 - 1.34)	0.81 (0.46 - 1.43)
Walking	0.61* (0.40 - 0.91)	0.74 (0.49 - 1.14)	0.74 (0.49 - 1.13)
Cycling	4.50** (1.68 - 12.04)	4.38* (1.37 - 14.00)	4.00* (1.31 - 12.19)
Commute mode (ref: Car) [e]			
Public transport	1.19 (0.61 - 2.35)	1.19 [f] (0.60 - 2.35)	1.27 [f] (0.61 - 2.62)
Walking	0.74 (0.44 - 1.26)	0.94 (0.52 - 1.67)	0.99 (0.56 - 1.76)
Cycling	1.85 (0.56 - 6.08)	1.88 (0.65 - 5.44)	1.81 (0.66 - 4.91)

*** p<0.001, ** p<0.01, * p<0.05

a) Model 1: adjusted for survey year
b) Model 2: adjusted for Model 1 + age, ethnic group, education, occupational class (hrp), equivalised household income, household size, government office region
c) Model 3: adjusted for Model 2 + total energy intake (kcal/day), time spent in moderate to vigorous physical activity (hours/day)
d) n=726 females
e) n=427 females
f) Proportional odds assumption not met; modelled using generalised ordered logit (*gologit2*)

Grey shading indicates associations that are statistically significant.

As can be seen in Table 4.3, among males the relationships between travel behaviour and FV consumption were not the same as those observed among females. For example, though any cycling was also positively associated with FV consumption among males, so too were any walking travel and any active travel overall. In fact, both of these behaviours had positive associations that grew stronger with further adjustment, which is known as a suppression effect[62] (MacKinnon et al., 2000).

Table 4.3 – Ordinal logistic models between HLC travel and FV consumption among NDNS males

TRAVEL VARIABLES	Males (n=594)		
	Model 1 [a]	**Model 2 [b]**	**Model 3 [c]**
	Adjusted OR (95% CI)		
Any active travel (ref: None)	1.51* (1.06 - 2.15)	1.65** (1.15 - 2.38)	1.73** (1.21 - 2.46)
Any walking (ref: None)	1.32 (0.90 - 1.95)	1.41 (0.95 - 2.10)	1.50* (1.03 - 2.19)
Any cycling (ref: None)	2.08* (1.04 - 4.15)	2.47* (1.08 - 5.63)	2.27* (1.00 - 5.13)
Non-work travel (ref: Car) [d]			
Public transport	0.43* (0.21 - 0.91)	0.57 (0.27 - 1.20)	0.55 (0.25 - 1.23)
Walking	1.08 (0.70 - 1.66)	1.20 (0.77 - 1.86)	1.26 (0.82 - 1.92)
Cycling	1.88 (0.90 - 3.94)	2.33* (1.02 - 5.34)	2.24 (0.99 - 5.08)
Commute mode (ref: Car) [e]			
Public transport	0.39** (0.20 - 0.76)	0.39* (0.18 - 0.85)	0.41* (0.18 - 0.95)
Walking	1.61 (0.82 - 3.15)	1.64 (0.78 - 3.45)	1.73 (0.85 - 3.53)
Cycling	3.63* (1.22 - 10.83)	4.00* (1.22 - 13.09)	3.44* (1.04 - 11.35)

*** p<0.001, ** p<0.01, * p<0.05

a) Model 1: adjusted for survey year
b) Model 2: adjusted for Model 1 + age, ethnic group, education, occupational class (hrp), equivalised household income, household size, government office region
c) Model 3: adjusted for Model 2 + total energy intake (kcal/day), time spent in moderate to vigorous physical activity (hours/day)
d) n=585 males
e) n=374 males

Grey shading indicates associations that are statistically significant.

[62] This effect occurs when one (or more) independent variables acts a *suppressor variable.* Suppressor variables are uncorrelated with the dependent variable but correlated with one or more other independent variables, and therefore suppress (control for) the irrelevant variance in the other predictor variables, increasing the partial correlation. In other words, they help to rid the analysis of noise (Lancaster, 1999, Statistica, 2017).

Overall, however, the strongest positive associations among males were observed between commuter cycling and FV consumption. In Model 3 for example, men who cycled to work were more than three times as likely to consume higher amounts of FV compared to those commuting by car: aOR=3.44; 95%CI 1.04, 11.35. In contrast, commuting by public transport was negatively associated with consuming higher amounts of FV, an effect that was only slightly attenuated by adjustment for lifestyle factors. With regard to the proportional odds assumption, none of the tests performed on the models in Table 4.3 indicated a violation.

4.3.1.3 Associations between travel modes and RPM consumption

Table 4.4 (females) and Table 4.5 (males) show the results of the sex-stratified ordinal regression models between HLC travel modes and RPM consumption. Associations are presented in the same way as for FV consumption (travel variables only), with full models in Appendix B (Table B.0.11 to Table B.0.20).

As can be seen in Table 4.4, engaging in non-work cycling was negatively associated with RPM consumption among females and was independent to adjustment with socio-demographic and lifestyle factors (but with a very wide confidence interval). This means that women who cycled for non-work journeys were significantly less likely to consume higher amounts of RPM (e.g. any versus none, >70 g versus ≤70 g) compared to women who travelled by car. No other significant associations were observed between travel and RPM consumption in this sample. All models in Table 4.4 met the proportional odds assumption.

Among males (Table 4.5), associations between HLC travel and RPM consumption were in the negative direction for all models, but none were statistically significant. Most of these models met the proportional odds assumption with the exception of Model 1 due to differences in RPM consumption across survey years. In this case, there was a higher number of males who consumed no RPM in Year 3 of the survey, so the relationship between survey year and RPM consumption was not consistent across all levels of the outcome variable (see Appendix B, Table B.0.16-Table B.0.20).

Table 4.4 – Ordinal logistic models between HLC travel and RPM consumption among NDNS females

TRAVEL VARIABLES	Females (n=755)		
	Model 1 [a]	Model 2 [b]	Model 3 [c]
	Adjusted OR (95% CI)		
Any active travel (ref: None)	1.00 (0.73 - 1.39)	1.02 (0.73 - 1.42)	1.04 (0.74 - 1.46)
Any walking (ref: None)	1.07 (0.78 - 1.48)	1.10 (0.80 - 1.53)	1.13 (0.81 - 1.58)
Any cycling (ref: None)	0.46 (0.14 - 1.45)	0.40 (0.12 - 1.34)	0.39 (0.11 - 1.35)
Non-work travel (ref: Car) [d]			
Public transport	1.09 (0.60 - 1.99)	1.33 (0.75 - 2.36)	1.39 (0.77 - 2.52)
Walking	1.16 (0.82 - 1.64)	1.27 (0.90 - 1.79)	1.30 (0.92 - 1.84)
Cycling	0.28* (0.08 - 0.97)	0.25* (0.07 - 0.91)	0.25* (0.06 - 0.98)
Commute mode (ref: Car) [e]			
Public transport	0.86 (0.38 - 1.96)	0.92 (0.45 - 1.88)	0.90 (0.44 - 1.86)
Walking	1.01 (0.62 - 1.64)	0.98 (0.55 - 1.72)	1.06 (0.60 - 1.87)
Cycling	0.42 (0.06 - 3.06)	0.29 (0.03 - 2.54)	0.29 (0.03 - 2.63)

*** p<0.001, ** p<0.01, * p<0.05

a) Model 1: adjusted for survey year
b) Model 2: adjusted for Model 1 + age, ethnic group, education, occupational class (hrp), equivalised household income, household size, government office region
c) Model 3: adjusted for Model 2 + total energy intake (kcal/day), time spent in moderate to vigorous physical activity (hours/day)
d) n=726 females
e) n=427 females

Grey shading indicates associations that are statistically significant.

Table 4.5 – Ordinal logistic models between HLC travel and RPM consumption among NDNS males

TRAVEL VARIABLES	Males (n=594)		
	Model 1 [a]	Model 2 [b]	Model 3 [c]
	Adjusted OR (95% CI)		
Any active travel (ref: None)	0.70 [f] (0.45 - 1.07)	0.70 (0.44 - 1.10)	0.70 (0.45 - 1.10)
Any walking (ref: None)	0.71 [f] (0.46 - 1.09)	0.69 (0.44 - 1.10)	0.71 (0.45 - 1.13)
Any cycling (ref: None)	0.73 [f] (0.29 - 1.79)	0.83 (0.32 - 2.13)	0.72 (0.31 - 1.68)
Non-work travel (ref: Car) [d]			
Public transport	0.90 [f] (0.48 - 1.67)	0.78 (0.40 - 1.52)	0.78 (0.41 - 1.49)
Walking	0.66 (0.41 - 1.06)	0.63 (0.38 - 1.04)	0.64 (0.39 - 1.07)
Cycling	0.63 (0.25 - 1.60)	0.65 (0.27 - 1.56)	0.60 (0.27 - 1.34)
Commute mode (ref: Car) [e]			
Public transport	0.92 (0.41 - 2.02)	0.97 (0.42 - 2.22)	1.09 (0.47 - 2.55)
Walking	0.64 (0.33 - 1.27)	0.57 (0.29 - 1.14)	0.60 (0.31 - 1.17)
Cycling	1.08 (0.24 - 4.82)	1.06 (0.24 - 4.78)	0.80 (0.18 - 3.56)

*** p<0.001, ** p<0.01, * p<0.05

a) Model 1: adjusted for survey year

b) Model 2: adjusted for Model 1 + age, ethnic group, education, occupational class (hrp), equivalised household income, household size, government office region

c) Model 3: adjusted for Model 2 + total energy intake (kcal/day), time spent in moderate to vigorous physical activity (hours/day)

d) n=585 males

e) n=374 males

f) Proportional odds assumption not met; modelled using generalised ordered logit (*gologit2*)

4.3.2 UKB

To facilitate understanding of the similarities and differences between the two datasets, comparisons will be made to the NDNS samples for the descriptive results in this section. Comparisons between the datasets for the associations between travel modes and dietary consumption will be handled in the Discussion (section 4.4).

4.3.2.1 Descriptive characteristics

After exclusions, the final sample (n=412,299) was 52.7% female and predominantly White (89.4% White British, 6.0% other White). Ages ranged from 38 to 73 and around 40% of the sample was aged 60+. Overall, 35.1% of the sample had attained a degree or higher and nearly 40% were classified as working in managerial or professional occupations. Household incomes were fairly evenly represented; however there was a higher proportion of females in the lower income categories and a higher proportion of males in the upper income categories. Nearly half of the sample (45.7%) was made up of two person households and the vast majority owned one or two cars (80.4%).

Higher proportions of the sample came from the assessment centres in London (Hounslow, Croydon, and St Bart's; 13.5%), Yorkshire and the Humber (Sheffield and Leeds; 15.1%), North East England (Newcastle and Middlesbrough; 11.8%) and North West England (Manchester, Bury, and Liverpool; 14.9%). Based on their postcode at recruitment, 85.9% of the sample lived in an urban setting and in areas that were typically less deprived on average. The full set of descriptive statistics can be seen in Table 4.6.

As expected, the UKB sample was older, had more qualifications, higher incomes, and lived in smaller households compared to the NDNS sample. There were also fewer individuals from central and south England (outside London), and more from the north of England and London area.

Table 4.6 – Descriptive characteristics of UKB sample (n=412,299)

	Males		Females		All	
	n	%	n	%	n	%
Total	195,131	47.33	217,168	52.67	412,299	100.00
Age at baseline (years) [a]						
< 45	20,476	10.49	23,892	11.00	44,368	10.76
45-49	25,246	12.94	31,543	14.53	56,789	13.77
50-54	28,821	14.77	36,394	16.76	65,215	15.82
55-59	34,774	17.82	40,910	18.84	75,684	18.36
60-64	46,955	24.06	50,174	23.10	97,129	23.56
65+	38,859	19.91	34,255	15.77	73,114	17.73
Ethnic group						
White British	175,294	89.83	193,220	88.97	368,514	89.38
Other White	10,855	5.56	13,903	6.40	24,758	6.01
South Asian	3,835	1.97	2,870	1.32	6,705	1.63
Black	2,403	1.23	3,306	1.52	5,709	1.38
Chinese	450	0.23	720	0.33	1,170	0.28
Mixed	891	0.46	1,448	0.67	2,339	0.57
Other	1,403	0.72	1,701	0.78	3,104	0.75
Highest qualification [b]						
College or University degree	70,136	35.94	74,613	34.36	144,749	35.11
A levels or equivalent	20,898	10.71	27,183	12.52	48,081	11.66
GCSEs or equivalent	36,862	18.89	51,055	23.51	87,917	21.32
CSEs or equivalent	10,560	5.41	11,730	5.40	22,290	5.41
NVQ or HND or HNC or equivalent	17,732	9.09	9,607	4.42	27,339	6.63
Other professional qualifications	8,560	4.39	12,375	5.70	20,935	5.08
No qualifications	30,383	15.57	30,605	14.09	60,988	14.79
Occupational Class [c]						
Higher managerial & professional	48,981	25.10	25,058	11.54	74,039	17.96
Lower managerial & professional	34,686	17.78	54,458	25.08	89,144	21.62
Intermediate occupations	14,933	7.65	36,723	16.91	51,656	12.53
Small employers & own accounts	9,345	4.79	4,958	2.28	14,303	3.47
Lower supervisory & technical	10,702	5.48	1,019	0.47	11,721	2.84
Semi-routine occupations	10,986	5.63	20,181	9.29	31,167	7.56
Routine occupations	10,162	5.21	5,365	2.47	15,527	3.77
Not classified	55,336	28.36	69,406	31.96	124,742	30.25
Household income (before tax)						
Less than £18,000	39,184	20.08	52,863	24.34	92,047	22.33
£18,000 to 30,999	47,701	24.45	57,347	26.41	105,048	25.48
£31,000 to 51,999	52,674	26.99	55,578	25.59	108,252	26.25
£52,000 to 100,000	43,674	22.38	40,867	18.82	84,541	20.51
Greater than £100,000	11,898	6.10	10,513	4.84	22,411	5.44

Table 4.6 (continued)

	Males		Females		All	
	n	%	n	%	n	%
Household size						
1	33,345	17.09	45,334	20.88	78,679	19.08
2	90,130	46.19	98,297	45.26	188,427	45.70
3	30,803	15.79	33,989	15.65	64,792	15.71
4	29,408	15.07	28,809	13.27	58,217	14.12
5+	11,445	5.86	10,739	4.94	22,184	5.38
Number of cars per household						
0	14,877	7.62	19,055	8.77	33,932	8.23
1	77,536	39.74	95,160	43.82	172,696	41.89
2	79,161	40.57	79,599	36.65	158,760	38.51
3	17,829	9.14	17,994	8.29	35,823	8.69
4+	5,728	2.94	5,360	2.47	11,088	2.69
Region [d]						
London	25,333	12.98	30,273	13.94	55,606	13.49
South East England	17,007	8.72	19,402	8.94	36,409	8.83
South West England	16,764	8.59	19,613	9.03	36,377	8.82
East Midlands	13,120	6.72	14,559	6.70	27,679	6.71
West Midlands	18,383	9.42	18,020	8.30	36,403	8.83
Yorkshire and the Humber	29,615	15.18	32,479	14.96	62,094	15.06
North East England	23,110	11.84	25,606	11.79	48,716	11.82
North West England	29,599	15.17	31,717	14.60	61,316	14.87
Wales	8,265	4.24	9,048	4.17	17,313	4.20
Scotland	13,935	7.14	16,451	7.58	30,386	7.37
Urban residence	167,547	85.86	186,617	85.93	354,164	85.90
Townsend score (mean, sd) [e]	-1.37	3.08	-1.37	3.00	-1.37	3.04

a) Continuous variable in models

b) A levels: academic advanced-levels, post compulsory education; GCSEs: academic General Certificate of Secondary Education, formerly Ordinary Levels, taken at age 15–16 years and the end of compulsory education ; CSEs: vocational Certificate of Secondary Education, formerly taken at age 15–16 years; NVQ, HND, HNC: National Vocational Qualifications, Higher National Diploma, Higher National Certificate, all intermediate semi-vocational qualifications

c) Based on National Statistics Socio-economic Classification (NS-SEC), where Not classified = those who were retired, unemployed, looking after home/family, unable to work because of sickness/disability, doing unpaid/voluntary work, or full-time students

d) Grouped based on assessment centre: London = St Barts, Croydon, Hounslow; South East England = Oxford, Reading; South West England = Bristol; East Midlands = Nottingham; West Midlands = Birmingham; Yorkshire and the Humber = Leeds, Sheffield; North East England = Middlesbrough, Newcastle; North West England = Liverpool, Manchester, Bury; Wales = Cardiff, Swansea, Wrexham; Scotland = Glasgow, Edinburgh.

e) Lower score = less deprived (min: -6.3; max: 11.0)

Travel modes

A descriptive overview of travel mode use in UKB can be seen in Table 4.7. Overall, 54.5% of the sample reported walking or cycling for either type of journey (any active travel), and walking was much more common than cycling (51.6% vs. 9.4%). Males were more likely to report any cycling travel (12.7% vs. 6.4% among females), and females were slightly more likely to report any walking travel (53.2% vs. 49.7% among males). These proportions are considerably higher than for active travel in the NDNS, which may be a reflection of the more health-conscious UKB sample (Fry et al., 2017) but also of greater flexibility in capturing non-work travel mode(s).

As in the NDNS, use of active travel modes was more common for non-work than for commuting journeys in UKB – only 39.5% used car only travel for non-work journeys, compared to 63.1% for commuting journeys. For non-work travel, 22.0% of participants mixed car use with active modes, and 14.0% mixed car, active modes and public transport use. Overall, 51.2% of participants incorporated at least some walking or cycling into their non-work travel, compared to only 22.1% for commuting travel. Across both types of journeys, men were more likely to cycle and drive exclusively and women were more likely to use public transport only.

Dietary consumption

As with the NDNS, there were considerable gender differences in RPM consumption in UKB, as 58.3% of males and 36.7% of females reported consuming RPM more than three times per week (Table 4.8). At the other end of the spectrum, only 5.3% of the sample reported never consuming any RPM (3.4% among males, 7.0% among females); this was lower than in the NDNS since it is a reflection of habitual RPM consumption and not just consumption over a three to four day recording period.

Nearly thirty-nine per cent of the UKB sample reported consuming 5+ portions of FV per day on average (31.4% among males, 43.3% among females). This was slightly higher than in the NDNS, which also had a higher proportion who consumed <3 portions per day. This difference may be due to the UKB sample being more health-conscious overall and/or because FV consumption was measured less precisely in UKB. As with the NDNS, males in UKB had a higher energy intake overall and were more physically active compared to females, however these data were only available for a smaller subset of the UKB sample (Table 4.8).

Table 4.7 – Descriptive overview of travel mode use in UKB (n=412,299)

	Males (n=195,131)		Females (n=217,168)		All (n=412,299)	
	n	**%**	**n**	**%**	**n**	**%**
Any active travel [a]	105,287	53.96	119,244	54.91	224,531	54.46
Any walking travel	96,976	49.70	115,573	53.22	212,549	51.55
Any cycling travel	24,806	12.71	13,877	6.39	38,683	9.38
Non-work journeys [b]						
Car only	79,582	40.86	82,980	38.27	162,562	39.49
Car + PT	6,058	3.11	8,822	4.07	14,880	3.61
Car + mixed (PT and AT)	25,683	13.19	32,024	14.77	57,707	14.02
Car + AT	44,488	22.84	46,117	21.27	90,605	22.01
PT only	9,957	5.11	13,277	6.12	23,234	5.64
PT + AT	11,793	6.05	16,020	7.39	27,813	6.76
Walking only	12,553	6.45	14,939	6.89	27,492	6.68
Cycling / cycling + walking	4,660	2.39	2,648	1.22	7,308	1.78
Missing	357		341		698	
Commuting journeys [c]						
Car only	74,043	65.47	73,736	60.91	147,779	63.11
Car + PT	6,735	5.96	7,519	6.21	14,254	6.09
Car + mixed (PT and AT)	3,649	3.23	3,578	2.96	7,227	3.09
Car + AT	7,573	6.70	8,727	7.21	16,300	6.96
PT only	8,383	7.41	12,042	9.95	20,425	8.72
PT + AT	4,861	4.30	5,081	4.20	9,942	4.25
Walking only	3,878	3.43	8,183	6.76	12,061	5.15
Cycling / cycling + walking	3,964	3.50	2,196	1.81	6,160	2.63
Missing / not applicable	82,045		96,106		178,151	

PT: public transport; AT: active travel

a) Includes walking or cycling for non-work or commuting travel

b) n=411,601 for non-work travel (0.2% missing), % are calculated from non-missing

c) n=234,148 for commuting travel (43.2% missing/not applicable), % are calculated from non-missing

Table 4.8 – Descriptive overview of dietary consumption and physical activity in UKB (n=412,299)

	Males (n=195,131)		Females (n=217,168)		All (n=412,299)	
	n	%	n	%	n	%
FV consumption (portions/day)						
< 3	66,672	34.17	45,669	21.03	112,341	27.25
3 - < 5	67,263	34.47	77,583	35.72	144,846	35.13
5+	61,196	31.36	93,916	43.25	155,112	37.62
RPM consumption (frequency/week)						
Never	6,615	3.39	15,250	7.02	21,865	5.30
≤ 3 times	74,766	38.32	122,148	56.25	196,914	47.76
> 3 times	113,750	58.29	79,770	36.73	193,520	46.94
Total energy intake, kcal/day (mean, sd) [a]	2,299	685	1,971	575	2,123	649
Meets physical activity guideline						
Yes	101,323	51.92	103,804	47.80	205,127	49.75
No	86,112	44.13	103,996	47.43	189,108	45.87
Missing	7,696	3.94	10,368	4.77	18,064	4.38

a) Based on n=98,853 females, n=85,392 males

4.3.2.2 Associations between travel modes and FV consumption

Table 4.9 shows the results of the unadjusted and adjusted sex-stratified ordinal logistic regression models for associations between HLC travel modes and average portions of FV consumed per day. Full models with all covariates can be seen in Appendix B, Table B.0.21 (females) and Table B.0.22 (males) (only any active travel is shown for space and simplicity).

As can be seen in Table 4.9, there were positive associations between all types of HLC travel and FV consumption among both males and females, with very little change even after adjustment for demographic, socio-economic, and environmental factors. Associations were generally much stronger for cycling than for other travel modes. In Model 2 for example, men and women who engaged in any cycling travel were nearly twice as likely to consume higher amounts of FV than those who did not cycle for transport (males: aOR=1.65, 95%CI 1.61, 1.69; females: aOR=1.67, 95%CI 1.62, 1.73).

Table 4.9 – Ordinal logistic models between HLC travel and FV consumption, stratified by gender in UKB (n=412,299)

TRAVEL VARIABLES	Males (n=195,131)		Females (n=217,168)	
	Model 1 [a]	Model 2 [b]	Model 1 [a]	Model 2 [b]
	OR (95% CI)			
Any active travel (ref: None)	1.37*** (1.34 - 1.39)	1.35*** (1.33 - 1.37)	1.42*** (1.40 - 1.44)	1.43*** (1.40 - 1.45)
Any walking (ref: None)	1.28*** (1.26 - 1.31)	1.25*** (1.23 - 1.27)	1.38*** (1.36 - 1.40)	1.38*** (1.36 - 1.41)
Any cycling (ref: None)	1.57*** (1.54 - 1.61)	1.65*** (1.61 - 1.69)	1.58*** (1.53 - 1.63)	1.67*** (1.62 - 1.73)
Non-work travel [c] (ref: Car only)				
Car + public transport	1.06* (1.01 - 1.11)	1.00 (0.95 - 1.05)	1.05* (1.01 - 1.09)	0.98 (0.94 - 1.02)
Car + mixed (public and active)	1.49*** (1.46 - 1.53)	1.37*** (1.33 - 1.40)	1.57*** (1.53 - 1.61)	1.41*** (1.38 - 1.45)
Car + active travel	1.27*** (1.24 - 1.29)	1.26*** (1.24 - 1.29)	1.37*** (1.34 - 1.40)	1.39*** (1.36 - 1.42)
Public transport only	1.03 (0.99 - 1.07)	1.13*** (1.08 - 1.18)	1.03 (0.99 - 1.06)	1.11*** (1.06 - 1.15)
Public transport + active travel	1.31*** (1.27 - 1.36)	1.43*** (1.37 - 1.49)	1.45*** (1.40 - 1.50)	1.52*** (1.47 - 1.58)
Walking only	1.34*** (1.29 - 1.38)	1.39*** (1.34 - 1.44)	1.47*** (1.42 - 1.52)	1.57*** (1.51 - 1.62)
Cycling / cycling + walking	2.06*** (1.95 - 2.17)	2.18*** (2.06 - 2.30)	2.34*** (2.17 - 2.52)	2.50*** (2.31 - 2.71)
Commuting travel [d] (ref: Car only)				
Car + public transport	1.03 (0.98 - 1.08)	0.97 (0.92 - 1.01)	1.02 (0.97 - 1.06)	0.99 (0.95 - 1.03)
Car + mixed (public and active)	1.44*** (1.36 - 1.53)	1.37*** (1.29 - 1.46)	1.45*** (1.36 - 1.54)	1.41*** (1.32 - 1.50)
Car + active travel	1.41*** (1.35 - 1.47)	1.47*** (1.41 - 1.54)	1.23*** (1.18 - 1.28)	1.30*** (1.24 - 1.35)
Public transport only	1.08*** (1.03 - 1.12)	1.03 (0.98 - 1.08)	0.91*** (0.88 - 0.95)	0.95* (0.91 - 0.99)
Public transport + active travel	1.41*** (1.33 - 1.48)	1.37*** (1.29 - 1.45)	1.26*** (1.19 - 1.32)	1.28*** (1.20 - 1.35)
Walking only	1.20*** (1.13 - 1.28)	1.24*** (1.16 - 1.32)	1.07*** (1.03 - 1.12)	1.20*** (1.14 - 1.25)
Cycling / cycling + walking	1.78*** (1.68 - 1.89)	1.82*** (1.71 - 1.93)	1.93*** (1.77 - 2.09)	2.00*** (1.84 - 2.18)

*** p<0.001, ** p<0.01, * p<0.05

a) Model 1: unadjusted

b) Model 2: adjusted for age, ethnic group, education, occupational class, household income, household size, number of cars, assessment centre location, population density, Townsend score

Note: A visual representation of the adjusted associations in Model 2 can also be seen in Appendix B, Figure B.0.1

c) n=194,774 males, n=216,827 females

d) n=113,086 males, n=121,062 females

Grey shading indicates associations that are statistically significant.

Looking across the more detailed travel classifications of non-work and commuting journeys, associations were generally weaker or non-significant for travel that did not involve any walking or cycling (e.g. car + public transport, public transport only). This pattern suggests that using active modes of travel and consuming higher amounts of FV are particularly related in UKB, even after adjusting for socio-demographic and environmental factors. Comparing across the two types of journeys, the associations were fairly similar in magnitude, though they were slightly stronger for non-work travel, and particularly for non-work cycling.

4.3.2.3 Associations between travel modes and RPM consumption

Table 4.10 shows the results of the unadjusted and adjusted sex-stratified ordinal logistic regression models for associations between HLC travel modes and frequency of RPM consumption. Full models with all covariates shown for any active travel can be seen in Appendix B Table B.0.23 (females) and Table B.0.24 (males).

In these models, the associations between HLC travel and RPM consumption were nearly all negative, the only exception was for car + public transport (versus car only travel) among females for non-work journeys (Table 4.10). Among both males and females, associations were only slightly attenuated with adjustment for demographic, socio-economic, and environmental factors. As with FV consumption, these associations were strongest for cycling, overall and across both types of journeys. Moreover, there was a clear gradient of effect for non-work travel, such that the more active the travel mode(s), the more negative the association with RPM consumption frequency. In Model 2 for example, men and women who cycled for non-work journeys were nearly half as likely to consume RPM more frequently compared to those who travelled by car (males: aOR=0.57; 95%CI 0.54, 0.60; females: aOR=0.54, 95%CI 0.50, 0.59).

Table 4.10 – Ordinal logistic models between HLC travel and RPM consumption, stratified by gender in UKB (n=412,299)

TRAVEL VARIABLES	Males (n=195,131)		Females (n=217,168)	
	Model 1 [a]	Model 2 [b]	Model 1 [a]	Model 2 [b]
	OR (95% CI)			
Any active travel (ref: None)	0.87*** (0.85 - 0.88)	0.89*** (0.87 - 0.91)	0.85*** (0.84 - 0.87)	0.88*** (0.87 - 0.90)
Any walking (ref: None)	0.91*** (0.89 - 0.93)	0.94*** (0.92 - 0.95)	0.88*** (0.86 - 0.89)	0.91*** (0.89 - 0.92)
Any cycling (ref: None)	0.75*** (0.73 - 0.77)	0.76*** (0.74 - 0.78)	0.67*** (0.65 - 0.69)	0.72*** (0.69 - 0.74)
Non-work travel [c] (ref: Car only)				
Car + public transport	0.99 (0.94 - 1.04)	1.01 (0.95 - 1.06)	1.12*** (1.07 - 1.17)	1.09*** (1.04 - 1.14)
Car + mixed (public and active)	0.92*** (0.89 - 0.94)	0.96* (0.94 - 0.99)	0.93*** (0.91 - 0.96)	0.95*** (0.93 - 0.98)
Car + active travel	0.95*** (0.93 - 0.98)	0.96*** (0.94 - 0.98)	0.94*** (0.92 - 0.96)	0.94*** (0.92 - 0.97)
Public transport only	0.91*** (0.87 - 0.95)	0.89*** (0.85 - 0.94)	0.87*** (0.84 - 0.90)	0.88*** (0.84 - 0.91)
Public transport + active travel	0.78*** (0.75 - 0.81)	0.77*** (0.74 - 0.81)	0.71*** (0.69 - 0.74)	0.76*** (0.73 - 0.79)
Walking only	0.76*** (0.73 - 0.78)	0.75*** (0.72 - 0.78)	0.70*** (0.68 - 0.72)	0.71*** (0.69 - 0.74)
Cycling / cycling + walking	0.56*** (0.53 - 0.59)	0.57*** (0.54 - 0.60)	0.50*** (0.46 - 0.54)	0.54*** (0.50 - 0.59)
Commuting travel [d] (ref: Car only)				
Car + public transport	0.94** (0.89 - 0.98)	1.00 (0.95 - 1.06)	1.00 (0.96 - 1.05)	1.04 (0.99 - 1.09)
Car + mixed (public and active)	0.82*** (0.76 - 0.87)	0.89** (0.84 - 0.96)	0.83*** (0.78 - 0.89)	0.93* (0.86 - 0.99)
Car + active travel	0.82*** (0.78 - 0.86)	0.83*** (0.79 - 0.87)	0.92*** (0.88 - 0.96)	0.89*** (0.85 - 0.93)
Public transport only	0.86*** (0.82 - 0.90)	0.95 (0.91 - 1.01)	0.89*** (0.85 - 0.92)	0.97 (0.93 - 1.01)
Public transport + active travel	0.70*** (0.66 - 0.74)	0.79*** (0.74 - 0.84)	0.71*** (0.67 - 0.75)	0.84*** (0.79 - 0.89)
Walking only	0.76*** (0.71 - 0.81)	0.80*** (0.75 - 0.86)	0.89*** (0.85 - 0.93)	0.86*** (0.82 - 0.91)
Cycling / cycling + walking	0.58*** (0.54 - 0.62)	0.60*** (0.56 - 0.64)	0.51*** (0.46 - 0.55)	0.55*** (0.50 - 0.60)

*** p<0.001, ** p<0.01, * p<0.05

a) Model 1: unadjusted

b) Model 2: adjusted for age, ethnic group, education, occupational class, household income, household size, number of cars, assessment centre location, population density, Townsend score

   Note: A visual representation of the adjusted associations in Model 2 can also be seen in Appendix B, Figure B.0.2

c) n=194,774 males, n=216,827 females

d) n=113,086 males, n=121,062 females

Grey shading indicates associations that are statistically significant.

Proportional odds assumption

All of the models in Table 4.9 and Table 4.10 violated the proportional odds assumption due to the large sample size in UKB and greater ability to detect minor variations in the data. To assess whether these differences were meaningful for the travel variables in particular, all of the models were re-run using a generalised ordered logit model for which the associations are presented in Appendix B Table B.0.25 (FV consumption) and Table B.0.26 (RPM consumption). In these models, the associations were generally of similar magnitude and in the same direction to the fully ordinal models, but when differences were present, the associations tended to be stronger for the two highest categories versus the lowest category of the outcome variables, for example, 3+ portions of FV versus <3, and RPM consumers versus never consumers. As this is a relatively minor difference, the most important finding is that the general directions of the associations (positive and negative) still hold.

Sensitivity analysis (any active travel only)

In the subset of the sample that had full data on energy intake and physical activity (n=95,475 females, n=83,213 males) adjusting for these variables in addition to the other socio-demographic and environmental factors slightly attenuated the associations between any active travel and FV consumption, but the relationship was still independent and highly significant among both males and females (males: aOR=1.28; 95%CI 1.24, 1.31 and females: aOR=1.35, 95%CI 1.32, 1.39).

Similarly, the associations between any active travel and RPM consumption were also very slightly attenuated, but even less so than for FV consumption (males: aOR= 0.89; 95%CI 0.87, 0.92 and females: aOR=0.90, 95%CI 0.88, 0.92). This difference may be due to the fact that energy intake and physical activity are less strongly related to consumption frequency (RPM) than to consumption quantity (FV). Full models with all covariates shown can be seen in Appendix B, Table B.0.27 to Table B.0.30.

4.4 Discussion

4.4.1 Summary of key findings

The aim of this chapter was to determine whether there are associations between use of HLC travel modes and consuming a more HLC diet in the UK population. Using these two datasets, this analysis has shown that engaging in active travel, and in particular cycling travel, is associated with increased consumption of FV and with reduced consumption of RPM (both in quantity and frequency). Associations were most consistent between cycling and increased FV (all four samples), but were less consistent between cycling and reduced RPM (three samples), walking and increased FV (three samples), and walking and reduced RPM (two samples, UKB only). Overall, associations between travel and diet were also strongest among people who cycled for both FV and RPM consumption. In nearly all cases, the associations remained independent to adjustment with both socio-demographic and behavioural factors, suggesting that these factors do not explain the observed relationships.

4.4.2 Variations by gender and data source

In the NDNS, there were several associations that appeared to vary between males and females. One clear point of difference was that non-work cycling was strongly and significantly associated with reduced RPM consumption among females, but none of the associations between travel and RPM consumption were significant among males. Reasons for this variation are unclear, and this finding should be viewed with caution and replicated in other representative samples as it was based on a very small number of female cyclists (n=11).

In addition, another difference in the NDNS was that walking travel was *positively* associated with FV consumption among males (similar to cycling) but *negatively* associated with FV consumption among females (opposite to cycling). Similar patterns were also present between walking and RPM consumption by gender, however these associations were weaker and did not reach statistical significance. Though reasons for this gender variation are unclear, the negative association for FV among females was largely explained by socio-demographic factors (particularly lower qualifications), which is consistent with previous research also reporting that walking for transport is more common among groups with lower socio-economic position in the UK (Laverty et al., 2013, Goodman, 2013, Olsen et al., 2017), and especially among disadvantaged mothers with young children (Bostock, 2001). These conflicting patterns may suggest that men and women do not necessary walk for the same reasons, and that among females, walking and cycling for transport may be distinct behaviours or practices, taken up by different groups of women for different purposes (Steinbach et al., 2011).

Notably, these differences were not present in UKB, perhaps because the UKB sample was made up of more health conscious and socially advantaged individuals, who were less likely to walk for reasons of necessity. Overall, associations were also more similar among males and females in UKB than in the NDNS, most likely due to differences in the sample populations and measures used in each study. For example, many of the males and females in UKB were married or cohabiting, since study participants were encouraged to recruit their partners if they were also in the eligible age range (Allen, 2015). The effect of this would be to make the men and women in UKB more alike in their behaviour than the men and women in the NDNS, who were unrelated and living in different households (since only one adult from each household could be recruited into the survey). Another explanation for the lack of gender variations with regard to RPM consumption in UKB could be that there are larger differences in the *quantity* of RPM consumption compared with *frequency* of RPM consumption, since men usually consume larger amounts of food overall, and of RPM in particular (Bates et al., 2014, Bradbury et al., 2017).

With regard to different types of journeys, the associations were generally similar in direction and magnitude; however there was some evidence in both datasets that the relationships between active travel and diet were stronger for non-work journeys among females and for commuting journeys among males. Reasons for this pattern are unclear, as there is very little UK data on travel behaviour for different purposes overall, let alone by gender. For example, a recent systematic review on gender differences in walking reported that women were more likely to walk for non-work purposes like errands, but the review found no UK studies on the subject (Pollard and Wagnild, 2017). One interpretation of these patterns could be that women's non-work travel is more closely associated with their dietary behaviour because they face additional constraints on their commuting travel. For example, some studies have reported that women may be less likely to engage in active commuting due to social pressures around their appearance in the workplace (Steinbach et al., 2011), or because women are more often responsible for escorting children to school and doing other household errands as part of their journey to work, which may be easier or faster by car (Garrard, 2003).

4.4.3 Results in relation to the literature

With regard to travel behaviour, mode use in the NDNS was fairly similar to estimates from other nationally representative surveys, particularly the National Travel Survey (NTS) for non-work travel and the Census for commuting travel (DfT, 2017b, Goodman, 2013). Overall, any active travel use was much higher in UKB than in other surveys, but this may be because the travel measures captured walking and cycling in combination with other modes. For non-work travel, estimates of multiple mode use which combined active travel with car travel were very similar to estimates of multimodality in the NTS (Heinen and Chatterjee, 2015). Dietary data in the NDNS were essentially the same as estimates released in other yearly reports (Bates et al., 2014, Bates et al., 2016) and consumption of FV and RPM in UKB were generally as expected given the health-conscious nature of the cohort (Fry et al., 2017).

As stated at the beginning of this chapter in section 4.1, there are no existing studies that have examined associations between travel modes and specific dietary elements, so it is difficult to make direct comparisons between this analysis and other studies in the literature. Nevertheless, if one considers the wider literature on health and environmental behaviours, the findings of this chapter do support much of the existing evidence with regard to correlations between physical activity and dietary consumption. Firstly, in relation to the epidemiological literature, these results add to studies that have reported clustering between increased physical activity and more nutritious diets (Noble et al., 2015, Poortinga, 2007, Tormo et al., 2003, Parsons et al., 2006, Gillman et al., 2001), by suggesting that comparable associations exist for *physically active travel* and healthy diets, independent of overall physical activity. My findings also confirm and corroborate other reports (based on cross-sectional, self-reported data) which suggest that cycling to work may be associated with making healthy dietary changes (Cyclescheme, 2015).

In addition, since many studies of physical activity and healthy diets have only assessed one element of diet (FV consumption), I also add to the evidence in this area by examining RPM consumption, which has been rarely explored in other studies. For example, in a recent systematic review of multiple health behaviours (Noble et al., 2015), of the 40 studies examining dietary behaviour, only three studies included meat consumption in any form. In relation to the environmental behaviour literature, my findings also support the results of other studies which have linked reduced car driving with reduced meat consumption, but which have only measured behavioural intentions rather than actual behaviours (de Boer et al., 2016, Lee and Simpson, 2016).

More indirectly, there are also interesting parallels between these findings and the growing body of research evidence relating active travel, and particularly active commuting, to positive health outcomes like lower obesity and reduced mortality (Laverty et al., 2013, Martin et al., 2015, Flint et al., 2014, Flint and Cummins, 2016, Celis-Morales et al., 2017). Two of the most recent studies, also conducted using UKB but only examining active commuting, have found particularly strong effects for cycling to work and lower obesity (Flint and Cummins, 2016) and reduced mortality (Celis-Morales et al., 2017), far over and above the effects found for walking. Combining these findings with my results on the dietary patterns of cyclists suggests that positive interactions between cycling travel and HLC diets could be one explanation for the enhanced health effects observed among individuals who cycle. As a result, my results underscore the importance of adjusting for dietary *quality* (e.g. what foods people eat) and not just dietary *quantity* (e.g. total energy intake) in studies of active travel and health outcomes, as there may be strong correlations between different HLC behaviours that have the potential to confound the effects.

4.4.4 Strengths and limitations

This is the first analysis to examine relationships between engaging in HLC travel and markers of a HLC diet, thus beginning to clarify the patterning of HLC lifestyles. Using multiple measures of travel and dietary behaviour, I have been able to assess these relationships very comprehensively across different travel modes, types of journeys, and relevant food groups, as well as adjust for a wide range of socio-demographic and lifestyle factors. This level of detail has allowed me to isolate and elucidate where the relationships between these behaviours are strongest and weakest, which is an important contribution to understanding which elements of travel and diet may share common causal pathways, as well as hold the best opportunities for potential synergies. Finally, I have also attempted to replicate and validate my results using two population-based data sources, giving further weight to my findings than would have been possible through either dataset alone.

4.4.4.1 Datasets

Use of these two complementary data sources has also allowed me to minimize the weaknesses inherent to each of these studies. In the NDNS, the major limitation was its relatively small sample size, which resulted in large confidence intervals around the effect estimates for cyclists, and also meant that it may have been underpowered to detect associations for travel modes with weaker relationships. In addition, there may have been some misclassification of travel behaviour in the NDNS since its measure of non-work travel was mutually exclusive, and participants could only be characterised by their single main mode. The most likely result of this on my findings would be an underestimation of the effect for walking and cycling travel since individuals who use these modes in combination with other modes would not have been captured, and were thus likely classified as exclusive car or public transport users.

In UKB, neither of these issues was a problem due to the large sample and flexible measures of travel behaviour, both of which enabled me to observe relatively fine grained differences in the data that were not possible to capture in the NDNS. Nevertheless, UKB is limited by its lack of representativeness. In particular, the study excludes large swathes of the population which may have different patterns of travel and dietary behaviour (e.g. those < age 40) and includes a biased sample of 'healthy volunteers' (Fry et al., 2017), which might cause the relationship between health behaviours such as physical activity and diet to be slightly overestimated. As a result, the fact that I also found similar relationships between travel and diet in the nationally representative NDNS sample helps to bolster the external validity of these findings.

4.4.4.2 Analysis

Other limitations that are applicable to both datasets include that the measures used were all self-reported and that the analyses are cross-sectional in nature. Self-reported data may be subject to both recall error and social desirability bias (Althubaiti, 2016), and if participants were more likely to report that they walked, cycled, ate more FV and ate less RPM then this could at least partially explain the observed associations between these behaviours. If this did happen then the effect would likely be worse in UKB since these participants were more health-conscious to begin with and information on food consumption was measured less precisely and collected at the same time as travel behaviour. Although existing technologies do not currently enable objective dietary measurement at a population level (Galante et al., 2016), it is presently possible to objectively measure people's travel behaviour using accelerometers and GPS trackers (Dunton et al., 2014, Panter et al., 2014, Kelly et al., 2013), however this could also potentially introduce other sources of bias since individuals may behave differently if they are being tracked.

The fact that the data are all cross-sectional means I cannot establish causality between these behaviours in terms of whether active travel precedes higher FV and lower RPM consumption or vice versa. Though these relationships could plausibly go in either direction, there are neurocognitive arguments which suggest that physical activity may be more likely to lead to dietary changes through improvements in cognitive executive function (Joseph et al., 2011, Loprinzi, 2015), as was previously described in Chapter 2 section 2.4.1.2. As a result, I have also chosen to model the associations in this way, in alignment with previous research (Gillman et al., 2001, Tormo et al., 2003) and theoretical perspectives in behavioural science (Joseph et al., 2011, Loprinzi, 2015). Future research with longitudinal data will help to confirm the direction of these relationships, as well as improve our understanding of behaviour dynamics over time.

In addition, another limitation was the relatively large number of participants that were excluded in both samples, primarily due to missing data for household income (14% in both samples)[63]. In both datasets, there were virtually no differences between the excluded and included samples in relation to the main variables of interest (travel behaviour, RPM consumption, FV consumption); however in UKB excluded participants were considerably more likely to be older (age 65+), female, and to have no qualifications. To assess the implications of these exclusions on my results I re-ran the analyses in both datasets including those with missing income data by adding an extra 'missing' category to the household income variables (Vogl et al., 2012). As these results were virtually identical to the original models, with no differences in direction of association or statistical significance, it did not seem that the exclusions had any impact on the findings so I did not feel it was necessary to impute the missing data.

One final limitation is that I only examined two dietary elements (FV and RPM), which is a very simplified way of measuring a HLC diet. My choice of these indicators was based on the fact that they are the two food groups with the clearest evidence of combined implications for human health and carbon emissions (Garnett et al., 2015), and they are also subject to dietary consumption guidelines from the UK government (PHE, 2014). Nevertheless, I acknowledge that two food groups alone cannot fully capture most people's overall dietary patterns, and within these broad categories, individual foods may not have equal health and environmental impacts. For example, consuming tropical fruit or berries grown under glass may be considered good for health but will likely have greater carbon impacts than eating root vegetables, and consuming beef or lamb from ruminant animals will have greater carbon emissions than pork, but may be healthier than eating processed meats such as bacon (Bouvard et al., 2015, Carlsson-Kanyama and Gonzalez, 2009, Eshel et al., 2014). These

[63] For all other variables the number of missing values was around 1%.

realities reinforce the fact that health and environmental impacts are not always in perfect alignment (Garnett et al., 2015), and highlight the challenges of selecting dietary indicators that are both healthy and low-carbon. Further research should aim to examine relationships between travel behaviour and eating patterns in more detail with greater attention to individual foods and food subgroups.

4.4.5 Implications

Overall, these findings have several important implications. Firstly, these results suggest that active travel and HLC diets are related and may share similar aetiologies, since theories of clustering stemming from ecological frameworks suggest that behaviours which cluster together share common causal pathways (McAloney et al., 2013, Spring et al., 2012a), and that the stronger the clustering between two behaviours, the more determinants they are likely to share (Flay and Petraitis, 1994). In previous research this has been seen most clearly for negative health behaviours such as alcohol consumption, smoking, drug use, and risky sexual behaviour, which have been often linked to common causal pathways of socio-economic disadvantage (Noble et al., 2015, Meader et al., 2016). In this study, strong relationships were seen most clearly between cycling and FV consumption, which had consistent associations across all four samples, even after adjusting for socio-demographic characteristics and behavioural factors like overall physical activity and energy intake. This suggests that these behaviours may be driven by common underlying factors, and supports the interpretation of both being related to health motivations, though there may also be other factors at play.

This interpretation might also explain why the associations were not as strong for RPM consumption, since the health impacts of RPM have been touted much more recently and less consistently compared with FV. For example, statements on the 'probable' carcinogenicity of RPM from the IARC were only made in 2015 (Bouvard et al., 2015), well after this data was collected, and the UK government's Eatwell Guide has only included an explicit recommendation to "Eat less red and processed meat" since its most recent iteration, published in 2016 (PHE, 2016, NHS, 2016). Whatever the cause, identifying the shared determinants of these relationships may help to improve our understanding of why some people engage in HLC behaviours, as well as how to better promote these lifestyles.

Identifying correlated behaviours is also important because if behaviours are related, engaging in one behaviour may modify the likelihood of engaging in others (McAloney et al., 2013, Spring et al., 2012a, Truelove et al., 2014, Dolan and Galizzi, 2015). This means that strategies which target multiple behaviours together may have additional benefits than the sum of individual interventions (Spring et al., 2012b), and may have the potential to produce synergistic outcomes. Based on the associations I have observed here, the results of this study suggest that there may be potential synergies between active travel and dietary consumption in the UK population, which supports the hypothesis of previous authors (de Nazelle et al., 2011). Though these relationships still need to be examined longitudinally, they suggest that HLC behaviours have the potential to mutually reinforce one another, and that more holistic promotion efforts could lead to enhanced benefits for both human health and the natural environment. Based on the present study, however, it can only be stated that these HLC behaviours often occur together – whether one causes the other or whether additional variables cause both cannot be investigated with sufficient rigour in these cross-sectional samples.

4.5 Conclusions and Chapter 4 Summary

In this chapter I have shown that there are positive associations between active travel and markers of a HLC diet (increased FV, decreased RPM). These associations were strongest between cycling and FV consumption, which suggests that these behaviours may be driven by common factors, independent of socio-demographic and lifestyle characteristics. Relationships between active travel and RPM consumption were also found, and associations were most consistent in relation to frequency of RPM consumption in UKB.

Together, these findings support existing evidence of clustering between greater physical activity and more healthy diets and suggest that increases in active travel (particularly cycling) may contribute to synergistic benefits for public health and the natural environment. Effective promotion of HLC lifestyles requires that we have a complete understanding of people's behaviour patterns, including how different behaviours influence, interact and intersect with one another across the life course. This chapter has specifically focused on the links between HLC behaviours, and in the next chapter I will expand on this to examine people's lifestyle patterns more broadly, using multiple travel and dietary behaviours, and with consideration to both ends of the health- and climate-relevant behaviour spectrum.

5 Prevalence and patterning of health- and climate-relevant lifestyles[64]

Chapter summary: Having established that there are associations between active travel and markers of a healthy, low-carbon diet in Chapter 4, in this chapter I expand on these findings by describing the full distribution of travel and dietary patterns in the UK population. Latent class analysis (LCA) is used to determine behaviour patterns in both the NDNS and UKB, using multiple indicators of travel and dietary behaviour. After selecting the best-fitting models, each behaviour pattern is described and classified as higher-carbon or lower-carbon based on its indicators. The chapter concludes with a discussion of the findings in relation to the literature, strengths and limitations, and implications for policy.

5.1 Introduction

As discussed in Chapter 1 section 1.2.1.2, the UK government has committed to reduce greenhouse gas (GHG) emissions by 80% from 1990 levels (CCC, 2008) and in light of the Paris climate agreement these reductions will need to be even more aggressive (CCC, 2016b). As a result, there remains a crucial need to better understand ways of maximizing emissions reductions and establishing whether there could be potential synergies between different sectors. Globally, meeting these targets will mean an annual emissions budget[65] of 2.1 tCO_{2eq} per person by 2050 (Girod et al., 2014), and the UK currently exceeds this amount through diet alone, with around 3.2 tCO_{2eq} attributable to food consumption (including waste) (Hoolohan et al., 2013) and around 1.6 tCO_{2eq} attributable to personal land-based travel (Brand et al., 2013). Notably, however, emissions in these sectors are not distributed equally: CO_2 from motorised transport is highly concentrated among those who travel the most by car (Brand et al., 2013) and dietary emissions tend to be highest among those who consume the greatest amounts of meat (Scarborough et al., 2014, Hoolohan et al., 2013).

[64] Part of this chapter was presented at the UK Public Health Science Conference on 24 November 2017 and published as follows: Smith, M.A., Böhnke, J.R., Graham, H., White, P.C.L. and Prady, S.L., 2017. Prevalence of travel and dietary behaviours with health and environmental co-benefits: a cross-sectional analysis of UK Biobank. *The Lancet*, *390*, p.S83. http://dx.doi.org/10.1016/S0140-6736(17)33018-0

[65] The concept of an annual emissions budget is analogous to a financial budget: it details the amount of GHG emissions (measured in tonnes of CO_2 equivalent) each person has available to 'spend' in a given year.

In light of this attribution, some authors have argued that the most effective policy option for reducing emissions would be to primarily target initiatives at those whose behaviours are most damaging (Brand and Preston, 2010, Brand et al., 2013); however, it remains to be seen whether people who drive the most are *also* those with the highest meat consumption. Since both of these behaviours are socially patterned, it is possible that they may overlap in certain population groups, but not in others; for example, car travel is higher in rural areas and among males, older people, and more affluent groups (DfT, 2015b), whereas RPM consumption tends to be higher among males, more disadvantaged individuals and larger households (Maguire and Monsivais, 2014, Leahy et al., 2010). As previously discussed in Chapter 2 section 2.3, these are examples of how different types of socio-demographic and environmental influences interact to structure the behaviours and lifestyles of individuals. Importantly, if these behaviours do cluster together, it might imply that a useful policy strategy could be to promote healthy, low-carbon travel and dietary behaviours *in tandem* to better align their shared health and environmental goals.

At the same time, however, understanding where healthy, low-carbon travel and dietary behaviours *do not* overlap is also important for policy development, since the dynamics between different types of behaviours may be complex and result in unintended consequences. For example, a recent study which linked car travel to eating practices argued that policies promoting '5-a-day' and consuming fresh, local or organic foods may inadvertently result in increased transport emissions if people choose to travel farther and shop more frequently (by car) to source these foods (Mattioli and Anable, 2017). Similarly, while active travel is obviously a healthy, low-carbon form of transport, estimating the full impact of a 'walking and cycling lifestyle' also needs to consider what is *fuelling* the active travel in question. In fact, some estimates have shown that walking for transport can be a more carbon-intensive form of travel than driving a fuel-efficient car when the GHG impacts of food production and the calories used for walking are accounted for (McKenzie, 2013)[66]. Consequently, it is imperative that we start to examine multiple behaviours, and the ways they may interact and intersect, within the field of health and environmental behaviour research.

Though there are many ways of studying relationships between multiple behaviours, clustering and latent variable techniques are growing in frequency and becoming increasingly used in public health research (McAloney et al., 2013, Noble et al., 2015). Broadly speaking, these methods involve classifying different individuals or items into

[66]Another related example: a cyclist fuelled exclusively by calories from cheeseburgers would have comparable emissions per mile to two people driving a fuel-efficient car (Berners-Lee, 2010). Of course, this illustration does not account for what the car drivers have eaten, but it aptly illustrates that comparing efficiencies between fossil fuels and food energy are not always straightforward.

distinct groups or categories, and they have numerous applications in many diverse fields, including data mining, bioinformatics, and market research (Everitt et al., 2011). Historically, 'traditional' clustering techniques such as hierarchal or K-means clustering have been used most commonly, as they are less computationally intensive and often incorporated into standard statistical packages (Kent et al., 2014). More recently, however, other approaches like latent class analysis (LCA) have been gaining popularity due to the increased speed of modern computers and because LCA offers many advantages over these conventional methods (Magidson and Vermunt, 2002). Firstly, LCA is a model-based approach, which means it uses a statistical model to identify probability distributions within the data and the likely placement of observations within those distributions (Kent et al., 2014, Everitt et al., 2011). Using this model, it is thus possible to determine the optimal number of underlying subgroups (latent classes) using diagnostic tools (e.g. goodness of fit) and class membership can be assigned on the basis of statistical probabilities (Lanza and Collins, 2010)[67]. By comparison, traditional clustering techniques use an *ad hoc* approach and arbitrary measures of distance to determine the number of clusters and assign group membership (Magidson and Vermunt, 2002). Other advantages of LCA that are particularly relevant in the context of this thesis include that it is better at handling missing data[68] and variables with mixed scale types (e.g. nominal, ordinal), and it can incorporate sampling weights and complex samples (as in the NDNS). Perhaps most importantly, in simulations and direct comparisons, LCA has also been shown to perform better than other clustering approaches, and to have greater classification accuracy (Vidden et al., 2016). LCA has been previously used to study patterns in travel behaviour (Kroesen, 2015, Molin et al., 2016) and dietary consumption (Wang et al., 2012), but these areas have yet to be brought together.

Due to these advantages, this chapter will use LCA to examine how travel and dietary behaviours are patterned together across the UK population. More specifically my research questions are:

- How many combinations of travel and dietary behaviour exist, and what is the prevalence of each behaviour pattern (type of lifestyle)?
- Do travel and dietary behaviours cluster together into healthy, low-carbon (HLC) and unhealthy, high-carbon (UHC) lifestyles?

[67] Notably, however, this statistical model can also be a drawback of LCA, as it assumes there is a causal relationship between the latent grouping variable and the patterns observed in the data due to the local independence assumption (see sections 5.2.1.2 and 5.2.1.4 for more on this). Traditional cluster models do not make this claim.

[68] Whilst traditional clustering methods exclude missing data, LCA assumes 'missing at random' - see section 5.2.1.1 for more details.

Examining clusters of travel and dietary behaviours in this way will help to better elucidate different health- and climate-relevant lifestyle groups so that it is easier to identify segments of the population that could be targeted to maximise emissions reductions and improve health outcomes.

5.2 Methods

5.2.1 NDNS

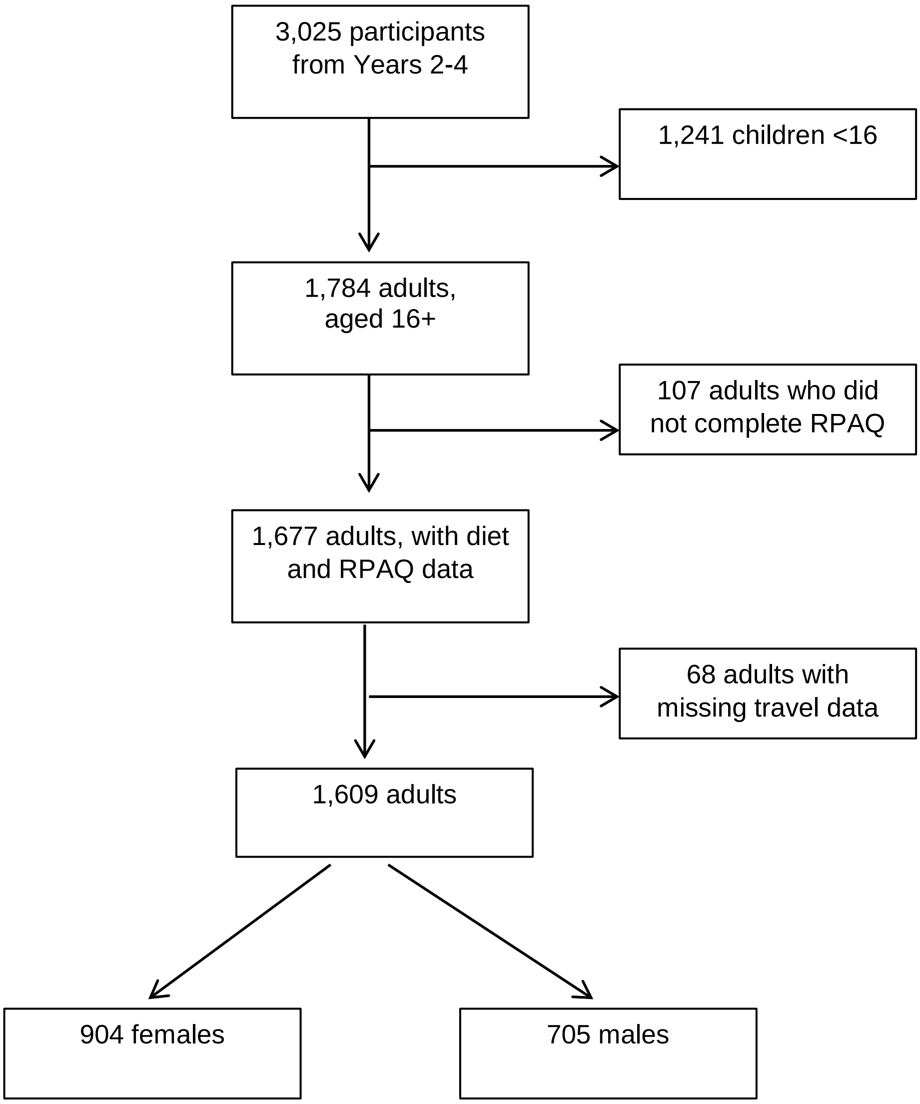
5.2.1.1 Sample

For this chapter, I returned to the sample of individuals in the NDNS that had provided any data on their travel behaviour (n=1,609), which was the maximum available sample before any exclusions. This sample included anyone who had answered at least one of the questions about their travel mode(s) on the RPAQ. Of these, 48 individuals (3%) had missing data on their non-work travel mode and 677 individuals (42%) did not commute, making the question on commuting travel mode not applicable. Fortunately, one of the advantages of LCA is that it does not require complete data for all variables under consideration, so it was not necessary to exclude those individuals with missing travel data or to impute the values. In practice, the LCA model utilises whatever data are available to assign observations to the appropriate classes and so case classification with missing values is simply based on the information that is observed for the case concerned[69] (Vermunt and Magidson, 2005). This feature was especially useful in the NDNS sample since the number of cyclists was very small and I wanted to make use of all of the available data (e.g. commuters and non-commuters) for classification purposes.

Based on the gender variations I observed for the associations between travel and diet in Chapter 4, in addition to the fact that dietary analyses are typically stratified by gender (Fahey et al., 2007, Fahey et al., 2012, Aston et al., 2013, Bates et al., 2014, Bates et al., 2016), I split the data into two samples of males (n=705) and females (n=904) (Figure 5.1).

[69] Nevertheless, it should be noted that LCA models with large amounts of missing values will typically have higher amounts of classification error, as more missing data means there is less information available with which to classify the observations. In the case of the large amount of non-commuters in this sample, I describe how this was handled in the next section on measures.

Figure 5.1 – Flowchart of participants in the NDNS LCA sample



5.2.1.2 Measures

Since LCA is designed to measure individual differences on a latent (*unobserved*) variable based on *observed* variables, the selection of these variables is of critical importance. In LCA, these observed variables are commonly referred to as *indicator*s since they help to define and describe the nature of the hidden homogenous groups in the population of interest. Broadly speaking, the goal of LCA is to estimate a model that explains all of the relationships between the indicators (this is known as the assumption of local independence) and that also explains as much variation as possible in the indicator variables themselves (Vermunt and Magidson, 2005). The selected indicators should also help distinguish between the latent classes in the model, otherwise their inclusion is superfluous.

Since the objective of my analysis was to estimate a model that described the prevalence and patterning of health- and climate-relevant lifestyles, I began by considering all of the travel and dietary behaviours that were applicable and available in the NDNS dataset, and then used an iterative process to decide which indicators to include and which form they should ultimately take. This process involved hypothesizing a set of indicators, estimating a model, and then examining model fit and selection criteria to decide whether further adjustments were needed. Travel and dietary indicators were introduced into the models at the same time but are described separately here for simplicity.

Indicators of travel behaviour

For travel behaviour, I began by including indicators for non-work travel mode and commuting travel mode, as well as for commuting distance and commuting frequency. Non-work travel mode was the same mutually exclusive variable used throughout Chapter 4, however for commuting travel mode I used all four variables on the RPAQ to allow for more descriptive detail in terms of modal frequency and multiple mode use (for more details on these variables see Chapter 3 section 3.2.5.2).

Of the 929 participants that provided data on their commute mode, only 284 (30.6%) gave a frequency response for all four modes; most participants (56.6%, n=526) just selected 'Always' for *one* of the modes (mainly car, n=375) and then left the other three modes blank[70]. In these cases, I assumed that the participant did not use any of the other modes and re-coded these values as 'Rarely/Never' to reduce the amount of classification error in the model. Similarly, for those who did not commute at all, I added another category to each commuting variable called 'No commute' to better capture the behaviour of non-commuters. This also greatly reduced the classification error in the models. Commuting distance and commuting frequency did not add any differentiation to the models beyond the other four commuting variables so these indicators were not included.

[70] The systematic nature of this pattern suggests that it may be due to a flaw in the layout or the wording of this question on the RPAQ.

Indicators of dietary behaviour

My original intention was to include each type of meat as a separate indicator (e.g. beef, pork, lamb, processed red meat) since each of these has different health and environmental implications (Green et al., 2015, Hoolohan et al., 2013, Milner et al., 2015, Aston et al., 2012). However, this approach had several problems. In particular, some of these food groups were rarely consumed and had very high proportions of non-consumers (e.g. >75% never ate pork or lamb). In such cases, a common solution is to dichotomize the variables into consumers and non-consumers (Fahey et al., 2007) but this would have resulted in loss of information on exact quantities of meat consumed (a major strength of the NDNS data), making it impossible to interpret whether someone was a high- or low-meat consumer in relation to national guidelines. In addition, there were also issues with model fit, as it was difficult to find a model that explained all of the relationships between the individual meat variables and the travel indicators previously described.

Ultimately, I decided the best approach was to use the same combined RPM variable used in Chapter 4, as this included all types of RPM and was easily interpretable in relation to recommended guidelines (None, >0-70 g, >70 g). To this, I also included two dichotomous indicators of habitual meat consumption based on whether participants reported never consuming RPM or never consuming any RPM, poultry or fish (e.g. following a vegetarian diet) on their CAPI interview (see Chapter 3 section 3.2.5.1 for more details on these questions). Together, these indicators were meant to distinguish between vegetarians, RPM non-consumers, and RPM consumers who ate large and small quantities of meat.

In addition, another variable included in the model to describe dietary behaviour was FV consumption. I included this indicator to help distinguish between diets that may be low-carbon (on the basis of meat consumption) from those that are *both* healthy and low-carbon (as described in Chapter 2 section 2.1.2). The importance of this distinction has been previously noted in a systematic review which found that diets that are strictly low-carbon may result in micronutrient deficiencies if high-carbon foods are not replaced with healthy, nutrient-rich alternatives (Payne et al., 2016). For example, someone could theoretically eat very little meat but consume plenty of crisps, chips, and cakes for a dietary pattern that would be low-carbon and energy-dense but with few nutrients.

An overview of the final selected indicators in the NDNS models is detailed in Table 5.1.

Table 5.1 – Indicator variables in the NDNS

Indicator	Categories	Source
Non-work travel mode (main mode only)	Car/motor vehicle Public transport Walking Cycling	RPAQ
Commuting travel mode (frequency of different modes used in combination)	Car – Always, Usually, Occasionally, Rarely/Never, No commute Public transport – Always, Usually, Occasionally, Rarely/Never, No commute Walking – Always, Usually, Occasionally, Rarely/Never, No commute Cycling – Always, Usually, Occasionally, Rarely/Never, No commute	RPAQ
Quantity of RPM consumption (average grams per day)	None >0-70 g >70 g (exceeds guideline)	4-day food diary
Quantity of FV consumption (average portions per day)	<3 3-<5 5+ (meets guideline)	4-day food diary
Habitual RPM consumption [a] (Ever eats meat)	No, Yes	CAPI questionnaire
Vegetarian diet [a] (Ever eats meat, poultry or fish)	No, Yes	CAPI questionnaire

RPAQ: Recent Physical Activity Questionnaire, RPM: red and processed meat, FV: fruit and vegetables, CAPI: Computer-Assisted Personal Interview

a) Measures of habitual consumption reflect people's meat consumption more generally beyond the food diary recording period, as it is possible that their consumption during this time may have been different from what they consume on a normal basis (see Chapter 3 section 3.2.5.1 for more details on these questions).

5.2.1.3 Decision not to adjust for covariates

Another advantage of LCA over other types of cluster analysis is that the models can be adjusted for other variables, however this involves conditioning class membership on these covariates (Magidson and Vermunt, 2002, Fahey et al., 2007). In this case, I experimented with conditioning my models on both energy intake and physical activity level, however I ultimately decided that the unadjusted models were preferable for my purposes. My reasons for this were twofold. Firstly, because including these factors as covariates seemed to have little effect on the typologies resulting from the models, and secondly, because adjusting for these factors obscured my interpretation of the health and carbon implications associated with each class, which was one of my main objectives. Comparing the adjusted and unadjusted models, the best example of this misrepresentation was for RPM consumption, where conditioning the models on energy intake made it appear as though the classes with the highest meat consumption were not exceeding the RPM guideline. This was especially problematic since it was my objective to detect those who were the highest RPM consumers and because the health and environmental impacts of RPM are based on absolute consumption.

5.2.1.4 Model estimation and selection

LCA models were estimated in the dedicated software package Latent Gold 5.1 (Statistical Innovations, 2016b). For each gender-specific sample I fitted a series of models from one through to 10 classes, as this was considered to be the maximum number of classes that would be interpretable based on the number of included indicators. Since Latent Gold allows for incorporation of survey weights into the model, these were included for the NDNS samples to represent their complex sampling structure.

Model selection criteria were compared to identify the best-fitting models. Typically this is done using the chi-squared goodness-of-fit test (based on the likelihood ratio chi-squared statistic, L^2), however this approach is not valid in the case of sparse data as it does not follow a chi-squared distribution (Vermunt and Magidson, 2005). For sparse data (as was the case in my samples[71]), the established approach is to use an information criterion, which weighs both model fit and parsimony (i.e. the number of estimated parameters). In LCA, the Bayesian information criterion (BIC) has been

[71] In the NDNS samples there were 90,000 possible response patterns (4 * 5 * 5 * 5 * 5 * 3 * 3 * 2 * 2)

shown to perform particularly well (Lanza and Collins, 2010), so this was used as my primary measure to compare between the different models, along with the Akaike information criterion (AIC), CAIC (a consistent version of AIC) and SABIC (sample size adjusted BIC) (Vermunt and Magidson, 2016). When using these criteria, the guideline is to select the one with the lowest value[72], so I used this as my starting point for model selection.

Once I had identified the model with the lowest BIC value, I examined its bivariate residuals (BVR). These values give a measure of local model fit in terms of how well the model is able to explain all of the relationships between the indicator variables (Vermunt and Magidson, 2005). High BVR values (>3.84)[73] are an indication that there are unexplained relationships between particular indicators, which is a violation of the fundamental LCA assumption of local independence – that all of the relationships between the indicators are explained by the latent variable – and suggest poor model fit (Vermunt and Magidson, 2005). As a result, if it was necessary additional latent classes were added until a model with sufficiently low BVR values was achieved, minimizing any local dependence.

Once I had selected a model based on these criteria, the final step was to examine the latent classes themselves to make sure they were interpretable – this meant that each group had to have a distinct pattern of behaviour that could be used to name and distinguish the classes, and that none of the classes were smaller than 1% of the sample (after rounding). At this stage I also checked whether each indicator was well represented by the model (based on R^2 values) and whether it helped to distinguish between the latent classes in a statistically significant way (based on Wald tests, $p<0.05$) (Vermunt and Magidson, 2005).

[72] Each information criterion is based on different assumptions, but generally speaking the model with the lowest value indicates the most optimal balance between sensitivity (having enough parameters to adequately model the relationships among the variables) and specificity (not over-fitting a model or suggesting nonexistent relationships). For the BIC, the model with the lowest value has the highest posterior probability of being the true model (Dziak et al., 2012).

[73] For categorical indicators, BVRs follow a chi square distribution; 3.84 is the critical value for a chi square test with 1 degree of freedom at alpha = 0.05.

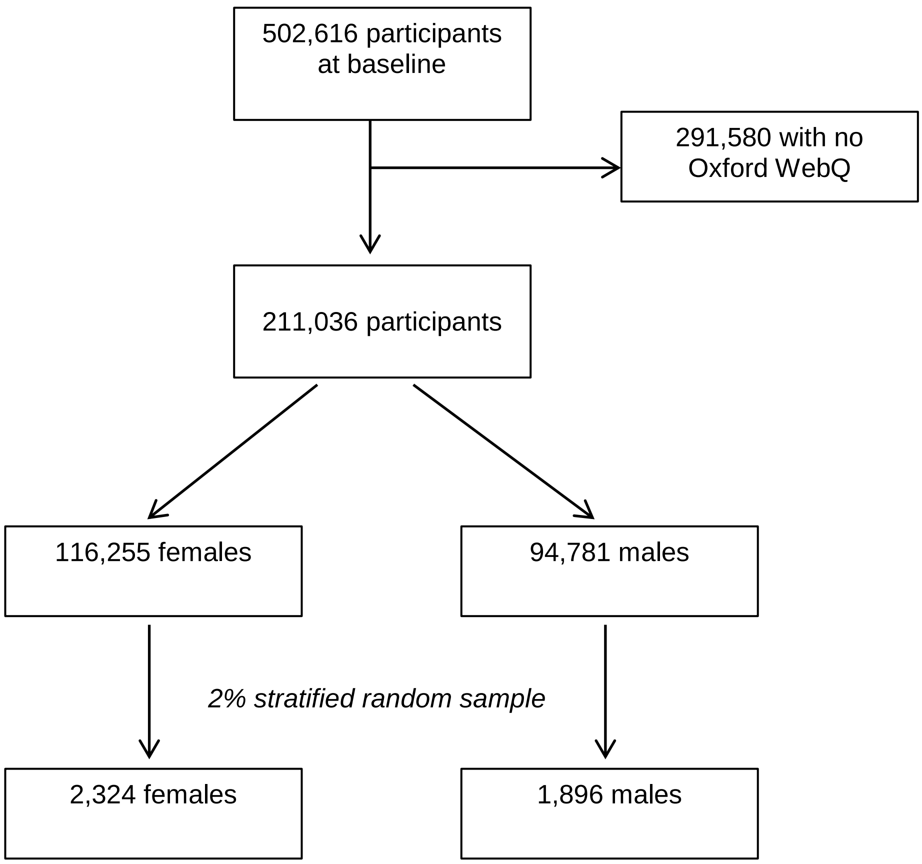
5.2.2 UKB

5.2.2.1 Sample

To create the analytical sample in UKB, I first restricted the sample to participants who had completed the Oxford WebQ (n=211,036; 116,255 females, 94,781 males), as this was the only source of data on *quantity* of RPM consumption. Including this information was important to make the UKB analysis as similar as possible to the NDNS to facilitate comparisons between the two datasets. For more details on the Oxford WebQ, please see Chapter 3 section 3.3.3.2.

Importantly, and in contrast to most statistical techniques, LCA does not work well in extremely large samples with tens or hundreds of thousands of individuals as it can be difficult to derive meaningful and interpretable models with such large numbers (Fahey et al., 2007). An approach to overcome this challenge that has been used in other large cohorts (e.g. the EPIC study) is to draw a random sample from the larger dataset and estimate the LCA model in this smaller sample (Fahey et al., 2012). In the study by Fahey et al. (2012), a 2% gender-specific random sample was used (n=6,009 of ~368 000 women), and though I experimented with taking random samples of larger sizes (10%, 5%), I also found that a 2% sample was the largest size that would consistently deliver a valid and interpretable model based on selection criteria and fit statistics (for more details see Appendix C, p. 285). As a result, to estimate my LCA models I used two gender-specific 2% random samples (1,896 males, 2,324 females), stratified by assessment centre (Figure 5.2). Each of these was approximately 2.5 times the size of the gender-specific NDNS samples.

Figure 5.2 – Flowchart of participants in the UKB LCA sample



5.2.2.2 Measures

In UKB, indicators of travel and dietary behaviour were selected to be similar and comparable to those in the NDNS as far as possible, while also being more informative where additional data were available. Full details of the final indicators in the UKB models are presented in Table 5.2.

Indicators of travel behaviour

For non-work travel mode, I used a slightly simplified version of the full range of travel mode categories used in Chapter 4 (e.g. I reduced the categories ‘car + public transport’, ‘car + public transport, walking and/or cycling’, and ‘car + walking and/or cycling’ into one mixed car category: car + public transport, walking or cycling). This resulted in a five-category indicator that was similar to the four-category NDNS indicator, but which also captured multiple mode use for non-work travel.

Table 5.2 – Indicator variables in UKB

Indicator	Categories	Source
Non-work travel mode (5 mutually exclusive combinations)	Car only Car + PT, walking or cycling PT only, PT + walking or cycling Walking only Cycling only, cycling + walking	Touchscreen questionnaire
Commuting travel mode (multiple modes in combination)	Car - No, Yes, No commute PT - No, Yes, No commute Walking - No, Yes, No commute Cycling - No, Yes, No commute	Touchscreen questionnaire
Time spent driving per day	None / do not drive <1 hour 1 hour 2-3 hours 4+ hours	Touchscreen questionnaire
Quantity of RPM consumption (average servings per day)	None >0-1 serving >1 servings (~exceeds guideline)	Oxford WebQ
Quantity of FV consumption (average portions per day)	<3 3-<5 5+ (meets guideline)	Touchscreen questionnaire
Habitual RPM consumption (Ever eats RPM)	No, Yes	Touchscreen questionnaire
Vegetarian diet (Ever eats RPM, poultry or fish)	No, Yes	Touchscreen questionnaire

PT: Public transport, RPM: red and processed meat, FV: fruit and vegetables

For commuting travel mode, I recoded the data into four dichotomous indicators reflecting use of each mode separately (e.g. car commuting – yes or no) but which allowed for multiple modes to be used in combination. This was similar to the four separate commuting indicators in the NDNS but without the frequency component (e.g. always, usually, occasionally). Similar to the NDNS, around 43% of the participants in the UKB sample did not commute, so I also added an additional category to each commute mode variable to capture these non-commuting participants (‘No commute’).

Since commuting distance and commuting frequency were not retained in the NDNS models I did not include them here, and instead included another measure of travel behaviour: average time spent driving per day. My expectation was that this indicator would be more informative for my LCA models since it is likely a more accurate measure of transport carbon emissions than car use alone, and it also captures the driving time of those who may primarily travel using non-car modes as well as those who drive a lot during their job or in their personal time. For more details on these variables and the survey questions used to create them, see Chapter 3 section 3.3.4.2.

Indicators of dietary behaviour

RPM consumption quantity was a combined variable reflecting average consumption of all types of RPM reported on the Oxford WebQ (previously described in Chapter 3 section 3.3.4.1). Overall, RPM consumption quantity was quite low in the UKB sample, as 31% of females and 26% of males reported not consuming any RPM at all on the previous day. For this reason, I first divided the data into RPM consumers and non-consumers and then created two quantiles of consumers split at the median value (1 serving per day). This resulted in a three-category ordinal variable (no RPM, >0-1 serving, >1 serving) that was approximately analogous to the RPM quantity variable from the NDNS, as people who are consuming >1 servings of RPM per day are very likely to exceed the 70 g daily guideline[74].

To account for habitual meat consumption, I used the meat frequency variables from the touchscreen questionnaire (previously described in Chapter 3 section 3.3.4.1) to create two additional dietary indicators: never consumes RPM (beef, pork, lamb, processed meat), and never consumes RPM, poultry or fish (vegetarian diet). For FV consumption, I included the same three-category ordinal variable that was used previously in Chapter 4. Together, these dietary variables replicated the indicators in the NDNS as closely as possible.

[74] For example, the cooked weight of a quarter pounder beef burger is 78 g, a typical portion of Sunday roast (three thin-cut slices of lamb, beef or pork) is 90 g, and a cooked breakfast of two standard British sausages and two thin-cut rashers of bacon is 130 g (NHS, 2015).

5.2.2.3 Model estimation, selection, and validation

Model estimation and selection followed the same procedure as in the NDNS samples (section 5.2.1.4). However, an additional step, validation of the models, was also necessary in UKB since the LCA models were based on small random samples of the larger dataset. Currently, there is no established methodology to assess whether a model validates adequately[75], and so I based my validation procedure on an approach used in a similar study of dietary patterns in the EPIC cohort (Fahey et al., 2012). This study used two random samples: one sample to estimate the model and a second sample to validate the model classifications (patterns in the data). To attempt to expand on this approach, in my study I used 10 additional 2% stratified random samples among both males and females. Random samples were drawn using Stata/SE 14.0 (StataCorp, 2015). Including my original estimation sample, this meant that I used nearly one quarter (22%) of the total Oxford WebQ sub-cohort to derive and validate my LCA models.

To complete the validation, each of the 10 validation samples was appended to the original estimation sample so that the estimation model could be re-run in the validation sample for comparison purposes. This step was done in Latent Gold using the 'holdout option' (Vermunt and Magidson, 2013) and then repeated separately for each of the 10 samples in males and in females (20 samples total). Once I had obtained each cross-classification in Latent Gold, I exported the case classifications into SPSS v24 (IBM Corp, 2015)[76] and then measured the strength of the relationship between each set of classifications using Cramer's V statistics (obtained through the *Crosstabs* procedure). In addition, I also visually inspected the cross-classifications to assess whether individuals with a particular pattern of behaviour were assigned to the same class or to an adjacent class, or if they were split up across several classes in each validation sample.

[75] Personal communication (Email), Statistical Innovations Support Team, 13 Sept 2016.

[76] This step had to be done in SPSS because Latent Gold is not compatible with other statistical programs.

5.2.3 Healthy, low-carbon classification (both datasets)

After model selection was complete, I developed a classification system to characterise each latent class as 'higher-carbon', 'lower-carbon' or 'mixed' based on the distribution of responses on the travel and dietary indicators in each class compared to the gender-specific sample average (Figure 5.3). As is standard practice when presenting LCA results, these differences were assessed descriptively and not using statistical tests.

Classes that had predominant car use received a high-carbon classification (red shading), classes that had some car use mixed with other modes received a mixed classification (blue shading), and classes that had predominant non-car use received a healthy, low-carbon classification (green shading). Similarly, dietary behaviour was classified as follows: classes with above average RPM consumption (e.g. more likely to exceed the recommended guideline) were given a high-carbon classification (red shading), classes with average RPM consumption or with below average RPM consumption and below average FV consumption were given a mixed classification (blue shading), and classes with below average RPM consumption and above average FV consumption were given a healthy, low-carbon classification (green shading).

Figure 5.3 – Healthy, low-carbon (HLC) classification system

Travel behaviour	Dietary behaviour	Rating	Colour
Predominant car use (> 50% or > average)	RPM > average	Unhealthy + high-carbon	
Some car use (< 50% + < average), mixed with non-car modes	RPM < average + FV < average or RPM = average	Mixed	
Predominant non-car use (> 50% or > average)	RPM < average + FV > average	Healthy + low-carbon	

Note: Whether dietary consumption was above or below average was interpreted in relation to the recommended national guidelines, that is, a class with above average RPM and above average FV consumption was considered more likely to *exceed* the RPM guideline but also more likely to *meet* the FV guideline, compared to the sample average.

5.3 Results

This section describes the best-fitting model in each of the four samples (NDNS females and males, UKB females and males) and summarises the latent classes resulting from each model. Detailed class descriptions are presented here for NDNS females only; the rest are presented in Appendix C, sections C.3 (p. 291), C.4 (p. 296) and C.5 (p. 302).

5.3.1 NDNS females

5.3.1.1 Model selection and description

Based on model fit statistics (Appendix Table C.0.5), a 5-class model had the lowest BIC value and a 4-class model had the lowest CAIC value in this sample. Using these models as a starting point, I inspected the BVR values and concluded that there were still numerous unexplained relationships between several of the indicators; in particular between RPM quantity and habitual RPM consumption and between commuter cycling and non-work travel (BVR values >10). This meant that more rare behaviours such as cycling and consuming no meat were not being adequately represented in a 5-class model. To resolve these issues, I progressively increased the number of latent classes until all of the BVRs were <3.84; the last large value to remain was between FV consumption and non-work travel in an 8-class model (4.85). Adding one more latent class thus resulted in a 9-class model as being best able to explain all of the relationships between the travel and dietary indicators (Appendix Table C.0.6).

Based on the Wald tests for each indicator, all of the included travel and dietary variables helped to discriminate between the classes in a statistically significant way ($p<0.05$) in this 9-class model. Based on the R^2 values for each indicator (Table 5.3), the selected model best explains the variation in cycle commuting (96%) and explains the least amount of variation in non-work travel mode (24%).

5.3.1.2 Class descriptions – 9 class model

The full results for this model, including all classes and indicators, can be seen in Table 5.3. The numbers for class size indicate the prevalence of each class in the sample population, ordered from largest (Class 1) to smallest (Class 9). The rest of the table presents the conditional probabilities of particular responses on each indicator variable given membership in each class. These values can be interpreted as frequency distributions for each travel and dietary variable within each class and are used to define and describe each lifestyle group. These groups are as follows:

Class 1 (26%) – Always car commuters with high RPM and low FV consumption

The largest class (26% of the sample) was defined by its high, virtually exclusive car use. Everyone in this class (100%) *always* commuted by car and 90% also travelled by car for non-work journeys, which was well above the sample average of 61%. Thirty-one per cent of this group exceeded the RPM guideline, which was slighter higher than the sample average of 29%. Similarly, only 27% of this group met the 5-a-day FV guideline, which was slightly below the overall sample average of 30%. HLC classification: red-red (see Figure 5.3).

Class 2 (25%) – Very low FV non-commuters with high RPM consumption

The second largest class was made up of non-commuters (100%) with below average car use (43%) and above average walking (38%) and PT use (19%) for non-work travel. Their RPM consumption was slightly higher than Class 1 (33% exceeded the guideline), and this group was much less likely to meet the FV guideline with 70% consuming <3 portions per day on average, the lowest of all classes. HLC classification: green-red.

Table 5.3 – 9-class LCA model for NDNS females (n=904)

Class number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Full sample**	**R^2**
Class size	**0.26**	**0.25**	**0.21**	**0.07**	**0.07**	**0.07**	**0.04**	**0.02**	**0.01**		
Non-work travel											
Car	0.90	0.43	0.75	0.72	0.18	0.15	0.66	0.64	0.01	0.61	
PT	0.01	0.19	0.08	0.10	0.03	0.60	0.17	0.12	0.00	0.13	0.24
Walk	0.08	0.38	0.17	0.18	0.78	0.25	0.17	0.13	0.00	0.25	
Cycle	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.11	0.99	0.01	
Commute by car											
Always	1.00	0.00	0.00	0.04	0.00	0.03	0.65	0.00	0.00	0.29	
Usually	0.00	0.00	0.00	0.66	0.00	0.00	0.00	0.00	0.22	0.05	
Occasionally	0.00	0.00	0.00	0.27	0.18	0.07	0.00	0.00	0.03	0.04	0.87
Rarely/Never	0.00	0.00	0.00	0.03	0.82	0.90	0.34	0.00	0.75	0.14	
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.01	0.48	
Commute by PT											
Always	0.00	0.00	0.00	0.00	0.02	0.83	0.23	0.00	0.00	0.07	
Usually	0.00	0.00	0.00	0.16	0.01	0.17	0.01	0.00	0.00	0.02	
Occasionally	0.01	0.00	0.00	0.30	0.08	0.00	0.00	0.00	0.00	0.03	0.84
Rarely/Never	0.99	0.00	0.00	0.54	0.89	0.00	0.76	0.00	0.99	0.40	
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.01	0.48	
Commute by bike											
Always	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	0.01	
Usually	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00	
Occasionally	0.00	0.00	0.00	0.05	0.02	0.00	0.00	0.00	0.22	0.01	0.96
Rarely/Never	1.00	0.00	0.00	0.92	0.98	1.00	1.00	0.00	0.01	0.50	
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.01	0.48	
Commute by foot											
Always	0.00	0.00	0.00	0.01	0.74	0.14	0.19	0.00	0.00	0.07	
Usually	0.00	0.00	0.00	0.11	0.26	0.00	0.01	0.00	0.00	0.03	
Occasionally	0.01	0.00	0.00	0.34	0.00	0.03	0.00	0.00	0.00	0.03	0.82
Rarely/Never	0.99	0.00	0.00	0.53	0.00	0.82	0.80	0.00	0.99	0.39	
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.01	0.48	
RPM consumption											
None	0.06	0.05	0.05	0.08	0.04	0.10	0.92	0.80	0.32	0.11	
>0-70 g / day	0.64	0.63	0.63	0.66	0.61	0.66	0.07	0.18	0.57	0.60	0.30
>70 g / day	0.31	0.33	0.31	0.26	0.36	0.24	0.00	0.01	0.11	0.29	
FV consumption											
<3 portions / day	0.32	0.70	0.09	0.26	0.35	0.31	0.16	0.23	0.10	0.35	
3-<5 portions / day	0.41	0.25	0.32	0.41	0.41	0.41	0.38	0.41	0.33	0.35	0.26
5+ portions / day	0.27	0.05	0.59	0.33	0.24	0.27	0.46	0.36	0.57	0.30	
Never eat RPM (Yes)	0.02	0.05	0.00	0.10	0.05	0.02	1.00	0.99	0.23	0.09	0.62
Vegetarian diet (Yes)	0.00	0.00	0.00	0.00	0.00	0.00	0.54	0.33	0.00	0.03	0.47

	1	2	3	4	5	6	7	8	9
Travel behaviour									
Diet behaviour									

PT: Public transport; RPM: red and processed meat; FV: fruit and vegetables; vegetarian: never eats any meat or fish

Yellow shading = higher than sample average (grey column); red = high-carbon, blue = mixed, green = low-carbon

R^2 = amount of variation explained by the LC model

Class 3 (21%) – Mostly car non-commuters with high RPM and high FV consumption

The third largest class was also made up of non-commuters (100%), but their non-work travel was primarily dominated by car use (75%). Their RPM consumption was identical to Class 1 (31% above guideline), however this group had much higher consumption of FV and the majority met the 5-a-day guideline (59%) – this was the highest FV consumption of all classes in the sample. HLC classification: red-red[77].

Class 4 (7%) – Usual car commuters with low RPM and high FV consumption

The next largest class was composed of people who *usually* commuted by car (66%) and had above average car use for non-work travel (72%). Some members of this group also commuted by PT and/or by walking on a usual or occasional basis. In contrast to the three previous groups, this class had RPM consumption that was *below* the sample average (26% above guideline) and FV consumption that was higher (33% meeting 5-a-day). 10% of this group reported never consuming any RPM. HLC classification: red-green.

Class 5 (7%) – Walking commuters with high RPM and low FV consumption

The fifth largest class was defined primarily by its predominant walking: 78% walked for non-work travel and 74% always commuted on foot. This group had the highest RPM consumption of all classes in this sample (36% above guideline), combined with below average FV consumption (24% meeting guideline). HLC classification: green-red.

Class 6 (7%) – PT commuters with low RPM and low FV consumption

The sixth class were predominant PT users: 60% used PT for their non-work travel, and 83% always commuted by public transport. Overall, this class consumed slightly less RPM than the previous five groups as 10% consumed no RPM over the food diary period and only 24% exceeded the RPM guideline. Nevertheless, only 27% of this group met the FV guideline, which was the below the sample average of 30%. HLC classification: green-blue.

[77] Note: As described in section 5.2.3, FV consumption is irrelevant if RPM is above average.

Class 7 (4%) – Low meat mostly car commuters with high FV consumption

This group was primarily defined by the fact that 100% of its members reported never consuming RPM on a habitual basis (as measured by the CAPI). As expected, their RPM consumption over the food diary recording period was also very low, although 7% reported consuming at least some RPM on their food diary[78]. Despite their low RPM consumption, only 54% of this class reported that they followed a strictly vegetarian diet (i.e. never consumed any meat, poultry, or fish). This group also had higher than average FV consumption with nearly half (46%) meeting the 5-a-day guideline. This group was made up of mostly car commuters (65% always) with slightly above average car use (66%) and PT use (17%) for non-work travel. Walking and PT use were also above the sample average for commuting travel. HLC classification: red-green.

Class 8 (2%) – Low meat non-commuters with high FV consumption

This non-commuting group had a mixed non-work travel pattern. Most travelled by car (64%), with the rest split across the other three modes including cycling (11%), which was above the sample average. This group also had very low RPM consumption with 80% consuming no RPM over the food diary period and nearly all (99%) reporting that they never consumed RPM on a habitual basis[79]. Compared to Class 7 however, fewer people reported being vegetarian (only 33%) and fewer met the 5-a-day guideline (36%) though their FV consumption was still higher than the sample average. HLC classification: red-green.

Class 9 (1%) – Cyclists with low RPM and high FV consumption

The smallest class was defined primarily by their cycling travel: 99% of this group cycled for non-work travel and 75% always cycled for their commute. This group had low RPM consumption, however not as low as the two previous groups: 32% reported consuming no RPM over the food diary period, and 23% reported never consuming RPM on a habitual basis, though none of this group reported being vegetarian. Notably, this group had the second highest FV consumption of all the classes with 57% meeting the 5-a-day guideline. HLC classification: green-green.

[78] As can be seen here, people’s reported consumption on the food diary does not always match up with their consumption the rest of the time: though 100% of this group reported never consuming RPM, 7% did consume some RPM over the diary recording period.

[79] Similar to Class 7, this means that 20% of Class 8 reported consuming RPM on the food diary, though virtually all (99%) reported that they never consumed RPM on their CAPI questionnaire.

5.3.2 NDNS males

5.3.2.1 Model selection and description

Based on model fit statistics (Appendix Table C.0.7), a 4-class model had the lowest BIC value and a 3-class model had the lowest CAIC value among NDNS males, however these models also had many unexplained relationships, particularly among the meat consumption indicators (e.g. BVRs >100). As a result, I progressively increased the number of latent classes until I reached an 8-class model, which resulted in all of the relationships being explained (Appendix Table C.0.8).

In this 8-class model, all of the indicators helped to discriminate between the classes in a statistically significant way ($p<0.05$). Based on the R^2 values for each indicator (Table 5.4), this model best explains the variation in car commuting (92%) and explains the least amount of variation in FV consumption (5%).

5.3.2.2 Class descriptions – 8 class model

The full results for this model, including all classes and indicators can be seen in Table 5.4. To avoid unnecessary duplication and improve readability, the full written descriptions of each class in this model are presented in Appendix C section C.3 (p. 291). Class names, sizes and HLC classifications are listed below:

Class 1 (38%) – Always car commuters with high RPM and high FV (red-red)

Class 2 (36%) – Mixed car non-commuters with low RPM and low FV (red-blue)

Class 3 (9%) – PT commuters with low RPM and low FV (green-blue)

Class 4 (6%) – Walking commuters with high RPM and high FV (green-red)

Class 5 (5%) – Usual car commuters with high RPM and low FV (red-red)

Class 6 (3%) – Cyclists with high RPM and high FV (green-red)

Class 7 (1%) – Low meat mixed car commuters with high FV (blue-green)

Class 8 (1%) – Low meat non-commuters with high FV (green-green)

Table 5.4 – 8-class LCA model for NDNS males (n=705)

Class number	1	2	3	4	5	6	7	8	Full sample	R^2
Class size	0.38	0.36	0.09	0.06	0.05	0.03	0.01	0.01		
Car	0.86	0.60	0.11	0.23	0.90	0.00	0.49	0.38	0.63	
PT	0.01	0.12	0.58	0.07	0.01	0.00	0.06	0.25	0.10	0.25
Walk	0.11	0.26	0.27	0.70	0.06	0.06	0.13	0.37	0.22	
Cycle	0.02	0.02	0.04	0.00	0.03	0.93	0.32	0.00	0.05	
Commute by car										
Always	1.00	0.00	0.00	0.04	0.00	0.00	0.52	0.01	0.39	
Usually	0.00	0.00	0.00	0.00	0.84	0.02	0.00	0.00	0.05	
Occasionally	0.00	0.00	0.08	0.11	0.15	0.00	0.12	0.00	0.02	0.92
Rarely/Never	0.00	0.00	0.92	0.84	0.00	0.97	0.35	0.00	0.17	
No commute	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.99	0.37	
Commute by PT										
Always	0.00	0.00	0.83	0.08	0.00	0.00	0.06	0.00	0.08	
Usually	0.00	0.00	0.17	0.00	0.11	0.00	0.10	0.00	0.02	
Occasionally	0.01	0.00	0.00	0.07	0.19	0.00	0.00	0.00	0.02	0.86
Rarely/Never	0.98	0.00	0.00	0.85	0.70	1.00	0.84	0.01	0.51	
No commute	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.99	0.37	
Commute by bike										
Always	0.00	0.00	0.00	0.00	0.00	0.82	0.00	0.00	0.02	
Usually	0.00	0.00	0.00	0.00	0.05	0.18	0.28	0.00	0.01	
Occasionally	0.02	0.00	0.06	0.00	0.24	0.00	0.15	0.00	0.03	0.88
Rarely/Never	0.98	0.00	0.94	1.00	0.72	0.00	0.57	0.01	0.57	
No commute	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.99	0.37	
Commute by foot										
Always	0.00	0.00	0.16	0.90	0.00	0.00	0.16	0.00	0.07	
Usually	0.00	0.00	0.00	0.10	0.02	0.00	0.06	0.00	0.01	
Occasionally	0.00	0.00	0.04	0.00	0.41	0.15	0.22	0.00	0.03	0.85
Rarely/Never	1.00	0.00	0.80	0.00	0.56	0.84	0.56	0.01	0.51	
No commute	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.99	0.37	
RPM consumption										
None	0.03	0.08	0.12	0.04	0.02	0.00	0.95	0.97	0.08	
>0-70 g / day	0.37	0.44	0.45	0.39	0.34	0.21	0.05	0.03	0.39	0.21
>70 g / day	0.60	0.48	0.43	0.57	0.64	0.79	0.01	0.00	0.53	
FV consumption										
<3 portions / day	0.34	0.40	0.51	0.28	0.46	0.07	0.12	0.12	0.37	
3-<5 portions / day	0.36	0.35	0.32	0.35	0.34	0.24	0.29	0.29	0.34	0.05
5+ portions / day	0.31	0.25	0.17	0.37	0.20	0.70	0.59	0.59	0.29	
Never eat RPM (Yes)	0.02	0.02	0.08	0.00	0.13	0.00	0.99	0.97	0.05	0.47
Vegetarian diet (Yes)	0.00	0.00	0.00	0.00	0.01	0.00	0.54	0.51	0.01	0.51
Travel behaviour										
Diet behaviour										

PT: Public transport; RPM: red and processed meat; FV: fruit and vegetables; vegetarian: never eats any meat or fish

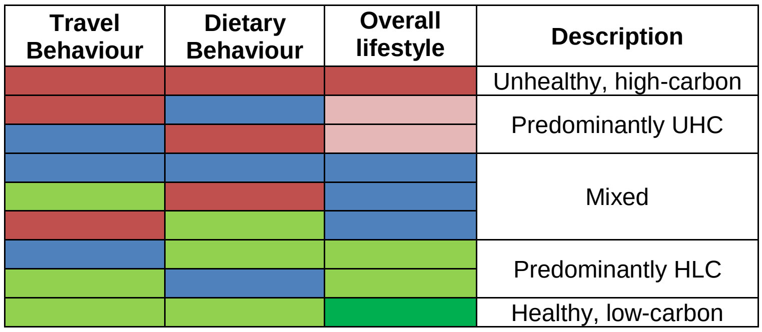
Yellow shading = higher than sample average (grey column); red = high-carbon, blue = mixed, green = low-carbon

R^2 = amount of variation explained by the LC model

5.3.3 Summary and comparison of NDNS classes

Based on the combined shading of the travel and dietary behaviours in each class, each group can also be given an overall lifestyle classification (Figure 5.4)

Figure 5.4 – Shading of overall lifestyle based on combinations of travel and dietary behaviour

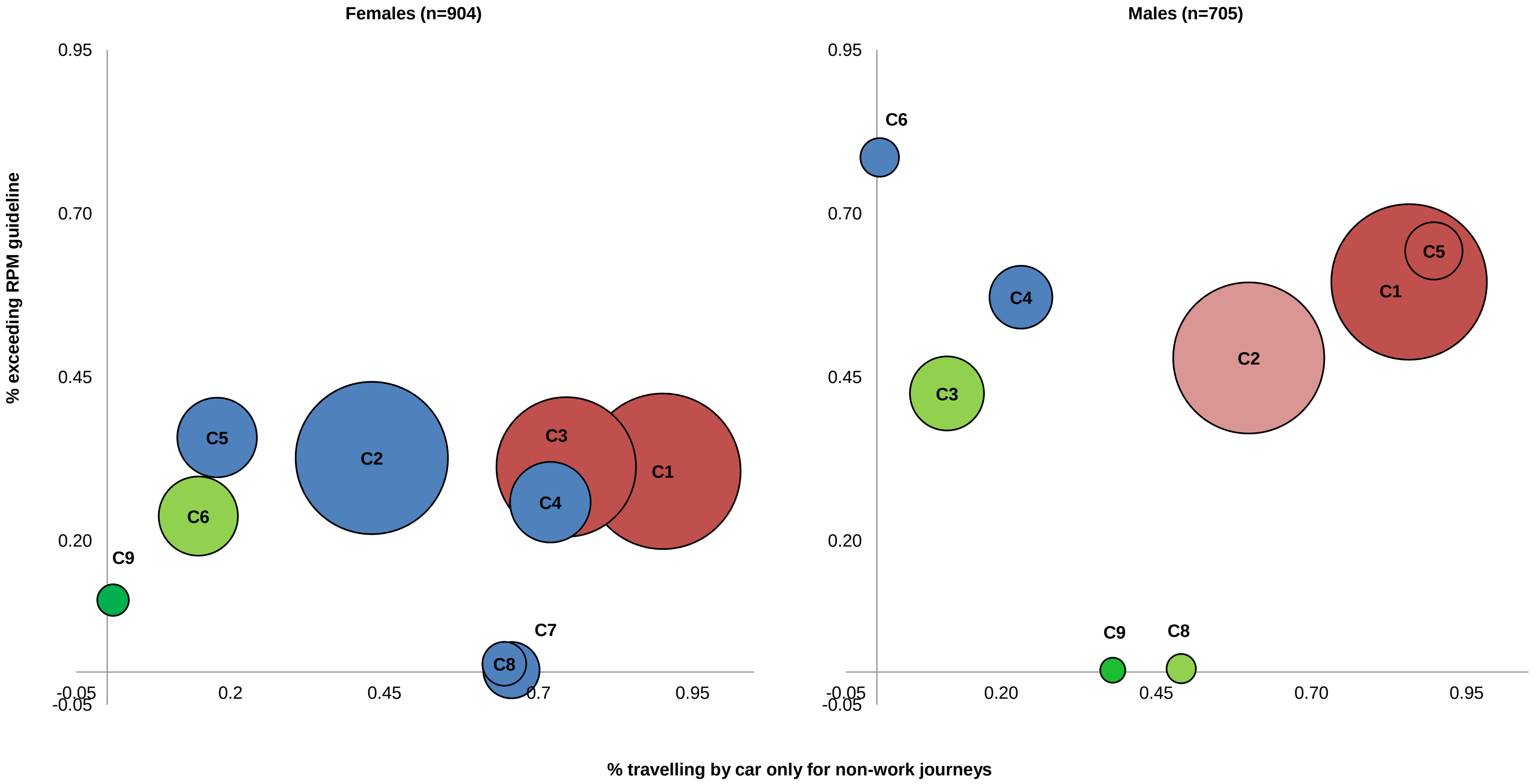


UHC: unhealthy, high-carbon, HLC: healthy, low-carbon

Together, the prevalence of each class in the NDNS samples and the typology of their lifestyles can be visualised in Figure 5.5, where I have plotted both male and female classes. On the x-axis is the percentage of each class traveling by car for non-work journeys and on the y-axis is the percentage of each class exceeding the RPM guideline of 70 g per day. The size of each circle corresponds to its prevalence in each sample.

Two main differences between the male and female classes in the NDNS can be seen in Figure 5.5. Firstly, there was much greater variation in RPM consumption among males than among females, as several of the male classes had large proportions (>50%) exceeding the RPM guideline. Secondly, there were two other large classes present among females (in addition to Class 1) and only one other large class among males. This was because there were two distinct groups of non-commuters among females, the Low FV non-commuters (Class 2, blue) and the Mostly car non-commuters (Class 3, red), whereas among males the non-commuters had a more mixed behaviour pattern (Class 2, pink).

Figure 5.5 – Comparison of NDNS classes by gender, RPM consumption (y-axis) by car travel (x-axis)



Notes: The size of each circle corresponds to its prevalence in each sample. C[x] is the class number. The colour corresponds to each group's combined classification for travel and diet behaviour: red = more high-carbon, green = more low-carbon, blue = mixed

There were also some more subtle variations, such as among the low meat classes that had *similar diets* among males and females but *different travel* behaviour. Among females for example, these groups were slightly larger (6% versus 2% among males) and used cars to a greater extent, which resulted in their blue (mixed) rather than green (healthy, low-carbon) shading. Similar to this were the patterns among Cyclists and Usual car commuters, which had *similar travel* behaviour but *opposite diets* among males and females. Female cyclists, for example, had the lowest RPM consumption (among consumers) whereas males had the highest overall, with 79% exceeding the RPM guideline. Among Usual car commuters, females had high FV and low RPM consumption, whereas males had high RPM and low FV consumption.

Overall, there were only three classes that had the same travel *and* dietary patterning across genders: the Always car commuters (red overall; Class 1 both), the Walking commuters (blue overall; Class 4 males, Class 5 females), and the PT commuters (light green overall; Class 5 males, Class 6 females). These three classes were also generally similar in size across the two samples, though the Always car commuters were a much larger group among males (38% versus 26%, respectively).

5.3.4 UKB females

5.3.4.1 Model selection and description

Based on model fit statistics (Appendix C Table C.0.9), a 8-class model had the lowest BIC value and a 7-class model had the lowest CAIC value among UKB females, however these models still had several unexplained relationships based on the BVRs. Increasing the number of latent classes up to 10 explained all of these relationships, except between FV consumption and non-work travel (BVR=4.77), however this value was quite close to the 3.84 cut-off value and so was considered adequate.

In this 10-class model, all of the indicators helped to discriminate between the classes except for vegetarian status (p=0.6). This meant that including vegetarian status in the model did not provide any additional distinctions beyond what was already represented by habitual RPM consumption; however I kept it in the model for descriptive purposes and to be consistent with the NDNS models. Based on the R^2 values for each indicator (Table 5.5), this 10-class model explained 92% of the variation in car commuting, 91% of the variation in cycle commuting, 91% of the variation in habitual RPM consumption (never versus ever), but only 2% of the variation in FV consumption. Despite this low R^2 value for FV, I kept this variable in the model to be consistent with the NDNS females model and because it was a statistically significant discriminator.

5.3.4.2 Class descriptions – 10 class model

The full results for this model, including all classes and indicators can be seen in Table 5.5. As with NDNS males, the full written descriptions of each class are presented in Appendix C section C.4 (p. 296). Class names, sizes and HLC classifications are listed below:

Class 1 (33%) – Exclusive car commuters with high RPM and low FV (red-red)

Class 2 (32%) – Mixed car non-commuters with high RPM and high FV (red-red)

Class 3 (9%) – PT non-commuters with high RPM and high FV (green-red)

Class 4 (8%) – Mixed car commuters with high RPM and high FV (blue-red)

Class 5 (7%) – PT commuters with low RPM and low FV (green-blue)

Class 6 (3%) – Low meat car commuters with high FV (red-green)

Class 7 (3%) – Walking commuters with low RPM and low FV (green-blue)

Class 8 (2%) – Low meat mixed non-commuters with high FV (blue-green)

Class 9 (2%) – Low meat mixed commuters with high FV (green-green)

Class 10 (1%) – Cyclists with low RPM and very high FV (green-green)

Table 5.5 – 10-class LCA model for UKB females (n=2,324)

Class number	1	2	3	4	5	6	7	8	9	10	Full sample	R^2
Class size	**0.33**	**0.32**	**0.09**	**0.08**	**0.07**	**0.03**	**0.03**	**0.02**	**0.02**	**0.01**		
Non-work travel												
Car only	0.54	0.40	0.06	0.17	0.14	0.39	0.17	0.11	0.10	0.07	0.36	
Car + mixed	0.39	0.56	0.29	0.74	0.26	0.59	0.40	0.55	0.26	0.01	0.46	
PT only (+ walk)	0.03	0.01	0.47	0.01	0.51	0.00	0.14	0.20	0.40	0.00	0.11	0.14
Walk only	0.03	0.03	0.13	0.07	0.09	0.02	0.26	0.07	0.24	0.00	0.06	
Cycle only (+ walk)	0.00	0.00	0.05	0.01	0.00	0.00	0.03	0.05	0.00	0.92	0.02	
Commute by car												
No	0.00	0.00	0.00	0.22	0.91	0.00	0.89	0.00	0.85	0.94	0.13	
Yes	1.00	0.00	0.00	0.78	0.09	1.00	0.11	0.00	0.15	0.06	0.44	0.92
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.43	
Commute by bike												
No	0.99	0.00	0.00	0.80	0.97	0.91	1.00	0.00	0.85	0.00	0.54	
Yes	0.01	0.00	0.00	0.20	0.03	0.09	0.00	0.00	0.15	0.99	0.03	0.91
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.43	
Commute by foot												
No	0.97	0.00	0.00	0.46	0.74	0.81	0.00	0.00	0.44	1.00	0.45	
Yes	0.03	0.00	0.00	0.54	0.26	0.19	1.00	0.00	0.56	0.00	0.12	0.83
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.43	
Commute by PT												
No	0.94	0.00	0.00	0.51	0.00	0.86	0.99	0.00	0.39	0.94	0.43	
Yes	0.06	0.00	0.00	0.49	1.00	0.14	0.00	0.00	0.61	0.06	0.14	0.84
No commute	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.43	
Daily driving time												
None	0.02	0.09	0.78	0.15	0.79	0.02	0.57	0.21	0.50	0.72	0.21	
<1 hour	0.28	0.55	0.21	0.60	0.20	0.34	0.41	0.61	0.46	0.27	0.40	
1 hour	0.42	0.30	0.01	0.22	0.00	0.41	0.03	0.16	0.04	0.01	0.27	0.43
2-3 hours	0.26	0.07	0.00	0.03	0.00	0.21	0.00	0.02	0.00	0.00	0.12	
4+ hours	0.03	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.01	
RPM consumption												
None	0.26	0.25	0.26	0.21	0.28	1.00	0.37	1.00	1.00	0.57	0.31	
>0-1 servings	0.49	0.49	0.49	0.49	0.49	0.00	0.47	0.00	0.00	0.37	0.45	0.13
>1 servings	0.25	0.26	0.25	0.31	0.23	0.00	0.16	0.00	0.00	0.06	0.23	
FV consumption												
<3 portions /day	0.24	0.18	0.15	0.18	0.22	0.10	0.20	0.07	0.11	0.04	0.19	
3-<5 portions /day	0.38	0.36	0.35	0.36	0.38	0.31	0.37	0.28	0.32	0.22	0.36	0.02
5+ portions /day	0.38	0.45	0.51	0.45	0.40	0.59	0.43	0.65	0.57	0.75	0.44	
Never eat RPM (Yes)	0.00	0.01	0.01	0.00	0.01	1.00	0.00	1.00	0.99	0.17	0.08	0.91
Vegetarian diet (Yes)	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.32	0.39	0.05	0.03	0.34
Travel behaviour												
Diet behaviour												

PT: Public transport; RPM: red and processed meat; FV: fruit and vegetables; vegetarian: never eats any meat or fish; Mixed = PT and/or walking and/or cycling

Yellow shading = higher than sample average (grey column); red = high-carbon, blue = mixed, green = low-carbon

R^2 = amount of variation explained by the LC model

5.3.5 UKB males

5.3.5.1 Model selection and description

Based on the model fit statistics (Appendix C Table C.0.11), a 6-class model had the lowest BIC value and a 5-class model had the lowest CAIC value among UKB males, however these models still had some unexplained variation in the meat consumption and travel variables. Increasing the number of latent classes up to 9 explained all of these relationships, except between FV consumption and non-work travel (BVR=6.25) and increasing up to 10 classes explained all relationships except between RPM servings and habitual RPM consumption (BVR=9.87). Of these two, the 9-class model was considered preferable, as it was more parsimonious.

In this 9-class model, all of the indicators helped to discriminate between the classes in a statistically significant way except for vegetarian status (p=0.88) and RPM servings (p=0.06). This meant that including these indicators in the model did not provide any additional distinctions beyond what was already represented by habitual RPM consumption; however as with UKB females I kept both variables in the model for descriptive purposes and to be consistent with other samples. Based on the R^2 values for each indicator (Table 5.6), this 9-class model explained 90% of the variation in car commuting and 90% of the variation in habitual RPM consumption (never versus ever) but only 2% of the variation in FV consumption (same as UKB females).

5.3.5.2 Class descriptions – 9 class model

The full results for this model can be seen in Table 5.6. Detailed descriptions of each class are presented in Appendix C section C.5 (p. 302). Class names, sizes and HLC classifications are below:

Class 1 (37%) – Exclusive car commuters with high RPM and low FV (red-red)

Class 2 (35%) – Mixed car non-commuters with high RPM and high FV (blue-red)

Class 3 (8%) – Mixed car commuters with high RPM and low FV (blue-red)

Class 4 (8%) – PT non-commuters with average RPM and high FV (green-blue)

Class 5 (5%) – PT commuters with low RPM and low FV (green-blue)

Class 6 (4%) – Commuter cyclists with average RPM and high FV (green-blue)

Class 7 (1%) – Low meat mixed commuters with high FV (green-green)

Class 8 (1%) – Low meat car commuters with high FV (red-green)

Class 9 (1%) – Low meat non-commuters with high FV (green-green)

Table 5.6 – 9-class LCA model for UKB males (n=1,896)

Class number	1	2	3	4	5	6	7	8	9	Full sample	R^2
Class size	**0.37**	**0.35**	**0.08**	**0.08**	**0.05**	**0.04**	**0.01**	**0.01**	**0.01**		
Non-work travel											
Car only	0.58	0.36	0.28	0.00	0.14	0.10	0.16	0.43	0.09	0.38	
Car + mixed	0.35	0.57	0.57	0.12	0.21	0.52	0.36	0.48	0.29	0.43	
PT only (+ walk)	0.02	0.02	0.10	0.65	0.50	0.06	0.19	0.00	0.38	0.11	0.15
Walk only	0.04	0.03	0.05	0.18	0.14	0.00	0.12	0.04	0.14	0.05	
Cycle only (+ walk)	0.01	0.01	0.00	0.05	0.01	0.33	0.17	0.04	0.10	0.03	
Commute by car											
No	0.00	0.00	0.40	0.00	1.00	0.70	0.77	0.00	0.00	0.12	
Yes	1.00	0.00	0.60	0.00	0.00	0.30	0.23	1.00	0.00	0.45	0.90
No commute	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.43	
Commute by bike											
No	0.95	0.00	0.87	0.00	0.92	0.00	0.53	1.00	0.00	0.49	0.88
Yes	0.05	0.00	0.13	0.00	0.08	1.00	0.46	0.00	0.00	0.08	
No commute	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.43	
Commute by foot											
No	0.99	0.00	0.54	0.00	0.47	0.92	0.66	1.00	0.00	0.49	
Yes	0.01	0.00	0.46	0.00	0.53	0.08	0.34	0.00	0.00	0.08	0.85
No commute	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.43	
Commute by PT											
No	0.95	0.00	0.33	0.00	0.24	0.76	0.32	0.96	0.00	0.43	
Yes	0.05	0.00	0.67	0.00	0.76	0.24	0.67	0.04	0.00	0.14	0.81
No commute	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.43	
Time driving (per day)											
None	0.00	0.03	0.03	0.76	0.78	0.39	0.45	0.01	0.44	0.14	
<1 hour	0.15	0.48	0.47	0.24	0.22	0.57	0.52	0.20	0.53	0.33	
1 hour	0.38	0.38	0.38	0.00	0.00	0.05	0.03	0.41	0.04	0.31	0.47
2-3 hours	0.32	0.10	0.10	0.00	0.00	0.00	0.00	0.28	0.00	0.16	
4+ hours	0.14	0.01	0.01	0.00	0.00	0.00	0.00	0.10	0.00	0.06	
RPM quantity (daily)											
None	0.23	0.23	0.23	0.24	0.30	0.25	1.00	0.99	0.99	0.26	
>0-1 servings	0.41	0.41	0.41	0.41	0.42	0.42	0.00	0.01	0.01	0.40	0.08
>1 servings	0.36	0.36	0.36	0.34	0.28	0.33	0.00	0.00	0.00	0.34	
FV consumption											
<3 portions /day	0.38	0.30	0.34	0.27	0.35	0.27	0.20	0.19	0.11	0.33	
3-<5 portions /day	0.35	0.35	0.35	0.35	0.35	0.35	0.33	0.33	0.28	0.35	0.02
5+ portions /day	0.27	0.35	0.31	0.38	0.30	0.38	0.47	0.49	0.61	0.32	
Never eat RPM (Yes)	0.00	0.00	0.00	0.01	0.00	0.02	0.99	0.98	0.99	0.04	0.90
Vegetarian diet (Yes)	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.26	0.39	0.01	0.40
Travel behaviour											
Diet behaviour											

PT: Public transport; RPM: red and processed meat; FV: fruit and vegetables; vegetarian: never eats any meat or fish;
Mixed = PT and/or walking and/or cycling
Yellow shading = higher than sample average (grey column); red = high-carbon, blue = mixed, green = low-carbon
R^2 = amount of variation explained by the LC model

5.3.6 Summary and comparison of UKB classes

Figure 5.6 plots the male and female classes with car only non-work travel on the x-axis and quantity of RPM consumption on the y-axis. As seen with the NDNS, the male classes in UKB also tended to have higher RPM consumption on average and more variation in the distribution of RPM consumption overall. Unlike the NDNS, however, there were the same number of non-commuting classes among both males and females, though there was an additional class of Walking commuters (Class 7, 3%) present among females but not among males.

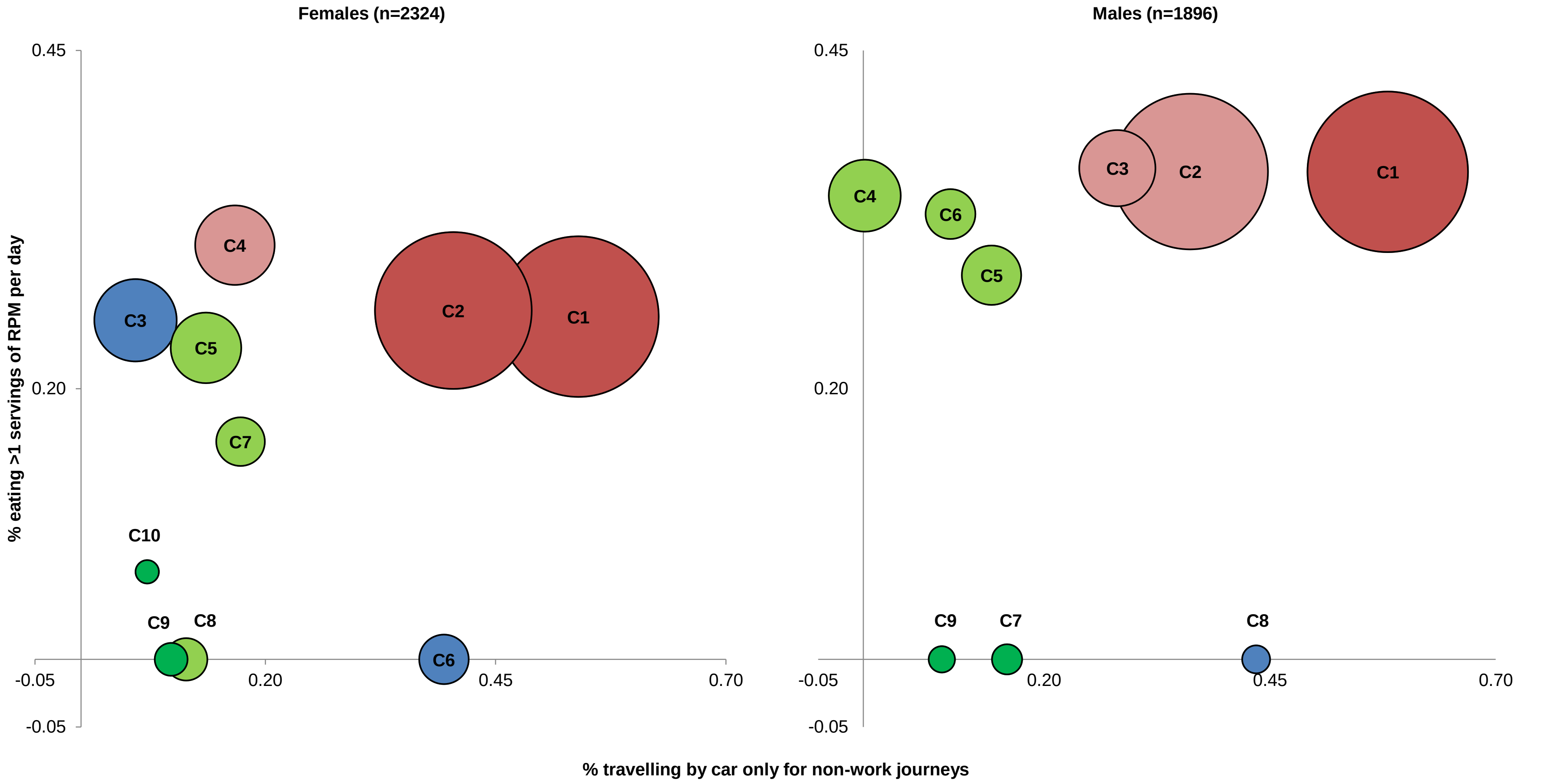
More subtle differences in the patterning were also detected. For example, among the Cyclist classes, the male group (Class 6, 4%) was more likely to use car travel in addition to cycling which resulted in a more mixed travel pattern overall. This group also consumed considerably more meat than females cyclists (Class 10, 1%), similar to the pattern found in the NDNS. In addition, another notable difference was that among the non-commuting groups, all three male classes (Mixed car non-commuters, PT non-commuters, Low meat non-commuters) used car travel less than the female classes (Mostly car non-commuters, PT non-commuters, Low meat non-commuters) and thus tended to have more low-carbon travel.

Overall, however, there were five groups common (same shading) across males and females: Exclusive car commuters (Class 1, both), Mixed car commuters (Class 3 males, Class 4 females), PT commuters (Class 5 both), Low meat car commuters (Class 8 males, Class 6 females), and Low meat mixed commuters (Class 7 males, Class 9 females). All of these groups were also generally similar in prevalence.

5.3.6.1 Validation of the UKB models

Since many of the classes were very similar in size (e.g. within 1% of each other in prevalence), the focus of the validation was more on confirming the accuracy of the behaviour patterns themselves, rather than the specific order of the classes. In other words, I was more concerned with validating whether the Exclusive car commuters were detected as a distinct class in the other random samples than whether they were Class 1 or Class 2 in the order of prevalence (e.g. in the estimation sample Class 1 was 33% and Class 2 was 32% among UKB females).

Figure 5.6 – Comparison of UKB classes by gender, RPM consumption (y-axis) by car travel (x-axis)



Notes: The size of each circle corresponds to its prevalence in each sample. C[x] is the class number. The colour corresponds to each group's combined classification for travel and diet behaviour: red = more high-carbon, green = more low-carbon, blue = mixed

Using this approach, both of the models validated well in the other random samples. Among females for example, 94% of the time the same behaviour pattern was detected as a distinct group (e.g. not split up into other classes) and 84% of the time the classes occurred in the same order or were switched with an adjacent class of similar size (e.g. Class 1 switched with Class 2, Class 3 switched with Class 4). Similarly, among males, 74% of the time the same behaviour pattern was detected as a distinct group and 76% of the time the classes occurred in the same order or were switched with an adjacent class. Across the 10 samples, the average Cramer's V was 0.83 among females and 0.81 among males indicating that the classifications from the estimation and validation samples were very strongly associated overall. Full details of the validation results are shown in Appendix C section C.6, Table C.0.13 and Table C.0.14.

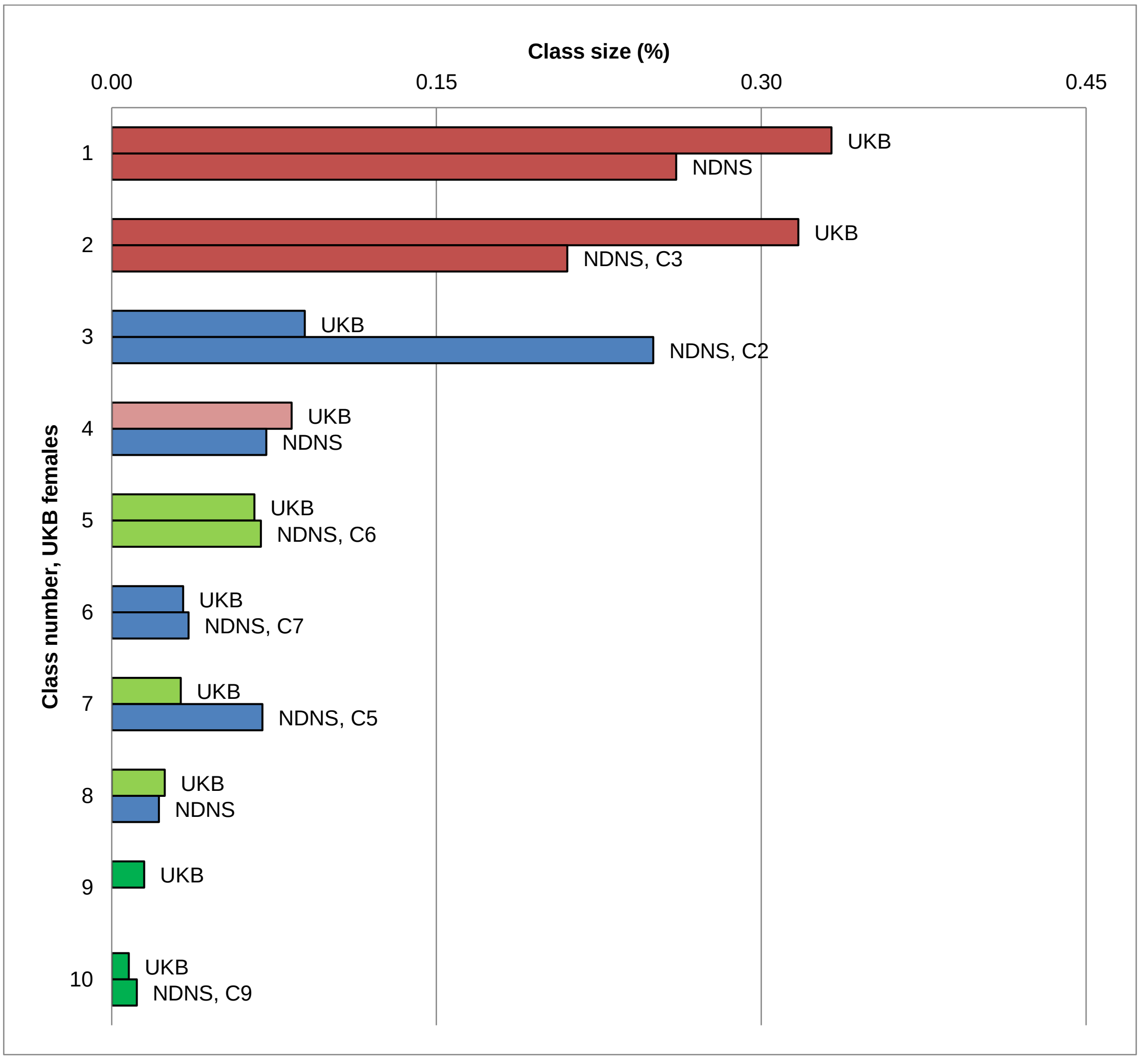
5.3.7 Comparing across the samples, by gender and overall

5.3.7.1 Females

Figure 5.7 compares the prevalence and patterning of the classes in the two female samples. Here, the figure is organised so that class numbers for UKB are on the y-axis and the NDNS classes have been re-ordered to match up with the class to which they are most similar (and are labelled where the class number is different). For example, Class 5 (PT commuters) in UKB females was the same as Class 6 in NDNS females.

As can be seen in Figure 5.7, there was generally very good agreement in the behaviour *patterns* detected in each of the female models, though there were some notable differences in the *prevalence* of the classes between the samples. For example, it can be seen that the prevalence of the groups with more car travel (e.g. Class 1 and Class 2 on y-axis) were larger in the UKB sample, whereas the prevalence of the groups with more walking, PT, and higher RPM consumption (Class 3 and Class 7 on y-axis) were much larger in the NDNS sample. These patterns are consistent with the fact that the UKB sample contained a smaller proportion of disadvantaged individuals. Overall, 60% of the female UKB classes (six out of 10) were similarly patterned to the NDNS in terms of their combined travel and dietary behaviour, these were: Class 1 (Exclusive car commuters), Class 2 (Mostly car non-commuters), Class 3 (PT non-commuters), Class 5 (PT commuters), Class 6 (Low meat car commuters), and Class 10 (Cyclists).

Figure 5.7 – Comparison of female classes (size and patterning)



Bar colour corresponds to each group's classification: red = unhealthy, high-carbon (UHC); pink = predominantly UHC blue = mixed, light green = predominantly healthy, low-carbon (HLC), dark-green = completely HLC

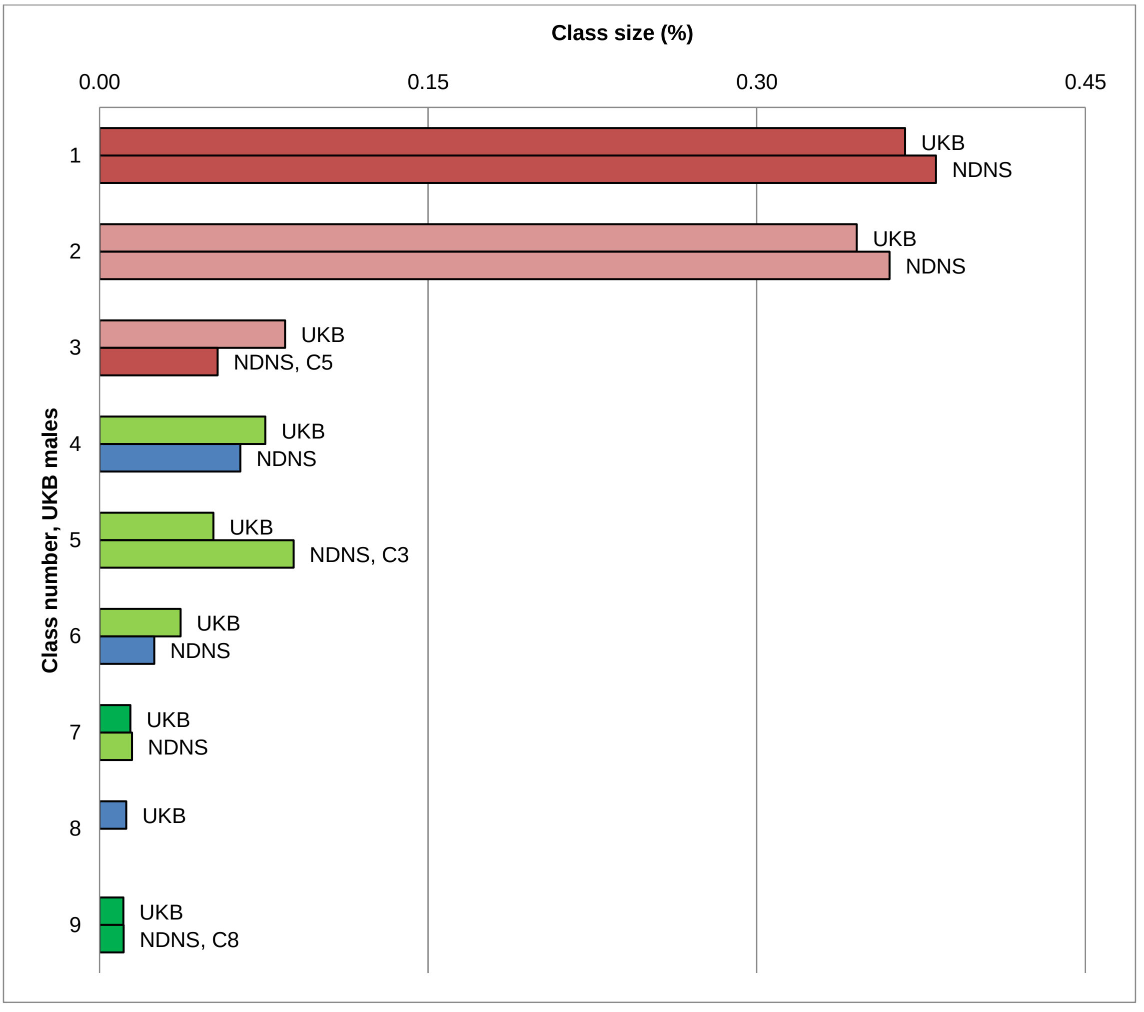
Numbering on y-axis corresponds to class numbers in UKB female sample; NDNS classes are labelled if different

Regarding differences, there were four classes in UKB females in which the patterns were not the same in the NDNS (Figure 5.7). Firstly, there was no equivalent group to the Low meat mixed commuters (Class 9 in UKB) detected in the NDNS, though this group may have been represented in the Low meat mostly car commuters (Class 7 in NDNS) as this class also had above average PT and walking. Other differences in the overall patterning were between Class 4, the Usual/Mixed car commuters and Class 7, the Walking commuters (Class 5 in NDNS), which both had opposite patterns of RPM consumption in each of the samples. Similarly, in Class 8 (Low meat non-commuters), the NDNS sample had a higher amount of non-work car travel, and thus a more mixed behaviour pattern overall.

5.3.7.2 Males

Figure 5.8 compares the prevalence and patterning of the classes in both of the male samples. Here there appears to be better agreement in the *prevalence* of the classes between the two male samples, but slightly less agreement in the *patterning*, when compared with the female models. For example, only 44% of the UKB classes (four out of nine) were similarly patterned in NDNS males. These were: Class 1 (Exclusive car commuters), Class 2 (Mixed car non-commuters)[80], Class 5 (PT commuters), and Class 9 (Low meat non-commuters).

Figure 5.8 – Comparison of male classes (size and patterning)



Bar colour corresponds to each group's classification: red = unhealthy, high-carbon (UHC); pink = predominantly UHC blue = mixed, light green = predominantly healthy, low-carbon (HLC), dark-green = completely HLC

Numbering on y-axis corresponds to class numbers in UKB male sample; NDNS classes are labelled if different

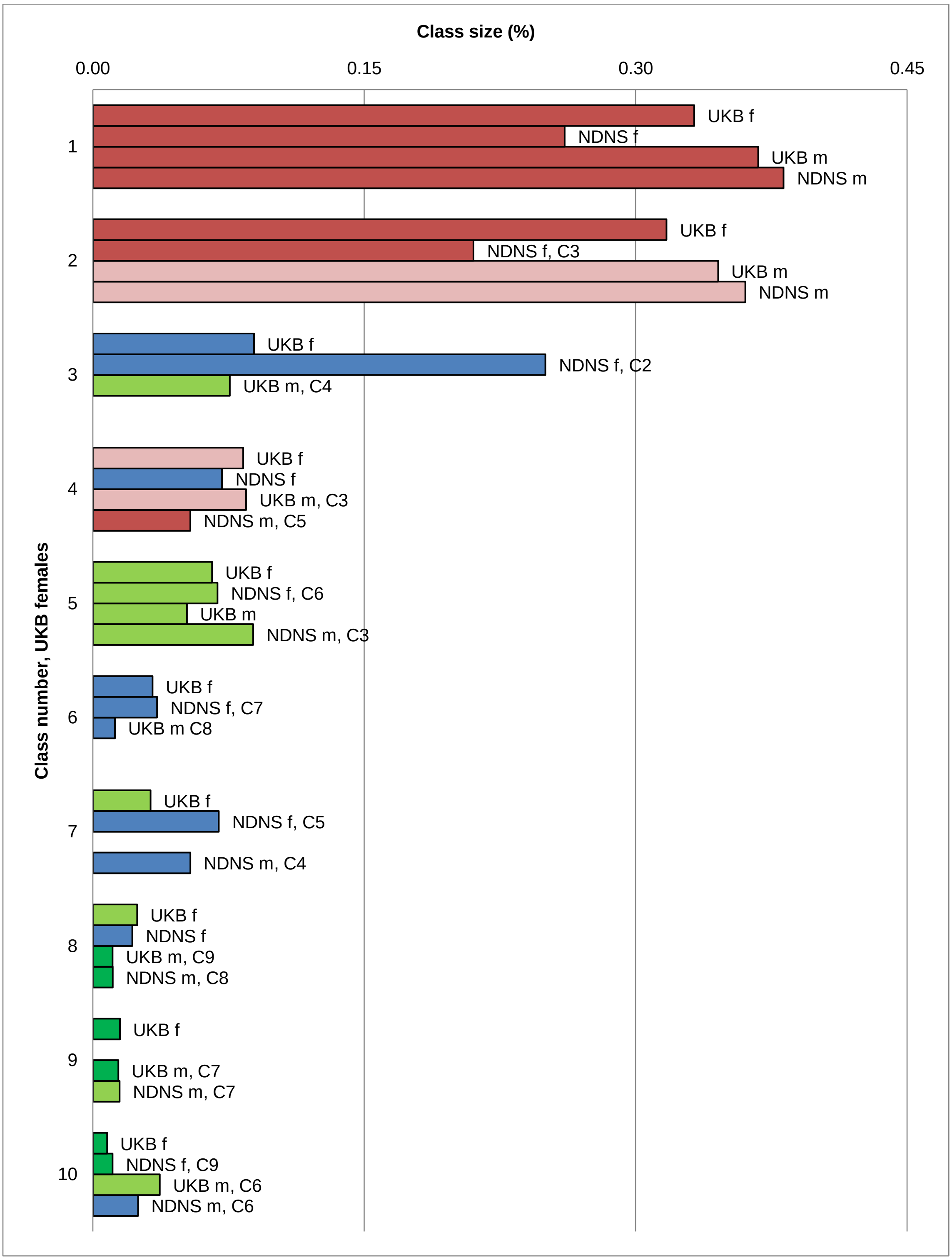
[80] Note that Class 2 is patterned the same overall but the individual patterns between travel and diet are actually opposite, e.g. UKB = blue-red, NDNS = red-blue. Both classes have slightly below average car use for non-work travel, but in the NDNS >50% of the class travels by car. Their dietary patterns are also different: UKB = high RPM, high FV and NDNS is low RPM, low FV.

Among males, the most notable differences were that Class 8 in UKB (Low meat car commuters) did not exist as a distinctive class in NDNS males and Class 4 was a different class in each of the samples: PT non-commuters in UKB and Walking commuters in the NDNS. More subtle variations included the fact that the Usual/Mixed car commuters (Class 3 UKB, Class 5 NDNS) and the Low meat mixed commuters (Class 7) both had similar diets but slightly different travel behaviour, and the Cyclist group (Class 6) had lower RPM consumption but more car driving in UKB. The prevalence of the PT commuters (Class 5 UKB) was also slightly larger in the NDNS, possibly because the latter sample was younger overall and had more people in working age.

5.3.7.3 Overall

A single figure summarising the prevalence and patterning results across all four samples (in the same format as Figure 5.7 and Figure 5.8) can be seen in Figure 5.9. This figure highlights two important patterns in the overall results. Firstly, that across all four samples, only two classes were consistently shaded: the Always/Exclusive car commuters (Class 1, red) and the PT commuters (Class 5, light green); and secondly, that there was greater consistency in the shading of the classes *within* genders (7/10) than *within* datasets (6/10). This suggests that despite the significant differences between the two data sources, there are broad similarities in the relationships between travel and dietary behaviours among males and females in the UK. Overall, the Usual/Mixed car commuters (Class 4), Low meat non-commuters (Class 8) and Cyclists (Class 10) were the most inconsistently patterned across the four samples.

Figure 5.9 – Comparison of all classes (size and patterning)



Bar colour corresponds to each group's classification: red = unhealthy, high-carbon (UHC); pink = predominantly UHC blue = mixed, light green = predominantly healthy, low-carbon (HLC), dark-green = completely HLC

Numbering on y-axis corresponds to class numbers in UKB female sample; other class numbers are labelled if different

Class 1: Always/Exclusive car commuters; Class 2: Mixed/Mostly car non-commuters; Class 3: Low FV/PT non-commuters; Class 4: Usual/Mixed non-commuters; Class 5: PT commuters; Class 6: Low meat car commuters; Class 7: Walking commuters; Class 8: Low meat non-commuters; Class 9: Low meat mixed commuters; Class 10: Cyclists

5.4 Discussion

5.4.1 Summary of key findings

The central aim of this chapter was to gain a better understanding of how travel and dietary behaviours are patterned together into different types of health- and climate-relevant lifestyles in the UK population. Across these four samples, I have found that there are between eight to 10 different groupings of combined travel and dietary behaviour, ranging from high RPM-eating car commuters to active travellers with low RPM and high FV consumption.

The largest classes in all four samples were characterised by predominant car use and higher than average RPM consumption, indicating that large proportions of the UK population engage in *multiple* high-carbon and health-damaging behaviours. Considering those groups that were classified as either completely or predominantly higher-carbon, these proportions ranged from 47-73% among females and from 79-80% among males across the two datasets. At the other end of the spectrum, this chapter also shows that less than one-fifth of the UK population (8-19%) engages in travel *and* dietary behaviours that can be considered HLC (completely or predominantly), and only 2-5% of the population had travel and dietary behaviour that were *both* classified as HLC.

5.4.2 Results in context

5.4.2.1 Unhealthy, higher-carbon (UHC) lifestyles

Previous evidence has already shown that most people in the UK travel by car (DfT, 2016b, Goodman, 2013, Laverty et al., 2013) and many people consume too much RPM (Bates et al., 2016), so it was not surprising that these behaviours were common in these samples. Nevertheless, it was not clear that these behaviours would overlap in the same groups of people since previous research has also reported that car use and RPM consumption typically follow opposite social gradients in the UK population (DfT, 2016b, Maguire and Monsivais, 2014, Aston et al., 2013). As a result, the findings of this chapter make an important contribution to knowledge by showing that these UHC behaviours do in fact cluster together in large proportions of the population. Comparing across the four samples, there was some evidence that car use and high RPM consumption were most strongly clustered among males in the NDNS, where in both classes of car commuters, around 60% of the group also exceeded the RPM guideline. This finding is consistent with previous evidence showing that men tend to consume higher amounts of RPM (Bates et al., 2016) and make more car trips than women (DfT, 2016b). Indeed, in the other three samples, the clustering between these behaviours did not seem to be as pronounced, as most of the other UHC groups had RPM consumption that was only slightly above the sample averages.

Regarding the distribution of these UHC behaviours, another pattern was that in three of the four samples (all but NDNS females), there was a higher number of classes with above average RPM consumption compared with above average car travel. This same pattern was also observed in relation to the prevalence of each of these behaviours: in three of the four samples (all but NDNS males), the proportion with above average RPM consumption was larger than the proportion with above average car travel. Together, these results suggest that high RPM consumption is a more widespread behaviour than high car travel in the UK population, and this pattern can also be visually observed in the bubble charts presented in Figure 5.5 and Figure 5.6. This finding is in accordance with evidence from the travel literature, which has previously shown that car travel and its associated carbon emissions are highly concentrated into certain subsets of the UK population (Brand and Preston, 2010, Brand et al., 2013, Mattioli and Anable, 2017).

5.4.2.2 Healthy, lower-carbon (HLC) lifestyles

Based on previous evidence on the prevalence of active travel (DfT, 2016b, DfT, 2016a, Goodman, 2013, Laverty et al., 2013) and of vegetarian / low-meat diets (Bates et al., 2016, Aston et al., 2013), it was not unexpected that HLC lifestyles would be rare in the UK population, however, this is the first study to quantify precisely how rare – only a small minority of those with HLC behaviour in one area (travel or diet) also had HLC behaviour in the other area. Across the four samples, these groups were: Cyclists (two samples, females only), Low meat non-commuters (two samples, males only), and Low meat mixed commuters (two samples, UKB only). Notably, these findings show that the patterning of HLC lifestyles is not the same among males and females in the UK, which helps to elucidate the results from Chapter 4 where I observed different associations between active travel and RPM consumption by gender, particularly in the NDNS.

Overall, there was a slightly higher prevalence of HLC lifestyles in UKB (15-19%) than in the NDNS (8-11%), which is also in accordance with the findings of Chapter 4, where I found more consistent associations between HLC travel and markers of a HLC diet among the UKB sample. This greater degree of overlap between HLC behaviours in UKB can be interpreted as evidence that these behaviours are more strongly related and have more common determinants in the UKB sample than in the NDNS (McAloney et al., 2013, Flay and Petraitis, 1994). Based on this interpretation, one possibility for a common underlying factor of HLC lifestyles in UKB could be greater health concern, since UKB participants are known to be more health-conscious than the UK general population (Fry et al., 2017, Hutchings et al., 2014).

5.4.2.3 Mixed lifestyles

That there were fewer HLC lifestyles in the NDNS reflects the fact that there were considerably more mixed lifestyles in these samples, and particularly among NDNS females where there were five classes (45% of the sample) that had travel and dietary behaviours that went in conflicting directions. These mixed classes came in two distinct patterns: those with HLC diets and high-carbon travel (five classes) and those with HLC travel and high-carbon diets (five classes), which suggests that they may be a reflection of the opposite socio-economic gradients in car travel and RPM consumption found in previous studies (DfT, 2016b, Maguire and Monsivais, 2014, Aston et al., 2013). Since both of these mixed lifestyles were more common among females, one possible interpretation of this pattern could be that car use and RPM consumption are more closely linked to socio-economic position among females than among males in the UK, however why this should be the case is unclear. One explanation could be the fact that car travel and high meat consumption are more ubiquitous among males (DfT, 2016b, Bates et al., 2016), which could make it more difficult to detect clear socio-economic gradients in these behaviours. Importantly, these mixed lifestyle patterns make clear that behaviours with similar impacts (e.g. UHC or HLC) are not always driven by the same factors, despite the fact that they may cluster together in some population groups.

5.4.2.4 Other patterns in travel and dietary behaviour

Though there are no similar studies examining combined patterns of travel and dietary behaviour, the results of this chapter also add to existing evidence on these behaviours, studied separately, in the literature.

Mode use across commuting and non-work journeys

As described previously in Chapter 2 section 2.2.1.1, there is relatively little evidence on mode use for other travel purposes besides commuting, especially when comparing across different types of journeys within individuals. Though previous research has shown that multiple mode use is common in the UK and that active travel is more likely to be used for non-work journeys (e.g. shopping) than for commuting journeys, this evidence is largely based on trip-level data (Heinen and Chatterjee, 2015, DfT, 2016b, Olsen et al., 2017) and one small study that may not be representative (Song et al., 2013). As a result, my study adds to this evidence by providing insights on mode use across different types of journeys, in the same individuals, from two national datasets. In line with previous work (Song et al., 2013, DfT, 2016b, Menai et al., 2015), my results confirm that active travel modes were used more frequently for non-work travel among most people (e.g. car and PT commuters), however I also found that the more rare classes who commuted by walking (all three classes) or by cycling (UKB males only) often had non-work travel that included car use. These results confirm the high degree of multimodality that exists in the UK population across different travel purposes, which suggests that characterising travel behaviour based on commuting alone is likely an incomplete assessment of overall mode use. Importantly, these patterns of multimodality support arguments that more research efforts should be directed at individuals who are already using cars in combination with other modes, and at understanding why different modes may be used for certain journeys among this group (Mattioli et al., 2016). For this, more in-depth study of the Usual/Mixed car commuters I have identified here could be particularly fruitful, as this class is already somewhat less car dependent and (potentially) more flexible with their mode use.

Notably, I did not find that average daily driving time added much differentiation to the group classifications once commuting mode was accounted for, which is why inclusion of this indicator in the UKB samples did not result in any major differences between the two datasets. This is likely because daily driving time was highly correlated with being a car commuter, which supports previous evidence that the strongest predictors of transport carbon emissions in the UK are related to car commuting (e.g. owning at least one car, being in full-time employment, and having a home–work travel distance of more than 10 kilometres) (Brand et al., 2013). Nevertheless, I did find daily driving time to be a useful indicator for descriptively distinguishing between the classes and for understanding and interpreting the travel behaviour of those who combined car use with other modes (multimodality).

Mode use among non-commuters

In this study I found that non-commuters made up nearly half of the UK population (43-48% among females, 37-44% among males), which is similar to evidence from the 2011 Census showing that >40% of adults in England and Wales do not commute, either because they are not employed (35.5%) or because they work from home (6.8%) (Goodman, 2013). Importantly, I also found that these non-commuting classes were highly car dependent, with large proportions using cars as their only travel mode (40-75% among female non-commuters, 36-60% among male non-commuters). Since there is currently very little research on mode use among non-commuters in the travel literature, these findings are a notable contribution to knowledge in this area. The existence of these groups is particularly important because transport policy is strongly focused on the journey to work (Mattioli et al., 2016) and much of the impetus around the promotion of HLC lifestyles has been centred on active commuting. As a result, these high-carbon non-commuting classes are a useful reminder that commuting is only one type of travel journey and that up to 75% of car travel and 65% of travel CO_2 emissions involve other destinations and activities (Mattioli et al., 2016, Brand et al., 2013).

Patterns among RPM consumers and non-consumers

Among people who consume meat, previous evidence has shown that there is not much variation in FV consumption across different levels of meat consumption (Aston et al., 2013, Leahy et al., 2010, Scarborough et al., 2014) but some studies have also reported that people who eat more red meat (Fahey et al., 2007) and more processed meat (Rohrmann et al., 2013, Leenders et al., 2013) tend to consume less FV on average, though with some variations by gender (Fahey et al., 2007, Rohrmann et al., 2013). My results add to this evidence by showing that FV consumption was indeed diverse across meat-eating groups in these samples; however, FV and RPM consumption did appear to be somewhat negatively correlated, especially among females. For example, across both samples, 50-66% of the female classes with below average RPM consumption had above average FV consumption, but this pattern was not observed in any of the male meat-eating classes. This finding could suggest that efforts to promote HLC diets may face additional barriers among males since the ‘low RPM, high FV’ dietary pattern was much less common in both of the male samples. This gender variation is different from that reported in a previous UK study (Fahey et al., 2007), possibly because that study adjusted for overall energy intake, or because dietary patterns may have changed overtime (Walthouwer et al., 2014) and the study by Fahey et al. (2007) used data that is now nearly 20 years old.

Among the low meat classes (habitual RPM non-consumers), there was also a larger prevalence in the female samples (6-7% vs. 2-3% among males) and all had above average FV consumption, both of which are consistent with previous evidence (Leahy et al., 2010, Aston et al., 2013). Importantly, however, these low meat classes did not always have the *highest* FV consumption (particularly among NDNS females), and several of these classes only had a minority that met the 5-a-day FV guideline. This result indicates that there was descriptive value in having FV consumption as a distinct dietary indicator from meat consumption, as it shows those who eat little or no meat do not necessarily consume sufficient amounts of FV.

Relatedly, another notable pattern among the low-meat classes was that none of these groups was completely vegetarian: at best the proportion of vegetarianism was around half of those who never consumed RPM (33-54% among females, 26-54% among males). This finding is consistent with previous reports that vegetarians and RPM non-consumers may have different socio-demographic patterning (Maguire and Monsivais, 2014, Leahy et al., 2010) and represent distinct groups of people. Nevertheless, whether the higher prevalence of the ‘no RPM’ pattern is an indication of greater acceptability in the UK population should be subject to further research, as studies have shown that switching to non-ruminant meats can substantially reduce dietary GHG emissions (Aleksandrowicz et al., 2016, Hoolohan et al., 2013) and negative health outcomes (Etemadi et al., 2017). A recent YouGov survey found that 34% of British people are willing to reduce their meat consumption in some way (Eating Better, 2017), but qualitative research from Scotland has also reported that people may be more resistant to cutting down if they are not aware of the links between meat and climate change (Macdiarmid et al., 2016).

5.4.3 Strengths and Limitations

This chapter has several strengths. Most importantly, to my knowledge it is the first study to provide evidence on the prevalence and patterning of health- and climate-relevant lifestyles in the UK or elsewhere. This was achieved by examining several aspects of travel and dietary behaviour in combination, which also highlights one of the major advantages of cluster analysis, and of LCA in particular. Using these combinations, I was able to provide a more comprehensive assessment of the different types of lifestyles existing in the UK population, which allowed me to further elucidate many of the relationships between travel and dietary behaviours previously established in Chapter 4.

5.4.3.1 Datasets

Another strength of this study is that I was able to replicate my findings in two datasets for comparison and verification purposes. This was particularly important due to the original nature of my results and the lack of comparable studies on this research topic. Though there were some variations in the prevalence and patterning of the classes between the NDNS and UKB samples, the overall findings were strikingly similar despite notable differences in both the indicators and underlying samples[81]. Importantly, this consistency suggests that these patterns of travel and dietary behaviour are most likely an accurate representation of health- and climate-relevant lifestyles in the UK. Though UKB is not representative of the UK general population (Fry et al., 2017), using its larger samples allowed me to make additional distinctions in some of the more rare subgroups, such as those with low meat consumption. For example, in both of the UKB samples I was able to detect three ‘Low meat’ classes (compared with only two in the NDNS), which helped to confirm that the patterning of these groups was distinct between males and females. Using UKB was also an advantage because it enabled me to make a methodological contribution regarding the feasibility of using LCA in larger samples. Expanding on the work of a previous study (Fahey et al., 2012), my results have helped to further illustrate that there is great potential for using LCA in large datasets, through the use of repeated random samples and cross-validation techniques.

At the same time, however, using two datasets also presented some challenges since the indicator variables in each sample were not exactly the same, though I tried to keep

[81] As previous described in Chapter 3 section 3.3.3.2, participants who completed the Oxford WebQ were very “highly selected” as they were more likely to be White, female, slightly older, less deprived and more educated than other UKB participants (Galante et al., 2016).

them as similar as possible. For example, the indicator for quantity of RPM consumption in UKB was much less precise than in the NDNS[82] and (perhaps as a result) there was much less variation in the data (e.g. fewer high RPM consumers). This difference may have contributed to the fact that it was more difficult to detect variations in RPM consumption quantity in UKB, particularly in the male sample where the model only explained 8% of the variation in this indicator. This difference may also have explained why there were fewer similarities in the patterning of the classes between NDNS males and UKB males (as shown in Figure 5.8).

5.4.3.2 Analysis

Another limitation was that the fit between the LCA models and the indicators was better for travel behaviour (particularly commuting) than for dietary behaviour (particularly FV consumption). In other words, a model that explains the variation in commuting behaviour and RPM consumption *well* may not necessarily explain variation in FV consumption to the same degree, as this was the case in three of the four samples. Notably, among NDNS females (the one sample in which more variation in FV consumption was explained) FV consumption was actually the main variable differentiating between the two large classes of non-commuters, and was thus strongly related to non-work travel mode (see Table 5.3). Based on the BVR values between FV consumption and non-work travel mode in the UKB models (see Appendix C Table C.0.10 and Table C.0.12), there was also some indication that there may have been similar distinctions among non-commuters in these samples, however I was not able to find a model where the classes split in the same way.

Variations in non-work travel mode were also less well represented compared with commuting travel in both datasets, and this may have been because the non-work travel indicators were an aggregate measure of many diverse travel purposes. For example, people may use a different travel mode depending on the specific characteristics of their journey, and may not use the same mode for a quick trip to the local shops as for a long trip to another part of the country (Mattioli et al., 2016). As there are currently very few studies that have collected this type of detail for non-work journeys in the UK population[83], this is an important area for future data collection in other health and social surveys. Similarly, another limitation of the travel indicators was that the available data only allowed me to observe whether multiple modes were used at all, but not to what extent. This was particularly problematic in UKB, where, for

[82] For example, self-reported servings in UKB versus grams calculated by NDNS survey team

[83] See, for example: the National Travel Survey (NTS), the Scottish Household Survey, the iConnect study (Ogilvie et al., 2012), and the British Time Use Studies.

example, someone could select that they commuted by car and by public transport, but it was not clear whether this was part of the same journey, whether these modes were used on different days, or whether one mode was used more frequently than the other. This lack of detail could have potentially resulted in some individuals being assigned to an erroneous class if their travel behaviour appeared to be more 'mixed' across multiple modes than it was in reality, though the effect is likely minor since mode use was well-correlated with daily driving time in the UKB samples.

The dietary indicators I used were the same as in Chapter 4, so they are subject to the same shortcomings previously discussed in section 4.4.4.2: that RPM and FV consumption are only two elements of overall diet and that GHG emissions can differ substantially between different foods within each grouping. While it is factual that emissions for FV can vary a great deal depending on where, when, or how a product is grown (and particularly whether it is air-freighted or hot-housed) (Hoolohan et al., 2013, Edwards-Jones, 2010), this level of detail was not available in either of my datasets and was thus beyond the scope of the study. Nevertheless, since plant-based foods have lower GHG emissions (per kg) than animal products in virtually all cases (Hoolohan et al., 2013, Aleksandrowicz et al., 2016), and FV consumption is the most well-established marker of the 'healthiness' of one's diet, I considered it to be an acceptable indicator of HLC diets for my purposes. RPM consumption is a similar case, though emissions from livestock depend more on the type of animal in question than on where or how it is raised (Hoolohan et al., 2013, Edwards-Jones, 2010, Garnett et al., 2017)[84]. Within the RPM category, ruminant animals (e.g. beef, lamb) and processed pork products (e.g. sausages, bacon, gammon) tend to be consumed in the largest quantities in the UK population (Aston et al., 2013, Bates et al., 2014). Since the former is worse from an emissions perspective (Eshel et al., 2014, Green et al., 2015) and the latter is worse from a health perspective (Bouvard et al., 2015), using an aggregate measure of RPM consumption is actually the most ideal representation of *combined* health and climate change impacts, which was my original intention.

Indeed, though there are many other dietary indicators that I could have included, my goal was to keep the models as simple and interpretable as possible, which is why I focused on indicators with the clearest evidence of complementary health and carbon impacts (e.g. *pro*-health, *low*-carbon or vice versa). From this perspective, foods such as cheese and butter could also have been included, as these are also health-

[84] For example, in a comparative study by DEFRA it was shown that New Zealand lamb can have lower emissions than British lamb, even when consumed in the UK, due to efficiencies in production, slaughter and processing and the fact that it is transported by boat (see Edwards-Jones, 2010 for more details)

damaging in large quantities and have a high emissions burden (though not as high as ruminant meat) (Green et al., 2015, Hoolohan et al., 2013). Nevertheless, I decided not to include these in the models mainly for reasons of simplicity—consumption of cheese[85] and butter are often correlated with RPM consumption (Fahey et al., 2007, Fahey et al., 2012, Greenwood et al., 2000), but they are usually eaten in much smaller quantities (Green et al., 2015, Bradbury et al., 2017), and are not yet subject to specific consumption guidelines. Since my focus was more on identifying which individuals have diets that are more or less HLC, and not on estimating the overall emissions of their diets, using RPM consumption as my primary indicator of higher dietary emissions likely met this intention. Where such data are available, future research that is focused on calculating the total emissions from different dietary patterns should consider incorporating these additional dietary measures, as well as individual fruits, vegetables, and types of meat.

5.4.4 Implications

The findings in this chapter have several important implications. Firstly, the fact that more car use and higher RPM consumption were found to overlap and cluster in large proportions of the UK population advances the idea that there may opportunities to target and shift these two unhealthy, high-carbon behaviours together. This interpretation stems from the theory that behaviours which cluster together often share common causal pathways (McAloney et al., 2013, Spring et al., 2012a), and that the stronger the clustering between two behaviours, the more determinants they are likely to share (Flay and Petraitis, 1994). This understanding suggests that increased car travel and high RPM consumption share at least some common determinants in the UK population, and especially among NDNS males where the clustering between these behaviours seemed to be particularly strong. Importantly, if these common determinants could be identified and better understood, it would help to improve our understanding of the drivers of lifestyles that are both higher-carbon and health-damaging in the UK, and potentially help to pinpoint upstream factors that could be modified to shift both of these behaviours in large subsets of the population.

Relatedly, these results also help to illustrate the different opportunities that exist for interventions and policy initiatives in terms of *who* exactly should be targeted with regard to increasing HLC lifestyles. This has parallels to the problem of treating

[85] Further complicating matters is the fact that emissions from cheese can also vary a lot depending on the type of cheese and its water content and this level of detail was also not available in either dataset. For example, Parmesan cheese requires twice the amount of milk per kg compared to Brie, which means it is twice as carbon intensive (British Cheese Board, 2017, Parmesan.com, 2017).

individuals versus populations in epidemiology (Rose, 2001), where a 'high-risk' approach would focus on 'treating' those individuals whose lifestyles are the most high-carbon and health-damaging, and a population approach would focus on shifting the wider societal conditions which facilitate excessive car use and meat consumption, thus making it easier for everyone to adopt more HLC lifestyles.

Since car use is highly concentrated in certain groups, high-risk approaches that aim to 'tame the few' may be most effective for reducing car travel (Brand and Preston, 2010, Brand et al., 2013), however, my results also help to highlight that high RPM consumption is a more widespread problem across more classes and larger proportions of the population, which suggests that dietary interventions may need to be more universally targeted. Indeed, the fact that eating large amounts of RPM was such a common issue in my findings makes it all the more glaring that reducing meat consumption was completely absent from the UK government's most recent plan to tackle climate change, the new Clean Growth Strategy (HM Government, 2017). Since dietary changes have been deemed critical to meeting global climate change goals (Wellesley et al., 2015) and current estimates suggest that the UK diet has a bigger carbon footprint than personal transport (see section 5.1), this omission is a particularly conspicuous missed opportunity.

More broadly, the patterns observed here between travel and dietary behaviours also reinforce the fact that none of these behaviours exist in isolation, and that high- and low-carbon behaviours can cluster together in ways that may often be unexpected. As a result, efforts to promote HLC lifestyles should be encouraged to think more holistically, and to consider the different dynamics that may exist between travel and dietary behaviours in practice. In psychological research, such dynamics have been called behavioural 'spillover' or rebound effects (Truelove et al., 2014, Dolan and Galizzi, 2015, Nash et al., 2017), and they are an important consideration in thinking through the consequences of different policies and interventions.

If, for example, engaging in active travel causes people to consume more food overall (because they have expended more energy), it is theoretically possible that efforts to increase walking and cycling for transport could unintentionally lead to higher meat consumption in some populations, and thus to higher dietary carbon emissions. Similarly, other authors have noted that public health messages around 'getting your 5-a-day' and consuming more local, organic, and seasonal foods could have the unintended effects of causing people to shop for food more frequently and to travel farther to source specialty ingredients, which may inadvertently result in more emissions from transport (Mattioli and Anable, 2017). Though these relationships remain unclear in the absence of longitudinal data, the typologies of diet and travel behaviour I have detected in these samples do suggest that such outcomes may be plausible[86].

Though it is not a complete solution, a first step towards more holistic thinking may be to shift policy discussions away from single, isolated behaviours, and instead frame HLC lifestyles more comprehensively across several different domains. One example of this approach can be seen in the Scottish Government's *Low Carbon Behaviours Framework*, an initiative which makes recommendations in 10 different behaviour areas across the sectors of home energy, transport, food consumption, and household purchasing and waste (Scottish Government, 2013). The framework describes its integrated approach as follows:

> While previous interventions have often tackled behaviours in isolation from one another, low carbon living is about a lot more than just changing one behaviour. 'Cherry-picking' from the ten key behaviours is no longer an option. People must be influenced across multiple areas in order to achieve real change, and this involves creating a 'low carbon package' for people to take on board (Scottish Government, 2013 p. 7).

5.5 Conclusions and Chapter 5 summary

Using a novel approach that combined several travel and dietary behaviours, this chapter has shown that completely HLC lifestyles are very rare in the UK, as most of the population engages in multiple unhealthy, high-carbon behaviours or more mixed behaviours. These findings provide a more comprehensive understanding of the patterning of health- and climate-relevant behaviours and give greater insights into the full impact of people's lifestyles. In the next chapter, I will focus on identifying the socio-demographic and environmental predictors of these behaviour patterns in order to clarify which conditions and contexts help to shape these different types of lifestyles in the UK.

[86] See, for example, Mostly car non-commuters (NDNS females), Cyclists with high RPM and high FV consumption (NDNS males), Low meat car commuters (NDNS females, UKB males and females).

6 Profiles and predictors of health- and climate-relevant lifestyles[87]

Chapter summary: Having determined the number and nature of different combinations of travel and dietary behaviour in Chapter 5, in this chapter I describe the social profile of each lifestyle group (latent class) and identify which factors are associated with different types of health- and climate-relevant lifestyles. Demographic, socio-economic and environmental factors are examined as predictors[88] of each lifestyle group, and different statistical approaches are used to identify predictors in the NDNS and UKB due to the characteristics of each sample. After summarizing my results, the chapter concludes with a discussion of my findings in relation to the literature as well as the strengths, limitations, and implications of this work.

6.1 Introduction

As discussed previously in Chapter 2 section 2.3, travel and dietary behaviours exhibit strong socio-demographic patterning in the UK population and these patterns can be broadly grouped into different 'layers' or types of influences (e.g. environmental, socio-economic, demographic). Travel behaviour, for example, appears to be most strongly shaped by the wider physical and socio-cultural environments (e.g. topography, infrastructure, social norms) (DfT, 2016b, DfT, 2016a, Steinbach et al., 2011), whereas dietary behaviour is often influenced by demographic and socio-economic factors, such as income, education, and household composition (Maguire and Monsivais, 2014, Leahy et al., 2010). Age, sex and ethnic group can also play a complicating role in these behaviour patterns, reflecting variations in gender norms, cultural practices, and trends across the life course. For example, whilst younger females and South Asian individuals tend to eat less meat, younger males and older females often consume more (Bates et al., 2014, Leahy et al., 2010). Similarly, cycling is more common among males and White individuals; however, walking is more common among females and non-White ethnic groups (DfT, 2015a, Steinbach et al., 2011).

[87] Part of this chapter was presented at the Society for Social Medicine Annual Scientific Meeting on 7 September 2017 and published as follows: Smith, M.A., Böhnke, J.R., Graham, H., White, P.C.L. and Prady, S.L., 2017. OP59 Prevalence and patterning of healthy, low-carbon lifestyles in the UK: a cross-sectional analysis of UK Biobank based on combinations of travel and dietary behaviour. *J Epidemiol Community Health* 2017;**71:**A30. http://jech.bmj.com/content/71/Suppl_1/A30.1

[88] To be clear, here I refer to statistical predictors (associations) not causal predictors.

Collectively, it is the combined effect of these influences (and the interconnections between them) that may cause certain behaviours to group together into different types of lifestyles. As a result, HLC behaviours may be most likely to cluster due to the joint influence of demographics (younger age, non-white ethnicity, female gender, smaller households), socio-economic factors (higher qualifications), and environmental context (living in more urban settings). In Chapters 4 and 5, it was found that HLC and UHC behaviours each cluster together to some degree, however there were also some groups with more mixed lifestyles, where travel and dietary behaviours with similar impacts did not occur together. This may be because car use and RPM consumption typically follow opposite socio-economic gradients (Maguire and Monsivais, 2014, Aston et al., 2013, DfT, 2016b), and these findings suggest that HLC behaviours may be driven by similar influences in some population groups, but not others.

Other research on higher- and lower-carbon lifestyles in the UK has reported that carbon emissions are positively associated with income, household size, and living in a rural area (Büchs and Schnepf, 2013, Druckman and Jackson, 2009, Baiocchi et al., 2010), however, these studies have only examined CO_2 emissions (thus underestimating dietary impacts), and all are based on household expenditure data, which can obscure individual behaviours occurring within the household. In addition, these studies have reported conflicting relationships for education, presence of children and for emissions across different domains (e.g. transport versus home energy) (Büchs and Schnepf, 2013, Baiocchi et al., 2010), and most have only examined a limited number of socio-demographic and environmental factors. To my knowledge, no studies have investigated predictors of lifestyles based on both travel and dietary behaviour, and with relevance to human health and to carbon emissions.

In light of these gaps, the aim of this chapter is to examine which socio-demographic and environment factors are associated with different types of health- and climate-relevant lifestyles in the UK population, in order to clarify the conditions and contexts that make certain lifestyles more or less likely to occur. Lifestyles are based on the latent classes (behaviour patterns) previously defined in Chapter 5.

More specifically, this chapter will examine my fourth research question:

- What is the socio-demographic profile of each class (behaviour pattern), and which factors, and types of influences, are associated with different lifestyles (higher-carbon, lower-carbon, mixed)?

6.2 Methods

6.2.1 National Diet and Nutrition Survey (NDNS)

6.2.1.1 Sample

Since this chapter builds on the analysis of the previous chapter, I used the same sample as in Chapter 5 to derive the LCA models (n=1609; 904 females, 705 males). As in Chapter 5, I conducted the analysis in Latent Gold 5.1 (Statistical Innovations, 2016b), so there were no exclusions for missing data in the NDNS sample.

6.2.1.2 Statistical Analysis

After performing a LCA, there are several ways to investigate the relationship between class membership and other variables of interest, and these can be broadly grouped into one-step and three-step approaches (Vermunt and Magidson, 2013). Of these, the three-step method is probably most intuitive: one first estimates the LCA model (Step 1), assigns individuals into latent classes using class membership probabilities[89] (Step 2), and then investigates associations between class membership and external variables using traditional statistical approaches such as logistic regression (Step 3) (Vermunt and Magidson, 2013). Unfortunately, it was not possible to use a three-step regression approach with the NDNS sample because there were too few participants in many of the more rare classes (e.g. four classes had <15 people, see Appendix D, Table D.0.1 and Table D.0.2), and so I used a one-step approach that would not require any further exclusions for missing data.

In Latent Gold, one-step approaches can be further subdivided into those where the variables of interest (covariates) are considered active or inactive. When using active covariates, the additional variables of interest are incorporated into the latent class model as predictors of class membership *whilst the model is being estimated* (Step 1). The advantage of this approach is that accounts for classification error in the models, however the main drawback is that it does not work well when performing an exploratory analysis with a large set of predictor variables (Vermunt and Magidson, 2013), as was the case here. In addition, the other major disadvantage for my purposes was that the class definitions themselves often change[90] when external variables are allowed to influence the model, and from a public health perspective, I felt

[89] Here it should be noted that this step often introduces classification error into the models, and this measurement error can potentially have an influence on the results (more on this in section 6.2.2.2).

[90] This was also discussed previously in Chapter 5 section 5.2.1.3.

it was conceptually important to first identify what the different behaviour groupings were, before relating them to external socio-demographic ‘risk factors’. As a result, the approach I ultimately decided to use was the *inactive* covariate approach, in which the model computes a descriptive measure for the association between each socio-demographic factor and the latent variable without influencing the obtained solution for the model (Vermunt and Magidson, 2016). These descriptive measures are the conditional probabilities of being in each socio-demographic category given membership in each class (including those with missing data for a given covariate) and can be interpreted similarly to the indicators in Chapter 5.

Assessment of difference between the classes was done by comparing the distribution of each covariate within each class to the overall distribution in each gender-specific sample. To identify differences that were particularly divergent, I exported the data into SPSS v24 (IBM Corp, 2015) and calculated standardised residuals for each cell value based on cross-tabulations between the class membership variable and each socio-demographic factor. These residuals represent a measure of how ‘extreme’ a value is by assessing the strength of the difference between the observed and expected counts in each cell relative to size (Agresti, 2002). Since it is expected that 95% of the cell values will be within +/-1.96 (2 by convention), I interpreted ‘extreme’ values as being those that were equal or greater than +/-2 for each value in the cross-tabulation, which provided a pragmatic but objective reference to guide my descriptive analyses.

The main limitation of this approach compared to the three-step method is that I was only able to assess bivariate relationships between class membership and each socio-demographic factor, as it is not possible to simultaneously adjust for any other variables when using inactive covariates.

6.2.1.3 Measures

Demographic, socio-economic, and environmental predictors were those described previously in my theoretical framework (Chapter 3, Figure 3.3) based on the factors that were related to travel and dietary behaviour in the literature and available in the NDNS dataset (Table 6.1). In addition, I also added employment status as a predictor for each individual since occupational class was measured at the household level (based on household reference person) in the NDNS. Further details of how these variables were created were described in Chapter 3, section 3.2.5.3.

In addition, and though not the main focus of this chapter, I also examined relationships between class membership and a variety of health indicators, as these may *result from* a healthy, low-carbon lifestyle, but also *contribute to* people's ability to engage in certain behaviours. These indicators were: total energy intake, time in physical activity, body mass index (BMI), self-reported overall health, and being limited by a long-term condition (Table 6.1).

Table 6.1 – Predictor variables examined in the NDNS

Type of factor	Variable	Categories / Details
Demographic	Age (16+)	16-24, 25-39, 40-54, 55-69, 70+
	Ethnic group	White, non-white
	Household size	1, 2, 3, 4, 5+
	Cohabitation status	Yes, no
	Living with children <18	Yes, no
Socio-economic	Highest qualifications	Degree or equivalent, higher education below degree, GCSE or equivalent, foreign qualification, no qualifications, still in full time education
	Employment Status	Employed, not employed
	Occupational Class (HRP)	Higher managerial and professional, lower managerial and professional, intermediate, small employers, lower supervisory or technical, semi-routine, routine, never worked
	Equivalised Household Income	0-£14,999, £15,000-24,999, £25,000-34,999, £35,000-49,999, £50,000+
Environmental	Quintile based on IMD score (England only)	0.53-8.49 (least deprived), 8.49-13.79, 13.79-21.35, 21.35-34.17, 34.17-87.80 (most deprived)
	Government Office Region	North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Scotland, Wales, Northern Ireland
Health	Total Energy intake	Kcal per day (average)
	Time in MVPA	Minutes per day (average)
	Body mass index (BMI)	<25, 25+ (overweight / obese)
	Overall health (self-reported)	Very good, good, fair, bad, very bad
	Limited by long-term condition	Yes, no, no long-term condition

HRP = household reference person; IMD = Index of multiple deprivation; MVPA = moderate to vigorous physical activity

Note: there are no reference categories in the NDNS since regression was not used for this analysis

6.2.2 UK Biobank (UKB)

6.2.2.1 Sample

In UKB, I wanted to make use of the full dataset from which I initially drew the random samples (n=211,036, 116,255 females, 94,781 males) so I used the LCA model from the estimation samples in Chapter 5 to assign class membership to the rest of the Oxford WebQ subsample. This was done using the ‘scoring’ procedure in Latent Gold, where the program generates scoring equations for a given LCA model so that new cases can be ‘scored’ based on their individual responses to the indicator variables (Vermunt and Magidson, 2013). These scoring equations were written into a SPSS syntax file[91] by Latent Gold and run separately in both males and females using their respective LCA models. The scoring equations calculated each case’s probability of being a member of each class, and then I manually assigned each case to the class with the highest membership probability by creating a class membership variable in Stata/SE 14.0 (StataCorp, 2015). Once this was complete, I checked the agreement between the class sizes (prevalence) in the estimation models compared to the scored datasets, for both males and females. In this comparison, class sizes were generally the same or within one percentage point or less indicating very good agreement in class assignment (Appendix D Table D.0.3 and Table D.0.4).

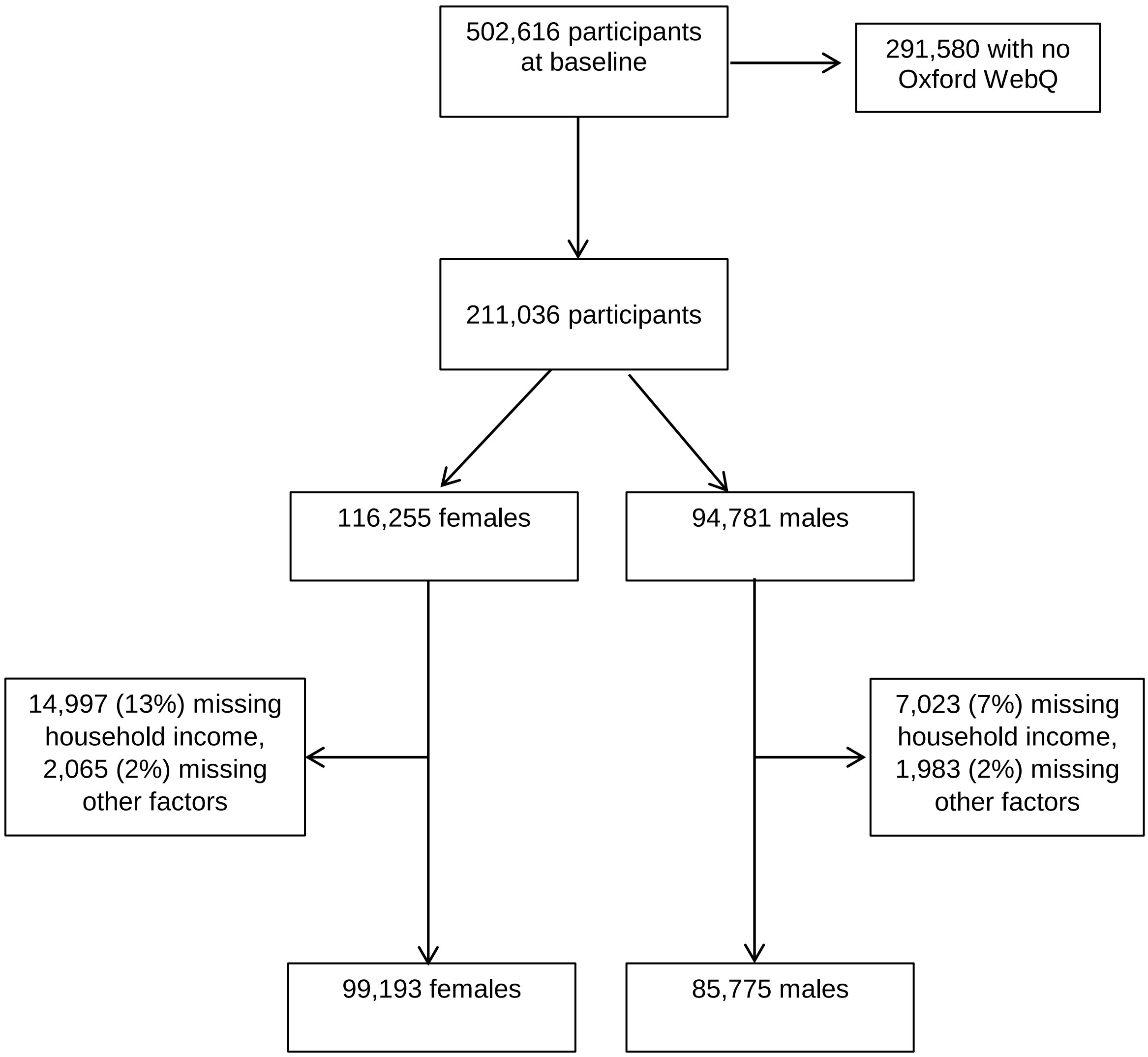
6.2.2.2 Statistical Analysis

Once class assignments had been generated for the full dataset, I used the three-step approach described previously to examine differences in socio-demographic factors across the classes. This approach was chosen due to the larger size of the UKB sample, which allowed for going beyond simple bivariate analysis with inactive covariates to a more powerful multivariate analysis. This three-step analysis was done in two ways: first, using simple cross-tabulations (similar to the inactive covariates method in the NDNS), and secondly, using multinomial logistic regression, where all classes were compared to Class 1, the *Exclusive car commuters*. Class 1 was chosen as the base class because it was the largest and most consistent class across all of the samples, and it was also the class predicted to have most carbon-intensive lifestyle, since it had the highest car use, and often the highest meat consumption. This meant that comparing all other classes to Class 1 would identify factors that were associated with lifestyles that were *relatively* lower in carbon.

[91] For an example of the syntax file used in UKB females see Appendix D, section D.1 (p. 312).

The cross-tabulations were mainly used to describe the socio-demographic patterning of Class 1, whereas predictors of the other classes were primarily identified from the multinomial regression model. The cross-tabulations used the full dataset including those with missing covariate data (to assess the % of missing data in each class), whereas participants with missing data on one or more predictors were excluded from the multinomial regression analysis, which resulted in final analytical samples of 99,193 females and 85,775 males (Figure 6.1). All socio-demographic predictors were included in one mutually adjusted model to assess the independent effect of each factor, and reference groups for each predictor were selected to maximise interpretability. Adjusted odds ratios (aOR) with 95% confidence intervals (CI) are presented and a threshold of alpha = 0.05 was used to assess statistical significance.

Figure 6.1 – Flowchart of participants in the UKB multinomial regression analysis



Sensitivity analysis

The main analyses were initially run in Stata/SE 14.0 (StataCorp, 2015), however, it has been shown that in a typical three-step analysis, there can be slightly downward biased estimates (e.g. towards the null value) of the association between the covariates and class membership, due to the classification errors introduced when assigning individuals to latent classes (Step 2) (Bolck et al., 2004). Since it is possible to adjust the estimates for this classification error using the 'Step3 module' in Latent Gold (Vermunt and Magidson, 2013), I re-ran my regression analyses using this approach to assess the amount of difference (if any) in the estimates compared with those from Stata. This approach, of running the analyses both ways for comparison purposes, has been used previously by other authors with minimal differences observed (Green et al., 2013).

In addition, another advantage of re-running the analyses in Latent Gold is that the program has a 'missing value' option which uses the design matrix to impute the missing values for predictor variables[92] (Vermunt and Magidson, 2016). In the case of a nominal predictor variable, the program imputes the parameter of the missing value category as equal to the unweighted mean of the parameters of the other categories[93] (Vermunt and Magidson, 2016). Thus, I conducted two sets of sensitivity analyses: one with missing values *excluded* to compare the adjusted effect estimates with those from Stata, and another with missing values *included* to compare the effect estimates with the imputed data from the full dataset.

Despite these advantages of the Step3 module in Latent Gold, I did not use it for the main analyses because I found it had very limited capabilities for regression modelling (as the program is not primarily designed for this purpose). For example, there is very little flexibility for selecting the base class and reference groups and very limited output and reporting options (e.g. no odds ratios and confidence intervals). I also found that there were problems with parameter identification when cells had small numbers (Vermunt and Magidson, 2005), which meant it was sometimes necessary to combine categories into groups that were less informative (e.g. from no car, 1, 2, 3, 4+ car households to 0-1 car, 2 car, 3+ car households).

[92] This is not the case for missing data on indicator variables; these are not imputed (as was previously described in Chapter 5).

[93] For example, for a 4-category nominal variable, ¼ would be imputed (one divided by the number of categories of the nominal variable concerned

As a result of these limitations, the associations that are presented for UKB are based on the results of the Stata models, as I found there were minimal differences when the models were re-run in Latent Gold, with and without missing covariate data included. Where there were differences between the Stata and Latent Gold models, these were usually in the expected direction (e.g. toward the null value), which means that the results from the Stata models were typically a slightly more conservative estimate of the association for each predicator (for more details on this and full model output for comparison purposes see Appendix D, Table D.0.29 to Table D.0.35). Nevertheless, this was not a major concern for my purposes since my focus was primarily on examining the *relative* influence of different types of factors, and not on calculating exact risk estimates between each factor and each lifestyle.

6.2.2.3 Measures

As in the NDNS, demographic, socio-economic and environmental predictors in UKB were based on previous literature and available data, as summarized in my theoretical framework in Chapter 3 Figure 3.3. These factors were generally very similar to those in the NDNS, with a few exceptions: in UKB some additional predictors were available (e.g. household car availability, population density), some predictors were more detailed (e.g. ethnic group, region of the UK) and some predictors were more comprehensive (e.g. Townsend scores for the whole dataset versus IMD for England only). Other factors, however, were more limited than in the NDNS, such as age (e.g. 40-70 versus 16+). Another difference was that I created a combined variable for household composition since household size, cohabitation status, and living with son/daughter were all to be included in the same model, and they were closely correlated (e.g. most people in two person households lived with their partner, most people in 3+ person households lived with their partner and son/daughter).

Health indicators were also examined in UKB, however these were analysed differently than the socio-demographic factors, whereby the relationship between each health indicator and class membership was examined in a separate multinomial regression model, adjusting only for age.

A full description of all predictors examined in UKB is presented in Table 6.2. More details of how these variables were created can be found in Chapter 3, section 3.3.4.3.

Table 6.2 – Predictor variables examined in UKB

Type of factor	Variable	Categories / Details
Demographic	Age at baseline assessment (40-70)	<45, 45-49, 50-54, 55-59, 60-64, 65+ (ref)
	Ethnic group	White British, Other White (ref), South Asian, Black, Chinese, Mixed, Other
	Household composition	Lives alone, lives with son/daughter and no partner, lives with partner only (ref), lives with partner and son/daughter, lives with others (relatives or non-relatives)
Socio-economic	Highest qualification	College or University degree, A levels or equivalent, O levels/GCSEs or equivalent (ref), CSEs or equivalent, NVQ or HND or HNC or equivalent, Other professional qualifications, No qualifications
	Employment Status [a]	Paid employment, Retired, Other
	Occupational Class [b]	Higher managerial and professional, lower managerial and professional, intermediate, small employers (ref), lower supervisory or technical, semi-routine, routine, not classified
	Household Income	<£18,000, £18,000-30,999, £31,000-51,999 (ref), £52,000-100,000, >£100,000
	Cars per household	None, 1, 2 (ref), 3, 4+
Environmental	Population density	Urban, rural (ref)
	Townsend score	Quintiles of full UKB cohort (ref = lowest quintile)
	Assessment Centre location [c]	Central London, Croydon, Hounslow, Oxford, Reading, Bristol, Nottingham, Birmingham Leeds, Sheffield, Middlesbrough, Newcastle, Liverpool, Manchester (ref), Bury, Cardiff, Swansea, Wrexham, Glasgow, Edinburgh
Health	Total Energy intake	Average kcal per day (continuous, no ref)
	Meets physical activity guideline	Yes, no (ref)
	Body mass index (BMI)	<25 (ref), 25+ (overweight / obese)
	Overall health (self-reported)	Excellent, good (ref), fair, poor
	Long-term condition / illness	Yes, no (ref)

ref: reference category in multinomial regression model

a) Employment status was included in the cross-tabulations but not in the multinomial regression models since there was 100% employment in all of the commuting classes

b) This was an individual level variable in UKB

c) Participants visited the assessment centre closest to their residence so this is an approximate measure of the region where they live

6.3 Results

Due to the large number of classes and predictors under investigation, detailed results tables for each of the four samples are presented in Appendix D (Table D.0.5 to Table D.0.28) to maintain readability and flow in this section. Instead, I present here a summary of the most important findings with regard to the profiles of each class based on differences that were ‘extreme’ in the NDNS and statistically significant in UKB. Summaries for the NDNS are in Table 6.3 (females) and Table 6.4 (males) and for UKB in Table 6.5 (females) and Table 6.6 (males).

In this section, results for each dataset are described differently due to the different analytical approaches used in each case. Findings from the NDNS are organised by class, highlighting the similarities and differences between males and females with similar classes grouped together by gender. Extreme values are emphasized for each class in comparison to the sample average for each factor. Findings for UKB are organized by type of factor (demographic, socio-economic, environmental, health) highlighting the similarities and differences between males and females where they occur. This approach was chosen because there were many statistically significant associations and fewer gender differences in UKB, so describing each class in detail was more duplicative and very lengthy. Instead, I focus on describing the broad patterns across the classes and any associations that are particularly strong compared to Class 1 (*Exclusive car commuters*).

6.3.1 NDNS

Classes are listed in order from largest to smallest prevalence in the female sample with male classes re-ordered to match up with the class to which they are most similar (when different). Prevalence values refer to the size of each class in the estimation model; *n* refers to the number of participants in each class based on the model classification (cases classified by highest membership probability). Percentages in the text come from the full results tables in Appendix D (Table D.0.5 to Table D.0.12).

6.3.1.1 Class profiles

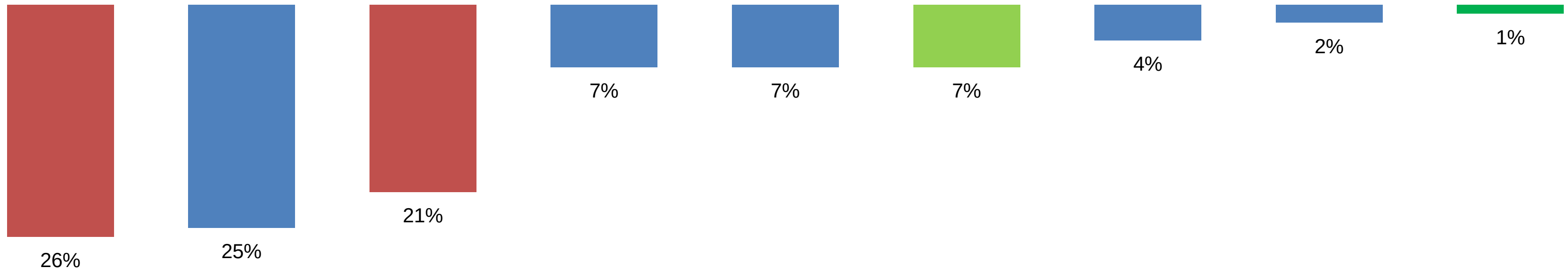
Class 1, Females – Always car commuters with high RPM and low FV (26%, n=241) Class 1, Males – Always car commuters with high RPM and high FV (38%, n=264)

Class 1 in both NDNS samples was patterned very similarly among males and females. Both classes were overrepresented in the 'working' age groups, particularly 40-54 among females (43%) and 25-54 (71%) among males. Both were also overrepresented in three-person households (31% females, 30% males) and were more likely to live with a partner (72% females, 78% males) and with children (38% females, 45% males). Females, but not males, were also less likely to be non-white (5%).

Both classes were also very socio-economically advantaged. They were more likely to have a degree (34% females) or other higher education (34% both), and almost all were in current employment (90% females, 95% males). Both classes also had higher household incomes than average, and were overrepresented in the £50,000+ category (17% females, 23% males). Females, but not males, were also particularly likely to have household reference persons (HRPs) in higher managerial and professional occupations (21%). Members of these classes were not overrepresented in any particular region, but were underrepresented in London (4% females, 5% males). In addition, both classes were unlikely to report their overall health as 'fair' (14% females, 12% males) or to be limited by a long-term condition (17% females, 10% males).

Table 6.3 – Summary of associations between socio-demographic factors, health indicators and class membership among NDNS females (n=904)

	1 Exclusive car commuters	**2** Low FV non-commuters	**3** Mostly car non-commuters	**4** Usual car commuters	**5** Walking commuters	**6** PT commuters	**7** Low meat mixed car commuters	**8** Low meat non-commuters	**9** Commuter Cyclists
Demographics	+ 40-54 age group - Non-white + 3 person hholds + Children and partner	- 40-54 age group	+ 55-69 age group + 1 person hholds + No children	- 70+ age group	+ 16-24 age group	+ 16-24 age group + Non-White + No partner		- 40-54 age group + Non-White	
Socio-economics	+ Degree + Higher ed <degree - Not employed + Higher man / prof occupations + >£50,000	+ GCSEs + No qualifications + Not employed + Routine occupations, never worked + Lowest incomes	+ Foreign qualifications + Not employed + Lower man / prof occupations, small employers	+ FT education + Employed	+ FT education + Employed	+ FT education	+ Degree + Employed	+ No qualifications + Not employed	
Residential environment	- London	+ Most deprived + Scotland	+ Least deprived		- Least deprived - South East	+ London - Wales	+ Average deprivation + East Midlands	+ London	+ Yorkshire + South East
Health indicators	- Fair health - Limited by LT condition	+ Fair & bad health + Limited by LT condition	+ Limited by LT condition	- Limited by LT condition		- Limited by LT condition	- Not limited by LT condition	+ Fair health	
Travel behaviour									
Diet behaviour									

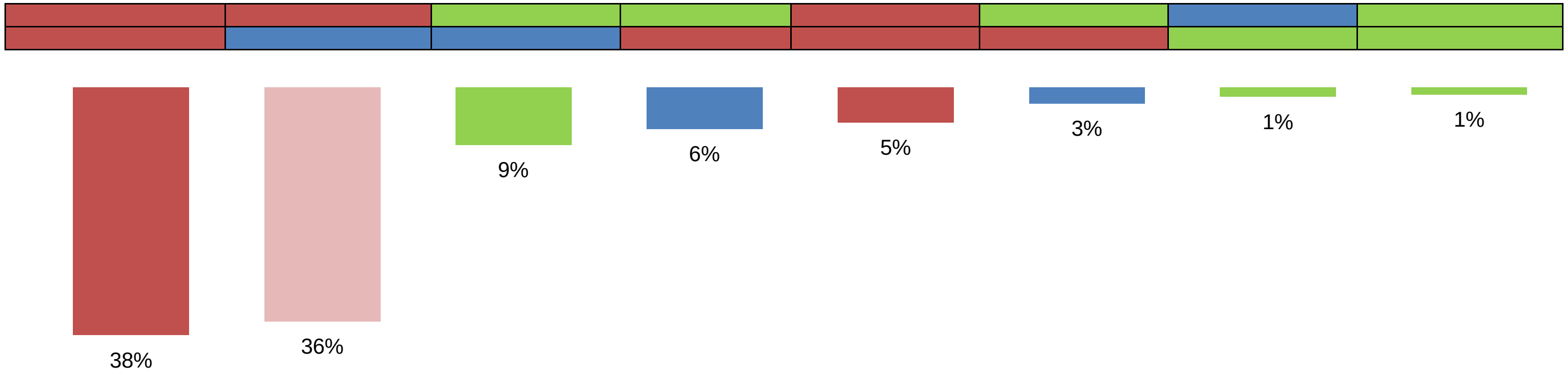


FV: fruit and vegetables; PT: public transport; FT: full-time; LT: long-term; '+' symbol indicates that a factor is overrepresented (positive extreme value) and '–' symbol indicates that a factor is underrepresented (negative extreme value).
Bar chart reflects the class size and shading of its overall lifestyle: red = higher-carbon, pink = predominantly higher-carbon, blue = mixed, light-green = predominantly lower-carbon, dark green = healthy, low-carbon

Table 6.4 – Summary of associations between socio-demographic factors, health indicators and class membership among NDNS males (n=705)

	1 Exclusive car commuters	2 Mixed car non-commuters	3 PT commuters	4 Walking commuters	5 Mostly car commuters	6 Commuter Cyclists	7 Low meat mixed car commuters	8 Low meat non-commuters
Demographics	+ 25-54 age group + 3 person hholds + Children and partner	+ 55+ age group + 1-2 person hholds + No children	+ 16-24 age group + Non-white + 4 person hholds + No partner		+ 16-24 age group + 4 person hholds			+ 55-69 age group
Socio-economics	+ Higher ed < degree + Employed + >£50,000	+ No qualifications + Not employed + Routine or semi-routine occupations + Lowest household income	+ FT education + Higher man / prof occupations - Low incomes	+ FT education				+ Not employed
Residential environment	- London	+ North East	+ London			+ South East		
Health indicators	- Fair health - Limited by LT condition	+ Fair, bad, very bad health + Limited by LT condition	+ BMI <25					

Travel behaviour
Diet behaviour



PT: public transport; FT: full-time; LT: long-term; '+' symbol indicates that a factor is overrepresented (positive extreme value) and '–' symbol indicates that a factor is underrepresented (negative extreme value).
Bar chart reflects the class size and shading of its overall lifestyle: red = higher-carbon, pink = predominantly higher-carbon, blue = mixed, light-green = predominantly lower-carbon, dark green = healthy, low-carbon

Class 2, Females – Very low FV non-commuters with high RPM[94] (25%, n=214)
Class 2, Males – Mixed car non-commuters with low RPM and low FV (36%, n=260)

Comparing across the two samples, these classes were less similar than Class 1, particularly with regard to demographic factors. Among females, for example, there were few distinguishing demographic characteristics except that they were underrepresented in the 40 to 54 age group (15%). Males, on the other hand, were overrepresented in the 55+ age group (59%) and tended to live in one or two person households (64%) and without children under 18 (82%).

Socio-economic characteristics were more similar between genders. Members of these classes were more likely to have no qualifications (35% females, 29% males) or to have attained GCSE or equivalent qualifications (25% females) and were more likely to have HRPs in semi-routine (17% males) or routine occupations (13% females, 15% males) or who had never worked (5% females). Both were more likely to be not employed (85% females, 74% males) and were overrepresented in the lowest household income groups (34% <£15,000 among females, 49% <£25,000 among males).

Among females, this class was overrepresented in the most deprived areas of England (22%) and in Scotland (11%), whereas males were slightly overrepresented in the North East of England (9%). Both classes were more likely to report their overall health as 'fair' (26% females, 29% males) or 'bad' (6% females, 8% males) and many reported that their activities were limited by a long-term condition (28% females, 32% males).

[94] Recall from Chapter 5 that class names are designed to reflect the most distinguishing features of each class, so class names will not always follow the same format. This can aid in interpretation, as the more different the class names, the more different the classes themselves.

Class 3, Females – Mostly car non-commuters with high RPM & high FV (21%, n=177)
No equivalent class, Males

Though there was no equivalent class detected among males, this class did have some demographic similarities to Class 2 in the male sample (see previous profile). For example, members of this class were particularly overrepresented in the 55 to 69 age group (31%) and in one-person households (28%) without children (78%). As another non-commuting class, they were also more likely to be not in employment (84%). Members of this class were also more likely to have no qualifications (28%) or foreign qualifications (11%) and were most likely to have HRPs in lower managerial and professional occupations (32%) or small employers (20%). They had household incomes that were comparable to the sample average, but were overrepresented in the least deprived areas of England (29%). Perhaps owing to their older age, 27% of this class reported having their activities limited by a long-term condition, however many also reported having good (43%) or very good (33%) health.

Class 4, Females – Usual car commuters with low RPM and high FV (7%, n=72)
Class 5, Males – Usual car commuters with high RPM and low FV (5%, n=40)

Small numbers in these classes made it difficult to detect extreme variations, particularly among males where only demographic differences were observed. For example, males in this class were overrepresented in the youngest age group (34% 16 to 24) and also in four-person households (29%). Females also appeared to be younger on average as they were particularly underrepresented in the 70+ age group (0%) and were overrepresented in the 'still in full-time education' category (15%). Females were also more likely to be in current employment (79%) and less likely to have their activities limited by a long-term condition (8%).

Class 5, Females – Walking commuters with high RPM and low FV (7%, n=67)
Class 4, Males – Walking commuters with high RPM and high FV (6%, n=46)

Among females, this class was particularly overrepresented in the 16 to 24 age group (22%) and both males and females had a higher proportion that were 'still in full-time education' (15% females, 19% males)—this was the only extreme value detected for males in this class. Females, but not males, were also more likely than expected to be in current employment (77%) and were underrepresented in areas of least deprivation (9%) and in the South East of England (8%).

Class 6, Females – PT commuters with low RPM and low FV (7%, n=70)
Class 3, Males – PT commuters with low RPM and low FV (9%, n=63)

In these classes, both males and females were overrepresented in the 16 to 24 age group (30% females, 42% males) and both also had a higher proportion of non-white individuals (22% females, 28% males). Males, but not females, were also overrepresented in four-person households (25%) and both were most likely of all classes in their respective samples to be not living with a partner (60% females, 57% males). In line with their younger age, both classes had higher proportions still in full-time education (19% females, 27% males), however males, but not females, were also overrepresented in higher managerial and professional occupations (31%) based on their HRP. Both classes were overrepresented in London (27% females, 42% males) and females were also particularly underrepresented in Wales (0%). Males in this class were less likely to be overweight or obese (43%) and females were less likely to be limited by a long-term condition (10%).

Class 7, Females – Low meat mostly car commuters with high FV (4%, n=33)
Class 7, Males – Low meat mixed commuters with high FV (1%, n=11)

Females in this class were more likely to have higher qualifications (43% degree or equivalent) and be in current employment (82%). They were also overrepresented in areas of average deprivation (37%) and in the East Midlands (16%) and they were most likely of all female NDNS classes to have no long-term conditions (90%).

Among males in this class, there were no extreme values detected for any of the factors, however, they appeared to be similar to females in qualifications (51% with degree or equivalent), employment (94% employed) and health status (92% with no long-term condition).

Class 8, Females – Low meat mixed car non-commuters with high FV (2%, n=21) Class 8, Males – Low meat mixed non-commuters with high FV (1%, n=6)

There were very few extreme values detected in these classes, particularly among males, due to the small numbers of participants. Females in this class were underrepresented in the 40 to 54 age group (5%) and males were overrepresented in the 55 to 69 age group (74%). Both were more likely not to be in current employment (84% females, 100% males). Females were also more likely to be non-white (21%) and to have no qualifications (56%). Females, but not males, were overrepresented in London (25%) and in areas with the least deprivation (43%) and were more likely to report their health as being ‘fair’ (39%).

Class 9, Females – Commuter cyclists with low RPM and high FV (1%, n=9) Class 6, Males – Commuter cyclists with high RPM and high FV (3%, n=15)

Possibly due to the small size of these classes, there were few extreme values detected except for region of the UK, where both groups were particularly overrepresented in the South East of England (32% females, 28% males) and females were also overrepresented in Yorkshire and the Humber (36%). Broadly speaking, both classes were also more likely to be White (100% females, 92% males), not overweight or obese (58% females, 60% males) and to report their health as ‘very good’ (60% females, 63% males).

6.3.2 UKB

Since this section does not contain detailed class profiles, class names and sizes are listed below for reference and comparison purposes. To improve the readability of this section, the name of each class will be shortened to its most defining characteristic(s) when it is mentioned in the text (e.g. *PT non-commuters with high RPM and high FV →* *PT non-commuters*). Adjusted odds ratios in the text come from the full results tables in Appendix D (Table D.0.13 to Table D.0.28).

Class descriptions in UKB:

Class 1, Females – Exclusive car commuters with high RPM and low FV (33%)
Class 1, Males – Exclusive car commuters with high RPM and low FV (36%)

Class 2, Females – Mostly car non-commuters with high RPM and high FV (31%)
Class 2, Males – Mixed car non-commuters with high RPM and high FV (35%)

Class 3, Females – PT non-commuters with high RPM and high FV (10%)
Class 4, Males – PT non-commuters with average RPM and high FV (7%)

Class 4, Females – Mixed car commuters with high RPM and high FV (7%)
Class 3, Males – Mixed car commuters with high RPM and low FV (9%)

Class 5, Females – PT commuters with average RPM and low FV (7%)
Class 5, Males – PT commuters with average RPM and low FV (6%)

Class 6, Females – Low meat car commuters with high FV (3%)
Class 8, Males – Low meat car commuters with high FV (1%)

Class 7, Females – Walking commuters with low RPM and low FV (3%)
Males – no equivalent class

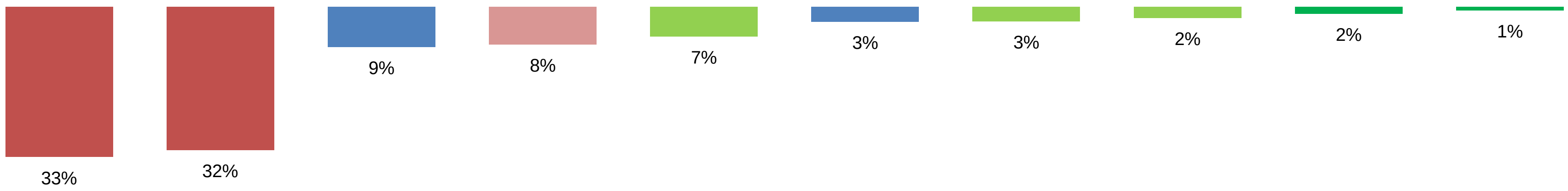
Class 8, Females – Low meat mixed car non-commuters with high FV (3%)
Class 9, Males – Low meat non-commuters with highest FV (1%)

Class 9, Females – Low meat mixed commuters with high FV (2%)
Class 7, Males – Low meat mixed commuters with high FV (1%)

Class 10, Females – Commuter cyclists with low RPM and high FV (1%)
Class 6, Males – Commuter cyclists with average RPM and high FV (3%)

Table 6.5 – Summary of associations (aORs) between socio-demographic factors, health indicators and class membership among UKB females (n=99,193)

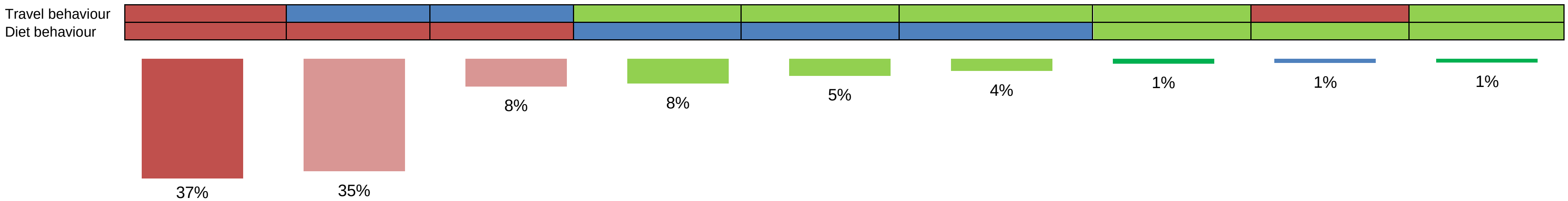
	1 **Exclusive car commuters**	2 **Mostly car non-commuters**	3 **PT non-commuters**	4 **Mixed car commuters**	5 **PT commuters**	6 **Low meat car commuters**	7 **Walking commuters**	8 **Low meat non-commuters**	9 **Low meat mixed commuters**	10 **Commuter Cyclists**
Demographics	49% 50-59 90% White British 39% Partner & children	+ Older - Non-White + Partner only	+ Older - White British, non-White + Partner & children	- South Asian, Black + Partner & children	- under 45 - White British + Partner & children	+ Younger + South Asian - Partner & children	- under 45 - South Asian, Black + Partner & children	+ Older + South Asian	+ under 50 + South Asian	- White British, South Asian, Black, Chinese + Partner + children
Socio-economics	42% Degree 100% employed 61% Manag / prof occupations 36% >£52,000 63% 2-3 cars	+ Degree, A-levels + Retired + Lower incomes + Fewer cars	+ Degree, A levels + Retired + Lower incomes + Fewer cars	+ Degree, A levels + Intermediate, routine, semi-routine occupations + Fewer cars	+ Degree + Higher man / prof, intermediate, semi-routine occupations + Higher incomes + Fewer cars	+ Degree, A levels - Highest income	+ A levels + Intermediate, semi-routine, routine occupations + Fewer cars	+ Degree, A levels, other professional qualifications + Retired + Fewer cars + Lower incomes	+ Degree, A levels + Intermediate occupations + Fewer cars	+ Degree, A levels + Fewer cars
Residential environment	24% Least deprived quintile 18% Rural 12% Bristol, 10% Sheffield, 7% Reading, 6% Middlesbrough	+ Less deprived - Urban + Outer London, Birmingham, Swansea	+ More deprived + Urban + London, Birmingham, Sheffield	+ More deprived + Urban + Central London, Edinburgh, other cities	+ More deprived + Urban + Central London, Edinburgh, other cities	+ More deprived	+ More deprived + Urban + Central London, Edinburgh, other cities	- Urban + London	+ More deprived + Urban + London, Edinburgh, other cities	+ More deprived + Urban + Central London, Oxford
Health indicators	43% meet PA guideline 56% BMI 25+ 62% Good health 23% LT condition	+ PA guideline - BMI 25+ + Fair, poor health + LT condition	+ PA guideline - BMI 25+ + Poor, fair health + LT condition	+ PA guideline - BMI 25+ + Excellent health - LT condition	- PA guideline - BMI 25+ + Poor, fair health + LT condition	+ PA guideline - BMI 25+ + Excellent health	+ PA guideline - BMI 25+	+ PA guideline - BMI 25+ + Poor, fair health + LT condition	+ PA guideline - BMI 25+ + Excellent health	+ PA guideline - BMI 25+ + Excellent health - LT condition
Travel behaviour										
Diet behaviour										



PT: public transport; FT: full-time; LT: long-term; '+' symbol indicates that a factor is positively associated (OR) and '–' symbol indicates that a factor is negatively associated (OR).
Bar chart reflects the class size and shading of its overall lifestyle: red = higher-carbon, pink = predominantly higher-carbon, blue = mixed, light-green = predominantly lower-carbon, dark green = healthy, low-carbo

Table 6.6 – Summary of associations (aORs) between socio-demographic factors, health indicators and class membership among UKB males (n=85,775)

	1 **Exclusive car commuters**	2 **Mostly car non-commuters**	3 **Mixed car commuters**	4 **PT non-commuters**	5 **PT commuters**	6 **Commuter Cyclists**	7 **Low meat mixed commuters**	8 **Low meat car commuters**	9 **Low meat non-commuters**
Demographics	44% 50-59 90% White British 46% Partner & children	+ Older + White British + Partner only	+ Older - South Asian + Partner & children	+ Older - South Asian, Black, Other + Partner & children	- under 50 - South Asian, Black, Other + Partner & children, living with others	+ under 55 - non-White + Partner & children	+ under 45 + South Asian + Partner & children	+ under 55 + South Asian - Partner & children	+ Older + South Asian - Living alone, single parent
Socio-economics	39% Degree 100% employed 64% manag / prof occupations 43% >£52,000 67% 2-3 cars	+ Degree, A-levels + Retired, manag / prof, intermediate occupations + Lower incomes	+ Degree, A levels + All occupations + Over 100 000 + Fewer cars	+ Degree, A levels + Retired, manag / prof, intermediate occupations + Lower incomes + Fewer cars	+ Degree, A levels + Manag / prof, intermediate, semi-routine occupations + Higher incomes + Fewer cars	+ Degree, A levels + Manag / prof, intermediate, semi-routine, routine occupations + Higher incomes + Fewer cars	+ Degree, A levels + Manag / prof, intermediate, semi-routine occupations + Fewer cars	+ Degree, A levels, other prof qualif - Higher man / prof, intermediate, routine occupations - Highest income	+ Degree, A levels + Retired, higher man / prof occupations + Lower incomes + Fewer cars
Residential environment	25% Least deprived quintile 17% Rural 12% Bristol, 10% Sheffield, 7% Reading, 6% Middlesbrough	+ Less deprived - Urban + Outer London, Birmingham, Swansea	+ More deprived + Urban + Cities in England, Scotland, particularly London	+ More deprived + Urban + London, English cities	+ More deprived + Urban + London, Edinburgh, Glasgow	+ More deprived + Urban + Central London, Oxford, Edinburgh, outer London, Bristol	+ More deprived + Urban + London, Cardiff, Edinburgh	+ More deprived - Edinburgh	+ More deprived + London
Health indicators	48% meet PA guideline 75% BMI 25+ 59% Good health 27% LT condition	+ PA guideline - BMI 25+ + Poor health + LT condition	- PA guideline - BMI 25+ + Excellent health	- BMI 25+ + Poor health + LT condition	- PA guideline - BMI 25+ + Excellent health + LT condition	+ PA guideline - BMI 25+ + Excellent health	+ PA guideline - BMI 25+ + Excellent health	- BMI 25+ + Excellent health	+ PA guideline - BMI 25+ + Poor health + LT condition



PT: public transport; FT: full-time; LT: long-term; '+' symbol indicates that a factor is positively associated (OR) and '–' symbol indicates that a factor is negatively associated (OR).
Bar chart reflects the class size and shading of its overall lifestyle: red = higher-carbon, pink = predominantly higher-carbon, blue = mixed, light-green = predominantly lower-carbon, dark green = healthy, low-carbon

6.3.2.1 Demographic predictors

In both of the UKB samples the profiles of the *Exclusive car commuters* (Class 1) were almost identical among males and females (Table 6.5 and Table 6.6). For example, both classes tended to be between the ages of 50 and 59 (49% females, 44% males), were overwhelmingly White British (90% both), and lived with their partner only (32% females, 36% males) or with a partner and son/daughter (39% females, 46% males).

Comparing across the rest of the classes, many other groups tended to be older than Class 1 among both males and females. This included the three non-commuting groups in both samples, as well as the *Mixed car commuters* among males. Compared with Class 1, *Walking commuters* and *PT commuters* were also less likely to be under age 45 among females and *PT commuters* were less likely to be under age 50 among males. Among females, only two classes were significantly younger than Class 1, both of which were low meat eating groups: the *Low meat car commuters* (aOR=2.08, 95%CI 1.54, 2.80 for < age 45) and *Low meat mixed commuters* (aOR=1.49, 95%CI 1.05, 2.10 for < age 45). Among males, the same two low meat classes were also significantly younger than Class 1, as were the *Commuter cyclists* (aOR=1.57, 95%CI 1.22, 2.02 for < age 45). Conversely, among females there were no significant age differences for the *Commuter cyclists* and *Mixed car commuters,* indicating that these groups were of similar age to Class 1.

For ethnic group, the most consistent finding among both males and females was that all of the low meat classes were significantly more likely to be South Asian, particularly the *Low meat car commuters* (females: aOR=4.46, 95%CI 3.46, 5.76; males: aOR=4.11, 95%CI 2.95, 5.70). Most other classes were less likely to be in various non-White groups (e.g. South Asian, Black, Chinese, Other) compared with Class 1, however, *PT non-commuters*, *PT commuters*, and *Commuter cyclists* were also significantly less likely to be White British among females. Among males, the *Mixed car non-commuters* were significantly more likely to be White British (aOR=1.22, 95% CI 1.09, 1.36) in comparison with Class 1.

For household structure, associations were often patterned as would be expected in relation to age and stage of life. For example, older groups like the *Mixed/Mostly car non-commuters* were more likely to live in two person households with a partner only, and younger groups like the *Low meat car commuters* were less likely to live with a partner and son/daughter (females: aOR=0.88, 95% CI 0.80, 0.97; males: aOR=0.77, 95% CI 0.66, 0.89). However, several other classes were also more likely than Class 1 to live in households with a partner and son/daughter, versus partner alone. These were: *PT non-commuters*, *Mixed car commuters*, *PT commuters*, *Commuter cyclists, Walking commuters* (females only), and *Low meat mixed commuters* (males only). Among males, the *PT commuters* were also significantly more likely to live with others (relatives or non-relatives) compared to Class 1 (aOR=1.31, 95% CI 1.07, 1.60), which may be because there is greater need to share accommodation in areas with more public transport due to the higher cost of housing in more dense areas.

6.3.2.2 Socio-economic predictors

Among both males and females, the *Exclusive car commuters* (Class 1) were very socio-economically advantaged. Large proportions of this class were educated to degree level (42% females, 39% males) and all were in current employment (100% both). Most of Class 1 were more likely to be working in managerial and professional occupations (61% females, 64% males) and many had household incomes above £52,000 (36% females, 43% males). Most members of Class 1 lived in two or three car households (63% females, 67% males).

Comparing across the classes, associations for education level followed a consistent pattern: in both samples, all other classes had significantly higher qualifications (degree or A-levels) compared with Class 1. Among females, *Commuter cyclists* had the highest odds of having a degree compared to Class 1 (aOR=2.84, 95% CI 2.17, 3.72), whereas among males, the *Low meat non-commuters* and *Low meat mixed commuters* had the highest odds of degree-level qualifications (aOR=3.53, 95% CI 2.88, 4.32 and aOR=3.40, 95% CI 2.76, 4.19, respectively). Notably, all three of these groups were classified as HLC with respect to their travel *and* dietary behaviour.

Among females, several classes were more likely to work in intermediate (*Mixed car commuters, PT commuters, Walking commuters, Low meat mixed commuters*) or routine (*Mixed car commuters, Walking commuters*) occupations compared with Class 1, and the only class more likely to work in higher managerial and professional occupations was *PT commuters* (aOR=1.42, 95% CI 1.15, 1.74). Among males these associations were not the same, as all classes except *Low meat car commuters* and *Low meat non-commuters* had significantly higher odds of working in managerial and professional or in intermediate occupations compared with Class 1. In both samples, all of the non-commuting groups were more likely to be retired (i.e. occupation not classified) and these classes also had significantly lower household incomes. Among females, only *PT commuters* had higher household incomes than Class 1, whereas among males, there were four classes with significantly higher household incomes: *Mixed car commuters*, *PT commuters*, *Commuter cyclists* and *Low meat PT commuters*. As with females, *PT commuters* had the highest odds of higher incomes among males, particularly those above £100,000 (aOR=2.17, 95% CI 1.90, 2.48).

Compared with the *Exclusive car commuters* (Class 1), all of the other classes were significantly more likely to have fewer cars per household (one or none) among both males and females. Based on the associations for car availability, the classes that were most similar to Class 1 were the *Low meat car commuters* and the *Mixed car non-commuters* (males only).

6.3.2.3 Environmental predictors

In both samples, *Exclusive car commuters* (Class 1) were more likely to live in areas with the lowest Townsend scores (24% females, 25% males) and in postcodes that were slightly more rural (18% females, 17% males) than average. Though Class 1 was not greatly overrepresented in any particular region of the UK, both males and females more commonly visited assessment centres in Bristol (12% both), Sheffield (10% both), Reading (7% both) and Middlesbrough (6% both).

Comparing across the classes, associations for the residential environment were more consistent than both socio-economic and demographic factors. With regard to population density, for example, all but three classes, *Mixed/Mostly car non-commuters*, *Low meat car commuters*, and *Low meat non-commuters* had higher odds of residing in urban postcodes compared to Class 1 among both males and females. Among females, the class with the highest odds living in an urban area was *Commuter cyclists* (aOR=3.97, 95% CI 2.63, 5.99) whereas among males, *PT commuters* had the highest odds of living in an urban postcode (aOR= 2.24, 95%CI 1.85, 2.71). A similar pattern was also seen for Townsend score, where all classes except *Mixed/Mostly car non-commuters* and *Low meat non-commuters* (females only) had higher odds of living in areas with higher Townsend scores (i.e. more deprived)[95].

[95] This pattern likely reflects the fact that Townsend scores may be a proxy for the degree of urbanization in an area, since three of the four indicators that make up the score (non-car ownership, non-home ownership, and household overcrowding) will generally all be higher in more urbanised areas.

Finally, the strongest and most consistent finding for region was that all classes except *Mixed/Mostly car non-commuters* and *Low meat car commuters* had significantly higher odds of living in central London. These associations were particularly strong among females, where *Low meat mixed commuters* and *PT commuters* were more than 10 times as likely as Class 1 to live in central London (versus Manchester): aOR=12.10, 95% CI 7.59, 19.27; aOR=11.07, 95% CI 8.24, 14.86, respectively. Similarly, *PT commuters* also had the highest odds of living in central London among males (aOR=9.49, 95% CI 6.78, 13.27)[96]. In addition, among both males and females, all classes except *Low meat car commuters* also had significantly higher odds of living in outer London (assessment centres in Hounslow and Croydon); however the effect estimates were not quite as large.

Outside the London area, there were also a few notable patterns for other parts of the UK. In particular, several classes also had significantly higher odds of living near Edinburgh: *Mixed car commuters*, *PT commuters*, *Low meat mixed commuters, Walking commuters* (females only), and *Commuter cyclists* (males only). In addition, among both males and females, *Commuter cyclists* had particularly high odds of living near Oxford (females: aOR=6.41, 95%CI 3.95, 10.41; males: aOR=3.49, 95%CI 2.55, 4.79).

6.3.2.4 Health indicators

In both samples, less than half of *Exclusive car commuters* (Class 1) met the recommended amount of PA (43% females, 48% males) and more than half had BMIs that were in the overweight or obese range (56% females, 75% males). Nevertheless, the majority in both classes reported that their overall health was 'good' (62% females, 59% males) and that they had no long-term health conditions (76% females, 72% males).

Among females, all classes except *PT commuters* were significantly more likely than Class 1 to meet the PA guideline, whereas among males, there were only four classes that had higher odds of meeting the PA guideline (*Mixed car non-commuters*, *Commuter cyclists*, *Low meat mixed commuters*, *Low meat non-commuters*) and two classes that were less likely to meet the guideline (*Mixed car commuters* and *PT*

[96] Because the influence of living in London was so strong, I conducted a post-hoc analysis where I re-ran the models with people in London removed (n=78,295 females, n=69,037 males) to see if this had any impacts on the associations for the other predictors. Besides greatly reducing the prevalence of the *PT commuters* in the sample and the numbers in some of the non-White ethnic groups, there were very few effects on the associations (see Appendix D, Table D.0.36 and Table D.0.37).

commuters). Among both males and females, *Commuter cyclists* had the highest odds of meeting the PA guideline compared to Class 1 (females: aOR=12.13, 95%CI 9.60, 15.32; males: aOR=6.91, 95%CI 6.20, 7.70). Associations for BMI status were even more consistent than for physical activity: among both males and females all of the other classes were significantly less likely to be overweight or obese in comparison with Class 1. Among females, the strongest effect was observed among *Commuter cyclists* (aOR=0.36, 95%CI 0.31, 0.41) whereas among males, it was the *Low meat mixed commuters* who were least likely of all to be overweight or obese (aOR=0.31, 95%CI 0.28, 0.35).

With regard to health status, there were several classes with higher odds of reporting excellent health compared to Class 1 among both males and females. These were: *Mixed car commuters*, *Low meat car commuters*, *Low meat non-commuters, Low meat mixed commuters* and *Commuter cyclists,* as well as *Mixed car non-commuters, PT non-commuters,* and *PT commuters* among males only. Among both males and females, *Commuter cyclists* had the highest odds of reporting excellent health (females: aOR=2.06, 95%CI 1.78, 2.38; males: aOR=1.96, 95%CI 1.80, 2.12). Even after adjusting for age, all of the classes reporting worse health were the older, non-commuting classes as well as *PT commuters* among females (aOR=1.40, 95%CI 1.19, 1.64 for poor health versus good health). These classes were also more likely to report the presence of a long-standing disability, illness, or infirmity, with *PT non-commuters* most likely to report this outcome (females: aOR=1.90, 95%CI 1.81, 2.00; males: aOR=2.16, 95%CI 2.04, 2.29) and to report having poor health (females: aOR=6.23, 95%CI 5.54, 7.00; males: aOR=6.91, 95%CI 6.13, 7.79).

6.4 Discussion

6.4.1 Summary of main findings

The central aim of this chapter was to identify which socio-demographic and environmental factors were associated with class membership in each sample, to gain a better understanding of the predictors of health- and climate-relevant lifestyles in the UK. Predictors of higher-carbon lifestyles were generally easiest to detect, as these classes were largest across the four samples, and I identified three diverse profiles of higher-carbon lifestyles based on combinations of different factors. In both samples, the largest class of *Always/Exclusive car commuters* were distinguished mainly by demographic and socio-economic factors as this group was associated with being

White, of working age, living with a partner and child(ren), and with having higher household incomes and more cars per household. In contrast, the *Mixed/Mostly car non-commuters* were typically older, not in current employment, and living in smaller households in more rural and less deprived areas. The third group, the *Usual/Mixed car commuters* were distinct largely on the basis of environmental factors, as they typically lived in more urban and deprived areas, though there was also some evidence that they were younger in the NDNS samples.

Predictors of lower-carbon lifestyles were mainly identified from UKB, as there were few differences in the associations detected for these classes in the NDNS. Here, the most consistent patterns across the classes were related to environmental and socio-economic factors, as lower-carbon lifestyles were associated with living in particular regions (e.g. London, Edinburgh, Oxford) and areas with greater population density and higher Townsend scores, as well as with having higher qualifications and fewer cars per household. Factors associated with mixed lifestyles were even more difficult to detect, as there were very few of these classes in UKB. Nevertheless, there was some evidence that mixed lifestyles were associated with socio-economic and demographic factors, such as lower incomes (*Low FV non-commuters*, *PT non-commuters*), higher qualifications (*Low meat car commuters*), and younger age (*Walking commuters* in the NDNS, *Low meat car commuters* in UKB).

6.4.2 Results in context

6.4.2.1 Environmental influences

There is a large body of existing evidence identifying aspects of the built environment as critical determinants of active travel (Ewing and Cervero, 2010, Pucher et al., 2010b, Giles-Corti and Donovan, 2002, Badland et al., 2013, Fraser and Lock, 2011) so it was not surprising that environmental factors were the strongest predictors of having a lower-carbon lifestyle in these samples. These environmental influences are representative of the physical conditions and contexts in which people live, and likely reflect the greater provision of public transport, active travel infrastructure, and shorter travel distances typically found in more dense urban areas. London, in particular, is the most extreme illustration of this pattern and living there was the strongest predictor by far of being in a lower-carbon class in UKB.

In addition to the physical built environment, the associations I observed for environmental predictors may also reflect differences in the *social* environment with regard to the norms and meanings that specific behaviours can take on in certain places. In the UK, for example, different social influences and contexts have been previously identified as important predictors of cycling behaviour (Sherwin et al., 2014, Steinbach et al., 2011), and indeed, I also found that the cycling classes in both of these samples were strongly associated with living in areas known to have unique local cycling cultures (e.g. Oxford, London, Hull) (Aldred and Jungnickel, 2014, Goodman et al., 2013). Notably, one interesting insight in relation to gender was that environmental factors were often stronger predictors of lower-carbon lifestyles (especially cycling) among females than among males, which supports previous research suggesting that women may be particularly influenced by environmental features, infrastructure and meanings / images associated with active travel (Garrard et al., 2008, Krizek et al., 2005, Gatersleben and Appleton, 2007, Shortt et al., 2014).

Local contexts and socio-cultural norms may also be important for dietary consumption, as nearly all of the low meat-eating groups in my samples were more commonly found in London and other urban areas, even after adjusting for other socio-demographic factors. Regional variations in meat and FV consumption have been reported previously in the UK (Leahy et al., 2010, Kamphuis et al., 2006, Roberts, 2014, Brown et al., 2016), but these differences have been often attributed to confounding by demographic and socio-economic factors, rather than true environmental variations in food consumption. In contrast, one of the more comprehensive attempts to link dietary patterns with residential geography was a recent analysis using the UK Women's Cohort Study that examined relationships between dietary clusters and two spatial measures: government office region and Output Area classification (OAC) Supergroup based on the 2001 Census (Morris et al., 2016). Similar to my findings, this study found that even when adjusting for socio-demographic characteristics, low meat (vegetarian) clusters were more common in greater London and in the 'City living' and 'Multicultural' Supergroups, and that clusters with higher meat consumption[97] were often associated with the 'Prospering Suburbs' and 'Countryside' Supergroups. Notably, Census data also show that these latter Supergroups typically have more cars per household (Morris et al., 2016), and another study which examined household CO_2 emissions found that these two segments also had the highest emissions of all groups in the UK population, even without fully accounting for their meat consumption (Druckman and Jackson, 2009). Nevertheless, limitations of the study by Morris et al. (2016) include that it only involved women and that its dietary clusters were based on data collected between

[97] For example, Traditional meat, chips and pudding eaters; High diversity traditional omnivores

1995 and 1998 (Greenwood et al., 2000). My findings add to this evidence by showing that regional variations in food consumption exist among both males and females using two recent samples of the UK population. Together, these patterns suggest that a cultural shift in meat consumption may be needed in some areas of the UK more than others, and that the reasons for these geographical differences in diet warrant further research and examination.

6.4.2.2 Socio-economic and material influences

Comparing across the classes, higher qualifications was the most consistent predictor of lower-carbon lifestyles, as all other classes in UKB were significantly more likely to have a degree and/or A-level qualifications among both males and females. Similarly, in the NDNS, *Low meat car commuters* and *Cyclists* were most likely of all to have degree-level qualifications or to still be in full-time education. This pattern is in accordance with existing literature, where higher qualifications are often positively associated with active travel (Hutchinson et al., 2014, Laverty et al., 2013, Whitmarsh, 2009, Thøgersen and Ölander, 2006) and with lower meat consumption (Maguire and Monsivais, 2014, Leahy et al., 2010, Whitmarsh, 2009, Aston et al., 2013), and with environmental values and behaviours more generally (Whitmarsh and O'Neill, 2010, Howell, 2013, Thøgersen and Ölander, 2006). Notably, in UKB, the classes with the most HLC behaviours of all (*Cyclists* and *Low meat non-commuters* among females and males, respectively) were also those with the highest odds of having higher qualifications.

Previous studies of higher- and lower-carbon lifestyles in the UK have consistently shown that carbon emissions are most strongly predicted by income (Büchs and Schnepf, 2013, Baiocchi et al., 2010, Druckman and Jackson, 2009), however these studies did not fully account for dietary impacts since they only examined CO_2 emissions[98], and their data were based on total household expenditures rather than on the actual behaviours of individuals. In my study, I also found that the *Always/Exclusive car commuters* were typically more affluent, however they were not necessarily the class with the highest household incomes. In both of the UKB samples, for example, *PT commuters* were significantly more likely than Class 1 to have incomes over £100,000, probably reflecting the fact that many of the highest paying jobs are located in more urban areas and particularly in London.

[98] As discussed in earlier chapters, many dietary emissions come from methane (CH_4) and nitrous oxide (N_2O) as they are commonly associated with food production.

Beyond the *PT commuter* group, there was also some evidence of different patterns for income and occupational class by gender, as lower-carbon lifestyles were often associated with higher household incomes and managerial / professional occupations among males, but not females. Though this could be related to individual income differences between men and women (which are not possible to assess in this study), this finding could also suggest that the relationships between socio-economic position (SEP) and lifestyle may differ by gender, since females with higher SEP were more often car commuters and females with lower SEP usually ate more RPM, especially in the NDNS. This pattern supports the assertion (from Chapter 5 section 5.4.2.3) that car travel and RPM consumption may be more closely linked to social stratification among females than among males in the UK, which may also explain why mixed lifestyles were more prevalent in the female samples in both datasets.

Household car availability, measured as the number of vehicles per household and only available in UKB, was the strongest socio-economic predictor of being in a lower-carbon lifestyle, and it was particularly correlated with daily driving time. This confirms the findings of a smaller UK study, which found that cars per household was the most important predictor of transport carbon emissions over and above other socio-economic factors such as income, education, and employment (Brand et al., 2013). This pattern may be explained by the fact that car ownership is not just a marker of affluence—it also represents the interplay that exists between environmental and socio-economic influences in shaping travel behaviour. In the UK, for example, research based on the National Travel Survey has shown that the socio-economic composition of 'car-less' households is a direct indicator of how car dependent an area is at the macro-level[99] (Mattioli, 2014). For example, in areas where there are few travel alternatives to the car, households without cars are subject to a large 'mobility gap' and often tend to be more socio-economically disadvantaged (Mattioli, 2014). This relationship has been also found in the UK Household Longitudinal Survey, where having fewer qualifications was positively associated with active travel in rural, but not urban, areas (Hutchinson et al., 2014).

[99] Car dependence can be measured and conceptualized at different levels: the macro-level refers to attributes of the wider environment and society; the meso-level refers to attributes of specific journeys, and the micro-level refers to attributes of individuals (Mattioli et al., 2016)

6.4.2.3 Demographic influences

Patterns in relation to age and ethnic group were generally as expected based on previous literature (DfT, 2015a, Marsh, 2016, Laverty et al., 2013, Leahy et al., 2010, Steinbach et al., 2011), as lower-carbon classes tended to be younger in both samples (notwithstanding the older, non-commuting groups) and, with the exception of cyclists, were often associated with being non-white in the NDNS and South Asian in UKB. Nevertheless, these relationships were notably less consistent across the classes than for the environmental and socio-economic factors, suggesting that these demographic influences were important predictors of being in particular lower-carbon classes, but not of all lower-carbon lifestyles.

More intriguing was the pattern in relation to household composition, as larger households and those with children have been often associated with higher meat consumption (Leahy et al., 2010), more car travel (Büchs and Schnepf, 2013, Brand et al., 2013) and higher carbon emissions overall (Büchs and Schnepf, 2013, Baiocchi et al., 2010). Although the *Always/Exclusive car commuters* typically lived in larger households with a partner and children in both samples, an unexpected pattern in the UKB multivariate models was that many of the lower-carbon classes were *more likely* than Class 1 to live in larger households with their partner and son/daughter. One explanation for this result could be the fact that there was no information on the age of the 'son/daughter' in UKB, which means this category could include 'adult children' still living at home with their parents. In support of this interpretation, all of the classes that exhibited this association were also more likely to live in urban areas where this pattern may be augmented by higher housing costs, which suggests there may be residual confounding by residential location. This relationship should be investigated further in other studies with more representative samples, as it runs counter to the commonly accepted narrative of carbon emissions over the life course, whereby younger people tend to start out with lower-carbon lifestyles and then adopt more high-carbon behaviours as they progress through life, before dropping again at older ages (Clark et al., 2014, Büchs and Schnepf, 2013). Importantly, these findings suggest that this may not be an inevitable path for all population groups and that lower-carbon lifestyles are not necessarily incompatible with larger households and families[100]. Again, these patterns reflect the interplay that exists between different environmental and demographic influences in shaping people's overall lifestyles.

[100] Although notably, a recent study has argued that having one fewer child is the most effective way to reduce one's personal carbon footprint (Wynes and Nicholas, 2017).

6.4.2.4 *Summary and comparison with other clustering studies*

Broadly speaking, these patterns are consistent with theories of clustering that stem from ecological frameworks, whereby clustered behaviours (e.g. HLC lifestyles) are more likely to share predictors that are more distal and wide-ranging (e.g. environmental context) than predictors that are more proximal (e.g. demographic factors) (Flay and Petraitis, 1994). This does not mean that demographic factors are not important: though they were the least consistent predictors of lower-carbon lifestyles across all classes, they were strong predictors of certain classes, and particularly those with mixed lifestyles (e.g. *Low meat car commuters*) where higher- and lower-carbon behaviours were less clustered. Together, these findings suggest that all 'layers' of influence are important, but the predictive value of each layer may vary by type of lifestyle, which indicates that structuring the variables in this way has been shown to be empirically meaningful.

Notably, these results also have parallels to the findings of other clustering studies that have examined travel and dietary behaviours separately in the UK population using different samples, indicators, and clustering methods. For example, several of the classes I observed in my samples have many similarities to groups previously detected in a recent segmentation of the English population (n=3,492) based on transport choices and attitudes to climate change (Costley and Gray, 2014). In particular, two of the groups identified in this segmentation study, Educated suburban families (17%) and Town and rural heavy car use (13%), closely resemble my class of *Always/Exclusive car commuters*, and together, make up a comparable proportion of the population (~30%). Similarly, other segments such as the Affluent Empty Nesters (9%), Older less mobile car owners (9%), and Less affluent older sceptics (12%) also shared many common features with my classes of *Mixed/Mostly car non-commuters* (21-36%), which indicates that there is likely greater diversity within these classes than was captured by my models. Importantly, these similarities and differences highlight the fact that clustering and segmentation results will vary based on the indicator variables that are used, and they also show that there is a trade-off between focusing on a single behaviour area to gain more detailed insights, and understanding the broader context of people's lifestyles and how multiple behaviours intersect. Another illustration of these trade-offs can also be seen when comparing my results to other dietary clustering studies, as these studies included more food groups, and detected more detailed dietary patterns, though both are based on data that is approximately 20 years old (Fahey et al., 2007, Greenwood et al., 2000).

6.4.2.5 HLC lifestyles and health outcomes

In UKB, the most consistent pattern for indicators of health was in relation to BMI, as all 17 classes among both males and females were significantly less likely to be overweight or obese compared to the *Exclusive car commuters.* This relationship may be primarily due to differences in travel behaviour, as this was the major distinguishing factor between the classes and existing evidence has shown that each additional hour spent in a car per day is associated with a 6% increase in the likelihood of obesity (Frank et al., 2004). Nevertheless, among the *Low meat car commuters*, a group who had a similarly high amount of car use to the *Exclusive car commuters*, consuming no RPM was associated with similar reductions in BMI.

These findings are consistent with previous UK research linking walking, cycling, and public transport use to lower BMIs both cross-sectionally (Laverty et al., 2013, Flint et al., 2014, Flint and Cummins, 2016) and longitudinally (Martin et al., 2015, Flint et al., 2016), as well as with cross-sectional evidence from two UK cohorts associating higher BMIs with higher meat consumption (Cade et al., 2004, Spencer et al., 2003). To my knowledge, however, my results are the first to examine both of these behaviours together, and I found that the groups with the lowest odds of overweight/obesity were those that had *both* HLC travel *and* HLC diets, though these were different classes among males and females (*Low meat mixed commuters* and *Cyclists*, respectively). This finding suggests that there may be positive synergies between these two HLC behaviours with respect to energy balance, and warrants further examination and replication in more representative and longitudinal studies.

There was also some evidence that members of lower-carbon classes had better self-rated health, particularly the cycling and low meat-eating groups, which were most likely to rate their health as ‘excellent’ or ‘very good’ and least likely to report any long-term limiting conditions. Notably, self-reported health is a strong predictor of mortality (Schnittker and Bacak, 2014), and cycling and low-meat diets have both been associated with reduced mortality in other studies (Celis-Morales et al., 2017, Soret et al., 2014, Scarborough et al., 2012). Of course, as these are cross-sectional relationships, an important caveat of all of these findings is that is it impossible to tease out whether HLC lifestyles actually result in better health outcomes, or whether those who are already in better health are more likely to adopt HLC behaviours. Indeed, this is an important consideration given that some classes may be more car-dependent (and thus higher-carbon) for mobility reasons, particularly the older groups who reported more long-term and limiting conditions across all four samples. When considering these older, non-commuting groups as a whole, however, the classes who reported the worst health (e.g. *Low FV non-commuters*, *PT non-commuters*) were generally less car-dependent than the classes who reported having better health (e.g. *Mostly car non-commuters*), which suggests that poor mobility does not necessarily equate with car dependence in the UK population.

6.4.3 Strengths and limitations

6.4.3.1 Datasets

Limitations of these datasets have already been discussed in previous chapters, however they are particularly apparent here as the size of the NDNS and the representativeness of UKB were somewhat problematic for the analyses in this chapter. Most notably, in the NDNS the small samples in the lower-carbon groups made it very difficult to detect predictors of these classes, and though this was not a problem in UKB, it was not ideal that the UKB samples were based on a ‘highly selected’ population (Galante et al., 2016) in a more limited age group (40-70). This raises questions about whether the results from the UKB analyses are entirely generalizable to the UK population as a whole, and particularly to those under age 40. In the NDNS for example, the *PT commuters* and *Walking commuters* tended to be very young (16-24) but in UKB these classes were both less likely to be younger than the *Exclusive car commuters*.

These limitations also affected my ability to detect whether predictors of different lifestyles varied by gender. Though the profiles and predictors of each class tended to be the same among males and females in UKB, this similarity may have been due to the non-representativeness of the sample, since many of the study participants were living together as couples, which would explain why their behaviour patterns were more similar and associated with the same factors. As in previous chapters, there seemed to be more distinctions among males and females in the NDNS, however the small number of participants, particularly among males, led to low statistical power in the search for predictors and made the class profiles unclear.

Strengths of the datasets were mainly the wide range of factors I was able to examine at different layers of influence, though I did not have data on other factors that are of interest in socio-ecological frameworks, such as individual preferences, social norms and relationships, and environmental features such as proximity to active travel infrastructure or different types of food outlets (Bopp et al., 2012, Sherwin et al., 2014, Ogilvie et al., 2012, Fraser et al., 2010). Further research incorporating more of these elements would contribute to greater understanding of the influences underlying these different lifestyle groups.

6.4.3.2 Analysis

Limitations of the analysis included the fact that all of the associations I detected were cross-sectional, which means that causality cannot be assumed, even in the case of the very strong associations observed for car ownership and region of the UK. Though where someone lives may certainly influence their behaviour, it may also be the case for some individuals that their (desired) behaviour determines where they decide to live (Molin et al., 2016). In other words, people with a preference for active travel may choose to live in places where car ownership is not necessary and walking and cycling are popular modes of transport. Relatedly, the predictor analysis in this chapter was also limited by the fact that the associations observed here largely describe the predictors of different commuting modes, since these variables were best represented by the LCA models (for more details refer back to Chapter 5 section 5.4.3.2).

A major strength of the analysis was the use of two datasets to compare my findings and help minimize the limitations inherent to each sample. Though I was only able to examine bivariate relationships in the NDNS analysis, the UKB analysis was more robust: associations were adjusted for a wide range of factors and I re-ran the models in multiple ways to examine the impact(s) of classification error and missing covariate data on the effect estimates. Nevertheless, despite these differences in the analyses used for each sample, the overall findings appeared to be broadly supportive of one another, as the *Always/Exclusive car commuters* were patterned almost identically in both samples and similar associations were also identified in several of the lower-carbon groups, though the larger size of UKB often allowed for more fine-grained detail in this regard. For example, in UKB I was able to detect that cyclists were more common in Oxford (similar to South West in the NDNS) and that the low meat eating groups were more likely to be South Asian (similar to non-White in the NDNS).

6.4.4 Implications

The results of this chapter have several implications. First, in relation to promoting and expanding HLC lifestyles, these findings suggest that environmental influences are most important, which indicates that initiatives should be directed at the wider physical and socio-cultural conditions that currently foster UHC lifestyles throughout most of the UK. For travel behaviour, this will likely require greater investments in transport infrastructure to increase the availability and efficiency of public transport, as well as strategies to increase the visibility and normalisation of active travel (particularly cycling) as safe and viable forms of personal transport (Pucher et al., 2010b). According to the UK government's recent *Cycling and Walking Investment Strategy* (DfT, 2017a), such changes may be already underway in relation to active travel, as more than £1 billion is being invested over the next five years to help make "cycling and walking the natural choices for shorter journeys" (p. 1).

Meanwhile, there is also evidence that changes are starting to occur in the dietary environment regarding the provision and accessibility of plant-based food options; for example, three meat-free locations of Pret A Manger (Veggie Pret) have opened in 2016-2017 (Pret A Manger, 2017) and more vegetarian and vegan options are now being offered at British supermarkets than ever before (Smithers, 2017). These changes appear to be largely led by the food industry, in response to consumer demand driven by combined health, environmental and animal-welfare concerns (Marsh, 2016). Though industry-led dietary change is not necessarily problematic, these shifts are almost certainly more about profit than achieving public health or environmental goals, and it is critical to remember that consuming only plant-based foods is not invariably associated with positive health outcomes. For example, a recent systematic review found that low-carbon diets have the potential to be high in sugar and low in essential micronutrients, and suggested that dietary guidelines integrating both health and sustainability are needed to address these issues and make them clear to consumers (Payne et al., 2016).

Several other countries (e.g. Sweden, Netherlands, Germany, Brazil) have already incorporated environmental sustainability into their national dietary guidelines (Head, 2017), and this is also something that should be considered by the UK since there is evidence that the public wants government leadership on the issue of low-carbon diets (Wellesley et al., 2015). Recommendations of this nature would also help to increase public awareness of the connections between diet and climate change, which is an on-going knowledge gap that needs to communicated more clearly (Macdiarmid et al., 2016, Clonan et al., 2015, Bailey et al., 2014). Though information alone is unlikely to result in extensive dietary change, the strong associations I observed between higher education and lower-carbon lifestyles across the majority of classes suggests that knowledge can play a critical role if the wider environment is also supportive of change.

In addition, another implication of this work is that strategies targeting higher-carbon lifestyles need to recognise the diversity of these lifestyles in the UK population, and the realities of their circumstances. For example, there has been a large amount of research and policy focus on active commuting (Flint et al., 2014, Flint and Cummins, 2016, Martin et al., 2014a, Celis-Morales et al., 2017), but my findings show that less than half of the UK adult population currently commutes by car. Of those who are car commuters, I identified only a small proportion (*Mixed car commuters*, 8% of males and females in UKB) that was more likely to live in urban areas where other transport options may be readily available or feasible. This shows the need for a broader approach beyond the promotion of active commuting as the primary way of achieving a HLC lifestyle, as not all higher-carbon groups commute, and not all have different commuting options available to them, particularly if they are located in areas with few travel alternatives. As a result, cultural shifts aimed at decreasing meat consumption, focused on populations in less urban areas, may offer a more immediate way forward. Such dietary changes may have the potential for more widespread impacts, as they would be relevant to a larger proportion of the population, including those who may be unable to change their travel behaviour for accessibility or mobility reasons.

In the context of fiscal policies (e.g. carbon taxes), my findings also suggest that some groups may be able to bear these additional costs better than others. In this line of thinking, the *Mixed/Mostly car non-commuters* might be of particular concern, as these classes predominantly travelled by car and often had higher than average RPM consumption, but also had lower incomes and were less economically active. Although these groups did not spend as much time driving as the *Exclusive car commuters*, other research has shown that older, non-working populations often travel for food shopping, and may generate a disproportionate amount of emissions for this purpose (Mattioli and Anable, 2017). Dietary carbon taxes also tend to be economically regressive, though it has been argued that less affluent groups stand to gain the largest health benefits from such policies, since those in lower socio-economic classes often consume larger amounts of RPM (Maguire and Monsivais, 2014) and tend to have a higher prevalence of chronic disease (Briggs et al., 2013). As taxes on meat are increasingly being seen as “inevitable” (Springmann et al., 2016b, Carrington, 2017), it will be even more important for governments to understand how vulnerable groups will be affected by such policies, by assessing the full impacts of people's lifestyles across different domains.

6.5 Conclusions and Chapter 6 summary

To my knowledge, this is the first study to examine predictors of health- and climate-relevant lifestyles in the UK or elsewhere. In this chapter I have shown that higher- and lower-carbon lifestyles, defined on the basis of travel and dietary behaviour, are associated with a multitude of factors involving several layers of influence. Environmental factors (e.g. population density, region of the UK) seemed to be most important for distinguishing between higher-carbon and lower-carbon lifestyles, whereas demographic (age) and socio-economic (income, education) factors primarily distinguished between those with higher-carbon and mixed lifestyles. There was also some evidence that people with more HLC lifestyles had better health indicators (BMI, self-reported health), however longitudinal data are needed to assess whether these relationships are causal.

7 General Discussion

Chapter summary: Previous chapters have discussed the findings, strengths and limitations, and implications of each set of analyses in detail, so this final chapter will focus on integrating these aspects together for the whole thesis. The chapter begins by summarising the main findings from this thesis, the new insights that have been gained, and the overall implications from this study. In the second section, I critically reflect on my overall study design, highlighting strengths and shortcomings, and describe several strategic directions for future research. The chapter concludes by reiterating the originality of the study and its place in the wider research context.

7.1 Summary of main findings and contributions to knowledge

The overall aim of this thesis was to advance current understanding of the patterning, prevalence, and predictors of health- and climate-relevant lifestyles in the UK, based on combinations of travel and dietary behaviour. This aim was achieved across the three analytical chapters of this thesis (Chapters 4, 5 and 6), whose findings complement, reinforce, and build upon each other to enhance existing knowledge of the relationship(s) between travel modes and dietary consumption in the UK context, including *how* and *why* they may cluster together.

7.1.1 Associations between travel modes and dietary consumption

In Chapter 4, I focused on the patterning objective and examined whether there were associations between use of HLC travel modes and markers of a HLC diet (increased FV, reduced RPM). To my knowledge, this was the first time relationships between these behaviours had been explicitly examined, as previous research had primarily focused on associations between general physical activity and FV consumption (Tormo et al., 2003, Noble et al., 2015, Parsons et al., 2006, Poortinga, 2007), or on behavioural intentions between engaging in more environmentally friendly travel and reduced meat consumption (Van der Werff et al., 2013, de Boer et al., 2016, Lee and Simpson, 2016). As a result, this chapter was intended to be somewhat of a ‘proof of concept’ to establish whether travel behaviour and dietary consumption were in fact related, as previous authors had proposed that there might be potential synergies between these behaviours that could be enhanced by well-designed policies (de Nazelle et al., 2011).

Here my analysis revealed that engaging in active travel, and particularly cycling travel, was associated with increased consumption of FV and with reduced consumption of RPM in both the NDNS and UKB. These associations suggest that active travel and HLC diets are connected in some way and may share similar aetiologies in the UK population (McAloney et al., 2013, Flay and Petraitis, 1994). In nearly all cases, the relationships I observed remained independent to adjustment for socio-demographic, environmental, and lifestyle variables, suggesting that these factors do not completely explain the associations. As a result, the main finding and contribution to knowledge from this chapter is that there are indeed clear links between engaging in active travel and consuming a HLC diet, and that a better understanding of the factors underlying and driving these relationships may contribute to more effective promotion of HLC lifestyles in the UK. These findings support the hypothesis of previous authors (de Nazelle et al., 2011), and help to advance the idea that there may be potential synergies between active travel and dietary consumption. For example, if engaging in active travel (particularly cycling) subsequently leads people to also adopt HLC dietary changes, then facilitating HLC travel has the potential to create positive synergies for public health and climate change. Though longitudinal data is ultimately needed to disentangle the dynamics between these behaviours, the results of this chapter provide some of the first evidence that HLC behaviours may have the potential to mutually reinforce one another, and that well-designed policies to promote these behaviours could lead to enhanced benefits for both human health and the natural environment.

7.1.2 Prevalence and patterning of health- and climate-relevant lifestyles

In Chapter 5, I expanded on these initial findings by investigating the full distribution of travel and dietary behaviour patterns in the samples, which I then used to estimate the prevalence of health- and climate-relevant lifestyles among males and females in both datasets. The aim of this analysis was to provide a more comprehensive assessment of the different travel- and diet-related lifestyle groups existing in the UK in order to identify segments of the population for which behaviour change would result in the greatest gains in emissions reductions and health outcomes. Here my decision to combine several travel and dietary behaviours was a particularly novel approach as previous studies had only examined carbon emissions from travel and diet separately (Brand et al., 2013, Mattioli and Anable, 2017, Scarborough et al., 2014, Hoolohan et al., 2013), and other research on higher-carbon lifestyles had restricted their focus to CO_2 emissions and therefore not fully examined the role of meat consumption (Büchs and Schnepf, 2013, Druckman and Jackson, 2009, Baiocchi et al., 2010). In particular, it was not clear to what extent car travel and RPM consumption would overlap or cluster together, as these behaviours are known to follow opposite social gradients in the UK population (DfT, 2016b, Maguire and Monsivais, 2014, Aston et al., 2013).

In this chapter my main finding was that the largest groups in both the NDNS and UKB were characterised by predominant car use and higher than average RPM consumption, which indicates that these UHC behaviours do cluster together in large proportions of the UK population (47-80%). Comparing the distribution of these behaviours across the classes, there was some evidence that car travel was particularly concentrated in certain groups, whereas high RPM consumption was more widespread throughout the population. In addition, this chapter also precisely quantified how rare HLC lifestyles truly are, as only 2-5% of the samples in the NDNS and UKB had travel and dietary behaviour that were *both* classified as HLC. This low prevalence helps to highlight that there is considerable potential for achieving health and environmental gains from even small shifts in travel and dietary behaviour. Lastly, this chapter also identified that there are several groups that had mixed lifestyles (travel and diet in opposite directions), which were most common among females and in the NDNS. Notably, these mixed lifestyle patterns make clear that behaviours with similar impacts (e.g. UHC or HLC) do not always share the same underlying factors, despite the fact that they may cluster together in some population groups.

Together, these findings represent an important contribution to knowledge as they provide a more comprehensive understanding of people’s lifestyles with regard to the patterning of health- and climate-relevant behaviours in the UK context. Importantly, though this chapter revealed that HLC and UHC behaviours both cluster together in certain segments of the population, it also showed that this clustering seems to be most strong among the rare groups with HLC lifestyles, due to the higher degree of overlap between HLC behaviours. This suggests that HLC lifestyles likely share more common underlying factors than do UHC lifestyles, as the latter were typically clustered to a lesser extent.

7.1.3 Predictors of health- and climate-relevant lifestyles

Having determined *how* travel and dietary behaviours cluster in Chapters 4 and 5, in Chapter 6 I focused on identifying predictors of different health- and climate-relevant behaviour patterns, using a socio-ecological framework based on the social determinants of health (SDH). Using this framework, I conceptualised my predictors as being organised into three different layers of influence: environmental, socio-economic, and demographic. Previous research had examined these influences in relation to travel modes and dietary consumption separately (Laverty et al., 2013, Hutchinson et al., 2014, Maguire and Monsivais, 2014, Leahy et al., 2010), but to my knowledge, this was the first study to examine predictors of lifestyles based on both of these behaviours, clustered into different health- and climate-relevant lifestyle groups.

Here my analysis pointed to environmental context (e.g. population density, region of the UK) and socio-economic factors (e.g. education level, car availability) as being the most important predictors for distinguishing between UHC and HLC lifestyles, whereas demographic and socio-economic influences primarily distinguished between those with UHC and mixed lifestyles. More specifically, I found that HLC lifestyles were most strongly and consistently associated with higher qualifications, reduced car access, and living in more urbanised environments such as London, which is generally in line with previous research, particularly related to lower-carbon travel (Hutchinson et al., 2014, Laverty et al., 2013, DfT, 2015b, Goodman, 2013, Leahy et al., 2010). UHC lifestyles were patterned more diversely, and three distinct profiles of these lifestyles emerged based on different combinations of factors: *Always/Exclusive car commuters* (White, working age, living with partner and children, higher household incomes, more cars per household); *Mixed/Mostly car non-commuters* (older, not in current employment, living in smaller households in more rural areas); and *Usual/Mixed car commuters* (younger, living in more urban and deprived areas). Together, these patterns reflect the interconnections that exist between the different influences in the SDH framework: though wider environmental context (where people live) most strongly predicts whether individuals will engage in higher- or lower-carbon behaviours, who they are (demographics) and the resources available to them (socio-economic conditions) also play an important role in shaping the extent to which their behaviours cluster into different types of lifestyles.

In addition, the other main finding in this chapter involved examining associations between HLC lifestyles and different health outcomes, where I found that those who engaged in multiple HLC behaviours had the lowest odds of overweight/obesity and better self-rated health. Though these relationships need to be examined longitudinally to rule out reverse causality, this is the first time such associations have been reported, so they also make a novel contribution to research evidence.

7.1.4 Summary and overall implications

Together, these findings have made several contributions to understanding health- and climate-relevant lifestyles in the UK context. Firstly, this thesis has shown that there are clear relationships between HLC travel modes (particularly cycling) and markers of a HLC diet (particularly FV consumption). Secondly, it has shown that there are many different patterns of travel and dietary behaviours, and these can be broadly grouped into UHC, HLC, and mixed lifestyles, with the first type being most prevalent and the second type most rare. Finally, this thesis has also identified that environmental and socio-economic factors were the most important predictors of HLC lifestyles, suggesting that these types of influences may help explain why UHC and HLC behaviours cluster together in certain subsets of the UK population.

Overall, these findings have several important implications. These have been previously discussed in detail in Chapter 4 (section 4.4.5), Chapter 5 (section 5.4.4) and Chapter 6 (section 6.4.4), but will be summarised briefly here for integration across the thesis as whole.

The first implication, stemming from Chapters 4 and 5, is that the clustering between HLC behaviours and between UHC behaviours suggests that each of these lifestyle patterns may be driven by similar underlying factors, and that there may be opportunities to target and shift travel and dietary behaviours together. Doing this successfully however, will require further research into how and why travel and dietary behaviours are linked in the UK population, as well as the extent to which different behaviours share common upstream determinants in certain clusters of people. Based on the results of Chapter 6, the most important predictors of HLC lifestyles were environmental and socio-economic factors, and this suggests that interventions directed at these influences may have the greatest potential for increasing HLC lifestyles in the UK. This involves contemplating the ways in which higher-carbon lifestyles are structured by society and how consumers often become ‘locked in’ to consumptive patterns of behaviour due to factors beyond their control (Egger, 2008, Shove, 2010, Shwom and Lorenzen, 2012). In other words, just as we accept that certain environments may be ‘obesogenic’ (i.e. promoting obesity) (Jones et al., 2007), we must also consider that our physical and social environments have the potential to be ‘envirogenic’ (Shove, 2010), meaning that they promote more sustainable (and healthy) ways of life. Facilitating HLC behaviour change means creating the structural conditions for change to occur, but also recognising that different population groups may have different capacities to change based on their own unique circumstances.

Notably, interventions of this scale and scope suggest a need for government involvement, and though there is some existing evidence for policies and investments in the area of HLC travel (DfT/DH, 2010, DfT, 2017a, HM Government, 2017), there appears to be little (if any) in the area of HLC diets (CCC, 2018). This seems problematic for several reasons. Firstly, because dietary consumption is associated with more GHG impacts than travel (Hoolohan et al., 2013, Brand et al., 2013), and secondly, because my findings suggest that high RPM consumption may be more widespread than car travel in the UK population. In addition, it is possible that changes in dietary consumption may be easier to achieve on shorter timescales, as they typically require fewer changes to large-scale infrastructure, and there is already some evidence that significant dietary shifts are happening in the UK (Marsh, 2016, Vegan Society, 2016, Smithers, 2017), perhaps more so than for travel behaviour (Goodman et al., 2013, DfT, 2018).

More broadly, my findings of relationships between travel and diet also point to the need for more comprehensive, holistic approaches to research and policy initiatives related to HLC lifestyles, including the need for more integration and understanding across the interlinked areas of travel and dietary behaviour. This implies a need for more 'joined-up' policy-making across different sectors and ministerial departments. As mentioned previously in Chapter 5, one illustration of this approach can be seen in Scotland's *Low Carbon Behaviours Framework*, in which several different elements of low-carbon lifestyles including transport and food consumption are discussed, promoted, and measured together (Scottish Government, 2013). Another example, albeit less integrated across different sectors, is the UK government's new *Cycling and Walking Investment Strategy*, which is led by the Department for Transport but features links with the Department of Health and Public Health England, among several other departments and organizations (DfT, 2017a). This new strategy builds on the earlier *Active Travel Strategy* (now archived), which was jointly published by the Department for Transport and the Department of Health (DfT/DH, 2010). At a minimum, comparable cohesive efforts strategically directed at HLC diets should also be prioritised. As recently stressed by the Committee on Climate Change (CCC), if the government does not take urgent action to strengthen its existing policies and find new ways of reducing emissions (particularly in the area of food and agriculture), the UK is currently on track to miss its legally binding climate change targets (CCC, 2018).

Since the government is currently designing its new agricultural strategy post-Brexit (Defra, 2018b), this is a prime opportunity to integrate food production in the UK with other health and environmental policy goals. As highlighted by several organizations, steps in this direction could include prioritising and increasing production of UK horticulture (Food Foundation, 2017) and plant protein crops (Speranza and Marquès-Brocksopp, 2015), but thus far there is no mention of links with diet or human health in the current agricultural strategy (Defra, 2018b). This is notably in direct contradiction with the recent recommendation from the CCC that new policy proposals to tackle carbon emissions should be integrated with other policy priorities such as human health (CCC, 2018).

Importantly, these suggestions for greater integration in relation to HLC lifestyles are also in line with existing government research priorities. A strategic priority for Defra, for example, is more research on 'cross-cutting issues' such as how activities in the UK impact on the natural environment globally and how different pressures in these areas (e.g. travel and dietary behaviours) may interact with one other (Defra, 2017). Defra has also just published its new 25 Year Environment Plan, which features a whole chapter linking the environment to human health and wellbeing (Defra, 2018a). Relatedly, in the Department of Health, an on-going research priority relates to understanding the drivers of 'healthy and unhealthy behaviours' and of 'lifestyle diseases' and obesity (DH, 2017)—this too would be well-served by more integrated efforts to study the links between travel and dietary behaviours and the health outcomes associated with HLC lifestyles. More research is particularly needed on understanding the dynamics between travel and dietary behaviours over time and across the life course if we are to design interventions targeted at multiple behaviours, and to shift them towards more HLC lifestyles without unintended consequences.

With regard to designing interventions, it is also worth reflecting on how cluster analyses are used to group people by their behaviours and lifestyles in other disciplines that are not health-related, such as geodemographics and market research. Geodemographics is a form of area-level classification which groups people with similar demographics and neighbourhood characteristics into small geographic units (Vickers and Rees, 2007), whereas market research uses many diverse pieces of information to group people into detailed 'segments' of the population so that each segment can be targeted in a personalized way (Vidden et al., 2016)[101]. Both of these applications of clustering are designed to identify homogenous groups from within a heterogeneous population (Laska et al., 2009), so that each different group can be understood and influenced using the most effective strategy. This has particular implications for designing interventions to change behaviour, because people are more

[101] See, for example: https://www.experian.co.uk/marketing-services/products/mosaic-uk.html

likely to respond to initiatives that are precisely targeted to their individual needs and ways of life (Costley and Gray, 2014).

In the context of this thesis, this suggests that behaviour change interventions directed at UHC groups like the *Always/Exclusive car commuters* and the *Mixed/Mostly car non-commuters* may need to be designed differently, as these groups had diverse socio-demographic profiles and patterns of behaviour, and largely represented distinct stages of life. For example, though both of these groups were heavy car users, their car travel was for different purposes and at different frequencies, which implies that interventions targeted at reducing car use among car commuters would not necessarily be effective at reducing car use among non-commuters who travel by car for other reasons. In line with this approach of targeting specific groups based on their unique profiles, it may also be useful to examine additional data outputs that are available from LCA, such as the probabilities of class membership given different socio-demographic characteristics[102]. Though these probabilities were not presented in this thesis, they are worth considering in future research, as they may offer a more intuitive way of understanding the relationships between external predictors and different types of health- and climate-relevant lifestyles.

7.2 Critical reflection on overall study design

7.2.1 Examining travel and dietary behaviours together

My decision to examine travel and dietary behaviours together was a novel approach that had not been previously attempted in the areas of health or environmental behaviour research. The strength of this approach was that it led to several new insights into the patterning (Chapters 4 and 5), prevalence (Chapter 5) and predictors (Chapter 6) of health- and climate-relevant lifestyles that would not have been possible without combining these areas together.

Nevertheless, my attempt to combine and explore both of these behaviour areas together did not always work as well as I had intended. The best example of this was in the LCA models in Chapter 5, where the latent classes were more strongly driven by commuting behaviour than by dietary consumption. The result of this was that the models explained very different amounts of variation in travel and dietary behaviours,

[102] For an example of this approach, see Graham et al. (2016).

which meant that the predictor analysis in Chapter 6 yielded more insights into predictors of travel behaviour than of dietary consumption. To improve on this, future research could consider including additional dietary indicators (e.g. more food groups) in similar models to give more weight to dietary factors, however this also creates other problems in finding a model that adequately explains the relationships between all indicators. These challenges emphasise the fact that multiple behaviour approaches are useful for understanding broad lifestyle patterns, but single behaviour approaches are still important for gleaning detailed insights into specific behaviours. A good example of such trade-offs was previously described in Chapter 6 section 6.4.2.4 where I compared my latent class models to other clustering studies that focused on travel (Costley and Gray, 2014) or diet alone (Fahey et al., 2007, Greenwood et al., 2000). The strength of these studies is that they can provide a more detailed understanding of how individual behaviour areas are clustered in the population, but their weakness is that they provide no information on people's overall lifestyles with regard to health outcomes or climate change impacts.

7.2.2 Use of two datasets

As reiterated previously, the use of two datasets to compare and replicate my findings was a major strength of my approach, as there were important limitations inherent to each data source that would have made it questionable to draw conclusions from either study alone. Reflecting on the results from across this thesis, had I only used the NDNS sample, the results from Chapters 4 and 6 would have been particularly limited due to the very small number of cyclists (in Chapter 4) and even smaller number of individuals in several of the HLC classes (in Chapter 6). In contrast, had I used UKB alone, there would not have been issues with sample size, but there would have been major questions around the external validity of my findings since this is the first study to examine these topics and UKB is known to be non-representative of the UK general population (Fry et al., 2017). Indeed, only using UKB would have been especially problematic in Chapter 5, where I used a 'highly selected' sub-sample of UKB to derive my LCA models (e.g. a subset of UKB that was older, more White, female, and educated than the rest of UKB, which was already more White, female, and less deprived than the rest of the UK population) (Galante et al., 2016). As a result, having the NDNS sample to compare with here was a very important strength that bolstered my findings.

Nevertheless, the obvious drawback to using two datasets was the duplicative nature of my analysis and results, which were more complicated to summarise and interpret than if only one dataset had been used. Replicating my results also made my analytical chapters quite lengthy and dense, and prohibited my ability to explore additional research questions, such as how health- and climate-relevant lifestyles vary over time (using repeat assessment data in UKB), or whether there is spatial clustering among people with similar lifestyles (using UK grid coordinates in UKB). Both of these are potential avenues for future research that would build on the findings of this thesis.

7.2.3 Gender stratification

Another duplicative aspect of this study was the decision to stratify all of my analyses by gender. This was a decision I made *a priori* on the basis of existing evidence on the patterning of travel mode use and dietary consumption among males and females in the UK. In particular, the vast majority of dietary studies I reviewed used sex-stratified analyses (Bates et al., 2014, Bates et al., 2016, Fahey et al., 2007, Fahey et al., 2012, Aston et al., 2013, Green et al., 2015, Greenwood et al., 2000, Parsons et al., 2006, Slimani et al., 2002), as this is the most appropriate way to examine well-known differences in food consumption (quantitative and qualitative) among males and females. Similarly, other studies of behavioural clustering involving diet and physical activity also stratified their analyses by gender (Graham et al., 2016, McAloney et al., 2014, Buck and Frosini, 2012, Poortinga, 2007, Laska et al., 2009), as did several others on active travel (Flint et al., 2014, Flint and Cummins, 2016, Falconer et al., 2017). Based on this literature, I suspected that the relationships between travel mode use and dietary consumption might vary between males and females, and when I found this to be true in my first set of analyses (NDNS, Chapter 4 section 4.3.1), I maintained the stratification throughout the rest of the thesis.

Upon reflection, this decision had both strengths and limitations. One major limitation of stratification was that it doubled all of my results and analysis; another was that I was not able to directly test whether there were quantitative differences between the male and female results. To do this, other approaches I could have used include interaction terms in my regression models (Chapters 4 and 6) or multiple-group LCA using gender as a grouping variable (Chapter 5). In Chapter 4, using interaction terms for gender would have allowed me to quantitatively assess whether associations were different between males and females, but this approach would have been limited by small sizes in the NDNS and interpretation would have been particularly complex when generalised ordered logit models were used. In Chapter 5, use of multiple-group LCA would have quantitatively assessed whether the underlying structure between travel and dietary behaviour was different between males and females in each sample by testing for measurement invariance across genders (Lanza et al., 2010). Based on the results of Chapter 4, it seemed likely that there were gender differences in the NDNS samples but not in the UKB sample, and so performing this test might have given conflicting results in each dataset that would have been problematic for my comparison.

Nevertheless, stratification also had some distinct advantages. Strengths of this approach included the fact that it was consistent with previous literature and made my findings more easily interpretable, which is particularly important for research that is policy-facing. It also allowed me to detect more subtle, descriptive gender differences in the patterning between travel and dietary behaviours and in the prevalence of health- and climate-relevant lifestyles that are informative for an exploratory study. In Chapter 4 for example, I observed that there were opposing relationships between cycling and RPM consumption and between walking and FV consumption among males and females in the NDNS, though these patterns were not always statistically significant. In Chapter 5 I detected an additional behaviour pattern (latent class) in each female sample, a higher prevalence of mixed lifestyles among females in both samples, different HLC groups among males and females, and ultimately found that the latent class behaviour patterns were more similar within genders than within datasets.

7.2.4 Theoretical framework

In this thesis, my theoretical framework was based on a socio-ecological representation of the SDH. This approach was chosen for several reasons. As described earlier (see section 2.3), socio-ecological models are frequently used to study and understand travel and dietary behaviours (Glanz et al., 2005, Sallis et al., 2006, Kamphuis et al., 2006, Sallis and Glanz, 2009, Badland et al., 2013), however usually these models are behaviour-specific. In fact, this is a common issue to most theoretical models of health behaviour, as these frameworks tend to focus on representing single behaviours in isolation, rather than as part of a wider lifestyle (Noar et al., 2008, Hagoel et al., 2002). As a result, there are actually few studies of clustering based around specific theoretical frameworks, however the SDH framework is an exception to this as it is commonly used in public health and epidemiological research to understand how lifestyles are socially structured, and to explain why unhealthy ‘risk’ behaviours often cluster in disadvantaged groups (Noble et al., 2015, Meader et al., 2016, Buck and Frosini, 2012). Since the SDH model is more broad than other types of socio-ecological frameworks, its ‘layers’ are flexible enough that they can be adapted to accommodate multiple behaviour areas with many different influences. Use of this framework was also well aligned with my datasets since health surveys and epidemiological studies typically collect information on socio-demographic determinants, as they often act as confounding factors.

Nevertheless, this approach was also not without its limitations. Though my framework was based on a socio-ecological perspective, it was not a typical socio-ecological model in which factors can be organised into distinct levels (e.g. individual, workplace, community, society), and which lends itself more clearly to interventions at several different levels of influence (Schneider and Stokols, 2009, Sallis et al., 2008). For example, some of my demographic and socio-economic factors were a mix of both individual (e.g. education), and household-level (e.g. household income, household size) variables. Though my framework helped to conceptualise the various factors as differences types of influences, my results ultimately highlighted that these theoretical ‘layers’ are interlinked in reality, and thus cannot be considered or targeted in isolation. Relatedly, though I was able to represent the SDH fairly well with the data I had available, I was also missing many factors commonly represented in socio-ecological frameworks, such as social networks and relationships, individual values and attitudes, and detailed characteristics of the physical and cultural environments (Stokols, 1992, Glanz et al., 2005, Sallis et al., 2006, Sallis et al., 2008). Lack of detail in the wider environment was particularly limiting, as I was able to identify that environment factors are critical determinants, but then not able to identify the specific contextual details that made them important. Ideally, these missing details should be captured and better incorporated in further research, to improve our understanding of the role played by environmental features, individual preferences, and social factors as predictors of health- and climate-relevant lifestyles. This might help to more clearly pinpoint what the common factors and shared determinants between different types of related behaviours may be.

7.3 Strategic directions for future research

There are several strategic directions for future research stemming from this thesis.

7.3.1 Better understanding of dynamics between multiple behaviours

Firstly, there is a need for more research into the relationships between different types of behaviours, and particularly into the dynamics that exist between multiple behaviours over time. This thesis has begun to provide some clarity regarding which health- and climate-relevant behaviours occur together cross-sectionally, but there is still relatively little research and understanding of the dynamics between travel and dietary behaviours across the life course as well as the process(es) through which people approach multiple behaviour change (Meader et al., 2017). For example, findings from a qualitative UK study of changes in diet and smoking behaviour have shown that multiple behaviour change can operate in both ‘vicious’ and ‘virtuous’ cycles, whereby perceived failure in one area of behaviour change can trigger failure in another area, and positive achievement in one area can trigger successful changes in another behaviour (Koshy et al., 2012). These results are similar to theories of positive and negative spillover in environmental psychology (Truelove et al., 2014, Nash et al., 2017), which suggests that there may be value in incorporating multi-disciplinary perspectives and different theoretical approaches into future research in this area.

Understanding the dynamics between multiple behaviours also has implications for understanding how to design multiple behaviour interventions, in terms of what works best for certain behaviours and whether changes should be concurrent or sequential. With regard to the temporal considerations of changing multiple behaviours, whether it is better to target different behaviours concurrently or sequentially is still a matter of on-going research and debate (Geller et al., 2017, Meader et al., 2016). A recent systematic review of RCTs for multiple risk behaviour interventions reported that concurrent interventions were associated with small changes in diet and physical activity, however there was not enough evidence to evaluate the effectiveness of sequential interventions (Meader et al., 2017). Another RCT that was not included in the previous review also reported significant positive changes in diet and physical activity behaviours from a concurrent intervention, but here the effect varied based on what type of changes people were advised to make (e.g. increase FV and physical activity, decrease fat and sedentary leisure, decrease fat and increase physical activity, or increase FV and decrease sedentary leisure) (Spring et al., 2012b), with the latter combination being most effective[103]. Together, this limited evidence suggests that concurrent interventions may have potential for increasing HLC lifestyles, however much more research is still needed into understanding and establishing the most effective ways of shifting multiple related behaviours. As policy initiatives like *Low Carbon Scotland* continue to move forward, there may be opportunities to glean important insights from comprehensive evaluation of these new integrated programs and policies.

In addition, another gap in this research area is that most multiple behaviour interventions have tended to focus on more proximal factors (e.g. information and skills training) (Meader et al., 2017), rather than on upstream determinants that are known to be related to behavioural clustering, both globally (Noble et al., 2015) and in the UK (Meader et al., 2016). Upstream determinants involving systemic factors and structural conditions are of course much harder to change, but as with reducing health inequalities, they likely offer the greatest potential for shifting multiple related behaviours.

7.3.2 Improved data sources and assessment methods

Another opportunity for future research relates to the need for better sources of data for the on-going study of health- and climate-relevant lifestyles in the UK. Locating data sources with both travel and dietary variables was one of the key challenges in the early part of this thesis, and despite their strengths, the two datasets I used here both have major limitations. As a result, future data sources need to be sufficiently large to examine more rare behaviours, and be as representative as possible of the general population, in order for externally valid conclusions to be drawn. In addition, another consideration is that data sources be up-to-date, as there is some evidence to suggest that certain HLC behaviours may be increasing rapidly in prevalence, particularly among certain subsets of the population. A good example of this can be seen in veganism, as a recent survey commissioned by the Vegan Society has reported that the number of full-time vegans in the UK has grown by more than 350% in the past 10 years, and that rates of veganism are particularly high among younger people (Marsh, 2016, Vegan Society, 2016). Since the most recent data used in this thesis was collected in 2012 (both datasets) and UKB did not include participants under age 40, it is unclear whether these evolving trends have been adequately captured in this study.

[103] Specifically, fruit/vegetables increased from 1.2 servings per day to 5.5; sedentary leisure decreased from 219.2 minutes per day to 89.3; saturated fat decreased from 12.0% of calories consumed to 9.5%.

To study dynamics and behaviour change, longitudinal data may also be needed, though it is recognised that obtaining such data on more rare behaviours can be difficult. For example, even in large datasets like UKB it can be challenging to capture enough people with changing behaviour over time: of the 20,346 participants who completed the repeat baseline assessment, only 44 commuters switched from car travel to walking or cycling and only 33 switched from walking or cycling to car commuting (Flint et al., 2016). Nevertheless, in the absence of large numbers of participants who change their behaviour *prospectively,* it is also possible to collect retrospective data that may yield insights into processes of change amongst multiple behaviours across the life course. These approaches are typically qualitative but can involve tangible elements such as 'life grids' or 'life history calendars' (Berney and Blane, 2003, Jones et al., 2014), which use local, global, or personal events to assist participants in recollecting their past behaviours and lifestyles. Though these types of life course approaches have been used most often in the social and health sciences (including for dietary research) (Devine, 2005), they have also been utilised more recently to retrospectively capture patterns of walking and cycling behaviour over time (Jones et al., 2014, Bonham and Wilson, 2012), so there is considerable potential to examine these behaviour areas together.

Of course, such subjective approaches are still susceptible to recall error and reporting bias, and so future research with the potential for new data collection should also consider collecting objective measurements of travel and dietary behaviour where possible. There is already considerable potential for this to be done using smartphone and GPS technology to track people's movements (Dunton et al., 2014, Panter et al., 2014, Kelly et al., 2013), though dietary consumption data cannot yet be collected passively and still needs to be entered by participants using text, voice recordings or digital photography (Pendergast et al., 2017, Martin et al., 2014b). In the United States, transport planners are already using data from Strava (a social networking 'app' for athletes) to better understand localised patterns in walking and cycling (Schneider, 2017), and other smartphone apps are being specifically developed to track carbon footprints in relation to travel and dietary behaviour (Sullivan et al., 2016).

7.3.3 Other theoretical approaches

One final strategic direction for future research is also to explore other theoretical approaches for understanding the relationships between multiple behaviours and how these may evolve into different lifestyles over time. For example, one approach that is starting to gain traction in several areas of behaviour research is *social practice theory*, where behaviours are conceptualised as ‘practices’ consisting of three essential elements (materials, competences, and meanings) that are integrated when a practice is performed (Shove, 2012). Viewing car use as a practice, for example, involves integrating the following elements: having access to a car and living in an area where road design and infrastructure make driving a convenient option (material); having a driver’s licence and knowing how to drive (competences); car travel being associated with certain social norms or higher social status (meanings). Notably, this perspective is increasing in prominence in public health (Blue et al., 2016) and among those who study environmental behaviours (Shove and Spurling, 2014, Nash et al., 2017) and transport behaviour in particular (Watson, 2012, Mattioli and Anable, 2017, Cairns et al., 2014, Spotswood et al., 2015, Nettleton and Green, 2014). Among its proponents, advantages of this approach include that it offers a useful explanation of how behaviours and lifestyles become ‘locked in’ to certain configurations due to the interplay between different materials and contexts, social norms and connotations, and individual proficiencies (Shove, 2010, Blue et al., 2016, Watson, 2012, Shove, 2012). In public health, it is also argued that social theories of practice may offer a better way of explaining how persistent health inequalities, driven by structural factors, become translated into the daily lives of different population groups (Blue et al., 2016).

Like most other theoretical models of behaviour, practice theory has been generally used to explain single practices or behaviours, but it can also be easily extended to incorporate multiple practices or behaviours, and there is a growing focus on using it for this purpose including in relation to behavioural spillover (Nash et al., 2017). In this way, different practices are seen to shape one another and link together to form larger, dependent ‘complexes’ based on their “sequence, synchronisation, proximity, or necessary coexistence” (Shove, 2012 p. 87). Research in this area can then examine how different practices may become bundled together by studying the interrelations between their elements; in the context of UHC lifestyles, for example, one might consider how the practice of car driving could become connected to the practice of meat consumption through material elements like ‘drive-thru’ takeaway restaurants. Though typically studies of practices have been based on qualitative interview or observation data (Browne et al., 2014, Hargreaves, 2011), this is now increasingly being expanded to larger quantitative datasets based on travel diaries (Mattioli and Anable, 2017) and time-use studies (Southerton et al., 2012, Mattioli et al., 2016). As a result, theories of practice appear to offer great potential for improving our understanding of the relationships between different behaviours and how they may become clustered together into different ways of life.

7.4 Conclusion

This thesis set out to advance current understanding of the patterning, prevalence, and predictors of health- and climate-relevant lifestyles, based on combinations of travel and dietary behaviour. As far as I am aware, this is the first study of this nature in the UK or elsewhere, so it represents an important contribution to knowledge. The findings show that HLC and UHC behaviours both cluster to some degree, which suggests that they may be driven by shared influences in certain population groups. These influences largely involve environmental and socio-economic factors and thus efforts to facilitate HLC lifestyles may be most effective if they are directed at the wider physical and socio-cultural conditions that currently foster UHC lifestyles in much of the UK.

Appendix A (Chapter 3)

Table A.0.1 – Summary of data sources that were considered but not chosen due to limitations (review conducted in late 2014 to early 2015)

Study / Survey	Notes and Limitations
Understanding Society (UKHLS)	Questions on active travel, commute mode and FV consumption but no data on meat consumption
Health Survey for England (HSE)	Questions on active travel and meat consumption are rotating modules, meat consumption last asked in 2008, no active travel data that year
Defra Surveys of Public Attitudes and Behaviours Toward the Environment (2007, 2009)	Some limited questions asked on 2007 survey, e.g. active commuting and self-identification as vegetarian or vegan. Questions on food waste, seasonal food, willingness to shift to a lower impact diet on 2009 survey but not meat consumption.
British Social Attitudes (BSA)	Questions on travel mode use and meat consumption asked in 2014, but data mainly pertains to attitudes rather than actual behaviour. Questions just happened to be commissioned by Vegetarian Society and Department for Transport in the same year.
Living Costs and Food Survey	Detailed information on household food expenditure (not necessarily consumption) but no data on travel behaviour.

UKHLS: UK Household Longitudinal Study

Defra: Department for Environment, Food and Rural Affairs

A.1 – Accuracy of dietary measures and reporting in the NDNS

To account for misreporting of food consumption, a common issue in all dietary surveys, the NDNS also uses a robust method of validating self-reported energy intake in a subsample of survey participants. This is known as the Doubly Labelled Water (DLW) method, where participants ingest water enriched in two naturally occurring stable isotopes and excretion of the isotopes from the body is measured using urine samples over one to two weeks. From this excretion a mean daily rate of CO_2 production is obtained for each participant, which is then used to calculate their total energy expenditure (TEE). In healthy adults who are not trying to lose weight, TEE should be equal to energy intake, so if a participant's self-reported energy intake (EI) is considerably lower, then this suggests underreporting of food consumption.

In Years 1-4 of the NDNS RP, 183 males and 188 females completed the DLW sub-study. Overall, across both genders and all age groups, the mean EI:TEE was 0.73, suggesting food consumption in the NDNS was underreported by 27% on average (ranging from 11% in girls aged 4 to 10 years to 36% in females aged 16-49 years), which is consistent with other studies using similar dietary assessment methods in free living adults. With regard to reporting of specific foods and food groups, previous research has suggested that people are less likely to underreport foods with a high protein content, and most likely to underreport foods high in fat and/or sugar, such as butter and cooking oils, soft drinks and confectionary, and alcoholic beverages. This suggests that though overall energy intake is underestimated in the NDNS, estimates of RPM consumption are likely fairly accurate, at least compared to other macronutrients. Similarly, we might expect that FV consumption is also less likely to be underreported due to the 'social desirability' of consuming these foods. For this reason, I assume that the measures of RPM and FV in the NDNS are a fairly accurate reflection of people's actual consumption of these food groups, or at least as accurate as is possible to obtain among free living populations. Full detail of the NDNS RP DLW sub-study is provided in Appendix X of the survey materials (PHE/FSA, 2014).

Appendix B (Chapter 4)

Table B.0.1 – Results of adjusted ordinal logistic models between any active travel and fruit and vegetable (FV) consumption among females in the NDNS (n=755)

VARIABLES	Model 1	Model 2	Model 3 [a] 1 v. 2 + 3	Model 3 [a] 1 + 2 v. 3
Any active travel (ref: None)	0.76	0.92	0.90	0.90
	(0.53 - 1.09)	(0.65 - 1.30)	(0.64 - 1.28)	(0.64 - 1.28)
Survey year (ref: 2)				
Survey year = 3	1.07	1.11	1.18	1.18
	(0.71 - 1.61)	(0.72 - 1.72)	(0.76 - 1.85)	(0.76 - 1.85)
Survey year = 4	1.00	1.07	1.05	1.05
	(0.68 - 1.46)	(0.72 - 1.61)	(0.69 - 1.61)	(0.69 - 1.61)
Age		1.03***	1.04***	1.04***
		(1.02 - 1.05)	(1.02 - 1.05)	(1.02 - 1.05)
Ethnicity = non-white (ref: White)		1.25	1.57	1.57
		(0.68 - 2.29)	(0.87 - 2.84)	(0.87 - 2.84)
Qualifications (ref: Degree level)				
Below degree level		0.48**	0.51**	0.51**
		(0.31 - 0.75)	(0.32 - 0.80)	(0.32 - 0.80)
No qualifications		0.23***	0.25***	0.25***
		(0.13 - 0.42)	(0.13 - 0.48)	(0.13 - 0.48)
Still in full-time education		0.45	0.45	0.45
		(0.19 - 1.07)	(0.20 - 1.03)	(0.20 - 1.03)
Occupation (ref: Manag / Profes)				
Intermediate		1.11	1.11	1.11
		(0.70 - 1.75)	(0.69 - 1.78)	(0.69 - 1.78)
Routine / Never worked		0.72	0.74	0.74
		(0.47 - 1.10)	(0.47 - 1.16)	(0.47 - 1.16)
Total number in household		0.94	0.94	0.94
		(0.78 - 1.14)	(0.78 - 1.13)	(0.78 - 1.13)
Equiv Household income		1.00	1.00*	1.00
		(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)				
North England		0.45*	0.46*	0.46*
		(0.22 - 0.91)	(0.22 - 0.96)	(0.22 - 0.96)
Central England		0.55	0.53	0.53
		(0.27 - 1.14)	(0.25 - 1.10)	(0.25 - 1.10)
South England		0.59	0.59	0.59
		(0.27 - 1.27)	(0.26 - 1.33)	(0.26 - 1.33)
Scotland/Wales/N Ireland		0.49	0.53	0.53
		(0.21 - 1.11)	(0.22 - 1.24)	(0.22 - 1.24)
Total energy (kcal) diet			1.00***	1.00***
			(1.00 - 1.00)	(1.00 - 1.00)
Time spent at MVPA			1.09	1.24**
			(0.96 - 1.24)	(1.09 - 1.42)
Observations	755	755	755	755

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = <3 portions FV, 2 = 3-<5 portions FV, 3 = 5+ portions FV

Table B.0.2 – Results of adjusted ordinal logistic models between any walking travel and fruit and vegetable (FV) consumption among females in the NDNS (n=755)

VARIABLES	Model 1	Model 2	Model 3 [a] 1 v. 2 + 3	Model 3 [a] 1 + 2 v. 3
Any walking travel (ref: None)	0.67*	0.80	0.80	0.80
	(0.46 - 0.96)	(0.56 - 1.14)	(0.56 - 1.15)	(0.56 - 1.15)
Survey year (ref: 2)				
Survey year = 3	1.07	1.11	1.18	1.18
	(0.71 - 1.61)	(0.72 - 1.72)	(0.76 - 1.84)	(0.76 - 1.84)
Survey year = 4	1.00	1.07	1.05	1.05
	(0.68 - 1.46)	(0.72 - 1.61)	(0.69 - 1.61)	(0.69 - 1.61)
Age		1.03***	1.04***	1.04***
		(1.02 - 1.05)	(1.02 - 1.05)	(1.02 - 1.05)
Ethnicity = non-white (ref: White)		1.24	1.55	1.55
		(0.68 - 2.26)	(0.86 - 2.80)	(0.86 - 2.80)
Qualifications (ref: Degree level)				
Below degree level		0.48**	0.51**	0.51**
		(0.31 - 0.75)	(0.33 - 0.80)	(0.33 - 0.80)
No qualifications		0.23***	0.26***	0.26***
		(0.13 - 0.43)	(0.14 - 0.48)	(0.14 - 0.48)
Still in full-time education		0.44	0.45	0.45
		(0.18 - 1.07)	(0.20 - 1.03)	(0.20 - 1.03)
Occupation (ref: Manag / Profes)				
Intermediate		1.09	1.09	1.09
		(0.69 - 1.71)	(0.68 - 1.75)	(0.68 - 1.75)
Routine / Never worked		0.72	0.74	0.74
		(0.47 - 1.11)	(0.47 - 1.17)	(0.47 - 1.17)
Total number in household		0.94	0.94	0.94
		(0.78 - 1.13)	(0.77 - 1.13)	(0.77 - 1.13)
Equiv Household income		1.00	1.00*	1.00
		(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)				
North England		0.44*	0.46*	0.46*
		(0.22 - 0.89)	(0.22 - 0.94)	(0.22 - 0.94)
Central England		0.55	0.53	0.53
		(0.27 - 1.13)	(0.25 - 1.09)	(0.25 - 1.09)
South England		0.58	0.58	0.58
		(0.27 - 1.25)	(0.26 - 1.31)	(0.26 - 1.31)
Scotland/Wales/N Ireland		0.47	0.51	0.51
		(0.21 - 1.08)	(0.22 - 1.21)	(0.22 - 1.21)
Total energy (kcal) diet			1.00***	1.00***
			(1.00 - 1.00)	(1.00 - 1.00)
Time spent at MVPA			1.09	1.24**
			(0.96 - 1.24)	(1.09 - 1.42)
Observations	755	755	755	755

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = <3 portions FV, 2 = 3-<5 portions FV, 3 = 5+ portions FV

Table B.0.3 – Results of adjusted ordinal logistic models between any cycling travel and fruit and vegetable (FV) consumption among females in the NDNS (n=755)

VARIABLES	Model 1	Model 2	Model 3 [a] 1 v. 2 + 3	Model 3 [a] 1 + 2 v. 3
Any cycling travel (ref: None)	3.27*	3.18*	2.69	2.69
	(1.18 - 9.04)	(1.04 - 9.77)	(0.96 - 7.53)	(0.96 - 7.53)
Survey year (ref: 2)				
Survey year = 3	1.06	1.10	1.17	1.17
	(0.70 - 1.59)	(0.71 - 1.70)	(0.75 - 1.83)	(0.75 - 1.83)
Survey year = 4	0.96	1.05	1.03	1.03
	(0.66 - 1.42)	(0.70 - 1.57)	(0.68 - 1.58)	(0.68 - 1.58)
Age		1.03***	1.04***	1.04***
		(1.02 - 1.05)	(1.02 - 1.05)	(1.02 - 1.05)
Ethnicity = non-white (ref: White)		1.28	1.61	1.61
		(0.69 - 2.38)	(0.88 - 2.94)	(0.88 - 2.94)
Qualifications (ref: Degree level)				
Below degree level		0.48**	0.51**	0.51**
		(0.32 - 0.74)	(0.33 - 0.80)	(0.33 - 0.80)
No qualifications		0.23***	0.25***	0.25***
		(0.13 - 0.42)	(0.13 - 0.48)	(0.13 - 0.48)
Still in full-time education		0.46	0.46	0.46
		(0.19 - 1.09)	(0.20 - 1.05)	(0.20 - 1.05)
Occupation (ref: Manag / Profes)				
Intermediate		1.12	1.12	1.12
		(0.72 - 1.75)	(0.71 - 1.78)	(0.71 - 1.78)
Routine / Never worked		0.73	0.74	0.74
		(0.47 - 1.12)	(0.47 - 1.18)	(0.47 - 1.18)
Total number in household		0.94	0.94	0.94
		(0.78 - 1.14)	(0.78 - 1.14)	(0.78 - 1.14)
Equiv Household income		1.00	1.00*	1.00
		(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)				
North England		0.44*	0.46*	0.46*
		(0.22 - 0.90)	(0.22 - 0.96)	(0.22 - 0.96)
Central England		0.56	0.54	0.54
		(0.27 - 1.16)	(0.26 - 1.12)	(0.26 - 1.12)
South England		0.57	0.57	0.57
		(0.26 - 1.23)	(0.25 - 1.29)	(0.25 - 1.29)
Scotland/Wales/N Ireland		0.49	0.53	0.53
		(0.21 - 1.13)	(0.22 - 1.27)	(0.22 - 1.27)
Total energy (kcal) diet			1.00***	1.00***
			(1.00 - 1.00)	(1.00 - 1.00)
Time spent at MVPA			1.08	1.23**
			(0.95 - 1.23)	(1.09 - 1.40)
Observations	755	755	755	755

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = <3 portions FV, 2 = 3-<5 portions FV, 3 = 5+ portions FV

Table B.0.4 – Results of adjusted ordinal logistic models between non-work travel and fruit and vegetable (FV) consumption among females in the NDNS (n=726)

VARIABLES	Model 1	Model 2	Model 3
Non-work travel (Ref: Car)			
Public transport	0.60	0.78	0.81
	(0.36 - 1.00)	(0.45 - 1.34)	(0.46 - 1.43)
Walking	0.61*	0.74	0.74
	(0.40 - 0.91)	(0.49 - 1.14)	(0.49 - 1.13)
Cycling	4.50**	4.38*	4.00*
	(1.68 - 12.04)	(1.37 - 14.00)	(1.31 - 12.19)
Survey year (ref: 2)			
Survey year = 3	1.05	1.08	1.17
	(0.69 - 1.60)	(0.69 - 1.69)	(0.75 - 1.84)
Survey year = 4	0.99	1.08	1.08
	(0.66 - 1.49)	(0.70 - 1.65)	(0.69 - 1.68)
Age		1.03***	1.03***
		(1.02 - 1.05)	(1.02 - 1.05)
Ethnicity = non-white (ref: White)		1.28	1.65
		(0.68 - 2.41)	(0.89 - 3.06)
Qualifications (ref: Degree level)			
Below degree level		0.49**	0.53**
		(0.31 - 0.77)	(0.33 - 0.83)
No qualifications		0.24***	0.27***
		(0.13 - 0.44)	(0.14 - 0.51)
Still in full-time education		0.47	0.48
		(0.20 - 1.12)	(0.21 - 1.11)
Occupation (ref: Manag / Profes)			
Intermediate		1.08	1.08
		(0.68 - 1.72)	(0.67 - 1.75)
Routine / Never worked		0.72	0.70
		(0.46 - 1.12)	(0.44 - 1.13)
Total number in household		0.92	0.92
		(0.76 - 1.13)	(0.75 - 1.13)
Equiv Household income		1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		0.45*	0.48*
		(0.22 - 0.92)	(0.23 - 0.98)
Central England		0.57	0.55
		(0.27 - 1.20)	(0.26 - 1.16)
South England		0.56	0.56
		(0.26 - 1.23)	(0.24 - 1.27)
Scotland/Wales/N Ireland		0.43	0.47
		(0.18 - 1.03)	(0.19 - 1.15)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.16*
			(1.00 - 1.33)
Observations	726	726	726

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.5 – Results of adjusted ordinal logistic models between commuting travel and fruit and vegetable (FV) consumption among females in the NDNS (n=427)

VARIABLES	Model 1	Model 2 [a] 1 v. 2 + 3	Model 2 [a] 1 v. 2 + 3	Model 3 [a] 1 v. 2 + 3	Model 3 [a] 1 v. 2 + 3
Commuting travel (ref: Car)					
Public transport	1.19	1.19	1.19	1.27	1.27
	(0.61 - 2.35)	(0.60 - 2.35)	(0.60 - 2.35)	(0.61 - 2.62)	(0.61 - 2.62)
Walking	0.74	0.94	0.94	0.99	0.99
	(0.44 - 1.26)	(0.52 - 1.67)	(0.52 - 1.67)	(0.56 - 1.76)	(0.56 - 1.76)
Cycling	1.85	1.88	1.88	1.81	1.81
	(0.56 - 6.08)	(0.65 - 5.44)	(0.65 - 5.44)	(0.66 - 4.91)	(0.66 - 4.91)
Survey year (ref: 2)					
Survey year = 3	0.96	0.78	1.55	1.12	1.12
	(0.55 - 1.66)	(0.41 - 1.46)	(0.84 - 2.88)	(0.62 - 2.02)	(0.62 - 2.02)
Survey year = 4	0.80	0.84	0.84	0.83	0.83
	(0.50 - 1.28)	(0.52 - 1.38)	(0.52 - 1.38)	(0.50 - 1.37)	(0.50 - 1.37)
Age		1.04***	1.04***	1.04***	1.04***
		(1.02 - 1.06)	(1.02 - 1.06)	(1.02 - 1.07)	(1.02 - 1.07)
Ethnicity = nonwhite (ref: White)		1.17	1.17	1.47	1.47
		(0.49 - 2.77)	(0.49 - 2.77)	(0.59 - 3.68)	(0.59 - 3.68)
Qualifications (ref: Degree lev)					
Below degree level		0.43**	0.43**	0.44**	0.44**
		(0.24 - 0.74)	(0.24 - 0.74)	(0.25 - 0.77)	(0.25 - 0.77)
No qualifications		0.21**	0.21**	0.26**	0.26**
		(0.09 - 0.53)	(0.09 - 0.53)	(0.10 - 0.65)	(0.10 - 0.65)
Still in full-time education		0.54	0.54	0.51	0.51
		(0.21 - 1.39)	(0.21 - 1.39)	(0.19 - 1.34)	(0.19 - 1.34)
Occupation (ref: Manag / Prof)					
Intermediate		1.11	1.11	1.14	1.14
		(0.64 - 1.93)	(0.64 - 1.93)	(0.65 - 1.99)	(0.65 - 1.99)
Routine / Never worked		0.80	0.80	0.78	0.78
		(0.47 - 1.36)	(0.47 - 1.36)	(0.45 - 1.36)	(0.45 - 1.36)
Total number in household		0.85	0.85	0.89	0.89
		(0.66 - 1.09)	(0.66 - 1.09)	(0.69 - 1.14)	(0.69 - 1.14)
Equiv Household income		1.00	1.00	1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)					
North England		0.30*	0.30*	0.32*	0.32*
		(0.11 - 0.77)	(0.11 - 0.77)	(0.13 - 0.80)	(0.13 - 0.80)
Central England		0.25**	0.25**	0.36*	0.17***
		(0.10 - 0.62)	(0.10 - 0.62)	(0.14 - 0.88)	(0.07 - 0.45)
South England		0.30*	0.30*	0.30*	0.30*
		(0.11 - 0.79)	(0.11 - 0.79)	(0.11 - 0.78)	(0.11 - 0.78)
Scotland/Wales/N Ireland		0.34	0.34	0.41	0.41
		(0.11 - 1.03)	(0.11 - 1.03)	(0.14 - 1.15)	(0.14 - 1.15)
Total energy (kcal) diet				1.00***	1.00***
				(1.00 - 1.00)	(1.00 - 1.00)
Time spent at MVPA				1.00	1.28**
				(0.86 - 1.17)	(1.09 - 1.52)
Observations	427	427	427	427	427

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = <3 portions FV, 2 = 3-<5 portions FV, 3 = 5+ portions FV

Table B.0.6 – Results of adjusted ordinal logistic models between any active travel and fruit and vegetable (FV) consumption among males in the NDNS (n=594)

VARIABLES	Model 1	Model 2	Model 3
Any active travel (ref: None)	1.51*	1.65**	1.73**
	(1.06 - 2.15)	(1.15 - 2.38)	(1.21 - 2.46)
Survey year (ref: 2)			
Survey year = 3	0.99	1.01	1.05
	(0.60 - 1.61)	(0.62 - 1.65)	(0.64 - 1.71)
Survey year = 4	1.16	1.15	1.11
	(0.76 - 1.77)	(0.74 - 1.78)	(0.71 - 1.74)
Age		1.04***	1.04***
		(1.02 - 1.05)	(1.03 - 1.06)
Ethnicity = non-white (ref: White)		1.84	2.41**
		(0.97 - 3.48)	(1.30 - 4.46)
Qualifications (ref: Degree level)			
Below degree level		0.83	0.91
		(0.51 - 1.34)	(0.57 - 1.45)
No qualifications		0.56	0.70
		(0.25 - 1.25)	(0.30 - 1.62)
Still in full-time education		0.89	1.09
		(0.29 - 2.76)	(0.37 - 3.23)
Occupation (ref: Manag / Profes)			
Intermediate		0.87	0.78
		(0.53 - 1.42)	(0.48 - 1.25)
Routine / Never worked		0.74	0.67
		(0.45 - 1.22)	(0.41 - 1.11)
Total number in household		1.12	1.14
		(0.94 - 1.34)	(0.95 - 1.37)
Equiv Household income		1.00**	1.00**
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		0.73	0.59
		(0.27 - 1.99)	(0.22 - 1.63)
Central England		1.09	0.93
		(0.40 - 3.00)	(0.34 - 2.54)
South England		1.16	0.98
		(0.41 - 3.30)	(0.35 - 2.73)
Scotland/Wales/N Ireland		1.34	1.08
		(0.46 - 3.88)	(0.38 - 3.10)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.06
			(1.00 - 1.12)
Observations	594	594	594

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.7 – Results of adjusted ordinal logistic models between any walking travel and fruit and vegetable (FV) consumption among males in the NDNS (n=594)

VARIABLES	Model 1	Model 2	Model 3
Any walking travel (ref: None)	1.32	1.41	1.50*
	(0.90 - 1.95)	(0.95 - 2.10)	(1.03 - 2.19)
Survey year (ref: 2)			
Survey year = 3	1.00	1.04	1.08
	(0.61 - 1.65)	(0.63 - 1.70)	(0.66 - 1.77)
Survey year = 4	1.15	1.14	1.11
	(0.75 - 1.75)	(0.74 - 1.77)	(0.71 - 1.73)
Age		1.04***	1.04***
		(1.02 - 1.05)	(1.03 - 1.06)
Ethnicity = non-white (ref: White)		1.76	2.28**
		(0.93 - 3.33)	(1.24 - 4.21)
Qualifications (ref: Degree level)			
Below degree level		0.80	0.86
		(0.49 - 1.29)	(0.54 - 1.38)
No qualifications		0.54	0.67
		(0.24 - 1.21)	(0.28 - 1.56)
Still in full-time education		0.94	1.16
		(0.29 - 3.10)	(0.36 - 3.66)
Occupation (ref: Manag / Profes)			
Intermediate		0.86	0.77
		(0.52 - 1.40)	(0.48 - 1.23)
Routine / Never worked		0.76	0.69
		(0.47 - 1.24)	(0.42 - 1.13)
Total number in household		1.12	1.14
		(0.94 - 1.34)	(0.95 - 1.37)
Equiv Household income		1.00**	1.00**
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		0.69	0.56
		(0.25 - 1.93)	(0.20 - 1.60)
Central England		1.03	0.88
		(0.37 - 2.89)	(0.31 - 2.46)
South England		1.12	0.94
		(0.39 - 3.23)	(0.33 - 2.70)
Scotland/Wales/N Ireland		1.24	1.00
		(0.42 - 3.68)	(0.34 - 2.95)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.06*
			(1.00 - 1.13)
Observations	594	594	594

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.8 – Results of adjusted ordinal logistic models between any cycling travel and fruit and vegetable (FV) consumption among males in the NDNS (n=594)

VARIABLES	Model 1	Model 2	Model 3
Any cycling travel (ref: None)	2.08*	2.47*	2.27*
	(1.04 - 4.15)	(1.08 - 5.63)	(1.00 - 5.13)
Survey year (ref: 2)			
Survey year = 3	1.01	1.05	1.09
	(0.62 - 1.67)	(0.64 - 1.71)	(0.66 - 1.78)
Survey year = 4	1.19	1.18	1.14
	(0.76 - 1.85)	(0.75 - 1.86)	(0.72 - 1.81)
Age		1.04***	1.04***
		(1.02 - 1.05)	(1.03 - 1.06)
Ethnicity = non-white (ref: White)		1.97*	2.52**
		(1.03 - 3.80)	(1.32 - 4.82)
Qualifications (ref: Degree level)			
Below degree level		0.90	0.97
		(0.55 - 1.47)	(0.60 - 1.56)
No qualifications		0.63	0.77
		(0.27 - 1.45)	(0.32 - 1.83)
Still in full-time education		0.97	1.17
		(0.35 - 2.70)	(0.43 - 3.16)
Occupation (ref: Manag / Profes)			
Intermediate		0.89	0.81
		(0.55 - 1.44)	(0.51 - 1.28)
Routine / Never worked		0.74	0.68
		(0.45 - 1.22)	(0.41 - 1.12)
Total number in household		1.13	1.15
		(0.95 - 1.34)	(0.96 - 1.38)
Equiv Household income		1.00**	1.00**
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		0.72	0.58
		(0.26 - 2.01)	(0.21 - 1.65)
Central England		1.11	0.94
		(0.39 - 3.11)	(0.33 - 2.64)
South England		1.17	0.98
		(0.40 - 3.37)	(0.34 - 2.81)
Scotland/Wales/N Ireland		1.37	1.10
		(0.46 - 4.10)	(0.36 - 3.30)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.06
			(0.99 - 1.12)
Observations	594	594	594

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.9 – Results of adjusted ordinal logistic models between non-work travel and fruit and vegetable (FV) consumption among males in the NDNS (n=585)

VARIABLES	Model 1	Model 2	Model 3
Non-work travel (Ref: Car)			
Public transport	0.43*	0.57	0.55
	(0.21 - 0.91)	(0.27 - 1.20)	(0.25 - 1.23)
Walking	1.08	1.20	1.26
	(0.70 - 1.66)	(0.77 - 1.86)	(0.82 - 1.92)
Cycling	1.88	2.33*	2.24
	(0.90 - 3.94)	(1.02 - 5.34)	(0.99 - 5.08)
Survey year (ref: 2)			
Survey year = 3	0.98	1.02	1.05
	(0.59 - 1.61)	(0.62 - 1.66)	(0.64 - 1.71)
Survey year = 4	1.13	1.14	1.11
	(0.72 - 1.76)	(0.72 - 1.79)	(0.70 - 1.76)
Age		1.04***	1.04***
		(1.02 - 1.05)	(1.03 - 1.06)
Ethnicity = non-white (ref: White)		1.80	2.41**
		(0.95 - 3.43)	(1.27 - 4.58)
Qualifications (ref: Degree level)			
Below degree level		0.86	0.95
		(0.53 - 1.42)	(0.59 - 1.53)
No qualifications		0.58	0.72
		(0.25 - 1.34)	(0.30 - 1.70)
Still in full-time education		1.14	1.37
		(0.40 - 3.31)	(0.49 - 3.84)
Occupation (ref: Manag / Profes)			
Intermediate		0.91	0.83
		(0.56 - 1.49)	(0.52 - 1.32)
Routine / Never worked		0.73	0.67
		(0.44 - 1.22)	(0.40 - 1.12)
Total number in household		1.11	1.13
		(0.93 - 1.32)	(0.94 - 1.34)
Equiv Household income		1.00**	1.00*
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		0.69	0.55
		(0.24 - 1.99)	(0.19 - 1.60)
Central England		1.04	0.88
		(0.35 - 3.06)	(0.30 - 2.60)
South England		1.13	0.94
		(0.38 - 3.37)	(0.32 - 2.76)
Scotland/Wales/N Ireland		1.28	1.02
		(0.41 - 3.99)	(0.33 - 3.17)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.05
			(0.98 - 1.12)
Observations	585	585	585

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.10 – Results of adjusted ordinal logistic models between commuting travel and fruit and vegetable (FV) consumption among males in the NDNS (n=374)

VARIABLES	Model 1	Model 2	Model 3
Commuting travel (ref: Car)			
Public transport	0.39**	0.39*	0.41*
	(0.20 - 0.76)	(0.18 - 0.85)	(0.18 - 0.95)
Walking	1.61	1.64	1.73
	(0.82 - 3.15)	(0.78 - 3.45)	(0.85 - 3.53)
Cycling	3.63*	4.00*	3.44*
	(1.22 - 10.83)	(1.22 - 13.09)	(1.04 - 11.35)
Survey year (ref: 2)			
Survey year = 3	0.92	0.95	1.02
	(0.51 - 1.67)	(0.53 - 1.72)	(0.56 - 1.85)
Survey year = 4	0.79	0.79	0.81
	(0.47 - 1.34)	(0.45 - 1.37)	(0.46 - 1.43)
Age		1.03**	1.04***
		(1.01 - 1.05)	(1.02 - 1.06)
Ethnicity = non-white (ref: White)		1.57	2.06
		(0.73 - 3.39)	(1.00 - 4.27)
Qualifications (ref: Degree level)			
Below degree level		0.74	0.77
		(0.43 - 1.29)	(0.44 - 1.32)
No qualifications		0.91	1.11
		(0.27 - 3.02)	(0.35 - 3.56)
Still in full-time education		0.96	1.08
		(0.33 - 2.77)	(0.37 - 3.19)
Occupation (ref: Manag / Prof)			
Intermediate		0.83	0.74
		(0.46 - 1.51)	(0.40 - 1.35)
Routine / Never worked		0.64	0.51*
		(0.35 - 1.18)	(0.27 - 0.96)
Total number in household		1.11	1.14
		(0.90 - 1.37)	(0.92 - 1.42)
Equiv Household income		1.00*	1.00*
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		0.82	0.66
		(0.27 - 2.46)	(0.21 - 2.08)
Central England		0.91	0.78
		(0.29 - 2.86)	(0.24 - 2.55)
South England		1.02	0.92
		(0.33 - 3.16)	(0.29 - 2.93)
Scotland/Wales/N Ireland		1.31	1.14
		(0.37 - 4.60)	(0.32 - 4.07)
Total energy (kcal) diet			1.00**
			(1.00 - 1.00)
Time spent at MVPA			1.05
			(0.98 - 1.13)
Observations	374	374	374

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.11 – Results of adjusted ordinal logistic models between any active travel and red and processed meat (RPM) consumption among females in the NDNS (n=755)

VARIABLES	Model 1	Model 2	Model 3
Any active travel (ref: None)	1.00	1.02	1.04
	(0.73 - 1.39)	(0.73 - 1.42)	(0.74 - 1.46)
Survey year (ref: 2)			
Survey year = 3	1.07	1.16	1.24
	(0.70 - 1.63)	(0.74 - 1.82)	(0.77 - 1.98)
Survey year = 4	1.28	1.37*	1.39*
	(0.96 - 1.71)	(1.00 - 1.87)	(1.02 - 1.90)
Age		1.00	1.00
		(0.99 - 1.02)	(0.99 - 1.02)
Ethnicity = non-white (ref: White)		0.57	0.64
		(0.30 - 1.12)	(0.32 - 1.28)
Qualifications (ref: Degree level)			
Below degree level		1.65*	1.77*
		(1.04 - 2.60)	(1.11 - 2.84)
No qualifications		1.86	2.05*
		(0.96 - 3.59)	(1.05 - 4.01)
Still in full-time education		1.48	1.50
		(0.75 - 2.91)	(0.75 - 3.00)
Occupation (ref: Manag / Profes)			
Intermediate		1.04	1.05
		(0.69 - 1.56)	(0.69 - 1.59)
Routine / Never worked		0.92	0.93
		(0.59 - 1.45)	(0.59 - 1.45)
Total number in household		0.98	0.98
		(0.84 - 1.14)	(0.84 - 1.15)
Equiv Household income		1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		1.61	1.79
		(0.83 - 3.14)	(0.91 - 3.50)
Central England		1.22	1.22
		(0.63 - 2.36)	(0.62 - 2.40)
South England		1.46	1.53
		(0.70 - 3.02)	(0.73 - 3.21)
Scotland/Wales/N Ireland		1.19	1.32
		(0.59 - 2.39)	(0.65 - 2.69)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.00
			(0.91 - 1.10)
Observations	755	755	755

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.12 – Results of adjusted ordinal logistic models between any walking travel and red and processed meat (RPM) consumption among females in the NDNS (n=755)

VARIABLES	Model 1	Model 2	Model 3
Any walking travel (ref: None)	1.07	1.10	1.13
	(0.78 - 1.48)	(0.80 - 1.53)	(0.81 - 1.58)
Survey year (ref: 2)			
Survey year = 3	1.07	1.16	1.23
	(0.70 - 1.63)	(0.74 - 1.82)	(0.77 - 1.98)
Survey year = 4	1.28	1.36	1.38*
	(0.95 - 1.71)	(1.00 - 1.87)	(1.01 - 1.89)
Age		1.00	1.00
		(0.99 - 1.02)	(0.99 - 1.02)
Ethnicity = non-white (ref: White)		0.58	0.65
		(0.30 - 1.12)	(0.32 - 1.29)
Qualifications (ref: Degree level)			
Below degree level		1.65*	1.77*
		(1.04 - 2.60)	(1.11 - 2.84)
No qualifications		1.85	2.04*
		(0.96 - 3.57)	(1.04 - 3.98)
Still in full-time education		1.49	1.51
		(0.75 - 2.94)	(0.76 - 3.04)
Occupation (ref: Manag / Profes)			
Intermediate		1.04	1.06
		(0.69 - 1.57)	(0.70 - 1.60)
Routine / Never worked		0.92	0.92
		(0.58 - 1.45)	(0.59 - 1.45)
Total number in household		0.98	0.98
		(0.84 - 1.14)	(0.84 - 1.15)
Equiv Household income		1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		1.62	1.80
		(0.83 - 3.14)	(0.92 - 3.52)
Central England		1.22	1.23
		(0.63 - 2.36)	(0.63 - 2.40)
South England		1.46	1.53
		(0.71 - 3.02)	(0.73 - 3.21)
Scotland/Wales/N Ireland		1.20	1.34
		(0.60 - 2.41)	(0.66 - 2.72)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.00
			(0.91 - 1.09)
Observations	755	755	755

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.13 – Results of adjusted ordinal logistic models between any cycling travel and red and processed meat (RPM) consumption among females in the NDNS (n=755)

VARIABLES	Model 1	Model 2	Model 3
Any cycling travel (ref: None)	0.46	0.40	0.39
	(0.14 - 1.45)	(0.12 - 1.34)	(0.11 - 1.35)
Survey year (ref: 2)			
Survey year = 3	1.07	1.17	1.25
	(0.71 - 1.64)	(0.74 - 1.83)	(0.78 - 2.00)
Survey year = 4	1.29	1.38*	1.40*
	(0.96 - 1.72)	(1.01 - 1.88)	(1.02 - 1.91)
Age		1.00	1.00
		(0.99 - 1.02)	(0.99 - 1.02)
Ethnicity = non-white (ref: White)		0.56	0.63
		(0.29 - 1.10)	(0.31 - 1.27)
Qualifications (ref: Degree level)			
Below degree level		1.62*	1.75*
		(1.03 - 2.56)	(1.09 - 2.79)
No qualifications		1.84	2.04*
		(0.95 - 3.56)	(1.04 - 3.99)
Still in full-time education		1.45	1.47
		(0.73 - 2.86)	(0.74 - 2.94)
Occupation (ref: Manag / Profes)			
Intermediate		1.04	1.05
		(0.69 - 1.57)	(0.69 - 1.59)
Routine / Never worked		0.92	0.92
		(0.59 - 1.44)	(0.59 - 1.44)
Total number in household		0.98	0.98
		(0.84 - 1.14)	(0.84 - 1.15)
Equiv Household income		1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		1.64	1.81
		(0.84 - 3.18)	(0.93 - 3.54)
Central England		1.21	1.21
		(0.62 - 2.36)	(0.62 - 2.39)
South England		1.51	1.57
		(0.73 - 3.13)	(0.74 - 3.32)
Scotland/Wales/N Ireland		1.18	1.31
		(0.59 - 2.38)	(0.65 - 2.67)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.00
			(0.91 - 1.10)
Observations	755	755	755

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.14 – Results of adjusted ordinal logistic models between non-work travel and red and processed meat (RPM) consumption among females in the NDNS (n=726)

VARIABLES	Model 1	Model 2	Model 3
Non-work travel (Ref: Car)			
Public transport	1.09	1.33	1.39
	(0.60 - 1.99)	(0.75 - 2.36)	(0.77 - 2.52)
Walking	1.16	1.27	1.30
	(0.82 - 1.64)	(0.90 - 1.79)	(0.92 - 1.84)
Cycling	0.28*	0.25*	0.25*
	(0.08 - 0.97)	(0.07 - 0.91)	(0.06 - 0.98)
Survey year (ref: 2)			
Survey year = 3	1.01	1.09	1.16
	(0.65 - 1.58)	(0.68 - 1.75)	(0.71 - 1.92)
Survey year = 4	1.21	1.28	1.31
	(0.90 - 1.62)	(0.94 - 1.75)	(0.96 - 1.80)
Age		1.00	1.01
		(0.99 - 1.02)	(0.99 - 1.02)
Ethnicity = non-white (ref: White)		0.55	0.62
		(0.28 - 1.10)	(0.30 - 1.26)
Qualifications (ref: Degree level)			
Below degree level		1.56	1.69*
		(0.98 - 2.49)	(1.05 - 2.74)
No qualifications		1.72	1.89
		(0.86 - 3.41)	(0.94 - 3.80)
Still in full-time education		1.42	1.46
		(0.69 - 2.92)	(0.70 - 3.03)
Occupation (ref: Manag / Profes)			
Intermediate		1.05	1.06
		(0.69 - 1.59)	(0.70 - 1.61)
Routine / Never worked		0.87	0.86
		(0.55 - 1.38)	(0.55 - 1.37)
Total number in household		0.99	1.00
		(0.85 - 1.16)	(0.85 - 1.16)
Equiv Household income		1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		1.76	1.94
		(0.90 - 3.44)	(0.99 - 3.82)
Central England		1.32	1.33
		(0.68 - 2.58)	(0.68 - 2.62)
South England		1.72	1.80
		(0.83 - 3.58)	(0.85 - 3.80)
Scotland/Wales/N Ireland		1.31	1.46
		(0.66 - 2.62)	(0.72 - 2.94)
Total energy (kcal) diet			1.00***
			(1.00 - 1.00)
Time spent at MVPA			1.00
			(0.91 - 1.09)
Observations	726	726	726

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.15 – Results of adjusted ordinal logistic models between commuting travel and red and processed meat (RPM) consumption among females in the NDNS (n=427)

VARIABLES	Model 1	Model 2	Model 3
Commuting travel (ref: Car)			
Public transport	0.86	0.92	0.90
	(0.38 - 1.96)	(0.45 - 1.88)	(0.44 - 1.86)
Walking	1.01	0.98	1.06
	(0.62 - 1.64)	(0.55 - 1.72)	(0.60 - 1.87)
Cycling	0.42	0.29	0.29
	(0.06 - 3.06)	(0.03 - 2.54)	(0.03 - 2.63)
Survey year (ref: 2)			
Survey year = 3	0.95	1.04	1.12
	(0.57 - 1.60)	(0.60 - 1.80)	(0.63 - 1.98)
Survey year = 4	1.27	1.30	1.35
	(0.82 - 1.97)	(0.81 - 2.08)	(0.84 - 2.17)
Age		1.01	1.01
		(0.99 - 1.04)	(0.99 - 1.04)
Ethnicity = non-white (ref: White)		0.56	0.63
		(0.24 - 1.27)	(0.26 - 1.51)
Qualifications (ref: Degree level)			
Below degree level		1.51	1.59
		(0.85 - 2.71)	(0.88 - 2.88)
No qualifications		2.23	2.55
		(0.75 - 6.57)	(0.88 - 7.40)
Still in full-time education		2.35	2.11
		(0.93 - 5.93)	(0.84 - 5.32)
Occupation (ref: Manag / Prof)			
Intermediate		1.03	1.08
		(0.58 - 1.81)	(0.61 - 1.93)
Routine / Never worked		0.82	0.81
		(0.46 - 1.45)	(0.45 - 1.43)
Total number in household		0.90	0.92
		(0.73 - 1.10)	(0.76 - 1.13)
Equiv Household income		1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		1.56	1.75
		(0.69 - 3.53)	(0.75 - 4.10)
Central England		1.12	1.19
		(0.49 - 2.53)	(0.51 - 2.81)
South England		1.78	1.86
		(0.73 - 4.38)	(0.74 - 4.71)
Scotland/Wales/N Ireland		1.21	1.40
		(0.47 - 3.16)	(0.52 - 3.75)
Total energy (kcal) diet			1.00*
			(1.00 - 1.00)
Time spent at MVPA			0.99
			(0.90 - 1.09)
Observations	427	427	427

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.16 – Results of adjusted ordinal logistic models between any active travel and red and processed meat (RPM) consumption among males in the NDNS (n=594)

VARIABLES	Model 1 [a] 1 v. 2 + 3	Model 1 [a] 1 v. 2 + 3	Model 2	Model 3
Any active travel (ref: None)	0.70 (0.45 - 1.07)	0.70 (0.45 - 1.07)	0.70 (0.44 - 1.10)	0.70 (0.45 - 1.10)
Survey year (ref: 2)				
Survey year = 3	0.42* (0.18 - 0.95)	1.00 (0.66 - 1.52)	0.90 (0.59 - 1.38)	0.85 (0.56 - 1.30)
Survey year = 4	0.73 (0.49 - 1.11)	0.73 (0.49 - 1.11)	0.73 (0.49 - 1.08)	0.68 (0.45 - 1.02)
Age			0.98* (0.97 - 1.00)	0.99* (0.97 - 1.00)
Ethnicity = non-white (ref: White)			0.56 (0.24 - 1.29)	0.71 (0.31 - 1.63)
Qualifications (ref: Degree level)				
Below degree level			1.48 (0.84 - 2.59)	1.77* (1.01 - 3.09)
No qualifications			1.43 (0.67 - 3.07)	1.86 (0.88 - 3.90)
Still in full-time education			0.83 (0.28 - 2.47)	0.99 (0.34 - 2.87)
Occupation (ref: Manag / Profes)				
Intermediate			1.63 (0.97 - 2.74)	1.59 (0.93 - 2.69)
Routine / Never worked			1.16 (0.71 - 1.89)	1.17 (0.72 - 1.91)
Total number in household			0.80** (0.69 - 0.93)	0.83* (0.71 - 0.96)
Equiv Household income			1.00 (1.00 - 1.00)	1.00 (1.00 - 1.00)
Region (ref: London)				
North England			0.75 (0.34 - 1.63)	0.63 (0.30 - 1.30)
Central England			0.74 (0.34 - 1.62)	0.63 (0.30 - 1.32)
South England			0.98 (0.44 - 2.19)	0.83 (0.38 - 1.79)
Scotland/Wales/N Ireland			0.79 (0.33 - 1.89)	0.63 (0.28 - 1.46)
Total energy (kcal) diet				1.00*** (1.00 - 1.00)
Time spent at MVPA				1.00 (0.94 - 1.07)
Observations	594	594	594	594

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = 0 g RPM, 2 = >0-70 g RPM, 3 = >70 g RPM

Table B.0.17 – Results of adjusted ordinal logistic models between any walking travel and red and processed meat (RPM) consumption among males in the NDNS (n=594)

VARIABLES	Model 1 [a] 1 v. 2 + 3	1 v. 2 + 3	Model 2	Model 3
Any walking travel (ref: None)	0.71 (0.46 - 1.09)	0.71 (0.46 - 1.09)	0.69 (0.44 - 1.10)	0.71 (0.45 - 1.13)
Survey year (ref: 2)				
Survey year = 3	0.42* (0.18 - 0.95)	0.99 (0.65 - 1.51)	0.89 (0.58 - 1.38)	0.85 (0.56 - 1.30)
Survey year = 4	0.74 (0.49 - 1.12)	0.74 (0.49 - 1.12)	0.73 (0.49 - 1.09)	0.68 (0.45 - 1.03)
Age			0.98* (0.97 - 1.00)	0.99* (0.97 - 1.00)
Ethnicity = non-white (ref: White)			0.58 (0.26 - 1.29)	0.73 (0.33 - 1.65)
Qualifications (ref: Degree level)				
Below degree level			1.53 (0.87 - 2.68)	1.83* (1.05 - 3.20)
No qualifications			1.49 (0.69 - 3.21)	1.92 (0.90 - 4.08)
Still in full-time education			0.80 (0.27 - 2.35)	0.96 (0.33 - 2.76)
Occupation (ref: Manag / Profes)				
Intermediate			1.65 (0.98 - 2.77)	1.60 (0.94 - 2.72)
Routine / Never worked			1.14 (0.70 - 1.88)	1.16 (0.70 - 1.90)
Total number in household			0.80** (0.69 - 0.93)	0.83* (0.71 - 0.96)
Equiv Household income			1.00 (1.00 - 1.00)	1.00 (1.00 - 1.00)
Region (ref: London)				
North England			0.77 (0.35 - 1.68)	0.64 (0.31 - 1.33)
Central England			0.76 (0.35 - 1.68)	0.65 (0.31 - 1.36)
South England			1.00 (0.44 - 2.24)	0.84 (0.39 - 1.83)
Scotland/Wales/N Ireland			0.83 (0.34 - 1.98)	0.67 (0.29 - 1.53)
Total energy (kcal) diet				1.00*** (1.00 - 1.00)
Time spent at MVPA				1.00 (0.94 - 1.06)
Observations	594	594	594	594

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = 0 g RPM, 2 = >0-70 g RPM, 3 = >70 g RPM

Table B.0.18 – Results of adjusted ordinal logistic models between any cycling travel and red and processed meat (RPM) consumption among males in the NDNS (n=594)

	Model 1 [a]			
VARIABLES	1 v. 2 + 3	1 v. 2 + 3	Model 2	Model 3
Any cycling travel (ref: None)	0.73	0.73	0.83	0.72
	(0.29 - 1.79)	(0.29 - 1.79)	(0.32 - 2.13)	(0.31 - 1.68)
Survey year (ref: 2)				
Survey year = 3	0.41*	0.98	0.88	0.84
	(0.18 - 0.94)	(0.65 - 1.49)	(0.58 - 1.35)	(0.55 - 1.28)
Survey year = 4	0.73	0.73	0.73	0.67
	(0.48 - 1.11)	(0.48 - 1.11)	(0.49 - 1.08)	(0.44 - 1.02)
Age			0.98*	0.99
			(0.97 - 1.00)	(0.97 - 1.00)
Ethnicity = non-white (ref: White)			0.57	0.71
			(0.25 - 1.30)	(0.31 - 1.62)
Qualifications (ref: Degree level)				
Below degree level			1.48	1.74
			(0.84 - 2.62)	(0.99 - 3.06)
No qualifications			1.42	1.80
			(0.65 - 3.07)	(0.85 - 3.81)
Still in full-time education			0.77	0.94
			(0.26 - 2.27)	(0.32 - 2.72)
Occupation (ref: Manag / Profes)				
Intermediate			1.60	1.54
			(0.96 - 2.67)	(0.91 - 2.61)
Routine / Never worked			1.13	1.15
			(0.70 - 1.85)	(0.71 - 1.88)
Total number in household			0.80**	0.82**
			(0.69 - 0.93)	(0.71 - 0.95)
Equiv Household income			1.00	1.00
			(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)				
North England			0.77	0.64
			(0.35 - 1.70)	(0.31 - 1.35)
Central England			0.76	0.64
			(0.34 - 1.68)	(0.30 - 1.35)
South England			0.98	0.82
			(0.43 - 2.21)	(0.38 - 1.80)
Scotland/Wales/N Ireland			0.82	0.65
			(0.34 - 1.98)	(0.28 - 1.52)
Total energy (kcal) diet				1.00***
				(1.00 - 1.00)
Time spent at MVPA				1.00
				(0.94 - 1.07)
Observations	594	594	594	594

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = 0 g RPM, 2 = >0-70 g RPM, 3 = >70 g RPM

Table B.0.19 – Results of adjusted ordinal logistic models between non-work travel and red and processed meat (RPM) consumption among males in the NDNS (n=585)

	Model 1 [a]			
VARIABLES	1 v. 2 + 3	1 v. 2 + 3	Model 2	Model 3
Non-work travel (Ref: Car)				
Public transport	0.90	0.90	0.78	0.78
	(0.48 - 1.67)	(0.48 - 1.67)	(0.40 - 1.52)	(0.41 - 1.49)
Walking	0.66	0.66	0.63	0.64
	(0.41 - 1.06)	(0.41 - 1.06)	(0.38 - 1.04)	(0.39 - 1.07)
Cycling	0.63	0.63	0.65	0.60
	(0.25 - 1.60)	(0.25 - 1.60)	(0.27 - 1.56)	(0.27 - 1.34)
Survey year (ref: 2)				
Survey year = 3	0.36*	0.95	0.83	0.78
	(0.16 - 0.81)	(0.62 - 1.43)	(0.55 - 1.25)	(0.52 - 1.16)
Survey year = 4	0.68	0.68	0.67	0.63*
	(0.45 - 1.02)	(0.45 - 1.02)	(0.45 - 1.00)	(0.41 - 0.95)
Age			0.98*	0.99
			(0.97 - 1.00)	(0.97 - 1.00)
Ethnicity = non-white (ref: White)			0.53	0.69
			(0.23 - 1.22)	(0.30 - 1.62)
Qualifications (ref: Degree level)				
Below degree level			1.47	1.77
			(0.83 - 2.60)	(1.00 - 3.13)
No qualifications			1.45	1.87
			(0.66 - 3.17)	(0.87 - 4.02)
Still in full-time education			1.22	1.47
			(0.47 - 3.17)	(0.59 - 3.63)
Occupation (ref: Manag / Profes)				
Intermediate			1.87*	1.84*
			(1.16 - 3.01)	(1.14 - 2.97)
Routine / Never worked			1.16	1.19
			(0.70 - 1.92)	(0.72 - 1.98)
Total number in household			0.81**	0.83*
			(0.70 - 0.95)	(0.71 - 0.97)
Equiv Household income			1.00	1.00
			(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)				
North England			0.77	0.64
			(0.35 - 1.68)	(0.31 - 1.32)
Central England			0.72	0.60
			(0.33 - 1.57)	(0.29 - 1.26)
South England			0.95	0.79
			(0.42 - 2.15)	(0.36 - 1.72)
Scotland/Wales/N Ireland			0.88	0.69
			(0.37 - 2.07)	(0.31 - 1.57)
Total energy (kcal) diet				1.00***
				(1.00 - 1.00)
Time spent at MVPA				0.99
				(0.93 - 1.06)
Observations	585	585	585	585

*** p<0.001, ** p<0.01, * p<0.05

a) Shading indicates generalized ordered logit model; boxes indicate variables with different relationships across the levels of the outcome variable: 1 = 0 g RPM, 2 = >0-70 g RPM, 3 = >70 g RPM

Table B.0.20 – Results of adjusted ordinal logistic models between commuting travel and red and processed meat (RPM) consumption among males in the NDNS (n=374)

VARIABLES	Model 1	Model 2	Model 3
Commuting travel (ref: Car)			
Public transport	0.92	0.97	1.09
	(0.41 - 2.02)	(0.42 - 2.22)	(0.47 - 2.55)
Walking	0.64	0.57	0.60
	(0.33 - 1.27)	(0.29 - 1.14)	(0.31 - 1.17)
Cycling	1.08	1.06	0.80
	(0.24 - 4.82)	(0.24 - 4.78)	(0.18 - 3.56)
Survey year (ref: 2)			
Survey year = 3	0.81	0.75	0.78
	(0.47 - 1.41)	(0.42 - 1.34)	(0.44 - 1.37)
Survey year = 4	0.80	0.73	0.75
	(0.49 - 1.30)	(0.45 - 1.18)	(0.46 - 1.21)
Age		0.99	1.00
		(0.97 - 1.02)	(0.97 - 1.02)
Ethnicity = non-white (ref: White)		0.99	1.26
		(0.34 - 2.84)	(0.42 - 3.78)
Qualifications (ref: Degree level)			
Below degree level		2.12*	2.32*
		(1.11 - 4.05)	(1.22 - 4.41)
No qualifications		1.32	1.57
		(0.46 - 3.75)	(0.61 - 4.03)
Still in full-time education		1.29	1.46
		(0.36 - 4.54)	(0.40 - 5.38)
Occupation (ref: Manag / Prof)			
Intermediate		1.71	1.58
		(0.86 - 3.39)	(0.79 - 3.17)
Routine / Never worked		1.50	1.30
		(0.80 - 2.82)	(0.69 - 2.47)
Total number in household		0.79**	0.82*
		(0.67 - 0.94)	(0.69 - 0.98)
Equiv Household income		1.00	1.00
		(1.00 - 1.00)	(1.00 - 1.00)
Region (ref: London)			
North England		0.97	0.82
		(0.37 - 2.57)	(0.32 - 2.12)
Central England		0.70	0.65
		(0.28 - 1.80)	(0.26 - 1.58)
South England		1.45	1.37
		(0.52 - 4.06)	(0.50 - 3.79)
Scotland/Wales/N Ireland		0.74	0.68
		(0.24 - 2.25)	(0.23 - 2.06)
Total energy (kcal) diet			1.00**
			(1.00 - 1.00)
Time spent at MVPA			1.02
			(0.95 - 1.10)
Observations	374	374	374

*** p<0.001, ** p<0.01, * p<0.05

Note: No generalized ordered logits are reported since all of these models met the proportional odds assumption.

Table B.0.21 – Results of ordinal logistic models between any active travel and fruit and vegetable (FV) consumption among females in UKB (n=217,168)

VARIABLES	Unadjusted	Adjusted
Any active travel (ref: None)	1.42***	1.43***
	(1.40 - 1.44)	(1.40 - 1.45)
Age at baseline		1.04***
		(1.04 - 1.05)
Ethnic group (ref: White British)		
Other white		1.38***
		(1.33 - 1.42)
South Asian		2.19***
		(2.04 - 2.37)
Black		1.63***
		(1.52 - 1.74)
Chinese		1.67***
		(1.45 - 1.93)
Mixed		1.16**
		(1.05 - 1.28)
Other		2.29***
		(2.08 - 2.53)
Highest qualification (ref: Degree level)		
A levels/AS levels or equivalent		0.86***
		(0.83 - 0.88)
O levels/GCSEs or equivalent		0.77***
		(0.75 - 0.79)
CSEs or equivalent		0.72***
		(0.70 - 0.75)
NVQ or HND or HNC or equivalent		0.79***
		(0.76 - 0.82)
Other professional qualifications		0.89***
		(0.86 - 0.92)
No qualifications		0.63***
		(0.62 - 0.65)
Occupation class (ref: Higher man / prof)		
Lower managerial / professional		1.08***
		(1.05 - 1.11)
Intermediate occupations		1.02
		(0.99 - 1.06)
Small employers & own accounts		1.11***
		(1.04 - 1.17)
Lower supervisory & technical		1.16*
		(1.03 - 1.31)
Semi-routine occupations		1.03
		(0.99 - 1.07)
Routine occupations		0.98
		(0.93 - 1.04)
Not classified		1.03
		(1.00 - 1.06)
Household income (ref: £<18 000)		
£18,000 to 30,999		1.10***
		(1.07 - 1.13)
£31,000 to 51,999		1.21***
		(1.17 - 1.24)
£52,000 to 100,000		1.29***
		(1.25 - 1.33)
£Greater than 100,000		1.32***
		(1.26 - 1.38)

Household size (ref: One)		
2		0.95***
		(0.93 - 0.97)
3		0.88***
		(0.86 - 0.91)
4		0.85***
		(0.82 - 0.87)
5+		0.87***
		(0.83 - 0.91)
Region (ref: London)		
North East England		1.07***
		(1.03 - 1.11)
Yorkshire and the Humber		0.99
		(0.96 - 1.02)
West Midlands		1.06***
		(1.03 - 1.10)
East Midlands		1.08***
		(1.04 - 1.12)
South East England		1.12***
		(1.08 - 1.16)
South West England		1.14***
		(1.10 - 1.18)
North West England		0.99
		(0.96 - 1.02)
Wales		1.12***
		(1.07 - 1.17)
Scotland		0.95**
		(0.91 - 0.98)
Townsend deprivation		0.98***
		(0.98 - 0.99)
Urban (ref: Rural)		0.94***
		(0.92 - 0.96)
Cars per household (ref: None)		
One		1.12***
		(1.08 - 1.16)
Two		1.10***
		(1.06 - 1.14)
Three		1.07**
		(1.02 - 1.12)
Four or more		1.09**
		(1.03 - 1.17)
Observations	217,168	217,168

*** p<0.001, ** p<0.01, * p<0.05

Table B.0.22 – Results of ordinal logistic models between any active travel and fruit and vegetable (FV) consumption among males in UKB (n=195,131)

VARIABLES	(1) Unadjusted	(2) Adjusted
Any active travel (ref: None)	1.37***	1.35***
	(1.34 - 1.39)	(1.33 - 1.37)
Age at baseline		1.03***
		(1.03 - 1.03)
Ethnic group (ref: White British)		
Other white		1.32***
		(1.27 - 1.36)
South Asian		2.24***
		(2.10 - 2.38)
Black		1.50***
		(1.39 - 1.63)
Chinese		1.68***
		(1.41 - 2.00)
Mixed		1.11
		(0.98 - 1.26)
Other		2.23***
		(2.02 - 2.47)
Highest qualification (ref: Degree level)		
A levels/AS levels or equivalent		0.79***
		(0.76 - 0.81)
O levels/GCSEs or equivalent		0.75***
		(0.73 - 0.77)
CSEs or equivalent		0.75***
		(0.72 - 0.78)
NVQ or HND or HNC or equivalent		0.83***
		(0.80 - 0.85)
Other professional qualifications		0.82***
		(0.79 - 0.86)
No qualifications		0.75***
		(0.73 - 0.77)
Occupation class (ref: Higher man / prof)		
Lower managerial / professional		1.03*
		(1.00 - 1.05)
Intermediate occupations		1.05**
		(1.01 - 1.09)
Small employers & own accounts		1.04
		(1.00 - 1.09)
Lower supervisory & technical		1.08***
		(1.03 - 1.12)
Semi-routine occupations		1.00
		(0.96 - 1.04)
Routine occupations		1.04
		(0.99 - 1.08)
Not classified		0.99
		(0.96 - 1.02)
Household income (ref: £<18 000)		
£18,000 to 30,999		1.11***
		(1.08 - 1.14)
£31,000 to 51,999		1.18***
		(1.15 - 1.22)
£52,000 to 100,000		1.26***
		(1.22 - 1.31)
£Greater than 100,000		1.33***
		(1.27 - 1.39)

Household size (ref: One)			
	2		1.12***
			(1.09 - 1.15)
	3		1.04*
			(1.01 - 1.08)
	4		1.03
			(1.00 - 1.07)
	5+		1.01
			(0.96 - 1.05)
Region (ref: London)			
	North East England		1.02
			(0.98 - 1.05)
	Yorkshire and the Humber		0.97
			(0.94 - 1.01)
	West Midlands		1.00
			(0.96 - 1.04)
	East Midlands		1.03
			(0.99 - 1.07)
	South East England		1.00
			(0.96 - 1.04)
	South West England		1.02
			(0.98 - 1.06)
	North West England		0.94***
			(0.91 - 0.97)
	Wales		1.05*
			(1.00 - 1.10)
	Scotland		0.83***
			(0.80 - 0.86)
Townsend deprivation			0.99***
			(0.98 - 0.99)
Urban (ref: Rural)			0.96**
			(0.94 - 0.98)
Cars per household (ref: None)			
	One		1.11***
			(1.07 - 1.15)
	Two		1.02
			(0.98 - 1.06)
	Three		0.94**
			(0.89 - 0.98)
	Four or more		0.92**
			(0.86 - 0.98)
Observations		195,131	195,131

*** p<0.001, ** p<0.01, * p<0.05

Table B.0.23 – Results of ordinal logistic models between any active travel and red and processed meat (RPM) consumption among females in UKB (n=217,168)

VARIABLES	Unadjusted	Adjusted
Any active travel (ref: None)	0.85***	0.88***
	(0.84 - 0.87)	(0.87 - 0.90)
Age at baseline		1.01***
		(1.01 - 1.01)
Ethnic group (ref: White British)		
Other white		0.99
		(0.95 - 1.02)
South Asian		0.27***
		(0.25 - 0.29)
Black		1.06
		(0.99 - 1.14)
Chinese		2.12***
		(1.83 - 2.45)
Mixed		0.97
		(0.88 - 1.08)
Other		0.91*
		(0.82 - 1.00)
Highest qualification (ref: Degree level)		
A levels/AS levels or equivalent		1.20***
		(1.17 - 1.24)
O levels/GCSEs or equivalent		1.27***
		(1.24 - 1.30)
CSEs or equivalent		1.30***
		(1.24 - 1.35)
NVQ or HND or HNC or equivalent		1.22***
		(1.17 - 1.28)
Other professional qualifications		1.16***
		(1.12 - 1.21)
No qualifications		1.35***
		(1.31 - 1.39)
Occupation class (ref: Higher man / prof)		
Lower managerial / professional		0.96**
		(0.93 - 0.99)
Intermediate occupations		1.06**
		(1.02 - 1.09)
Small employers & own accounts		1.00
		(0.94 - 1.07)
Lower supervisory & technical		1.07
		(0.94 - 1.21)
Semi-routine occupations		1.08***
		(1.04 - 1.13)
Routine occupations		1.20***
		(1.13 - 1.27)
Not classified		1.21***
		(1.17 - 1.25)
Household income (ref: £<18 000)		
£18,000 to 30,999		1.00
		(0.98 - 1.03)
£31,000 to 51,999		0.94***
		(0.92 - 0.97)
£52,000 to 100,000		0.93***
		(0.90 - 0.96)
£Greater than 100,000		0.93**
		(0.88 - 0.97)

Household size (ref: One)		
2		1.45***
		(1.41 - 1.48)
3		1.57***
		(1.52 - 1.63)
4		1.79***
		(1.73 - 1.86)
5+		1.92***
		(1.83 - 2.01)
Region (ref: London)		
North East England		0.97
		(0.94 - 1.01)
Yorkshire and the Humber		1.01
		(0.98 - 1.05)
West Midlands		0.97
		(0.93 - 1.00)
East Midlands		1.00
		(0.96 - 1.04)
South East England		1.03
		(0.99 - 1.07)
South West England		0.94***
		(0.90 - 0.97)
North West England		1.15***
		(1.11 - 1.19)
Wales		0.89***
		(0.85 - 0.94)
Scotland		1.20***
		(1.15 - 1.24)
Townsend deprivation		1.00
		(1.00 - 1.00)
Urban (ref: Rural)		0.96**
		(0.94 - 0.98)
Cars per household (ref: None)		
One		1.04*
		(1.01 - 1.08)
Two		1.17***
		(1.12 - 1.21)
Three		1.24***
		(1.18 - 1.30)
Four or more		1.29***
		(1.20 - 1.38)
Observations	217,168	217,168

*** p<0.001, ** p<0.01, * p<0.05

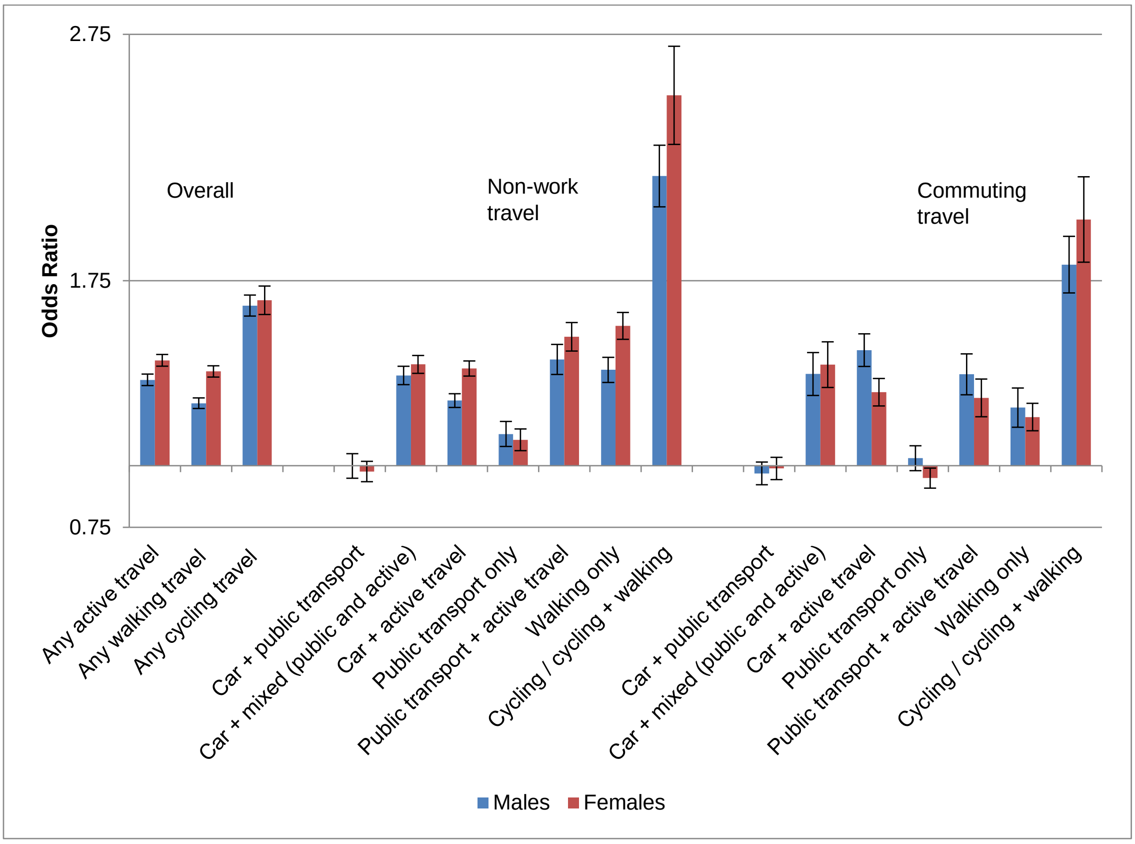
Table B.0.24 – Results of ordinal logistic models between any active travel and red and processed meat (RPM) consumption among males in UKB (n=195,131)

VARIABLES	Unadjusted	Adjusted
Any active travel (ref: None)	0.87*** (0.85 - 0.88)	0.89*** (0.87 - 0.91)
Age at baseline		1.00 (1.00 - 1.00)
Ethnic group (ref: White British)		
Other white		1.01 (0.97 - 1.05)
South Asian		0.26*** (0.25 - 0.28)
Black		0.82*** (0.76 - 0.90)
Chinese		1.33** (1.09 - 1.61)
Mixed		1.08 (0.94 - 1.23)
Other		0.74*** (0.66 - 0.82)
Highest qualification (ref: Degree level)		
A levels/AS levels or equivalent		1.20*** (1.16 - 1.23)
O levels/GCSEs or equivalent		1.22*** (1.19 - 1.26)
CSEs or equivalent		1.22*** (1.17 - 1.27)
NVQ or HND or HNC or equivalent		1.20*** (1.16 - 1.24)
Other professional qualifications		1.09*** (1.04 - 1.14)
No qualifications		1.16*** (1.13 - 1.20)
Occupation class (ref: Higher man / prof)		
Lower managerial / professional		0.95*** (0.92 - 0.98)
Intermediate occupations		1.01 (0.97 - 1.05)
Small employers & own accounts		1.19*** (1.14 - 1.25)
Lower supervisory & technical		1.18*** (1.13 - 1.23)
Semi-routine occupations		1.20*** (1.15 - 1.26)
Routine occupations		1.28*** (1.22 - 1.34)
Not classified		1.14*** (1.11 - 1.18)
Household income (ref: £<18 000)		
£18,000 to 30,999		0.96* (0.94 - 0.99)
£31,000 to 51,999		0.97 (0.94 - 1.01)
£52,000 to 100,000		0.91*** (0.88 - 0.95)
£Greater than 100,000		0.89*** (0.85 - 0.94)

Household size (ref: One)			
	2		1.06***
			(1.03 - 1.09)
	3		1.17***
			(1.13 - 1.21)
	4		1.25***
			(1.20 - 1.29)
	5+		1.35***
			(1.29 - 1.42)
Region (ref: London)			
	North East England		0.99
			(0.95 - 1.03)
	Yorkshire and the Humber		1.02
			(0.98 - 1.06)
	West Midlands		1.02
			(0.98 - 1.07)
	East Midlands		0.97
			(0.93 - 1.01)
	South East England		1.03
			(0.99 - 1.07)
	South West England		0.96*
			(0.92 - 1.00)
	North West England		1.15***
			(1.11 - 1.19)
	Wales		0.91***
			(0.87 - 0.96)
	Scotland		1.16***
			(1.11 - 1.21)
Townsend deprivation			1.01***
			(1.01 - 1.01)
Urban (ref: Rural)			0.99
			(0.97 - 1.02)
Cars per household (ref: None)			
	One		0.98
			(0.94 - 1.02)
	Two		1.08***
			(1.04 - 1.13)
	Three		1.23***
			(1.17 - 1.30)
	Four or more		1.30***
			(1.21 - 1.39)
Observations		195,131	195,131

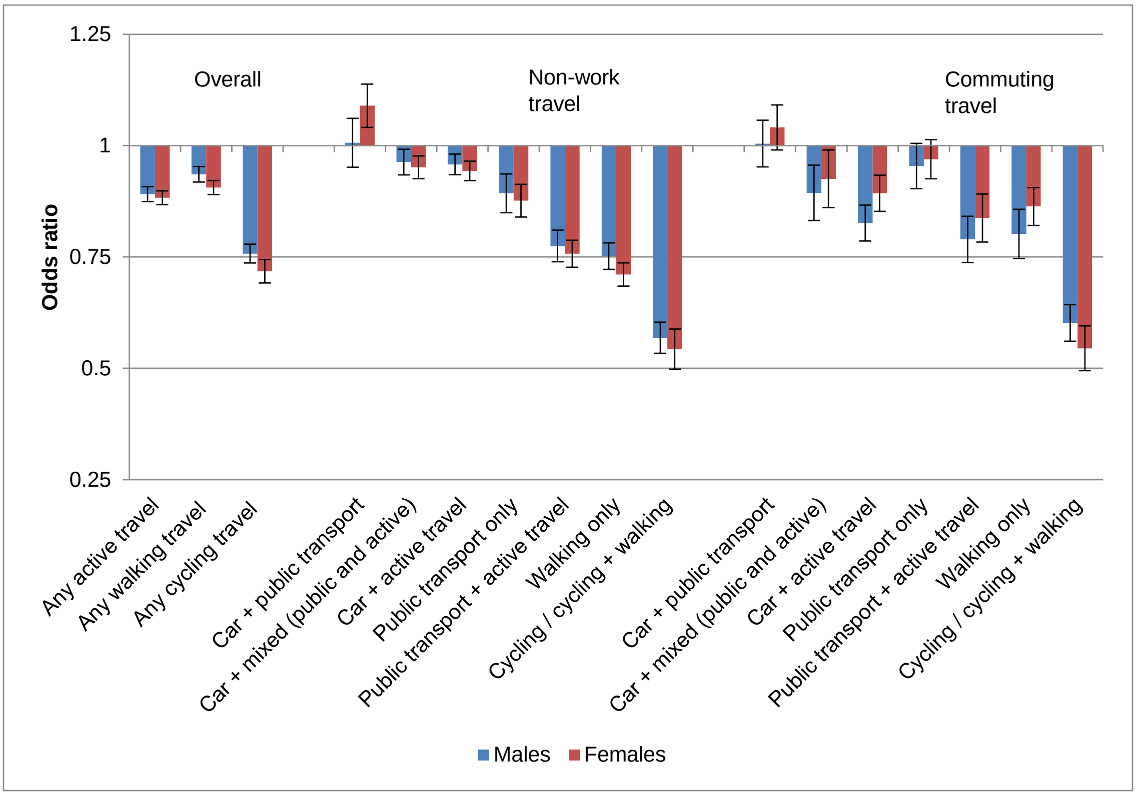
*** p<0.001, ** p<0.01, * p<0.05

Figure B.0.1 – Associations between travel and FV consumption (Model 2, Table 4.9)



Whiskers = 95% confidence interval

Figure B.0.2 – Associations between travel and RPM consumption (Model 2, Table 4.10)



Whiskers = 95% confidence interval

Table B.0.25 – Results of generalized ordered logit models between measures of active travel and FV consumption, stratified by gender in UKB (n=412,299)

TRAVEL VARIABLES	Males (n=195,131)		Females (n=217,168)	
	Model 2 [a]		Model 2 [a]	
	1 v. 2 + 3 [b]	1 + 2 v. 3	1 v. 2 + 3 [b]	1 + 2 v. 3
Any active travel (ref: No)	1.37*** (1.35 - 1.40)	1.32*** (1.30 - 1.35)	1.53*** (1.49 - 1.56)	1.38*** (1.35 - 1.40)
Any walking (ref: No)	1.28*** (1.26 - 1.31)	1.23*** (1.20 - 1.25)	1.47*** (1.44 - 1.51)	1.34*** (1.32 - 1.36)
Any cycling (ref: No)	1.71*** (1.66 - 1.76)	1.61*** (1.57 - 1.66)	1.93*** (1.84 - 2.04)	1.60*** (1.55 - 1.66)
Non-work travel [b] (ref: Car only)				
Car + public transport	1.00 (0.95 - 1.05)	1.00 (0.95 - 1.05)	0.98 (0.94 - 1.02)	0.98 (0.94 - 1.02)
Car + mixed (public and active)	1.42*** (1.38 - 1.47)	1.32*** (1.28 - 1.36)	1.55*** (1.50 - 1.61)	1.36*** (1.32 - 1.39)
Car + active travel	1.29*** (1.26 - 1.32)	1.24*** (1.21 - 1.27)	1.49*** (1.45 - 1.54)	1.35*** (1.32 - 1.38)
Public transport only	1.14*** (1.09 - 1.19)	1.14*** (1.09 - 1.19)	1.11*** (1.07 - 1.16)	1.11*** (1.07 - 1.16)
Public transport + active travel	1.47*** (1.40 - 1.54)	1.39*** (1.33 - 1.46)	1.66*** (1.58 - 1.74)	1.45*** (1.40 - 1.51)
Walking only	1.39*** (1.34 - 1.44)	1.39*** (1.34 - 1.44)	1.62*** (1.55 - 1.69)	1.53*** (1.48 - 1.59)
Cycling / cycling + walking	2.27*** (2.11 - 2.44)	2.10*** (1.97 - 2.23)	2.84*** (2.50 - 3.21)	2.39*** (2.21 - 2.60)
Commuting travel [c] (ref: Car only)				
Car + public transport	0.97 (0.92 - 1.02)	0.97 (0.92 - 1.02)	0.99 (0.95 - 1.03)	0.99 (0.95 - 1.03)
Car + mixed (public and active)	1.38*** (1.29 - 1.47)	1.38*** (1.29 - 1.47)	1.53*** (1.39 - 1.67)	1.37*** (1.28 - 1.47)
Car + active travel	1.47*** (1.41 - 1.54)	1.47*** (1.41 - 1.54)	1.35*** (1.28 - 1.43)	1.28*** (1.22 - 1.33)
Public transport only	1.03 (0.99 - 1.09)	1.03 (0.99 - 1.09)	0.95* (0.91 - 0.99)	0.95* (0.91 - 0.99)
Public transport + active travel	1.37*** (1.29 - 1.46)	1.37*** (1.29 - 1.46)	1.27*** (1.20 - 1.35)	1.27*** (1.20 - 1.35)
Walking only	1.19*** (1.11 - 1.28)	1.29*** (1.20 - 1.38)	1.20*** (1.14 - 1.25)	1.20*** (1.14 - 1.25)
Cycling / cycling + walking	1.82*** (1.71 - 1.94)	1.82*** (1.71 - 1.94)	2.00*** (1.84 - 2.18)	2.00*** (1.84 - 2.18)

*** p<0.001, ** p<0.01, * p<0.05

a) Adjusted for: age, ethnic group, education, occupational class, household income, household size, number of cars, assessment centre location, population density, Townsend score

b) Shading and boxes indicate variables with different relationships across the levels of the outcome variable: 1 = <3 portions FV, 2 = 3-<5 portions FV, 3 = 5+ portions FV

Table B.0.26 – Results of generalized ordered logit models between measures of active travel and RPM consumption, stratified by gender in UKB (n=412,299)

TRAVEL VARIABLES	Males (n=195,131)		Females (n=217,168)	
	Model 2 [a]		Model 2 [a]	
	1 v. 2 + 3 [b]	1 + 2 v. 3	1 v. 2 + 3 [b]	1 + 2 v. 3
Any active travel (ref: No)	0.72*** (0.68 - 0.76)	0.90*** (0.89 - 0.92)	0.79*** (0.76 - 0.81)	0.90*** (0.89 - 0.92)
Any walking (ref: No)	0.86*** (0.81 - 0.90)	0.94*** (0.92 - 0.96)	0.83*** (0.80 - 0.86)	0.92*** (0.91 - 0.94)
Any cycling (ref: No)	0.56*** (0.52 - 0.59)	0.78*** (0.76 - 0.81)	0.63*** (0.60 - 0.67)	0.77*** (0.75 - 0.80)
Non-work travel [b] (ref: Car only)				
Car + public transport	1.01 (0.95 - 1.06)	1.01 (0.95 - 1.06)	1.10*** (1.05 - 1.15)	1.10*** (1.05 - 1.15)
Car + mixed (public and active)	0.78*** (0.72 - 0.84)	0.97 (0.94 - 1.00)	0.87*** (0.83 - 0.92)	0.97* (0.94 - 0.99)
Car + active travel	0.83*** (0.77 - 0.89)	0.96** (0.94 - 0.99)	0.86*** (0.82 - 0.90)	0.96*** (0.93 - 0.98)
Public transport only	0.75*** (0.67 - 0.84)	0.89*** (0.85 - 0.94)	0.87*** (0.83 - 0.90)	0.87*** (0.83 - 0.90)
Public transport + active travel	0.60*** (0.54 - 0.66)	0.79*** (0.75 - 0.82)	0.67*** (0.62 - 0.71)	0.79*** (0.75 - 0.82)
Walking only	0.62*** (0.56 - 0.68)	0.76*** (0.73 - 0.79)	0.64*** (0.60 - 0.68)	0.73*** (0.70 - 0.76)
Cycling / cycling + walking	0.37*** (0.33 - 0.41)	0.61*** (0.58 - 0.65)	0.49*** (0.44 - 0.55)	0.60*** (0.55 - 0.66)
Commuting travel [c] (ref: Car only)				
Car + public transport	1.00 (0.95 - 1.05)	1.00 (0.95 - 1.05)	0.95 (0.87 - 1.04)	1.06* (1.01 - 1.11)
Car + mixed (public and active)	0.58*** (0.51 - 0.67)	0.93* (0.87 - 0.99)	0.77*** (0.69 - 0.85)	0.98 (0.91 - 1.06)
Car + active travel	0.65*** (0.58 - 0.73)	0.84*** (0.80 - 0.88)	0.81*** (0.75 - 0.87)	0.92*** (0.88 - 0.96)
Public transport only	0.82*** (0.73 - 0.92)	0.96 (0.91 - 1.01)	0.96 (0.92 - 1.01)	0.96 (0.92 - 1.01)
Public transport + active travel	0.57*** (0.50 - 0.65)	0.82*** (0.77 - 0.88)	0.73*** (0.66 - 0.80)	0.89*** (0.83 - 0.95)
Walking only	0.65*** (0.56 - 0.75)	0.82*** (0.76 - 0.87)	0.79*** (0.73 - 0.86)	0.88*** (0.84 - 0.93)
Cycling / cycling + walking	0.39*** (0.35 - 0.44)	0.65*** (0.61 - 0.70)	0.46*** (0.41 - 0.52)	0.65*** (0.59 - 0.71)

*** p<0.001, ** p<0.01, * p<0.05

a) Adjusted for: age, ethnic group, education, occupational class, household income, household size, number of cars, assessment centre location, population density, Townsend score

b) Shading and boxes indicate variables with different relationships across the levels of the outcome variable: 1 = 0 g RPM per day; 2 = >0-70 g RPM per day; 3 = >70 g RPM per day

Table B.0.27 – Sensitivity analysis: results of ordinal logistic models between any active travel and FV consumption among females in UKB (n=95,475)

VARIABLES	Unadjusted	Model 1	Model 2
Any active travel (ref: None)	1.42*** (1.38 - 1.45)	1.42*** (1.38 - 1.45)	1.35*** (1.32 - 1.39)
Age at baseline		1.05*** (1.04 - 1.05)	1.05*** (1.04 - 1.05)
Ethnic group (ref: White British)			
Other white		1.39*** (1.32 - 1.46)	1.38*** (1.31 - 1.45)
South Asian		2.05*** (1.81 - 2.33)	2.09*** (1.84 - 2.37)
Black		1.60*** (1.43 - 1.80)	1.58*** (1.41 - 1.76)
Chinese		1.54*** (1.23 - 1.94)	1.55*** (1.23 - 1.95)
Mixed		1.06 (0.91 - 1.22)	1.05 (0.90 - 1.21)
Other		2.13*** (1.82 - 2.48)	2.16*** (1.85 - 2.53)
Highest qualification (ref: Degree level)			
A levels/AS levels or equivalent		0.87*** (0.84 - 0.90)	0.87*** (0.84 - 0.91)
O levels/GCSEs or equivalent		0.78*** (0.75 - 0.81)	0.79*** (0.76 - 0.81)
CSEs or equivalent		0.71*** (0.66 - 0.75)	0.71*** (0.67 - 0.76)
NVQ or HND or HNC or equivalent		0.82*** (0.77 - 0.88)	0.82*** (0.76 - 0.88)
Other professional qualifications		0.92** (0.87 - 0.97)	0.91** (0.86 - 0.96)
No qualifications		0.68*** (0.64 - 0.71)	0.68*** (0.64 - 0.72)
Occupation class (ref: Higher man / prof)			
Lower managerial / professional		1.07*** (1.03 - 1.11)	1.05** (1.01 - 1.10)
Intermediate occupations		1.01 (0.97 - 1.06)	1.00 (0.96 - 1.05)
Small employers & own accounts		1.12** (1.04 - 1.22)	1.08 (0.99 - 1.17)
Lower supervisory & technical		1.14 (0.96 - 1.37)	1.04 (0.87 - 1.25)
Semi-routine occupations		1.10** (1.04 - 1.16)	1.06 (1.00 - 1.12)
Routine occupations		0.96 (0.86 - 1.07)	0.89* (0.80 - 0.99)
Not classified		1.04 (0.99 - 1.09)	0.99 (0.95 - 1.04)
Household income (ref: £<18 000)			
£18,000 to 30,999		1.11*** (1.06 - 1.15)	1.11*** (1.07 - 1.16)
£31,000 to 51,999		1.23*** (1.18 - 1.28)	1.25*** (1.19 - 1.30)
£52,000 to 100,000		1.31*** (1.25 - 1.37)	1.32*** (1.26 - 1.39)
£Greater than 100,000		1.34*** (1.25 - 1.43)	1.33*** (1.24 - 1.42)

Household size (ref: One)			
2		0.94***	0.93***
		(0.90 - 0.97)	(0.90 - 0.97)
3		0.90***	0.90***
		(0.86 - 0.94)	(0.86 - 0.94)
4		0.84***	0.84***
		(0.80 - 0.89)	(0.80 - 0.88)
5+		0.84***	0.82***
		(0.79 - 0.90)	(0.77 - 0.88)
Region (ref: London)			
North East England		1.11***	1.14***
		(1.05 - 1.16)	(1.08 - 1.20)
Yorkshire and the Humber		1.06**	1.07**
		(1.01 - 1.11)	(1.02 - 1.12)
West Midlands		1.05	1.07**
		(1.00 - 1.11)	(1.02 - 1.13)
East Midlands		1.15***	1.17***
		(1.09 - 1.22)	(1.11 - 1.25)
South East England		1.18***	1.21***
		(1.12 - 1.24)	(1.15 - 1.27)
South West England		1.19***	1.21***
		(1.14 - 1.26)	(1.16 - 1.28)
North West England		1.07**	1.09***
		(1.02 - 1.12)	(1.04 - 1.14)
Wales		1.16***	1.20***
		(1.08 - 1.26)	(1.11 - 1.29)
Scotland		1.09**	1.12***
		(1.03 - 1.16)	(1.05 - 1.19)
Townsend deprivation		0.99***	0.99***
		(0.99 - 0.99)	(0.99 - 1.00)
Urban (ref: Rural)		0.93***	0.95**
		(0.90 - 0.97)	(0.91 - 0.98)
Cars per household (ref: None)			
One		1.00	1.01
		(0.95 - 1.06)	(0.95 - 1.06)
Two		0.96	0.95
		(0.90 - 1.02)	(0.90 - 1.01)
Three		0.92*	0.91*
		(0.86 - 0.99)	(0.85 - 0.98)
Four or more		0.96	0.95
		(0.87 - 1.06)	(0.86 - 1.05)
Meets physical activity guideline (ref: No)			1.65***
			(1.61 - 1.69)
Total energy intake (kcal)			1.00***
			(1.00 - 1.00)
Observations	95,475	95,475	95,475

*** p<0.001, ** p<0.01, * p<0.05

Table B.0.28 – Sensitivity analysis: results of ordinal logistic models between any active travel and FV consumption among males in UKB (n=83,213)

VARIABLES	Unadjusted	Model 1	Model 2
Any active travel (ref: None)	1.38*** (1.34 - 1.41)	1.35*** (1.32 - 1.39)	1.28*** (1.24 - 1.31)
Age at baseline		1.03*** (1.03 - 1.03)	1.03*** (1.03 - 1.03)
Ethnic group (ref: White British)			
Other white		1.28*** (1.21 - 1.35)	1.28*** (1.21 - 1.35)
South Asian		2.02*** (1.81 - 2.25)	2.13*** (1.91 - 2.38)
Black		1.42*** (1.25 - 1.62)	1.44*** (1.26 - 1.64)
Chinese		1.59** (1.20 - 2.12)	1.65*** (1.24 - 2.20)
Mixed		1.14 (0.94 - 1.37)	1.12 (0.93 - 1.35)
Other		2.04*** (1.72 - 2.43)	2.10*** (1.76 - 2.49)
Highest qualification (ref: Degree level)			
A levels/AS levels or equivalent		0.78*** (0.75 - 0.82)	0.79*** (0.76 - 0.82)
O levels/GCSEs or equivalent		0.76*** (0.73 - 0.79)	0.76*** (0.73 - 0.79)
CSEs or equivalent		0.74*** (0.69 - 0.79)	0.73*** (0.68 - 0.78)
NVQ or HND or HNC or equivalent		0.84*** (0.80 - 0.89)	0.83*** (0.79 - 0.87)
Other professional qualifications		0.87*** (0.82 - 0.93)	0.86*** (0.80 - 0.92)
No qualifications		0.79*** (0.75 - 0.84)	0.78*** (0.74 - 0.83)
Occupation class (ref: Higher man / prof)			
Lower managerial / professional		1.03 (1.00 - 1.07)	1.02 (0.99 - 1.06)
Intermediate occupations		1.06* (1.01 - 1.12)	1.05 (1.00 - 1.11)
Small employers & own accounts		1.08 (1.00 - 1.16)	0.99 (0.92 - 1.07)
Lower supervisory & technical		1.13*** (1.06 - 1.21)	1.02 (0.95 - 1.09)
Semi-routine occupations		0.99 (0.92 - 1.06)	0.92* (0.86 - 0.98)
Routine occupations		1.04 (0.97 - 1.13)	0.94 (0.87 - 1.01)
Not classified		0.96* (0.92 - 1.00)	0.92*** (0.88 - 0.95)
Household income (ref: £<18 000)			
£18,000 to 30,999		1.09*** (1.04 - 1.14)	1.08** (1.03 - 1.13)
£31,000 to 51,999		1.20*** (1.15 - 1.26)	1.20*** (1.14 - 1.25)
£52,000 to 100,000		1.28*** (1.21 - 1.35)	1.29*** (1.23 - 1.37)
£Greater than 100,000		1.35*** (1.26 - 1.45)	1.35*** (1.27 - 1.45)

Household size (ref: One)			
2		1.13***	1.12***
		(1.08 - 1.18)	(1.07 - 1.17)
3		1.02	1.02
		(0.97 - 1.07)	(0.97 - 1.07)
4		1.02	1.01
		(0.96 - 1.07)	(0.96 - 1.06)
5+		0.99	0.97
		(0.93 - 1.06)	(0.91 - 1.04)
Region (ref: London)			
North East England		1.05	1.06*
		(1.00 - 1.11)	(1.01 - 1.12)
Yorkshire and the Humber		1.03	1.03
		(0.99 - 1.08)	(0.99 - 1.08)
West Midlands		0.98	0.98
		(0.93 - 1.03)	(0.93 - 1.04)
East Midlands		1.11**	1.11**
		(1.04 - 1.18)	(1.04 - 1.18)
South East England		1.04	1.06*
		(0.98 - 1.10)	(1.01 - 1.12)
South West England		1.07*	1.08**
		(1.02 - 1.13)	(1.02 - 1.13)
North West England		1.00	1.00
		(0.95 - 1.05)	(0.96 - 1.05)
Wales		1.12**	1.14**
		(1.03 - 1.21)	(1.05 - 1.23)
Scotland		0.91**	0.93*
		(0.85 - 0.97)	(0.87 - 0.99)
Townsend deprivation		1.00	1.00
		(0.99 - 1.00)	(0.99 - 1.00)
Urban (ref: Rural)		0.95**	0.96*
		(0.92 - 0.99)	(0.93 - 1.00)
Cars per household (ref: None)			
One		1.01	1.00
		(0.95 - 1.07)	(0.94 - 1.06)
Two		0.92**	0.89***
		(0.86 - 0.98)	(0.83 - 0.95)
Three		0.84***	0.81***
		(0.78 - 0.91)	(0.75 - 0.87)
Four or more		0.81***	0.78***
		(0.73 - 0.90)	(0.71 - 0.87)
Meets physical activity guideline (ref: No)			1.69***
			(1.64 - 1.73)
Total energy intake (kcal)			1.00***
			(1.00 - 1.00)
Observations	83,213	83,213	83,213

*** p<0.001, ** p<0.01, * p<0.05

Table B.0.29 – Sensitivity analysis: results of ordinal logistic models between any active travel and RPM consumption among females in UKB (n=95,475)

VARIABLES	Unadjusted	Model 1	Model 2
Any active travel (ref: None)	0.86***	0.89***	0.90***
	(0.83 - 0.88)	(0.87 - 0.91)	(0.88 - 0.92)
Age at baseline		1.01***	1.01***
		(1.01 - 1.01)	(1.01 - 1.01)
Ethnic group (ref: White British)			
Other white		1.02	1.02
		(0.97 - 1.07)	(0.97 - 1.07)
South Asian		0.32***	0.33***
		(0.28 - 0.36)	(0.29 - 0.37)
Black		1.09	1.09
		(0.98 - 1.23)	(0.97 - 1.22)
Chinese		1.83***	1.87***
		(1.46 - 2.30)	(1.49 - 2.35)
Mixed		1.00	1.01
		(0.86 - 1.17)	(0.86 - 1.18)
Other		0.75***	0.75***
		(0.65 - 0.88)	(0.65 - 0.87)
Highest qualification (ref: Degree level)			
A levels/AS levels or equivalent		1.21***	1.22***
		(1.16 - 1.26)	(1.18 - 1.27)
O levels/GCSEs or equivalent		1.28***	1.30***
		(1.23 - 1.32)	(1.26 - 1.35)
CSEs or equivalent		1.29***	1.33***
		(1.20 - 1.38)	(1.24 - 1.42)
NVQ or HND or HNC or equivalent		1.20***	1.24***
		(1.11 - 1.29)	(1.15 - 1.33)
Other professional qualifications		1.15***	1.16***
		(1.08 - 1.21)	(1.10 - 1.23)
No qualifications		1.29***	1.34***
		(1.22 - 1.37)	(1.27 - 1.42)
Occupation class (ref: Higher man / prof)			
Lower managerial / professional		0.96	0.96*
		(0.92 - 1.00)	(0.92 - 1.00)
Intermediate occupations		1.06*	1.06*
		(1.01 - 1.11)	(1.01 - 1.11)
Small employers & own accounts		1.00	1.01
		(0.92 - 1.09)	(0.93 - 1.10)
Lower supervisory & technical		1.04	1.07
		(0.86 - 1.26)	(0.89 - 1.29)
Semi-routine occupations		1.07*	1.07*
		(1.01 - 1.14)	(1.01 - 1.14)
Routine occupations		1.19**	1.19**
		(1.06 - 1.33)	(1.07 - 1.34)
Not classified		1.16***	1.16***
		(1.11 - 1.21)	(1.11 - 1.22)
Household income (ref: £<18 000)			
£18,000 to 30,999		1.04	1.05*
		(1.00 - 1.08)	(1.01 - 1.09)
£31,000 to 51,999		0.99	1.00
		(0.95 - 1.03)	(0.96 - 1.05)
£52,000 to 100,000		0.99	1.01
		(0.94 - 1.04)	(0.96 - 1.06)
£Greater than 100,000		0.99	1.04
		(0.93 - 1.06)	(0.97 - 1.11)

Household size (ref: One)			
2		1.41***	1.41***
		(1.36 - 1.47)	(1.35 - 1.46)
3		1.52***	1.50***
		(1.45 - 1.60)	(1.43 - 1.58)
4		1.77***	1.74***
		(1.68 - 1.87)	(1.65 - 1.83)
5+		1.91***	1.86***
		(1.78 - 2.05)	(1.74 - 2.00)
Region (ref: London)			
North East England		0.95*	0.94*
		(0.90 - 1.00)	(0.89 - 0.99)
Yorkshire and the Humber		0.99	0.98
		(0.95 - 1.04)	(0.94 - 1.03)
West Midlands		0.93**	0.92**
		(0.88 - 0.98)	(0.87 - 0.97)
East Midlands		0.97	0.95
		(0.91 - 1.03)	(0.90 - 1.02)
South East England		1.03	1.02
		(0.98 - 1.09)	(0.96 - 1.08)
South West England		0.91***	0.90***
		(0.87 - 0.96)	(0.86 - 0.95)
North West England		1.07**	1.06*
		(1.02 - 1.12)	(1.01 - 1.11)
Wales		0.85***	0.84***
		(0.78 - 0.92)	(0.77 - 0.91)
Scotland		1.08*	1.06
		(1.02 - 1.15)	(1.00 - 1.13)
Townsend deprivation		0.99***	0.99***
		(0.98 - 0.99)	(0.98 - 0.99)
Urban (ref: Rural)		0.97	0.96*
		(0.93 - 1.01)	(0.93 - 1.00)
Cars per household (ref: None)			
One		1.19***	1.19***
		(1.12 - 1.26)	(1.13 - 1.26)
Two		1.34***	1.36***
		(1.26 - 1.43)	(1.27 - 1.45)
Three		1.42***	1.45***
		(1.32 - 1.54)	(1.35 - 1.57)
Four or more		1.36***	1.40***
		(1.23 - 1.51)	(1.26 - 1.55)
Meets physical activity guideline (ref: No)			0.81***
			(0.79 - 0.83)
Total energy intake (kcal)			1.00***
			(1.00 - 1.00)
Observations	95,475	95,475	95,475

*** p<0.001, ** p<0.01, * p<0.05

Table B.0.30 – Sensitivity analysis: results of ordinal logistic models between any active travel and RPM consumption among males in UKB (n=83,213)

VARIABLES	Unadjusted	Model 1	Model 2
Any active travel (ref: None)	0.86***	0.89***	0.89***
	(0.84 - 0.88)	(0.86 - 0.91)	(0.87 - 0.92)
Age at baseline		1.00*	1.00***
		(1.00 - 1.00)	(1.00 - 1.01)
Ethnic group (ref: White British)			
Other white		0.99	0.99
		(0.93 - 1.05)	(0.94 - 1.05)
South Asian		0.27***	0.28***
		(0.24 - 0.30)	(0.25 - 0.31)
Black		0.95	0.99
		(0.82 - 1.09)	(0.86 - 1.15)
Chinese		1.36	1.42*
		(1.00 - 1.86)	(1.03 - 1.94)
Mixed		1.17	1.19
		(0.96 - 1.44)	(0.97 - 1.46)
Other		0.59***	0.60***
		(0.49 - 0.70)	(0.50 - 0.71)
Highest qualification (ref: Degree level)			
A levels/AS levels or equivalent		1.16***	1.17***
		(1.11 - 1.22)	(1.11 - 1.22)
O levels/GCSEs or equivalent		1.20***	1.22***
		(1.15 - 1.25)	(1.17 - 1.27)
CSEs or equivalent		1.19***	1.22***
		(1.11 - 1.28)	(1.14 - 1.32)
NVQ or HND or HNC or equivalent		1.20***	1.23***
		(1.13 - 1.27)	(1.16 - 1.30)
Other professional qualifications		1.01	1.03
		(0.94 - 1.09)	(0.96 - 1.11)
No qualifications		1.10**	1.13***
		(1.04 - 1.17)	(1.07 - 1.20)
Occupation class (ref: Higher man / prof)			
Lower managerial / professional		0.97	0.96*
		(0.93 - 1.01)	(0.92 - 1.00)
Intermediate occupations		1.02	1.02
		(0.97 - 1.08)	(0.97 - 1.08)
Small employers & own accounts		1.07	1.06
		(0.99 - 1.16)	(0.98 - 1.15)
Lower supervisory & technical		1.13**	1.14***
		(1.05 - 1.22)	(1.05 - 1.22)
Semi-routine occupations		1.19***	1.18***
		(1.10 - 1.28)	(1.10 - 1.27)
Routine occupations		1.22***	1.23***
		(1.12 - 1.33)	(1.13 - 1.33)
Not classified		1.13***	1.13***
		(1.08 - 1.18)	(1.08 - 1.18)
Household income (ref: £<18 000)			
£18,000 to 30,999		0.91***	0.92***
		(0.87 - 0.96)	(0.87 - 0.96)
£31,000 to 51,999		0.96	0.97
		(0.91 - 1.01)	(0.92 - 1.02)
£52,000 to 100,000		0.90***	0.92**
		(0.85 - 0.96)	(0.87 - 0.98)
£Greater than 100,000		0.85***	0.88***
		(0.79 - 0.91)	(0.82 - 0.95)

Household size (ref: One)			
2		1.04	1.05*
		(1.00 - 1.09)	(1.00 - 1.09)
3		1.16***	1.15***
		(1.10 - 1.22)	(1.09 - 1.22)
4		1.27***	1.26***
		(1.21 - 1.35)	(1.19 - 1.33)
5+		1.31***	1.28***
		(1.22 - 1.41)	(1.19 - 1.38)
Region (ref: London)			
North East England		0.94*	0.94*
		(0.89 - 1.00)	(0.89 - 1.00)
Yorkshire and the Humber		0.94**	0.94*
		(0.89 - 0.98)	(0.90 - 0.99)
West Midlands		0.91**	0.91**
		(0.86 - 0.97)	(0.86 - 0.97)
East Midlands		0.86***	0.86***
		(0.80 - 0.92)	(0.80 - 0.92)
South East England		1.00	1.00
		(0.94 - 1.06)	(0.94 - 1.06)
South West England		0.91**	0.91**
		(0.86 - 0.97)	(0.86 - 0.96)
North West England		1.06*	1.07*
		(1.01 - 1.12)	(1.01 - 1.12)
Wales		0.80***	0.80***
		(0.73 - 0.87)	(0.73 - 0.87)
Scotland		1.05	1.04
		(0.98 - 1.12)	(0.97 - 1.12)
Townsend deprivation		1.00	1.00
		(0.99 - 1.00)	(0.99 - 1.00)
Urban (ref: Rural)		0.97	0.97
		(0.94 - 1.01)	(0.93 - 1.01)
Cars per household (ref: None)			
One		1.11**	1.11**
		(1.04 - 1.18)	(1.04 - 1.19)
Two		1.27***	1.28***
		(1.18 - 1.36)	(1.19 - 1.37)
Three		1.44***	1.46***
		(1.33 - 1.57)	(1.34 - 1.59)
Four or more		1.40***	1.43***
		(1.26 - 1.57)	(1.28 - 1.60)
Meets physical activity guideline (ref: No)			0.84***
			(0.82 - 0.87)
Total energy intake (kcal)			1.00***
			(1.00 - 1.00)
Observations	83,213	83,213	83,213

*** p<0.001, ** p<0.01, * p<0.05

Appendix C (Chapter 5)

C.1 – Selecting the size of the random samples in UKB

10% sample (n=11,628)

Based on the fit statistics (Table C.0.1), the best fitting model had 11 classes, however this model still had unexplained variation between several indicators, which was not improved by increasing the number of latent classes (Table C.0.2). As a result of these problems, I experimented with a smaller sample (5%).

Table C.0.1 – LCA model fit statistics for UKB females, 10% sample (n=11,628)

Class #	LL	BIC(LL)	AIC(LL)	CAIC(LL)	SABIC(LL)	Npar	L²	df	p-value	Class.Err.
1	-100244	200692.9	200531.5	200714.9	200623	22	64598.1	11337	2.3e-7285	0.00
2	-76529.9	153433.4	153139.9	153473.4	153306.3	40	17170.4	11319	4.00E-249	0.00
3	-72931.7	146405	145979.4	146463	146220.7	58	9974.0	11301	1	0.02
4	-72185.4	145080.4	144522.8	145156.4	144838.9	76	8481.4	11283	1	0.02
5	-71570.3	144018.4	143328.6	144112.4	143719.6	94	7251.2	11265	1	0.05
6	-71058.8	143163.4	142341.6	143275.4	142807.5	112	6228.2	11247	1	0.04
7	-70608.7	142431.3	141477.3	142561.3	142018.1	130	5327.9	11229	1	0.08
8	-70323.5	142029	140943	142177	141558.7	148	4757.6	11211	1	0.07
9	-70115.1	141780.4	140562.3	141946.4	141252.8	166	4340.9	11193	1	0.09
10	-69811.9	141342	139991.9	141526	140757.3	184	3734.5	11175	1	0.09
11	-69718.5	141323.2	139841	141525.2	140681.3	202	3547.5	11157	1	0.06
12	-69678.2	141410.8	139796.5	141630.8	140711.7	220	3467.1	11139	1	0.14
13	-69610	141442.3	139696	141680.3	140686	238	3330.5	11121	1	0.16
14	-69608.2	141606.9	139728.4	141862.9	140793.4	256	3327.0	11103	1	0.10
15	-69585.2	141728.9	139718.4	142002.9	140858.2	274	3281.0	11085	1	0.16
16	-69560.9	141848.5	139705.8	142140.5	140920.5	292	3232.4	11067	1	0.23
17	-69525.2	141945.1	139670.4	142255.1	140959.9	310	3161.0	11049	1	0.17
18	-69465.2	141993.1	139586.4	142321.1	140950.8	328	3040.9	11031	1	0.22
19	-69501.2	142233.2	139694.4	142579.2	141133.7	346	3113.0	11013	1	0.17
20	-69409.6	142218.1	139547.1	142582.1	141061.3	364	2929.7	10995	1	0.28

Shading indicates the lowest value for a given information criterion

Table C.0.2 – Bivariate residuals between each pair of indicators for each model among UKB females (11-class, 12-class, 13-class), 10% sample (n=11,628)

11-class model

Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
multitrav2	.								
carcom2	0.42	.							
bikecom2	1.33	0.34	.						
walkcom2	0.37	0.49	0.19	.					
pubcom2	0.69	0.06	0.06	0.33	.				
timedriving	9.47	3.10	1.87	0.45	0.14	.			
veg2	1.38	0.00	0.35	0.01	0.44	0.76	.		
avoidredmeat	0.13	0.00	0.00	0.00	0.01	0.00	0.22	.	
rpmtotalcat	0.80	0.02	0.59	0.17	0.07	6.12	0.02	2.10	.
portions3cat	18.56	0.47	0.48	0.68	0.00	0.79	0.33	0.18	24.84

12 –class model

Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
multitrav2	.								
carcom2	0.13	.							
bikecom2	0.72	0.08	.						
walkcom2	0.49	0.22	0.07	.					
pubcom2	1.21	0.07	0.08	0.32	.				
timedriving	5.71	0.15	0.39	0.86	0.21	.			
veg2	1.11	0.00	0.29	0.00	0.42	0.23	.		
avoidredmeat	0.11	0.00	0.00	0.00	0.01	0.03	0.20	.	
rpmtotalcat	0.79	0.00	0.28	0.30	0.02	1.74	0.01	3.56	.
portions3cat	13.73	0.12	0.13	0.48	0.02	3.42	0.55	0.23	27.80

13-class model

Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
multitrav2	.								
carcom2	0.15	.							
bikecom2	0.74	0.08	.						
walkcom2	0.49	0.18	0.09	.					
pubcom2	1.21	0.07	0.08	0.33	.				
timedriving	2.70	0.05	0.43	0.77	0.22	.			
veg2	0.98	0.00	0.29	0.00	0.42	0.03	.		
avoidredmeat	0.09	0.00	0.00	0.00	0.01	0.02	0.26	.	
rpmtotalcat	0.92	0.00	0.28	0.30	0.02	5.37	0.01	1.16	.
portions3cat	6.72	0.13	0.14	0.48	0.02	2.71	0.58	0.07	25.83

Shading indicates bivariate residuals that are greater than >3.84, which indicates unexplained relationships between a pair of indicators, and thus, local dependence in the model.

5% sample (n=5,815)

Based on the fit statistics (Table C.0.3), the best fitting model had 11 classes, however this model still had unexplained variation between several indicators, which was not improved by increasing the number of latent classes (Table C.0.4). As a result of these problems, I experimented with a smaller sample (2%).

Table C.0.3 – LCA model fit statistics for UKB females, 5% sample (n=5,815)

Class #	LL	BIC(LL)	AIC(LL)	CAIC(LL)	SABIC(LL)	Npar	L^2	df	p-value	Class.Err.
1	-50168.6	100527.3	100381.1	100549.3	100457.4	22	33288.8	5651	7.0e-3829	0.00
2	-38255.9	76857.5	76591.8	76897.5	76730.4	40	9463.4	5633	7.30E-200	0.00
3	-36534.5	73570.4	73185.1	73628.4	73386.1	58	6020.7	5615	8.90E-05	0.02
4	-36170.2	72997.3	72492.4	73073.3	72755.8	76	5292.0	5597	1	0.02
5	-35806.6	72425.7	71801.2	72519.7	72127.0	94	4564.8	5579	1	0.05
6	-35549.9	72067.9	71323.8	72179.9	71712.0	112	4051.4	5561	1	0.05
7	-35332.6	71788.8	70925.2	71918.8	71375.7	130	3616.8	5543	1	0.08
8	-35160.3	71599.8	70616.6	71747.8	71129.5	148	3272.2	5525	1	0.08
9	-35061.1	71556.9	70454.1	71722.9	71029.4	166	3073.7	5507	1	0.08
10	-35025.7	71641.7	70419.3	71825.7	71057.0	184	3002.9	5489	1	0.09
11	-34881.4	71508.7	70166.7	71710.7	70866.8	202	2714.4	5471	1	0.09
12	-34875.7	71652.9	70191.4	71872.9	70953.8	220	2703.0	5453	1	0.14
13	-34820.0	71697.1	70116.0	71935.1	70940.8	238	2591.6	5435	1	0.11
14	-34807.9	71828.5	70127.8	72084.5	71015.0	256	2567.4	5417	1	0.14
15	-34795.8	71959.8	70139.5	72233.8	71089.1	274	2543.1	5399	1	0.16
16	-34758.6	72041.1	70101.2	72333.1	71113.2	292	2468.8	5381	1	0.26
17	-34730.2	72139.8	70080.3	72449.8	71154.7	310	2412.0	5363	1	0.16
18	-34714.1	72263.2	70084.2	72591.2	71220.9	328	2379.8	5345	1	0.19
19	-34705.7	72402.1	70103.5	72748.1	71302.6	346	2363.1	5327	1	0.17
20	-34690.8	72527.9	70109.6	72891.9	71371.2	364	2333.3	5309	1	0.10

Shading indicates the lowest value for a given information criterion

Table C.0.4 – Bivariate residuals between each pair of indicators for each model among UKB females (11-class, 12-class, 13-class), 5% sample (n=5,815)

11-class model

Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
multitrav2	.								
carcom2	0.21	.							
bikecom2	0.92	0.07	.						
walkcom2	0.49	0.08	0.67	.					
pubcom2	0.64	0.08	0.11	0.09	.				
timedriving	3.78	0.15	1.05	0.38	0.02	.			
veg2	0.54	0.09	0.72	0.02	0.06	0.58	.		
avoidredmeat	0.02	0.00	0.04	0.03	0.00	0.05	0.23	.	
rpmtotalcat	2.30	0.14	0.15	0.20	0.05	0.00	0.00	0.53	.
portions3cat	7.22	0.04	3.80	0.05	0.14	0.00	1.68	0.14	22.55

12-class model

Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
multitrav2	.								
carcom2	0.33	.							
bikecom2	1.20	0.19	.						
walkcom2	0.95	0.06	0.40	.					
pubcom2	0.34	0.37	0.65	0.51	.				
timedriving	4.23	0.02	1.66	0.45	0.04	.			
veg2	0.66	0.08	0.71	0.02	0.07	0.25	.		
avoidredmeat	0.05	0.00	0.04	0.04	0.00	0.05	0.20	.	
rpmtotalcat	0.56	0.43	0.17	0.16	0.05	1.22	0.00	1.15	.
portions3cat	3.84	0.00	4.43	0.01	0.49	0.52	1.88	0.29	24.11

13-class model

Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
multitrav2	.								
carcom2	0.51	.							
bikecom2	1.74	0.47	.						
walkcom2	0.53	0.07	0.09	.					
pubcom2	0.41	0.07	0.28	0.06	.				
timedriving	1.17	0.73	3.08	0.00	0.00	.			
veg2	0.78	0.08	0.66	0.08	0.09	0.07	.		
avoidredmeat	0.01	0.01	0.02	0.00	0.02	0.02	0.26	.	
rpmtotalcat	0.72	0.56	0.27	0.17	0.15	0.25	0.01	0.40	.
portions3cat	3.02	0.01	4.09	0.01	0.09	0.13	1.79	0.09	26.87

Shading indicates bivariate residuals that are greater than >3.84, which indicates unexplained relationships between a pair of indicators, and thus, local dependence in the model.

C.2 – NDNS females: overview of model selection (9 class)

Table C.0.5 – LCA model fit statistics for NDNS females sample (n=904)

Class #	LL	BIC(LL)	AIC(LL)	CAIC(LL)	SABIC(LL)	Npar	L²	df	p-value	Class.Err.
1	-6856.0	13882.1	13762.0	13907.1	13802.7	25	6081.6	879	9.2e-764	0.00
2	-4973.2	10279.9	10044.4	10328.9	10124.3	49	2316.0	855	6.40E-135	0.00
3	-4689.9	9876.7	9525.8	9949.7	9644.8	73	1749.4	831	1.40E-67	0.01
4	-4585.9	9832.0	9365.8	9929.0	9524.0	97	1541.4	807	1.80E-48	0.01
5	-4501.1	9825.8	9244.2	9946.8	9441.6	121	1371.9	783	8.00E-35	0.01
6	-4428.6	9844.3	9147.3	9989.3	9383.8	145	1227.0	759	1.10E-24	0.01
7	-4379.1	9908.6	9096.3	10077.6	9371.9	169	1127.9	735	4.10E-19	0.02
8	-4331.8	9977.2	9049.5	10170.2	9364.3	193	1033.2	711	2.50E-14	0.02
9	-4310.9	10098.9	9055.8	10315.9	9409.8	217	991.5	687	1.90E-13	0.09
10	-4281.7	10203.9	9045.4	10444.9	9438.5	241	933.1	663	1.90E-11	0.02

Shading indicates the lowest value for a given information criterion

Box indicates the final model that was selected based on bivariate residuals and interpretability.

Table C.0.6 – Bivariate residuals between each pair of indicators for each model among NDNS females

4-class model

Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
gentrav2	.							
wrkbycar4	0.63	.						
wrkbypubtran4	4.27	0.52	.					
wrkbybike4	10.19	0.17	1.06	.				
wrkbyfoot4	4.19	1.19	3.88	0.70	.			
meatcat2	2.10	0.07	0.66	1.05	0.54	.		
avoidmeat	2.57	0.03	0.38	0.60	0.09	248.34	.	
veg2	2.39	0.00	0.10	0.12	0.05	120.47	211.12	.
portions3	7.35	0.07	0.56	1.11	0.38	10.33	3.52	3.91

5-class model

Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
gentrav2	.							
wrkbycar4	1.08	.						
wrkbypubtran4	4.41	0.59	.					
wrkbybike4	10.56	0.37	0.85	.				
wrkbyfoot4	3.68	1.31	3.55	0.48	.			
meatcat2	0.50	0.07	0.60	0.23	0.28	.		
avoidmeat	0.26	0.02	0.69	0.26	0.15	23.21	.	
veg2	0.29	0.01	0.04	0.49	0.06	2.74	10.15	.
portions3	6.46	0.06	0.47	0.78	0.37	3.40	0.00	0.06

6-class model

Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
gentrav2	.							
wrkbycar4	1.91	.						
wrkbypubtran4	1.35	0.98	.					
wrkbybike4	5.88	1.98	0.65	.				
wrkbyfoot4	0.59	2.10	0.62	0.49	.			
meatcat2	0.15	0.07	0.19	0.26	0.12	.		
avoidmeat	0.16	0.05	0.48	0.37	0.04	22.38	.	
veg2	0.26	0.01	0.04	0.50	0.05	2.70	9.85	.
portions3	6.34	0.38	0.31	0.68	0.46	3.32	0.00	0.09

7-class model

Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
gentrav2	.							
wrkbycar4	0.86	.						
wrkbypubtran4	1.12	0.59	.					
wrkbybike4	7.57	0.54	0.53	.				
wrkbyfoot4	1.07	1.85	0.78	0.84	.			
meatcat2	0.10	0.10	0.21	0.26	0.02	.		
avoidmeat	0.55	0.02	0.54	0.47	0.09	1.60	.	
veg2	0.49	0.02	0.05	0.63	0.06	0.35	1.07	.
portions3	6.12	0.18	0.32	0.73	0.26	1.91	0.30	0.01

8-class model

Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
gentrav2	.							
wrkbycar4	0.48	.						
wrkbypubtran4	0.87	0.69	.					
wrkbybike4	0.14	0.51	0.23	.				
wrkbyfoot4	0.20	2.04	0.76	0.26	.			
meatcat2	0.06	0.12	0.21	0.31	0.07	.		
avoidmeat	0.38	0.09	0.36	0.40	0.04	2.69	.	
veg2	1.48	0.05	0.03	0.00	0.03	0.27	0.16	.
portions3	4.85	0.41	0.36	0.40	0.49	2.43	0.11	0.02

9-class model

Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
gentrav2	.							
wrkbycar4	0.46	.						
wrkbypubtran4	0.93	0.72	.					
wrkbybike4	0.11	0.54	0.24	.				
wrkbyfoot4	0.18	2.10	0.82	0.22	.			
meatcat2	0.06	0.13	0.20	0.36	0.07	.		
avoidmeat	0.25	0.07	0.39	0.40	0.04	2.76	.	
veg2	1.53	0.04	0.03	0.00	0.03	0.30	0.13	.
portions3	0.89	0.43	0.40	0.49	0.45	1.77	0.18	0.00

Shading indicates bivariate residuals that are greater than >3.84, which indicates unexplained relationships between a pair of indicators, and thus, local dependence in the model.

C.3 – NDNS males: overview of model selection (8 class)

Table C.0.7 – LCA model fit statistics for NDNS males sample (n=705)

Class #	LL	BIC(LL)	AIC(LL)	CAIC(LL)	SABIC(LL)	Npar	L²	df	p-value	Class.Err.
1	-5349.6	10863.2	10749.2	10888.2	10783.8	25	4757.5	680	2.5e-601	0.00
2	-3943.0	8207.4	7984.1	8256.4	8051.9	49	1944.4	656	1.10E-127	0.00
3	-3651.9	7782.5	7449.8	7855.5	7550.7	73	1362.1	632	1.40E-55	0.00
4	-3566.9	7769.9	7327.7	7866.9	7461.9	97	1192.0	608	2.80E-40	0.00
5	-3495.5	7784.6	7233.0	7905.6	7400.4	121	1049.3	584	5.40E-29	0.01
6	-3437.5	7826.0	7165.0	7971.0	7365.6	145	933.3	560	4.00E-21	0.01
7	-3399.8	7907.9	7137.6	8076.9	7371.3	169	857.9	536	2.80E-17	0.00
8	-3363.5	7992.7	7113.0	8185.7	7379.9	193	785.3	512	7.40E-14	0.01
9	-3348.8	8120.8	7131.7	8337.8	7431.8	217	756.0	488	7.10E-14	0.01
10	-3327.0	8234.5	7136.0	8475.5	7469.3	241	712.3	464	8.90E-13	0.03

Shading indicates the lowest value for a given information criterion

Box indicates the final model that was selected based on bivariate residuals and interpretability.

Table C.0.8 – Bivariate residuals between each pair of indicators for each model among NDNS males

3	Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
	gentrav2	.							
	wrkbycar4	0.52	.						
	wrkbypubtran4	4.12	4.57	.					
	wrkbybike4	7.93	3.27	4.14	.				
	wrkbyfoot4	3.10	9.84	3.68	3.41	.			
	meatcat2	0.66	0.21	0.57	2.03	0.16	.		
	avoidmeat	1.09	1.51	0.80	2.51	4.99	112.99	.	
	veg2	0.98	0.73	0.14	2.09	0.09	92.05	167.64	.
	portions3	5.70	0.50	3.44	4.55	0.90	0.00	2.40	9.65

4	Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
	gentrav2	.							
	wrkbycar4	0.46	.						
	wrkbypubtran4	2.64	4.89	.					
	wrkbybike4	0.26	3.14	2.26	.				
	wrkbyfoot4	1.70	9.62	5.13	1.34	.			
	meatcat2	0.77	0.19	0.45	2.21	0.19	.		
	avoidmeat	1.14	1.52	0.96	1.63	4.16	114.96	.	
	veg2	0.55	0.77	0.05	0.65	0.03	96.90	155.36	.
	portions3	2.83	0.54	2.16	1.00	2.40	0.01	1.90	7.86

5	Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
	gentrav2	.							
	wrkbycar4	1.39	.						
	wrkbypubtran4	2.96	0.67	.					
	wrkbybike4	0.18	0.56	0.13	.				
	wrkbyfoot4	2.56	1.11	2.64	0.47	.			
	meatcat2	0.80	0.21	0.90	2.12	0.49	.		
	avoidmeat	1.28	0.03	0.55	1.55	1.11	119.05	.	
	veg2	0.50	1.55	0.08	0.72	0.04	93.85	160.83	.
	portions3	3.27	0.27	1.31	0.66	1.22	0.00	2.46	7.57

6	Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
	gentrav2	.							
	wrkbycar4	0.23	.						
	wrkbypubtran4	0.58	1.90	.					
	wrkbybike4	0.23	0.62	0.91	.				
	wrkbyfoot4	0.17	2.40	0.76	0.44	.			
	meatcat2	1.14	1.02	0.27	2.56	0.33	.		
	avoidmeat	0.89	0.77	0.77	1.79	0.30	97.36	.	
	veg2	0.66	2.79	0.20	0.87	0.35	78.65	71.73	.
	portions3	1.65	0.41	1.89	1.07	0.97	0.06	2.40	8.16

7	Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
	gentrav2	.							
	wrkbycar4	0.59	.						
	wrkbypubtran4	0.54	1.46	.					
	wrkbybike4	0.39	1.02	1.04	.				
	wrkbyfoot4	0.26	2.45	1.08	0.59	.			
	meatcat2	0.69	0.03	0.33	0.26	0.43	.		
	avoidmeat	0.62	0.03	0.91	0.02	0.58	10.71	.	
	veg2	0.24	0.20	0.32	0.29	0.34	0.00	0.31	.
	portions3	2.32	0.27	1.64	0.44	0.92	0.42	0.14	0.19

8	Indicators	gentrav2	wrkbycar4	wrkbypubtran4	wrkbybike4	wrkbyfoot4	meatcat2	avoidmeat	veg2
	gentrav2	.							
	wrkbycar4	0.33	.						
	wrkbypubtran4	0.79	1.39	.					
	wrkbybike4	0.38	0.75	0.75	.				
	wrkbyfoot4	0.16	1.90	0.72	0.29	.			
	meatcat2	0.85	0.05	0.01	0.70	0.20	.		
	avoidmeat	0.32	0.01	0.37	0.29	0.29	2.02	.	
	veg2	0.32	0.15	0.12	0.38	0.34	0.00	0.39	.
	portions3	1.69	0.17	1.67	0.32	0.45	0.67	0.00	0.92

Shading indicates bivariate residuals that are greater than >3.84, which indicates unexplained relationships between a pair of indicators, and thus, local dependence in the model.

Class descriptions – NDNS males (8 class model)

Class 1 (38%) – Always car commuters with high RPM and high FV consumption

The largest class (38% of the sample) was defined by its high, virtually exclusive car use. Overall, 100% of this group commuted by car and 86% also travelled by car for non-work journeys, which was well above the sample average of 63%. With regard to diet, 60% of this group exceeded the RPM consumption guideline, which was higher than the sample average of 53%. Similarly, only 31% of this group met the 5 a day FV guideline, but this was still slightly above the overall sample average of 29%. Based on the distribution of car use and RPM consumption in this class, this group receives a red-red rating on the healthy, low-carbon scale. This class was similar to Class 1 (Always car commuters, 26%) among NDNS females, though slightly larger in size.

Class 2 (36%) – Mixed car non-commuters with low RPM and low FV consumption

The second largest class (36%) was made up of non-commuters (100%) with slightly above average walking (26%) and PT use (12%) and slightly below average car use (60%) for non-work travel. Their consumption of RPM was lower than Class 1 as only 48% exceeded the RPM guideline, though virtually all were still habitual RPM consumers. With regard to FV, this group was less likely to meet the 5-a-day guideline (25%) with the largest proportion (40%) consuming <3 portions per day on average. Based on its car use and RPM consumption, this group receives a red-blue rating. Overall, this class was most similar to Class 2 (Low FV non-commuters, 25%) among NDNS females, but also seemed to incorporate some elements of Class 3 (Mostly car non-commuters, 21%).

Class 3 (9%) – PT commuters with low RPM and low FV consumption

The third class (9%) were predominant PT users who also walked: 58% used PT for their non-work travel, and 83% always commuted by public transport, however walking was also above the sample average for both types of travel. Overall, this class consumed less RPM than the previous two groups as 12% consumed no RPM over the food diary period and only 43% exceeded the RPM guideline (lowest among all RPM consuming groups). Similarly, 8% of this group reported being non-consumers of RPM on a habitual basis. Notably, however, this group's FV consumption was the lowest of all the classes as only 17% met the 5-a-day FV guideline. Based on its car use and RPM consumption, this group receives a green-blue rating. This class was very similar in size and typology to Class 6 (PT commuters, 7%) among NDNS females.

Class 4 (6%) – Mostly walkers with high RPM and high FV consumption

The fourth largest class (6% of the sample) was primarily defined by its high proportion of walking: 70% walked for non-work travel and 90% always commuted by foot. With regard to diet, this group had higher than average RPM consumption (57% above guideline), combined with higher than average FV consumption (37% meeting guideline). Based on its car use and RPM consumption, this group receives a green-red rating. This class was similar in size and typology to Class 5 (Mostly walkers, 7%) among NDNS females, except that FV consumption was higher among males.

Class 5 (5%) – Usual car commuters with high RPM and low FV consumption

The fifth class (5%) was composed of mostly car commuters (84% usually) with above average car use for non-work travel (90%). This was the highest non-work car travel of all the classes, though some members of this group also commuted by PT, cycling, and/or walking on a usual or occasional basis. With regard to diet, this group had above average RPM consumption (64% above guideline, the second highest of all classes), combined with below average FV consumption (only 20% meeting guideline). Despite their high RPM consumption, 13% of this group reported not consuming RPM on a habitual basis. Based on its car use and RPM consumption, this group receives a red-red rating. This class was similar to Class 4 (Usual car commuters, 7%) among NDNS females, except for a reversal of its dietary indicators (low RPM, high FV).

Class 6 (3%) – Cyclists with high RPM and high FV consumption

The sixth class (3%) was primarily defined by their cycling travel: 93% of this group cycled for non-work travel and 82% always cycled for their commute. In contrast to the cycling group among NDNS females, however, this group had the highest RPM consumption of all classes: the vast majority (79%) exceeded the RPM guideline and all were habitual RPM consumers. Notably, however, this group also had the highest FV consumption of all classes with 70% meeting the 5 a day guideline. Thus, based on its car use and RPM consumption, this group receives a green-red rating. This group was similar to Class 9 (Cyclists, 1%) among NDNS females, except for its very high RPM consumption.

Class 7 (1%) – Low meat mixed car commuters with high FV consumption

This group was primarily defined by the fact that virtually all (99%) of its members reported never consuming RPM on a habitual basis. Their actual self-reported RPM consumption was also very low, with 95% consuming no RPM over the food diary period. This group was a mixed transport group made up of mostly car commuters (52% always) with slightly below average non-work travel car use (49%). They also had higher than average cycling for non-work and commuting travel (32% and 43% usually/occasionally, respectively). This group also had higher than average FV consumption with (59%) meeting the 5-a-day guideline. Despite their low RPM consumption, only 54% of this class reported that they followed a strictly vegetarian diet (i.e. never consumed any meat, poultry, or fish). Based on its car use and RPM consumption, this group receives a blue-green rating. Notably, this class was similar to Class 7 (Low meat mostly car commuters, 4%) among NDNS females, but with lower car travel.

Class 8 (1%) – Low meat non-commuters with high FV consumption

The last and smallest class (1%) was another non-commuting group with a mixed non-work travel pattern. Non-work walking and PT use were above the sample average (37% and 25%, respectively) and car travel was below (38%). Nearly all members of this group reported consuming no RPM over the food diary period (97%) and nearly all (97%) reported that they never consumed RPM on a habitual basis. Compared to the previous class, about the same proportion reported being vegetarian (only 51%) and meeting the 5-a-day guideline (59%) though their FV consumption was still well above the sample average of 29%. Based on its car use and RPM consumption, this group receives a green-green rating. This class was somewhat similar to Class 8 (Low meat non-commuters, 2%) among NDNS females, but with lower car travel.

C.4 – UKB females: overview of model selection (10 class)

Table C.0.9 – LCA model fit statistics for UKB females sample (n=2,324)

Class #	LL	BIC(LL)	AIC(LL)	CAIC(LL)	SABIC(LL)	Npar	L²	df	p-value	Class.Err.
1	-20426.5	41023.5	40897.0	41045.5	40953.6	22	14502.1	2302	1.4e-1732	0.00
2	-15595.8	31501.7	31271.7	31541.7	31374.6	40	4840.8	2284	2.30E-185	0.00
3	-14875.2	30200.0	29866.5	30258.0	30015.7	58	3399.6	2266	6.50E-49	0.02
4	-14681.8	29952.6	29515.5	30028.6	29711.1	76	3012.6	2248	2.60E-25	0.02
5	-14556.2	29840.9	29300.3	29934.9	29542.3	94	2761.4	2230	6.30E-14	0.02
6	-14457.8	29783.7	29139.6	29895.7	29427.9	112	2564.8	2212	2.10E-07	0.05
7	-14360.8	29729.2	28981.6	29859.2	29316.2	130	2370.7	2194	0.0045	0.08
8	-14283.9	29715.0	28863.8	29863.0	29244.7	148	2216.9	2176	0.27	0.08
9	-14232.8	29752.4	28797.7	29918.4	29224.9	166	2114.8	2158	0.74	0.09
10	-14175.6	29777.5	28719.3	29961.5	29192.9	184	2000.4	2140	0.99	0.08

Shading indicates the lowest value for a given information criterion

Box indicates the final model that was selected based on bivariate residuals and interpretability.

Table C.0.10 – Bivariate residuals between each pair of indicators for each model among UKB females

7	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	portions3cat	avoidredmeat	veg2
	multitrav2	.								
	carcom2	0.35	.							
	bikecom2	12.10	0.17	.						
	walkcom2	2.08	0.61	2.48	.					
	pubcom2	5.01	0.18	2.14	3.86	.				
	timedriving	0.21	1.95	0.07	0.56	0.05	.			
	portions3cat	4.65	0.09	0.63	0.10	0.00	1.71	.		
	avoidredmeat	0.33	0.00	0.87	0.02	0.26	0.01	1.07	.	
	veg2	0.27	0.05	0.41	0.16	0.00	0.00	0.01	10.98	.
	rpmtotalcat	2.74	0.00	0.52	0.33	2.55	0.18	1.99	7.79	2.70

8	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	portions3cat	avoidredmeat	veg2
	multitrav2	.								
	carcom2	0.49	.							
	bikecom2	6.06	0.17	.						
	walkcom2	2.69	0.40	4.63	.					
	pubcom2	2.56	0.07	0.33	1.07	.				
	timedriving	0.60	1.83	0.26	0.45	0.14	.			
	portions3cat	4.72	0.04	0.19	0.24	0.20	1.49	.		
	avoidredmeat	0.49	0.01	0.21	0.00	0.21	0.03	0.19	.	
	veg2	1.02	0.01	0.07	0.29	0.45	0.01	0.11	5.56	.
	rpmtotalcat	1.47	0.00	0.12	0.06	0.71	0.26	1.17	0.28	0.00

9	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	portions3cat	avoidredmeat	veg2
	multitrav2	.								
	carcom2	0.18	.							
	bikecom2	2.41	0.32	.						
	walkcom2	0.87	0.09	0.99	.					
	pubcom2	2.16	0.39	1.64	0.08	.				
	timedriving	0.53	0.13	0.96	0.36	0.05	.			
	portions3cat	4.30	0.06	0.06	0.10	0.05	1.74	.		
	avoidredmeat	1.26	0.01	0.80	0.07	0.35	0.00	0.16	.	
	veg2	1.41	0.00	1.01	0.06	0.21	0.03	0.53	5.46	.
	rpmtotalcat	1.79	0.16	0.01	0.02	0.10	0.22	1.32	2.88	0.07

10	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	portions3cat	avoidredmeat	veg2
	multitrav2	.								
	carcom2	0.03	.							
	bikecom2	0.21	0.14	.						
	walkcom2	0.22	0.07	0.37	.					
	pubcom2	0.44	0.45	0.37	0.44	.				
	timedriving	0.65	0.10	0.76	0.20	0.01	.			
	portions3cat	4.77	0.04	0.08	0.14	0.18	1.63	.		
	avoidredmeat	0.11	0.01	0.00	0.00	0.00	0.02	0.29	.	
	veg2	0.41	0.11	0.01	0.27	0.14	0.06	0.06	1.10	.
	rpmtotalcat	1.54	0.09	0.02	0.03	0.18	0.34	1.54	0.50	0.01

Shading indicates bivariate residuals that are greater than >3.84, which indicates unexplained relationships between a pair of indicators, and thus, local dependence in the model.

Class descriptions – UKB females (10 class model)

Class 1 (33%) – Exclusive car commuters with high RPM and low FV consumption

The largest class (33% of the sample) was primarily defined by its high car use. In total, 100% of this group commuted by car and 54% also travelled by car exclusively for non-work journeys, which was well above the sample average of 36% and highest of all classes. Overall, 70% of this group reported driving for 1+ hours per day confirming their heavy car use. With regard to diet, this group had higher than average RPM consumption and lower than average FV consumption. 25% of this group consumed >1 servings of RPM per day (sample average 23%) and 24% consumed <3 portions of FV per day (sample average 19%). Based on the distribution of car use and RPM consumption in this class, this group receives a red-red rating on the healthy, low-carbon scale.

Class 2 (32%) – Mixed car non-commuters with high RPM and high FV consumption

The second largest class (32%) was made up of non-commuters (100%) with above average mixed car travel (56%). In other words, more than half of this group reported using PT, walking or cycling in addition to their car travel; however exclusive car travel was also higher than the sample average (40%). Compared to Class 1 however, this group also spent less time driving per day, as most drove for <1 hour (55%). With regard to diet, their consumption of RPM was slightly higher than Class 1 and their FV consumption was also higher: 26% consumed >1 serving of RPM per day and 45% met the 5-a-day guideline. Based on the distribution of car use and RPM consumption in this class, this group receives a red-red rating.

Class 3 (9%) – PT non-commuters with high RPM and high FV consumption

The third largest class (9%) was made up of non-commuters (100%) who primarily used public transport in combination with walking (47%). Compared to the two previous classes, this group also spent very little time driving per day, as 78% never drove. With regard to diet, their consumption of RPM was slightly higher than the sample average (25% >1 serving per day) but their FV consumption was much higher as 51% met the 5-a-day guideline. Based on the distribution of car use and RPM consumption in this class, this group receives a green-blue rating.

Class 4 (8%) – Mixed car commuters with high RPM and high FV consumption

The fourth class (8%) was a mixed commuting group with above average mixed car travel (74%). 78% reported commuting by car, however commuting by PT, walking and cycling were all also above the sample average (49%, 54%, 20%, respectively). This mixed-mode commuting pattern meant that their time spent driving was closer to the non-commuters of Class 2 than to the commuters of Class 1: 60% spent <1 hour per day driving. With regard to diet, this group had the highest RPM consumption of all classes (31% >1 serving per day), combined with slightly above average FV consumption (45% achieved 5+ portions per day). Based on its car use and RPM consumption, this group receives a blue-red rating.

Class 5 (7%) – PT commuters with low RPM and low FV consumption

The fifth class (7%) were predominant PT users: 51% travelled by PT for non-work journeys, and 100% commuting using PT. Smaller proportions also reported mixed car non-work travel (26%) and commuting by foot (26%). Similar to the previous class of PT non-commuters, most of this group (79%) spent no time driving per day. With regard to diet, this group had slightly below average RPM and FV consumption: only 23% consumed >1 serving of RPM per day and only 40% met the 5-a-day guideline. Based on the distribution of car use and RPM consumption in this class, this group receives a green-blue rating.

Class 6 (3%) – Low meat car commuters with high FV consumption

This group was primarily defined its absence of RPM consumption and its predominant car commuting. 96% of this group consumed no servings of RPM on the online dietary questionnaire; however 100% reported never consuming any RPM on a habitual basis, and 37% reported following a vegetarian diet (no meat, poultry or fish ever). 59% reportedly met the 5-a-day FV guideline, which was higher than all previous classes. With regard to transport, this group was a ‘car heavy’ class made up of car commuters (100%) and mixed car non-work travel (56%). 42% also reported exclusive car use for non-work travel and more than 60% reported driving for more than 1 hour per day. Based on its car use and RPM consumption, this group receives a red-green rating.

Class 7 (3%) – Walking commuters with low RPM and low FV consumption

The seventh class was primarily defined by the fact that 100% of its members commuted on foot. For non-work travel, PT use and exclusive walking were also above the sample average, however the largest proportion travelled by car mixed with other modes (40%). As a result, time spent driving per day was relatively low in this class: 57% reported that they spent no time driving, and 41% reported driving for <1 hour per day. With regard to diet, this group had below average RPM consumption and slightly below average FV consumption: only 16% consumed >1 serving of RPM per day and 43% met the 5-a-day FV guideline. Based on its car use and RPM consumption, this group receives a green-blue rating.

Class 8 (2%) – Low meat mixed non-commuters with high FV consumption

This group was another non-commuter group with a mixed non-work travel pattern. Non-work travel PT use, walking and cycling were all above the sample average (20%, 8% and 5% respectively) but mixed car travel was also higher (56%). Similar to Class 4, most of this class (61%) drove for <1 hour per day. With regard to diet, 100% of this class consumed no servings of RPM on the online dietary questionnaire and 100% reported never consuming any RPM on a habitual basis. Only 32% reported following a vegetarian diet (no meat, poultry or fish ever) and 65% met the 5-a-day FV guideline. Based on its car use and RPM consumption, this group receives a blue-green rating.

Class 9 (2%) – Low meat mixed commuters with high FV consumption

This group was another primarily defined by its absence of RPM consumption: 100% consumed no servings of RPM on the online dietary questionnaire and 100% reported never consuming any RPM on a habitual basis. 39% reported following a vegetarian diet (no meat, poultry or fish ever) and 57% met the 5-a-day FV guideline, which was above the sample average. For transport this group primarily used PT in combination with walking: 61% commuted by PT and 40% used PT for non-work travel. Walking was also above the sample average for both commuting and non-work journeys (55% and 24%, respectively). 50% of this group never drove and 46% drove for <1 hour per day. Thus, based on its car use and RPM consumption, this group receives a green-green rating.

Class 10 (1%) – Cyclists with low RPM and very high FV consumption

The last and smallest class (1%) was primarily defined by their cycling travel: 92% of this group cycled for non-work travel and 99% cycled for their commute. This was also a group with low RPM consumption, however not as low as the never consuming groups: 57% reported consuming no RPM on the online questionnaire, and 17% reported never consuming RPM on a habitual basis, though only 5% reported being vegetarian. Notably, this group had the highest FV consumption of all the classes with 75% meeting the 5-a-day guideline. Based on its car use and RPM consumption, this group receives a green-green rating.

C.5 – UKB males: overview of model selection (9 class)

Table C.0.11 – LCA model fit statistics for UKB males sample (n=1,896)

Class #	LL	BIC(LL)	AIC(LL)	CAIC(LL)	SABIC(LL)	Npar	L²	df	p-value	Class.Err.
1	-16835.5	33837.0	33715.0	33859.0	33767.1	22	12293.2	1874	2.0e-1500	0.00
2	-12831.0	25963.9	25742.0	26003.9	25836.8	40	4284.2	1856	7E-193	0.00
3	-12207.2	24852.2	24530.5	24910.2	24667.9	58	3036.6	1838	3E-62	0.02
4	-12059.7	24693.0	24271.4	24769.0	24451.6	76	2741.6	1820	2E-40	0.03
5	-11971.1	24651.6	24130.1	24745.6	24353.0	94	2564.3	1802	1E-29	0.03
6	-11897.0	24639.3	24018.0	24751.3	24283.5	112	2416.2	1784	6E-22	0.07
7	-11828.4	24638.0	23916.9	24768.0	24225.0	130	2279.0	1766	1E-15	0.06
8	-11792.1	24701.3	23880.3	24849.3	24231.1	148	2206.5	1748	4E-13	0.06
9	-11748.9	24750.8	23829.9	24916.8	24223.4	166	2120.1	1730	3E-10	0.06
10	-11726.8	24842.2	23821.5	25026.2	24257.7	184	2075.7	1712	3E-09	0.13

Shading indicates the lowest value for a given information criterion

Box indicates the final model that was selected based on bivariate residuals and interpretability.

Table C.0.12 – Bivariate residuals between each pair of indicators for each model among UKB males

5	Indicators	Nonwork t	Car com	Bike com	Walk com	PT com	Drive time	Veg'n	RPM never	RPM quant
	Nonwork t	.								
	Car com	0.65	.							
	Bike com	7.94	0.07	.						
	Walk com	2.87	0.06	2.46	.					
	PT com	3.23	0.25	5.02	0.18	.				
	Drive time	2.65	2.49	4.10	0.13	0.43	.			
	Veg'n	0.55	0.03	0.01	0.28	0.21	1.48	.		
	RPM never	0.45	0.00	0.02	0.03	0.11	0.55	11.03	.	
	RPM quant	0.18	0.16	0.00	0.24	0.05	0.02	4.32	30.11	.
	FV quant	7.06	0.05	0.41	0.49	0.04	2.92	0.02	3.18	2.32

6	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
	multitrav2	.								
	carcom2	0.16	.							
	bikecom2	6.59	0.19	.						
	walkcom2	2.64	0.13	3.70	.					
	pubcom2	2.68	0.50	7.26	0.16	.				
	timedriving	1.24	1.05	3.69	0.14	0.04	.			
	veg2	0.34	0.18	0.04	0.10	0.03	0.26	.		
	avoidredmeat	0.23	0.00	0.02	0.00	0.00	0.29	11.05	.	
	rpmtotalcat	0.56	0.03	0.16	0.01	0.00	0.47	4.70	34.81	.
	portions3cat	6.47	0.01	0.14	1.08	0.03	1.60	0.05	3.87	2.73

Shading indicates bivariate residuals that are greater than >3.84, which indicates unexplained relationships between a pair of indicators, and thus, local dependence in the model.

7	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
	multitrav2	.								
	carcom2	0.34	.							
	bikecom2	0.30	0.07	.						
	walkcom2	0.90	0.07	0.13	.					
	pubcom2	1.06	0.36	0.44	2.78	.				
	timedriving	1.30	1.49	1.12	0.02	0.15	.			
	veg2	0.31	0.39	0.00	0.16	0.10	0.27	.		
	avoidredmeat	0.39	0.01	0.00	0.02	0.04	0.50	10.90	.	
	rpmtotalcat	0.46	0.02	0.07	0.04	0.02	0.57	4.13	36.66	.
	portions3cat	6.39	0.00	0.01	0.48	0.03	1.83	0.02	3.85	2.73

8	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
	multitrav2	.								
	carcom2	0.28	.							
	bikecom2	0.35	0.11	.						
	walkcom2	0.96	0.07	0.06	.					
	pubcom2	1.02	0.14	0.79	3.15	.				
	timedriving	1.29	0.56	0.44	0.00	0.03	.			
	veg2	0.47	0.10	0.11	0.29	0.13	0.08	.		
	avoidredmeat	0.28	0.01	0.05	0.00	0.01	0.25	11.17	.	
	rpmtotalcat	0.40	0.02	0.05	0.04	0.01	0.49	4.15	14.20	.
	portions3cat	6.32	0.00	0.00	0.48	0.03	1.93	0.02	1.16	1.95

9	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
	multitrav2	.								
	carcom2	0.28	.							
	bikecom2	0.35	0.11	.						
	walkcom2	0.95	0.07	0.06	.					
	pubcom2	1.02	0.15	0.79	3.16	.				
	timedriving	1.36	0.57	0.44	0.00	0.03	.			
	veg2	0.26	0.10	0.11	0.29	0.13	0.09	.		
	avoidredmeat	0.07	0.01	0.05	0.00	0.01	0.13	0.30	.	
	rpmtotalcat	0.29	0.02	0.05	0.04	0.01	0.29	0.00	0.54	.
	portions3cat	6.25	0.00	0.00	0.48	0.03	2.04	0.35	0.00	1.20

10	Indicators	multitrav2	carcom2	bikecom2	walkcom2	pubcom2	timedriving	veg2	avoidredmeat	rpmtotalcat
	multitrav2	.								
	carcom2	0.05	.							
	bikecom2	0.08	0.08	.						
	walkcom2	0.24	0.07	0.08	.					
	pubcom2	0.74	0.08	0.12	0.19	.				
	timedriving	0.42	1.65	1.39	0.00	0.34	.			
	veg2	0.35	0.14	0.03	0.30	0.24	0.26	.		
	avoidredmeat	0.12	0.00	0.05	0.02	0.09	0.55	0.16	.	
	rpmtotalcat	0.15	0.00	0.31	0.12	0.04	1.06	0.00	9.87	.
	portions3cat	1.85	0.01	0.33	0.00	0.05	0.16	0.26	0.07	0.16

Class descriptions – UKB males (9 class model)

Class 1 (37%) – Exclusive car commuters with high RPM and low FV consumption

The largest class (37% of the sample) was primarily defined by its high car use. In total, 100% of this group commuted by car and 58% also travelled by car exclusively for non-work journeys, which was well above the sample average of 38%. Most of this group reported driving for 1 hour (38%) or 2-3 hours (32%) per day confirming their heavy car use. With regard to diet, this group had higher than average RPM consumption and lower than average FV consumption: 36% of this group consumed >1 serving of RPM per day (sample average 34%) and 38% consumed <3 portions of FV per day (sample average 33%). Based on its distribution of car use and RPM consumption, this group receives a red-red rating on the healthy, low-carbon scale. This class is similar in size and typology to Class 1 (Exclusive car commuters, 33%) among UKB females.

Class 2 (35%) – Mixed car non-commuters with high RPM and high FV consumption

The second largest class (35%) was made up of non-commuters (100%) with above average mixed car travel (57%). In other words, more than half of this group reported using PT, walking or cycling in addition to their car travel. Compared to the previous class, this group also spent less time driving per day, 48% for <1 hour. With regard to diet, their consumption of RPM was the same as the Class 1 but their FV consumption was much higher: 35% met the 5-a-day guideline (sample average of 32%). Based on the distribution of car use and RPM consumption in this class, this group receives a blue-red rating. This class is similar to Class 2 (Mixed car non-commuters, 32%) among UKB females.

Class 3 (8%) – Mixed car commuters with high RPM and low FV consumption

The third class (8%) was a mixed commuting group with above average mixed car travel (57%). 67% reported commuting by PT and 60% reported commuting by car, and smaller proportions also commuted by walking and cycling. This mixed-mode commuting pattern meant that their time spent driving was closer to the non-commuters of Class 2 than to the commuters of Class 1: 47% spent <1 hour driving per day and 38% drove for 1 hour daily. With regard to diet, this group had above average RPM consumption (36% >1 serving per day, the highest of all classes), combined with slightly below average FV consumption (34% <3 portions per day). Based on its car use and RPM consumption, this group receives a blue-red rating. This class was similar to Class 4 (Mixed car commuters, 8%) among UKB females.

Class 4 (8%) – PT non-commuters with average RPM and high FV consumption

The fourth largest class (8%) was made up of non-commuters (100%) who primarily used PT in combination with walking (65%). Compared to the three previous classes, this group also spent very little time driving per day, as 76% never drove. With regard to diet, their consumption of RPM was about the same as the sample average but their FV consumption was much higher: 38% met the 5-a-day guideline. Based on the distribution of car use and RPM consumption in this class, this group receives a green-blue rating. This class was similar in size and typology to Class 3 (PT non-commuters, 9%) among UKB females.

Class 5 (5%) – PT commuters with low RPM and low FV consumption

The fifth class (5%) were predominant PT users who also walked: 50% travelled by PT for non-work purposes, and large proportions reported commuting using PT and on foot (76% and 53%, respectively). Similar to the previous class of PT non-commuters, most of this group (78%) spent no time driving per day. With regard to diet, this group had below average RPM and FV consumption. Only 28% consumed >1 serving of RPM per day and only 30% met the 5-a-day guideline. Based on the distribution of car use and RPM consumption in this class, this group receives a green-blue rating. This class is similar to Class 5 (PT commuters, 7%) among UKB females.

Class 6 (4%) – Commuter cyclists with average RPM and high FV consumption

The sixth class (4%) was primarily defined by their commuter cycling: 100% of this group cycled for their commute, though smaller proportions also reported commuting by car or PT. With regard to non-work travel, 33% also cycled however a larger proportion travelled by car in combination with other modes (52%). Reflecting this car use, 57% of this group drove for <1 hour per day though 39% also reported never driving. This group had RPM consumption that was similar to the sample average (33% >1 serving per day), however, FV consumption was higher such that 38% achieved the 5-a-day guideline. Thus, based on its car use and RPM consumption, this group receives a green-blue rating. This class was somewhat similar to Class 10 (Cyclists, 1%) among UKB females, except that members of this class drove more and ate more RPM and less FV.

Class 7 (1%) – Low meat mixed commuters with high FV consumption

This group was primarily defined its absence of RPM consumption: 100% consumed no servings of RPM on the online dietary questionnaire and 99% reported never consuming any RPM on a habitual basis. Nearly half (49%) reported following a vegetarian diet (no meat, poultry or fish ever) and FV consumption was above the sample average (47% met the 5-a-day FV guideline). This group was a mixed transport group made up of mostly PT commuters (67%) and mixed car non-work travel (36%). Notably, however, this group also had above average walking, cycling and PT use for both types of travel journeys. 52% of this group drove for <1 hour per day and 45% never drove. Based on its car use and RPM consumption, this group receives a green-green rating. This class was similar in size and typology to Class 9 (Low meat mixed commuters, 2%) among UKB females.

Class 8 (1%) – Low meat car commuters with high FV consumption

This group was primarily defined by its absence of RPM consumption and its exclusive car commuting. Similar to the previous class, 99% consumed no servings of RPM on the online dietary questionnaire and 98% reported never consuming any RPM on a habitual basis, however, only 26% reported following a vegetarian diet (no meat, poultry or fish ever). 49% met the 5-a-day FV guideline, which was above the sample average. This group was a ‘car heavy’ transport group made up of car commuters (100%) and mixed car non-work travel (48%). 43% also reported exclusive car use for non-work travel and nearly 80% reported driving for more than 1 hour per day. Based on its car use and RPM consumption, this group receives a red-green rating. This group is similar in typology to Class 6 (Low meat car commuters, 3%) among UKB females.

Class 9 (1%) – Low meat non-commuters with high FV consumption

The last and smallest class (1%) was another non-commuting group with a mixed non-work travel pattern. Non-work travel PT use, walking and cycling were all above the sample average (38%, 14% and 10% respectively) and car travel was below (29%). Similar to Class 7, 53% of this group drove for <1 hour per day and 44% never drove. With regard to diet, 99% of this class consumed no servings of RPM on the online dietary questionnaire and 99% reported never consuming any RPM on a habitual basis. Only 39% reported following a vegetarian diet (no meat, poultry or fish ever) and 61% met the 5-a-day FV guideline, which was highest across all classes. Based on its car use and RPM consumption, this group receives a green-green rating. Based on size and typology, this class was very similar to Class 8 (Low meat non-commuters, 2%) among UKB females.

C.6 – UKB LCA validation results

Table C.0.13 – UKB females LCA validation, each sample n=2,324 (2% of 116,255)

	Class assignment in validation sample (samples 2 to 11)												
Class assignment in estimation model (sample 1)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**% assigned to same class, same order**	**Notes**	**Class name**
1	2	2	2, 3	1	2	1	2	2	1	2	0.3	most often switched for 2	Exclusive car commuters
2	1	1	1	2	1	2	1	1	2	1	0.3	most often switched for 1	Mostly car non-commuters
3	3	3	5	3	3	3	4	4	3	4	0.6	well validated	PT non-commuters
4	4	4	4	4	4	5	3	3	4	3	0.6	well validated	Mixed car commuters
5	5	5	6	5	5	4	5	5	5	5	0.8	most well validated	PT commuters
6	7	7	7	7	7	7	7	7	7	7	0	always switched to 7	Low meat car commuters
7	9	6	4	6	4	6	6	6	6	8	0	most often switched for 6	Walking commuters
8	8	9	8	8	8	8	8	9	8	9	0.7	well validated	Low meat non-commuters
9	5	5, 6	9	9	6, 7	10	9	5, 6, 7	5, 6	5, 7	0.3	often split	Low meat mixed commuters
10	5	6	4	4	9	9	9	6	9	10	0.1	most often switched for 9	Cyclists
Cramer's V between samples	0.791	0.792	0.802	0.916	0.794	0.892	0.884	0.759	0.859	0.846	Average Cramer's V = 0.834		

Notes: multiple numbers in a cell indicates that original class from estimation model was spilt in that sample; a split was defined as <60% of individuals being assigned to a single class
Blue = same behaviour pattern in same order; orange = same behaviour pattern in adjacent order; yellow = behaviour pattern split across different classes

Same order = same estimated size (prevalence)

Summary

Across 10 validation samples:

- 6 class assignments split (94% did not split)
- 37% validated with same pattern in same order (blue)
- 47% validated with same pattern in adjacent order (orange)
- Best validated (same pattern, same order): PT commuters, Low meat non-commuters, PT non-commuters, Mixed car commuters
- Well validated (same pattern, different order): Exclusive car commuters, Mostly car non-commuters, Low meat car commuters
- Least well validated: Walking commuters, Low meat mixed commuters, Cyclists

Table C.0.14 – UKB males LCA validation, each sample n=1,896 (2% of 94,781)

	Class assignment in validation sample (samples 2 to 11)												
Class assignment in estimation model (sample 1)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**% assigned to same class, same order**	**Notes**	**Class name**
1	1	2	1	1	2	2	2	1	2	2	0.4	most often switched with 2	Exclusive car commuters
2	2, 3	1	2	2	1	1	1	2	1	1	0.3	most often switched with 1	Mixed car non-commuters
3	4	3	3	4	3	3	3	4	3, 5	3	0.6	well validated	Mixed car commuters
4	5	4	4	3	4	4	4	5	4	5	0.6	well validated	PT non-commuters
5	6	5	5	5	5	5	5	3	5	4	0.7	most well validated	PT commuters
6	8	3, 6	3, 6	6	6	3, 6	6	4, 6	3, 6	3, 7	0.3	most often split	Cyclists
7	6, 8, 9	5, 6, 8	5, 6	5, 6, 8	5, 6, 7	6, 7, 8	5, 6, 8	9	5, 6, 8	6, 7, 8	0	almost always split	Low meat mixed commuters
8	9	8	8	8	9	7	8	8	8	8	0.7	most well validated	Low meat car commuters
9	5	9	9	9	8	9	9	7	9	9	0.7	most well validated	Low meat non-commuters
Cramer's V between samples	0.741	0.808	0.838	0.831	0.835	0.827	0.808	0.86	0.787	0.76	Average Cramer's V = 0.8095		

Notes: multiple numbers in a cell indicates that original class from estimation model was spilt in that sample; a split was defined as <60% of individuals being assigned to a single class
Blue = same behaviour pattern in same order; orange = same behaviour pattern in adjacent order; yellow = behaviour pattern split across different classes

Same order = same estimated size (prevalence)

Summary

Across 10 validation samples:

- 21 class assignments split (out of 90 -> 74% did not split)
- 48% validated with same pattern in same order (blue)
- 28% validated with same pattern in adjacent order (orange)
- Best validated (same pattern, same order): PT commuters, Low meat car commuters, Mixed car commuters, PT non-commuters, Low meat non-commuters
- Well validated (same pattern, different order): Exclusive car commuters, Mixed car non-commuters
- Least well validated: Cyclists, Low meat mixed commuters

Appendix D (Chapter 6)

Table D.0.1 and Table D.0.2 compare the size of each class (prevalence) between the estimation model (Step 1) and the class assignments (Step 2) and show the number of participants (n) in each class in each NDNS sample. The small discrepancy between the class sizes is due to the classification error in the LCA model[104].

Table D.0.1 – Class assignments based on LCA model among NDNS females

Class #	Estimation model %	Classification %	n
1	0.26	0.27	241
2	0.25	0.24	214
3	0.21	0.20	177
4	0.07	0.08	72
5	0.07	0.07	67
6	0.07	0.08	70
7	0.04	0.04	33
8	0.02	0.02	21
9	0.01	0.01	9
Total	1.00	1.00	904

Table D.0.2 – Class assignments based on LCA model among NDNS males

Class #	Estimation model %	Classification %	n
1	0.38	0.37	264
2	0.36	0.37	260
3	0.09	0.09	63
4	0.06	0.07	46
5	0.05	0.06	40
6	0.03	0.02	15
7	0.02	0.02	11
8	0.01	0.01	6
Total	1.00	1.00	705

[104] To illustrate how this works, consider a three-class model where the membership probabilities for cases having a given response pattern are 0.2 (for class 1), 0.7 (for class 2), and 0.1 (for class 3). Here, the modal probability is 0.7 and class assignment based on this means that *all* such cases will be assigned to class 2. However, such assignment is expected to be correct for only 70% of these cases, since 20% truly belong to class 1 and the remaining 10% belong to class 3. The expected misclassification rate for these cases will be 20% + 10% = 30% (Statistical Innovations, 2016).

D.1 – SPSS syntax for scoring UKB females dataset

```
* Encoding: UTF-8.
* Create auxiliary variables.
DO IF MISSING(multitrav2).
  COMPUTE #multitrav2_lg_1=1/5.
  COMPUTE #multitrav2_lg_2=1/5.
  COMPUTE #multitrav2_lg_3=1/5.
  COMPUTE #multitrav2_lg_4=1/5.
  COMPUTE #multitrav2_lg_5=1/5.
ELSE.
  DO IF multitrav2=1.
    COMPUTE #multitrav2_lg_1=1.
    COMPUTE #multitrav2_lg_2=0.
    COMPUTE #multitrav2_lg_3=0.
    COMPUTE #multitrav2_lg_4=0.
    COMPUTE #multitrav2_lg_5=0.
  ELSE IF multitrav2=2.
    COMPUTE #multitrav2_lg_1=0.
    COMPUTE #multitrav2_lg_2=1.
    COMPUTE #multitrav2_lg_3=0.
    COMPUTE #multitrav2_lg_4=0.
    COMPUTE #multitrav2_lg_5=0.
  ELSE IF multitrav2=3.
    COMPUTE #multitrav2_lg_1=0.
    COMPUTE #multitrav2_lg_2=0.
    COMPUTE #multitrav2_lg_3=1.
    COMPUTE #multitrav2_lg_4=0.
    COMPUTE #multitrav2_lg_5=0.
  ELSE IF multitrav2=4.
    COMPUTE #multitrav2_lg_1=0.
    COMPUTE #multitrav2_lg_2=0.
    COMPUTE #multitrav2_lg_3=0.
    COMPUTE #multitrav2_lg_4=1.
    COMPUTE #multitrav2_lg_5=0.
  ELSE IF multitrav2=5.
    COMPUTE #multitrav2_lg_1=0.
    COMPUTE #multitrav2_lg_2=0.
    COMPUTE #multitrav2_lg_3=0.
    COMPUTE #multitrav2_lg_4=0.
    COMPUTE #multitrav2_lg_5=1.
  ELSE.
    COMPUTE #multitrav2_lg_1=1/5.
    COMPUTE #multitrav2_lg_2=1/5.
    COMPUTE #multitrav2_lg_3=1/5.
    COMPUTE #multitrav2_lg_4=1/5.
    COMPUTE #multitrav2_lg_5=1/5.
  END IF.
END IF.
DO IF MISSING(carcom2).
  COMPUTE #carcom2_lg_1=1/3.
  COMPUTE #carcom2_lg_2=1/3.
  COMPUTE #carcom2_lg_3=1/3.
ELSE.
  DO IF carcom2=0.
    COMPUTE #carcom2_lg_1=1.
    COMPUTE #carcom2_lg_2=0.
    COMPUTE #carcom2_lg_3=0.
  ELSE IF carcom2=1.
    COMPUTE #carcom2_lg_1=0.
    COMPUTE #carcom2_lg_2=1.
    COMPUTE #carcom2_lg_3=0.
  ELSE IF carcom2=2.
    COMPUTE #carcom2_lg_1=0.
    COMPUTE #carcom2_lg_2=0.
    COMPUTE #carcom2_lg_3=1.
  ELSE.
    COMPUTE #carcom2_lg_1=1/3.
    COMPUTE #carcom2_lg_2=1/3.
    COMPUTE #carcom2_lg_3=1/3.
  END IF.
END IF.
DO IF MISSING(bikecom2).
  COMPUTE #bikecom2_lg_1=1/3.
  COMPUTE #bikecom2_lg_2=1/3.
  COMPUTE #bikecom2_lg_3=1/3.
ELSE.
  DO IF bikecom2=0.
    COMPUTE #bikecom2_lg_1=1.
    COMPUTE #bikecom2_lg_2=0.
    COMPUTE #bikecom2_lg_3=0.
  ELSE IF bikecom2=1.
    COMPUTE #bikecom2_lg_1=0.
    COMPUTE #bikecom2_lg_2=1.
    COMPUTE #bikecom2_lg_3=0.
  ELSE IF bikecom2=2.
    COMPUTE #bikecom2_lg_1=0.
    COMPUTE #bikecom2_lg_2=0.
    COMPUTE #bikecom2_lg_3=1.
  ELSE.
    COMPUTE #bikecom2_lg_1=1/3.
    COMPUTE #bikecom2_lg_2=1/3.
    COMPUTE #bikecom2_lg_3=1/3.
  END IF.
END IF.
DO IF MISSING(walkcom2).
  COMPUTE #walkcom2_lg_1=1/3.
  COMPUTE #walkcom2_lg_2=1/3.
  COMPUTE #walkcom2_lg_3=1/3.
ELSE.
  DO IF walkcom2=0.
    COMPUTE #walkcom2_lg_1=1.
    COMPUTE #walkcom2_lg_2=0.
    COMPUTE #walkcom2_lg_3=0.
  ELSE IF walkcom2=1.
    COMPUTE #walkcom2_lg_1=0.
    COMPUTE #walkcom2_lg_2=1.
    COMPUTE #walkcom2_lg_3=0.
  ELSE IF walkcom2=2.
    COMPUTE #walkcom2_lg_1=0.
    COMPUTE #walkcom2_lg_2=0.
    COMPUTE #walkcom2_lg_3=1.
  ELSE.
    COMPUTE #walkcom2_lg_1=1/3.
    COMPUTE #walkcom2_lg_2=1/3.
    COMPUTE #walkcom2_lg_3=1/3.
  END IF.
END IF.
DO IF MISSING(pubcom2).
  COMPUTE #pubcom2_lg_1=1/3.
  COMPUTE #pubcom2_lg_2=1/3.
  COMPUTE #pubcom2_lg_3=1/3.
ELSE.
  DO IF pubcom2=0.
    COMPUTE #pubcom2_lg_1=1.
    COMPUTE #pubcom2_lg_2=0.
    COMPUTE #pubcom2_lg_3=0.
  ELSE IF pubcom2=1.
    COMPUTE #pubcom2_lg_1=0.
    COMPUTE #pubcom2_lg_2=1.
    COMPUTE #pubcom2_lg_3=0.
  ELSE IF pubcom2=2.
    COMPUTE #pubcom2_lg_1=0.
    COMPUTE #pubcom2_lg_2=0.
```

```
    COMPUTE #pubcom2_lg_3=1.
  ELSE.
    COMPUTE #pubcom2_lg_1=1/3.
    COMPUTE #pubcom2_lg_2=1/3.
    COMPUTE #pubcom2_lg_3=1/3.
  END IF.
END IF.
DO IF MISSING(timedriving).
  COMPUTE #timedriving_lg_1=1/5.
  COMPUTE #timedriving_lg_2=1/5.
  COMPUTE #timedriving_lg_3=1/5.
  COMPUTE #timedriving_lg_4=1/5.
  COMPUTE #timedriving_lg_5=1/5.
ELSE.
  DO IF timedriving=0.
    COMPUTE #timedriving_lg_1=1.
    COMPUTE #timedriving_lg_2=0.
    COMPUTE #timedriving_lg_3=0.
    COMPUTE #timedriving_lg_4=0.
    COMPUTE #timedriving_lg_5=0.
  ELSE IF timedriving=1.
    COMPUTE #timedriving_lg_1=0.
    COMPUTE #timedriving_lg_2=1.
    COMPUTE #timedriving_lg_3=0.
    COMPUTE #timedriving_lg_4=0.
    COMPUTE #timedriving_lg_5=0.
  ELSE IF timedriving=2.
    COMPUTE #timedriving_lg_1=0.
    COMPUTE #timedriving_lg_2=0.
    COMPUTE #timedriving_lg_3=1.
    COMPUTE #timedriving_lg_4=0.
    COMPUTE #timedriving_lg_5=0.
  ELSE IF timedriving=3.
    COMPUTE #timedriving_lg_1=0.
    COMPUTE #timedriving_lg_2=0.
    COMPUTE #timedriving_lg_3=0.
    COMPUTE #timedriving_lg_4=1.
    COMPUTE #timedriving_lg_5=0.
  ELSE IF timedriving=4.
    COMPUTE #timedriving_lg_1=0.
    COMPUTE #timedriving_lg_2=0.
    COMPUTE #timedriving_lg_3=0.
    COMPUTE #timedriving_lg_4=0.
    COMPUTE #timedriving_lg_5=1.
  ELSE.
    COMPUTE #timedriving_lg_1=1/5.
    COMPUTE #timedriving_lg_2=1/5.
    COMPUTE #timedriving_lg_3=1/5.
    COMPUTE #timedriving_lg_4=1/5.
    COMPUTE #timedriving_lg_5=1/5.
  END IF.
END IF.
DO IF MISSING(portions3cat).
  COMPUTE #portions3cat_lg_1=1/3.
  COMPUTE #portions3cat_lg_2=1/3.
  COMPUTE #portions3cat_lg_3=1/3.
ELSE.
  DO IF portions3cat=1.
    COMPUTE #portions3cat_lg_1=1.
    COMPUTE #portions3cat_lg_2=0.
    COMPUTE #portions3cat_lg_3=0.
  ELSE IF portions3cat=2.
    COMPUTE #portions3cat_lg_1=0.
    COMPUTE #portions3cat_lg_2=1.
    COMPUTE #portions3cat_lg_3=0.
  ELSE IF portions3cat=3.
    COMPUTE #portions3cat_lg_1=0.
    COMPUTE #portions3cat_lg_2=0.
    COMPUTE #portions3cat_lg_3=1.
  ELSE.
    COMPUTE #portions3cat_lg_1=1/3.
    COMPUTE #portions3cat_lg_2=1/3.
    COMPUTE #portions3cat_lg_3=1/3.
  END IF.
END IF.
DO IF MISSING(avoidredmeat).
  COMPUTE #avoidredmeat_lg_1=1/2.
  COMPUTE #avoidredmeat_lg_2=1/2.
ELSE.
  DO IF avoidredmeat=0.
    COMPUTE #avoidredmeat_lg_1=1.
    COMPUTE #avoidredmeat_lg_2=0.
  ELSE IF avoidredmeat=1.
    COMPUTE #avoidredmeat_lg_1=0.
    COMPUTE #avoidredmeat_lg_2=1.
  ELSE.
    COMPUTE #avoidredmeat_lg_1=1/2.
    COMPUTE #avoidredmeat_lg_2=1/2.
  END IF.
END IF.
DO IF MISSING(veg2).
  COMPUTE #veg2_lg_1=1/2.
  COMPUTE #veg2_lg_2=1/2.
ELSE.
  DO IF veg2=0.
    COMPUTE #veg2_lg_1=1.
    COMPUTE #veg2_lg_2=0.
  ELSE IF veg2=1.
    COMPUTE #veg2_lg_1=0.
    COMPUTE #veg2_lg_2=1.
  ELSE.
    COMPUTE #veg2_lg_1=1/2.
    COMPUTE #veg2_lg_2=1/2.
  END IF.
END IF.
DO IF MISSING(rpmtotalcat).
  COMPUTE #rpmtotalcat_lg_1=1/3.
  COMPUTE #rpmtotalcat_lg_2=1/3.
  COMPUTE #rpmtotalcat_lg_3=1/3.
ELSE.
  DO IF rpmtotalcat=0.
    COMPUTE #rpmtotalcat_lg_1=1.
    COMPUTE #rpmtotalcat_lg_2=0.
    COMPUTE #rpmtotalcat_lg_3=0.
  ELSE IF rpmtotalcat=1.
    COMPUTE #rpmtotalcat_lg_1=0.
    COMPUTE #rpmtotalcat_lg_2=1.
    COMPUTE #rpmtotalcat_lg_3=0.
  ELSE IF rpmtotalcat=2.
    COMPUTE #rpmtotalcat_lg_1=0.
    COMPUTE #rpmtotalcat_lg_2=0.
    COMPUTE #rpmtotalcat_lg_3=1.
  ELSE.
    COMPUTE #rpmtotalcat_lg_1=1/3.
    COMPUTE #rpmtotalcat_lg_2=1/3.
    COMPUTE #rpmtotalcat_lg_3=1/3.
  END IF.
END IF.

* Compute classification logits.

COMPUTE Cluster_lg_1=(0.635359)
  +(0.870432)*#multitrav2_lg_1
  +(0.102447)*#multitrav2_lg_2
  +(-0.322896)*#multitrav2_lg_3
  +(-0.51402)*#multitrav2_lg_4
  +(-0.135964)*#multitrav2_lg_5
  +(3.05082)*#carcom2_lg_1
  +(12.432)*#carcom2_lg_2
  +(-15.4829)*#carcom2_lg_3
```

```
 +(1.10914)*#bikecom2_lg_1
 +(-1.27176)*#bikecom2_lg_2
 +(0.162621)*#bikecom2_lg_3
 +(1.19391)*#walkcom2_lg_1
 +(-1.33846)*#walkcom2_lg_2
 +(0.144551)*#walkcom2_lg_3
 +(1.02291)*#pubcom2_lg_1
 +(-0.945015)*#pubcom2_lg_2
 +(-0.0778951)*#pubcom2_lg_3
 +(-4.40821)*#timedriving_lg_1
 +(-1.84589)*#timedriving_lg_2
 +(0.181136)*#timedriving_lg_3
 +(2.09131)*#timedriving_lg_4
 +(3.98165)*#timedriving_lg_5
 +(0.370619)*#portions3cat_lg_1
 +(-0.00864795)*#portions3cat_lg_2
 +(-0.361971)*#portions3cat_lg_3
 +(1.71344)*#avoidredmeat_lg_1
 +(-1.71344)*#avoidredmeat_lg_2
 +(2.64395)*#veg2_lg_1
 +(-2.64395)*#veg2_lg_2
 +(-1.99177)*#rpmtotalcat_lg_1
 +(0.000798987)*#rpmtotalcat_lg_2
 +(1.99098)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_2=(-7.08054)
 +(1.85118)*#multitrav2_lg_1
 +(1.53183)*#multitrav2_lg_2
 +(0.0887577)*#multitrav2_lg_3
 +(0.424185)*#multitrav2_lg_4
 +(-3.89595)*#multitrav2_lg_5
 +(-16.1104)*#carcom2_lg_1
 +(-16.6531)*#carcom2_lg_2
 +(32.7635)*#carcom2_lg_3
 +(0.273198)*#bikecom2_lg_1
 +(0.308938)*#bikecom2_lg_2
 +(-0.582136)*#bikecom2_lg_3
 +(0.379058)*#walkcom2_lg_1
 +(0.142439)*#walkcom2_lg_2
 +(-0.521498)*#walkcom2_lg_3
 +(0.459293)*#pubcom2_lg_1
 +(0.0360811)*#pubcom2_lg_2
 +(-0.495374)*#pubcom2_lg_3
 +(-2.69996)*#timedriving_lg_1
 +(-2.1858)*#timedriving_lg_2
 +(-0.42265)*#timedriving_lg_3
 +(1.61316)*#timedriving_lg_4
 +(3.69525)*#timedriving_lg_5
 +(0.370137)*#portions3cat_lg_1
 +(0.0201785)*#portions3cat_lg_2
 +(-0.390316)*#portions3cat_lg_3
 +(1.33874)*#avoidredmeat_lg_1
 +(-1.33874)*#avoidredmeat_lg_2
 +(2.58052)*#veg2_lg_1
 +(-2.58052)*#veg2_lg_2
 +(-1.98328)*#rpmtotalcat_lg_1
 +(-0.0018643)*#rpmtotalcat_lg_2
 +(1.98514)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_3=(-6.1343)
 +(-2.38196)*#multitrav2_lg_1
 +(-1.43882)*#multitrav2_lg_2
 +(1.40752)*#multitrav2_lg_3
 +(-0.331563)*#multitrav2_lg_4
 +(2.74482)*#multitrav2_lg_5
 +(-14.7251)*#carcom2_lg_1
 +(-15.0329)*#carcom2_lg_2
 +(29.758)*#carcom2_lg_3
 +(0.306934)*#bikecom2_lg_1
 +(0.257562)*#bikecom2_lg_2
 +(-0.564496)*#bikecom2_lg_3
 +(0.60754)*#walkcom2_lg_1
 +(-0.0531159)*#walkcom2_lg_2
 +(-0.554424)*#walkcom2_lg_3
 +(0.488167)*#pubcom2_lg_1
 +(0.0218268)*#pubcom2_lg_2
 +(-0.509993)*#pubcom2_lg_3
 +(3.52138)*#timedriving_lg_1
 +(0.924871)*#timedriving_lg_2
 +(-0.42265)*#timedriving_lg_3
 +(-1.49751)*#timedriving_lg_4
 +(-2.52609)*#timedriving_lg_5
 +(0.208484)*#portions3cat_lg_1
 +(0.0201785)*#portions3cat_lg_2
 +(-0.228662)*#portions3cat_lg_3
 +(0.990566)*#avoidredmeat_lg_1
 +(-0.990566)*#avoidredmeat_lg_2
 +(1.93637)*#veg2_lg_1
 +(-1.93637)*#veg2_lg_2
 +(-1.9551)*#rpmtotalcat_lg_1
 +(-0.0018643)*#rpmtotalcat_lg_2
 +(1.95697)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_4=(4.62687)
 +(-0.443718)*#multitrav2_lg_1
 +(0.59906)*#multitrav2_lg_2
 +(-1.52174)*#multitrav2_lg_3
 +(0.0909348)*#multitrav2_lg_4
 +(1.27546)*#multitrav2_lg_5
 +(7.76527)*#carcom2_lg_1
 +(7.49144)*#carcom2_lg_2
 +(-15.2567)*#carcom2_lg_3
 +(-0.138474)*#bikecom2_lg_1
 +(0.991477)*#bikecom2_lg_2
 +(-0.853003)*#bikecom2_lg_3
 +(-0.321146)*#walkcom2_lg_1
 +(0.886636)*#walkcom2_lg_2
 +(-0.56549)*#walkcom2_lg_3
 +(-0.104414)*#pubcom2_lg_1
 +(0.663877)*#pubcom2_lg_2
 +(-0.559463)*#pubcom2_lg_3
 +(-1.55193)*#timedriving_lg_1
 +(-0.417755)*#timedriving_lg_2
 +(0.181136)*#timedriving_lg_3
 +(0.66317)*#timedriving_lg_4
 +(1.12537)*#timedriving_lg_5
 +(0.148059)*#portions3cat_lg_1
 +(-0.00864795)*#portions3cat_lg_2
 +(-0.139411)*#portions3cat_lg_3
 +(3.44969)*#avoidredmeat_lg_1
 +(-3.44969)*#avoidredmeat_lg_2
 +(1.9506)*#veg2_lg_1
 +(-1.9506)*#veg2_lg_2
 +(-2.19047)*#rpmtotalcat_lg_1
 +(0.000798987)*#rpmtotalcat_lg_2
 +(2.18967)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_5=(-0.572698)
 +(0.208762)*#multitrav2_lg_1
 +(0.435667)*#multitrav2_lg_2
 +(3.10554)*#multitrav2_lg_3
 +(1.2163)*#multitrav2_lg_4
 +(-4.96626)*#multitrav2_lg_5
 +(9.28929)*#carcom2_lg_1
 +(5.43308)*#carcom2_lg_2
 +(-14.7224)*#carcom2_lg_3
 +(0.594028)*#bikecom2_lg_1
 +(-0.21626)*#bikecom2_lg_2
 +(-0.377768)*#bikecom2_lg_3
 +(0.313683)*#walkcom2_lg_1
```

+(0.288623)*#walkcom2_lg_2
+(-0.602306)*#walkcom2_lg_3
+(-5.53606)*#pubcom2_lg_1
+(3.03566)*#pubcom2_lg_2
+(2.50041)*#pubcom2_lg_3
+(3.9612)*#timedriving_lg_1
+(2.33881)*#timedriving_lg_2
+(0.181136)*#timedriving_lg_3
+(-2.09339)*#timedriving_lg_4
+(-4.38775)*#timedriving_lg_5
+(0.30109)*#portions3cat_lg_1
+(-0.00864795)*#portions3cat_lg_2
+(-0.292442)*#portions3cat_lg_3
+(1.38815)*#avoidredmeat_lg_1
+(-1.38815)*#avoidredmeat_lg_2
+(1.83495)*#veg2_lg_1
+(-1.83495)*#veg2_lg_2
+(-1.89884)*#rpmtotalcat_lg_1
+(0.000798987)*#rpmtotalcat_lg_2
+(1.89804)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_6=(2.1588)
+(2.68594)*#multitrav2_lg_1
+(2.64112)*#multitrav2_lg_2
+(-3.53535)*#multitrav2_lg_3
+(1.07695)*#multitrav2_lg_4
+(-2.86866)*#multitrav2_lg_5
+(1.45619)*#carcom2_lg_1
+(8.30399)*#carcom2_lg_2
+(-9.76019)*#carcom2_lg_3
+(0.301416)*#bikecom2_lg_1
+(0.480985)*#bikecom2_lg_2
+(-0.782401)*#bikecom2_lg_3
+(0.537566)*#walkcom2_lg_1
+(0.121415)*#walkcom2_lg_2
+(-0.658982)*#walkcom2_lg_3
+(0.772376)*#pubcom2_lg_1
+(-0.259202)*#pubcom2_lg_2
+(-0.513174)*#pubcom2_lg_3
+(-4.00385)*#timedriving_lg_1
+(-1.64372)*#timedriving_lg_2
+(0.181136)*#timedriving_lg_3
+(1.88913)*#timedriving_lg_4
+(3.5773)*#timedriving_lg_5
+(-0.279279)*#portions3cat_lg_1
+(-0.00864795)*#portions3cat_lg_2
+(0.287927)*#portions3cat_lg_3
+(-3.85085)*#avoidredmeat_lg_1
+(3.85085)*#avoidredmeat_lg_2
+(-3.41773)*#veg2_lg_1
+(3.41773)*#veg2_lg_2
+(4.26681)*#rpmtotalcat_lg_1
+(0.000798987)*#rpmtotalcat_lg_2
+(-4.26761)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_7=(-1.00254)
+(-1.20249)*#multitrav2_lg_1
+(-0.805393)*#multitrav2_lg_2
+(0.188381)*#multitrav2_lg_3
+(0.569799)*#multitrav2_lg_4
+(1.2497)*#multitrav2_lg_5
+(8.06916)*#carcom2_lg_1
+(4.48853)*#carcom2_lg_2
+(-12.5577)*#carcom2_lg_3
+(2.56311)*#bikecom2_lg_1
+(-4.02724)*#bikecom2_lg_2
+(1.46413)*#bikecom2_lg_3
+(-5.11005)*#walkcom2_lg_1
+(3.15479)*#walkcom2_lg_2
+(1.95526)*#walkcom2_lg_3
+(2.0024)*#pubcom2_lg_1
+(-2.5429)*#pubcom2_lg_2
+(0.540501)*#pubcom2_lg_3
+(1.88519)*#timedriving_lg_1
+(1.3008)*#timedriving_lg_2
+(0.181136)*#timedriving_lg_3
+(-1.05539)*#timedriving_lg_4
+(-2.31174)*#timedriving_lg_5
+(0.232595)*#portions3cat_lg_1
+(-0.00864795)*#portions3cat_lg_2
+(-0.223947)*#portions3cat_lg_3
+(2.78663)*#avoidredmeat_lg_1
+(-2.78663)*#avoidredmeat_lg_2
+(1.46733)*#veg2_lg_1
+(-1.46733)*#veg2_lg_2
+(-1.58192)*#rpmtotalcat_lg_1
+(0.000798987)*#rpmtotalcat_lg_2
+(1.58112)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_8=(-0.914652)
+(-1.71697)*#multitrav2_lg_1
+(-0.773987)*#multitrav2_lg_2
+(0.57565)*#multitrav2_lg_3
+(-0.890334)*#multitrav2_lg_4
+(2.80564)*#multitrav2_lg_5
+(-12.9231)*#carcom2_lg_1
+(-12.9546)*#carcom2_lg_2
+(25.8777)*#carcom2_lg_3
+(0.527252)*#bikecom2_lg_1
+(-0.142657)*#bikecom2_lg_2
+(-0.384595)*#bikecom2_lg_3
+(0.515102)*#walkcom2_lg_1
+(-0.0446616)*#walkcom2_lg_2
+(-0.47044)*#walkcom2_lg_3
+(0.347573)*#pubcom2_lg_1
+(0.152512)*#pubcom2_lg_2
+(-0.500085)*#pubcom2_lg_3
+(-1.27908)*#timedriving_lg_1
+(-1.47536)*#timedriving_lg_2
+(-0.42265)*#timedriving_lg_3
+(0.902721)*#timedriving_lg_4
+(2.27436)*#timedriving_lg_5
+(-0.261233)*#portions3cat_lg_1
+(0.0201785)*#portions3cat_lg_2
+(0.241054)*#portions3cat_lg_3
+(-3.83974)*#avoidredmeat_lg_1
+(3.83974)*#avoidredmeat_lg_2
+(-3.3233)*#veg2_lg_1
+(3.3233)*#veg2_lg_2
+(4.00219)*#rpmtotalcat_lg_1
+(-0.0018643)*#rpmtotalcat_lg_2
+(-4.00033)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_9=(4.77653)
+(-0.515319)*#multitrav2_lg_1
+(0.0328024)*#multitrav2_lg_2
+(2.46603)*#multitrav2_lg_3
+(1.76923)*#multitrav2_lg_4
+(-3.75275)*#multitrav2_lg_5
+(6.80825)*#carcom2_lg_1
+(3.52228)*#carcom2_lg_2
+(-10.3305)*#carcom2_lg_3
+(0.0215955)*#bikecom2_lg_1
+(0.840838)*#bikecom2_lg_2
+(-0.862434)*#bikecom2_lg_3
+(-0.374975)*#walkcom2_lg_1
+(0.892035)*#walkcom2_lg_2
+(-0.51706)*#walkcom2_lg_3
+(-0.412378)*#pubcom2_lg_1
+(0.818925)*#pubcom2_lg_2

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 +(-0.406548)*#pubcom2_lg_3
 +(1.38234)*#timedriving_lg_1
 +(1.04938)*#timedriving_lg_2
 +(0.181136)*#timedriving_lg_3
 +(-0.803965)*#timedriving_lg_4
 +(-1.8089)*#timedriving_lg_5
 +(-0.222361)*#portions3cat_lg_1
 +(-0.00864795)*#portions3cat_lg_2
 +(0.231009)*#portions3cat_lg_3
 +(-3.70483)*#avoidredmeat_lg_1
 +(3.70483)*#avoidredmeat_lg_2
 +(-3.43853)*#veg2_lg_1
 +(3.43853)*#veg2_lg_2
 +(4.24553)*#rpmtotalcat_lg_1
 +(0.000798989)*#rpmtotalcat_lg_2
 +(-4.24633)*#rpmtotalcat_lg_3.

COMPUTE Cluster_lg_10=(3.50717)
 +(0.644138)*#multitrav2_lg_1
 +(-2.32473)*#multitrav2_lg_2
 +(-2.4519)*#multitrav2_lg_3
 +(-3.41147)*#multitrav2_lg_4
 +(7.54396)*#multitrav2_lg_5
 +(7.31968)*#carcom2_lg_1
 +(2.96918)*#carcom2_lg_2
 +(-10.2889)*#carcom2_lg_3
 +(-5.55821)*#bikecom2_lg_1
 +(2.77812)*#bikecom2_lg_2
 +(2.78008)*#bikecom2_lg_3
 +(2.25931)*#walkcom2_lg_1
 +(-4.0497)*#walkcom2_lg_2
 +(1.79039)*#walkcom2_lg_3
 +(0.960135)*#pubcom2_lg_1
 +(-0.981757)*#pubcom2_lg_2
 +(0.0216219)*#pubcom2_lg_3
 +(3.19291)*#timedriving_lg_1
 +(1.95466)*#timedriving_lg_2
 +(0.181135)*#timedriving_lg_3
 +(-1.70925)*#timedriving_lg_4
 +(-3.61946)*#timedriving_lg_5
 +(-0.868111)*#portions3cat_lg_1
 +(-0.00864796)*#portions3cat_lg_2
 +(0.876759)*#portions3cat_lg_3
 +(-0.271797)*#avoidredmeat_lg_1
 +(0.271797)*#avoidredmeat_lg_2
 +(-2.23415)*#veg2_lg_1
 +(2.23415)*#veg2_lg_2
 +(-0.913159)*#rpmtotalcat_lg_1
 +(0.000798986)*#rpmtotalcat_lg_2
 +(0.91236)*#rpmtotalcat_lg_3.

* Compute probabilities from logits.

COMPUTE #max_lg=Cluster_lg_1.
IF(Cluster_lg_2>#max_lg)
#max_lg=Cluster_lg_2.
IF(Cluster_lg_3>#max_lg)
#max_lg=Cluster_lg_3.
IF(Cluster_lg_4>#max_lg)
#max_lg=Cluster_lg_4.
IF(Cluster_lg_5>#max_lg)
#max_lg=Cluster_lg_5.
IF(Cluster_lg_6>#max_lg)
#max_lg=Cluster_lg_6.
IF(Cluster_lg_7>#max_lg)
#max_lg=Cluster_lg_7.
IF(Cluster_lg_8>#max_lg)
#max_lg=Cluster_lg_8.
IF(Cluster_lg_9>#max_lg)
#max_lg=Cluster_lg_9.
IF(Cluster_lg_10>#max_lg)
#max_lg=Cluster_lg_10.

COMPUTE Cluster_lg_1=exp(Cluster_lg_1-
#max_lg).
COMPUTE Cluster_lg_2=exp(Cluster_lg_2-
#max_lg).
COMPUTE Cluster_lg_3=exp(Cluster_lg_3-
#max_lg).
COMPUTE Cluster_lg_4=exp(Cluster_lg_4-
#max_lg).
COMPUTE Cluster_lg_5=exp(Cluster_lg_5-
#max_lg).
COMPUTE Cluster_lg_6=exp(Cluster_lg_6-
#max_lg).
COMPUTE Cluster_lg_7=exp(Cluster_lg_7-
#max_lg).
COMPUTE Cluster_lg_8=exp(Cluster_lg_8-
#max_lg).
COMPUTE Cluster_lg_9=exp(Cluster_lg_9-
#max_lg).
COMPUTE Cluster_lg_10=exp(Cluster_lg_10-
#max_lg).

COMPUTE
#sum_lg=Cluster_lg_1+Cluster_lg_2+Cluster_lg
_3+Cluster_lg_4+Cluster_lg_5+Cluster_lg_6+Cl
uster_lg_7+Cluster_lg_8+Cluster_lg_9+Cluster_l
g_10.
COMPUTE Cluster_lg_1=Cluster_lg_1/#sum_lg.
COMPUTE Cluster_lg_2=Cluster_lg_2/#sum_lg.
COMPUTE Cluster_lg_3=Cluster_lg_3/#sum_lg.
COMPUTE Cluster_lg_4=Cluster_lg_4/#sum_lg.
COMPUTE Cluster_lg_5=Cluster_lg_5/#sum_lg.
COMPUTE Cluster_lg_6=Cluster_lg_6/#sum_lg.
COMPUTE Cluster_lg_7=Cluster_lg_7/#sum_lg.
COMPUTE Cluster_lg_8=Cluster_lg_8/#sum_lg.
COMPUTE Cluster_lg_9=Cluster_lg_9/#sum_lg.
COMPUTE
Cluster_lg_10=Cluster_lg_10/#sum_lg.
EXECUTE.


SAVE OUTFILE= 'I:\BBfemscored.sav'
 /KEEP n_eid n_31_0_0 Cluster_lg_1
Cluster_lg_2 Cluster_lg_3 Cluster_lg_4
Cluster_lg_5 Cluster_lg_6 Cluster_lg_7
Cluster_lg_8 Cluster_lg_9 Cluster_lg_10.
```

Table D.0.3 – Comparison of class sizes between estimation model and scored dataset, UKB females

Class #	Estimation model (%, n=2,324)	Scored dataset (%, n=116,255)	% difference
1	0.33	0.33	0.00
2	0.32	0.31	0.00
3	0.09	0.10	0.01
4	0.08	0.07	-0.01
5	0.07	0.07	0.00
6	0.03	0.03	0.00
7	0.03	0.03	0.00
8	0.02	0.03	0.00
9	0.02	0.02	0.00
10	0.01	0.01	0.00

Table D.0.4 – Comparison of class sizes between estimation model and scored dataset, UKB males

Class #	Estimation model (n=1,896)	Scored dataset (n=94,781)	% difference
1	0.37	0.36	-0.01
2	0.35	0.35	0.01
3	0.08	0.09	0.01
4	0.08	0.07	-0.01
5	0.05	0.06	0.01
6	0.04	0.03	0.00
7	0.01	0.01	0.00
8	0.01	0.01	0.00
9	0.01	0.01	0.00

Table D.0.5 – Demographic factors among NDNS females, by class assignment (n=904)

Class number	1	2	3	4	5	6	7	8	9	Full sample
Class size	0.26	0.25	0.21	0.07	0.07	0.07	0.04	0.02	0.01	
Age group										
16-24	0.14	0.17	*0.04*	0.18	**0.22**	**0.30**	0.15	0.10	0.33	0.15
25-39	0.26	0.22	*0.15*	0.32	0.26	0.26	0.30	0.37	0.20	0.24
40-54	**0.43**	*0.15*	*0.14*	0.32	0.33	0.31	0.40	*0.05*	0.38	0.27
55-69	*0.14*	0.23	**0.31**	0.18	0.17	0.12	0.10	0.13	0.09	0.20
70+	*0.03*	0.23	0.36	*0.00*	*0.02*	*0.01*	0.06	0.36	0.00	0.15
Ethnic group										
White	0.95	0.90	0.91	0.87	0.83	0.78	0.79	0.79	1.00	0.90
Non-white	*0.05*	0.10	0.09	0.13	0.17	**0.22**	0.21	**0.21**	0.00	0.10
Household size										
1	*0.05*	0.21	**0.28**	0.08	0.14	0.18	0.18	0.16	0.00	0.16
2	0.32	0.32	0.42	0.38	0.35	0.35	0.35	0.40	0.53	0.36
3	**0.31**	0.17	*0.13*	0.25	0.30	0.19	0.20	0.18	0.33	0.22
4	0.23	0.20	*0.09*	0.20	0.18	0.23	0.22	0.09	0.14	0.18
5+	0.09	0.11	0.08	0.09	0.03	0.06	0.05	0.17	0.00	0.09
Children in household										
No	0.62	0.67	**0.78**	0.60	0.68	0.65	0.64	0.64	0.77	0.68
Yes	**0.38**	0.33	*0.22*	0.40	0.32	0.35	0.36	0.36	0.23	0.32
Living with partner										
No	*0.28*	0.46	0.40	0.35	0.45	**0.60**	0.37	0.35	0.33	0.40
Yes	**0.72**	0.54	0.60	0.65	0.55	*0.40*	0.63	0.65	0.67	0.60

Travel behaviour									
Diet behaviour									

Yellow shading = above sample average, **bolding = extreme positive value**, *italics/underline = extreme negative value*

'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.6 – Socio-economic factors among NDNS females, by class assignment (n=904)

Class number	1	2	3	4	5	6	7	8	9	Full sample
Class size	0.26	0.25	0.21	0.07	0.07	0.07	0.04	0.02	0.01	
Education level										
Degree or equiv	**0.34**	0.11	0.17	0.22	0.19	0.14	**0.43**	0.14	**0.45**	0.21
Higher ed <degree	**0.34**	*0.17*	0.20	0.20	0.27	0.34	0.27	0.20	0.29	0.25
GCSE or equiv	0.19	**0.25**	0.21	0.31	0.20	0.16	0.12	0.03	0.24	0.21
Foreign qual	*0.02*	0.06	**0.11**	0.05	0.03	0.01	0.00	0.00	0.00	0.05
No qualifications	*0.06*	**0.35**	0.28	*0.05*	0.16	0.16	0.07	**0.56**	0.00	0.20
Still in school	*0.05*	0.05	*0.02*	**0.15**	**0.15**	**0.19**	0.12	0.06	0.02	0.07
Missing	0.00	0.02	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.01
Current Employment										
No	*0.10*	**0.85**	**0.84**	*0.21*	*0.23*	0.27	*0.18*	**0.84**	0.24	0.49
Yes	**0.90**	*0.16*	*0.16*	**0.79**	**0.77**	0.73	**0.82**	*0.16*	0.76	0.51
Occupational class (hrp)										
Higher man/prof	**0.21**	*0.06*	0.12	0.11	0.11	0.14	0.16	0.00	0.24	0.13
Lower man/prof	0.31	*0.22*	**0.32**	0.28	0.29	0.15	0.42	0.17	0.23	0.28
Intermediate	0.12	0.09	0.10	0.04	0.03	0.15	0.04	0.10	0.32	0.10
Small employers	0.10	0.14	**0.20**	0.18	0.05	0.06	0.05	0.13	0.13	0.13
Lower superv/tech	0.10	0.10	*0.06*	0.12	0.19	0.08	0.03	0.15	0.09	0.09
Semi routine	0.12	0.18	*0.08*	0.22	0.13	0.22	0.16	0.26	0.00	0.14
Routine	*0.06*	**0.13**	0.06	0.05	0.13	0.15	0.01	0.18	0.00	0.09
Never worked	*0.00*	**0.05**	0.04	0.01	0.01	0.00	0.05	0.00	0.00	0.02
Missing	0.00	0.02	0.02	0.01	0.06	**0.07**	0.06	0.00	0.00	0.02
Eqv Household income										
0-£14 999	*0.12*	**0.34**	0.19	0.18	0.27	0.28	0.13	0.35	0.22	0.22
£15 000-24 999	0.18	0.19	0.20	0.23	0.20	0.21	0.22	0.33	0.22	0.20
£25 000-34 999	0.20	0.13	0.18	0.16	0.15	0.13	0.12	0.02	0.25	0.16
£35 000-49 999	**0.20**	*0.05*	0.10	0.20	0.20	0.11	0.12	0.17	0.12	0.13
£50 000+	**0.17**	*0.07*	0.11	0.13	0.10	0.18	0.24	0.01	0.20	0.12
Missing	0.12	0.22	**0.22**	0.09	0.08	0.08	0.16	0.11	0.00	0.16
Travel behaviour										
Diet behaviour										

Yellow shading = above sample average, **bolding = extreme positive value**, *italics/underline = extreme negative value*

'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.7 – Environmental factors among NDNS females, by class assignment (n=904)

Class number	1	2	3	4	5	6	7	8	9	Full sample
Class size	0.26	0.25	0.21	0.07	0.07	0.07	0.04	0.02	0.01	
IMD quintile (England only)										
1 (lowest)	0.21	0.11	**0.29**	0.15	*0.09*	0.09	0.23	0.43	0.23	0.18
2	0.20	0.15	0.17	0.25	0.15	0.18	0.08	0.17	0.00	0.17
3	0.13	0.17	0.16	0.22	0.20	0.18	**0.37**	0.15	0.22	0.17
4	0.15	0.15	0.13	0.15	0.26	0.24	0.13	0.10	0.31	0.16
5 (highest)	0.11	**0.22**	*0.08*	0.15	0.18	0.23	0.09	0.10	0.13	0.15
Outside England	0.20	0.20	0.17	0.08	0.12	0.08	0.10	0.05	0.11	0.16
Gov Office Region										
North East	0.04	0.05	0.05	0.02	0.04	0.01	0.02	0.01	0.00	0.04
North West	0.15	0.09	0.07	0.17	0.14	0.14	0.07	0.02	0.22	0.11
Yorkshire and the Humber	0.08	0.12	0.08	0.11	0.11	0.12	0.05	0.01	**0.36**	0.10
East Midlands	0.06	0.06	0.08	0.08	0.07	0.07	**0.16**	0.10	0.00	0.07
West Midlands	0.08	0.10	0.07	0.10	0.13	0.04	0.09	0.14	0.00	0.09
East of England	0.09	0.04	0.10	0.08	0.05	0.07	0.12	0.09	0.00	0.07
London	*0.04*	0.14	0.10	0.12	0.11	**0.27**	0.20	**0.25**	0.00	0.11
South East	0.19	0.11	0.17	0.18	*0.08*	0.17	0.10	0.32	**0.32**	0.16
South West	0.07	0.08	0.11	0.07	0.15	0.04	0.10	0.00	0.00	0.08
Wales	0.08	0.07	0.07	0.01	0.02	*0.00*	0.02	0.04	0.00	0.06
Scotland	0.08	**0.11**	0.07	0.04	0.05	0.07	0.07	0.00	0.11	0.08
Northern Ireland	0.04	0.02	0.03	0.03	0.06	0.01	0.00	0.01	0.00	0.03
Travel behaviour										
Diet behaviour										

Yellow shading = above sample average, **bolding = extreme positive value**, *italics/underline = extreme negative value*

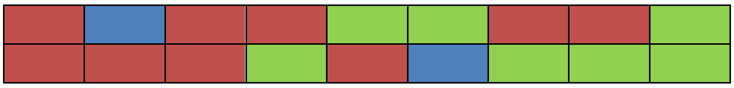
'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.8 – Health and lifestyle indicators among NDNS females, by class assignment (n=904)

Class number	1	2	3	4	5	6	7	8	9	Full sample
Class size	0.26	0.25	0.21	0.07	0.07	0.07	0.04	0.02	0.01	
Energykcal (Mean)	1599	1479	1581	1652	1573	1590	1570	1624	1648	1567
MVPAmin (Mean)	73	37	56	85	103	64	53	43	146	62
BMI grouping										
<25	0.36	0.41	0.37	0.33	0.35	0.49	0.46	0.56	0.58	0.40
25+	0.58	0.52	0.53	0.56	0.59	0.44	0.49	0.38	0.31	0.53
Missing	0.06	0.07	0.09	0.11	0.05	0.08	0.06	0.06	0.11	0.08
Self-rated health										
Very good	0.33	*0.28*	0.33	0.45	0.28	0.28	0.39	0.25	0.60	0.32
Good	0.51	0.38	0.43	0.38	0.52	0.52	0.50	0.30	0.40	0.44
Fair	*0.14*	**0.26**	0.20	0.16	0.19	0.19	0.11	**0.39**	0.00	0.19
Bad	0.02	**0.06**	0.03	0.02	0.00	0.01	0.00	0.06	0.00	0.03
Very bad	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Activities limited due to long-term condition?										
Yes	*0.17*	**0.28**	**0.27**	*0.08*	0.13	*0.10*	0.07	0.36	0.11	0.20
No	0.20	0.15	0.23	0.20	0.18	0.21	*0.04*	0.01	0.20	0.18
No long term condition	0.63	0.56	*0.50*	0.73	0.70	0.69	0.90	0.63	0.69	0.61

Travel behaviour

Diet behaviour



Yellow shading = above sample average, **bolding = extreme positive value**, *italics/underline = extreme negative value*

'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.9 – Demographic factors among NDNS males, by class assignment (n=705)

Class number	1	2	3	4	5	6	7	8	Full Sample
Class size	0.38	0.36	0.09	0.06	0.05	0.03	0.01	0.01	
Age group									
16-24	*0.12*	*0.09*	**0.42**	0.19	**0.34**	0.35	0.06	0.20	0.16
25-39	**0.38**	*0.14*	0.20	0.35	0.20	0.25	0.30	0.00	0.26
40-54	**0.33**	*0.18*	0.33	0.26	0.38	0.15	0.26	0.05	0.27
55-69	0.16	**0.29**	*0.04*	0.14	0.07	0.15	0.38	**0.74**	0.20
70+	*0.01*	**0.30**	*0.01*	0.05	*0.00*	0.10	0.00	0.01	0.12
Ethnic group									
White	0.92	0.92	0.72	0.78	0.84	0.92	0.78	0.64	0.88
Non-White	0.08	0.08	**0.28**	0.22	0.16	0.08	0.22	0.36	0.12
Household size									
1	*0.09*	**0.18**	0.21	0.26	0.08	0.14	0.20	0.05	0.15
2	0.28	**0.46**	0.25	0.22	0.22	0.60	0.49	0.38	0.35
3	**0.30**	*0.14*	0.10	0.22	0.10	0.11	0.15	0.20	0.20
4	0.20	*0.15*	**0.25**	0.17	**0.29**	0.08	0.10	0.36	0.19
5+	0.12	*0.06*	0.19	0.13	0.31	0.07	0.06	0.00	0.11
Children in household									
No	*0.55*	**0.82**	0.56	0.62	0.58	0.74	0.69	1.00	0.66
Yes	**0.45**	*0.18*	0.44	0.38	0.42	0.26	0.31	0.00	0.34
Living with partner									
No	*0.22*	0.32	**0.57**	0.40	0.41	0.24	0.26	0.26	0.31
Yes	**0.78**	0.68	*0.44*	0.60	0.59	0.76	0.74	0.74	0.69

	1	2	3	4	5	6	7	8
Travel behaviour	red	red	green	green	red	green	blue	blue
Diet behaviour	red	blue	blue	red	red	red	green	green

Yellow shading = above sample average, **bolding = extreme positive value**, *italics/underline = extreme negative value*

'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.10 – Socio-economic factors among NDNS males, by class assignment (n=705)

Class number	1	2	3	4	5	6	7	8	Full Sample
Class size	0.38	0.36	0.09	0.06	0.05	0.03	0.01	0.01	
Education level									
Degree or equiv	0.31	*0.17*	0.34	0.18	0.39	0.20	0.51	0.25	0.26
Higher ed <degree	**0.34**	0.23	0.24	0.25	0.18	0.07	0.28	0.01	0.27
GCSE or equiv	0.21	0.18	0.09	0.21	0.12	0.25	0.04	0.31	0.18
Foreign qual	0.03	0.08	0.02	0.04	0.09	0.00	0.11	0.01	0.05
No qualifications	*0.09*	**0.29**	*0.04*	0.13	0.11	0.12	0.00	0.41	0.16
Still in full-time education	*0.02*	0.04	**0.27**	**0.19**	0.10	0.37	0.06	0.00	0.07
Missing	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Current Employment									
No	*0.05*	**0.74**	0.31	0.32	0.12	0.39	0.06	**1.00**	0.36
Yes	**0.95**	*0.26*	0.69	0.68	0.88	0.61	0.94	0.00	0.64
Occupational Class (hrp)									
Higher man/prof	0.22	*0.13*	**0.31**	0.19	0.21	0.25	0.32	0.25	0.19
Lower man/prof	0.32	0.24	0.25	0.22	0.49	0.26	0.39	0.13	0.29
Intermediate	0.10	0.07	0.10	0.07	0.01	0.02	0.08	0.00	0.08
Small employers	0.08	0.08	0.08	0.10	0.04	0.00	0.00	0.00	0.07
Lower superv/techn	0.08	0.13	0.08	0.07	0.12	0.11	0.11	0.05	0.10
Semi routine	0.11	**0.17**	0.06	0.12	0.02	0.12	0.01	0.00	0.12
Routine	0.08	**0.15**	0.03	0.10	0.12	0.19	0.09	0.56	0.11
Never worked	0.01	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.01
Missing	0.00	0.01	0.08	0.12	0.00	0.04	0.00	0.00	0.02
Eqv Household Income									
0-£14 999	*0.08*	**0.21**	0.16	0.15	0.17	0.19	0.00	0.00	0.15
£15 000-24 999	0.18	**0.28**	*0.08*	0.22	0.27	0.30	0.04	0.37	0.22
£25 000-34 999	0.16	0.16	0.12	0.25	0.19	0.09	0.21	0.17	0.17
£35 000-49 999	0.21	*0.09*	0.28	0.12	0.13	0.11	0.37	0.14	0.16
£50 000	**0.23**	*0.07*	0.18	0.09	0.10	0.23	0.21	0.00	0.15
Missing	0.13	0.18	0.18	0.18	0.13	0.08	0.17	0.32	0.16

Travel behaviour								
Diet behaviour								

Yellow shading = above sample average, **bolding = extreme positive value**, *italics/underline = extreme negative value*

'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.11 – Environmental factors among NDNS males, by class assignment (n=705)

Class number	1	2	3	4	5	6	7	8	Full Sample
Class size	0.38	0.36	0.09	0.06	0.05	0.03	0.01	0.01	
IMD quintile (England only)									
1 (lowest)	0.22	0.18	0.19	0.16	0.11	0.17	0.13	0.12	0.19
2	0.18	0.18	0.25	0.09	0.35	0.15	0.04	0.12	0.18
3	0.18	0.14	0.13	0.21	0.18	0.15	0.20	0.21	0.16
4	0.13	0.16	0.14	0.20	0.10	0.10	0.39	0.36	0.15
5 (highest)	0.12	0.19	0.18	0.23	0.14	0.29	0.17	0.06	0.16
Outside England	0.17	0.16	0.11	0.11	0.11	0.14	0.07	0.14	0.15
Government Office Region									
North East	0.04	**0.09**	0.00	0.01	0.05	0.11	0.00	0.00	0.05
North West	0.13	0.11	0.07	0.10	0.09	0.09	0.11	0.01	0.11
Yorkshire and the Humber	0.06	0.05	0.04	0.09	0.09	0.00	0.12	0.20	0.06
East Midlands	0.10	0.06	0.02	0.10	0.09	0.04	0.06	0.12	0.08
West Midlands	0.09	0.07	0.07	0.11	0.11	0.05	0.09	0.05	0.08
East of England	0.14	0.13	0.10	0.06	0.10	0.00	0.04	0.11	0.12
London	*0.05*	0.11	**0.42**	0.20	0.15	0.24	0.39	0.36	0.13
South East	0.12	0.12	0.08	0.14	0.18	**0.28**	0.13	0.00	0.12
South West	0.10	0.10	0.08	0.08	0.04	0.03	0.00	0.00	0.09
Wales	0.05	0.06	0.00	0.02	0.01	0.06	0.00	0.00	0.04
Scotland	0.09	0.08	0.04	0.09	0.08	0.08	0.07	0.14	0.08
Northern Ireland	0.03	0.02	0.07	0.00	0.02	0.00	0.00	0.00	0.03

Travel behaviour

Diet behaviour

Yellow shading = above sample average, **bolding = extreme positive value**, *italics/underline = extreme negative value*

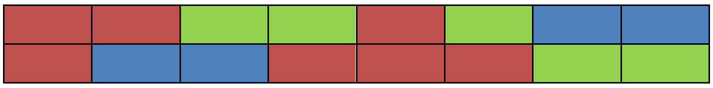
'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.12 – Health and lifestyle indicators among NDNS males, by class assignment (n=705)

Class number	1	2	3	4	5	6	7	8	Full Sample
Class size	0.38	0.36	0.09	0.06	0.05	0.03	0.01	0.01	
Energykcal (Mean)	2182	1943	2090	2094	2014	2645	2255	1804	2060
MVPAmin (Mean)	181	78	84	164	187	180	124	57	131
BMI grouping									
<25	0.31	0.26	0.43	0.23	0.31	0.60	0.42	0.25	0.33
25+	0.66	0.64	0.49	0.72	0.55	0.35	0.58	0.74	0.60
Missing	0.03	0.11	0.07	0.06	0.14	0.06	0.00	0.01	0.07
Self-rated health									
Very good	0.42	*<u>0.24</u>*	0.36	0.54	0.18	0.63	0.63	0.14	0.35
Good	0.45	0.36	0.47	0.26	0.67	0.34	0.21	0.59	0.41
Fair	*<u>0.12</u>*	**0.29**	0.14	0.19	0.12	0.02	0.15	0.25	0.19
Bad	0.01	**0.08**	0.02	0.00	0.03	0.00	0.00	0.00	0.04
Very bad	0.00	**0.03**	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Activities limited due to long-term condition?									
Yes	*<u>0.10</u>*	**0.32**	0.10	0.07	0.06	0.08	0.04	0.62	0.18
No	0.15	0.21	0.07	0.18	0.17	0.12	0.04	0.14	0.17
No long term condition	0.75	*<u>0.47</u>*	0.83	0.75	0.77	0.80	0.92	0.23	0.66

Travel behaviour

Diet behaviour



Yellow shading = above sample average, **bolding = extreme positive value**, *<u>italics/underline = extreme negative value</u>*

'Extreme' values represent standardised residuals that were equal or greater than +/-2 for each value in the cross-tabulation.

Table D.0.13 – Cross-tabulation of demographic factors and class assignments in UKB females based on scoring equations, classwise proportions only (n=116,255)

Class #	1	2	3	4	5	6	7	8	9	10	Total
Class size	0.33	0.31	0.10	0.07	0.07	0.03	0.03	0.03	0.02	0.01	1.00
Total	38,111	36,583	11,748	8,127	8,156	3,692	3,696	3,290	1,996	856	116,255
Age at baseline assessment											
< 45	0.15	0.04	0.05	0.16	0.16	0.21	0.14	0.09	0.21	0.21	0.11
45-49	0.21	0.06	0.05	0.22	0.20	0.22	0.20	0.07	0.23	0.23	0.14
50-54	0.25	0.08	0.07	0.25	0.24	0.23	0.24	0.10	0.22	0.24	0.17
55-59	0.24	0.16	0.13	0.22	0.22	0.22	0.25	0.17	0.20	0.20	0.20
60-64	0.12	0.38	0.38	0.12	0.14	0.10	0.14	0.35	0.12	0.10	0.24
65+	0.02	0.28	0.31	0.03	0.03	0.02	0.03	0.23	0.02	0.03	0.14
Ethnic group											
White British	0.90	0.92	0.85	0.88	0.76	0.86	0.87	0.83	0.78	0.80	0.88
Other White	0.06	0.05	0.09	0.08	0.13	0.06	0.09	0.08	0.12	0.16	0.07
South Asian	0.01	0.01	0.01	0.01	0.02	0.05	0.01	0.05	0.05	0.00	0.01
Black	0.01	0.00	0.02	0.01	0.05	0.01	0.01	0.01	0.02	0.01	0.01
Chinese	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Mixed	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Other	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Household structure											
Live alone	0.16	0.18	0.23	0.16	0.27	0.21	0.16	0.26	0.28	0.19	0.19
Child(ren), no partner	0.11	0.04	0.06	0.09	0.11	0.12	0.10	0.06	0.10	0.10	0.08
Partner, no child(ren)	0.32	0.58	0.53	0.30	0.30	0.30	0.32	0.43	0.29	0.27	0.42
Partner + child(ren)	0.39	0.19	0.15	0.43	0.26	0.34	0.39	0.19	0.27	0.39	0.29
Live with others	0.02	0.01	0.02	0.02	0.05	0.03	0.02	0.04	0.05	0.05	0.02
Missing	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00

Travel behaviour										
Diet behaviour										

Yellow shading = above sample average

Table D.0.14 – Cross-tabulation of socio-economic factors and class assignments in UKB females based on scoring equations, classwise proportions only (n=116,255)

Class #	1	2	3	4	5	6	7	8	9	10	Total
Class size	0.33	0.31	0.10	0.07	0.07	0.03	0.03	0.03	0.02	0.01	1.00
Total	38,111	36,583	11,748	8,127	8,156	3,692	3,696	3,290	1,996	856	116,255
Qualifications											
College or University	0.42	0.34	0.35	0.51	0.49	0.58	0.35	0.47	0.62	0.69	0.41
A levels/AS levels or	0.15	0.14	0.11	0.16	0.13	0.14	0.16	0.14	0.12	0.11	0.14
O levels/GCSEs or equv	0.23	0.25	0.22	0.20	0.20	0.16	0.24	0.18	0.14	0.10	0.23
CSEs or equivalent	0.06	0.03	0.03	0.04	0.05	0.03	0.08	0.02	0.03	0.03	0.04
NVQ or HND or HNC or	0.04	0.03	0.03	0.03	0.04	0.03	0.04	0.02	0.03	0.02	0.03
Other professional qu	0.06	0.07	0.06	0.03	0.03	0.05	0.04	0.06	0.03	0.03	0.06
No qualif	0.04	0.12	0.18	0.03	0.05	0.02	0.09	0.09	0.03	0.03	0.08
Missing	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
Employment											
Paid employment	1.00	0.09	0.08	1.00	1.00	1.00	1.00	0.13	1.00	1.00	0.60
Retired	0.00	0.71	0.70	0.00	0.00	0.00	0.00	0.59	0.00	0.00	0.31
Other	0.00	0.18	0.21	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.08
Missing	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.01
Occupational class											
Higher manag profess	0.20	0.06	0.05	0.23	0.23	0.24	0.12	0.06	0.25	0.29	0.14
Lower manag profess	0.41	0.15	0.14	0.36	0.33	0.45	0.27	0.17	0.37	0.38	0.28
Intermed	0.23	0.10	0.11	0.24	0.29	0.17	0.27	0.08	0.23	0.17	0.18
Small employers	0.03	0.02	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.04	0.03
Lower sup techn	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.00
Semi-routine	0.10	0.03	0.05	0.11	0.10	0.09	0.25	0.03	0.10	0.09	0.08
Routine	0.02	0.01	0.02	0.02	0.02	0.02	0.06	0.01	0.02	0.02	0.02
Not classified	0.00	0.60	0.59	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.27
Missing	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.01
Household income											
Less than 18,000	0.07	0.21	0.31	0.07	0.11	0.07	0.14	0.28	0.12	0.09	0.15
18,000 to 30,999	0.19	0.26	0.25	0.18	0.23	0.18	0.24	0.23	0.21	0.18	0.22
31,000 to 51,999	0.30	0.19	0.14	0.29	0.27	0.31	0.28	0.17	0.28	0.31	0.24
52,000 to 100,000	0.29	0.11	0.08	0.28	0.23	0.30	0.19	0.10	0.25	0.26	0.20
Greater than 100,000	0.07	0.04	0.03	0.09	0.08	0.06	0.05	0.04	0.06	0.10	0.06
Missing	0.08	0.18	0.20	0.09	0.08	0.08	0.11	0.19	0.08	0.06	0.13
Cars per household											
None	0.00	0.00	0.26	0.02	0.30	0.00	0.15	0.14	0.29	0.21	0.07
One	0.33	0.44	0.55	0.48	0.51	0.42	0.50	0.48	0.53	0.56	0.43
Two	0.49	0.45	0.15	0.38	0.15	0.45	0.28	0.30	0.14	0.19	0.39
Three	0.14	0.08	0.02	0.09	0.03	0.09	0.06	0.05	0.03	0.03	0.09
4+	0.04	0.02	0.01	0.03	0.01	0.03	0.02	0.01	0.01	0.00	0.03
Missing	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00

Travel behaviour

Diet behaviour

Yellow shading = above sample average

Table D.0.15 – Cross-tabulation of environmental factors and class assignments in UKB females based on scoring equations, classwise proportions only (n=116,255)

Class #	1	2	3	4	5	6	7	8	9	10	Total
Class size	0.33	0.31	0.10	0.07	0.07	0.03	0.03	0.03	0.02	0.01	1.00
Total	38,111	36,583	11,748	8,127	8,156	3,692	3,696	3,290	1,996	856	116,255
Townsend score (quintiles)											
1 (Lowest)	0.24	0.26	0.13	0.18	0.08	0.19	0.13	0.18	0.09	0.07	0.21
2	0.23	0.25	0.16	0.19	0.11	0.21	0.14	0.19	0.10	0.13	0.21
3	0.22	0.21	0.19	0.21	0.15	0.22	0.18	0.19	0.16	0.17	0.21
4	0.19	0.18	0.24	0.24	0.27	0.24	0.27	0.24	0.27	0.29	0.21
5 (Highest)	0.12	0.10	0.28	0.19	0.39	0.14	0.28	0.20	0.38	0.34	0.17
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Assessment centre											
Manchester	0.02	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.03	0.02
Oxford	0.03	0.02	0.02	0.04	0.01	0.03	0.02	0.03	0.02	0.14	0.03
Cardiff	0.03	0.02	0.01	0.02	0.01	0.04	0.02	0.02	0.02	0.02	0.02
Glasgow	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.00	0.02
Edinburgh	0.03	0.02	0.03	0.05	0.05	0.03	0.04	0.02	0.04	0.04	0.03
Stoke	0.02	0.02	0.01	0.01	0.00	0.02	0.01	0.02	0.00	0.00	0.02
Reading	0.07	0.07	0.03	0.06	0.02	0.05	0.05	0.04	0.03	0.04	0.06
Bury	0.04	0.04	0.02	0.02	0.02	0.04	0.02	0.03	0.02	0.00	0.03
Newcastle	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.04	0.03	0.02	0.05
Leeds	0.07	0.07	0.05	0.06	0.04	0.08	0.07	0.06	0.05	0.02	0.07
Bristol	0.12	0.11	0.08	0.12	0.04	0.12	0.14	0.11	0.09	0.13	0.11
Barts (Central London)	0.01	0.01	0.06	0.04	0.10	0.01	0.06	0.04	0.12	0.14	0.03
Nottingham	0.06	0.06	0.05	0.05	0.03	0.06	0.06	0.05	0.04	0.03	0.06
Sheffield	0.10	0.10	0.11	0.08	0.07	0.09	0.09	0.09	0.07	0.03	0.09
Liverpool	0.08	0.09	0.07	0.05	0.05	0.07	0.05	0.07	0.04	0.04	0.08
Middlesbrough	0.06	0.06	0.04	0.03	0.01	0.04	0.04	0.04	0.01	0.01	0.05
Hounslow	0.06	0.08	0.14	0.11	0.17	0.08	0.09	0.12	0.15	0.17	0.09
Croydon	0.06	0.08	0.14	0.11	0.22	0.06	0.09	0.11	0.18	0.11	0.09
Birmingham	0.07	0.06	0.06	0.06	0.07	0.09	0.06	0.07	0.05	0.03	0.07
Swansea	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Wrexham	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Urban/rural											
Rural / Fringe	0.18	0.20	0.08	0.09	0.03	0.15	0.07	0.15	0.04	0.03	0.15
Urban	0.81	0.79	0.91	0.90	0.96	0.83	0.92	0.84	0.95	0.96	0.84
Missing	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Travel behaviour										
Diet behaviour										

Yellow shading = above sample average

Table D.0.16 – Cross-tabulation of health / lifestyle factors and class assignments in UKB females based on scoring equations, classwise proportions only (n=116,255)

Class #	1	2	3	4	5	6	7	8	9	10	Total
Class size	0.33	0.31	0.10	0.07	0.07	0.03	0.03	0.03	0.02	0.01	1.00
Total	38,111	36,583	11,748	8,127	8,156	3,692	3,696	3,290	1,996	856	116,255
Energykcal (Mean)	*1953*	1977	1964	2016	1969	*1939*	*1961*	*1960*	*1947*	2035	1968
Meets PA guideline											
No	0.53	0.42	0.43	0.46	0.55	0.45	0.47	0.36	0.44	0.09	0.47
Yes	0.43	0.53	0.51	0.51	0.41	0.51	0.48	0.58	0.51	0.90	0.49
Missing	0.04	0.05	0.05	0.03	0.04	0.04	0.05	0.06	0.05	0.01	0.04
BMI											
<25	0.43	0.41	0.42	0.48	0.45	0.58	0.50	0.56	0.63	0.68	0.45
25+	0.56	0.59	0.58	0.52	0.55	0.42	0.50	0.43	0.37	0.31	0.55
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Self-rated health											
Excellent	0.21	0.19	0.16	0.26	0.19	0.26	0.21	0.20	0.26	0.39	0.20
Good	0.62	0.61	0.57	0.61	0.60	0.59	0.61	0.57	0.58	0.54	0.60
Fair	0.15	0.17	0.20	0.12	0.18	0.13	0.15	0.17	0.15	0.07	0.16
Poor	0.02	0.03	0.06	0.01	0.02	0.02	0.02	0.05	0.02	0.01	0.03
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Long-term condition											
Yes	0.23	0.31	0.36	0.20	0.25	0.22	0.22	0.33	0.20	0.18	0.27
No	0.76	0.67	0.61	0.78	0.73	0.76	0.76	0.63	0.77	0.80	0.71
Missing	0.02	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.02

	1	2	3	4	5	6	7	8	9	10
Travel behaviour										
Diet behaviour										

Shading = above sample average

Table D.0.17 – Multinomial regression between demographic factors and class membership, UKB females (n=99,193)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Age group (ref 65+)									
< 45	0.04***	0.02***	0.88	0.81*	2.08***	0.72*	0.07***	1.49*	0.97
	(0.03 - 0.04)	(0.02 - 0.03)	(0.73 - 1.05)	(0.68 - 0.97)	(1.54 - 2.80)	(0.55 - 0.92)	(0.06 - 0.09)	(1.05 - 2.10)	(0.60 - 1.57)
45-49	0.04***	0.02***	0.97	0.96	1.71***	0.88	0.05***	1.48*	1.07
	(0.03 - 0.04)	(0.02 - 0.03)	(0.82 - 1.16)	(0.81 - 1.15)	(1.27 - 2.30)	(0.68 - 1.13)	(0.04 - 0.06)	(1.05 - 2.08)	(0.67 - 1.72)
50-54	0.04***	0.04***	1.00	1.10	1.53**	1.02	0.07***	1.38	1.06
	(0.04 - 0.05)	(0.03 - 0.04)	(0.84 - 1.19)	(0.93 - 1.31)	(1.14 - 2.05)	(0.79 - 1.30)	(0.05 - 0.08)	(0.98 - 1.95)	(0.66 - 1.71)
55-59	0.08***	0.07***	0.93	1.12	1.46*	1.17	0.11***	1.40	0.96
	(0.08 - 0.09)	(0.07 - 0.08)	(0.79 - 1.11)	(0.94 - 1.32)	(1.09 - 1.96)	(0.92 - 1.49)	(0.10 - 0.13)	(0.99 - 1.96)	(0.60 - 1.54)
60-64	0.35***	0.37***	0.98	1.10	1.22	1.13	0.43***	1.31	0.90
	(0.32 - 0.38)	(0.33 - 0.41)	(0.82 - 1.17)	(0.93 - 1.31)	(0.90 - 1.66)	(0.88 - 1.45)	(0.38 - 0.50)	(0.92 - 1.85)	(0.55 - 1.48)
Ethnic group (ref Other White)									
White Brit	1.07	0.85**	1.06	0.82***	1.04	0.93	1.02	1.01	0.80*
	(0.97 - 1.18)	(0.76 - 0.96)	(0.96 - 1.17)	(0.74 - 0.91)	(0.90 - 1.20)	(0.81 - 1.07)	(0.86 - 1.22)	(0.86 - 1.19)	(0.64 - 0.98)
South Asian	0.63**	0.53***	0.55***	0.95	4.46***	0.62*	2.21***	2.82***	0.19**
	(0.47 - 0.83)	(0.37 - 0.75)	(0.40 - 0.76)	(0.74 - 1.23)	(3.46 - 5.76)	(0.41 - 0.95)	(1.54 - 3.17)	(2.04 - 3.90)	(0.06 - 0.62)
Black	0.47***	0.36***	0.63***	0.86	0.60**	0.41***	0.37***	0.49***	0.15***
	(0.35 - 0.64)	(0.26 - 0.51)	(0.49 - 0.81)	(0.70 - 1.06)	(0.41 - 0.88)	(0.28 - 0.59)	(0.22 - 0.61)	(0.33 - 0.73)	(0.06 - 0.36)
Chinese	0.60*	0.76	0.76	0.83	0.42	0.73	0.28*	0.13**	0.30*
	(0.37 - 0.97)	(0.44 - 1.32)	(0.49 - 1.18)	(0.54 - 1.26)	(0.17 - 1.03)	(0.40 - 1.34)	(0.08 - 0.96)	(0.03 - 0.56)	(0.09 - 0.98)
Mixed	0.85	0.82	0.75	0.77	1.19	0.82	1.22	0.82	0.55
	(0.60 - 1.21)	(0.55 - 1.24)	(0.54 - 1.05)	(0.57 - 1.05)	(0.79 - 1.78)	(0.53 - 1.25)	(0.73 - 2.06)	(0.50 - 1.34)	(0.26 - 1.16)
Other	0.55***	0.63*	0.83	1.17	0.95	0.75	0.64	1.00	0.36*
	(0.39 - 0.78)	(0.44 - 0.92)	(0.60 - 1.16)	(0.88 - 1.56)	(0.59 - 1.54)	(0.48 - 1.16)	(0.38 - 1.10)	(0.64 - 1.58)	(0.15 - 0.86)
Household Structure (ref: Partner only)									
Live alone	0.36***	0.09***	0.42***	0.27***	1.00	0.23***	0.28***	0.27***	0.22***
	(0.33 - 0.39)	(0.08 - 0.10)	(0.39 - 0.46)	(0.24 - 0.29)	(0.88 - 1.13)	(0.20 - 0.26)	(0.25 - 0.32)	(0.23 - 0.31)	(0.17 - 0.28)
Child(ren), no partner	0.29***	0.13***	0.53***	0.34***	0.91	0.42***	0.26***	0.33***	0.37***
	(0.26 - 0.33)	(0.11 - 0.15)	(0.47 - 0.58)	(0.31 - 0.38)	(0.80 - 1.05)	(0.36 - 0.49)	(0.21 - 0.32)	(0.27 - 0.39)	(0.28 - 0.49)
Partner and child(ren)	0.86***	1.11*	1.35***	1.11*	0.88*	1.62***	1.01	1.01	1.60***
	(0.80 - 0.92)	(1.01 - 1.23)	(1.26 - 1.44)	(1.02 - 1.20)	(0.80 - 0.97)	(1.47 - 1.79)	(0.87 - 1.16)	(0.88 - 1.16)	(1.32 - 1.95)
Live with others	0.50***	0.27***	0.77**	0.76**	1.20	0.46***	0.83	0.71*	0.81
	(0.41 - 0.61)	(0.21 - 0.35)	(0.63 - 0.93)	(0.63 - 0.92)	(0.94 - 1.52)	(0.34 - 0.61)	(0.62 - 1.12)	(0.53 - 0.94)	(0.53 - 1.23)
Travel behaviour									
Diet behaviour									

Base class = Class 1, Exclusive car commuters; note that Table D.0.17, Table D.0.18, and Table D.0.19 refer to one multivariate model

Yellow shading = positive association, grey shading =negative association

Table D.0.18 – Multinomial regression between socio-economic factors and class membership, UKB females (n=99,193)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Highest qualification (ref GCSEs)									
College or University degree	1.31***	1.53***	1.40***	1.12*	1.91***	1.06	2.63***	2.38***	2.83***
	(1.22 - 1.40)	(1.39 - 1.68)	(1.29 - 1.51)	(1.02 - 1.22)	(1.71 - 2.13)	(0.95 - 1.19)	(2.31 - 3.00)	(2.02 - 2.81)	(2.16 - 3.71)
A levels/AS levels or equiv	1.31***	1.28***	1.23***	1.05	1.35***	1.22**	1.89***	1.53***	1.65**
	(1.21 - 1.43)	(1.15 - 1.44)	(1.13 - 1.35)	(0.95 - 1.17)	(1.18 - 1.54)	(1.08 - 1.38)	(1.61 - 2.22)	(1.26 - 1.86)	(1.20 - 2.28)
CSEs or equiv	0.75***	0.78*	0.76***	0.85*	0.73**	1.14	0.56***	0.75	1.02
	(0.65 - 0.87)	(0.64 - 0.94)	(0.66 - 0.88)	(0.73 - 1.00)	(0.58 - 0.91)	(0.97 - 1.34)	(0.40 - 0.77)	(0.54 - 1.03)	(0.62 - 1.68)
NVQ or HND or HNC or equiv	0.69***	0.67***	0.76**	0.79**	1.10	0.77*	0.56***	0.94	1.06
	(0.60 - 0.80)	(0.55 - 0.81)	(0.64 - 0.90)	(0.66 - 0.93)	(0.88 - 1.38)	(0.63 - 0.95)	(0.41 - 0.78)	(0.67 - 1.31)	(0.61 - 1.85)
Other professional qualifications	0.96	0.84*	0.69***	0.61***	1.11	0.89	1.26*	0.94	1.18
	(0.85 - 1.07)	(0.73 - 0.98)	(0.59 - 0.81)	(0.52 - 0.73)	(0.91 - 1.35)	(0.72 - 1.09)	(1.02 - 1.55)	(0.68 - 1.30)	(0.72 - 1.94)
None	0.98	1.08	0.72***	0.87	0.61***	0.98	0.86	0.74	1.08
	(0.88 - 1.09)	(0.95 - 1.22)	(0.61 - 0.84)	(0.75 - 1.02)	(0.46 - 0.81)	(0.82 - 1.16)	(0.71 - 1.05)	(0.53 - 1.04)	(0.65 - 1.81)
Occupational class (ref Small employers)									
Higher manag / profess	0.48***	0.46***	1.09	1.42***	1.00	0.82	0.46***	1.14	0.85
	(0.42 - 0.55)	(0.37 - 0.57)	(0.92 - 1.29)	(1.15 - 1.74)	(0.80 - 1.26)	(0.63 - 1.07)	(0.34 - 0.62)	(0.83 - 1.57)	(0.58 - 1.24)
Lower manag / profess	0.41***	0.41***	0.87	1.01	1.00	0.83	0.42***	0.86	0.62*
	(0.36 - 0.47)	(0.34 - 0.50)	(0.74 - 1.02)	(0.82 - 1.23)	(0.81 - 1.25)	(0.65 - 1.07)	(0.32 - 0.55)	(0.63 - 1.17)	(0.43 - 0.90)
Intermediate	0.38***	0.43***	1.26**	1.94***	0.84	1.53**	0.33***	1.47*	0.82
	(0.33 - 0.43)	(0.35 - 0.53)	(1.06 - 1.48)	(1.58 - 2.37)	(0.67 - 1.06)	(1.18 - 1.97)	(0.24 - 0.45)	(1.06 - 2.02)	(0.55 - 1.23)
Lower supervisory technical	0.37***	0.39***	1.15	0.74	0.93	1.10	0.39*	0.79	0.28
	(0.26 - 0.52)	(0.22 - 0.68)	(0.82 - 1.62)	(0.46 - 1.20)	(0.56 - 1.52)	(0.65 - 1.86)	(0.16 - 0.92)	(0.38 - 1.66)	(0.07 - 1.19)
Semi-routine	0.24***	0.31***	1.29**	1.38**	1.03	2.96***	0.25***	1.34	1.14
	(0.20 - 0.27)	(0.25 - 0.39)	(1.08 - 1.54)	(1.11 - 1.72)	(0.80 - 1.32)	(2.28 - 3.83)	(0.17 - 0.35)	(0.94 - 1.90)	(0.74 - 1.77)
Routine	0.40***	0.41***	1.52***	1.34	1.18	3.64***	0.40***	0.97	1.03
	(0.32 - 0.49)	(0.30 - 0.56)	(1.19 - 1.96)	(0.99 - 1.81)	(0.82 - 1.71)	(2.67 - 4.95)	(0.24 - 0.67)	(0.57 - 1.65)	(0.52 - 2.03)
Not classified	859***	868***	0.75	1.24	0.65	0.90	765***	0.86	0.00
	(638 - 1,158)	(623 - 1,210)	(0.35 - 1.61)	(0.60 - 2.60)	(0.20 - 2.11)	(0.32 - 2.56)	(523 - 1,121)	(0.20 - 3.64)	(0.00 -0.00 .)
Household income (ref £31,000 to 51,999)									
Less than £18,000	3.73***	3.71***	1.04	0.75***	1.02	0.96	4.62***	0.99	0.91
	(3.42 - 4.08)	(3.32 - 4.14)	(0.93 - 1.17)	(0.67 - 0.85)	(0.88 - 1.19)	(0.83 - 1.11)	(3.97 - 5.38)	(0.82 - 1.21)	(0.67 - 1.24)
£18,000 to 30,999	1.76***	1.80***	1.03	1.02	0.98	1.08	1.86***	1.05	0.94
	(1.65 - 1.89)	(1.64 - 1.97)	(0.95 - 1.11)	(0.93 - 1.11)	(0.88 - 1.09)	(0.97 - 1.20)	(1.64 - 2.12)	(0.91 - 1.21)	(0.75 - 1.17)
£52,000 to 100,000	0.78***	0.70***	0.95	1.08	0.99	0.89*	0.68***	1.01	0.77**
	(0.73 - 0.84)	(0.63 - 0.78)	(0.89 - 1.02)	(0.99 - 1.17)	(0.90 - 1.09)	(0.80 - 0.99)	(0.58 - 0.79)	(0.88 - 1.16)	(0.63 - 0.94)
Greater than £100,000	0.97	0.74***	1.05	1.37***	0.74***	0.94	0.69**	0.86	0.90
	(0.86 - 1.08)	(0.62 - 0.87)	(0.94 - 1.17)	(1.21 - 1.56)	(0.63 - 0.88)	(0.78 - 1.13)	(0.54 - 0.87)	(0.68 - 1.08)	(0.68 - 1.19)

# of vehicles per household (ref 2)										
	0	2.19***	885***	30.2***	1,024***	1.42	315***	115***	1,025***	663***
		(1.56 - 3.07)	(659 - 1,189)	(22.1 - 41.4)	(772 - 1,358)	(0.67 - 3.00)	(233 - 425)	(83 - 160)	(742 - 1,418)	(453 - 971)
	1	1.28***	5.86***	2.60***	6.47***	1.30***	4.03***	2.10***	7.18***	5.97***
		(1.20 - 1.36)	(5.38 - 6.38)	(2.43 - 2.78)	(5.96 - 7.01)	(1.18 - 1.43)	(3.66 - 4.43)	(1.87 - 2.36)	(6.16 - 8.37)	(4.87 - 7.31)
	3	0.89*	0.72***	0.73***	0.59***	0.71***	0.59***	0.80*	0.64**	0.51**
		(0.81 - 0.98)	(0.60 - 0.85)	(0.67 - 0.81)	(0.50 - 0.70)	(0.62 - 0.81)	(0.50 - 0.70)	(0.64 - 0.98)	(0.46 - 0.89)	(0.33 - 0.80)
	4+	1.19*	0.87	0.80**	0.39***	0.82	0.44***	0.89	0.41*	0.23*
		(1.02 - 1.38)	(0.64 - 1.19)	(0.68 - 0.93)	(0.28 - 0.55)	(0.66 - 1.02)	(0.32 - 0.61)	(0.61 - 1.30)	(0.20 - 0.83)	(0.07 - 0.72)
Travel behaviour										
Diet behaviour										

Base class = Class 1, Exclusive car commuters; note that Table D.0.17, Table D.0.18, and Table D.0.19 refer to one multivariate model

Yellow shading = positive association, grey shading =negative association

Table D.0.19 – Multinomial regression between area-level factors and class membership, UKB females (n=99,193)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Townsend score (ref Quintile 1)									
2	0.88***	1.00	0.99	1.21**	1.08	1.14	0.89	0.99	1.63**
	(0.82 - 0.95)	(0.90 - 1.11)	(0.91 - 1.07)	(1.08 - 1.37)	(0.97 - 1.21)	(0.99 - 1.31)	(0.77 - 1.03)	(0.79 - 1.23)	(1.17 - 2.27)
3	0.83***	1.10	1.08	1.37***	1.18**	1.39***	0.86*	1.27*	1.76***
	(0.77 - 0.89)	(0.99 - 1.23)	(0.99 - 1.17)	(1.22 - 1.54)	(1.06 - 1.33)	(1.22 - 1.60)	(0.74 - 1.00)	(1.04 - 1.55)	(1.28 - 2.42)
4	0.79***	1.26***	1.22***	1.85***	1.38***	1.94***	1.12	1.58***	2.34***
	(0.73 - 0.86)	(1.13 - 1.40)	(1.12 - 1.33)	(1.65 - 2.06)	(1.23 - 1.55)	(1.70 - 2.21)	(0.97 - 1.29)	(1.30 - 1.91)	(1.72 - 3.17)
5 (Highest deprivation)	0.72***	1.37***	1.35***	2.20***	1.33***	2.23***	0.95	1.89***	2.46***
	(0.66 - 0.79)	(1.22 - 1.54)	(1.22 - 1.48)	(1.96 - 2.48)	(1.16 - 1.52)	(1.93 - 2.57)	(0.80 - 1.12)	(1.54 - 2.30)	(1.78 - 3.40)
UKB assessment centre (ref Manchester)									
Oxford	0.31***	0.69*	3.24***	1.49*	1.08	2.01***	0.42***	1.97*	6.42***
	(0.24 - 0.39)	(0.50 - 0.97)	(2.54 - 4.12)	(1.08 - 2.04)	(0.79 - 1.48)	(1.37 - 2.94)	(0.28 - 0.64)	(1.16 - 3.33)	(3.96 - 10.42)
Cardiff	0.18***	0.22***	1.32*	0.86	1.26	1.51*	0.16***	1.48	0.67
	(0.14 - 0.24)	(0.15 - 0.32)	(1.02 - 1.72)	(0.61 - 1.21)	(0.94 - 1.69)	(1.03 - 2.21)	(0.10 - 0.26)	(0.86 - 2.53)	(0.34 - 1.34)
Glasgow	0.19***	0.20***	1.42**	1.64**	0.75	1.23	0.12***	1.06	0.13***
	(0.13 - 0.26)	(0.13 - 0.31)	(1.09 - 1.86)	(1.21 - 2.22)	(0.53 - 1.05)	(0.83 - 1.84)	(0.07 - 0.21)	(0.61 - 1.84)	(0.04 - 0.42)
Edinburgh	0.31***	0.57**	3.18***	3.33***	0.90	2.89***	0.26***	2.65***	1.32
	(0.24 - 0.40)	(0.41 - 0.80)	(2.52 - 4.03)	(2.54 - 4.38)	(0.65 - 1.24)	(2.04 - 4.09)	(0.17 - 0.40)	(1.65 - 4.27)	(0.76 - 2.31)
Stoke	0.73**	0.83	1.13	0.47**	1.17	1.25	0.72	0.70	0.38
	(0.58 - 0.92)	(0.58 - 1.19)	(0.82 - 1.54)	(0.29 - 0.78)	(0.83 - 1.65)	(0.80 - 1.95)	(0.46 - 1.12)	(0.32 - 1.55)	(0.13 - 1.12)
Reading	0.28***	0.32***	1.89***	1.11	0.94	1.99***	0.24***	1.58	1.16
	(0.23 - 0.34)	(0.24 - 0.44)	(1.50 - 2.37)	(0.83 - 1.49)	(0.71 - 1.23)	(1.42 - 2.80)	(0.16 - 0.35)	(0.96 - 2.60)	(0.66 - 2.04)
Bury	0.70***	0.72*	0.87	0.82	1.11	0.92	0.58**	0.86	0.15***
	(0.58 - 0.85)	(0.53 - 0.98)	(0.66 - 1.13)	(0.60 - 1.13)	(0.83 - 1.48)	(0.63 - 1.35)	(0.39 - 0.87)	(0.49 - 1.50)	(0.05 - 0.43)
Newcastle	0.17***	0.23***	1.24	1.27	0.85	0.89	0.14***	1.06	0.37**
	(0.13 - 0.21)	(0.17 - 0.32)	(0.98 - 1.58)	(0.96 - 1.68)	(0.64 - 1.12)	(0.62 - 1.27)	(0.09 - 0.21)	(0.65 - 1.73)	(0.19 - 0.72)
Leeds	0.46***	0.55***	1.41**	1.29	1.14	1.54**	0.43***	1.44	0.29***
	(0.39 - 0.56)	(0.42 - 0.73)	(1.12 - 1.77)	(0.99 - 1.69)	(0.88 - 1.48)	(1.11 - 2.14)	(0.30 - 0.62)	(0.90 - 2.28)	(0.15 - 0.56)
Bristol	0.25***	0.36***	2.13***	0.96	1.21	2.57***	0.28***	1.89**	1.40
	(0.21 - 0.31)	(0.27 - 0.48)	(1.72 - 2.64)	(0.74 - 1.26)	(0.95 - 1.56)	(1.88 - 3.52)	(0.20 - 0.39)	(1.21 - 2.94)	(0.86 - 2.26)
Central London	1.12	4.44***	7.05***	11.07***	1.24	9.41***	2.18***	12.10***	8.38***
	(0.84 - 1.48)	(3.17 - 6.21)	(5.33 - 9.31)	(8.24 - 14.86)	(0.80 - 1.92)	(6.52 - 13.60)	(1.42 - 3.34)	(7.59 - 19.27)	(5.01 - 14.00)
Nottingham	0.27***	0.45***	1.61***	1.37*	1.13	1.85***	0.28***	1.56	0.65
	(0.22 - 0.33)	(0.33 - 0.61)	(1.28 - 2.03)	(1.04 - 1.82)	(0.86 - 1.47)	(1.32 - 2.59)	(0.19 - 0.40)	(0.97 - 2.53)	(0.36 - 1.18)
Sheffield	1.04	1.58***	1.50***	1.63***	1.05	1.45*	0.89	1.63*	0.39**
	(0.89 - 1.23)	(1.21 - 2.05)	(1.20 - 1.87)	(1.26 - 2.10)	(0.81 - 1.36)	(1.05 - 2.00)	(0.64 - 1.25)	(1.04 - 2.55)	(0.22 - 0.69)
Liverpool	1.01	1.17	1.09	1.20	1.02	0.87	0.80	0.95	0.51*
	(0.86 - 1.20)	(0.89 - 1.53)	(0.87 - 1.38)	(0.92 - 1.57)	(0.79 - 1.33)	(0.62 - 1.22)	(0.57 - 1.13)	(0.59 - 1.54)	(0.29 - 0.89)
Middlesbrough	0.15***	0.17***	0.87	0.57***	0.85	1.16	0.13***	0.54*	0.21***
	(0.12 - 0.20)	(0.12 - 0.23)	(0.67 - 1.12)	(0.41 - 0.79)	(0.64 - 1.13)	(0.82 - 1.65)	(0.09 - 0.19)	(0.30 - 0.97)	(0.09 - 0.49)
Hounslow	1.46***	3.22***	2.83***	3.98***	0.98	2.15***	1.56**	3.15***	1.88**
	(1.23 - 1.72)	(2.47 - 4.19)	(2.28 - 3.52)	(3.10 - 5.11)	(0.75 - 1.28)	(1.56 - 2.96)	(1.12 - 2.18)	(2.05 - 4.86)	(1.17 - 3.02)
Croydon	1.76***	3.78***	3.21***	5.86***	1.05	2.25***	1.92***	4.78***	1.61
	(1.49 - 2.09)	(2.90 - 4.92)	(2.58 - 4.00)	(4.57 - 7.51)	(0.80 - 1.38)	(1.63 - 3.11)	(1.38 - 2.68)	(3.11 - 7.34)	(0.99 - 2.63)
Birmingham	1.29**	1.69***	1.38**	1.81***	1.28	1.22	1.18	1.44	0.45**

	(1.09 - 1.53)	(1.29 - 2.22)	(1.10 - 1.74)	(1.39 - 2.34)	(0.99 - 1.66)	(0.88 - 1.70)	(0.83 - 1.66)	(0.91 - 2.28)	(0.25 - 0.82)
Swansea	1.41*	0.96	1.28	0.49	1.36	1.68	0.63	1.22	0.87
	(1.03 - 1.92)	(0.55 - 1.66)	(0.79 - 2.09)	(0.22 - 1.07)	(0.80 - 2.31)	(0.90 - 3.12)	(0.29 - 1.41)	(0.45 - 3.35)	(0.25 - 3.02)
Wrexham	1.23	0.90	1.10	0.00	1.11	0.42	0.67	1.90	0.00
	(0.70 - 2.18)	(0.32 - 2.52)	(0.42 - 2.89)	(0.00 - .)	(0.39 - 3.19)	(0.08 - 2.22)	(0.15 - 3.04)	(0.44 - 8.17)	(0.00 - .)
Urban postcode (ref Rural)	0.75***	1.18**	1.70***	1.99***	1.02	1.94***	0.74***	2.21***	3.97***
	(0.69 - 0.80)	(1.06 - 1.32)	(1.56 - 1.86)	(1.72 - 2.30)	(0.92 - 1.13)	(1.68 - 2.25)	(0.65 - 0.85)	(1.70 - 2.87)	(2.63 - 5.98)
Travel behaviour									
Diet behaviour									

Base class = Class 1, Exclusive car commuters; note that Table D.0.17, Table D.0.18, and Table D.0.19 refer to one multivariate model

Yellow shading = positive association, grey shading =negative association

Table D.0.20 – Age-adjusted bivariate multinomial regression between class membership and health / lifestyle indicators among UKB females

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Energy intake (kcal)[a]	1.00***	1.00*	1.00***	1.00*	1.00	1.00	1.00	1.00	1.00***
	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)
Meets PA guideline (ref No)[b]	1.50***	1.42***	1.38***	0.93**	1.38***	1.26***	1.91***	1.40***	12.11***
	(1.45 - 1.55)	(1.36 - 1.49)	(1.31 - 1.45)	(0.89 - 0.98)	(1.29 - 1.48)	(1.18 - 1.35)	(1.77 - 2.06)	(1.28 - 1.54)	(9.59 - 15.30)
BMI 25+ (ref BMI <25)[c]	0.93***	0.90***	0.82***	0.92**	0.57***	0.76***	0.52***	0.45***	0.36***
	(0.90 - 0.97)	(0.86 - 0.94)	(0.78 - 0.86)	(0.88 - 0.97)	(0.53 - 0.61)	(0.71 - 0.81)	(0.48 - 0.56)	(0.41 - 0.50)	(0.31 - 0.41)
Overall health (ref Good)[d]									
Excellent	1.00	0.91**	1.21***	0.93*	1.27***	1.01	1.13**	1.27***	2.05***
	(0.96 - 1.04)	(0.86 - 0.97)	(1.14 - 1.28)	(0.87 - 0.99)	(1.17 - 1.37)	(0.93 - 1.10)	(1.03 - 1.24)	(1.14 - 1.42)	(1.78 - 2.37)
Fair	1.33***	1.73***	0.83***	1.27***	0.92	1.05	1.39***	1.05	0.52***
	(1.27 - 1.39)	(1.63 - 1.83)	(0.77 - 0.89)	(1.19 - 1.35)	(0.83 - 1.02)	(0.95 - 1.15)	(1.25 - 1.54)	(0.92 - 1.20)	(0.39 - 0.68)
Poor	3.32***	6.23***	0.56***	1.40***	1.02	0.92	4.94***	0.99	0.36*
	(3.00 - 3.67)	(5.54 - 7.00)	(0.44 - 0.70)	(1.19 - 1.64)	(0.79 - 1.31)	(0.70 - 1.20)	(4.14 - 5.90)	(0.70 - 1.41)	(0.15 - 0.87)
Long-term condition (ref No)[e]	1.50***	1.90***	0.88***	1.13***	1.02	0.94	1.70***	0.90	0.77**
	(1.44 - 1.55)	(1.81 - 2.00)	(0.83 - 0.93)	(1.07 - 1.20)	(0.94 - 1.10)	(0.87 - 1.03)	(1.57 - 1.84)	(0.81 - 1.01)	(0.64 - 0.92)
Travel behaviour									
Diet behaviour									

Base class = Class 1, Exclusive car commuters

Yellow shading = positive association, grey shading =negative association

a) n=116,255; derived based on 24 dietary recall questionnaire(s), mean value taken if multiple questionnaires completed

b) n=111,273; PA guideline is 150 minutes per week of moderate physical activity, or 70 minutes per week of vigorous physical activity

c) n=115,963; BMI of 25+ is considered overweight or obese

d) n=115,939; self-reported, participants were asked: "In general how would you rate your overall health?"

e) n=113,640; self-reported, participants were asked: “Do you have any long-standing illness, disability or infirmity?”

Table D.0.21 – Cross-tabulation of demographic factors and class assignments in UKB males based on scoring equations, classwise proportions only (n=94,781)

Class #	1	2	3	4	5	6	7	8	9	Total
Class size	0.36	0.35	0.09	0.07	0.06	0.03	0.01	0.01	0.01	1.00
Total	33,932	33,619	8,554	6,236	5,463	3,222	1,336	1,192	1,227	94,781
Age at baseline assessment										
< 45	0.15	0.02	0.15	0.05	0.19	0.23	0.24	0.18	0.07	0.10
45-49	0.19	0.03	0.18	0.06	0.19	0.22	0.23	0.23	0.09	0.13
50-54	0.21	0.06	0.21	0.09	0.21	0.22	0.21	0.21	0.10	0.15
55-59	0.23	0.14	0.21	0.13	0.20	0.19	0.19	0.21	0.19	0.18
60-64	0.18	0.36	0.19	0.33	0.17	0.12	0.11	0.13	0.30	0.25
65+	0.05	0.39	0.06	0.34	0.04	0.03	0.02	0.03	0.25	0.19
Ethnic group										
White British	0.90	0.93	0.87	0.85	0.80	0.87	0.79	0.81	0.80	0.90
Other White	0.05	0.04	0.07	0.09	0.12	0.10	0.10	0.06	0.06	0.06
South Asian	0.02	0.01	0.02	0.01	0.02	0.01	0.06	0.10	0.08	0.02
Black	0.01	0.00	0.02	0.02	0.03	0.01	0.02	0.01	0.01	0.01
Chinese	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00
Other	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Missing	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.03	0.00
Household structure										
Live alone	0.13	0.13	0.14	0.33	0.28	0.14	0.23	0.17	0.28	0.16
Child(ren), no partner	0.03	0.02	0.03	0.02	0.02	0.02	0.01	0.04	0.01	0.02
Partner, no child(ren)	0.36	0.65	0.35	0.45	0.31	0.26	0.31	0.35	0.47	0.46
Partner + child(ren)	0.46	0.18	0.46	0.15	0.31	0.54	0.40	0.42	0.19	0.33
Live with others	0.03	0.02	0.03	0.05	0.07	0.03	0.05	0.03	0.05	0.03

Travel behaviour									
Diet behaviour									

Shading = above sample average

Table D.0.22 – Cross-tabulation of socio-economic factors and class assignments in UKB males based on scoring equations, classwise proportions only (n=94,781)

Class #	1	2	3	4	5	6	7	8	9	Total
Class size	0.36	0.35	0.09	0.07	0.06	0.03	0.01	0.01	0.01	1.00
Total	33,932	33,619	8,554	6,236	5,463	3,222	1,336	1,192	1,227	94,781
Highest qualification										
College or University degree	0.39	0.40	0.57	0.44	0.59	0.66	0.70	0.58	0.54	0.44
A levels or equivalent	0.12	0.11	0.13	0.12	0.13	0.10	0.11	0.11	0.10	0.12
GCSEs or equivalent	0.21	0.19	0.15	0.16	0.12	0.11	0.10	0.13	0.14	0.18
CSEs or equivalent	0.07	0.02	0.03	0.03	0.04	0.03	0.02	0.04	0.02	0.04
NVQ / HND / HNC or equivalent	0.09	0.09	0.05	0.07	0.05	0.05	0.03	0.05	0.05	0.08
Other professional qualifications	0.04	0.05	0.03	0.04	0.02	0.02	0.01	0.04	0.04	0.04
No qualifications	0.07	0.12	0.04	0.15	0.04	0.03	0.03	0.05	0.09	0.09
Missing	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.01
Employment status										
Employed or self-employed	1.00	0.13	1.00	0.11	1.00	1.00	1.00	1.00	0.18	0.62
Retired	0.00	0.76	0.00	0.64	0.00	0.00	0.00	0.00	0.56	0.32
Other	0.00	0.10	0.00	0.23	0.00	0.00	0.00	0.00	0.21	0.05
Missing	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.05	0.01
Occupational Class										
Higher managerial / professional	0.39	0.18	0.46	0.16	0.41	0.48	0.42	0.38	0.17	0.31
Lower managerial / professional	0.25	0.12	0.27	0.12	0.28	0.25	0.32	0.31	0.14	0.20
Intermediate occupations	0.10	0.05	0.12	0.05	0.15	0.10	0.13	0.09	0.06	0.08
Small employers / own account workers	0.06	0.03	0.03	0.02	0.02	0.02	0.02	0.07	0.03	0.04
Lower supervisory / technical	0.07	0.02	0.03	0.02	0.02	0.05	0.03	0.06	0.01	0.04
Semi-routine occupations	0.06	0.02	0.05	0.02	0.08	0.06	0.05	0.06	0.02	0.04
Routine occupations	0.06	0.02	0.04	0.02	0.03	0.04	0.04	0.04	0.01	0.04
Not classified	0.00	0.55	0.00	0.57	0.00	0.00	0.00	0.00	0.53	0.24
Missing	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.04	0.01
Household income (before tax)										
Less than £18,000	0.04	0.21	0.04	0.35	0.08	0.04	0.07	0.05	0.30	0.13
£18,000 to 30,999	0.16	0.30	0.13	0.23	0.18	0.13	0.16	0.18	0.27	0.21
£31,000 to 51,999	0.31	0.25	0.27	0.18	0.26	0.28	0.27	0.28	0.19	0.27
£52,000 to 100,000	0.34	0.12	0.35	0.10	0.30	0.38	0.35	0.34	0.09	0.24
Greater than £100,000	0.09	0.03	0.15	0.03	0.13	0.14	0.10	0.08	0.02	0.07
Missing	0.06	0.10	0.05	0.11	0.05	0.04	0.04	0.06	0.14	0.07
# of cars per household										
0	0.00	0.01	0.02	0.38	0.37	0.10	0.22	0.00	0.19	0.06
1	0.27	0.45	0.47	0.44	0.47	0.54	0.54	0.35	0.48	0.39
2	0.53	0.44	0.40	0.14	0.13	0.30	0.21	0.52	0.26	0.42
3	0.14	0.08	0.09	0.02	0.02	0.05	0.02	0.09	0.03	0.09
4+	0.05	0.02	0.02	0.00	0.00	0.01	0.01	0.03	0.01	0.03
Missing	0.00	0.01	0.00	0.02	0.00	0.00	0.01	0.01	0.02	0.01

Travel behaviour									
Diet behaviour									

Shading = above sample average

Table D.0.23 – Cross-tabulation of environmental factors and class assignments in UKB males based on scoring equations, classwise proportions only (n=94,781)

Class #	1	2	3	4	5	6	7	8	9	Total
Class size	0.36	0.35	0.09	0.07	0.06	0.03	0.01	0.01	0.01	1.00
Total	33,932	33,619	8,554	6,236	5,463	3,222	1,336	1,192	1,227	94,781
Townsend score (quintiles)										
1 (Lowest)	0.25	0.26	0.18	0.11	0.07	0.16	0.09	0.20	0.15	0.22
2	0.23	0.25	0.19	0.13	0.10	0.16	0.13	0.19	0.15	0.21
3	0.21	0.21	0.21	0.16	0.15	0.19	0.17	0.21	0.19	0.20
4	0.19	0.17	0.23	0.23	0.27	0.26	0.28	0.22	0.23	0.20
5 (Highest)	0.12	0.11	0.19	0.37	0.41	0.23	0.34	0.17	0.28	0.17
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Assessment centre										
Manchester	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.03	0.02	0.02
Oxford	0.02	0.02	0.02	0.02	0.02	0.06	0.02	0.02	0.02	0.02
Cardiff	0.03	0.02	0.02	0.01	0.01	0.02	0.03	0.03	0.03	0.02
Glasgow	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.01	0.02
Edinburgh	0.02	0.03	0.05	0.03	0.04	0.05	0.04	0.01	0.03	0.03
Stoke	0.03	0.02	0.01	0.01	0.00	0.01	0.00	0.02	0.01	0.02
Reading	0.07	0.06	0.06	0.03	0.03	0.05	0.04	0.05	0.04	0.06
Bury	0.05	0.04	0.02	0.02	0.01	0.01	0.02	0.04	0.03	0.04
Newcastle	0.05	0.05	0.04	0.04	0.03	0.03	0.04	0.04	0.04	0.05
Leeds	0.07	0.07	0.06	0.05	0.04	0.04	0.05	0.08	0.07	0.07
Bristol	0.12	0.10	0.09	0.06	0.05	0.13	0.09	0.09	0.09	0.10
Barts	0.01	0.01	0.03	0.08	0.13	0.07	0.08	0.01	0.05	0.02
Nottingham	0.06	0.06	0.04	0.04	0.02	0.07	0.05	0.08	0.06	0.06
Sheffield	0.10	0.11	0.08	0.08	0.06	0.06	0.09	0.11	0.09	0.10
Liverpool	0.08	0.09	0.05	0.07	0.04	0.04	0.05	0.07	0.05	0.08
Middlesbrough	0.06	0.06	0.03	0.03	0.01	0.03	0.01	0.05	0.03	0.05
Hounslow	0.06	0.07	0.13	0.16	0.18	0.13	0.13	0.10	0.13	0.09
Croydon	0.05	0.07	0.15	0.16	0.22	0.10	0.14	0.06	0.11	0.08
Birmingham	0.07	0.07	0.06	0.07	0.06	0.05	0.06	0.08	0.08	0.07
Swansea	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00
Wrexham	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Urban/rural										
Rural / Fringe	0.17	0.19	0.10	0.06	0.03	0.07	0.05	0.14	0.10	0.15
Urban	0.81	0.80	0.89	0.93	0.96	0.91	0.94	0.84	0.89	0.84
Missing	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Travel behaviour									
Diet behaviour									

Shading = above sample average

Table D.0.24 – Health and lifestyle factors in UKB males, by class assignment (n=94,781)

Class #	1	2	3	4	5	6	7	8	9	Total
Class size	0.36	0.35	0.09	0.07	0.06	0.03	0.01	0.01	0.01	1.00
Total	33,932	33,619	8,554	6,236	5,463	3,222	1,336	1,192	1,227	94,781
Energykcal (Mean)	2293	2279	2329	2274	2283	2437	2298	2264	2222	2293
Meets PA guideline										
No	0.48	0.43	0.51	0.48	0.54	0.12	0.36	0.44	0.37	0.45
Yes	0.49	0.54	0.46	0.49	0.44	0.87	0.61	0.52	0.58	0.52
Missing	0.03	0.03	0.03	0.04	0.03	0.01	0.03	0.04	0.05	0.03
BMI grouping										
<25	0.25	0.26	0.30	0.34	0.35	0.46	0.51	0.41	0.47	0.28
25+	0.75	0.73	0.70	0.67	0.64	0.53	0.48	0.58	0.53	0.71
Missing	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.00
Self-rated health										
Excellent	0.18	0.17	0.20	0.15	0.19	0.33	0.29	0.24	0.23	0.18
Good	0.59	0.58	0.60	0.51	0.57	0.57	0.54	0.57	0.52	0.58
Fair	0.20	0.20	0.18	0.25	0.21	0.09	0.15	0.17	0.17	0.20
Poor	0.02	0.05	0.02	0.09	0.03	0.01	0.02	0.02	0.06	0.04
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Long-term condition										
Yes	0.27	0.39	0.27	0.47	0.30	0.21	0.23	0.24	0.38	0.32
No	0.72	0.59	0.72	0.51	0.69	0.78	0.75	0.75	0.59	0.66
Missing	0.02	0.02	0.02	0.03	0.02	0.01	0.02	0.02	0.03	0.02

Travel behaviour									
Diet behaviour									

Shading = above sample average

Table D.0.25 – Multinomial regression between demographic factors and class membership, UKB males (n=85,775)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Age group (ref 65+)								
< 45	0.04***	0.65***	0.03***	0.79*	1.57***	2.24***	1.77**	0.10***
	(0.03 - 0.04)	(0.57 - 0.74)	(0.02 - 0.04)	(0.66 - 0.95)	(1.22 - 2.02)	(1.46 - 3.43)	(1.22 - 2.57)	(0.07 - 0.14)
45-49	0.05***	0.69***	0.03***	0.75**	1.36*	2.04**	1.93***	0.12***
	(0.04 - 0.05)	(0.61 - 0.79)	(0.03 - 0.04)	(0.63 - 0.91)	(1.06 - 1.75)	(1.33 - 3.12)	(1.34 - 2.77)	(0.09 - 0.16)
50-54	0.07***	0.76***	0.06***	0.92	1.45**	2.16***	1.60*	0.14***
	(0.06 - 0.08)	(0.67 - 0.87)	(0.05 - 0.07)	(0.77 - 1.10)	(1.13 - 1.85)	(1.41 - 3.30)	(1.11 - 2.30)	(0.10 - 0.18)
55-59	0.13***	0.76***	0.09***	0.93	1.26	1.93**	1.40	0.23***
	(0.12 - 0.14)	(0.67 - 0.86)	(0.08 - 0.11)	(0.78 - 1.11)	(0.98 - 1.61)	(1.26 - 2.94)	(0.98 - 2.01)	(0.18 - 0.28)
60-64	0.31***	0.91	0.31***	1.14	1.17	1.67*	1.06	0.39***
	(0.28 - 0.33)	(0.81 - 1.04)	(0.28 - 0.35)	(0.96 - 1.35)	(0.90 - 1.50)	(1.08 - 2.57)	(0.73 - 1.53)	(0.32 - 0.47)
Ethnic group (ref Other White)								
White Brit	1.22***	1.04	0.94	0.94	0.87	0.91	0.82	1.23
	(1.09 - 1.36)	(0.94 - 1.16)	(0.81 - 1.09)	(0.82 - 1.07)	(0.76 - 1.00)	(0.74 - 1.12)	(0.64 - 1.05)	(0.92 - 1.65)
South Asian	0.41***	0.69***	0.26***	0.68**	0.14***	1.83***	4.11***	2.15***
	(0.32 - 0.52)	(0.55 - 0.86)	(0.18 - 0.37)	(0.52 - 0.89)	(0.08 - 0.23)	(1.30 - 2.56)	(2.95 - 5.70)	(1.40 - 3.28)
Black	0.45***	0.91	0.26***	0.48***	0.20***	0.48**	0.72	0.39*
	(0.33 - 0.63)	(0.72 - 1.15)	(0.17 - 0.39)	(0.35 - 0.65)	(0.13 - 0.32)	(0.29 - 0.79)	(0.39 - 1.32)	(0.19 - 0.80)
Chinese	0.45**	0.85	0.78	0.99	0.24**	0.00	0.24	0.66
	(0.25 - 0.82)	(0.51 - 1.41)	(0.37 - 1.63)	(0.54 - 1.83)	(0.08 - 0.68)	(0.00 - .)	(0.03 - 1.74)	(0.15 - 2.92)
Mixed	0.75	0.74	0.65	0.68	0.55*	0.61	0.63	0.50
	(0.49 - 1.15)	(0.51 - 1.06)	(0.36 - 1.17)	(0.44 - 1.07)	(0.33 - 0.92)	(0.30 - 1.27)	(0.25 - 1.58)	(0.15 - 1.69)
Other	0.39***	0.82	0.20***	0.49***	0.37***	0.59	0.93	0.48
	(0.27 - 0.59)	(0.60 - 1.11)	(0.12 - 0.34)	(0.33 - 0.72)	(0.23 - 0.59)	(0.32 - 1.06)	(0.47 - 1.85)	(0.22 - 1.05)
Household Structure (ref: Partner only)								
Live alone	0.44***	0.61***	0.36***	0.52***	0.47***	0.47***	0.94	0.39***
	(0.40 - 0.47)	(0.56 - 0.67)	(0.32 - 0.41)	(0.46 - 0.58)	(0.41 - 0.54)	(0.39 - 0.56)	(0.77 - 1.16)	(0.32 - 0.48)
Child(ren), no partner	0.52***	0.84*	0.44***	0.54***	0.74*	0.26***	1.10	0.30***
	(0.44 - 0.61)	(0.71 - 0.99)	(0.33 - 0.58)	(0.42 - 0.69)	(0.56 - 0.98)	(0.15 - 0.46)	(0.78 - 1.54)	(0.17 - 0.53)
Partner and child(ren)	0.85***	1.26***	1.19**	1.34***	2.02***	1.27**	0.77***	0.93
	(0.80 - 0.91)	(1.18 - 1.34)	(1.07 - 1.33)	(1.22 - 1.47)	(1.83 - 2.23)	(1.09 - 1.47)	(0.66 - 0.89)	(0.76 - 1.13)
Live with others	0.59***	0.84	0.87	1.31**	0.94	0.67*	1.05	0.78
	(0.49 - 0.71)	(0.70 - 1.02)	(0.68 - 1.11)	(1.07 - 1.60)	(0.72 - 1.23)	(0.47 - 0.97)	(0.72 - 1.51)	(0.53 - 1.16)
Travel behaviour								
Diet behaviour								

Base class = Class 1, Exclusive car commuters; note that Table D.0.25, Table D.0.26, and Table D.0.27 refer to one multivariate model

Yellow shading = positive association, grey shading =negative association

Table D.0.26 – Multinomial regression between socio-demographic factors and class membership, UKB males (n=85,775)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Highest qualification (ref GCSEs)								
College or University degree	1.66***	1.67***	2.43***	2.01***	2.60***	3.40***	2.70***	3.53***
	(1.55 - 1.79)	(1.54 - 1.80)	(2.16 - 2.73)	(1.79 - 2.26)	(2.28 - 2.97)	(2.76 - 4.19)	(2.21 - 3.29)	(2.88 - 4.32)
A levels/AS levels or equiv	1.31***	1.36***	1.57***	1.54***	1.36***	1.85***	1.59***	1.57**
	(1.20 - 1.44)	(1.24 - 1.50)	(1.35 - 1.82)	(1.33 - 1.77)	(1.15 - 1.61)	(1.43 - 2.38)	(1.24 - 2.05)	(1.20 - 2.05)
CSEs or equiv	0.69***	0.71***	0.69**	0.95	0.79	0.59*	0.83	0.35***
	(0.59 - 0.80)	(0.61 - 0.82)	(0.52 - 0.90)	(0.76 - 1.18)	(0.62 - 1.01)	(0.38 - 0.93)	(0.58 - 1.18)	(0.20 - 0.62)
NVQ or HND or HNC or equiv	0.75***	0.78***	0.82*	0.91	1.09	0.79	0.85	0.73
	(0.67 - 0.83)	(0.69 - 0.89)	(0.69 - 0.97)	(0.75 - 1.10)	(0.89 - 1.34)	(0.54 - 1.15)	(0.61 - 1.19)	(0.53 - 1.02)
Other professional qualifications	0.85*	0.75**	0.85	0.95	0.85	0.70	1.84***	1.01
	(0.75 - 0.97)	(0.64 - 0.90)	(0.68 - 1.05)	(0.74 - 1.21)	(0.62 - 1.17)	(0.40 - 1.22)	(1.31 - 2.60)	(0.69 - 1.47)
None	0.79***	0.71***	0.86	0.83	0.87	0.71	1.32	0.68*
	(0.71 - 0.87)	(0.61 - 0.82)	(0.73 - 1.01)	(0.67 - 1.02)	(0.68 - 1.12)	(0.46 - 1.10)	(0.94 - 1.83)	(0.50 - 0.92)
Occupational class (ref Small employers)								
Higher manag / profess	1.77***	1.63***	2.60***	2.51***	1.99***	2.46***	0.73*	1.64*
	(1.57 - 1.98)	(1.41 - 1.90)	(2.01 - 3.36)	(1.96 - 3.21)	(1.52 - 2.60)	(1.57 - 3.85)	(0.55 - 0.96)	(1.08 - 2.49)
Lower manag / profess	1.47***	1.60***	2.18***	2.38***	1.80***	2.97***	0.96	1.51
	(1.31 - 1.66)	(1.37 - 1.86)	(1.68 - 2.83)	(1.86 - 3.04)	(1.37 - 2.36)	(1.90 - 4.65)	(0.73 - 1.27)	(0.99 - 2.31)
Intermediate	1.28***	1.98***	1.89***	3.18***	2.29***	3.46***	0.72*	1.52
	(1.12 - 1.46)	(1.69 - 2.33)	(1.43 - 2.51)	(2.46 - 4.10)	(1.72 - 3.04)	(2.18 - 5.51)	(0.52 - 1.00)	(0.96 - 2.40)
Lower supervisory technical	0.74***	0.94	0.92	1.02	1.90***	1.62	0.77	0.48*
	(0.64 - 0.86)	(0.77 - 1.15)	(0.66 - 1.28)	(0.74 - 1.41)	(1.38 - 2.60)	(0.93 - 2.83)	(0.54 - 1.11)	(0.25 - 0.93)
Semi-routine	0.57***	1.45***	0.76	2.57***	2.47***	1.82*	0.84	0.59
	(0.48 - 0.66)	(1.20 - 1.74)	(0.55 - 1.05)	(1.95 - 3.39)	(1.82 - 3.36)	(1.08 - 3.07)	(0.59 - 1.20)	(0.33 - 1.04)
Routine	0.43***	1.26*	0.47***	0.94	1.66**	1.57	0.58**	0.27***
	(0.36 - 0.50)	(1.04 - 1.53)	(0.33 - 0.67)	(0.68 - 1.28)	(1.19 - 2.31)	(0.91 - 2.70)	(0.38 - 0.86)	(0.13 - 0.56)
Not classified	1,342***	2.62***	1,934***	1.30	1.35	0.00	1.12	990***
	(981 - 1,834)	(1.49 - 4.62)	(1,315 - 2,846)	(0.50 - 3.40)	(0.41 - 4.47)	(0.00 - .)	(0.27 - 4.71)	(602 - 1,626)
Household income (ref £31,000 to 51,999)								
Less than £18,000	5.50***	1.01	4.62***	0.78**	0.84	1.12	1.30	7.38***
	(4.99 - 6.07)	(0.88 - 1.16)	(4.02 - 5.30)	(0.66 - 0.93)	(0.67 - 1.05)	(0.85 - 1.47)	(0.97 - 1.75)	(5.92 - 9.21)
£18,000 to 30,999	2.13***	0.99	1.80***	0.88*	0.89	1.02	1.32**	2.62***
	(1.99 - 2.29)	(0.91 - 1.08)	(1.61 - 2.00)	(0.78 - 0.99)	(0.78 - 1.02)	(0.84 - 1.23)	(1.10 - 1.59)	(2.17 - 3.16)
£52,000 to 100,000	0.59***	1.16***	0.69***	1.49***	1.24***	1.40***	1.04	0.49***
	(0.55 - 0.63)	(1.09 - 1.24)	(0.61 - 0.78)	(1.35 - 1.64)	(1.12 - 1.37)	(1.20 - 1.63)	(0.89 - 1.22)	(0.39 - 0.63)
Greater than £100,000	0.46***	1.64***	0.47***	2.17***	1.40***	1.33*	0.86	0.28***
	(0.41 - 0.51)	(1.49 - 1.79)	(0.38 - 0.58)	(1.90 - 2.48)	(1.21 - 1.61)	(1.05 - 1.67)	(0.67 - 1.10)	(0.17 - 0.44)
# of vehicles per household (ref 2)								
0	1.31	10.82***	338***	879***	136***	300***	1.18	55.8***
	(0.97 - 1.75)	(8.15 - 14.37)	(260 - 439)	(687 - 1,125)	(104 - 179)	(221 - 406)	(0.47 - 2.96)	(39.6 - 78.4)
1	1.43***	2.71***	4.65***	8.51***	5.09***	6.11***	1.19*	2.42***
	(1.34 - 1.52)	(2.55 - 2.89)	(4.20 - 5.15)	(7.70 - 9.42)	(4.62 - 5.61)	(5.21 - 7.16)	(1.02 - 1.39)	(2.04 - 2.86)
3	1.05	0.74***	0.60***	0.46***	0.60***	0.38***	0.71**	0.69
	(0.96 - 1.14)	(0.67 - 0.81)	(0.47 - 0.76)	(0.36 - 0.58)	(0.50 - 0.72)	(0.25 - 0.57)	(0.57 - 0.89)	(0.48 - 1.01)
4+	1.10	0.61***	0.57*	0.32***	0.45***	0.42*	0.75	1.32
	(0.95 - 1.26)	(0.52 - 0.72)	(0.37 - 0.89)	(0.20 - 0.50)	(0.32 - 0.62)	(0.21 - 0.82)	(0.52 - 1.09)	(0.78 - 2.22)

Travel behaviour								
Diet behaviour								

Base class = Class 1, Exclusive car commuters; note that Table D.0.25, Table D.0.26, and Table D.0.27 refer to one multivariate model

Yellow shading = positive association, grey shading =negative association

Table D.0.27 – Multinomial regression between environmental factors and class membership, UKB males (n=85,775)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
UKB assessment centre (ref Manchester)								
Oxford	0.39***	1.43**	1.01	1.37	3.49***	1.31	0.72	0.63
	(0.31 - 0.50)	(1.12 - 1.81)	(0.66 - 1.55)	(0.95 - 1.96)	(2.55 - 4.79)	(0.75 - 2.29)	(0.41 - 1.25)	(0.32 - 1.24)
Cardiff	0.26***	1.20	0.27***	0.77	1.15	1.83*	0.90	0.46*
	(0.20 - 0.34)	(0.94 - 1.52)	(0.17 - 0.44)	(0.51 - 1.16)	(0.80 - 1.65)	(1.08 - 3.08)	(0.55 - 1.49)	(0.24 - 0.86)
Glasgow	0.28***	1.41**	0.33***	1.58*	0.58*	0.89	0.66	0.28***
	(0.21 - 0.38)	(1.10 - 1.79)	(0.21 - 0.53)	(1.11 - 2.24)	(0.38 - 0.89)	(0.49 - 1.61)	(0.37 - 1.18)	(0.13 - 0.57)
Edinburgh	0.40***	2.37***	1.13	2.90***	2.37***	1.84*	0.49*	0.66
	(0.32 - 0.52)	(1.90 - 2.96)	(0.75 - 1.69)	(2.11 - 3.99)	(1.72 - 3.26)	(1.10 - 3.07)	(0.26 - 0.92)	(0.35 - 1.23)
Stoke	0.64***	0.79	0.73	0.49*	0.77	0.22*	0.98	0.52
	(0.52 - 0.80)	(0.59 - 1.04)	(0.46 - 1.16)	(0.28 - 0.84)	(0.49 - 1.21)	(0.07 - 0.75)	(0.57 - 1.66)	(0.25 - 1.09)
Reading	0.37***	1.36**	0.52***	1.18	1.23	1.34	0.73	0.48*
	(0.30 - 0.44)	(1.11 - 1.68)	(0.35 - 0.77)	(0.85 - 1.64)	(0.90 - 1.68)	(0.82 - 2.19)	(0.47 - 1.14)	(0.27 - 0.86)
Bury	0.73***	0.59***	0.72	0.63*	0.31***	0.60	0.87	0.80
	(0.60 - 0.88)	(0.46 - 0.75)	(0.49 - 1.08)	(0.43 - 0.92)	(0.20 - 0.48)	(0.33 - 1.08)	(0.55 - 1.37)	(0.45 - 1.43)
Newcastle	0.23***	1.11	0.38***	1.19	0.82	1.24	0.73	0.31***
	(0.19 - 0.29)	(0.90 - 1.38)	(0.26 - 0.56)	(0.87 - 1.64)	(0.59 - 1.15)	(0.76 - 2.02)	(0.46 - 1.16)	(0.17 - 0.55)
Leeds	0.60***	1.24*	0.89	1.11	0.71*	1.05	0.97	0.89
	(0.50 - 0.72)	(1.01 - 1.52)	(0.62 - 1.27)	(0.81 - 1.51)	(0.51 - 0.98)	(0.65 - 1.70)	(0.64 - 1.46)	(0.53 - 1.52)
Bristol	0.32***	1.24*	0.56**	1.16	1.75***	1.54	0.78	0.51*
	(0.27 - 0.39)	(1.02 - 1.51)	(0.39 - 0.80)	(0.86 - 1.56)	(1.31 - 2.33)	(0.98 - 2.41)	(0.52 - 1.18)	(0.30 - 0.87)
Central London	1.27	4.48***	7.82***	9.49***	7.67***	5.76***	0.76	4.80***
	(0.94 - 1.72)	(3.40 - 5.90)	(5.19 - 11.79)	(6.78 - 13.27)	(5.40 - 10.90)	(3.52 - 9.43)	(0.34 - 1.71)	(2.62 - 8.81)
Nottingham	0.29***	0.96	0.51***	0.96	1.70***	1.55	1.30	0.48**
	(0.24 - 0.35)	(0.77 - 1.19)	(0.35 - 0.74)	(0.69 - 1.34)	(1.25 - 2.31)	(0.96 - 2.50)	(0.86 - 1.97)	(0.28 - 0.83)
Sheffield	1.11	1.19	1.51*	1.19	0.86	1.47	1.08	1.21
	(0.94 - 1.30)	(0.97 - 1.45)	(1.07 - 2.13)	(0.88 - 1.60)	(0.63 - 1.17)	(0.94 - 2.30)	(0.72 - 1.61)	(0.72 - 2.02)
Liverpool	1.11	0.93	1.63**	0.88	0.75	1.01	0.89	0.73
	(0.94 - 1.31)	(0.76 - 1.15)	(1.15 - 2.31)	(0.65 - 1.21)	(0.55 - 1.03)	(0.62 - 1.63)	(0.59 - 1.35)	(0.42 - 1.26)
Middlesborough	0.23***	0.79*	0.23***	0.60**	0.73	0.42**	0.82	0.18***
	(0.18 - 0.28)	(0.63 - 1.00)	(0.15 - 0.34)	(0.41 - 0.88)	(0.51 - 1.04)	(0.22 - 0.81)	(0.53 - 1.29)	(0.10 - 0.33)
Hounslow	1.67***	2.31***	5.95***	3.25***	2.08***	1.84**	0.96	2.65***
	(1.42 - 1.98)	(1.90 - 2.81)	(4.26 - 8.32)	(2.45 - 4.30)	(1.56 - 2.78)	(1.19 - 2.86)	(0.64 - 1.46)	(1.59 - 4.41)
Croydon	2.27***	3.73***	7.28***	5.82***	2.50***	2.89***	0.95	3.15***
	(1.91 - 2.69)	(3.06 - 4.55)	(5.19 - 10.20)	(4.39 - 7.71)	(1.86 - 3.35)	(1.86 - 4.49)	(0.61 - 1.47)	(1.88 - 5.28)
Birmingham	1.36***	1.17	2.12***	1.25	0.90	1.16	0.95	1.33
	(1.15 - 1.60)	(0.95 - 1.44)	(1.50 - 3.00)	(0.93 - 1.69)	(0.66 - 1.23)	(0.73 - 1.85)	(0.63 - 1.44)	(0.79 - 2.26)
Swansea	1.52*	0.67	1.52	0.92	1.39	1.79	0.72	1.94
	(1.10 - 2.08)	(0.39 - 1.15)	(0.78 - 2.96)	(0.45 - 1.85)	(0.73 - 2.64)	(0.74 - 4.36)	(0.25 - 2.07)	(0.78 - 4.85)
Wrexham	1.62	0.53	2.11	0.53	0.52	1.47	1.64	1.35
	(0.94 - 2.78)	(0.16 - 1.77)	(0.63 - 7.06)	(0.07 - 4.14)	(0.07 - 3.98)	(0.18 - 11.74)	(0.38 - 7.14)	(0.17 - 10.94)
Urban postcode (ref Rural)	0.80***	1.37***	1.28***	2.24***	1.88***	1.66***	1.07	0.97
	(0.74 - 0.86)	(1.26 - 1.49)	(1.11 - 1.48)	(1.85 - 2.71)	(1.62 - 2.18)	(1.28 - 2.16)	(0.89 - 1.28)	(0.78 - 1.21)

Townsend score (ref Quintile 1)								
2	1.06	1.13**	1.15*	1.22**	1.08	1.42**	1.02	1.00
	(0.98 - 1.14)	(1.04 - 1.23)	(1.00 - 1.31)	(1.06 - 1.42)	(0.94 - 1.23)	(1.11 - 1.82)	(0.84 - 1.24)	(0.79 - 1.25)
3	0.90**	1.22***	1.14	1.38***	1.18*	1.64***	1.18	1.18
	(0.84 - 0.97)	(1.12 - 1.32)	(1.00 - 1.30)	(1.20 - 1.59)	(1.03 - 1.34)	(1.30 - 2.08)	(0.98 - 1.43)	(0.95 - 1.48)
4	0.90*	1.27***	1.31***	1.73***	1.38***	2.14***	1.23*	1.28*
	(0.84 - 0.98)	(1.17 - 1.38)	(1.15 - 1.50)	(1.52 - 1.98)	(1.21 - 1.57)	(1.70 - 2.68)	(1.01 - 1.49)	(1.02 - 1.60)
5 (Highest deprivation)	0.80***	1.39***	1.36***	2.01***	1.37***	2.63***	1.40**	1.11
	(0.73 - 0.88)	(1.26 - 1.53)	(1.18 - 1.57)	(1.74 - 2.32)	(1.18 - 1.58)	(2.07 - 3.34)	(1.12 - 1.74)	(0.87 - 1.42)
Travel behaviour								
Dietary behaviour								

Base class = Class 1, Exclusive car commuters; note that Table D.0.25, Table D.0.26, and Table D.0.27 refer to one multivariate model

Yellow shading = positive association, grey shading =negative association

Table D.0.28 - Age-adjusted bivariate multinomial regression between class membership and health / lifestyle indicators among UKB males

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Energy intake (kcal)[a]	1.00***	1.00***	1.00	1.00	1.00***	1.00	1.00	1.00*
	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)	(1.00 - 1.00)
Meets PA guideline (ref No)[b]	1.23***	0.87***	1.00	0.78***	6.91***	1.63***	1.13	1.53***
	(1.18 - 1.27)	(0.83 - 0.92)	(0.94 - 1.05)	(0.74 - 0.83)	(6.20 - 7.70)	(1.45 - 1.83)	(1.00 - 1.27)	(1.36 - 1.73)
BMI 25+ (ref BMI <25)[c]	0.89***	0.77***	0.62***	0.60***	0.38***	0.31***	0.46***	0.35***
	(0.85 - 0.92)	(0.73 - 0.81)	(0.58 - 0.66)	(0.57 - 0.64)	(0.36 - 0.41)	(0.28 - 0.35)	(0.41 - 0.52)	(0.32 - 0.40)
Overall health (ref Good)[d]								
Excellent	1.07**	1.15***	1.04	1.12**	1.96***	1.81***	1.39***	1.57***
	(1.02 - 1.12)	(1.08 - 1.22)	(0.96 - 1.13)	(1.04 - 1.21)	(1.80 - 2.12)	(1.59 - 2.05)	(1.21 - 1.60)	(1.36 - 1.82)
Fair	1.10***	0.86***	1.54***	1.06	0.47***	0.80**	0.88	1.02
	(1.05 - 1.15)	(0.80 - 0.91)	(1.44 - 1.66)	(0.98 - 1.14)	(0.42 - 0.53)	(0.69 - 0.94)	(0.75 - 1.03)	(0.87 - 1.19)
Poor	3.59***	0.82*	6.91***	1.14	0.32***	0.85	0.74	3.91***
	(3.26 - 3.96)	(0.69 - 0.97)	(6.13 - 7.79)	(0.95 - 1.36)	(0.21 - 0.48)	(0.57 - 1.26)	(0.48 - 1.15)	(3.03 - 5.04)
Long-term condition (ref No)[e]	1.51***	0.98	2.16***	1.16***	0.74***	0.86*	0.88	1.56***
	(1.45 - 1.57)	(0.93 - 1.04)	(2.04 - 2.29)	(1.09 - 1.24)	(0.68 - 0.81)	(0.76 - 0.98)	(0.77 - 1.01)	(1.39 - 1.76)
Travel behaviour								
Diet behaviour								

Base class = Class 1, Exclusive car commuters

Yellow shading = positive association, grey shading =negative association

a) n=94,781; derived based on 24 dietary recall questionnaire(s), mean value taken if multiple questionnaires completed
b) n=91,783; PA guideline is 150 minutes per week of moderate physical activity, or 70 minutes per week of vigorous physical activity
c) n=94,476; BMI of 25+ is considered overweight or obese
d) n=94,530; self-reported, participants were asked: "In general how would you rate your overall health?"
e) n=93,084; self-reported, participants were asked: “Do you have any long-standing illness, disability or infirmity?”

D.2 – Comparison of effect estimates between Stata and Latent Gold

Table D.0.30 to Table D.0.35 show the full multinomial regression models among UKB females and males in Stata and Latent Gold with missing data excluded and included. Stata models are the same as presented previously but have been re-run here so the output (coefficients, standard errors) and reference groups (first category) are the same as in Latent Gold. In addition, the 'cars per household' variable was condensed to a three-category variable (0-1 cars, 2 cars, 3+ cars) due to small numbers in some categories (0 cars, 4+ cars), which caused problems in the Latent Gold models.

Table D.0.29 presents a summary of the estimates from the different models based on a few examples for illustration purposes. Classes 2, 3, and 8 are shown because these classes had the largest amount of missing data; most of this was for household income and these three non-commuting classes tended to have lower household incomes overall. As expected, the estimates from the Stata models are more conservative than those from the Latent Gold models with bias adjustment. Imputing the missing values does not seem to change the direction or significance of the estimates.

Table D.0.29 – Comparison between models for coefficients, standard errors, and odds ratios (OR) based on select examples

UKB females, Class 5, urban versus rural			
	coeff	st err	OR
Stata no missing	0.75	0.07	2.12
LG no missing, with bias adjustment	0.82	0.09	2.27
LG with missing imputed and bias adjustment	0.81	0.08	2.25
UKB females, Class 2, Chinese versus White British			
	coeff	st err	OR
Stata no missing	-0.57	0.24	0.57
LG no missing, with bias adjustment	-0.75	0.28	0.47
LG with missing imputed and bias adjustment	-0.27	0.22	0.76
UKB females, Class 3, £100 000+ versus >£18 000			
	coeff	st err	OR
Stata no missing	-1.93	0.1	0.15
LG no missing, with bias adjustment	-1.99	0.12	0.14
LG with missing imputed and bias adjustment	-1.22	0.1	0.30
UKB females, Class 8, no qualifications versus degree level			
	coeff	st err	OR
Stata no missing	-1.07	0.1	0.34
LG no missing, with bias adjustment	-1.23	0.11	0.29
LG with missing imputed and bias adjustment	-0.93	0.09	0.39

Table D.0.30 – UKB females, multinomial regression model in Stata (n=99,193)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Age group (ref: <45)									
45-49	-0.02	0.04	0.11*	0.13**	-0.20***	0.18**	-0.38***	-0.04	0.06
	(0.06)	(0.09)	(0.04)	(0.05)	(0.06)	(0.07)	(0.11)	(0.08)	(0.11)
50-54	0.19**	0.36***	0.13**	0.22***	-0.30***	0.31***	-0.13	-0.16*	0.02
	(0.06)	(0.08)	(0.04)	(0.05)	(0.06)	(0.06)	(0.11)	(0.08)	(0.11)
55-59	0.85***	1.00***	0.06	0.20***	-0.35***	0.43***	0.37***	-0.18*	-0.09
	(0.06)	(0.08)	(0.05)	(0.05)	(0.06)	(0.07)	(0.10)	(0.08)	(0.12)
60-64	2.28***	2.54***	0.11*	0.13*	-0.52***	0.37***	1.70***	-0.31**	-0.21
	(0.06)	(0.08)	(0.05)	(0.06)	(0.08)	(0.08)	(0.10)	(0.10)	(0.15)
65+	3.33***	3.53***	0.12	0.03	-0.72***	0.24	2.53***	-0.59***	-0.12
	(0.07)	(0.08)	(0.09)	(0.09)	(0.15)	(0.13)	(0.11)	(0.18)	(0.24)
Ethnic group (ref: White British)	-0.05	0.22***	-0.05	0.30***	-0.05	0.13	0.01	0.10	0.31**
Other White	(0.05)	(0.06)	(0.05)	(0.05)	(0.08)	(0.07)	(0.09)	(0.08)	(0.11)
	-0.51***	-0.54**	-0.66***	0.12	1.45***	-0.41*	0.76***	1.00***	-1.44*
South Asian	(0.14)	(0.17)	(0.16)	(0.12)	(0.11)	(0.20)	(0.17)	(0.15)	(0.59)
	-0.95***	-0.57***	-0.50***	0.15	-0.54**	-0.74***	-0.86***	-0.62***	-1.59***
Black	(0.14)	(0.15)	(0.12)	(0.09)	(0.18)	(0.18)	(0.24)	(0.19)	(0.46)
	-0.57*	-0.07	-0.28	0.06	-0.93*	-0.19	-1.20*	-1.90**	-0.91
Chinese	(0.24)	(0.27)	(0.22)	(0.20)	(0.46)	(0.30)	(0.61)	(0.72)	(0.60)
	-0.27	0.12	-0.32*	0.06	0.14	-0.07	0.24	-0.13	-0.29
Mixed	(0.17)	(0.19)	(0.16)	(0.14)	(0.19)	(0.20)	(0.25)	(0.24)	(0.37)
	-0.61***	-0.16	-0.22	0.55***	-0.12	-0.10	-0.35	0.19	-0.60
Other	(0.17)	(0.18)	(0.16)	(0.13)	(0.24)	(0.21)	(0.26)	(0.21)	(0.43)
Highest qualification (ref: Degree level)									
A levels/AS levels or equivalent	-0.00	-0.15**	-0.12**	-0.07	-0.34***	0.13*	-0.32***	-0.46***	-0.56***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)	(0.07)	(0.08)	(0.12)
O levels/GCSEs or equivalent	-0.27***	-0.40***	-0.33***	-0.13**	-0.64***	-0.06	-0.95***	-0.88***	-1.06***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)	(0.06)	(0.07)	(0.08)	(0.14)
CSEs or equivalent	-0.56***	-0.58***	-0.59***	-0.23**	-0.96***	0.11	-1.50***	-1.12***	-1.01***
	(0.07)	(0.09)	(0.07)	(0.07)	(0.11)	(0.08)	(0.16)	(0.16)	(0.24)
NVQ or HND or HNC or equivalent	-0.66***	-0.71***	-0.59***	-0.30***	-0.54***	-0.30**	-1.48***	-0.91***	-0.97***
	(0.07)	(0.09)	(0.08)	(0.08)	(0.11)	(0.10)	(0.16)	(0.16)	(0.26)
Other professional qualifications	-0.31***	-0.58***	-0.70***	-0.55***	-0.54***	-0.17	-0.73***	-0.91***	-0.86***
	(0.05)	(0.07)	(0.08)	(0.08)	(0.09)	(0.10)	(0.10)	(0.15)	(0.22)
No qualifications	-0.30***	-0.27***	-0.65***	-0.23**	-1.14***	-0.07	-1.07***	-1.16***	-0.96***
	(0.06)	(0.06)	(0.08)	(0.07)	(0.14)	(0.09)	(0.10)	(0.16)	(0.25)
Occupational class (ref: Higher man / prof)									
Lower managerial / professional	-0.15***	-0.08	-0.22***	-0.29***	-0.00	0.04	-0.07	-0.23***	-0.28**
	(0.04)	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)	(0.09)	(0.07)	(0.09)
Intermediate	-0.24***	-0.03	0.14**	0.36***	-0.18**	0.64***	-0.32**	0.29***	0.00
	(0.04)	(0.07)	(0.04)	(0.05)	(0.06)	(0.07)	(0.11)	(0.08)	(0.13)
Small employers	0.74***	0.81***	-0.08	-0.29**	0.00	0.23	0.80***	-0.08	0.24
	(0.07)	(0.10)	(0.08)	(0.10)	(0.12)	(0.13)	(0.15)	(0.16)	(0.19)
Lower supervisory technical	-0.24	-0.22	0.05	-0.58**	-0.07	0.35	-0.19	-0.31	-1.08
	(0.17)	(0.27)	(0.16)	(0.21)	(0.23)	(0.24)	(0.43)	(0.34)	(0.72)
Semi-routine	-0.70***	-0.36***	0.17**	0.04	0.02	1.32***	-0.61***	0.23*	0.34*
	(0.06)	(0.08)	(0.06)	(0.06)	(0.08)	(0.08)	(0.15)	(0.11)	(0.16)
Routine	-0.19	-0.00	0.35***	0.05	0.17	1.56***	-0.09	-0.07	0.27
	(0.10)	(0.13)	(0.11)	(0.12)	(0.16)	(0.11)	(0.24)	(0.23)	(0.31)
Not classified	7.49***	7.66***	-0.35	0.00	-0.44	0.16	7.47***	-0.16	-12.19
	(0.14)	(0.15)	(0.38)	(0.36)	(0.60)	(0.52)	(0.16)	(0.72)	(386.46)
Household income (ref: £<18 000)									
£18,000 to 30,999	-0.78***	-0.98***	-0.07	-0.04	-0.04	-0.12	-1.07***	-0.27**	-0.23
	(0.04)	(0.05)	(0.06)	(0.05)	(0.08)	(0.07)	(0.07)	(0.09)	(0.15)
£31,000 to 51,999	-1.36***	-1.60***	-0.11	-0.16**	-0.01	-0.23**	-1.70***	-0.42***	-0.25
	(0.05)	(0.05)	(0.06)	(0.05)	(0.08)	(0.07)	(0.08)	(0.09)	(0.15)
£52,000 to 100,000	-1.60***	-1.94***	-0.15*	-0.10	-0.01	-0.33***	-2.09***	-0.42***	-0.52**
	(0.05)	(0.07)	(0.06)	(0.06)	(0.09)	(0.08)	(0.09)	(0.11)	(0.17)
Greater than £100,000	-1.38***	-1.93***	-0.04	0.11	-0.30**	-0.27*	-2.08***	-0.62***	-0.39
	(0.07)	(0.10)	(0.08)	(0.08)	(0.11)	(0.12)	(0.13)	(0.14)	(0.20)
Household type (ref: Lives alone)									
Children, no partner	-0.20***	0.10	0.19***	-0.01	-0.08	0.43***	-0.22*	-0.06	0.30*
	(0.06)	(0.07)	(0.06)	(0.05)	(0.07)	(0.08)	(0.11)	(0.09)	(0.14)
Partner, no children	1.08***	1.75***	0.82***	0.81***	0.00	1.14***	1.02***	0.86***	1.13***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)	(0.07)	(0.07)	(0.12)
Partner and children	0.94***	1.78***	1.12***	0.87***	-0.12	1.61***	1.00***	0.82***	1.57***
	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.08)	(0.12)
Lives with others	0.37***	0.74***	0.55***	0.80***	0.18	0.50***	0.90***	0.74***	1.12***
	(0.10)	(0.12)	(0.10)	(0.09)	(0.13)	(0.15)	(0.15)	(0.14)	(0.21)
Cars per household (ref: 0-1)									
2	-0.27***	-1.88***	-0.97***	-2.02***	-0.26***	-1.48***	-0.81***	-2.10***	-1.89***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.08)	(0.10)
3+	-0.32***	-2.13***	-1.26***	-2.56***	-0.57***	-2.04***	-0.98***	-2.57***	-2.66***
	(0.05)	(0.08)	(0.05)	(0.08)	(0.07)	(0.08)	(0.10)	(0.15)	(0.21)

Townsend score (ref: Quintile 1)									
2	-0.13***	-0.02	-0.01	0.18**	0.08	0.12	-0.12	-0.02	0.47**
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)	(0.07)	(0.07)	(0.11)	(0.17)
3	-0.19***	0.13*	0.08	0.34***	0.17**	0.33***	-0.14	0.26**	0.57***
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)	(0.07)	(0.07)	(0.10)	(0.16)
4	-0.23***	0.34***	0.21***	0.72***	0.32***	0.70***	0.16*	0.56***	0.91***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.07)	(0.07)	(0.10)	(0.16)
5	-0.35***	0.67***	0.34***	1.11***	0.28***	0.98***	0.14	0.95***	1.12***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.07)	(0.07)	(0.08)	(0.10)	(0.16)
Assessment Centre (ref: Manchester)									
Oxford	-1.15***	-0.35*	1.18***	0.48**	0.08	0.72***	-0.85***	0.77**	1.91***
	(0.12)	(0.17)	(0.12)	(0.15)	(0.16)	(0.19)	(0.21)	(0.26)	(0.24)
Cardiff	-1.71***	-1.53***	0.28*	-0.15	0.23	0.40*	-1.85***	0.40	-0.41
	(0.15)	(0.19)	(0.13)	(0.17)	(0.15)	(0.19)	(0.25)	(0.27)	(0.35)
Glasgow	-1.68***	-1.50***	0.36**	0.60***	-0.30	0.26	-2.05***	0.19	-2.00**
	(0.16)	(0.20)	(0.14)	(0.15)	(0.17)	(0.20)	(0.27)	(0.28)	(0.62)
Edinburgh	-1.17***	-0.47**	1.16***	1.29***	-0.12	1.10***	-1.31***	1.08***	0.34
	(0.13)	(0.17)	(0.12)	(0.13)	(0.16)	(0.18)	(0.22)	(0.24)	(0.28)
Stoke	-0.31**	-0.13	0.13	-0.71**	0.15	0.24	-0.30	-0.27	-0.91
	(0.12)	(0.18)	(0.16)	(0.24)	(0.17)	(0.22)	(0.23)	(0.40)	(0.55)
Reading	-1.27***	-1.12***	0.64***	0.12	-0.07	0.69***	-1.43***	0.47	0.14
	(0.10)	(0.15)	(0.12)	(0.14)	(0.14)	(0.17)	(0.19)	(0.25)	(0.29)
Bury	-0.36***	-0.29	-0.14	-0.18	0.10	-0.07	-0.51*	-0.13	-1.92***
	(0.10)	(0.15)	(0.14)	(0.15)	(0.15)	(0.19)	(0.20)	(0.28)	(0.55)
Newcastle	-1.78***	-1.40***	0.23	0.36**	-0.17	-0.06	-1.93***	0.18	-0.92**
	(0.12)	(0.16)	(0.12)	(0.13)	(0.14)	(0.18)	(0.20)	(0.25)	(0.33)
Leeds	-0.77***	-0.53***	0.35**	0.33*	0.13	0.47**	-0.80***	0.44	-1.21***
	(0.09)	(0.14)	(0.12)	(0.13)	(0.13)	(0.17)	(0.18)	(0.23)	(0.34)
Bristol	-1.37***	-0.97***	0.76***	0.01	0.19	0.96***	-1.25***	0.70**	0.38
	(0.09)	(0.14)	(0.11)	(0.13)	(0.13)	(0.16)	(0.17)	(0.22)	(0.24)
Barts	0.16	1.61***	1.97***	2.57***	0.19	2.32***	0.84***	2.67***	2.25***
	(0.14)	(0.17)	(0.14)	(0.14)	(0.22)	(0.18)	(0.22)	(0.23)	(0.26)
Nottingham	-1.30***	-0.79***	0.48***	0.35*	0.12	0.63***	-1.27***	0.48*	-0.42
	(0.10)	(0.15)	(0.12)	(0.14)	(0.14)	(0.17)	(0.19)	(0.24)	(0.30)
Sheffield	0.03	0.55***	0.41***	0.56***	0.05	0.41*	-0.06	0.57*	-0.91**
	(0.08)	(0.13)	(0.11)	(0.12)	(0.13)	(0.16)	(0.17)	(0.23)	(0.30)
Liverpool	0.01	0.24	0.10	0.25*	0.02	-0.11	-0.18	0.02	-0.60*
	(0.08)	(0.13)	(0.12)	(0.13)	(0.13)	(0.17)	(0.17)	(0.24)	(0.28)
Middlesbrough	-1.86***	-1.75***	-0.13	-0.45**	-0.17	0.21	-2.01***	-0.50	-1.49***
	(0.12)	(0.16)	(0.13)	(0.16)	(0.15)	(0.18)	(0.20)	(0.30)	(0.44)
Hounslow	0.36***	1.22***	1.04***	1.41***	-0.02	0.76***	0.47**	1.20***	0.65**
	(0.09)	(0.13)	(0.11)	(0.12)	(0.14)	(0.16)	(0.17)	(0.22)	(0.24)
Croydon	0.56***	1.41***	1.17***	1.83***	0.03	0.83***	0.69***	1.65***	0.53*
	(0.09)	(0.13)	(0.11)	(0.12)	(0.14)	(0.16)	(0.17)	(0.22)	(0.25)
Birmingham	0.25**	0.61***	0.33**	0.65***	0.25	0.23	0.21	0.43	-0.75*
	(0.09)	(0.13)	(0.12)	(0.13)	(0.13)	(0.17)	(0.17)	(0.23)	(0.30)
Swansea	0.33*	0.02	0.25	-0.70	0.30	0.52	-0.40	0.21	-0.14
	(0.16)	(0.27)	(0.25)	(0.39)	(0.27)	(0.31)	(0.40)	(0.50)	(0.63)
Wrexham	0.24	0.34	0.15	-17.28	0.10	-0.11	-0.17	1.35*	-17.70
	(0.29)	(0.48)	(0.49)	(3,139.12)	(0.54)	(0.76)	(0.76)	(0.66)	(8,085.44)
Urban (ref: Rural)	-0.29***	0.21***	0.53***	0.75***	0.02	0.69***	-0.28***	0.86***	1.42***
	(0.04)	(0.06)	(0.05)	(0.07)	(0.05)	(0.07)	(0.07)	(0.13)	(0.21)
Constant	-0.76***	-3.33***	-2.58***	-3.15***	-1.71***	-4.67***	-1.99***	-3.64***	-5.09***
	(0.11)	(0.17)	(0.13)	(0.16)	(0.16)	(0.20)	(0.21)	(0.28)	(0.37)
Observations	99,193	99,193	99,193	99,193	99,193	99,193	99,193	99,193	99,193

*** p<0.001, ** p<0.01, * p<0.05

Table D.0.31 – UKB females, multinomial regression model in Latent Gold (n=99,193)

Model for Classes

Intercept	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.	Cluster10	s.e.
	-0.84	0.11	-3.94	0.21	-2.92	0.19	-3.42	0.18	-1.78	0.16	-4.98	0.22	-2.05	0.23	-3.80	0.31	-5.51	0.43

Covariates	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.	Cluster10	s.e.
Age group																		
< 45 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
45-49	-0.02	0.07	0.09	0.10	0.18	0.06	0.11	0.05	-0.19	0.06	0.18	0.07	-0.39	0.12	-0.03	0.08	0.02	0.12
50-54	0.20	0.06	0.44	0.10	0.24	0.06	0.22	0.05	-0.29	0.06	0.36	0.07	-0.13	0.11	-0.14	0.08	-0.03	0.12
55-59	0.87	0.06	1.05	0.09	0.19	0.06	0.20	0.05	-0.33	0.06	0.49	0.07	0.37	0.11	-0.16	0.09	-0.13	0.13
60-64	2.32	0.06	2.62	0.09	0.38	0.07	0.12	0.06	-0.46	0.08	0.41	0.09	1.71	0.10	-0.29	0.11	-0.26	0.17
65+	3.39	0.07	3.58	0.10	0.45	0.12	-0.01	0.10	-0.68	0.16	0.23	0.15	2.54	0.11	-0.56	0.18	-0.11	0.26
Ethnic group																		
White British (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Other white	-0.08	0.06	0.29	0.07	-0.03	0.07	0.34	0.05	-0.03	0.08	0.18	0.08	0.03	0.09	0.12	0.09	0.31	0.12
South Asian	-0.61	0.15	-0.60	0.19	-1.03	0.25	0.11	0.13	1.43	0.12	-0.50	0.23	0.78	0.18	0.95	0.16	-1.75	0.78
Black	-1.11	0.17	-0.58	0.16	-0.77	0.20	0.15	0.10	-0.58	0.19	-0.78	0.20	-0.93	0.26	-0.74	0.21	-1.76	0.54
Chinese	-0.75	0.28	0.00	0.29	-0.61	0.32	0.07	0.22	-0.94	0.46	-0.04	0.31	-1.46	0.73	-1.84	0.72	-1.31	0.73
Mixed	-0.38	0.20	0.18	0.21	-0.47	0.23	0.08	0.15	0.11	0.21	-0.04	0.23	0.25	0.26	-0.12	0.24	-0.45	0.39
Other	-0.77	0.19	-0.08	0.20	-0.49	0.27	0.62	0.15	-0.13	0.25	-0.08	0.25	-0.40	0.28	0.16	0.23	-0.69	0.45
Household type																		
Lives alone (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Children, no partner	-0.18	0.06	0.12	0.08	0.23	0.08	0.01	0.06	-0.05	0.07	0.51	0.08	-0.20	0.11	-0.09	0.10	0.33	0.16
Partner, no children	1.15	0.04	1.93	0.05	1.08	0.06	1.00	0.05	0.03	0.07	1.34	0.07	1.16	0.07	1.07	0.08	1.33	0.12
Partner and children	1.06	0.05	2.02	0.07	1.54	0.07	1.05	0.05	-0.05	0.07	1.87	0.08	1.18	0.09	1.08	0.09	1.83	0.13
Lives with others	0.46	0.11	0.78	0.14	0.76	0.15	0.92	0.10	0.26	0.14	0.52	0.18	1.03	0.16	0.84	0.15	1.34	0.21
Highest qualification																		
Degree level (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
A levels/AS levels	0.00	0.04	-0.21	0.06	-0.13	0.05	-0.10	0.05	-0.38	0.06	0.16	0.07	-0.36	0.07	-0.46	0.08	-0.70	0.14
O levels/GCSEs or equivalent	-0.28	0.04	-0.49	0.05	-0.38	0.05	-0.17	0.05	-0.67	0.06	-0.06	0.06	-1.05	0.07	-0.97	0.09	-1.25	0.16
CSEs or equivalent	-0.56	0.08	-0.77	0.11	-0.87	0.11	-0.22	0.08	-1.02	0.12	0.16	0.09	-1.64	0.17	-1.27	0.17	-1.07	0.25
NVQ or HND or HNC	-0.69	0.08	-0.83	0.11	-0.83	0.12	-0.33	0.09	-0.59	0.12	-0.32	0.12	-1.59	0.17	-1.00	0.17	-1.12	0.29
Other profess qualifications	-0.34	0.05	-0.71	0.08	-0.93	0.11	-0.62	0.09	-0.59	0.09	-0.19	0.11	-0.83	0.10	-0.98	0.16	-0.97	0.25
No qualifications	-0.34	0.06	-0.37	0.07	-0.97	0.12	-0.24	0.08	-1.19	0.15	0.00	0.09	-1.23	0.11	-1.31	0.18	-1.15	0.29

Occupational class																		
Higher manag / profess (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Lower manag / professional	-0.16	0.04	-0.16	0.07	-0.30	0.04	-0.30	0.04	-0.01	0.05	0.08	0.08	-0.09	0.10	-0.27	0.07	-0.31	0.10
Intermediate	-0.23	0.05	-0.02	0.08	0.14	0.05	0.42	0.05	-0.16	0.07	0.76	0.08	-0.32	0.12	0.30	0.09	0.04	0.13
Small employers	0.82	0.08	0.55	0.14	-0.01	0.11	-0.27	0.12	0.03	0.12	0.26	0.17	0.80	0.17	-0.07	0.17	0.28	0.21
Lower supervisory technical	-0.20	0.20	-0.33	0.33	0.13	0.21	-0.68	0.26	-0.02	0.24	0.40	0.28	-0.24	0.47	-0.42	0.38	-1.11	0.80
Semi-routine	-0.70	0.06	-0.33	0.10	0.16	0.07	0.08	0.07	0.03	0.09	1.48	0.09	-0.60	0.16	0.29	0.12	0.39	0.17
Routine	-0.14	0.11	-0.06	0.16	0.28	0.15	0.10	0.13	0.20	0.17	1.76	0.12	-0.05	0.26	-0.08	0.25	0.26	0.33
Not classified	7.52	0.15	7.68	0.17	-0.23	0.45	0.21	0.38	-0.42	0.68	0.00	0.62	7.48	0.18	-0.18	0.89	-47.68	0.00
Household income																		
Less than 18,000 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
18,000 to 30,999	-0.76	0.04	-1.10	0.05	-0.18	0.08	-0.05	0.06	-0.05	0.08	-0.15	0.07	-1.10	0.07	-0.30	0.10	-0.22	0.17
31,000 to 51,999	-1.36	0.05	-1.71	0.06	-0.22	0.08	-0.21	0.06	-0.02	0.08	-0.27	0.08	-1.75	0.08	-0.50	0.10	-0.27	0.17
52,000 to 100,000	-1.61	0.06	-1.98	0.08	-0.27	0.09	-0.11	0.07	-0.02	0.09	-0.38	0.09	-2.15	0.10	-0.50	0.11	-0.52	0.18
Greater than 100,000	-1.35	0.08	-1.99	0.12	-0.12	0.10	0.17	0.09	-0.32	0.12	-0.36	0.14	-2.14	0.14	-0.63	0.15	-0.36	0.22
Cars per household																		
0-1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	-0.28	0.04	-2.56	0.06	-1.12	0.05	-2.43	0.05	-0.28	0.05	-1.74	0.06	-0.95	0.06	-2.41	0.09	-2.23	0.12
3+	-0.37	0.05	-3.04	0.15	-1.61	0.07	-3.09	0.10	-0.63	0.08	-2.34	0.09	-1.19	0.11	-3.01	0.18	-3.09	0.27
Townsend score																		
1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	-0.11	0.04	0.00	0.06	0.04	0.05	0.21	0.07	0.10	0.06	0.12	0.08	-0.11	0.08	-0.05	0.12	0.53	0.20
3	-0.18	0.04	0.26	0.06	0.10	0.05	0.41	0.07	0.18	0.06	0.36	0.08	-0.11	0.08	0.27	0.11	0.54	0.20
4	-0.24	0.04	0.55	0.06	0.21	0.05	0.87	0.06	0.33	0.06	0.76	0.07	0.21	0.08	0.59	0.10	1.03	0.19
5	-0.43	0.05	0.99	0.07	0.32	0.06	1.33	0.07	0.30	0.07	1.10	0.08	0.20	0.09	1.02	0.11	1.30	0.19
Assessment Centre																		
Manchester (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Oxford	-1.09	0.13	0.18	0.21	1.65	0.17	0.53	0.18	0.19	0.16	0.77	0.23	-0.69	0.23	0.97	0.28	2.24	0.25
Cardiff	-1.70	0.16	-1.42	0.24	0.39	0.19	-0.17	0.19	0.25	0.15	0.45	0.21	-1.86	0.27	0.42	0.28	-0.29	0.35
Glasgow	-1.64	0.17	-1.31	0.24	0.68	0.18	0.65	0.16	-0.26	0.18	0.27	0.22	-2.03	0.29	0.23	0.29	-2.01	0.73
Edinburgh	-1.08	0.14	0.03	0.21	1.64	0.17	1.47	0.15	-0.06	0.17	1.15	0.20	-1.18	0.24	1.26	0.25	0.57	0.29
Stoke	-0.31	0.12	-0.01	0.23	0.02	0.24	-0.69	0.28	0.16	0.18	0.41	0.23	-0.33	0.24	-0.38	0.46	-1.05	0.67
Reading	-1.25	0.11	-0.95	0.20	0.95	0.16	0.08	0.17	-0.03	0.14	0.72	0.19	-1.41	0.21	0.51	0.27	0.14	0.31
Bury	-0.38	0.10	-0.15	0.19	-0.23	0.20	-0.11	0.17	0.10	0.15	-0.03	0.21	-0.54	0.21	-0.20	0.31	-1.70	0.56
Newcastle	-1.77	0.12	-1.19	0.19	0.34	0.17	0.46	0.14	-0.15	0.15	-0.01	0.20	-1.93	0.22	0.18	0.26	-1.04	0.39
Leeds	-0.75	0.09	-0.35	0.17	0.47	0.16	0.43	0.14	0.14	0.14	0.55	0.18	-0.80	0.19	0.50	0.24	-1.26	0.39

Bristol	-1.34	0.10	-0.66	0.18	1.08	0.16	-0.09	0.15	0.22	0.13	1.06	0.17	-1.18	0.18	0.83	0.23	0.52	0.25
Barts	0.14	0.19	2.35	0.21	2.46	0.22	3.05	0.17	0.26	0.29	2.83	0.21	1.24	0.24	3.10	0.26	2.73	0.27
Nottingham	-1.29	0.11	-0.53	0.18	0.70	0.17	0.36	0.15	0.15	0.14	0.68	0.18	-1.21	0.20	0.52	0.26	-0.55	0.34
Sheffield	0.04	0.08	0.86	0.16	0.65	0.16	0.65	0.14	0.06	0.13	0.43	0.17	-0.04	0.18	0.65	0.24	-0.94	0.33
Liverpool	0.01	0.08	0.42	0.17	0.22	0.17	0.33	0.14	0.04	0.14	-0.06	0.18	-0.19	0.18	-0.02	0.26	-0.62	0.30
Middlesbrough	-1.87	0.12	-1.54	0.20	-0.13	0.19	-0.39	0.17	-0.14	0.15	0.31	0.19	-2.01	0.22	-0.62	0.33	-1.44	0.48
Hounslow	0.41	0.09	1.75	0.16	1.55	0.16	1.62	0.13	0.07	0.14	0.82	0.18	0.60	0.18	1.38	0.23	0.83	0.25
Croydon	0.59	0.09	1.97	0.16	1.60	0.16	2.08	0.13	0.06	0.15	0.94	0.18	0.82	0.18	1.87	0.23	0.74	0.25
Birmingham	0.25	0.08	0.91	0.17	0.54	0.16	0.73	0.14	0.27	0.14	0.25	0.18	0.21	0.18	0.48	0.24	-0.83	0.33
Swansea	0.31	0.15	0.31	0.30	0.34	0.34	-0.67	0.42	0.35	0.27	0.51	0.33	-0.45	0.43	0.07	0.52	-0.21	0.75
Wrexham	0.22	0.24	0.79	0.50	0.28	0.58	-2.42	1.75	0.21	0.54	-0.22	0.73	-0.10	0.75	1.35	0.60	-3.54	8.60
Urban/rural																		
Rural (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Urban	-0.26	0.04	0.49	0.07	0.72	0.06	0.82	0.09	0.04	0.05	0.76	0.08	-0.23	0.07	1.05	0.16	1.78	0.30

Table D.0.32 – UKB females, multinomial regression model in Latent Gold, including missing (n=116,255)

Model for Classes																		
Intercept	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.	Cluster10	s.e.
	-0.90	0.10	-4.04	0.19	-2.89	0.18	-3.46	0.17	-1.80	0.16	-4.92	0.21	-2.43	0.21	-3.89	0.29	-5.49	0.40
Covariates	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.	Cluster10	s.e.
Age group																		
< 45 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
45-49	-0.01	0.06	-0.03	0.09	0.17	0.05	0.09	0.05	-0.18	0.06	0.19	0.07	-0.29	0.11	-0.04	0.08	-0.02	0.11
50-54	0.21	0.06	0.37	0.09	0.22	0.05	0.20	0.05	-0.29	0.06	0.35	0.07	-0.04	0.10	-0.14	0.08	-0.08	0.12
55-59	0.90	0.05	1.01	0.08	0.21	0.06	0.20	0.05	-0.29	0.06	0.49	0.07	0.55	0.09	-0.16	0.08	-0.17	0.13
60-64	2.29	0.05	2.59	0.08	0.35	0.07	0.11	0.06	-0.43	0.08	0.35	0.08	1.77	0.09	-0.30	0.10	-0.36	0.16
65+	3.39	0.06	3.60	0.09	0.44	0.11	-0.11	0.09	-0.64	0.15	0.20	0.14	2.68	0.10	-0.53	0.17	-0.14	0.25
Ethnic group																		
White British (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Other white	-0.04	0.05	0.32	0.06	-0.03	0.07	0.37	0.05	-0.04	0.08	0.21	0.08	0.14	0.08	0.11	0.08	0.28	0.11
South Asian	-0.51	0.12	-0.28	0.15	-1.02	0.23	0.14	0.12	1.58	0.11	-0.54	0.21	1.36	0.13	1.11	0.15	-1.52	0.63
Black	-0.88	0.14	-0.10	0.13	-0.64	0.18	0.25	0.09	-0.38	0.18	-0.67	0.18	-0.33	0.18	-0.54	0.19	-1.79	0.54
Chinese	-0.27	0.22	0.51	0.25	-0.25	0.28	0.26	0.21	-0.98	0.44	-0.05	0.32	0.03	0.29	-1.77	0.69	-0.78	0.59
Mixed	-0.21	0.16	0.40	0.18	-0.36	0.21	0.15	0.14	0.17	0.20	-0.06	0.22	0.47	0.21	-0.06	0.24	-0.36	0.37
Other	-0.40	0.17	0.34	0.17	-0.25	0.24	0.80	0.14	-0.13	0.25	-0.09	0.25	0.24	0.21	0.25	0.22	-0.58	0.42
Household type																		
Lives alone (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Children, no partner	-0.18	0.06	0.23	0.07	0.25	0.08	0.01	0.06	-0.06	0.07	0.48	0.08	-0.16	0.10	-0.11	0.10	0.37	0.15
Partner, no children	1.09	0.04	1.78	0.05	1.06	0.06	0.97	0.05	0.03	0.06	1.30	0.07	1.04	0.06	1.04	0.07	1.31	0.12
Partner and children	0.91	0.05	1.80	0.07	1.51	0.07	1.00	0.05	-0.09	0.07	1.82	0.07	0.96	0.08	1.04	0.08	1.78	0.12
Lives with others	0.59	0.09	1.20	0.11	0.88	0.13	1.05	0.09	0.25	0.13	0.59	0.17	1.36	0.12	1.04	0.14	1.57	0.19
Highest qualification																		
College or University degree (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
A levels/AS levels or equivalent	0.04	0.04	-0.14	0.05	-0.11	0.05	-0.08	0.05	-0.41	0.06	0.17	0.07	-0.28	0.07	-0.45	0.08	-0.68	0.14
O levels/GCSEs or equivalent	-0.20	0.03	-0.36	0.05	-0.39	0.05	-0.15	0.05	-0.68	0.06	-0.04	0.06	-0.87	0.06	-0.91	0.08	-1.20	0.15
CSEs or equivalent	-0.41	0.06	-0.51	0.09	-0.78	0.09	-0.23	0.08	-0.98	0.11	0.14	0.09	-1.30	0.14	-1.18	0.15	-1.11	0.25
NVQ or HND or HNC or equivalent	-0.62	0.07	-0.70	0.09	-0.83	0.11	-0.35	0.08	-0.65	0.11	-0.35	0.11	-1.34	0.14	-1.00	0.16	-1.02	0.27
Other professional qualifications	-0.27	0.05	-0.56	0.07	-0.79	0.10	-0.62	0.08	-0.54	0.09	-0.15	0.11	-0.64	0.09	-0.94	0.15	-0.86	0.23
No qualifications	-0.20	0.05	-0.09	0.06	-0.97	0.11	-0.16	0.07	-1.15	0.14	0.07	0.09	-0.93	0.09	-1.17	0.16	-1.15	0.28

Occupational class																		
Higher managerial / professional (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Lower managerial / professional	-0.15	0.04	-0.11	0.06	-0.29	0.04	-0.33	0.04	-0.01	0.05	0.06	0.07	-0.03	0.09	-0.27	0.07	-0.28	0.10
Intermediate	-0.19	0.04	0.08	0.07	0.16	0.05	0.42	0.05	-0.13	0.06	0.79	0.08	-0.14	0.10	0.33	0.08	0.11	0.13
Small employers	0.90	0.08	0.78	0.12	0.13	0.10	-0.25	0.11	0.09	0.12	0.32	0.16	1.02	0.14	0.02	0.16	0.31	0.20
Lower supervisory technical	0.66	0.16	0.76	0.22	0.73	0.21	-0.26	0.25	0.20	0.25	0.66	0.29	1.23	0.23	0.14	0.35	-0.46	0.73
Semi-routine	-0.55	0.06	-0.10	0.08	0.21	0.07	0.17	0.06	0.09	0.08	1.51	0.08	-0.27	0.13	0.35	0.11	0.39	0.16
Routine	0.21	0.09	0.35	0.13	0.55	0.14	0.30	0.12	0.30	0.16	1.91	0.12	0.76	0.17	0.31	0.22	0.47	0.30
Not classified	7.68	0.21	7.93	0.22	-376.88	0.00	-382.32	0.00	-371.43	0.00	-372.44	0.00	7.68	0.22	-371.23	0.00	-361.60	0.00
Household income																		
Less than 18,000 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
18,000 to 30,999	-0.76	0.04	-1.05	0.05	-0.24	0.08	-0.05	0.06	-0.07	0.08	-0.19	0.07	-1.04	0.07	-0.32	0.09	-0.24	0.17
31,000 to 51,999	-1.31	0.05	-1.52	0.06	-0.28	0.08	-0.20	0.06	-0.04	0.08	-0.31	0.08	-1.59	0.07	-0.47	0.10	-0.26	0.16
52,000 to 100,000	-1.51	0.05	-1.64	0.07	-0.31	0.08	-0.08	0.07	-0.04	0.09	-0.41	0.09	-1.84	0.09	-0.44	0.11	-0.47	0.18
Greater than 100,000	-1.11	0.07	-1.22	0.10	-0.09	0.10	0.25	0.09	-0.30	0.12	-0.30	0.13	-1.54	0.12	-0.49	0.15	-0.24	0.21
Cars per household																		
0-1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	-0.28	0.03	-2.57	0.05	-1.10	0.04	-2.43	0.05	-0.27	0.05	-1.73	0.05	-0.96	0.06	-2.40	0.08	-2.24	0.11
3+	-0.36	0.05	-2.92	0.10	-1.57	0.06	-3.10	0.09	-0.59	0.07	-2.32	0.09	-1.14	0.09	-2.96	0.16	-3.17	0.26
Townsend score																		
1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	-0.10	0.03	0.04	0.06	0.06	0.05	0.23	0.07	0.10	0.06	0.07	0.08	-0.05	0.07	-0.03	0.12	0.53	0.19
3	-0.17	0.03	0.27	0.06	0.12	0.05	0.43	0.06	0.18	0.06	0.35	0.07	-0.03	0.07	0.32	0.10	0.58	0.19
4	-0.22	0.04	0.55	0.05	0.23	0.05	0.86	0.06	0.30	0.06	0.76	0.07	0.24	0.07	0.67	0.10	1.05	0.18
5	-0.43	0.04	0.98	0.06	0.32	0.06	1.33	0.06	0.24	0.07	1.12	0.07	0.24	0.08	1.06	0.10	1.30	0.18
Assessment Centre																		
Manchester (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Oxford	-0.97	0.12	0.29	0.19	1.61	0.16	0.60	0.18	0.27	0.16	0.82	0.22	-0.53	0.21	1.04	0.27	2.29	0.24
Cardiff	-1.67	0.15	-1.49	0.23	0.35	0.17	-0.14	0.18	0.26	0.15	0.45	0.20	-1.74	0.25	0.35	0.28	-0.17	0.34
Glasgow	-1.50	0.16	-1.13	0.22	0.61	0.17	0.70	0.16	-0.21	0.17	0.30	0.21	-1.79	0.26	0.22	0.29	-1.95	0.69
Edinburgh	-1.05	0.13	0.00	0.19	1.62	0.15	1.57	0.14	0.05	0.16	1.19	0.19	-1.06	0.22	1.31	0.24	0.60	0.29
Stoke	-0.27	0.11	-0.02	0.21	0.03	0.21	-0.64	0.27	0.13	0.18	0.54	0.22	-0.24	0.22	-0.40	0.45	-1.09	0.68
Reading	-1.21	0.10	-0.96	0.18	0.92	0.15	0.11	0.16	-0.06	0.14	0.75	0.18	-1.36	0.19	0.60	0.26	0.20	0.31
Bury	-0.35	0.09	-0.13	0.17	-0.26	0.19	0.00	0.16	0.11	0.14	-0.01	0.19	-0.41	0.19	-0.20	0.30	-1.72	0.56
Newcastle	-1.71	0.11	-1.14	0.18	0.29	0.16	0.53	0.14	-0.11	0.14	-0.01	0.19	-1.79	0.20	0.27	0.25	-1.08	0.40
Leeds	-0.66	0.09	-0.21	0.16	0.45	0.15	0.53	0.14	0.15	0.13	0.61	0.17	-0.69	0.17	0.60	0.24	-1.27	0.39
Bristol	-1.27	0.09	-0.65	0.16	1.05	0.14	0.01	0.15	0.25	0.13	1.11	0.16	-1.07	0.17	0.91	0.23	0.63	0.24

	Barts	0.30	0.19	2.45	0.21	2.69	0.23	3.33	0.18	0.49	0.29	3.07	0.22	1.43	0.23	3.32	0.26	2.96	0.28
	Nottingham	-1.21	0.10	-0.51	0.17	0.66	0.15	0.42	0.15	0.19	0.14	0.74	0.17	-1.12	0.18	0.55	0.25	-0.43	0.32
	Sheffield	0.11	0.08	0.93	0.15	0.62	0.15	0.72	0.13	0.10	0.13	0.47	0.17	0.06	0.16	0.70	0.23	-0.95	0.33
	Liverpool	0.06	0.08	0.47	0.15	0.18	0.15	0.40	0.14	0.06	0.13	-0.03	0.17	-0.12	0.17	0.10	0.25	-0.52	0.29
	Middlesbrough	-1.67	0.11	-1.38	0.18	-0.14	0.18	-0.30	0.16	-0.11	0.14	0.35	0.18	-1.83	0.20	-0.40	0.31	-1.48	0.49
	Hounslow	0.40	0.08	1.68	0.15	1.48	0.15	1.69	0.13	0.13	0.13	0.87	0.17	0.58	0.16	1.40	0.22	0.95	0.24
	Croydon	0.63	0.08	1.97	0.15	1.60	0.15	2.16	0.13	0.11	0.14	0.97	0.17	0.85	0.16	1.92	0.22	0.81	0.25
	Birmingham	0.28	0.08	0.95	0.15	0.49	0.15	0.78	0.13	0.28	0.13	0.25	0.17	0.32	0.17	0.49	0.24	-0.76	0.32
	Swansea	0.32	0.14	0.40	0.27	0.15	0.33	-0.38	0.36	0.36	0.26	0.47	0.32	-0.42	0.39	0.22	0.48	-0.20	0.73
	Wrexham	0.08	0.25	0.52	0.50	0.18	0.56	-2.53	1.83	0.15	0.53	0.36	0.58	0.04	0.64	1.29	0.60	-3.48	8.05
Urban/rural																			
	Rural (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
	Urban	-0.24	0.03	0.47	0.06	0.76	0.06	0.81	0.08	0.08	0.05	0.73	0.08	-0.20	0.06	1.00	0.14	1.69	0.26

Table D.0.33 – UKB males, multinomial regression model in Stata (n=85,775)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Age group (ref: <45)								
45-49	0.28***	0.07	0.04	-0.06	-0.14*	-0.10	0.08	0.20
	(0.07)	(0.05)	(0.11)	(0.06)	(0.06)	(0.09)	(0.10)	(0.17)
50-54	0.70***	0.17***	0.53***	0.09	-0.09	-0.07	-0.10	0.27
	(0.07)	(0.05)	(0.10)	(0.06)	(0.06)	(0.09)	(0.10)	(0.17)
55-59	1.33***	0.15***	0.94***	0.04	-0.25***	-0.23*	-0.23*	0.74***
	(0.06)	(0.05)	(0.10)	(0.06)	(0.06)	(0.09)	(0.10)	(0.16)
60-64	2.22***	0.34***	1.95***	0.13*	-0.36***	-0.44***	-0.51***	1.21***
	(0.06)	(0.05)	(0.09)	(0.06)	(0.08)	(0.11)	(0.12)	(0.15)
65+	3.40***	0.42***	3.07***	-0.08	-0.55***	-1.00***	-0.57**	2.14***
	(0.07)	(0.07)	(0.10)	(0.09)	(0.13)	(0.22)	(0.19)	(0.16)
Ethnic group (ref: White British)								
Other White	-0.19***	-0.04	0.14*	0.20**	0.18*	0.17	0.19	-0.18
	(0.06)	(0.05)	(0.07)	(0.06)	(0.07)	(0.10)	(0.13)	(0.15)
South Asian	-1.11***	-0.42***	-1.28***	-0.40***	-1.88***	0.66***	1.61***	0.55**
	(0.11)	(0.10)	(0.16)	(0.12)	(0.26)	(0.15)	(0.13)	(0.17)
Black	-1.01***	-0.12	-1.12***	-0.48***	-1.37***	-0.51*	-0.13	-1.03**
	(0.16)	(0.11)	(0.19)	(0.12)	(0.23)	(0.23)	(0.29)	(0.34)
Chinese	-1.02***	-0.24	-0.16	0.05	-1.35*	-18.91	-1.23	-0.66
	(0.30)	(0.25)	(0.35)	(0.28)	(0.53)	(5,375.67)	(1.01)	(0.75)
Mixed	-0.54*	-0.34	-0.25	-0.32	-0.45	-0.43	-0.26	-0.88
	(0.21)	(0.18)	(0.26)	(0.20)	(0.25)	(0.36)	(0.46)	(0.61)
Other	-1.15***	-0.23	-1.28***	-0.44**	-0.80***	-0.33	0.12	-0.79*
	(0.19)	(0.15)	(0.24)	(0.17)	(0.23)	(0.28)	(0.33)	(0.36)
Highest qualification (ref: Degree level)								
A levels/AS levels or equivalent	-0.25***	-0.20***	-0.38***	-0.24***	-0.64***	-0.60***	-0.52***	-0.78***
	(0.04)	(0.04)	(0.06)	(0.05)	(0.07)	(0.10)	(0.10)	(0.11)
O levels/GCSEs or equivalent	-0.52***	-0.51***	-0.84***	-0.72***	-0.96***	-1.23***	-0.99***	-1.24***
	(0.04)	(0.04)	(0.06)	(0.05)	(0.07)	(0.11)	(0.10)	(0.10)
CSEs or equivalent	-0.90***	-0.85***	-1.14***	-0.74***	-1.19***	-1.73***	-1.18***	-2.26***
	(0.07)	(0.07)	(0.12)	(0.09)	(0.12)	(0.21)	(0.17)	(0.28)
NVQ or HND or HNC or equivalent	-0.81***	-0.76***	-1.07***	-0.79***	-0.87***	-1.46***	-1.15***	-1.56***
	(0.05)	(0.06)	(0.08)	(0.08)	(0.09)	(0.17)	(0.15)	(0.15)
Other professional qualifications	-0.68***	-0.80***	-1.11***	-0.86***	-1.16***	-1.64***	-0.38*	-1.28***
	(0.06)	(0.08)	(0.10)	(0.11)	(0.16)	(0.27)	(0.16)	(0.18)
No qualifications	-0.75***	-0.86***	-1.02***	-0.86***	-1.09***	-1.52***	-0.72***	-1.65***
	(0.05)	(0.07)	(0.07)	(0.09)	(0.12)	(0.21)	(0.16)	(0.14)
Occupational class (ref: Higher managerial / profess)								
Lower managerial / professional	-0.19***	-0.02	-0.13*	-0.00	-0.09	0.21**	0.28***	-0.07
	(0.03)	(0.03)	(0.06)	(0.04)	(0.05)	(0.07)	(0.08)	(0.12)
Intermediate	-0.32***	0.20***	-0.26**	0.29***	0.16*	0.38***	-0.01	-0.07
	(0.05)	(0.05)	(0.08)	(0.06)	(0.07)	(0.10)	(0.12)	(0.15)
Small employers	-0.58***	-0.50***	-0.97***	-0.99***	-0.72***	-0.97***	0.32*	-0.53*
	(0.06)	(0.08)	(0.12)	(0.11)	(0.14)	(0.23)	(0.14)	(0.21)
Lower supervisory technical	-0.87***	-0.55***	-1.01***	-0.85***	-0.04	-0.41*	0.06	-1.23***
	(0.06)	(0.07)	(0.12)	(0.11)	(0.10)	(0.19)	(0.15)	(0.29)
Semi-routine	-1.15***	-0.12	-1.08***	0.16*	0.25**	-0.22	0.14	-1.00***
	(0.06)	(0.07)	(0.11)	(0.08)	(0.10)	(0.17)	(0.15)	(0.24)
Routine	-1.42***	-0.25***	-1.58***	-0.82***	-0.14	-0.36*	-0.24	-1.79***
	(0.07)	(0.07)	(0.13)	(0.10)	(0.12)	(0.18)	(0.18)	(0.33)
Not classified	6.63***	0.50	6.81***	-0.41	-0.30	-12.97	0.42	6.50***
	(0.15)	(0.28)	(0.16)	(0.47)	(0.60)	(506.00)	(0.73)	(0.18)
Household income (ref: £<18 000)								
£18,000 to 30,999	-0.96***	-0.07	-1.32***	-0.32***	-0.19	-0.43**	0.01	-1.23***
	(0.05)	(0.07)	(0.06)	(0.07)	(0.11)	(0.13)	(0.15)	(0.10)
£31,000 to 51,999	-1.74***	-0.07	-1.99***	-0.47***	-0.17	-0.61***	-0.27	-2.22***
	(0.05)	(0.07)	(0.07)	(0.07)	(0.11)	(0.13)	(0.15)	(0.11)
£52,000 to 100,000	-2.28***	0.09	-2.36***	-0.13	0.04	-0.29*	-0.22	-2.92***
	(0.06)	(0.07)	(0.08)	(0.08)	(0.11)	(0.14)	(0.16)	(0.14)
Greater than £100,000	-2.51***	0.43***	-2.78***	0.19*	0.16	-0.36*	-0.42*	-3.49***
	(0.07)	(0.08)	(0.12)	(0.09)	(0.13)	(0.17)	(0.19)	(0.24)
Household type (ref: Lives alone)								
Children, no partner	0.21*	0.29**	-0.15	-0.29*	0.29*	-0.84**	0.17	-0.49
	(0.09)	(0.09)	(0.13)	(0.12)	(0.14)	(0.28)	(0.18)	(0.30)
Partner, no children	0.88***	0.46***	0.45***	0.15**	0.53***	0.40***	0.07	0.67***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.09)	(0.10)	(0.09)
Partner and children	0.72***	0.69***	0.52***	0.30***	1.21***	0.57***	-0.19	0.54***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)	(0.09)	(0.11)	(0.12)
Lives with others	0.34***	0.29**	0.49***	0.65***	0.55***	0.16	0.12	0.46*
	(0.10)	(0.10)	(0.12)	(0.09)	(0.13)	(0.18)	(0.19)	(0.20)
Cars per household (ref: 0-1)								
2	-0.36***	-1.01***	-1.71***	-2.33***	-1.68***	-1.91***	-0.17*	-0.96***
	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)	(0.08)
3+	-0.30***	-1.36***	-2.17***	-3.10***	-2.23***	-2.81***	-0.50***	-1.13***
	(0.05)	(0.05)	(0.11)	(0.11)	(0.08)	(0.18)	(0.12)	(0.16)

Townsend score (ref: Quintile 1)								
2	0.05	0.12**	0.15*	0.20**	0.07	0.34**	0.02	-0.00
	(0.04)	(0.04)	(0.07)	(0.07)	(0.07)	(0.12)	(0.10)	(0.12)
3	-0.09*	0.19***	0.14*	0.38***	0.17*	0.52***	0.17	0.17
	(0.04)	(0.04)	(0.07)	(0.07)	(0.07)	(0.12)	(0.10)	(0.11)
4	-0.11**	0.24***	0.41***	0.68***	0.35***	0.82***	0.20*	0.28*
	(0.04)	(0.04)	(0.06)	(0.07)	(0.07)	(0.11)	(0.10)	(0.11)
5	-0.26***	0.36***	0.74***	1.10***	0.46***	1.20***	0.34**	0.31*
	(0.05)	(0.05)	(0.07)	(0.07)	(0.07)	(0.12)	(0.11)	(0.12)
Assessment Centre (ref: Manchester)								
Oxford	-0.90***	0.36**	-0.11	0.41*	1.27***	0.32	-0.34	-0.52
	(0.12)	(0.12)	(0.20)	(0.17)	(0.16)	(0.28)	(0.28)	(0.34)
Cardiff	-1.32***	0.18	-1.49***	-0.31	0.13	0.57*	-0.10	-0.88**
	(0.13)	(0.12)	(0.22)	(0.20)	(0.18)	(0.26)	(0.26)	(0.32)
Glasgow	-1.27***	0.35**	-1.03***	0.55***	-0.50*	-0.06	-0.41	-1.29***
	(0.15)	(0.12)	(0.22)	(0.16)	(0.22)	(0.30)	(0.29)	(0.36)
Edinburgh	-0.89***	0.86***	0.02	1.11***	0.88***	0.64*	-0.72*	-0.49
	(0.12)	(0.11)	(0.19)	(0.15)	(0.16)	(0.26)	(0.33)	(0.32)
Stoke	-0.43***	-0.24	-0.49*	-0.87**	-0.29	-1.56*	-0.03	-0.74*
	(0.11)	(0.14)	(0.21)	(0.27)	(0.23)	(0.62)	(0.27)	(0.37)
Reading	-0.99***	0.31**	-0.81***	0.19	0.21	0.31	-0.32	-0.81**
	(0.10)	(0.11)	(0.18)	(0.15)	(0.16)	(0.25)	(0.23)	(0.29)
Bury	-0.30**	-0.53***	-0.45*	-0.48**	-1.17***	-0.50	-0.15	-0.28
	(0.09)	(0.13)	(0.18)	(0.18)	(0.23)	(0.30)	(0.23)	(0.29)
Newcastle	-1.44***	0.11	-1.13***	0.20	-0.19	0.23	-0.32	-1.26***
	(0.11)	(0.11)	(0.18)	(0.15)	(0.17)	(0.25)	(0.24)	(0.29)
Leeds	-0.49***	0.22*	-0.26	0.11	-0.34*	0.05	-0.04	-0.18
	(0.09)	(0.10)	(0.16)	(0.14)	(0.16)	(0.24)	(0.21)	(0.27)
Bristol	-1.11***	0.21*	-0.75***	0.10	0.55***	0.41	-0.25	-0.76**
	(0.09)	(0.10)	(0.16)	(0.14)	(0.15)	(0.23)	(0.21)	(0.27)
Barts	0.32*	1.49***	1.95***	2.41***	2.07***	1.83***	-0.27	1.49***
	(0.15)	(0.14)	(0.19)	(0.16)	(0.18)	(0.25)	(0.41)	(0.31)
Nottingham	-1.21***	-0.04	-0.90***	-0.07	0.53***	0.42	0.26	-0.84**
	(0.10)	(0.11)	(0.17)	(0.16)	(0.15)	(0.24)	(0.21)	(0.28)
Sheffield	0.11	0.18	0.37*	0.20	-0.14	0.40	0.07	0.16
	(0.08)	(0.10)	(0.15)	(0.14)	(0.15)	(0.23)	(0.20)	(0.26)
Liverpool	0.12	-0.07	0.40*	-0.08	-0.27	0.03	-0.12	-0.36
	(0.08)	(0.11)	(0.16)	(0.15)	(0.16)	(0.24)	(0.21)	(0.28)
Middlesbrough	-1.47***	-0.23*	-1.52***	-0.58**	-0.33	-0.90**	-0.20	-1.76***
	(0.11)	(0.12)	(0.18)	(0.18)	(0.18)	(0.33)	(0.23)	(0.31)
Hounslow	0.53***	0.83***	1.68***	1.21***	0.74***	0.62**	-0.04	0.91***
	(0.09)	(0.10)	(0.15)	(0.13)	(0.15)	(0.22)	(0.21)	(0.26)
Croydon	0.82***	1.32***	1.97***	1.84***	0.94***	1.11***	-0.07	1.11***
	(0.09)	(0.10)	(0.15)	(0.13)	(0.15)	(0.22)	(0.23)	(0.26)
Birmingham	0.31***	0.16	0.72***	0.22	-0.10	0.15	-0.05	0.26
	(0.08)	(0.10)	(0.16)	(0.14)	(0.16)	(0.23)	(0.21)	(0.27)
Swansea	0.42**	-0.40	0.28	-0.27	0.28	0.50	-0.33	0.60
	(0.16)	(0.28)	(0.31)	(0.34)	(0.33)	(0.45)	(0.54)	(0.46)
Wrexham	0.47	-0.63	0.74	-0.92	-0.73	0.24	0.50	0.29
	(0.28)	(0.61)	(0.54)	(1.04)	(1.04)	(1.06)	(0.75)	(1.06)
Urban (ref: Rural)	-0.23***	0.32***	0.30***	0.85***	0.64***	0.54***	0.06	-0.01
	(0.04)	(0.04)	(0.07)	(0.09)	(0.08)	(0.13)	(0.09)	(0.11)
Constant	-0.27*	-1.82***	-2.07***	-2.24***	-2.47***	-2.98***	-2.60***	-2.21***
	(0.12)	(0.13)	(0.19)	(0.18)	(0.20)	(0.29)	(0.27)	(0.32)
Observations	85,775	85,775	85,775	85,775	85,775	85,775	85,775	85,775

*** p<0.001, ** p<0.01, * p<0.05

Table D.0.34 – UKB males, multinomial regression model in Latent Gold (n=85,775)

Model for Classes																
Intercept	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.
	-0.36	0.12	-2.13	0.18	-2.45	0.22	-2.26	0.21	-2.67	0.23	-3.00	0.31	-2.58	0.28	-2.14	0.33
Covariates	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.
Age group																
< 45 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
45-49	0.29	0.08	0.09	0.06	0.05	0.11	-0.07	0.06	-0.13	0.07	-0.12	0.10	0.06	0.10	0.21	0.18
50-54	0.73	0.07	0.25	0.06	0.54	0.11	0.10	0.06	-0.04	0.07	-0.08	0.10	-0.10	0.10	0.27	0.18
55-59	1.36	0.07	0.27	0.06	0.97	0.10	0.01	0.06	-0.24	0.08	-0.24	0.10	-0.23	0.11	0.72	0.16
60-64	2.26	0.07	0.52	0.06	1.96	0.10	0.05	0.07	-0.44	0.09	-0.45	0.12	-0.52	0.13	1.16	0.16
65+	3.46	0.07	0.65	0.08	3.00	0.10	-0.23	0.10	-0.66	0.17	-1.07	0.24	-0.53	0.19	2.07	0.17
Ethnic group																
White British (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Other white	-0.21	0.06	-0.06	0.07	0.16	0.08	0.21	0.07	0.21	0.08	0.22	0.11	0.18	0.13	-0.16	0.15
South Asian	-1.15	0.13	-0.49	0.13	-1.37	0.18	-0.42	0.13	-4.24	2.07	0.62	0.16	1.62	0.13	0.58	0.18
Black	-0.99	0.17	-0.07	0.14	-1.22	0.21	-0.57	0.14	-2.26	0.53	-0.45	0.24	-0.19	0.31	-1.06	0.34
Chinese	-1.08	0.34	-0.31	0.31	-0.11	0.34	0.09	0.27	-1.90	0.68	-48.10	0.00	-0.77	0.71	-0.65	0.75
Mixed	-0.59	0.22	-0.30	0.22	-0.21	0.25	-0.39	0.21	-0.43	0.29	-0.42	0.37	-0.22	0.46	-0.93	0.64
Other	-1.11	0.21	-0.16	0.19	-1.32	0.27	-0.47	0.19	-0.89	0.30	-0.31	0.31	0.28	0.32	-0.85	0.38
Household type																
Lives alone (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Children, no partner	0.25	0.10	0.46	0.12	-0.09	0.14	-0.38	0.13	0.37	0.18	-1.03	0.33	0.22	0.19	-0.43	0.29
Partner, no children	0.94	0.04	0.57	0.06	0.46	0.05	0.19	0.05	0.69	0.08	0.44	0.09	0.12	0.11	0.71	0.10
Partner and children	0.81	0.05	0.89	0.06	0.57	0.07	0.37	0.06	1.51	0.08	0.62	0.09	-0.15	0.11	0.61	0.12
Lives with others	0.37	0.11	0.43	0.14	0.62	0.12	0.75	0.10	0.58	0.18	0.22	0.20	0.16	0.20	0.55	0.21
Highest qualification																
College or University degree (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
A levels/AS levels or equivalent	-0.27	0.04	-0.26	0.05	-0.41	0.07	-0.31	0.06	-0.78	0.08	-0.63	0.10	-0.57	0.11	-0.84	0.12
O levels/GCSEs or equivalent	-0.54	0.04	-0.62	0.05	-0.97	0.06	-0.83	0.06	-1.18	0.08	-1.31	0.11	-1.03	0.11	-1.33	0.11
CSEs or equivalent	-0.94	0.08	-1.10	0.11	-1.30	0.12	-0.90	0.10	-1.40	0.14	-1.85	0.24	-1.28	0.18	-2.37	0.30
NVQ or HND or HNC or equivalent	-0.83	0.05	-0.92	0.08	-1.26	0.09	-0.90	0.09	-0.96	0.11	-1.55	0.18	-1.23	0.16	-1.73	0.17
Other professional qualifications	-0.71	0.06	-0.90	0.11	-1.28	0.11	-1.05	0.13	-1.37	0.21	-1.68	0.28	-0.43	0.16	-1.34	0.18
No qualifications	-0.80	0.05	-1.18	0.11	-1.18	0.08	-0.93	0.10	-1.26	0.15	-1.77	0.24	-0.77	0.16	-1.77	0.15

Occupational class																
Higher managerial / professional (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Lower managerial / professional	-0.17	0.03	-0.05	0.04	-0.19	0.07	0.01	0.05	-0.07	0.06	0.22	0.08	0.28	0.08	-0.10	0.12
Intermediate	-0.29	0.05	0.27	0.06	-0.28	0.09	0.33	0.06	0.17	0.08	0.43	0.10	-0.01	0.12	-0.08	0.16
Small employers	-0.56	0.07	-0.58	0.10	-1.26	0.15	-1.14	0.13	-0.82	0.16	-1.05	0.25	0.32	0.14	-0.62	0.23
Lower supervisory technical	-0.87	0.06	-0.53	0.10	-1.07	0.14	-1.01	0.13	-0.03	0.12	-0.59	0.23	0.10	0.15	-1.38	0.32
Semi-routine	-1.11	0.07	-0.04	0.09	-1.15	0.13	0.18	0.08	0.37	0.11	-0.20	0.17	0.18	0.15	-1.04	0.25
Routine	-1.37	0.07	-0.07	0.10	-1.79	0.15	-0.94	0.12	-0.15	0.15	-0.41	0.20	-0.23	0.19	-1.89	0.35
Not classified	6.70	0.17	0.83	0.31	6.90	0.18	-0.49	0.58	-1.20	1.23	-26.85	0.00	0.47	0.74	6.56	0.20
Household income																
Less than 18,000 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
18,000 to 30,999	-0.96	0.05	-0.10	0.10	-1.43	0.06	-0.37	0.08	-0.31	0.14	-0.47	0.14	0.00	0.16	-1.26	0.10
31,000 to 51,999	-1.74	0.05	-0.07	0.10	-2.08	0.07	-0.56	0.08	-0.23	0.13	-0.69	0.14	-0.28	0.16	-2.28	0.11
52,000 to 100,000	-2.26	0.06	0.15	0.11	-2.34	0.09	-0.12	0.08	0.01	0.14	-0.27	0.14	-0.25	0.17	-2.95	0.15
Greater than 100,000	-2.49	0.08	0.58	0.11	-2.49	0.13	0.25	0.10	0.13	0.15	-0.30	0.18	-0.42	0.20	-3.55	0.27
Cars per household																
0-1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	-0.37	0.03	-1.14	0.04	-2.25	0.07	-2.71	0.06	-2.02	0.06	-2.15	0.09	-0.20	0.08	-1.08	0.09
3+	-0.34	0.05	-1.64	0.06	-3.08	0.19	-3.53	0.14	-2.73	0.11	-3.18	0.23	-0.56	0.13	-1.34	0.18
Urban/rural																
Rural (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Urban	-0.22	0.04	0.37	0.06	0.62	0.10	0.91	0.11	0.81	0.09	0.59	0.15	0.07	0.09	-0.02	0.12
Townsend score																
1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	0.05	0.04	0.14	0.05	0.33	0.08	0.27	0.08	0.06	0.08	0.36	0.14	0.04	0.10	0.01	0.13
3	-0.09	0.04	0.24	0.05	0.36	0.08	0.46	0.08	0.20	0.08	0.55	0.13	0.18	0.10	0.19	0.12
4	-0.11	0.04	0.29	0.05	0.72	0.08	0.78	0.08	0.39	0.08	0.89	0.13	0.21	0.10	0.34	0.12
5	-0.30	0.05	0.36	0.06	1.09	0.08	1.25	0.08	0.56	0.09	1.31	0.13	0.33	0.12	0.40	0.13
Assessment Centre																
Manchester (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Oxford	-0.90	0.13	0.53	0.16	0.22	0.23	0.45	0.20	1.48	0.18	0.28	0.31	-0.28	0.29	-0.43	0.37
Cardiff	-1.30	0.14	0.31	0.16	-1.55	0.26	-0.29	0.22	0.23	0.20	0.56	0.28	-0.02	0.26	-0.80	0.34
Glasgow	-1.25	0.15	0.48	0.16	-0.86	0.23	0.64	0.18	-0.74	0.28	0.03	0.30	-0.40	0.31	-1.27	0.39
Edinburgh	-0.82	0.13	1.14	0.14	0.27	0.21	1.26	0.17	1.02	0.18	0.76	0.27	-0.70	0.34	-0.35	0.34
Stoke	-0.44	0.11	-0.34	0.20	-0.63	0.25	-0.83	0.30	-0.40	0.29	-1.90	0.93	-0.04	0.28	-0.71	0.40
Reading	-0.97	0.10	0.48	0.14	-0.64	0.20	0.21	0.18	0.36	0.18	0.31	0.26	-0.30	0.24	-0.74	0.31

Bury	-0.30	0.09	-0.63	0.18	-0.51	0.20	-0.42	0.19	-1.42	0.31	-0.56	0.32	-0.12	0.24	-0.29	0.31
Newcastle	-1.42	0.12	0.23	0.14	-1.11	0.20	0.25	0.16	-0.27	0.19	0.28	0.25	-0.31	0.24	-1.23	0.30
Leeds	-0.47	0.09	0.32	0.13	-0.23	0.18	0.23	0.16	-0.46	0.19	0.09	0.25	-0.01	0.22	-0.13	0.28
Bristol	-1.10	0.09	0.31	0.13	-0.61	0.18	0.12	0.16	0.72	0.16	0.41	0.24	-0.23	0.21	-0.65	0.28
Barts	0.41	0.19	1.88	0.21	2.41	0.22	2.88	0.19	2.53	0.22	2.24	0.27	-0.27	0.55	1.95	0.33
Nottingham	-1.21	0.10	0.04	0.14	-0.82	0.19	-0.09	0.18	0.63	0.17	0.40	0.25	0.29	0.22	-0.80	0.29
Sheffield	0.13	0.08	0.29	0.13	0.43	0.17	0.28	0.15	-0.23	0.18	0.43	0.23	0.06	0.21	0.21	0.27
Liverpool	0.13	0.08	0.02	0.14	0.44	0.17	0.00	0.16	-0.38	0.19	0.02	0.25	-0.08	0.22	-0.33	0.29
Middlesbrough	-1.47	0.12	-0.13	0.15	-1.42	0.20	-0.61	0.20	-0.50	0.22	-1.01	0.37	-0.22	0.24	-1.77	0.33
Hounslow	0.56	0.09	1.05	0.13	1.94	0.16	1.42	0.15	0.86	0.17	0.75	0.23	0.06	0.21	1.07	0.27
Croydon	0.90	0.09	1.59	0.13	2.33	0.16	2.18	0.15	1.08	0.17	1.33	0.23	0.05	0.23	1.37	0.27
Birmingham	0.32	0.08	0.27	0.14	0.79	0.17	0.31	0.15	-0.16	0.18	0.21	0.24	-0.05	0.22	0.33	0.28
Swansea	0.41	0.16	-0.76	0.47	0.16	0.36	-0.18	0.36	0.28	0.35	0.45	0.48	-0.30	0.55	0.67	0.47
Wrexham	0.47	0.28	-0.31	0.66	1.15	0.46	-1.27	1.18	-0.92	1.24	0.34	0.98	0.53	0.74	0.44	1.09

Table D.0.35 – UKB males, multinomial regression model in Latent Gold, including missing (n=94,781)

Model for Classes																
Intercept	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.
	-0.29	0.11	-1.88	0.17	-2.40	0.21	-2.26	0.20	-2.67	0.23	-2.99	0.30	-2.58	0.27	-2.45	0.32
Covariates	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Cluster6	s.e.	Cluster7	s.e.	Cluster8	s.e.	Cluster9	s.e.
Age group																
< 45 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
45-49	0.28	0.07	0.10	0.06	0.00	0.10	-0.09	0.06	-0.14	0.07	-0.11	0.09	0.10	0.10	0.18	0.16
50-54	0.71	0.07	0.24	0.05	0.47	0.10	0.07	0.06	-0.09	0.07	-0.14	0.09	-0.05	0.10	0.29	0.16
55-59	1.33	0.06	0.25	0.06	0.88	0.09	0.01	0.06	-0.27	0.07	-0.26	0.10	-0.18	0.11	0.73	0.15
60-64	2.21	0.06	0.48	0.06	1.87	0.09	0.03	0.07	-0.50	0.09	-0.52	0.12	-0.46	0.12	1.19	0.14
65+	3.43	0.07	0.64	0.08	2.97	0.09	-0.26	0.10	-0.69	0.16	-1.11	0.23	-0.54	0.19	2.14	0.15
Ethnic group																
White British (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Other white	-0.18	0.05	-0.05	0.07	0.21	0.07	0.23	0.06	0.19	0.08	0.21	0.11	0.13	0.13	-0.03	0.13
South Asian	-1.02	0.11	-0.45	0.13	-1.16	0.16	-0.40	0.13	-3.12	0.63	0.71	0.15	1.68	0.12	0.96	0.15
Black	-0.82	0.15	-0.04	0.14	-0.87	0.17	-0.49	0.13	-2.22	0.47	-0.26	0.22	-0.13	0.30	-0.55	0.25
Chinese	-0.23	0.26	0.19	0.28	0.56	0.29	0.32	0.28	-1.12	0.51	-2.57	0.87	-0.55	0.64	0.73	0.39
Mixed	-0.31	0.19	-0.28	0.22	0.23	0.21	-0.42	0.21	-0.32	0.26	-0.22	0.33	-0.03	0.41	0.13	0.32
Other	-0.63	0.18	-0.01	0.19	-0.61	0.22	-0.24	0.18	-0.73	0.28	-0.15	0.30	0.27	0.32	0.02	0.27
Household type																
Lives alone (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Children, no partner	0.27	0.09	0.42	0.12	0.02	0.12	-0.38	0.13	0.37	0.17	-0.84	0.29	0.16	0.19	-0.20	0.20
Partner, no children	0.86	0.04	0.52	0.06	0.35	0.05	0.17	0.05	0.65	0.08	0.43	0.09	0.13	0.11	0.49	0.09
Partner and children	0.71	0.05	0.85	0.06	0.43	0.07	0.35	0.05	1.46	0.08	0.57	0.09	-0.12	0.11	0.33	0.11
Lives with others	0.38	0.09	0.46	0.13	0.88	0.10	0.88	0.09	0.75	0.16	0.61	0.16	0.06	0.20	0.73	0.16
Highest qualification																
College or University degree (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
A levels/AS levels or equivalent	-0.25	0.04	-0.28	0.05	-0.41	0.06	-0.29	0.06	-0.80	0.08	-0.65	0.10	-0.58	0.10	-0.76	0.11
O levels/GCSEs or equivalent	-0.52	0.04	-0.64	0.05	-0.93	0.06	-0.82	0.06	-1.17	0.08	-1.34	0.11	-1.00	0.10	-1.21	0.10
CSEs or equivalent	-0.88	0.07	-1.12	0.10	-1.24	0.11	-0.86	0.10	-1.42	0.14	-1.92	0.23	-1.23	0.17	-2.01	0.22
NVQ or HND or HNC or equivalent	-0.80	0.05	-0.90	0.07	-1.22	0.08	-0.87	0.09	-0.98	0.11	-1.53	0.18	-1.13	0.14	-1.63	0.15
Other professional qualifications	-0.63	0.06	-0.84	0.10	-1.19	0.10	-1.07	0.12	-1.38	0.21	-1.75	0.27	-0.41	0.15	-1.13	0.16
No qualifications	-0.72	0.05	-1.28	0.10	-1.02	0.07	-0.95	0.09	-1.28	0.15	-1.67	0.21	-0.78	0.15	-1.44	0.12

Occupational class																
Higher managerial / professional (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Lower managerial / professional	-0.15	0.03	-0.05	0.04	-0.14	0.06	0.02	0.05	-0.04	0.06	0.21	0.07	0.30	0.08	-0.03	0.11
Intermediate	-0.21	0.04	0.28	0.05	-0.17	0.08	0.37	0.06	0.17	0.08	0.45	0.10	0.06	0.12	0.00	0.15
Small employers	-0.42	0.06	-0.52	0.10	-1.03	0.13	-1.11	0.12	-0.79	0.16	-0.96	0.24	0.35	0.14	-0.39	0.19
Lower supervisory technical	-0.74	0.06	-0.50	0.09	-0.90	0.12	-0.95	0.12	0.00	0.12	-0.55	0.22	0.16	0.14	-0.98	0.23
Semi-routine	-0.93	0.06	0.02	0.08	-0.96	0.11	0.22	0.08	0.39	0.11	-0.09	0.16	0.17	0.15	-0.75	0.20
Routine	-1.21	0.07	-0.07	0.09	-1.50	0.13	-0.88	0.11	-0.15	0.14	-0.35	0.18	-0.12	0.17	-1.56	0.25
Not classified	6.97	0.23	-376.45	0.00	7.23	0.24	-375.28	0.00	-371.24	0.00	-367.13	0.00	-361.61	0.00	6.90	0.25
Household income																
Less than 18,000 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
18,000 to 30,999	-0.98	0.05	-0.22	0.10	-1.42	0.06	-0.39	0.08	-0.30	0.15	-0.49	0.14	-0.06	0.15	-1.19	0.09
31,000 to 51,999	-1.73	0.05	-0.22	0.10	-2.00	0.07	-0.57	0.08	-0.22	0.14	-0.70	0.14	-0.36	0.15	-2.09	0.11
52,000 to 100,000	-2.20	0.06	0.01	0.10	-2.20	0.08	-0.14	0.08	0.03	0.14	-0.27	0.14	-0.32	0.16	-2.62	0.14
Greater than 100,000	-2.33	0.07	0.45	0.11	-2.19	0.12	0.25	0.10	0.17	0.16	-0.31	0.17	-0.46	0.19	-2.78	0.19
Cars per household																
0-1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	-0.41	0.03	-1.13	0.04	-2.21	0.06	-2.67	0.06	-2.01	0.06	-2.11	0.08	-0.19	0.08	-1.11	0.08
3+	-0.37	0.04	-1.59	0.06	-2.72	0.12	-3.46	0.13	-2.73	0.11	-2.93	0.20	-0.54	0.12	-1.32	0.15
Urban/rural																
Rural (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Urban	-0.22	0.04	0.34	0.05	0.59	0.09	0.89	0.10	0.81	0.09	0.65	0.15	0.05	0.09	0.05	0.11
Townsend score																
1 (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
2	0.03	0.03	0.12	0.05	0.34	0.08	0.28	0.08	0.07	0.08	0.37	0.14	0.03	0.10	0.06	0.12
3	-0.09	0.04	0.22	0.05	0.35	0.07	0.47	0.08	0.22	0.08	0.56	0.13	0.13	0.10	0.23	0.11
4	-0.13	0.04	0.29	0.05	0.73	0.07	0.80	0.07	0.38	0.07	0.91	0.12	0.19	0.10	0.35	0.11
5	-0.29	0.05	0.39	0.06	1.09	0.07	1.28	0.08	0.56	0.08	1.32	0.12	0.33	0.11	0.48	0.12
Assessment Centre																
Manchester (ref)	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.	0.00	.
Oxford	-0.92	0.12	0.46	0.15	0.15	0.22	0.54	0.19	1.50	0.18	0.26	0.29	-0.23	0.28	-0.31	0.36
Cardiff	-1.30	0.14	0.23	0.15	-1.51	0.24	-0.27	0.21	0.24	0.20	0.43	0.27	-0.03	0.25	-0.71	0.33
Glasgow	-1.25	0.15	0.48	0.15	-0.88	0.22	0.66	0.17	-0.67	0.27	0.02	0.29	-0.48	0.31	-1.18	0.37
Edinburgh	-0.79	0.13	1.12	0.14	0.26	0.20	1.28	0.16	1.06	0.18	0.72	0.26	-0.71	0.33	-0.26	0.33
Stoke	-0.41	0.11	-0.40	0.19	-0.72	0.24	-0.84	0.30	-0.39	0.28	-1.87	0.82	-0.08	0.27	-0.66	0.39
Reading	-0.93	0.10	0.47	0.13	-0.62	0.19	0.26	0.17	0.46	0.17	0.23	0.25	-0.26	0.23	-0.59	0.30
Bury	-0.29	0.09	-0.61	0.17	-0.53	0.19	-0.39	0.19	-1.48	0.32	-0.64	0.31	-0.10	0.23	-0.20	0.30

Newcastle	-1.39	0.11	0.21	0.14	-1.05	0.18	0.23	0.16	-0.25	0.19	0.20	0.24	-0.26	0.24	-1.19	0.30
Leeds	-0.47	0.09	0.28	0.13	-0.24	0.17	0.21	0.15	-0.41	0.19	0.03	0.24	0.03	0.21	0.01	0.27
Bristol	-1.05	0.09	0.31	0.13	-0.59	0.17	0.14	0.16	0.75	0.16	0.32	0.22	-0.20	0.21	-0.47	0.27
Barts	0.46	0.18	1.91	0.20	2.39	0.21	2.94	0.19	2.60	0.22	2.20	0.26	-0.03	0.49	2.01	0.32
Nottingham	-1.17	0.10	0.03	0.14	-0.83	0.18	-0.11	0.18	0.66	0.17	0.32	0.24	0.28	0.21	-0.62	0.28
Sheffield	0.15	0.08	0.23	0.13	0.47	0.16	0.29	0.15	-0.19	0.18	0.35	0.22	0.07	0.21	0.28	0.26
Liverpool	0.16	0.08	0.01	0.13	0.47	0.16	0.03	0.16	-0.36	0.19	-0.04	0.24	-0.07	0.21	-0.14	0.28
Middlesbrough	-1.43	0.11	-0.14	0.15	-1.40	0.19	-0.67	0.20	-0.40	0.21	-1.06	0.36	-0.20	0.23	-1.52	0.31
Hounslow	0.55	0.08	1.06	0.12	1.85	0.15	1.44	0.14	0.89	0.17	0.68	0.22	0.13	0.21	1.08	0.26
Croydon	0.88	0.08	1.58	0.12	2.29	0.16	2.18	0.14	1.13	0.17	1.30	0.22	0.08	0.23	1.49	0.26
Birmingham	0.35	0.08	0.24	0.13	0.80	0.16	0.30	0.15	-0.11	0.18	0.13	0.23	-0.01	0.21	0.55	0.26
Swansea	0.37	0.15	-0.86	0.45	0.23	0.32	-0.24	0.36	0.30	0.34	0.46	0.45	-0.40	0.55	0.69	0.46
Wrexham	0.38	0.26	-0.49	0.67	0.98	0.45	-1.37	1.16	-0.95	1.21	0.20	0.97	0.41	0.74	0.37	1.12

Table D.0.36 – UKB females, multinomial regression model in Stata with participants from London removed (n=78,295)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Age (ref: 65+)									
< 45	0.04***	0.02***	0.81	0.88	2.07***	0.72*	0.08***	1.39	1.21
	(0.03 - 0.04)	(0.02 - 0.03)	(0.65 - 1.01)	(0.67 - 1.16)	(1.47 - 2.91)	(0.53 - 0.99)	(0.06 - 0.10)	(0.85 - 2.29)	(0.57 - 2.58)
45-49	0.04***	0.02***	0.91	1.08	1.66**	0.86	0.05***	1.30	1.57
	(0.03 - 0.04)	(0.02 - 0.03)	(0.73 - 1.14)	(0.82 - 1.41)	(1.18 - 2.34)	(0.63 - 1.17)	(0.04 - 0.07)	(0.79 - 2.13)	(0.74 - 3.32)
50-54	0.04***	0.04***	0.95	1.26	1.49*	1.04	0.07***	1.16	1.28
	(0.04 - 0.05)	(0.03 - 0.05)	(0.76 - 1.18)	(0.97 - 1.65)	(1.06 - 2.09)	(0.77 - 1.42)	(0.06 - 0.09)	(0.71 - 1.91)	(0.61 - 2.69)
55-59	0.08***	0.08***	0.86	1.33*	1.40	1.20	0.12***	1.22	1.05
	(0.07 - 0.09)	(0.07 - 0.09)	(0.69 - 1.07)	(1.02 - 1.72)	(1.00 - 1.96)	(0.89 - 1.63)	(0.10 - 0.14)	(0.75 - 1.99)	(0.50 - 2.21)
60-64	0.34***	0.38***	0.98	1.23	1.13	1.10	0.43***	1.21	0.92
	(0.31 - 0.38)	(0.34 - 0.43)	(0.79 - 1.23)	(0.94 - 1.61)	(0.80 - 1.61)	(0.81 - 1.50)	(0.37 - 0.51)	(0.73 - 2.01)	(0.42 - 2.01)
Ethnic group (ref: Other white)									
White British	1.05	0.83*	0.91	0.85*	0.98	0.99	1.05	0.89	0.71*
	(0.92 - 1.20)	(0.70 - 0.99)	(0.80 - 1.03)	(0.72 - 0.99)	(0.83 - 1.15)	(0.82 - 1.20)	(0.82 - 1.33)	(0.69 - 1.13)	(0.52 - 0.97)
South Asian	0.58*	0.58	0.52*	1.19	3.01***	0.42*	1.95*	2.29**	0.00
	(0.37 - 0.92)	(0.31 - 1.07)	(0.32 - 0.86)	(0.76 - 1.86)	(2.12 - 4.28)	(0.19 - 0.89)	(1.06 - 3.58)	(1.30 - 4.03)	(0.00 - .)
Black	0.46**	0.29***	0.53**	0.98	0.54*	0.39**	0.27**	0.42*	0.20*
	(0.28 - 0.75)	(0.15 - 0.58)	(0.35 - 0.80)	(0.67 - 1.45)	(0.32 - 0.90)	(0.21 - 0.74)	(0.11 - 0.69)	(0.19 - 0.92)	(0.05 - 0.86)
Chinese	0.64	0.61	0.72	0.53	0.56	0.55	0.19	0.29	0.18
	(0.31 - 1.32)	(0.24 - 1.57)	(0.40 - 1.29)	(0.23 - 1.23)	(0.22 - 1.41)	(0.21 - 1.46)	(0.02 - 1.53)	(0.06 - 1.35)	(0.02 - 1.41)
Mixed	1.01	0.93	0.68	0.82	1.00	0.91	1.50	0.68	0.54
	(0.64 - 1.59)	(0.51 - 1.69)	(0.43 - 1.07)	(0.48 - 1.38)	(0.61 - 1.65)	(0.50 - 1.66)	(0.76 - 2.99)	(0.28 - 1.63)	(0.16 - 1.82)
Other	0.61	0.72	0.73	0.99	0.91	0.61	0.35	0.58	0.34
	(0.36 - 1.05)	(0.37 - 1.41)	(0.45 - 1.20)	(0.57 - 1.72)	(0.50 - 1.65)	(0.29 - 1.27)	(0.11 - 1.05)	(0.22 - 1.53)	(0.08 - 1.50)
Qualifications (ref: GSCEs)									
College or University degree	1.30***	1.43***	1.35***	0.90	2.00***	1.17*	2.74***	2.42***	3.12***
	(1.20 - 1.41)	(1.28 - 1.60)	(1.24 - 1.48)	(0.81 - 1.01)	(1.78 - 2.26)	(1.03 - 1.33)	(2.35 - 3.18)	(1.97 - 2.97)	(2.24 - 4.36)
A levels/AS levels or equivalent	1.34***	1.29***	1.23***	0.99	1.38***	1.27**	1.98***	1.49**	1.50*
	(1.21 - 1.47)	(1.13 - 1.47)	(1.12 - 1.36)	(0.87 - 1.13)	(1.20 - 1.59)	(1.10 - 1.46)	(1.65 - 2.38)	(1.17 - 1.91)	(1.00 - 2.26)
CSEs or equivalent	0.76**	0.80*	0.74***	0.88	0.69**	1.16	0.56**	0.62*	1.09
	(0.65 - 0.90)	(0.64 - 0.99)	(0.63 - 0.87)	(0.73 - 1.05)	(0.54 - 0.89)	(0.97 - 1.39)	(0.39 - 0.81)	(0.41 - 0.94)	(0.61 - 1.93)
NVQ or HND or HNC or equivalent	0.67***	0.65***	0.76**	0.75**	1.09	0.77*	0.50***	0.72	1.00
	(0.57 - 0.79)	(0.52 - 0.81)	(0.63 - 0.91)	(0.61 - 0.93)	(0.86 - 1.39)	(0.61 - 0.96)	(0.34 - 0.72)	(0.46 - 1.11)	(0.50 - 1.99)
Other professional qualifications	0.98	0.83*	0.69***	0.53***	1.11	0.85	1.26	0.93	1.37
	(0.86 - 1.12)	(0.70 - 1.00)	(0.58 - 0.82)	(0.42 - 0.67)	(0.89 - 1.37)	(0.67 - 1.09)	(0.99 - 1.60)	(0.61 - 1.42)	(0.74 - 2.53)
No qualifications	0.97	1.14	0.70***	0.85	0.53***	1.01	0.82	0.67	1.19
	(0.86 - 1.09)	(0.99 - 1.32)	(0.59 - 0.84)	(0.70 - 1.01)	(0.38 - 0.74)	(0.84 - 1.22)	(0.66 - 1.03)	(0.44 - 1.01)	(0.64 - 2.22)
Occup Class (ref: Small employers)									
Higher managerial / professional	0.37***	0.23***	1.12	1.33	0.98	0.76	0.37***	1.46	0.95
	(0.32 - 0.43)	(0.18 - 0.31)	(0.92 - 1.37)	(0.99 - 1.78)	(0.76 - 1.26)	(0.55 - 1.03)	(0.26 - 0.53)	(0.90 - 2.35)	(0.55 - 1.63)
Lower managerial / professional	0.34***	0.28***	0.87	0.90	0.97	0.77	0.32***	0.96	0.62
	(0.30 - 0.39)	(0.22 - 0.35)	(0.72 - 1.06)	(0.68 - 1.19)	(0.76 - 1.24)	(0.57 - 1.03)	(0.23 - 0.44)	(0.60 - 1.53)	(0.37 - 1.06)
Intermediate	0.29***	0.28***	1.27*	1.85***	0.83	1.37*	0.23***	1.77*	0.97
	(0.25 - 0.34)	(0.22 - 0.35)	(1.04 - 1.55)	(1.39 - 2.47)	(0.64 - 1.07)	(1.02 - 1.85)	(0.16 - 0.32)	(1.10 - 2.87)	(0.55 - 1.69)
Lower supervisory technical	0.36***	0.32**	1.31	0.80	0.80	1.39	0.48	1.33	0.69
	(0.24 - 0.53)	(0.16 - 0.66)	(0.88 - 1.94)	(0.42 - 1.53)	(0.45 - 1.43)	(0.78 - 2.48)	(0.20 - 1.18)	(0.51 - 3.47)	(0.15 - 3.08)

Semi-routine	0.20***	0.23***	1.38**	1.23	1.02	2.85***	0.17***	1.63	1.31
	(0.17 - 0.24)	(0.17 - 0.30)	(1.12 - 1.71)	(0.91 - 1.66)	(0.77 - 1.33)	(2.11 - 3.85)	(0.11 - 0.26)	(0.98 - 2.71)	(0.73 - 2.37)
Routine	0.33***	0.30***	1.58**	1.07	1.14	3.49***	0.27***	0.95	1.36
	(0.26 - 0.42)	(0.21 - 0.43)	(1.19 - 2.11)	(0.73 - 1.59)	(0.76 - 1.71)	(2.45 - 4.97)	(0.14 - 0.50)	(0.45 - 2.03)	(0.59 - 3.14)
Not classified	736.85***	607.42***	0.59	1.51	0.49	1.00	581.30***	1.44	0.00
	(535.27 - 1,014.35)	(420.01 - 878.44)	(0.23 - 1.51)	(0.68 - 3.38)	(0.12 - 2.04)	(0.35 - 2.89)	(380.57 - 887.91)	(0.32 - 6.38)	(0.00 - .)
Hhold income (ref: <£31,000- 51,999)									
Less than 18,000	3.75***	3.72***	1.05	0.83*	1.06	1.03	4.88***	1.22	1.05
	(3.39 - 4.16)	(3.27 - 4.25)	(0.92 - 1.19)	(0.71 - 0.96)	(0.90 - 1.25)	(0.87 - 1.21)	(4.10 - 5.82)	(0.95 - 1.57)	(0.71 - 1.54)
18,000 to 30,999	1.79***	1.78***	1.03	1.08	0.98	1.12	1.92***	1.21*	1.04
	(1.66 - 1.94)	(1.60 - 1.98)	(0.94 - 1.12)	(0.97 - 1.20)	(0.87 - 1.10)	(0.99 - 1.26)	(1.65 - 2.23)	(1.00 - 1.45)	(0.79 - 1.37)
52,000 to 100,000	0.79***	0.69***	0.94	0.96	0.99	0.86*	0.65***	1.00	0.80
	(0.72 - 0.86)	(0.60 - 0.80)	(0.87 - 1.02)	(0.86 - 1.08)	(0.90 - 1.10)	(0.76 - 0.98)	(0.54 - 0.79)	(0.83 - 1.21)	(0.62 - 1.04)
Greater than 100,000	1.04	0.66**	0.99	0.95	0.73**	0.95	0.77	0.77	0.90
	(0.90 - 1.20)	(0.50 - 0.88)	(0.87 - 1.13)	(0.76 - 1.19)	(0.61 - 0.88)	(0.74 - 1.21)	(0.57 - 1.04)	(0.52 - 1.13)	(0.58 - 1.38)
Household Structure (ref: Partner only)									
Live alone	0.35***	0.08***	0.39***	0.19***	0.94	0.20***	0.28***	0.22***	0.20***
	(0.31 - 0.38)	(0.07 - 0.09)	(0.35 - 0.44)	(0.17 - 0.22)	(0.82 - 1.07)	(0.17 - 0.23)	(0.24 - 0.33)	(0.18 - 0.27)	(0.15 - 0.28)
Child(ren), no partner	0.31***	0.14***	0.50***	0.30***	0.89	0.38***	0.25***	0.29***	0.34***
	(0.27 - 0.35)	(0.11 - 0.17)	(0.44 - 0.57)	(0.26 - 0.35)	(0.77 - 1.03)	(0.32 - 0.46)	(0.19 - 0.33)	(0.23 - 0.38)	(0.23 - 0.49)
Partner and child(ren)	0.86***	1.32***	1.36***	1.27***	0.87*	1.71***	1.01	1.07	1.40**
	(0.79 - 0.93)	(1.17 - 1.49)	(1.26 - 1.47)	(1.15 - 1.42)	(0.78 - 0.97)	(1.52 - 1.91)	(0.85 - 1.19)	(0.89 - 1.28)	(1.09 - 1.80)
Live with others	0.53***	0.28***	0.74*	0.63***	1.27	0.39***	0.94	0.57*	0.72
	(0.42 - 0.67)	(0.21 - 0.39)	(0.58 - 0.94)	(0.48 - 0.82)	(0.98 - 1.65)	(0.27 - 0.56)	(0.66 - 1.34)	(0.37 - 0.88)	(0.40 - 1.29)
Cars per household (ref: 2)									
None	1.75**	1,064***	32.51***	1,708***	0.97	368***	87.99***	1,130***	741***
	(1.17 - 2.62)	(7501 - 1,509)	(22.46 - 47.07)	(1,227 - 2,377)	(0.35 - 2.72)	(260 - 521)	(59.65 - 129.81)	(764 - 1,670)	(457 - 1,201)
One	1.28***	6.41***	2.77***	7.89***	1.35***	4.50***	2.17***	7.49***	7.30***
	(1.19 - 1.39)	(5.78 - 7.10)	(2.56 - 2.99)	(7.10 - 8.76)	(1.22 - 1.51)	(4.04 - 5.01)	(1.89 - 2.48)	(6.21 - 9.03)	(5.63 - 9.45)
Three	0.88*	0.72**	0.73***	0.59***	0.73***	0.56***	0.79	0.57**	0.85
	(0.79 - 0.98)	(0.58 - 0.88)	(0.66 - 0.81)	(0.48 - 0.73)	(0.63 - 0.84)	(0.46 - 0.68)	(0.63 - 1.01)	(0.38 - 0.87)	(0.53 - 1.35)
Four or more	1.27**	0.90	0.83*	0.35***	0.82	0.44***	0.94	0.36*	0.13*
	(1.08 - 1.50)	(0.63 - 1.30)	(0.70 - 0.99)	(0.22 - 0.55)	(0.65 - 1.03)	(0.31 - 0.62)	(0.61 - 1.44)	(0.15 - 0.88)	(0.02 - 0.90)
Townsend score (ref: Quintile 1)									
2	0.89**	1.02	0.98	1.19*	1.08	1.13	0.88	1.08	1.55*
	(0.82 - 0.97)	(0.91 - 1.14)	(0.90 - 1.07)	(1.04 - 1.35)	(0.96 - 1.22)	(0.97 - 1.31)	(0.75 - 1.03)	(0.85 - 1.37)	(1.08 - 2.23)
3	0.82***	1.09	1.06	1.24**	1.21**	1.33***	0.84*	1.25	1.73**
	(0.76 - 0.90)	(0.97 - 1.22)	(0.97 - 1.16)	(1.08 - 1.41)	(1.08 - 1.36)	(1.15 - 1.54)	(0.72 - 0.99)	(0.99 - 1.57)	(1.21 - 2.46)
4	0.78***	1.19**	1.19***	1.60***	1.37***	1.89***	1.10	1.65***	2.44***
	(0.72 - 0.86)	(1.05 - 1.35)	(1.08 - 1.30)	(1.41 - 1.82)	(1.21 - 1.55)	(1.64 - 2.17)	(0.93 - 1.29)	(1.33 - 2.06)	(1.74 - 3.43)
5	0.65***	1.09	1.30***	1.80***	1.35***	2.18***	0.81*	1.80***	2.26***
	(0.58 - 0.73)	(0.95 - 1.26)	(1.17 - 1.45)	(1.56 - 2.06)	(1.17 - 1.57)	(1.86 - 2.54)	(0.66 - 0.98)	(1.42 - 2.28)	(1.55 - 3.30)
Assessment Centre (ref: Manchester)									
Oxford	0.31***	0.69*	3.25***	1.53**	1.09	2.01***	0.43***	1.99*	6.59***
	(0.24 - 0.39)	(0.50 - 0.97)	(2.56 - 4.14)	(1.11 - 2.11)	(0.80 - 1.48)	(1.37 - 2.95)	(0.28 - 0.65)	(1.17 - 3.37)	(4.05 - 10.71)
Cardiff	0.18***	0.21***	1.33*	0.83	1.26	1.51*	0.16***	1.49	0.67
	(0.13 - 0.24)	(0.14 - 0.31)	(1.02 - 1.72)	(0.59 - 1.18)	(0.94 - 1.69)	(1.03 - 2.22)	(0.10 - 0.26)	(0.87 - 2.55)	(0.34 - 1.34)
Glasgow	0.19***	0.20***	1.44**	1.68**	0.74	1.26	0.13***	1.12	0.13***
	(0.14 - 0.26)	(0.14 - 0.31)	(1.10 - 1.88)	(1.23 - 2.30)	(0.53 - 1.05)	(0.85 - 1.89)	(0.08 - 0.22)	(0.64 - 1.96)	(0.04 - 0.44)
Edinburgh	0.32***	0.58**	3.21***	3.40***	0.89	2.90***	0.27***	2.73***	1.35
	(0.25 - 0.40)	(0.41 - 0.81)	(2.54 - 4.06)	(2.57 - 4.50)	(0.65 - 1.23)	(2.04 - 4.10)	(0.17 - 0.42)	(1.70 - 4.40)	(0.77 - 2.36)

Stoke	0.73**	0.80	1.12	0.44**	1.18	1.23	0.72	0.70	0.37
	(0.58 - 0.91)	(0.55 - 1.15)	(0.82 - 1.53)	(0.27 - 0.72)	(0.84 - 1.67)	(0.79 - 1.92)	(0.46 - 1.13)	(0.32 - 1.53)	(0.13 - 1.10)
Reading	0.28***	0.32***	1.89***	1.13	0.95	2.04***	0.24***	1.61	1.19
	(0.23 - 0.34)	(0.23 - 0.43)	(1.50 - 2.37)	(0.84 - 1.53)	(0.72 - 1.24)	(1.45 - 2.87)	(0.16 - 0.35)	(0.98 - 2.66)	(0.68 - 2.09)
Bury	0.70***	0.71*	0.86	0.77	1.12	0.92	0.60**	0.85	0.15***
	(0.58 - 0.85)	(0.52 - 0.96)	(0.66 - 1.12)	(0.56 - 1.07)	(0.84 - 1.49)	(0.62 - 1.34)	(0.40 - 0.88)	(0.48 - 1.49)	(0.05 - 0.43)
Newcastle	0.17***	0.23***	1.25	1.20	0.85	0.89	0.15***	1.09	0.38**
	(0.13 - 0.21)	(0.16 - 0.31)	(0.98 - 1.58)	(0.90 - 1.59)	(0.64 - 1.13)	(0.62 - 1.28)	(0.10 - 0.22)	(0.66 - 1.78)	(0.20 - 0.73)
Leeds	0.47***	0.54***	1.41**	1.24	1.15	1.55**	0.44***	1.45	0.29***
	(0.39 - 0.56)	(0.41 - 0.72)	(1.12 - 1.77)	(0.94 - 1.63)	(0.89 - 1.49)	(1.11 - 2.15)	(0.31 - 0.63)	(0.91 - 2.31)	(0.15 - 0.56)
Bristol	0.25***	0.35***	2.13***	0.93	1.22	2.58***	0.28***	1.88**	1.41
	(0.21 - 0.30)	(0.26 - 0.46)	(1.72 - 2.65)	(0.71 - 1.22)	(0.95 - 1.57)	(1.89 - 3.53)	(0.20 - 0.40)	(1.21 - 2.93)	(0.87 - 2.28)
Nottingham	0.27***	0.44***	1.61***	1.32	1.14	1.86***	0.28***	1.59	0.65
	(0.22 - 0.33)	(0.32 - 0.59)	(1.28 - 2.03)	(0.99 - 1.76)	(0.87 - 1.48)	(1.33 - 2.60)	(0.20 - 0.41)	(0.98 - 2.58)	(0.36 - 1.19)
Sheffield	1.05	1.55**	1.48***	1.51**	1.06	1.44*	0.92	1.62*	0.39**
	(0.89 - 1.24)	(1.19 - 2.03)	(1.19 - 1.85)	(1.16 - 1.96)	(0.82 - 1.37)	(1.04 - 1.99)	(0.66 - 1.28)	(1.03 - 2.53)	(0.22 - 0.70)
Liverpool	1.02	1.15	1.08	1.11	1.03	0.87	0.82	0.96	0.54*
	(0.86 - 1.20)	(0.88 - 1.51)	(0.86 - 1.36)	(0.85 - 1.46)	(0.80 - 1.34)	(0.62 - 1.22)	(0.59 - 1.16)	(0.59 - 1.55)	(0.30 - 0.94)
Middlesbrough	0.15***	0.16***	0.87	0.52***	0.86	1.15	0.13***	0.54*	0.21***
	(0.12 - 0.19)	(0.11 - 0.22)	(0.67 - 1.12)	(0.37 - 0.72)	(0.64 - 1.14)	(0.81 - 1.64)	(0.09 - 0.20)	(0.30 - 0.98)	(0.09 - 0.50)
Birmingham	1.31**	1.71***	1.37**	1.73***	1.32*	1.25	1.23	1.47	0.46*
	(1.11 - 1.55)	(1.30 - 2.25)	(1.09 - 1.72)	(1.33 - 2.26)	(1.02 - 1.70)	(0.90 - 1.75)	(0.87 - 1.74)	(0.92 - 2.33)	(0.25 - 0.84)
Swansea	1.43*	0.96	1.27	0.47	1.35	1.66	0.65	1.24	0.88
	(1.05 - 1.95)	(0.55 - 1.67)	(0.78 - 2.07)	(0.21 - 1.05)	(0.79 - 2.30)	(0.89 - 3.09)	(0.29 - 1.45)	(0.45 - 3.39)	(0.25 - 3.04)
Wrexham	1.23	0.85	1.09	0.00	1.12	0.44	0.69	1.67	0.00
	(0.70 - 2.17)	(0.30 - 2.42)	(0.41 - 2.87)	(0.00 - .)	(0.39 - 3.22)	(0.08 - 2.30)	(0.15 - 3.14)	(0.38 - 7.40)	(0.00 - .)
Urban (ref: Rural)	0.76***	1.19**	1.71***	1.91***	1.02	1.95***	0.76***	2.20***	4.06***
	(0.70 - 0.82)	(1.06 - 1.33)	(1.56 - 1.87)	(1.64 - 2.21)	(0.92 - 1.13)	(1.68 - 2.26)	(0.66 - 0.87)	(1.69 - 2.87)	(2.66 - 6.18)
Constant	91.57***	3,077.68***	1.78*	19.27***	0.04***	3.59***	198.07***	2.15	0.72
	(55.93 - 149.93)	(1,792.62 - 5,283.95)	(1.04 - 3.04)	(10.60 - 35.06)	(0.01 - 0.12)	(1.84 - 6.97)	(102.32 - 383.44)	(0.83 - 5.57)	(0.20 - 2.55)
Observations	78,295	78,295	78,295	78,295	78,295	78,295	78,295	78,295	78,295

*** p<0.001, ** p<0.01, * p<0.05

Table D.0.37 – UKB males, multinomial regression model in Stata with participants from London removed (n=69,037)

VARIABLES	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Age (ref: 65+)								
< 45	0.04***	0.66***	0.04***	0.79	1.68**	2.75**	2.07**	0.13***
	(0.03 - 0.05)	(0.56 - 0.78)	(0.03 - 0.05)	(0.60 - 1.04)	(1.22 - 2.32)	(1.50 - 5.02)	(1.34 - 3.19)	(0.09 - 0.18)
45-49	0.05***	0.70***	0.03***	0.73*	1.45*	2.50**	2.14***	0.12***
	(0.04 - 0.06)	(0.59 - 0.82)	(0.03 - 0.04)	(0.55 - 0.96)	(1.05 - 2.00)	(1.37 - 4.57)	(1.40 - 3.28)	(0.09 - 0.18)
50-54	0.07***	0.76***	0.06***	0.94	1.47*	2.49**	1.72*	0.15***
	(0.07 - 0.08)	(0.65 - 0.89)	(0.05 - 0.08)	(0.72 - 1.23)	(1.07 - 2.02)	(1.36 - 4.53)	(1.12 - 2.63)	(0.11 - 0.20)
55-59	0.13***	0.75***	0.10***	1.01	1.29	2.25**	1.47	0.24***
	(0.12 - 0.15)	(0.65 - 0.88)	(0.09 - 0.12)	(0.78 - 1.31)	(0.94 - 1.78)	(1.24 - 4.10)	(0.97 - 2.24)	(0.19 - 0.31)
60-64	0.31***	0.96	0.32***	1.07	1.16	1.83	1.12	0.39***
	(0.28 - 0.33)	(0.82 - 1.12)	(0.28 - 0.37)	(0.82 - 1.38)	(0.84 - 1.61)	(0.99 - 3.37)	(0.73 - 1.72)	(0.31 - 0.48)
Ethnic group (ref: Other white)								
White British	1.15*	1.02	0.80*	0.84	0.73***	0.92	0.83	1.48
	(1.00 - 1.33)	(0.89 - 1.17)	(0.64 - 0.98)	(0.69 - 1.01)	(0.61 - 0.86)	(0.69 - 1.21)	(0.63 - 1.10)	(0.97 - 2.25)
South Asian	0.48***	0.73	0.27***	0.72	0.17***	1.64	3.45***	1.87
	(0.32 - 0.71)	(0.51 - 1.03)	(0.13 - 0.53)	(0.44 - 1.20)	(0.08 - 0.37)	(0.95 - 2.86)	(2.24 - 5.31)	(0.89 - 3.91)
Black	0.50**	0.92	0.21***	0.42**	0.20***	0.43	0.61	0.70
	(0.31 - 0.82)	(0.63 - 1.35)	(0.09 - 0.48)	(0.23 - 0.77)	(0.09 - 0.46)	(0.18 - 1.03)	(0.25 - 1.44)	(0.25 - 1.99)
Chinese	0.37*	0.73	0.48	0.73	0.15*	0.00	0.29	0.00
	(0.16 - 0.86)	(0.37 - 1.44)	(0.13 - 1.75)	(0.27 - 1.92)	(0.04 - 0.67)	(0.00 - .)	(0.04 - 2.12)	(0.00 - .)
Mixed	0.77	0.72	0.52	0.53	0.40*	0.42	0.72	0.81
	(0.43 - 1.37)	(0.43 - 1.19)	(0.20 - 1.35)	(0.24 - 1.16)	(0.19 - 0.83)	(0.13 - 1.41)	(0.25 - 2.02)	(0.17 - 3.80)
Other	0.64	0.95	0.38*	0.58	0.50*	0.77	1.10	0.62
	(0.37 - 1.10)	(0.61 - 1.48)	(0.16 - 0.89)	(0.29 - 1.17)	(0.26 - 0.98)	(0.31 - 1.90)	(0.49 - 2.49)	(0.17 - 2.31)
Qualifications (ref: GSCEs)								
College or University degree	1.69***	1.69***	2.39***	2.00***	2.52***	4.29***	2.92***	3.49***
	(1.56 - 1.83)	(1.55 - 1.85)	(2.08 - 2.76)	(1.71 - 2.33)	(2.17 - 2.93)	(3.30 - 5.56)	(2.35 - 3.64)	(2.77 - 4.40)
A levels/AS levels or equivalent	1.26***	1.37***	1.38***	1.55***	1.22	2.06***	1.61***	1.52**
	(1.14 - 1.40)	(1.23 - 1.53)	(1.15 - 1.66)	(1.28 - 1.86)	(1.00 - 1.48)	(1.50 - 2.82)	(1.22 - 2.12)	(1.12 - 2.06)
CSEs or equivalent	0.69***	0.73***	0.64**	0.84	0.81	0.43**	0.93	0.37**
	(0.58 - 0.81)	(0.62 - 0.86)	(0.46 - 0.88)	(0.64 - 1.11)	(0.62 - 1.05)	(0.23 - 0.78)	(0.64 - 1.36)	(0.20 - 0.69)
NVQ or HND or HNC or equivalent	0.77***	0.77***	0.80*	0.93	1.13	0.70	0.84	0.74
	(0.69 - 0.86)	(0.67 - 0.89)	(0.66 - 0.98)	(0.74 - 1.17)	(0.90 - 1.41)	(0.43 - 1.13)	(0.58 - 1.21)	(0.51 - 1.06)
Other professional qualifications	0.96	0.75**	0.91	0.97	0.75	0.85	1.87**	0.89
	(0.83 - 1.11)	(0.61 - 0.91)	(0.70 - 1.18)	(0.70 - 1.36)	(0.50 - 1.11)	(0.43 - 1.66)	(1.27 - 2.75)	(0.56 - 1.42)
No qualifications	0.80***	0.68***	0.88	0.75*	0.88	0.48*	1.28	0.65*
	(0.71 - 0.90)	(0.58 - 0.81)	(0.73 - 1.06)	(0.57 - 0.98)	(0.66 - 1.17)	(0.26 - 0.89)	(0.88 - 1.86)	(0.46 - 0.92)
Occup Class (ref: Small employers)								
Higher managerial / professional	1.37***	1.49***	1.71**	2.25***	2.28***	2.36**	0.72*	1.70
	(1.21 - 1.57)	(1.25 - 1.79)	(1.22 - 2.40)	(1.59 - 3.19)	(1.60 - 3.25)	(1.30 - 4.29)	(0.53 - 0.99)	(0.96 - 3.01)
Lower managerial / professional	1.14	1.45***	1.56*	2.01***	1.97***	3.14***	0.96	1.59
	(1.00 - 1.30)	(1.21 - 1.74)	(1.11 - 2.20)	(1.42 - 2.85)	(1.38 - 2.82)	(1.73 - 5.69)	(0.71 - 1.31)	(0.90 - 2.82)
Intermediate	0.99	1.88***	1.16	3.19***	2.55***	3.31***	0.68*	1.50
	(0.86 - 1.15)	(1.55 - 2.28)	(0.79 - 1.69)	(2.23 - 4.56)	(1.76 - 3.70)	(1.79 - 6.13)	(0.48 - 0.98)	(0.80 - 2.79)
Lower supervisory technical	0.63***	0.89	0.79	0.94	2.33***	1.90	0.71	0.48
	(0.53 - 0.74)	(0.71 - 1.12)	(0.52 - 1.20)	(0.61 - 1.45)	(1.56 - 3.46)	(0.94 - 3.87)	(0.47 - 1.06)	(0.20 - 1.11)

Semi-routine	0.47***	1.44***	0.58**	2.49***	3.07***	1.70	0.72	0.67
	(0.40 - 0.56)	(1.16 - 1.78)	(0.38 - 0.88)	(1.71 - 3.64)	(2.09 - 4.52)	(0.85 - 3.40)	(0.48 - 1.09)	(0.32 - 1.39)
Routine	0.38***	1.19	0.39***	0.97	1.91**	1.58	0.62*	0.33*
	(0.32 - 0.45)	(0.95 - 1.49)	(0.25 - 0.60)	(0.64 - 1.48)	(1.26 - 2.89)	(0.77 - 3.25)	(0.40 - 0.95)	(0.14 - 0.80)
Not classified	1,169.68***	1.52	1,449.06***	1.13	1.43	0.00	1.35	1,045.56***
	(836.16 - 1,636.23)	(0.72 - 3.20)	(922.25 - 2,276.78)	(0.33 - 3.85)	(0.33 - 6.15)	(0.00 - 2.12e+299)	(0.32 - 5.73)	(556.52 - 1,964.31)
Hhold income (ref: <£31,000- 51,999)								
Less than 18,000	5.68***	0.99	5.25***	0.76*	0.84	1.32	1.43*	6.71***
	(5.10 - 6.33)	(0.85 - 1.17)	(4.45 - 6.18)	(0.61 - 0.94)	(0.65 - 1.09)	(0.95 - 1.84)	(1.03 - 1.97)	(5.20 - 8.65)
18,000 to 30,999	2.21***	1.00	2.01***	0.93	0.93	1.16	1.31**	2.42***
	(2.05 - 2.38)	(0.91 - 1.10)	(1.76 - 2.29)	(0.80 - 1.07)	(0.80 - 1.08)	(0.93 - 1.45)	(1.07 - 1.60)	(1.96 - 3.00)
52,000 to 100,000	0.57***	1.12**	0.75***	1.40***	1.18**	1.36**	1.04	0.44***
	(0.53 - 0.62)	(1.03 - 1.21)	(0.64 - 0.89)	(1.23 - 1.59)	(1.05 - 1.33)	(1.13 - 1.64)	(0.87 - 1.23)	(0.33 - 0.58)
Greater than 100,000	0.44***	1.48***	0.39***	1.64***	1.26*	1.16	0.83	0.41***
	(0.38 - 0.50)	(1.33 - 1.66)	(0.26 - 0.58)	(1.32 - 2.04)	(1.05 - 1.51)	(0.84 - 1.61)	(0.63 - 1.09)	(0.24 - 0.69)
Household Structure (ref: Partner only)								
Live alone	0.46***	0.60***	0.38***	0.43***	0.45***	0.40***	0.90	0.46***
	(0.42 - 0.51)	(0.54 - 0.66)	(0.33 - 0.44)	(0.37 - 0.50)	(0.38 - 0.53)	(0.32 - 0.51)	(0.72 - 1.13)	(0.37 - 0.58)
Child(ren), no partner	0.55***	0.83	0.44***	0.46***	0.71*	0.22***	1.13	0.23***
	(0.45 - 0.67)	(0.68 - 1.01)	(0.30 - 0.64)	(0.33 - 0.65)	(0.51 - 0.98)	(0.11 - 0.44)	(0.78 - 1.64)	(0.10 - 0.53)
Partner and child(ren)	0.87***	1.25***	1.41***	1.40***	1.90***	1.21*	0.76**	1.09
	(0.81 - 0.94)	(1.16 - 1.34)	(1.23 - 1.63)	(1.24 - 1.59)	(1.69 - 2.14)	(1.01 - 1.45)	(0.65 - 0.90)	(0.87 - 1.37)
Live with others	0.66***	0.72**	0.97	1.25	0.90	0.69	1.10	0.90
	(0.53 - 0.83)	(0.56 - 0.91)	(0.70 - 1.34)	(0.95 - 1.65)	(0.64 - 1.25)	(0.43 - 1.10)	(0.73 - 1.66)	(0.56 - 1.46)
Cars per household (ref: 2)								
None	1.21	14.17***	384***	1,522***	160***	355***	0.77	46.51***
	(0.84 - 1.74)	(9.92 - 20.23)	(275 - 537)	(1,111 - 2,085)	(114 - 224)	(242 - 522)	(0.19 - 3.21)	(30.27 - 71.45)
One	1.39***	2.76***	4.48***	9.76***	5.12***	6.30***	1.17	2.25***
	(1.30 - 1.49)	(2.57 - 2.98)	(3.95 - 5.07)	(8.53 - 11.17)	(4.57 - 5.72)	(5.23 - 7.58)	(0.99 - 1.39)	(1.86 - 2.73)
Three	1.08	0.75***	0.61***	0.46***	0.60***	0.37***	0.75*	0.74
	(0.98 - 1.19)	(0.67 - 0.83)	(0.46 - 0.81)	(0.34 - 0.63)	(0.49 - 0.73)	(0.23 - 0.60)	(0.59 - 0.96)	(0.50 - 1.10)
Four or more	1.22*	0.63***	0.54*	0.13***	0.47***	0.53	0.82	1.40
	(1.04 - 1.43)	(0.52 - 0.76)	(0.30 - 0.95)	(0.05 - 0.35)	(0.32 - 0.68)	(0.26 - 1.09)	(0.55 - 1.21)	(0.79 - 2.46)
Townsend score (ref: Quintile 1)								
2	1.04	1.11*	1.11	1.28**	1.09	1.44**	1.05	0.97
	(0.96 - 1.12)	(1.02 - 1.21)	(0.96 - 1.28)	(1.08 - 1.52)	(0.95 - 1.26)	(1.11 - 1.87)	(0.86 - 1.28)	(0.76 - 1.24)
3	0.90**	1.17***	1.05	1.38***	1.16*	1.64***	1.20	1.24
	(0.83 - 0.97)	(1.08 - 1.28)	(0.91 - 1.22)	(1.17 - 1.63)	(1.01 - 1.34)	(1.27 - 2.11)	(0.98 - 1.46)	(0.98 - 1.57)
4	0.86***	1.26***	1.11	1.67***	1.38***	2.17***	1.27*	1.34*
	(0.79 - 0.94)	(1.15 - 1.39)	(0.95 - 1.29)	(1.42 - 1.96)	(1.20 - 1.59)	(1.70 - 2.78)	(1.03 - 1.56)	(1.05 - 1.71)
5	0.75***	1.37***	1.11	2.05***	1.22*	2.70***	1.41**	1.12
	(0.67 - 0.83)	(1.22 - 1.53)	(0.94 - 1.32)	(1.72 - 2.44)	(1.03 - 1.45)	(2.07 - 3.53)	(1.11 - 1.79)	(0.85 - 1.49)
Assessment Centre (ref: Manchester)								
Oxford	0.40***	1.44**	1.06	1.40	3.53***	1.31	0.71	0.63
	(0.31 - 0.50)	(1.13 - 1.83)	(0.69 - 1.62)	(0.97 - 2.03)	(2.58 - 4.84)	(0.75 - 2.29)	(0.41 - 1.24)	(0.32 - 1.23)
Cardiff	0.26***	1.21	0.27***	0.78	1.14	1.80*	0.89	0.45*
	(0.20 - 0.33)	(0.95 - 1.53)	(0.17 - 0.44)	(0.52 - 1.19)	(0.80 - 1.64)	(1.06 - 3.04)	(0.54 - 1.47)	(0.24 - 0.85)
Glasgow	0.28***	1.42**	0.34***	1.61**	0.60*	0.90	0.66	0.29***
	(0.21 - 0.38)	(1.11 - 1.81)	(0.21 - 0.55)	(1.12 - 2.31)	(0.39 - 0.92)	(0.50 - 1.62)	(0.37 - 1.17)	(0.14 - 0.59)
Edinburgh	0.41***	2.41***	1.17	3.08***	2.44***	1.85*	0.48*	0.66
	(0.32 - 0.52)	(1.93 - 3.01)	(0.78 - 1.76)	(2.22 - 4.27)	(1.77 - 3.35)	(1.10 - 3.09)	(0.25 - 0.91)	(0.35 - 1.24)

Stoke	0.63***	0.78	0.72	0.48**	0.76	0.22*	0.97	0.52
	(0.51 - 0.78)	(0.59 - 1.03)	(0.45 - 1.14)	(0.27 - 0.84)	(0.48 - 1.18)	(0.07 - 0.74)	(0.57 - 1.65)	(0.25 - 1.07)
Reading	0.36***	1.39**	0.53**	1.29	1.24	1.37	0.73	0.47*
	(0.30 - 0.44)	(1.13 - 1.71)	(0.36 - 0.78)	(0.92 - 1.80)	(0.91 - 1.70)	(0.84 - 2.25)	(0.46 - 1.13)	(0.27 - 0.84)
Bury	0.72***	0.58***	0.71	0.63*	0.30***	0.60	0.87	0.79
	(0.60 - 0.86)	(0.45 - 0.75)	(0.48 - 1.06)	(0.43 - 0.92)	(0.19 - 0.47)	(0.33 - 1.08)	(0.55 - 1.37)	(0.44 - 1.41)
Newcastle	0.23***	1.12	0.38***	1.20	0.83	1.25	0.73	0.32***
	(0.18 - 0.29)	(0.90 - 1.39)	(0.26 - 0.57)	(0.87 - 1.67)	(0.59 - 1.16)	(0.77 - 2.04)	(0.46 - 1.16)	(0.18 - 0.56)
Leeds	0.59***	1.24*	0.89	1.11	0.71*	1.05	0.97	0.89
	(0.50 - 0.71)	(1.01 - 1.52)	(0.62 - 1.28)	(0.81 - 1.53)	(0.51 - 0.98)	(0.65 - 1.69)	(0.64 - 1.46)	(0.53 - 1.51)
Bristol	0.32***	1.24*	0.56**	1.20	1.75***	1.52	0.77	0.51*
	(0.27 - 0.38)	(1.02 - 1.52)	(0.39 - 0.80)	(0.88 - 1.63)	(1.31 - 2.33)	(0.97 - 2.38)	(0.51 - 1.15)	(0.30 - 0.85)
Nottingham	0.28***	0.96	0.51***	0.97	1.70***	1.55	1.29	0.49*
	(0.23 - 0.35)	(0.77 - 1.19)	(0.35 - 0.74)	(0.69 - 1.37)	(1.25 - 2.30)	(0.96 - 2.51)	(0.85 - 1.95)	(0.28 - 0.85)
Sheffield	1.10	1.17	1.49*	1.17	0.85	1.46	1.08	1.19
	(0.93 - 1.29)	(0.96 - 1.43)	(1.05 - 2.10)	(0.86 - 1.58)	(0.63 - 1.16)	(0.93 - 2.29)	(0.72 - 1.61)	(0.71 - 1.98)
Liverpool	1.09	0.93	1.62**	0.87	0.75	1.02	0.89	0.71
	(0.93 - 1.29)	(0.75 - 1.14)	(1.14 - 2.30)	(0.63 - 1.19)	(0.54 - 1.03)	(0.63 - 1.65)	(0.59 - 1.35)	(0.41 - 1.23)
Middlesbrough	0.22***	0.80*	0.23***	0.60*	0.73	0.42*	0.82	0.19***
	(0.18 - 0.28)	(0.63 - 1.00)	(0.15 - 0.34)	(0.41 - 0.89)	(0.51 - 1.03)	(0.22 - 0.82)	(0.52 - 1.29)	(0.10 - 0.34)
Birmingham	1.34***	1.16	2.11***	1.23	0.89	1.18	0.97	1.32
	(1.14 - 1.59)	(0.94 - 1.42)	(1.48 - 3.00)	(0.90 - 1.67)	(0.65 - 1.22)	(0.74 - 1.88)	(0.65 - 1.47)	(0.78 - 2.24)
Swansea	1.50*	0.65	1.52	0.92	1.38	1.75	0.72	1.84
	(1.09 - 2.06)	(0.38 - 1.12)	(0.78 - 2.98)	(0.45 - 1.87)	(0.73 - 2.63)	(0.72 - 4.26)	(0.25 - 2.08)	(0.74 - 4.58)
Wrexham	1.58	0.52	2.02	0.53	0.48	1.43	1.64	1.28
	(0.92 - 2.72)	(0.16 - 1.74)	(0.60 - 6.87)	(0.07 - 4.20)	(0.06 - 3.71)	(0.18 - 11.56)	(0.38 - 7.15)	(0.16 - 10.33)
Urban (ref: Rural)	0.79***	1.36***	1.26**	2.08***	1.88***	1.63***	1.07	0.99
	(0.74 - 0.85)	(1.25 - 1.48)	(1.09 - 1.46)	(1.71 - 2.53)	(1.62 - 2.19)	(1.25 - 2.11)	(0.89 - 1.29)	(0.80 - 1.24)
Constant	16.52***	0.76	79.90***	2.83**	0.49*	0.13***	0.02***	3.19*
	(10.54 - 25.91)	(0.46 - 1.24)	(42.70 - 149.51)	(1.47 - 5.45)	(0.25 - 0.98)	(0.04 - 0.39)	(0.00 - 0.08)	(1.20 - 8.47)
Observations	69,037	69,037	69,037	69,037	69,037	69,037	69,037	69,037

*** p<0.001, ** p<0.01, * p<0.05

Abbreviations

AIC	Akaike information criterion
ALS	Active Lives Survey
APS	Active People Survey
BIC	Bayesian information criterion
BMI	Body Mass Index
BSA	British Social Attitudes
BVR	Bivariate residual
CAPI	Computer Assisted Personal Interview
CCC	Committee on Climate Change
CH_4	Methane
CO_2	Carbon dioxide
Defra	Department for Environment, Food & Rural Affairs
DfT	Department for Transport
DINO	Diet In Nutrients Out
EPIC	European Prospective Investigation into Cancer and Nutrition
FSA	Food Standards Agency
FV	Fruit and vegetables
GCSE	General Certificate of Secondary Education
GHG	Greenhouse gases
HLC	Healthy, low-carbon
HNC	Higher National Certificate
HND	Higher National Diploma
HRP	Household reference person
HSE	Health Survey for England
IARC	International Agency for Research on Cancer
IMD	Indices of Multiple Deprivation
LCA	Latent class analysis
MRC	Medical Research Council
MVPA	Moderate to vigorous physical activity
N_2O	Nitrous oxide
NatCen	NatCen Social Research
NDNS	National Diet and Nutrition Survey
NHS	National Health Service
NS-SEC	National Statistics Socio-economic Classification
NTS	National Travel Survey

NVQ	National Vocational Qualifications
OAC	Output Area classification
OR	Odds ratio
PA	Physical activity
PHE	Public Health England
PT	Public transport
RPAQ	Recent Physical Activity Questionnaire
RPM	Red and processed meat
SDH	Social determinants of health
SEP	Socio-economic position
SHS	Scottish Household Survey
UHC	Unhealthy, high-carbon
UKB	UK Biobank
UKHLS	UK Household Longitudinal Survey
WHO	World Health Organization

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