An exploration of the determinants and health impacts of active commuting

A thesis submitted for the degree of Doctor of Philosophy

by

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List of abbreviations

APS: Active People Survey
BHPS: British Household Panel Survey
BMI: Body mass index
ELSA: English Longitudinal Study of Ageing
GHQ12: Twelve-item General Health Questionnaire
GRADE: Grading of Recommendations Assessment, Development, and Evaluation systems
MGI: McKinsey Global Institute (the research arm of the international consultancy firm)
MOOSE: Meta-analysis of Observational Studies in Epidemiology
MRC guidance: Medical Research Council guidance on evaluating natural experiments
HSE: Health Survey for England
NICE: National Institute for Health and Care Excellence
N/A: Not applicable
NHS: National Health Service
NRTS: National Road Traffic Survey
NTS: National Travel Survey
ONS: Office for National Statistics
OR: Odds Ratio
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT: Randomised controlled trial
SLOTH: Sleep, Leisure, Occupation, Transport and Home based activities
UK: United Kingdom
WHO: World Health Organisation

ABSTRACT

Encouraging more walking or cycling amongst commuters in the United Kingdom could help reduce physical inactivity and contribute various health, environmental and other economic benefits. Existing empirical studies of the determinants and impact of active commuting are limited however, since they typically use cross-sectional, observational study designs or focus on small scale behavioural interventions. This thesis explored how the impact of larger scale population-level changes in the design of urban built environments and other transport policies could be assessed using theories and techniques often employed in health economics. There are three main sections. First, a literature review which found few studies of the health impact of changes to the built environment that had used randomisation or advanced econometric techniques (e.g. instrumental variables). This included an assessment of whether the chosen methodological approach critically affected the results obtained and the development of a guide to aid policy makers in distinguishing between, and assessing the quality of, observational studies that used different analytical techniques. Second, an empirical analysis of twenty-one waves of the British Household Panel Survey (BHPS) which included an exploration of the determinants of active commuting including life events (e.g. moving home and changing job) and studies of the impact on body mass index and subjective wellbeing of switching commute mode from car travel to walking, cycling or public transport. Third, an exploration of the potential impact of financial incentives to promote active travel. This included an empirical review of intervention studies as well as a theoretical element, including development of a simple analytical framework and review of behavioural economic concepts. Whilst the identified health improvements could support the case for investment in policies that promote active commuting, the thesis recommended that more robust evaluation of population-level policies is required so that scarce resources can be targeted more effectively.

SECTION A:

1 General Introduction

1.1 Overview of chapter

This chapter begins, first (section 1.2), with a descriptive summary of the problem of physical inactivity amongst people of working age in the United Kingdom (UK) (section 1.2.1), travel behaviour trends (section 1.2.2), and key aspects of the current policy making environment in relation to public health and transportation (section 1.2.3).

Second (section 1.3), this chapter seeks to highlight four fundamental strands of research from the discipline of health economics which, it is argued, could be used to provide some additional insights to existing research on walking and cycling within the broader disciplines of public health and transportation. Briefly, these four strands of research relate to: (i.) how people make decisions, drawing on the standard economic assumptions of utility-maximising behaviour as well as more recent work in behavioural economics (section 1.3.1), (ii.) the economic rationale for policy intervention in the event of market failure (section 1.3.2), (iii.) the types of policies that might be justified from the perspective of correcting market failure (section 1.3.3), and (iv.) the economic evaluation of policies, with a particular focus on techniques used in the analysis of large-scale panel data sets (section 1.3.4).

Third (section 1.4), the chapter concludes with a summary of the main objectives of the thesis and the individual studies that have been undertaken, including an explanation of how they relate to the four strands of health economics research outlined above.

1.2 Physical inactivity, obesity and travel behaviour amongst working aged adults: a description of trends and current policies

This section begins with a description of the prevalence of physical inactivity and related health outcomes (section 1.2.1) amongst working aged adults in the UK population, as well as trends in travel behaviour (section 1.2.2). It concludes by describing relevant features of the policy landscape (section 1.2.3), in terms of current funding and institutional arrangements, including a summary of recent changes to the role of local authorities in relation to public health and transportation policy.

1.2.1 Prevalence of physical inactivity and the impact on health and health inequality

Physical inactivity is associated with at least twenty chronic health conditions including coronary heart disease, cancer, diabetes and stroke,(1, 2) and identified by the World Health Organisation (WHO) as the fourth leading risk factor for global mortality.(3) It is also a significant determinant of obesity (a definition of obesity, and its long term prevalence, is shown in Figure 1-1), since physical activity is a key determinant of energy expenditure.(4, 5) Evidence also shows an association between physical activity and psychological wellbeing,(6-9) which is sometimes used by Governments at the national level as an indicator of social progress or development, complementing standard measures such as GDP per capita.(10-13)

In 2011, updated physical activity guidelines were published jointly by the four Chief Medical Officers of England, Scotland, Wales and Northern Ireland. Reflecting recent evidence on the incremental health benefits of physical activity, and broadly consistent with other international guidelines,(1, 3, 14-16) they state that working aged adults should accumulate at least 150 minutes of weekly, moderate intensity physical activity in bouts of ten or more minutes (or equivalent).(1) One way to approach this, they say, "is to do thirty minutes of moderate intensity physical activity on at least 5 days a week."(1)

Data from recent years indicate that significant numbers of individuals do not meet these minimum recommended levels of physical activity. In England, self-reported data from a recent Health Survey for England (HSE) showed that, in 2012, 67% of men and 55% of women met the minimum levels of physical activity recommended in these guidelines (similar data is also reported in the Northern Ireland Health Survey, Scottish Health Survey and Welsh Health Survey, however these surveys are independent of the HSE and are not reviewed here).(2) Equivalent data from the 2012 Active People Survey (APS), which used telephone interviews, indicated a similar proportion of men (61%) and women (51%) met the guidelines in England.(17) However, these surveys are limited by the use of self-reported data, which may lead to a significant over-estimation of physical activity levels.(18) For example, self-reported data from the 2008 HSE, the most recent HSE to include an objective physical activity measure using accelerometer data, showed that 39% of men and 29% of women were meeting the minimum levels of activity recommended in the previous version of the guidelines, whereas the objective data showed that only 6% of men and 4% of women had achieved the necessary physical activity levels. (In contrast to the 2011 physical activity guidelines described above, the previous version differed in terms of what constituted a single bout of physical activity, and recommended that adults undertake 30 minutes of moderate or vigorous physical activity on at least five days per week. Hence the HSE data on the proportion of adults meeting the physical activity guidelines in 2008 and 2012 are not comparable).(18)

The HSE data, and other equivalent data from the rest of the UK, also shows that the proportion of individuals complying with the minimum levels of physical activity recommended in the guidelines varies with socio-economic status, highest level of educational attainment,(19) ethnicity and geographical area. This may contribute to inequalities in the distribution of various related health outcomes across the population in England and the UK.(20, 21) Using the (self-reported) data on participants in the HSE data for 2012, Figure 1-2 shows that, for both men and women, the proportion of individuals meeting the minimum levels of physical activity was lower in the third, fourth and fifth quintiles of the age-standardised, equivalised household income distribution when compared to participants with higher incomes. In the highest quintile, for example, 76% of men and 63% of women met the guidelines, falling to 55% of men and 47% of women in the lowest quintile.(2) The data also shows that, for both men and women, the proportion of individuals who were classed as inactive, since they reported accumulation of less than 30 minutes of weekly, moderate intensity physical activity, was higher in the lower income households. In the lowest income quintile, for example, 29% of men and 34% of women were classed as inactive compared to 11% of men and 18% of women in the highest income quintile. In terms of ethnicity, an assessment of equivalent self-reported HSE data for 1999, 2003 and 2004 showed that people of South Asian origin were substantially less likely to meet the guidelines when compared to white participants (Odds Ratio (OR) 0.41, 95% CI 0.38 to 0.45).(22)

In terms of age, using the self-reported HSE data for 2012, Figure 1-3 shows that, amongst working-aged men, the proportion meeting minimum levels of physical activity generally decreased with age from 83% in the 16-24 age range, to 55% amongst those aged 55-64. For working-aged women, the proportion rose to a peak of 66% amongst those aged 35-44, before declining with age to a low of 55% amongst those aged 55-64. However, relatively little is known about changes in overall physical activity over the life course,(23, 24) at least in the UK.(25)

1.2.2 Trends in travel behaviour

This section begins with an overview of long term trends in the use of different travel modes and then concentrates specifically on the behaviour of commuters, which is the main focus of this thesis.

1.2.2.1 Long-term trends in all-purpose travel behaviour

The rise of car travel, and dramatic growth in total distances travelled by any travel mode, were the two dominant changes in travel behaviour in the UK during the latter half of the twentieth century. Data from the National Road Traffic Survey (NRTS), which uses a combination of manual and automatic road side traffic counts to calculate the number of vehicle miles travelled each year in Great Britain (England, Scotland and Wales) by vehicle type, shows that distance travelled by car (or taxi) increased every year, with the exception of 1956 and 1974, and that growth was especially strong during the 1980s (see Figure 1-4).(26) By 1999, car travel accounted for 234.5 billion miles, or 80% of total distance travelled by road, compared to 12.6 billion miles in 1949, or just 28% of total distance travelled.(26)

In terms of active travel (defined in this thesis as walking and cycling for any purpose), and in some contrast to car travel, the NRTS data shows that during the same period the number of miles travelled by bicycle fell, especially during the 1950s and 1960s, both in absolute terms and as a proportion of total distance covered by any road transport mode. In 1949, cycling accounted for 14.7 billion miles per year, or 34% of total distance travelled, compared to a relatively stable level of between 2 and 4 billion miles, or 1% to 2% of total distance travelled, since the 1970s (see Figure 1-5, however it should be noted that NTRS data most likely underestimates distance travelled by bicycle since non-road journeys on routes that are inaccessible to motorised vehicles are not included).(26) Data from the National Travel Survey (NTS), a household survey which collects detailed information on personal travel using face-to-face interviews and self-completed travel diaries, also shows that average distance travelled on foot declined in Great Britain from 255 miles per person per year in 1976, when the survey began, to 189 miles in 1999.(27)

On most measures, year-on-year variation in the demand for public transport (defined in this thesis as bus, coach and rail travel) has tended to be negative or unchanged during the period, particularly during the 1950s, 1960s and 1970s. NRTS data shows that a fall in the total distances travelled by bus or coach (per vehicle, not per passenger) between 1949 and 1979 was accompanied by a reduction in the proportion of road traffic accounted for by these modes from 6% to 1%. This proportion remained relatively unchanged for the rest of the century, although a small increase in distances travelled by bus or coach were observed during the 1980s and 1990s.(26) On the railways, Department for Transport statistics show that total mileage in Great Britain (per passenger, not per vehicle) fell from 21.1 billion passenger miles in 1949 to 17.8 billion miles in 1994, with the most substantial decline occurring during the 1960s, although by the turn of the century mileage had jumped to 23.7 billion miles.(28, 29)

Since the turn of the century some notable changes in these long term trends have been observed. First, the rate of growth in car travel fell dramatically. Between 2000 and 2010, distance travelled by car increased by just 2.6% from 233.7 to 239.8 billion miles. Second, the upward trend in rail passenger miles that had begun after 1994 continued. Between 2000 and 2010, passenger mileage increased by 42% from 23.7 to 33.6 billion miles.(28) Third, there were some indications that active travel was no longer in decline. In terms of cycling, NRTS data shows that total distance travelled increased for the fourth consecutive year between 2010 and 2011, by 2.2 per cent, and NTS data shows that average distance cycled per person per year increased from lows of 36 miles in 2002 and 2005 (the lowest recorded in the survey since it began in 1976), before rising to a new high of 53 miles in 2012. In terms of walking, distance travelled per person per year increased from 181 to 198 miles between 2002 and 2012. Nevertheless, England and the UK generally has lower rates of cycling and walking than other European countries, and lags behind 23 other European countries in the proportion of adults who cycle at least once a day.(30)

Reasons for recent changes in travel behaviour, and the likely impact on long term forecasts, are currently debated. Although it is probable that the recession arising from the 2008 financial crisis will have had some negative impact on traffic volumes in the short term, some commentators have proposed a novel yet disputed ‘peak car’ hypothesis, whereby a longer term decline in per person distances travelled by car is expected.(29, 31) They point to empirical data, including from the NTS,(32) showing that since the turn of century, young people aged under 30 years are less likely to hold a valid driving licence when compared to earlier generations. Long term trends in the travel behaviour of commuters

Of 23.7 million adult commuters (defined as those participants aged 16-74 in work but not working from home) in the 2011 Census of England and Wales (data for Scotland and Northern Ireland are reported in separate Census datasets), 14.0% were active commuters (defined in this thesis as those who used active travel modes for the journey between home and work). A further 17.8% used public transport, and 67.1% used private motorised transport (defined in this thesis as travel by car, van or motorcycle).(33)

The broad population-level trends in the behaviour of commuters observed in the data since 1971 are similar to those observed in the overall all-purpose travel behaviour statistics outlined in the previous section. Substantial reductions in commuting by public transport, cycling and walking observed between 1971 and 1991, which was accompanied by an increase in the proportion of commuters travelling by private motorised transport, have since slowed and in some cases reversed (see Figure 1-6). For the whole period, 1971-2011, combined data for England and Wales show the proportion of commuters that travelled by bicycle fell from 4.9% to 3.1%, and the proportion walking declined from 18.5% to 11.0%.(33) However, between 2001 and 2011, the proportion using bicycles increased slightly from 3.0% to 3.1%, and the proportion using public transport increased from 16.0% to 17.8%. In 2011, the proportion driving (67.1%) was also slightly lower than the proportion driving in 1991 (67.3%) and 2001 (68.9%).

Within these broad trends, considerable variation is observed between populations in terms of the proportion of people using active travel modes. First, the 2011 Census data showed regional variation within England and Wales. In Cambridge, for example, 29% of adult commuters cycled to work, compared to less than 1% in 29 other local authorities. Differences of a similar magnitude are also observed between areas in the 2011/2012 Active People Survey.(17) Second, there are substantial differences in average distances travelled on foot or by bicycle between age groups and genders. The 2011 Census data showed cycling to be most common amongst people in work who are male, living in urban areas, aged 30-34, and in elementary and professional occupations. Similarly, the 2012 NTS shows that, for males and females, average distance travelled per person per year is highest amongst those aged 30-39. Yet within this age group there are stark differences between genders: males on average cycled 141 miles per year, compared with just 27 miles amongst their females counterparts.

1.2.3 Public policy landscape

This section provides a brief description of how decision making in the health and transportation sectors might overlap, and includes a summary of recent changes in the funding and responsibilities of local authorities in England which might support greater collaboration between the health and transportation sectors in the future.

In modern times, health policy has been characterised not only by the provision and funding of medical care focused on the treatment of individuals, but also by an explicit concern for the prevention of ill health across the whole population. This population health approach is defined as “the health outcomes of a group of individuals, including the distribution of such outcomes within the group.”(34) A critical component of this approach is the discipline of public health, which is defined by the Faculty of Public Health in the UK as “the science and art of promoting and protecting health and wellbeing, preventing ill health and prolonging life through the organised efforts of society.” Hence discouraging physical inactivity, alongside other life style-related behaviours such as smoking and excessive drinking, is an important aspect of health policy in the UK,(1) as well as at the European and international level.(35, 36)

In England, public health policy is currently shaped by the Government’s “Healthy lives, Healthy people” White Paper published in 2010.(37) The focus of this paper was on “lifestyle-driven health problems” related to diet and physical inactivity, which have led “Britain to become the most obese nation in Europe”, as well as other issues including smoking, sexually transmitted diseases, illicit drug use, poor mental health and health inequalities. Across England, a number of initiatives to encourage physical activity were launched at the time of the Olympic Games held in London in 2012 and, since April 2013, there have also been two physical activity targets in the Quality and Outcomes Framework (or QOF), an incentive scheme for General Practitioners designed to reward the provision of high quality care. In recent years a number of organisations in the health sector have also sought to raise awareness of walking and cycling,(38, 39) and campaigned for more funding and specific policies to encourage active travel. Examples include reports published since 2012 by Public Health England,(40) professional organisations such as the Faculty of Public Health(41) and the British Medical Association,(42) which called for “ambitious growth targets for walking and cycling at national and regional levels, with increased funding and resources proportional to target levels.”

Indicative of potential synergies across the health and transport sectors, a 2013 Department for Transport report stated that: “The Government wants more journeys to be made by sustainable transport: public transport, supported by cycling and walking. This is essential to our goal of reducing carbon emissions from transport.”(43)

1.2.3.1 An emerging role of local authorities

A key tenet of the “Healthy lives, Healthy people” White Paper was the transfer to England’s local authorities of substantial responsibilities for public health services and central Government funding worth £2.66 billion per annum in 2013-14,(44) or 2.4% of the Department of Health’s total budget (in England). In a further change, it was announced in February 2015 that responsibility for allocating annual funds of £6 billion for NHS health services would be transferred from the Department of Health to the Greater Manchester local authority (if successful, other large cities may be expected to follow suit). Since local authorities already had considerable jurisdiction over a number of relevant policy areas, including transport policy and urban planning,(20) the new single pool of money presented a potential opportunity for policy makers to encourage higher levels of physical activity beyond the traditional organisational boundaries of the health care sector (just as the Greater Manchester authority might take the opportunity to integrate local health and social care services for older people).

The resulting administrative changes that occurred in the health sector included the establishment of multi-stakeholder health and wellbeing boards at the local level, to coordinate decision making, and Public Health England at the national level to provide advice and support as well as some services (although recent reports have highlighted considerable uncertainty about the respective roles and responsibilities of the different bodies involved which may have had a detrimental impact on the delivery of priorities in some geographic areas, particularly in terms of action to reduce known health inequalities.(45, 46)) In 2013, for example, Public Health England produced guidance on walking and cycling for local authorities, with separate briefings for directors of public health and transport departments, as well as for elected officials. Similarly, in 2012, the National Institute for Health and Care Excellence (NICE) published guidance for local authorities on encouraging people to be physically active,(47) and in 2013 on promoting walking and cycling,(48) as part of its remit to advise on best practice in the promotion of good health and the prevention and treatment of ill health. Some examples of its recommendations included making sure that planning applications prioritise the need for people to be physically active and using road design to reduce motor vehicle speeds.

Whilst local authorities already had jurisdiction over many areas of the transport policy, a Department for Transport White Paper published in 2011 'Creating growth, cutting carbon' made a particular commitment to local decision making,(49) and in recent years funding has been granted to individual local authorities for new walking and cycling schemes on a competitive basis. In one scheme, eighteen 'Cycling Towns and Cities' (or 'Cycle Demonstration Towns') in England received substantial capital funding for cycle infrastructure projects between 2005 and 2011.(50) Between 2011 and 2015, the 'Local Sustainable Transport Fund' awarded funding of £600 million to 77 local authorities for 96 projects which typically involved new walking and cycling infrastructure,(51) and in 2013 the Department for Transport announced a further £114m of funding under the 'Cycle City Ambition Grants' to improve cycling facilities in eight cities and four national parks in England.(52)

This new funding and responsibilities nevertheless came at a challenging time for local authorities which have faced an estimated real-terms reduction in funding from central Government of 37% between 2010-11 and 2015-16.(53)

1.3 Economic perspectives

The purpose of this section is to highlight four key strands of research from the discipline of health economics which could provide some distinctive theoretical insights or methodological approaches when compared to existing research on active travel within the broader disciplines of public health and transportation. These key strands of research provide the main justification for the work presented in each of the remaining chapters of this thesis which are outlined in the next section (section 1.4).

Briefly, as also set out in the opening section of this chapter (section 1.1), the four strands of research relate to: (i.) how individuals make decisions, drawing on the standard economic assumptions of utility-maximising behaviour as well as relevant insights on market failure, and recent 'behavioural economics' work (section 1.3.1), (ii.) the economic rationale for policy intervention when market failure interferes with utility-maximising behaviour (section 1.3.2), (iii.) the types of policies that might be justified from the perspective of correcting these market failures (section 1.3.3), and (iv.) the economic evaluation of policies (section 1.3.4), with a particular focus on techniques used in the analysis of large-scale panel data sets.

1.3.1 How people make decisions

From an economics perspective, the process whereby individuals are free to make choices in order to maximise their own 'utility' is important. For any consumption decision, individuals are expected to make an informed, rational assessment of the costs and benefits of different options in order to make choices that will maximise their own individual 'utility' (in this context, 'utility' represents the satisfaction, or happiness, that is gained from consumption).(54) This is the main assumption of the 'expected utility hypothesis,' which remains the predominant descriptive and normative model of choice under uncertainty in economics.(55)

Recent research in 'behavioural economics' has identified significant caveats to the expected utility hypothesis by applying relevant insights from psychology.(56) The beginning of this process is perhaps best traced back to a paper published in 1979 in 'Econometrica,' a top-ranking economics journal, by the psychologists Daniel Kahneman and Amos Tversky (although it is clear that behavioural science and economics were closely aligned during their early development in the eighteenth century (57)).(58) Through a series of experiments in social science laboratories, 'Prospect theory: an analysis of decision under risk' argued that, in practice, individuals deviate from the standard assumptions of the expected utility hypothesis when making risky decisions. A number of key observations were made, and these remain core components of behavioural economics today. Briefly, they include (but are not limited to) the idea that people are risk averse (i.e. they are more sensitive to the negative impact of losses, when compared to the positive impact of gains), people tend to judge their utility relative to others, rather than in absolute terms, and people's decisions depend on the way choices are presented (more detailed reviews in the context of transportation are provided by Van de Kaa et al. and others). (57, 59, 60)

These behavioural insights are likely to have implications for travel behaviour models, including those used in 'mode choice analysis', which seeks to understand how various factors (e.g. journey time and price) impact on the utility associated with different travel modes for specific journeys, and hence the likelihood of using them.(61, 62) Since the 1970s, these models have been developed primarily by economists,(57) with the expectation that people make rational choices and interact with one another to form a state of equilibrium.(59) Considering the idea of 'risk aversion,' for example, people may be more likely than would be expected in standard economic models to avoid particular travel modes (e.g. bus travel) or route choices (e.g. cross-country routes) which they perceive to be associated with the highest risk of arriving late at their destination.(57) Other insights from behavioural economics which may influence travel behaviour include (but are not limited to) the influence of habits, ingrained social norms and simple rules of thumb,(63, 64) all of which could encourage people to favour private car travel without giving proper consideration to alternatives.(65)

Other related areas of research where psychological theories have had some impact on the way economists analyse people's behaviour include the fields of public economics, where the impact of public policy on behaviour and wellbeing is studied,(66) and the economics of health behaviours, which concerns decisions with important health consequences including diet, exercise, and alcohol and tobacco consumption.(67)

In recent years there has been considerable interest amongst policy makers in identifying those influences on behaviour which might lead people to deviate from the expectations of the standard economic models. Recent guidance published by the UK's Cabinet Office has encouraged all Government departments to put these insights to practical use by designing policy interventions which appeal directly to tackling specific behavioural influences.(68) The Department of Transport's 'Behavioural insights toolkit,' for example, argues that behaviour change interventions should be tailored to address 'strong habitual behaviour' and other forms 'irrational' behaviour.(57, 64)

1.3.2 The economic justification for policy intervention

In classical economics, a fundamental theoretical principle is that the process whereby individuals are free to make choices not only ensures that they maximise their own utility, but also that ‘efficiency’ is achieved in the allocation of resources across society (in this case ‘efficiency’ might be defined in terms of Pareto efficiency, whereby utility is maximised in a society if scarce resources are allocated so that it is not possible to make any one individual better off without making at least one individual worse off). This principle was originally outlined in the writings of the economist Adam Smith in the eighteenth century and now forms the basis of what has become known as the first fundamental theorem of welfare economics.(69) If this was the full story, then current levels of physical activity might be considered at optimal levels (for individuals themselves as well as for society), because they have arisen as a result of people making rational choices within given market conditions. Of course this is not the case, and it is generally accepted that this fundamental theorem is supported only by a partial understanding of the factors that determine how individuals make choices. In addition to the various theoretical and experimental insights from psychology,(56) there is also the potential problem of ‘market failure.’

The idea that ‘market failure’ may interfere in people’s decision making processes was first considered in various sub-fields of economics that developed during the twentieth century, including health economics,(70) transport economics(62) and environmental economics.(71) The main argument is that, if left uncontrolled, individuals will make sub-optimal choices from the perspective of society and that the market mechanism will deliver an inefficient allocation of resources. For example, an early paper published in 1924 by the British economist Arthur Pigou identified the problem of ‘externalities’, where individuals do not take into account the full societal costs of their actions, as a significant cause of market failure. Entitled ‘The Economics of Welfare’,(72) a tax on industrial emissions was proposed, so that producers were incentivised to take account of all external environmental costs in their decision making.

Another seminal paper published in 1963 by the Nobel prize-winning American economist Kenneth Arrow is often regarded as marking the beginning of research in health economics. Entitled ‘Uncertainty and the Welfare Economics of Medical Care’,(73) the paper made the case that market failure in the form of asymmetric information, where producers (including medical practitioners) have greater knowledge and information than consumers (i.e. patients), is a widespread problem in medical care transactions.

In the US, across all policy areas, there is a general requirement that Federal (national-level) agencies must "determine whether there exists a market failure that is likely to be significant"(74) before proceeding with any regulatory changes.(75)

In the UK, the two papers by Arthur Pigou and Kenneth Arrow may be used to provide the principal theoretical foundation for large scale Government intervention in the form of state-run healthcare or health insurance systems, including the NHS, and the widespread use of policies, including financial incentives, to tackle various environmental problems. Whilst there may be relatively little current debate about the correct level of Government intervention in these particular instances, debates about the appropriate level of Government interference in public health are ongoing. One feature of the 2010 "Healthy lives, Healthy people"(37) White Paper, for example, was a shift towards a greater role for individual responsibility, with an accompanying strategy paper on tackling obesity which stated that "it is the responsibility of individuals to change their behaviour to lose weight" and that "it is simply not possible to promote healthier lifestyles through Whitehall diktat and nannying about the way people should live."(76) This may be contrasted with the outcome of two high-profile reviews on health policy commissioned by the previous Labour Government. The first, by Sir Derek Wanless in 2004,(77) which argued for greater public investment in population health to help curtail rising healthcare expenditure,(77) and the second, by Lord Ara Darzi in 2008,(78) which emphasised the importance of "making more people more physically active."(78) A more recent report on obesity by McKinsey Global Institute (MGI), the research arm of the international consultancy firm not generally known for promoting Government interference, was nonetheless forthright in suggesting that policies including "portion control", "educating parents" and "restricting high calorie food and drink" would be justified given the scale of the problem.(79)

In the health economics literature, three principal sources of market failure are commonly used to provide a justification for policy intervention in the public health sector, beyond the narrower boundaries of medical care.(1, 21, 54, 80, 81)

1.3.2.1 Three principal sources of market failure

First, there is the 'public goods' argument.(81) Public goods are characterised by two features relating to their consumption (not their production, although they are typically provided by the 'public' sector): they are non-rival, in the sense that the ability of an individual to consume the product or service is not impacted by others having also consumed the product or service, and non-excludable, in that it is not possible to exclude any individual or groups of individuals from consuming it. Radio broadcasts of important information related to public health might be considered a good example of a public good which satisfies both criteria, and would thus provide a significant justification for Government to fund their delivery. Some transport infrastructure projects may also feature these characteristics, at least to some extent. For example, if a cycle path with sufficient capacity were built, then one person's use of it would not diminish the potential for others to benefit. Furthermore, it is probable that the owner would find the cost of limiting access to certain individuals to be prohibitively expensive. Such a scenario would lead to a free-rider problem, whereby individuals would always expect to use facilities provided by others. In the absence of government intervention, this would lead to an under-provision of infrastructure since no one would be willing to own or fund new facilities.

Second, 'information imperfections' may exist whereby individuals are poorly informed so they fail to take actions which are in their own best interests, and which are inconsistent with their desire to maximise utility. Engaging in risky health behaviours, or failing to access appropriate health services, are classic examples.

Third, there are 'externalities,' which may be defined formally as an unintended consequence of market decisions which affect individuals other than the decision maker. These are typically categorised as 'positive externalities', whereby the private decision of an individual does not take into account the positive impact on others, or 'negative externalities', where the private action of an individual does not take into account the negative impact on others. These are assessed in relation to the markets for active travel and private motorised travel in greater detail below.

1.3.2.2 Positive externalities associated with active travel

Whereas rational utility-maximising commuters would consider the private health benefits of physical activity when choosing whether to walk or cycle to work, they would nonetheless be expected to ignore some of the potential societal benefits arising from reduced costs of physical inactivity since these are borne by the wider economy.

First, there are the potential cost savings to the NHS, which is funded through general taxation (including National Insurance contributions). Drawing on existing literature in health economics, the costs associated with those diseases for which inactivity is a risk factor may be quantified using NHS cost data and 'population attributable fractions' (or PAFs), which are used to assess the proportional reduction in those diseases that would occur if everyone in the population achieved minimum recommended levels of physical activity.(82) These could indicate the size of the positive externality associated with more physical activity (however they might lead to overestimates since individual-level contributions to the NHS via taxation might have some positive impact on individual-level physical activity levels). Using 2006-7 cost data for England, one study published in 2011 estimated the annual cost of physical inactivity (in all activity domains, not just transport) in the UK to be £0.9 billion. This compares to an estimated £3.3 billion costs associated with smoking.(82) Using 1992-3 data, another similar study published in 2007 estimated the annual costs of physical inactivity to be £1.06 billion,(83) although this was considered an underestimate since some disease or event costs were excluded (particularly those that affect older people, such as osteoporosis and falls).(83) Estimates from a recent study which modelled the long term effects of more walking and cycling in the population of England and Wales identified potential savings of £17 million to the NHS arising from increased physical activity levels.(84)

Second, there is the potential reduction in other costs to society, including lost output outside of the NHS, which may arise as a result of physical inactivity in terms of sickness absence, productivity losses, or premature death amongst adults in work. Although these could justifiably be considered, few published studies have attempted to quantify them and estimates are necessarily subject to a greater degree of uncertainty. One unpublished study which is often cited in Department of Health and the Cabinet Office literature,(1, 85) by MEDTAP International, a consultancy firm,(86) reportedly identified annual costs of £5.5 billion from sickness absence (72,000 days lost) and £1 billion from premature death (86,000 lives) arising from all 'lifestyle-related' diseases in the UK. More recently, in 2014, a study by the Centre for Economics and Business Research (or CEBR), a consultancy firm which was commissioned by 'StreetGames,' a sports charity, predicted future costs of £45.2 billion over the lifespan of a cohort of current 11-25 year olds who do not currently meet recommended physical activity levels. These costs arose as a result of reduced quality and length of life and were in addition to £8.1 billion of future health care costs associated with treating diabetes, chronic heart disease, stroke and colon cancer.(87) However, it is also conceivable that the increased life expectancy associated with higher levels of physical activity would impose additional costs on other state-funded programmes such as pensions and other welfare payments to pensioners. Factoring in these longer term costs, one early study estimated that sedentary lifestyles nonetheless still imposed a net cost on society, however in the absence of further evidence, these results are unlikely to be conclusive (the study also found that smokers more than paid their own way to the extent that they subsidised non-smokers, however contradictory findings have since been reported elsewhere(88)).(54, 89-91)

Third, there are so-called 'network externalities', whereby each individual that joins a network confers additional benefits on other participants in the network.(92, 93) For example, concerns about personal safety at night that could arise when using dedicated traffic-free cycle routes would be reduced as more walkers and cyclists used the facility. This argument might be used to support the continued expansion of Britain's 15,000-mile National Cycle Network, which could attract more cyclists to an area by linking up local routes and providing people the opportunity to cycle to a larger number of destinations.(51) A similar case is sometimes made for in favour of Government intervention in public transport networks, in terms of investment, the coordination of services and even ownership. For example, if expansion of one part of the public transport network led to additional fare-paying passengers using other services across the network, then existing passengers would benefit from higher frequency services, greater geographical and late night or early morning coverage, for example, that wouldn't have been affordable without the additional passengers.

Fourth, a decision to use active travel modes could also have a positive health impact on the behaviour of others in the immediate family, including children who may be encouraged to cycle to school for example, or others in society who may not have otherwise considered active travel to be an option.

1.3.2.3 Negative externalities associated with private motorised transport

In addition to the focus from the public health perspective on the positive externalities associated with active travel, other literature in environmental economics and transport economics has typically focused on the negative externalities associated with car travel and other forms of private motorised travel.(94) These include road congestion, road traffic crashes that result in significant costs in terms of damage to property, personal injury or death, and local and global environmental pollution, such as noise, air pollution and greenhouse gases. Car travel can also make walking and cycling unpleasant and have a detrimental impact on social interaction within communities.(33, 95) Following Pigou's proposed environmental tax, financial incentives have long been used to encourage behaviour change. In the UK, these include fuel (petrol and diesel) duty, which generated revenue of £26.9 billion in 2011-12, and vehicle excise duty worth £5.8 billion (although there is considerable debate about the most efficient and equitable design of these behaviour change interventions).(96) (95, 97, 98) While some related epidemiological studies have modelled the impact on road traffic emissions if commuters switched from private motorised transport to active travel modes (one such study argued that the reduction in emissions would be larger than would be the case if people increased their recreational physical activity, since active commuting is more likely to lead to reduced car journeys),(33, 99, 100) a paper by Sallis et al. argues that the focus amongst transport researchers on these road traffic externalities is excessive since they are dwarfed by the costs of physical inactivity by a magnitude of at least four times.(101)

1.3.3 Potential forms of policy intervention to promote active travel

From an economics perspective, alongside the identification of market failure or other factors identified in behavioural economics which lead people to deviate from the standard assumption of ‘rational’ behaviour, an important factor in determining whether or not Government intervention is justified would be the identification of suitable policies that could be implemented.

Reflecting the specific sources of market failure identified in the previous section, three main forms of policy interventions in public health are proposed by a team of economists in a recent paper ‘Equity and efficiency in public health: the contribution of health economics’ (see Table 1-1).(81) A fourth potential intervention, the imposition of rules and regulations, tends to be reserved for the most dangerous activities and hence is likely to be considered undesirable for tackling physical inactivity. Nevertheless, obvious examples from the UK transport sector include compulsory driving licences, annual vehicle safety tests and drink driving legislation which may be deemed necessary due to the potential for catastrophic consequences or because other interventions would fail to have an impact, and similarly draconian measures have been proposed in the food industry in the recent McKinsey MGI report on tackling obesity.(79)

First, Governments may be involved directly in the provision of public health programmes, particularly those with public good characteristics. For example, in terms of promoting active travel, this could include improvements to walking and cycling infrastructure,(51) including those projects funded since 2005 through the ‘Local Sustainable Transport Fund’ or ‘Cycle Demonstration Towns’ schemes (as mentioned in section 1.2.3.1).(50)

Second, Governments might deliver information campaigns to correct information imperfections. These could include the provision of individually targeted information about local public transport or active travel routes, for example. The Department for Transport’s 2011 ‘Behavioural Insights Toolkit’, for example, information campaigns which attempt to alter habitual travel behaviours should be targeted during key ‘transition points’ or ‘moments of change’, such as moving house, changing job or having children, when people are thought to be particularly receptive.(64, 102-104) Exploiting the opportunity presented by the Olympic Games held in London in 2012, Transport for London (London’s local transport authority) ran an information campaign targeted at regular London commuters who were faced with significant, large scale and unprecedented disruption to their usual, habitual travel routes. Prior to the opening ceremony, one survey suggested that 88% of regular London commuters were aware of, and 64% had made use of the ‘Get Ahead of the Games’ website which had encouraged commuters to consider walking and cycling.(105)

Third, Governments may use financial incentives, including taxes or subsidies, to bring about an efficient level of consumption of goods and services. Individually targeted taxes are imposed on activities, such as fuel consumption, which are deemed to be used excessively when compared to the efficient level of consumption. Conversely, subsidies are used to support public transport services(106) and could be used to encourage higher levels of active travel, if current levels of walking and cycling were deemed to be at sub-optimal levels.

1.3.4 Economic evaluation of policies that promote walking or cycling

This section begins with an overview of the standard techniques used in economic evaluation, in both the health and transportation sectors, including a short review of existing published literature on the effectiveness of interventions to promote active travel. Its purpose is to set out the challenges that would be faced by researchers seeking to evaluate the impact of interventions to promote walking or cycling as a potential means of encouraging higher levels of physical activity. It highlights the potential for analysing large scale panel data sets using some analytical techniques more commonly used in economics than in other areas of public health research.

1.3.4.1 Overview of methodologies used in economic evaluation

Economic evaluation is a well-established tool used by decision makers across most areas of specialisation in economics, including health economics, transport economics and environmental economics, and can be used to determine whether specific policy interventions represent an efficient use of scarce resources when compared to other competing demands.

In the health economics literature, full economic evaluation is commonly defined as "the comparative analysis of alternative courses of action in terms of both their costs and consequences" and is contrasted with other forms of evaluation which are limited because they do not include costs, benefits, or a comparison group (see Table 1-2).(107) In the UK, the health economics literature is dominated by cost-utility analyses of healthcare technologies, such as new pharmaceutical and biopharmaceutical products, to inform commissioning guidance produced by NICE.(108) In this particular form of full economic evaluation, costs are measured in monetary units, while consequences are typically measured in Quality Adjusted Life Years (QALYs), a generic health outcome measure which avoids the explicit monetisation of different health states yet enables interventions to be compared across disease areas (a cost-effectiveness analysis, in contrast, is more limited in the sense that the health outcome is uni-dimensional so only comparisons of interventions in a single disease area can be supported). A particular characteristic of the health economics approach is the measurement of benefits not only in terms of improvements in length of life, but also in terms of quality of life and subjective wellbeing. Hence there is a significant body of health economics research concerning the measurement of quality of life which might be an important component in the evaluation of interventions to promote active commuting. NICE typically uses a cost-per-QALY threshold of between £20,000 and £30,000 to determine whether or not new healthcare technologies are cost-effective, relative to existing demands on the healthcare budget (although there is considerable current debate on the exact value, or range of values, the threshold takes (109)). This method is sometimes referred to as an 'extra-welfarist' approach and is distinguished from a more conventional 'welfarist' approach to economic evaluation since the objective is to maximise utility arising only from consumption that has an impact on health. This avoids the need to draw comparisons with utility that is gained from consumption of other goods or services beyond the health sector.

In transport economics, it is the welfarist approach which underpins the widespread use of the more conventional cost-benefit analysis, where both costs and consequences are measured in monetary units. This allows comparisons of interventions across all areas of departmental spending in terms of their net benefit-to-cost ratios, but may mean that some wider economic, environmental, social and distributional benefits are overlooked. Although the Department for Transport has revised its guidance on economic evaluation in recent years,(110) in an era when passengers can make productive use of their journeys for work purposes,(111) a common criticism is the over-emphasis on the monetary benefits of travel time savings. For example, while ‘walking’ does feature in the official cost-benefit analysis of the £43 billion ‘High Speed 2’ rail project, a proposed new railway running between London, the Midlands and the North of England with an official cost-benefit ratio of 1:2.3, it is surprising that this is only in terms of the £1,330 million of benefits (2% of total benefits) estimated to be gained from a ‘reduction in walking’ at railway stations.(112) This indicates that some potential health benefits of walking might have been overlooked. These could including the walking to and from railway stations which form part of the overall journey, or the potential benefits arising from building high-quality walking and cycling infrastructure alongside major new rail or bus infrastructure, as has been investigated in a recent study of the Cambridgeshire Guided Busway.(113)

1.3.4.2 Summary of published economic evaluations

Since 2006 NICE has assumed a new role in publishing evidence-based guidance for public health commissioners,(114-116) building on its longer standing responsibilities in the evaluation of clinical interventions for the NHS. During this time, related health economics publications in public health, and the determinants of health and ill-health, have also increased.(117) However, while there is a general expectation that public health interventions offer good value for money when considering the current cost-effectiveness thresholds used by NICE,(116) a number of systematic reviews have highlighted the relative dearth of health economic evaluations of public health interventions when compared to published economic evaluations of interventions in clinical settings. A systematic review of health economic evaluations published between 1995 and 2005 of interventions aimed at reducing cardiovascular disease event or risk reduction (where risk factors include smoking, high blood pressure, high body mass index (BMI) and low physical activity) found that just 10% of studies evaluated health promotion activities such as education, advertising or legislation.(118) Of 195 studies included in the review, the remaining 90% were clinical studies that focused mainly on lipid-lowering drugs. Only five of the identified studies focused solely on physical activity. A second review by Weatherly et al. of full health economic evaluations of public health interventions published between 2000 and

2005 identified a total of just 154 studies, of which 14% related to obesity and physical activity, the second most common subject after prevention of accidents.(119)

In the public health literature, existing reviews have identified a small number of studies which have investigated the impact of interventions to promote active travel. A systematic review published in 2007 by Ogilvie et al. of studies of interventions to promote walking identified 48 studies, although just six of these were deemed to include some aspect of economic evaluation,(120) none of which could be described as a full economic evaluation in the health economics sense (in most cases since there were no control or comparison groups). A complementary systematic review of interventions to promote cycling published in 2010 by Yang et al. identified 25 studies.(121) A key issue, which was also highlighted in two similar reviews that identified a small number of additional economic evaluations of interventions to promote physical activity (in all activity domains, not just transport),(122, 123) was that most identified studies were of individually targeted behavioural interventions including, for example, the provision of advice on physical activity in workplaces, schools, or clinical settings, often characterised by small sample sizes and short follow-up times. Few studies evaluated larger scale changes to the built environment (such as infrastructure changes including cycle paths), despite the apparent potential to influence the behaviour of large numbers of people.(124) Some of the review authors concluded that this was because of the complexity of assessing the impact of such interventions and, in common with the review by Weatherly et al., it was noted that randomised controlled trials (RCTs) in particular were rarely used (even though they were not uncommon in studies of smaller scale behavioural interventions e.g. of the studies identified in the review by Ogilvie et al., 40% were RCTs). Since RCTs are considered the ‘gold standard’ study design for estimating the effect of an intervention, as observed effect sizes can generally be attributed to the intervention rather than to unobserved differences between individuals, there was a concern that decision makers might be tempted to invest scarce resources in the smaller scale individual-level interventions, simply because RCTs of such interventions are more common. This would overlook the opportunity costs, in terms of the larger scale population-level interventions, regardless of their relative cost-effectiveness.(125)

Three further reviews published in the transportation literature identified additional economic assessments of transport infrastructure and policies which included the health impact of changes in walking and cycling. These studies drew more heavily on methods used in the transport sector and hence used cost-benefit analysis and measured health outcomes in monetary units. In common with the studies identified in the public health reviews described above, these could not be described as full economic evaluations in the health economics sense. This was because, although health outcomes were included, a cost of illness approach was typically used, whereby the reported costs of physical inactivity in terms of mortality and/or morbidity were used to derive an estimate of the value of anticipated increases in walking or cycling levels at the population-level. A similar methodology has been used by the WHO to create the Health Economic Assessment Tool (HEAT), which aids decision makers in conducting economic assessments of the potential health benefits of new cycling or walking infrastructure.(35) The tool has been used widely by local authorities and incorporated into the Department of Transport's own 'Transport Analysis Guidance' (also known as WebTAG) for assessing the impact of new transport infrastructure, including walking and cycling infrastructure.(110)

Of the three reviews of studies using these methods, the most recent was published in 2014 by the Department for Transport and concluded that the mean benefit-to-cost ratio for all active travel schemes identified was 6.28:1 (or 5.62:1 if non-UK studies were excluded). Compared to other transport projects that had been assessed by the Department for Transport, investment in such schemes was deemed good value for money, since existing criteria ranks 'very highly' any scheme which returns a benefit-to-cost ratio greater than 4:1. The included studies had been undertaken predominantly by the Department for Transport,(126) local authorities, Sustrans (a cycling charity), and a consultancy firm on behalf of 'Cycling England' (an independent body which was funded by the Department for Transport to promote cycling in England from 2005-2011) to assess the impact of local schemes to promote active travel.(110) The other two similar reviews of studies using these methods were published in academic journals and focused on large scale infrastructure improvement. One, published by Powell et al. in 2010 identified five studies published between 1989 and 2009,(127) and the other by Cavill et al. in 2009 identified 16 studies.(128)

1.3.4.3 Methodological challenges in the evaluation of large scale infrastructure changes

Drawing on the findings of the reviews discussed above, and other related discussion papers,(80, 116, 119, 123, 129) a number of common issues are raised about the need to develop more robust methodologies for the purpose of evaluating public health interventions (a key recommendation of the 2004 report by Sir Derek Wanless).(77) In the context of the economic evaluation of large scale infrastructure improvements to promote active travel, three particular issues are discussed in turn.

First, it is important to account for the full range of societal costs and benefits across all sectors. These include, for example, the health benefits of physical activity and the environmental costs of motorised transport that are summarised in section 1.3.2.1. Other economic benefits might impact on local tourism,(130) arising from increased leisure cycling, or the impact on the local economy (including the housing market) where new rail stations are built, for example. A related issue is how best to incorporate widely-accepted societal judgments about the need for an equitable distribution of health across the population which, although reflected in current Department for Health policy,(20, 115, 131, 132) is less likely to be a major consideration in transport planning. Consider an information campaign to encourage commuters to switch from cars or public transport to active travel modes, for example. From the perspective of the transport sector, an efficient allocation of resources might include targeting the intervention at individuals who are most likely to respond (i.e. the 'low hanging fruit'), or those who live in areas with the most highly congested roads or rail networks. However, from the perspective of the health sector, there may be concern about an 'equity-efficiency' trade-off which would arise if the desire to maximise 'efficiency' conflicted with a need to design targeted interventions for specific population groups in order to reduce health inequalities. In principle these additional factors could be incorporated into the conventional cost-utility or cost-benefit frameworks, however some authors have proposed alternatives (e.g. by developing a new outcome measure based on Sen's capability approach, or using another willingness to pay approach).(123)

Second, there are difficulties in assessing the long term impact of interventions to promote active commuting since they will conceivably extend over many decades, giving rise to uncertainty about who benefits, by how much, and when. In this regard, decision-analytic modelling, including dynamic micro-simulation modelling,(133-136) is a widely used tool for handling uncertainty in economic evaluations of clinical interventions (in essence, alternative policy options are compared in these models by incorporating the expected costs and benefits of many different outcomes, weighted by the estimated probability of each outcome). A related issue is the sensitivity of results to the choice of discount rate, which is perpetuated over longer time periods, and so may be a particular issue in the assessment on preventive health programmes.(137) Discount rates are applied to costs and benefits in economic evaluations to account for positive time preferences, the phenomena whereby individuals are said to prefer consumption sooner rather than later (this could be for various reasons, including an expectation that they will be wealthier in the future), however there is much debate about whether the discount rate used by NICE in health economic evaluations should be the same as that used by other Government departments, including the Department for Transport (since, for example, the cost-utility framework measures health, not monetary values, which cannot be traded over time).(137, 138)

Third, there is the need to identify alternatives to RCTs for measuring the impact of large scale infrastructure changes to promote active travel. A number of techniques drawn from various disciplines including health economics, health geography and epidemiology, could provide a promising alternative for evaluating observational data and natural experiments (natural experiments are defined by the UK's Medical Research Council (MRC) as events, interventions or policies which are not under the control of researchers, but which are amenable to research which uses the variation in exposure that they generate to analyse their impact).(139) For example, instrumental variables and regression discontinuity are widely used for evaluating public policies that are typically not tested in randomised experiments in public economics and labour economics,(140) yet seem underutilised in public health research. Such techniques are an important component of current research in health econometrics,(141) which is a term used to describe the development and application of econometric methods within health economics and encompasses ex-post evaluative techniques including econometric policy evaluation with or without experimental data (broadly defined, econometrics aims to give empirical content to economic phenomena for testing economic theories, forecasting, decision making, and for ex post decision/policy evaluation).(142, 143) A particular focus of research in this field is the use of large, longitudinal panel datasets.(143)

1.4 Summary of chapter and overview of thesis

This section provides a summary of the current chapter and an overview of the remainder of the thesis.

1.4.1 Summary of this chapter

This chapter began by reporting trends in physical inactivity and travel behaviour amongst people of working age in the UK.

This chapter then highlighted four strands of research from the discipline of health economics which, it was proposed, could enable economists to contribute some distinctive role in research on walking and cycling when compared to existing work in public health and transportation (section 1.3). In order to assist an explanation of how these four strands of research are linked to the core objectives of this thesis, Figure 1-7 provides an overview of these research strands (shown as i. to iv.) including some of the key ideas that were highlighted in this chapter, and how each research strand provided the basis for the work that is reported in the remaining chapters of the thesis (chapters 2-8).

First, in section 1.3.1 (shown as (i.) in Figure 1-7), recent work in behavioural economics and the problem of market failure were introduced, in terms of how people may behave differently to what would be expected in standard economic models which rely only on the expected utility hypothesis. These factors provide a basic economic justification for policy intervention.

Second, in section 1.3.2 (shown as (ii.) in Figure 1-7), examples of market failure in the markets for active travel and private motorised travel were identified, in order to provide an explicit justification for policy intervention in those areas.

Third, in section 1.3.3, potential forms of policy intervention were discussed in relation to the specific forms of market failure which had previously been identified (e.g., as shown in Figure 1-7, financial incentives may be a suitable response to the problem of externalities).

Fourth, in section 1.3.4, there was discussion of the role of economics in the evaluation of those policy interventions. Two key findings from the summary of current evidence on the effectiveness of interventions to promote active travel were the predominance of small scale behavioural interventions rather than large scale changes to the built environment, and the use of observational study designs, rather than RCTs. The use of existing observational data from large scale panel datasets, combined with analytical techniques often used in econometrics which mimic some features of RCTs, was proposed as a potential way forward (and these two points are shown in Figure 1-7).

1.4.2 Overview of the remainder of the thesis

The three core objectives of this thesis, which are addressed in turn in the three remaining substantive sections of this thesis, are shown in Table 1-3.

The purpose of this section is to describe how the remaining chapters in this thesis address the core objectives and how these objectives relate to the four strands of research summarised in the previous section.

The first substantive section of this thesis (Section B/Chapters 2 and 3) focused on the challenges involved in evaluating the impact of (large scale) public health programmes, such as cycling infrastructure (the first of four policy interventions listed in Figure 1-7 and Table 1-1). Chapter 2 begins with a review of those analytical techniques which seem underused in existing public health and transportation research, and which might be used to estimate the causal impact of infrastructure changes which are designed to support an increase in walking and cycling at the population-level (evidence of which is currently lacking). The main feature of this chapter was a literature review, which was designed primarily to identify relevant examples where these techniques had been used. Rather than restricting the inclusion criteria only to a potentially small number of studies where improvements in active travel infrastructure had been assessed, studies of the relationship between a wider range of features of the urban built environment and obesity were identified. It was proposed that some general lessons might be drawn from these studies to inform future analyses of the impact of large scale changes to cycling infrastructure. An important objective of the chapter was to explore whether the choice of methodology critically affected the results obtained since, if this were the case, then policy makers surely need to consider how they weigh evidence gathered from studies that use different methods. Chapter 3 builds on Chapter 2 with the aim of providing policy makers with a tool for interpreting studies which use more advanced analytical techniques. In theory at least, these studies could provide a better guide to policy making than other studies which used more standard regression techniques and cross-sectional data, for example. The chapter goes someway to developing a taxonomy which would aid decision makers in the process of distinguishing between studies which use different methodological techniques according to the likelihood that robust causal inferences can be supported. The taxonomy is applied to the studies identified in three separate reviews, including the studies identified in Chapter 2. The potential added value of the taxonomy in the context of existing guidelines for reviewers of observational studies is then explored whilst also highlighting the limitations of this approach, including the importance of assessing whether or not a particular analytical technique has been used correctly. In the case of instrumental variables, a good practice checklist is devised so that reviewers can assess whether or not the technique has been appropriately used.

The second substantive section of this thesis (Section C/Chapters 4 to 6) reported three separate analyses of the British Household Panel Survey (BHPS), a large-scale, multi-purpose longitudinal study of private households in Great Britain (later extended to the UK) that began in 1991-1992 as an annual survey of each adult member of a nationally representative sample and continues today (since 2009, the BHPS has been relaunched and expanded as ‘Understanding Society’). Chapter 4 began with an introduction to the dataset and a series of logistic regression analyses which explored the characteristics of people who are most likely to walk or cycle to work, and some of the ‘life events’ or ‘life changes’ which might be associated with travel behaviour change. Some implications for the targeting of behaviour change interventions, including the Department for Transport’s proposal to deliver information campaigns (the second of four policy interventions listed in Figure 1-7 and Table 1-1) at key 'transition points' (such as moving house, changing job or having children) are discussed. Chapter 5 explored the impact of switching travel modes on overall subjective wellbeing using linear fixed effects models, and on twelve specific aspects of wellbeing using fixed effects logit models. A purpose of this chapter was to provide an example of how one of the econometric approaches identified in Chapter 2 can be used in the analysis of a large scale panel data set. A similar study design was also used in Chapter 6 to explore longitudinal associations between switching travel mode and BMI. Together, these two studies contributed an additional justification for policy intervention (in addition to the more theoretical justification explored in Section 1.3.2), since they represent a contribution to existing literature on the relationship between active commuting and health which is otherwise dominated by cross-sectional studies.(144-148)

Having developed a case supporting the idea of policy intervention in the market for active travel, the third substantive section of this thesis (Section D/Chapters 7 and 8) focused specifically on the potential role of financial incentives (the third of four policy interventions identified in the Introduction, see Table 1-1). Chapter 7 sought to provide a theoretical justification for considering the role of financial incentives to promote active travel, particularly when compared to the possibility of providing financial incentives for active leisure pursuits (e.g. swimming). The chapter took a theoretical, rational choice perspective, and developed a simple analytical framework for assessing the utility-maximising behaviour of commuters in terms of their travel mode choices. Whilst the framework is rooted in the standard economic assumptions of rational behaviour, attention was also given to the importance of behavioural economic concepts on travel behaviour, as introduced in section 1.3.1. Having first presented a theoretical framework to support the idea of using financial incentives to promote active travel, Chapter 8 goes on to present a literature review of studies that have assessed the impact of financial incentives on the demand for active travel.

With reference to Figure 1-7, each section of this thesis considered (at least to some extent) one of the potential forms of policy interventions outlined in Table 1-1 (Section B: public health programmes, Section C: information campaigns, Section D: financial incentives). Furthermore, the role of econometric methods and large panel data sets were core themes in Section B and Section C.

This thesis concludes with an overview of the main findings and suggestions for future research in Chapter 9 (Conclusion).

Table 1-1: A summary of four proposed forms of policy interventions in public health

(1) Governments may be involved directly in the provision of public health programmes, particularly those with public good characteristics.
(2) Governments might deliver information campaigns to correct for information imperfections
(3) Governments may use financial incentives, including taxes or subsidies, to bring about an efficient level of consumption of goods and services.
(4) Governments could impose rules and regulations.

Source: Morris et al. (2010)(81)

Table 1-2: Characteristics of different types of health economic evaluation

		Are both costs (inputs) and consequences (outputs) of the alternatives examined?				
		NO		**YES**		
Is there comparison of two or more alternatives?	**NO**	Examines only consequences	Examines only costs			
		<u>PARTIAL EVALUATION</u> **Outcome description**	**Cost description**	<u>PARTIAL EVALUATION</u> **Cost-outcome description**		
	YES	<u>PARTIAL EVALUATION</u>		<u>FULL ECONOMIC EVALUATION</u> Costs are measured using monetary units and benefits are measured using:		
		Efficacy or effectiveness evaluation	**Cost analysis**	A single clinical or natural measure of effectiveness: **Cost-effectiveness analysis**	A multidimensional measure of utility arising from health: **Cost-utility analysis**	Monetary units: **Cost-benefit analysis**

Source: Drummond et al. (2005)(107)

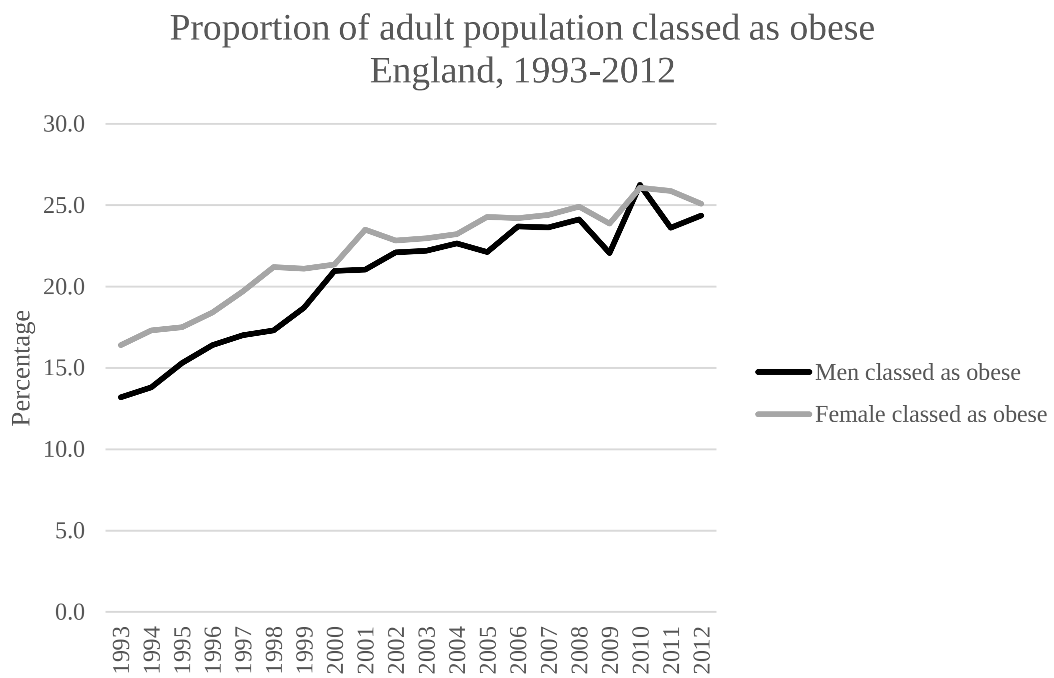
Table 1-3: Overview of the core objectives of the thesis

- Objective 1 (Section B):   *To explore the potential value of analytical techniques typically used in health econometrics in the evaluation of the causal relationship between active commuting, policy interventions and health outcomes.*   ***- Objective 2 (Section C):***   *To examine the health impact of switching from sedentary travel modes to more active travel modes for the daily commute to work using multiple waves of the BHPS.*   ***- Objective 3 (Section D):***   *To explore the potential for using financial incentives as a policy intervention to encourage uptake of active travel.*

Figure 1-1: Obesity: definition and trends in adult prevalence

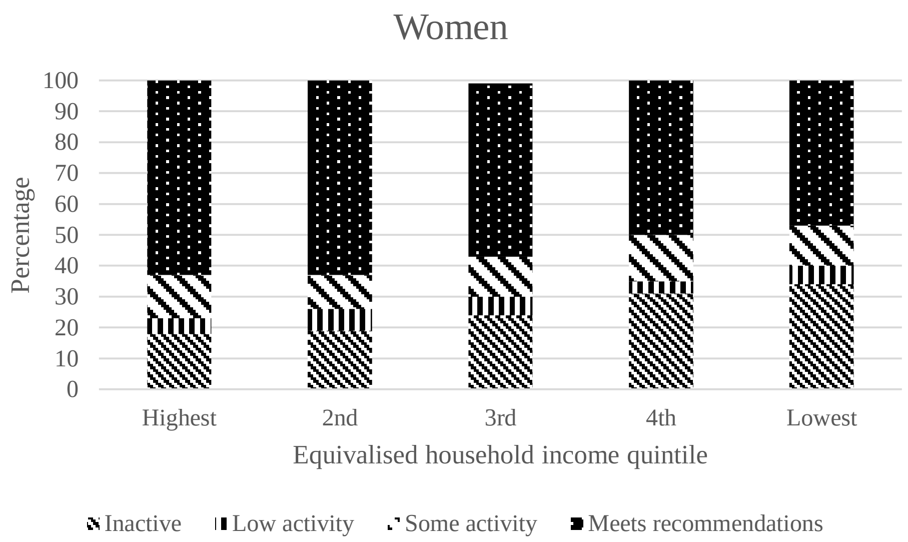
The most common measure of obesity uses data on body mass index (BMI) which is calculated by dividing a person's weight measurement (kilograms) by the square of their height (metres). Adults are considered overweight if they have a BMI of 25kg/m^2 to 29.9kg/m^2, and obese if they have a BMI of 30kg/m^2 or above. A BMI of 18.5 kg/m^2 to 24.9kg/m^2 is considered a healthy BMI. Like physical inactivity, obesity is a risk factor for a wide range of diseases including diabetes, hypertension, cancer, heart disease and stroke as well as poorer psychological wellbeing.

Objective measures from the Health Survey for England (HSE) show that, in common with other developed countries,(4) the proportion of adults classed as obese has risen in recent decades. Between 1993 and 2012, the proportion of men classed as obese rose from 13.2% to 24.4%, and the proportion of women from 16.4% to 25.1%:



Source of data: Health Survey for England (HSE), 1993-2012(149)

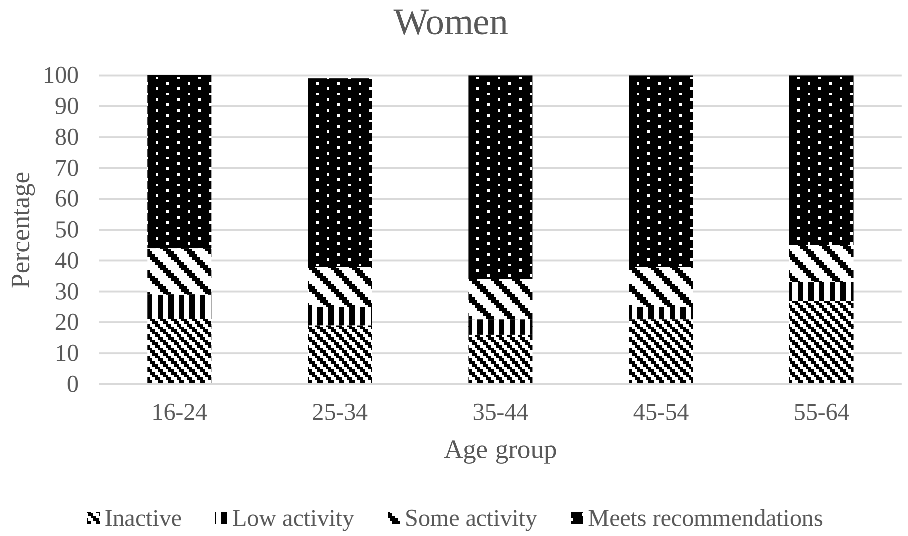
Figure 1-2: Self-reported data on the proportion of adults meeting physical activity recommendations, by age-standardised, equivalised household income and gender

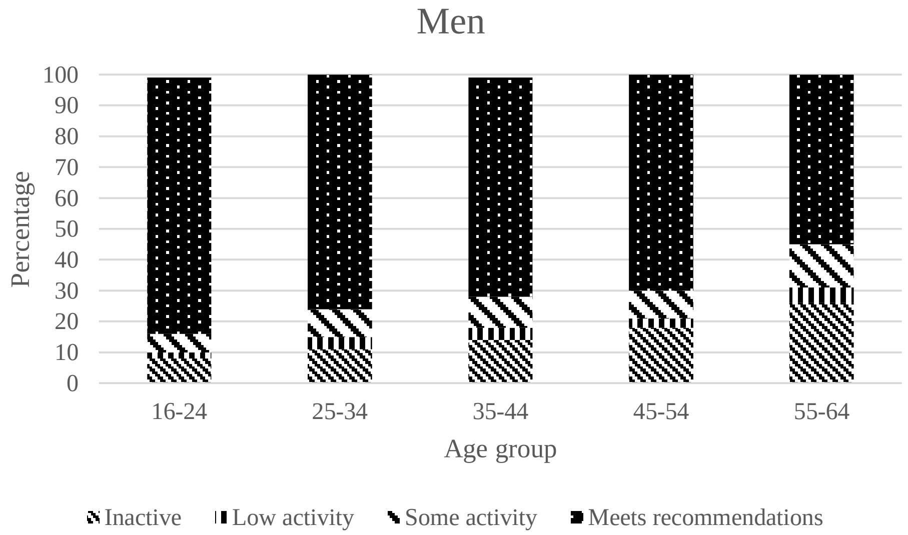


'Inactive' if reported less than 30 minutes/week of MPA or less than 15 minutes/week of VPA[a]
'Low activity' if reported 30-59 minutes/week of MPA, 15-29 minutes/week of VPA[a]
'Some activity' if reported 60-149 minutes/week of MPA, 30-74 minutes/week of VPA[a]
'Meets recommendations' if reported 150 minutes/week of MPA, 75 minutes/week of VPA[a,b]
MPA: moderate intensity activity. VPA: vigorous intensity activity.
[a] Or an equivalent combination (minutes of VPA were given twice the credit of minutes of MPA when combining moderate and vigorous intensity to calculate the equivalent combination)
[b] Only bouts of 10 minutes or more were included towards the 150 minutes/week target

Source of data: Health Survey for England (HSE), 2012(2)

Figure 1-3: Self-reported activity levels, by age and gender

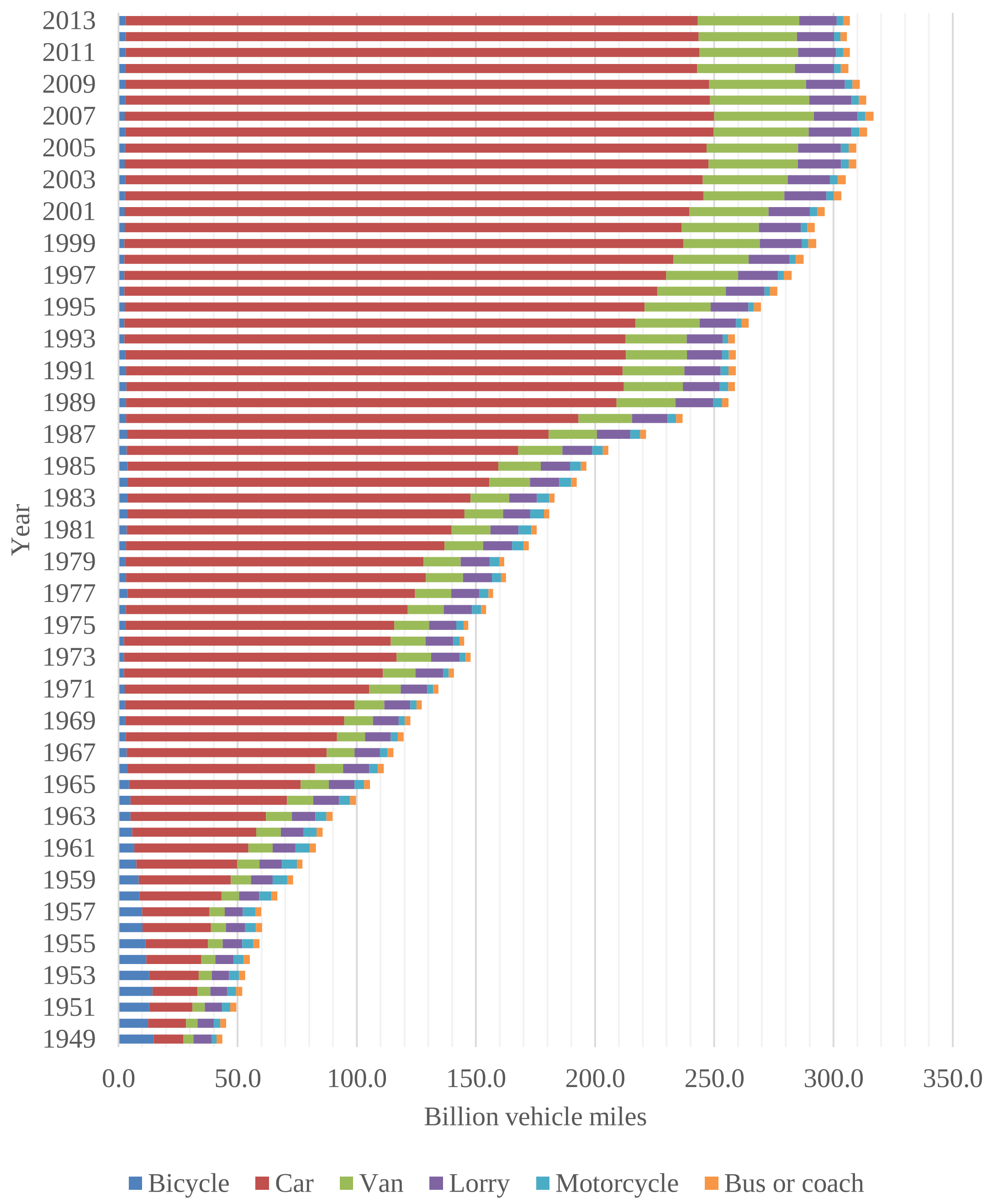




'Inactive' if reported less than 30 minutes/week of MPA or less than 15 minutes/week of VPA[a]
'Low activity' if reported 30-59 minutes/week of MPA, 15-29 minutes/week of VPA[a]
'Some activity' if reported 60-149 minutes/week of MPA, 30-74 minutes/week of VPA[a]
'Meets recommendations' if reported 150 minutes/week of MPA, 75 minutes/week of VPA[a,b]
[a] Or an equivalent combination (minutes of VPA were given twice the credit of minutes of MPA when combining moderate and vigorous intensity to calculate the equivalent combination)
[b] Only bouts of 10 minutes or more were included towards the 150 minutes/week target

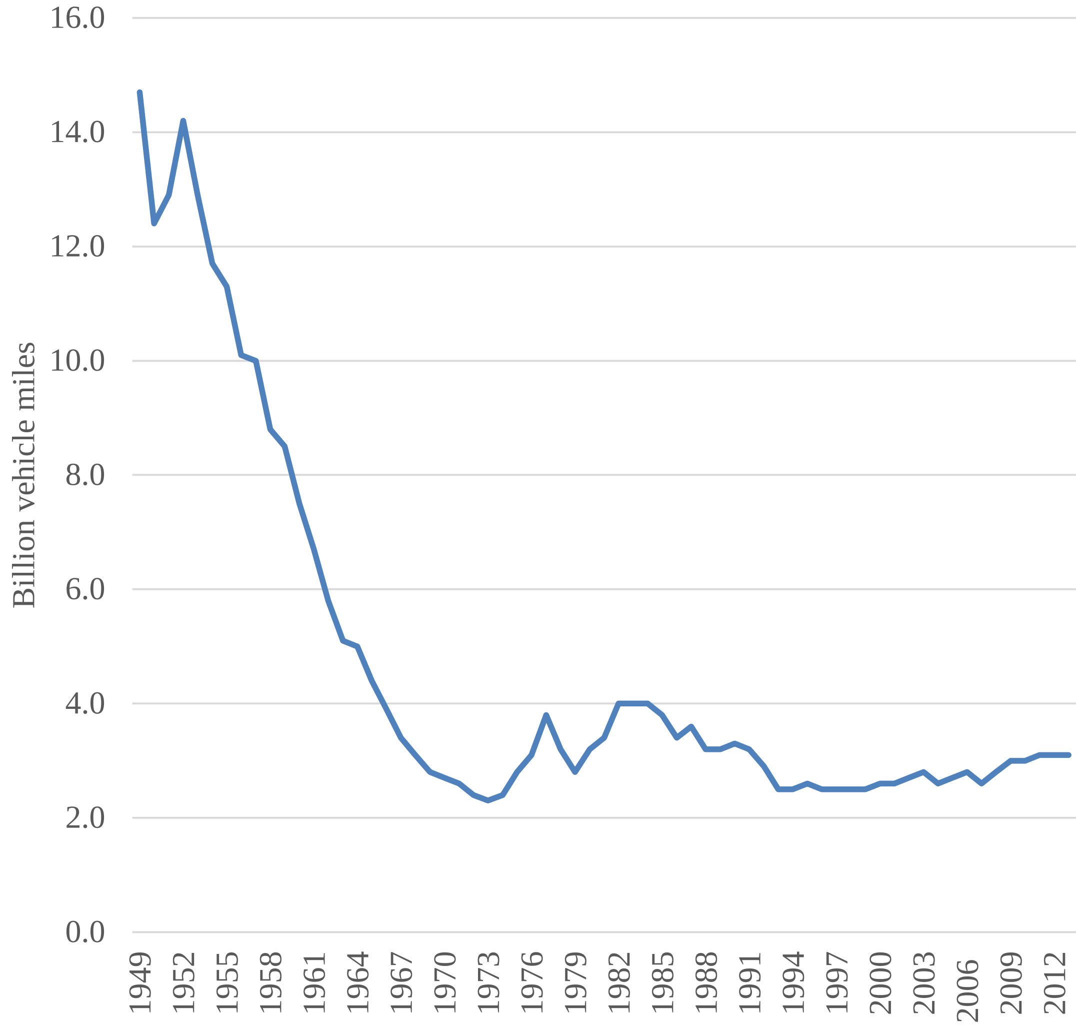
Source of data: Health Survey for England (HSE), 2012(2)

Figure 1-4: Billion vehicle miles, Great Britain, by travel mode



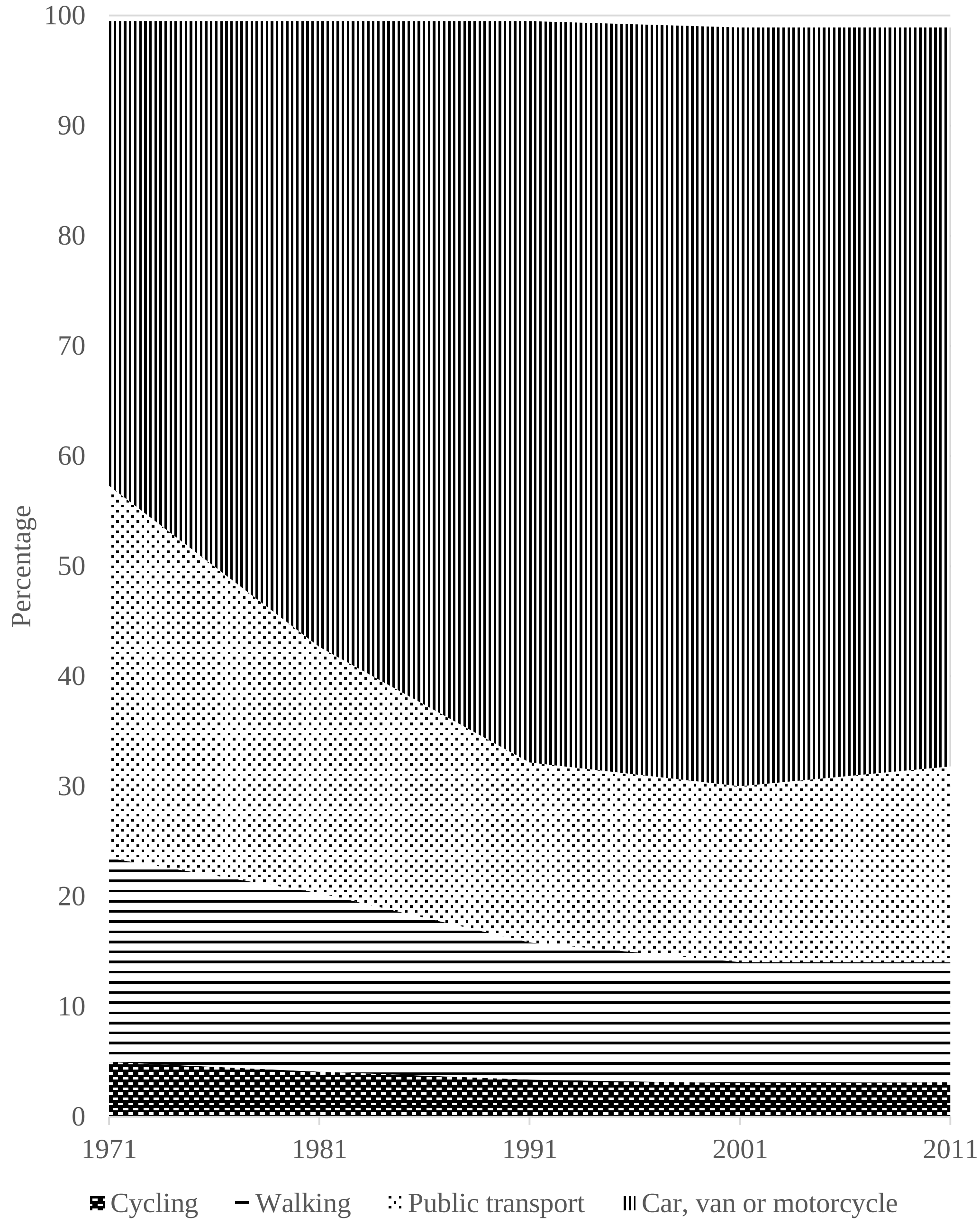
Source of data: National Road Traffic Survey (NRTS), 1949-2013(26, 150)

Figure 1-5: Billion vehicle miles, Great Britain (bicycle)



Source of data: National Road Traffic Survey (NRTS), 1949-2013(150)

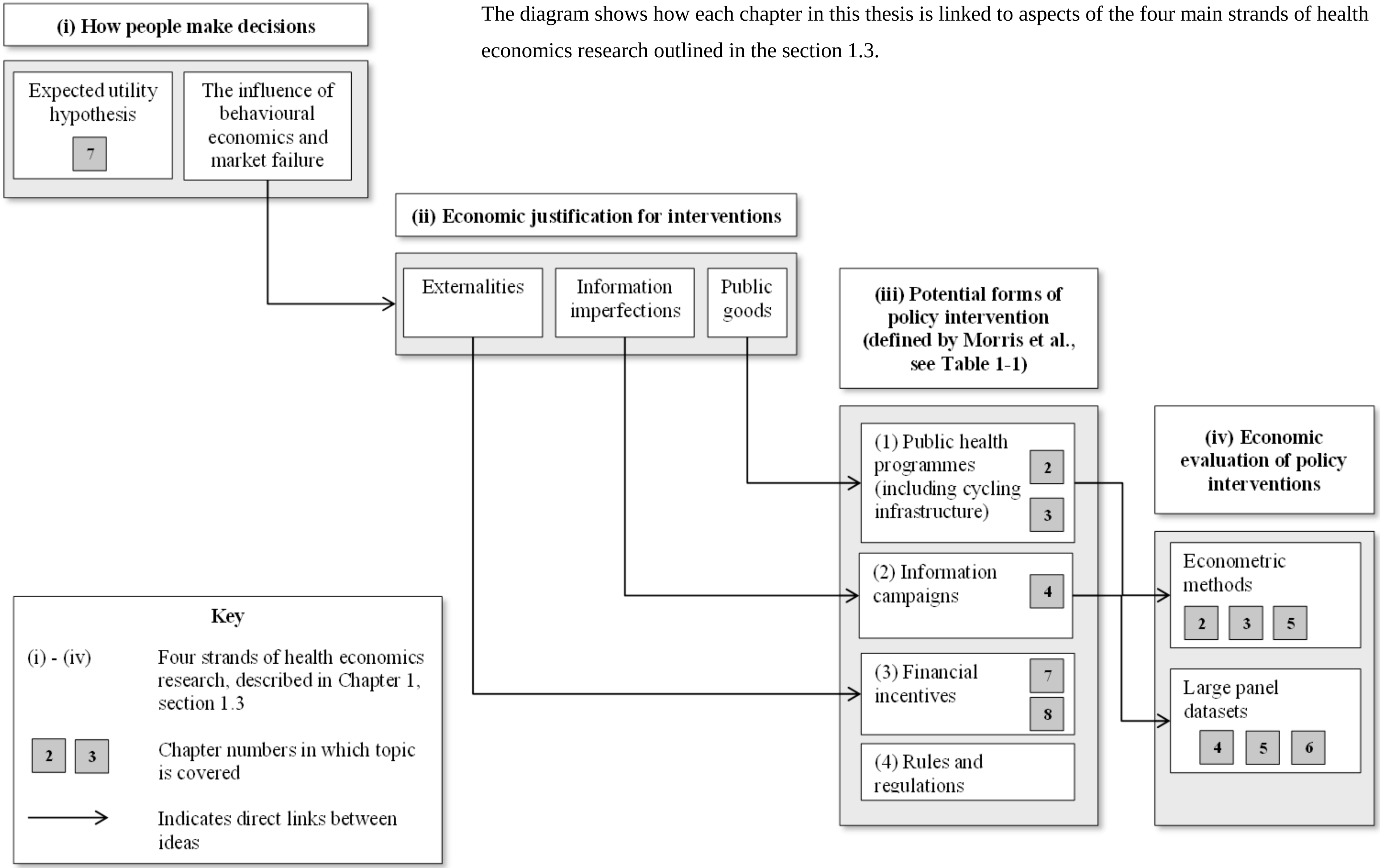
Figure 1-6: Commute mode share (England and Wales), 1971-2011



Source of data: Census data (England and Wales) reported in a paper by Goodman et al. (2013)(33)

Figure 1-7: Plan of thesis

The diagram shows how each chapter in this thesis is linked to aspects of the four main strands of health economics research outlined in the section 1.3.



SECTION B: AN OVERVIEW OF ECONOMETRIC METHODS USED IN OBSERVATIONAL STUDIES OF THE URBAN BUILT ENVIRONMENT

2 Evaluating causal relationships in the absence of evidence from randomised controlled trials: a review of observational studies

2.1 Overview of chapter

This chapter presents a review of observational studies of the relationship between urban built environment characteristics, a potentially justified intervention due to its ‘public good’ characteristics (see Table 1-1), and obesity, an important health outcome (see Figure 1-1). Rather than focusing solely on studies of built environment changes that might support more walking or cycling, the primary purpose of this review was to identify studies which had attempted to use particular analytical approaches, and so the search strategy included a broader range of built environment terms, beyond what would typically be expected to have a direct impact on walking or cycling behaviour.

The focus of the review is on methodological approaches which go beyond single equation analytical techniques used in cross sectional study designs, since these feature extensively in existing reviews and cannot be used to support robust causal inferences. More advanced analytical techniques, including those recommended for use in the MRC guidance on evaluating natural experiments (see section 1.3.4 and Table 2-1) can help mitigate biases that arise from differences in observable and unobservable characteristics between intervention and control groups, and may represent a realistic alternative to randomised experiments which are scarcely used in public health research, let alone built environment research.

In addition to identifying relevant studies, a second objective of the chapter is to draw within- and between- study comparisons of results in order to explore whether the choice of methodological approach critically affects the results obtained. Should this be the case then there would be implications for evidence synthesis processes and these are discussed in Chapter 3.

2.2 Background

A small number of existing reviews have documented many studies of the association between characteristics of the urban built environment and physical inactivity or health outcomes.(151-154) Indicative of the apparent importance of the issue in current policy debates, two of these reviews were commissions by agencies of the UK Government including the Government Office for Science in 2007, as part of its 'Foresight' project which aims to use published scientific evidence to provide strategic options for policy makers on a variety of complex long-term issues, and by NICE in 2008.(152, 153)

A third highly-cited review which focused specifically on the relationship between characteristics of the urban built environment and BMI, a health outcome measure which is used to determine obesity or overweight status (see Figure 1-1 for definition and prevalence data for England), was published in 2010 by Feng et al. This review identified 63 papers which studied the impact of physical activity facilities (31 studies, e.g. children's play areas), land use and transportation facilities (34 papers, e.g. bus stop density) or the local food environment (22 papers, e.g. distance to local grocery shop) amongst both adults (45 studies) and children (21 studies) in urban (60 papers) and rural settings (7 papers).(151) Of 80 associations identified in total, only half were statistically significant, leading the authors to conclude that the existing evidence was not sufficiently clear or strong to be sure that changes to urban built environments in general are associated with changes in the risk of obesity or overweight. However, they also identified much heterogeneity between studies, not least in terms of the way the built environment was measured, which prevented estimation of pooled effects and limited the scope for drawing more specific conclusions or policy recommendations.(151)

A fourth review, published in 2011 by McCormack et al. identified studies of the relationship between characteristics of the urban built environment and physical activity. Primarily this review focused on studies that had used survey questions to elicit information about neighbourhood preferences and satisfaction while using standard regression adjustment techniques and was the only identified review that addressed the specific problem of 'self-selection bias.' Although the review by Feng et al. made brief mention of 'selection bias' — "many, but not all, studies obtained subjects by random sampling or extracting data from ongoing studies, both methods deemed to be free of selection bias"(151) — it was assumed that this referred to the sampling bias that can arise when participants are chosen to take part in an experimental research. Yet it is reasonable to expect that the problem of 'self-selection bias', which occurs when individuals allocate themselves into groups, would be common in built environment research since people's decisions about where they live are likely to be correlated with unmeasured individual-level characteristics, such as attitude towards physical activity, as well as the health outcome of interest.(154-156) For example, adults with a BMI classed in the healthy range may have chosen to live in neighbourhoods with better than average physical activity facilities, such as nearby parks or playgrounds, and might have been more willing to pay extra to live in such areas or campaign for improvements in facilities. Conversely, adults classed as obese or overweight might be more likely than average to live in areas with poor access to physical activity facilities since these facilities played no role in their choice of residential location, or in areas with a higher density of fast-food restaurants (furthermore, profit seeking fast-food companies would be expected to locate in those areas). If such preferences for healthy, or unhealthy, lifestyles are unobservable (or at least unmeasurable) then self-selection bias would be a problem in cross sectional, single equation studies.

As a result of self-selection bias, cross-sectional, single equation studies can only really be used to "generate hypotheses and provide measures of association,"(157) and so are typically of limited value to decision makers (except in low income countries where data may be especially scarce).(158) Hence there is an argument that reviewers of evidence ought to distinguish these studies from other studies that used more advanced analytical techniques because they can support more robust causal inferences, and thus provide a more credible guide for policy makers.

Since RCTs are relatively little used in public health research,(119, 159, 160) and in research on active travel specifically (see section 1.3.4.2), the more advanced analytical techniques recommended by the MRC in their guidance on natural experiments, such as difference-in-differences,(161, 162) instrumental variables,(163, 164) and propensity scores (164-166) (see Table 2-1) could represent a promising alternative. Although RCTs are normally regarded as the 'gold standard' method for estimating the effect of an intervention, these natural experimental studies are similarly intended to mitigate the bias resulting from differences in observable or unobservable characteristics between intervention and control groups.

2.3 Methods

This review was undertaken in two-phases and was designed to elicit studies which examined at least one built environment metric and its association with an individual-level weight-related outcome using methods that may support more robust causal inferences than observational studies which used cross-sectional, single equation approaches (studies which looked at associations with area-level weight-related outcomes were excluded from this review). The review used a narrative format and did not follow standard procedures for devising search strategies in systematic reviews(167) due primarily to significant heterogeneity in the types of urban built environment characteristics to be included in the review, and other acknowledged challenges in designing search filters on the basis of built environment characteristics,(168) study design labels or design features across disciplines.(169)

In both phases of the review, single equation, cross-sectional studies which feature extensively in the existing review by Feng et al. were excluded, as were other cohort, longitudinal or repeated cross-sectional studies which could not account for unobserved differences between individuals. In common with the review by Feng et al., the search was restricted to studies of human subjects published in English language.

2.3.1 Phase 1: Ovid Medline

In the first phase, the Ovid Medline was searched for peer-reviewed studies published in any academic discipline (from 1950 to June 2015). This stage was primarily designed as an update to the existing review of studies of the relationship between urban built environment characteristics and BMI by Feng et al. (which had been completed in 2008) and to encompass a broader range of built environment terms, drawing on the built environment terms used in the review published by NICE in 2008 (153) and the 'Foresight' report by Jones et al. in 2007 (152).

In common with Feng et al., the health outcomes of interest were captured using the medical subject headings (MeSH) “obesity” and “overweight.”

When compared to the existing review by Feng et al., the key difference was that studies were suitable for inclusion in the review only if they were (i.) observational studies which had used matching, (ii.) propensity scores, (iii.) difference in differences, (iv.) instrumental variables, (v.) regression discontinuity, (vi.) structural equation modelling, or (vii.) fixed effects modelling (with panel data). Although they were expected to be scarce, (viii.) randomised experiments were also included in the review, in order assess the frequency of their use, and the potential for their future use.

A specific objective of the review was to identify studies which had used the analytical methods described in the (recently published) MRC guidance on natural experiments (see Table 2-1),(139) and hence the first five analytical approaches listed above (i.)-(v.) are drawn from the MRC guidance. However, the search also encompassed structural equation modelling (170) and fixed effects modelling which may not necessarily require use of the particular advanced analytical techniques specified in MRC guidance but may, nonetheless, support more robust causal inference by accounting for otherwise unobserved factors. First, structural equation modelling is used in research across the social sciences. The defining feature of the approach is the use of latent variables which are not directly observed but are inferred from other observable variables. The latent variables are used to account for factors which are not easily measured directly, such as intelligence (in the context of education) or the neighbourhood social environment (in the context of research on the relationship between urban built environments and obesity),(170, 171) but would likely result in biased effect estimates if they were excluded from standard, single equation regression models. The structural equation model is developed a priori in diagrammatic form, based on existing theory, and includes a ‘measurement model’, which defines the latent variables using one or more observed variables, and a ‘regression model’ that links the latent variables together. Second, fixed effects modelling is a technique used widely by economists, but perhaps less often in the broader social sciences, to analyse panel data where individual-level data on the same individuals is observed over a period of time. As in those studies using the difference-in-difference approach, only changes within individuals over time are analysed, thus eliminating the risk of bias arising from time-invariant differences (e.g. some unobserved dimensions of socioeconomic status) between individuals which may confound the relationship between characteristics of the built environment and health outcomes.(143, 172) For example, current neighbourhood preferences may have to a great extent developed in childhood or early adulthood, based on influences from parents and peers. Given that influences that happened earlier in life can be considered as fixed, or time-invariant, individual-level fixed effects models may be suited to deal with this sort of self-selection bias.

2.3.2 Phase 2: Working papers

The second phase of the review (completed in June 2015) built on Phase 1 by encompassing the Google Scholar, EconLit (the American Economic Association's electronic bibliography), REPEC (a central index of economics research, including working papers) and two further online literature repositories for working papers published by key research institutes in the US and the UK - the NBER (National Bureau of Economic Research), and the Centre for Health Economics (CHE) at the University of York. This was in recognition of the likelihood that most recent papers to use the more advanced analytical methods, or randomised experimental approaches, would likely be published by researchers in economics (this was borne out in the results of the Phase 1 review discussed in the next section). Since such research generally appears in ‘working paper’ format (often some years) prior to being published more formally in academic journals (this publication strategy is common practice amongst economists working in universities and other research institutes), the (Phase 2) search was focused primarily on identifying ‘working papers’ published by researchers in economics.

2.3.3 Data extraction

Data were extracted from each of the identified studies relating to the methods, including characteristics of the study population, the dependent and independent variables, analytical technique(s) and study design(s) employed; and to the results, including parameter estimates for one or more methods of analysis, noting any mismatch between the results of analyses that used different approaches so that within-study comparisons of results could be drawn.

2.4 Results

This section provides a description of the studies identified in the review and a summary of the data extracted from those studies.

2.4.1 Characteristics of the included studies

In total, 13 observational studies (shown in Table 2-2 and 2-3) and three randomised experiments (shown in Table 2-4) were identified in the review.

2.4.1.1 Observational studies (n=13)

Of the 13 observational studies identified, nine studies had used methods that were highlighted in MRC guidance (9/13), three studies (3/13) had used fixed effects modelling (with panel data) and one study (1/13) had used structural equation modelling.

Instrumental variables studies

Of the nine studies (9/13) which used analytical approaches featured in the MRC guidance, eight studies (8/13) used instrumental variables (Table 2-2). Of these, six were cross sectional and two were repeat cross sectional studies.

Five of the eight (5/8) instrumental variable studies were alike in that they had used proximity to the US 'Interstate Highway' as an exogenous source of variation in the main independent variable of interest. Proximity to the highway was usually measured in terms of the distance of travel to the highway, although an alternative measure based on the number of nearby highway exits was sometimes used (the studies by Anderson et al. and Dunn et al. (2010), which compared both measures, concluded that the choice of measure had little impact on the results).

In four (of the five) studies which had used highway proximity as an instrument, the independent variable of interest was availability of fast-food restaurants. This was usually measured in terms of the distance of travel (or total travel cost to support a direct economic interpretation) between an individual's main residence and the nearest restaurant, or area (e.g. ZIP code area) with a restaurant. The main idea behind choosing proximity to the 'Interstate Highway' as a potential instrument for the availability of fast-food restaurants was that restaurants were expected to increase near to highways because they attracted non-resident travellers, independent of the demand from, or characteristics of, local settlements and residents. In the fifth study, by Zhao et al., urban sprawl was the independent variable of interest, a process which, it was argued, was more likely in neighbourhoods furthest from the highway. In all five studies, this choice of instrument was supported by the argument that the initial building and expansion of the highway had followed a plan drawn-up in the 1940s to enable the movement of industrial and military goods over large distances between major industrial centres across the country. Thus, it was argued, the likelihood that any particular settlement was adjacent to a highway had been determined by a 'historical accident' (i.e. randomised).

In all five studies, the case for using proximity to the highway as an instrumental variable was justified, at least to some extent, using theoretical and/or empirical evidence to support two key assumptions.

First, the assumption that the exposure (fast-food restaurants in four studies, and urban sprawl in one study) was associated with the location of the highway (the instrument) was examined using standard first stage statistical testing in four (of the five) studies. For example, Anderson et al. reported significant differences in the likelihood of having at least one restaurant when comparing ZIP code areas located less than five miles from the highway ('adjacent' areas) with those located five to ten miles from the highway ('non-adjacent' or 'distant' areas). Adjacent areas were 38% more likely to have at least one restaurant, with the majority of residents in those areas living under five miles away from their nearest restaurant, whereas the majority of residents in non-adjacent areas had a five to fifteen mile journey to their nearest restaurant (equivalent to an additional roundtrip travel time of 10 to 40 minutes which the authors argued represented a substantial cost to individuals relative to the cost of the meal, for example). Similarly, Chen et al. and Dunn et al. (2012) identified a significant negative relationship between distance to the nearest highway and number of fast-food restaurants within a particular radius (and a positive relationship between distance to the nearest highway and distance to the nearest restaurant). In the study by Zhao et al., which was the only study in this group of five studies to use longitudinal data, a significant negative relationship was identified between the number of highways that were planned in the 1940s and change in population density which occurred in subsequent decades.

All four studies assessed this first assumption (the association between exposure and instrument) using partial F-statistics: e.g. 15.6 in Anderson et al., 162.4 in Chen et al. (although in the study by Chen et al. it was not entirely clear that the reported F-statistic was the partial F-statistic rather than the F-statistic for the whole model), 11.7 – 284.4 (depending on the model specification) in Dunn et al. (2012) and 15.0 – 42.2 in Zhao et al.. Since the standard rule-of-thumb applied to studies with a single instrument says that an F-statistic of at least 10 is sufficient to minimise the risk of 'weak' instruments (i.e. large standard errors and asymptotic biases),(173-175) it seemed reasonable to conclude that the first assumption (sometimes called the relevance assumption) was well supported. Nevertheless, the four studies varied considerably in terms of the space allocated to discussion of this issue. For example, in the studies by Anderson et al. and Dunn et al (2012), the relationship between the exposure and instrument was tested under numerous scenarios including different restaurant availability measures, different groups of ZIP code areas and various subgroups of towns (e.g. excluding those with the highest or lowest population density), whereas in the studies by Chen et al. and Zhao et al., relatively little further discussion accompanied the initial calculation of the F-statistic. In contrast, in the fifth study by Dunn et al. (2010), no formal statistical test was used to assess the relationship between the number of interstate exits and the number of fast-food restaurants (although some reference was made in the text to correlation between the two variables, and the authors also stated that other studies had used comparable instruments and study designs, albeit when using different datasets).

Second, the assumption that the instrument (highway location) was uncorrelated with potential determinants of BMI other than the exposure of interest (i.e. fast-food restaurants or urban sprawl) was explored to varying degrees in all five studies. Various explanations can be proposed as to how this exclusion restriction might be violated. For example, unobserved opportunities for physical activity, including walking or cycling, could be lower in areas adjacent to the highway because of increased traffic, noise or pollution levels. Differences in the availability (and consumption) of unhealthy food or drink from outlets other than fast-food restaurants could also occur if, for example, petrol stations or convenience shops were more prominent in areas adjacent to the highway. If this were the case, then a person's unobserved weight-related behaviour could be expected to vary according to whether or not they happened to live near to the highway. Furthermore, people with a preference for eating out may have a different level of some other unobserved determinant of BMI which might lead them to choose to live near to the highway. Conversely, healthier individuals could conceivably choose areas further from the highway with better physical activity facilities or other attributes.

To the extent that it is possible using observable variables, this second assumption was addressed at least to some extent in all five studies. For example, the studies by Anderson et al. and Zhao et al., reported that the relationship between various observable characteristics (including gender, age, educational attainment, employment and marital status) and BMI was statistically significant, but that those characteristics were not associated with the location of the highway. Anderson et al. also showed how the population distribution of BMI was comparable between groups of individuals living in adjacent and distant towns. The studies by Chen et al. and Dunn et al. (2010) went a little further than the other studies in providing evidence to support the exclusion restriction by assessing the association between the presence of highways and other health-related behaviours which would be expected to affect BMI, e.g. fruit and vegetable consumption and physical activity behaviour, but which were (presumably) unobserved in the datasets used in other studies. Both studies showed no statistically relationship between the instrument and those other health-related behaviours, thus strengthening the credibility of the instrument. Dunn et al. (2012) included the least discussion of this issue, and reported no formal statistical testing, however readers were referred to the tests reported in earlier studies (discussed above) by Dunn et al. (2010), which had used the same dataset, and Anderson et al. (2009).

One further instrumental variables study by Courtemanche et al., which used distance from Walmart headquarters as an instrumental variable, similarly provided good discussion of the two key assumptions underpinning instrumental variables analysis.

In comparison to the six studies (of eight instrumental variables studies) described above, all of which had provided relatively good discussion of the assumptions behind the choice of instrument, the other two instrumental variables studies (2/8) may have left some readers questioning the credibility of the instrument chosen. The cross-sectional instrumental variables studies by Fish et al. and Zick et al., for example, did provide an F-statistic for the first stage regression, but almost no discussion of the exclusion restriction, including the fundamental problem that unobserved determinants of BMI could be associated with the instrument. In the study by Zick et al., which examined the relationship between neighbourhood walkability and BMI, individual-level data on 14,689 US women was linked to an area-level walkability measure incorporating characteristics relating to land-use diversity, population density and neighbourhood design. Instrumental variables were derived from three characteristics (the number of children aged under 16 years of age and the number of churches and schools within a given area) which, it was argued, were associated with BMI, but only because those characteristics were associated with the walkability of the neighbourhood. Yet, in the absence of any evidence to the contrary, it is reasonably plausible to suggest that churches or schools might provide a focal point for a varied programme of events for the whole community which could have some impact on BMI (e.g. walking groups, lunch clubs, health drop-in centres…and so on).

The study by Zick et al., and the other studies where applicable, also reported the results of over-identification tests since multiple instruments were used for a single endogenous variable. However, the assumptions on which the test is based (e.g. that there is a high level of confidence in at least one of the instruments used to identify the endogenous variable – the instrument used in the just identified model – in that it is not correlated with unobserved determinants of BMI) was not discussed in any of those studies.

Other observational studies

In addition to the eight instrumental variables studies discussed above (8/13), five further observational studies were identified (5/13).

Only one of these studies (1/13) used an analytical approach which featured in the MRC guidance. This study, by Drichoutis et al., combined difference-in-differences (which aimed to address time-invariant unobserved differences between individuals) with propensity score matching (which aimed to address time-varying unobserved differences between individuals).(176) The study used a large panel dataset of children living in the US state of Arkansas. The data was collected each year since the passing of an Act in 2004 which mandated BMI screenings for all children who attended state-funded schools. Using data on the location of 'dollar stores' (discount food shops characterised by a narrow range of cheap food items and limited offerings of healthier foods including fresh fruit and vegetables), the researchers compared children in a control group who experienced no change in whether or not a dollar store was located within a one mile radius of their house (or 10 miles in rural areas) to children in two treatment groups. In the first treatment group, where children experienced a change from having a dollar store within a one mile radius to not having a dollar store within a one mile radius, there was a statistically significant increase in weight (this seemed counterintuitive, and was probably due to dollar store closures that reflected local economic circumstances or other time-varying unobserved factors that affected weight gain). In the second treatment group, where children experienced the opposite (i.e. they previously did not have a dollar store but later on in the study they did), no statistically significant change in weight was observed.

Of the four studies (4/13) to use methods not featured in MRC guidance (Table 2-3), three studies were individual-level fixed effects panel data studies. For example, Sandy et al. studied the impact of built environment changes in close proximity to individual households (derived from aerial photographs) on changes in the BMI of individual children over eight years. The fourth study was described as a structural equation modelling study. Using cross-sectional data, physical activity and obesity status were modelled using latent variables for the physical and social environments.(171)

No studies identified in the review had used the regression discontinuity analytical technique (which is featured in the MRC guidance).

General observations

Across six (6/13) observational studies that used data from multiple time periods, although BMI data were collected in multiple time periods (up to 25 different time periods), data on built environment characteristics were collected less frequently and were fixed at a single time point in half of the studies (n=3/6, 50%). This could reflect the relative difficulty in collecting historical built environment data which limits within-individual analysis to people who move location, rather than those exposed to changes in the built environment around them.(177, 178)

Amongst the observational studies, seven studies (7/13, 54%) reported statistically significant relationships between built environment characteristics and obesity in the main analysis. Of these, four were instrumental variable studies. This compared to 48 of 63 studies (76%) in the review by Feng et al. which reported statistically significant results.

All observational studies included in the review (n=13) were published after the review by Feng et al. had been completed in 2008, and all used data on US participants, compared to 83% of the studies identified in the review by Feng et al. Nine studies (9/13) were published in sources that included 'economic' or 'economics' in their title, while none of the identified studies in the review by Feng et al. came from such sources (hence only four of these studies were identified exclusively in Phase 1/Ovid Medline review). Although just two of the identified studies appeared only in the grey literature (the studies by Drichoutis et al. and Sandy et al.), seven of the peer-reviewed publications were also identified in an (earlier) working paper format (one further study, by Kostova identified in the review could not be accessed,(179) despite attempts to contact the author).

A number of further studies screened during Phase 2 of the review had assessed the relationship between characteristics of the urban built environment and area- or school-level obesity (these included e.g. (180-182)). These were excluded from the current review since they did not analyse individual-level data, however they indicated that the scope of studies in this area may be broader than studies which looked only at individual-level characteristics.

Another study was screened during Phase 2 of the review which reported using a structural equation model.(183) However, although the study included a diagram showing the proposed causal relationships between income, green space, physical activity and BMI, the analysis did not use latent variables and so was excluded from this review since it was not clear that an analytical procedure had been used to account for self-selection bias (or endogeneity). Similarly, another study reported using a ‘fixed effects model’ to study the relationship between fast-food restaurant location and obesity in pregnant women,(184) however it relied on repeated cross sectional data rather than panel data and so was excluded from this review.

2.4.1.2 Randomised experiments

Three randomised experiments were identified in the review and these are summarised in Table 2-4.

In the first study, by Arcaya et al., researchers used individual-level data on individuals (n=280) who had been forced to relocate from eight US counties in the New Orleans-area to 76 different counties across the country following the 2005 hurricane, ‘Katrina.’(185) Since individuals had little or no control over their neighbourhood placement after the hurricane, the researchers sought to assess associations between observed differences in urban sprawl in the counties residents had moved to, and change in (self-reported) BMI pre- and post- the hurricane disaster, whilst controlling for individual-level socioeconomic characteristics. Urban sprawl was measured using an external dataset which incorporated six county-level variables collected in the 2000 US Census (e.g. measures of residential density and street connectivity) (this index was also used in other studies of the urban built environment by Ewing et al. discussed in Chapter 3 (186, 187)). A higher value on the index indicated a more compact and less sprawling county. The index had a mean value of 100 and, in this study, an average change in urban sprawl of -30 points was observed for individuals after relocation had occurred. The results of the analysis showed that a one point decrease in the urban sprawl index (i.e. an increase in urban sprawl) was associated with a statistically significant increase in BMI of 0.05kg/m^2 (95% CI: 0.01-0.08) over a time period of one to four years (depending on when participants responded to the survey).

In the second study, by Kapinos et al., the exposure (not administered by researchers) resulted from the random (and hence exogenous) allocation of first year students to different university campus accommodation.(188) On average, students assigned to dormitories with on-site dining halls gained more weight and exhibited more behaviours consistent with weight gain during their first year than students not assigned to such dormitories.

Finally, in the 'Moving to Opportunity' study,(189) 4,600 families living in public housing in high poverty areas of five US cities were randomly assigned housing vouchers for private housing in lower-poverty neighbourhoods. Significant reductions in obesity likelihood were observed after five years amongst voucher recipients when compared to non-recipients.

Of the three randomised experimental studies, two studies were identified in Phase 1 of the review (they were published in the 'Journal of Adolescent Health' and 'Preventive Medicine') whilst the third study (the study using data from 'Moving to Opportunity') was identified in Phase 2 of the review and is currently only available in the grey literature as an NBER working paper published in 2004 (although many further studies using other data from 'Moving to Opportunity' have appeared in peer-reviewed journals (190)).

2.4.2 Comparison of results using different methodological approaches

Of the 13 observational studies identified in the review, within-study comparisons of results were possible in ten cases (these were in six of the eight instrumental variable studies (Table 2-2), the difference in difference/PSM study by Drichoutis et al. (Table 2-2) and three of the panel data studies (Table 2-3)). However, within-study comparisons were not possible in the two remaining instrumental variable studies (191, 192), the structural equation modelling study, or the randomised experiments (Table 2-4), since no results were not reported for any alternative method of analysis.

Of those ten studies where a comparison of results was possible, a 'mismatch' was identified in eight studies (i.e. a statistically significant difference was observed between the results arising from the more advanced method of analysis and comparable results using another method of analysis). Of these eight studies, no studies were identified in which the application of at least two methods led to contradictory results in the sense that one estimate showed a (statistically significant) positive impact whilst the other showed a (statistically significant) negative impact. These eight studies are discussed below. In contrast, in two of these ten studies,(193, 194) all the results were statistically insignificant in both the main analysis and the comparable single equation regression adjustment analyses.

2.4.2.1 Studies where the analysis which hadn't used the advanced analytical technique 'underestimated' the impact of built environment characteristics

The following studies indicated that failure to use the more advanced analytical techniques would have led to a statistically insignificant association (or 'under-estimate') between built environment characteristics and obesity, whereas the main analysis had produced statistically significant results.

In four of the instrumental variable studies identified,(195-198) statistically significant results reported in the instrumental variable analysis, in the expected directions, were not replicated in comparable single equation analyses (Table 2-2). For example, in the study by Chen et al., the impact on an individual's BMI of an additional chain grocery store within a 0.5 mile radius of their household was estimated to be statistically significant in the main analysis, with a parameter estimate of +0.90 kg/m^2, but statistically insignificant in the single-equation OLS analysis. This was also the case in subgroup analyses such as for females or non-white ethnic groups in the other two studies.

In the difference in difference/PSM study by Drichoutis et al., the (positive) statistically significant association between change in BMI and the change from having to not having a dollar store within a 1 mile radius of the home was not replicated in any of the comparable analyses (i.e. those which did not feature matching, including difference in differences without matching, and panel data fixed or random effects models without matching). However, in the second treatment group, where children initially did not have a dollar store but later on in the study they did, no statistically significant change in weight was observed in any method of analysis.

Similar 'under-estimates' were also observed in the panel data study by Gibson et al. (see **Table 2-3**).(199)

In addition to these six studies where 'under-estimates' were identified in the main analysis, 'under-estimates' were also observed in some subgroup analyses of the panel data study by Sandy et al. in which statistically significant negative relationships between BMI and the density of fitness, kickball and volleyball facilities were statistically insignificant in the cross-sectional analysis.

2.4.2.2 Studies in which the single equation, cross sectional analysis overestimated the impact of built environment characteristics

In contrast to the more common cases (above) in which the relatively less advanced analytical approaches had 'under-estimated' the impact of the built environment, in a small number of subgroup analyses in two of the panel data studies identified in the review, statistically significant cross-sectional parameter estimates were not replicated in the main panel data results (although in these two studies, the majority of parameter estimates were statistically insignificant regardless of the method of analysis).(200, 201) For example, the individual-level impact of an additional physical activity facility per 10,000 people in the study of adolescents by Powell et al. was statistically significant in the cross-sectional analysis, with a parameter estimate of -0.16 kg/m^2, but statistically insignificant in the fixed effects panel data analysis.

A more unexpected result in the study by Sandy et al. was the statistically significant negative relationship identified between the number of fast-food restaurants and BMI in the panel data analysis, which contrasted with a statistically insignificant estimate in the cross-sectional analysis. The authors did not suggest that fast-food restaurants actually reduced BMI in children, but concluded that a recent moratorium on new outlets in the US city of Los Angeles might be ineffective, perhaps because outlets are already so commonplace that children can access fast food regardless of whether a restaurant is present in their immediate neighbourhood.(201)

2.5 Discussion

In some contrast to the review by Feng et al., this review of studies of the relationship between built environment characteristics and individual-level weight-related outcomes has focused specifically on (i.) identifying studies which used more advanced analytical techniques or randomised experimental approaches to tackle the problem of 'self-selection' bias, and (ii.) explored whether use of the more advanced analytical techniques had an impact on results using within- and between- study comparisons. The existing review by McCormack et al. of studies of the relationship between built environment characteristics and physical activity, and one further review published in a transportation journal in 2009 by Cao et al. of the relationship between built environment characteristics and travel behaviour (although this review did not include physical inactivity or health outcomes),(156, 202) also focused on the problem of self-selection bias. However, the primary focus of those reviews was on studies that had used survey questions to elicit information about neighbourhood preferences and satisfaction, an approach that is associated with other sources of bias, with relatively little (if any) attention given to analytical techniques that can be used to control for unobserved characteristics. Hence this chapter provides a novel contribution to the existing literature.

2.5.1 Use of more advanced methodological approaches

Despite increasing use of randomised experiments in policy areas where they are not normally expected,(119, 203-205) just three randomised experiments were identified in the review.(185, 188, 189) Of these, just one (the 'Moving to Opportunity' study, Table 2-4) could be classified as an RCT in the sense that randomisation was arranged and managed by researchers. If only the needs of policy evaluation were routinely considered alongside policy implementation plans, argue some public health researchers, then surely more opportunities for RCTs would arise.(204, 206-208) In addition to being considered the most rigorous 'best available' form of evidence,(159) RCTs also have clear advantages in that they are sufficiently intuitive to be readily understood by policy makers, the media and the general public when compared to more complicated instrumental variables approaches, for example. However, the 'Moving to Opportunity' study required 4,600 low-income families with children being provided with vouchers to move into more expensive housing areas. Hence this study alone provides a clear indicator of how costly, impractical, unethical and politically untenable such research is likely to be and so it seems reasonable to suggest that built environment RCTs are destined to remain the 'best unavailable evidence.'(119, 159, 160) Whilst the other two randomised experiments exploited a randomisation process beyond the control of researchers, it also seems unlikely that such opportunities would arise often. Furthermore, in the two studies identified in this review, the sample sizes and follow-up times were relatively small, at least compared to what is available to researchers using the secondary datasets used in the observational studies identified in the review.

The 13 observational studies that used the more advanced analytical techniques were all published during the past six years, indicating that alternatives to RCTs are feasible and increasingly employed. Since the review by Feng et al. had identified 63 predominantly cross sectional, single equation studies in 2009, these 13 studies already represent a sizeable contribution to the existing literature on the relationship between built environment characteristics and obesity.

Of the 13 studies identified, eight studies (8/13, 62%) had used instrumental variables. A particular issue in those studies identified in this review was the variation between studies in terms of the attention given to justifying the choice of instrument. Whilst the majority of studies did report standard statistical tests where these are appropriate (e.g. the first-stage F-test to demonstrate the relevance of the instrument), the assumption that the instrument (e.g. highway location) was uncorrelated with potential determinants of BMI other than the exposure of interest relies on the author of the study persuading the reader that this is supported by theoretical considerations, other related evidence, or intuition. At least some studies had acknowledged this to be a potential issue, yet some studies did not discuss the point at all. Many readers, including policy makers, who may be unfamiliar with this methodology, would surely appreciate a better explanation of the assumptions on which the study relies in order to inform their interpretation of the findings. A further oversight in the majority of the identified studies was the failure to discuss the population subsample for whom the results are applicable (i.e. the compliers - those for whom the instrument – e.g. highway location – led to a change in the value of the endogenous variable – e.g. fast-food restaurants).(209, 210) Yet this could have significant implications for readers, including policy makers, if they failed to take into account that the reported (point estimate of the) local average (causal) treatment effect may not easily extrapolate to the population average treatment effect.

In contrast to the relatively high usage of instrumental variables, of the other techniques highlighted in the MRC guidance, only one study (1/13, 8%) had used difference-in-differences and PSM methods (they were used in the same study by Drichoutis et al.) and no study used the regression discontinuity technique. The latter may be explained partly by a lack of suitable data and the relative inapplicability of the approach to built environment research, since policy interventions — particularly those involving the clear eligibility cut-offs that are required in the regression discontinuity study design — may be relatively scarce. Furthermore, where longitudinal data is available, researchers may choose to exploit gradual and multiple changes in the built environment which occur over time, hence fixed effects panel data models are perhaps more likely to be used.

Most of the identified studies were published in economics journals, which could indicate the relative infrequency with which these techniques are used amongst public health researchers or are familiar to peer reviewers who are not economists.(211) Furthermore, some of the studies had been published in ‘working paper’ format. Although this was advantageous from the perspective of identifying studies which had used the more advanced analytical techniques, policy makers may treat such evidence with caution if it has not been subjected to rigorous peer-review processes. Since all the studies had used US data, perhaps the potential for using these techniques is more limited in other countries, especially in low and middle income countries where suitable datasets may be unavailable.(158, 212)

The review also revealed wide-spread use of ambiguous or confusing study design labels (an issue that has been recognised elsewhere (169, 213)). Owing perhaps to the relative novelty of their use, 'natural experiments' are, for example, sometimes defined in broad terms as studies 'in which subsets of the population have different levels of exposure to a supposed causal factor,'(214, 215) or more narrowly, where 'random or 'as if' random assignment to treatment and control conditions constitutes the defining feature.'(139, 216) Of the two studies identified that used 'natural experiment' in their titles, the study by Sandy et al. only constitutes a natural experiment using the former definition;(201) the other, by Kapinos et al., is better defined using the latter.(188) Yet these are not intervention studies and may therefore lie outside the scope of the natural experimental studies described in MRC guidance, despite their having exploiting variation which was outside the researcher's control.

Established definitions of other terms, including 'self-selection bias' (which is also widely referred to as 'allocation bias,' 'residual confounding,' 'endogeneity' or just 'selection bias'(142, 154, 156, 217)), 'fixed effects,'(218) 'quasi-experiments',(154, 213) 'difference-in-difference' and 'structural equation modelling' may also vary between disciplines. In the present review, for example, the study by Franzini et al, had used the term 'structural equation modelling' to describe an observational study that used latent variables for the physical environment based on various built environment indicators,(171) whereas another study (excluded from the review for this reason) had used the term to 'map-out' a proposed process whereby an exposure led to change in an outcome of interest.(183) In further contrast, the study by Zick et al.,(197) in common with other examples,(219, 220) used the term 'structural equation modelling' more broadly to encompass instrumental variables.

2.5.1.1 *Potential advantages of natural experimental studies when compared to RCTs*

In addition to the potential for eliminating the problem of self-selection bias when compared to cross-sectional, single equation analyses, use of the advanced analytical techniques in a natural experimental study design might in some cases also be preferable to using an RCT study design.(212, 221-224)

First, natural experimental studies can potentially limit the threats to internal validity associated with RCTs which arise in public health or social research experiments because, unlike in placebo-controlled clinical trials, participants cannot generally be blinded to their group allocation (i.e. their own neighbourhood environment in this case). This can affect researchers' treatment of participants as well as participants' behaviour and attrition rates. For example, 'Hawthorne' effects could occur in the intervention group amongst participants who wish the project to fail, for example if they consider it to be wasteful of scarce resources, or succeed, if for example participation in the study encourages them to lead healthier lifestyles than they otherwise would have done, particularly if they felt continued provision of an intervention relied on the trial's outcome. Similarly, so-called 'John Henry' effects could occur in the control group if participants are spurned into compensating themselves for perceived disadvantages, especially if keen researchers overstate the potential benefits of an intervention or tell communities that the experiment is part of a phased expansion of a program (in an attempt to encourage higher control group compliance).(212) Participants with strong opposition to the intervention may also be more likely than average to refuse to participate, or withdraw early. Although the impact on results was unclear, a potential problem with the 'Moving to Opportunity' RCT was that one-quarter of the New York participants were lost during follow-up.(190)

Second, large scale, individual-level, panel datasets which can be used in natural experimental studies may also be preferable to RCT study designs in terms of external validity (a relatively neglected concern considering the extensive guidelines and procedures for ensuring internal validity(225)). For example, six of the studies identified in the review used the large scale US National Longitudinal Surveys (NLSY) and Behavioral Risk Factor Surveillance System (BRFSS) datasets. Such data can offer larger sample sizes (e.g. the study by Courtemanche et al. included 1.64 million observations),(198) longer follow-up periods (an important concern in obesity research since the full impact of an intervention could take some time to emerge), and a wider range of variables relating to individual-level characteristics (including through the linking individuals to spatially referenced exposure variables identified in other datasets), for example. Hence such data may be used to support robust analysis of large, population-level interventions or risk factors, as well as analysis of smaller population subgroups.(139) In one of the identified studies, Dunn et al. (2012) reported that statistically significant effect sizes were observed only amongst ethnic minorities, for example.(193) In contrast, the term-time study of 386 students living in car-free campus accommodation by Kapinos et al. (see Table 2-4) may be of only limited relevance to wider population groups. The use of secondary or even retrospective data may also limit the risk of bias arising from incomplete or absent reporting of some outcomes, or stopping trials early.

Third, given an apparent mismatch in the schedules of experimental researchers and policy makers,(226) natural experimental studies can also support more rapid analyses than would be possible with the lengthy planning processes associated with RCTs.(203) For example, studies of the Cambridgeshire Guided Busway (113) and the Connect2 initiative (a collection of 79 local projects to improve walking and cycling routes around the UK)(51, 227) demonstrate how researchers might exploit interventions which have already passed the planning and funding stages, while a recent regression discontinuity study of London's congestion charge indicates how secondary data can be used without the need for time consuming primary data collection or ethical approval processes.(228)

2.5.2 Comparing effect sizes arising from different analytical approaches

Significant differences are — with some exceptions(229) — generally observed between the results of observational studies and randomised experiments.(230-234) However, comparisons of the results of observational studies that used different analytical techniques, such as those reported in this chapter, are much less common. One unique series of studies in which different analytical techniques were used to evaluate the US National Supported Work Demonstration programme, a 1970s job guarantee scheme for disadvantaged workers, is particularly insightful because statistically significant differences in effect sizes were observed when regression-adjustment, propensity score matching (235, 236) and difference-in-difference (237) study designs were used in analyses of comparable data arising from the same RCT.(140, 238)

The main conclusion which can be drawn from the comparison of results presented in this chapter was that statistically significant relationships between features of the urban built environment and obesity were less likely when weaker, cross-sectional, (typically) single-equation analyses were used. This was unexpected, given the expectation that self-selection bias would have led to an overestimate of effect size since people of normal weight would prefer living in walkable neighbourhoods. In attempting to find an explanation for this unexpected finding, the authors of the study by Zick et al. concluded that some neighbourhood features were positively associated with walkability and hence healthy living, but negatively related to other competing factors that people consider when choosing where to live, such as school quality, traffic levels and housing costs.(197) Similarly, although fast-food restaurants were expected to locate in areas with high demand,(239) the study by Dunn et al. (2010) suggested that a possible explanation for the statistically insignificant results identified in their instrumental variables study could be that these profit-maximizing firms operated in areas with low (not high) levels of obesity.(194) This may be because of higher average levels of education and income and lower levels of crime in those areas.(193)

A second related conclusion, arising from the observation that even when more advanced methods were used there remained a statistically significant relationship between built environment characteristics and BMI, is that current interest in altering the design of urban built environments, amongst research and policymaking communities alike, seems warranted. Although the estimated effect sizes were still modest, all the reported statistically significant results in those studies that used more advanced analytical techniques were also in directions that would be expected (except in one subgroup analysis). While this conclusion is based on the small number of heterogeneous studies identified in this review, the finding nonetheless also corresponds with the findings of the reviews of physical activity and travel behaviour by McCormack et al., which concluded that observed associations likely exist independent of residential location choices,(154) and Cao et al.,(202) which concluded that virtually all the identified studies found a statistically significant influence of the built environment after self-selection was accounted for. This is in some contrast to the conclusions of the review by Feng et al. which had been more cautious about overstating the potential role of policy changes in this area (see section 2.2).

2.6 Conclusion

Randomised experiments, including RCTs and natural experimental approaches, are likely to remain scarce in built environment research. Yet most observational studies cannot be used to support robust casual inference since they use single equation, cross-sectional methods. More advanced analytical techniques may offer a more promising alternative.

The main conclusions of this chapter are:

- The differences in results that were observed when alternative methods of analysis were used indicated that current interest in altering the design of urban built environments is likely strengthened, not weakened, by evidence which used more advanced approaches.
- The more advanced analytical methods, including those featured in MRC guidance, should be considered by researchers in future built environment research
- Researchers using the advanced analytical techniques (e.g. instrumental variables) should always justify the choice of method and the assumptions underlying their use, or else risk their results being misinterpreted
- Researchers and policymakers need to consider how evidence gathered from studies using different analytical techniques is appraised, compared and aggregated in evidence synthesis processes.

Table 2-1: Advanced analytical techniques included in Medical Research Council (MRC) guidance on natural experimental studies

Analytical technique	Brief description
Controlling for observable characteristics	
Matching	Involves finding unexposed individuals (or clusters of individuals) which are similar to those receiving the intervention, and comparing outcomes in the two groups
Propensity scores	An estimate of the likelihood of being exposed given a set of covariates, propensity scores are usually estimated by logistic regression, and can be used to match exposed with unexposed units (which may be individuals or clusters of some kind) using values of the propensity score rather than the covariates themselves
Controlling for unobservable characteristics	
Difference in differences	Involves comparison of change over time in exposed and unexposed groups, which enables control of unobserved individual differences and common trends
Instrumental variables	An instrumental variable is a factor associated with exposure to an intervention, but independent of other factors associated with exposure, and associated with outcomes only via its association with exposure
Regression discontinuity	This approach exploits a step change or 'cutoff' in a continuous variable used to assign treatment, or otherwise determine exposure to an intervention. The assumption is that units (individuals, areas, etc.) just below and just above this threshold will otherwise be similar in terms of characteristics that may influence outcomes

Source: Medical Research Council (2011)(139)

Table 2-2: Results – cross-sectional and longitudinal observational studies that used more advanced analytical techniques specified in MRC guidance (n=9)

Bibliographic details First author, date, journal	**Study population**	**Description of variables**				**Results (for two different methods of analysis, when reported)**			
		Independent variables		**Dependent variables**		***Main method of analysis*** **i.e. more advanced analytical technique**			***Alternative method of analysis***
		Description	Areal unit precision	Descr-iption	Source	Description of analytical technique	Data type	Effect sizes (95% confidence interval)[a]	Methods used and reported effect sizes (95% confidence interval)[a,b]
CROSS SECTIONAL STUDIES (6 STUDIES IN TOTAL)									
Anderson, 2011, American Economic Journal (191)	US adults (11 States)	Miles between home and fast-food restaurant	Telephone /ZIP codes	BMI	BRFSS	Instrumental variable derived from distance to the main highway	Cross sectional	0.09 (-0.17, 0.17)	None reported
Chen, 2012, Health Economics (195)	US adults (Indianapolis, Indiana)	Number of (a.)restaurants and (b.) chain grocery stores, and (c.) proportion of park land, within a 0.5 mile radius	Individual addresses	BMI	Obesity Needs Assessment Survey	Instrumental variable derived from distance to arterial roads & non-residential zoning	Cross sectional	(a.) 0.37* (CI missing) (b.) 0.90* (0.12, 1.68) (c.) 2.85* (0.03, 5.67)	OLS. All reported effect sizes were "under-estimates": (a.) 0.06 (-0.03, 0.14) (b.) 0.14 (-0.21, 0.50) (c.) 2.39 (-0.66, 5.45)
Dunn, 2010, American Journal of Agricultural Economics (194)	US adults (all States)	Number of fast food restaurants (at County level; author collected)	County level	BMI	BRFSS, 2004-2006	Instrumental variable derived from number of interstate highway exits in the county	Cross sectional	No statistically significant results were reported, except in two subgroup analyses: Female participants in medium density counties: 0.06* (0.01, 0.11) Non-white participants in medium density counties: 0.20* (0.02, 0.38)	OLS. No statistically significant results were reported. Hence "under-estimates" in just two subgroups: Female participants in medium density counties: -0.01 (-0.02, 0.01) Non-white participants in medium density counties: 0.01 (-0.02, 0.04)

Bibliographic details First author, date, journal	Study population	Description of variables				Results (for two different methods of analysis, when reported)			
		Independent variables		Dependent variables		*Main method of analysis* i.e. more advanced analytical technique			*Alternative method of analysis*
		Description	Areal unit precision	Descr-iption	Source	Description of analytical technique	Data type	Effect sizes (95% confidence interval)[a]	Methods used and reported effect sizes (95% confidence interval)[a,b]
Dunn, 2012, Economics and Human Biology (193)	US adults (Brazos Valley, Texas)	(a.) miles to nearest fast-food restaurant, and number of fast-food restaurants within a (b.) 1 mile and (c.) 3 mile radius	Individual addresses	Obes-ity likeli-hood	BRFSS	Instrumental variable derived from distance to nearest highway	Cross sectional	No statistically significant results were reported, except in two subgroup analyses e.g. Non-white participants: (a.) -0.100* (-0.178, -0.022) (b.) 0.189* (0.030, 0.348)	Probit model. No statistically significant results were reported. Hence "under-estimates" in just two subgroups: Non-white participants: (a.) -0.088 (-0.188, 0.012) (b.) 0.052 (-0.021, 0.125)
Fish, 2010, Am J Public Health (196)	US adults (Los Angeles County)	Resident perception of neighbourhood safety (self-reported dichotomous variable where 1= extremely or somewhat dangerous' and 0=fairly or completely safe)	Individual level survey data	BMI	L.A. Family and Neighbour hood Survey	Instrumental variable derived from measures of social cohesion, experience of household crime, etc.	Cross sectional	2.81* (0.11, 5.52)	OLS (using first wave 2001/2 data) No statistically significant results, i.e. "under-estimate": -0.07 (-1.07, 0.93)
Zick, 2013, IJBNPA (197)	US females (Salt Lake, Utah)	Neighbourhood walkability	Census block (typically 1,500 people)	BMI	Utah Populatio n Database	Instrumental variable derived from neighbourhood characteristics e.g. churches and schools	Cross sectional	-0.24*	OLS. No statistically significant results, i.e. "under-estimate": 0.00

Bibliographic details First author, date, journal	**Study population**	**Description of variables**				**Results (for two different methods of analysis, when reported)**			
		Independent variables		**Dependent variables**		***Main method of analysis*** **i.e. more advanced analytical technique**			***Alternative method of analysis***
		Description	Areal unit precision	Description	Source	Description of analytical technique	Data type & number of time periods	Effect sizes (95% confidence interval)[a]	Methods used and reported effect sizes (95% confidence interval)[a,b]
LONGITUDINAL STUDIES (3 STUDIES IN TOTAL)									
Courtemanche, 2011, Journal of Urban Economics (198)	US adults (all States)	Number of Walmart Supercenters per 100,000 residents (these stores provide low cost food and encourage sedentary lifestyles)	County level	(i.) BMI (ii.) obesity likelihood	BRFSS, 1996-2005	Instrumental variable derived from distance to Walmart head office (expansion over time of Walmart stores was shown to be correlated with distance from the head office)	Repeated cross sectional 10	(i.) 0.24* (0.06, 0.41) (ii.) 0.023* (0.011, 0.035)	OLS: No statistically significant results, i.e. "under-estimates": (i.) 0.024 (-0.003, 0.051) (ii.) 0.001 (-0.001, 0.003)
Zhao, 2010, Journal of Health Economics (192)	US adults (all States)	Proportion of people living in densely populated areas with >9000 people per square mile	MSA level (there are 366 of these areas in the US)	(i.) BMI (ii.) Obesity likelihood	National Health Interview Survey, 1976-2001	Instrumental variable derived from exogenous expansion over time of the US interstate highway system	Repeated cross sectional 25	(i.) −0.01 (-0.03, 0.01) (ii.) −0.0013* (-0.002, 0.000) [c]	None reported

Bibliographic details First author, date, journal	Study population	Description of variables				Results (for two different methods of analysis, when reported)			
		Independent variables		**Dependent variables**		***Main method of analysis*** **i.e. more advanced analytical technique**			***Alternative method of analysis***
		Description	Areal unit precision	Description	Source	Description of analytical technique	Data type & number of time periods	Effect sizes (95% confidence interval)[a]	Methods used and reported effect sizes (95% confidence interval)[a,b]
Drichoutis, 2014, Department of Agricultural Economics, Agricultural University of Athens Working Paper (176)	US children living in Arkansas attending public (i.e. state) schools	The treatment was a change in the whether or not individuals had at least one dollar store (a cheap, discount shop) located within a 1 mile radius (or 10 miles if living in a rural area) of a child's residence The change could have occurred due to change of residence, or change in location of dollar store.	1 mile radius of child's house	BMI z-score	Mandatory BMI screenings for public (i.e. state) schoolchildren	Propensity score matching combined with difference in differences	Panel data 4	Two treatment groups: (A.) change from having at least one dollar store to having no dollar store (within 1 mile radius): 0.055* (CI missing) (B.) change from having no dollar store to having at least one dollar store (within 1 mile radius): 0.007 (CI missing) These results are compared to a control group of children who did not experience change in the number of dollar stores within 1 mile of their house.	No statistically significant results, i.e. in treatment group A, "under-estimate": Difference in differences without matching: (A.) 0.005 (B.) 0.004 Panel data fixed-effects regression without matching (A.) and (B.) combined: -0.009

OLS: Ordinary-Least-Squares
BRFSS: Behavioural Risk Factor Surveillance System dataset
[a] * Indicates statistical significance at the $p<0.05$ level.
[b] When compared to results in the main analysis, where a mismatch in the results is observed: "Under-estimate" if statistically significant results in the main analysis were not statistically significant the alternative method of analysis; "Over-estimate" if statistically insignificant results in the main analysis were statistically significant in the alternative method of analysis.
[c] The interpretation of this result is that for each additional percentage point decrease in the proportion of the population living in the densely populated area, obesity is approximately 0.1-0.2 percentage points higher.

Table 2-3: Results - observational studies that used more advanced analytical techniques not specified in MRC guidance (n=4)

Bibliographic details First author, date, journal	**Study population**	**Description of variables**				**Results (for two different methods of analysis, when reported)**			
		Independent variables		**Dependent variables**		***Main method of analysis*** **i.e. more advanced analytical technique**			***Alternative method of analysis***
		Description	Areal unit precision	Description	Source	Description of analytical technique	Data type & number of time periods	Effect sizes (95% confidence interval)[a]	Methods used and reported effect sizes (95% confidence interval)[a,b]
Franzini, 2009, Am J Public Health (171)	US children (all States; 10-12 year olds)	Traffic levels, physical disorder, residential density and land use	Individual Systemic Social Observat-ions	BMI	Interviews with students and their parents, 2003	Structural equation modelling (SEM)	Cross sectional 1	0.03 (-0.40, 0.46) (these results relate to physical activity z-scores which contributed to the SEM. Physical environment had no significant impact on physical activity or BMI in the model)	N/A
Gibson, 2011 (199), Am J Public Health	US young people (all States)	Five measures relating to food environment, including: (a.) supermarkets, (b.) small grocery stores, and (c.) full-service restaurants per square mile	Zip-code level	BMI (obesity likelihood was also reported)	NLSY, 1998-2004	Fixed effects panel data analysis	Cohort/ panel data 2	<u>Change in BMI:</u> <u>(a.)</u> -1.98* (-1.94,-2.02) <u>(b.)</u> -0.15* (-0.33,0.04) <u>(c.)</u> 0.20* (0.03, 0.36)	OLS. No statistically significant results, hence “under-estimates”: <u>Change in BMI:</u> <u>(a.)</u> -0.04 (-0.18, 0.10) <u>(b.)</u> 0.02 (0.00, 0.04) <u>(c.)</u> 0.00 (-0.01, 0.01)

Bibliographic details First author, date, journal	Study population	Description of variables				Results (for two different methods of analysis, when reported)			
		Independent variables		**Dependent variables**		***Main method of analysis*** **i.e. more advanced analytical technique**			***Alternative method of analysis***
		Description	Areal unit precision	Description	Source	Description of analytical technique	Data type & number of time periods	Effect sizes (95% confidence interval)[a]	Methods used and reported effect sizes (95% confidence interval)[a,b]
Powell, 2009, Journal of Health Economics (200)	US young people (all States)	Measures included: (a.) restaurants, (b.) grocery stores (c.) physical activity facilities per 10,000 people	County level	BMI	NLSY, 1997-2000	Fixed effects panel data analysis	Panel data 4	No statistically significant results in any of the measures e.g. (a.) -0.03 (-0.09, 0.02) (b.) -0.03 (-0.11, 0.05) (c.) -0.12 (-0.30, 0.05)	OLS. No statistically significant results observed except in one case ("over-estimate"): (c.) -0.16* (-0.30 ,-0.02)
Sandy, 2009, National Bureau of Economic Research (201)	US young children (Indianapolis, Indiana)	Twenty different measures, including: (a.) restaurants (b.) supermarkets (c.)fitness, (d.) kickball, (e.) volleyball facilities	Individual addresses	BMI (z scores)	Clinical records, 1996-2006	Fixed effects panel data analysis	Panel data Many observati-ons collected during a 10 year period)	Few statistically significant results,[c] however, some selected exceptions (within 0.25 miles, including children of all ages, unless otherwise stated): (a.) -0.08* [-0.13 at 0.1 miles] (b.) 0.05 (0.1 miles) (c.) -2.26* (d.) -0.08* (e.) -0.90* (0.1 miles; children < 8 years only)	Cross-sectional OLS. Few statistically significant results, except "over-estimates" in two cases[c]: (a.) 0.02 [0.08* at 0.1 mile] (b.) -0.19* (0.1 miles) "under-estimates" in three cases: (c.) 0.25, (d.) 0.04 (e.) 0.03 (0.1 miles; children < 8 years only) All within 0.25 miles, unless otherwise stated

OLS: Ordinary-Least-Squares. NLSY: National Longitudinal Survey of Youth dataset

[a] * Indicates statistical significance at the $p<0.05$ level.

[b] When compared to results in the main analysis, where a mismatch in the results is observed: "Under-estimate" if statistically significant results in the main analysis were not statistically significant the alternative method of analysis; "Over-estimate" if statistically insignificant results in the main analysis were statistically significant in the alternative method of analysis.

[c] Although in the study by Sandy et al. 80 results were reported in total, the results reported in this table were for those variables deemed by the authors of that study to be most relevant to policy makers. Results were reported for four different sized areas/buffer zones (ranging from 0.1 to 1 mile).

Table 2-4: Results: description of randomised experiments identified in the review (n=3)

Study details		**Description of variables**					**Results of randomised experiment**		
		Independent variables			**Dependent variables**				
First author, date, journal (reference)	Study population	Description	Time varying	Areal unit	Description	Source	Description of study design	Data type (time periods)	Effect sizes (95% confidence interval)[a]
Arcaya, 2014, Preventive Medicine (185)	US (from New Orleans) Hurricane-survivors: aged 18-34, relatively poor adults with dependent children. Predominantly African Americans.	County sprawl index: based on an external dataset which used six county-level variables (e.g. residential density and street connectivity) to assess the level of urban sprawl (higher value indicates a more compact and less sprawling county, and mean value=100)	No (the index was created using data from 2000 Census)	County	Self-reported BMI (calculated from self-reported height and weight)	Resilience in Survivors of Katrina (RISK) project: a longitudinal study of Hurricane survivors	Individual-level pre- and post-hurricane data was analysed for residents (n=280) who were displaced from their homes in 8 New Orleans-area counties to 76 counties across the US after the hurricane. Variation in urban sprawl between different counties was associated with changes in BMI. Individuals had little or no control over their neighbourhood placement after the hurricane. Those who chose to remain in New Orleans were excluded from the analysis.	Cohort data (2 times periods, pre- and post-moving. Follow-up ranged from 1 to 4 years).	A one point decrease in the sprawl index (i.e. increasing urban sprawl) was associated with statistically significant 0.05* increase in BMI kg/m^2 (CI: 0.01-0.08) (The sprawl index decreased after re-location by an average 30 points).

Study details		Description of variables					Results of randomised experiment		
		Independent variables			Dependent variables				
First author, date, journal (reference)	Study population	Description	Time varying	Areal unit	Description	Source	Description of study design	Data type (time periods)	Effect sizes (95% confidence interval)[1]
Kapinos, 2011, Journal of Adolescent Health (188)	US undergraduate students (on a single university campus)	Characteristics of dormitory accommodation: (a.) on-site dining hall (b.) distance to gym (km) (c.) distance to central campus (km)	No (short follow-up)	Specific to the location of the dormitory accommodation	Weight (kg) (other results related to exercise and diet were included in the study but are not reported here)	Individual-level survey instrument (39 questions)	Random allocation of first year students to different campus accommodation across various US universities. Each building varied in terms of the distance to class, the shops and transport facilities as well as other amenities.	Cohort data (2) One-year follow-up	Male participants: (a.) 0.19 (-2.37, 2.76) (b.) -0.25 (-1.37, 0.87) (c.) -0.08 (-0.80, 0.63) Female participants: (a.) 0.85* (0.12, 1.57) (b.) 0.13 (-0.32, 0.59) (c.) -0.45 (-1.15, 0.25) (a.)-(c.) here corresponds to (a.)-(c.) in column 3 of this table.
Kling, 2004, National Bureau of Economic Research (189)	US (five cities; families with children)	Moving from a high poverty (public housing area) to low poverty (a census tract with poverty rate <10%) neighbourhood	No (once for each neighbour-hood)	Poverty rate was measured at the census tract level	Obesity likelihood	Individual-level survey	Families living in public housing in high poverty areas of five different cities were randomly assigned housing vouchers (intervention group) which allowed them to move into private housing in lower-poverty neighbourhoods and be compared to those who remained (control group).	Cohort data (2) Five-year follow-up	(a.) intent-to-treat effect i.e. of being offered a housing voucher or the average effect of an attempted policy intervention on the entire target population: -0.048* (-0.091, -0.005) (b.) treatment-on-treated i.e. those using voucher -0.103* (-0.195, -0.011)

[a] * Indicates statistical significance at the $p<0.05$ level.

3 Development of a study design taxonomy to distinguish between observational studies

3.1 Overview of chapter

The purpose of this chapter is to devise a method which could support reviewers and policy makers in making more nuanced, fine-grained methodological distinctions between observational studies that use different analytical techniques than would be possible when using existing tools for rating the quality of evidence. The taxonomy is applied to the studies identified in the review presented in Chapter 2 and two other published reviews of the relationship between characteristics of the urban built environment, obesity and physical activity. The chapter also seeks to explore the potential added value of the taxonomy in the context of existing guidelines for authors and reviewers of observational studies.

3.2 Background

Of the four existing reviews of the relationship between urban built environment characteristics and obesity or physical activity which were discussed in Chapter 2 (by Feng et. al, McCormack et al., NICE and the 'Foresight' report by Jones et al., see section 2.2), none had used any tool to rank studies according to their study design, despite the likelihood that some methods were more likely than others to exhibit self-selection bias.

Existing tools for rating the quality of published research typically focus on RCTs. Guidance produced for systematic reviews of health care interventions by the Cochrane Collaboration in the Cochrane Handbook for Systematic Reviews of Interventions,(240) the University of York's Centre for Reviews and Dissemination,(167) and PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses),(241) for example are well-established and widely used. However they necessarily focus on biases likely to be present in experimental research, such as allocation concealment and attrition bias,(240) while omitting other important sources of bias, including self-selection bias, which are of greatest concern to reviewers of observational studies. A further problem for reviewers of observational evidence is that these tools also typically advise that greater weight should be given to RCTs over all other observational study designs, while failing to consider that in some cases observational studies may be better suited to addressing particular research questions, and that there may wide ranging differences between observational studies in terms of their quality and the analytical methods that are used.

Alternative tools designed specifically for authors, editors and reviewers of observational studies in policy areas where non-randomised study designs are the norm are, in contrast, relatively under-developed and less widely used.(242-245) Although one review identified 194 such tools that could be used for distinguishing between observational studies in epidemiological reviews, just six were considered to be sufficiently well developed for use in systematic reviews.(231) The authors of another similar review concluded that most existing tools required significant methodological improvement(246) and, in a 2010 paper, Shemilt et al. argued that "further methodological work is needed to develop such methods for evidence synthesis in policy areas where RCTs and other experimental study designs are less common."(247)

Yet there is increasing demand amongst decision makers (e.g. in Government, charity or third sector organisations) for reliable tools to rank different types of evidence across a range of policy areas including health, criminology, education, international development and the labour market.(169, 242-244, 246, 247) For example, in 2013 the British Government announced funding for a network of independent 'What Works' centres to provide policy makers with robust evidence on the effectiveness of interventions, complementing and apparently mimicking the work already done in the health sector by NICE (described in section 1.3.4) but in policy areas where RCTs are less common. The current work of these centres focuses on collating and synthesising published evidence in the specific areas of crime reduction, active and independent ageing, early intervention, educational attainment and local economic growth.(248) Similar work is undertaken for the US Government in the education sector by the What Works

Clearinghouse, and in the areas of child welfare, juvenile justice and mental health by the Washington State Institute for Public Policy, for example.

Two existing and commonly used tools for assessing the quality of observational studies in health research are known as MOOSE (Meta-analysis of Observational Studies in Epidemiology, see Figure 3-2) and GRADE (Grading of Recommendations Assessment, Development, and Evaluation systems, see Figure 3-3).(249, 250) Although these tools recommend an assessment of likely confounding variables and sources of bias, they do not explicitly address the differences between more advanced analytical techniques applied to observational studies (including those listed in the MRC guidance on natural experiments) when compared to cross sectional, single equation study designs.(247, 251, 252) Users of the MOOSE guidelines (Figure 3-2) are merely advised (under 'Reporting of Methods') to make 'an assessment of confounding', an 'assessment of study quality', and a 'description of statistical methods', for example. Users of GRADE must give each individual study a score between 1 and 4 (with one of these reserved for RCT study designs). Users are instructed to 'rate down' studies if risk of bias is 'serious' or 'very serious', and 'rate up' otherwise low-scoring observational evidence when any of three conditions are met (Figure 3-3).(217) However, the first two conditions, 'if there is a large magnitude of effect' and 'when a dose response gradient exists', do not relate to the analytical technique chosen for the analysis. The third condition, 'when all plausible confounders or other biases would lead to an under-estimation of the observed impact', seems irrelevant in this case since the within-study comparisons of results using different analytical approaches in the review presented in chapter 2 (see section 2.4.2) demonstrated that, despite expectations (see section 2.5.2), it was not possible to conclude that self-selection bias would lead to a reduction in effect sizes.

Two further examples come from outside the health sector. The Maryland Scale of Scientific Methods was originally developed by criminologists but now forms the basis of recent guidance published by the UK Government(234, 253-255) and other scales recently developed by the 'What Works' centres (Figure 3-4).(226, 245) In addition to the RCT study design, which is ranked at the highest level (Level 5), observational studies are differentiated on four further levels (levels 1-4) depending mainly on the extent to which other factors are controlled (levels 3-4) or whether a regression analysis which can control for other factors has been used at all (levels 1-2). Like the GRADE guidelines this seems too insensitive to the differences that exist between the analytical methods that can be used in a regression analysis. The Cambridge Quality Checklists,(244) which were designed for reviews of studies in criminology, are similar to GRADE in that users are instructed to give individual studies a score. With more available levels than the Maryland Scale of Scientific Methods, reviewers may distinguish different types of observational evidence according to the type of data that was used (the 0-3 'risk factor score') and the extent to which dependent and independent ('risk factor') variables are controlled (the 0-7 'causal risk factor score').

With the possible exception of the Cambridge Quality Checklists, in their current form, these tools do not include sufficient detail to capture the differences between the advanced analytical techniques that were included in the review in the chapter 2.

3.3 Methods

3.3.1 Development of taxonomy

A taxonomy was devised for categorising studies according to the likelihood that causal inferences may be drawn. The theoretical basis of the taxonomy was Bradford-Hill's seminal causal considerations (See Figure 3-6).(256) Rather than relying on analytical method or study design 'labels', which cannot alone be used to distinguish studies,(169) the design of the taxonomy was informed primarily by features of the data and the different analytical techniques that had been used in studies identified in Chapter 2, as well as aspects of existing evidence synthesis guidelines (particularly GRADE, the Maryland Scale of Scientific Methods and the Cambridge Quality Checklists, see section 3.2). A review by Sanderson et al. of existing tools for assessing the quality of observational epidemiological studies was also informative.(251) The review recommended that such tools should be as specific as possible, focusing on particular study design issues, topic areas and the principal potential sources of bias. The review concluded that scales which incorporate too many aspects of quality assessment and result in numerical summary scores should generally be avoided.(251)

3.3.2 Application of the taxonomy

The taxonomy was applied, first, to the 16 studies of the relationship between urban built environment characteristics and BMI which had been identified in the review presented in Chapter 2 (which consisted of three randomised experiments, and 13 observational studies using more advanced analytical techniques); second, to 63 studies of the relationship between built environment characteristics and BMI which were included in the review by Feng et al. in order to gauge the frequency with which single equation analytical techniques are typically employed in this literature (this review did not impose any restrictions in the search strategy relating to study design, see section 2.2); and, third, to 33 studies of the relationship between built environment characteristics and physical activity identified in the review by McCormack et al.(154) Separately, in Chapter 8, the taxonomy was also used to categorise studies that were identified in a review of studies which evaluated the impact of financial incentives on the demand for active travel.

3.4 Results

3.4.1 Development of the taxonomy

Two of the Bradford-Hill considerations (Figure 3-6) were selected for inclusion in the taxonomy since they are determined by the analytical technique that is used. These were: ‘experimental evidence’ (associations are examined using manipulation and controls) and ‘temporality/precedence’ (cause precedes effect). Considering the specific issue of self-selection bias, the third consideration included in the taxonomy was the extent to which observed and unobserved built environment characteristics are controlled. While this third consideration is already reflected in existing guidelines, such as the Cambridge Quality Checklists and the Maryland Scale of Scientific Methods which require reviewers to consider the extent to which important potential confounding factors are controlled, the taxonomy was designed to go further than existing tools by explicitly encouraging reviewers to separate studies that had controlled for observed characteristics from those that had also controlled for unobserved characteristics.

The other Bradford-Hill considerations, such as evidence of a ‘dose response gradient,’ and those included in the GRADE guidelines (see Figure 3-3) , were excluded from the taxonomy since they are not determined by the choice of analytical technique. However these ought to be considered alongside the taxonomy where relevant. For example, the study identified in Chapter 2 by Sandy et al.(201) which explored the impact on BMI of variation over time in exposure to a wide range of variables related to fast food restaurants, grocery stores and other amenities, could be considered to provide an important indicator of consistency (‘results repeated in multiple observations’). Some of the other causal considerations may be less relevant. For example, coherence (‘no conflict with current knowledge’) and plausibility (‘observations confirm currently accepted theories’) are unlikely to affect an assessment of individual studies since existing reviews have stated that the exact mechanism or processes through which built environment characteristics influence health-related outcomes is unclear. For example, the ‘Foresight’ review by Jones et al. concluded that “mechanisms by which environmental components may operate are as yet unclear, and that the exact environmental components that affect body weight and activity are yet to be identified.”(152)

The taxonomy itself is shown in Figure 3-1 and has eight distinct categories, each varying according to the extent to which the three causal considerations are met (study designs that do not meet any of the criteria are left ‘uncategorised’).

Randomised experiments — which incorporate experimental evidence, evidence of temporality or precedence, and controls for all observed and unobserved built environment characteristics— are allocated to distinct categories (as in the GRADE, the Maryland Scale of Scientific Methods and Cambridge Quality Checklists) to ensure that such studies are distinguished from observational studies. The randomised experiments were allocated to Category ‘A’ if researchers controlled the randomisation process, or to Category ‘B’ if researchers exploited a naturally occurring randomisation process outside of their control.

Single equation regression analyses which used cross sectional data were assigned Category 'H' since these studies do not use experimental evidence, do not provide evidence of temporality or precedence, and do not control unobserved built environment characteristics.

Categories 'C' to 'H' were intended to capture differences between analytical techniques used in observational study designs which are not usually captured in existing checklists. Categories 'C' to 'E' vary in terms of the independent variables that were controlled and whether longitudinal (categories 'C', 'D' and 'F') or cross-sectional (category 'E') data were used. Although, like other single equation analytical techniques, propensity score matching cannot control for unobserved characteristics, this was assigned to category 'G'. The potential advantages of propensity scores and matching over other techniques that control only for observable characteristics are not always acknowledged in existing guidelines, including the MRC guidelines,(139) despite the potential to mitigate important sources of bias. First, they overcome the problem of wrongly specified functional forms, a recognised issue in existing built environment research (257). Second, assuming that they are correctly applied,(166) these techniques limit the potential for non-comparable individuals being included in the treatment and control groups.(165, 258, 259) This lack of common support could be problematic if, for example, the most walkable neighbourhoods were home to individuals with levels of observed characteristics, such as higher income and education levels, that do not feature at all amongst the population of the least walkable neighbourhoods.(165) Figure 3-1 indicates how each of the other study designs identified in the MRC guidance on natural experiments are assigned to the taxonomy categories.

The taxonomy represents an extension of existing guidelines. For example, as shown alongside the taxonomy in the final column of Figure 3-1, the taxonomy expands level 4 of the Maryland Scale of Scientific Methods. The distinction between Levels 3 and 4 of the Maryland Scale falls within Category 'H', depending on a subjective judgement about the control variables that are used in the analysis. When compared to the GRADE scoring system, the taxonomy could support the requirement to 'rate down' observational studies where there is a 'serious' or 'very serious' risk of bias.' The taxonomy is perhaps closest to the Cambridge Quality Checklists, and extends the 'causal risk factor' component of that checklist.

Although the categorisation of different studies allows reviewers to distinguish between different study designs, such categorisation should not be interpreted as a formal ranking mechanism. Unlike the relatively straight-forward distinction which is made in all guidelines between RCT and non-RCT research (i.e. between category 'A' and all other taxonomy categories), it is not generally possible to state that any one analytical technique is universally preferable to another in all settings.(237, 260) Rather, a researcher's choice of technique should be based on various pragmatic and subjective judgements relating, for example, to the data which is available and the research question that is being asked. In many instances, some or even all of the advanced analytical techniques reviewed in this chapter would be unsuitable, and rarely would they be interchangeable. For example, regression discontinuity can be applied only when a researcher has access to high-quality individual-level longitudinal data and seeks to assess the impact of a policy or intervention with a clear eligibility cut-off. Even then, as detailed in the MRC guidance, the researcher must demonstrate that individuals just below and just above the cut-off point will otherwise be comparable in terms of characteristics that may influence the outcome of interest. If the technique were to be used in other circumstances, then it is likely that it has been used incorrectly and that other techniques, including cross sectional analysis, could be more appropriate. For these reasons, the design of the taxonomy followed the advice of Petticrew and Roberts in a discussion of evidence synthesis in public health research which suggested a 'typology' of evidence would be preferable to a more rigid 'hierarchy of evidence,'(261) and the advice of Sanderson et al.(251) in their review of existing quality assessment scales which concluded assignment of numerical scores should be avoided.

Application of the taxonomy

Of the 16 studies identified in Chapter 2, the 'Moving to Opportunity' RCT was assigned to category 'A',(189) since researchers controlled the randomisation process, and the studies by Arcaya et al. and Kapinos et al. were assigned to category 'B' since randomisation was beyond the control of researchers (see Table 2-4 for a description of these randomised experiments).(188) Twelve observational studies were allocated to categories 'C', 'D' and 'E' since they had used a range of different analytical techniques, including for example fixed-effects panel data analyses which were allocated category 'C', and instrumental variable analyses in a cross-sectional data which were allocated to category 'E.' Finally, the cross-sectional structural equation modelling study by Franzini et al. was allocated to category 'H.' Although this study had used latent variables, it nevertheless still controlled only for observable characteristics.

Fifty-four studies (54/63) identified in the review by Feng et al., and 16 studies (16/33) identified in the review by McCormack et al. were cross-sectional studies that used single equation analytical techniques and controlled for some observable variables (i.e. regression adjustment using Ordinary Least Squares) and so were allocated to category 'H'. This included the studies identified in the review by McCormack et al. (and one further study identified in the review by Feng et al.(262)) which had attempted to adjust for individual-level attitudes to healthy living by using survey questions to elicit information about neighbourhood preferences and satisfaction, but nevertheless still controlled only for observable characteristics.(154) A further eight studies, generally population-level before-and-after analyses (e.g. a study by Painter et al.(263)) were left 'uncategorised' since they didn't control even for observed characteristics.

Fifteen further studies identified in the reviews by Feng et al. (4/63) and McCormack et al. (11/33) used longitudinal data in which individual-level variables were recorded before and after a significant environmental modification (e.g. a new railway station(264)) or relocation to a different neighbourhood (these studies were described as "quasi-experiments" in the review by McCormack et al.). For example, Ewing et al. used seven years' worth of individual-level data from the National Longitudinal Survey of Youth (NLSY) to study the association between suburbanisation and BMI change for individual youth who remained in the same county compared to those who moved between counties.(186) Although the same individuals or neighbourhoods are included in the analysis at each time point, unlike the fixed effects panel data studies, these studies draw inferences from between- as well as within- individual variation, and hence they cannot control for unobserved time-invariant differences between individuals (e.g. attitude towards physical activity) and were designated category 'F'. One further study identified in the review by McCormack et al. used propensity scores to study the effect of suburban neighbourhood design on walking behaviour in eight neighbourhoods of Northern California and was designated category 'G'.(165)

3.5 Discussion

3.5.1 Application of the taxonomy

Drawing on existing tools for distinguishing between observational studies, in this chapter a taxonomy has been devised and then applied to three separate reviews of studies. Since the vast majority of studies identified in the two existing reviews by Feng et al. and McCormack et al. were allocated to a single category, category 'H', this chapter has confirmed the assumption made in Chapter 2 that existing reviews of studies of the relationship between built environment characteristics and obesity are dominated by this approach. Since fifteen (15/16) studies identified in the third review (Chapter 2) were allocated to five categories other than 'H,' it is clear that the taxonomy represents a modest development of existing tools and so could aid reviewers in making a decision about those studies which are most likely to support robust causal inferences. Had these studies been categorised using the tools currently available to reviewers of observational evidence then they would most likely have been classed in the same group as the all the other (single equation, cross sectional) studies identified in the review by Feng et al.. Alternatively, had one of the more established methods used in health research been used (e.g. PRISMA) then there may have been a problem of 'empty' systematic reviews, whereby all non-RCT study designs are simply and crudely excluded from evidence synthesis processes.(265) Nevertheless, whilst it is useful to distinguish between studies according to their study design, there are numerous additional factors that would need to be considered before a full assessment about the quality of individual studies can be made. Some of these issues are discussed in the next section, 3.5.2.

3.5.2 Other considerations beyond the taxonomy

In order to assess the internal and external validity of individual studies, reviewers must also take into account a variety of additional considerations beyond those that have been included in the taxonomy.

First, it is important that reviewers assess whether the chosen study design is appropriate for the research question being addressed. As Petticrew and Roberts point out in their discussion paper mentioned above (entitled 'Horses for Courses'),(261) different research questions may require different methods. For example, just because an advanced analytical method is deemed "best" for assessing the quantitative relationship between built environment, health behaviours and health outcomes, alternative methods may be better suited in other situations. Research questions about how people perceive health behaviour change interventions, or how those interventions might best be implemented, could be better addressed using qualitative techniques, including short interviews to elicit expert opinions. Yet such methods are not included in the checklists reviewed in this chapter (e.g. the Maryland scale), and are sometimes dismissed as "low quality" studies.

Second, each analytical technique included in the taxonomy has distinct features and relies on specific assumptions which authors ought to address in their studies so that reviewers can make an informed judgement about whether or not the technique has been used correctly. For example, with reference to the earlier description in Chapter 2 (section 2.4.1.1) of the eight instrumental variables studies identified in the review, some authors provided only a brief justification for their choice of instrument. Alongside the necessity to report the first-stage association between exposure and instrument, perhaps the main risk in instrumental variable analyses is that reviewers of evidence have to rely on subjective, un-testable judgments about the quality of the instrument.(266-270) (211). Hence the choice of instrument may need to be discussed at some length, using theoretical or empirical evidence, with a full explanation of the rationale that has been used. Otherwise, from the perspective of internal validity, perhaps is would be wise for reviewers to assume that the method has been used inappropriately. From the perspective of external validity, reviewers of instrumental variable analyses must also consider whether the local average treatment effect is applicable to their research question. If not, then the assumptions that are made in extrapolating beyond the subsample of participants who would change their behaviour as a result of a change in the instrumental variable need to be considered.(209, 210) Other methodological techniques used in observational studies, as well as in RCTs, will also require specific checks to ensure that they have been used properly. For example, in propensity score analyses, the characteristics of participants for whom there is common support must be reported.(166, 271) Yet these details are often overlooked or left unreported by study authors.(166) In panel data analyses, attrition between waves of the data (or non-response) could be a significant source of bias if, over time, individuals who leave the panel (or do not respond) have different characteristics to those who remain. If these characteristics are related directly or indirectly to the outcome of interest then it seems probably that this would lead to misleading results. One approach to testing whether or not this is the case, at least in terms of observable characteristics, is described by Verbeek and Nijman (1992).(272) Essentially, for each wave of data, the approach amounts to comparing the characteristics of individuals who left the panel at the next wave (or failed to respond) with those who remained in the panel (or responded). Alternatively, the relationship between observable individual-level characteristics and the length of time individuals remain in the panel can be assessed. If there is evidence of attrition (or non-response) bias then weighting can be used in the regression analysis to account for the likelihood that certain characteristics are associated with the likelihood of remaining in the panel. Whilst this method is described in standard econometric textbooks,(143, 172, 273) and so would likely be expected when publishing in 'economics' journals, the studies identified in Chapter 2 indicated that this method is not applied universally. Hence reviewers of studies ought to determine whether or not such a method has been used when assessing the reliability of the reported results.

Third, even if a reviewer concluded that the methodological approach was appropriate to the research question, and that it had been used correctly, they must also consider wider issues beyond the chosen analytical approach when considering the quality of individual studies. For example, in the built environment studies identified in Chapter 2, there may have been bias in studies which used self-reported rather than objectively measured BMI outcomes,(151) and in studies which used perceived rather than objectively measured characteristics of the built environment.(152) Longitudinal studies also differed in terms of the strength of temporal evidence (i.e. whether a change in environmental characteristics actually preceded a change in outcome). Reviewers must also consider the trade-off between using large pre-existing administrative boundaries (e.g. in the study of adolescent BMI by Powell et al.(200)) and more sophisticated approaches based on geo-referenced micro-data (e.g. the study by Chen et al.(195)). While the latter can provide a detailed description of each individual's immediate living environment, a possible bias would likely arise if individuals engage in dietary or physical activity behaviours outside their immediate area.(274)

These additional factors that go beyond those reflected in the taxonomy could be addressed through improved reporting guidelines for authors of observational studies. The STROBE guidelines,(275, 276) for example, could be updated and enhanced so that authors of studies would be expected to report critical information related to the appropriate use of each analytical technical in a way that comes closer to the rigour that is expected in the reporting of RCTs.(230) Likewise, reviewers would also benefit from enhanced tools so that they can better assess the strengths and weaknesses of different studies. To address the need to consider whether or not a technique has been used correctly, for example, a good practice checklist could be provided to raise awareness of potential issues of concern. Figure 3-7 shows how this might be developed in the case of instrumental variables studies, summarising the issues that have been discussed in Chapters 2 and 3.

In light of an assessment of these additional issues that go beyond a consideration of the chosen analytical technique, it is plausible that reviewers or policymakers may reasonably conclude that the results of other, cross-sectional, single equation studies provide them a more reliable guide, despite the associated higher risk of self-selection bias (or endogeneity).

3.6 Conclusion

Since randomised experiments are scarcely used in studies of the relationship between built environment and health outcomes, it is inevitable that systematic reviews should incorporate observational evidence. Whilst advanced analytical techniques can be used to support more robust causal inferences, they generally rely on significant, sometimes unverifiable, assumptions and their suitability is context specific. Thus interpretation of evidence requires an assessment of many factors, including whether or not the statistical techniques have been used correctly. Thus these factors preclude the assignment of a simple rank or numerical score to studies based only on the choice of analytical technique. The taxonomy described in this chapter nonetheless enables reviewers to distinguish between alternative methodological approaches, including those listed in the MRC guidance on natural experiments, and thus represents a development of existing tools. The taxonomy, and the MRC guidance, ought to be complemented with tools for reviewers on the appropriate use of each technique and the potential sources of bias that may arise. This could include development of a best practice checklist to enable reviewers to make a judgement about whether or not particular methods have been used appropriately.

Figure 3-1: A taxonomy of study designs

This table shows (i.) the taxonomy of study designs, (ii.) the causal considerations which have informed the taxonomy categories, (iii.) the number of studies identified in three existing reviews, and (iv.) the Maryland Scale of Scientific Methods (MSSM) to provide a comparison with the taxonomy categories.

(i.) Taxonomy		**(ii.) Causal considerations**			**(iii.) Identified studies and methods**					**(iv.) MSSM**
Category	Category description	Experi-mental evidence	Evidence of temporality or precedence	Extent to which observed and unobserved variables are controlled for	Number of studies identified in each review			Example methods identified in the reviews or MRC guidance on natural experiments	Example studies identified in the reviews	Level
					Obesity		Physical activity			
					Chapter 2 review n=16	Feng et al. review n=63	McCormack et al. review n=33			
A	Randomised experiment in which researcher controls allocation of individuals to two or more groups	Yes	Yes, at the individual-level	Observed and unobserved individual-level characteristics, assuming that any differences that exist by chance are insignificant	1	0	N/A	Randomised Controlled Trial (RCT)	Moving to Opportunity study – Kling (2004)(189)	5
B	Observational study that mimics a randomised experiment using a naturally occurring randomisation process beyond the researchers' control	Yes	Yes, at the individual-level	Observed and unobserved individual-level characteristics, assuming that any differences that exist by chance are insignificant	2	0	N/A	Randomised experiment *- and -* Regression discontinuity	Kapinos (2011), see (**Table 2-4**) (188)	
C	Observational study using panel or cohort data which controls for unobserved individual-level characteristics	No	Yes, at the individual-level	Observed and unobserved individual-level characteristics	4	0	0	Difference in differences *- and –* Panel data analysis controlling for fixed effects	Powell (2009)(200)	4
D	Observational repeated cross-sectional study which controls for unobservable individual-level characteristics	No	Yes, at the population-level	Observed and unobserved individual-level characteristics	2	0	0	Instrumental variables analysis using repeated cross-sectional data	Zhao (2010)(192)	
E	Observational cross-sectional study which controls for unobservable individual-level characteristics	No	No	Observed and unobserved individual-level characteristics	6	0	2	Instrumental variables analysis using cross-sectional data	Zick, (2013)(197)	

(i.) Taxonomy		**(ii.) Causal considerations**			**(iii.) Identified studies and methods**					**(iv.) MSSM**
Category	Category description	Experi-mental evidence	Evidence of temporality or precedence	Extent to which observed and unobserved variables are controlled for	Number of studies identified in each review			Example methods identified in the reviews or MRC guidance on natural experiments	Example studies identified in the reviews	Level
					Obesity		Physical activity			
					Chapter 2 review n=16	Feng et al. review n=63	McCormack et al. review n=33			
F	Observational study using panel or cohort data which does not control for unobserved individual-level characteristics	No	Yes, at the individual-level	Observed individual-level characteristics	0	4	11	Cohort study analysing change in individual-level characteristic following an environmental modification *- and -* Panel data analysis controlling for random effects	Ewing (2006)(186)	4
G	Observational cross-sectional study which controls for observable individual-level characteristics and rejects observations when there is no common support	No	No	Observed individual-level characteristics	0	0	1	Propensity score matching	Cao (2010)(165)	
H	Observational cross-sectional study which controls for observed individual-level characteristics	No	No	Observed individual-level characteristics	1	54	16	Ordinary Least Squares in a cross-sectional study design	See the reviews by Feng et al. and McCormack et al. for examples	3
Uncateg-orised	Observational study which does not include controls for important observed characteristics	No	No	No	0	5	3	Population-level before and after study	Painter (1996)(263)	1 & 2

Figure 3-2: MOOSE guidelines for systematic reviews of observational studies

Reporting of background should include
Problem definition
Hypothesis statement
Description of study outcomes
Type of exposure or intervention used
Type of study designs used
Study population
Reporting of search strategy should include
Qualifications of searchers (eg librarians and investigators)
Search strategy, including time period used in the synthesis and key words
Effort to include all available studies, including contact with authors
Databases and registries searched
Search software used, name and version, including special features used (eg explosion)
Use of hand searching (eg reference lists of obtained articles)
List of citations located and those excluded, including justification
Method of addressing articles published in languages other than English
Method of handling abstracts and unpublished studies
Description of any contact with authors
Reporting of methods should include
Description of relevance or appropriateness of studies assembled for assessing the hypothesis
Rationale for the selection and coding of data (eg sound clinical principles or convenience)
Documentation of how data were classified and coded (eg blinding and interrater reliability)
Assessment of confounding (eg comparability of cases and controls in studies where appropriate)
Assessment of study quality, including blinding of quality assessors, stratification or regression on possible predictors of study results
Assessment of heterogeneity
Description of statistical methods (eg complete description of fixed or random effects models, dose-response models, or cumulative meta-analysis) in sufficient detail to be replicated
Provision of appropriate tables and graphics
Reporting of results should include
Graphic summarizing individual study estimates and overall estimate
Table giving descriptive information for each study included
Results of sensitivity testing (eg subgroup analysis)
Indication of statistical uncertainty of findings
Reporting of discussion should include
Quantitative assessment of bias (eg publication bias)
Justification for exclusion (eg exclusion of non-English language citations)
Assessment of quality of included studies
Reporting of conclusions should include
Consideration of alternative explanations for observed results
Generalization of the conclusions (eg appropriate for the data presented)
Guidelines for future research
Disclosure of funding source

Source: Stroup et al (2000)(277)

Figure 3-3: Quality assessment criteria proposed in GRADE

<table>
<tr><td colspan="5"><u>1. Quality of evidence scale:</u>
RCTs start as high-quality evidence and observational studies as low-quality evidence supporting estimates of intervention effects. Five factors may lead to rating down the quality of evidence and three factors may lead to rating up. Ultimately, the quality of evidence for each outcome falls into one of four categories from high to very low.</td></tr>
<tr><td>Study design</td><td>Initial quality of a body of evidence</td><td>Lower if</td><td>Higher if</td><td>Quality of evidence</td></tr>
<tr><td>Randomised trials >>>></td><td>High</td><td rowspan="4">Risk of bias:
1 Serious
2 Very serious

Inconsistency:
1 Serious
2 Very serious

Indirectness:
1 Serious
2 Very serious

Imprecision:
1 Serious
2 Very serious

Publication bias:
1 Likely
2 Very likely</td><td rowspan="4">Large effect:
1 Large
2 Very Large

Dose response:
1 Evidence of a gradient

All plausible confounding & bias:
1 Would reduce a demonstrated effect,
1 Would suggest a spurious effect if no effect was observed</td><td>High</td></tr>
<tr><td></td><td>Moderate</td><td>Moderate</td></tr>
<tr><td>Observational studies >>>></td><td>Low</td><td>Low</td></tr>
<tr><td></td><td>Very Low</td><td>Very Low</td></tr>
<tr><td colspan="5"><u>2. Factors that may increase the quality of evidence:</u></td></tr>
<tr><td colspan="5">Large magnitude of effect (direct evidence, relative risk [RR]=2–5 or RR=0.5–0.2 with no plausible confounders); very large with RR>5 or RR<0.2 and no serious problems with risk of bias or precision (sufficiently narrow confidence intervals); more likely to rate up if effect rapid and out of keeping with prior trajectory; usually supported by indirect evidence.</td></tr>
<tr><td colspan="5">Dose-response gradient.</td></tr>
<tr><td colspan="5">All plausible residual confounders or biases would reduce a demonstrated effect, or suggest a spurious effect when results show no effect</td></tr>
</table>

Source: Guyatt et al 2011, Chapter 1 and Chapter 9.(217, 249)

Figure 3-4: The Maryland Scale of Scientific Methods

Level 5	Random assignment and analysis of comparable units to intervention and control groups
Level 4	Comparison between multiple units with and without the intervention, controlling for other factors or using comparison units that evidence only minor differences
Level 3	A comparison between two or more comparable units of analysis, one with and one without the intervention
Level 2	Temporal sequence between the intervention and the outcome clearly observed; or the presence of a comparison group that cannot be demonstrated to be comparable
Level 1	Observed correlation between an intervention and outcomes at a single point in time

Source: Cabinet Office (2013)(253, 254)

Figure 3-5: The Cambridge Quality Checklists

Correlate score (out of 5)	
Sampling	
1	Total population or random sampling
0	Convenience or case–control sampling
Response rates	
1	Response and retention rates ≥70% and differential attrition ≤10%
0	Response rate <70% or retention rate <70% or differential attrition >10%
Sample size	
1	Sample size ≥400
0	Sample size <400
Measure of correlate	
1	Reliability coefficient ≥.75 and reasonable face validity, or criterion or convergent validity coefficient ≥.3, or more than one instrument or information source used to assess correlate
0	None of the above
Measure of outcome	
1	Reliability coefficient ≥.75 and reasonable face validity, or criterion or convergent validity coefficient ≥.3, or more than one instrument or information source used to assess correlate
0	None of the above
Risk factor score (out of 3)	
1	Cross-sectional data
2	Retrospective data
3	Prospective data (or study of fixed risk factor)
Causal risk factor score (out of 7)	
1	Study without variation in the risk factor. No analysis of change.
2	Study with variation in the risk factor but inadequately balanced. No analysis of change.
3	Study without variation in the risk factor. With analysis of change.
4	Study with variation in the risk factor but inadequately balanced. With analysis of change.
5	Study with variation in the risk factor and adequately balanced. No analysis of change.
6	Study with variation in the risk factor and adequately balanced. With analysis of change.
7	Randomised experiment. Targeting a risk factor.

Source: Murray et al. (2009)(244)

Figure 3-6: The Bradford-Hill considerations for inferring causality

Considerations	**Description**
Temporality and precedence	Cause precedes effect
Experimental evidence	Associations are examined using manipulation and controls
Strength	Magnitude of measured association
Consistency	Repeated in multiple observations
Coherence	No conflict with current knowledge
Plausibility	Observations confirm currently accepted theories
Dose response relationship	An increasing amount of exposure increases the risk
Specificity	Causation is likely if there is a very specific population at a specific site and disease with no other likely explanation
Analogy	The effect of similar factors may be considered

Source: Hill (1965)(256)

Figure 3-7: Good practice checklist for reviewers of instrumental variables studies

Consideration	**Description**	**Reported in study? Yes or No**
Relevance test	Reporting of a statistical test of the first-stage association between exposure and instrument (typically requiring a partial F-statistic >10 plus some theoretical justification)	*To be completed by the reviewer*
Exclusion restriction	Reporting of a statistical test of the relationship between potential observed confounding variables with the exposure and the instrument, plus theoretical or empirical evidence on the relationship between potential unobserved confounding variables with the exposure and instrument	
Local average treatment effect	A description of the assumptions that would be necessary to extrapolate the local average treatment effect to the population average (causal) treatment effect	
Attrition bias (in studies using panel data)	An assessment (and ideally accounting for using weights) of the scope (or impact) of attrition.	
Over-identification (in studies with multiple instruments)	Reporting of standard tests for over-identification	

SECTION C: EMPIRICAL ANALYSES USING THE BRITISH HOUSEHOLD PANEL SURVEY

4 An overview of the BHPS and analyses of the correlates of commuting behaviour and commuting behaviour change

4.1 Overview of chapter

This chapter begins (Section 4.2) with a general overview of the BHPS and 'Understanding Society' datasets which is relevant to the analyses presented later in chapter 4, as well as in chapters 5 and 6 of this thesis.

The BHPS is a large scale annual survey of nationally representative households which began in 1991-2. 'Understanding Society' began in 2009-10 as a successor to the BHPS. The main analytical sample used in this thesis consists of individual-level panel data from all 18 waves of BHPS data and three waves of 'Understanding Society' (that is, waves 2, 3 and 4 of the 'Understanding Society' dataset).

The remainder of this chapter (Sections 4.3, 4.4 and 4.5) presents some descriptive analyses of all 21 waves the BHPS and 'Understanding Society' data. These analyses explored individual-level correlates of walking and cycling behaviour, and behaviour change. This information could be helpful in the design of behaviour change interventions, including information campaigns designed to encourage people to switch travel mode for their commute to work (the second of four policy options outlined in Table 1-1), in terms of gaining an understanding of the types of commuters who might be most willing to switch travel mode.

The dependent variables used in the analyses are derived from a survey question on the usual main mode of travel used for getting to work, which is asked of individuals in each wave of the BHPS and 'Understanding Society.' In addition to data from the main annual surveys, the chapter also demonstrates the potential for linking BHPS participants to other participants in the dataset, in this case an individual's current partner, and data from other datasets, in this case the separate BHPS youth questionnaire and interview. Since some adult participants in the BHPS or 'Understanding Society' survey also completed the BHPS youth questionnaire and interview when they were younger, this dataset provides variables on the travel behaviour of adult participants during their own childhood.

4.2 Overview of the BHPS and 'Understanding Society'

This section provides an introduction to the BHPS and 'Understanding Society' datasets. The information is relevant to the analyses presented later in chapter 4, and in chapters 5 and 6.

4.2.1 Description

The BHPS is a large-scale, multi-purpose panel data study of private households in the UK that began in 1991-92 as an annual survey of each household member aged over 16 years of age from a nationally representative sample and ended after 18 waves in 2008-09.(278) The first wave of the BHPS (1991-92) consisted of 5,500 households and 10,300 individuals drawn from across Great Britain (i.e. England, Wales and Scotland). The same individuals were then surveyed in each wave. New entrants joined the survey in wave 9 and wave 11. In wave 9, two additional samples of participants from Scotland and Wales were added (3,000 additional households). In wave 11, participants were added to the sample from Northern Ireland for the first time (2,000 households) to increase the sample to cover the whole of the UK.

A separate youth questionnaire and interview was introduced in wave 4 of the BHPS (1994-5), and was used in all subsequent BHPS waves. The youth questionnaire and interview was completed by children and young people aged 11-15 years of age living in each of the households in the main BHPS sample. Questions in this survey focused mainly on general attitudes, leisure time activities, relationships with family and friends, and school or educational issues. In wave 4 there were 773 participants, and this increased to over 1,200 participants in the later waves. On turning 16 years of age, young people who had previously completed the youth questionnaire and interview were invited to join the main BHPS sample and their responses to both surveys can be linked using personal identification numbers. This means that it is possible to trace some individuals from the age of 11 through to adulthood, including periods of time when they may have moved away from their childhood home.

Since 2009-10 the BHPS was significantly enhanced, with a greater number of variables and larger sample sizes, and re-launched as ‘Understanding Society’.(279) There are two groups of participants in ‘Understanding Society.’ The first group were new recruits who were interviewed in the first round of data collection (in 2009-10) and all subsequent years. The second group included 6,700 (from 8,000 who were eligible) former participants of the BHPS who were invited to join ‘Understanding Society’ from wave 2 onwards. In this second group, responses to each of the two surveys can be linked at the individual-level using personal identification numbers. With over 40,000 households and 100,000 individuals in the UK, ‘Understanding Society’ is now thought to be the largest study of its type in the world.(279) Interviews are typically carried out face-to-face in respondents’ homes by trained interviewers.

4.2.2 Sample selection

Figure 4-1 provides an illustration of how the samples used in the analyses presented in chapters 4-6 were selected from the BHPS and ‘Understanding Society’ datasets. The data was accessed through the UK Data Archive.

In this thesis, data was used from 21 waves of the BHPS (all 18 waves) and ‘Understanding Society’ (waves 2, 3 and 4). Wave 1 of the ‘Understanding Society’ survey was excluded because it did not include any of the BHPS participants. In total, across all 21 waves, there are 271,835 person-year observations (see Figure 4-1).

Participants were eligible for inclusion in the analyses presented in this thesis (chapters 4, 5 and 6) if, in any of the 21 waves, they were aged 16-65 years (a reduction in total sample size from

271,835 to 222,822, see Figure 4-1), reported their usual main mode of travel to work (a further reduction in total sample size to 141,876) and reported being in paid part-time or full-time employment or self-employment (further reduction in total sample size to 137,251).

Further sample selection criteria were applied in each chapter.

In chapters 4 and 5, person-year observations were excluded if participants reported using ‘Underground/tube’, ‘Motor cycle/moped’, Car/van passenger’ and ‘Other’ as their main mode of travel for work (further reduction in sample size to 120,061, see Figure 4-1). This was due to relatively small sample sizes in each of those modes and probable differential effects which could obscure the main focus of attention on the differences between active commuting, car travel and the two most common public transport modes (nevertheless, ‘Underground/tube’, ‘Motor cycle/moped’, Car/van passenger’ were included in chapter 6 because the sample size was restricted to just two waves of data and so the exclusion of these modes was only examined in sensitivity analyses – see Figure 6-1). Descriptive statistics for this sample (n=120,061) are shown in Table 4-3.

In chapter 5, further person-year observations were excluded if participants were aged under 18 (the reason for inclusion of under 18s in chapter 4 was that this increased the sample of over 16s in the dataset who had completed the BHPS youth questionnaire and interview when they were younger) and if data was missing on wellbeing (the outcome variable used in chapter 5) (see figure 4-1). The analyses were further restricted to the first 18 waves of data from BHPS, excluding data from Understanding Society. Descriptive statistics for this sample (n=102,502) are shown in Table 5-3.

In chapter 6, the sample was selected from 15,791 participants in wave 14 of the BHPS. The exclusion criteria are shown in Figure 6-1. Descriptive statistics for this sample (n=4,056) are shown in Table 6-2 and Table 6-3.

4.2.3 Disclaimer and ethical approval

Data used in this thesis from the BHPS and 'Understanding Society' were supplied by the UK Data Archive. Neither the original collectors of the data nor the Archive bear any responsibility for the analysis or interpretations presented.

The surveys have adopted, in full, the ethical guidelines of the Social Research Association. No further ethical approval was required for the secondary analyses presented in this thesis.

4.2.4 Comparable datasets

A description of the relative strengths of the BHPS and 'Understanding Society' datasets when compared to other alternative sources of data which could have been chosen for analysis in this thesis is provided in Table 4-1 (further detail on these alternative sources of data is also available in a recent review by Cavoli et al.(280)). For the purpose of undertaking studies on active travel and health, these relative strengths may be summarised as follows. First, when compared to studies that used primary data collection, the BHPS and 'Understanding Society' data includes: (i.) a nationally representative sample of individuals and households, (ii.) large sample sizes which can support analysis of small effect sizes and small subgroups, (iii.) long follow-up periods (more than two decades) which could support, for example, analysis of the impact of childhood behaviour on adult behaviour, or the long term impact of behaviour changes on health. Second, when compared to other large-scale nationally representative datasets, such as the Census, NTS or HSE, the main advantages are: (iv.) the same individuals are tracked over time, supporting within-individual longitudinal analyses which may support more robust causal inferences than would be possible using between-individual cross-sectional regression analyses, (v.) the scope of the survey, in terms of the variety of variables relating to health and transportation, which can be used to support, for example, analysis of the impact of commuting behaviour on health outcomes, and (vi.) the potential to link with external sources of data at the individual-level, for example on characteristics of the urban built environment (subject to an application procedure for access to a secure data release, which was beyond the scope of this thesis).

4.3 Background

This section provides a brief overview of the objectives of the analyses presented in this chapter (section 4.3.1) and a short review of existing literature on (i.) correlates of commute mode choice, (ii.) Individual-level patterns of commuting behaviour over time, and (iii.) Individual-level determinants of commute mode change.

4.3.1 Objectives of chapter

The analyses presented in this chapter have three core objectives. First, to identify correlates of commute mode choice, primarily using data on the individual-level characteristics of commuters. Second, to explore patterns of commuting behaviour over time, including an examination of the relative stability of travel mode choices between survey waves, and third, to identify factors which have an impact on the likelihood of changing commute mode when compared to maintaining existing travel behaviour. These factors included changes in household structure, home location, employment and relationship status.

4.3.2 Short review of literature in relation to three objectives of chapter 4

4.3.2.1 Correlates of commute mode choice (Objective 1)

Existing population-level surveys provide a detailed examination of the prevalence of walking and cycling at the aggregate-level amongst adults travelling to work in the UK.(26, 33) This evidence was reviewed in section 1.2.2. For example, the 2011 Census of England and Wales showed that 14.0% of commuters used active travel modes (Figure 1-6).

Population-level Census data has been used in existing studies, for example to explore the socio-economic patterning of commute modes across different population groups.(33) However, with the exception of annual reports based on NTS data, no published studies have used data from any of the UK's large scale, population-representative surveys to explore associations between individual-level characteristics and travel mode choices.

4.3.2.2 Individual-level patterns of commuting behaviour over time (Objective 2)

Aggregate-level Census data can be used to explore how the proportion of commuters using different travel modes has changed over time. For example, the proportion of adult commuters using active commuting modes fell between 1971 and 1991, before entering a period of relative stability between 1991 and 2011 (Figure 1-6).(33) But few studies have explored how changes in individual-level commuting behaviour has contributed to observed long-term changes at the population-level. In part this is because few suitable datasets support the tracking of individuals over time. Publically accessible Census data, for example, does not link individuals between Census waves and, in any case, the survey is completed only once every ten years.

Studies which have explored patterns in individual-level commuting behaviour over time have typically focused on car travel or other private motor transport modes, rather than on walking or cycling.(29, 281) Hence little is known about the number of commuters that switched to and from active travel modes between two census years. In one study, Dargay et al. explored the ‘volatility’ of car use and car ownership during the period 1991-2001 using BHPS data. By comparing pairs of consecutive survey waves, the authors found that individuals had switched between car use and other travel modes in 11% of cases, despite an apparent stability in the population-level prevalence of car use and car ownership during the period.(281) Some studies have used individual-level data to examine how overall physical activity evolves over the lifespan, from early adulthood to old age for example,(25) however these studies have not explored the specific contribution of travel to work to overall physical activity levels.

4.3.2.3 Individual-level determinants of commute mode change (Objective 3)

Within the existing literature on travel behaviour, a small number of quantitative longitudinal studies have observed that significant changes in travel behaviour, including switching to and from different commuting modes, are more likely to occur when other significant changes are happening in people’s lives. For example, one analysis of the first two waves of ‘Understanding Society’ published in 2014 by Clark et al. found that changes in car ownership and changes in commute mode were associated with changes in employment, household structure and residential location.(104) Another recent longitudinal study by Oakil et al. analysed data on individual-level travel behaviour over two decades in the Netherlands. One finding was that birth of a first child had a significant association with take-up of private motor transport.(282) However, this study was limited to just under 200 individuals and, like other studies in this area of research, the questioned were asked of participants retrospectively.

With a more specific focus on active travel modes than the other studies, a small number of quantitative longitudinal studies published in the public health literature have explored changes in walking and cycling behaviour that occurred after people had moved to new housing developments. For example, Beenackers et al. found that people moving to new neighbourhoods in Perth, Australia with higher residential density, street connectivity and park access were more likely to take up cycling.(283) In a study of low-income, primarily African-American women in the US, Wells et al. also found that people moving to areas with higher street connectivity reported more walking.(284) Others have explored the topic using qualitative methods.(102) However, when compared to the data available in the BHPS and 'Understanding Society' (including the study by Clark et al.), these studies were limited not least by short follow-up times, small sample sizes (n=32 in the study by Wells et al.) and some risk of endogeneity.

4.4 Methods

This section includes a description of the data to be used in the analyses (section 4.4.1), the variables to be used in the analyses (section 4.4.2), and the methods of analysis in relation to each of the three core objectives set out in the previous section (section 4.3.1).

4.4.1 Sample selection

This main analytical sample used in this chapter consisted of 120,061 person-year observations as described above in section 4.2.2 and in Figure 4-1.

- Main analytical sample: (N=120,061)

In addition to this main analytical sample, two smaller subsamples of person-year observations were used:

- Subsample 1: person-year observations for people who reported their partner's travel mode (N=55,348)

- Subsample 2: person-year observations for people who reported their parents travel mode or childhood physical activity variables in any of the 15 waves (waves 4-18, see Figure 4-1) of the separate BHPS youth questionnaire and interview (N=5,896)

4.4.2 Variables used in the analyses

This section provides a description of the dependent and independent variables to be used in the analyses (see Table 4-2 for a list).

4.4.2.1 Dependent variables

The dependent variables used in this chapter were all derived from the BHPS question on the usual main mode of travel to work. Responses to the question 'What usually is your main means of travel to work?' were categorised as follows (five categories): car travel (if responded 'Car or van'), walk (if responded 'Walks all way'), cycle (if responded 'Pedal cycle'), train (if responded 'Train'), and bus (if responded 'Bus or coach').

Separate binary variables were created for each of the five travel mode categories (e.g. 'cycling' = 1, other travel modes = 0). Two further binary variables for 'active travel' ('cycling' or 'walking' = 1, other = 0) and for 'public transport' ('Train' or 'Bus or coach' = 1, other = 0) were also created for use in some analyses.

In order to capture the impact of switching to a new travel mode, when compared to maintaining existing travel behaviour, two separate binary 'transition' variables were also created for use in some analyses if lagged (t-1) and current (t) travel mode status were known. To study associations with switching from car travel to active travel when compared to maintaining car travel, an active travel transition variable was created where: 'switched to active travel'= 1 if 'active travel' in t and 'car travel' in t-1; 'maintenance of car travel' = 0 if 'car travel' in t and t-1. Cases where lagged or current travel mode were unknown, or where other combinations of lagged and current travel mode were observed (e.g. switched from cycling to car travel, or maintained cycling), would be excluded from this particular analysis. A car travel transition variable was also created where: 'switched to car travel'= 1 if 'car travel' in t and 'active travel' in t-1; 'maintenance of active travel' = 0 if 'active travel' in t and t-1. Similar transition variables were created for use in another BHPS study by Flint et al. which explored the impact on wellbeing of moving into and out of employment.(285) Although this necessarily resulted in some transitions being excluded from some analyses, it enabled comparisons to be made between specific behavioural changes and maintainance of an existing behaviour.

4.4.2.2 Independent variables

Individual-level characteristics

The following variables were created for those individual-level characteristics which are reported in all BHPS and 'Understanding Society' waves and selected for use in the regression analyses presented in this chapter: age (years), gender (binary variable =1 if male, =0 if female), whether or not children aged under-16 years lived in the household (binary variable=1 if one or more children, =0 otherwise), whether or not individual is in a relationship (including marriage) (binary variable=1 if in a relationship, =0 otherwise), work hours (binary variable =1 if 'full-time', =0 if 'part-time'), income group (using the BHPS variable 'Total income last month', a single discrete variable taking a value of 1-5 was created based on the quintile in which an individual's income falls – quintiles were created using the data on income from the full sample of participants), and occupational status based on the Registrar General's Social Class classification (binary variables were created for each category e.g. =1 if professional occupation, =0 if other occupation). Three further binary variables were created for residential location: (i.) =1 if one of the six urbanised areas outside of London which were designated in 1974 as the 'metropolitan counties' of England - Greater Manchester, Merseyside, South Yorkshire, Tyne and Wear, West Midlands, West Yorkshire, =0 if one of the other 13 Government Office regions reported in the publically accessible BHPS data (ii.) = 1 if 'Inner London', =0 if otherwise, and (iii.) =1 if 'Outer London', =0 if otherwise. Binary variables for each survey year were also created.

In addition to the variables selected for use in the regression analyses, a number of additional variables were used in the descriptive statistics. These included: number of children aged under-16 years in the household (=0…n), highest educational attainment (including a binary variable derived from seven educational status categories in the BHPS where =1 if degree or higher education, =0 otherwise), work hours (in addition to the full-time work binary variable above, a second was: night time work=1, other time work=0) self-employment status (binary variable: =1 if self-employed, =0 otherwise), self-assessed health status (a single continuous variable representing four health states: 'excellent', 'good', 'fair' and 'poor or very poor', and a binary variable where =1 if 'poor or very poor' health, =0 other health state), smoking status (=1 if smoker, =0 otherwise), daily commuting distance (reported in miles, but only in the three waves of 'Understanding Society') and daily commuting time (reported in minutes).

Changes that occurred between waves

Many changes that occurred between waves, including change from (or to) full-time work, or change from (or to) a household with at least one child, were captured in the fixed effects model specification using the variables listed above.

Changes in work and home location were captured by creating new discrete variables: number of previous residences (=0…n) (derived from responses to the BHPS question "have you yourself lived in this house/flat for more than a year?") and workplaces (=0...n), where n=number of residences or workplaces an individual has reported living in since entering the sample so that, in the fixed effects model specification, house or job moves can be accounted for (whilst a change in state from having not lived in a house or flat for more than a year in one wave, to having lived in a house or flat for more than a year in the following wave can be ignored in the analysis).

Similarly, if one of seven possible reasons for moving home location was given, then these were captured by creating new discrete variables: number of times a particular reason has been given (=0…n), where n=number of times the particular reason had been given since entering the sample. Five of these variables were created representing five groups of particular reasons for moving house: (i). 'Employer relocated' if individual responded: "Employer moved job to another workplace", (ii.) 'Moved for a new job' if responded "Got a different job with the same employer which meant moving workplace" or "Moved to start a new job with a new employer" (iii.) 'Moved closer to same job' if responded: "Moved to be nearer work but didn't move workplace", (iv.) 'Change in own business' if responded: "Moved to start own business" or "Decided to relocate own business" and (v.) 'Salary increased' if responded: "Salary increased so could afford to move home."

Linked BHPS data from previous waves and other related individuals

In addition to the individual-level variables derived from data reported by participants in each wave, further individual-level variables were also created using data from previous waves or other related individuals in the BHPS.

The following were used in the descriptive statistics:

First, in waves where participants reported living with a partner (subsample 1), the partner's usual main mode of travel for work was collected using the personal identification number of the partner which is reported for each individual in the main survey when they are living in the same household as their partner. Binary travel mode variables were created for the partner's travel mode in each wave using the five travel mode categories described under 'Dependent variables' above.

Second, if participants aged over 16 in the main BHPS survey had also completed the youth questionnaire and interview at any time point when they were aged 11-15 years of age, then additional variables were created to account for their own and their parent's travel and physical activity behaviour when they were a child (subsample 2). Two separate approaches were taken here: first, responses to the question 'How do you usually travel to and from school?' which was asked of participants in the youth questionnaire in waves 14 and 15 (potential responses were: 'Walk all the way,' 'Ride a bike,' 'By bus or tube,' 'By car,' 'By train' or 'Some other way') were used to create a childhood active travel binary variable (=1 if cycled or walked in either wave 14 or 15, 0=otherwise). Second, responses to the question 'How often do you play sport or go walking or swimming,' which was asked of participants in the youth questionnaire in waves 12, 13 and 17, were used to create a binary variable for physical activity (five potential responses were coded as follows: =1 if 'At least once/week,' or 'At least once/month,' in any of the three waves 12, 13 or 17; =0 otherwise if 'Several times/year,', 'Once/year or less,' or 'Never/almost never' was reported at least once).

The following were used in the regression analysis (as well as in the descriptive statistics):

Using data on the parent(s) or guardian(s) responsible for the child during the years when the participant was aged 11-15 (identified using the personal identification number of the adult members of the household which are reported for each individual in the youth questionnaire), variables on the number of cars in the household (two binary variables were created: first, 0=no cars, 1=one or more cars, and second, 0=no cars or one car, 1= more than one car), the main travel mode used for work by one or more parent(s) or guardian(s) (for analytical purposes a binary variable was created: 0= use of other travel modes by parents at any time point when aged 11-15, 1=one or more parent(s) or guardian(s) used active travel modes at any time point when aged 11-15), and the occupational status of one or more parent(s) or guardian(s) using the Registrar General's Social Class categories (for analytical purposes a binary variable was created to reflect the highest reported occupational status of any parent or guardian at any time point when each participant was aged 11-15).

Lagged dependent variables

Three lagged dependent variables were also created using data on the usual main mode of travel to work in the preceding wave for 'walking', 'cycling' and 'public transport' (e.g. 'cycling in t-1'=1, 'other mode in t-1'=0).

4.4.3 Statistical analyses

This section describes the statistical analyses to be used in relation to the three core objectives listed at the beginning of the chapter. All analyses were conducted using STATA, version 13.1, and an overview of the regression analyses is provided in Figure 4-2.

4.4.3.1 Correlates of commute mode choice (Objective 1)

First, descriptive statistics relating to the socioeconomic characteristics of participants were reported for the full sample of participants (N=120,061, see Table 4-3), and those in each of the five main travel mode categories (car, train, bus, cycling, walking). These were typically the mean values of the individual-level variables listed in the previous section under ‘Individual-level characteristics’. Chi-squared, Mann-Whitney and Student’s t tests were used to identify any statistically significant differences between train, bus, cycling and walking users when compared to car travel. Similarly, descriptive statistics were also reported for Subsample 1 (Table 4-4, when participants lived with their partner) and Subsample 2 (Table 4-5, where data was available from the BHPS youth questionnaire).

Second, multivariate random effects logistic regression models were used to explore associations between individual-level characteristics (the independent variables) and the likelihood of using active commuting modes (the outcome variable). These analyses were completed in two groups: one for the full sample (models 1A-1C) and the second group for ‘subsample 2’ (models 2A-2D, see Figure 4-2).

The model specification for models 1A-2D is shown in Equation 4-1.

$$\Pr(\textit{active}_{it}=1)=F(\beta_0+\beta_1 X_{k,it}+u_i+e_{it})$$

Equation 4-1

In this model, the outcome variable *active* takes on two unique values: 0 if travel by public transport (train or bus) or car, and 1 if travel by active travel (cycling or walking), for each individual (i=i….n) in the dataset in wave t ($1 \leq t \leq 21$). $X_{k,it}$ represents a set of k explanatory variables which may impact on travel mode choice, including gender, age and occupation. β_1 is a vector of parameters to be estimated. The error term e_{it} is time and individual specific, and should be assumed to be uncorrelated with $X_{k,it}$ and u_i. Across individuals it is assumed to be drawn from a distribution with mean zero and constant variance. u_i represents the individual specific time invariant random error component, assumed to be drawn from a distribution with a mean zero and constant variance.

An important reason for choosing the random effects model in this case was the need to estimate the association between the likelihood of using active travel and time-invariant independent variables (such as whether or not people's parents cycled to work during their childhood). Limitations of this choice are nonetheless acknowledged in section 4.6.2.

4.4.3.2 Individual-level patterns of commuting behaviour over time (Objective 2)

Individual-level data from pairs of consecutive waves were used to compute (unadjusted) transition probabilities which showed the proportion of commuters who switched to a new travel mode, and those who maintained an existing travel mode, between any year t and year t-1. These probabilities were reported for the full sample of individuals and for different subgroups in order to provide an indicator of possible differences between genders, age groups (16-34 and 50+), residential location (London, and London and other metropolitan areas in England), and previous commuting behaviour. The latter was assessed using a subsample of person-year observations where data on usual main mode of travel to work was available in at least five lagged waves of data. Participants who had previously walked or cycled in one or more of those five waves were compared to those who had never walked or cycled in any of the five waves.

4.4.3.3 Individual-level determinants of commute mode change (fixed effects models) (Objective 3)

Three further groups of regression analyses were conducted and these are summarised in Figure 4-2 (subsequently referred to as models 3A-3P). These models used a fixed effects logistic regression model specification. The key advantage of this is that they eliminate the risk that some unobserved time-invariant variables (e.g. attitude to physical activity or characteristics of the built environment) confound the relationship between observed characteristics (e.g. whether an individual cycled to school as a child) and travel mode choice. Unlike the analyses described under Objective 2 above, which focused on associations between travel mode and time invariant characteristics, the fixed effects models were appropriate for capturing the impact of changes that occurred over time during people's lives.

In the first group of fixed effects logit models (Models 3A-3E), the dependent variable was active travel (=1 if active travel, =0 if other travel mode) (see Figure 4-2).

In the second group of fixed effects logit models (Models 3F-3J), the dependent variable was the active travel transition variable (where 1=switched from car travel to active travel and 0=maintained car travel).

In the third group (3K-3P), the dependent variable was the car travel transition variable (where 1=switched from active travel to car travel and 0=maintained active travel).

Models within this section (3A-3P) also varied in terms of the range of individual-level characteristics and variables related to work and home location that were included.

4.5 Results

This section describes the results of the analyses in relation to the three core objectives outlined in section 4.3.1.

4.5.1 Predictors of commute mode choice (Objective 1)

4.5.1.1 Descriptive statistics

Data relating to the full sample of participants are shown in Table 4-3. The sample consisted of 19,222 participants and 120,061 person-year observations. The most common travel mode was car travel (accounting for 73.4% of person-year observations and used at some point by 74.7% of all individuals). Walking was second most common (accounting for 12.7% of person-year observations and used at some time point by 27.0% of individuals). In contrast, relatively few people ever travelled by train, bus or cycle.

The descriptive statistics showed that, compared to car drivers, cyclists and walkers were significantly younger (mean age 37.8 and 38.1, versus 40.0 for car drivers), less likely be living with their partner (70.4% and 65.1%, versus 76.6%), less likely to hold a ‘professional’ or ‘managerial’ occupational status (28.5% and 22.7%, versus 43.8%), less likely to be self-employed (3.1% and 5.3%, versus 9.3%), more likely to reside in ‘Inner London’ (4.4% and 2.4%, versus 1.3%) (walkers were also more likely than other travel mode users to live in ‘Outer London’), have fewer cars in the household (mean: 1.0 versus 1.8) and a shorter distance to work (as shown in the ‘Understanding Society’ subsample – 3.78 and 1.37 miles, versus 11.2 miles).

Data relating to the subsample of participants who lived with their partner (subsample 1) are shown in Table 4-4. In a sample of 50,207 person-year observations accounted for by people who travelled to work by any mode, 76.5% of cases involved people living with a partner who travelled to work by car, 11.3% of cases involved people living with a partner who travelled to work on foot, and 2.8% lived with a partner who travelled to work by bike. In contrast, of the 1,456 person-year observations accounted for by people who cycled to work, only 61.6% lived with a partner who travelled to work by car whereas 13.3% lived with a partner who travelled to work by bike and 16.6% lived with a partner who travelled to work on foot.

Data relating to the subsample of participants who reported travel or physical activity characteristics during their childhood (subsample 2) are shown in Table 4-5. Amongst those observations that involved travel to work by car, 21.4% had reported either parent (or guardian) using active travel for work in at least one time period when they were a child, compared to 38.8% for those who currently cycled to work and 38.0% for those who currently walked to work. Furthermore, amongst those observations that involved travel to work by car, 95.1% had reported at least one car in the household during childhood, compared to just 85.7% for current cyclists and 86.3% for current walkers. Similarly, whereas 44.5% of car drivers reported that they had cycled or walked to school, significantly more current cyclists (67.6%) and walkers (57.6%) had reported doing so.

4.5.1.2 Regression models (1A-2E)

The results of the analyses of correlates of active commuting are shown in Table 4-6.

In the analyses which used the full sample of participants (1A-1C), the likelihood of cycling or walking to work when compared to driving or public transport decreased significantly amongst people who lived with children under 16 years (OR=0.85, models 1B and 1C), people in full time work and those in the higher occupational status categories (e.g. OR=0.49 for 'professional' status when compared to 'unskilled'). This was the case in both model specifications which controlled for a variety of additional factors, including a lagged travel mode (dependent) variable. One model (1B) also showed that living in Inner London increased the odds of using active travel, whereas another (1C) showed living in other metropolitan areas decreased the likelihood of using active travel modes.

In the case of the occupational status categories, the interpretation of the reported odds ratios is that being in a professional occupation decreases the odds of using active travel (versus using car travel or public transport) by a factor of 0.49 when compared to being in an 'unskilled' occupation.

In the analyses that used data from the participant's own responses to the BHPS youth questionnaire and interview using subsample 2 (models 2A-2E), active travel use during childhood by at least one parent (or guardian) increased the odds of cycling in four separate model specifications (e.g. OR=1.79, model 2D – fully adjusted model), after adjustment for the parent's RGSC work status.

All models (1A-2E) were significant overall at the $p<0.001$ level according to the likelihood ratio and Wald tests.

4.5.2 Individual-level patterns of commuting behaviour over time (Objective 2)

4.5.2.1 Transition probabilities

Transition probabilities for the full sample of participants are shown in Table 4-7.

Of 96,369 pairs of consecutive waves included in sample, the most common occurrence was maintenance of car travel between t-1 and t in 69,425 cases. Amongst those pairs of consecutive waves where car travel was observed at time t-1 (n=72,327), 96.1% of observations involved a continuation of car travel at time t, compared to just 1.4% of cases where people switched to public transport, 0.7% where people switched to cycling, and 1.9% where people switched to walking. However, compared to car travel, users of other travel modes appeared to exhibit substantially less stability between waves. For example, just 77.3% of public transport users at time t-1 (n=9,655) continued using public transport at time t, while 77.1% of walkers (n=11,615) and 67.1% of cyclists (n=2,772) maintained use of the same travel mode.

Walkers were more likely than users of public transport or car travel to switch to cycling between t-1 and t, in 2.4% of cases, compared to 1.2% of public transport users and 0.7% of car users. Also, cyclists had the greatest tendency to switch to walking, in 9.4% of cases, compared to 7.1% of public transport users and just 1.9% of car users.

The transition probabilities reported for each subgroup showed that, for all travel modes, stability of travel mode choice increased with age. For example, the proportion of walkers in t-1 aged 18-34 who continued to walk in t was 67.3% compared to 87.9% amongst the 50-65 age group. Younger people were also more likely than older people to switch from car to walking or cycling. For example, 2.6% of car drivers aged 18-34 in t-1 started walking in t, compared to 1.2% amongst those aged 50-65. Car users who had previously used active travel modes in any of the past five waves were also more likely than those who had not used active travel modes during that period to switch to active travel modes. For example, of those car drivers who had previously used active travel, 6.7% switched to walking and 2.3% switched to cycling, compared to 1.4% and 0.5% amongst those who had never used active travel. Individual-level determinants of commute mode change

4.5.2.2 Regression models (1C-2D)

In the regression models reported in section 4.5.1.2 which adjusted for a lagged dependent variable (i.e. models 1C and 2D, see Table 4-7), use of non-car commute modes in the previous wave (t-1) was associated with a significant increase in the likelihood of walking or cycling (e.g. OR=3.25 for public transport use in the previous wave, model 1C).

4.5.3 Individual-level determinants of commute mode change (Objective 3, fixed effects models)

4.5.3.1 Determinants of active travel (Fixed effects models 3A-3E)

Table 4-8 shows the results of fixed effects analyses where the dependent variable takes two unique values: car travel or public transport (=0) and active travel (=1). In the fully adjusted model (3E), the likelihood of using active commute modes (walking or cycling) when compared to car travel or public transport decreased significantly when participants were in a couple compared to being single (OR=0.77, model 3E).

In terms of changes that occurred in work, participants were significantly less likely to use active travel when they changed jobs (OR=0.96), when in full-time work compared to part-time work (OR=0.73), when they moved to a higher income group (OR=0.84) and when they joined any of the highest ranking occupational categories (e.g. a professional occupation, OR=0.48).

In terms of changes that occurred in residential characteristics, people were more likely to use active travel when living in Inner London (OR=2.37) and if they moved house for some stated reasons including that their employer had relocated (OR=2.28) and that they had moved closer to their existing workplace (OR=5.49). Other stated reasons, such as moving house for a new job, or moving house because of a salary increase, where not associated with active travel in this analysis.

The interpretation of the reported odds ratios in this context is that living in Inner London increases the odds of using active travel (versus using car travel or public transport) by a factor of 2.37 when compared to living in other regions.

All models (3A-3E) were significant at the $p<0.001$ level according to the model chi-squared statistic, which shows the models fit significantly better than a model with no predictors. The fully adjusted model (3E) correctly identified 67.82% of cases.

4.5.3.2 Determinants of switching from car travel to active travel (fixed effects models 3F-3J)

Table 4-9 shows the results of fixed effects analyses where the dependent variable takes two unique values: maintenance of car travel (=0) or switching from car travel to active travel (=1). In the fully adjusted model (3J), the likelihood of switching to active travel (walking or cycling) increased significantly when participants took a new job (OR=1.15, model 3J) or moved house (e.g. OR=1.13, model 3I). In particular, people were more likely to switch to active travel if they moved house to a metropolitan area (outside London, OR=2.51, model 3J) and if they stated they were moving house to be closer to work (OR=4.09, model 3J) or due to a change in their own business (OR=15.76, model 3J).

All models (3F-3J) were significant at the $p<0.001$ level according to the model chi-squared statistic. The fully adjusted model (3J) correctly identified 78.20% of cases. However, when compared to models 3A-3E, the sample size was significantly smaller.

4.5.3.3 Determinants of switching from active travel to car travel (fixed effects models 3K-3P)

Table 4-10 shows the results of fixed effects analyses where the dependent variable takes two unique values: maintenance of active travel (=0) or switching from active travel to car travel (=1). In the fully adjusted model (3P) the likelihood of switching to car travel increased significantly when participants took a new job (OR=1.42, model 3P) or moved into a higher income group (e.g. OR=1.23). In the case of moving house, people were less likely to switch to car travel (i.e. more likely to maintain active travel) if they moved to Inner London (OR=0.09) or if they stated that they had moved house in order to be closer to work (OR=0.08) or due to a change in their own business (OR=0.03) or an increase in salary (OR=0.04).

All models (3F-3J) were significant at the $p<0.001$ level according to the model chi-squared statistic. The fully adjusted model (3J) correctly identified 81.90% of cases. However, when compared to models 3A-3E, the sample size was significantly smaller.

A Hausman test was also performed on all fixed effects models reported in this section to show that fixed effects, rather than random effects, was an appropriate model specification (e.g. in Model 3J) (Prob>chi2 <0.001). The Hausman test is a standard statistical test used with panel data. The null hypothesis was that the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator.

4.6 Discussion

This chapter began with an introduction to the BHPS and 'Understanding Society' data and illustrated the broad scope for drawing cross-sectional and longitudinal insights on the travel behaviour of commuters in the UK. This section provides a brief discussion of some of the main findings, limitations of the analyses, and some suggestions for future research.

4.6.1 Main findings and implications

4.6.1.1 Correlates of commute mode choice (Objective 1)

Both the unadjusted descriptive statistics (Table 4-3) and the regression analyses which controlled for multiple individual-level characteristics (Table 4-6) showed that cyclists were typically younger, more likely male than female, more likely to be single and more likely to be in lower professional occupations when compared to car drivers. The analyses also provided some evidence of geographic variation in the likelihood of cycling. For example, even after controlling for multiple individual-level characteristics, compared to the UK as a whole, people living in 'Inner London' were more likely to cycle, whereas those in other English metropolitan areas were less likely to cycle (at least in some model specifications).

Other findings, that participants who used active travel were less likely than average to be from the managerial or technical occupational status categories, and more likely to work part-time, might be indicative of the potential for behaviour change interventions to support strategies to reduce health inequalities.

A particular feature of the BHPS and 'Understanding Society' data was the opportunity to link individuals who live in the same household. The cross-sectional unadjusted descriptive statistics (Table 4-4) indicated that travel mode choice was associated with the travel mode of a partner living in the same household. Although no other known studies have explored the impact of a partner's behaviour on active commuting, studies of a partner's behaviour on overall physical activity or other health behaviours are more common. Published longitudinal studies include, for example, a recent analysis of ELSA data by Jackson et al. which found that when one partner changed to a healthier behaviour, the other partner was more likely to make a concurrent positive health change.(286) A small number of studies have also explored associations in BMI between spouses, including a study by Christakis et al using a large cohort from the Framingham Heart Study (1971–2003).(287) In an analysis of data from two waves of the BHPS, Brown et al also identified a significant association in the BMI of couples. The study attributed this association to environmental factors shared by couples, rather than through learning from one another.(288) Such findings might be an important aspect of establishing the wider impact of health behaviour change interventions.

The analyses that included adult participants who had also completed the BHPS youth questionnaire and interview showed that walking or cycling to school during childhood was associated with increased likelihood of using active travel modes for the commute to work during early adulthood (Table 4-5). Other studies have documented an association between physical activity (or obesity) in childhood and physical activity (or obesity) in adulthood.(297)(298) For example, a 21-year cohort study of Finnish children concluded that high levels of physical activity between the ages of 9 and 18, especially when continuous, significantly predicted high levels of physical activity in adulthood.(299) However, no known UK study has explored the association between active travel to school and physical activity or active commuting during adulthood. Hence these results could indicate that there are long-term benefits of encouraging more children to walk or cycle to and from school (300, 301) (Although these are unadjusted analyses and so should be treated with some caution – see section 4.6.2).

The related finding of an association between active travel use by a participant's parents during childhood and their own use of active commuting modes during adulthood could indicate that parental habits are transferred to children (this analysis used multivariable regression, although also had limitations – see section 4.6.2). This could support the argument that policy intervention is justified due to the existence of positive externalities in the market for active commuting (as highlighted in section 1.3.2.2). Whilst there are limitations, and more data on individual- and family-level characteristics would be required in order to identify the exact causal mechanism by which a commuter's mode choice is associated with their parent's behaviour during childhood, no other known studies have explored the impact of childhood travel behaviour on travel to work during adulthood. Other related strands of research include studies of the impact of a parent's health behaviours, and changes in health behaviours, on that of their children during childhood. For example, Anderssen et al. explored associations between changes in leisure-time physical activity in adolescents and their parents using data from an eight year longitudinal study.(302)

4.6.1.2 Individual-level patterns of commuting behaviour over time (objective 2)

The regression models which included lagged travel mode (dependent) variables (models 1C and 2D), together with the unadjusted transition probabilities reported in Table 4-7, showed a strong tendency for commuters to maintain the same travel mode, rather than switch travel mode, between waves. However, important differences in the stability of commute mode choice were observed between different commute modes and different population subgroups. One finding in the unadjusted transition probabilities was that travel to work by car was significantly more stable when compared to all other modes, including cycling. This relative instability of cycling was greatest in particular subgroups, including younger people aged 18-34. This may indicate that policy makers face a particular challenge in encouraging younger commuters to maintain active commuting, when compared to those who use public transport, for example. This study also showed that there may be a role for policy makers in encouraging people who have recently switched to active commuting to maintain their new travel behaviour, especially younger people aged 18-34, for example. The findings may also lend weight to the idea that policy makers seeking to decrease the proportion of commuters using cars could target specific groups of car drivers, including those with a previous history of walking, cycling or public transport use, for example.

Data from this study could also be used to inform the economic evaluation of active travel interventions, which have otherwise tended to rely on assumptions about the long-term travel patterns of participants who have changed travel mode which are based on substantive evidence. A recent review of economic analyses of active travel interventions which was summarised in the General Introduction (section 1.3.4.2), for example, found that many studies had relied on the assumption that after switching to active travel, walking or cycling behaviour is maintained for a period of ten years.(110, 128)

4.6.1.3 Impact of 'life changes' on the likelihood of switching commute mode (Objective 3, Fixed effects models)

Since significant relationships were identified between life changes (e.g. job and residential location changes) and changes in travel mode, this study provided new evidence to support the notion expressed in recent guidance on behaviour change interventions which stated that people "are likely to be most open to changing habitual behaviours at key 'transition points' or 'moments of change'."(64, 104) Furthermore, the analyses presented here showed that people were more likely to switch from car travel to active travel when moving house (as shown in models 3I and 3J) than they are likely to switch from active travel to car travel when moving house (as shown in models 3N and 3P). In particular, moving to metropolitan areas, including Inner London, increased the likelihood of switching to active travel. Nevertheless, since there is little evidence on the effectiveness of policy interventions that target commuters who are experiencing these 'transition points,' it seems premature to draw the inference made in the Department for Transport report that such points present a good opportunity for delivering behaviour change interventions. After all, if people are already switching travel mode when they move house, then perhaps behaviour change interventions would be better targeted at people when they are not moving house.

4.6.2 Study limitations

The analyses presented in this chapter are relatively novel compared to existing literature, however they come with significant limitations which must be considered when drawing policy conclusions. First was the use of a random effects model (in Models 1 and 2) which could not account for unobserved individual-level characteristics which are likely to be correlated with observed independent variables. More advanced analytical techniques, including instrumental variables and the Hausman-Taylor estimator, could have provided a good solution to this problem of endogeneity; however it was not possible to identify a suitable instrument that met the requirements of a good instrument (as listed in Figure 3-7). The Hausman-Taylor estimator requires there to be at least one time-varying regressor to be uncorrelated with the unobserved error term. Lags of this time-varying regressor can then be used as instruments (a further difficulty with the Hausman-Taylor estimator is that there is no suitable STATA command within the logit model specification). A second significant limitation was the risk of attrition bias if participants who left the BHPS, particularly the large numbers who left between childhood and adulthood, were more likely to exhibit particular characteristics which are likely to be associated with the travel mode outcome of interest. Third, there are limits to lessons that can be drawn from the descriptive statistics, particularly the unadjusted transitions probabilities, since these did not even control for the basic individual-level characteristics.

From a policy perspective, a major limitation of the analyses presented in this chapter was that, irrespective of the methodological considerations, no policy intervention had been evaluated.

4.6.3 Future research

4.6.3.1 Cross sectional studies

While the cross-sectional regression analyses presented in this chapter identified significant differences between geographic areas in terms of the likelihood of cycling, further consideration could be given to the reasons for observed differences. In this study, for example, the differences between 'Inner London' and other English metropolitan areas were notable. Rather than limiting the analysis to three large groups of metropolitan areas, future studies could examine smaller areas, such as the 33 local authority boroughs in London, for example. Linked individual-level data on local environmental characteristics, including those factors identified in the literature review in Chapter 2, could also be used to provide insights into the role of green spaces, road design, cycling infrastructure and local traffic congestion, for example. A study of whether there are regional differences in the observed associations between individual-level characteristics and the likelihood of cycling or walking could also be warranted. If, for example, there were particular areas of the UK, where female or older cyclists were as likely to cycle to work as the rest of the population, as in Holland for example, then these areas could be used to provide insights for neighbourhood design elsewhere in the UK.

4.6.3.2 Longitudinal studies

Data on local built environment characteristics could also be added to the longitudinal regression analyses which examined the impact of changes in individual-level circumstances on the likelihood of switching travel mode. Studies of the impact of changes in local environmental characteristics after residential relocation are limited to the small number of non-UK studies reviewed in section 4.3.2.3. Yet a focus on individuals who had moved location would help overcome the issue identified in the review in Chapter 2 which found that most secondary built environment data suitable for linking to individuals in the BHPS are available to researchers at a single point in time, preventing built environment changes that have occurred over time being analysed. Such studies could provide useful insights for neighbourhood design. For example, although residential moves were not examined, a related UK study using primary data on commuters in Cambridge, found that convenient public transport facilities predicted uptake of walking and cycling, convenient cycle routes predicted uptake of cycling, pleasant walking routes predicted maintenance of walking, and a lack of free workplace parking also predicted uptake of walking.(303) Future studies could also explore how the observed associations between changes in travel mode and changes in life circumstances, such as moving house, vary amongst different population groups.

The longitudinal analyses could also be extended to provide insights on the extent to which travel mode choices of different population groups have changed over time. A recent report by Le Vine et al., for example, proposed that further quantitative research is necessary to better understand the extent of the so-called “peak car” phenomenon, whereby distances travelled by car are hypothesised to fall in the coming years because young people today are thought to be less likely to hold a driving licence than in previous generations. (29, 31) Such a study could have significant implications for the Department for Transport’s road traffic projections and the economic evaluation of new cycling or road infrastructure schemes.

4.7 Conclusion

This chapter has provided an overview of the travel to work data available in the BHPS and ‘Understanding Society’ datasets, and some new insights into the characteristics of commuters in the UK and the circumstances in which they are most likely to switch to active commuting modes. Whilst very few existing studies have examined changes in commute mode using a large, UK-based panel dataset, the analyses presented in this chapter would be enhanced significantly if the effectiveness of a policy intervention designed to encourage more walking or cycling could be evaluated.

Figure 4-1: Sample sizes used in the analyses

Wave	Youth survey	Adult survey
BHPS 1	-	10264
BHPS 2	-	9845
BHPS 3	-	9600
BHPS 4	773	9481
BHPS 5	749	9249
BHPS 6	748	9438
BHPS 7	720	11193
BHPS 8	946	10906
BHPS 9	938	15623
BHPS 10	1414	15603
BHPS 11	1413	18867
BHPS 12	1279	16597
BHPS 13	1219	16238
BHPS 14	1397	15791
BHPS 15	1413	15617
BHPS 16	1360	15392
BHPS 17	1245	14873
BHPS 18	1222	14419
USOC 2	-	11780
USOC 3	-	10967
USOC 4	-	10092
Total	16836	271835

The table to the left shows the sample sizes of 18 waves of BHPS data and 3 waves of Understanding Society (USOC) data. **The chart below** illustrates how these samples were used to form the samples analysed in Chapters 4, 5 and 6.

Key:

Sample sizes at different stages of application of exclusion criteria

Exclusion criteria resulting in reduction of sample size

Resulting sample size used in Chapters of this dissertation

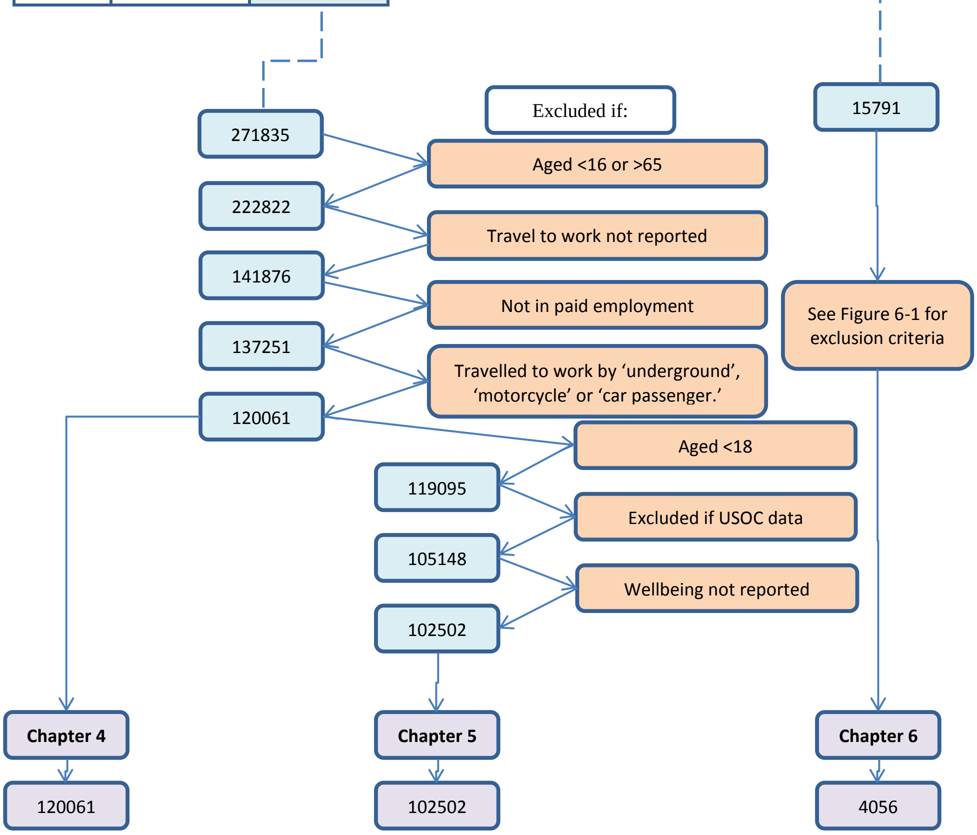


Figure 4-2: Description of five groups of panel data regression analyses presented in Chapter 4

<table>
<tr><td colspan="5">Five groups of analyses:</td></tr>
<tr><th>Models 1A-1C</th><th>Models 2A-2D</th><th>Models 3A-3E</th><th>Models 3F-3J</th><th>Models 3K-3P</th></tr>
<tr><td colspan="5">Dependent variable:</td></tr>
<tr><td colspan="3">Travel mode binary variable</td><td colspan="2">Travel mode transition variable</td></tr>
<tr><td colspan="3">0=car travel or public transport
1=active travel</td><td>0=maintained car travel
1=switched from car to active travel</td><td>0=maintained active travel
1=switched from active to car travel</td></tr>
<tr><td colspan="5">Independent variables of interest:</td></tr>
<tr><td>Individual-level characteristics, including work, residence and lagged travel mode variable</td><td>Individual-level characteristics, including work, residence, lagged travel mode variable and characteristics of parents</td><td colspan="3">Individual-level characteristics, as well as changes in work and residence, including reasons for a change in residence</td></tr>
<tr><td colspan="5">Sample used in analysis:</td></tr>
<tr><td>Full sample</td><td>Subsample 2 (i.e. where there is data on parents)</td><td>Full sample</td><td colspan="2">Full sample (although note that the travel mode transition variable leads to some observations being excluded when compared to models 1A-3E)</td></tr>
<tr><td colspan="5">Description of regression model used:</td></tr>
<tr><td colspan="2">Random effects logistic regression model</td><td colspan="3">Fixed effects logistic regression model</td></tr>
</table>

Table 4-1: A description of six large-scale UK surveys and their suitability for use in research on active travel behaviour

Survey	**BHPS and 'Understanding Society'**	**National Travel Survey (NTS)(27)**	**EPIC (European Prospective Investigation into Cancer) Norfolk(304)**	**Sport England's Active People Survey(17)**	**Health Survey For England (HSE)(2)**	**Census for England and Wales**
Area	UK	UK	Norfolk only	UK	England only	England and Wales
Sample size (approx.)	10,000 households	20,000 individuals	30,000 individuals	163,000 adults	16,000 individuals	Whole population (individual-level data in a 5% sample)
Study design	Individual-level panel data	Individual-level repeated cross sectional study	Cohort study	Cross sectional population-level study	Cross-sectional individual-level study	Cross-sectional individual-level study
Individuals tracked over time	Yes	No	Yes	No	No	No (except in the ONS Longitudinal Study)
Travel data	**Yes**	**Yes**	**Yes**	**Yes**	**No**	**Yes**
Details	Two questions in BHPS: main commute mode and time taken to get to work. Additionally, work distance is reported in 'Understanding Society'	Detailed one-week travel diary including questions about how travel to work and other activities, and how frequently different travel modes are used	Two questions: how many hours do you spend (i.) cycling and (ii.) walking each week	Number of people who walk or cycle for at least 30 minutes, at least once per month		Main mode of travel for work, and distance to work (categorised)
Individual level data (Y/N)	Yes	Yes, but repeated cross sectional data unsuitable for analysis over time	Yes	No, population-level data reported for each Local Authority		Yes, in the 5% sample
Years data collected	Annually 1991-present	Annually 1988-present	1993, 1995, 1996, 2006	Annually 2005-present		Every ten years including 2011

This table is continued on the next page

Survey	BHPS and 'Understanding Society'	National Travel Survey (NTS)(27)	EPIC (European Prospective Investigation into Cancer) Norfolk(304)	Sport England's Active People Survey(17)	Health Survey For England (HSE)(2)	Census for England and Wales
Health outcome data	**Yes**	**No**	**Yes**	**No**	**Yes**	**Yes**
Details	Self-reported height and weight GHQ12 wellbeing		Interviewer recorded height and weight Wellbeing		Detailed health assessment which included data on height, weight and wellbeing	Self-assessed health status (further health data available in the Census Longitudinal Study)
Individual level data (Y/N)	Yes		Yes		Yes	Yes, in the 5% sample
Years / follow-up	In BHPS: Self-reported height and weight reported only in 2 waves. GHQ12 recorded in all waves		1993, 1995, 1996, 2006		Annually since 1991	Every ten years including 2011
Other variables of interest:						
Travel-related	Car ownership and number of cars	Lots of detail e.g. walking time to nearest bus stop/rail station/school etc.; perceived quality of local transport infrastructure e.g. cycling facilities; car ownership; etc.	None	None	Only overall physical activity	Car ownership
Diet-related	No	No	Yes	No	Yes: Fruit and vegetable consumption	No
Individual-level geographic ID	Regional level, with other lower levels including postcodes available by application for a special licence	Local authority-level	Eastings – Northings (requires ethical approval)	None	None	Local authority level in the 5% publically available sample

Table 4-2: Variable definitions

Variable[1]	Definition	Analyses where used:
Dependent variables		**Analyses where used:**
Separate binary variables for each travel mode		
Car travel	=1 if car travel, =0 if other travel mode	Descriptive statistics (table 4-3, 4-4, 4-5) and transition probabilities (table 4-7)
Walking	=1 if walking, =0 if other travel mode	
Cycling	=1 if cycling, =0 if other travel mode	
Train	=1 if train, =0 if other travel mode	
Bus	=1 if bus, =0 if other travel mode	
Active travel and public transport binary variables		
Active travel	=1 if walking or cycling, =0 if other travel mode	Models 1, 2 (table 4-6) and 3A-3E (table 4-8)
Public transport	=1 if train or bus, =0 if other travel mode	Transition probabilities (table 4-7)
Travel mode transition/switching variables		
Active travel transition	=1 if car travel in t-1 and active travel in t =0 if car travel in t-1 and t	Models 3F-EJ (table 4-9)
Car travel transition	=1 if active travel in t-1 and car travel in t =0 of active travel in t-1 and active travel in t	Models 3K-3P (table 4-10)
Independent variables		
Age	Years of age	
Gender	=1 if male, =0 if female	
Children under 16	=1 if at least one child living in the household =0 otherwise	
Full time work	=1 if full time work, =0 other work	
Couple (incl. marriage)	=1 if in a couple (including marriage), =0 if other relationship status	
Income group	5 point scale (1-5, where 5 is highest), representing five quintiles of the income distribution calculated using the full analytical sample (N=120,061)	
Occupational status[2]		
Professional	=1 if professional, =0 if other	
Managerial and technical	=1 if managerial and technical, =0 if other	
Skilled non-manual	=1 if skilled non-manual, =0 if other	
Skilled manual	=1 if skilled manual, =0 if other	
Partly skilled occupation	=1 if partly skilled occupation, =0 if other	
Armed forces	=1 if armed forces occupation, =0 if other	

This table is continued on the next page

[1] Further variables were created for use in the descriptive statistics only, and these are described in section 4.4.2.2

[2] No variable was created for unskilled occupational status since this was included in the reference category in the analyses

Variable	Definition
Independent variables (continued)	
Wave	Dummy variables were created for each wave of data
Residential location	
Inner London	=1 if Inner London, =0 if other
Outer London	=1 if Outer London, =0 if other
Metropolitan country	=1 if Greater Manchester, Merseyside, South Yorkshire, Tyne and Wear, West midlands or West Yorkshire, =0 if other
Change in residential location (devised for use in the fixed effects model specifications)	
Moved job	Number of previous jobs since joining the sample, =0…n
Moved house	Number of previous residences since joining the sample, =0…n
Employer relocated	Number of times reported moving house because employer relocated, =0…n
Moved for new job	Number of times reported moving house for a new job, =0…n
Moved closer to the same job	Number of times reported moving closer to the same job, =0…n
Change in own business	Number of times reported moving house due to a change in own business, =0…n
Salary increased	Number of times reported moving house due to a salary increase, =0…n
Lagged travel mode binary variables	
Cycling	=1 if cycled in t-1, =0 if used other travel mode in t-1
Walking	=1 if walked in t-1, =0 if used other travel mode in t-1
Public transport	=1 if train or bus in t-1, =0 if other travel mode in t-1
Variables derived from linked data in BHPS youth questionnaire and interview	
Active travel (parent)	=1 if parent used active travel mode at least once during childhood, =0 if parent used did not use active travel during childhood (but did report another travel mode at least once)
At least one car (during childhood)	=1 at least one car in the household at any time during childhood, 0=if reported having no car during childhood
More than one car (during childhood)	=1 more than one car in the household at any time during childhood, 0=if having one or fewer cars during childhood
Parent's RGSC status	Six RGSC status variables as listed above under 'occupational status'.

Table 4-3: Descriptive statistics for BHPS and Understanding Society commuters included in the main analytical sample[a]

	Sample size		Mean values[c]									
			Individual and family characteristics					Education and work characteristics				
	N observations (% of total)	n individuals (% of individuals used each mode > 0)	Age (s.d.)[b]	Male, %	Couple (including married), %	Children in the household, %	Number of children in household (s.d.)[b]	Degree or higher education (%)	Professional or managerial occupation	Full time work	Night time work	Self-employed, %
All	120,061[a]	19,222	39.2 (11.7, 4.2)	50.7%	73.0%	41.0%	0.70 (0.98, 0.56)	17.5%	39.8%	80.1%	1.5%	7.9%
Car	**88,101 (73.4%)**	**14,358 (74.7%)**	**40.0 (11.2, 4.1)**	**54.1%**	**76.6%**	**42.4%**	**0.73 (0.99, 0.56)**	**18.3%**	**43.8%**	**82.8%**	**1.5%**	**9.3%**
Train	4,057 (3.4%)	1,362 (7.1%)	36.2*** (11.2, 3.0)	57.4%***	68.0%***	34.9%***	0.58*** (0.90, 0.44)	37.3%***	61.7%***	89.9%***	0.3%***	4.8%***
Bus	9,049 (7.5%)	3,470 (18.1%)	35.7*** (13.2, 2.8)	32.7%***	55.1%***	33.8%***	0.52*** (0.85, 0.37)	13.4%***	24.7%***	76.1%***	1.5%	2.2%***
Bike	3,575 (3.0%)	1,401 (7.3%)	37.8*** (11.9, 2.86)	72.5%***	70.4%***	44.1%*	0.77 (0.99, 0.39)	16.2%**	28.5%***	82.7%	1.6%	3.1%***
Walk	15,279 (12.7%)	5,185 (27.0%)	38.1*** (12.9, 2.9)	34.7%***	65.1%***	37.7%***	0.64*** (0.97, 0.40)	10.6%***	22.7%***	63.4%***	1.3%	5.3%***

This table is continued on the next page

[a] See Figure 4-1 for details of the exclusion criteria which led to this sample size. [b] s.d. = standard deviation (overall, within individuals)

Table 4-3: Descriptive statistics (Contd.)

	Mean values[c]									
	Health			Residential location			Own travel characteristics			
	Smoker	Poor or very poor health	Self-assessed health (s.d.)[b]	Inner London	Outer London	Other metropolitan area	Commuting time, mins. (s.d.)[b]	Whether access to a car, %	Number of cars in household (s.d.)[b]	Distance to work (miles) (N=9242), only reported in 'USoc') (s.d.)[b]
All	26.7%	4.3%	1.96 (0.81, 0.55)	2.1%	4.5%	16.1%	23.5 (21.0, 13.3)	87.0%	1.56 (0.83, 0.48)	10.4 (17.3, 7.1)
Car	**24.6%**	**4.1%**	**1.94 (0.80, 0.55)**	**1.3%**	**3.9%**	**15.9%**	**22.9 (19.5, 12.2)**	**99.3%**	**1.77 (0.72, 0.47)**	**11.2 (16.0, 6.1)**
Train	20.3%***	4.1%	1.94 (0.80, 0.46)	10.4%***	17.3%***	10.7%***	61.3*** (32.2, 18.4)	71.1%***	1.26*** (0.80, 0.35)	30.4*** (43.5, 4.93)
Bus	35.1%***	5.8%***	2.08*** (0.83, 0.48)	5.5%***	5.2%***	24.2%***	34.9*** (21.0, 10.6)	29.5%***	0.77*** (0.76, 0.33)	6.94*** (8.53, 1.13)
Bike	27.1%**	3.9%	1.92 (0.81, 0.46)	4.4%***	3.5%	10.6%***	15.3*** (10.8, 4.4)	55.8%***	1.02*** (0.79, 0.31)	3.78*** (3.33, 0.72)
Walk	34.8%***	4.7%**	2.03*** (0.81, 0.49)	2.4%***	4.6%***	15.5%	12.0*** (9.9, 4.2)	50.5%***	1.01*** (0.83, 0.38)	1.37*** (2.47, 1.17)

[c] Chi-squared or Mann-Whitney tests were used to study differences in the mean values between each travel mode category when compared to car travel. The statistical significance of the observed differences (when compared to car travel) are shown using: *** where p<0.001, ** where p<0.01, * where p<0.05.

Table 4-4: Descriptive statistics for BHPS and Understanding Society commuters who reported living with their partner (n=50,207) (subsample 1)

Travel mode	Sample size		Mean values[a]				Partner's current travel mode				
			Individual and family characteristics		Education and work characteristics						
	N observations (% of total)	n individuals (% of individuals used each mode > 0)	Age (s.d.)[b]	Male, %	Degree or higher educ. (%)	Professional or manager. occupation	Car	Train	Bus	Cycle	Walk
All	50,207	10,443	40.2	50.6%	17.5%	41.7%	76.5%	3.4%	6.0%	2.8%	11.3%
Car	**38,445 (76.6%)**	**8,324 (79.7%)**	**40.4**	**54.2%**	**18.4%**	**44.8%**	80.0%	2.9%	5.3%	2.3%	9.6%
Train	1,704 (3.4%)	615 (5.9%)	37.6***	57.0%*	37.3%***	66.3%***	64.5%	21.7%	2.8%	1.4%	9.6%
Bus	2,982 (5.9%)	1,216 (11.6%)	38.7***	29.6%***	12.3%***	27.5%***	67.2%	1.8%	16.5%	3.2%	11.5%
Bike	1,456 (2.9%)	594 (5.7%)	39.7*	69.8%***	15.5%**	31.1%***	61.6%	1.7%	6.7%	13.3%	16.6%
Walk	5,620 (11.2%)	2,059 (19.7%)	40.3	30.4%***	8.9%***	23.5%***	65.0%	2.8%	6.1%	4.1%	22.0%

[a] Chi-squared or Mann-Whitney tests were used to study differences in the mean values between each travel mode category when compared to car travel. The statistical significance of the observed differences (when compared to car travel) are shown using: *** where p<0.001, ** where p<0.01, * where p<0.05. [b] s.d. = standard deviation (overall, within individuals).

Table 4-5: Descriptive statistics for BHPS and Understanding Society commuters included in subsample 2 (n=5,896)

Travel mode	Sample size		Mean values[c]				Travel/physical activity characteristics when a child[c]							
			Individual and family characteristics		Education and work characteristics (%)		Household characteristics					Cycled or walked to school (N=941)	Played sport (N= 1,648)	Cycled to school or played sport (N= 1,760)
	N observations (%)	n individuals (% of individuals used each mode > 0)	Age	Male, %	Degree or higher education	Professional or managerial occupation	Mother used active travel modes (N=4,903)	Father used active travel modes (N=4,371)	Either parent used active travel modes (N=5,686)[b]	>1 car in household (N=5,886)[b]	>2 cars in household (N=5,886)[b]			
All	5,896[a]	1,694	21.9	50.0%	14.4%	25.6%	25.9%	10.4%	27.2%	90.8%	45.2%	48.5%	92.4%	89.3%
Car	**3,202 (54%)**	**998 (58.9%)**	**22.7**	**51.8%**	**15.7%**	**31.9%**	**20.0%**	**7.2%**	**21.4%**	**95.1%**	**52.7%**	**44.5%**	**92.2%**	**88.9%**
Train	301 (5.1%)	157 (9.3%)	22.7	48.2%	26.8%***	37.9%*	22.9%	12.1%*	26.2%	97.5%	48.9%*	42.4%	96.8%	93.8%
Bus	949 (16.1%)	514 (30.3%)	20.8***	40.0%***	10.8%**	17.6%***	31.6%***	13.5%***	30.9%***	82.0%***	33.8%***	41.9%	91.1%	87.0%
Bike	224 (3.8%)	143 (8.4%)	21.1***	85.7%***	9.5%*	14.0%***	30.7%**	21.7%***	38.8%***	85.7%***	40.6%***	67.6%**	96.8%	95.2%*
Walk	1,220 (20.7%)	632 (37.3%)	20.7***	47.1%**	11.9%**	14.1%***	37.5%***	14.7%***	38.0%***	86.3%***	35.0%***	57.6%***	92.2%	89.9%

[a] This figure refers to the number of observations which can be linked to at least one observation in the BHPS youth survey on parent travel mode, number of cars in childhood home or physical activity during childhood

[b] This figure refers to the number of observations used in Analysis 2A (Table 4-6), which explores the impact on current travel behaviour of parents travel behaviour during childhood.

[c] Chi-squared or Mann-Whitney tests were used to study differences in the mean values between each travel mode category when compared to car travel. The statistical significance of the observed differences (when compared to car travel) are shown using: *** where p<0.001, ** where p<0.01, * where p<0.05.

Table 4-6: Correlates of active commuting (Objective 1)

Sample used in the analysis	Full sample			Subsample 2: Participants with data on parents			
Model characteristics	Minim-ally adjusted	+ addition-nal charact-eristics	+additional characterist-ics and lagged dependent variable	Minim-ally adjusted	+ additional character-stics	+number of cars in household when child	+lagged dependent variable
Model reference	1A	1B	1C	2A	2B	2C	2D
Independent variables							
Age (years)	0.96***	0.96***	0.99	0.81***	0.84***	0.83***	0.93***
Gender	0.41***	0.53***	0.94	1.62**	1.81**	1.88***	1.40*
Child<16		0.85***	0.86***		1.12	1.09	0.83
Couple (inld marriage)		0.66***	0.93		1.06	1.06	1.18
Full time work		0.48***	0.67***		0.46***	0.46***	0.81
RGSC status							
Professional occupation		0.24***	0.49***		0.36	0.37	0.43
Managerial/technical		0.24***	0.42***		0.48*	0.49*	0.36*
Skilled non-manual		0.41***	0.59***		0.63	0.64	0.49
Skilled manual		0.47***	0.62***		0.59	0.59	0.44
Partly skilled occupation		0.78**	0.87		1.06	1.07	0.82
Armed forces		1.32	1.77		2.14	2.04	4.95
Residential area							
Inner London		1.64***	1.13		0.65	0.61	0.69
Outer London		0.92	0.86		1.35	1.33	1.01
Other metropolitan		0.99	0.81***		1.04	1.05	1.10
Lagged travel mode							
t-1 Walk			148.37***				61.82***
t-1 Cycle			116.44***				35.66***
t-1 Public transport			3.25***				3.79***
Parent's travel mode							
Active travel				4.30***	3.66***	3.11***	1.79***
Parent's RGSC status							
Professional occupation					0.76	1.03	1.19
Managerial and technical					0.78	1.02	0.99
Skilled non-manual					0.55	0.66	0.80
Skilled manual					0.75	0.89	0.94
Partly skilled occupation					1.48	1.60	1.35
Armed forces					n/a	n/a	n/a
Parent's car status							
1 car						0.91	0.91
>1 car						0.53*	0.91
n	19,222	19,099	14.297	1,589	1,575	1,572	986
N	120,061	118,228	89,127	5,686	5,599	5,595	3,449

Table 4-6 Correlates of active commuting (Objective 1) (Contd.)

Notes:

Table shows random effects logit model estimates of the odds of active commuting compared to using car travel or public transport as the main usual mode of travel to work.
All models also control for survey year (1<=t<=21).
* Indicates statistical significance at the p<0.05 level
** Indicates statistical significance at the p<0.01 level
*** Indicates statistical significance at the p<0.001 level
n=number of individuals
N=number of person-year observations

Table 4-7: Unadjusted transition probabilities (Objective 2)

Travel mode in t-1	**Full sample or *subgroup***	**Travel mode in wave t**				
		Walk	**Cycle**	**Car**	**Train/bus**	**All modes[a]**
All modes	Full sample	n=11,285 11.7%	n=2,735 2.8%	n=73,107 75.9%	n=9,242 9.6%	n=96,369 100%
Car travel	Full sample	1.9%	0.7%	96.1%	1.4%	n=72,327
	Male	1.6%	0.9%	96.2%	1.3%	n=39.481
	Female	2.3%	0.4%	95.9%	1.4%	n=32,844
	London	1.9%	0.8%	94.9%	2.4%	n=3,629
	London/other metro. areas	1.6%	0.5%	96.0%	1.9%	n=14,132
	Aged 18-34	2.6%	0.9%	94.3%	2.1%	n=22,071
	Aged 50-65	1.2%	0.4%	97.6%	0.8%	n=15,539
	Previous active	6.7%	2.3%	89.2%	1.9%	n=4,900
	Never active	1.4%	0.5%	96.8%	1.3%	n=65,954
Train or bus	Full sample	7.1%	1.2%	14.4%	77.3%	n=9,655
	Male	5.2%	2.0%	16.7%	76.1%	n=3,951
	Female	8.3%	0.7%	12.8%	78.2%	n=5,704
	London	4.2%	1.4%	7.8%	86.6%	n=1,420
	London/other metro. areas	5.4%	1.2%	12.3%	81.2%	n=3,307
	Aged 18-34	9.2%	2.1%	18.3%	70.4%	n=4,396
	Aged 50-65	4.7%	0.5%	8.0%	86.8%	n=1,663
	Previous active	13.4%	2.3%	12.0%	72.2%	n=1,156
	Never active	5.7%	1.0%	14.6%	78.7%	n=8.153
Cycle	Full sample	9.4%	67.1%	19.1%	4.4%	n=2,772
	Male	8.7%	67.0%	19.9%	4.4%	n=2,040
	Female	11.0%	67.5%	16.9%	4.5%	n=732
	London	5.3%	68.9%	15.8%	10.1%	n=209
	London/other metro. areas	7.9%	66.5%	17.4%	8.2%	n=474
	Aged 18-34	13.9%	54.9%	23.0%	8.2%	n=995
	Aged 50-65	5.7%	81.7%	11.2%	1.5%	n=546
	Previous cyclist	5.9%	79.1%	11.9%	3.1%	n=1,276
	Never cyclist	12.8%	55.0%	26.7%	5.6%	n=971
	Previous active	8.5%	75.3%	12.9%	3.2%	n=1,499
	Never active	10.0%	56.8%	27.5%	5.7%	n=771
Walk	Full sample	77.1%	2.4%	14.8%	5.8%	n=11,615
	Male	70.6%	4.3%	19.3%	5.7%	n=3,975
	Female	80.5%	1.4%	12.4%	5.8%	n= 7,640
	London	80.2%	1.5%	10.5%	7.2%	n=782
	London/other metro. areas	78.8%	2.0%	12.3%	6.9%	n=2,441
	Aged 18-34	67.3%	3.2%	20.0%	9.5%	n=4,238
	Aged 50-65	87.9%	1.1%	7.6%	3.4%	n=2,666
	Previous walker	84.1%	1.9%	10.0%	4.0%	n=6,070
	Never walker	68.0%	3.5%	20.8%	7.7%	n=3,307
	Previous active	83.4%	2.3%	10.3%	4.0%	n=6,229
	Never active	68.8%	2.6%	20.7%	7.9%	n=3,168

Table 4-7 Transition probabilities (Contd.)

<u>Notes:</u>

The table shows the average probability (%) of commuters maintaining the same travel mode, or switching to a different travel mode, using a total of 96,369 pairs of consecutive person-year observations (n=96,369). These probabilities are calculated using the full analytical sample of person-year observations used in this chapter (n=120,061, see Figure 4-1 and Table 4-3). Not all person-year observations can be paired with data in the next wave when there is missing data (for example if the individual has left the dataset, or is in and out of work).

Horizontal rows in the table represent travel mode in lagged waves (t-1) (which add up to 100%) and vertical columns represent travel mode in current wave (t).

The final column, which is a sum of all other columns (which add up to 100%), shows the total sample size (n) used in each row of the table.

Table 4-8: Determinants of active travel (Objective 3, Fixed effects models 3A-3E)

Model characteristics	Minimally adjusted	+work characteristics	+change in job	+moving home	+reason for moving
Model reference	Model 3A	Model 3B	Model 3C	Model 3D	Model 3E
Age	0.99	0.99	0.96	0.97	0.96
Child<16	0.98	0.95	1.05	1.06	1.04
Couple (inld. marriage)	0.77***	0.80***	0.80***	0.80***	0.77***
Work characteristics					
Full time work		0.78***	0.72***	0.73***	0.73***
Income group		0.81	0.84***	0.84***	0.84***
New job			0.96*	0.96*	0.96***
-RGSC occupational status					
Professional occupation			0.52***	0.52***	0.48***
Managerial and technical			0.55***	0.57***	0.53***
Skilled non-manual			0.70**	0.72**	0.72**
Skilled manual			0.71**	0.72**	0.70**
Partly skilled occupation			0.91	0.94	0.94
Armed forces			1.22	1.29	1.18
Home characteristics					
Moved house				0.95	
Inner London				2.74***	2.37***
Outer London				1.27	1.26
Other metropolitan area				0.76	0.81
-Reasons for moving home					
Employer relocated					2.28**
Moved for a new job					1.01
Moved closer to same job					5.49***
Change in own business					5.91***
Salary increased					0.56
n	3,673	3,623	3,256	3,131	3,131
N	32,702	31.964	26,116	24,315	24,315

Table shows fixed effects logit model estimates of the odds of switching to active travel when compared to maintaining car travel as the main usual mode of travel to work.

All models also control for survey year (1<=t<=21).

n=number of individuals, N=number of person-year observations.

* Indicates statistical significance at the p<0.05 level,

** Indicates statistical significance at the p<0.01 level,

*** Indicates statistical significance at the p<0.001 level.

Table 4-9: Determinants of switching from car travel to active travel (Objective 3, Fixed effects models 3F-3J)

Model characteristics	Minimally adjusted	+work characteristics	+change in job	+moving home	+reason for moving
Model reference	Model 3F	Model 3G	Model 3H	Model 3I	Model 3J
Age	1.02	1.02	1.10	1.11	1.10
Child<16	0.84	0.84	0.86	0.85	0.87
Couple (inld. marriage)	1.01	1.00	1.08	1.03	1.04
Work characteristics					
Full time work		0.91	0.80	0.80	0.80
Income group		0.92*	0.93	0.93	0.93
New job			1.14**	1.14**	1.15**
-RGSC occupational status					
Professional occupation			1.93	1.89	1.98
Managerial and technical			1.16	1.16	1.18
Skilled non-manual			1.32	1.32	1.35
Skilled manual			1.25	1.25	1.25
Partly skilled occupation			1.56	1.54	1.56
Armed forces			1.79	1.77	1.84
Home characteristics					
Moved house				1.13*	
Inner London				3.99	4.08
Outer London				1.87	2.04
Other metropolitan area				2.45*	2.51*
-Reasons for moving home					
Employer relocated					1.18
Moved for a new job					1.12
Moved closer to same job					4.09**
Change in own business					15.76*
Salary increased					0.56
n	1,117	1,102	941	940	940
N	7,930	7,780	6,029	6,020	6,020

Table shows fixed effects logit model estimates of the odds of switching to active travel when compared to maintaining car travel as the main usual mode of travel to work.
All models also control for survey year (1<=t<=21).
n=number of individuals, N=number of person-year observations.
* Indicates statistical significance at the p<0.05 level, ** Indicates statistical significance at the p<0.01 level, *** Indicates statistical significance at the p<0.001 level.

Table 4-10: Determinants of switching from active travel to car travel (Objective 3, Fixed effects models 3K-3P)

Model characteristics	Minimally adjusted	+work characteristics	+change in job	+moving home	+reason for moving
Model reference	Model 3K	Model 3L	Model 3M	Model 3N	Model 3P
Age	1.37	1.35	1.38	1.35	1.35
Child<16	1.00	0.98	1.06	1.04	1.07
Couple (inld. marriage)	1.02	1.00	1.03	0.98	1.01
Work characteristics					
Full time work		0.96	1.14	1.16	1.13
Income group		1.17**	1.20**	1.20**	1.23**
New job			1.38	1.34***	1.42***
-RGSC occupational status					
Professional occupation			1.52	1.40	1.48
Managerial and technical			1.15	1.08	1.05
Skilled non-manual			0.76	0.70	0.67
Skilled manual			1.10	1.02	1.01
Partly skilled occupation			0.82	0.76	0.73
Armed forces			n/a	n/a	n/a
Home characteristics					
Moved house				1.11	
Inner London				0.09	0.09*
Outer London				0.09	0.08
Other metropolitan area				3.53	9.15
-Reasons for moving home					
Employer relocated					1.08
Moved for a new job					1.00
Moved closer to same job					0.08**
Change in own business					0.03*
Salary increased					0.04*
N	895	873	771	770	770
N	3,935	3,780	3,236	3,236	3,236

Table shows fixed effects logit model estimates of the odds of switching to active travel when compared to maintaining car travel as the main usual mode of travel to work.
All models also control for survey year (1<=t<=21).
n=number of individuals, N=number of person-year observations.
* Indicates statistical significance at the p<0.05 level, ** Indicates statistical significance at the p<0.01 level, *** Indicates statistical significance at the p<0.001 level.

5 Impact of active commuting on psychological wellbeing

5.1 Overview of chapter

In this chapter the impact on subjective wellbeing of switching from car travel to walking, cycling and public transport is explored using data from eighteen waves of the BHPS (no data from the Understanding Society survey was used in this chapter). This analysis complements the analysis to be presented in Chapter 6 which explores the impact of switching travel modes on individual-level BMI.

5.2 Background

A concern in many developed countries is that, despite long-term growth in GDP per capita observed over many decades, various measures of population-level wellbeing have not improved at anywhere near the same rate. For example, long-term trends in UK happiness levels are reported in the UK by the Office for National Statistics (ONS) using data from the 'World Database of Happiness,' an international compilation of various empirical studies.(305) The data indicates that life satisfaction (based on responses on a ten point scale to the question: 'On the whole how satisfied are you with the life you lead?') has remained relatively stable during the period 2002-11, falling only negligibly in 2007-08 at the start of the global financial crisis.(306) Such evidence may be consistent with the well-known (although not universally accepted(307)) 'Easterlin Paradox', after the American economist Richard Easterlin (1926-).(308) Briefly, his argument states that despite a significant positive cross-sectional relationship between income and happiness observed within-countries, people in rich countries are generally no happier when average incomes in their own country rise, or when they are compared to people on a similar rank in the income distribution in other less wealthy countries.

Although the notion that Government ought to pursue factors beyond simply the maximisation of GDP is not new,(309, 310) in recent years Governments at the national level have begun to recognise the importance of measuring wellbeing or quality of life alongside more traditional economic measures such as GDP per capita.(10-13, 311) Since November 2010, following a speech by the British Prime Minister, David Cameron, the ONS has collated various measures of national wellbeing and is currently consulting on a preferred series of measures to be used for tracking national wellbeing over time.(11) During the 2015 General Election campaign, the Leader of the Opposition Labour Party, Ed Miliband, promised that under his leadership, a national 'Living Standards Index' would be monitored by independent officials and have equal status with GDP figures.(312)

An important current source of national wellbeing data reported in a number of recent ONS publications is that collected in the BHPS and 'Understanding Society,'(313) which is based on individual-level responses to separate questions which together form the twelve-item General Health Questionnaire (GHQ12) (see Table 5-1).

While an existing literature provides some evidence that regular physical activity is predictive of higher psychological wellbeing,(6-9, 314-317) only a small number of predominantly cross-sectional studies have specifically explored the impact on wellbeing of physical activity undertaken whilst travelling to work.(144-146) Such studies necessarily focused on statistical associations between wellbeing and travel mode choice, or time spent in active commuting, and hence only contribute causal or interventional hypotheses.(144, 146, 157) One of these cross-sectional studies, published in February 2014 by the ONS identified some statistically significant negative associations between wellbeing and active commuting when compared to car driving using data from the Annual Population Survey.(146) Another study, published in 2013 by Humphreys et al.,(144) did not identify any relationship between wellbeing and time spent walking or cycling to work.

Studies that examine the impact on wellbeing of active travel for recreational purposes, such as visiting friends,(144, 316, 318, 319) or as an intervention in clinical settings,(7, 320, 321) are more common than those that examine more routine active commuting. However, behaviour change in these non-work domains may be impractical for large numbers of working-aged people for whom the opportunity cost of physical activity outside of work hours is relatively high.(322, 323)

Other related studies which have used the wellbeing variables in the BHPS include a study by Roberts et al. which documented the predominantly negative associations with time spent commuting on the basis of analysis of the first 14 waves.(145) However this study did not focus on the impact of changes in individual-level active commuting decisions, which would be of particular use in assessing the case for behaviour change interventions. White et al. identified an association between wellbeing and green space in urban residential environments,(178) and Flint et al explored the explored the impact on wellbeing of moving into and out of employment.(285) The econometric approaches used in these studies have been used to inform the analyses presented in this chapter.

5.3 Methods

5.3.1 Data source and sample selection

Data from all 18 waves of the BHPS was used in this analysis (further details about the BHPS are provided in section 4.2). Figure 4-1 provides an illustration of how the sample size used in this chapter is smaller than that used in Chapter 3. This was because (i.) people aged 16 and 17 were excluded from the analysis, (ii.) the three ‘Understanding Society’ waves of data were not used and (iii.) there were a small number of missing values for the dependent variable used in the analysis. The resulting sample size used in this chapter was 102,502 (consisting of 17,985 adults), compared to 120,061 used in Chapter 4.

5.3.2 Variables used in the analysis

Dependent variables

The dependent variable used in most analyses presented in this chapter is the 36-point 'Likert' scale, a measure of psychological wellbeing reported in each wave of the BHPS. Although it is reported in the BHPS as decreasing in wellbeing, as in other similar analyses,(145) the scale has been reversed in the analyses reported in this chapter (since it is more intuitive to increase in wellbeing). The 36-point 'Likert' scale is itself derived from the sum of scores drawn from individual-level responses to each of 12 separate GHQ12 questions.(324, 325) As shown in Table 5-1, each question (e.g. 'Have you recently been able to concentrate on whatever you're doing?') has four possible responses (e.g. 'much less than usual', 'less than usual', 'same as usual' or 'better than usual') which are scored from 0 (e.g. 'much less than usual') to 3 (e.g. 'better than usual').

The GHQ12 is one of the most widely applied self-completion assessment measure of minor psychiatric morbidity in the UK.(311, 324, 326, 327) Although not supported by all studies,(328) the GHQ12 is nonetheless widely used to measure psychiatric morbidity among general population samples and has been advocated as a short and valid indicator of current psychological wellbeing.(329, 330) It has been found to be a valid instrument in large general population samples,(330-332)) as well as the elderly,(333) young adults,(334) high school students,(335) and adolescents.(329)

Twelve binary dependent variables were also created for use in this chapter based on participants' ratings of the twelve specific psychological symptoms included in the GHQ12, from which the Likert scale is derived (symptom present: 'not at all' or 'same as usual'=0, 'rather more' or 'much more than usual'=1).(315)

Independent variables

The main exposures of interest were the same as those used in Chapter 4 (see section 4.4.2 for full details). Derived from the question "What usually is your main means of travel to work?", four mode-specific binary variables were created representing 'car travel,' 'public transport,' 'cycling', and 'walking' (e.g. 'cycling' = 1, other travel modes= 0). In some analyses, cycling and walking were accounted for together using a single active travel binary variable ('cycling' or 'walking' = 1, other = 0). As described in Section 4.2.2, and shown in Figure 4-1, 'Other' travel mode, 'Car/van passenger', 'Underground/metro' and 'Motorcycle' were excluded from the analyses presented in this chapter (although these were included in sensitivity analyses).

Two further exposures of interest were also used in some models. First, the four mode-specific binary variables were used to create interaction terms with commuting time (derived from the question 'Minutes spent travelling to work': About how much time does it usually take for you to get to work each day, door to door?') and gender (as in the study by Roberts et al.)(145) (e.g. 'cycling' × 'commuting time' = minutes cycling, other travel modes= 0). Second, binary 'transition' variables were also created used if lagged (t-1) and current (t) travel mode status were known. Again, as in Chapter 4, this was to capture the impact of switching to a new travel mode, when compared to maintaining existing travel behaviour, For example, to understand the specific impact of switching from car travel to active travel when compared to maintaining car travel, a transition variable was created where: 'switched to active travel' = 1 if 'cycling' or 'walking' in t and 'car/van' in t-1; 'maintained car travel' = 0 if 'car/van' in t and t-1. Cases where lagged or current travel mode were unknown, or where other combinations of lagged and current travel mode were observed (e.g. switched from active to car travel, or maintained active travel), were excluded from the analysis.

Following the study by Roberts et al., the covariates included in the fully adjusted models were: age squared (rather than age, which would be invalid in the fixed effects model described below), adjusted gross annual household income (four categories, accounting for size of household, including children's ages, using the McClements equivalence scale),(278) number of children, self-assessed health status (three binary variables for 'excellent', 'good' and 'fair', each with 'poor' and 'very poor' in the reference category),(13) educational attainment* (seven categories as in BHPS), work hours* ('full-time' =1, 'part-time' =0), neighbourhood characteristics* (binary variable derived from question: "Overall, do you like living in this neighbourhood?"), daily commuting time* (minutes) and job satisfaction* (1= 'completely dissatisfied', to 7= 'completely satisfied') (those marked * were excluded from the minimally adjusted models due to missing data being more common in these variables – see section 5.4). Additional potential time-varying confounding variables were also included in the fully adjusted models: number of previous residences (=1…n) and workplaces (=1...n) (where n=number of residences or workplaces individual has reported since entering the sample, to account for house or job moves) (104, 336, 337). Binary variables for each region and year were included in all models.

5.3.3 Statistical analyses

The purpose of the statistical analyses was to explore associations between wellbeing and (i.) travel mode choice, (ii.) changes in time spent commuting by specific travel modes and (iii.) switching to and from more active travel modes.

As in comparable BHPS analyses by Flint et al.,[344] White et al.,(178, 285) Roberts et al.,(145) the impact of change in the exposures of interest on a change in the outcome were assessed through variations within individuals over time using fixed effects models. These fixed effects models are typically used by economists and are well suited to the analysis of large-scale panel data. In this case, as outlined in Chapter 2, the main advantage of using individual fixed effects models is that they eliminate the risk that some time-invariant variables (e.g., some unobserved dimensions of socioeconomic status) may confound the relationship between travel mode choice and wellbeing. Hence causal inference is better supported using panel, rather than cross-sectional data.(143, 172)

Table 5-2 provides a summary of four separate groups of analyses (subsequently referred to as 'I' to 'IV') that were completed using the following model specification:

$$Y_{it} = \alpha_i + \beta X_{k,it} + \gamma Z_{j,it} + u_{it}$$

Equation 5-1

In the first three groups of analyses (I-III), Y_{it} represented psychological wellbeing for each individual (i=i….n) for n individuals in the dataset in wave t ($1 \leq t \leq 18$). Linear individual FE models were used, based on the commonly held assumption that once FE are accounted for, the 36-point scale may be considered continuous (rather than ordinal).(145, 338) In the fourth group of analyses (IV), Y_{it} represented twelve binary dependent variables used in separate FE logit models of each of the GHQ12 symptoms.

The main exposure of interest was represented by $X_{k,it}$. In each group of analyses (excluding II), models varied in terms of the number of binary variables (k=1…K for individual i in wave t) depending on how travel mode (analyses I and IV) or travel mode transition (III) was represented (e.g. in the first group of analyses, active travel was first represented by a single binary variable, and then by separate binary variables for walking and cycling). In the second group of analyses (II), $X_{k,it}$ in equation 1 is replaced by continuous interaction terms of travel time (D, minutes) with travel mode and gender (S):

$$\beta_1 D_{it} + \beta_k (D_{it} \times X_{k,it}) + \beta_2 (D_{it} \times S_i)$$

Equation 5-2

In all analyses, $Z_{j,it}$ represented a vector of J covariates (j=1…J). α_i (i=1…N) was the unobserved individual specific intercept (assumed to be time-invariant and correlated with observed explanatory variables); β and γ were the coefficients, and u_{it} was the error term (assumed to be independent, identically distributed).

Sensitivity analyses explored the impact of excluding groups of individuals with the shortest commutes, as well as observations where participants experienced adverse health states, self-employment and house or job moves.

5.4 Results:

5.4.1 Sample description

The selection criteria for the sample of 102,502 observations used in this chapter are shown in Figure 4-1. Basic descriptive statistics for this sample are shown in Table 5-2. There was an even gender split among the 17,985 individuals and the mean age was 39 years. The mean value of the 36-point wellbeing scale was 25.3 and the within-individual standard deviation was 3.6. A histogram showing the distribution of the 36-point wellbeing scale across all observations is shown in Figure 5-1. This illustrates how the data is left skewed and includes a full range of values from 0 to 36 (observations with extreme values were excluded in one of the sensitivity analyses later in this chapter). 73.4% of observations were car travel, 15.8% active travel (of which 3.0% of total observations were cyclists, and 12.8% walkers), and 10.9% public transport (3.3% were rail and 7.6% bus users). Of 75,428 pairs of consecutive waves, maintenance of car travel was most common in 54,727 cases (72.6% of total). Switching occurred between active travel and other modes in 3,911 cases (5.2% of total), and between public transport and other modes in 2,763 cases (3.7%)

5.4.2 Fixed effects analyses

Results for each group of analyses are shown in Table 5-4 (Analysis I), Table 5-5 (Analysis II), Table 5-6 and Table 5-7 (Analysis III), and Table 5-8 (Analysis IV). Sensitivity analyses for the first group of analyses are shown in Table 5-9.

(I): Impact of travel mode on wellbeing

In the minimally adjusted model, wellbeing was higher by 0.145 on the GHQ12 scale amongst participants who used active travel modes when compared to car travel or public transport (Model A, Table 5-4: $p=0.017$). After adjustment for all covariates, a positive association was also found with active travel when compared to car travel (Model C: 0.185, $p=0.008$). Many of the covariates also had a comparable statistically significant impact on the GHQ12 scale. For example, wellbeing was higher by 0.432 ($p<0.05$) amongst participants who reported being in a relationship (including marriage) when compared to those who were single. Wellbeing was also higher by 0.434 ($p<0.05$) amongst participants who reported that they liked living in their current neighbourhood when compared to those who did not, whereas an additional child was associated with a reduction in the GHQ12 of 0.077 ($p<0.05$) (Model C).

Sensitivity analyses using Model C (the fully adjusted model of travel mode on psychological wellbeing with active travel and public transport binary variables) showed these results were robust to exclusion of the self-employed (7.76% of observations) (sensitivity analysis [c]: 0.187, $p<0.01$), between-wave changes in work or home location, and to inclusion of 'motorcycle', but not 'car/van passenger', in the reference group. Larger effect sizes were identified when chest or breathing difficulties were reported (0.483, $p<0.05$) compared to cases where participants had reported good or better SAH (0.192, $p<0.01$), and when shortest commute times were excluded (rising from 0.309 to 0.509 for observations where commute times exceeded 10 and 30 minutes respectively, $p<0.05$).

A positive wellbeing effect was also found with public transport (Model C, Table 3: 0.195, $p=0.017$), and with walking (Model D: 0.222, $p=0.004$) and bus/coach travel (0.216, $p=0.019$), when compared to car travel.

A Hausman test was performed to show that fixed effects, rather than random effects, was an appropriate model specification (in Model C) (Prob>chi2 <0.001) using the null hypothesis that the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator.

(II): Impact of travel time on wellbeing

Positive associations were identified between time spent walking (per ten minute change) and wellbeing (with car travel in the reference category) (Model G: a ten minute increase in walking was associated with an increase in the GHQ12 of 0.083, $p=0.042$). Negative associations were identified between time spent driving and wellbeing (with all other travel modes in the reference category). A negative association was also found between travel time and wellbeing for women in the models that did not include the travel mode interaction terms (Models E and F).

(III): Impact of switching to and from more active travel modes on wellbeing

In the models which examined switching to active travel modes, some statistically significant results were identified. In the minimally adjusted model, switching from car travel or public transport to active travel was associated with an improvement in wellbeing of 0.537 on the GHQ12 scale (during the wave in which the switching took place) when compared to maintaining car travel or public transport (Model J: $p<0.001$). After full adjustment, switching from car to active travel (Model L), or from car to walking (Model M: 0.618, $p<0.001$), was also associated with improvement in wellbeing when compared to maintaining car travel.

In contrast, no statistically significant results were reported in the models which examined switching from active travel modes. This included the fully adjusted models of switching from active travel to car travel or public transport when compared to maintaining active travel (Model N: $p=0.812$) as well as those which looked at switching from active travel or public transport to car travel compared to maintenance of active travel or public transport (Model P and Model Q).

(IV): Impact of travel mode on specific aspects of wellbeing

The likelihood of reporting being constantly under strain or unable to concentrate were at least 13% higher when participants used car travel, when compared to active travel, after Bonferroni correction for multiple comparisons (Table 5-8: the odds ratios for experiencing these symptoms of 0.884 and 0.847 were statistically significant for active travel when compared to car travel).(339) The Bonferroni correction is a simple adjustment that is made to P values when several statistical tests representing multiple hypotheses are being performed on a single data set. This is to account for the fact that as more hypotheses are tested, the likelihood of incorrectly rejecting a null hypothesis increases. In this case, the P value was divided by the number of comparisons being made (12) to determine whether or not the result was statistically significant.

In the absence of the Bonferroni correction, Table 5-8 shows that the likelihood of reporting being less able to make decisions and being unable to enjoy normal daily activities was also significantly higher when participants used car travel when compared to active travel.

Furthermore, the likelihood of reporting lost sleep over worry or being constantly under strain was also higher when participants used car travel when compared to public transport.

5.5 Discussion

5.5.1 Active travel and wellbeing

The main observation of a positive association between active travel use and wellbeing was supported by four distinct groups of analyses. Causal inference was better supported, when compared to existing cross-sectional studies, by using the individual-level fixed effects framework. Some potential time-varying confounding variables, including job satisfaction, residence, workplace and health were also accounted for. A specific effect of switching to more active travel modes, in addition to statistical associations between travel mode and wellbeing, was also identified (although no statistically significant result was identified when switching in the opposite direction, from active travel modes). Furthermore, the commuting time analyses showed a positive relationship between time spent walking and wellbeing which, together with the observed increased effect sizes as participants with shorter commutes were progressively excluded from the travel mode choice analyses, indicate a dose-response relationship.

These main findings contrast the two recent UK cross-sectional studies previously introduced in section 5.2. These studies did not identify any statistically significant positive association between active travel and wellbeing,(146) or between time spent in active commuting and wellbeing.(144, 146) In the cross-sectional study published by the ONS, statistically significant negative associations were identified between walking (or cycling for journeys of 15-30 minutes) and most aspects of psychological wellbeing when compared to car travel. Nonetheless, these findings are consistent with other studies (315), including randomised studies of exercise interventions (321, 340), which identified positive associations between some aspects of wellbeing and physical activity in other domains.

5.5.2 Public transport and wellbeing

The positive association observed between wellbeing and public transport when compared to car travel was of a comparable magnitude to that observed between wellbeing and active travel. This finding contrasts with the cross-sectional ONS study that identified statistically significant negative associations between commuting by bus or rail (for journeys of at least 30 minutes) and all or some aspects of wellbeing (when compared to shorter journeys by any mode).(146) A partial explanation for our finding could be that public transport journeys typically feature physical activity when accessing bus stops or railway stations.(147, 341-345) However, there are other explanatory factors that may well have both positive and negative effects. For instance, public transport may provide important opportunities for catching up with work or friends, while crowded carriages may soon become unpleasant.(111, 145, 316, 346-350)

5.5.3 Travel mode choices may be more important than travel time

The negative association observed between wellbeing and travel time amongst women (Model F: a ten minute increase in commuting time using any travel mode was associated with a reduction in the GHQ12 of 0.04) and car drivers (Model H: a ten minute increase reduced the GHQ12 by 0.03) is broadly consistent with existing studies (a ten minute increase reduced the GHQ12 by 0.06 in Roberts et al.) (145, 146). Nevertheless, given that these are small effect sizes and a similar positive relationship was identified between time spent walking and wellbeing (Model G: a ten minute increase in walking increased the GHQ12 by 0.08), we conclude that the potential benefits available to car drivers if they switched to active travel (Model L: switching was associated with an increase in the GHQ12 of 0.48), and walking in particular (Model M: 0.62), exceed any potential benefits associated with reducing commuting time. Besides, only a small journey time mean and variance was observed amongst car drivers in the sample (mean=22.9 minutes, within-individual standard deviation=12.0).

Together, these results appear to suggest that avoiding car driving may be beneficial to wellbeing. This view complements existing evidence of a negative association between driving and physical health,(351, 352) and is consistent with the hypothesis that car driving (a non-passive travel mode that requires constant concentration(145)) can give rise to boredom,(353) social isolation and stress.(145, 146, 354) However, this view is also consistent with the hypothesis that intrinsic enjoyment is gained from the exercise or relaxation associated with active travel.(350, 353, 355) Hence despite being this study being the first longitudinal study to identify associations between travel mode choices and specific aspects of wellbeing included in the GHQ12, further research is necessary on the exact causal mechanism by which car driving appears to impact negatively on wellbeing.

5.5.4 Study limitations

Whilst the sample size used in this study was larger than any comparable study using primary data, relatively few participants were ever active travel users. Switching to cycling or rail travel were especially rare occurrences, limiting the opportunities to explore the impact on wellbeing in these specific cases.

Since the dependent variable (wellbeing) and independent variables of interest (including travel time) were self-reported it is likely that some bias was introduced into the results due to measurement error. Nevertheless, since the analyses presented in this chapter focused on within-individual changes in pairs of consecutive waves, the results were probably subject to a lower risk of bias than might be the case for between-individual comparisons. This is because, although unobserved, the magnitude and direction of bias for a particular individual might be expected to remain relatively constant from one wave to the next. In contrast, if the analyses were comparing individuals, then assumptions would have to be made about unobserved differences in the magnitude and direction of bias between individuals.

Whilst the use of fixed effects models strengthened the case supporting a causal relationship between wellbeing and travel behaviour when compared to cross-sectional methods, or a random effects model specification, the approach used in this chapter nonetheless had some limitations. First, since the change in wellbeing occurred between the same two consecutive waves as the change in travel behaviour, it is possible that an improvement in wellbeing triggered a change in travel behaviour rather than the other way around (i.e. a problem of reverse causality). Second, since the changes in wellbeing which are observed in this study related only to the changes that occurred between two pairs of consecutive waves, the longer term impact of changes in travel behaviour on wellbeing was not assessed. From the perspective of policy-making, it would be useful to know whether the magnitude of change in wellbeing increased or decreased over time, thus strengthening or weakening the case for investment in policies to promote travel behaviour change, and whether or not the observed impact was long lasting. Similarly, the finding that the impact of switching to more active travel modes was statistically significant, whilst the impact of switching from more active travel modes was not statistically significant also warrants further research. It would be of interest to consider whether or not the impact of switching from more active travel modes is larger over longer time periods, for example. Third, the effect of attrition bias was not assessed in this chapter. As described in section 3.5.2., attrition between waves of the data could be a significant source of bias if, over time, individuals who leave the panel have different characteristics to those who remain. In this chapter, individuals may drop out of the panel if they are no longer in employment and therefore no longer commute, if they remain in employment but fail to respond to the question about travel to work, or if they stop completing the BHPS. Although it seems plausible that these forms of attrition could be related to psychological wellbeing, another study using the first 14 waves of BHPS by Roberts et al. found no evidence of attrition bias using one of the tests described in section 3.5.2 by Verbeek and Nijman (1992). Nevertheless, it would be wise to address all three of these limitations in future analyses of the data that has been used in this chapter – particularly given the availability of appropriate methods and a large amount of data from multiple time periods.

As in the analyses presented in Chapter 4, richer data relating to unobserved features of the built environment, or physical activity behaviour, could have supported more detailed study of causal mechanisms or differential effects between individuals and contexts. For example, active commuting could be more beneficial in natural environments, when compared to urban environments(356, 357) where other factors (e.g. the perceived security or safety of car travel)(355) may dominate. Walking pace could also have been a more informative measure of physical activity than time spent walking.(358)

The results presented in this chapter complement existing UK studies, however in other countries cultural factors may have an important influence on attitudes towards different travel modes and the associated impact on wellbeing. Compared to the US, for example, where active travel and public transport use is not so mainstream and communities have been designed with little consideration for these modes,(101) European countries are said to benefit from unbroken traditions of utilitarian cycling, better facilities and more supportive road traffic regulations for walkers and cyclists, as well as less corporate power in the transport sector.(359, 360)

Considering the relatively large sample variance of the wellbeing variable (SD=3.63), the observed effect of switching travel mode was also relatively small. Hence complementary evidence on physical activity and physical health outcomes, including BMI which is explored in Chapter 6, ought to be considered when assessing the potential population-level impact of behaviour change interventions. Policy makers would also be better supported if further work were undertaken on the types of interventions that could lead to improved wellbeing via an increase in the proportion of people using more active travel modes for the commute to work.

5.6 Conclusion

The positive psychological wellbeing effects identified in this study should be considered in cost-benefit assessments of interventions seeking to promote active travel. This study complements other studies on the physical health benefits of active commuting.

Table 5-1: The twelve-item General Health Questionnaire (GHQ-12)

Twelve questions in total: Have you recently…	**Four possible responses to each question:**			
1. Been able to concentrate on what you're doing?	Better than usual (0)	Same as usual (1)	Less than usual (2)	Much less than usual (3)
2. Lost much sleep over worry?	Not at all (0)	No more than usual (1)	Rather more than usual (2)	Much more than usual (3)
3. Felt you were playing a useful part in things?	More so than usual (0)	Same as usual (1)	Less useful than usual (2)	Much less useful (3)
4. Felt capable of making decisions about things?	More so than usual (0)	Same as usual (1)	Less so than usual (2)	Much less capable (3)
5. Felt constantly under strain?	Not at all (0)	No more than usual (1)	Rather more than usual (2)	Much more than usual (3)
6. Felt you couldn't overcome your difficulties?	Not at all (0)	No more than usual (1)	Rather more than usual (2)	Much more than usual (3)
7. Been able to enjoy your normal day-to-day activities?	More so than usual (0)	Same as usual (1)	Less so than usual (2)	Much less than usual (3)
8. Been able to face up to your problems?	More so than usual (0)	Same as usual (1)	Less so than usual (2)	Much less able (3)
9. Been feeling unhappy and depressed?	Not at all (0)	No more than usual (1)	Rather more than usual (2)	Much more than usual (3)
10. Been losing confidence in yourself?	Not at all (0)	No more than usual (1)	Rather more than usual (2)	Much more than usual (3)
11. Been thinking of yourself as a worthless person?	Not at all (0)	No more than usual (1)	Rather more than usual (2)	Much more than usual (3)
12. Been feeling reasonably happy, all things considered	More so than usual (0)	About same as usual (1)	Less so than usual (2)	Much less than usual; (3)

The table shows twelve questions in the GHQ12. Each question has four possible responses. The numbers in brackets show the score for the answers to each question which, when summed for each individual, provides a measure of wellbeing on a 0-36 point scale.

Table 5-2: Description of key features of four groups of analyses on the relationship between commuting mode and wellbeing

Features of the analysis	**Four groups of analyses**			
	I	**II**	**III**	**IV**
Dependent variable (Y_{it})	Psychological wellbeing (Likert Scale, increasing in wellbeing, 0-36)			Binary variable representing a specific psychological symptom
Main exposure of interest ($X_{k,it}$)	Travel mode binary variable(s)	Commuting time-travel mode interaction terms	Travel mode transition variable(s)	Travel mode binary variable(s)
Description of models used	Four separate models, varying in terms of number of travel mode binary variables and number of covariates	Four separate models, varying in terms of number of interaction terms and number of covariates	Eight separate models, varying in terms of number of transition variables and number of covariates	Twelve separate models, with binary dependent variables representing each of the GHQ12 symptoms
Method of regression analysis	Linear fixed effects			Fixed effects logit

Table 5-3: Descriptive statistics for selected variables and transition probabilities

	Sample size		Mean values								Number of transitions Total=75,428[a]		
	N observ-ations (% of total)	n individ-uals (% used each mode>0)	Age (s.d.)[c]	Male, %	Couple (incl. married) %	Commuting time, minutes (s.d.)[c]	Equivalised household income (s.d.)[c,i] £	Psychological wellbeing (36 point Likert scale) (s.d.)[c]	Job satisfaction (7 point scale) (s.d.)[c]	Self-employed, %	Car (transition probability)[b]	Active (transition probability)[b]	Public transport (transition probability)[b]
All	102,502[d] (100%)	17,985 (100%)	39.0 (11.50, 3.59)	50.9%	73.6%	23.41 (20.86, 18.39)	28844 (20277, 15477)	25.3 (5.0, 3.6)	5.38 (1.29, 0.962)	7.8%	57,280 (75.94%)	10,967[e] (14.54%)	7,181[f] (9.52%)
Car users	75,218 (73.4%)	13,508 (75.1%)	39.6 (11.10, 3.53)	54.8%	76.8%	22.90 (19.66, 12.03)	30141 (19636, 13102)	25.4 (4.9, 3.5)	5.38 (1.27, 0.940)	9.1%	54,727 (96.45%)	1,293 (2.28%)	722 (1.27%)
Active travel	16,140[g] (15.8%)	5,354 (29.8%)	38.4 (12.38, 2.67)	41.1%	66.6%	12.33 (9.91, 4.39)	23407 (22398, 14344)	25.2 (5.1, 3.3)	5.46 (1.33, 0.833)	4.8%	1,565 (13.91%)	9.152 (81.37%)	531 (4.72%)
Public transp.	11,144[h] (10.9%)	3,972 (22.1%)	36.1 (12.26, 2.65)	39.4%	59.5%	42.65 (26.29, 12.17)	27961 (19954, 9831)	25.0 (5.3, 3.3)	5.28 (1.38, 0.889)	2.9%	988 (13.28%)	522 (7.02%)	5,928 (79.70%)

[a] Pairs of individual-specific consecutive waves
[b] The final three columns of the table show transition probabilities in which horizontal rows represent travel mode in lagged waves (t-1) (which add to 100%) and vertical columns represent travel mode in current wave (t).
[c] s.d. = standard deviation (overall, within individuals)
[d] See Figure 4-1 for explanation of exclusion criteria which led to N=102,502.
[e] Of which, 8,791 (11.65% of total) were walkers in time t, and 2,176 (2.88%) were cyclists in time t. [f] Of which, 2,375 (3.15%) were railway users in time t, and 4,806 (6.37%) were bus users in time t.
[g] Of which 13,089 (12.8% of total) were walkers and 3,051 (2.98%) were cyclists. [h] Of which 3,408 (3.32%) were railway users and 7,736(7.6%) were bus users.
[i] Accounting for number of people in the household and the age of children on living standards.

Table 5-4: Results: Impact of commuting mode on psychological wellbeing

	Minimally adjusted models[a]	Fully adjusted models[b]		
	Model A	**Model B**	**Model C**[c]	**Model D**
	Active travel binary independent variable only		Active travel and public transport binary independent variables	Mode-specific binary independent variables
Active travel modes				
Cycling and walking	0.145* (0.017)	0.137* (0.040)	0.185** (0.008)	
Cycling only				0.077 (0.521)
Walking only				0.222** (0.004)
Public transport modes				
Train, bus and coach			0.195* (0.017)	
Train only				0.161 (0.222)
Bus and coach only				0.216* (0.019)
Obs.	101671[d]	86065[e]	86065	86065
r^2	0.04	0.08	0.08	0.08

Table shows fixed effects estimates of the impact of travel mode on psychological health (higher score=better psychological health).
Model A and Model B: Car travel and public transport are in the reference category. Model C and Model D: Car travel is in the reference category

[a] Minimally adjusted models controlled for region, year, age squared, adjusted gross annual household income, number of children and self-assessed health status.

[b] Fully adjusted models controlled additionally for educational attainment, work hours, neighbourhood characteristics, daily commuting time, job satisfaction and number of previous residences and workplaces.

[c] Sensitivity analyses for Model C are shown in Table 5-9. The covariates which had a statistically significant impact on wellbeing were: number of children (+0.07), being in a couple (including marriage) (+0.44), self-assessed health status (+2.24 to +4.10 when compared to poor or worse health), reporting that the participant liked living in their current neighbourhood (+0.43), job satisfaction (+0.79 per unit change), moving job (+0.06), moving house (+0.07), age squared (+) and each of the year dummies (-).

[d] Compared to N=102,502 in Table 5-3, an additional 831 observations were excluded from the analysis due to missing values in the adjusted gross annual household income and educational attainment variables.

[e] 15,606 observations were excluded from Model B, when compared to Model A, due to missing values in the following variables: educational attainment, work hours, neighbourhood characteristics, daily commuting time, job satisfaction and number of previous residences and workplaces.

Table 5-5: Results: Impact of commuting time-travel mode interaction terms on psychological wellbeing

	Minimally adjusted models[a]	Fully adjusted models[b]		
	Model E	**Model F**	**Model G**	**Model H**
	No travel-mode interaction terms		Non-car interaction terms	Car interaction term only
Time (mins)	0.000 (0.996)	-0.000 (0.933)	-0.002 (0.214)	0.001 (0.436)
Time × gender[3]	-0.004* (0.039)	-0.004* (0.048)	-0.004 (0.070)	-0.004 (0.066)
Commuting time-active travel				
Time × walk			0.008* (0.042)	
Time × bike			-0.001 (0.827)	
Commuting time-public transport				
Time × train			0.003 (0.124)	
Time × bus/coach			0.003 (0.160)	
Commuting time-car				
Time × car				-0.003* (0.040)
Obs.	109169	96222	86065	86065
r^2	0.04	0.08	0.08	0.08

Table shows fixed effects estimates of the impact of commuting time-travel mode interaction terms on psychological health (higher score=better psychological health).
Model G: Car travel is in the reference category. Model H: Active travel and public transport are in the reference category.
[a] Minimally adjusted models controlled for region, year, age squared, adjusted gross annual household income, number of children and self-assessed health status.
[b] Fully adjusted models controlled additionally for educational attainment, work hours, neighbourhood characteristics, daily commuting time, job satisfaction and number of previous residences and workplaces.

Table 5-6: Results: Impact of travel mode transitions on psychological wellbeing (Models J-M)

	Minimally adjusted models[a]	Fully adjusted models[b]		
	Model J	**Model K**	**Model L**	**Model M**
	Active travel binary variable only		Active travel and public transport binary variables	Mode-specific binary variables
Switching to active travel from car travel or public transport				
Cycling and walking	0.537** (<0.001)	0.468** (0.001)		
Switching to active travel from car travel				
Cycling and walking			0.479*** (0.001)	
Cycling				0.168 (0.506)
Walking				0.618***(<0.001)
Switching to public transport from car travel				
Train, bus and coach			0.240 (0.206)	
Train				0.266 (0.360)
Bus and coach				0.221 (0.372)
Obs.	63642	56387	51305	51305
r^2	0.04	0.09	0.09	0.09

Table shows fixed effects estimates of travel mode transitions on psychological health (higher score=better psychological health). P-values are shown in parentheses.
Model J and Model K: Maintenance of car travel and maintenance of public transport are in the reference category
Model L and Model M: Maintenance of car travel is in the reference category
[a] Minimally adjusted models controlled for region, year, age squared, adjusted gross annual household income, number of children and self-assessed health status.
[b] Fully adjusted models controlled additionally for educational attainment, work hours, neighbourhood characteristics, daily commuting time, job satisfaction and number of previous residences and workplaces.

Table 5-7: Results: Impact of travel mode transitions on psychological wellbeing (Models N-Q)

	Minimally adjusted models[a]	Fully adjusted models[b]		
	Model N	**Model O**	**Model P**	**Model Q**
	Active travel binary variable only		Active travel and public transport binary variables	Mode-specific binary variables
Switching from active travel to car travel or public transport				
Cycling and walking	0.077 (0.591)	0.037 (0.812)		
Switching from active travel to car travel				
Cycling and walking			0.098 (0.557)	
Cycling				-0.049 (0.882)
Walking				0.144 (0.444)
Switching from public transport to car travel				
Train, bus and coach			-0.324 (0.114)	
Train				-0.159 (0.665)
Bus and coach				-0.392 (0.103)
Obs.	11,310	10,473	16,816	16,816
r^2	0.05	0.09	0.09	0.09

Table shows fixed effects estimates of travel mode transitions on psychological health (higher score=better psychological health). P-values are shown in parentheses.
Model N and Model O: Maintenance of active travel is in the reference category
Model L and Model M: Maintenance of active travel and maintenance of public transport is in the reference category
[a] Minimally adjusted models controlled for region, year, age squared, adjusted gross annual household income, number of children and self-assessed health status.
[b] Fully adjusted models controlled additionally for educational attainment, work hours, neighbourhood characteristics, daily commuting time, job satisfaction and number of previous residences and workplaces.

Table 5-8: Twelve models of the effect of travel mode on specific aspects of the GHQ12

	Constantly under strain	Feelings of being worthless	General unhappiness	Less able to make decisions	Less able to play a useful role	Losing confidence	Lost sleep over worry	Problems overcoming difficulties	Unable to concentrate	Unable to enjoy normal daily activities	Unable to face problems	Unhappy/ depressed
Public transport	0.889[a] (0.023)	0.127 (0.204)	0.931 (0.280)	0.934 (0.427)	1.009 (0.911)	1.091 (0.218)	0.872[a] (0.022)	0.926 (0.254)	0.944 (0.351)	0.981 (0.760)	1.019 (0.812)	0.983 (0.757)
Active travel	0.884* (0.006)	0.958 (0.604)	0.890 (0.052)	0.834[a] (0.018)	1.054 (0.449)	0.995 (0.941)	0.914 (0.084)	0.911 (0.116)	0.847* (0.003)	0.894[a] (0.042)	0.916 (0.214)	0.937 (0.188)
Observations	60,855	21,811	42,055	28,298	32,298	36,004	50,633	40,688	47,874	48,572	32,047	53,645

Table shows conditional logit fixed effects estimates of the odds of active travel and public transport users experiencing twelve symptoms of the GHQ12 when compared to car travel.
Dependent variable in each model: 1 = symptoms, 0 = no symptoms.
P-values shown in parentheses.
All models control for the same exposure of interest and covariates as Model C (see Table 5-4)
* Indicates statistical significance at the p b 0.05 level after the Bonferroni adjustment for multiple comparisons.(339)
a Indicates statistical significance at the p b 0.05 level without adjustment for multiple comparisons.

Table 5-9: Results: Sensitivity analyses

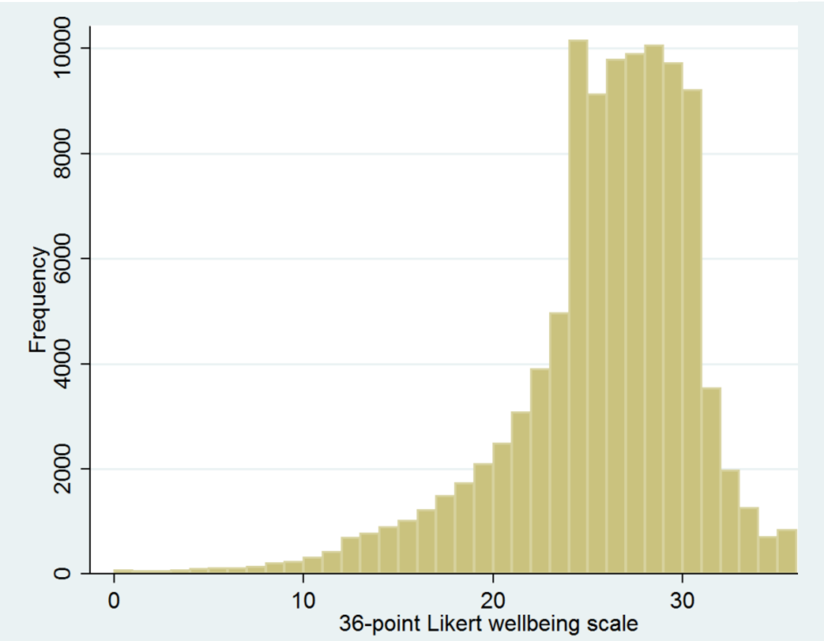
<u>This table shows the following subgroup analyses:</u>
(a) Excluding between-wave transitions where participants moved job, and (b) excluding between-wave transitions where participants moved residence, since these may impact on wellbeing.
(c) Excluding observations where participants reported being self-employed, since travel patterns may vary when compared to the majority of workers who are employed.
(d) Excluding observations where participants reported fair or worse self-assessed health, and (e) including only observations where participants reported having chest or breathing difficulties, since these may be a proxy for overall fitness and/or potential confounding variables.
Including only observations where commuting time was (f) greater than 10 minutes, (g) greater than 20 minutes, and (h) greater than 30 minutes, in order to identify potential dose-response relationship between physical activity and wellbeing.
(l) Exclusion of observations with Likert wellbeing score less than 10.

<u>Inclusion of additional travel modes in the travel mode categories</u>
(i) Inclusion of underground in the public transport group, and motorcycle in the reference group, and (j) inclusion of underground in the public transport group, and motorcycle and car/van passenger in the reference group, since these travel modes had been excluded from the main analyses due to small sample sizes.

	Model C	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**	**(i)**	**(j)**	**(l)**
Public transport	0.1950*	0.2083*	0.0566	0.1997*	0.1572	0.3652	0.2864**	0.3924***	0.5129***	0.1493	0.0856	0.1651*
Active travel	0.1849**	0.2003**	0.1953*	0.1873**	0.1918**	0.4831*	0.3089**	0.3373*	0.5085*	0.1590*	0.0953	0.1525**
Observations	86065	61488	75007	85801	68845	13769	62029	37347	15787	88382	95677	85027
r^2	0.0803	0.0724	0.0786	0.0803	0.0583	0.0930	0.0793	0.0764	0.0648	0.0802	0.0779	0.0747

Table shows fixed effects estimates of the impact of travel mode on psychological health (higher score=better psychological health) using the same covariates as fully adjusted models shown in Table 5-6.
Model C is shown for comparison.
* indicates statistical significance at the p < 0.05 level
** indicates statistical significance at the p < 0.01 level
Car travel was in the reference category.

Figure 5-1: Frequency distribution of 36-point Likert wellbeing scale, N=102,502



6 Impact of active commuting on body mass index

6.1 Overview of chapter

In this chapter, the impact on BMI of switching from car travel to walking, cycling and public transport is explored using data from three waves of the BHPS. This analysis complements the analysis presented in Chapter 5 which explored the impact of switching travel modes on individual-level psychological wellbeing.

6.2 Background

As described in the Introduction (Chapter 1), internationally recognised public health guidelines encourage adults to undertake at least thirty minutes of moderate-intensity physical activity each day to help prevent obesity and several other chronic conditions.(3)

Incorporating walking or cycling into the journey to and from work may represent a relatively low-cost, more feasible option for many people, when compared to opportunities to increase time spent being active at home or during leisure or work time which can be costly or limited.(120, 322, 361) This could include journeys by public transport, or other modes such as park-and-ride, which could involve some walking or cycling to the station or stop.

Existing cross-sectional studies have identified individual-level associations between walking and cycling to work and various health outcomes including lower BMI(147, 362) and lower prevalence of cardiovascular disease or diabetes.(147, 363) Of thirty individual-level studies of the association between active travel and BMI identified in a recent review, twenty-five reported statistically significant negative relationships ($p<0.05$).(16) However, just one study identified in the review,(364) and one further study of the relationship between active travel and overall physical activity in adults,(227) used longitudinal study designs. This limits the potential for drawing reliable causal inferences, not least because other studies have indicated that increases in body weight may precede reductions in physical activity.(16, 365, 366)

Other longitudinal studies have demonstrated population-level correlations between decreasing active travel,(367) increasing car use(351, 352, 368) and increasing prevalence of adult obesity or average BMI over time. However, no known longitudinal studies have used data from a nationally representative dataset to examine the individual-level impact on BMI of switching between modes of travel.(280)

6.3 Methods

6.3.1 Data source and sample selection

Data from just three waves of the BHPS was used in this analysis (further details about the BHPS are provided in section 4.2). This was because the primary outcome variable, based on self-reported height and weight data, were reported only in two waves: wave 14 (2004-05; subsequently referred to in this chapter as t0, where n=15,791) and wave 16 (2006-07; subsequently referred to as t2, where n=15,392). A third, intermediate wave, (wave 15, 2005-06, subsequently referred to as t1) was also used.

Participants eligible for inclusion in the analyses (n=4,056) were those aged over 18 years who reported various socioeconomic and health-status variables listed below under 'Covariates and other participant characteristics', and who reported their usual main mode of travel to work and height and weight data at t0 and t2. Figure 6-1 shows how this subsample was selected from the original sample included in the BHPS at t0 (BHPS wave 14, n=15,791) (an assessment of attrition bias and missing values bias was made by comparing participants in the original BHPS sample with those retained in the analytical sample, see Results and Table 6-6). In comparison to the analyses presented in Chapters 4 and 5 (see Figure 4-1), the sample selection criteria did not exclude the 'underground/metro', 'car/van passenger' and 'motorcycle' travel modes, and there was no upper age restriction. This was due to the relatively small number of potential participants in this analysis, compared with the analyses presented in earlier chapters.

6.3.2 Variables used in the analysis

6.3.2.1 Dependent variable

The outcome variable used in the analyses was change in BMI between t0 and t2. BMI in each wave was calculated by dividing self-reported weight (reported in kg, or converted to kg from stones and pounds) by the square of self-reported height (reported in metres, or converted to metres from feet and inches). Where height differed between waves, baseline height was used to prevent small artefactual differences in height affecting the results (if, for example, height was reported using metric units in one wave and imperial units in the other). Follow-up height measures were used to replace implausible baseline values attributable to obvious data entry errors in three cases. A small number of participants were excluded from analysis due to implausible values for weight (<30kg, n=7) or change in weight (>87kg, n=7). Following contact with BHPS administrators, other adjustments were also made for a simple coding error in the imperial measurements.

6.3.2.2 Independent variables

The main variable of interest was change in usual mode of travel to work which was derived from the reported usual main mode of travel to work at t0, t1 and t2. For each wave, participants were categorised as using active modes of travel ('walking' or 'cycling'), public transport ('bus/coach', or rail: 'train' or 'underground/metro'*), or private motor transport ('car or van', 'car/van passenger'* or 'motorcycle'*) (For clarification, those marked * were excluded from the analyses in Chapters 4 and 5. However, as in Chapters 4 and 5, participants who reported using 'other' modes of travel were excluded from this analysis).

Covariates and other participant characteristics

Covariates were used to account for selected individual-level characteristics reported at t0, and changes in individual-level characteristics between t0 and t2, which have previously been shown to be associated with active travel and obesity,(104, 147, 351, 362, 369-371) and hence were hypothesised to act as potential confounders of the relationship between active travel and BMI.

The covariates reported at t0 were: age, gender, occupational status (for analytical purposes, binary variables were created for each of the seven Registrar General's Social Class (RGSC) categories), working hours (two binary variables: weekly hours of work ≥30 ('full-time') vs. <30 ('part-time'), and night-time vs. other-time work), annual household income (quintiles to account for the impact of household size and age of children on living standards, using the McClements equivalence scale),(278) educational level (degree or higher qualification vs. less than degree), number of children under 16 in the household (one or more vs. none), self-reported health status (five categories from 'excellent' to 'very poor'), and number of cars in the household (one or more vs. none). Participants had to report these covariates to be eligible for use in the analysis, as shown in Figure 6-1 and stated in the 'Data source and sample selection' section above.

The covariates which accounted for changes that occurred between t0 and t2 were: home location (a single variable: ≥1 move between t0 and t2), household income (two variables: increase and decrease of >2 quintiles), health status (two variables: increase and decrease of ≥2 categories), car access (two variables: gaining and losing household access to ≥1 car), pregnancy (two variables: becoming and no longer being pregnant).

Other variables reported at t0 were also selected for use in the descriptive statistics: commuting time (minutes), region (13 categories), annual frequency of primary care and hospital outpatient visits, smoking status, and frequency of leisure activities in three separate categories: playing sport, walking or swimming (hereafter leisure time physical activity or LTPA), gardening, and eating out. In a minority of cases, these were not reported by all participants included in the analysis (see Table 6-2).

6.3.3 Statistical analysis

Since BMI is reported only twice in the BHPS, the outcome of interest, change in BMI, was only reported once for each individual included the analysis. Hence there was insufficient within-individual variation in the main outcome of interest to use the more rigorous fixed effects model for panel data used in Chapter 5. The method of statistical analysis chosen for use in this chapter was a standard regression analysis, of change in travel mode on change in BMI, using methods more typically used by epidemiologists (in cohort studies, for example) than perhaps would be expected in the mainstream economics or econometrics literature.

The variables and subsamples selected for use in 18 separate analytical models (Models A-R) are summarised in Table 6-1. To assess the effects of switching to and from active commuting, two separate analyses were conducted.

First, the effect of switching from private motor transport at t0 to active travel or public transport at t2 on change in BMI was examined (Analysis 1). Participants who switched ("the exposed") were compared to those who maintained use of the same mode of private motor transport at t0, t1 and t2 ("the unexposed"). Those participants in the exposed group who had switched between t0 and t1 were also compared to those in the unexposed group in order to study temporal effects.

Second, the effect of switching from active travel or public transport at t0 to private motor transport at t1 or t2 on BMI was examined (Analysis 2). Participants who switched were compared to those who maintained use of the same mode of active travel or public transport at t0, t1 and t2.

Participants who switched between different modes of private motor transport (Analysis 1) or of active travel or public transport (Analysis 2) were excluded from the respective unexposed groups. Chi-squared, Mann-Whitney and Student's t tests were used to compare the characteristics of the exposed and unexposed groups.

Multivariable linear regression models were used to estimate the association between change in usual mode of transport (binary or multinomial independent variable) and change in BMI with progressive adjustment for (i.) individual characteristics (age, gender and BMI at t0), (ii.) further characteristics at t0 (occupational status, working hours, household income, education, children, health status and car access) and (iii.) changes in home location, income, health, car access and pregnancy status. Additional analyses were used to explore dose-response relationships using sub-samples of participants with different baseline commute times (in three separate categories >10, >20 and >30 min), a reasonable proxy for distance to work, since all participants in a given analysis used the same usual mode of travel at t0.

An assessment of attrition bias and missing values bias was also made using a descriptive analysis of differences between individuals who were in the original BHPS sample at Wave 14 (t0) with those retained in the analytical sample at t0.

6.4 Results

6.4.1 Characteristics of the sample

Histograms show the distribution of BMI in the sample of n=4,056 used in both analyses at t0 (Figure 6-2) and t2 (Figure 6-3). At t0 the mean BMI was 26.7 (SD=4.3) and, at t2, the mean BMI was 27.1 (SD=4.4).

Table 6-2 shows basic descriptive statistics and comparisons of groups used in two separate analyses (Analysis 1 and Analysis 2) at t0 and t2.

6.4.1.1 Analysis 1: Switching from private motor transport to active travel or public transport

Of 3,269 individuals included in this analysis, 179 were in the exposed group. Of these, 109 switched to active travel (most often walking, n=83) and 70 to public transport (most often rail, n=32) (see Figure 6-1). Switchers were significantly younger on average than non-switchers (e.g. for active travel: 37.8 vs. 41.2 years at t0, Table 6-2) and less likely to have access to a car (e.g. for active travel: 95.4% vs. 98.8%). No statistically significant differences were observed between groups in terms of mean BMI, although those who switched to active travel were less likely to be classified as overweight or obese at baseline (52.3% vs. 64.7%). Those who switched to active travel, but not those who switched to public transport, also had a significantly lower mean adjusted household income (£28,087 vs. £32,495); a higher likelihood of smoking (31.2% vs 22.8%); a shorter mean commute time (16.5 vs. 23.0 min at t0), which became shorter still after taking up active travel (13.9 min at t2); and a higher likelihood of weekly

LTPA (68.8% vs. 57.8% at t0) than non-switchers. Those who switched to public transport were significantly more likely to hold a degree or higher qualification (34.3% vs 19.4%). No statistically significant differences in household composition or health status were observed between groups.

Attrition bias and missing values bias

Table 6-6 shows descriptive statistics and group comparisons for samples of participants before and after sample restrictions marked (a) and (b) in Figure 6-1 were imposed. The test for missing values compared participants who remained in the sample (n=7,471) with those excluded because they did not report BMI at t0 (n=339). The test for attrition bias compared individuals who remained in the sample (n=6,634) with those excluded from the analysis because they were no longer in the dataset at t2 (n=837). The results show significant differences in the characteristics of individuals, notably in terms of age, gender, income and baseline BMI were identified when comparing participants in the original BHPS sample with those retained in the analytical sample, indicating that attrition and missing values are likely to be a source of bias in the results.

6.4.1.2 Analysis 2: Switching from active travel or public transport to private motor transport

Of 787 individuals included in this analysis, 268 were in the exposed group. Of these, 156 switched from active travel (most often walking, n=121) and 112 from public transport (most often bus or coach, n=73) (see Figure 6-1). As in Analysis 1, switchers were significantly younger on average than non-switchers (e.g. for active travel: 35.1 vs. 41.2 years at t0, Table 6-2), but other differences in baseline working hours, income, education, children, health status, mean BMI and obesity status were not significant. Car access was more prevalent amongst those who switched from active travel at t0 and t2 and also amongst those who switched from public transport at t2. Those who switched from active travel were significantly less likely than either non-switchers or those who switched from public transport to hold a professional or managerial occupation (e.g. 24.4% for switchers from active travel vs 34.5% for non-switchers) and more likely to undertake weekly LTPA (74.4% vs 64.7%), and had a shorter mean commute time (13.7 min vs 27.4 min at t0) which increased after switching to private motor transport (18.0 min at t2). In contrast, those who switched from public transport had a longer mean commute time (42.4 min at t0) which was reduced after switching to private motor transport (29.5 min at t2).

6.4.2 Effect on BMI

Results for the analyses are shown in Table 6-4.

6.4.2.1 Analysis 1: Switching from private motor transport to active travel or public transport

The impact of switching from private motor transport to active travel or public transport was associated with a significant reduction in BMI of -0.32kg/m^2 (95% CI: -0.60 to -0.05) after adjustment for all covariates (Table 6-4, Model C). For the typical person, this equates to a reduction in weight of around 1kg.[3] Smaller, statistically insignificant effect sizes were

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[3] This calculation was based on an man of average height 176 cm, weight 86 kg and BMI 27.8, and an a woman of average height 163 cm, weight 72.8 kg and BMI 27.4.

estimated in the two models that did not control for time-varying potential confounding factors (e.g. Model B: -0.21kg/m^2, 95% CI: -0.47 to 0.06). When the effects of switching to active travel and public transport were modelled separately, larger and statistically significant adjusted effect sizes were associated with switching to active travel between t0 and t2 (Model D: -0.45kg/m^2, -0.78 to -0.11) and in the analysis restricted to participants who switched to active travel between t0 and t1 (Model F: -0.59kg/m^2, -1.11 to -0.06). Effect sizes associated with switching from private motor transport to active travel also consistently became larger as participants with shorter baseline journeys were excluded from the analysis, rising to -0.75kg/m^2 amongst those switching to active travel with journey times >10 min to -2.25kg/m^2 for those >30 min (Table 6-4, Models G-I).

6.4.2.2 Analysis 2: Switching from active travel or public transport to private motor transport

Switching from active travel or public transport to private motor transport was associated with a significant increase in BMI of 0.34kg/m^2 (0.05 to 0.64) after adjustment for all covariates (Table 6-4, Model L). When the effects of switching from active travel and public transport were modelled separately, a statistically significant adjusted effect size was associated with switching from public transport (Model M: 0.46kg/m^2, 0.06 to 0.86). Statistically significant effects were not observed in the models restricted to participants who switched between t0 and t1.

6.4.3 Discussion

6.4.3.1 Principal findings

Whilst previous studies have demonstrated cross-sectional associations between BMI and mode of travel to work, this is the first known study using cohort data from a longitudinal study of nationally representative households to link changes in BMI with changes in the usual main mode of travel to work.

The observation that switching from private motor transport to active travel or public transport was associated with a small reduction in individual-level BMI, even in a relatively short time period of under two years, suggests that a shift in the proportion of commuters using more active modes of travel could contribute to efforts to reduce population mean BMI. Although, for the average person, the clinical significance of the resulting change in weight would likely be small, when considering the other potential health, economic and environmental benefits associated with walking, cycling and public transport,(16, 99, 147, 148, 363, 372, 373) the findings of this study add to the case for interventions to promote the uptake of these more sustainable forms of transport.(120, 374) If large numbers of people could be enabled to take up active travel to work, for example through environmental and policy interventions in the transport and planning sectors, the benefits for population health may be larger than those of alternative interventions targeted at producing larger individual health benefits for relatively small numbers of people.(375)

Switching to active travel

This study found significant negative associations between change in BMI and switching from private motor transport in models that accounted for the uptake of active travel and public transport both together (Model C) and separately (Model D). The case for causal inference is further strengthened by three key findings. First, we found a statistically significant effect in the analysis restricted to participants who switched to active travel between t0 and t1 (Model F) in which the exposure is more likely to have temporally preceded the outcome. Second, we found stronger effect sizes when participants with shorter commutes were excluded from the analysis (Models G-I), which is indicative of a dose-response relationship. For example, amongst those with a commute of more than 30 minutes, there was an average reduction of 2.25 BMI units, or around 7 kg for the average person. Third, significant positive associations were observed in a separate sample of commuters who switched in the opposite direction (Models J-L).(256)

The direction and size of effects observed in this study are comparable to those of recent cross-sectional analyses of UK commuters which showed negative associations between BMI and walking (e.g. -0.48 kg/m^2)(147) and cycling (-0.97 kg/m^2)(147) compared to private motor transport,(147, 362) and with those reported in reviews of interventions to promote walking,(361, 376) including a review of sixteen randomised controlled trials which reported an average reduction in BMI of -0.67 kg/m^2 associated with uptake of regular, brisk walking.(377)

The finding that participants who switched to active travel were, on average, from lower income households, less likely to be educated to degree-level or higher and more likely to work part-time than other participants in the study (see Table 6-2) could be indicative of the potential for interventions in the transport and planning sectors to support strategies to reduce health inequalities.(147, 378)

Switching to public transport

The significant negative association observed between change in BMI and switching from private motor transport to active travel or public transport (Model C), and the significant positive association with switching from public transport to private motor transport (Models J-M), supports the implications of existing studies showing that public transport users can undertake meaningful levels of physical activity when accessing stations or stops.(147, 341-345)

The cross-sectional UK studies referred to above also identified an association between BMI and public transport use compared to private motor transport (e.g. -0.24 kg/m^2)(147).(147, 362)

Nevertheless, we did not observe significant associations in our analyses of switching from private motor transport which accounted for public transport separately from active travel (Models D and F). This may reflect important differences between bus and rail travel. First, this could be indicative of a finding in two US studies that rail users walked significantly further to access stations than users of other public transport modes.(342, 379) In one study, for example, commuters who met physical activity recommendations solely by walking for more than 30 minutes to and from public transport stops were 1.67 times more likely to be rail than bus users.(342) Not only may this be because bus stop density is generally higher (particularly in urban areas)(379), but also since commuters may be willing to travel further to access railway stations due to the higher perceived benefits of rail travel.(147, 341-345) These differences could not be adequately explored in this study because of small sample sizes. Second, large differences were also identified in the socioeconomic characteristics of participants who switched to rail travel compared to those who switched to bus travel (e.g. mean household income: £45,113 vs £25,959). While rail travel in Great Britain has grown at a much faster rate than road traffic or bus travel in recent years,(29) future studies could explore the size and distribution of benefits associated with these changes and their implications for strategies to reduce health inequalities.

Study limitations

In contrast to existing cross-sectional studies, the main strength of this study lies in its use of cohort data from a longitudinal study of nationally representative households to examine associations between changes in mode of travel to work and changes in BMI over time. This study design was also able to account for a number of potential time-varying confounding variables (such as substantial changes in health and income). Nevertheless, because the BMI outcome variable was not reported at t1 we cannot be sure that the changes in mode of travel preceded the changes in BMI. A further limitation is that BMI was based on self-reported measures, which are typically biased when compared to direct measurements.(380) However, our reliance on within-individual changes over a two-year period was probably subject to a lower risk of bias than might be the case for between-individual comparisons. Because the main exposure of interest was the usual main mode of travel to work, the analysis could not take full account of multimodal trips such as park-and-ride, or other trips undertaken during leisure or work time.

Missing data, attrition (see Figure 6-1 and Table 6-6) and the differences in some observed characteristics between exposed and unexposed groups (see Table 6-2) is likely to have introduced some bias. Furthermore, some potential time-varying confounding variables, including other physical activity and dietary behaviours, were unobserved. While small sample sizes and limited within-individual variation prevented the use of more advanced analytical approaches such as fixed effects models or instrumental variables, these are desirable approaches which could contribute to mitigating the impact of various sources of bias and ought therefore to be pursued in future research. The relatively short follow-up time also precluded the examination of longer-term health effects.

6.4.4 Conclusion

This study has extended existing literature on the health benefits of active travel by providing longitudinal evidence from a national survey of a relationship between switching to and from more active modes of travel to work and modest changes in weight which amounted to between 1kg and 7kg for the average person. Physical health benefits such as these should be included in the assessment of interventions to promote active commuting, along with other psychological health benefits including those identified in Chapter 5.

Table 6-1: Summary of the independent variables and sample restrictions used in the statistical models

Analysis	**Model**								
Analysis 1: Impact of switching from private motor transport to active travel or public transport (n)	**Model A**	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	**Model G**	**Model H**	**Model I**
	(3269)		(3253)		(3144)		(2244)	(1289)	(752)
Analysis 2: Impact of switching to private motor transport from active travel or public transport (n)	**Model J**	**Model K**	**Model L**	**Model M**	**Model N**	**Model O**	**Model P**	**Model Q**	**Model R**
	(787)		(785)		(658)		(500)	(342)	(239)
	Independent variables								
Travel mode change variable	Binary			Multi-nomial	Binary	Multi-nomial			
Other covariates									
Basic individual characteristics (age, gender and BMI at t0)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other individual/socioeconomic characteristics (occupational status, working hours, household income, education, children, health status, car access at t0)		✓	✓	✓	✓	✓	✓	✓	✓
Changes between t0 and t2 in individual and socioeconomic characteristics (home location, income, health, car access and pregnancy)			✓	✓	✓	✓	✓	✓	✓
	Sample restrictions								
Excluded participants	None				Exposed group restricted to participants who switched between t0 and t1		Restricted to participants with longer commute times at t0		
							>10 minutes	>20 minutes	>30 minutes

Table 6-2: Descriptive statistics and group comparisons for participants used in Analysis 1

	Un-exposed	Switched to active travel		Switched to public trans.	
n (minimally adjusted Models A & B) [c]	3090	109		70	
Characteristic (at t0 unless indicated)	% or mean	% or mean	p [a]	% or mean	p [a]
Socio demographic characteristics					
Age (mean years)	41.2	37.8**	**0.002**	36.8**	**0.001**
Male[b]	61.7%	58.7%	0.527	57.1%	0.437
Professional or managerial occupation[b]	44.1%	41.3%	0.559	41.4%	0.655
Full time work[b]	85.5%	77.1%*	**0.014**	78.6%	0.103
Works at night time[b]	2.2%	2.8%	0.701	1.4%	0.662
Household income (mean £)	32,495	28,087**	**0.002**	35,141	0.460
High income[b]	45.2%	33.9%*	**0.020**	47.1%	0.748
Education: degree or higher qualification[b]	19.4%	13.8%	0.139	34.3%**	**0.002**
One or more children in the household[b]	17.1%	22.0%	0.184	10.0%	0.117
Lives in London or South-East England[b]	11.7%	10.1%	0.617	18.6%	0.076
Health related characteristics:					
BMI (mean kg/m^2)[d]	26.9	26.1	0.056	26.0	0.140
WHO-classified overweight[b]	64.7%	52.3%**	**0.008**	54.3%	0.071
'Poor' or 'very poor' self-assessed health[b]	3.6%	4.6%	0.585	7.1%	0.118
Self-reported smoker[b]	22.8%	31.2%*	**0.041**	21.4%	0.784
More than 3 annual hospital visits[b]	10.4%	9.2%	0.675	11.4%	0.785
More than 6 annual primary care visits[b]	9.1%	8.3%	0.765	10.0%	0.794
Travel related:					
One or more cars in household[b]	98.8%	95.4%**	**0.003**	90.0%***	**<0.001**
One or more cars in household (t2)[b c]	99.0%	93.6%***	**<0.001**	80.0%***	**<0.001**
Number of cars in household (mean)	1.8%	1.8%	0.707	1.4%***	**<0.001**
Number of cars in household (t2, mean)[c]	1.8%	1.6%**	**0.002**	1.2%***	**<0.001**
Private transport user in t0-1 & t0-2[b c]	91.9%	70.5%***	**<0.001**	64.4%***	**<0.001**
Commute time (mean minutes)[c]	23.0	16.5***	**0.000**	33.7***	**<0.001**
Commute time (t2, mean minutes)[c]	23.6	13.9***	**0.000**	45.8***	**<0.001**
Other lifestyle related characteristics:					
At least weekly LTPA[b]	57.8%	68.8%*	**0.022**	58.6%	0.901
At least weekly LTPA (t2)[b]	59.2%	78.9%***	**0.000**	68.6%	0.113
At least weekly gardening[b]	25.8%	17.4%	0.050	14.3%*	**0.029**
At least weekly gardening (t2)[b]	28.8%	22.0%	0.122	15.7%*	**0.016**
At least weekly eating out[b]	16.8%	14.7%	0.555	20.0%	0.484
At least weekly eating out (t2)[b]	16.7%	14.7%	0.578	17.1%	0.922

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

[a] The results of Chi-squared tests (or Mann-Whitney tests for number of cars, age, income and commute time, or student's t-tests for BMI), where the null hypothesis was that the difference between the exposed and unexposed group was equal to zero.

[b] Binary variables were created as described in the Methods section. Additionally, binary variables were created for the highest occupational status (professional/managerial=1) compared to all other occupations (=0), the two highest income quintiles (=1) compared to all other income quintiles (=0), resident in London or South East England (=1) compared to all other regions (=0), being classed as overweight or obese (=1) compared to any other weight status (=0), poor or very poor self-assessed health (=1) compared to fair or good self-assessed health (=0), and for three indicators of leisure activities (=1 if undertaken at least once a week, =0 if undertaken less frequently).

[c] Values for some variables were not reported for all individuals included in the minimally adjusted models.

[d] A histogram of BMI (at baseline) is shown in Figures 6-2 and 6-3.

Table 6-3: Descriptive statistics and group comparisons for participants used in Analysis 2

	Un-exposed	Switched from active trav.		Switched from PT	
n (minimally adjusted Models J & K) [c]	519	156		112	
Characteristic (at t0 unless indicated)	% or mean	% or mean	p [a]	%or mean	p [a]
Age (mean years)	41.2	35.1***	**<0.001**	33.9***	**<0.001**
Male[b]	49.9%	54.5%	0.315	52.7%	0.594
Professional or managerial occupation[b]	34.5%	24.4%*	**0.018**	38.4%	0.433
Full time work[b]	73.0%	71.8%	0.762	77.7%	0.309
Works at night time[b]	1.7%	0.6%	0.322	0.9%	0.518
Household income (mean £s)	31,829	29,842	0.131	33,865	0.421
High income[b]	37.2%	32.1%	0.241	39.3%	0.677
Education: degree or higher qualification[b]	20.4%	13.5%	0.051	19.6%	0.852
One or more children in the household[b]	17.0%	16.0%	0.785	14.3%	0.490
Lives in London or South-East England[b]	20.2%	14.1%	0.086	22.3%	0.620
Health related characteristics:					
BMI (mean kg/m^2)	26.1	26.3	0.634	25.7	0.339
WHO-classified overweight[b]	54.7%	49.4%	0.239	49.1%	0.280
'Poor' or 'very poor' self-assessed health[b]	4.2%	4.5%	0.893	7.1%	0.190
Self-reported smoker[b]	26.6%	27.6%	0.810	27.7%	0.813
More than 3 annual hospital visits[b]	11.2%	7.7%	0.211	15.2%	0.235
More than 6 annual primary care visits[b]	10.4%	10.3%	0.958	6.3%	0.177
Travel related:					
One or more cars in household[b]	73.4%	81.4%*	**0.042**	72.3%	0.813
One or more cars in household (t2) [b c]	74.9%	92.3%***	**<0.001**	91.0%***	**<0.001**
Number of cars in household (mean)	1.0	1.2**	**0.001**	1.0	0.624
Number of cars in household (t2, mean)[c]	1.0	1.5***	**<0.001**	1.4***	**<0.001**
Private transport user in t0-1 & t0-2[b c]	4.6%	22.0%***	**<0.001**	17.8%***	**<0.001**
Commute time (mean minutes)[c]	27.4	13.7***	**<0.001**	42.4***	**<0.001**
Commute time (t2, mean minutes)[c]	28.2	18.0**	**0.002**	29.5	0.115
Other lifestyle related characteristics:					
At least weekly LTPA[b]	64.7%	74.4%*	**0.025**	56.3%	0.091
At least weekly LTPA (t2) [b]	65.5%	65.4%	0.977	65.2%	0.947
At least weekly gardening[b]	20.2%	21.8%	0.672	17.0%	0.430
At least weekly gardening (t2) [b]	20.8%	21.2%	0.926	17.9%	0.481
At least weekly eating out[b]	17.1%	21.2%	0.254	17.9%	0.857
At least weekly eating out (t2) [b]	15.6%	17.9%	0.486	20.5%	0.202

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

[a] The results of Chi-squared tests (or Mann-Whitney tests for number of cars, age, income and commute time, or student's t-tests for BMI), where the null hypothesis was that the difference between the exposed and unexposed group was equal to zero.

[b] Binary variables were created as described in the Methods section. Additionally, binary variables were created for the highest occupational status (professional/managerial=1) compared to all other occupations (=0), the two highest income quintiles (=1) compared to all other income quintiles (=0), resident in London or South East England (=1) compared to all other regions (=0), being classed as overweight or obese (=1) compared to any other weight status (=0), poor or very poor self-assessed health (=1) compared to fair or good self-assessed health (=0), and for three indicators of leisure activities (=1 if undertaken at least once a week, =0 if undertaken less frequently).

[c] Values for some variables were not reported for all individuals included in the minimally adjusted models.

[d] A histogram of BMI (at baseline) is shown in Figures 6-2 and 6-3.

Table 6-4: Associations between change in commute mode and change in body mass index (Analysis 1)

Model characteristics[a]	<------------------------> **Minimally adjusted**		<--> **Maximally adjusted models**						
	<--> **All participants**				<------------------------> **As models C and D, except restricting the exposed group to participants who switched between t0 and t1**		<------------------------------------> **As model D, except restricting analysis to participants with longer commuting times at t0**		
							>10 minutes	**>20 minutes**	**>30 minutes**
Analysis 1: Impact of switching from private motor transport to active travel or public transport									
	Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	**Model G**	**Model H**	**Model I**
Switch from car to public transport or active travel	-0.18 (-0.45 to 0.00)	-0.21 (-0.47 to 0.06)	-0.32* (-0.60 to -0.05)	n/a	-0.33 (-0.76 to 0.09)	n/a	n/a	n/a	n/a
Switch from car to public transport				-0.12 (-0.55 to 0.30)		0.12 (-0.57 to 0.80)	-0.20 (-0.67 to 0.27)	-0.23 (-0.75 to 0.29)	-0.42 (-1.05 to 0.22)
Switch from car to active travel				-0.45** (-0.78 to -0.11)		-0.59* (-1.11 to -0.06)	-0.75** (-1.23 to -0.28)	-1.64*** (-2.35 to -0.94)	-2.25*** (-3.33 to -1.18)
Observations	3269		3253		3144		2244	1289	752

Values tabulated are beta coefficients and 95% confidence intervals. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. [a] See Table 6-1 for details of variables and samples used in each model.

Table 6-5: Associations between change in commute mode and change in body mass index (Analysis 2)

Model characteristics[a]	<------------------------> **Minimally adjusted**		<--> **Maximally adjusted models**						
	<--> **All participants**				<------------------------> **As models L and M, except restricting the exposed group to participants who switched between t0 and t1**		<------------------------------------> **As model M, except restricting analysis to participants with longer commuting times at t0**		
							>10 minutes	**>20 minutes**	**>30 minutes**
Analysis 2: Impact of switching to private motor transport from active travel or public transport									
	Model J	**Model K**	**Model L**	**Model M**	**Model N**	**Model O**	**Model P**	**Model Q**	**Model R**
Switch to car from public transport or active travel	0.34** (0.06 to 0.62)	0.33* (0.04 to 0.62)	0.34* (0.05 to 0.64)	n/a	0.37 (0.00 to 0.75)	n/a	n/a	n/a	n/a
Switch to car from public transport				0.46* (0.06 to 0.86)		0.44 (-0.10 to 0.98)	0.51* (0.06 to 0.96)	0.61* (0.13 to 1.1)	0.35 (-2.22 to 0.93)
Switch to car from active travel				0.26 (-0.09 to 0.62)		0.33 (-0.13 to 0.79)	0.39 (-0.14 to - 0.93)	0.52 (-0.19 to 1.22)	0.52 (-0.53 to 1.58)
Observations	787		785		658		500	342	239

Values tabulated are beta coefficients and 95% confidence intervals. * p<0.05, ** p<0.01, *** p<0.001. [a] See Table 6-1 for details of variables and samples used in each model.

Table 6-6: An assessment of attrition bias and missing values bias

Characteristic (at t0)	Test for missing values (height and weight data) bias (See [a] in **Figure 6-1**)			Test for attrition bias (See [b] in **Figure 6-1**)		
	% or mean		p[b]	% or mean		p[b]
	Participants retained in the sample	Participants excluded from analysis due to missing BMI at t0		Participants retained in the sample	Participants excluded from analysis due to leaving the dataset before t2	
n[a]	7,471	339		6,634	837	
Age (mean years)	39.6	37.2**	**0.001**	35.6	40.1	**<0.001**
Male[c]	50.4	19.8***	**<0.001**	52.1	50.2	0.298
Professional or managerial occupation[c]	39.2	33.9	0.052	37.5	39.4	0.296
Full time work[c]	78.0	66.7***	**<0.001**	79.9	77.8	0.152
Works at night time[c]	2.1	2.9	0.319	2.3	2.1	0.785
Household income (mean £s)	31,126.8	29,021.5*	**0.011**	29,417.9	31,342.4	0.008
Education: Degree or higher qualification[c]	19.2	13.6**	**0.009**	20.0	19.1	0.576
One or more children in the household[c]	19.6	30.7***	**<0.001**	14.1	20.3	**<0.001**
Lives in London or South-East England[c]	13.9	13.3	0.737	16.1	13.6	0.050
BMI (mean kg/m^2)	n/a	n/a	n/a	25.2	26.0	**>0.001**
WHO-classified overweight[c]	n/a	n/a	n/a	47.2	52.9	**0.002**
‘Poor’ or ‘very poor’ self-assessed health[c]	4.8	6.8	0.091	5.0	4.7	0.716
Self-reported smoker[c]	25.9	23.3	0.278	31.7	25.2	**<0.001**
More than 3 annual hospital visits [a c]	11.4	15.1*	**0.039**	10.3	11.6	0.268
More than 6 annual primary care visits [a c]	10.7	13.3	0.130	10.0	10.8	0.510
One or more cars in household[c]	91.2	86.1**	**0.001**	88.1	91.6	**0.001**
Number of cars in household (mean)	1.6	1.5	0.122	1.5	1.6	0.005
Commute time (mean minutes)[a]	23.8	20.4**	**0.002**	24.8	23.7	0.031
At least weekly LTPA [a c]	59.0	52.8*	**0.023**	58.5	59.1	0.735
At least weekly gardening [a c]	22.4	16.8*	**0.015**	15.1	23.3	<0.001
At least weekly eating out [a c]	18.3	15.3	**0.172**	21.3	17.9	0.016

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

[a] Sample sizes used in a small number of cases was less than shown since values were not reported for some variables for all individuals.

[b] The results of Chi-squared tests (or Mann-Whitney tests for number of cars, age, income and commute time, or student’s t-tests for BMI), where the null hypothesis was that the difference between the two groups was equal to zero.

[c] Binary variables were created as described in Table 6-2.

Figure 6-1: Samples used in the analyses and description of sample selection criteria

Sample selection criteria	n
Full sample of participants in BHPS at t0	15,791
↓	
Participants aged over 18 years at t0	15,176
↓	
Participants reporting necessary work characteristics at t0	9,136
↓	
Participants reporting necessary socioeconomic and health-related variables at t0 (occupational status, household income, education, children, health status, car access)	8,442
↓	
Participants reporting usual main mode of travel to work at t0	7,921
↓	
Participants reporting usual main mode of travel mode to work other than 'Other' at t0	7,810
↓a	
Participants reporting height and weight (to derive BMI) at t0	7,471
↓b	
Participants remaining in BHPS until t2	6,634
↓	
Participants reporting travel mode other than 'Other' at t2	5,882
↓	
Participants reporting height and weight (to derive BMI) at t2	4,800
↓	
Excluding participants with implausible height and weight data	4,786

Private motor transport at t0	n=3,787	Active travel or public transport at t0	n=999
↓		↓	
Analysis 1		**Analysis 2**	

Analysis 1				Analysis 2			
Same private motor mode at t0, t1, t2 (n=3090)	Switched to active travel or public transport (n=179)		n=3,269	Same active travel or public transport mode at t0, t1, t2 (n=519)	Switched to private motorised transport (n=268)		n=787
	To active travel (n=109)[c]	To public transport (n=70)[d]			From active travel (n=156)[c]	From public transport (n=112)[d]	

Sample size used in the analyses=4,056

Key:

[a] To assess missing variables bias (height and weight data), characteristics of individuals who reported travel mode other than 'other' at t0 but not height and weight at t0 are compared with individuals who remained in the sample (see Table 6-6)

[b] To assess attrition bias, characteristics of individuals who reported height and weight at t0 but had dropped out of the sample before t2 are compared with individuals who remained in the sample (see Table 6-6)

[c] Of whom 10 had a commute time of >30 min at t0, 42 switched between t0 and t1, and the most common travel mode switched to was walking (n=83)

[d] Of whom 32 had a commute time of >30 min at t0, 26 switched between t0 and t1, and the most common travel mode switched to was rail travel (n=32)

[e] Of whom 10 had a commute time of >30 min at t0, 84 switched between t0 and t1, and the most common travel mode switched from was walking (n=121)

[f] Of whom 59 had a commute time of >30 min at t0, 56 switched between t0 and t1, and the most common travel mode switched from was bus/coach travel (n=73)

Figure 6-2: Distribution of BMI at baseline (t0), N=4,056

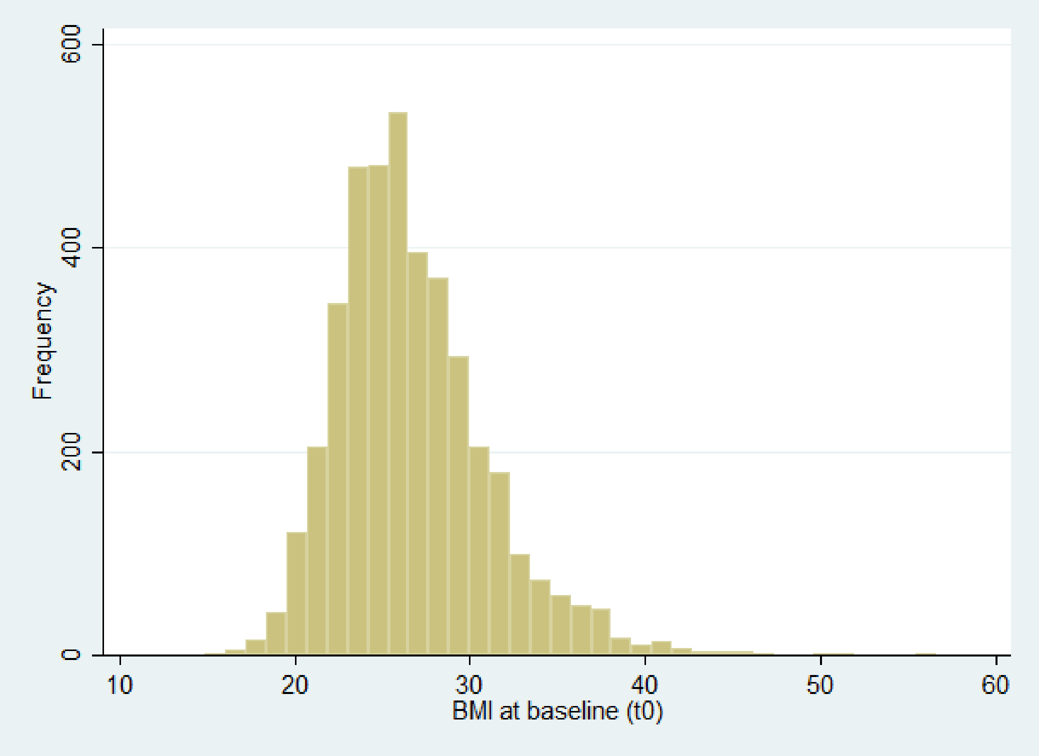
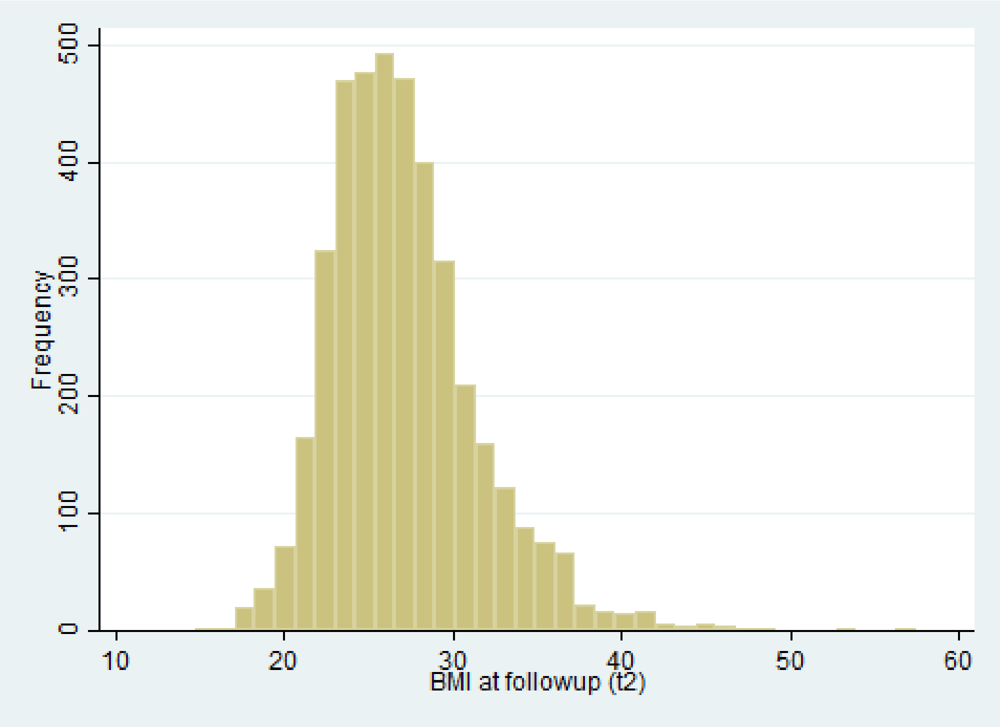


Figure 6-3: Distribution of BMI at followup (t2), N=4,056



SECTION D: EXPLORING THE ROLE OF FINANCIAL INCENTIVES IN PROMOTING ACTIVE TRAVEL

7 Development of an economic framework to explore active travel decisions

7.1 Overview of chapter

In this chapter a simple analytical framework is developed for assessing the utility-maximising behaviour of commuters in terms of their travel mode choices. The starting point is the SLOTH model which was developed in a 2004 paper by Cawley et al. to provide insights into how individuals allocate their scarce resources of time and money in relation to physical activity and diet. The main rationale for developing the framework in this chapter was to provide a broad picture of how people might respond to financial incentives for active travel (the second of four proposed policy interventions listed in Table 1-1. In particular, and in contrast to the argument put forward by Cawley et al., this chapter makes a case that financial incentives to encourage active travel could be more effective at increasing physical activity than financial incentives to encourage active leisure pursuits (e.g. going to the gym or taking up swimming). Briefly, this is because the opportunity costs of active commuting are likely to be lower than the opportunity cost of active leisure pursuits. Thus the framework developed in this chapter provides a theoretical basis for the literature search for empirical evidence on financial incentives which follows in Chapter 8,

Like Cawley et al., and other similar models introduced in this chapter from the health behaviour and transport modelling literatures, the framework is based on the standard assumptions of the expected utility hypothesis with little consideration of the potential importance of concepts from behavioural economics or psychology (see section 1.3.1). Hence this chapter also includes an overview of how these concepts might impact on people's responses to financial incentives in the transport sector. Whilst it is argued that there is a shortage of empirical evidence in the transportation field to demonstrate that the basic assumptions of the expected utility theory are fundamentally flawed, it nonetheless seems probable that simple models based on the assumptions of the expected utility theory are unlikely to provide a full picture of people's behaviour.

7.2 Background

Economic models of behaviour typically incorporate the standard utility-maximisation model outlined in section 1.3.2.(381) For any particular consumption decision it is expected that individuals will weigh up the perceived costs and benefits of different options in order to maximise their own individual utility within a budget constraint which is typically defined in terms of time and/or income. A recent review of studies concluded that there was a shortage of economic modelling of physical activity behaviour.(381) Of thirty-two studies included in the review, the author categorised the identified economic models as follows: leisure-consumption (n=10), health behaviour (n=9), allocation of time (n=5), labour supply (n=3), household production (n=3), and physical activity (n=2). No study identified in the review had a specific focus on active travel or active commuting behaviour.

The economic framework developed in this chapter draws on key aspects of three existing economic models of health behaviours and applies them to the specific context of active commuting. First, an economic framework of human behaviour which was presented in a 2004 paper by the Cawley et al. This study may be categorised as an 'allocation of time' model and sought to provide insights into how individuals allocate their scarce resources of time and money in relation to physical activity and nutrition decisions in five separate domains: Sleep, Leisure, Occupation, Transport and Home (or SLOTH)-based activities. Second, a dynamic theory of body weight which may be categorised as a 'health behaviour' model and was developed in a paper first published in 2002 by Lakdawalla and Philipson.(382) The authors hypothesised that technological change in recent decades has simultaneously increased the cost of physical activity (via growing opportunity costs of physical activity) and decreased the cost of calorie consumption (via reduced food prices).(382) Empirical evidence relating to long-term trends in obesity, diet and physical activity behaviours were also presented alongside both models to support the view that the increased prevalence of obesity and overweight in recent decades should be attributed to the rational response of utility-maximising individuals to technological change.(75, 383)

A summary of the likely impact on individual-level utility maximising behaviour of technological change is developed in Table 7-1 for each of the five domains of the SLOTH model in terms of energy expenditure and energy intake. For example, technological innovation in agriculture, food production and retail has contributed to reduced costs (including time costs) of energy-dense meals in the home and leisure domains, while working environments in the occupation domains have typically become more office-based and sedentary.(75, 384) In the context of the urban built environment characteristics identified in the review of studies presented in Chapter 2, the costs (including time costs) of active travel (including commuting) may be relatively high in suburban areas, for example, where cul-de-sac housing developments are common, compared to densely populate urban areas where distances between home, leisure and work activities are shorter. At least in the US, features of suburban areas including fewer footpaths, cycle routes and public transport facilities, as well as less road traffic congestion, may reinforce this price differential. However, the high physical activity costs in suburban areas may contrast with the relatively low cost of accessing healthy foods, which are more readily accessible in larger out-of-town supermarkets(192) than in some deprived inner city areas which have even been described as 'food deserts' due to the perceived high costs of accessing affordable fresh fruit or vegetables.(385)

In the third model, Yaniv et al. explored the impact on individual-level obesity of policy interventions in the form of a junk-food tax and a subsidy for healthy cooking ingredients.(386) To demonstrate that the impact of these policies may vary between individuals, with some unintended consequences, the authors distinguished between (i.) non-weight conscious individuals who do not take into account the negative impact of obesity on their own health, (ii.) weight-conscious individuals, who are physically active, and (iii.) weight-conscious individuals who are physically inactive. For example, they conclude that for weight-conscious individuals who are physically active, a junk food tax would likely lead to a higher likelihood of obesity. This was because people were expected to substitute eating junk-food with more cooking of healthy ingredients at home but, being more time consuming, this left less time for physical activity.

7.3 Development of the framework

This section presents the framework, first by drawing on aspects of Cawley's SLOTH time-budget model,(383, 387, 388) and second by incorporating elements of Lakdawalla-Philipson's utility maximisation model.(382) A number of simplifying assumptions are made and these are presented in Table 7-2. The main implications of the model in relation to active travel decisions and a financial incentive are then explored in section 7.4, drawing on the approach used in the model by Yaniv et al.

7.3.1 Resource constraints (income, Y, and time, Z)

Individuals are subject to:

- a time constraint (Z hours in the current period) such that time is allocated to **S**leep, **L**eisure, w**O**rk, **T**ravel or **H**ome (SLOTH) activities and, within those domains, to sedentary or physically active behaviours:

$$\mathbf{S} + \mathbf{L} + \mathbf{O} + \mathbf{T} + \mathbf{H} = \mathbf{S}\mathrm{s} + \mathbf{L}\mathrm{s} + \mathbf{L}\mathrm{p} + \mathbf{O}\mathrm{s} + \mathbf{O}\mathrm{p} + \mathbf{T}\mathrm{s} + \mathbf{T}\mathrm{p} + \mathbf{H}\mathrm{s} + \mathbf{H}\mathrm{p} = \mathrm{Z}$$

Equation 7-1

[bold letters indicate time allocated to domain-based activities; lower-case s stands for sedentary activity; p stands for physically active behaviours]

- an income constraint such that expenditure ($ per unit of time) on leisure ($L, e.g. cost of a swimming ticket), transport ($T, e.g. cost of a rail ticket) and home ($H, e.g. cost of cooking ingredients) cannot exceed income (Y):

$$\$L + \$T + \$H = Y$$

Equation 7-2

Income (Y) is determined by time allocated to work and the wage rate (w, $ per unit of time):

$$Y = \mathbf{O} \times w$$

Equation 7-3

7.3.2 Utility maximisation

An individual's current period utility depends on consumption of Sleep, Leisure, Home and Transport activities (**S, L, T** and **H**), weight in the current period (W) and their own valuation of their expected weight in the next period (βv (W')):

$$U(W) = U(S, L(\$L, mL), T(\$T), H(\$H), W) + \beta v\,(W')$$

[U=utility; mL=distance (miles) travelled to leisure activity; $L/$H=leisure or home-based expenditure; W=current weight; W'=expected weight in next period; βv=discounted value of future weight]

Equation 7-4

$$W' = (1 - \delta)W + g(E, F)$$

[δ <1; g is continuous, concave, increasing in food consumption (F) and decreasing in energy expenditure (E)](382)

Equation 7-5

Utility increases or decreases in weight, depending on whether the individual is above or below their (own notion of) “ideal weight” (W_0). They prefer weight gain when below W_0 and weight loss when above W_0. Future weight (W’) is influenced by current period choices about physical activity and food consumption (E and F). Energy expenditure (E) increases with domain-based physical activity (e.g. **L**p) and is treated as a ratio of time allocated to physical relative to sedentary activities:

$$E = \frac{(\mathbf{L}p + \mathbf{O}p + \mathbf{T}p + \mathbf{H}p)}{(\mathbf{S}s + \mathbf{L}s + \mathbf{O}s + \mathbf{T}s + \mathbf{H}s)}$$

Equation 7-6

Standard economic assumptions state that utility rises with consumption of **S, L** and **H** at diminishing marginal rates and, for given **L** and **H**, increases with expenditure ($H and $L). Distance from home to any specific work (mO) or leisure (mL) activity (e.g. a person’s own workplace, or their preferred gym) is fixed, since individuals cannot influence the locations of those destinations in the short term. All else equal, people seek to minimise travel distances, but will choose to travel further (higher mL) to access particular leisure activities which offer higher marginal utility than those available locally or at home (e.g. a leisure park is only chosen over gardening if it provides higher utility). In the same way, individuals will only choose to spend more money on an activity (e.g. swimming) if it provides higher marginal utility than cheaper alternatives (e.g. gardening).

Choices about **S, L** and **H** are determined by the ‘last hour’ and ‘last dollar’ rules which state that if the last hour or dollar invested in one activity (e.g. swimming) provides greater utility than the last unit invested in another (e.g. home cooking), then each day individuals will reallocate resources in favour of activities that deliver higher returns (i.e. all else equal, reduce home cooking [d**H** < 0] and increase swimming [d**L**p > 0]).(387)

This implies that energy expenditure (E) increases only if the utility associated with additional investment in some physical activity (e.g. swimming, Lp) rises. Budget constraints mean that the investment necessary for overweight individuals to achieve their ideal weight (W_0) must compete with other (i.e. sedentary) activities that offer higher utility. This suggests that financial incentives ought to be targeted at activities where the opportunity cost of physical activity is the lowest.

People choose resource allocations that maximise their utility (U) subject to resource constraints (Y and Z) such that the opportunity cost of time allocated to Leisure (**L**), which increases utility directly, are:

- Sleep (**S**) and Home (**H**) activities which increase utility directly

- Work (**O**), which does not affect utility directly, but provides income (Y) for expenditure in other domains ($L, $T, $H)

- Travel (**T**), which increases with distance (mO, mL) travelled to Work and Leisure facilities, decreases with speed, and typically provides modest utility (e.g. car drivers may enjoy their in-car entertainment systems, while cyclists may enjoy being outside), or even disutility (e.g. the frustration arising from unpredictable traffic queues).

7.4 The impact of financial incentives

Financial incentives are interpreted as increasing or decreasing the cost of any given activity. Sufficient reduction in the price of swimming (d$Lp < 0), for example, alters the utility-maximising allocation of resources for some individuals and encourages more swimming.

However, the impact in terms of overall energy expenditure (E) is complex and unpredictable unless more information about personal preferences (including their valuation of future weight βv (W')) and willingness to trade one activity for another is taken into account.

Consider just two different types of people proposed in the model by Yaniv et al.(386) First, the financial incentive might encourage non-swimmers ('non health-conscious people') to start swimming at the expense of sedentary leisure activities (a 'substitution effect'). But second, the financial incentive simply increases the income (Y) of existing swimmers ('health conscious people' who place a high value on βv (W')). If they also cycle to work, they might be inclined to respond by increasing travel expenditure ($T) in order to get to work faster by switching to sedentary travel modes (the 'income effect'). Although both types of people have benefited from the financial incentive (in terms of overall utility), energy expenditure (E) only increases in the first case. In the second, it might fall. These alternative scenarios are explored in **Table 7-3**.

Although their impact seems ambiguous, financial incentives may be most useful for encouraging physical activity in 'non health-conscious people' since (for them) the opportunity cost of additional physical activity is always sedentary activity (so E unambiguously increases). Of course this assumes they are actually persuaded to forgo their sedentary activities. So the remaining question is how large does the incentive need to be?

A financial incentive for active leisure (d$Lp) requires a payment that offsets the difference between utility losses from sedentary activities (e.g. watching less television, d**L**s<0) and utility gains arising from more physical activity (e.g. more swimming, d**L**p>0):

$$\mathrm{d\$Lp} > \left[\frac{\mathrm{dU}}{\mathrm{d}\mathbf{L}\mathrm{s}}\ \mathrm{d}\mathbf{L}\mathrm{s} \quad + \quad \frac{\mathrm{dU}}{\mathrm{d}\mathbf{L}\mathrm{p}}\ \mathrm{d}\mathbf{L}\mathrm{p}\right]$$

Equation 7-7

Consider 'non health-conscious' people who may place little value on their future weight (βv (W')) and may gain very little direct utility from active leisure (e.g. swimming). The incentive payment (d\$Lp) must reimburse forgone sedentary leisure activities (e.g. watching television, **L**s) which are of greater value than an equal allocation of time to active leisure (e.g. swimming, **L**p). According to the 'last hour rule', the opportunity cost of sedentary leisure activities is equal to utility associated with any other activity, including work. In order to change behaviour, the incentive might need to be relatively large, perhaps equivalent to the amount they are paid at work (i.e. the wage rate per unit of time, \$O).

In contrast, an active travel financial incentive requires a payment that reimburses the difference in an individual's valuation of forgone sedentary travel (d**T**s < 0) and new active travel (d**T**p > 0):

$$\mathrm{d\$Tp} > \left[\frac{\mathrm{dU}}{\mathrm{d}\mathbf{T}\mathrm{s}} \; \mathrm{d}\mathbf{T}\mathrm{s} \quad + \quad \frac{\mathrm{dU}}{\mathrm{d}\mathbf{T}\mathrm{p}} \; \mathrm{d}\mathbf{T}\mathrm{p} \right]$$

Equation 7-8

This active travel incentive could be much smaller than the active leisure incentive (d\$Tp < d\$Lp) in some cases. First, consider a 'non health-conscious' individual who works reasonably near home so that active travel is viable in terms of distance, but who currently always drives. Noting that their drive to work provides minimal utility directly (compared to sedentary leisure) but access to work facilities, the opportunity cost of sedentary travel is relatively small since active travel also allows them equal accessibility. In this framework, the only losses arise if sedentary modes are slower, so that the time taken to travel increases (d**T** > 0) resulting in forgone **O, L** and **H**, or are less comfortable (although this may be negligible for short urban journeys). Individuals may also save money if active travel is cheaper than sedentary travel (\$Ts **-** \$Tp). Second, even if the financial incentive does not increase the energy expenditure in 'health conscious people' who are already very active in their leisure time, these individuals would gain utility if they substitute active travel for active leisure and use the additional time and income to enjoy more expensive (sedentary) leisure activities.

7.5 Discussion

This section begins with discussion of the general (and modest) insights about financial incentives to promote active travel that can be drawn from the framework. It goes on to highlight some concepts from literature in behavioural economics and psychology which would also need to be considered when designing interventions that incorporate financial incentives.

7.5.1 Implications of the framework on the case for financial incentives to promote active travel

This chapter presented a simple rational-choice framework which can be used to draw some broad insights into people's likely behavioural responses to financial incentives. Two conclusions about people's probable response to financial incentives that promote active travel may be drawn. These insights are in some contrast to existing SLOTH-based analyses, including the initial model developed by Cawley et al., which suggest that "leisure becomes the most likely area for increasing physical activity"(383) because (for simplicity) the trade-offs associated with leisure and travel decisions had been treated as though they were identical.

Firstly, the framework suggests that individuals are likely to be at least as responsive to financial incentives for active travel as those for active leisure. This is a view reflected in an earlier analysis of the BHPS which showed that active leisure "comes and goes" whereas "exercise as part of travel and work must be emphasised."(323)

Secondly, active travel allows people to access work and leisure activities but, unlike sedentary travel, is also 'productive' in the sense of enabling energy expenditure. Yet established methods for transport appraisal place large monetary values on travel time savings to justify investment in transport infrastructure on the basis that (for travel in work hours) savings in travel time convert non-productive time to productive use.(111, 389, 390) In contrast to car travel, others have argued that this overlooks the potential to use rail travel productively for work activities.(391, 392) Similarly, these methods probably favour faster sedentary travel (private motorised transport and public transport) over active travel, despite active travel being suitable for most journeys.(393) These methods may also have encouraged decline in the availability of local services that are particularly accessible by active travel. In the UK, where travel time savings have accounted for around 80% of the claimed monetary benefits of major road schemes, the average time that people spend travelling has remained constant since the 1960s.(394) This suggests that motorway expansion has encouraged long distance travel for access to work and leisure opportunities much further from home. People who choose active travel may then experience mobility-related social exclusion,(391) whereby they are disadvantaged in terms of access to services.

7.5.2 Possible implications of behavioural economics on the design of financial incentives to promote active travel

In its current form, like the original SLOTH model, the framework reflects only the standard, rational behaviour assumptions of classical economics and the expected utility hypothesis that were outlined in section 1.3.2. These assumptions typically remain the core foundations of existing health behaviour and transportation models and are valued, in part, because of their inherent simplicity and potential for drawing broad, general lessons about human behaviour. Thus this chapter has not sought to provide a detailed characterisation of how individuals might respond to different types of financial incentives within the domain of active travel. Rather it has used the simple economic model to provide a basic theoretical argument which supports the idea of financial incentives to promote active travel in general, when compared to financial incentives for active leisure pursuits, for example. Nevertheless, such models ought not to be viewed in isolation of insights which can be drawn from the behavioural economics or psychology literature on the particular circumstances in which people may deviate from the standard assumptions of 'rational behaviour.'(57, 59) Such insights are likely to play an important role in terms of the optimal design of financial incentive schemes, for example in terms of the best pricing strategy in terms of maximising revenue or minimising congestion. Hence the remainder of this chapter aims to provide an overview of key concepts in behavioural economics and, where possible using empirical evidence, discusses how these concepts might influence the way in which people respond to financial incentives in the transport sector.

Behavioural economics may be defined as seeking to "increase the exploratory and predictive power of economic theory by providing it with more psychologically plausible foundations."(57) There is no single, universally accepted taxonomy of all behavioural economics concepts since they have emerged over time from a range of different sources on the basis of theoretical as well as empirical work. Furthermore, some concepts will be applicable only in particular settings. However, in a recent review by Metcalfe and Dolan (2012) of the implications of behavioural economics on transport,(59)the MINDSPACE framework was emphasised. MINDSPACE is an acronym for 'Messenger', 'Incentives', 'Norms', 'Defaults', 'Salience', 'Priming', 'Affect', 'Commitment' and 'Ego' and was developed by the UK's Cabinet Office as a way of capturing key contextual factors that impact on behaviour. These nine factors are summarised in Table 7-4.

Under the 'Incentives' heading of the MINDSPACE framework ("our responses to incentives are shaped by predictable mental shortcuts such as strongly avoiding losses"), the review by Metcalfe and Dolan (2012) particularly emphasised Kahneman and Tversky's 'Prospect Theory' (see section 1.3.1) which provides a theoretical basis for ideas such as 'people dislike losses,' 'they focus on changes' and 'overweight small chances' (see Table 7-4 for a full list).(60) The notion that people dislike losses when compared to gains (i.e. they are risk averse) is well documented in transportation literature on congestion charging, at least in terms of evidence from a number of stated preference choice experiments (which are not reviewed by Metcalfe and Dolan (2012)). De Borger et al. (2008), for example, conducted a large choice experiment in which participants were presented with simple trade-offs related to losses or gains in travel time or costs and concluded that losses were valued at approximately four times an equivalent gain.(395) Similarly, a stated preference survey of commuters by Leblanc and Walker (2013) explored the impact on behaviour of various financial incentive schemes in the forms of charges (i.e. negative financial incentives) and rewards (i.e. positive financial incentives in the form of cash, credit towards Apple Store, donations, lottery, or rewards such as guaranteed parking, free coffee or privileged status). Consistent with the expectation that people value losses more than gains, they concluded that commuters were more sensitive to congestion charging than they were to the positive financial incentives.(396) In another study by, Lindsey (2012) explored the optimal design of a congestion charge. From the perspective of a standard neoclassical economic model, it was argued that it would be optimal to have constantly varying charges based on the level of road congestion at a particular time. However, despite the increasing feasibility of this approach from a technological perspective, it was argued that this option is rarely chosen by policy makers because the impact on behaviour of uncertainty about price, and the potential for large monetary charges for travel at peak times, would be larger than that expected in standard economic models. Furthermore, the study showed that, owing to established views of what a reasonable road charge should be (i.e. a reference point), people's 'focus on changes' would make them responsive even to the smallest price variations. Hence policy makers would risk losing revenue if highly differentiated congestion charges were implemented.(397) The idea that uncertainty about price could have be a significant influence on behaviour is supported by a further stated preference study by Link et al (2015) which looked at the response of car drivers to a (hypothetical) variable congestion charge. The study concluded that people likely avoid travel options when the price is not known in advance (a phenomenon they called 'ambiguity avoidance').(398)

In addition to 'Incentives,' other aspects of the MINDSPACE framework may also have implications for financial incentives in transportation. In the case of 'Salience,' whereby behaviour is greatly influenced by what our attention is drawn to, a seminal experimental study by Chetty et al. (2009) compared the purchasing behaviour of shoppers in a US grocery shop where product labels reported the tax-inclusive price with control products or nearby control stores where the (same) tax was instead only added at the checkout.(399) During the course of a three week experiment, which involved 750 products, an 8% fall in sales was observed in the intervention shops. Three further studies from the transportation literature (which are not reviewed by Metcalfe and Dolan (2012)) reported similar findings supporting the idea that people may be more responsive to salient information. First, in a theoretical model, Michael and Zhao (2015) argued that acceptability of charges in transportation (e.g. car ownership charges, fuel tax and parking fees) decreases in salience. Hence it seems that by making taxes less obvious, Governments could generate more revenue (for investment transportation infrastructure, for example).(400) Second, in a well-publicised paper by Larrick and Soll (2008), a choice experiment found that the proportion of undergraduates who picked more fuel efficient cars increased if fuel efficiency ratings were reported in gallons per mile (GPM) rather than miles per gallon (MPG). This was because most people thought (incorrectly) that there was a linear relationship between improvements in MPG ratings and reductions in fuel consumption.(401) Third, Finkelstein (2007) found that road toll charges were 20%-40% higher than they otherwise would have been after revenue collection systems were upgraded from manual, where drivers pay in cash at checkpoints (salient), to electronic, where car drivers are charged automatically (less salient).(402) A further example of salience in the transportation sector is that people might be inclined to choose driving over other transport modes because the high sunk (i.e. retrospective and non-recoverable) costs they incurred when buying a car remain prominent in their thinking for some time. Furthermore, like rail commuters with annual season tickets,(403) they find additional journeys incur low marginal costs. Though the evidence is limited, 'car clubs', in which car drivers hire cars for short periods rather than owning them outright, are reported to have reduced car mileage (by 33% in the Netherlands),(404) increased cycling,(405) and reduced motor vehicle ownership.(406) Bicycle hire schemes might have a similar impact in the sense that car drivers are not deterred by the monetary and other costs (e.g. those arising from unfamiliarity) of bike purchase. Also in the Netherlands, a before-and-after study has attributed reductions in car use and increases in cycling to such schemes.(407) Public transport 'clubs', which encourage passengers to consider marginal (rather than average) costs by making a large upfront payment for future discounted public transport tickets, have also encouraged higher tram and bus use in some Swiss cities,(408) although any association with fewer car journeys is unknown.

Beyond the concepts emphasised in the MINDSPACE framework, a further feature of the behavioural economics approach emphasised by some authors is the contrast between the 'reflective' and the 'automatic' systems of thinking.(68) The 'reflective system' has limited capacity, but offers more systematic and deeper analysis which is more likely to take into account all the costs and benefits of individual decisions as would be expected in expected utility theory. In contrast, the 'automatic system' processes many things at the same time and often unconsciously. The 'automatic system' is more likely to be associated with 'irrational' behaviour and 'short-cuts.'

Finally, another theory that features strongly in existing psychological research on travel behaviour is Ajzen's Theory of Planned Behaviour (TPB).(57, 409) The TPB says that 'intentions' (i.e. the readiness to perform certain tasks) are the best predictor of an individual's behaviour. These 'intentions' are determined by a 'deliberative system,' which assesses options with a broad, goal-based perspective, and an 'affective system' that encompasses emotions and motivational drives.(410) The 'deliberative system' consists of attitudes, subjective norms and perceived behavioural control. In this view, a financial incentive to encourage active commuting might be considered more likely to be effective if, for example, the individual has a favourable view towards cycling (attitude) and if they believe that people around them think they should take-up cycling (subjective norm). In a randomised experimental study by Thøgersen (2009), the TPB is used as a framework in empirical testing of the impact of financial incentives on commuting behaviour. The experiment involved one-thousand car drivers in the Copenhagen area and was designed to test whether or not a free, six-month travel pass could entice habitual car drivers to switch to public transport.(411) The price promotion led to a doubling of public transport use in the intervention group during the six-month period, and a positive effect even after the free pass had been withdrawn. Using the responses of commuters to questions about the factors that influenced their decisions, the authors concluded that the effect had disrupted people's 'automatic' decision making processes in a way that encouraged them to go beyond their habitual behaviour and think more about their travel mode choices and/or reassess their 'attitude' towards public transport by giving it a go. However, whilst attitudes and beliefs are an important part of behavioural economics, some authors have argued that the TPB cannot really be described as a behavioural economics theory since at its core is idea that people behave 'rationally' (in the sense that they use high level cognitive processes to make choices that could be described as planned and consistent).(57) In contrast, they argue that the behavioural economics concepts summarised in the MINDSPACE report lie in the gap between 'intentions' and actual observed behaviour.(59)

7.6 Conclusion

This chapter began with a modest expansion of a simple economic framework originally devised by Cawley et al. for analysing how people allocate their scarce resources of time and money. The framework enabled some general comparisons to be made between financial incentives for active travel and financial incentives for active leisure pursuits. It was concluded that the former may have a more promising role in promoting physical activity than was acknowledged in the original paper by Cawley et al.

Whilst economic frameworks of this kind may be used to draw broad insights into the likely impact of behaviour change interventions, the overview of concepts from behavioural economics and psychology reported in section 7.5.2. showed that, as in other sectors of the economy, people's choices in relation to transportation are likely to be influenced by numerous factors which go beyond the standard assumptions of the expected utility hypothesis. However, despite a number of studies in the transportation sector, there was a notable lack of empirical evidence on the impact of behavioural economic concepts on people's responses to financial incentives in the domain of active travel. So it remains debateable as to which of the insights from non-transport contexts (e.g. Chetty's study of US grocery stores) or other travel modes (e.g. studies of road tolls) are directly transferrable to the active travel context. Furthermore, an ongoing challenge in economics is the extent to which these behavioural economic concepts can or should be incorporated into more traditional economic models since, in doing so, the original value of the models in terms of their simplicity and generalisability would probably be lost. Some leading proponents of behavioural economics have argued that, in order to prevent them becoming arbitrary and unwieldy, just one or two behavioural economics concepts should be introduced at any one time. For example, Richard Thaler argued that trying to unify every psychological idea into a single model maybe pointless.(412)

Future research could focus on examining the impact of particular behavioural economic concept (e.g. the idea that people value losses more than gains) on financial incentives to promote active travel. Some of the studies identified in this chapter from elsewhere in transportation sector indicate that they could play an important role in explaining people's choices. Such research could therefore play a valuable role in the design of financial incentive schemes to promote active travel in the future

Table 7-1: Impact of technological progress on the costs of energy intake and expenditure

Activity domain	**Costs of energy expenditure**		**Costs of energy intake**
	Increasing opportunity costs of energy expenditure	**Increasing monetary costs of energy expenditure**	**Decreasing costs of food consumption**
Sleep	N/A (The time spent sleeping has remained broadly constant)		
Leisure	Greater opportunity for sedentary leisure activities (e.g., television, computers, and the Internet)	Greater availability of active leisure facilities away from home that incur a financial cost (e.g., leisure centres, swimming pools, and gyms)	Increased availability of restaurants (including fast-food)
Occupation	Greater availability of, and higher wages associated with, sedentary work	The change from an agricultural or industrial society means that, in a sense, people are no longer paid to exercise at work	Greater availability of mass-produced, energy-dense, packaged, snack foods which can be consumed "on the go" (and are often heavily marketed, perhaps appealing to a lack of self-control and hyperbolic discounting which apparently characterises food consumption)
Transportation	Availability of motorized transport and investment in road networks has provided greater opportunities for faster and longer-distance journeys which are not well suited to active travel modes	N/A	Expansion of "Drive-Thru" takeaway services which allow consumption of fast-food while travelling
Home	Modern technology (e.g., gardening tools and kitchen appliances) allows household chores to be done more quickly with less physical effort	N/A	Transfer of labour-intensive food preparation to intensive farming, supermarkets, and factories, has dramatically reduced the costs (including time costs) associated with food preparation at home. The availability and quality of kitchen appliances such as microwaves, refrigerators, and freezers also have improved.

Table 7-2: Summary of simplifying assumptions used in the economic framework

Domain	Time allocated to domain (in the short term)	Physical activity (in the short term)	Rationale and other assumptions
Sleep	Variable	Fixed– None	Hours of sleep are not affected by changes in other (time, money) resource allocations or physical activity.
Leisure	Variable	Variable	
Occupation	Fixed	Fixed	At least in the short-term, job, wage, working hours, and work and home locations (and therefore distance traveled) are fixed (although in the longer term, people make choices about their job and work hours as with any other decision in the economic framework). Wages cannot be saved in one period for spending in another period
Transport	Variable (in terms of speed and therefore time), but distance travelled (mO and mL) is fixed for given activities	Variable	Distance travelled to leisure activities is determined by the quality of local facilities (which are fixed, at least in the short-term). The time and expenditure investment required to travel a given distance varies by travel mode (sedentary travel is likely to be more expensive and, in many cases, faster). Time allocated to active travel has a similar impact on energy expenditure and weight as time allocated to active leisure
Home	Fixed	Variable	

Note: In the long-term, all domains are variable (e.g., people can move home and change their working hours; and better leisure facilities might open locally), but for the purposes of analysing the impact of financial incentives for active travel and active leisure, the economic rational-choice framework described in the Appendix makes the simplifying assumptions shown in the table. mO and mL=distance from home to any specific work (mO) or leisure (mL) activity (e.g., a person’s own workplace, or their preferred gym).

Table 7-3: Description of how the actual impact of financial incentives may deviate from the expected or desired impact

Financial incentive policy to promote:		**(1) Active leisure**	**(2) Active travel**	**(3) Healthy eating (an example from Yaniv et al.(386))**
Example		Free swimming lessons	Free bikes	Thin subsidy
Desired impact	On relative prices	Reduction in relative price of physical leisure activities (d$Lp < 0)	Reduction in relative price of active travel (d$Tp < 0)	Reduction in relative price of healthy food
	On utility max position	U(last hour of active leisure) > U(last hour of other activities)	U(last hour of active travel) > U(last hour of other activities)	U(last hour of home cooking) > U(last hour of other activities)
	On W’	Increase in energy expenditure (E) and decrease in W’	Increase in energy expenditure (E) and decrease in W’	Decrease in food consumption (F) and decrease in W’
Example of actual impact on behaviour of ‘health-conscious people’ (i.e. people with low fast-food food consumption/high exercise consumption)	Income effect	If swim already, then more income to spend on other activities (perhaps sedentary, e.g. Ts) Decrease in E	If cycle (to work or leisure) already, then more income to spend on other activities (perhaps sedentary, e.g. Ls) Decrease in E	If home cook already, then more income to spend on other activities (perhaps sedentary, e.g. Ls) Decrease in E
	Substitution effect	If swim already, then may swim more often at the expense of other sedentary or physical activities No change or an increase in E	If cycle already, then may increase length of existing journeys at the expense of other sedentary travel or other activities No change or an increase in E	May cook more healthy food, which is time consuming and sedentary, at the expense of other physical activities Decrease in E and F
Example of actual impact on behaviour of ‘non health-conscious people’ (i.e. high junk food consumption/low energy expenditure)	Income	N/A	N/A	N/A
	Substitution effect	If not a swimmer, then may swim more often at the expense of other sedentary leisure activities Increase in E	If not a cyclist, then may cycle more often at the expense of other sedentary travel Increase in E	If not a cook, then may eat more healthy food instead of junk food, using time at the expense of other sedentary activities Decrease in F
Empirical Evidence		Limited (See Fordham et al.)(413)	See Chapter 8	More widely studied

Table 7-4: Key concepts in behavioural economics

(i.) Contextual factors that impact on behaviour - MINDSPACE

M	**M**essenger: We are heavily influenced by who communicates information
I	**I**ncentives: Our responses to incentives are shaped by predictable mental shortcuts such as strongly avoiding losses
N	**N**orms: We are strongly influenced by what others do
D	**D**efaults: We "go with the flow" of pre-set options
S	**S**alience: Our attention is drawn to what is novel and seems relevant to us
P	**P**riming: Our acts are often influenced by sub-conscious cues
A	**A**ffect: Our emotional associations can powerfully shape our actions
C	**C**ommitments: We seek to be consistent with our public promises, and reciprocate acts
E	**E**go: We act in ways that make us feel better about ourselves

Source: Dolan et al(68)

(ii.) The main effects of incentives on behaviours

We find that people:
(1.) Really dislike losses
(2.) Focus on changes
(3.) Overweight small chances
(4.) Think in discrete bundles
(5.) Value right now very highly and inconsistently
(6.) Care about other people
(7.) Can be negatively impacted by incentives

Source: Metcalfe and Dolan (59)

8 Financial incentives to promote active travel: a literature review

8.1 Overview of chapter

This chapter presents a literature review of financial incentives to encourage physical activity through active travel and influence related health outcomes. Financial incentives were the second of four policy interventions proposed in the Introduction (Table 1-1).

The rationale for the literature review is, first, that the simple framework developed in Chapter 7 suggested that financial incentives could play an important role in health and transportation behaviour change and, second, that existing reviews of financial incentives to promote active travel are limited. The review also seeks to identify any evidence which addresses the question about whether or not people's responses to financial incentives for active travel deviate substantially from the expectations of the expected utility theory.

The literature review presented in this chapter encompasses interventions at the macro-environmental (e.g. government) and micro-environmental (e.g. worksite) levels,(414) including positive financial incentives, which reward active travel,(415) and negative financial incentives which penalise sedentary travel.

8.2 Background

Financial incentives are defined in this review as policies involving a targeted payment to, or withdrawal of monetary resources from, an individual's budget. Financial incentives are already commonplace in transport policy, for tackling externalities associated with use of private motorised transport, and in public health, for influencing smoking behaviours and alcohol consumption. In contrast, financial incentives to alter physical activity and diet are less common and their impact less predictable and more complex, despite interest in their potential use increasing recently amongst policy makers and researchers alike.(415-417) A recent large scale review of economic incentives to influence diet and physical activity behaviours by Shemilt et al. identified 880 eligible studies, including 192 intervention studies and 768 studies that explored the impact of changing prices or income as correlates or determinants of diet, physical activity or health outcomes.(416) They concluded that there was a particular shortage of studies relating to physical activity behaviours, when compared to diet behaviour, and that, in general, the quality of the evidence was limited to small scale observational studies, limiting the scope for drawing robust causal inferences. No other existing review was identified that had focused specifically on the role of financial incentives to promote active travel.

8.3 Methods

The review identified studies of financial incentives relating to any mode of travel in which the impact on active travel, physical activity or obesity levels were reported. The ECONLIT, Google Scholar, National Bureau of Economic Research (NBER) and PUBMED electronic databases were searched between May 2011 and January 2012 with terms relating to "physical activity", "transport", "built environment" and "prices". Non-English language papers, and studies published before 1997, were excluded.

Information was extracted on: study place and year; study design; intervention and population characteristics; and results. Quality assessment focused on the likelihood that causal inferences may be drawn using the study design taxonomy developed in Chapter 3.

8.4 Results

Studies of positive financial incentives are shown in Table 8-1. Studies of negative financial incentives are shown in Table 8-2. Five relevant reviews (labelled R1-R5, three of which were included in the General Introduction, section 1.3.4) and 20 primary studies (of which nine were not included in the five reviews) were identified. The majority of studies (70%) presented evidence for a particular micro-environmental scheme. Together, only a small range of schemes were represented, predominantly involving free bicycles or local road pricing at specific locations and generally within particular population subgroups. The majority (67%) of intervention studies used uncontrolled cross sectional analysis of population-level data which were allocated to Category 'H' on the study design taxonomy presented in Chapter 3 which cannot be used to support robust causal inference. Furthermore, most considered only changes in travel behaviour or physical activity (87%), so improvements in health or reductions in obesity can only be estimated. Higher quality study designs used included randomised controlled trials (RCT) (20%). Although these were allocated to Category 'A' using the study design taxonomy, like other intervention studies these were limited by short follow-up periods (average 7 months).

8.4.1 Positive financial incentives

Of the evidence identified in the five existing reviews, just three studies evaluated positive financial incentives at the micro-environmental level and, of these, all involved the provision of free bicycles.(120, 121, 374, 418, 419) One RCT involving Swedish women with abdominal obesity reported a significant increase in the proportion of women cycling more than 2km per day after 18 months.(420) Two uncontrolled studies found that the Danish 'Bikebusters' and the Australian 'Cycle100' schemes led to significant increases in the proportion of trips made by bicycle (from 9% to 28% in 'Bikebusters'), although both involved selected participants.(421, 422)

Additional evidence, not captured in the five reviews, included an RCT involving 51 older Americans in which significant differences in average daily 'aerobic minutes' were identified between a group receiving fixed weekly payments of $75 and a comparison group receiving $50 plus $10 (or $25) contingent on averaging at least 15 (or 40) 'aerobic minutes' per day each week (423). 'Aerobic minutes' were measured using pedometers and defined as continuous walking (not necessarily for transport), jogging, or running at a rate above 60 steps per minute for at least 10 minutes. Two further studies reported stated preference data.(424, 425) One of these showed that a £2 daily payment to cyclists could increase cycling by 88% (425), although these studies relied on individuals choosing between hypothetical alternatives.

Many studies in transport economics showed a negative price elasticity of demand for public transport,(426) indicating that price reductions would lead to increased demand. If, as three studies showed,(427-429) this displaces car journeys (rather than active travel), then increased physical activity would be expected since public transport use is typically accompanied by some walking.(342-345) At the micro-environmental level, in the first study, an RCT reported statistically significant increases in the proportion of people using public transport (from 18% to 47%) and reductions in car use (from 50% to 33%) in an intervention group that received free public transport passes in Stuttgart, Germany. Respective changes in the control group were not statistically significant and there were no statistically significant changes in cycling or walking trips.(427) In the second study, higher employee physical activity levels were shown in US workplaces that provided subsidised public transport passes compared to those that did not.(428) However, the effect may have been over estimated since work places were more likely to provide a subsidy if public transport facilities were within walking distance.

At the macro-environmental level, the impact of free bus passes, available to older people in England since 2006, was examined using a logistic regression analysis of the English Longitudinal Study of Ageing (ELSA).(429) Eligibility for the free pass was associated with a 51% increase in the odds of using public transport, while public transport use in old age was associated with 21% lower odds of being obese, even after adjustment for previous weight status. A fourth study, of free bus passes available to young people in London since 2008, showed that although increased public transport demand displaced some active travel journeys, physical activity increased because the pass generated more journeys overall.(430)

8.4.2 Negative financial incentives

At the micro-environmental level, one of the reviews identified limited evidence from two intervention studies about the impact of road user charging on physical activity.(431) In

Durham, a 10% increase in pedestrian activity was reported one year after the scheme started, and in London, distances cycled increased by 30% in London over a three year period.(432, 433)

In Zoetermeer, the Netherlands, a study showed that 14% of car drivers switched to alternative travel modes after daily financial incentives of €3 to €7 were given to regular commuters in return for avoiding specific road sections.(434, 435) In Stockholm, Sweden, another found a 25% reduction in the number of car journeys in response to a temporary $2 congestion charge.(436) Small increases in public transport use and self-reported physical activity levels were also identified. In Trondheim, Norway, one study attributed an increase in car journeys and decreases in public transport use, cycling, walking and car occupancy, to the withdrawal of road pricing.(437)

Other micro-environmental evidence included a study reporting a three-fold increase in cycling amongst employees at Manchester Airport, attributed to a workplace travel plan that included increased car parking charges,(438) and other reports that those workplace travel plans which included car-sharing financial incentives had the greatest chance of reducing car use.(439) A further study of eight workplaces in the US state of California reported a 39% increase in active commuting attributable to 'cashing out', in which individuals receive payment for not using their free workplace car parking space.(440) However, these three studies were poorly controlled and the changes were small in absolute terms.

8.4.2.1 Petrol prices

At the macro-environmental level, two studies identified a statistically significant inverse relationship between petrol prices and obesity prevalence (as defined in **Table 1-1**). The first study by Rabin et al drew cross national comparisons of 24 European countries.(441) Using US data, the second study by Courtemanche et al suggested that 8% of the rise in obesity prevalence between 1979 and 2004 was attributable to declining petrol prices (via reduced walking and increased restaurant visits). It implied that a $1 per gallon petrol tax would reduce obesity prevalence by 10%, with some evidence that women, ethnic minorities and lower income groups were most responsive to price changes (although this may have been due to their living in urban areas with public transport facilities).(442)

One further study involving 20 years' worth of cohort data from 5,115 US individuals demonstrated a positive association between petrol prices and physical activity equating to roughly 17 minutes of additional walking each week after a 25c per gallon increase.(443) The study also suggested that the price change might encourage individuals to replace physical activity away from home (e.g. bowling) with activities in the immediate area (e.g. jogging).

8.5 Discussion

This review identified only a limited amount of evidence on financial incentives for active travel. Although the identified studies may provide useful insights into the overall effectiveness of specific interventions for particular populations, it is not possible to draw more general lessons from this literature about how people might be expected to respond to financial incentives. Furthermore, it is not possible to provide a judgment about the extent to which people's behaviour deviates from the assumptions of the expected utility theory, and none of the identified papers sought to explore, or even addressed, the potential role of any behavioural economic concept in determining people's responses to financial incentives.

A partial explanation for the shortage of empirical evidence, particularly at the macro-environmental level may be that, politically, financial incentives are considered controversial and risky to implement. For example, negative financial incentives typically require strong justification since they penalise individuals who happen to have made particular choices, while positive financial incentives require significant financial investment which could be difficult to justify when compared to other competing demands on scarce resources.(444, 445)

Nevertheless, there are also various arguments which suggest financial incentives could be a potentially attractive method for promoting active travel. First, beyond the physical health benefits of increased physical activity, financial incentives to promote active travel could reinforce other existing policy priorities including environmental sustainability, economic growth (via reduced congestion and absenteeism) and wellbeing (chapter 5). Furthermore, implementation may prove relatively straightforward if integrated with existing incentive schemes designed to internalise externalities in the transport sector, including congestion, injuries, pollution,(98) and dangerous driving.(446, 447)

Second, recent technological developments, including new electronic ticketing and smart payment systems on public transport networks, GPS (Global Positioning System) technology which can be used to track individual travel behaviour (including time and location), and the ubiquitous use of smartphones, might also provide new opportunities for implementing financial incentives. For example, ‘black boxes’ are currently used by some insurers to track the speed, location, time and driving style (such as harsh braking or acceleration) of younger drivers in order to reward safer driving. In Milan, Italy, the same technology is used to provide financial incentives for commuters who leave their car at home.(447) In London, a 2014 report of the London Health Commission recommended that commuters using London Underground could be incentivised to walk or cycle more if they were provided with financial rewards when they tap in or tap out with their contactless payment card at least one mile from their registered place of home or work.(448)

Third, in an era when Government’s seem keen to limit the extent to which public health interventions restrict individual and corporate liberties,(449) financial incentives might be viewed somewhat favourably because they provide an alternative to more intrusive policies, such as rules and regulations (a potential policy intervention listed in Table 1-1), while perhaps being more effective than the least intrusive policy options, such as providing feedback.

The apparent trade-off between the intrusiveness and effectiveness of alternative policy options is illustrated neatly in the Nuffield Council on Bioethics’ intervention ladder which ranks different interventions according to their relative level of effectiveness and their intrusiveness in individual-level decision making.(445) The ladder has gained a relatively high profile following inclusion, for example, in the “Healthy lives, Healthy people” White Paper (37), and the House of Lords Science and Technology Select Committee report on Behaviour Change, both published during the last Parliament. Figure 8-1 develops the intervention ladder in order to compare alternative policies to promote active travel. For example, the diagram illustrates how the provision of public health information campaigns (the third of four policies proposed in Table 1-1) might not be highly effective when used in isolation, whereas rules or regulations (the fourth policy in Table 1-1), such as motor vehicle access restrictions which have been imposed in some European cities,(450) may be regarded as overly restricting choice.(417, 445) Meanwhile, negative financial incentives, such as the London Congestion Charge,(228) are considered somewhat less acceptable and more intrusive than positive financial incentives, such as the provision of subsidised bicycles.

Whilst the Nuffield Ladder provides a useful way to characterise the relationship between effectiveness, loosely defined, and intrusiveness, it is important that other aspects of policies are not overlooked. In written evidence to the House of Commons Health Committee,(451) the Nuffield Council on Bioethics warned against viewing the intervention ladder in isolation and suggested that the "Healthy lives, Healthy People" White Paper had failed to place it in broader context of the "Stewardship model" within which it had originally been conceived. The "Stewardship model" sets out some guiding principles for making decisions about public health policy.(445) Although the model does highlight constraints on decision makers, such as the need to avoid coercing adults into leading healthy lives, it also includes the explicit aim to "reduce unfair health inequalities"(445) which is not reflected in the intervention ladder. Yet some policies or interventions may me more likely than others to increase existing health inequalities by being least effective among those population groups that are already least likely to use active travel modes, or at highest risk of health outcomes related to physical inactivity. Whilst the evidence collected in this review is insufficient to conclude which policies to promote active travel are likely to increase or decrease existing health inequalities, there is sufficient evidence from elsewhere in public health to suggest that preventative interventions in general are unlikely to benefit all sub groups of the population equally.(452, 453) This has been termed "intervention generated inequalities."(452, 453) For example, a recent systematic review of socioeconomic inequalities associated with interventions to promote healthy eating found that a combination of positive and negative financial incentives may preferentially improve healthy eating outcomes for people of lower socioeconomic status, thus potentially reducing inequalities,(454) and (in this context) strengthening the case for financial incentives to promote health behaviour change. On the other hand, they found that personalised nutritional education and dietary counselling interventions targeted at healthy populations may have greater benefits for individuals of higher socioeconomic status.

Further criticism of the intervention ladder includes the emphasis on intrusiveness, while failing to consider other factors that might influence the acceptability of policies amongst the general public. For example, smoking bans in public spaces and strict rules on the wearing of car seat belts and motorcycle helmets are now relatively well accepted in society (even if not when they were first implemented).(449) In addition to the intrusiveness of interventions, a recent review of the acceptability of interventions to alter tobacco, alcohol, diet, and physical activity behaviours found the following factors to be important: whether or not the intervention had already been implemented (greater support being reported for interventions already implemented), the target of the intervention (interventions targeting children and young people were generally more strongly supported) and individual characteristics (those engaging in the targeted behaviour being less supportive of interventions to stop the behaviour than others, and women and older respondents more likely to endorse more restrictive measures).(455) Finally, the British Medical Association have argued that individual freedom of choice should be promoted not by focusing solely on opposing policies that are considered overly intrusive, but also in terms of taking necessary actions to ensure that people live in conditions which enable and support freedom of choice, for example by investing in and taking necessary actions to support healthy neighbourhoods where people have access to a wider range of healthier options.(449)

8.6 Conclusion

In order to gain a more comprehensive understanding of the complex individual-level impact of financial incentives on travel behaviour and health, higher quality studies that support more robust causal inference are required. In addition to the more general problems with uncontrolled or single equation cross sectional studies discussed in Chapter 3, many identified studies also had short follow-up periods which limit the potential for understanding long term changes in body weight.

Small scale studies may also have limited external validity if they include only small population subsets, such as ethnic minority, low income groups in high density urban areas,(342) or people who have recently moved house.(427, 456)

Furthermore, biased effect estimates can occur if the quality of the built environment, which may support or hinder active travel,(152, 457) or other factors such as climate or the supportiveness of employers are not controlled for.

Since RCTs may be unrealistic or politically untenable, perhaps particularly in the case of negative financial incentives, the alternative natural experimental studies proposed in Chapter 3 which use large, individual-level panel datasets could provide a promising alternative. This might include intervention studies, or in the case of negative financial incentives, non-intervention studies which exploit observed relationships between population-level behaviour and price changes over time. Similar econometric evidence supported the initial case for tobacco taxation.(458) Such analyses could contribute to a deeper understanding of the distribution of health benefits across different population groups and provide important insights into the types of financial incentives most likely to deliver long term behaviour change.

Future studies should also consider a number of specific issues not addressed in the studies identified in the review. For example, the issue of how to tackle the recognised difficulty of preventing people from returning to old habits after financial incentives are withdrawn,(290, 415, 418) and the need to explore any differential effects of financial incentives on known health inequalities.

Table 8-1: Summary of studies of positive financial incentives to promote active travel

Details	Study design		Study description			Results						
									Reported outcomes			
First author (Year) [Review reference - see footnote[a]]	Study design description (quality assessment - study design category, see taxonomy, Chapter 3)	Intervention study	Country	Population	Description of intervention	Outcome	Comparator	Follow-up (months)	Travel mode	Active travel or Physical activity	Obesity, BMI or weight	Data: Individual (I) or Population (P) level
Walking and cycling												
Hemming-son (2009)(420) [R4,R5]	RCT (A)	✔	Sweden	Middle aged women with abdominal obesity	A moderate intensity programme including free bicycles	Statistically significant increase in women cycling more than 2km per day	Control group involving a low intensity programme (excluding free bicycles)	18	✔	✔	✔	I
Bunde (1997)(421) [R2,R4]	Uncontrolled before and after study (uncategorised)	✔	Denmark	Adults	Free bicycles ('Bikebusters')	Increase in proportion of trips made by bike (from 9% to 28%)	Proportion of trips made by bike before the intervention	11	✔	✔		P
Bauman (2008)(422) [R1]	Uncontrolled, before and after study (uncategorised)	✔	Australia	Adults	Free bicycles ('Cycle 100')	Increase in proportion of trips made by bike	Proportion of trips made by bike before the intervention	Not rep-orted	✔	✔		P
Finkelstein (2008)(423)	RCT (A)	✔	US	Older adults	Payments contingent on exercise levels (number of "aerobic minutes")	Significant differences in exercise levels	Individuals who receive a fixed payment irrespective of exercise levels	1	✔	✔		I
Ryley (2006)(424) & Wardman (2007)(425)	Stated Preference Data (N/A)		UK	Adults	Hypothetical payment to individuals in return for cycling more often	In one case, an increase in proportion of trips made by bike of 88%	Hypothetical case where payments are not made to individuals	N/A	✔	✔		I

Details	Study design		Study description			Results						
									Reported outcomes			
First author (Year) [Review reference - see footnote[a]]	Study design description (quality assessment - study design category, see taxonomy, Chapter 3)	Intervention study	Country	Population	Description of intervention	Outcome	Comparator	Follow-up (months)	Travel mode	Active travel or Physical activity	Obesity, BMI or weight	Data: Individual (I) or Population (P)
Public transport												
Lachapelle (2009)(428) [R1]	Observational study (H)	✔	US	Workplace employees	Subsidised public transport passes	Statistically significant increases in physical activity levels	Workplaces that do not offer subsidised public transport passes	N/A (Cross section)	✔	✔		P
Bamberg (2006)(427) [R1]	RCT (A)	✔	Germany, Stuttgart	People who have recently (within 6 months) moved to the city	Subsidised public transport passes	Statistically significant increases in the proportion of people using public transport and reductions in car use	Before and after the intervention (in the intervention group) and compared to respective analysis in the control group	1.5	✔	✔		I
Webb (2011)(429)	Controlled study with analysis of change at individual level (F)	✔	England	Older people	Subsidised public transport passes	Free pass was associated with increased public transport use. Public transport use was associated with lower obesity	Logistic regression analysis using panel data	24	✔	✔	✔	I
Jones (2012)(430)	Qualitative observational study (N/A)	✔	England, London	Young People	Subsidised public transport passes	Physical activity increased since young people reported an increase in journeys made	Young people's own accounts of bus travel arising from interviews and focus groups	N/A	✔	✔		I

Key to table 8-1:

[a] R1-R5 indicates that the study was also included in the following reviews:

R1: Mackett (2011) Transport, Physical Activity and Health: Present knowledge and the way ahead(418)
R2: Ogilvie (2004) Promoting walking and cycling as an alternative to using cars: systematic review(374)
R3: Ogilvie (2007) Interventions to promote walking: systematic review(120)
R4: Pucher (2010) Infrastructure, programs, and policies to increase bicycling: An international review(419)
R5 Yang (2010) Interventions to promote cycling: systematic review (121)

Table 8-2: Summary of studies of negative financial incentives to promote active travel

Details	Study design		Study description			Results							
									Reported outcomes				
First author (Year) [Review reference, - see footnote[a]]	Study design description (quality assessment - study design category, see taxonomy, Chapter 3)	Intervention study	Country	Population	Description of intervention	Outcome	Comparator	Follow-up (months)	Travel mode	Active travel or Physical activity	Obesity, BMI or weight	Data: Individual (I) or Population (P) level
Walking and cycling												
Durham Council (2006)(432) [R1]	Uncontrolled, before and after study (uncategorised)	✔	England, Durham	Drivers	Road pricing	A 10% increase in pedestrian activity	Before the road pricing was introduced	9	✔	✔		P
Transport for London (2006)(433) [R1]	Uncontrolled, before and after study (uncategorised)	✔	England, London	Drivers	Road pricing	Distances cycled increased by 30%	Before the road pricing was introduced	36	✔	✔		P
Ben-Elia (2011)(434) and Bliemer (2010)(435)	Uncontrolled, before and after study (uncategorised)	✔	The Netherlands, Zoetermeer	Car drivers	Financial incentives of $3 to $7	14% of drivers switched to alternative travel modes	Individual behaviour before the financial incentive introduced	3	✔			I
Bergman (2010)(436) [R1]	Uncontrolled, before and after study (uncategorised)	✔	Sweden, Stockholm	Car drivers	$2 congestion charge	25% reduction in number of car journeys	Before the road pricing was introduced (and comparisons with similar cities to suggest a real effect attributable to the policy)	30	✔	✔		P

Details	Study design		Study description			Results						
									Reported outcomes			
First author (Year) [Review reference, - see footnote[a]]	Study design description (quality assessment - study design category, see taxonomy, Chapter 3))	Intervention study	Country	Population	Description of intervention	Outcome	Comparator	Follow-up (months)	Travel mode	Active travel or Physical activity	Obesity, BMI or weight	Data: Individual (I) or Population (P) level
Meland (2010)(437) [R1,R2]	Uncontrolled, before and after study (uncategorised)	✔	Norway, Trondheim	Car drivers	Removal of a road pricing system	Increased car journeys and decreases in public transport and active travel	Before the withdrawal of road pricing	Up to 12	✔	✔		P
Shoup (1997)(440) [R2,R4, R5]	Uncontrolled, before and after study (uncategorised)	✔	US, California	Car drivers (commuters)	Payment for not using a car park	39% increase in active commuting	Before the scheme	Up to 36	✔	✔		P
Rye (2002)(438) [R4]	Uncontrolled, before and after study (uncategorised)	✔	UK, Manchester Airport	Car drivers (commuters)	Car park charging (as part of a Work Place Travel Plan)	A threefold increase in cycling	Before the scheme	Not reported	✔	✔		P
Petrol prices												
Rabin (2007)(441)	Cross sectional, observational study using linear regression (H)		24 European countries	Country level data	None	Statistically significant inverse relationship with obesity levels (and with obesity prevalence)	Cross-national comparisons are made	N/A (Cross section)	✔		✔	P
Courtemarche (2011)(442)	Individual level repeated cross sectional study (uncategorised)		US	Adults	None	Statistically significant inverse relationship with obesity levels (and with obesity prevalence)	Changes in gas prices over time	20 years	✔	✔	✔	I

Details	Study design		Study description			Results						
									Reported outcomes			
First author (Year) [Review reference, - see footnote[a]]	Study design description (quality assessment - study design category, see taxonomy, Chapter 3)	Intervention study	Country	Population	Description of intervention	Outcome	Comparator	Follow-up (months)	Travel mode	Active travel or Physical activity	Obesity, BMI or weight	Data: Individual (I) or Population (P) level
Hou (2011) (443)	Random-effect longitudinal regression using individual level data (F)		US, four cities	Young adults (18-30 at baseline)	None	Statistically significant relationship between gas prices and physical activity	Changes in gas prices over time (the individuals act as their own controls)	15 years	✔	✔	✔	I
Rashad (2009) (459)	Cross sectional multivariate regression analysis (H)		US	Adults	None	Statistically significant relationship between gas prices and self-reported cycling	Comparison of individuals in different areas with different gas prices	N/A - cross section	✔	✔		I

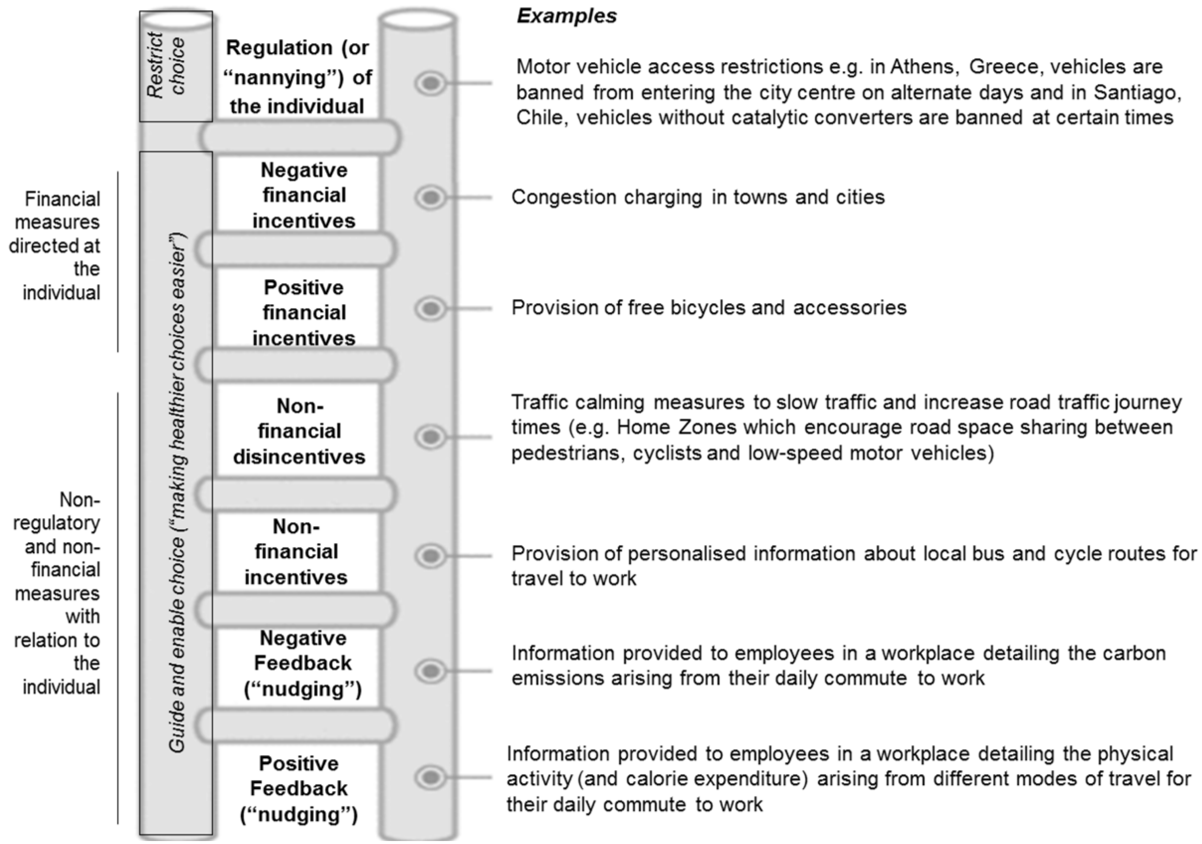
Key to Table 8-2:

[a] R1-R5 indicates that the study was also included in the following reviews:

R1: Mackett (2011) Transport, Physical Activity and Health: Present knowledge and the way ahead(418)
R2: Ogilvie (2004) Promoting walking and cycling as an alternative to using cars: systematic review(374)
R3: Ogilvie (2007) Interventions to promote walking: systematic review(120)
R4: Pucher (2010) Infrastructure, programs, and policies to increase bicycling: An international review(419)
R5 Yang (2010) Interventions to promote cycling: systematic review (121)

Figure 8-1: A hierarchy of policy interventions to promote active travel

Higher rungs on the ladder represent decreasing public acceptability and increasing intrusiveness, as suggested in the Nuffield Intervention Ladder.(445) Decision makers should only consider policies on higher rungs of the ladder if policies on lower rungs are deemed to be ineffective.



SECTION E:

9 General Discussion

9.1 Overview of chapter

This chapter includes a summary of the thesis, beginning with a discussion which aims to draw together the main findings in the context of four key strands of research from the discipline of health economics which, as argued in chapter 1, could provide a distinctive contribution to existing research on active travel.

The chapter then concludes with sections on the limitations of the thesis and recommendations for future research.

9.2 Discussion of main findings

The challenge posed by high levels of physical inactivity in the UK across the working-age population, particularly amongst those in the lowest income groups, was presented in the General Introduction (Chapter 1) alongside long-term trends in travel and commuting behaviour.

During the past decade, it was noted that changes have occurred in long-term travel behaviour trends, particularly in terms of reductions in the rate of growth of car travel and increased use of the railways, despite the post-2008 recession and above-inflation increases in rail fares. Yet, at the national level, when considering significant reductions in the proportion of people walking or cycling to work that occurred during the latter half of the twentieth century, the proportion of people using active commute modes remains at historically low levels.

Despite these long term trends, increased cycling and walking is increasingly viewed as an attractive option for tackling a number of current societal problems, including physical inactivity as well as wider economic and environmental issues such as congestion and road traffic pollution in urban areas. Some towns and cities, including London and the Cycle Demonstration Towns in England,(50) have also made substantial efforts in recent years to support more cycling and walking, through increased investment in cycle infrastructure for example. Recently, the 2015 Infrastructure Bill, which sought to address transport, housing development and nationally significant infrastructure projects, included an unprecedented commitment to dedicated funding for cycling and walking infrastructure across the UK. Thus there is a current and pressing need for rigorous research on active travel to inform decision making.

Drawing on the explanation provided in Chapter 1 (see Figure 1-7) of how the intervening chapters were linked by four key strands of research in health economics, section 9.2.1 (below) discusses some of the main findings in terms of the extent to which the discipline of health economics can provide a distinctive view of active travel when compared to existing research in public health. This section then concludes in 9.2.2 with a summary of the main findings in respect of the three core objectives of the thesis listed in Table 1-3.

9.2.1 The potential contribution of four key strands of health economics to existing research on active travel

The **first strand** was about how people make decisions. Central to a (classical) economists' way of thinking is that, for any particular consumption decision, individuals should be free to make choices and that they are assumed to weigh up the costs and benefits of competing options in order to maximise their own utility within a budget constraint (which is typically defined in terms of time and/or income). This view provides the basis for economic models of human behaviour which were discussed in Chapter 7. When compared to research from other disciplines in public health, these models provide quite a different starting point for thinking about individual-level human behaviour, and behaviour change interventions, than would be expected in other research in public health (387) (although, as a short review in section 7.2 showed, economic models of physical activity remain relatively scarce (381)). For example, in this thesis, Table 7-1 and related discussion explored the potential role of technological change on people's energy expenditure and energy intake. Innovation in agriculture, food production and retail, it was argued, has contributed to reductions in the cost (including time costs) of energy-dense meals, whilst working environments have typically become more office-based and sedentary. These models could add value by providing a theoretical basis for the selection or design of policy interventions to tackle physical inactivity, or other unfavourable health behaviours. In this thesis, for example, the economic framework devised in response to Cawley et al.'s SLOTH model in section 7.3 was used to make a case that financial incentives could be a potentially effective economic intervention for encouraging more walking and cycling. Similarly, Pratt et al. have used the same SLOTH model to argue that financial incentives could be used to improve the demand and supply of home exercise equipment, or to incentivise employers to provide health promotion facilities for their employees.(383)

In addition to the potential for developing policy proposals on the basis of theoretical economic models which rely on the assumptions of classical economics, section 7.5.2 (and Table 7-4) provided an overview of recent developments in behavioural economics which can also be used to generate relatively novel insights into the optimal design of behaviour change interventions. A key finding was that empirical work was limited in terms of providing evidence on which behavioural economic concepts are most applicable to the transportation context, and to walking and cycling in particular. However, evidence from other sectors of the economy demonstrated substantial potential for improving the effectiveness of interventions if they are designed with these concepts in mind.

The **second strand** was about the development of an economic justification for policy interventions. In addition to the idea that behavioural economics concepts might lead people to behave in ways which are inconsistent with the assumptions of the expected utility hypothesis (discussed in sections 1.3.1 and 7.5.2), this justification is typically based on three sources of market failure ('public goods,' 'information imperfections' and 'externalities'), evidence for which was reviewed in section 1.3.2.

There are two reasons to suggest that the explicit identification of market failure might be important.

First, in an era when the public are apparently wary of any interference in individual health and lifestyle decisions (as claimed in section 8.5), and when healthcare and public health budgets are under strain, perhaps more than ever it is necessary to provide an explicit justification for policy interventions. Particularly this may be the case if scarce resources are to be secured for investment in more intrusive, unpopular polices which (as described in section 8.5) could be the most effective in terms of tackling unfavourable health behaviours and health inequalities.

Whilst the differences may be subtle, this explicit economic justification might nonetheless be distinguished from a tendency in existing public health literature to rely on vague or implicit views about 'social justice' to support the case for policy interventions. For example, it might be implicitly assumed that citizens have a 'right' to good health and so health should be improved regardless of the costs or consequences.(21, 75) In contrast, it could be argued that the recent report by McKinsey MGI made a more convincing case for a series of interventionist policies including restrictions on food portions and high calorie drinks because an explicit economic justification was provided through an examination of the external costs of obesity.(79) Whilst reflecting that in reality there may be few cases where the two perspectives have led to strongly conflicting views, the economist Roland Sturm nonetheless argues that the best policies are those which are supported by both public health and economics reasoning.(75)

Second, the process of systematically identifying specific sources of market failure in the market for walking and cycling means that policy makers are able to select policies which are most likely to be effective in terms of tackling the identified form of market failure. Four potential forms of policy intervention in public health were proposed for tackling each form of market failure (see Table 1-1), and these represent the **third strand** of health economics to be addressed in this thesis. For example, as indicated in Figure 1-7, the most appropriate tool for targeting externalities is likely to be a market-based intervention in the form of financial incentives (reviewed in chapter 8) whereas changes to the urban built environment (reviewed in chapter 2), including investment in walking or cycling infrastructure (reviewed in section 1.3.4.2), would more likely be justified through the identification of public good characteristics.

Once a potential policy intervention has been identified, the **fourth strand** of health economics to be highlighted in this thesis was the role of economic evaluation in assessing whether or not the 'costs' (including opportunity costs[4]) of implementing a policy exceed the 'benefits.' Again, this economic perspective has been contrasted with a 'mainstream' public health perspective which, as argued in a paper by Epstein et al. (21), is unlikely to give much attention to the opportunity cost of policy interventions and this could lead to conflicting views. For example, policies may be recommended from a public health perspective on the basis of their apparent

[4] 'Opportunity costs' are defined as the benefits that are forgone by not devoting resources to the next best alternative. This is an important concept in economics since, unlike a 'financial cost,' 'opportunity costs' explicitly reflect the reality of scarce resources.

effectiveness, but rejected by economists on the basis that scarce resources would be better deployed elsewhere in order to have a greater impact on health or health inequalities. This may lead to the conclusion that some markets are best left alone, even in the presence of market failure. Considering earlier debates which have questioned the existence of scarce resources and opportunity costs in medical care,(460, 461) it is reasonable to expect scepticism from some commentators about the merits of introducing such ideas into the domain of public health.(54, 381, 462-464) Even in cases where the two perspectives do not lead to conflicting views, it is important to note that economic evaluation can contribute an important role in terms of providing a higher degree of transparency about how decisions are made.

This thesis examined two particular features of the methods used in health economic evaluation which seemed to be underused in existing public health research, given their potential role in assessing the impact of large-scale, population-level interventions (a shortage of evidence on the impact of large-scale, population-level interventions was a key finding of the reviews in chapter 8, in terms of macro-level financial incentives, and chapter 2, in terms of changes to the urban built environment). First was the use of advanced analytical methods to address the problem of endogeneity when assessing impact or effectiveness. Although some of these methods are gaining increased visibility in public health (e.g. see the MRC guidance, Table 2-1), the review in chapter 2 showed that studies which used these methods are published primarily in economics journals. In chapter 3, the case was made for improved guidance for policy makers in terms of interpreting and assessing the quality of studies that used different analytical techniques in order to support evidence-based policy making, which is said to be a priority across all Government departments.(465) Second was the use of large panel datasets which could also be used to support the assessment of large-scale population-level interventions. Studies which used these data were highlighted in the reviews in chapters 2 and 8, and the BHPS was used in the empirical work presented in chapters 4, 5 and 6. Perhaps the main illustration of the potential influence of health economics on research in active travel to be provided in this thesis was the empirical analysis in chapter 5 which combined an advanced analytical method with panel data. The fixed effects model provided stronger support for robust causal inferences when compared to cross-sectional studies by accounting for important unobserved, time-invariant individual-level characteristics.

9.2.2 Main findings of thesis in respect of three core objectives

This section provides an overview of the main findings of the thesis in respect of the three core objectives outlined in Chapter 1 (Table 1-3).

Section A: To explore the potential value of analytical techniques typically used in health econometrics in the evaluation of the causal relationship between active commuting, policy interventions and health outcomes.

Relatively few studies of the relationship between urban built environment characteristics and obesity identified in the review in Chapter 2 had used methodological approaches other than single equation regression analysis in cross-sectional study designs. Whilst three studies were notable from a methodological perspective because participants had been allocated at random to different environments, it seems unlikely that such an approach can be replicated often. Hence the potential advantages of using other more advanced econometric techniques recommended for use in the MRC guidance on natural experiments were explored using thirteen observational studies which had been identified. These studies typically used panel data and the most commonly used methodological approach was instrumental variables which, as in randomised experiments, allows exogenous variation of an explanatory factor to be exploited.

Despite a prior concern about the reliance on single equation, cross-sectional studies to support the view that urban built environment design can influence population-level health outcomes, the review in chapter 2 provided new evidence that statistically significant relationships between urban built environment characteristics and obesity were not undermined by the use of more advanced methodological approaches. Hence current interest in altering the design of urban built environments is likely strengthened, not weakened, by evidence which used more advanced approaches.

Since significant differences were observed in the results of studies identified in the review in Chapter 2, the checklist in Chapter 3 was devised in order to support better decision making by providing a guide for distinguishing between different types of evidence. Nevertheless, this chapter emphasised the difficulty in ranking observational studies according to the methodological (or econometric) approach without also taking into account numerous other substantial sources of heterogeneity between studies. Hence it was argued that the taxonomy ought to be complemented by guidelines for reviewers on the appropriate use of each technique and the potential sources of bias that may arise. This could include development of a best practice checklist to enable reviewers to make judgements about whether or not particular methods have been used appropriately. Researchers using the advanced analytical techniques should always justify the choice of method and the assumptions underlying their use, or else risk their results being misinterpreted.

Section B: To examine the health impact of switching from sedentary travel modes to more active travel modes for the daily commute to work using multiple waves of the BHPS.

Using data on 18,000 commuters in eighteen waves of the BHPS, this section included the first longitudinal study to use a large panel dataset to explore the impact on subjective wellbeing of switching from car travel to more active travel modes (Chapter 5). The fixed effects model specification, which analysed only the impact of within-individual changes over time, was used to eliminate various potential sources of bias, including those arising from unobserved differences between individuals. After accounting for changes in individual-level socioeconomic characteristics and potential confounding variables relating to work, residence and health, the results showed that switching from car travel to active commuting or public transport improved wellbeing. Active commuting was also associated with reductions in the odds of experiencing two specific psychological symptoms when compared to car travel. In a separate analysis of travel time, wellbeing increased with travel time for walkers, but decreased for drivers. The results contradicted a well-documented cross-sectional study by the ONS which showed a negative relationship between active commuting and some aspects of wellbeing when compared to driving.

A further study using data from three waves of the BHPS was the first study to use data from a large scale nationally representative survey to explore the impact on individual-level BMI of switching between different modes of travel (Chapter 6). Multivariable linear regression analyses were used to assess associations between switching to and from active commuting (over one and two years) and change in BMI (over two years). After adjustment for socioeconomic and health-related covariates, the results showed a statistically significant net reduction in BMI over a two year period amongst commuters who switched from private motor transport to active commuting or public transport when compared to continued private motor vehicle use. Larger adjusted effect sizes were associated with switching to active commuting, particularly among those who switched within the first year and those with the longest journeys. Switching from active commuting or public transport to private motor transport was also associated with a significant increase in BMI.

Together the results of these two studies provided better support for causal inference than existing studies and so strengthened the case for policy makers to promote population health by incentivising walking or cycling. Although these studies do not provide a guide as to the types of interventions which could be effective, the health benefits shown in these studies could nonetheless be incorporated into tools used for forecasting the impact of new walking or cycling infrastructure (e.g. HEAT - the WHO Health Economic Assessment Tool – and WebTAG - the Department of Transport's 'Transport Analysis Guidance').

Section C: To explore the potential for using financial incentives as a policy intervention to encourage uptake of active travel.

The theoretical framework provided in Chapter 7 was used to argue that financial incentives could be an effective policy for promoting the use of active travel modes. In chapter 8, the evidence identified on financial incentives to promote active travel was dominated by small scale interventions which could realistically only provide insights into the impact of interventions in specific settings over relatively short time periods.

9.3 General limitations

Having highlighted in the review chapters of this thesis a significant number of shortcomings of existing research, the general limitations of this thesis are around the failure to address some of those shortcomings in the empirical work.

Most notably, a particular recurring shortcoming identified in the literature reviews was the shortage of high-quality evidence on the impact of policy interventions to encourage more walking or cycling, particularly at the population-level. For example, the review in section 1.3.4.2 identified no full health economic evaluations that had looked specifically at large-scale infrastructure changes to promote active travel. The review in chapter 7 also revealed that most studies of the impact of financial incentives to promote active travel were concerned with small-scale policies in specific settings, and were characterised generally by short follow-up times. Of a small number of identified studies that had used large, national-level datasets to assess the impact of macro-level fuel prices on active travel or health, these were mostly cross-sectional studies which had used population-level data. The other reviews which took a broader view by including any observed change in the urban built environment which impacted on obesity (not necessarily through changes in travel behaviour) (chapter 2), and by including studies which looked at determinants of active commuting without necessarily measuring health outcomes (e.g. associations between travel behaviour and moving house or moving job) (section 4.3.2), also revealed few studies that had assessed the impact of an actual policy intervention.

Whilst the thesis identified the methods and approaches used in health economics which could be of value to researchers in addressing this shortage of evidence on interventions, policy makers would have been better served if the empirical work presented in this thesis had assessed the impact on commuting behaviour (or health) of a change in a specific policy instrument. One reason why this was not possible was the shortage of national-level interventions relating to cycling or walking infrastructure which could have been evaluated using the BHPS data. A good candidate might have been the Cycle Demonstration Towns programme which involved additional funding for cycle infrastructure in some English local authorities. This has been evaluated to some extent elsewhere, (50) but not using panel data which follows the same individuals over time. The problem with BHPS was that the sample sizes in particular geographical areas were too small to capture changes that occurred in most local authority areas. Although not reported elsewhere in this thesis, an attempt was made to explore the potential relationship between changes over time in the demand for active commuting and macro-level fuel prices using data sourced from the Automobile Association (AA). Whilst similar studies have been undertaken in the US (as identified in chapter 7), this analysis was not pursued further due to various challenges, for example in attributing observed changes in travel behaviour to the fuel price variable (which was reported at a regional level) which could in fact have been picking up other factors that vary over time between regions (e.g. house prices).

From a methodological point of view, a particular shortcoming of existing literature was the failure to use methods which account for endogeneity caused by unobserved factors. Although it was argued in section B that advanced analytical techniques such as instrumental variables could provide better causal evidence, it was not possible in the analyses presented in chapters 4, 5 and 6 could to identify suitable instruments. A significant shortcoming of the analysis in chapter 4, for example, was that the impact of childhood cycling on adult cycling relied on a random effects model which likely violated the critical assumption that the individual-level (unobserved) error term is not correlated with explanatory variables. Of course instrumental variables would be a good method for overcoming this issue, however as in the exploration of AA fuel prices described above, the identification of credible instruments is challenging. Perhaps this is illustrative of a broader problem touched on in chapter 3– that although in theory these methods should provide new insights in active travel research, in practice it is difficult to implement them appropriately.

Three further general methodological limitations were notable in the empirical analyses presented in this thesis. First was the risk of attrition bias in panel data, as discussed in more detail in chapters 4, 5 and 6. Second was the possibility that reverse causality may have been overlooked in some cases This could be a consequence of focusing attention on the fixed effects model, which although well suited to tackling some forms of bias, nevertheless considers only changes in dependent and independent variables which happen between the same two consecutive waves of data. Given the quality of panel data that is available in BHPS, and the length of follow-up, it seems a missed opportunity not to use the data to examine the temporal sequencing of observed changes. Third is a related issue that, despite having data which followed participants for long periods of up to two decades, little or no research has yet been done using the BHPS (or other similar panel data) on the longer term health or wellbeing impact of active travel. As mentioned in chapter 4, further work would also be warranted on understanding relative stability of commute mode choices over time, and the length of time that people typically use specific modes.

A consequence of failing to address in the empirical work the shortcomings that had been identified in the literature reviews meant that, from the point of view of policy making, the practical lessons to be drawn from this thesis were more modest than might have been expected at the outset. In particular, the relatively limited scope of the empirical work meant that the proposed aim of exploring how four strands of health economics could provide a distinctive contribution to research on active travel was generally addressed in terms of highlighting the *potential* contribution of these approaches, rather than through the application of health economic techniques to produce new findings. Thus the thesis should give the reader the idea that health economics does provide a different way for researchers to view and study active travel, but not necessarily a conclusive answer on the extent to which health economics can actually produce distinctive insights or policy recommendations when compared to existing research in public health.

9.4 Recommendations for future research

Given recent commitments to increased investment in walking and cycling schemes, it is important that further evidence is gathered on the effectiveness and cost-effectiveness of policy interventions in terms of travel behaviour change and health outcomes, including the impact on health inequalities. In particular, this thesis has highlighted the importance of undertaking research on evaluating interventions that incorporate financial incentives, and interventions which appeal to some of the biases in human behaviour highlighted in research in behavioural economics.

In order to address this challenge, future studies might attempt to exploit large-scale panel data surveys to a greater degree than was achieved in this thesis. Other nationally-representative surveys, including Census data, could also be used. For example, the ONS Longitudinal Study enables longitudinal, individual-level analysis of a 1% sample of participants in the Census of England and Wales between 1971 and 2011, linked to data on critical illness and death, including information on cancer registrations and road traffic incidents.

Whilst it may be unlikely to identify cases where individuals have been randomised to different neighbourhoods, as occurred in case of the study of Hurricane Katrina reported in Chapter 2, opportunities for exploiting the impact of regional or geographical variations in policy should be explored further. In one example, Nakamura et al. evaluated the London congestion charge (a policy implemented by the Greater London local authority) by comparing people who lived just inside the charging zone with those who lived just outside the boundary using data from the London Travel Demand Survey.(228) Recent moves to decentralise Government decision making and funding in relation to active travel (discussed in section 1.2.3) may result in further regional variations. This could prove valuable from the perspective of policy evaluation and, as argued for in the recent report on obesity by McKinsey MGI, would enable society to experiment with alternative interventions, rather than waiting for evidence to emerge from small-scale intervention studies.(79) Even so, it may also be desirable for decision makers and researchers to consider how they can work together more closely to ensure that opportunities for policy evaluation are fully exploited,(466) by addressing the design requirements of economic evaluations early on in the policy implementation stages,(226) for example.

Although variables included in panel data may be limited in their scope for addressing specific questions about transportation and health,(280) since unlike studies which use primary data collection these surveys were designed for multiple research purposes, these data can often be linked to richer geographic data using external datasets. Subject to approved access to a secure release of the dataset, the 'Understanding Society' survey, for example, enables researchers to link individual participants to postcode-level data using Geographical Information Systems (GIS) software. As an indicator of the potential to provide more informative policy insights, participants could be linked, for example, to UK-wide Ordnance Survey (OS) data on green spaces (using the OS MasterMap dataset), fast-food restaurants (using the OS Points of Interest dataset) or the location of pedestrianised streets and urban walking or cycling routes (using the OS Integrated Transport Network dataset, or other data available from specialist organisations including Sustrans, for example).

Studies from the US of the relationship between urban built environment characteristics and obesity identified in chapter 2 indicated the scope for using external data of this type to support an instrumental variables analysis. For example, proximity to major roads was used in several studies as an exogenous source of variation in the availability of fast-food restaurants or large food superstores. No similar studies were identified which had used UK data, but they could provide templates for future research. Some potential instrumental variables which might be used to further develop the studies on the health and wellbeing impact of active commuting presented in this thesis could include, for example: the proportion of local accommodation available for rent when compared to home ownership (this was used in recent US study presented at a conference in January 2015 which used data from the National Health and Nutrition Examination Survey (or NHANES) to explore the relationship between active commuting and BMI)(467), local road traffic incidents, weather-related factors such as rainfall, and season of the year in which participants responded to the survey. However, as emphasised in chapter 3, a key responsibility for researchers is in ensuring that these methods are used appropriately.

9.5 Conclusion

Over a decade ago, in 2004, a report by England's Chief Medical Officer for the Department for Health included a simple message: "For most people, the easiest and most acceptable forms of physical activity are those that can be incorporated into everyday life. Examples include walking or cycling instead of driving."(468) This thesis has provided new evidence on the health and wellbeing benefits of following that advice. In the same year, a report by Sir Derek Wanless for HM Treasury stated: "The body of economic evidence relating to public health interventions is small in comparison to that related to health care. There are practical difficulties but they should be capable of being overcome to produce high quality, convincing evaluations of public health interventions." This thesis has provided some insights into how specific challenges in the development of high quality economic evaluations of cycling and walking infrastructure could be addressed in the future. As additional resources are being made available for new cycling and walking infrastructure in some locations, and as walking and cycling become a little more commonplace, it is suggested that health economics can support the development of a stronger evidence base for policies to promote active travel in the coming years.

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