A Population Perspective on Physical Activity and Health

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Abstract: A Population Perspective on Physical Activity and Health

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Regular physical activity reduces the risk of many chronic diseases. Consequently, the promotion of it and particular types (e.g. walking and cycling for travel), have become a priority for governments seeking to improve health and constrain rising demand on health services. Despite this many uncertainties persist. The aim of this thesis is to address two particular areas of uncertainty: a) the association of walking and cycling for travel with indices of health and well-being; b) and the extent to which increases in physical activity will reduce need for health and social care.

The first part of my thesis consists of three studies that describe the health benefits associated with walking and cycling to work among working age adults. The first is a longitudinal study of the associations between maintenance of active commuting with sickness absence and well-being using the Commuting and Health in Cambridge dataset. The second, using the same dataset, describes the longitudinal associations between maintenance of active commuting and self-reported body mass index. Building on this, the third study using a large cohort study (the Fenland Study) with detailed characterisation of diet and physical activity (including objective measurement) describes the baseline associations between active commuting and objective measures of adiposity.

The second part of my thesis describes the development of a combined microsimulation multi-state life table model that is used to characterise the effects of a population 'shift' in physical activity on the burden of six major diseases at the population-level. Specifically, it seeks to better describe the effect of increases in physical activity on healthcare need considering not just the effect of physical activity on disease incidence but also the effect on healthcare need arising from consequent survival to an older age (at which disease incidence is higher), and contrasts this with a method that does not make allowance for increased survival.

The findings of this thesis provide evidence of the importance of walking or cycling to work in maintaining or improving the health and well-being of working age adults. It suggests that increases in physical activity, even after allowance for increased survival, are likely to reduce need for healthcare, although the reductions in need are less than might be assumed when allowance is not made for increased survival. Taken together this work provides a stronger empirical basis to inform public health practice. A stronger 'health case' for active travel can be made. The benefits of which should be communicated to individuals choosing how to travel as well as policy makers and others who can influence the determinants of active travel. It also provides a more realistic and nuanced understanding of how increases in physical activity may affect future healthcare need.

Declaration

This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the statement setting out my contribution (page ten), stated in the acknowledgements and specified elsewhere in the text.

It is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my dissertation has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University of similar institution except as declared in the Preface and specified in the text.

This dissertation does not exceed 60,000 words (excluding tables, figures, footnotes and references).

Oliver Mytton

9 October 2016

For Ella

Why would you lie when you can sit?

Why would you sit when you can stand?

Why would you stand when you can climb?

You were born to move.

Contents

Acknowledgments

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Statement setting out my contribution

The epidemiological analyses reported in Chapter Two and Chapter Three were planned and undertaken by me, after discussion and guidance from David Ogilvie and Jenna Panter. I wrote the original papers that described the study rationale, methods, results and discussion, receiving critical feedback from David Ogilvie and Jenna Panter. David Ogilvie is the Principal Investigator on the Commuting and Health in Cambridge Study. I was not involved in the design of the original study nor collecting of the data.

The idea to conduct the analyses reported in Chapter Four arose after discussion flowing from the work reported in Chapter Three and Chapter Two, and after I explored a number of options for extending those first analyses. The epidemiological analyses reported in Chapter Four were planned and undertaken by me, after discussion and guidance from David Ogilvie, Jenna Panter and other collaborators (Simon Griffin and Soren Brage). Soren Brage and Kate Westgate helped me interpret and make use of the objective physical activity epidemiology data. A draft paper has been circulated amongst some study authors (David Ogilvie and Jenna Panter), from whom I have received feedback. I was not involved in the design of the Fenland Study nor collecting of the data.

The idea to describe the additional impact of changes in life expectancy on indicators of healthcare need was conceived by me, following discussions with others. I designed and built the model. The part of the model that describes the relationship between physical activity and health is based on the Integrated Transport and Health Impact Modelling Tool, developed by James Woodcock and colleagues. I identified, sourced and manipulated suitable data, including the processing of the epidemiological data in DisMod. The modelling work was primarily supervised by James Woodcock, with input from David Ogilvie and Jenna Panter. Linda Cobiac introduced me to the concept of life table modelling. Marko Tainio has assisted with the programming of the model. A draft paper has been submitted for publication, for which I have received feedback from David Ogilvie, Jenna Panter, James Woodcock, Marko Tainio and Linda Cobiac.

List of abbreviations

AT	Active travel
AC	Active commuting
BMI	Body mass index
CFR	Case fatality rate
CI	Confidence interval
cm	centimetres
CRA	Comparative risk assessment
CT	Computed tomography
CVD	Cardiovascular disease
DALYs	Disability adjusted life years
DEXA	Dual-energy X-ray absorptiometry
e.g.	Exempli gratia or “for example”
EPIC	European Prospective Investigation into Cancer and Nutrition
FETA	Food frequency questionnaire European Prospective Investigation into Cancer and Nutrition tool for analysis
FFQ	Food frequency questionnaire
g	Grams
GHQ	General household questionnaire
GPS	Global positioning system
HNA	Health needs assessment
i.e.	Id est or “That is”
IHD	Ischaemic heart disease
Intl.$	International dollar
IQR	Inter-quartile range
ITHIM	Integrated Transport and Health Impact Modelling tool
Kg	kilogram
kJ	kilojoules
LE	Life expectancy
m	Metre
MCS-8	Mental component score 8
MET	Metabolic equivalent of task
mins	Minutes
MVPA	Moderate-to-vigorous physical activity
n	Number (used to indicate number of participants in a study)

p	p-value
PA	Physical activity
PAEE	Physical activity energy expenditure
PAF	Population attributable fraction
PCS-8	Physical component score 8
PIF	Population impact fraction
rMED	Relative Mediterranean diet score
RPAQ	Recent physical activity questionnaire
SES	Socio-economic status
SF-8	Short form 8 questionnaire
US	United States
UK	United Kingdom
VAT	Visceral adipose tissue
YLL	Years of life lost
YLD	Years lived with disability
(m)	Male
(w)	Women
$	Dollar
£	Pound
%	Percentage
>	Greater than
<	Less than
≥	Greater than or equal to
≤	Less than or equal to
*	Indicates significant ($p<0.05$)
**	Indicates significant ($p<0.01$)
***	Indicates significant ($p<0.001$)

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1 Introduction

“Public health is the science and art of preventing disease, prolonging life and promoting health through the organized efforts of society”

Donald Acheson

“Lack of activity destroys the good condition of every human being, whilst movement and methodical physical exercise save it and preserve it”

Plato

1.1 Public health

"What do you do?" It is a common question. And in recent years it is not one that I have found easy to answer. The words 'public health' are usually met with a confused look. Further explanation is always possible, but never quite does it justice. Invoking 'the science and the art' can come across as remote. Focusing on the activities of a public health professional answers the question but doesn't convey the richness or the importance of the work. Occasionally my reply is met with an excited response. But invariably I am left disappointed as that person's view of public health does not accord with my own. Public health is about more than preventing disease by encouraging individuals to live healthily.

In the UK, the Faculty of Public Health defines public health "as the science and art of promoting and protecting health and well-being, preventing ill-health and prolonging life through the organised efforts of society."[1] The Faculty also stresses other key elements of public health, that it is population based; depends on collective responsibility; requires working in partnership; and recognises an important role for the state. Similar themes are echoed by definitions offered by others.[2–5] For me one of the most important aspects, particularly as I moved from medicine into public health, is a focus on populations instead of individuals. This notion is explicit or implicit in all these definitions,[1–5] although none of these definitions fully explains the richness of a 'population approach' to health.

1.1.1 The population approach to preventive medicine

Rose distinguished between a population approach and an individual approach to medicine.[6,7] He was primarily concerned with the prevention of cardiovascular disease. His argument was predicated on two simple assumptions. First, the risk of disease (normally) increases as exposure to a risk factor increases, in a linear or curvilinear fashion[i]. Second, there will be a distribution of risk within the population and for many risk factors this will tend towards a normal or bell-shaped distribution.

Given these two assumptions, Rose observed that the majority of incident cases are not likely to occur amongst those individuals at highest risk. The number of individuals at highest risk is relatively small. In contrast the number of individuals at low or moderate risk is relatively large. He argued that the majority of cases would occur amongst this population, as the size of that population was so

[i] Rose outlined four relationships between exposure to a risk factor and disease risk. For one of these relationships (a U-shaped relationship), within certain limits increasing exposure to a risk factor was associated with decreasing risk. Rose gave two examples, the relationship between blood pressure with symptoms and body mass index with mortality.

much larger than the size of the high-risk population. A large number of people at moderate risk will give rise to more incident cases than a few people at high risk[ii].

He further observed that medical practice tends to focus on those who are at high risk. Whilst these individuals have the most to gain from treatment aimed at reducing their risk, this approach is inherently limited because it will only prevent a relatively small proportion of all incident cases within a population. To prevent more cases requires shifting the thresholds for treatment, so that more people who are at 'moderate' risk are offered treatment. Whilst theoretically this approach may work, in practice it creates problems. Symptoms, illness and even disease may be created as side-effects from treatment.[8] It may not be financially sustainable. Furthermore, 'medicalising' risk factors in otherwise healthy people is rejected by some doctors and some patients.[9]

An alternative approach is a population approach. Instead of focusing just on those at highest risk Rose advocated an approach targeted at the whole population with the aim of 'shifting' the distribution of risk towards lower risk. He observed that there were marked differences in the distribution of risk in different geographic settings (e.g. the mean blood pressure of Kenyan nomads is noticeably lower than that of London civil servants).[7] He suggested that such differences were unlikely to be explained by genetics, and that environmental differences might explain most or all of the observed differences between populations. As many environmental differences are modifiable, the identification and modification of important environmental differences may offer a means to shift the population distribution of risk towards a more favourable (lower) distribution of risk. Moreover, that approach offers much greater opportunity to prevent disease as it reduces the risk of disease for those at moderate and low risk, in whom the majority of incident cases will arise.

Rose further argued that the population-approach should be "radical", by which he meant it should address the root or fundamental causes of health behaviours. Health education, whilst often politically acceptable, was described as "superficial" because it does not address the underlying (social, environmental and economic) determinants of behaviour and so has limited ability to shift the distribution of risk. This radical approach to improving health shares much in common with socio-ecological models of health that emphasise a role for social, culture, economic and other environmental factors in determining health behaviours and health.[10,11]

[ii] The extent to which the 'normal' majority will give rise to more cases than the high-risk minority is variable. It will, for example, depends on the shape of the dose-response relationship, distribution of risk within the population and the definition of high-risk.

1.1.2 Practice of public health in England

Alongside these theoretical concepts of public health, one also needs to consider public health practice in England today, which delivers both services for the public (e.g. preventive programmes, health education) as well as providing a broad set of functions which are equally important but less visible to the public (e.g. surveillance, evaluation, advocacy, guidance, research). The delivery of these services and functions is widely distributed, although there are several bodies with key roles.

Public Health England has a wide ranging remit "to protect and improve the nation's health and address inequalities". It undertakes a number of public health functions: e.g. surveillance, development of standards or guidelines, management of infectious diseases outbreaks, offering expertise, analysis and publication of health data, and running health education campaigns. However, it does not directly deliver, or even commission, most preventive services. Such preventive programmes (e.g. vaccination, screening) and health improvement programmes (e.g. weight loss clinics, smoking cessation clinics) are typically commissioned by local government or NHS England, with services being delivered by the NHS and other providers. Other organisations also provide important functions (e.g. Department of Health sets health and health policy, National Institute for Health and Care Excellence sets guidelines and standards).

The Health and Social Care Act 2012 was responsible for instituting the changes that led to the present arrangement.[12,13] One of the key changes was the movement of local public health departments out of the NHS and into local government. This potentially gives the discipline a greater ability to focus on prevention and health improvement, in part because local government has responsibility for many of the local determinants of health (e.g. planning, education and leisure services) and in part because public health specialists may be freed from dealing with immediate needs of the health service. However, it also poses challenges for the discipline (e.g. local public health officials may be politically restrained from advocating for health). The act also led to the establishment of local Health & Well-being boards, chaired by local government and bringing together the NHS, local government and other local stakeholders.

Public health practice in England is increasingly organised into three domains or sub-specialties: health protection, health services public health and health improvement.[1,14] Health protection is primarily concerned with prevention and control of infectious diseases and other environmental hazards. Health services public health is concerned with the commissioning of appropriate services for the needs of the local population and assuring the quality of those services. Health improvement

aims to improve the health and well-being of individuals or communities by enabling and encouraging healthy behaviours.

There are different arrangements in the devolved nations of Wales, Scotland and Northern Ireland.

1.1.3 My perspective

1.1.3.1 Medicine and public health

My interest in public health predates medical school. I first began reading about epidemiology (John Snow on *Cholera* and Richard Doll on smoking) when I was at school. At various points, prior to starting formal public health training in 2010, I've had an opportunity to express or develop my interests in population health and quantitative methods.

There were two particularly formative experiences that led me to academic public health. The first experience was working at the Shoklo Malaria Research Unit on the Thai-Burmese border (2004 and 2006). The experience showed me the importance of population-level thinking. The introduction of good systems of care (e.g. surveillance, anti-malarial stewardship, quality controlled laboratory diagnostics) had dramatically improved health.[15,16] It was also an excellent model of clinical research, where the clinical problems framed the research questions, and led to evolution of practice. The second experience was undertaking a two-year placement in the Department of Health working with Sir Liam Donaldson, the Chief Medical Officer for England and the country's most senior public health doctor.[17] I saw that scientific evidence could shape policy. I also saw and learnt how it failed to have an impact on policy.

Equally I am very conscious that my background is in medicine. This has given me a broad experience of health and healthcare. I have practised both general medicine and psychiatry. I've worked in different healthcare settings (e.g. community settings, small hospitals, larger hospitals) in different countries (New Zealand, Thailand, as well as England) and partly through my public health training I've worked in different parts of the public health system (locally, nationally and internationally as well as working for government bodies and non-governmental organisations). Whilst data and studies give me one perspective, the clinical experience gives me a different perspective around what health and disease means for families and individuals. The health services and policy experience gives me another perspective on how things do (or do not) change: what studies or statistics might be a motivator for action; and what the practical implications of any research findings are across a complicated and diverse system.

1.1.3.2 Diet and physical activity

Whilst I have explored different topics within public health, one interest that has persisted is population approaches to prevent obesity, which first began as a medical student. Studying in Oxford, I was very cognisant of Richard Doll's work on smoking and health. I thought, perhaps naïvely, that the 'tobacco epidemic' was drawing to a close. I reasoned that other risk factors, notably obesity which was becoming a concern,[18] would pose a bigger threat to the public's health. I also thought the era of chronic disease epidemiology was drawing to a close as epidemiologists had identified most of the important risk factors for health. I thought that public health research needed to move beyond describing associations between obesity and health, and instead should research solutions. It was also around this time that I first learnt of Rose's work and the concept of shifting the population distribution. Influenced by the success of tobacco taxation and using some of Rose's arguments, I wrote my finals dissertation on the potential for taxes on unhealthy foods to reduce obesity. With colleagues at Oxford I have developed that line of work,[19,20] and more recently I have focussed on taxes on sugar sweetened beverages.[21,22] I have also undertaken work concerned with physical activity. My Masters in Public Health dissertation described the associations between greenspace near the home and physical activity in England.[23]

Some of this work has been influential and some has been highly cited. However, neither topic was quite right for my PhD. Both topics were relatively narrow, and not in keeping with a broader appreciation of public health. I was also unsure how to advance the work. Empirical evidence from real world taxes, rather than more modelling studies, appeared necessary to address many residual uncertainties and to persuade governments to tax sugar sweetened beverages. The greenspace work was hindered by poor measurement, and I was unsure what the practical intervention might be as it did not seem feasible to increase greenspace in urban environments to the extent that my research appeared to suggest it was necessary.

1.1.3.3 Approach to PhD

All of these experiences have influenced my PhD. There were several strands that I have wanted to bring together. First, I wanted to take a population approach. Second, I wanted to combine and develop quantitative methods I have used before (epidemiology and public health modelling). Third, I was very conscious of my background in medicine, and I wanted to find ways both to make use of that knowledge and to consider the implications of my work for healthcare. Fourth, being grounded in public health practice and having experience of policy, I wanted to ask relevant or critical questions with the potential to influence public health practice or policy.

1.2 Physical activity and health

1.2.1 Physical activity

Physical activity can be defined as any bodily movement produced by skeletal muscles that requires energy expenditure.[24] It is a broad set of behaviours that can take place in a variety of contexts. It is, and always has been, an intrinsic part of human life. The ability of humans to be active was essential for survival in the pre-historic period, and for the subsequent development of civilisation. The main parts of human life focusing around work or home, until comparatively recently, required physical activity. Cultural and social life has always celebrated a physical dimension to life, from the ritualised dance undertaken by early primitive societies to modern global sporting events.[25,26]

Its importance for health has been recognised for a long time. Organised exercise as a form of health promotion took place in China in 2500 BC.[25] The ancient Greek physician Hippocrates (c.460 BC to 370 BC) and other Greek scholars (Plato and Galen) wrote about the benefits of physical activity for health and well-being.[25–28]

1.2.2 Early studies of physical activity and health

Whilst the notion that physical activity is beneficial for health and well-being may be very old, scientific evidence of its effect on health is comparatively new.[28] One of the earliest reports describing associations between physical activity and disease was produced by Ramazzini in 1700. He compared the diseases experienced by different occupational groups and reported that professional messengers, who walked or ran, avoided some of the diseases experienced by those who undertook relatively sedentary occupations (e.g. tailors and cobblers).[29,30] In 1843, Guy reported that mortality rates were higher amongst sedentary workers compared to those undertaking more active work.[31] Foreshadowing a shift in focus towards recreational activity, Hartley and Llewellyn in 1939, reported increased longevity amongst those who rowed for either Cambridge or Oxford University, in comparison with the general population.[32]

The findings from these early reports may have been suggestive, but were far from conclusive. Confounding, for example by age or socio-economic status, and selection bias, for example self-selection into less active occupations amongst those with pre-existing illness, might explain the findings.

1.2.3 Modern studies of physical activity and health

Beginning in the 1950s Morris and co-workers undertook a series of studies that described the associations between physical activity and cardiovascular disease. Their initial study reported a lower incidence of fatal coronary heart disease among bus conductors who, by walking up and down the stairs on the bus throughout their working day, were relatively active compared to bus drivers.[33] Although based on observational data, a strength of this study was that the two groups of busmen were relatively comparable in many other habits and behaviours. Morris's subsequent work drew on a range of emerging epidemiological techniques to provide a much stronger basis for causal inference.[34,35]

Morris and colleagues established cohort studies in bus workers and civil servants to test the association of physical activity (both occupational and recreational) with coronary heart disease.[36–39] They explicitly measured and adjusted for other potential confounding factors, such as hypertension and diet,[36] as well as testing the extent to which other factors, principally job stress, might account for the differences in observed incidence between occupations.[33] They also documented differences in extent of ischaemic heart disease at post-mortem between those who had been employed in sedentary and in active occupations,[40] and a dose-response relationship between physical activity and disease risk.[38,39]

Others have built on this work. Today there is a large body of scientific evidence, mostly although not exclusively from cohort studies, demonstrating the importance of physical activity for health. The focus of much of this work is moderate-to-vigorous physical activity (MVPA), i.e. physical activity that requires an energy expenditure three times basal metabolic rate. The evidence is summarised below.

1.2.3.1 All-cause mortality

Many cohort studies have reported that regular physical activity is associated with reduced all-cause mortality. A recent meta-analysis of cohort studies (70 studies, 1,525,377 participants, with an average follow-up of 11.1 years and 111,125 deaths) reported a 31% lower risk of all-cause mortality in the most active individuals.[41] A clear dose-response relationship was observed, with the greatest reduction in risk associated with the change from being inactive to undertaking some activity. Risk reduction was similar for males and females. In a separate meta-analysis of cohort studies (80 studies, 1,338,143 participants, 10.7 years follow-up, 118,121 deaths) a reduction in risk was associated with increased activity in all three 'domains' of physical activity (leisure-time, activities of daily living and occupational).[42] Risk reduction was reported to be greater for females than males.[42] In another meta-analysis of cohort studies focusing on non-vigorous physical activity (22 studies,

977,925 participants, follow-up from 4.1 to 17 years) non-vigorous physical activity (light or moderate physical activity) was also associated with reduced risk of mortality.[43] The authors estimated that 2.5 hours of non-vigorous physical activity (compared to no activity) was associated with a 19% reduction in mortality compared to no physical activity.

1.2.3.2 Cardiovascular disease

A recent dose-response meta-analysis of cohort studies (33 studies, 1,683,693 participants, 12.8 years average follow-up, 89,493 events) of the association between physical activity and cardiovascular disease (including the outcomes of CVD incidence, CVD mortality, stroke incidence, coronary heart disease incidence, coronary heart disease mortality, heart failure incidence and myocardial infarction incidence), reported that adherence to guidelines was associated with a 23% reduction in CVD morality and 17% reduction in CVD incidence.[44] As with mortality a dose-response (inverse) relationship was reported with the greatest reductions in risk associated with increases in physical activity amongst the least active.

A previous meta-analysis of cohort studies (59 studies, 726,474 participants, average follow-up 14.1 years, 34,815 events) estimated a 33% reduction in incident disease comparing the most active with the least active.[41] The association between physical fitness (an objective assessment of ability to undertake work without fatigue, and which is associated with physical activity) and cardiovascular disease is stronger. The authors also suggested that the association between physical activity and cardiovascular disease may have been under estimated because of over-adjustment by multivariate control and a failure to adequately account for within person variation in physical activity.[41,45]

The epidemiological evidence, from which a causal relationship between physical activity and cardiovascular disease cannot be proven,[35] is supported by evidence from trials and laboratory studies. For example, randomised controlled trials have shown that exercise can lead to beneficial changes in cardio-metabolic risk factors, such as a reduction in blood pressure,[46,47] weight loss and changes in fat distribution.[48,49]. Laboratory studies have shown how physical activity leads to short-term differences in metabolism that may explain the changes in risk factors or disease risk, for example acute exercise and endurance training are linked to beneficial changes in post-prandial lipoprotein metabolism.[50–52]

Moreover, randomised trials of physical activity, more usually referred to as ‘exercise’ or ‘exercise based cardiac rehabilitation’, in patients with diagnosed cardiovascular disease have been shown to reduce cardiovascular mortality and measures of disease severity (e.g. hospital admission). A meta-analysis of 47 studies randomising 10,794 patients to exercise-based cardiac rehabilitation or usual care reported a 13% reduction in all-cause and a 26% reduction in cardiovascular mortality in the

medium to long term (i.e. after 12 months or more of follow-up).[53] Taking all the evidence together provides a strong basis for inferring a causal relationship between physical activity and cardiovascular disease.

1.2.3.3 Type 2 diabetes

A recent meta-analysis (28 studies, 261,991 participants, 5 to 23 years follow-up, 84,134 incident cases) estimated that compliance with physical activity guidelines was associated with a 26% reduction in risk of type 2 diabetes.[54] Whilst the studies in this review related primarily to leisure-time physical activity and overall physical activity, associations have been observed between occupational physical activity and travel-related physical activity with incident diabetes.[55] Similar to other clinical conditions, the dose-response relationship observed suggests that small increases in physical activity amongst the least active are associated with marked reductions in the risk for type 2 diabetes, although considerable benefits (in terms of type 2 diabetes risk reduction) can be realised at levels of physical activity considerably higher than recommended by present guidelines.[56]

1.2.3.4 Obesity and overweight

In contrast to some of the other outcomes reported here, some of the evidence of the importance of physical activity for weight loss or prevention of weight gain comes from randomised controlled trials. For example, one recent meta-analysis of 25 small randomised controlled studies reported that walking interventions of greater than four weeks duration were associated with a reduction in body weight (1.37kg), reduction in percentage body fat (1.22%) and reduction in BMI (0.53kg/m^2).[57] However, there is also a body of observational data (from cohort studies), suggesting that physical activity (principally leisure-time physical activity) is associated with reduced risk of obesity and reduced weight gain over time over a period of years.[58–61]

It has been suggested that relatively high levels of physical activity are required to prevent weight gain (e.g. 150-250 minutes of physical activity per week), and particularly to cause weight loss (e.g. 225-420 minutes of physical activity per week to cause 5-7.5kg weight loss),[62] although it is acknowledged that there is uncertainty about the type intensity, frequency and duration of physical activity to prevent weight gain or enable weight loss.[63]

1.2.3.5 Cancer

Physical activity guidelines typically report that physical activity is protective for breast and colon cancer.[41,63–65] Consistent with this meta-analyses of cohort studies (12 cohort studies using individual level data on 1,440,000 participants) have shown the physical activity is associated with reduced risk

of colon cancer and breast cancer. A recent meta-analysis estimated that the high levels of physical activity (relative to low levels) were associated with a 14% reduction in colon cancer incidence and a 10% reduction in breast cancer incidence.[66] As with cardiovascular disease there is evidence to suggest that physical activity reduces risk of incident disease and improves disease-specific survival after diagnosis.[67,68]

One systematic review has highlighted evidence that physical activity, in cohort studies, was associated with risk of other cancers, notably lung cancer, prostate cancer, pancreatic cancer, ovarian cancer, endometrial cancer and non-Hodgkin's lymphoma,[69] and a recent meta-analysis of individual-level data from 12 cohorts reported that leisure-time physical activity was associated with reduced risk of 13 types of cancer (oesophageal adenocarcinoma, lung, kidney, gastric cardia, endometrial, myeloid leukaemia, myeloma, colon, head and neck, rectal, bladder and breast) and increased risk of two types of cancer (malignant melanoma and prostate cancer) out of 26 that were studied.[66]

1.2.3.6 Mental Health

A recent meta-analysis of randomised controlled trials in a non-clinical population found that physical activity was associated with a moderate[iii] reduction in symptoms of depression (standardised mean difference = 0.50; 92 studies, 4310 participants) and a small[iii] reduction in anxiety symptoms (standardised mean difference = 0.38; 306 studies, 10,775 participants).[70] Physical activity or exercise has also been shown, in randomised controlled trials, to be an effective treatment for depression (standardised mean difference = 0.62; 35 trials, 1356 participants).[71].
Cohort studies show that physical activity, particularly in mid-life, is associated with reduced risk of dementia in late life.[72–74] One recent meta-analysis (26 cohorts, follow-up one to 26 years) suggested that higher levels of physical activity, compared to lower levels, were associated with a 14% reduction in dementia incidence. It has also been suggested based on some observational studies (both cross-sectional and prospective) that physical activity may be important for general mood or psychological well-being.[75,76]

1.2.3.7 Musculoskeletal health

In meta-analyses of randomised controlled trials physical activity (both aerobic and resistance training) have been shown to have a beneficial effect on bone mineral density, which is a predictor of

[iii] Cohen defined a small effect as a standardised mean different of 0.20 to <0.50, a medium effect as 0.50 to <0.80, and a large effect as >0.80.[364]

development of osteoporosis.[77–79] One systematic review estimated exercise training programme prevented or reversed about 1% of bone loss per year in both pre- and post-menopausal women.[77] There is also some evidence from randomised controlled trials that exercise training programmes in older persons, which typically focus on balance and strength, reduce the risk of falls.[80,81] However relatively few studies have described the association between physical activity and osteoporosis.[41] One cohort study (n=8734 women) has described an inverse dose-response relationship between physical activity and osteoporosis prevalence.[82]

1.2.4 Sedentary behaviour and its relationship to physical activity

Recently evidence has also emerged that sedentary behaviour, independent of (moderate-to-vigorous) physical activity, is also a risk factor for disease. Sedentary behaviour can be defined as any waking activity in a sitting or lying posture that requires an energy expenditure between one and 1.5 times basal metabolic energy expenditure.[83] Sedentary behaviour is not the same as lack of moderate-to-vigorous physical activity. Activity that is not moderate-to-vigorous includes both sedentary behaviour and other light intensity activity, such as standing activities with an energy expenditure less than three times basal metabolic rate.[84] Thus, it is possible to be both highly sedentary and active (i.e. undertaking 150 minutes of MVPA per week with >8hrs of sedentary time per week), termed an 'active couch potato'.[84] Nonetheless sedentary behaviour may relate to MVPA. High levels of MVPA can offset the risk associated with being sedentary,[85] and reducing sedentary behaviour may be associated with an increase in MVPA.

Prospective cohort studies have shown that sedentary behaviour is associated with all-cause mortality, cardiovascular disease, type 2 diabetes, metabolic syndrome and development of cardiovascular risk factors, and some cancers (e.g. colon, ovarian and endometrial).[84–87]

1.3 Physical activity and public health

1.3.1 Public health guidelines on physical activity

Based on the scientific evidence outlined in the previous section many western countries have established recommendations or "public health guidelines" about the amount and types of physical activity that individuals should engage in to prevent disease.[41,62–64,88,89] Public health guidelines first emerged, in the UK and the USA, in the 1990s.[90,91] This was partly in response to the emerging evidence base and partly in response to a growing focus on the prevention of non-communicable diseases, including obesity.[18,92,93]

The UK guidelines were last updated in 2011.[63,88] There are now separate guidelines for children, adults (19-64 years) and older adults (aged 65 years and over). The recommendations for adults are as follows:

> 1) Adults should aim to be active daily. Over a week, activity should add up to at least 150 minutes (2½ hours) of moderate intensity activity[iv] in bouts of 10 minutes or more – one way to approach this is to do 30 minutes on at least 5 days a week.
>
> 2) Alternatively, comparable benefits can be achieved through 75 minutes of vigorous intensity activity spread across the week or combinations of moderate and vigorous intensity activity.
>
> 3) Adults should also undertake physical activity to improve muscle strength on at least two days a week.
>
> 4) All adults should minimise the amount of time spent being sedentary (sitting) for extended periods.

[iv] Moderate intensity activity results in an energy expenditure between three and six times basal metabolic rate. Vigorous intensity activity results in an energy expenditure of more than six times basal metabolic rate. The guidelines state that "moderate intensity physical activities will cause adults to get warmer and breathe harder and their hearts to beat faster, but they should still be able to carry on a conversation", and that "vigorous intensity physical activities will cause adults to get warmer and breathe much harder and their hearts to beat rapidly, making it more difficult to carry on a conversation".

The recommendations for older adults are similar, but with additional recommendations (e.g. benefits of small increases in physical activity from a low baseline, recommendation to incorporate balance or co-ordination activities).

Guidelines in other countries are similar, although some of these (e.g. in the USA and Australia) include explicit encouragement to undertake higher levels of physical activity (300 minutes, i.e. 5 hours, of moderate or 150 minutes of vigorous activity per week).[64,94,95]

Alongside the public health guidelines, which are population based and focus on prevention, physical activity is increasingly recognised as a treatment for some conditions and explicitly included in the treatment pathways for some conditions, for example the management of depression and ischaemic heart disease.[96,97]

1.3.2 Prevalence and trends in inactivity

In the UK, and globally, a large proportion of the adult population is not meeting these guidelines. In England in 2012, it was estimated that around one third of men (33%) and just under half of women (45%) were not meeting the physical activity guidelines.[v,98] Globally around one in three adults (31%) are classified as 'inactive',[vi] with women tending to be less active than men.[99]

Whilst there is some evidence that levels of leisure-time physical activity have increased in the past 20 years in the UK, any increases are relatively small.[98,100] Moreover these comparisons should be treated with some caution as the measuring instruments have changed over time and increases in leisure-time activity may have been accompanied by decreases in occupational activity.[99] Looking further back in time, it is likely that levels of physical activity were much higher 50 or 100 years ago. Although there are no long term measures of physical activity, population indices that do exist suggest large declines in physical activity, for example changes in travel patterns such as a shift away

[v] Reflecting the convention used by others, not meeting the guidelines refers only to parts 1 and 2 (i.e. not achieving 150 minutes of moderate-to-vigorous physical activity or 75 minutes of vigorous physical activity per week). The equivalent figures in 2008 appeared much worse, 61% of men and 78% of women were classified as not meeting the guidelines.[365] The difference in reported activity levels reflect a change in the UK physical activity guidelines in 2010. Before 2010 a minimum of 150 minutes of moderate-to-vigorous physical activity was recommended (rather than 150 minutes of moderate or 75 minutes of vigorous) in bouts of at least 20 minutes (rather than 10 minutes).[88]

[vi] Physical inactivity was defined as not meeting any of three criteria: 30 minutes of moderate-intensity physical activity on at least 5 days every week, 20 minutes of vigorous-intensity physical activity on at least 3 days every week, or an equivalent combination of moderate or vigorous activities achieving the equivalent of 10 MET-hours per week. MET-hours is a measure of energy expenditure (intensity multiplied by time) and is discussed in detail in Chapter 5 (section 5.3.6.1).

from bicycle use and walking towards car use.[101,102] Comparisons between typical modern and traditional living show very large differences in daily physical activity energy expenditure, suggesting large declines in physical activity are likely to have occurred.[102]

In England the proportion of the population that is meeting guidelines varies by age, ethnicity and socio-economic group.[98,103,104] For example, for men it declines with age, from 83% of men aged 16-24 years to 30% of men aged 75 years and over, whereas for women it rises during early adult life, from 57% of women aged 16-24 years to 66% for women aged 35-44 years of age, and then declines with age, to 13% among women aged 75 years and over.[98] There are also differences in the types of physical activity undertaken by age (and between the sexes), with a shift in focus away from sport and exercise with increasing age.[105]

Given this decreasing trend in physical activity with age and the increasing incidence of disease with age, the burden of disease attributable to lack of physical activity is likely to be particularly large amongst those in mid- and later-life. Consequently, strategies to engage those in mid and later-life may be particularly important (although engagement at younger ages may also be important, for example to establish lifelong habits).

1.3.3 Burden of disease and costs attributed to lack of physical activity

Lack of physical activity contributes to a substantial burden of diseases. In the UK it is estimated to account for 5% of disability-adjusted life-years in 2010, making it the fourth largest risk factor[vii] for burden of disease and responsible for a similar burden of disease as alcohol.[106] Globally lack of physical activity accounts for 9% of premature mortality (5.3 million deaths per year) and it is the fourth leading risk factor for mortality and burden of disease (measured in DALYs).[107]

Lack of physical activity has significant financial costs for health services and society more broadly. In England lack of physical activity costs society an estimated £7.4 billion annually.[108] Globally it was estimated conservatively that lack of physical activity costs healthcare systems 53.8 billion international dollar[viii] (Intl.$) and a further Intl.$13·7 billion in productivity losses in 2013 and was responsible for 13·4 million DALYs worldwide.[109]

[vii] Whilst it is common to draw comparisons between risk factors, a degree of caution should be exercised. Others have pooled together all dietary risk factors and suggested that diet is the second largest risk factor, although this may involve double counting. Hypertension and overweight rank above physical inactivity, and it is unclear whether the contribution of physical activity to these risk factors has been considered within physical activity or within those risk factors.

[viii] International dollar is a hypothetical unit of currency that has the same purchasing power parity that the US dollar had in the United States at the time of measurement.

All of these estimates are based on increasing the levels of physical activity of those who are not achieving recommended amount of moderate-to-vigorous physical activity up to the recommended levels (i.e. 150 minutes of moderate-to-vigorous physical activity per week). However further health gains are likely to occur from exceeding the recommended levels,[42,43,110] so these estimates may understate the health gains and cost savings that could accrue from increases in physical activity.

1.3.4 Approaches to promotion of physical activity

This apparent failure of previous approaches to increase levels of physical activity has led to calls for different approaches to the promotion of physical activity.[26,108] A 'traditional approach' to promoting physical activity might be characterised as offering advice to, educating and motivating people to adopt an active lifestyle. For example, offering 'exercise on prescription' to high-risk or less-active individuals.[111] Using Rose's language, exercise on prescription and similar interventions targeting individuals could be characterised as individual-level interventions. Mass education campaigns might be characterised as population level interventions, but, again using Rose's language, would be 'superficial' (rather than 'radical') in their approach. Accordingly, such approaches may have limited ability to reduce the burden of disease and are unlikely to be sustainable.

There is recognition, at least from some organisations, that attention needs to shift from an individual approach to a population approach.[26,108,112–114] The latter approach seeks to shift the distribution of physical activity by modifying the underlying social, economic and environmental determinants of physical activity.[6,115] As physical inactivity is prevalent and the risk of most diseases, for which physical activity is protective, is widely distributed, there is a strong case for a population approach.

Past approaches have also placed particular emphasis on leisure-time activities (sport, exercise and recreational activities). Leisure-time activity, particularly sport and exercise, may require relatively high levels of motivation and have associated economic and time costs. They may not appeal to many people, particularly the least active, who have the most to gain from increasing physical activity.

Much less emphasis has been given to physical activity as an integral (or incidental) part of everyday life,[26] although this is now being addressed.[108,116] Conceptualising physical activity in this way (sometimes termed 'active living'), the scope for increasing physical activity is much broader as it crosses four domains: travel, domestic, occupational, as well as sport and recreation.[115] The

promotion of walking and cycling as forms of travel (active travel), instead of car-use, is an integral part of promoting active living.

1.4 Walking and cycling

There are several reasons why promoting walking and cycling as forms of travel may be able to shift the distribution of physical activity. Such incidental physical activity may be more acceptable than more structured 'exercise'. The high prevalence of walking for travel (e.g. London) and cycling for travel (e.g. Cambridge, the Netherlands) in some areas suggests that it can be acceptable to large number of adults.[117,118] Changes in behaviour are hard to sustain, but changes that become habitual or embedded as partly of daily routines,[119] as travel patterns can be, may have more likelihood of being sustained for many years, which is necessary to realise health improvements throughout life. Lack of time is a reported barrier to being physically active.[120,121] The average journey to work in the UK is 29 minutes.[122] Being active for only a portion of this journey (e.g. 10 minutes) would sum up to a large dose of physical activity across the week (e.g. 10 minutes times two commuters per day times five days, equates to 100 minutes per week).

1.4.1 Co-benefits of walking and cycling

The promotion of active travel, particularly in large urban areas, may be associated with many other co-benefits.[123–125] These include other health benefits. Reduced car use, as a consequence of increased active travel, is likely to be associated with reduced air pollution and a reduction in road traffic accidents (involving motor vehicles). It may also be associated with improvements in well-being and mental health, through reductions in severance (division of communities by major roads or other infrastructure routes) and by improving the attractiveness or liveability of the local environment.

The promotion of walking and cycling, often alongside or facilitated by public transport, may help reduce congestion and carbon emissions. It is for this reason that some cities, such as London have invested significantly in cycling, walking and public transport infrastructure and successfully shifted travel patterns away from car-use towards walking and cycling.[126]

1.4.2 Existing studies of active travel and health

There is an extensive body of evidence describing the associations between physical activity and health (outlined in section 1.2.3).[41,63] However most of this work has, following Morris' lead,[ix] focused

[ix] Morris' later work shifted attention away from occupational physical activity to leisure physical activity. This was a strategic decision, partly driven by a wish to study activities of different intensities (the range of intensity is greater for

on leisure-time physical activity (sport, exercise and recreation) and not on walking or cycling as forms of travel. This is necessary as there may be differences between travel-related physical activity and leisure-time physical activity in terms of the frequency, duration and intensity, as well as associated risks (e.g. injury or air pollution), that may influence the associations with health and may also be context dependent.

1.4.2.1 Epidemiological studies

Associations of active travel with all-cause mortality,[127,128] cardio-vascular mortality, incident diabetes,[129] incident hypertension and obesity have been reported.[130,131] Relatively few studies have explored the associations of active travel with cancer, mental health and other indices, such as sickness absence or well-being.[132] Subjective indices of health, like well-being, are increasingly recognised as being important outcomes in their own right and may contribute to engaging a broader set of actors in promoting active travel.[133,134] Sickness absence is another indicator that is infrequently studied, but is of economic importance and of interest to those outside the health sector.[135] While, some of the associations between active travel and health have been described in longitudinal studies, much of the evidence, particularly for obesity and other indices of health, is based on smaller and often cross-sectional studies. Cross-sectional studies provide a weak basis for inference because the exposure has not been shown to precede the outcome and reverse causation (e.g. obesity determining active travel) may sometimes explain the observed associations.

Many studies of active travel have focused on active commuting,[132] which may be considered a sub-set of active travel. Active commuting is frequently studied because it is relatively easy to record, is captured in many standard physical activity questionnaires (e.g. the Recent Physical Activity Questionnaire) and is regularly undertaken (i.e. the 'exposure' is consistent and may continue for a period of time). However most of the studies of active commuting classify commuting based on 'usual mode of travel' (reflecting limitations with the study questionnaire). Usual mode of travel does not reflect the reality of commuting for some people who may either combine modes of travel (e.g. walk to train station, train to work) or people who may use alternative modes on different days (e.g. cycle to work on some days and drive on other days).[136,137] Individuals who adopt these travel patterns may be incorrectly classified as 'passive' commuters when they do undertake some commuting. Such classifications also result in comparisons being drawn between individuals who cycle or walk (the whole journey) to work with individuals who only use the car. Whilst such comparisons have a role, many journeys to work are too far to be undertaken solely by foot or

recreational activity than occupational activity) and partly a belief that a relatively sedentary society could only become 'active' by undertaking recreational physical activity.[28]

bicycle (the average commute in the UK in 2014 was 8.7 miles).[122] More meaningful comparisons that reflect actual travel options may be possible.

1.4.2.2 Public health modelling studies

The epidemiological evidence is also complemented by public health or health impact modelling studies. Whilst shifting the population distribution can realise large health gains, in practice these gains are either not directly observable or cannot be observed immediately. Public health modelling is one approach to estimate the gains (or harms) of such interventions. It effectively translates the findings of epidemiological studies (typically expressed as relative risk for individuals) into estimates of population-level health impact that are more relevant (e.g. number of incident cases) for policy makers and practitioners, and may be more salient for the public.[138] For public health practice it is a valuable complement to epidemiological work.

Several physical activity models have been developed, such as the Health Economic Assessment Tool (HEAT) for cycling and the Integrated Transport and Health Impact Modelling Tool (ITHIM). HEAT estimates the economic benefits from changes in health due to increases in physical activity from walking or cycling for travel. It has been used in several countries to inform the economic appraisal of transport planning, which had not previously accounted for such health benefits.[139] ITHIM estimates the health impacts of changes in walking and cycling, considering physical activity, air pollution and road traffic accidents. It considers a range of health outcomes: depression, stroke, ischaemic heart disease, type 2 diabetes, colon cancer, breast cancer and all-cause mortality. It has been used to estimate the potential health benefits and consequent savings in NHS expenditure from a shift away from car-use to walking and cycling,[125,140,141] as well as the health benefits associated with particular interventions, such as the London cycle hire scheme.[142]

Both these models, like other public health models,[143] are comparative risk assessment models. Comparative risk assessment models do not make allowance for changes in life expectancy, which may be important. Increases in physical activity reduce risk of disease, but also increase life expectancy resulting in an increase in the number of years lived at old age when disease incidence is higher. It is conceivable that disease events could be postponed rather than prevented, but comparative risk assessment models (by assuming all other factors, including life expectancy are unchanged) cannot model such effects. This may be particularly important for understanding the impact of shifts in the distribution of physical activity on demand or need for healthcare.

1.5 Overview of thesis

This thesis aims to address the two areas of uncertainty highlighted in the previous section:

a) the associations of active commuting with indices of health and well-being

b) the extent to which increases in physical activity, when making allowance for changes in life expectancy, will reduce need for health and social care.

My thesis, therefore, is divided into these two parts, which use different and complementary methods, observational epidemiology and public health modelling.

1.5.1 Part I: Associations between active travel and health

In this section, I will describe the associations between active travel and indices of health (sickness absence, well-being and adiposity). The unique contribution of this work will be, first to describe the little-explored associations of active travel with well-being and sickness absence, second to describe the longitudinal associations between active travel and body mass index, and third to describe the associations of active travel with objective measures of adiposity (visceral adipose tissue and percentage body fat) in a large dataset which has accurately characterised physical activity and dietary behaviour.

I will use two datasets, Commuting and Health in Cambridge and the Fenland Study. I describe these datasets and the rationale for choosing them below.

1.5.1.1 Commuting and Health in Cambridge

The Commuting and Health in Cambridge study (2009-2012) was established to study the effect of changes to the environment (principally the development and opening of the Cambridge guided busway) on commuter behaviour, physical activity and health. A full description of this study has been published elsewhere.[144,145]

The study had multiple elements and used both quantitative (e.g. repeat annual questionnaire, intercept survey of busway users, in-depth objective physical activity monitoring) and qualitative approaches (e.g. semi-structured interviews, photo-elicitation interviews). It has been described as a natural experimental study, although I only make use of one element of the study, the cohort of commuters who were followed for up to three years. I refer to this as the Commuting and Health in Cambridge dataset, and below I describe the key elements that are relevant to the analysis reported in my thesis.

Briefly, the study recruited adults who worked in Cambridge and did not reside at their work address. Participants (n=1434) were recruited over four waves (2009, 2010, 2011, 2012), with the majority recruited in 2009. Each year participants were invited to complete a questionnaire including information on socio-demographic characteristics, a validated seven-day retrospective travel record, the Recent Physical Activity Questionnaire (RPAQ), health (sickness absence, well-being assessed using the Short Form 8 Questionnaire, self-reported height and self-reported weight) as well as other factors related to travel to work.

This dataset had several advantages. The prevalence of active commuting, principally cycling, was relatively high compared to the UK average (in Cambridge 29% of the population report cycling as their usual mode of travel compared to 3% in the UK) and many western settings.[117,146] Unlike in other settings, cycling to work was not restricted to younger males, which might improve the generalizability of the findings. The detailed characterisation of commuting behaviour may facilitate a more nuanced representation of how people commute as well as reduce measurement error.[147] Whilst, small compared to some studies, this and the high prevalence of active commuting meant the study was relatively well powered compared to some larger studies.

The study was also longitudinal. In contrast many studies of the association of active travel with sickness absence, well-being and body mass index are cross-sectional. Being focused on active commuting and health, the study had also captured other important factors, e.g. occupational and leisure-time physical activity and travel factors (e.g. distance from home to work).

1.5.1.2 Fenland Study

The Fenland Study (International Standard Randomised Controlled Trials Number 72077169) is an ongoing population-based cohort study of adults born between 1950 and 1975 and living in part of Cambridgeshire, UK. It was designed to investigate the interaction between environmental and genetic factors in determining obesity, type 2 diabetes, and related metabolic disorders. The level of detail it collects about the health and behaviours of its participants is unusual.

Participants (n=12,434) were recruited from general practice lists between 2005 and 2015. They attended one of three clinical research facilities, where they completed a general questionnaire, a food frequency questionnaire (FFQ) and the Recent Physical Activity Questionnaire (RPAQ). In addition they underwent a number of tests, including assessment of body composition by dual-energy X-ray absorptiometry and up to six days of objective physical activity monitoring (Actiheart®, combined heart rate and accelerometer sensing).[148]

Compared to other studies of active travel and adiposity this study had a number of advantages. It has measured adiposity objectively by DEXA (Dual-Energy X-ray Absorptiometry) scan. Thus rather than only measure body mass index (BMI), it includes different measures of regional (e.g. visceral adipose tissue, android to gynoid fat mass) and total adiposity (e.g. percentage body fat, total fat mass). Such measures are more strongly associated with cardio-metabolic disease than BMI.[149–151] It has detailed characterisation of both diet and physical activity (both self-reported and objective), in contrast to most other studies of active travel and adiposity.

It includes information on both mode and frequency of travel to work, so will facilitate a more appropriate appraisal of commuting patterns than usual mode of travel. Being in Cambridgeshire and being a cohort of working age adults the prevalence of active commuting is relatively high.

It complements the Commuting and Health in Cambridge dataset. It is larger, is more socially diverse, has more appropriate and objective measurements of adiposity, and includes detailed measures of diet and physical activity. However, it is cross-sectional and does not characterise commuting in as much detail.

1.5.2 Part II: Estimating the effect of shifting the distribution of physical activity on healthcare need

The second part of this thesis aims to understand the effect of increases in physical activity on indicators of need for healthcare. The unique contribution of this work is to model the effect of changes in life expectancy and demonstrate the effect that this has on estimates of need for healthcare. In contrast to other work I do not seek an aggregate measure of healthcare need (e.g. disability adjusted life years), but I try to understand the changing patterns of need for each disease. To do this I developed a life table based model. The model was parameterised for the English population.

Below I justify the choice of modelling (over observational studies), the choice of modelling techniques and briefly set out the data used to parameterise the model.

1.5.2.1 Modelling approach

Observational epidemiology has been used to describe the association between physical activity and healthcare usage.[152,153] However, cross-sectional studies are problematic as an inverse association between physical activity and healthcare utilisation may be explained by reverse causation, e.g.

those who have high healthcare utilisation are not able to be physically active. Similar problems may occur with prospective studies. Observational studies also lack some of the flexibility of modelling studies, such as modelling several different scenarios. Nor can they readily observe the effects of a change in physical activity throughout the whole life, which is necessary to understand the extent to which disease may be postponed rather than prevented.

Modelling studies that model ageing or time may be a more appropriate means to understand the effect of increasing longevity as long follow-up (throughout life) is possible. The two common health impact modelling techniques that would permit this are microsimulation and life table modelling.

Microsimulation involves simulating many individuals. When these individuals are followed over time, this becomes computationally very demanding. This requires the use of more complicated software, more programming, often more data, and either larger computer servers or more computer time. It becomes particularly useful when granular outcomes (e.g. breakdown by socio-economic group or activity status), granular scenarios or interaction between risk factors (e.g. anti-hypertensive treatment and lipid lowering treatment) are important. In the absence of these demands, multistate life table modelling probably yields comparable answers to microsimulation modelling, although I am not aware of any direct comparisons.

Given the constraints of the modelling project, within the scope of a broader PhD, I chose a compromise. The effect of changes in physical activity on disease risk was modelled using a microsimulation approach. The effect of changes in disease risk on disease and survival was modelled using a multistate life table approach. This combined approach used some of the flexibility of microsimulation (principally in terms of modelling scenarios), ensured the core health impact modelling explicitly modelled time, whilst limiting the computational demands and programming needs of the overall model. However, the core part of the model which describes the effects on health is a proportional multistate life table model and consequently I refer to the model as a "life table model" throughout this thesis.

1.5.3 Datasets

I used the Health Survey for England (2012) to describe physical activity levels of my simulated population.[98] This is a representative sample of the English population, from which the published estimates of the prevalence of inactivity are derived. Whilst it is an annual survey, not every year includes detailed questions on physical activity. The last module that did include physical activity was 2012, using a modified version of the validated Health Survey for England physical activity

questionnaire. This asks about the type, frequency and duration of activity across three areas: housework; manual/gardening/do-it-yourself activities; walking and sports and exercise.[98]

I used routine data to estimate the incidence and case fatality from the diseases included in the model (e.g. mortality statistics, cancer registry data for incidence, primary care audit for prevalence of diabetes). Estimates of the effect of physical activity on relative risk of disease and mortality were taken from appropriate meta-analyses.

1.5.3.1 Scope

My focus is moderate-to-vigorous physical activity. Whilst the work may have implications for sedentary behaviour and other aspects of physical activity included in the guidelines (e.g. muscular strength and balance), I predominantly limit the work to consideration of its implications for moderate-to-vigorous physical activity (hereafter referred to as "physical activity"). Given the focus on physical activity, I do not consider other health effects of travel (e.g. air pollution, road traffic injuries). My focus includes adults, but does not include children.

1.5.4 Thesis structure

Chapter Two describes the longitudinal associations of active travel with sickness absence and well-being in the Commuting and Health in Cambridge dataset. An abbreviated version of this work has been published as: Mytton OT, Panter J, Ogilvie D. Longitudinal associations of active commuting with well-being and sickness absence. Prev Med. 2016 Mar;84:19-26.[154]

Chapter Three describes the longitudinal associations between active travel and body mass index in the Commuting and Health in Cambridge study. This work draws on similar methods to the work reported in Chapter Two, consequently the methods section is relatively brief and principally covers aspects of the method that are different. An abbreviated version of this work has been published as: Mytton OT, Panter J, Ogilvie D. Longitudinal associations of active commuting with body mass index. Prev Med. 2016 Sep;90:1-7.[155]

Chapter Four addresses some of the limitations identified in Chapter Three. It describes the associations of active travel with visceral adipose tissue and body fat in the Fenland Study at baseline.

Chapter Five begins with an introduction to Part II of this thesis. It discusses the different ways that physical activity may affect 'need' for healthcare. It introduces the concept of 'need' and how this

relates to burden of disease. It then sets out the modelling methods: describing the model structure, the health outcomes studied, the scenarios modelled, sensitivity and uncertainty analyses undertaken, and finally sources of data.

Chapter Six sets out the results, including sensitivity analyses, from the modelling study.

Chapter Seven includes a detailed discussion of the modelling work, which includes consideration of model validity.

Chapter Eight presents a discussion of this thesis. It summarises the key findings, discusses over-arching themes, sets out implications for practice and policy and offers suggestions for future research.

Part I

Observational epidemiology: associations between active travel and indices of health

2 Longitudinal associations of active travel with sickness absence and well-being

"I would say I'm much calmer now I drive and I don't cycle. As I mentioned I was getting very stressed [when I cycled] because of the behaviour of others on the road."

"I've been cycling now for well over 35 years... [For] me it's the only way to travel around Cambridge. It's so easy. I choose to do it because I used to do a lot of sports years ago and as you get older you can't do those sort of things ... so cycling now is my main exercise."

Participants in the Commuting and Health in Cambridge Study

2.1 Introduction

This chapter describes the longitudinal associations of active travel with sickness absence and well-being in the Commuting and Health in Cambridge dataset. An abbreviated version of this chapter has been published in Preventive Medicine.[155]

2.1.1 Chapter outline

This chapter describes in detail the Commuting and Health in Cambridge dataset (which is also used in the subsequent chapter). Data was collected over four years, and I explain why I have chosen to use data from only two time-points in this analysis, before then going on to describe the methods (exposure and outcome measurement and the analytic approach). I have chosen to use two complementary analyses and the rationale for these is set out in the methods, and interpretation of each is further discussed in the discussion section. Study results are presented separately for cycling and walking, as it was only for the former that significant associations were observed. The discussion includes the following: a summary of the findings; strengths and limitations; comparisons with other studies; interpretation and implications; unanswered questions and future research. The chapter finishes with a summary of the chapter.

2.1.2 Background

As discussed briefly in Chapter One relatively little work has explored the associations of active travel with sickness absence[156] and well-being,[157–160] although other work has described the association between leisure-time physical activity and these indices.[156,161–166]

2.1.2.1 Well-being

The Oxford English Dictionary defines well-being as "the state of being healthy, happy, or prosperous; physical, psychological, or moral welfare." Within the scientific literature there is no agreed definition of well-being.[133,167–169] Whilst it may loosely equate with happiness or satisfaction, most authors agree that "well-being" constitutes more than this, for example developing as a person, being fulfilled, and/or making a contribution to the community.[170]

Well-being is increasingly recognised as an important driver for public policy. For example the past Government chose to systematically measure and publish estimates of national well-being.[133] They also established Health & Well-being boards as a forum where key leaders, at a local level, from the health and social care system work together to improve the health and well-being of their local population and reduce health inequalities at the local level.[151]

Very limited work to date has described the associations between active travel and well-being (see Table 2.1). These studies have reported mixed findings, with some reporting positive associations, some null findings and some negative associations, although the studies have all used different measures of well-being. They have tended to either report associations for walking to work[160] or have studied a population who predominantly walked.[158,159] Three of the five studies were cross-sectional in design.

Table 2.1 Summary of studies describing the association of active travel with well-being and sickness absence

Author, Year	Settings and dataset (size)	Analytic Approach	Exposure	Outcome	Co-variates	Significant Findings
Martin, 2014[159]	British Household Panel Survey 1991/2-2008/9 (n=17,985)	Longitudinal	Active commuting Public transport Walking to work	Psychological well-being assessed using a 12-item general health questionnaire	Age, sex, SES, commute duration, work satisfaction, neighbourhood characteristics	Active commuting, public transport and walking to work associated with better psychological well-being
Humphrey, 2013[157]	Commuters in Cambridge (n=989)	Cross-sectional	Active commuting (i.e. walking or cycling)	Well-being assessed using the Short Form 8 questionnaire	Age, sex, SES, home to work distance, BMI	Active commuting associated with an increases in physical well-being (but not mental well-being) score
Gomez, 2013[160]	Women living in low and middle income areas of Cali, Columbia (n=1,263)	Cross-sectional	Walking for transport	Health related quality of life	Age, SES, leisure time PA, neighbourhood level deprivation	Walking for transport negatively associated with both physical and mental dimension of health related quality of life (leisure time PA positively associated)
Hendrikssn, 2010[156]	Commuters in Netherlands (n=1236)	Cross-sectional	Cycling to work	Sickness absence	Age, sex, SES, home to work distance, physical fitness, BMI, subjective health, smoking	Decreases sickness absence (1 day per year) amongst those who cycle to work compared to those who do not
Mutrie, 2002[158]	Glasgow, Scotland (n=295)	RCT of intervention to promote active commuting	Walking or cycling to work	Well-being assessed using the Short Form-36 questionnaire		Significant improvement in three of eight domains of well-being in the intervention group relative to control group (the intervention group significantly increased walking to work)

PA=physical activity; BMI=body mass index; SES=socio-economic status.

2.1.2.2 Sickness absence

Sickness absence is typically measured as the number or days absent from work due to ill-health. It may cost employers as much as £15 billion per annum in the UK.[172] In 2014 it was estimated that 131 million working days were lost to sickness absence (an average of 4.4 days per employee).[173] As well

as being of interest to employers,[173] sickness absence is also associated with future disability or death, so may be a good proxy for 'general health'.[174–176]

To some extent sickness absence and well-being (at work) may be related. In the UK, there has been a focus on improving workplace well-being, not only because well-being is important in its own right but also because it may be associated with productivity and sickness absence.[134,135]

Only one study, which was cross-sectional, has described the association between active travel (cycling to work) and sickness absence.[156] However, several studies have described the associations between other domains of physical activity, principally leisure-time physical activity, and sickness absence or absenteeism. In prospective studies leisure-time physical activity at baseline or increases in leisure-time physical activity were associated with reduced sickness absence,[161,163,177–180] although occupational physical activity has been reported to be inversely associated with sickness absence.[178] Physical activity appears to be important for sickness absence attributable to both musculo-skeletal problems and mental well-being, although its association with the former may be stronger.[180]

2.1.2.3 Study rationale and aims

Both sickness absence and well-being are important measures in their own right, but they are also of interest to employers and governments who can influence the social, economic and physical environmental determinants of active commuting. If either measure were shown to be associated with active travel, this might strengthen the case for employers investing in its promotion. These measures may also be more sensitive to change than disease outcomes in a relatively healthy population of working age, and therefore may represent a pragmatic health outcomes in studies of interventions designed to promote active travel.

This chapter seeks to build on the limited existing literature describing the associations of active travel with sickness absence and well-being. In particular it will employ a longitudinal design and study separately both cycling to work and walking to work. It aims to describe the longitudinal associations of active commuting with physical well-being, mental well-being and sickness absence.

2.2 Methods

As discussed in the first chapter (section 1.5.1), I chose to use the Commuting and Health in Cambridge dataset, which for the purposes of my work may be considered a cohort study of commuters who work in Cambridge.

Below I describe the key elements of the study (under study settings and data collection) as they apply to the analyses reported in this chapter (on sickness absence and well-being) and the next chapter (on body mass index). Many parts of the method (e.g. classification of exposure, co-variates, analytic approach) are the same or similar, across the two chapters and are described fully in this chapter and only briefly in the next chapter.

2.2.1 Study setting and data collection

2.2.1.1 Study setting

The city of Cambridge lies in the east of England. The surrounding area is largely rural with a number of towns (Ely, Royston, St Neots, New Market and Huntingdon) and smaller settlements. It lies approximately 80km northeast of London.

In contrast to most of the UK, Cambridge has a strong cycling culture related to a combination of factors including its flat topography, its large student population and traffic congestion. The reported prevalence of cycling to work (amongst Cambridge residents) was 29% in the 2011 Census, compared with 3% as a national average (based on 'usual mode' of commuting).[146]

Cambridge has good road transport links. The M11 motorway links it with London and the south east. The A14 trunk road provides a major east-west route, linking to the Midlands in the west and Norwich and East Anglia to the east. There are 'Park and Ride' facilities at a number of sites to the south (Trumpington and Brabham Road), east (Newmarket Road) and west (Maddingley Road) of the city, which allow car drivers to park at the edge of the city and continue the rest of the journey by bus, bicycle or foot. The city is also well served by frequent train services to London, and nearby towns (Royston) and cities (Norwich and Ely), as well as smaller towns and settlements in the immediate area. Public transport to other rural areas is relatively limited.

The population of Cambridge was 124,000 in 2011 Census.[181] Reflecting its status as a university city, the population is relatively young, with a population 'bulge' between the ages of 15 and 34 years. It

is also a relatively prosperous and educated city. Unemployment is relatively low (3.8% vs 5.1% for England).[182] A relatively large proportion of the population are employed in professional occupations (40.2% vs 20.0% for England) with a relatively small proportion employed in service related roles (6.5% vs 16.7% for England) or machine operative roles and elementary occupations (10.6% vs 17.1%).[182,183] Nearly two-thirds (66.5%) of the population have a degree, compared to a third in England (36.8%). Median earnings are above the English average (£15.76 per hour compared to £13.41 in England). These patterns contrast with the surrounding county of Cambridgeshire (population of 621,000)[x], which tends to be close to the English average.

2.2.1.2 Participants

The study population comprised adults aged 16 and over who worked in areas of Cambridge served by the Cambridgeshire Guided Busway and thus includes both residents of Cambridge and the surrounding areas (both inside and outside of Cambridgeshire).

Participants were eligible for inclusion irrespective of their employer, workplace, type or grade of occupation, length of employment contract or working hours; whether they also worked at single or multiple locations; and whether they had any disability that may limit their mobility.

Participants were ineligible if they were currently taking part in another research study that involved measuring their physical activity or if they lived in on-site (staff) accommodation and therefore did not routinely commute to their workplace.

2.2.1.3 Recruitment

Since the study was focused on travel to work, participants were recruited through workplaces rather than from the general population. They were approached using a combination of recruitment stands, newspaper and magazine advertisements, posters, fliers, and announcements distributed on the investigators' behalf by employers through corporate email distribution lists, intranets and staff newsletters. Participants who opted in to the study were entered into a prize draw to win one of eight £50 gift vouchers.

Recruitment commenced in March 2009. During the first phase of recruitment, there were 2163 expressions of interest to participate, with 1582 participants meeting the inclusion criteria, of which 1164 completed the baseline questionnaire in 2009. New participants were recruited during each of

[x] Estimates for Cambridgeshire include the city of Cambridge.

the subsequent phases of the study (in year two, year three and year four), although the majority of participants were recruited in 2009 (81.2% 1164/1434).

2.2.1.4 Core questionnaire

The core questionnaire collected information related to the main outcomes (well-being and sickness absence), travel behaviour, usual physical activity, socio-demographic characteristics and other co-variates. The core questionnaire was mailed to all participants.

The core questionnaire included the Medical Outcomes Study Short Form 8 (SF-8) questionnaire, a series of eight questions used to assess general physical and mental well-being,[184] and an item on self-reported sickness absence. It also asked participants to report their height and weight. It included a seven-day retrospective travel record focusing on the journey to and from work, which was based on an instrument used in other studies of active commuting and shown to have acceptable test-retest reliability.[185] This instrument asked participants to list all modes of travel used to travel to or from work. Separately participants who reported cycling to or from work were asked to report the duration of the cycling part of the journey. The same questions were asked for walking to or from work. Usual physical activity was assessed using a validated questionnaire, the Recent Physical Activity Questionnaire (RPAQ), which assess usual physical activity in the past four weeks across four domains of physical activity (domestic, travel, occupational, leisure).[186]

A copy of the questionnaire used during the first wave of recruitment in 2009 is shown in the Appendix.

2.2.1.5 Ethics

Ethical approval was granted by the Hertfordshire Research Ethics Committee for phases one (08/H0311/208), two (09/H0311/166) and three (10/H0311/65) of the cohort study (08/OH0311/208) and the Cambridge Psychology Research Ethics Committee for phase four (2012.14). All participants gave written informed consent.

2.2.2 Choice of approach to longitudinal analysis

Data was available, on both the exposure and the outcome, from four time points representing the four annual waves of data collection. In theory this could permit a number of different analytic approaches (e.g. interrupted time-series analyses, analysis of change).[187,188]

Whilst it might appear attractive to use data from all four-time points, only a small number of participants (24%, 347/1434) participated in all four waves. As travel patterns could change in multiple ways across four time points[xi], the number of participants who adopted any particular trajectory across the four time points would be relatively small. Splitting the limited sample size into sub-groups risked loss of power. Missing data might further exacerbate the issue of small sample size, or alternatively require techniques to impute missing data.

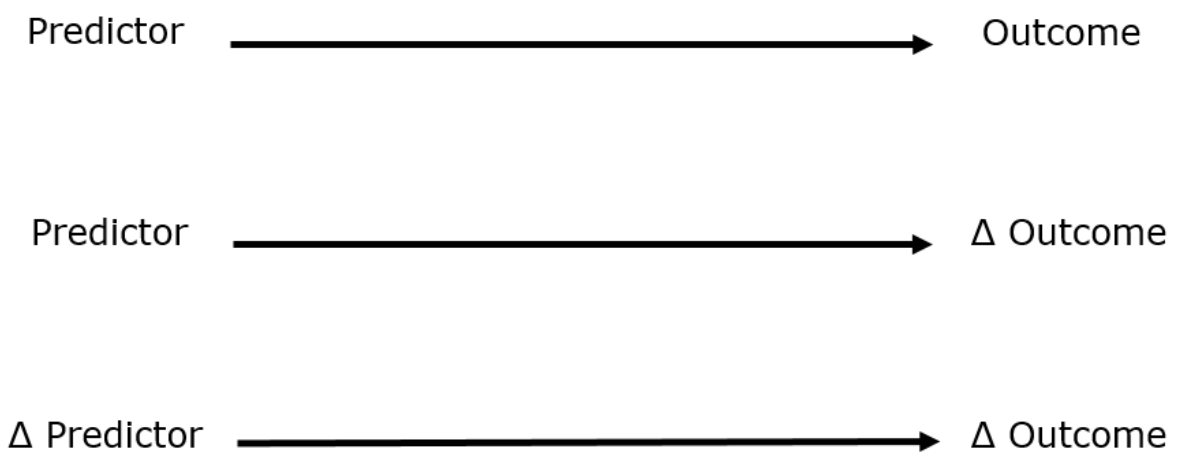
For reasons of parsimony and power, I chose to restrict my analysis to using data from two time-points and I included participants who completed two consecutive questionnaires (i.e. took part in two consecutive phases of the study) rather than restrict the analysis to only the first two waves of data collection to increase the number of eligible participants and thus improve study power.

A number of potential analytic approaches using data from two time-points were identified (see Figure 2.1). I chose to use two complementary approaches, a 'predictor' analysis and a change analyses, rather than use a single approach. More may be learnt from combining approaches than using either approach in isolation.

Furthermore, I further chose to restrict the 'predictor' analysis to those who were confirmed at follow-up to have comparatively stable commuting behaviour (i.e. their classification of commuting behaviour was the same at follow-up). This ensured that estimates of association would not be influenced by the potential misclassification of those who changed their behaviour during the period of observation (e.g. if a participant switched from cycling to work to not cycling to work two weeks after baseline data collection). Misclassification of commuting behaviour in this way may be considered a form of measurement error, akin to regression dilution, that would tend to bias estimates to the null.[189] Consequently, I termed the 'predictor' analysis the maintenance analysis.

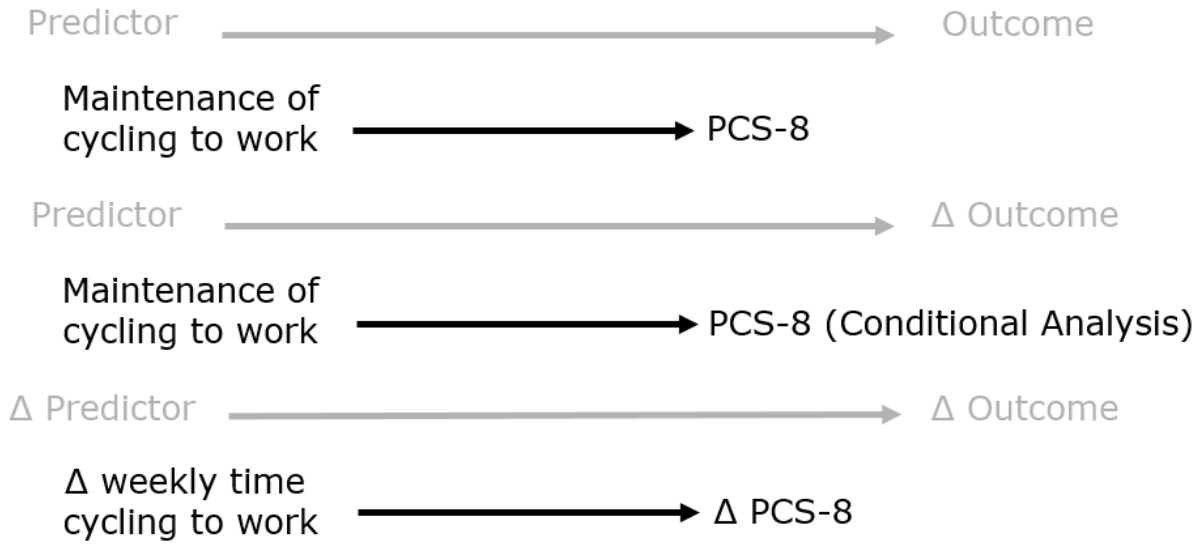
[xi] In theory two different travel behaviours (e.g. active travel and non-active travel) could yield 16 different permutations or trajectories)

Figure 2.1 Approaches to longitudinal analysis with two time points



In addition, I separately conditioned the maintenance analysis on the baseline measure of the outcome of interest (i.e. analysis of covariance or conditional analysis). This is similar to, but slightly different, from testing the association between maintenance of active commuting and change in the outcome at follow-up.[188,190] Thus it may be considered a third type of longitudinal analysis (Figure 2.2.).

Figure 2.2 Summary of longitudinal analyses undertaken



PCS-8=physical component score, scored using the short form eight questionnaire; △=change.

2.2.3 Inclusion and exclusion criteria

I restricted the analysis to those who completed two consecutive waves of the study (n=866) from the original sample who completed a questionnaire at baseline (n=1434). I excluded those with missing exposure (n=25), outcome (n=5) or covariate data (n=35), such that I undertook a complete case analysis (n=801).

Some of these participants completed more than two consecutive phases of data (e.g. phase 1, phase 2 and phase 3). I defined the baseline questionnaire for each participant as their first questionnaire with complete information on exposure. The follow-up questionnaire for each participant was the questionnaire completed one year after their baseline questionnaire.

2.2.4 Exposure measures

The primary exposures of interest were maintenance of cycling to work and maintenance of walking to work. The secondary exposures of interest were change in weekly time spent cycling to work and change in weekly time spent walking to work.

I choose change in weekly time spent cycling (or walking) to work rather than comparing uptake (i.e. no cycling at baseline, cycling at follow-up) with continued abstinence (i.e. no cycling at baseline and no cycling at follow-up) and comparing stopping (i.e. cycling at baseline, no cycling at follow-up) with continuation (i.e. cycling at baseline and follow-up) as the number of changers was relatively small (n=110 for cycling, n=144 for walking) and the sample would have been effectively divided into two (one sample for uptake analyses, and one sample for the stopping analyses), potentially reducing power.

2.2.4.1 Classification of cycling maintenance

Weekly time spent cycling to work at each time point was estimated by summing the total number of trips to and from work involving any cycling that was reported in the seven day travel record (copy included in the Appendix, page 249), and multiplying this by the typical duration of cycling per trip (assessed in a separate question).[191] Thus maintenance of cycling to work, included both cycling to work and cycling from work, but for simplicity I only refer to cycling to work. Maintenance of cycling to work was defined as weekly cycling time > 0 minutes at both baseline and follow-up. The reference group consisted of those who did not cycle to work at both baseline and follow-up (weekly cycling time = 0 minutes at both baseline and follow-up), i.e. this group maintained not cycling to work.

Consequently, participants who stopped cycling to work (weekly cycling time > 0 minutes at baseline and weekly cycling time = 0 minutes at follow-up) or took up cycling to work (weekly cycling time = 0 minutes at baseline and weekly cycling time > 0 minutes at baseline) were not categorised, and were therefore excluded from the maintenance analyses that used this exposure measure.

The same process was followed for walking to work.

After excluding those who stopped or started cycling between the two time points (n=110), 691 participants were included in the maintenance of cycling analyses. After excluding those who stopped or started walking between the two time points (n=144), 657 participants were included in the maintenance of walking analyses.

2.2.4.2 Change in weekly time spent cycling to work

Change in weekly time cycling to work between baseline and follow-up was categorised as either any increase, no change, or any decrease, based on the difference in the estimates of time cycling to work at baseline and follow-up.

As small increases or decreases might reflect reporting errors rather than true changes, I also conducted a sensitivity analysis in which only large increases or decreases in cycle commuting time (≥50 mins/week) were categorised as 'change', and smaller changes were re-categorised as 'no-change'.[192]

The same process was followed for walking to work.

2.2.5 Outcome measures

2.2.5.1 Well-being

Physical Component Summary (PCS-8) score and Mental Component Summary (MCS-8) score were derived from responses to the Medical Outcomes Study Short Form eight (SF-8) questionnaire.[184] The SF-8 questionnaire comprised eight ordinal response questions concerning participants' well-being in the past four weeks (see Appendix, page 250), with different weights being applied to each question to derive the scores as described by Ware et al.[184] The PCS-8 score had a theoretical score range of 9.1 to 69.0, and had a mean of 50 in the US adult population. MCS-8 score had a theoretical score range of 9.1 to 69.0, with a mean of 50 in the US adult population.[184]

I treated the scores as continuous variables. I analysed each as separate outcomes, as one might expect each measure to have different associations with active travel.[157,193]

2.2.5.2 Sickness absence

Sickness absence was ascertained by asking the following: "In the past twelve months how many days were you off sick for health reasons?" It was thus measured in days. This simple question has been shown to have good agreement with employer certified sickness absence.[162] Sickness absence was not normally distributed. The distribution had a right skew, with a large number of zero counts.

2.2.6 Covariates

2.2.6.1 Assessment and categorisation

Date of birth, date of questionnaire completion, education, sex, height, weight, difficulty walking, limitation of physical activity, home postcode, home to work distance, and physical activity (Recent Physical Activity Questionnaire)[186] were assessed by questionnaire. Dates of birth and questionnaire completion were used to calculate age. Weight status (low or healthy weight, overweight, obese) was assigned based on participant's body mass calculated by dividing weight by height squared.[194] Education was the preferred measure of socio-economic status as it was measured at the individual-level. An alternative measure was area-level deprivation[xii] but as this is geographic measure it may not reflect an individual's socio-economic status.

A physical limitation variable (yes/no) was created, with participants being assigned to 'yes' if they either (a) reported difficultly walking for a quarter of a mile on the level or (b) reported that physical health problems limited their ability to do usual physical activities.

Physical activity level (inactive, moderately inactive, moderately active, active) was assigned based on occupation and time spent in recreational activity following the Cambridge Physical Activity Index.[195] Individuals are assigned to one of four categories (inactive, moderately inactive, moderately active and active) based on reported physical activity at work and reported recreational physical activity[xiii]. The index has been shown to be associated with overall physical activity energy

[xii] Area level deprivation is measured using the Index of Multiple Deprivation 2010 score (based on a series of indicators for income, employment, health, crime, education, housing and the environment) for small geographic units known as Lower Super Output Area. It can be linked to individuals based on the postcode of residence.[202]

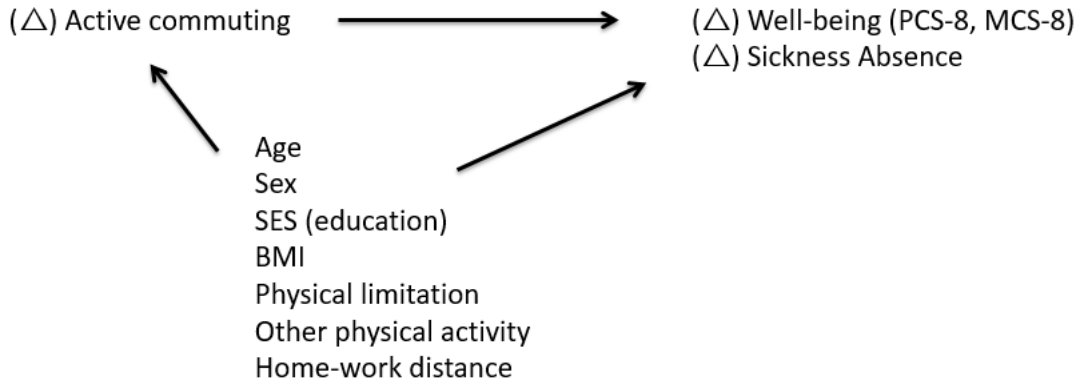
[xiii] Inactive = Sedentary job with no recreational activity; Moderately inactive = sedentary job with <0.5 hours per day of recreational activity or standing job with no recreational activity; Moderately active

expenditure and all-cause mortality.[195,196] Whilst the original index incorporated walking and cycling to work, I discounted time spent in these activities when assigning participants.

2.2.6.2 Choice of covariates

A directed acyclic graph showing the hypothesised relationship between active commuting, indices of health (well-being and sickness absence) and confounders is shown in Figure 2.3. Confounders were identified based on empirical evidence from others studies (e.g. age is a determinant of active travel and is associated with PCS-8)[137,184,197] or observation of univariate associations consistent with confounding that appeared biologically plausible (e.g. physical limitation may be a determinant of active travel and may be associated with PCS-8, which was supported by univariate analysis).

Figure 2.3 Hypothesised relationship between active commuting and indices of well-being



Home-work distance has been associated with active commuting in the same study.[136,191,198] It was also associated with PCS-8, MCS-8 and sickness absence on univariate analysis. In other analyses commute duration has been shown to be associated with reduced well-being.[168,199] Given that a long commute may also reduce time available for other health-promoting activities that have not been adjusted for (e.g. sleep), it seemed conceivable that distance to work was a confounding factor. Within the study population, home-work distance may be a marker of socio-economic status, for example the price of housing in Cambridge is high, resulting in some people living out of Cambridge and commuting into the city.

Study year was also included as a covariate as participants were drawn from three different years of entry to the cohort.

Sedentary job with 0.5 to 1 hours recreational activity per day or standing job with < 0.5 hours recreational activity per day or physical job with no recreational activity; Active = sedentary job with 1 hour of recreational activity per day or standing job with > 0.5 hours recreational activity per day or Physical job with at least some recreational activity or heavy manual job.

2.2.7 Analysis

I used two complementary approaches to test longitudinal associations. In the first set of analyses, I tested the associations between maintenance of cycling (or walking) to work and indices of well-being at follow-up. These 'maintenance analyses' were intended to contribute to establishing evidence of a temporal relationship, because the exposure was ascertained before the outcome.[35]

In the second set of analyses, I used linear regression to test the associations between change in cycling (or walking) to work and changes in indices of well-being. By focusing on individuals who changed their behaviour, these 'change analyses' were intended to provide a more direct estimate of the association attributable to increasing or decreasing a given behaviour.

2.2.7.1 Maintenance analyses

I used linear regression to test the associations of maintenance of cycling (or walking) to work with PCS-8 and MCS-8. Given the nature (discrete data) and distribution of sickness absence (positive skew with a large number of zero counts), following the approach described by Zhou et al,[200] I fitted different models (e.g. linear, binomial, negative binomial, zero-inflated). I found the data were fitted best by a negative binomial distribution. Consequently, I used negative binomial regression to test the associations with sickness absence.

Regression models were adjusted for all covariates (age, sex, education, physical activity, weight status, physical limitation, home-work distance and study year), which I will term Model A.

I further conditioned each analysis on the baseline value of the outcome variable in question (i.e. analysis of covariance) (model B). In this context, analysis of covariance addresses whether there is a difference in the change in outcome between cyclists and non-cyclists *who have the same initial value of the outcome*? It is considered the most appropriate approach to test for differences in change between two groups, when there are baseline differences in the outcome of interest between groups.[188,190] It is similar to, although different from testing the association between maintenance of cycling (or walking) to work with change scores (i.e. well-being at follow-up minus well-being at baseline). Thus it could be considered as another form of longitudinal analysis (see Figure 2.2).

I also undertook sensitivity analyses adjusting the 'maintenance' analyses for the reciprocal commuting behaviour (e.g. models using cycling to work as the exposure were additionally adjusted for walking to work).

2.2.7.2 Change analyses

I used linear regression to test the association between change in active commuting and change in outcome. I used the same approaches to adjustment for covariates described above (model A and model B). The conditional analysis addressed the following question: whether there was a difference in the change in outcome between those whose cycle commute time increased, decreased or stayed the same, after adjusting for covariates and assuming the same baseline measure of the outcome of interest.

I considered adjusting for time varying covariates (i.e. other variables that may have changed and might confound the relationship), but such variables were either unavailable (e.g. change in diet or change in sleep), liable to be on the causal pathway (e.g. change in recreational physical activity is likely to be associated with a change in well-being, and the change in recreational physical activity might arise as a result of change in commuting), or of uncertain association with well-being (e.g. change in home location might be associated with a set of other changes e.g. sleep, time pressure or stress, and the direction of these effects would be uncertain). Adjustment for variables on the causal pathway (i.e. mediators) would be inappropriate.[201]

Change in sickness absence had a positive kurtosis, and I truncated outliers (to +/- 30 days) so that residuals were normally distributed.

2.2.7.3 Software

Analyses were undertaken using Stata Statistical Software: Release 13 (College Station, TX: StataCorp LP) using the "regress" and "nbreg" commands for linear and negative binomial regression respectively.

2.2.7.4 Analysis summary

In summary, I used two analytic approaches ('maintenance' and 'change'), each with two stages of adjustment for covariates (model A and model B), applied to two exposures (cycling and walking to work) and for three outcomes (PCS-8, MCS-8 and sickness absence). These analyses are summarised in Table 2.2, for the outcome of PCS-8. Across all three outcomes, this yielded a total of 24 different regression analyses.

Table 2.2 Summary of analyses and research questions for physical well-being (PCS-8)

Exposure	Categorisation	Outcome	Adjustment	Research question
Maintenance of cycling	None vs some	PCS-8 at one-year follow-up	Model A	What is the difference in physical well-being at one-year follow-up between those who maintain commuting by bicycle during the year of follow-up and those who maintain not doing so, after adjustment for covariates?
Maintenance of cycling	None vs some	PCS-8 at one-year follow-up	Model B (conditional)	What is the difference in *change* in physical well-being at one-year follow-up between those who maintain commuting by bicycle during the year of follow-up and those who maintain not doing so, after adjustment for covariates *assuming the same baseline physical well-being at baseline*?
Any change in weekly cycle time	No change, increase, decrease	Change in PCS-8 (follow-up PCS-8 minus baseline PCS-8)	Model A	What is the difference in change in physical well-being between those whose cycle commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates?
Any change in weekly cycle time	No change, increase, decrease	Change in PCS-8 (follow-up PCS-8 minus baseline PCS-8)	Model B (conditional)	What is the difference in change in physical well-being between those whose cycle commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates *assuming the same* baseline PCS-8?
Maintenance of walking	None vs some	PCS-8 at one-year follow-up	Model A	What is the difference in physical well-being at one-year follow-up between those who maintain commuting by foot during the year of follow-up and those who maintain not doing so, after adjustment for covariates?
Maintenance of walking	None vs some	PCS-8 at one-year follow-up	Model B (conditional)	What is the difference in *change* in physical well-being at one-year follow-up between those who maintain commuting by foot during the year of follow-up and those who maintain not doing so, after adjustment for covariates *assuming the same baseline physical well-being at baseline*?
Any change in weekly walk time	No change, increase, decrease	Change in PCS-8 (follow-up PCS-8 minus baseline PCS-8)	Model A	What is the difference in change in physical well-being between those whose walk commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates?
Any change in weekly walk time	No change, increase, decrease	Change in PCS-8 (follow-up PCS-8 minus baseline PCS-8)	Model B (conditional)	What is the difference in change in physical well-being between those whose walk commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates *assuming the same* baseline PCS-8?

PCS-8 = physical component score derived from the Short Form 8 questionnaire; Model A co-variates: age, sex, education, body mass index, other physical activity and home-work distance; Model B co-variates: age, sex, education, body mass index, other physical activity, home-work distance and baseline PCS-8; an analogous set of questions apply to the other outcomes (mental well-being and sickness absence).

2.3 Results

2.3.1 Descriptive characteristics

The participants included in analysis were predominantly women (69.7%), educated to degree level or higher (70.2%), of low or healthy bodyweight (65.4%), and slightly more than half reported cycling to work (54.3%) (Table 2.3). The average scores for physical well-being (median PCS-8 55.5, IQR 51.5 to 58.0) and for mental well-being (median MCS-8 52.5, IQR 48.5 to 57.5) were higher than the specified population average (50). Sickness absence (mean = 3.6 days, median 1 day, IQR 0 to 4 days) was lower than the UK mean (4.4 days).[173]

Baseline differences between those who cycled to work and those who did not (and the equivalent for walking) are shown in Table 2.3. Those who reported maintenance of some cycling to work, compared to maintenance of not cycling to work, were more likely to be male, be younger, live close to their workplace and have a degree. Their health status at baseline appeared to be better as indicated by fewer days of sickness absence and a lower prevalence of obesity, although differences in MCS-8 and PCS-8 were slight. Those who reported maintenance of some walking to work, compared to maintenance of not walking to work, were more likely to be female and there were few differences in other socio-demographic characteristics. Their health status (obesity prevalence, PCS-8 and MCS-8) at baseline appeared similar to those who reported maintenance of not walking to work, although those who maintained walking to work reported more days of sickness absence at baseline.

Differences between participants included in and excluded from the analysis are shown in Table 2.4. Those who were excluded tended to be younger, but there were no other notable differences between those included and excluded.

2.3.2 Cycling maintenance and well-being

In univariable analysis, those who maintained cycling to work were found to report higher PCS-8 and MCS-8 scores at follow-up relative to those who did not cycle to work (Table 2.5). For PCS-8 the association was not significant after adjustment for covariates (model A) or when additionally conditioning on baseline PCS-8 (model B), although the estimates of effect size were of similar magnitude to the unadjusted estimate.

Table 2.3 Characteristics of participants included in the analyses (n=801)

	Cycling to work at baseline		Walking to work at baseline	
	None (n=366)	**Some (n=435)**	**None (n=597)**	**Some (n=204)**
	N (%)	**N (%)**	**N (%)**	**N (%)**
Sex				
Female	283 (50.7)	275 (49.3)	404 (72.4)	154 (27.6)
Male	83 (34.2)	160 (65.8)	193 (79.4)	50 (20.6)
Age				
Median	44.4 (34.7-52.9)	43.0 (33.1-51.6)	43.2 (34.0-52.0)	43.3 (33.7-52.2)
16-29 years	42 (39.6)	64 (60.4)	73 (68.9)	33 (31.1)
30-39 years	103 (46.8)	117 (53.2)	169(76.8)	51 (23.2)
40-49 years	93 (44.3)	117 (55.7)	160 (76.2)	50 (23.8)
50-59 years	92 (46.2)	107 (53.8)	148 (74.4)	51 (25.6)
≥60 years	36 (54.6)	30 (45.5)	47 (71.1)	19 (28.8)
Highest educational qualification				
Less than degree	140 (58.6)	99 (41.4)	177 (74.1)	62 (25.9)
degree or higher	226 (40.2)	336 (59.8)	420 (74.5)	142 (25.3)
Deprivation quintile				
1 (= least deprived)	181 (49.7)	183 (50.3)	269 (73.9)	95 (26.1)
2	110 (46.8)	125 (53.2)	180 (76.6)	55 (23.4)
3	50 (48.1)	54 (51.9)	71 (68.3)	33 (31.8)
4	22 (23.9)	70 (76.1)	73 (79.3)	19 (20.7)
5 (= most deprived)	3 (50.0)	3 (50.0)	4 (66.7)	2 (33.3)
Weight status				
low or healthy weight	213 (40.6)	311 (59.4)	395 (75.4)	129 (24.6)
Overweight	102 (49.8)	103 (50.2)	148 (72.2)	57 (27.8)
Obese	51 (70.8)	21 (29.2)	54 (75.0)	18 (25.0)
PCS-8 score				
Median (IQR)	55.2 (51.1-58.0)	55.7 (52.2-58.0)	55.5 (51.7-58.0)	55.4 (51.6-58.0)
MCS-8 score				
Median (IQR)	52.3 (47.1-57.5)	52.6 (49.4-57.5)	52.5 (49.2-57.5)	52.3 (47.3-57.5)
Sickness Absence (days per year)				
Median (IQR)	2 (0-4)	1 (0-3)	1 (0-3)	2 (0-5)
Physical limitation				
Yes	350 (45.4)	421 (54.6)	575 (74.6)	196 (25.4)
No	16 (53.3)	14 (46.7)	22 (73.3)	8 (26.7)
Home to work distance				
Median (IQR)	19.3 (8.0-27.4)	4.8 (3.2-8.1)	8.0 (4.8-19.3)	8.0 (3.2-24.1)
0-9.99 km	117 (24.8)	354 (75.2)	361 (76.7)	110 (23.4)
10-19.99 km	71 (60.7)	46 (39.3)	89 (76.1)	28 (23.9)
≥20 km	178 (83.6)	35 (16.4)	147 (69.0)	66 (31.0)
Physical activity index				
Inactive	9 (37.5)	15 (62.5)	19 (79.2)	5 (20.8)
Moderately inactive	111 (50.5)	109 (49.5)	162 (73.6)	58 (26.4)
Moderately active	113 (46.1)	132 (53.9)	180 (73.5)	65 (26.5)
Active	133 (42.6)	179 (57.4)	236 (75.6)	76 (24.4)
Weekly time cycling to work (minutes)				
Median (IQR)	0 (0-0)	150 (90-200)	100 (0-180)	0 (0-45)
Weekly time walking to work (minutes)				
Median (IQR)	0 (0-90)	0 (0-0)	0 (0-0)	100 (60-180)
Changed behaviour				
Started walking/cycling to work	42 (9.7)	0 (0)	75 (36.7)	0 (0)
Stopped walking/cycling to work	0 (0)	68 (18.6)	0 (0)	67 (11.2)
Time frame				
2009-10 (reference)	305 (47.0)	344 (53.0)	477 (73.5)	172 (26.5)
2010-11	16 (39.0)	25 (61.0)	25 (61.0)	16 (39.0)
2011-2	45 (40.5)	66 (59.5)	95 (85.6)	16 (14.4)

IQR=Interquartile range; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire, deprivation quintile is based on national quintiles of deprivation ranked using the Index of Multiple Deprivation 2010 score for the Lower Super Output Area (assigned based on postcode or residence)[202]; unless otherwise stated characteristics are measured at baseline; changed behaviour describes the number of individuals who started or stopped active travel between baseline and follow-up (e.g. cycle to work at baseline and not cycling to work at follow-up).

Table 2.4 Characteristics of participants included and excluded from the analyses (n=1434)

	Included (n=801)	Excluded (n=633)
	N (%)	N (%)
Sex		
Female	558 (69.7)	414 (69.0)
Male	243 (30.3)	186 (31.0)
Age		
Median (IQR)	43.3 (33.7-52.2)	38.5 (31.0-48.1) [n=607]
16-29 years	106 (13.2)	133 (21.9)
30-39 years	220 (27.5)	196 (32.3)
40-49 years	210 (26.2)	153 (25.2)
50-59 years	199 (24.8)	90 (14.8)
≥60 years	66 (8.2)	35 (5.7)
Highest educational qualification		
Less than degree	239 (39.8)	188 (31.6)
Bachelor or higher	562 (70.2)	406 (68.4)
Deprivation quintile		
1 (= least deprived)	364 (45.4)	266 (41.3)
2	235 (29.3)	187 (31.1)
3	104 (13.0)	91 (15.1)
4	92 (11.5)	55 (9.2)
5 (= most deprived)	6 (0.7)	2 (0.3)
Weight status		
Normal or underweight	524 (65.4)	351 (60.0)
Overweight	205 (25.6)	168 (28.7)
Obese	72 (9.0)	66 (11.2)
PCS-8 score		
Median (IQR)	55.5 (51.6-58.0)	55.0 (51.5-57.7) [n=602]
MCS-8 score		
Median (IQR)	52.5 (48.5-57.5)	52.1 (45.8-56.4) [n=602]
Sickness Absence (days per year)		
Median (IQR)	1 (0-4)	2 (0-4) [n=584]
Disability		
Yes	30 (3.7)	21 (3.4)
No	771 (96.3)	589 (96.6)
Home to work distance		
Median (IQR)	8.0 (4.8-22.5)	8.0 (3.2-20.9) [n=608]
0-9.99 km	471 (58.8)	348 (57.2)
10-19.99 km	117 (14.6)	104 (17.1)
≥20 km	213 (26.6)	156 (25.7)
Physical activity index		
Inactive	24 (3.0)	20 (3.3)
Moderately inactive	220 (27.5)	165 (27.2)
Moderately active	245 (30.6)	200 (33.0)
Active	312 (39.0	221 (36.4)
Weekly time cycling to work (minutes)		
Median (IQR)	56 (0-150)	40 (0-150) [n=610]
Weekly time walking to work (minutes)		
Median (IQR)	0 (0-10)	0 (0-30) [n=605]

IQR=Interquartile range; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; deprivation quintile is based on national quintiles of deprivation ranked using the Index of Multiple Deprivation 2010 score for the Lower Super Output Area (assigned based on postcode or residence).

Table 2.5 Associations between maintenance of cycling to work and well-being (n=691)

	Physical Well-being (PCS-8)			Mental Well-being (MCS-8)		
	Unadjusted	**Model A**	**Model B**	**Unadjusted**	**Model A**	**Model B**
	Coefficient (95% CI)	Coefficient (95% CI)	Coefficient (95% CI)	Coefficient (95% CI)	Coefficient (95% CI)	Coefficient (95% CI)
Cycling						
None (reference)						
Some	**1.05 (0.13, 1.96)**	1.08 (-0.06, 2.23)	0.87 (-0.17, 1.93)	**1.33 (0.19, 2.48)**	**1.50 (0.10, 2.90)**	0.82 (-0.42, 2.08)
Sex						
Male (reference)						
Female	0.24 (-0.76, 1.25)	0.31 (-0.72, 1.24)	0.14 (-0.81, 1.09)	**-1.81 (-3.06, -0.56)**	-1.14 (-2.41, 0.12)	-0.95 (-2.09, 0.17)
Age						
16-29 years (reference)						
30-39 years	-0.37 (-1.97, 1.21)	-0.24 (-1.85, 1.36)	-0.12 (-1.59, 1.35)	**2.43 (0.47, 4.39)**	**2.64 (0.68, 4.61)**	**1.83 (0.07, 3.58)**
40-49 years	-0.33 (-1.92, 1.26)	-0.26 (-1.86, 1.35)	-0.07 (-1.54, 1.41)	**3.92 (1.96, 5.88)**	**3.88 (1.91, 5.85)**	**3.06 (1.30, 4.82)**
50-59 years	-1.25 (-2.84, 0.35)	-1.09 (-2.72, 0.54)	-0.73 (-2.23, 0.75)	**3.74 (1.77, 5.71)**	**3.67 (1.68, 5.66)**	**2.69 (0.91, 4.48)**
≥60 years	-1.30 (-3.33, 0.74)	-0.91 (-2.98, 1.17)	-0.68 (-2.58, 1.21)	**5.49 (2.98, 7.99)**	**5.87 (3.33, 8.40)**	**3.72 (1.44, 6.05)**
Degree						
No (reference)						
Yes	0.14 (-0.85, 1.15)	-0.38 (-1.46, 0.70)	-0.73 (-1.73, 0.25)	0.03 (-1.22, 1.29)	-0.27 (-1.59, 1.05)	-0.23 (-1.40, 0.94)
Home to work distance						
0-9.99 km (reference)						
10-19.99 km	-0.10 (-1.43, 1.22)	0.54 (-0.88, 1.98)	0.47 (-0.84, 1.77)	0.07 (-1.59, 1.72)	0.04 (-1.71, 1.78)	0.35 (-1.20, 1.54)
≥20 km	-0.60 (-1.66, 0.46)	0.13 (-1.18, 1.44)	-0.01 (-1.21, 1.19)	-0.46 (-1.79, 0.86)	0.23 (-1.37, 1.82)	0.54 (-0.88, 1.97)
Physical limitation						
No (reference)						
Yes	**-4.10 (-6.55, -1.66)**	**-3.84 (-6.33, -1.35)**	**4.03 (1.39, 6.68)**	**-4.30 (-7.36, -1.23)**	**-3.81 (-6.86, -0.77)**	**-3.16 (-5.88, -0.45)**
Physical Activity						
Inactive (reference)						
Moderately inactive	0.73 (-2.10, 3.57)	0.41 (-2.47, 3.29)	-1.14 (-3.79, 1.49)	**4.33 (0.81, 7.86)**	**4.96 (1.45, 8.48)**	2.68 (-0.47, 5.83)
Moderately active	1.57 (-1.26, 4.40)	1.14 (-1.76, 4.03)	-0.81 (-3.49, 1.85)	**4.37 (0.86, 7.88)**	**5.09 (1.54, 8.06)**	2.58 (-0.58, 5.76)
Active	1.53 (-1.26, 4.34)	1.02 (-1.84, 3.89)	-0.77 (-3.41, 1.87)	**5.58 (2.10, 9.06)**	**6.00 (2.49, 9.50)**	2.88 (-0.28, 6.03)
Weight status						
Low or healthy (reference)						
Overweight	-0.68 (-1.75, 0.39)	0.56 (-1.39, 0.82)	-0.30 (-1.32, 0.71)	-0.25 (-1.60, 1.09)	-0.37 (-1.72, 0.98)	-0.39 (-1.60, 0.81)
Obese	**-1.72 (-3.35, 0.09)**	-1.11 (-2.82, 0.59)	-0.51 (-2.08, 1.05)	0.29 (-1.76, 2.33)	0.80 (-1.29, 2.89)	0.47 (-1.39, 2.34)
Study Year						
2009-10 (reference)						
2010-11	0.05 (-2.09, 2.19)	-0.29 (-2.44, 1.85)	-0.11 (-2.08, 1.84)	1.14 (-1.52, 3.81)	1.14 (1.47, 3.76)	0.13 (-2.20, 2..47)
2011-2	-0.74 (-2.10, 0.60)	-1.08 (-2.47, 0.32)	-0.86 (-2.14, 0.41)	-0.06 (-1.74, 1.62)	-0.06 (-1.76, 1.65)	-0.42 (-1.94, 1.10)
Baseline well-being	**0.42 (0.36, 0.50)**		**0.48 (0.40, 0.56)**			**0.46 (0.39, 0.53)**

Linear regression coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; physical activity is categorised using the Cambridge Physical Activity Index; weight status is categorised using body mass index; study year refers to the time period when data were collected; Model A is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status and study year; Model B is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status, study year and baseline well-being (baseline PCS-8 for PCS-8 model or baseline MCS-8 for MCS-8 model); bold indicates significant results ($p<0.05$).

The association between maintenance of cycling to work and MCS-8 remained significant after adjustment for covariates (model A), but not after additional adjustment for baseline MCS-8 (model B). Sensitivity analysis, adjusting for walking to work, resulted in a similar pattern and magnitude of findings, although the only significant finding was for PCS-8 (model A: 1.45, 95% CI 0.06 to 2.84; n=573).

2.3.3 Cycling maintenance and sickness absence

Maintenance of cycling to work was associated with reduced sickness absence in univariable analysis (Table 2.6). The association remained significant after adjustment for covariates (model A) and additionally adjusting for baseline sickness absence (model B). The estimate of effect size (approximately 0.5) was equivalent to just over one day of sickness absence per year, and was similar in univariable and adjusted analyses.

2.3.4 Association of changes in weekly cycling time with changes in well-being and sickness absence

There were no significant associations between change in weekly cycling time and changes in PCS-8, MCS-8 or sickness absence (Table 2.7). However, I note that the adjusted estimate of the effect size from the change analysis for well-being (both PCS-8 and MCS-8) is of similar magnitude to the estimated effect size for the maintenance analyses, when conditioning on baseline well-being (Model B: PCS-8, 1.01 in change analyses vs 0.87 in maintenance analyses; MCS-8, 0.69 vs 0.82 respectively).

Using the alternative definition of change (i.e. large changes or changes > 50 minutes per week), the pattern of results was similar (Table 2.8). There were no significant associations.

2.3.5 Walking

There were no significant associations between maintenance of walking and PCS-8, MCS-8 or sickness absence (Table 2.9 and Table 2.10). The associations for MCS-8 were borderline significant and the direction of the association was negative, i.e. those who reported maintaining walking to work tended to report lower MCS-8 scores. These associations remained non-significant after adjusting for cycling to work (data not shown).

There were no significant associations between either any change or a large change in walking and change in any of the outcomes (PCS-8, MCS-8 or sickness absence). Results for any change in walking are shown in Table 2.11, and for large changes (>50 minutes per week) in Table 2.12.

Table 2.6 Association between maintenance of cycling to work and sickness absence (n=691)

		Unadjusted	**Model A**	**Unadjusted**
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Cycling	None (reference)			
	Some	**-0.51 (-0.76, -0.26)**	**-0.47 (-0.80, -0.14)**	**-0.46 (-0.77, -0.14)**
Sex	Male (reference)			
	Female	0.18 (-0.10, 0.46)	0.12 (-0.14, 0.40)	0.17 (-0.10, 0.43)
Age	16-29 years (reference)			
	30-39 years	**-0.42 (-0.85, 0.02)**	**-0.50 (-0.93, -0.06)**	**-0.43 (-0.84, -0.01)**
	40-49 years	**-0.79 (-1.22, -0.35)**	**-0.88 (-1.31, -0.44)**	**-0.80 (-1.21, -0.37)**
	50-59 years	-0.27 (-0.70, 0.14)	**-0.44 (-0.89, 0.00)**	-0.42 (-0.85, 0.01)
	≥60 years	**-0.56 (-1.11, -0.02)**	**-0.79 (-1.35, -0.22)**	**-0.56 (-1.10, -0.02)**
Degree	No (reference)			
	Yes	**-0.34 (-0.62, -0.07)**	-.10 (-0.39, 0.19)	-0.01 (-0.29, 0.27)
Home to work distance	0-9.99 km (reference)			
	10-19.99 km	0.14 (-0.21, 0.50)	-0.10 (-0.50, 0.29)	-0.09 (-0.47, 0.28)
	≥20 km	**0.38 (0.09, 0.66)**	-0.07 (-0.44, 0.29)	-0.12 (-0.47, 0.22)
Physical limitation	No (reference)			
	Yes	**1.22 (0.59, 1.86)**	**0.97 (0.34, 1.61)**	0.51 (-0.11, 1.13)
Physical Activity	Inactive (reference)			
	Moderately inactive	-0.19 (-0.96, 0.57)	-0.02 (-0.78, 0.74)	0.70 (-0.08, 1.48)
	Moderately active	-0.11 (-0.88, 0.65)	-0.04 (-0.81, 0.73)	0.72 (-0.07, 1.51)
	Active	-0.33 (-1.09, 0.43)	-0.08 (-0.86, 0.68)	0.54 (-0.25, 1.33)
Weight status	Low or healthy (reference)			
	Overweight	0.13 (-0.16, 0.42)	0.17 (-0.12, 0.47)	0.18 (-0.10, 0.47)
	Obese	0.59 (0.15, 1.02)	0.31 (-0.14, 0.76)	0.28 (-0.15, 0.72)
Study Year	2009-10 (reference)			
	2010-11	0.11 (-0.47, 0.70)	0.23 (-0.34, 0.80)	0.17 (-0.37, 0.72)
	2011-2	0.30 (-0.06, 0.67)	0.13 (-0.24, 0.51)	0.30 (-0.05, 0.67)
Baseline sickness absence		0.09 (0.06, 0.11)		**0.07 (0.05, 0.09)**

Negative binomial coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; physical activity is categorised using the Cambridge Physical Activity Index; weight status is categorised using body mass index; study year refers to the time period when data were collected; Model A is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status and study year; Model B is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status, study year and baseline sickness absence; bold indicates significant results ($p<0.05$).

Table 2.7 Associations of change in weekly cycle commuting time with change in PCS-8, MCS-8 and sickness absence (n=801)

		Unadjusted	Model A	Model B
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Physical Well-being (PCS-8)	No change (reference)			
	Increase (n=183)	0.62 (-0.54, 1.79)	0.94 (-0.22, 2.11)	1.01 (-0.05, 2.07)
	Decrease (n=223)	-0.49 (-1.58, 0.60)	-0.47 (-1.59, 0.64)	-0.31 (-1.33, 0.69)
Mental Well-being (MCS-8)	No change (reference)			
	Increase (n=183)	-0.31 (-1.68, 1.06)	0.20 (-1.26, 1.65)	0.69 (-0.59, 1.97)
	Decrease (n=223)	-0.51 (-1.79, 0.77)	-0.11 (-1.51, 1.29)	-0.18 (-1.41, 1.05)
Sickness Absence (days)	No change (reference)			
	Increase (n=183)	-0.14 (-1.20, 0.90)	-0.40 (-1.51, 0.72)	-0.37 (-1.33, 0.59)
	Decrease (n=223)	0.23 (-0.75, 1.21)	0.03 (-1.03, 1.10)	-0.14 (-1.06, 0.79)

Linear regression coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; Model A is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status and study year; Model B is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status, study year and appropriate baseline health index (baseline PCS-8 for PCS-8 model, baseline MCS-8 for MCS-8 model or baseline sickness absence for sickness absence model).

Table 2.8 Associations of large changes in weekly walk commuting time (≥ 50 minutes per week) with change in PCS-8, MCS-8 and sickness absence (n=801)

		Unadjusted	Model A	Model B
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Physical Well-being (PCS-8)	No change or change less than 50 minutes (reference)			
	Large increase (n=114)	0.70 (-0.65, 2.05)	0.80 (-0.50, 2.10)	1.10 (-0.08, 2.28)
	Large decrease (n=158)	-0.03 (-1.21, 1.15)	-0.37 (-1.52, 0.79)	-0.13 (-1.18, 0.91)
Mental Well-being (MCS-8)	No change or change less than 50 minutes (reference)			
	Large increase (n=114)	-0.28 (-1.86, 1.30)	0.17 (-1.44, 1.79)	0.60 (-0.82, 2.02)
	Large decrease (n=158)	-0.61 (-2.00, 0.78)	-0.25 (-1.69, 1.18)	-0.47 (-1.73, 0.79)
Sickness Absence (days)	No change or change less than 50 minutes (reference)			
	Large Increase (n=114)	0.21 (-0.99, 1.42)	0.19 (-1.05, 1.43)	-0.34 (-1.41, 0.73)
	Large decrease (n=158)	0.96 (-0.10, 2.02)	0.93 (-0.17, 2.03)	0.46 (-0.49, 1.41)

Linear regression coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; Model A is adjusted for gender, age, degree, home to work distance, physical limitation, physical activity, weight status and study year; Model B is adjusted for gender, age, degree, home to work distance, physical limitation, physical activity, weight status, study year and appropriate baseline health index (baseline PCS-8 for PCS-8 model, baseline MCS-8 for MCS-8 model or baseline sickness absence for sickness absence model); Large increase defined as increase of more than 50 minutes per week and a large decrease defined as a decrease of more than 50 minutes per week; Total sample size: n=801; Study undertaken in Cambridge, UK (2009-12).

Table 2.9 Associations between maintenance of walking to work and well-being (n=659)

	Physical Well-being			Mental Well-being		
	Unadjusted	**Model A**	**Model B**	**Unadjusted**	**Model A**	**Model B**
	Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Walking						
None (reference)						
Some	-0.18 (-1.39, 1.02)	-0.18 (-1.39, 1.03)	-0.15 (-1.27, 0.97)	-1.50 (-3.01, 0.02)	-1.36 (-2.86, 0.14)	-0.65 (-1.99, 0.68)
Sex						
Male (reference)						
Female	-0.34 (-1.40, 0.71)	-0.46 (-1.53, 0.61)	-0.46 (-1.46, 0.52)	**-1.78 (-3.11, 0.45)**	-1.13 (-1.25, 1.57)	-0.86 (-2.03, 0.32)
Age						
16-29 years (reference)						
30-39 years	0.64 (-1.01, 2.31)	0.72 (-0.94, 2.40)	1.13 (-0.41, 2.68)	**3.36 (1.31, 5.42)**	**3.29 (1.22, 5.36)**	**1.99 (0.15, 3.84)**
40-49 years	-0.24 (-1.91, 1.42)	-0.24 (-1.93, 1.44)	0.14 (-1.42, 1.71)	**4.64 (2.59, 6.71)**	**4.64 (2.55, 6.73)**	**3.45 (1.59, 5.32)**
50-59 years	-0.87 (-2.55, 0.81)	-0.81 (-2.53, 0.91)	-0.50 (-2.10, 1.10)	**5.31 (3.22, 7.39)**	**5.30 (3.17, 7.44)**	**3.81 (1.90, 5.72)**
≥60 years	-1.62 (-3.83, 0.59)	-1.47 (-3.72, 0.77)	-0.97 (-3.05, 1.11)	**6.33 (3.58, 9.07)**	**6.67 (3.89, 9.45)**	**4.26 (1.75, 6.75)**
Higher Degree						
No (reference)						
Yes	-0.36 (-1.44, 0.72)	-0.89 (-2.04, 0.25)	**-1.24 (-2.30, -0.18)**	0.16 (-1.21, 1.52)	0.16 (-1.26, 1.58)	-0.11 (-1.37, 1.15)
Home to work distance						
0-9.99 km (reference)						
10-19.99 km	0.34 (-1.05, 1.74)	0.62(-0.78, 2.31)	0.62 (-0.68, 1.92)	1.25 (-0.51, 3.02)	0.54 (-1.20, 2.29)	0.67 (-0.87, 2.23)
≥20 km	-0.58 (-1.73, 0.58)	-0.59 (-1.79, 0.61)	-0.70 (-1.81, 0.41)	0.58 (-0.88, 2.03)	0.55 (-0.93, 2.04)	0.90 (-0.42, 2.22)
Disability						
No (reference)						
Yes	**-5.38 (-7.81, -2.95)**	**-5.22 (-7.69, -2.77)**	2.59 (-0.13, 5.31)	**-4.42 (-7.52, -1.33)**	**-3.93 (-6.99, -0.89)**	**-3.31 (-6.03, -0.61)**
Physical Activity						
Inactive (reference)						
Moderately inactive	1.88 (-1.29, 5.06)	1.15 (-2.06, 4.36)	-0.12 (-3.11, 2.86)	**6.46 (2.47, 10.5)**	**6.61 (2.63, 10.6)**	**3.91 (0.35, 7.47)**
Moderately active	2.90 (-0.26,6.05)	1.94 (-1.28,5.18)	0.37 (-2.63, 3.39)	**6.76 (2.80, 10.7)**	**6.99 (2.99, 11.0)**	**3.90 (0.32, 7.50)**
Active	2.89 (-0.23, 6.02)	1.87 (-1.33, 5.07)	0.61 (-2.35, 3.59)	**7.25 (3.32, 11.2)**	**7.42 (3.45, 11.4)**	**3.79 (0.23, 7.36)**
Weight status						
Low or healthy (reference)						
Overweight	-0.71 (-1.84, 0.43)	-0.25 (-1.42, 0.93)	-0.28 (-1.37, 0.86)	-0.55 (-1.99, 0.90)	-1.18 (-2.63, 0.28)	-0.94 (-2.24, 0.36)
Obese	**-1.92 (-3.62, -0.22)**	**-1.65 (-3.42, -0.13)**	-0.68 (-2.34, 0.97)	0.03 (-2.11, 2.19)	-0.02 (-2.20, 2.27)	0.10 (-1.85, 2.04)
Study Year						
2009-10 (reference)						
2010-11	0.05 (-2.09, 2.19)	-1.11 (-3.34, 1.12)	-1.02 (-3.09, 1.05)	1.09 (-1.75, 3.94)	1.16 (-1.59, 3.93)	0.42 (2.04, 2.88)
2011-2	-0.74 (-2.10, 0.60)	-0.94 (-2.41, 0.52)	-1.04 (-2.40, 0.33)	-0.58 (-2.38, 1.21)	-0.79 (-2.11, 1.02)	-0.68 (-2.30, 0.94)
Baseline health	**0.42 (0.36, 0.50)**		**0.47 (0.38, 0.55)**	0.52 (0.45, 0.59)		**0.48 (0.41, 0.55)**

Linear regression coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; physical activity is categorised using the Cambridge Physical Activity Index; weight status is categorised using body mass index; study year refers to the time period when data were collected; baseline well-being refers to the appropriate well-being measure for each outcome (e.g. for the outcome of physical well-being it refers to baseline physical well-being); bold indicates significant results ($p<0.05$).

Table 2.10 Associations between maintenance of walking to work and sickness absence (n=659)

		Unadjusted	**Model A**	**Model B**
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Walking	None (reference)			
	Some	-0.02 (-0.35, 0.31)	0.20 (-0.13, 0.53)	0.12 (-0.19, 0.43)
Sex	Male (reference)			
	Female	0.45 (0.16, 0.75)	0.23 (-0.06, 0.53)	0.27 (-0.01, 0.54)
Age	16-29 years (reference)			
	30-39 years	**-1.05 (-1.49, 0.62)**	**-0.84 (-1.28, -0.40)**	**-0.79 (-1.20, -0.37)**
	40-49 years	**-1.09 (-1.53, 0.65)**	**-0.97 (-1.42, -0.53)**	**-0.87 (-1.29, -0.44)**
	50-59 years	**-0.89 (-1.33, -0.44)**	**-0.81 (-1.27, -0.35)**	**-0.73 (1.18, -0.29)**
	≥60 years	**-1.10 (-1.68, -0.51)**	**-0.98 (-1.57, -0.38)**	**-0.66 (-1.23, -0.09)**
Higher Degree	No (reference)			
	Yes	**-0.10 (-0.40, 0.19)**	-0.04 (-0.34, 0.27)	0.08 (-0.21, 0.36)
Home to work distance	0-9.99 km (reference)			
	10-19.99 km	-0.15 (-0.53, 0.24)	0.12 (-0.25, 0.51)	0.07 (-0.30, 0.44)
	≥20 km	**0.03 (-0.29, 0.34)**	0.11 (-0.21, 0.43)	0.07 (-0.24, 0.37)
Disability	No (reference)			
	Yes	**1.06 (0.41, 1.72)**	**1.01 (0.39, 1.63)**	0.45 (-0.16, 1.06)
Physical Activity	Inactive (reference)			
	Moderately inactive	**-1.82 (-2.64, -1.01)**	-0.82 (-1.69, 0.04)	0.35 (-0.53, 1.22)
	Moderately active	**-1.77 (-2.58, -0.96)**	**-1.02 (-1.87, -0.16)**	0.23 (-0.65, 1.10)
	Active	**-1.73 (-2.53, -0.93)**	-0.82 (-1.68, 0.02)	0.27 (-0.60, 1.13)
Weight status	Normal (reference)			
	Overweight	-0.02 (-0.33, 0.29)	0.11 (-0.20, 0.42)	0.12 (-0.18, 0.42)
	Obese	0.99 (0.54, 1.43)	0.34 (-0.14, 0.82)	0.22 (-0.24, 0.69)
Study Year	1 (reference)			
	2	0.09 (-0.52, 0.69)	0.19 (-0.40, 0.77)	0.13 (-0.43, 0.70)
	3	0.93 (0.56, 1.30)	0.63 (0.24, 1.03)	0.77 (0.40, 1.14)
Baseline sickness absence		**0.09 (0.07, 1.22)**		**0.07 (0.05, 0.10)**

Negative binomial coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; physical activity is categorised using the Cambridge Physical Activity Index; weight status is categorised using body mass index; study year refers to the time period when data were collected; bold indicates significant results ($p<0.05$).

Table 2.11 Associations of changes in weekly walk commuting time with change in PCS-8, MCS-8 and sickness absence (n=801)

		Unadjusted	Model A	Model B
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Physical Well-being (PCS-8)	No change (reference)			
	Increase (n=139)	-0.36 (-1.61, 0.88)	-0.07 (-1.26, 1.13)	-0.21 (-1.29, 0.88)
	Decrease (n=126)	0.02 ((-1.29, 1.31)	-0.07 (-1.31, 1.15)	-0.22 (-1.34, 0.90)
Mental Well-being (MCS-8)	No change (reference)			
	Increase (n=139)	0.94 (-0.52, 2.39)	0.93 (-0.56, 2.42)	0.38 (-0.93, 1.69)
	Decrease (n=126)	-0.25 (-1.78, 1.26)	-0.14 (-1.68, 1.39)	-0.44 (-1.78, 0.91)
Sickness Absence (days)	No change (reference)			
	Increase (n=139)	-0.87 (-1.98, 0.25)	-0.65 (-1.79, 0.48)	-0.33 (-1.31, 0.66)
	Decrease (n=126)	-0.50 (-1.66, 0.66)	-0.41 (-1.58, 0.76)	0.20 (-0.81, 1.22)

Linear regression coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; Model A is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status and study year; Model B is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status, study year and appropriate baseline health index (baseline PCS-8 for PCS-8 model, baseline MCS-8 for MCS-8 model or baseline sickness absence for sickness absence model).

Table 2.12 Associations of large changes in weekly walk commuting time (≥ 50 minutes per week) with change in PCS-8, MCS-8 and sickness absence (n=801)

		Unadjusted	Model A	Model B
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Physical Well-being (PCS-8)	No change or change less than 50 minutes (reference)			
	Large Increase (n=114)	-0.23 (-1.76, 1.30)	-0.02 (-1.48, 1.45)	-0.06 (-1.39, 1.27)
	Large Decrease (n=158)	-0.35 (-1.84, 1.15)	-0.33 (-1.76, 1.10)	-0.53 (-1.82, 0.77)
Mental Well-being (MCS-8)	No change or change less than 50 minutes (reference)			
	Increase (n=82)	1.63 (-0.16, 3.43)	1.74 (-0.07, 3.57)	1.15 (-0.45, 2.74)
	Decrease (n=87)	-0.24 (-1.99, 1.51)	0.07 (-1.69, 1.85)	-0.34 (-1.90, 1.22)
Sickness Absence (days)	No change or change less than 50 minutes (reference)			
	Increase (n=82)	-0.75 (-2.12, 0.63)	-0.60 (-1.99, 0.80)	-0.53 (-1.73, 0.68)
	Decrease (n=87)	-0.97 (-2.31, 0.37)	-0.96 (-2.33, 0.40)	0.22 (-1.40, 0.96)

Linear regression coefficients shown; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; Model A is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status and study year; Model B is adjusted for sex, age, degree, home to work distance, physical limitation, physical activity, weight status, study year and appropriate baseline health index (baseline PCS-8 for PCS-8 model, baseline MCS-8 for MCS-8 model or baseline sickness absence for sickness absence model); Large increase defined as increase of more than 50 minutes per week and a large decrease defined as a decrease of more than 50 minutes per week; Total sample size: n=801.

2.4 Discussion

2.4.1 Summary of findings

Cycling to work was associated with sickness absence. Maintenance of cycling to work was associated with reduced sickness absence during the year of follow-up after adjustment for covariates and baseline sickness absence. In the studied cohort, the effect size was equivalent to about one day less of sickness absence per year. Changes in cycling to work were not significantly associated with changes in sickness absence, although increases in cycling tended to be associated with reductions in sickness absence (around one day per year).

There was also some evidence that cycling to work was associated with well-being. Maintenance of cycling to work was associated with a reduced MCS-8 score at follow-up, although the effect size was attenuated and no longer significant after conditioning on baseline MCS-8. Whilst there were no significant associations between cycling to work and PCS-8 after adjustment for co-variates, the pattern of results was consistent with an association and many of the observed associations were close to significance. Taken together, then the results are consistent with cycling to work being important for both mental and physical well-being.

I did not find any significant associations between walking to work and either well-being or sickness absence. Whilst some indices were in the expected direction (i.e. indicating that walking to work was associated with better health), some indices were also in the opposite direction or close to null, notably the association between maintenance of walking and MCS-8 was negative, whereas the association between increase in walking and change in MCS-8 was positive and the association between a decrease in walking and change in MCS-8 was close to zero.

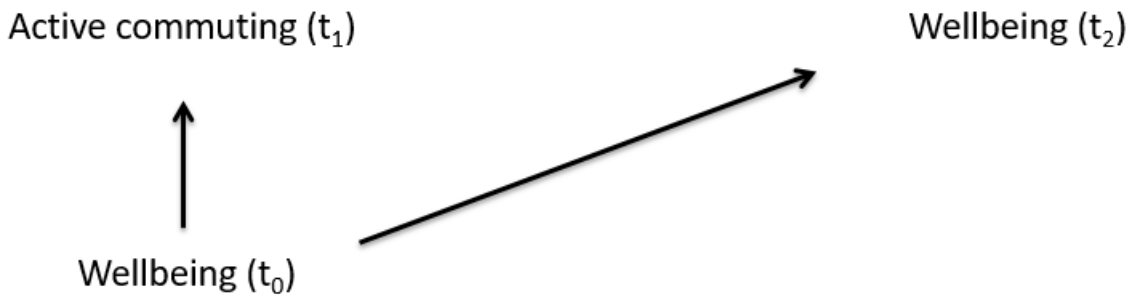
2.4.2 Strengths and limitations

2.4.2.1 Longitudinal analyses

The primary strength of this study lies in the use of complementary longitudinal analyses to test the little-studied associations of active commuting with sickness absence and well-being. Considering the maintenance analyses, the outcomes were measured after the exposure (active commuting), which is important for building a case for causal association.[35] However the findings, particularly when not adjusting for the baseline outcome, might be explained by reverse causation, for example

well-being prior to baseline being causally associated with both active travel at baseline and well-being at follow-up. Such a scenario is shown in Figure 2.4, where both active commuting at baseline (t1) and well-being at follow-up (t2) share a common cause or 'ancestor', well-being before baseline (t0). Under these circumstances a crude association between the two variables would be expected.[203] The change analyses provided an alternative test of causation, although should be interpreted with caution as it is possible for the change in well-being or sickness absence (or an associated underlying change in health status) to have caused the change in active commuting.

Figure 2.4 Diagram outlining possible relationship between active commuting and well-being



t=timepoint, with numbers indicated successive points in time, such that t_0 is prior to baseline, t_1 is baseline and t_2 is follow-up; single headed arrows represent direct links from causes to effects

The principle of the maintenance analysis was to reduce misclassification error from individuals that would tend to bias estimates towards the null.[189] Consistent with this I observed that restricting the analyses in this way tended to result in stronger associations (data not shown). However, it is also possible that this restriction may have introduced bias that led to an overestimate of the association. For example, if a participant's cycling to work resulted in an accident and he or she no longer cycled to work, he or she would have been excluded from the analysis. It is likely that such an event would be associated with consequent sick leave and/or decline in well-being, which would not be captured in my estimates. Furthermore, there is a risk that other medical events that are independent of commuting behaviour (e.g. development of multiple sclerosis) could prevent cycling to work but not prevent car commuting, which would bias the estimates of the control group in a negative direction, although the likelihood of such major events in a young and relatively healthy population is small. The estimates for maintenance should not be interpreted as estimate of the association for cycling (or walking) to work, but may be better interpreted as an estimate for cycling to work *if* that behaviour is maintained.

2.4.2.2 Study power

This study may appear comparatively small and thereby lack power compared to some cohort studies. However, it is larger than some other studies focusing on active travel and health[158,204] and has also accurately characterised the exposure by asking about active travel on any part of the journey over a seven-day period. The exposure might be considered as being more accurately measured. All other things being equal reducing measurement error should improve study power.[147]

2.4.2.3 Self-reported measures

The study relies on self-reported measures of exposure and outcome, this is entirely appropriate for well-being (which depends on self-report) and appears unlikely to have resulted in important biases for the other measures (sickness absence and active commuting). It has previously shown good agreement between self-reported and objective estimates of time spent in active commuting using this dataset, although a bias to overestimating may exist[205–207] and the measure of self-reported sickness absence has been shown to have good agreement with employer records of sickness absence in another UK cohort.[162] Nonetheless, because I used data from a study designed to investigate the relationships between commuting and health, it is possible that responses might have been influenced by social desirability bias. Whilst such a bias could account for differences in well-being between those who did and did not use active modes of travel, it is unclear why this might have occurred only for cycling and not for walking.

2.4.2.4 Socio-demographic characteristics of sample

The study population was relatively educated compared to the English population (70% had a degree compared to 37% for England).[182] Others have also described the study sample as being relatively affluent and white-collar.[136,157] The prevalence of cycling to work was high relative to the English average, although the measurement methods are different (47% reported some cycling to work at baseline in the sample, compared to 3% who report cycling as their usual mode of travel to work in the Census).[208]

Some of these differences will be explained by the population from which the study sample was drawn. As I set out in the methods (under study setting, 2.2.1.1) the socio-demographics of the City of Cambridge, although not the surrounding county, are not typical of the English population. A focus on commuters and thus working age adults, necessarily focuses on a younger population, which will also be different from the English average (e.g. older adults are less likely to have a degree). It is unclear to what extent the sample is not representative of the population from which it

is drawn, as the characteristics of this population, the working population who live within or outside Cambridge, are poorly characterised.

The socio-demographic characteristics of the sample and the nature of Cambridge (it is by UK standards relatively cycle friendly) may suggest the findings are not generalizable to other populations, such as the UK population. Whilst the Cambridge setting may affect the likelihood of cycling to work compared to other settings, it doesn't seem likely that it (or socio-cultural differences) will influence the physiological effects of cycling to work, where these benefits are attributed to energy expenditure, cardio-metabolic stress or musculoskeletal work. However, it seems plausible that the Cambridge setting may influence perceptions, social acceptability and ease of cycling, which could affect enjoyment associated with cycling to work. This may influence the association between cycling to work and mental well-being, and so these findings may be less generalizable. The findings for sickness absence and physical well-being may be relatively generalizable, although it is likely that mental health or well-being will contribute to both these indices.

2.4.3 Comparison with other studies

2.4.3.1 Mental Well-being

My finding is in keeping with some previous research, but differs from other findings.[157–160] First in a study that shared some similarities to the one described here (a longitudinal study of adult commuters in the UK), Martin et al reported positive associations between active travel and psychological well-being as assessed using the General Health Questionnaire (GHQ-12).[159] Specifically they reported that active commuting (either walking or cycling) or public transport was associated with increased psychological well-being (0.19 units[xiv]) relative to car commuting. Comparable analyses in my work, association between maintenance of cycling to work and MCS-8 at follow-up, were also significant. They also reported that switching to active commuting from car commuting or public transport was associated with an increase in psychological well-being (0.53 units) relative to maintaining car commuting. Comparable analyses in my work (the change analyses), was not significant. Martin et al's study had a larger sample (n=17,895) so is likely to have had more power.

[xiv] The GHQ scale is not directly comparable with the SF-8 scale. By way of context being in a relationship was associated with increased psychological well-being (0.43 units) as was living in a neighbourhood that participants reported liking (0.43 units).

In a randomised controlled trial of an intervention to increase walking to work (and in which walking increased in the intervention group), Mutrie et al. found improvements in three of eight sub-scales of well-being assessed using the SF-36 amongst the intervention group compared to the control group. As this study did not compute MCS and PCS scores, direct comparisons with my findings are not possible, but I note that mental health was one of the three domains in which they observed significant improvements, paralleling the increase in MCS-8 that I observed for cycling.[158] As this study was a randomised controlled trial it is possible that the observed differences in well-being might relate to the intervention rather than the change in physical activity[xv]. Elements of the intervention (e.g. advice on route choice, maintaining safety) might conceivably influence mental well-being. The intervention was not placebo controlled raising the possibility that the psychological benefits might relate to a placebo effect.

However, my findings also contrast with those of Martin et al. and Mutrie et al.[158,159] In both these studies the primary form of active commuting was walking. In addition, Martin et al reported an association between each additional 10 minutes of walk commuting and psychological well-being,[159] whereas I found mixed and non-significant associations for walk commuting.

In contrast to the other two UK studies, a study of women living in low and middle income neighbourhoods in the urban area of Cali, Colombia observed negative associations of walking for transport with MCS-8.[160] This might give more credence to a possible negative association between maintenance of walk commuting and MCS-8. However, there are also different contextual factors. For example, walking for transport may be more associated with activities perceived as burdensome, or concerns about personal safety, in Cali compared to Cambridge. Some commuters in Cambridge, in part because of their financial resources, can exert choice over their mode of travel to work, and if travel mode is chosen rather than constrained, then active travel may be experienced as being more pleasant.[136]

I also note my findings may appear to contrast with baseline (cross-sectional) associations observed in the same dataset. An earlier study, using the Commuting and Health in Cambridge study, did not report a significant association between active commuting (either walking or cycling) and MCS-8.[157] However the exposure was categorised differently considering weekly minutes of active commuting (grouped into four categories), and so may have had reduced power to detect an association. The reported associations in that analysis (0.29, 0.27 and 0.71 for 30-149 min/week, 150-224 min/week

[xv] No analysis was undertaken between change (or increase in) walking and well-being

and ≥225 min/week respectively compared ≤30 min/week) are in keeping with the positive association observed between cycling to work and MCS-8 that I observed.

The positive associations between active commuting and well-being are also consistent with a much broader evidence base showing positive associations between physical activity (typically leisure-time physical activity) and mental well-being among healthy adults.[166] My own analysis is also showed a strong association between physical activity index and MCS-8 (see 'physical activity index' in Table 2.9).

2.4.3.2 Physical well-being

The associations between active commuting and physical well-being have been described less frequently. The Colombian study reported a negative association between walking for transport and physical well-being.[160] Contextual differences between Cali and Cambridge may account for the differences, for example the nature of walking for transport may be more hazardous in Cali than in Cambridge. It is also possible that walking for transport is an indicator of low socio-economic status and that this may contribute to the observed associations.

The baseline analysis of the Commuting and Health in Cambridge dataset, reported positive associations between active commuting and PCS-8. Whilst I did not observe a significant association for PCS-8 after adjustment for co-variates the association was marginally non-significant and of magnitude consistent with previous observations (0.48, 0.79 and 1.21 for 30-149 min/week, 150-224 min/week and ≥225 min/week respectively compared ≤30 min/week).

2.4.3.3 Sickness absence

Concerning sickness absence, my findings are very similar to those of Hendriksen et al., who found that cycling to work was associated with just over one fewer day of employer-recorded sickness absence per year in a sample of Dutch workers.[156] Their analysis was in a population with a higher level of sickness absence (mean of 8 days) than the one I studied (3.6 days). It was also cross-sectional and consequently was not adjusted for baseline sickness absence, although it was adjusted for self-reported health and measures of chronic disease. My findings are also consistent with a broader literature suggesting positive associations between physical activity (predominantly recreational physical activity) or physical fitness and sickness absence.[161,163]

2.4.4 Interpretation

Taken together my findings provide some evidence that cycling to work may contribute to improved well-being and reduced sickness absence.

2.4.4.1 Observed effect size

The effect sizes observed for PCS-8 and MCS-8 fall below the thresholds that some have posited for clinical significance, typically three units,[157] although those who developed the score only gave examples of the differences in scores observed between a healthy population and population with disease (a variety of disease states were offered for comparison) and refrained from using the term "clinical significance".[184] Whilst the observed differences may appear small relative to the changes associated with onset of disease, small shifts in the population average can be important for population health and well-being (see section 1.1.1. on population approaches). Moreover, generally it is hard for shifts in the population average to match individual treatment effects, particularly when those treatments are targeted at individuals at high risk (e.g. reduction of population salt intake by 1-2g in the UK may have lowered mean blood pressure by 2-3mmHg, whereas a single anti-hypertensive might lower blood pressure by around 9mmHg).[209,210]

For well-being, more appropriate comparisons may be made by comparing between population groups. For example, a one-unit difference in PCS-8 score is similar to the differences observed in the study cohort between the young (16-29 years) and old (>50 years), or between those with obesity and those of low or healthy bodyweight. The effect size for MCS-8 is similar to that which I observed between men and women in the study cohort.

The observed effect size for sickness absence was equivalent to one day per annum. In the context of relatively low levels of sickness absence this is likely to be important, and consequently could represent a modest proportion of total days of sickness absence across an organisation. The financial burden of sickness absence is an important cost to employers (£15 billion per annum in the UK), including the NHS.[134,135,172]

My findings also provide an indicative estimates of effect sizes that might be observed in future studies of the health benefits of interventions to promote active travel. This may form the basis for power calculations.

2.4.4.2 Conditional analysis

For both the 'maintenance' and the 'change' analyses I estimated two sets of models, one adjusting for covariates, and a second additionally conditioning on the baseline value of the outcome in question. The pattern of results for MCS-8 (significant after adjustment for covariates, not significant after additionally conditioning on baseline MCS-8) suggests that the differences observed between those who cycled to work and those who did not are, at least partly, explained by differences in MCS-8 between the two groups at baseline. In contrast, the equivalent models for sickness absence produced effect size estimates that were both statistically significant and similar in magnitude to each other. This suggests that even after allowing for differences in sickness absence between those who cycled to work at baseline and those who did not, those who maintained cycling to work were still likely to report less sickness absence at follow-up.[188]

2.4.4.3 Null findings for walking

In light of the positive findings for cycling to work, the null findings for walking to work may appear unexpected. It seems unlikely that they can be explained simply by many non-walkers cycling to work, as additional adjustment for cycling to work did not reveal any significant associations. Among those who reported walking to work in this analysis, the average weekly duration of time walking (median 20 minutes per day) was relatively low compared to other studies and to estimates of walking undertaken by the average office worker at work (3700 steps per day, equivalent to about 2 miles of walking).[211]

This partly reflects how I chose to categorise the walking exposure. *Any* walking on the commute included both short walking journeys as part of a longer journey (e.g. by public transport) as well as trips made entirely by foot. Whilst the same problem might occur for cycling, the duration of cycling time tended to be higher[212] and it may be less common to use cycling to bridge parts of a longer commute.

I also note that walking is undertaken at a lower intensity than cycling [212,213] and that intensity of physical activity may be important for some health outcomes, such as sickness absence.[214] This may be true for sickness absence, for which only vigorous but not moderate physical activity has been associated with reduced absence.[161].

It is possible then that the average 'dose' of walking to work (duration, intensity or both) in the exposed group in the study was too low for an association with well-being or sickness absence to be

observed. Other differences between cycling and walking in Cambridge for example in relation to motivations or perceptions of the activity may contribute to the differences.[215,216] There may also be unmeasured socio-economic differences between those who walk to work and those who cycle to work and the measures of socio-economic status used (presence or absence of a degree) may not have captured such differences.

2.4.5 Unanswered questions and future research

Considerable uncertainty remains concerning the dose, frequency and intensity of active commuting (or active travel) necessary to reduce sickness absence and improve well-being. There are also unresolved questions about the relative value of walking to work compared to cycling to work, as well as the value of other commuting practices (e.g. using public transport or multi-modal commuting) relative to car-use alone.

Future research should seek to reduce this uncertainty and test more thoroughly whether changes in travel behaviour are associated with changes in well-being or sickness absence. It should also seek to replicate my findings in different populations, particularly in more deprived communities in which commuting choices may be more constrained and active travel perceived differently. Exploring the differential benefits of active travel among those who are obese or sedentary would also be of value as they may have more to gain.[196] Some large cohort studies (e.g. Fenland, UK Biobank) have not enquired about sickness absence, whilst others that do (e.g. Whitehall II) have not recorded active travel. Given it can be ascertained by a single simple question and its importance, it should be considered for inclusion in future studies or rounds of data collection in existing studies.

2.5 Chapter summary

This chapter has described the longitudinal associations of active commuting with mental well-being (MCS-8), physical well-being (PCS-8) and sickness absence in the Commuting and Health in Cambridge dataset. Two complementary approaches to testing longitudinal associations (maintenance analyses and change analyses) were used, adjusting first for co-variates and the additionally conditioning on the baseline outcome of interest.

Maintenance of cycling to work, compared to maintenance of not cycling to work, was associated with increased MCS-8 scores and reduced sickness absence. Whilst the observed associations for PCS-8 were not significant, the pattern of findings was suggestive that cycling to work was likely to be associated with PCS-8. No significant findings were observed for walking to work.

3 Longitudinal associations of active commuting with body mass index

"I wanted to lose weight and get fitter…so I went to the gym for three months at the beginning of the year but… I'm not someone who will exercise for the sake of exercising, I don't enjoy it and don't tend to stick to it. The commute to work, it means that I'm doing exercise consistently for a reason and I'll stick to it."

"I've put on a stone in the past two years since I started working here and I don't think it's due to a change in my diet… Before I came here I would walk [to work which was] 25 minutes in the morning and… [again] in the evening. I don't have that anymore and I think I miss that. So over the past two years my weight has crept up and up."

Participants in the Commuting and Health in Cambridge Study, reflecting on active commuting and body weight.

3.1 Introduction

This chapter describes the longitudinal associations between active commuting and body mass index in the Commuting and Health in Cambridge dataset. An abbreviated version of this chapter has been published in Preventive Medicine.[155]

3.1.1 Chapter outline

This chapter briefly discusses the importance of active travel and obesity from a public health perspective. It then describes limitations with existing studies reporting associations between active travel and adiposity. In this chapter, I make use of the same dataset and analytic approach (maintenance and change analyses), that was described in the previous chapters. Consequently, the methods section is relatively brief and primarily describes parts of the methods that are different. I present results. The discussion includes the following: a summary of the findings; strengths and limitations; comparisons with other studies; interpretation and implications; unanswered questions and future research. The chapter finishes with a summary.

3.1.2 Active travel and obesity

Overweight and obesity are major public health concerns. Obesity is a risk factor for cardio-metabolic diseases, some cancers, as well as some other conditions (e.g. osteoarthritis, infertility and liver disease).[217–223] In England, 26% of adults are classified as obese.[224] In the UK, it is estimated that obesity costs the National Health Service £5.1 billion per year, and society as a whole £27 billion per year.[225]

Obesity also appears to be a driver for policy changes in the UK, as reflected in the recent desire to tackle childhood obesity.[226,227] In contrast lack of physical activity or poor dietary consumption may contribute to a similar or greater burden of disease,[106,196] but neither issue alone seems as able to capture public and political concern.

The promotion of walking and cycling for transport has been proposed as one means to reduce the prevalence of obesity.[108,228] Ecological evidence, either from comparisons between countries or cities[117,229] or temporal trends of obesity and active travel,[101] suggest that shifts in travel patterns might have potential to reduce the prevalence of obesity by relatively large amounts. For example, a higher proportion of trips undertaken by foot or bicycle, 20% compared to 10%, is associated with a lower prevalence of obesity, 20% to 25%.[229]

Ecological studies are a weak form of evidence for making causal inference or estimating effect sizes. Other evidence of an association between active travel and obesity comes from cross-sectional studies (with measurement at the individual level) and prospective observational studies. These studies are summarised in Table 3.1.

A number of criticisms of the studies can be made. Many studies are cross-sectional,[130,230–240] rather than longitudinal. Many studies have identified active travel based on usual mode of travel, which forces individuals to identify only one mode of travel. This may not capture the true complexity of travel behaviour that can involve multiple modes (e.g. walk to bus-stop, bus journey, walk from bus-stop to workplace) or alternating modes on different days (e.g. cycling to work twice a week, driving to work on the other days). Use of such a question may also result in some multi-modal commuters who regularly cycle or walk being (inappropriately) classified as not undertaking active travel.

The outcome of all studies is body mass index (BMI),[130,131,230–240] and for many studies this is based on self-reported[131,231,233,236,237,240] rather than objectively measured height and weight. BMI can be a poor indicator of total body fat, because it is also affected by muscle mass.[241,242] More biologically relevant measures, in terms of their association with metabolic disease, are indicators of visceral adiposity (e.g. waist circumference, or waist-to-hip ratio),[149–151,243] but the association between active travel and these other measures of adiposity has seldom been studied.

Non-travel physical activity and diet may be important confounders, but very few studies have adjusted for both behaviours.[130,234–236,238] Moreover those studies that have adjusted for both, may not have adequately adjusted for these behaviours. Studies that have adjusted for diet have either used measures that may be less appropriate (e.g. energy intake)[xvi,130] or used measures that only characterise part of the diet (e.g. fruit and vegetable intake).[232,234–236,238] Whilst several studies have adjusted for leisure-time physical activity[130,155,230,234–236,238,239] only three have explicitly adjusted for occupational physical activity.[155,234,239] No study has adjusted for objectively measured physical activity.

Finally, few studies have demonstrated a dose-response relationship between active travel and body mass index. Demonstration of a dose-response relationship is one suggested 'test' of causation.[35]

[xvi] Dietary energy intake tends to be poorly measured and much of the intra-participant variation may be accounted for by differences in physical activity.[366]

Table 3.1 Summary of observational studies describing the associations between active travel and adiposity

Author, Year	Settings and dataset (size)	Analytic Approach	Exposure	Outcome	Co-variates	Significant Findings
Larouche, 2016[230]	Canada using the Canadian Health Measures Survey (n=7,160)	Cross-sectional	Time spent in utilitarian (travel to work and doing errands) walking and cycling	BMI (objective) Waist circumference	Age, sex, SES, Leisure time PA	Cycling more than one hour per week associated with reduced BMI (1.9 kg/m^2)
Berglund, 2016[231]	Sweden using a postal questionnaire (random sample) (n=1,786)	Cross-sectional	Usual mode of travel to work and for other activities: inactive and active (walking and cycling)	BMI (self-report)	Age, sex, SES, smoking, food choice based on health	Inactive travel associated with higher odds of being obese (OR=1.42).
Flint, 2016[130]	UK using UK Biobank (n=156,666)	Cross-sectional	Frequency and mode of travel used to assign participants to: car-only, car and public transport, mixed public/active travel, walking and cycling	BMI (objective) Body fat	Age, SES, health status, occupational and leisure-time physical activity, diet (energy intake)	Relative to car-only, for women mixed public/active travel (0.7 kg/m^2), cycling (1.7 kg/m^2), for men mixed public/active travel (1.0 kg/m^2), cycling (1.8 kg/m^2)
Laverty, 2015[232]	Six middle income countries (China, India, Mexico, Ghana, Russia and South Africa) using WHO Study on Global Aging and Adult Health (n=40,477)	Cross-sectional	Time and frequency spent travelling by foot or bicycle (extracted from general physical activity questionnaire)	BMI Waist-to-hip ratio (all likely measured objective but not stated in the manuscript)	Age, sex, SES, smoking, alcohol use, diet quality (fruit and vegetable consumption), urban-rural status.	High-use of active travel associated lower risk of overweight (RR=0.71), high waist-to-hip ration (RR=0.71) and lower BMI (-0.54 kg/m^2)
Martin, 2015[131]	UK using British Household Panel Survey (n=4056)	Longitudinal (one and two years)	Usual mode of travel to work: private motor transport, public transport, active travel. Active travel predominantly walking (switched too, 83/109; switched from, 121/156)	BMI (self-reported)	Age, sex, SES, car ownership, major life event	Switching from private motor transport to AT associated with decrease in BMI (0.45 kg/m^2), and switching from AT to private motor or public transport was associated with an increase in BMI (0.34 kg/m^2)
Wojan, 2015[233]	USA using American Time Use Survey (n=13,206)	Cross-sectional (using an "endogenous treatment model")	Active commuting, passive commuting. Multi-modal commuting that included an active component as classified as active commuting.	BMI (self-reported)	Murder rate, adverse weather and bicycle friendly community	Active commuting associated with reduced BMI
McKay, 2015[234]	India (Goa and Chennai) and Bangladesh (Matlab) using the Chronic Disease Risk Factor Study (n=2,122)	Cross-sectional	Duration of active travel (walking and cycling) extracted from general physical activity questionnaire	BMI (objective)	Age, sex, SES, smoking, diet (oil/butter consumption), additional PA, study site	≥150 minutes of active travel per week associated with lower BMI (0.39 kg/m^2)

Table 3.1 cont'd

Flint, 2014[235]	UK using UK Household Longitudinal study (n=7534)	Cross-sectional	Primary mode of travel to work: Private transport, public transport, active travel. Active travel predominantly walking (11% modal share, vs 3% for cycling).	BMI (objective) Body fat (%)	Age, SES, PA in workplace, sporting activity, diet quality (vegetables consumption), urban-rural status	-0.97 and -1.10 for men for active and public relative to private modes; -0.87 and -0.72 for women
Rissel, 2014[236]	New South Wales, Australia using the New South Wales Health Survey (n=66,101)	Cross-sectional	Usual mode of travel to work: walking, cycling, other	BMI (self-reported)	Age, SES, diet (fruit, fast food, vegetables, meat), other PA, urban-rural status	Decreased BMI for both men who commute actively (cycling: 2.15 kg/m^2, walking 2.47 kg/m^2) and women (cycling 1.22 kg/m^2, walking 2.95 kg/m^2) relative to other modes of travel
Laverty, 2013[237]	UK using Understanding Society (n=19,380)	Cross-sectional	Usual mode of travel to work: private transport, public transport, cycling, walking.	BMI (self-reported)	Age, sex, SES, ethnicity, region.	Walking and cycling to work associated with reduced odds of being obese (OR= 0.80 for walking; 0.63 for cycling). For walking only those who reported walking ≥2 miles to work (and not those walking <2 miles) had a significantly lower BMI relative to users of private transport.
Millett, 2013[238]	India using Indian Migration Study (n=3,902)	Cross-sectional	Usual mode of travel to work: private transport, public transport, walking or cycling	BMI (objective)	Age, sex, caste, SES, region, leisure time PA, diet (fat intake), smoking status and alcohol)	Reduced risk of obesity among those walking to work (RR=0.72) or cycling to work (RR=0.66) relative to private transport.
Gordon-Larsen, 2009[239]	USA using the CARDIA study (n=2,364)	Cross-sectional	Active commuting, defined as any walking or cycling on the journey to work	BMI (objective)	Age, SES, race, region, smoking, alcohol consumption, physical activity (leisure and occupational)	Active commuting associated with reduced odds of being obese for men (OR=0.51), but not for women (OR=0.91)
Lindstrom, 2008[240]	Skane, Sweden using the 2004 public health survey in Skane	Cross-sectional	Means of transportation: car, walking/bicycling, public transport or other (use of more than one mode)	BMI (self-reported)	Age, country of origin, SES, time to travel to work.	Walking/bicycling associated with reduced odds of obesity (RR=0.79).

PA=physical activity; AT=active travel; SES=socio-economic status; BMI=body mass index; study size refers to the analytic sample; studies identified by using the search terms: active travel, active commuting, adiposity, obesity, BMI.

3.2 Methods

3.2.1 Study setting and data collection

The analysis used the Commuting and Health in Cambridge dataset. This was described in the previous chapter.

3.2.2 Inclusion and exclusion criteria

I used the same inclusion and exclusion criteria that were described in the previous chapter. Applying these criteria gave an analytic sample of 809[xvii].

3.2.3 Exposure measures

I used the same exposure measures that were described in the previous chapter: i.e. maintenance of cycling (and the equivalent for walking); change in weekly time cycling (and the equivalent for walking).

In addition I created a second (categorical) measure of maintenance of cycling (0 minutes, 1-149 minutes, >150 minutes). Participants who reported 0 minutes of cycling to work at both baseline and follow-up were categorised as maintaining 0 minutes of cycling. Similarly participants who reported 1-149 minutes of cycling to work at both baseline and follow-up were categorised as maintaining 1-149 minutes of cycling, and those who reported >150 minutes at both baseline and follow-up as maintain >150 minutes of cycling to work. The same approach was followed for walking. Participants who moved between categories between baseline and follow-up were not categorised and thus excluded from analyses using this variable.

Thus again I undertook two complementary approaches to longitudinal analysis (maintenance analyses and change analyses)

3.2.4 Outcome measures: body mass index

I estimated body mass index (BMI) by dividing self-reported weight by the square of self-reported height.[194] Change in BMI was estimating by subtracting baseline from follow-up values. Extreme values for BMI and change in BMI were identified. Height and weight measures were checked against

[xvii] This is different from the 801 for the sickness absence and well-being analyses, due to the different outcomes and co-variates.

measurements at other time points, and then either modified if I was confident of the true value (n=8) or deleted if the true value was unclear (n=2).

3.2.5 Covariates

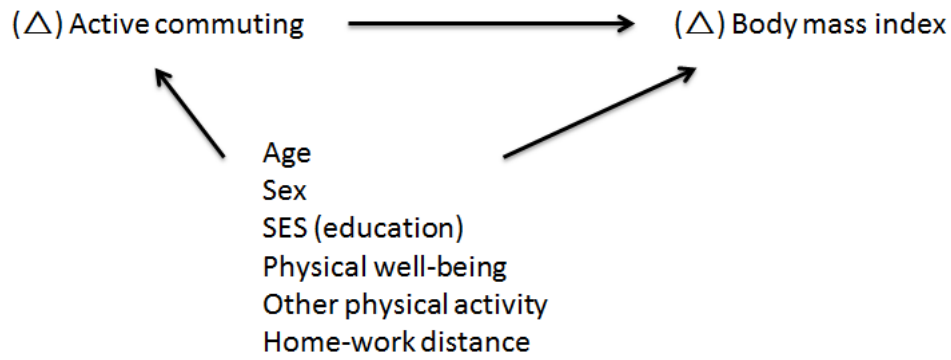
I hypothesised that the following factors may confound the relationship between active commuting and BMI: age; sex; education; physical well-being; distance from home to work; and other physical activity. Study year was also included as a co-variate. The included co-variates are different from those in the well-being and sickness absence analyses.

The rationale for the inclusion of the co-variates for the BMI analyses is set out below. The description of how these covariates were measured is set out in the previous chapter.

3.2.5.1 Rationale for inclusion of co-variates

The assumed relationship between active commuting and BMI is shown in Figure 3.1.

Figure 3.1 Directed acyclic graph showing the hypothesised relationship between active commuting and body mass index



Age and sex: BMI varies with age and sex.[244]. Both are also determinants of active travel.[136,137,191,215]

Socio-economic status: Obesity is patterned by socio-economic status (SES).[244] In previous analyses of the Commuting and Health in Cambridge dataset, SES was shown to be associated with active travel.[136,137,191] There were two measures of SES in the Commuting and Health in Cambridge study (area-level deprivation and education status). I chose education status because it is an individual measure (rather than an area-level measure) and in the data, it was strongly associated with BMI for both men and women. The further addition of an area-level measure of deprivation (quintile of index of multiple deprivation) did not materially alter the findings.

Physical well-being: I hypothesised that poor physical health could restrict ability to walk or cycle to work. Univariable analysis in the dataset supported this hypothesis. I also hypothesised that poor physical health would restrict ability to be active in other areas of life (beyond that captured by recreational physical activity). Reduced physical activity in other areas of life could also affect BMI.[41,62]

Other physical activity: Physical activity is associated with BMI.[41,62] It is commonly suggested that individuals who travel actively may also undertake more recreational physical activity,[130] and thus it is important to adjust for it and other forms of physical activity.

Home-work distance: Home-work distance was associated with active commuting in the study sample [136,191,198] and may be associated with other factors such as SES (the price of housing in Cambridge is high, resulting in some people living out of Cambridge and commuting into the city). Commute duration is associated with reduced well-being.[168,199] A long commute duration may also reduce time available for other health-promoting activities (e.g. sleep, healthy eating, leisure-time physical activity) and so might conceivably be associated with obesity. Home-work distance was also strongly associated with BMI in the study dataset.

3.2.5.2 Application of co-variates in change analyses

I applied the same set of covariates to the two approaches to longitudinal analysis (maintenance analyses and change analyses). For the second approach (change analyses), I considered adjusting for time varying covariates (i.e. other variables that may have changed and might confound the relationship), but such variables were either unavailable (e.g. change in diet or change in sleep), liable to be on the causal pathway (e.g. change in recreational physical activity, which might arise, at least in part, as a result of change in commuting physical activity leading to a change in well-being and change in other non-commuting physical activity), or of uncertain association with BMI (e.g. change in home location, which might be associated with a set of other changes in e.g. sleep, time pressure or stress that might influence BMI in either direction).

Adjustment for variables on the causal pathway (i.e. mediators) would be inappropriate.[201] Adjustment for variables whose association with BMI is uncertain or mixed (i.e. could be a positive or negative confounder) is unlikely to aid comprehension. A change in home (or work) location may be one such variable. Whether it acts as a positive or negative confounder may depend on other contextual factors. If it is acting in both ways, then including participants who have changed home or work location may inappropriately bias the results and/or increase the width of the confidence

interval. Consequently, I chose to undertake a sensitivity analysis in which the change analyses were restricted to those who had not moved home or work.

3.2.6 Analysis

As before, I used two complementary approaches to test longitudinal associations.

I included both maintenance of cycling to work and maintenance of walking to work as explanatory variables in a single model so that the estimates were mutually adjusted, because the two behaviours contribute separately to physical activity energy expenditure. For the same reason I also include change in weekly cycling time and change in weekly walking time in a single 'change' model.

To explore the dose-response relationship I repeated the maintenance analysis using a three-way categorical measure for both cycling and walking (0 minutes, 1-149 minutes, >150 minutes). To maintain sample size the maintenance of cycling (using the 3-way categorical variable) was adjusted for the dichotomous measure of maintenance of walking to work. The same approach was followed for maintenance of walking to work, using the 3-way categorical variable.

I also tested for effect modification by sex and home-work distance, following the findings of previous research[131,235] and by weight status (BMI ≤25 kg/m^2 vs BMI>25 kg/m^2), as I hypothesised that the association between physical activity and BMI may vary by weight status.[245,246]

A summary of all analyses for cycling and the research questions that each analysis addresses is given in Table 3.2. An analogous set of questions exists for walking.

3.2.6.1 Software

Analyses were undertaken using Stata Statistical Software: Release 13 (College Station, TX: StataCorp LP) using the "regress" command for linear regression.

Table 3.2 Summary of analyses and research questions considering cycle commuting

Exposure	Categorisation	Outcome	Adjustment	Research question
Maintenance of cycling	None vs some	BMI at one-year follow-up	Model A	What is the difference in body mass index at one-year follow-up between those who maintain commuting by bicycle during the year of follow-up and those who maintain not doing so, after adjustment for covariates?
Maintenance of cycling	None vs some	BMI at one-year follow-up	Model B (conditional)	What is the difference in *change* in body mass index at one-year follow-up between those who maintain commuting by bicycle during the year of follow-up and those who maintain not doing so, after adjustment for covariates *assuming the same baseline body mass index*?
Maintenance of cycling	0 minutes per week; 1-149 minutes per week; >150 minutes per week	BMI at one-year follow-up	Model A	What is the difference in body mass index at one-year follow-up between those who maintain commuting: a) by bicycle for at least 150 minutes per week; b) by bicycle for 1-149 minutes per week; and c) not commuting by bicycle, after adjustment for covariates? This serves as a test for a dose-response relationship.
Maintenance of cycling	0 minutes per week; 1-149 minutes per week; >150 minutes per week	BMI at one-year follow-up	Model B	What is the difference in body mass index at one-year follow-up between those who maintain commuting: a) by bicycle for at least 150 minutes per week; b) by bicycle for 1-149 minutes per week; and c) not commuting by bicycle, after adjustment for covariates *assuming the same baseline body mass index*? This serves as a test for a dose-response relationship.
Change in time per week	No change, increase, decrease	Change in BMI (follow-up BMI minus baseline BMI)	Model A	What is the difference in change in body mass index between those whose cycle commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates?
Change in time per week	No change, increase, decrease	Change in BMI (follow-up BMI minus baseline BMI)	Model B (conditional)	What is the difference in change in body mass index between those whose cycle commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates *assuming the same* baseline BMI?
Change in cycling time per week	No or small change, large increase (> 50 minutes per week), large decrease (>50 minutes per week)	Change in BMI (follow-up BMI minus baseline BMI)	Model A	What is the difference in change in body mass index between those whose cycle commuting time: a) increased by 50 minutes or more per week; b) decreased by 50 minutes or more per week; and c) did not change or changed by less than 50 minutes per week, after adjusting for co-variates?
Change in cycling time per week	No or small change, large increase (> 50 minutes per week), large decrease (>50 minutes per week)	Change in BMI (follow-up BMI minus baseline BMI)	Model B (conditional)	What is the difference in change in body mass index between those whose cycle commuting time: a) increased by 50 minutes or more per week; b) decreased by 50 minutes or more per week; and c) did not change or changed by less than 50 minutes per week, after adjusting for co-variates *assuming the same* baseline BMI?
Change in time per week (excluding movers)	No change, increase, decrease	Change in BMI (follow-up BMI minus baseline BMI)	Model A	What is the difference in change in body mass index between those whose cycle commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates among those whose active commuting time changed for reasons other than changing work or home location? This may be a better test of the effect of a change *in active commuting* on BMI as it only considers those whose activity pattern changed whilst continuing to commute between the same home and work locations.
Change in time per week (excluding movers)	No change, increase, decrease	Change in BMI (follow-up BMI minus baseline BMI)	Model B (conditional)	What is the difference in change in body mass index between those whose cycle commuting time: a) increased; b) decreased; and c) did not change, after adjusting for co-variates and *assuming the same* baseline BMI, among those whose active commuting time changed for reasons other than changing work or home location? This may be a better test of the effect of a change *in active commuting* on BMI as it only considers those whose activity pattern changed whilst continuing to commute between the same home and work locations.

Model A co-variates: age, sex, education, physical well-being, other physical activity, walking (maintenance or change in weekly time walking to work) and home-work distance; Model B co-variates: age, sex, education, physical well-being, other physical activity, walking (maintenance or change in weekly time walking to work) home-work distance and baseline BMI; an analogous set of questions apply to walking.

3.3 Results

3.3.1 Descriptive characteristics

The included participants were predominantly women (69.6%) and educated to at least degree level (69.8%), and slightly more than half reported cycling to work (53.9%). Many of those who walked to work (48.5%) also reported some car commuting (compared to 27.3% amongst those who cycled to work) (Table 3.3). The prevalence of obesity and overweight (men: 37.8%; women: 33.2%) was lower than the national average for England (67.1% and 57.2% respectively).[247] There were no major differences between participants included in and excluded from the analysis (Table 3.4).

3.3.2 BMI and maintenance of cycling to work

Those who maintained cycling to work had a significantly lower BMI at follow-up, after adjustment for covariates (Table 3.5, Model A; change in BMI -1.14 kg/m^2, 95% CI -2.00 to -0.32), than those who did not cycle to work. Adjustment for maintenance of walking strengthened the observed association, and adjustment for home-work distance attenuated it (Model A, without adjustment for maintenance of walking: -0.86 kg/m^2, 95% CI -1.64 to -0.08; Model A, without adjustment for home-work distance: -1.45 kg/m^2, 95% CI -2.14 to -0.75). Adjusting the analysis for baseline BMI markedly attenuated the association such that it was no longer significant (Table 3.5, Model B). The effect size of maintaining 1-149 minutes of cycling to work per week was similar to that of maintaining 150 minutes or more of cycling per week (-1.28 kg/m^2, 95% CI -2.32 to -0.23 vs. -1.26 kg/m^2, 95% CI -2.26 to -0.27; n=493).

Under Model A significant interactions were observed between maintenance of cycling to work and home-work distance (p=0.001) and weight status at baseline (p=0.02), but not sex (p=0.23). Stratifying by home-work distance, a stronger association with BMI was observed amongst those living further from work (0-9.99 km: 0.04 kg/m^2, 95% CI -0.83 to 0.93, n=395; 10-19.99km: -1.27 kg/m^2, 95% CI -3.03 to 0.49, n=105; ≥20km: -2.77 kg/m^2, 95% CI -4.35 to -1.19, n=199). Stratifying by weight status, a stronger association was observed among those who were overweight or obese at baseline (-1.02 kg/m^2, 95% CI -2.08 to 0.02, n=375; vs. 0.05 kg/m^2, 95% CI -0.41 to 0.52, n=204, for those with a BMI ≤25 kg/m^2).

Table 3.3 Baseline characteristics of participants included in the analyses (n=809)

	Cycling to work		Walking to work	
	None (n=373)	**Some (n=436)**	**None (n=597)**	**Some (n=204)**
	N (%)	**N (%)**	**N (%)**	**N (%)**
Sex				
Female	289 (51.3)	274 (48.7)	197 (80.1)	49 (19.9)
Male	84 (34.2)	162 (65.9)	408 (72.5)	155 (27.5)
Age				
Median (years)	44.1 (34.8-52.9)	42.9 (33.1-51.5)	43.3 (34.0-52.0)	43.4 (42.7-52.8)
16-29 years	42 (39.6)	64 (60.4)	73 (68.9)	33 (31.1)
30-39 years	106 (47.5)	117 (52.5)	170 (76.2)	53 (23.8)
40-49 years	95 (44.6)	118 (55.4)	165 (77.5)	48 (22.5)
50-59 years	94 (46.5)	108 (53.5)	151 (74.8)	51 (25.2)
≥60 years	36 (55.4)	29 (44.6)	46 (70.8)	19 (29.2)
Highest educational qualification				
Less than degree	142 (58.2)	102 (41.8)	183 (75.0)	61 (25.0)
Degree or higher	231 (40.9)	334 (59.1)	422 (74.7)	143 (25.3)
Weight status				
Underweight/normal weight	217 (41.0)	312 (59.0)	400 (75.6)	129 (24.4)
Overweight	105 (50.2)	104 (49.8)	152 (72.7)	57 (27.3)
Obese	51 (71.8)	20 (28.2)	53 (74.7)	18 (25.4)
Body Mass Index (kg/m²)				
Median (IQR)	24.4 (21.5-27.3)	23.3 (21.4-25.4)	23.7 (21.5-26.3)	23.6 (21.3-26.4)
PCS-8 score				
Median (IQR)	55.2 (51.1-58.0)	55.7 (52.5-58.0)	55.4 (51.7-58.0)	55.4 (51.4-58.1)
Home-work distance				
0.01-9.99 km	120 (25.3)	355 (74.7)	361 (76.8)	109 (23.2)
10-19.99 km	71 (61.2)	45 (38.8)	89 (76.7)	27 (23.3)
≥20 km	182 (83.5)	36 (16.5)	147 (68.4.0)	68 (31.6)
Physical activity index				
Inactive	9 (37.5)	15 (62.5)	19 (79.2)	5 (20.8)
Moderately inactive	115 (50.9)	109 (49.1)	168 (74.3)	58 (25.7)
Moderately active	113 (46.5)	132 (53.5)	178 (73.3)	65 (26.7)
Active	136 (43.0)	180 (57.0)	240 (76.9.0)	76 (24.1)
Weekly time cycling to work				
Median (IQR) (min)	0 (0-0)	150 (90-200)	90 (0-180)	0 (0-30)
Weekly time walking to work				
Median (IQR) (min)	0 (0-90)	0 (0-0)	0 (0-0)	100 (60-180)
Use of other modes for commuting				
Car	245 (65.7)	119 (27.3)	265 (43.8)	99 (48.5)
Public transport	115 (30.8)	43 (9.9)	64 (10.6)	94 (46.1)
Changed behaviour				
Started walking/cycling to work	43 (11.5)	0 (0)	76 (12.6)	0 (0)
Stopped walking/cycling to work	0 (0)	67 (15.4)	0 (0)	68 (33.3)
Time frame				
2009-10	313 (47.5)	346 (52.5)	486 (73.8)	173 (26.3)
2010-11	15 (39.5)	23 (60.5)	23 (60.5)	15 (39.5)
2011-12	45 (40.2)	67 (59.8)	96 (85.7)	16 (14.3)

IQR=Interquartile range; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire, theoretical score range is 9.1 to 69.0, with a mean of 50 in the US adult population; unless otherwise stated characteristics are measured at baseline; changed behaviour describes the number of individuals who started or stopped active travel between baseline and follow-up (e.g. cycle to work at baseline and not cycling to work at follow-up); use of other modes, includes any use of the stated mode to commute to or from work, including for part of the journey, in the past seven days; car use includes the use of taxis.

Table 3.4 Characteristics of participants included and excluded from the analyses

	Included (n=809)	Excluded
	N (%)	**N (%)**
Sex		
Female	563 (69.6)	409 (69.1)
Male	246 (30.4)	183 (30.9)
Age		
Median (IQR)	43.3 (33.7-52.2)	38.4 (31.0-48.1) [n=599]
16-29 years	106 (13.1)	133 (22.2)
30-39 years	223 (27.6)	193 (32.3)
40-49 years	213 (26.3)	150 (25.0)
50-59 years	202 (25.0)	87 (14.5)
≥60 years	65 (8.0)	36 (6.0)
Highest educational qualification		
Less than degree	244 (30.2)	183 (31.2)
Bachelor or higher	565 (69.8)	403 (68.8)
Weight status		
Normal or underweight	529 (65.4)	346 (60.0)
Overweight	209 (25.8)	164 (28.4)
Obese	71 (8.8)	67 (11.6)
BMI (kg/m^2)		
Median (IQR)	23.7 (21.5-26.3)	24.1 (21.8-27.1)
PCS-8 score		
Median (IQR)	55.5 (51.5-58.0)	55.1 (51.5-57.7) [n=594]
Home to work distance		
Median (IQR)	8.0 (4.8-22.5)	8.0 (3.2-20.9) [n=600]
0-9.99 km	475 (58.7)	344 (57.3)
10-19.99 km	116 (14.3)	105 (17.5)
≥20 km	218 (27.0)	151 (25.2)
Physical activity index		
Inactive	24 (3.0)	20 (3.3)
Moderately inactive	226 (27.9)	159 (26.6)
Moderately active	243 (30.0)	202 (33.8)
Active	316 (39.1)	217 (36.3)
Weekly time cycling to work (minutes)		
Median (IQR)	50 (0-150)	0 (0-150) [n=602]
Weekly time walking to work (minutes)		
Median (IQR)	0 (0-10)	0 (0-50) [n=597]

IQR=Interquartile range; PCS-8 = Physical Component Summary score derived from the Short Form 8 Questionnaire; MCS-8 = Mental Component Summary score derived from the Short Form 8 Questionnaire; deprivation quintile is based on national quintiles of deprivation ranked using the Index of Multiple Deprivation 2010 score for the Lower Super Output Area (assigned based on postcode or residence).

Table 3.5 Associations of maintenance of cycling to work and maintenance of walking to work with BMI (n=579)

		Unadjusted	**Model A**	**Model B**
		Coefficient (95% CI)	Coefficient (95% CI)	Coefficient (95% CI)
Cycling to work	None (reference)			
	Some	**-1.25 (-1.83, -0.67)**	**-1.14 (-1.98, -0.30)**	-0.12 (-0.42, 0.17)
Walking to work	None (reference)			
	Some	-0.19 (-0.99, 0.62)	-0.80 (-1.63, 0.04)	-0.18 (-0.48, 0.11)
Sex	Male (reference)			
	Female	**-0.71 (-1.41, -0.00)**	**-0.80 (-1.49, -0.11)**	-0.02 (-0.26, 0.22)
Age	16-29 years (reference)			
	30-39 years	**1.62 (0.49, 2.77)**	**1.28 (0.17, 2.39)**	-0.17 (-0.56, 0.22)
	40-49 years	**2.23 (1.09, 3.37)**	**1.77 (0.66, 2.88)**	0.06 (-0.32, 0.45)
	50-59 years	**2.65 (1.51, 3.80)**	**2.29 (1.17, 3.40)**	-0.16 (-0.56, 0.22)
	≥60 years	**2.94 (1.48, 4.41)**	**2.09 (0.64, 3.53)**	0.07 (-0.44, 0.57)
Degree	No (reference)			
	Yes	**-1.03 (-1.75, -0.31)**	**-0.78 (-1.51, -.04)**	0.01 (-0.24, 0.27)
Home-work distance	0.01-9.99 km (reference)			
	10-19.99 km	0.73 (-0.19, 1.65)	0.06 (-0.90, 1.03)	-0.14 (-0.48, 0.19)
	≥20 km	**1.41 (0.65, 2.16)**	0.64 (-0.26, 1.53)	-0.08 (-0.40, 0.23)
Physical well-being (PCS-8)		**-0.08 (-0.13, -0.02)**	-0.05 (-0.10, 0.00)	-0.02 (-0.04, -0.00)
Physical activity	Inactive (reference)			
	Moderately inactive	**-3.67 (-5.82, -1.52)**	**-3.44 (-5.54, -1.34)**	0.19 (-0.55, 0.93)
	Moderately active	**-4.72 (-6.86, -2.57)**	**-4.33 (-6.44, -2.22)**	0.22 (-0.53, 0.96)
	Active	**-4.30 (-6.42, -2.17)**	**-4.07 (-6.16, -1.99)**	0.34 (-0.39, 1.08)
Study year	2009-10 (reference)			
	2010-11	-0.67 (-2.23, 0.88)	-0.11 (-1.60, 1.37)	-0.09 (-0.60, 0.43)
	2011-2	-0.27 (-1.24, 0.69)	-0.43 (-1.38, 0.52)	-0.06 (-0.39, 0.27)
Baseline BMI		**0.94 (0.91, 0.96)**	-	**0.94 (0.91, 0.97)**

Linear regression coefficients shown; - not included; CI=confidence interval; PCS-8 = Physical Component Summary score derived from the Short Form 8 questionnaire; physical activity is categorised using a modified form of the Cambridge Physical Activity Index; study year refers to the time period when data were collected; bold indicates significant results ($p<0.05$); Model A is adjusted for sex, age, education, home-to-work distance, physical well-being, physical activity and study year; Model B is adjusted for adjusted for sex, age, education, home-to-work distance, physical well-being, physical activity, study year and BMI at baseline.

3.3.3 BMI and maintenance of walking to work

There was no significant association between maintenance of walking to work and BMI (Table 3.5), despite the observation that adjustment for maintenance of cycling to work strengthened the association (Model A, without adjustment for maintenance of cycling to work: -0.36 kg/m^2, 95% CI -1.13 to 0.43). All specified interactions were non-significant. There was some evidence of a possible dose-response relationship between walking to work and BMI (1-149 minutes: -0.51 kg/m^2, 95% CI -1.68 to 0.65; >150 minutes: -0.95 kg/m^2, 95% CI -2.36 to 0.47; n=542), although the differences were not significant.

3.3.4 Change in BMI and changes in weekly time spent cycling or walking to work

There were no significant associations between either change in weekly cycle commute time or change in weekly walking commute time and change in BMI, in my primary analysis (Table 3.6). Interaction terms for sex, home-work distance and BMI were not significant. The associations between large increases/decreases and change in BMI were non-significant for both walking and cycling (Table 3.7). When restricting the change analysis to those who did not move home or work (n=651), a significant association between an increase in weekly time walking to work and decrease in BMI was observed (Table 3.8).

Table 3.6 Associations of changes in weekly cycle commuting time and weekly walking commuting time with change in BMI (n=809)

		Unadjusted	**Model A**	**Model B**
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Cycling to work	No change (reference)			
	Increase in weekly time (n=182)	0.14 (-0.09, 0.37)	0.09 (-0.15, 0.34)	0.06 (-0.18, 0.31)
	Decrease in weekly time (n=224)	0.16 (-0.06, 0.38)	0.15 (-0.08, 0.39)	0.14 (-0.10, 0.37)
Walking to work	No change (reference)			
	Increase in weekly time (n=139)	-0.20 (-0.45, 0.05)	-0.20 (-0.45, 0.04)	-0.23 (-0.48, 0.02)
	Decrease in weekly time (n=126)	0.25 (-0.01, 0.51)	0.24 (-0.02, 0.50)	0.25 (-0.01, 0.50)

Linear regression coefficients shown; CI=confidence interval; Model A is adjusted for age, education, sex, study year, home-work distance, Physical Component Summary score derived from the Short Form 8 questionnaire, physical activity categorised using a modified form of the Cambridge Physical Activity Index; Model B is adjusted for age, education, sex, study year, home-work distance, Physical Component Summary score derived from the Short Form 8 questionnaire, physical activity categorised using a modified form of the Cambridge Physical Activity Index and baseline BMI.

Table 3.7 Associations of large changes (≥ 50 minutes per week) in weekly cycling and walking commuting time with change in BMI (n=809)

		Unadjusted	Model A	Model B
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Cycling to work	No change (reference)			
	Increase in weekly time (n=106)	0.16 (-0.12, 0.44)	0.12 (-0.16, 0.41)	0.12 (-0.17, 0.40)
	Decrease in weekly time (n=149)	0.21 (-0.03, 0.45)	0.20 (-0.05, 0.45)	0.20 (-0.05, 0.45)
Walking to work	No change (reference)			
	Increase in weekly time (n=76)	-0.23 (-0.55, 0.08)	-0.23 (-0.55, 0.09)	-0.24 (-0.56, 0.07)
	Decrease in weekly time (n=80)	0.29 (-0.02, 0.59)	0.25 (-0.06, 0.57)	0.27 (-0.04, 0.58)

Linear regression coefficients shown; CI=confidence interval; Model A is adjusted for age, education, sex, study year, home-work distance, Physical Component Summary score derived from the Short Form 8 questionnaire, physical activity categorised using a modified form of the Cambridge Physical Activity Index; Model B is adjusted for age, education, sex, study year, home-work distance, Physical Component Summary score derived from the Short Form 8 questionnaire, physical activity categorised using a modified form of the Cambridge Physical Activity Index and baseline BMI.

Table 3.8 Associations of changes in weekly cycle commuting time and weekly walking commuting time with change in BMI, restricted to those who did not move home or work (n=651)

		Unadjusted	Model A	Model B
		Co-efficient (95% CI)	Co-efficient (95% CI)	Co-efficient (95% CI)
Cycling to work	No change (reference)			
	Increase in weekly time (n=141)	0.21 (-0.06, 0.48)	0.19 (-0.09, 0.48)	0.15 (-0.13, 0.43)
	Decrease in weekly time (n=169)	0.21 (-0.04, 0.46)	0.25 (-0.02, 0.53)	0.23 (-0.05, 0.50)
Walking to work	No change (reference)			
	Increase in weekly time (n=105)	**-0.29 (-0.58, -0.00)**	**-0.29 (-0.59, -0.00)**	**-0.32 (-0.62,-0.03)**
	Decrease in weekly time (n=101)	**0.30 (0.01, 0.59)**	0.29 (-0.01, 0.59)	0.29 (-0.01, 0.59)

Linear regression coefficients shown; CI=confidence interval; bold indicates significant results (p<0.05); Model A is adjusted for age, education, sex, study year, home-work distance, Physical Component Summary score derived from the Short Form 8 questionnaire, physical activity categorised using a modified form of the Cambridge Physical Activity Index; Model B is adjusted for age, education, sex, study year, home-work distance, Physical Component Summary score derived from the Short Form 8 questionnaire, physical activity categorised using a modified form of the Cambridge Physical Activity Index and baseline BMI.

3.4 Discussion

3.4.1 Summary of findings

Maintenance of cycling to work was associated with a lower BMI at one-year follow-up, after adjustment for covariates. This association was stronger for those who had a longer commuting distance or who were overweight or obese at baseline, but there was no evidence of a 'dose-response' between weekly time cycling to work and BMI. However, the conditional analysis (adjusting for baseline BMI) was not significant. Change in weekly time cycling to work was not associated with change in BMI.

Increasing weekly time walking to work was associated with a reduction in BMI, but only when restricted to those who had not moved home or work. Whilst other associations for walking were non-significant, the pattern of results for walking was consistent with the findings of past research that has observed associations between walking to work and BMI.

3.4.2 Strengths and limitations

Many of the same strengths and limitations that were described in the previous chapter apply to this analysis (longitudinal analyses, study power, measurement of commuting behaviour) and are not described here. The strengths and limitations of this analysis that relate to body mass index are described below.

3.4.2.1 Self-reported weight

Body mass index was estimated based on self-reported weight and height. Weight is prone to systematic biases in reporting, in that heavier individuals tend to under-report their body weight.[248,249] As heavier participants were less likely to report active commuting in the study, this reporting bias may have attenuated the observed associations. Conversely, because the study was designed to investigate the relationships between commuting and health, it is possible that some responses may have been affected by a social desirability bias whereby those who travelled by active or 'healthy' means were more likely to under-report their body weight. Such a bias would have strengthened the observed relationship.

3.4.2.2 Unmeasured confounders

Although the analyses were adjusted for the complementary commuting activity (walking or cycling) and other forms of physical activity, I have not adjusted for other aspects of behaviour, which were not measured but are associated with BMI, such as diet or sleep. Nor have I adjusted for car driving.

This was not well captured (neither time nor distance were recorded),[250,251] although it is unclear to what extent the associations between car driving and BMI may be attributed to an absence of active travel or other factors, such as snacking whilst driving.

3.4.3 Comparison with other studies

The findings broadly corroborate and build on the existing literature, providing further evidence of inverse associations between active travel and BMI.[130,131,230–240]

Taken together the findings for walking appear weaker than those for cycling, but are consistent with the literature. Most studies have reported stronger associations for cycling relative to walking,[130,230,237,238] although one study found comparable (or larger) effect size estimates for walk commuting relative to cycle commuting.[236] These studies also demonstrated significant associations for walking, whereas the associations I observed were not significant. Some of these studies defined walkers as those who used walking as the 'main mode' of travel,[130,236–238] in contrast I defined walkers as those who undertook any walking on their commute and consequently included many people who used other travel modes. The relatively low average quantity of walking to work (median 90 min/week), relatively high car use among walkers or limited number of walkers (low power), may all have contributed to the non-significant findings.

My estimates of effect size are consistent with estimates from other studies. For example, my findings for change in walking are comparable to a previous effect size estimate of 0.3 kg/m^2 for commuters changing from the car to active travel.[131] My findings for maintenance of cycling appear slightly conservative relative to cross-sectional estimates from developed countries, e.g. 2.2 kg/m^2 and 1.2 kg/m^2 (comparing men and women respectively in New South Wales who usually cycle to work, relative to men and women who usually use non-active means),[236] 1.8 kg/m^2 and 1.7 kg/m^2 (for men and women in the UK Biobank Study,[130] relative to car-users), and 1.9 kg/m^2 (for more than one hour of utilitarian cycling in the Canadian Health Survey, relative to those reporting less than one hour).[230] This may reflect the relatively low prevalence of obesity in the sample compared to the UK average and in other study settings (e.g. mean BMI of 27.2 kg/m^2 in the Canadian Health Survey).[230] Smaller effect size estimates from cross-sectional studies have been reported in other settings with a lower prevalence of obesity, although these are not specific to cycling (e.g. 0.4 kg/m^2 comparing those who undertake 150 minutes or more of active travel a week with those who do not in India and Bangladesh, with an obesity prevalence of 3%).[234]

3.4.4 Interpretation

3.4.4.1 Maintenance analyses

I had hypothesised that the maintenance analyses might provide a test of a temporal relationship. However, although the exposure was ascertained prior to the outcome, the pattern of results (with a marked attenuation resulting in a near-null association after conditioning on baseline BMI) could be explained by baseline BMI (or BMI prior to baseline) determining the likelihood of cycling (i.e. acting as a confounder). Such an explanation would undermine an argument about the biological plausibility of a causal effect of active commuting on BMI.

However, the findings are also consistent with the explanation that cycling to work prior to baseline contributed to differences in baseline BMI. From my analyses I cannot distinguish between these alternative explanations and consequently one should be cautious about drawing unequivocal causal inference from the findings.

Bi-directional relationship, i.e. cycling to work determines BMI and BMI determines cycling to work, should also be considered.

3.4.4.2 Change analyses

Only one set of change analyses was significant, that for non-movers whose walking increased. Whilst the sample size for the change analyses was larger than for the maintenance analyses, they may have had less power to detect an association. First, the exposure of participants may have been misclassified if other factors (e.g. annual leave, weather or variable work commitments) produced an *apparent* change in travel behaviour between the two time points, biasing the association towards the null. My experience from the maintenance analyses suggested that removing misclassified participants produced stronger associations. Second, there is a lag between changes in physical activity and the full change in BMI.[245] Given that the change in active commuting could have happened at any time between baseline and follow-up, the study design is unlikely to have permitted observation of the full effect of changes in active commuting on BMI. Third, other changes may have co-occurred with the change in active travel that might influence BMI in either direction and could not readily be accounted for. I note that excluding movers from the analysis (who might be subject to other life changes that could influence BMI) tended to strengthen the observed associations. One should therefore be cautious of over-interpreting the null results from the change analyses.

Whilst non-significant I note that the increases in cycling were associated with a small increase in BMI. In contrast the direction of the association for decrease in cycling and for walking (both increase and decrease) is in the expected direction. As exercise can be associated with increases in lean or muscle mass without decreases in body fat,[252] it is possible that the small increase could be explained by gain in muscle mass, particularly as cycling engages large muscle groups in the legs.

3.4.4.3 Interactions

There was a significant interaction between maintenance of cycling and home-work distance, with a stronger association between maintenance of cycle commuting and BMI among those who lived 20km or more from work, mirroring previous findings.[131] This could be explained by those who lived further from work being at greater risk of obesity (those who lived 20km or more from work had a mean BMI of 25.2 kg/m^2, compared to 23.7 kg/m^2 for those who lived within 10km) perhaps because of reduced time for activities that prevent weight gain (e.g. healthy eating or sleep).[253,254] Equally it may reflect residual confounding by age, SES (e.g. high living costs in Cambridge),[136] or other covariates.[250] In keeping with this finding, I also observed a stronger absolute effect size estimate among those who were overweight at baseline. Taken together these findings suggest a particular role for active commuting among populations who are more liable to be obese.

3.4.5 Summary

Whilst this study has demonstrated associations between active commuting and BMI, it has a number of short comings. These include: small size and limited power (with consequent inability to look at sub-groups); no adjustment for dietary confounding; use of self-reported BMI; use of an imprecise measure of adiposity and no testing of a dose-response relationship. These are areas that I plan to address in the next chapter using the Fenland Study, a larger dataset with detailed characterisation of physical activity, diet and adiposity.

As the next chapter also describes the associations between active commuting and obesity, some elements of the discussion (implications and future directions) are not considered here. These issues are considered in the next chapter, reflecting the findings across both this and the next chapter.

3.5 Chapter summary

This chapter has described the longitudinal associations between active commuting and body mass index in the Commuting and Health in Cambridge dataset. As before, I have used two complementary approaches, maintenance and change analyses, to test the associations.

Those who maintained cycling to work reported a lower BMI at follow-up compared to those who maintained not cycling to work after adjustment for sociodemographic variables, other physical activity, physical well-being and maintenance of walking. The observed difference was markedly attenuated and no longer significant after adjusting for baseline BMI. After excluding those who reported a change in work or home address, an increase in walking time was associated with a reduction in BMI after adjustment for co-variates and baseline BMI. Whilst there were no other significant associations, the pattern of findings for both cycling and walking was generally in keeping with an inverse association between active travel and body mass index. There was a suggestion that the associations may be stronger in populations who are more liable to be obese.

4 Associations of active commuting with objectively measured adiposity

"Physical activity does not promote weight loss"

Aseem Malhotra and colleagues writing in the British Journal of Sports Medicine about the relative contributions of poor diet and lack of physical activity to obesity[255]

"Physical activity is a minor distraction"

Simon Capewell, professor of clinical epidemiology, commenting on the contribution of lack of physical activity to the epidemic of obesity on Inside Health on Radio 4 (13 September, 2015)

"Average recorded energy intake in Britain has declined substantially as obesity rates have escalated. The implication is that levels of physical activity, and hence energy needs, have declined even faster. Evidence suggests that modern inactive lifestyles are at least as important as diet in the aetiology of obesity and possibly represent the dominant factor."

Andrew Prentice and Susan Jebb discussing the contribution of lack of physical activity to the epidemic of obesity in the British Medical Journal[101]

4.1 Introduction

This chapter describes the associations between active commuting and adiposity in the Fenland Study at baseline. This chapter builds on and complements the previous chapter. It addresses a different set of deficiencies identified in the existing literature to those addressed in Chapter Three.

4.1.1 Chapter outline

This chapter introduces two measures of adiposity (volume of visceral adipose tissue and percentage body fat) and explains why I chose to study these two measures. I describe aspects of the Fenland Study relevant to this analysis. A different approach to the categorisation of active commuting is used to that used in Chapter Two and Three. This approach (stratifying by distance and identifying 'patterns' of commuting behaviour) has not been used by other authors. I explain why I chose it and how the categorisation has been operationalised. Results are presented separately for men and women and stratified by distance for the two outcomes (body fat and visceral adipose tissue).

The discussion focuses on the results presented in this chapter, but interprets these in light of the findings presented in the previous chapter. It first summarises the key findings and presents the strengths and limitations specific to this analysis. I then compare the study results with past studies and the results presented in the previous chapter. I describe my interpretation of certain aspects of the results presented in this chapter, before giving an overall interpretation of the findings across the two studies relating to adiposity. I give some suggestions for future research, principally focused on using the Fenland dataset. Overarching comments in terms of implications and future research are discussed in the final chapter. The chapter finishes with a summary.

4.1.2 Adiposity

Body mass index is a common measure of adiposity. However, it is a poor indicator of total body adiposity as it is also affected by lean tissue mass.[241,242] It is also thought that the cardio-metabolic outcomes associated with a raised BMI are primarily attributed to visceral adipose tissue. Other measures of adiposity that indirectly assess visceral adipose tissue such as waist-to-hip ratio are more strongly associated with cardio-metabolic disease than BMI.[149–151,243] Total adiposity or body weight is still an important determinant of some other health outcomes, such as osteoarthritis, sleep apnoea.[219,256]

The Fenland Study estimated eleven measures of adiposity using: simple measurement techniques (BMI, waist-to-hip ratio); Dual-energy x-ray absorptiometry (DEXA) scanning (total fat mass, trunk fat

mass, android fat mass, gynoid fat mass, visceral adipose tissue mass, peripheral fat mass); and ultrasound scanning (medial thickness, subcutaneous adipose tissue, liver fat).

As my focus was on the public health implications of active travel, rather than understanding biological mechanisms, I chose two measures that reflected the way that adipose tissue may cause disease (i.e. one measure of visceral adipose tissue, which is important for cardio-metabolic diseases; and one measure of total body fat, which is important for some other health outcomes). These two measures were volume of visceral adipose tissue and percentage body fat.

Studies describing the association between active travel and adiposity were summarised in Chapter Three (Table 3.1). No study has reported the association between active travel and visceral adipose tissue, although some studies have reported associations for waist-to-hip ratio[232] or waist circumference.[230] Two studies have described the association between active commuting and percentage body fat.[130,235]

4.2 Methods

4.2.1 Study settings

I used data from the Fenland Study, an ongoing population-based cohort study of adults born between 1950 and 1975 in Cambridgeshire, UK. Volunteers (n=12,434) were recruited from general practice lists between 2005 and 2015. There were 19 participating practices; five in Wisbech (including the town of Whittlesey); seven in Ely (including the nearby settlements in Sutton, Chatteris, Haddenham and Burwell); and seven in Cambridge (including the villages of Comberton and Cottenham). Thus participants were recruited from Cambridgeshire, predominantly from Cambridge and the north to north-eastern parts of the county.

The socio-demographic characteristics of the populations of Cambridge and the (whole) county of Cambridgeshire were described in Chapter Two (section 2.2.1.1). The northern part of Cambridgeshire is relatively rural with a low population density. As this study included participants from both Cambridge and the north to north-eastern part of the county, the sample population from which the participants were recruited, was more socio-economically diverse than the sample population of the Commuting and Health in Cambridge study.

A description of travel connections in the Cambridge area was also given in Chapter Two. The northern part of the county, compared to Cambridge, has fewer transport links. Ely is served by a train line connected to Cambridge, although Wisbech is not on the rail network. With the exception of the A1(M), which skirts the western part of the recruitment area there are no motorways serving that part of the county. Other towns in Cambridgeshire do not have 'park and ride' facilities.

4.2.2 Data collection

On entry to the study all participants were invited to attend one of three clinical research facilities (Princess of Wales Hospital, Ely, UK; the North Cambridgeshire Hospital, Wisbech, UK; or the Institute of Metabolic Science, Cambridge, UK), where they completed a general questionnaire, a food frequency questionnaire (FFQ) and the Recent Physical Activity Questionnaire (RPAQ).[xviii,186] Recruitment started in Cambridge in December 2004 and the first volunteer was measured in January 2005. The second site was opened at the North Cambridgeshire Hospital in Wisbech in February 2006 and a third was opened at the Princess of wales Hospital in Ely in March 2006.

[xviii] Copies of the questionnaire are available to view at the following website: http://epi-meta.medschl.cam.ac.uk/includes/fenland/fenland.html

On visiting one of the clinical research facilities, body composition was assessed by dual-energy X-ray absorptiometry (DEXA; Lunar Prodigy Advanced fan beam scanner; GE Healthcare). After their visit each participant completed six days of objective physical activity monitoring, wearing an Actiheart® device (combined heart rate and accelerometer).[148]

Study exclusion criteria were pregnancy, diabetes, an inability to walk unaided, psychosis, or terminal illness. The study was approved by the Cambridge Local Research Ethics Committee (Ref 04/Q0108/19). All participants gave written informed consent.

4.2.3 Exposure measures: active commuting

Commuting mode was assessed in the RPAQ, with the question "how did you normally travel to work?" (see Appendix, Fenland Recent Physical Activity Questionnaire Part B, page 252). Participants could indicate both travel mode (car/motor vehicle, works or public transport, bicycle, and walking) and frequency (always, usually, occasionally or never). This in theory yields 256 unique combinations of mode and frequency.

4.2.3.1 Approach to categorisation

My aim was to categorise participants in order to enable comparisons between real-world choices that commuters face, reflecting the constraints on travel choice imposed by distance to work.[137,191,257]. My approach was partly driven by theory and partly driven by data. I hypothesised that those living close to work had the following choices for travelling to work:

- walking
- cycling
- car-use
- public transport (likely combined with walking or cycling at the ends of the journey),
- a combination of these options (most likely using different options on different days).

Conversely beyond a certain distance from home to work, travelling only by foot or bicycle to work becomes impractical, and thus I hypothesised the options would become:

- car-use,
- public transport (likely combined with some walking or cycling)
- car-use with active travel[xix]

[xix] Car-use with active travel may be an option principally for those working in Cambridge, as Cambridge is the only town in the region that is served by 'park and ride' facilities.

I decided an appropriate cut-point to segregate these two groups was five miles (from home to work). This cut-point was partly informed by the Commuting and Health in Cambridge study, which suggested that people who lived five miles or further from work were much less likely to only walk or cycle to work. It was also partly informed by a preliminary analysis of the data (40.9%, 1379/3368, of participants living within five miles of work reported regularly, i.e. usually or always, cycling or walking compared to 7.5%, 357/4726, of participants who lived five miles or further from work).

I was also conscious from previous analyses that home-work distance had been an effect moderator (associations between cycling to work and BMI were greater amongst those living further from work, see section 3.3.2). The appropriate way to handle effect moderation is to stratify and present estimates for appropriate strata (although the chosen strata may only partially address this issue).

4.2.3.2 Testing and modification of proposed categories

Participants living within five miles of work: Of those participants who lived within five miles of work, approximately two-thirds could be categorised as car-only, walking only or cycling. The remaining participants could be categorised either as walking or cycling regularly with occasional car-use or regularly using the car with occasional walking or cycling.

The prevalence of public transport use was low (1.9%, 65/3368 reported regularly using public transport). There was also limited evidence of 'multi-modal' commuting, i.e. commuters combining two or more modes of a travel to undertake a single journey to work (e.g. car journey to station; train to work; walk from train station to work) that involved active commuting.[xx]
Consequently, I retained the car only group. I assumed that participants who regularly cycled or walk with occasional car-use would be more similar to those who reported only walking or cycling to work than those who reported only using the car. Thus I created two groups, 'regular walking' and 'regular cycling', which included participants who made use of other modes.

Reflecting the different associations observed in the previous chapters for walking and cycling, I further divided those who reported regularly using the car with occasional walking or cycling, into those who reported occasional walking and those who reported occasional cycling. This yielded a total of five categories (Table 4.1).

[xx] In theory multi-modal commuting should be indicated by using two (or more) modes of travel at the same frequency (e.g. always using the car and always walking). Among those who lived within five miles of walk only a minority reported this pattern of commuting (5.1%; 172/3368 reported the same frequency of walking or cycling as public transport or car-use)

The 'public transport group' was dropped as a category and those participants reallocated to other groups. I assumed that public transport use involved some walking regardless of whether this was reported, and consequently users of public transport were assigned to the relevant walking group (either regular walking or regular car use with occasional walking). If participants reported cycling and walking they were assigned to the cycling group.

Participants living five miles or further from work: Amongst those living five miles or further from work, a small number of participants reported regularly cycling with either occasional or no use of car/public transport (n=86), or regularly walking with either occasional or no use of car/public transport use (n=8). As the number of these participants was low and these commuting patterns were unlikely to be achievable for most commuters who live more than five miles from work, I excluded these participants.

The remaining participants could be readily grouped into the three hypothesised categories (car only; 82.0%, 3875/4726; public transport, 9.2%, 435/4726; car with some active travel, 8.8%, 416/4726). Consequently, I used this categorisation system, which is summarised in Table 4.1.

4.2.3.3 Post-hoc classification of participants living five miles or further from work

I re-classified participants who combined car or public transport use with active travel, reflecting the positive findings for cycling and null findings for walking amongst the sample who lived within five miles of work (as well as the similar pattern of results observed in the Commuting and Health in Cambridge study). Participants were categorised based on their active mode of travel (i.e. walking or cycling) rather than their 'passive mode' of travel (i.e. car or public transport). A full description of the categories is given in Table 4.1.

4.2.4 Outcomes: body fat and visceral adipose tissue

Whole and regional body fat was estimated from the DEXA scan using Encore software (v14.10.022).[258] Percentage total body fat was estimated using a three-compartment model (fat mass, fat-free mass, and bone mineral mass). The software used an inbuilt algorithm to determine visceral adipose tissue (cm^3) within the android region (the region outlined by iliac crest and with a superior height equivalent to 20% of the distance from the top of the iliac crest to the base of the skull).

Estimates of visceral adipose tissue (VAT) derived from DEXA scans have been shown to have good agreement with gold-standard estimates from Computed Tomography (CT) scan.[259–261] The distribution of estimates of VAT was highly skewed and was transformed using a square root function.

Table 4.1 Commuting categories

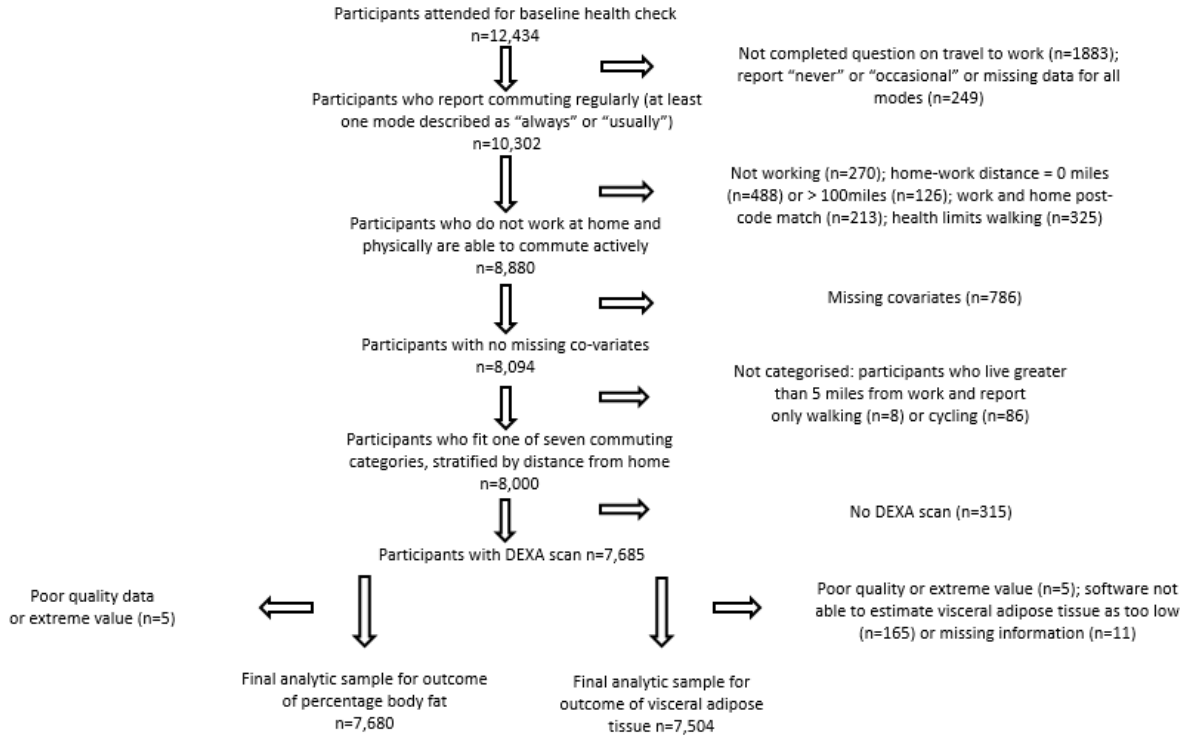
Category Name	Definition
Participants living within five miles of work	
Car only	Report regular (i.e. frequency is always or usual) car-use to travel to work. This group only includes those who use the car alone – there is no use of other modes.
Regular walking	Report walking to work regularly. Those who regularly used public transport in the absence of car-use were also assumed to walk regularly. This group includes those who use other modes, although those who report both regularly walking and regularly cycling were assigned to the 'regular cycling' group.
Regular cycling	Report cycling to work regularly. This group includes those who report both regularly walking and regularly cycling, as well as use of other modes.
Car with occasional walking	Report regular car-use to travel to work and additionally report either occasional walking or occasional public transport use. This group excludes those who regularly use active travel (walking, cycling or public transport) and who undertake any cycling to work.
Car with occasional cycling	Report regular car-use to travel to work and additionally report occasional cycling to work. This groups includes those who report both occasional cycling and occasional walking/public transport use. This group excludes those who regularly use active travel (walking, cycling or public transport).
Participants living five miles or further from work	
Car only	Report regular car-use to travel to work. This group only includes those who use the car alone – there is no use of other modes.
Public Transport	Report regular public transport use to travel to work. This group includes those who report other modes of travel.
Car with active travel	Report regular car-use to travel to work and additionally report some active travel (walking, cycling or public transport). Public transport use is occasional only, those using public transport regularly are assigned to the 'public transport' group.
Participants living five miles or further from work (alternative classification)	
Car only	Report regular car-use to travel to work. This group only includes those who use the car alone – there is no use of other modes.
Public Transport only	Report regular public transport use to travel to work. This group only includes those who report public transport and car-use. User who report walking or cycling in combination with public transport are assigned to one of the two groups below.
Car or public transport with walking	Report regular car-use or public transport to travel to work and additionally report some walking. Frequency of walking may be regular or occasional.
Car or public transport with cycling	Report regular car-use or public transport to travel to work and additionally report some cycling. Those who report some cycling and some walking are included in this group. Frequency of cycling may be regular or occasional.

Regular implies a frequency of use that is 'always or usually'

4.2.5 Inclusion and exclusion criteria

Only participants who were employed and reported regular travel to work (reported frequency either 'always' or 'usually') were included. Exclusion criteria were: any missing data, reported difficultly walking, not completing 48 hours of objective physical activity monitoring, living at work (home-work distance equals zero, or home postcode equals work post code), living more than 100 miles from work. These are summarised in Figure 4.1.

Figure 4.1 Flow chart illustrating inclusions and exclusions of study participants



4.2.6 Co-variates

Age, sex, education, difficultly walking, smoking status and alcohol consumption were assessed on the general questionnaire. Distance from home to work, home postcode, work postcode, occupational activity (sedentary, standing or manual occupation) and usual mode of travel (excluding travel to work) were assessed on the RPAQ.

Dietary consumption was assessed using a 130-item food frequency questionnaire.[262] I chose a measure of overall diet quality, the Mediterranean diet score, which has been associated with adiposity.[263,264] The relative Mediterranean diet score (rMED) (range 0-18) was estimated by assigning a score to each of nine dietary components based on sex specific tertiles. Estimates of rMED and alcohol consumption (g per week) and were made using the FETA software program.[265]

Leisure-time physical activity was estimated by multiplying the energy expenditure (measure in metabolic equivalent of task)[266] for each activity[213] by the weekly duration of activity, reported in the RPAQ. Values for each reported activity were summed to give a total estimate.

Estimates of objective physical activity energy expenditure (PAEE) were made using the branched equation framework.[148,267] Estimates of PAEE were individually calibrated, based on a partial (n=475) or complete treadmill test (n=6942). If no adequate treadmill test was available estimates were calibrated based on age and sex averages (n=199). For participants with a poor heart rate trace, estimates were derived using accelerometer data only (n=64).

4.2.7 Analysis

I used linear regression to test the association of active commuting with body fat and VAT, stratified by home-work distance and by sex.

4.2.7.1 Stratification by sex

I stratified by sex, as others have done,[130,235] because of the different absolute levels and distribution of fat, differences in commuting patterns,[136] and possible differences in activity intensity between the sexes.

4.2.7.2 Adjustment of co-variates

I adjusted for three sets of co-variates. Model A was adjusted for socio-demographic characteristics (age, education level), non-physical activity health behaviours (alcohol consumption, Mediterranean diet score and smoking status), test site and difficulty walking.

I then adjusted for physical activity, using two complementary approaches (Model B and C). Model B was adjusted for Model A co-variates and other self-reported physical activity (leisure-time physical activity, usual method for getting about and occupational activity). Model C was adjusted for Model A co-variates and objectively measured PAEE. The former approach might be considered as treating physical activity as a confounder and the latter approach as a variable on the causal pathway. Consequently, Model B might provide the best estimate of the association between active commuting and adiposity after adjustment for confounders.

4.2.7.3 Dose-response relationship

Finally, I tested for a dose-response relationship between distance from home to work and measures of adiposity, for a) those who only cycle to work; and b) those who only walk to work, adjusting for

model B co-variates and sex. Demonstration of a dose-response relationship would strengthen causal inference.[35]

4.2.7.4 Software

Analyses were undertaken using Stata Statistical Software: Release 13 (College Station, TX: StataCorp LP) using the “regress” command for linear regression.

4.3 Results

4.3.1 Descriptive characteristics

Descriptive characteristics of the sample are shown in Table 4.2. Compared to the national average the sample was relatively educated (in the UK 36.9% of adults aged 16-64 years have a degree)[182], healthy (in Great Britain 19% of adults smoked in 2014[268]; in England 23% of men and 16% of women exceed recommended intake of alcohol in 2012)[269] and had a high prevalence of cycling to work (in the UK 3% of adults report cycling as their 'usual' means of travel to work in 2011).[208] Compared to women, men had a lower percentage body fat and greater volume of VAT. Men were more likely to travel further to work, to have a manual job and to consume excess alcohol. Participants who lived further from work were more likely to be male, have a degree, and more likely to use the car rather than other modes of travel for non-commuting travel. Men who lived five mile or further from work tended to have higher body fat and more VAT, compared to men who lived within five miles of work.

Frequency of travel mode by the different patterns of active commuting is shown in Table 4.3 and Table 4.4. People who lived within five miles of work and reported regularly walking or cycling also reported limited car and public transport use. People who used the car in combination with occasional walking or cycling used the car less frequently than those who only reported using the car.

Amongst those who lived far from work and who undertook active travel, walking tended to be undertaken regularly and was combined with either public transport or car-use. In contrast cycling was undertaken occasionally and predominantly combined with car-use.

Interaction terms for sex and adiposity were only significant for VAT amongst those living near to work (p=0.04, n=3171), but not for those living far from work or for percentage body fat among those living near to work.

4.3.2 Body fat

Associations between active commuting and body fat are shown in Table 4.5. Among those living within five miles of work, people who reported regularly cycling had a lower body fat, compared to those who only used the car (Model B: women, 1.74%, 95% CI: 0.76% to 2.27%; men, 1.30%, 95% CI: 0.33% to 2.26%). People who reported regularly walking did not have reduced body fat. Women who reported regular car-use combined with occasional walking reported higher body fat compared to women who only used the car (Model B; 1.34%, 95% CI: 0.22% to 2.47%).

Table 4.2 Descriptive characteristics of sample (n=7,680)

	People living within 5 miles of work		People living 5 miles or further from work		Total
	Women (n=1,999)	**Men (n=1,268)**	**Women (n=1,950)**	**Men (n=2,463)**	
Car only	845 (42.3)	489 (38.6)	1639 (84.1)	1958 (79.5)	4931 (64.2)
Regular walking	339 (17.0)	122 (9.6)	n/a	n/a	461 (6.0)
Regular cycling	480 (24.0)	460 (36.3)	n/a	n/a	940 (12.2)
Car with occasional walking	141 (7.1)	48 (3.8)	n/a	n/a	189 (2.5)
Car with occasional cycling	194 (9.7)	149 (11.8)	n/a	n/a	343 (4.5)
Public Transport	n/a	n/a	154 (7.9)	265 (10.8)	419 (5.5)
Car with active travel	n/a	n/a	157 (8.1)	240 (9.7)	397 (5.2)
Age (years)	48.8 (43.4-54.1)	48.2 (42.2-54.5)	48.2 (42.5-53.8)	47.9 (42.2-53.8)	48.3 (42.6 to 54.0)
Education					
Degree or equivalent	624 (31.2)	556 (43.9)	790 (40.5)	1052 (42.7)	3022 (39.4)
A-Level or equivalent	910 (45.5)	463 (36.5)	858 (44.0)	1067 (43.3)	3298 (42.9)
GCSE or equivalent	465 (23.3)	249 (19.6)	302 (15.5)	344 (14.0)	1360 (17.7)
Smoking status					
Never	1116 (55.8)	671 (52.9)	1106(56.7)	1323 (53.7)	4293 (55.0)
Ex-smoker	654 (32.7)	437 (34.5)	653 (33.5)	836 (33.9)	2616 (33.5)
Current smoker	229 (11.5)	160 (12.6)	191 (9.8)	304 (12.3)	897 (11.5)
Alcohol consumption					
None	422 (21.1)	141 (11.1)	339 (17.4)	221 (9.0)	1123 (14.6)
Within guidelines (<16g per day)	1420 (71.0)	840 (66.2)	1459 (74.8)	1711 (69.5)	5430 (70.7)
Moderate (16-34.99g per day)	132 (6.6)	182 (14.4)	129 (6.6)	346 (14.1)	789 (10.3)
Heavy (>35g per day)	25 (1.3)	105 (8.2)	23 (1.2)	185 (7.5)	338 (4.4)
Mediterranean Diet Score	9 (7-11)	9 (7-11)	9 (7-11)	9 (7-11)	9 (7-11)
Usual method of getting about					
Motor vehicle/car	1194 (59.7)	723 (57.0)	1497 (76.8)	1890 (76.7)	5304 (69.1)
Public Transport	475 (23.8)	237 (18.7)	356 (18.3)	411 (16.7)	97 (1.2)
Walking	21 (1.1)	10 (0.8)	33 (1.7)	33 (1.3)	1479 (19.3)
Cycling	309 (15.5)	298 (23.5)	64 (3.3)	129 (5.2)	800 (10.4)
Occupation					
Sedentary	986 (49.3)	629 (49.6)	1206 (61.9)	1391 (56.5)	4212 (54.8)
Standing	832 (41.6)	219 (17.3)	616 (31.6)	337 (13.7)	2004 (26.1)
Manual	181 (9.1)	420 (33.1)	128 (6.5)	735 (29.8)	1464 (19.1)
Leisure time physical activity (MET-hours)	2.63 (1.25-4.78)	3.99 (2.02-6.90)	2.75 (1.32-4.95)	4.11 (2.28-7.27)	3.3 (1.7-6.0)
Physical Activity Energy Expenditure (kJ/day/kg)	48.1 (36.1-61.8)	58.9 (44.0-75.7)	45.6 (35.1-58.4)	56.4 (42.1-73.2)	51.4 (38.5-66.9)
Difficultly walking					
None	1385 (69.3)	933 (73.6)	1334 (68.4)	1757 (71.3)	5409 (70.4)
Very Little	395 (19.8)	214 (16.9)	389 (20.0)	451 (18.3)	1449 (18.9)
Somewhat	147 (7.4)	89 (7.0)	147 (7.1)	134 (5.4)	508 (6.6)
Question not asked	72 (3.6)	32 (2.5)	72 (4.6)	121 (4.9)	314 (4.1)
Home to work distance (miles)	2.0 (1.0-3.0)	2.0 (2.0-3.0)	14.0 (9.0-20.0)	17.0 (11.0-30.0)	8.0 (3.0-17.0)
Test Site					
Cambridge	818 (40.9)	660 (52.1)	591 (30.3)	735 (29.8)	2804 (36.5)
Ely	613 (30.7)	246 (19.4)	976 (50.1)	1182(48.0)	3017 (39.3)
Wisbech	568 (28.4)	362 (28.6)	383 (19.6)	546 (22.2)	1859 (24.2)
Percentage Body Fat (%)	37.5 (32.4-42.3)	28.8 (24.8-32.6)	37.4 (32.5-42.2)	29.3 (25.6-32.7)	32.7 (28.1-38.5)
Visceral Adipose Tissue (cm^3)	514 (226-948)	1229 (700-1880)	492 (220-949)	1348 (798-1985)	848 (376-1520)
BMI (kg/m^2)	25.2 (22.7-29.1)	26.4 (24.1-28.9)	25.3 (22.8-28.9)	26.9 (24.7-29.6)	26.1 (23.6-29.2)

Median and inter-quartile range shown for continuous variables; counts (n) and frequency (%) for categorical variables; ‡for visceral adipose tissue, n=7,504; n/a = not applicable; BMI = body mass index and was measured objectively at one of three assessment centres.

Table 4.3 Description of the frequency of modes of travel undertaken by participants categorised by commuting patterns (n=7,680)

	Reported frequency of mode use			
	Always	**Usually**	**Occasional**	**Never**
Near (n=3267)				
Car only (n=1334)				
Car	1296 (97.2)	38 (2.9)	0 (0)	0 (0)
Public Transport	0 (0.0)	0 (0.0)	0 (0.0)	1334 (100.0)
Walking	0 (0.0)	0 (0.0)	0 (0.0)	1334 (100.0)
Cycling	0 (0.0)	0 (0.0)	0 (0.0)	1334 (100.0)
Regular walking (n=461)				
Car-use	17 (3.7)	13 (2.8)	119 (25.8)	312 (67.8)
Public Transport	30 (6.5)	22 (4.8)	15 (3.3)	394 (85.5)
Walking	263 (57.1)	156 (33.8)	11 (2.4)	31 (6.7)
Cycling	0 (0.0)	0 (0.0)	51 (11.1)	410 (88.9)
Regular cycling (n=940)				
Car	3 (0.3)	21 (2.3)	215 (22.9)	701 (74.6)
Public Transport	6 (0.6)	3 (0.3)	31 (3.3)	900 (95.7)
Walking	7 (0.7)	24 (2.6)	166 (17.7)	743 (79.0)
Cycling	594 (63.2)	346 (36.8)	0 (0.0)	0 (0.0)
Car with occasional walking (n=189)				
Car	42 (22.2)	147 (77.8)	0 (0)	0 (0)
Public Transport	0 (0.0)	0 (0.0)	31 (16.4)	158 (83.6)
Walking	0 (0.0)	0 (0.0)	166 (87.8)	23 (12.2)
Cycling	0 (0.0)	0 (0.0)	0 (0.0)	189 (100.0)
Car with occasional cycling (n=343)				
Car	51 (14.9)	292 (85.1)	0 (0)	0 (0)
Public Transport	0 (0.0)	0 (0.0)	17 (5.0)	326 (95.0)
Walking	0 (0.0)	0 (0.0)	108 (31.5)	235 (68.5)
Cycling	0 (0.0)	0 (0.0)	343 (100.0)	0 (0.0)
Far (n=4413)				
Car only (n=3597)				
Car	3574 (99.4)	23 (0.6)	0 (0)	0 (0)
Public Transport	0 (0.0)	0 (0.0)	0 (0.0)	3597 (100.0)
Walking	0 (0.0)	0 (0.0)	0 (0.0)	3597 (100.0)
Cycling	0 (0.0)	0 (0.0)	0 (0.0)	3597 (100.0)
Public Transport (n=419)				
Car	82 (19.6)	23 (5.5)	79 (18.9)	235 (56.1)
Public Transport	314 (74.9)	105 (25.1)	0 (0.0)	0 (0.0)
Walking	114 (27.2)	33 (7.9)	23 (5.5)	249 (59.4)
Cycling	60 (14.3)	33 (7.9)	18 (4.3)	308 (73.5)
Car with active travel (n=397)				
Car	139 (35.0)	258 (65.0)	0 (0.0)	0 (0.0)
Public Transport	0 (0.0)	0 (0.0)	173 (43.6)	224 (56.4)
Walking	14 (3.5)	8 (2.0)	50 (12.6)	325 (81.9)
Cycling	16 (4.0)	21 (5.3)	179 (45.1)	181 (45.6)

Near = live within five miles of work; Far = live five miles or further from work; numbers and percentage shown in brackets.

Table 4.4 Description of the frequency of modes of travel undertaken by participants who live five or miles from home, using the four category classification of commuting behaviour (n=4,413)

	Reported frequency of mode use			
	Always	**Usually**	**Occasional**	**Never**
Car only (n=3597)				
Car	3574 (99.4)	23 (0.6)	0 (0)	0 (0)
Public Transport	0 (0.0)	0 (0.0)	0 (0.0)	3597 (100.0)
Walking	0 (0.0)	0 (0.0)	0 (0.0)	3597 (100.0)
Cycling	0 (0.0)	0 (0.0)	0 (0.0)	3597 (100.0)
Public Transport (n=322)				
Car-use	76 (23.6)	89 (27.6)	40 (12.4)	117 (36.3)
Public Transport	146 (45.3)	47 (14.6)	129 (40.1)	0 (0.0)
Walking	0 (0.0)	0 (0.0)	0 (0.0)	322 (100.0)
Cycling	0 (0.0)	0 (0.0)	0 (0.0)	322 (100.0)
Walking (n=167)				
Car	80 (47.9)	27 (16.2)	17 (10.2)	43 (25.8)
Public Transport	93 (55.7)	22 (13.2)	16 (9.6)	36 (21.6)
Walking	99 (59.3)	25 (15.0)	43 (25.8)	0 (0.0)
Cycling	0 (0.0)	0 (0.0)	0 (0.0)	167 (0.0)
Cycling (n=327)				
Car	65 (19.8)	165 (50.5)	22 (6.7)	75 (22.9)
Public Transport	75 (22.9)	36 (11.1)	28 (8.6)	188 (57.5)
Walking	29 (8.9)	16 (4.9)	30 (9.2)	252 (77.1)
Cycling	76 (23.2)	54 (16.5)	197 (60.2)	0 (0.0)

Numbers and percentage shown in brackets.

Table 4.5 Associations between active commuting and percentage body fat stratified by distance from home to work and by sex (n=7,680)

	Unadjusted	Model A	Model B	Model C
Participants living within five miles of work (n=3267)				
Women (n=1999)				
Car only (reference)				
Regular walking	-0.59 (-1.44, 0.25)	-0.14 (-0.95, 0.66)	-0.05 (-0.94, 0.85)	-0.21 (-0.96, 0.54)
Regular cycling	-3.01*** (-3.76, -2.26)	-2.08*** (-2.85, -1.30)	-1.74*** (-2.72, -0.76)	-1.37*** (-2.10, -0.64)
Car with occasional walking	1.73** (0.53, 2.93)	1.37* (0.24, 2.50)	1.34* (0.22,2.47)	0.93 (-0.12, 1.99)
Car with occasional cycling	-0.89 (-1.94, 0.16)	-0.20 (-1.20, 0.80)	-0.15 (-1.15,0.84)	0.26 (-0.67, 1.19)
Men (n=1268)				
Car only (reference)				
Regular walking	0.37 (-0.77, 1.51)	0.82 (-0.34, 1.97)	0.91 (-0.32, 2.15)	0.26 (-0.85, 1.37)
Regular cycling	-2.31*** (-3.05, -1.58)	-1.59*** (-2.42, -0.77)	-1.30** (-2.26, -0.33)	-1.42*** (-2.20, -0.63)
Car with occasional walking	-0.26 (-1.96, 1.45)	-0.09 (-1.75, 1.57)	-0.35 (-2.01, 1.31)	-0.31 (-1.90, 1.27)
Car with occasional cycling	-1.39* (-2.44, -0.33)	0.99 (-2.04, 0.05)	-0.88 (-1.92, 0.16)	-0.81 (-1.81, 0.19)
Participants living five miles or further from work (n=4413)				
Women (n=1950)				
Car only (reference)				
Public Transport	-1.32* (-2.45, -0.19)	-0.59 (-1.66, 0.49)	-0.38 (-1.52, 0.76)	-0.47 (-1.47, 0.54)
Car with active travel	-2.11*** (-3.23, -0.98)	-1.55** (-2.62, -0.49)	-1.18* (-2.23, -0.13)	-1.30* (-2.30, -0.31)
Men (n=2463)				
Car only (reference)				
Public Transport	-0.64 (-1.37, 0.10)	-0.13 (-0.86, 0.61)	-0.17 (-0.95, 0.60)	-0.02 (-0.72, 0.68)
Car with active travel	-1.63*** (-2.40, -0.87)	-1.38*** (-2.13, -0.62)	-1.19** (-1.93, -0.44)	-1.20** (-1.92, -0.48)

Model A adjusted for age, education, difficulty walking, alcohol consumption, Mediterranean diet score, smoking status and site; Model B adjusted for all co-variates in Model A and leisure time physical activity, usual method for getting about and work type; Model C adjusted for all co-variates in Model A and physical activity energy expenditure. Significance level: * p<0.05; ** p<0.01; *** p<0.001; adjusted co-efficient shown that represent difference in percentage body fat (%) for given commuting pattern relative to reference.

Among those who lived five miles or further from work, people who reported regular car-use with active travel had lower body fat relative compared to those who only used the car (Model B: women; 1.18%, 95% CI: 0.13% to 2.23%; men, 1.19%, 95% CI: 0.44% to 1.93%). Using the alternative four-category classification (Table 4.6), only those who reported combining cycling with either regular car-use or public transport had lower body fat relative to those only using the car (Model B: women, 2.58%, 95% CI: 1.20 to 3.92%; men, 1.71%, 95% CI: 0.92% to 2.50%).

Adjustment for objective PAEE (Model C vs Model A) and self-reported physical activity (Model C vs Model A) tended to attenuate the reported associations but did not alter the statistical significance.

Table 4.6 Associations of commuting pattern with body fat and visceral adipose tissue for participants who live five miles or further from work (using the alternative categorisation of commuting behaviour)

	Unadjusted	Model A	Model B	Model C
Percentage body fat (%) (n=4,413)				
Women (n=1,950)				
Car only (reference)				
Public transport	0.09 (-1.16,1.34)	0.57 (-0.61,1.75)	0.61 (-0.58,1.81)	0.43 (-0.68,1.54)
Some walking	-1.26 (-2.74,0.22)	-0.71 (-2.10,0.68)	-0.88 (-2.28,0.51)	-0.85 (-2.15,0.45)
Some cycling	-4.29*** (-5.65,-2.92)	-3.48*** (-4.79,-2.17)	-2.58*** (-3.92,-1.24)	-2.60*** (-3.83,-1.37)
Men (n=2,463)				
Car only (reference)				
Public transport	0 (-0.83,0.83)	0.19 (-0.63,1.00)	0.01 (-0.82,0.83)	0.1 (-0.68,0.88)
Some walking	0.21 (-1.05,1.47)	0.58 (-0.66,1.83)	0.37 (-0.88,1.61)	0.42 (-0.77,1.60)
Some cycling	-2.56*** (-3.35,-1.78)	-2.06*** (-2.85,-1.27)	-1.71*** (-2.50,-0.92)	-1.60*** (-2.36,-0.85)
Square root of visceral adipose tissue ($cm^{3/2}$) (n=4,333)				
Women (n=1,875)				
Car only (reference)				
Public transport	-0.53 (-2.60,1.53)	0.07 (-1.89,2.02)	0.28 (-1.72,2.28)	-0.17 (-2.04,1.70)
Some walking	-2.92* (-5.30,-0.54)	-1.87 (-4.12,0.37)	-1.84 (-4.13,0.44)	-2.04 (-4.20,0.11)
Some cycling	-5.89*** (-8.11,-3.66)	-4.56*** (-6.70,-2.42)	-3.82*** (-6.03,-1.62)	-3.33** (-5.38,-1.27)
Men (n=2,458)				
Car only (reference)				
Public transport	-0.09 (-1.80,1.62)	0.90 (-0.73,2.52)	0.68 (-0.96,2.33)	0.79 (-0.79,2.36)
Some walking	-0.59 (-3.18,2.00)	0.83 (-1.64,3.30)	0.51 (-1.97,2.99)	0.56 (-1.84,2.96)
Some cycling	-5.00*** (-6.60,-3.39)	-3.01*** (-4.57,-1.45)	-2.25** (-3.83,-0.67)	-2.29** (-3.81,-0.77)

Model A adjusted for age, education, difficulty walking, alcohol consumption, Mediterranean diet score and smoking status; Model B additionally adjusted for leisure time physical activity, usual method for getting about and work type. Significance level: * p<0.05; ** p<0.01; *** p<0.001; adjusted co-efficient shown that represent difference in percentage body fat (%) or difference in square root of visceral adipose tissue ($cm^{3/2}$) for given commuting pattern relative to reference.

4.3.3 Visceral adipose tissue

The pattern of associations for VAT (Table 4.6 and Table 4.7) was very similar to those observed for body fat, although the association for women living far from work who reported regular car-use was (marginally) not significant when adjusting for other self-reported physical activity (Model B: 1.70$cm^{3/2}$, 95% CI: -0.05 $cm^{3/2}$ to 3.44$cm^{3/2}$). It was significant when adjusted for objective physical activity (Model C: 1.73$cm^{3/2}$, 95% CI: 0.06$cm^{3/2}$ to 3.40$cm^{3/2}$).

4.3.4 Usual mode of travel

The full regression model (i.e. showing the coefficients for all variables included in Model B, including usual mode of travel) are shown in the Tables 4.8-4.11. Usual mode of travel was associated with adiposity, particularly for those living far from work (e.g. walking, for women, and cycling were associated with reduced body fat relative to car as the usual mode of travel, Table 4.9).

Table 4.7 Associations between active commuting and visceral adipose tissue stratified by distance from home to work and by sex (n=7,504)

	Unadjusted	Model A	Model B	Model C
Participants living within five miles of work (n=3171)				
Women (n=1904)				
Car only (reference)				
Regular walking	-0.79 (-2.14, 0.57)	-0.08 (-1.38, 1.21)	0.30 (-1.17, 1.76)	-0.21 (-1.45, 1.03)
Regular cycling	-3.44*** (-4.66, -2.23)	-1.81** (-3.08, -0.55)	-1.92* (-3.51, -0.33)	-0.93 (-2.14, 0.29)
Car with occasional walking	3.19** (1.28, 5.10)	2.85** (1.04, 4.67)	2.89** (1.07, 4.71)	2.28* (0.54, 4.02)
Car with occasional cycling	-1.11 (-2.78, 0.56)	-0.13 (-1.73, 1.47)	-0.07 (-1.67, 1.53)	0.50 (-1.04, 2.04)
Men (n=1267)				
Car only (reference)				
Regular walking	-2.03 (-4.40, 0.35)	-0.16 (-2.48, 2.15)	-0.63 (-1.85, 3.11)	-1.10 (-3.36, 1.15)
Regular cycling	-5.69*** (-7.21, -4.17)	-2.79*** (-4.44, -1.15)	-1.95* (-3.88, -0.02)	-2.49** (-4.09, -0.90)
Car with occasional walking	-2.54 (-6.08, 1.00)	-1.48 (-4.80, 1.84)	-1.82 (-5.14, 1.49)	-1.85 (-5.07, 1.37)
Car with occasional cycling	-2.95** (-5.14, -0.77)	-1.19 (-3.28, 0.90)	-1.04 (-3.12, 1.04)	-0.88 (-2.91, 1.14)
Participants living five miles or further from work (n=4333)				
Women (n=1875)				
Car only (reference)				
Public Transport	-2.90** (-4.74, -1.06)	-1.91* (-3.66, -0.16)	-1.60 (-3.48, 0.27)	-1.71* (-3.39, -0.03)
Car with active travel	-3.04** (-4.88, -1.21)	-2.04* (-3.78, -0.29)	-1.70 (-3.44, 0.05)	-1.73* (-3.40, -0.06)
Men (n=2458)				
Car only (reference)				
Public Transport	-1.65* (-3.16, -0.15)	0.42 (-1.04, 1.88)	0.61 (-0.93, 2.16)	0.61 (-0.80, 2.03)
Car with active travel	-3.15*** (-4.71, -1.58)	-2.14** (-3.63, -0.64)	-1.79* (-3.27, -0.32)	-1.86* (-3.31, -0.41)

Model A adjusted for age, education, difficulty walking, alcohol consumption, Mediterranean diet score, smoking status and site; Model B adjusted for all co-variates in Model A and leisure time physical activity, usual method for getting about and work type; Model C adjusted for all co-variates in Model A and physical activity energy expenditure. Significance level: * p<0.05; ** p<0.01; *** p<0.001; adjusted co-efficient shown that represent difference in visceral adipose tissue ($cm^{3/2}$) for given commuting pattern relative to reference.

4.3.5 Dose-response analysis

There was an association between distance to work and body fat amongst those who reported only cycling to work and lived within five miles of work (-0.54 % per mile, 95% CI: -1.01 to -0.08, n=554), but the equivalent associations for VAT and for walking were not significant (cycling and VAT: -0.64 $cm^{3/2}$ per mile, 95% CI: -1.53 to 0.25, n=530; walking and body fat: -0.32 % per mile, 95% CI: -1.51 to 0.88, n=243; walking and VAT: -1.24 $cm^{3/2}$ per mile, 95% CI: -3.40 to 0.59, n=242).

Table 4.8 Linear regression (Model B) showing the correlates of body fat for men and women who live within five miles of work (n=3,267)

	Women (n=1999)	**Men (n=1268)**
Commuting (reference = car only)		
Regular walking	-0.05 (-0.94,0.85)	0.91 (-0.32,2.15)
Regular cycling	-1.74*** (-2.72,-0.76)	-1.30** (-2.26,-0.33)
Car with occasional walking	1.34* (0.22,2.47)	-0.35 (-2.01,1.31)
Car with occasional cycling	-0.15 (-1.15,0.84)	-0.88 (-1.92,0.16)
Age	0.16*** (0.12,0.20)	0.12*** (0.08,0.17)
Education (reference = degree)		
A-level	1.80*** (1.08,2.51)	1.02* (0.17,1.86)
GSCE	2.15*** (1.29,3.01)	0.93 (-0.07,1.93)
Difficulty walking (reference = "not at all")		
Very little	2.80*** (2.09,3.51)	0.56 (-0.27,1.39)
Somewhat	3.31*** (2.23,4.39)	1.83** (0.61,3.04)
Not asked	1.95* (0.38,3.51)	1.95 (-0.14,4.05)
Smoking status (reference = never)		
Ex-smoker	0.29 (-0.32,0.91)	0.54 (-0.15,1.22)
Current smoker	-1.42** (-2.34,-0.50)	-1.15* (-2.15,-0.15)
Alcohol consumption (reference = none)		
Within guidelines	-1.08** (-1.78,-0.38)	-0.01 (-1.01,0.99)
Moderate (16-35 g/~)	-1.29* (-2.55,-0.03)	0.35 (-0.92,1.61)
Heavy (>35g/day)	-1.07 (-3.62,1.48)	0.9 (-0.54,2.34)
Mediterranean Diet Score	-0.15** (-0.25,-0.05)	-0.17** (-0.28,-0.05)
Study site (reference=Cambridge)		
Ely	-0.52 (-1.30,0.25)	-0.68 (-1.64,0.28)
Wisbech	0.82* (0.02,1.62)	1.12* (0.24,1.99)
Usual method of travel (reference = car)		
Walking	-0.23 (-0.99,0.53)	-0.53 (-1.41,0.36)
Public transport	0.11 (-2.67,2.89)	-3.13 (-6.69,0.42)
Cycling	-0.51 (-1.61,0.60)	-0.77 (-1.76,0.22)
Occupation type (reference = sedentary)		
Standing	-0.26 (-0.86,0.34)	-0.46 (-1.38,0.45)
Manual	-0.84 (-1.88,0.19)	-1.32** (-2.15,-0.49)
Leisure physical activity	-0.13*** (-0.19,-0.07)	-0.05 (-0.10,0.00)

Significance level: * p<0.05; ** p<0.01; *** p<0.001; co-efficient shown that represent difference in percentage body fat (%); all co-variates included in linear regression model are shown

Table 4.9 Linear regression (Model B) showing the correlates of percentage body fat for men and women who live five miles or further from work (n=4,413)

	Women (n=1950)	Men (n=2463)
Commuting (reference = car only)		
Public Transport	-0.38 (-1.52,0.76)	-0.17 (-0.95,0.60)
Car with active travel	-1.18* (-2.23,-0.13)	-1.19** (-1.93,-0.44)
Age	0.18*** (0.14,0.22)	0.09*** (0.06,0.12)
Education (reference = degree)		
A-level	1.51*** (0.87,2.15)	0.97*** (0.45,1.50)
GSCE	1.86*** (0.96,2.75)	1.11** (0.37,1.85)
Difficulty walking (reference = "not at all")		
Very little	2.94*** (2.22,3.65)	1.58*** (1.01,2.15)
Somewhat	3.02*** (1.91,4.14)	3.09*** (2.13,4.05)
Not asked	1.74* (0.33,3.15)	1.40** (0.34,2.45)
Smoking status (reference = never)		
Ex-smoker	0.28 (-0.34,0.89)	1.00*** (0.52,1.48)
Current smoker	-1.74*** (-2.73,-0.75)	-0.86* (-1.56,-0.16)
Alcohol consumption (reference = none)		
Within guidelines	-0.66 (-1.42,0.11)	-0.4 (-1.18,0.37)
Moderate (16-35 g/~)	-0.77 (-2.07,0.53)	-0.16 (-1.11,0.79)
Heavy (>35g/day)	2.84* (0.17,5.50)	0.8 (-0.29,1.88)
Mediterranean Diet Score	-0.18*** (-0.29,-0.08)	-0.05 (-0.13,0.03)
Study site (reference=Cambridge)		
Ely	-0.49 (-1.17,0.19)	0.12 (-0.42,0.66)
Wisbech	0.33 (-0.53,1.19)	0.51 (-0.15,1.16)
Usual method of travel (reference = car)		
Walking	-0.90* (-1.64,-0.16)	-0.52 (-1.11,0.07)
Public transport	-0.22 (-2.53,2.09)	0.44 (-1.54,2.43)
Cycling	-2.80*** (-4.43,-1.17)	-2.46*** (-3.48,-1.45)
Occupation type (reference = sedentary)		
Standing	-0.73* (-1.35,-0.11)	-0.17 (-0.83,0.49)
Manual	-0.45 (-1.61,0.71)	-1.36*** (-1.91,-0.81)
Leisure physical activity	-0.24*** (-0.30,-0.17)	-0.13*** (-0.17,-0.09)

Significance level: * p<0.05; ** p<0.01; *** p<0.001; co-efficient shown that represent difference in square root of visceral adipose tissue ($cm^{3/2}$); all co-variates included in linear regression model are shown.

Table 4.10 Linear regression (Model B) showing the correlates of visceral adipose tissue for men and women who live within five miles of work (n=3,171)

	Women (n=1904)	**Men (n=1267)**
Commuting (reference = car only)		
Regular walking	0.30 (-1.17,1.76)	0.63 (-1.85,3.11)
Regular cycling	-1.92* (-3.51,-0.33)	-1.95* (-3.88,-0.02)
Car with occasional walking	2.89** (1.07,4.71)	-1.82 (-5.14,1.49)
Car with occasional cycling	-0.07 (-1.67,1.53)	-1.04 (-3.12,1.04)
Age	0.31*** (0.24,0.38)	0.45*** (0.37,0.54)
Education (reference = degree)		
A-level	2.95*** (1.79,4.11)	2.03* (0.34,3.73)
GSCE	3.68*** (2.27,5.08)	1.70 (-0.30,3.71)
Difficulty walking (reference = "not at all")		
Very little	3.54*** (2.40,4.68)	1.12 (-0.55,2.79)
Somewhat	4.11*** (2.36,5.86)	2.73* (0.30,5.17)
Not asked	1.2 (-1.29,3.69)	2.61 (-1.59,6.80)
Smoking status (reference = never)		
Ex-smoker	0.81 (-0.19,1.80)	1.71* (0.34,3.09)
Current smoker	0.46 (-1.03,1.95)	-0.95 (-2.95,1.05)
Alcohol consumption (reference = none)		
Within guidelines	-0.91 (-2.04,0.22)	0.92 (-1.08,2.92)
Moderate (16-35 g/~)	-0.82 (-2.85,1.20)	1.94 (-0.59,4.47)
Heavy (>35g/day)	0.35 (-3.68,4.39)	4.49** (1.61,7.37)
Mediterranean Diet Score	-0.17* (-0.33,-0.00)	-0.27* (-0.50,-0.04)
Study site (reference=Cambridge)		
Ely	-0.04 (-1.29,1.22)	1.37 (-0.55,3.30)
Wisbech	0.98 (-0.31,2.28)	3.72*** (1.96,5.47)
Usual method of travel (reference = car)		
Walking	-0.72 (-1.96,0.51)	-1.78* (-3.55,-0.00)
Public transport	-1.05 (-5.56,3.46)	-8.46* (-15.57,-1.35)
Cycling	0.24 (-1.55,2.03)	-2.11* (-4.09,-0.12)
Occupation type (reference = sedentary)		
Standing	0.10 (-0.87,1.08)	-1.20 (-3.03,0.63)
Manual	-0.98 (-2.65,0.70)	-2.33** (-3.99,-0.66)
Leisure physical activity	-0.12* (-0.22,-0.02)	0.00 (-0.10,0.10)

Significance level: * p<0.05; ** p<0.01; *** p<0.001; co-efficient shown that represent difference in square root of visceral adipose tissue ($cm^{3/2}$); all co-variates included in linear regression model are shown.

Table 4.11 Linear regression (Model B) showing the correlates of visceral adipose tissue for men and women who live five miles or further from work (n=4,333)

	Women (n=1875)	Men (n=2458)
Commuting (reference = car only)		
Public Transport	-1.60 (-3.48,0.27)	0.61 (-0.93,2.16)
Car with active travel	-1.70 (-3.44,0.05)	-1.79* (-3.27,-0.32)
Age	0.33*** (0.26,0.40)	0.37*** (0.31,0.43)
Education (reference = degree)		
A-level	1.54** (0.48,2.59)	2.83*** (1.77,3.88)
GSCE	2.00** (0.54,3.46)	2.04** (0.57,3.52)
Difficulty walking (reference = "not at all")		
Very little	4.78*** (3.61,5.96)	3.05*** (1.91,4.18)
Somewhat	4.01*** (2.19,5.82)	5.75*** (3.83,7.67)
Not asked	0.09 (-2.23,2.41)	0.00 (-2.10,2.10)
Smoking status (reference = never)		
Ex-smoker	1.45** (0.44,2.46)	2.35*** (1.39,3.30)
Current smoker	-0.49 (-2.10,1.13)	-0.54 (-1.93,0.86)
Alcohol consumption (reference = none)		
Within guidelines	-1.04 (-2.29,0.21)	0.21 (-1.33,1.74)
Moderate (16-35 g/~)	-0.05 (-2.18,2.09)	1.84 (-0.05,3.74)
Heavy (>35g/day)	5.69* (1.21,10.18)	4.49*** (2.34,6.65)
Mediterranean Diet Score	-0.23** (-0.41,-0.06)	-0.17* (-0.33,-0.01)
Study site (reference=Cambridge)		
Ely	0.47 (-0.64,1.59)	2.36*** (1.29,3.44)
Wisbech	0.79 (-0.62,2.20)	2.99*** (1.68,4.30)
Usual method of travel (reference = car)		
Walking	-1.44* (-2.65,-0.22)	-0.92 (-2.10,0.25)
Public transport	-1.28 (-5.06,2.50)	-0.18 (-4.13,3.77)
Cycling	-1.81 (-4.50,0.87)	-5.45*** (-7.47,-3.43)
Occupation type (reference = sedentary)		
Standing	-1.04* (-2.05,-0.02)	-0.47 (-1.78,0.85)
Manual	-0.93 (-2.83,0.98)	-2.57*** (-3.66,-1.48)
Leisure physical activity	-0.24*** (-0.35,-0.13)	-0.15*** (-0.23,-0.07)

Significance level: * p<0.05; ** p<0.01; *** p<0.001; co-efficient shown that represent difference in square root of visceral adipose tissue ($cm^{3/2}$); all co-variates included in linear regression model are shown.

4.4 Discussion

4.4.1 Summary of findings

Among those living within five miles of work, people who reported regularly cycling to work had reduced body fat and VAT compared to those using the car. Among those living five miles or further from work, people who reported regular car-use combined with active travel had reduced body fat and VAT compared to those using the car. Using an alternative approach to classifying participants who lived five miles or further from work, only participants who reported combining car or public transport use with cycling (and not those who reported combining car or public transport use with walking) had significantly reduced adiposity.

People who reported walking or cycling as their usual mode of travel also had reduced adiposity compared to people who usually used the car. Amongst those who cycled to work, there was an inverse association between distance to work and percentage body fat.

4.4.2 Strengths and limitations

4.4.2.1 Cross-sectional

The study was cross-sectional so provides a very weak basis from which to draw causal inference. The observed associations might be attributable to reverse causation, i.e. that adiposity influences choice of commute mode. I note that most studies describing the associations between active travel and health are cross-sectional,[130,230–240] but because the study has several other unique factors it makes an important contribution.

4.4.2.2 Classification of active commuting

Stratifying the sample by distance to work and focusing on patterns of commuting may facilitate more meaningful comparisons. Nonetheless the choice of groups was partly limited by data. Public transport use was relatively low compared to some parts of the country, such as London. Moreover, public transport may be different in other places, in terms of the opportunity to sit (or stand) and the extent to which it is combined with car-use or active travel, so one should be cautious about generalising the findings to other settings.

Whilst associations for walking as part of commuting were not significant the number of participants categorised to one of the walking groups was relatively small, and consequently some of these analyses were under-powered. Participants who were categorised as walking also included public

transport users, who might undertake very little or no walking, which might have biased some of the estimates of walking to zero. I also note that unadjusted estimates of physical activity energy expenditure (data not shown) for those participants who reported regularly walking were relatively low, lower than those participants who reported only using the car, which might suggest that these participants were relatively inactive in other areas of their life as well undertaking a low amount of walking as part of travel to work.

With the exception of participants who reported only walking to work or only cycling to work, I do not have a good means of reporting the 'dose' of active commuting in terms of either distance or duration.

4.4.2.3 Detailed characterisation adiposity

An important strength of this study is the objective measurement of adiposity, including visceral adipose tissue. VAT is strongly associated with cardio-metabolic disease, and may be a better predictor of health outcomes than other measures of adiposity.[149–151] No other study has reported the associations between active travel and visceral adiposity, although two studies have reported the associations for waist-to-hip ratio which is an indicator of visceral adipose tissue.

Whilst DEXA measurement of visceral adipose tissue is not equivalent to the gold standard measure of CT measurement. CT scanning in large epidemiological study is unlikely to be feasible or ethical (due to radiation dose). DEXA measurement has been shown to be sufficiently accurate for population based studies.[259–261]

This study has also reported percentage body fat (again measured by DEXA). This is a better measure of total adiposity than the measure more usually used, BMI, as it is not affected by fat free mass, such as skeletal muscle. However, using body fat measured by DEXA and visceral adipose tissue means the findings from this study are not directly comparable with the findings from other studies.

4.4.2.4 Detailed characterisation of diet

In contrast to other studies,[130,232,234–236] this study has characterised diet in detail using a 130-item food frequency questionnaire and used a measure of dietary behaviour that reflects the overall pattern of dietary consumption, rather than focusing on single elements. This measure has been shown to be associated with obesity.[263,264] Nonetheless residual confounding by diet is still possible, and some potentially important components of dietary behaviour as they relate to active travel (e.g. snacking) have not been captured.

4.4.2.5 Measurement of physical activity

This study has made use of two measures of physical activity, first self-reported physical activity (assessed using the RPAQ) and secondly objective measurement of physical activity (measured by an Acitheart® device).

The former has enabled adjustment not only for active commuting but also usual mode of travel, so has effectively allowed consideration of two dimensions of active travel, as well as adjustment for other physical activity both at work and in leisure time. Both of these other types of physical activity were independently associated with adiposity.

The latter, objective physical activity, potentially offers a better means to capture all physical activity, including short bouts of activity (e.g. walking up a flight of stairs) that may not be well captured by a questionnaire. A particular strength of using Actiheart® (as opposed to other measures, e.g. accelerometer) is that by recording heart rate it can better detect and measure the energy expenditure associated with a wider range of activities (e.g. cycling, which is poorly recorded by a hip mounted accelerometer).[148]

Physical activity energy expenditure has to be estimated or inferred. It is not directly observed in the way that one may observe height. Estimates of physical activity energy expenditure are based in part on the association between heart rate and energy expenditure.[267,270] This depends on accurate individual-level calibration of the relationship between heart rate and energy expenditure. At lower heart rate levels estimates are made based on the accelerometer trace. A large number of inferences have to be made in order to estimate physical activity energy expenditure. Nonetheless physical activity energy expenditure has been shown to compare favourably to other estimates of physical activity energy, such as questionnaire or accelerometer, relative to gold-standard estimates of total energy expenditure made using double-labelled water or whole body calorimetry.[271,272]

The time period of observation of self-reported physical activity and objectively measured physical activity was different. The former was reported for the four weeks prior to visiting the clinical research facility and the latter was undertaken in the week after visiting the clinical research facility.

4.4.3 Comparison with other studies

My findings are consistent with other reports, including the analysis of the Commuting and Health in Cambridge dataset, that active travel is associated with reduced BMI relative to car-use.[130,131,155,230–240]

4.4.3.1 Walking

The findings of stronger associations for cycling than walking also mirror the findings reported in the previous chapter and much of the literature (see section 3.4.3). As before these differences may reflect some behaviour specific characteristics, i.e. lower intensity of walking relative to cycling or tendency for walking to be of shorter duration than cycling. They may also reflect other factors like the inclusion of public transport users in some walking groups, who may undertake relatively little walking (although the number of such participants was relatively low).

Whilst non-significant, I note a trend for women participants who lived within five miles of work and reported car use with occasional walking to have greater adiposity (relative to those only using the car). Reverse causation may also contribute, for example being overweight and choosing to walk to work in order to lose weight (which might account for the higher adiposity among women living near to work and who reported regular car-use with occasional walking). Sex specific associations were not explored in the previous chapter as the sample was too small. Nonetheless it remains possible that such behaviour could contribute to the observation of non-significant associations between walking to work and BMI reported in the previous chapter.

Nonetheless, the study, as with the analysis using Commuting and Health in Cambridge, does provide some evidence of the value of walking. Walking as a usual mode of travel was associated with reduced adiposity relative to car-use. The associations for walking for men or in combination with car-use (men living near to work, women living far from work) were in the expected direction and nearly reached the threshold for significance ($p<0.05$).

4.4.3.2 Public Transport

Some studies have demonstrated significant associations between public transport use and reduced adiposity, although some reported non-significant associations.[130,235,238,240] I did not observe any significant associations between commuting by public transport and adiposity, although the estimated effect sizes were in the expected direction (and the sample relatively small). Moreover only 40% of public transport users reported some walking and 27% some cycling. Estimates of effect size were close to zero when isolating individuals who did not report combining public transport with active travel. Differences in the categorisation of public transport and how much physical activity is associated with its use may account for these differences. Other differences in use of public transport (e.g. snacking, standing vs sitting) may also contribute.

4.4.3.3 Percentage body fat

Two previous studies have described associations between active commuting and body fat. Both studies reported a similar estimated effect size (1.5% reduction for cycling to work and 1.4% for active travel, relative to car-use) to those described here, although the categorisation of active commuting was different in these other studies.[130,235] I am not aware of any studies that have described the association between active commuting and VAT.

4.4.3.4 Dose-response

Previous work has demonstrated a dose-response association, between 'intensity' of active travel and BMI,[130] and duration of active travel and BMI[131]. My findings show a relationship between distance cycled to work and body fat.

4.4.4 Study interpretation

4.4.4.1 Adjustment of physical activity

Additional adjustment for both other self-reported and physical activity energy expenditure (PAEE) attenuated the observed relationship. These findings are consistent with other physical activity being a confounder and PAEE being a mediator of the relationship between active commuting and adiposity. Adjusting for objective PAEE I only observed partial attenuation, this may be because I had not accounted for past PAEE or because there may be other pathways between commuting and adiposity (e.g. snacking in cars).

4.4.4.2 Participants who live five miles or further from work

Participants who reported regular car-use combined with active travel had reduced adiposity. Whilst this group are likely to have done this in different ways, it seems likely that a minority of commuters were doing this by driving to 'park and ride' facilities as very few participants reported regularly (i.e. usually or always) walking or cycling. Moreover, in contrast to Commuting and Health in Cambridge, not everyone in the Fenland Study worked in Cambridge and whilst it may be possible to park on the edge of other cities and then cycle or walk into the centre, it is only Cambridge that has specific facilities ('park and ride' sites) to enable this.

An alternative means for participants to combine cycling and car-use and one that appears better supported by the data, is to cycle (the relatively long distance) from home to work occasionally and

to drive on other occasions. Walking more than five miles to work is possible[xxi], but seems less likely. Another approach is combining public transport with walking or cycling on non-driving days. These approaches seem more likely with over half the sample reporting cycling (most of which was occasional) and nearly half the sample reporting occasional public transport use.

It is also notable that active travel (either cycling or walking) as the usual mode of non-work travel was more commonly associated with reduced adiposity amongst those living five miles or further from work than amongst those living within five miles of work. This may be because those who live further from work are more predisposed to being obese (see section 3.4.4.3) and/or reflect the lower levels of active commuting relative to those living within five miles of work.

4.4.5 Overall interpretation of adiposity studies

Looking across the two studies (Fenland and Commuting and Health in Cambridge) a stronger case for a causal association between active travel and adiposity can be made, than looking at either study in isolation. Associations of both active commuting and non-commuting active travel with reduced adiposity have been observed. Longitudinal associations were reported in Commuting and Health in Cambridge, although these were not significant after conditioning on baseline BMI. Some of the deficiencies in that study (self-reported weight, no adjustment for diet, limited adjustment for other physical activity) were addressed by the Fenland Study. A dose-response relationship was also demonstrated in the Fenland Study, which is one 'test' of a causal association.[35]

A consistent theme across both studies was that stronger associations were observed for cycling, although taken together there is some evidence that walking is important (e.g. in Fenland walking as usual mode of travel was associated with adiposity and in Commuting and Health in Cambridge the pattern of findings for walking to work whilst not significant was suggestive of an association).

The findings across the two studies also underscore the potential for and benefits of incorporating active travel into commuting. The exposures across the two studies were different, but in each case I tried to identify commuters who were undertaking some active travel, either for whole or part of the journey to work, rather than only cycling or walking to work.

The effect size estimates may appear comparatively small from an individual perspective. Considering the first study (for which the measures are more readily understandable), a difference in

[xxi] It is conceivable that some participants might run these distances to work on an infrequent basis. Running was not included in the modes of travel in the RPAQ.

BMI of 1.2 kg/m^2 equates to a difference of 3kg for a person 1.6m or 5 feet 3 inches tall. At a population level such differences are important, given an average weight gain of 10kg in the US during the thirty years when obesity prevalence among adults has risen from around 10% to over 35%.[245,273] This suggests that increasing active commuting could be an important component of a strategy for reducing or preventing obesity.

4.4.6 Future Research

4.4.6.1 Active travel and adiposity

Uncertainty remains concerning the relationship between dose (duration, intensity and frequency) of active travel and adiposity. Addressing this is likely to require objective measurement of active travel. This will also be important for understanding the different associations observed for walking and cycling.

The commuting categories identified using the Fenland dataset have not been formally validated. They could be validated using the Commuting and Health in Cambridge dataset by comparing answers to the RPAQ with the seven-day retrospective travel record. The commuting question on the RPAQ has been used in other large studies, such as European Prospective Investigation into Cancer (EPIC) and UK Biobank. Validation may facilitate future work in such studies.

4.4.6.2 Active travel and health in the Fenland Study

The Fenland Study is longitudinal study (participants are currently being invited for follow-up assessment), in due course a longitudinal analysis will be possible. Before then, there are other ways that the Fenland analyses could be extending in the short term, notably describing the associations of active commuting with other risk factors for cardiovascular disease (e.g. blood pressure, serum cholesterol and glycosylated haemoglobin) and well-being (assessed using the Short Form 8 questionnaire)

Future work should also seek to develop methods to estimate physical activity energy attributable to commuting in the Fenland Study. It may be possible to develop existing methods that can estimate physical activity energy attributable to commuting using Actiheart®data,[212] although these methods presently rely on using a seven-day travel record (and this instrument was not used in the Fenland Study).

4.5 Chapter summary

This chapter has described the associations of active commuting with body fat and visceral adipose tissue in the Fenland dataset at baseline.

Participants who reported active commuting (principally cycling to work among participants living within five miles of work and car-use combined with active commuting amongst participants living five miles or further from work) had reduced adiposity after adjustment for diet, other physical activity and other co-variates. There was also some evidence that walking for travel (e.g. walking for non-commuting travel) was also associated with reduced adiposity.

Part II

Public health modelling: the estimated impact of increases in physical activity on need for healthcare

5 Modelling introduction and methods

"The sustainability of the NHS now depends on a radical upgrade in prevention and public health".

NHS Five Year Forward View

5.1 Introduction

The preceding chapters have described the associations between active commuting and different indices of health. Promoting active travel may be one approach to shift (increase) the distribution of physical activity. In this, the second, part of my thesis I consider the effect this might have on need for healthcare. Rather than consider indices of health and well-being, as I did in the first part, in this part of my thesis I focus on major non-communicable diseases.

It appears relatively common to assume that if physical activity levels increase (or if similar changes are made to the distribution of other risk factors for non-communicable disease) that need for and consequently demand on health services should fall. However, I am not sure these assumptions have properly accounted for increases in life expectancy that may occur, resulting in more time lived at older ages when disease incidence is higher. The aim of this second part of my thesis is to begin to understand whether increases in survival, due to increases in physical activity, will reduce demand for care, principally considering the diseases for which physical activity is protective.

5.1.1 Chapter overview

This chapter introduces the modelling work. It outlines why I undertook the work and outlines the different pathways through which physical activity influences the number of people living with disease (an important indicator of healthcare utilisation) (section 5.2.1.). It discusses ambiguity in the use of the phrase “burden of disease”, and introduces the concept of ‘need’, as used within the public health literature (section 5.2.2). I argue that need is a more appropriate term than “burden of disease” or “healthcare utilisation” to describe what I am interested in measuring and reflects what can be measured. Whilst no work has directly addressed the question I set out to answer, other work has addressed related questions which partially address my research questions. I discuss this literature and its relevance to study design (section 5.2.4). I also describe the study aims, including research questions, and study scope (section 5.2.5).

The chapter then sets out the modelling methods. It first describes the model structure before elaborating in detail about the different parts. It then describes the health outcomes studied (section 5.3.3), the scenarios modelled (section 5.3.4), sensitivity and uncertainty analyses undertaken (including justification) (section 5.3.5), and the sources of data (section 5.3.6).

5.2 Background

Investments in interventions to promote physical activity have to compete alongside other spending priorities. Practising as a public health physician I have noticed increasing pressure to "justify" investment in public health or preventive interventions on the grounds that they may reduce demand on the NHS and so reduce healthcare expenditure. This pressure was particularly noticeable when I worked in a Primary Care Trust (an organisation with responsibility both for delivering public health programmes and commissioning healthcare for its local community) from 2010 to 2012, at that time the NHS was seeking to make £20 billion of efficiency savings (16% of its budget) in a four year period.[274]

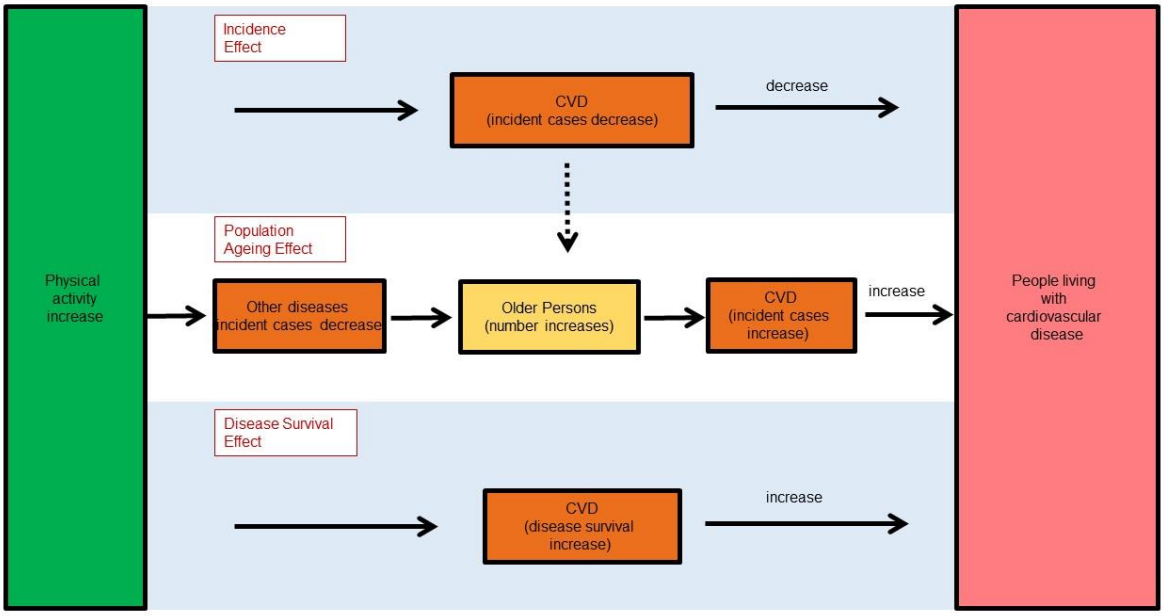
More recently the *Five Year Forward View* suggested that the "sustainability of the NHS…depends on a radical upgrade in prevention and public health".[275] The apparent implication being that more or better prevention initiatives would reduce the burden of disease, reduce need for healthcare and reduce demand on health and social care systems. This was a reassertion of a case made over ten years earlier in the Wanless report, which described options for ensuring the long-term viability of a state funded NHS.[276] Public Health England's recent report, *Everybody Active Every Day* emphasised the costs of physical inactivity to and potential cost saving for the NHS.[108]

The implicit logic in much of this thinking appears to be that improving the population distribution of a risk factor such as physical activity will reduce the incidence rate of disease, thereby resulting in fewer incident cases and fewer people living with disease who require care. However, this may overlook the importance of increased survival, more people living to an older age at which the incidence of many common chronic diseases is higher.

5.2.1 How physical activity affects the number of people living with disease

Increases in physical activity may affect the number of people living with disease by several pathways, not all of which will act to reduce the number of people living with disease (see Figure 5.1). First a reduction in relative risk, arising from an increase in physical activity, will lead to a reduction in the incidence rate of disease. For a fixed number of people at each age, this will result in fewer incident cases of diseases and consequently fewer people living with disease. I term this the 'incidence effect'.

Figure 5.1 How increases in physical activity may affect the number of people living with cardiovascular disease



A second opposing effect, is one I term the 'population ageing effect' (shown in yellow in Fig 1). If the incidence rate of a specific disease (and of chronic disease in general) decreases, the attributable mortality will also decrease, resulting in greater life expectancy and more people living to an older age. Because the incidence rate of many chronic diseases increases with age,[277–279] this will result in an increase in the absolute number of incident cases, and therefore also in the number of people living with disease.

A third effect may also occur, which I will term the 'disease survival effect'. Physical activity may increase disease-specific survival, for example it is used as a treatment for some diseases, such as ischaemic heart disease.[53] The average duration of disease survival will increase, resulting in more people living with disease. It will also contribute to population ageing. Consequently, when considering these later two effects ('population ageing' and 'disease survival'), it is no longer clear whether and the extent to which increases in physical activity will be associated with reductions in the number of incident cases or the number of people living with disease.

From an individual perspective all three effects are a form of health gain. Respectively they result in reduced risk of disease onset, increased life expectancy, increased disease-specific life expectancy (and likely an associated reduction in disease severity). However, my interest is in exploring their cumulative effect at the population level as it applies to the burden of disease that impacts on health and social care.

5.2.2 Burden of disease and healthcare utilisation

The term "burden of disease" may be used in different ways. Sometimes it refers to a comprehensive assessment of the health status of a population, including a diverse set of metrics (e.g. life expectancy, disability adjusted life years (DALYs), contribution of risk factors to DALYs).[280,281] Sometimes it is used to refer to the quantity of disease in a population, reflecting the literal meaning of burden. Used in this way it is commonly linked to demand for healthcare.[282]

My interest and focus is in the 'quantity' definition, with a specific focus on measures of quantity that relate to healthcare. I think this is best captured by the concept of 'need', as defined within the health needs assessment[xxii] literature.[283–285]

5.2.3 Definition of need

"Need", within this literature, is defined as a capacity to benefit from healthcare interventions. There are different types of need (e.g. felt, expressed, normative).[283–285] Normative need is what health professionals identify as need, i.e. based on clinically recognised disease states. In contrast expressed (or felt need) is what individuals identify as their need for care. Whilst the latter may be a better indicator of demand for healthcare, it is the former that aligns with the defined disease states that are outcomes of epidemiological studies describing the association between physical activity and disease. For this reason I have chosen to focus on normative need for healthcare rather than demand (i.e. expressed or felt need) for healthcare.

5.2.3.1 Epidemiological approach to needs assessment

Furthermore, I draw on the epidemiological approach to a needs assessments, i.e. using epidemiological parameters to quantify need for healthcare.[284] Some of these indices may be relatively crude (e.g. prevalence, incidence, disease-specific mortality), whereas others may be more tightly linked to healthcare utilisation (e.g. admissions, procedures, consultations).

I will limit my indices of need for healthcare to incidence and prevalence (or related measures), in part reflecting the existing literature on physical activity and health and part because these two indices capture the two broad patterns of disease presentation: chronic disease with ongoing

[xxii] A health needs assessment (HNA) is a systematic approach to identifying met and unmet healthcare needs of a population, which can be used to plan the provision of health services

presentation over many years and acute (including sub-acute) presentation where significant resources are invested at or around the time of diagnosis.

5.2.4 Summary of existing research

There is limited research which has explored the extent to which risk factor modification or preventive interventions can reduce need or demand for health care.

5.2.4.1 Literature on expansion and compression of morbidity

The question I pose could be reframed as whether increases in physical activity are associated with disease events being postponed or reduced (or even increased). These questions have been explored before, most often making reference to disease expansion and disease compression. Respectively these refer to an increase and a decrease in the mean duration an individual person lives with disease or disability.[286–288] Diseases compression implies a reduction in disease burden on individuals and reduction in the need for healthcare.

Authors have tended to argue that that changes in behavioural risk factors or other preventative measures will both postpone the onset of disability and reduce total disability.[288] However this literature is focused on measures of total disease or disability (i.e. aggregating across all disease states), so gives an incomplete description of changes or differences that may happen at the level of individual diseases, which might be different. It also overlooks the potential effect of behaviours on survival (e.g. physical activity is used to improve survival after a diagnosis of myocardial infarction).[53] Medical treatments, in contrast to prevention, by improving survival and if not curative, may result in disease expansion.[288]

More generally the focus of much of this literature is understanding how patterns of health and disease have changed in the past or may change in the future, rather than understanding the potential effect of changes in particular risk factors.[286,287,289]

5.2.4.2 Observational studies

A few observational studies have reported inverse associations between physical activity and healthcare utilisation.[152,153,290] However these studies were either cross-sectional or had a short period of follow-up. The findings could be explained by reverse causation, poor health status limited physical activity. These studies do not adequately account for disease events that have been postponed past the period of observation.

5.2.4.3 Modelling studies

Modelling studies[138] that model ageing or time may be a more appropriate means to understand the effect of increasing longevity than cohort studies. To fully understand the effect of increased longevity a long period with complete follow-up until death is needed to capture all disease events that are postponed, which may not be practical in a cohort study. However, it is possible to model such complete follow-up until death. To date these studies have seldom been used to describe the effects of changes in physical activity on need for healthcare.[291–296] They have tended to focus on single diseases, often cardiovascular disease,[292–294] and so may not adequately consider how one disease may affect another disease (e.g. changes in dementia incidence may be brought about by reduced incidence of and increased survival from cardiovascular disease). They report only a single measure of healthcare need, i.e. average years lived with disease or disability, which offers a limited perspective on need for healthcare. Time lived with disease may change because the average duration of illness changes or because the number of incident events may change, which may have implications for need for healthcare (e.g. acute care and chronic disease management).

A popular health impact modelling technique is comparative risk assessment.[19,21,125,143,297] This approach does not make allowance for changes in life expectancy and so risks overestimating the benefits that may accrue in terms of reduction in disease prevalence or incident events. A secondary aim of this part of my thesis is to understand the extent to which comparative risk assessment models may overestimate the benefits attributable to reductions in physical activity.

5.2.5 Study aims and scope

The aim of the modelling research is to contribute to a richer understanding of how physical activity may affect disease in a population as it relates to health and social care, making allowance for changes in longevity. I am primarily interested in diseases for which regular physical activity is protective and do not consider in detail diseases whose incidence is independent of physical activity (e.g. some cancers) but whose incidence rises with age.

5.2.5.1 Research questions

My research questions are:

1) What is the modelled effect of increases in physical activity in a population on changes in indices of need for health or social care, considering individual diseases for which physical activity is protective, when allowance is made for the effect of physical activity on survival?
2) How do these estimates compare with estimates that do not make allowance for changes in survival?
3) When allowance is made for increased survival do indices of need still decrease?

5.3 Methods

The model consists of two parts: a microsimulation model and a proportional multistate life table model. As I stated in Chapter One, I will predominantly refer to the model as a life table model as this is the part which describes health impacts.

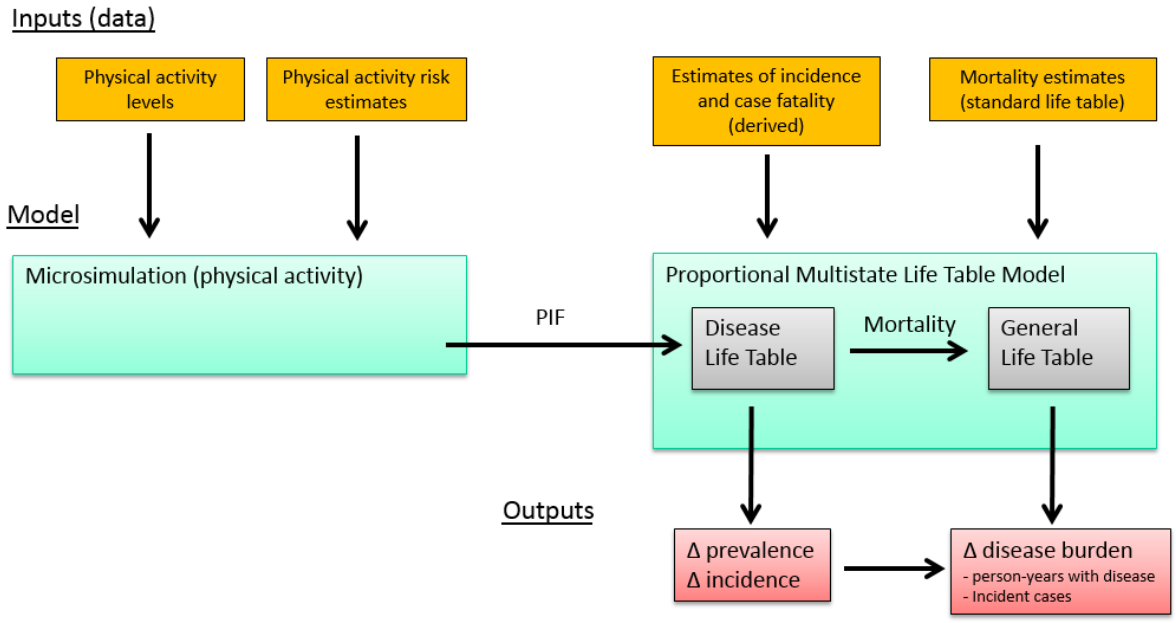
A schematic overview of the model is show in Figure 5.2. Data inputs are shown in orange, the two parts of the model (microsimulation and multistate life table model) are shown in green, and the key model outputs are shown in red. The microsimulation model, which describes the effect of changes in physical activity on disease risk at the individual level, is used to estimate population impact fractions. The estimates of population impact fraction are 'inputs' for the proportional multistate life table model, and describe the change in incidence or case fatality attributable to changes in physical activity. The multistate life table model has two component parts, disease specific life tables and a general life table model. The former is used to estimate the prevalence and incidence (rate) of disease, and the latter to estimate the number of people alive. By multiplying prevalence and incidence rate by the number of people alive, one can estimate the total number of people living with disease and the number of incident cases.

Below, I first describe the two parts of the model (microsimulation and life table) in more detail. I then describe the outcomes, scenarios modelled, sensitivity and uncertainty analyses and finally data sources.

5.3.1 Microsimulation model

I simulated a population of 8,118 adults based on the Health Survey of England 2012 sample, which is representative of the English adult (aged 16 years and over) population in terms of age and sex.[298] Each individual's physical activity level was related to their disease risk (see Figure 5.3), and could change independently. Changes in physical activity for any individual were modelled as movement along the physical activity relative risk curve. By summing together these changes for multiple individuals, I estimated the mean change for sub-populations (defined by age or sex), expressed as population impact fractions. The modelling of the relationship between physical activity and disease risk, as well as the calculation of population impact fractions are described in more detail below.

Figure 5.2 Schematic outline of model



PIF = population impact fraction

5.3.1.1 Modelled relationship between physical activity and disease risk

Most studies report a curvilinear relationship between physical activity and disease or mortality, although different approaches have been used to mathematically describe the relationship between physical activity level and disease risk (e.g. log linear, square root transformation).[43,44,110,299] Following the approach used by others,[142] I assumed changes in risk of disease to be log linearly associated with a power transformation of the physical activity exposure, where the power transformation take a value of 0.5 (range 0.25 to 1.0 with a triangular distribution) for all relationships, following the range used within the Integrated Transport and Health Impact Modelling tool (ITHIM).[125]

This relationship can be written as follows:

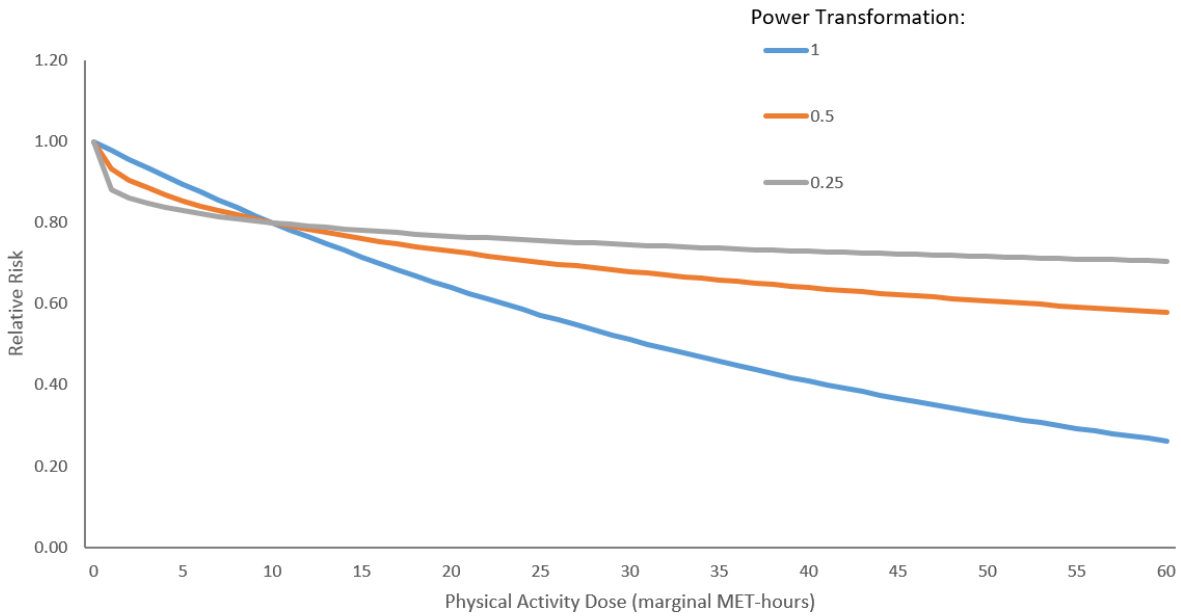
$$RR = a^{(PA\ dose/b)^{\wedge}t}$$

Where RR=relative risk, PA dose=physical activity dose measured in marginal MET-hours, t=power transformation, a is the reported relative risk from the meta-analysis, b is the physical activity level at which the reported relative risk occurred.

Examples of this relationship are shown in Figure 5.3. Where possible I took estimates of relative risk and physical activity level (parameters a and b) from the original ITHIM model.[125] Where estimates of the these parameters were not given in the work of Woodcock et al,[125] I sought estimates from the

literature. The search strategy and data extraction technique are explained later in the chapter (Section 5.3.6.2).

Figure 5.3 Example relationship between physical activity level and relative risk



In this example, a=0.80, and b=10 marginal MET-hours

5.3.1.2 Calculation of population impact fraction

Population impact fractions were estimated by a weighted sum of the ratio of the relative risk observed under each scenario of interest compared to baseline. First relative risks were calculated under the baseline scenario (no change in physical activity) for each individual and then under the alternative or counterfactual scenario (an increase in physical activity levels) for each individual.

The population impact fraction was then estimated as:

$$PIF = \sum_{i=1}^{n} \frac{RR_i'}{RR_i}$$

Where PIF is the Population Impact Fraction, RR_i' is the relative risk under the counterfactual scenario and RR_i is the relative risk under the baseline scenario. This is a similar approach to estimating a Population Attributable Fraction (PAF). Although when estimating a PAF the 'scenario' is eliminating that risk factor.[300]

5.3.2 Proportional multistate life table model

A proportional multistate life table model was used to estimate the effect of changes in physical activity on population health and survival. The technique been adopted by others to model the effect of physical activity,[292,301] or other risk factors, on health.[291,302]

5.3.2.1 General description of proportional multistate life table

The proportional multistate life table was first described by Barendregt et al.[303] It consists of two parts: a general life table and a set of disease life tables. The general life table very closely resembles the life table first described by John Graunt in the 17th Century.[304] The table consists of two states: dead and alive, with transitions describing the hazard or probability of moving from one state ('alive') to the other state ('dead'). This probability is age and sex dependent.

The size of the population alive at the end of the first year of life is thus the starting or birth population multiplied by the probability of death in that first year of life. The population alive at the end of the second year of life is thus the population alive at the end of the first year of life multiplied by the probability of death in the second year of life. These calculations continue through to the upper limit of the life table, typically 100 years, above which transition hazards tend not to be reported. Thus the general life table describes the survival of a cohort from birth through to death or some fixed upper limit.

The disease life tables are similar. It has three states: alive and living without disease; alive and living with disease; and dead. Transition hazards (incidence, remission and case fatality) are used to describe the probability of moving between states in any given year of life. Within each disease life table mortality from all other causes is assumed to be zero. In other words the disease life tables only considers mortality that is attributable to the diseases being modelled in that life table. These hazards are age and sex dependent.

A similar process is followed to estimate the number of people in each state. The size of the population with disease at the end of the first year of life is thus the starting or birth population multiplied by the probability of disease incidence in that first year of life. The population with disease at the end of the second year of life is thus the population alive at the end of the first year with disease less those who died from disease (those alive with disease at the start of that year multiplied by case fatality in that year of life) and less those who recovered (those alive with disease at the start of the year multiplied by remission in that year).

Assuming independence (i.e. that disease incidence is independent and that causes of death are independent), the disease life table provides an unbiased estimate of disease prevalence and disease-specific mortality. Prevalence at any age is estimated by the number alive with disease divided by the total population alive, and mortality by dividing the number of deaths in that year by the population living with disease at the start of that year.

Scenarios are modelled by applying a new set of transition hazards to the disease life tables (incidence, remission and case fatality). These changes will lead to a new estimate of the disease-specific mortality by age and sex. Changes in disease-specific mortality are summed to give an overall estimate of the change in mortality. These are added to the mortality hazards in the general life table, to calculate a new set of hazards (by age and sex), which describes the survival of the cohort under the given scenario.

5.3.2.2 Application of proportional multistate life table model

I assumed no disease remission or recovery, so that the disease life table only made use of two sets of transition hazards (incidence and case fatality).

As others have done,[301] I did not allow changes in type 2 diabetes mortality to affect changes in overall mortality. This was to prevent a violation of the assumption of independence. Type 2 diabetes is a direct cause of ischaemic heart disease and stroke, so its full inclusion in the model (i.e. in a way that would affect mortality) would undermine the assumption. It also avoided the risk of double counting, as these forms of mortality are already considered within the model.

5.3.2.3 Diseases included in model

I included diseases if: a) the disease was an important cause of morbidity or mortality; b) disease incidence was reduced by physical activity according to consensus; and c) estimates of the relative risk could be extracted from published meta-analyses. I defined consensus as being included in the physical activity guidelines from three of the following four countries: Australia, Canada, UK and USA.[41,64,65,88]

Diseases included were ischaemic heart disease, stroke, type 2 diabetes, dementia, colon cancer and breast cancer. The nature and strength of the evidence base concerning the relationship between physical activity and these health outcomes was described in Chapter 1 (section 1.2.3). For all these diseases, I assumed that physical activity affected risk of disease incidence. For ischaemic heart disease, breast cancer and colon cancer, I additionally assumed that physical activity affected disease survival.

Depression was not included because the existing meta-analyses described the association between physical activity and depression score, rather than incident depression, effectively treating mood as a continuous trait.[305] The multistate life table model cannot readily handle continuous traits as it is a Markov type model with discrete states. The parameters in published meta-analyses could not readily be transformed into relative risk of disease incidence (or remission).

I assumed that physical activity did not affect survival from a stroke, dementia or diabetes. For stroke, whilst physical activity is recommended after stroke, the nature of the activity has to be tailored to the individual and any residual disability, it is advocated primarily as a means to improve functional performance and quality of life, and I found no evidence (either observational epidemiology or randomised controlled trials) that quantified the relationship between physical activity after stroke and mortality due to stroke.[306,307] For dementia, I found no studies (either observation or randomised controlled trials) that quantified the relationship between physical activity after a diagnosis of dementia and subsequent mortality from dementia.

As discussed earlier (see section 5.3.2.2), I have not included a direct effect of physical activity on diabetes related survival, because much of the mortality attributable to diabetes occurs through ischaemic heart disease and stroke, and modelling diabetes in this way would likely violate the underlying assumptions of a proportional multi-state life table model.[303]

5.3.3 Outcomes

I chose two primary indices of healthcare need: number of people living with disease and number of incident cases.[283,284] As discussed in the previous chapter (section 5.2.3.1) epidemiological parameters may be used to assess need for healthcare, with different parameters assessing different aspects of need.[283–285] The former outcome (number with disease) may be an important indicator of need for healthcare for diseases that require continuous input throughout life (e.g. type 2 diabetes). The latter may be an important indicator of need for diseases that require significant input around the time of diagnosis (e.g. cancer). Some diseases may have elements of both (e.g. stroke).

To ensure I recorded disease that was postponed until later life, a cohort was followed from birth to death (or 100 years of age). Measuring the two indices (number with disease and incident cases) across the life of the cohort gave two outcomes: person-years lived with disease and total incident cases.

I estimated the person-years lived with disease by summing the product of the age-specific prevalence (taken from the disease life table) and the number of people alive at each age (taken from the general life table). I estimated total incident cases by summing the product of the age-specific disease incidence (taken from the disease life table) and the number of people alive at that age. I then estimated percentage change under the scenario being studied (relative to baseline) for these two outcomes.

To compare these estimates with measures that do not make allowance for increasing life expectancy, I used comparative risk assessment (CRA) methods to estimate the change in person-years with disease, by summing the product of: the age-specific prevalence (at baseline), the number of people alive (at baseline) and the population impact fraction.[143,300] I then estimated the percentage change relative to baseline. I have called this metric 'person-years with disease (unchanged life expectancy)'.

I also estimated the change in life expectancy for each scenario using the general life table (the total number of person-years lived during the life of the cohort divided by the total population).

5.3.4 Scenarios

For all scenarios, I assumed that physical activity only changed for adults (people aged 16 years and over). Physical activity levels for children were thus assumed to be unchanged. This reflected the microsimulation model which only described the effect of physical activity on disease for people aged 16 years and over.

I explored two scenarios where the levels of physical activity that adults achieved changed. The primary scenario was based on all adults meeting the UK adult physical activity (PA) guidelines, which I labelled as "all adults meeting PA guidelines".[63] I assumed this was achieved by walking for 150 minutes on flat ground at 3mph (equivalent to 3.3 MET; i.e. at relatively low intensity within the range of values for intensity that correspond to moderate intensity). The walking scenario was chosen as it is likely to be the most feasible way for the population to meet this goal (as outlined in the introductory chapter). This 'dose' of physical activity is equivalent to 5.75 marginal MET-hours per week (see section 5.3.6.1 for full explanation of marginal MET-hours). Those individuals who were already undertaking at least this amount did not change their physical activity level, all other individuals increased their physical activity level to 5.75 marginal MET-hours. Thus meeting physical

activity guidelines was defined as undertaking at least 5.75 marginal MET-hours of physical activity.[xxiii]

The secondary scenario was labelled 'all adults increase', in which I assumed that all adults, irrespective of their current physical activity level, increased their physical activity by 5.75 marginal MET-hours, i.e. the existing distribution of physical activity shifted 5.75 marginal MET-hours to the right without changing in shape. I also modelled the effect of everyone increasing by half this amount (2.875 marginal MET-hours, equivalent to 75 minutes walking or similar MVPA per week) and 50% more than this amount (8.625 marginal MET-hours, equivalent to 225 minutes of walking or other MVPA per week). I label these 'all adults increase PA (150 minutes walking)', 'all adults increase PA (75 minutes walking)', and 'all adults increase PA (225 minutes walking)' respectively. Whilst other changes in physical activity would result in equivalent changes, for simplicity the labels for the scenarios reflect change in walking.

5.3.5 Uncertainty and sensitivity analyses

Uncertainty and sensitivity analyses are often ill-defined and overlap. I use the term 'uncertainty analysis' to refer to techniques that quantify uncertainty surrounding the model's parameters and structure, and 'sensitivity analysis' to refer to techniques that identify which explicit assumptions are critical to the model (in terms of having a significant impact on the model outcome).[138]

I used Monte Carlo analyses (a form of uncertainty analysis) to estimate '95% uncertainty intervals' that quantify the effect of parametric uncertainty on point estimates. These are similar to, but are different from, 95% confidence intervals. I used tornado plots (as a form of sensitivity analysis) to describe the relative importance of different sources of parametric uncertainty on the three outcomes. I made changes to the model's structure to examine the effect of structural uncertainty (i.e. the effect of making different assumptions concerning the model's structure or configuration), which could be described as either a sensitivity analysis or an uncertainty analysis. I only undertook uncertainty and sensitivity analyses for the primary scenario ('meeting guidelines').

[xxiii] The guidelines are expressed in minutes rather than marginal MET-hours. Undertaking 5.75 marginal MET-hours of physical activity may be equivalent to meeting the guidelines for most individuals but is not exactly the same. One hour of intense activity (e.g. at 10 METs) would exceed 5.75 marginal MET-hours, but would not meet the recommendation of a minimum of 75 minutes or vigorous activity.

5.3.5.1 Monte Carlo analyses to estimate uncertainty intervals

I estimated 95% uncertainty intervals (2.5th to the 97.5th percentile) from 5000 iterations of a Monte Carlo analysis. Testing of model convergence (repeatedly running the model with increasing number of iterations) showed that 5000 iterations produced stable estimates for the uncertainty intervals.

I modelled uncertainty for three sets of parameters: the power transformation; the association of physical activity with relative risk of disease incidence; the association of physical activity with relative risk of case fatality. For each iteration a random value was drawn from the described distribution for each parameter, i.e. a normal distribution for all parameters except for the power transformation was assumed to have a triangular distribution.

5.3.5.2 Tornado Plots

To test the relative importance of the different sources of parametric uncertainty, tornado plots were constructed for the following outcomes: change in person-years lived with disease, change in total incident cases and for change in life expectancy. Plots were constructed for each of the six diseases.

Tornado plots are a special type of bar chart, where the bars are arranged horizontally and in order of size. Typically the largest bar is at the top and the smallest bar at the bottom so that the diagram forms a visual 'tornado'. Tornado plots are a common means to undertake 'deterministic sensitivity analyses', where the relative importance of variation in different parameters is compared. Used in this way each bar represents the range of outcome values expected consistent with the reported or described uncertainty for the given input. The inputs whose uncertainty contributes most to uncertainty in the outcome will have the largest bars and thus be at the top of the diagram. The tornado plot is centred around the mid-point (median) estimate for all parameters.

The 95% confidence interval for parameters were used to describe variation in most parameters, except for the power transformation where the 2.5th and 97.5th percentile were taken from the (triangular) distribution of values used as inputs to the modelling.

5.3.5.3 Testing Structural Uncertainty

I examined structural uncertainty by making changes to the model structure (omitting, adding or changing parts of the model). These changes, and the rationale for their choice, are summarised in Table 5.1.

Table 5.1 Structural changes to model

Name of model variant	Description	Rationale for change
Cancer Survival (no effect)	Physical activity does not affect cancer case fatality	An association between physical activity and cancer survival was reported in observational studies and could be explained by confounding by indication rather than a true effect of physical activity on survival.
No lag	No lag was assumed between physical activity and its effect on disease risk	There is very little published information on the duration of lags and I wanted to explore the extent to which lags affected the model outcomes.
Leisure only	Only walking, sport and recreational physical activity contribute to baseline physical activity	Current epidemiological studies of physical activity and disease, predominantly considers either leisure time physical activity or walking (and thus excluded domestic, transport and occupation activity). Including these other types of physical activity results in an overestimate of baseline physical activity and consequently an underestimate of the effect of increases in physical activity on health.
Cancer Incidence	Physical activity reduces the risk of incidence of other cancers	There is good evidence that physical activity affects the incidence of other cancers.
Mortality	Physical activity has a direct effect on all-cause mortality (i.e. on the general life table) rather than through its effect on each disease	The effect of physical activity on all-cause mortality may be greater than the effect attributed by modelling the effect through each disease

Changes to cancer survival were made because I was concerned that the associations were based on observational studies of cancer survival and might be influenced by confounding by cancer severity (cancer severity being associated with physical activity and survival). Other changes were chosen because they would result in a greater population ageing effect (i.e. increased all-cause survival). Early work with the model suggested that the estimates of increases in physical activity on changes in life expectancy were low compared to other estimates. I made three changes to the model to 'enhance' the effect of physical activity on disease incidence and all-cause survival.

First, I recalculated the baseline levels of physical activity to only include leisure activity (sport, recreation and walking[xxiv]). This resulted in a lower estimate of baseline levels of physical activity, and because the effect of physical activity is greatest amongst the least active[xxv], lower baseline levels of physical activity would be expected to lead to greater improvements in health. This approach may be more appropriate. The studies that estimated the association between physical activity and disease risk (see section 5.3.6.2) tended to only consider walking or leisure time physical activity. The baseline levels of physical activity in these studies was relatively low compared to the

[xxiv] The questionnaire did not distinguish between walking for travel and walking for leisure. The definition of leisure physical activity thus still includes walking for travel and so may overestimate leisure time physical activity.

[xxv] This is represented in the dose-response relationship between physical activity and relative risk. Steep initial decline in risk, followed by flattening of the curve, see Figure 5.3.

baseline levels of physical activity estimated for the English population in the microsimulation model, which including all domains of physical activity (occupation, domestic, travel and leisure).

Second, I assumed that physical activity reduced the incidence of other cancers (lung, prostate and pancreatic). Whilst not incorporated into some physical activity guidelines,[41,63,65] a recent review highlighted new evidence of associations between physical activity and risk of several other cancers.[69] For three major cancers[xxvi] (pancreatic, prostate and lung) the evidence of a causal association was described as "probable" or "possible".[69] It seems plausible that the effect of physical activity on disease is not limited to the six diseases that I initially chose to incorporate into the model. The incorporation of these other cancers may be considered a broader test of the extent to which including more diseases affects the model outcomes. For lung cancer I assumed that physical activity only affected lung cancer attributable to smoking, in keeping with recent findings.[308,309] Given the attributable fraction for smoking with respect to lung cancer is 80%,[310] I assumed the incidence of lung cancer that was attributable to smoking was 80% of all reported lung cancer incident cases of lung cancer.

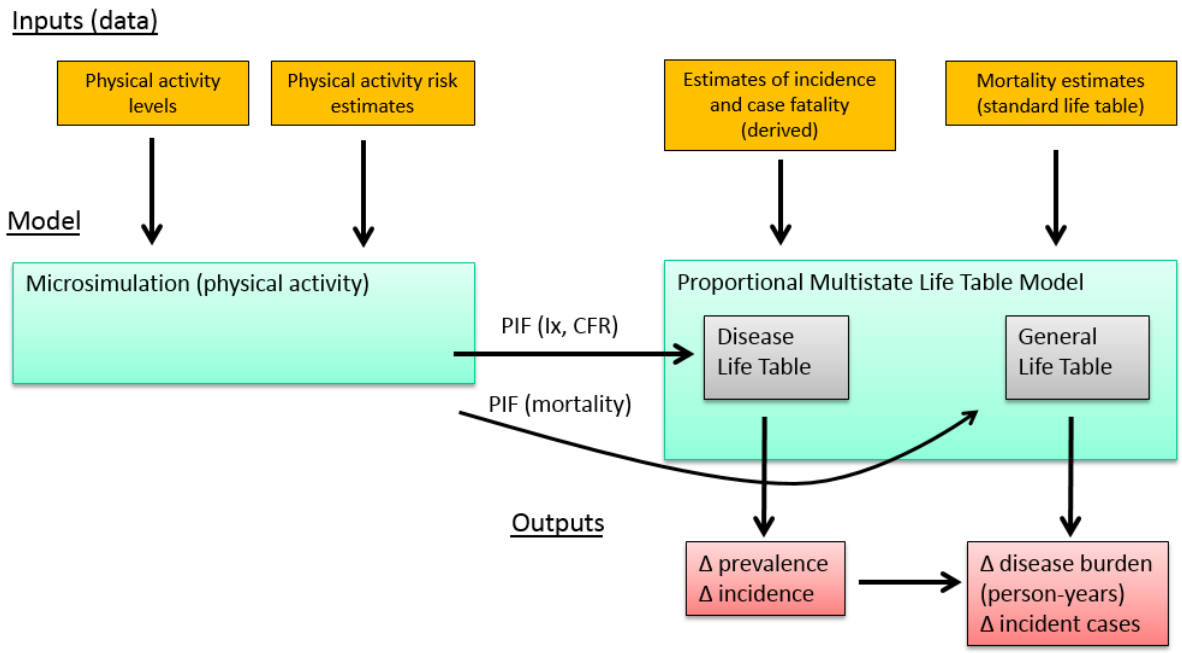
Finally, I modelled the effect of physical activity on mortality directly, rather than indirectly through its effect on different diseases. I refer to this as the 'mortality model'. This also resulted in an enhanced effect of physical activity on all-cause survival (although not on disease incidence).

5.3.5.4 Mortality Model

A schematic overview of the mortality model is set out in Figure 5.4. In the mortality model physical activity has a direct effect on mortality as modelled in the general life table (shown by the line going directly from the green microsimulation box to the general life table box, Figure 5.4), and the corresponding links describing the indirect effect of physical activity on mortality through the different diseases (i.e. the link between the disease life tables and general life tables is lost). In doing this the model violates the principle that changes in all-cause mortality are estimated from the summing of change in each disease-specific mortality, described in the original proportional multistate life table model.[303] However similar models have been described in which physical activity affects all-cause mortality and affects disease incidence.[292,311]

[xxvi] Together with colon and breast cancer, these three cancers are the cancers responsible for the most deaths in the UK.[367]

Figure 5.4 Schematic outline of mortality model



PIF = population impact fraction; Ix = incidence; CFR = Case Fatality Rate

5.3.6 Data

The model had four principles data inputs: physical activity levels; relationship between physical activity and disease; transition hazards (incidence and case fatality) for the disease life tables; mortality for the general life table. In all cases I sought data that were representative of the English population.

5.3.6.1 Physical activity level

Physical activity level was defined as the product of duration and intensity of physical activity. Estimates of the duration and type of physical activity were taken from the Health Survey for England 2012.[298] Estimates of the intensity of each type of physical activity were taken from the Compendium of Physical Activity.[213]

The Health Survey for England in 2012 included the International Physical Activity Questionnaire (IPAQ).[312] The questionnaire seeks information on the type, duration, frequency and sometimes intensity of all forms of physical activity undertaken in the past four weeks. Weekly duration of each activity was estimated by multiplying the weekly frequency by the reported average duration of activity.

Each activity was assigned a value of intensity or energy expenditure, measured in metabolic equivalent of task[xxvii], taken from the Compendium of Physical Activity.[213] I included the following types of physical activity: occupational (walking, stair climbing, lifting), domestic (housework and gardening), travel (walking) and recreational. Where the activity described in the IPAQ did not clearly map to an activity in the Compendium of Physical Activities, I identified a set of activities that could fit the description of the physical activity recorded in the IPAQ, and took an average (median) value of those activities. These values are shown in Table 5.2. I only included physical activity that was moderate or vigorous intensity (i.e. ≥ 3 MET). This is because the large empirical evidence base that considers moderate-to-vigorous physical activity, which was used to parametrise my model.[41,63,65]

I then converted these measures of intensity, in MET, to marginal-MET, by subtracting one MET. This is an adjustment made by some authors that discounts energy expenditure due to basal metabolism (as this level of expenditure would occur independent of physical activity).[125] Using marginal-MET instead of MET results in low intensity activities undertaken for a long period of time 'scoring' less.

5.3.6.2 Relationship between physical activity and disease

As described in earlier section of this chapter (section 5.3.1.1), I modelled the relationship between physical activity level and relative risk as a log linear relationship with a power transformation. The relationship between physical activity level and relative risk was partly defined by estimates of relative risk (parameter labelled 'a') and the corresponding 'dose' of physical activity (parameter labelled 'b').

The parameters 'a' and 'b' were extracted from published meta-analyses of cohort studies or randomised controlled trials. This data is summarised in Table 5.3. Where possible, I took the parameters 'a' and 'b' from the original Integrated Travel and Health Impact Modelling (ITHIM) tool, published in 2009).[125] Where this was not possible, I undertook a literature review to identify suitable parameters. The theoretical basis for the inclusion of diseases was outlined in section 5.3.2.3.

[xxvii] One metabolic equivalent of task (MET) is the amount of oxygen consumed whilst sitting at rest, and is equal to 3.5 ml per kg per minute. MET are used a measure of physical activity energy expenditure (or intensity). The energy expenditure of the activity is estimated by dividing its energy cost (ml of O_2 per kg per minute) by 3.5.[266] An activity with an energy expenditure of 3.00 to 6.00 MET is categorised as moderate intensity, and an activity with an energy expenditure greater than 6.00 MET is categorised as vigorous.[24]

Table 5.2 Estimates of intensity of different activities

Activity in IPAQ	Assigned Physical Activity Intensity (MET)	How assigned value was estimated (numbers refer to code used in the Compendium of Physical Activity)
Occupation		
Occupation, Walking at work	3.5	Median value of the following codes: walking on the job at speeds of less than 2mph to 3.5mph (11791, 2.0 MET; 11792, 3.5 MET; 11793, 4.3 MET), and walking on the job carrying light objects (11795, 3.5 MET).
Occupation, Climbing stairs/ladders	6.3	Median value of the following codes: carrying light load upstairs (17026, 5.0 MET), stair climbing or climbing a ladder (17130, 8.0 MET), stair climbing at a slow pace (17133, 4.0 MET), stair climbing at a fast pace (17134, 8.8 MET), climbing hills with no load (17033, 6.3 MET).
Occupation, Lifting, carrying or moving heavy loads	7.5	Median of walking or standing whilst carrying objects weighing from 25lbs to 100lbs or more (11820, 5.0 MET; 11830, 6.5 MET; 11840, 7.5 MET; 11850, 8.5 MET), loading and unloading truck (11766, 6.5 MET), standing and continuously lifting items (11615, 4.5 MET), carrying heavy loads (11050, 8.0 MET), moving boxes (11060, 8.0 MET), and moving or carrying objects of 75lbs or more (11490, 7.5 MET)
Domestic		
Heavy housework	3.5	Median of multiple household tasks at light (05025, 2.8 MET), moderate (05026, 3.5 MET) and vigorous intensity (05027, 4.3 MET)
Heavy manual work at home (DIY, gardening or building work)	4.15	Median of gardening – general (08245, 3.8 MET), and home repair at light (06126, 2.5 MET), moderate (06127, 4.5 MET) and vigorous intensity (06128, 6.0 MET).
Walking at a brisk or fast pace (4mph or greater)	3.9	Median of walking on a flat surface from 2.5mph to 4mph (17170, 3.0 MET; 17190, 3.5 MET; 17200, 4.3 MET; 17220, 5.0 MET)
Sport		
Swimming	6.0	Swimming general (18310)
Cycling	6.8	Bicycling to/from work, self-selected pace (01015)
Working out (e.g. weight training or exercise bike)	6.0	Median of exercise bike (02010, 7.0 MET), weight lifting (02030, 6.0 MET), and calisthenics (02020, 3.8 MET)
Aerobics, keep fit and gymnastics	7.3	Aerobics (03015, 7.3 MET) – assume this is predominantly aerobics/keep fit rather than gymnastics
Dancing	5.0	Ballet, modern, jazz or general dancing (03010)
Running or jogging	8.4	Median of jogging in general (12020, 7.0 MET) and running at 6mph (12050, 9.8 MET)
Football or rugby	7.65	Median of soccer – competitive (15605, 10.0 MET), soccer – casual (15610, 7.0 MET), rugby – competitive (15560, 8.3 MET), and rugby – non-competitive (15562, 6.3 MET)
Badminton or tennis	7.0	Median of tennis – general (15675, 7.3 MET), badminton – social (15030, 5.5 MET) and badminton – competitive (15020, 7.0 MET)
Squash	7.3	Squash general (15652)
Exercises (e.g. press ups)	8.0	Calisthenics (02020)
Any other sport	6.0	
Travel		
Walking	Dependent on speed	Slow = 2.5 MET (17152) was discounted unless the participant was aged over 65 years and reported breathlessness on walking, in which case I assumed this was equivalent to achieving moderate intensity physical activity; average pace = 3.0 MET (17170); fairly brisk = 3mph = moderate pace = 3.3 MET (17190); fast pace = 4.0mph = 5.0 MET (17220)

MET= Metabolic Equivalent of Task; raw values in column three were taken from the compendium of physical activity.[213]

Table 5.3 Summary of parameters characterising the relationship between physical activity and risk

Disease	Study	Relative Risk (95% CI)	Physical activity level (marginal MET-hours per week)	Standardised Relative Risk	Lag (years)
Incident Disease					
Breast cancer	Monninkhof et al, 2007[313]	0.94 (0.92-0.97)	3.5	0.97	1-30
Cardiovascular disease	Hamer et al, 2008[129]	0.84 (0.79-0.90)	5.4	0.94	1-5
Colon Cancer	Harriss et al, 2009[68]	Men: 0.80 (0.67-0.96) Women: 0.86 (0.76-0.98)	Men: 23 Women: 14	0.98	1-30
Diabetes	Jeon et al, 2006[314]	0.83 (0.75-0.91)	10	0.94	1-5
Dementia	Hamer et al, 2009[315]	0.72 (0.60-0.86)	24.5	0.95	1-30
Lung cancer	Buffart et al, 2014[309]	0.82 (0.77-0.87)	21	0.97	1-30
Pancreatic cancer	O'Rorke et al, 2010[316]	0.72 (0.52-0.99)	24	0.95	1-30
Prostate cancer	Liu et al, 2011[317]	0.90 (0.84-0.95)	28	0.98	1-30
Case Fatality					
Breast cancer	Schmid et al, 2014[67]	0.72 (0.60-0.85)	24	0.94	1-5
Colon cancer	Schmid et al, 2014[67]	0.61(0.40-0.92)	11	0.89	1-5
Ischaemic Heart Disease	Heran et al, 2011 [53]	0.87 (0.75-0.99)	6	0.90	1-5

Standardised relative risk is the relative risk re-calculated for an increase of one marginal MET-hour per week. Estimates of relative risk were taken from meta-analyses of cohort studies, with the exception of case fatality from ischaemic heart disease, which was taken from a meta-analysis of randomised controlled trials.

These literature reviews are described below. Once suitable studies were identified not only was it necessary to extract a measure of relative risk, but also to describe the dose of physical activity at which that relative risk occurred. The process of estimating that dose is also described below.

Estimates of relative risk of disease incidence for the main model

For estimates of the relative risk of incidence for ischaemic heart disease, stroke, type 2 diabetes, breast cancer, colon cancer and dementia were taken from ITHIM.[125] A systematic review undertaken as part of the development of ITHIM had identified and extracted relevant parameters based on cohort studies describing the relationship between physical activity and disease incidence.[125]

Literature search to describe the effect of physical activity on disease survival

For estimates of other cancers (i.e. prostate cancer, pancreatic cancer and lung cancer), which were included only within sensitivity analyses (see section 5.3.5.3), and were not included in ITHIM, I undertook a literature review to identify suitable estimates of relative risk.

I identified studies that described the effect of physical activity on disease survival using the following search terms in Pubmed on 1 April 2015: “systematic review” or “meta-analysis” and “physical activity” or “exercise” and “incidence” or “relative risk” and “prostate cancer” or “pancreatic cancer” or “lung cancer”. The identified meta-analyses were of cohort studies.

Literature search to describe the effect of physical activity on disease survival

There were no estimates of case fatality used within ITHIM.[125] As it was a comparative risk assessment model, it did not explicitly model an effect of physical activity on case fatality. Consequently, I undertook a literature search to identify whether physical activity affects disease-specific survival (after disease onset for ischaemic heart disease, breast cancer and colon cancer), and where appropriate extracted the relevant parameters.

I identified studies that described the effect of physical activity on disease survival using the following search terms in Pubmed on 1 April 2015: “systematic review” or “meta-analysis” and “physical activity” or “exercise” and “survival” or “case fatality” and “colon cancer” (including bowel cancer and colo-rectal cancer) or “breast cancer” or “ischaemic heart disease” (including myocardial infarction, IHD and cardiovascular disease).

A meta-analysis of randomised controlled trials of physical activity (‘exercise based cardiac rehabilitation’) after a diagnosis of ischaemic heart disease was used to describe the relationship between physical activity and survival from ischaemic heart disease. Meta-analyses of cohort studies were used to describe the relationship between physical activity and survival from breast cancer and colon cancer.

Extraction of physical activity dose from identified studies

None of the meta-analyses identified provided an estimate of the physical activity dose or level that pertained to the reported relative risk. Estimates of this dose were made using the approach outlined by Woodcock et al.[125] Having identified a value for relative risk from a meta-analysis, I then sought to identify the largest single study within the meta-analysis. I then sought an estimate of the median physical activity level in the highest exposure group (or whichever group corresponds to the relative risk value used within the meta-analysis) from this study. Most studies quantified the duration and intensity for the relevant group from which an estimate of physical activity level in marginal MET-hours could be made. If no such estimate could be made, then I reviewed the second largest study.

I used adjusted estimates of relative risk to describe the un-confounded association between physical activity and disease risk. A summary of the extracted parameters is presented in Table 5.3,

including estimates of the 'standardised relative risk'. The standardised relative risk recalculates the relative risk for an increase in physical activity comparing zero marginal MET-hours per week to one marginal MET-hour per week, and thus serves as a means to compare the association between physical activity and different disease outcomes across studies that have observed different changes in physical activity. In calculating these estimates I assumed a log linear relationship with a 0.5 power transformation.

5.3.6.3 Transition Hazards (incidence and case fatality)

Transition hazards were estimated from routine data sources. A program called DisMod II v1.05 (World Health Organisation, 2001-09) was used to convert routine epidemiological parameters to estimates of incidence and case fatality by one year age bands.[318] Remission was assumed to be zero. Separate estimates were made for men and women.

I used estimates of epidemiological parameters published in routine or comprehensive datasets where possible. No routine data existed for dementia, consequently I took prevalence estimates from a recent large UK based prevalence study,[278] and estimates of relative mortality from a recent UK based study of general practice records.[319] The sources of the epidemiological parameters are summarised in Table 5.4.

5.3.6.4 Mortality (General Life table)

I used the interim life table for England for the years 2010-2012[320] to parameterise the general life table of the model.

Table 5.4 Sources of disease parameters used as inputs for DisMod to estimate transition hazards for disease models

Disease	First Parameter		Second Parameter	
	Parameter	Source	Parameter	Source
Breast cancer	Mortality	Mortality Statistics 2011[321]	Incidence	National Cancer Registry (2011)[279]
Colon Cancer	Mortality	Mortality Statistics 2011[321]	Incidence	National Cancer Registry (2011)[279]
Lung cancer	Mortality	Mortality Statistics 2011[321]	Incidence	National Cancer Registry (2011)[279]
Pancreatic cancer	Mortality	Mortality Statistics 2011[321]	Incidence	National Cancer Registry (2011)[279]
Prostate cancer	Mortality	Mortality Statistics 2011[321]	Incidence	National Cancer Registry (2011)[279]
Ischaemic Heart Disease	Mortality	Mortality Statistics 2012[322]	Prevalence	Health Survey for England 2012[323]
Stroke	Mortality	Mortality Statistics 2012[322]	Prevalence	Health Survey for England 2012[323]
Diabetes	Standardised mortality rate	National audit of general practice 2011-12; report 2[324]	Prevalence	National audit of general practice 2011-12; report 1[325]
Dementia	Relative risk of mortality	Analysis of primary care data[319]	Incidence	CFAS II study[278]

5.4 Chapter summary

It is common to assume that improvements in the distribution of a risk factor through improvements in health will reduce need for healthcare. The implicit assumption in much of this thinking, and explicit assumptions (when modelled using comparative assessment or similar approaches) is that increases in life expectancy, which also result from the same changes, will not materially affect need for healthcare.

This has been little considered and inadequately explored in the existing literature. Observational studies are either cross-sectional or short-term and fail to account adequately for reverse causation or disease events being postponed. Modelling studies have not considered how changes in disease incidence (arising from changes in physical activity) may affect survival and indices of healthcare need at the disease-level.

The modelling section of thesis aims to better illustrate or understand how improvements in the distribution of physical activity, when making allowance for changes in survival, may affect need of healthcare. Whilst predominantly referred to as a life table model the model consists of two parts: a micro-simulation model to describe the effects of changes in physical activity on disease risk from which population impact fractions are estimated; and a proportional multi-state life table model that describes the health impacts of changes in physical activity on six diseases. The former part modelled the relationship between physical activity level, using a continuous measure of physical activity (which combined intensity and duration).

I have outlined two scenarios (‘all adults meeting PA guidelines’ and ‘all adults increase PA’) and described two primary outcomes or indices of healthcare need (person-years lived with disease and incident cases). I described a number of approaches to dealing with uncertainty (uncertainty intervals, tornado plots and testing of structural assumptions).

6 Modelling Results

"Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise"

John Tukey

6.1 Chapter outline

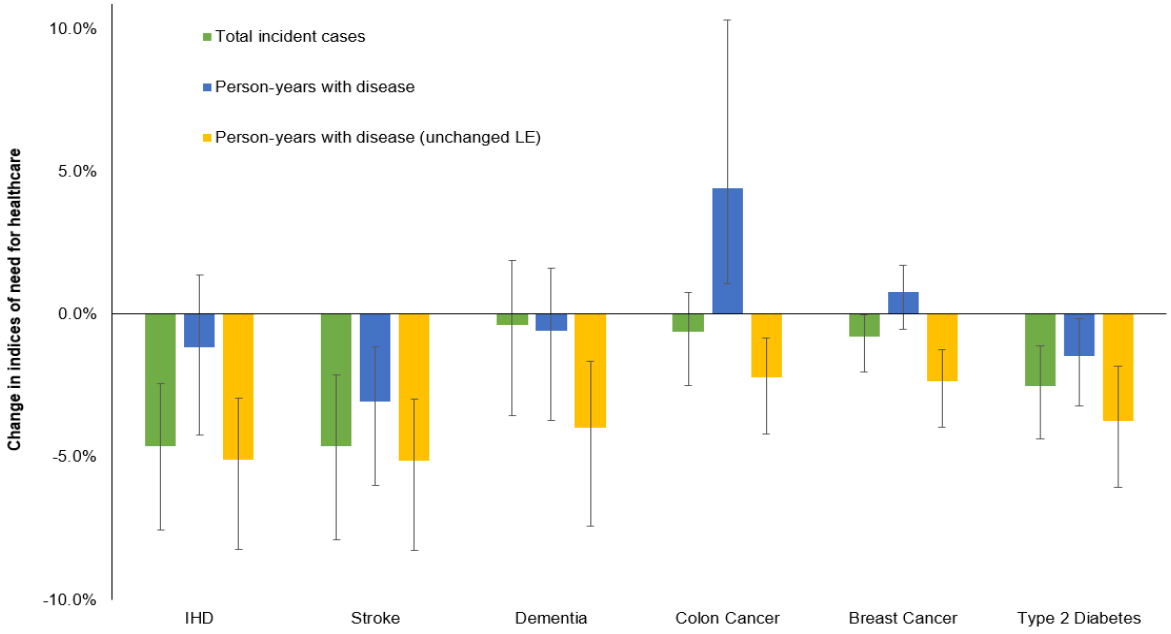
This short chapter describes the modelling results.

6.2 Results for all adults meeting physical activity guidelines

Under the 'all adults meeting PA guidelines' scenario estimated life expectancy increased by 95 days (95% uncertainty intervals: 68 to 126 days), or 89 days for men (60 to 123 days) and 101 days for women (75-131 days).

Changes in person-years with disease and total incident cases are shown in Figure 6.1. Person-years lived with disease decreased for ischaemic heart disease, stroke, type 2 diabetes and dementia, and increased for colon cancer (uncertainty intervals not including zero) and breast cancer (uncertainty intervals including zero). The decreases observed for ischaemic heart disease and dementia were small (with uncertainty intervals that included zero).

Figure 6.1 Effect of meeting physical activity guidelines on the change in indices of healthcare need



All adults meeting PA guidelines scenario assumes that all adults who are not presently doing 5.75 marginal MET-hours of physical activity (equivalent to 150 minutes of walking at 3mph on flat ground (3.3 MET) per week) increase their physical activity to 5.75 marginal MET-hours, the physical activity level of adults who are doing more than 5.75 marginal MET-hours per week is unchanged; Whisker plots indicate 95% uncertainty intervals; LE = life expectancy; IHD = ischaemic heart disease

Total incident cases decreased for all six diseases, although the 95% uncertainty intervals included zero for dementia and colon cancer. Estimates of the decrease in person-years lived with disease were considerably smaller than estimates made using comparative risk assessment methods (labelled "person-years with disease (unchanged LE)" and shown in yellow, Figure 6.1). The differences were particularly marked for IHD, dementia, colon cancer and breast cancer.

6.3 Results for all adults increase physical activity

The estimated increases in life expectancy for the 'all adults increase PA' scenarios are shown in Table 6.1. The increases in life expectancy for 'all adults increase PA" by 150 and by 225 minutes of walking per week were greater than the increase observed for the scenario 'all adults meeting PA guidelines'. The increase in life expectancy for 75 minutes per week walking was similar to the increase observed for the 'all adults meeting PA guidelines' scenario.

Changes in person-years with disease and total incident cases for the 'everyone increase' scenarios are shown in Figure 6.2. Broadly, the pattern of results (i.e. comparing the relative changes between diseases, and relative changes between indices of healthcare need) was similar across the different scenarios. The one noticeable difference between the 'all adults increase PA' scenarios and 'all adults meeting PA guidelines' scenario was the estimate of the change in person-years lived with breast cancer (a small decrease for all three scenarios of 'all adults increase PA' and a small increase under the 'all adults meeting PA guidelines' scenario, although for all scenarios the uncertainty interval included zero).

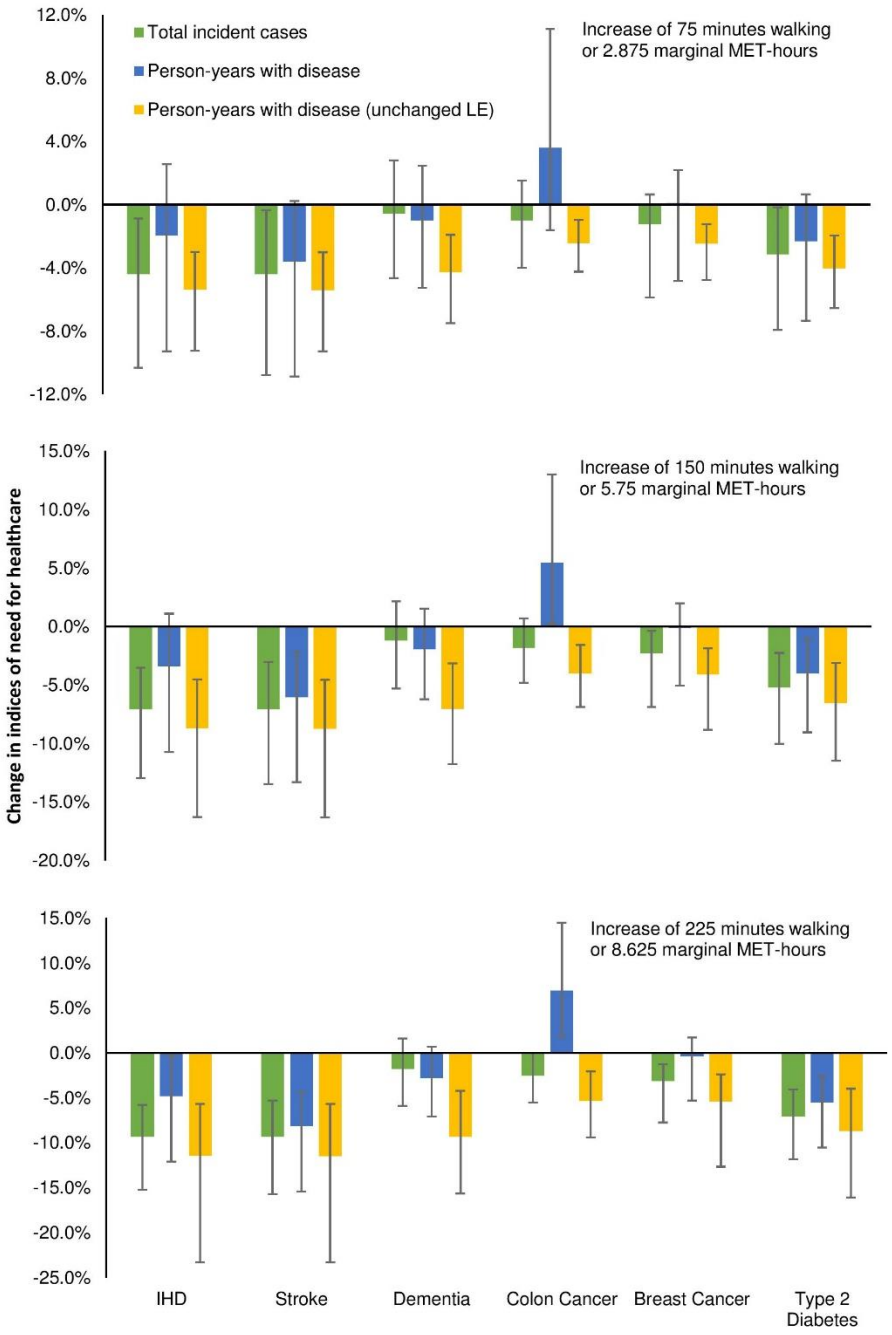
Table 6.1 Estimated increase in life expectancy under three 'all adults increase PA' scenarios of an increase in physical activity

	Increase in life expectancy at birth (days)		
Scenario	**'All adults increase PA' (75 mins walking)**	**'All adults increase PA' (150 mins walking)**	**'All adults increase PA' (225 mins walking)**
Women	96 (71-123)	154 (111-201)	203 (143-274)
Men	86 (60-117)	138 (93-194)	182 (119-262)
Combined	91 (66-119)	147 (103-197)	193 (133-267)

95% uncertainty intervals shown in brackets; the everyone increase scenario assumes that all adults increase their physical activity by the same amount, respectively 2.875 marginal MET-hours, 5.75 marginal MET-hours and 8.625 marginal MET-hours; these increases are equivalent to an additional 75 minutes, 150 minutes and 225 minutes respectively of walking at 3mph on flat ground (3.3 MET) per week.

The absolute magnitude of the changes varies between the scenarios. The largest changes were observed for the increase of 225 minutes of walking per week, and the smallest changes were observed for the increase of 75 minutes of walking per week.

Figure 6.2 Effect of all adults increasing physical activity on change in indices of need for healthcare



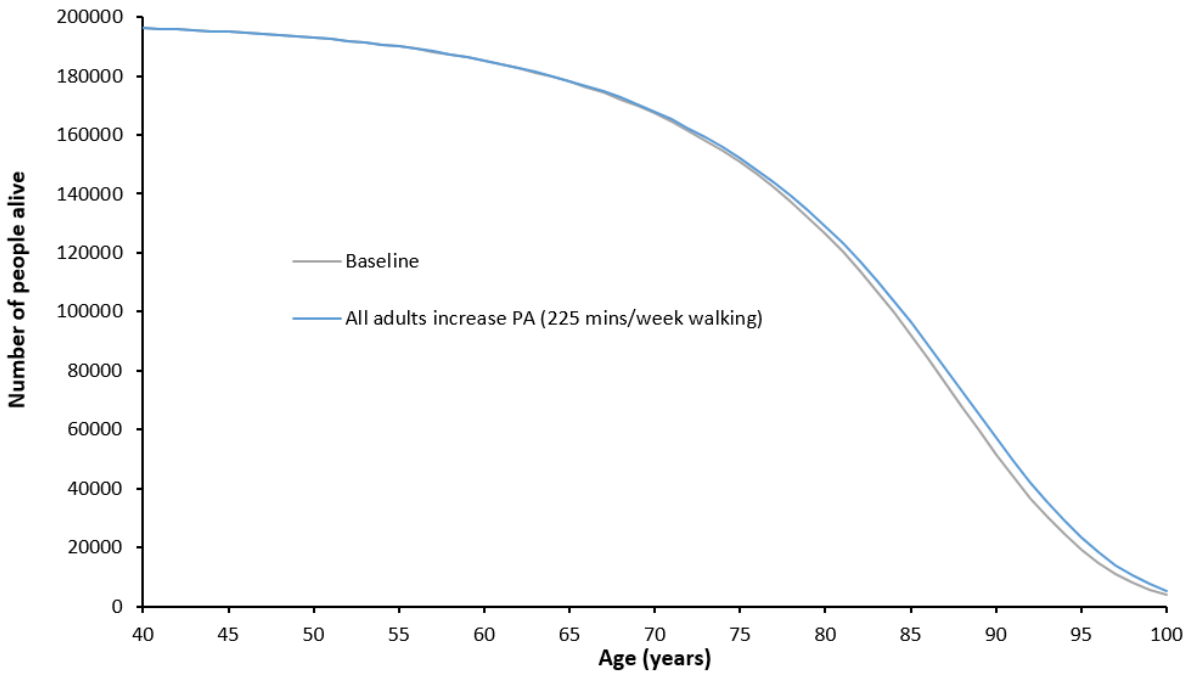
The 'all adults increase PA' scenarios assumes that all adults increase their physical activity by the same amount equal to 2.875 marginal MET-hours, 5.75 marginal MET-hours and 8.625 marginal MET-hours; these increases are equivalent to an additional 75 minutes, 150 minutes and 225 minutes respectively of walking at 3mph on flat ground (3.3 MET); Whisker plots indicate 95% uncertainty intervals; LE = life expectancy; IHD = ischaemic heart disease.

6.4 Change in incidence, prevalence an incident cases by age

I display results by age for only one scenario, 'all adults increase PA' by 225 minutes of walking per week. The pattern of changes observed was similar for other scenarios. However, the absolute changes were greatest for this scenario, and consequently the visual differences between baseline and the scenario in the displayed figures are more apparent.

The number of people alive by age is shown in Figure 6.3. It was only at older ages that the baseline and 'all adults increase PA' curves visibly departed. Incidence and prevalence by age are shown in Figure 6.4 and Figure 6.5. Incidence was lower under the scenario of increased physical activity, labelled 'all adults increase PA (225 minutes)' at all ages for all diseases. Prevalence was lower under the scenario of increased physically at all ages for stroke, type 2 diabetes and dementia.

Figure 6.3 Number of people alive by age comparing baseline and the scenario of all adults increase PA by 225 minutes walking per week



Baseline scenario = no change in physical activity; the 'all adults increase PA (225 mins walking) scenario assumes that all adults increase their physical activity by the same amount equal to 8.625 marginal MET-hours (equivalent to an additional 225 minutes of walking at 3mph on flat ground (3.3 MET) per week).

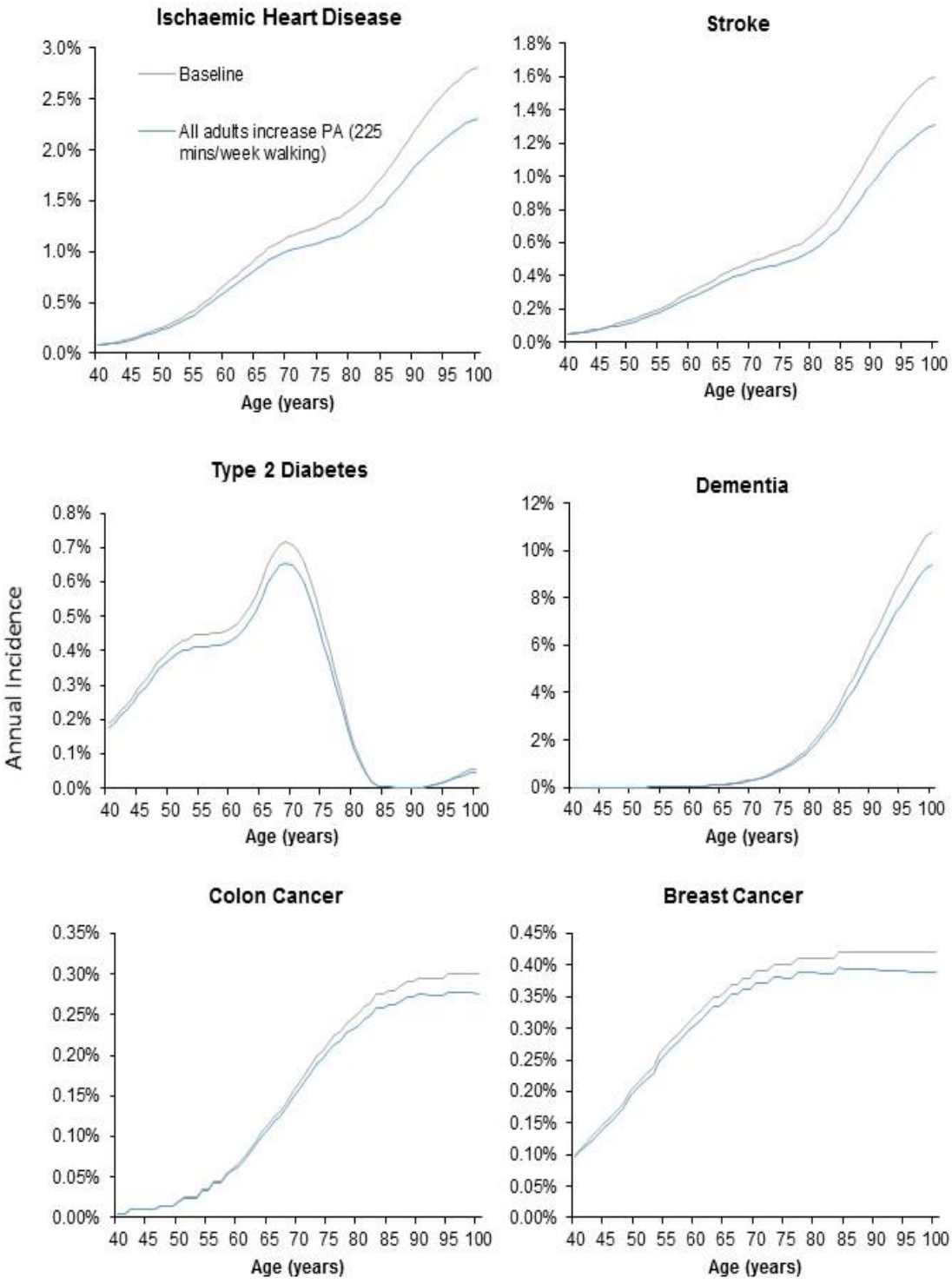
However, for the diseases for which physical activity was modelled to have a direct effect on disease survival (i.e. colon cancer, breast cancer and ischaemic heart disease), prevalence was higher under the scenario of increased physical activity compared to baseline for some age groups. For example, the prevalence of colon cancer and ischaemic heart disease under the scenario of increased physical

activity was higher relative to baseline at older ages (above 75 years for colon cancer; and above 90 years for ischaemic heart disease). Differences in prevalence comparing baseline with increased physical activity were slight for breast cancer.

The number of incident cases and number of people living with disease by age are shown in Figure 6.6 and Figure 6.7 respectively. The number of incident cases is the product of the number of people alive (Figure 6.3) and incidence (Figure 6.4). Whilst the number of people living with disease by age is the product of the number of people alive (Figure 6.3) and prevalence (Figure 6.5). In contrast to incidence (shown in Figure 6.4), incident cases peaked and declined with age. Moreover, for some diseases (e.g. dementia) the number of incident cases at older ages was greater under the scenario of increased physical activity compared with the baseline scenario.

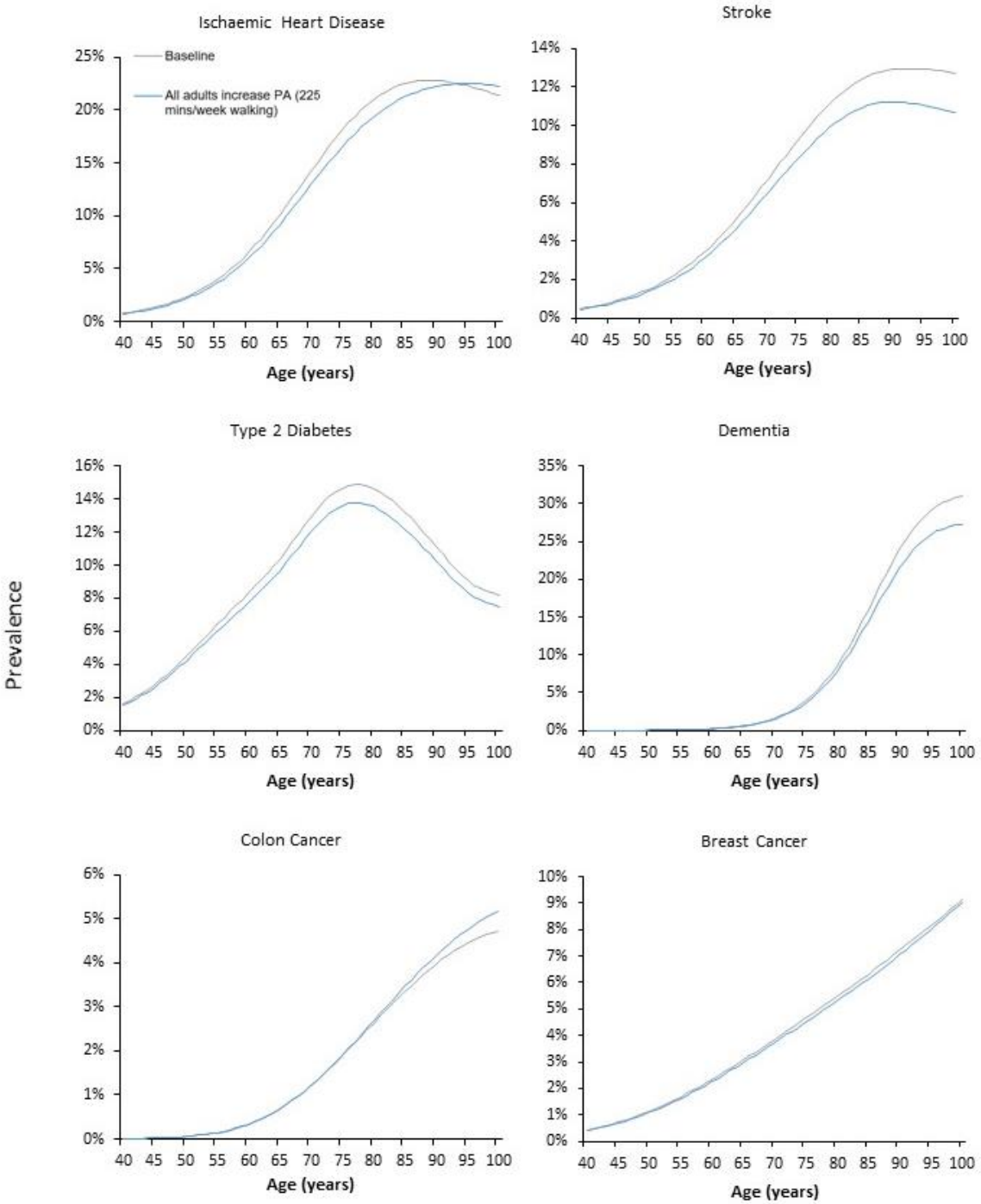
Number of people living with disease peaked with age and then declined, whilst for most diseases the prevalence increased with age. At older ages the number of people living with disease (a product of prevalence and number of people alive) is similar comparing increased physical activity with baseline. In some instances, (e.g. dementia above 90 years of age, breast cancer above 85 years of age) the number of people living with disease increased with increased physical activity.

Figure 6.4 Disease incidence by age comparing baseline with all adults increasing physical activity by the equivalent of additional 225 minutes walking per week



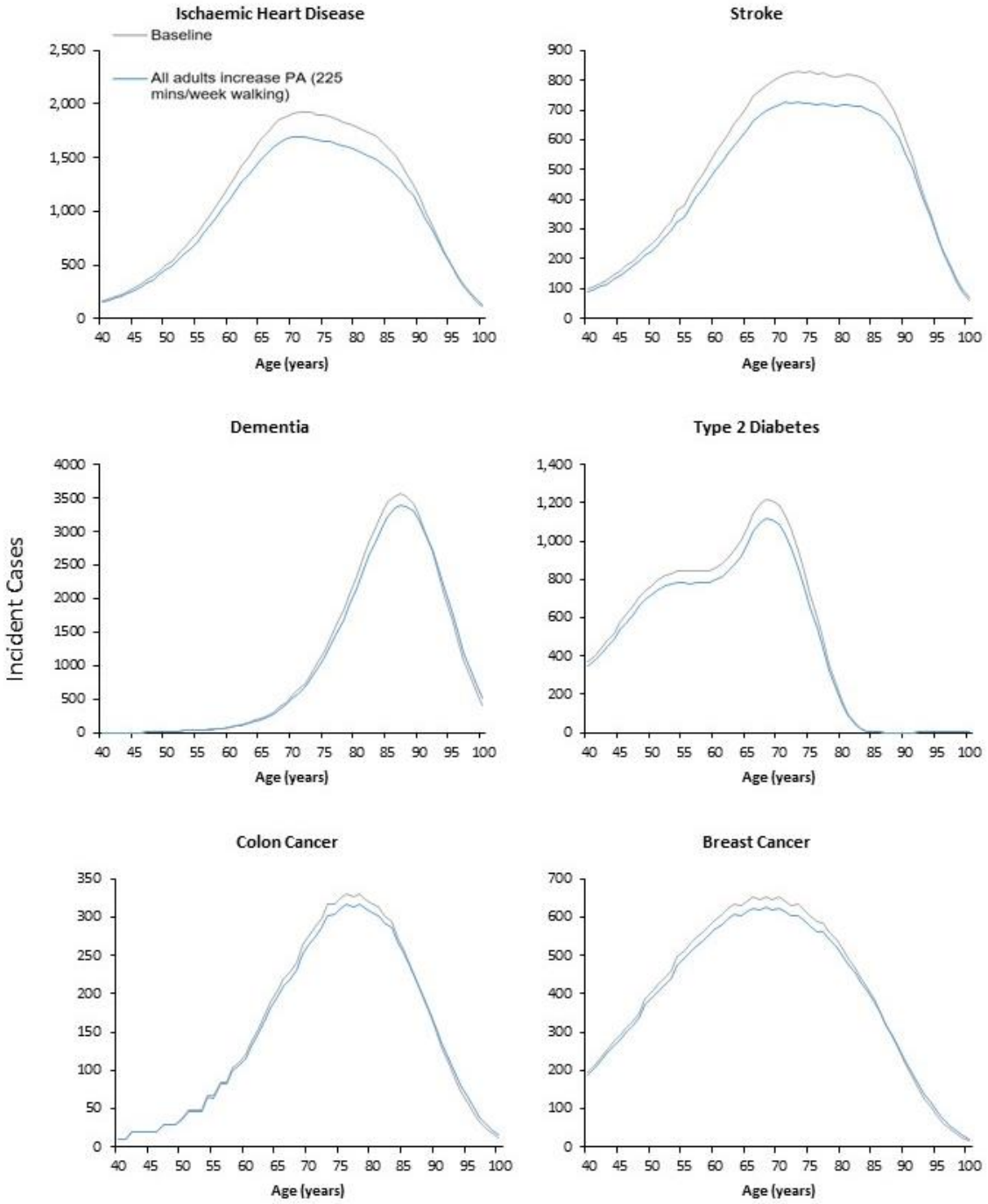
Baseline scenario = no change in physical activity; the all adults increase PA scenario assumes that all adults increase their physical activity by the same amount equal to 8.625 marginal MET-hours (equivalent to an additional 225 minutes of walking at 3mph on flat ground (3.3 MET) per week).

Figure 6.5 Disease prevalence by age comparing baseline with all adults increasing physical activity by the equivalent of additional 225 minutes walking per week



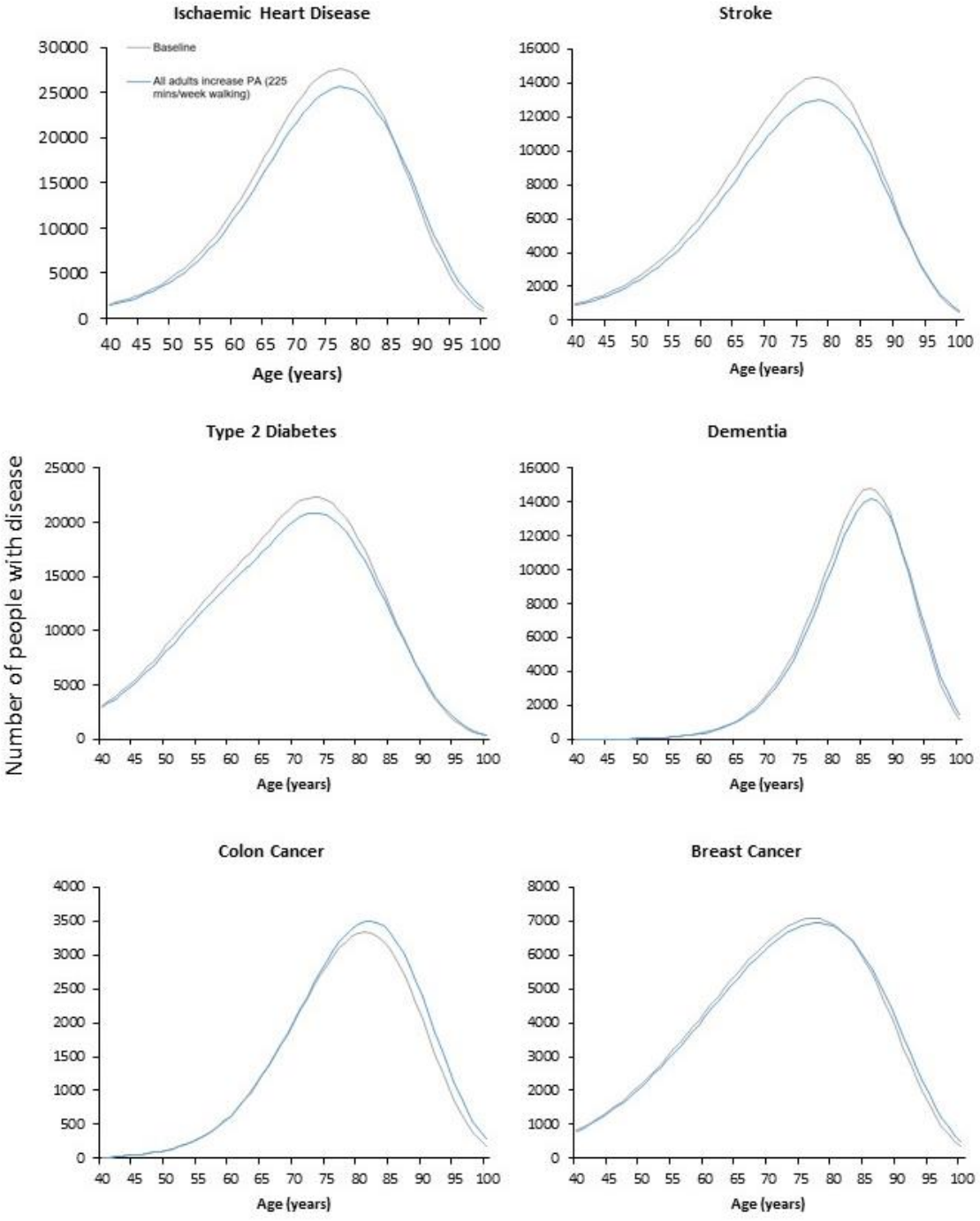
Baseline scenario = no change in physical activity; the all adults increase PA scenario assumes that all adults increase their physical activity by the same amount equal to 8.625 marginal MET-hours (equivalent to an additional 225 minutes of walking at 3mph on flat ground (3.3 MET) per week).

Figure 6.6 Incident cases by age comparing baseline with all adults increasing physical activity by the equivalent of additional 225 minutes walking per week



Baseline scenario = no change in physical activity; the all adults increase PA scenario assumes that all adults increase their physical activity by the same amount equal to 8.625 marginal MET-hours (equivalent to an additional 225 minutes of walking at 3mph on flat ground (3.3 MET) per week).

Figure 6.7 Number of people living with disease comparing baseline with all adults increasing physical activity by the equivalent of additional 225 minutes walking per week



Baseline scenario = no change in physical activity; the all adults increase PA scenario assumes that all adults increase their physical activity by the same amount equal to 8.625 marginal MET-hours (equivalent to an additional 225 minutes of walking at 3mph on flat ground (3.3 MET) per week).

6.5 Estimates of mean age of disease onset

Figure 6.6 shows that disease events are postponed (and/or prevented). Estimates of the change mean age of disease onset are shown in Table 6.2. Generally, these show that disease onset is deferred. However, these estimates are based only on the people who develop disease and it is noticeable that some estimates are negative (i.e. earlier age of onset), despite an apparent rightwards shift of the related curves (e.g. Figure 6.6).

Table 6.2 Change in mean age of disease onset

	Change in mean age of onset (days)			
Scenario	**'All adults meeting PA guidelines'**	**'All adults increase PA (75 mins walking'**	**'All adults increase PA (150 mins walking)'**	**'All adults increase PA (225 mins walking)'**
IHD	**-52 (-87 to -18)**	5 (-37 to 80)	22 (-37 to 155)	39 (-35 to 224)
Stroke	-40 (-93 to 14)	23 (-32 to 98)	50 (-26 to 178)	76 (-18 to 249)
Type 2 Diabetes	**76 (54 to 100)**	**79 (55 to 108)**	**127 (85 to 185)**	**168 (110 to 254)**
Dementia	**39 (3 to 70)**	**47 (14 to 74)**	**77 (28 to 126)**	**102 (40 to 172)**
Breast Cancer	23 (-4 to 51)	**39 (18 to 65)**	**66 (33 to 114)**	**89 (46 to 158)**
Colon Cancer	**-39 (-67 to -16)**	-16 (-43 to 10)	-21 (-55 to 21)	-24 (-62 to 31)

All adults meeting PA guidelines scenario assumes that all adults who are not presently doing 5.75 marginal MET-hours of physical activity (equivalent to 150 minutes of walking at 3mph on flat ground (3.3 MET) per week) increase their physical activity to 5.75 marginal MET-hours, the physical activity level of adults who are doing more than 5.75 marginal MET-hours per week is unchanged; the all adults increase PA scenario assumes that all adults increase their physical activity by the same amount, respectively 2.875 marginal MET-hours, 5.75 marginal MET-hours and 8.625 marginal MET-hours; these increases are equivalent to an additional 75 minutes, 150 minutes and 225 minutes respectively of walking at 3mph on flat ground (3.3 MET); IHD = ischaemic heart disease; 95% uncertainty intervals shown in brackets; bold type indicates that the uncertainty intervals do not overlap with zero.

6.6 Sensitivity analyses

Sensitivity analyses were performed only on the primary scenario ('all adults meeting PA guidelines').

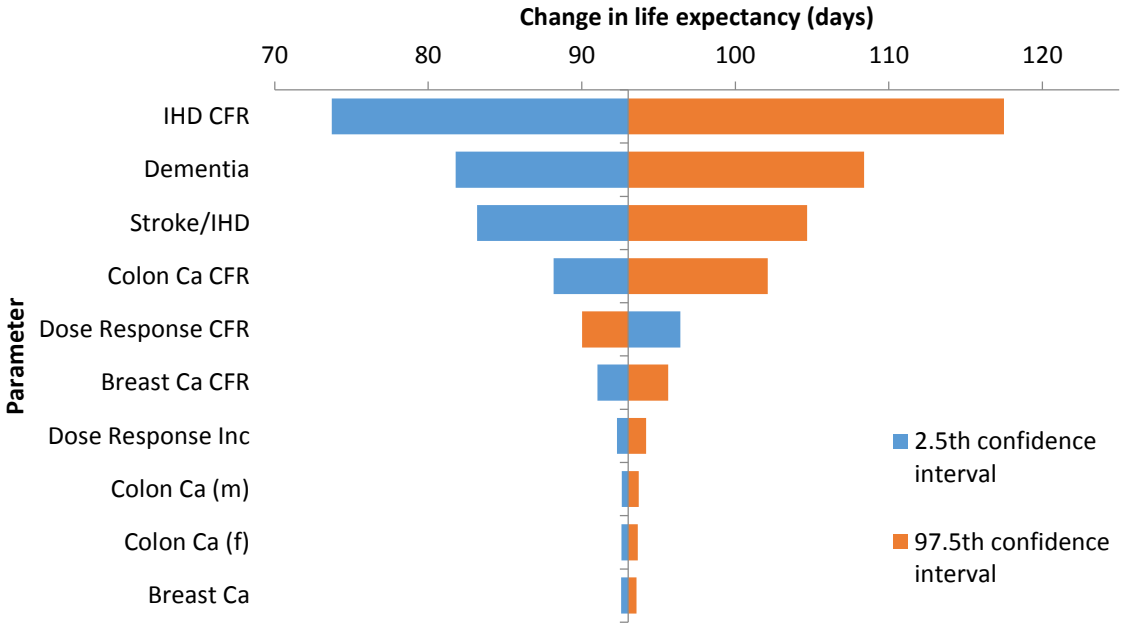
6.6.1 Tornado Plots

The effect of parametric uncertainty on estimates of changes in life expectancy (comparing baseline with 'all adults meeting PA guidelines' scenario) is shown in Figure 6.8. Uncertainty in estimates of the effect of physical activity on case fatality (for both ischaemic heart disease and colon cancer) were relatively important, as was uncertainty in the estimates of incidence for dementia and ischaemic heart diseases.

The effects of parametric uncertainty on estimates of changes in person-years lived with disease (comparing baseline with 'all adults meeting PA guidelines' scenario) is shown in Figure 6.9. Of note, the range of estimates of the change in person-years lived with ischaemic heart disease crossed zero for two parameters (relative risk of ischaemic heart disease/stroke incidence for physical activity, and relative risk of case fatality of ischaemic heart disease for physical activity). In other words, an increase in the person-years lived with ischaemic heart disease is a possible outcome, given the published uncertainty for these parameters. A similar pattern was exhibited for dementia for the following parameters, relative risk of dementia incidence, relative risk of ischaemic heart disease case fatality and the power transformation describing the log linear relationship between physical activity and disease risk.

The effects of parametric uncertainty on estimates of changes in incident cases (comparing baseline with 'all adults meeting PA guidelines' scenario) is shown in Figure 6.10.

Figure 6.8 Tornado plot showing the effect of parametric uncertainty on estimates of change in life expectancy (baseline vs 'all adults meeting PA guidelines')



Stroke/IHD = relative risk of stroke incidence and ischaemic heart disease incidence for physical activity; Dementia = relative risk of dementia incidence for physical activity; Colon Ca (m) = relative risk of colon cancer incidence amongst men for physical activity; Colon Ca (w) = relative risk of colon cancer inci

dence amongst women for physical activity; Breast Ca = relative risk of breast cancer incidence amongst women for physical activity; Diabetes = relative risk of type 2 diabetes incidence for physical activity; IHD CFR = relative risk of mortality amongst people with diagnosed IHD for physical activity; Breast Ca CFR = relative risk of mortality amongst women with diagnosed breast cancer for physical activity; Colon Ca CFR = relative risk of mortality for people with diagnosed colon cancer for physical activity; Dose response inc = log linear power transformation for association between physical activity and disease incidence; Dose response CFR = log linear power transformation for association between physical activity and mortality from disease (either IHD, colon cancer or breast cancer); baseline = no change in physical activity; 'All adults meeting PA guidelines' scenario assumes that all adults who are not presently doing 5.75 marginal MET-hours of physical activity (equivalent to 150 minutes of walking at 3mph on flat ground (3.3 MET) per week) increase their physical activity to 5.75 marginal MET-hours, the physical activity level of adults who are doing more than 5.75 marginal MET-hours per week is unchanged. Tornado plots are a special type of bar chart, where the bars are arranged horizontally and in order of bar size, typically with the largest bar at the top and the smallest bar at the bottom so that the diagram forms a visual 'tornado'. Tornado plots are a common means to undertake 'deterministic sensitivity analyses', where the relative importance of variation in different parameters is compared. Used in this way each bar represents the range of outcome values expected consistent with the reported or described uncertainty for the given input. The inputs whose uncertainty contributes most to uncertainty in the outcome will have the largest bars and thus be at the top of the diagram. The tornado plot is centred around the mid-point (median) estimate for all parameters.

Figure 6.9 Tornado plots showing the effect of parametric uncertainty on estimates of change in person-years lived with disease (baseline vs 'all adults meeting PA guidelines')

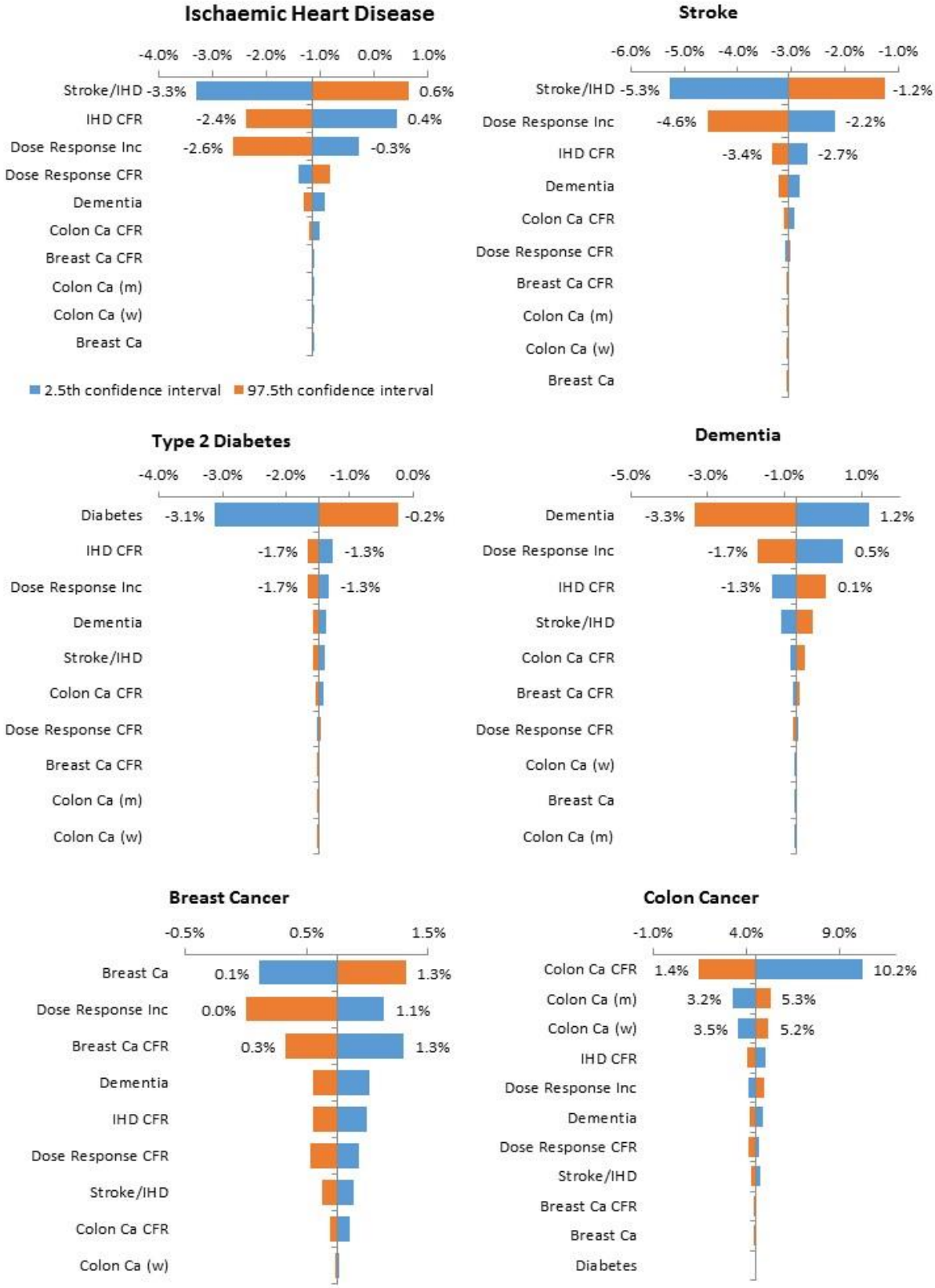
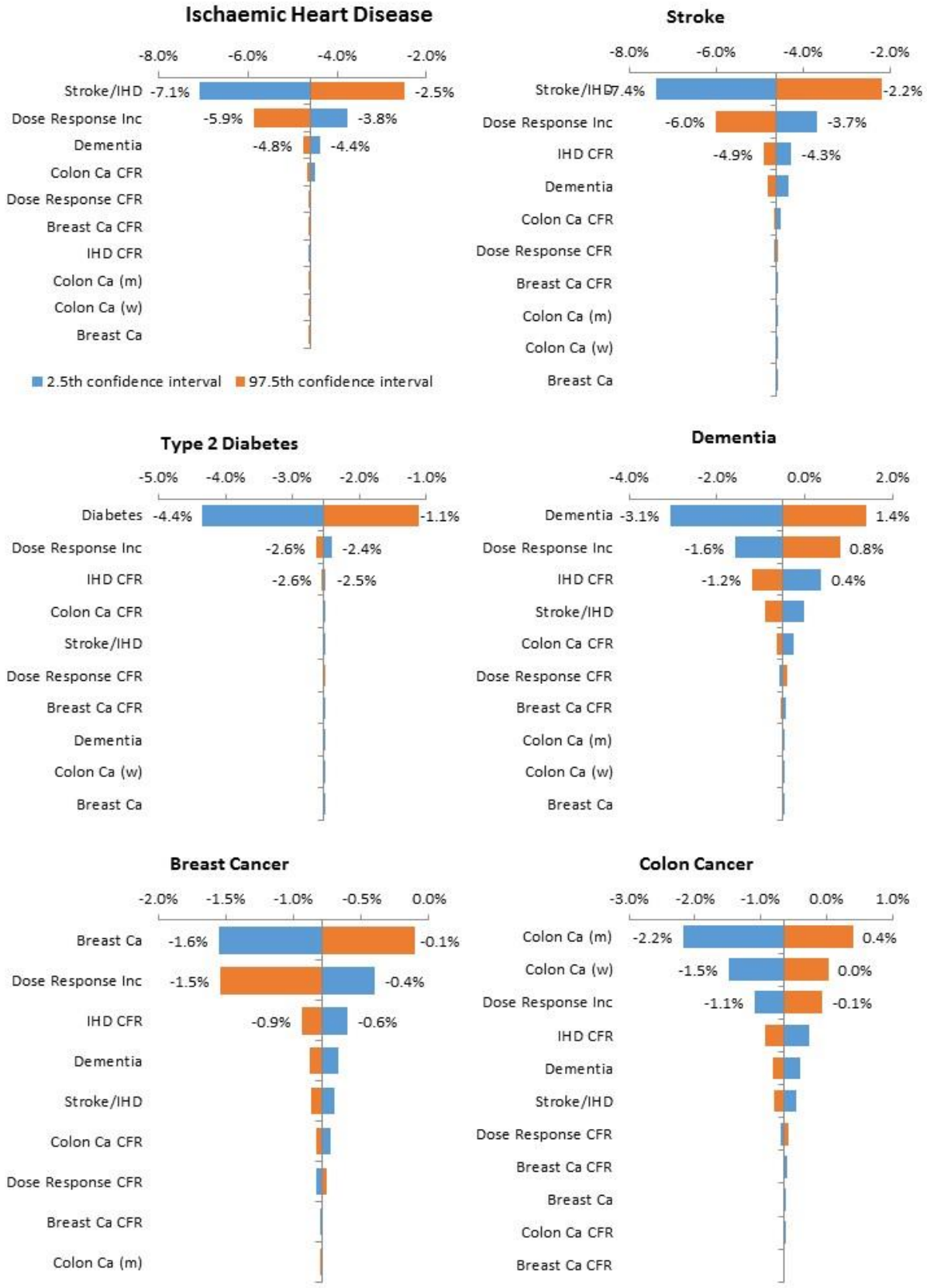


Figure 6.10 Tornado plots showing the effect of parametric uncertainty on estimates of change in incident cases (baseline vs 'all adults meeting PA guidelines')



Footnote for Figure 6.9 and Figure 6.10

Stroke/IHD = relative risk of stroke incidence and ischaemic heart disease incidence for physical activity; Dementia = relative risk of dementia incidence for physical activity; Colon Ca (m) = relative risk of colon cancer incidence amongst men for physical activity; Colon Ca (w) = relative risk of colon cancer incidence amongst women for physical activity; Breast Ca = relative risk of breast cancer incidence amongst women for physical activity; Diabetes = relative risk of type 2 diabetes incidence for physical activity; IHD CFR = relative risk of mortality amongst people with diagnosed IHD for physical activity; Breast Ca CFR = relative risk of mortality amongst women with diagnosed breast cancer for physical activity; Colon Ca CFR = relative risk of mortality for people with diagnosed colon cancer for physical activity; Dose response inc = log linear power transformation for association between physical activity and disease incidence; dose response CFR = log linear power transformation for association between physical activity and mortality from disease (either IHD, colon cancer or breast cancer); baseline = no change in physical activity; 'All adults meeting PA guidelines' scenario assumes that all adults who are not presently doing 5.75 marginal MET-hours of physical activity (equivalent to 150 minutes of walking at 3mph on flat ground (3.3 MET) per week) increase their physical activity to 5.75 marginal MET-hours, the physical activity level of adults who are doing more than 5.75 marginal MET-hours per week is unchanged. Tornado plots are a special type of bar chart, where the bars are arranged horizontally and in order of bar size, typically with the largest bar at the top and the smallest bar at the bottom so that the diagram forms a visual 'tornado'. Tornado plots are a common means to undertake 'deterministic sensitivity analyses', where the relative importance of variation in different parameters is compared. Used in this way each bar represents the range of outcome values expected consistent with the reported or described uncertainty for the given input. The inputs whose uncertainty contributes most to uncertainty in the outcome will have the largest bars and thus be at the top of the diagram. The tornado plot is centred around the mid-point (median) estimate for all parameters.

6.6.2 Structural Uncertainty

Results for the five structural variants of the model, together with the original or standard model, are summarised in

Table 6.3. Results for the mortality variant (or mortality model) were noticeably different compared to the standard model. These results are therefore discussed separately and presented first.

6.6.2.1 Mortality Model

Results for the mortality model are show in In general estimates of change shifted towards being more positive (i.e. decreases became smaller decreases or became increases; increases became larger). The extent of this shift tended to be more marked for change person-years with disease than for change in incident cases. It was also particularly marked for dementia, for which estimates of change in person-years with dementia and change in incident cases switched from small decreases to modest increases (change in incident cases, -0.4% using the standard model vs 3.3% using the mortality model; change in person-years, -0.6% vs 2.8%).

6.6.2.2 Other model variants

With the exception of the mortality variant, broadly the relative pattern of results between indices is similar under each variant of the original model (Table 6.3). The relatively large differences in the estimate of change in person-years lived with disease using the life table method (that allowed life expectancy to change) compared with comparative risk assessment method (that assumed life expectancy was unchanged) persisted across all model variants.

Compared to the standard model the first variant, labelled ‘cancer survival (no effect)’, the increase in life expectancy was reduced by 11 days. The estimated large increase in person-years lived with colon cancer was attenuated when no effect of physical activity on cancer survival was modelled, such that uncertainty intervals included zero, and the point estimate for breast cancer changed from a small increase to a small decrease (uncertainty intervals including zero). Other measures of change in disease burden were very similar, compared to the standard model.

Compared to the standard model the second variant, labelled ‘no lag’, the increase in life expectancy was increased by 20 days. Measures of disease burden were principally different for dementia, breast cancer and colon cancer, i.e. the diseases for which long lag are assumed in the standard model.

Compared to the standard model, the third variant, labelled 'leisure only', the increase in life expectancy was increased by 20 days. Measures of disease burden were noticeably different for all diseases. In general measures of the disease burden that were negative became greater (i.e. more negative), and measure of disease burden that were positive also become greater. The exception to this pattern was breast cancer. The change in person-years lived with breast cancer was 0.8% under the standard model and decreased to 0.3% under the 'leisure only' variant.

Compared to the standard model, the fourth variant, labelled 'cancer incidence', the increase in life expectancy was 6 days greater. Under this variant, it was assumed that physical affected the incidence of lung cancer, prostate cancer and pancreatic cancer. The change in incident cases of these cancers was negative under this variant, whereas it was positive under the standard model. The change in person-years lived with lung cancer and pancreatic cancer was negative, where as it was positive for prostate cancer.

The fifth variant, the mortality model, was discussed previously (section 6.6.2.1). Compared to the other variants it is noticeable that the increase in life expectancy, relative to the standard model was much greater, 103 days, whereas the changes were of the order of 5-20 days for the other variants. Changes in other measures of disease burden were also large, although not always larger than changes observed with other variants.

Figure 6.11 Figure 6.11 and (alongside other findings, including the 'standard model') and in Table 6.3. Increases in life expectancy using the mortality model were approximately twice as great compared with the standard model (198 days vs 95 days). The direction of change for some indices of need for healthcare was different from that observed with the standard model. In contrast to the standard model, change in person-years lived with dementia and change in incident cases of dementia were both positive, although the uncertainty intervals included zero. Also in contrast to the standard model, there was a small increase in person-years lived with ischaemic heart disease (uncertainty interval includes zero). The increase in person-years lived with breast cancer was larger than in the standard and the uncertainty intervals no longer included zero.

In general estimates of change shifted towards being more positive (i.e. decreases became smaller decreases or became increases; increases became larger). The extent of this shift tended to be more marked for change person-years with disease than for change in incident cases. It was also particularly marked for dementia, for which estimates of change in person-years with dementia and change in incident cases switched from small decreases to modest increases (change in incident

cases, -0.4% using the standard model vs 3.3% using the mortality model; change in person-years, -0.6% vs 2.8%).

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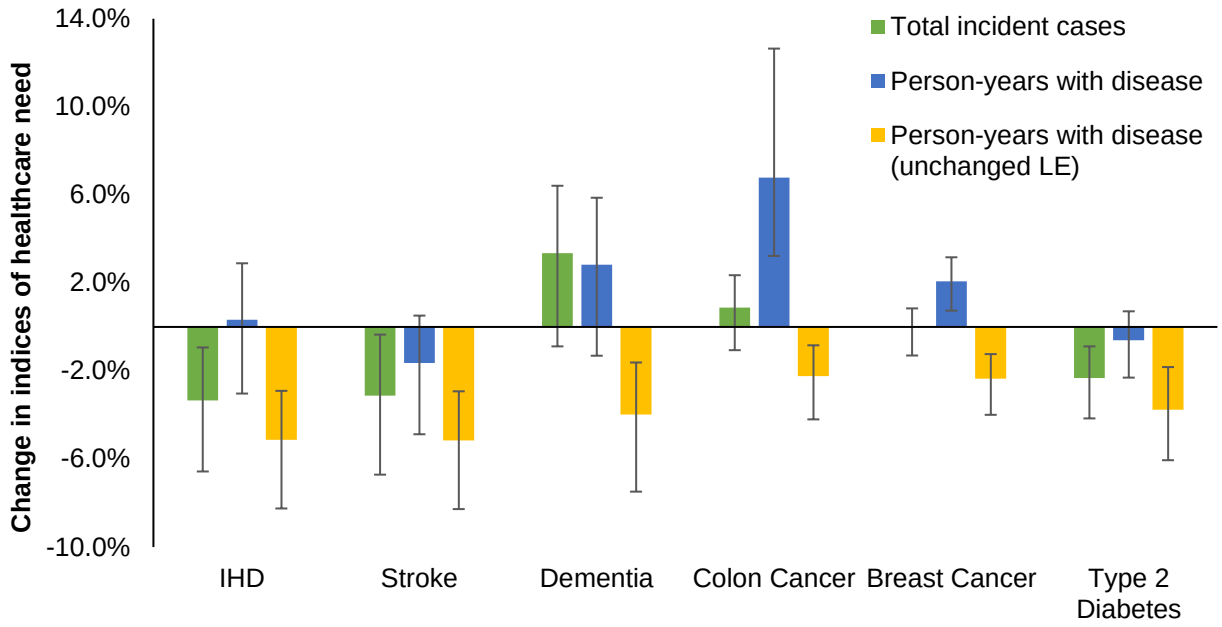
Figure 6.11 Estimates of change in indices of healthcare need under the 'all adults meeting PA guidelines' scenario using the mortality model



All adults meeting PA guidelines scenario assumes that all adults who are not presently doing 5.75 marginal MET-hours of physical activity (equivalent to 150 minutes of walking at 3mph on flat ground (3.3 MET) per week) increase their physical activity to 5.75 marginal MET-hours, the physical activity level of adults who are doing more than 5.75 marginal MET-hours per week is unchanged; Whisker plots indicate 95% uncertainty intervals; LE = life expectancy; IHD = ischaemic heart disease

Table 6.3 Results summary for different 'structural' configurations of the model under the 'all adults meeting PA guidelines' scenario

	Original Model	Model Variant				
		Cancer survival (no effect)	No lag	Leisure only	Cancer incidence	Mortality
Increase in LE (days)						
Women	**101 (75-131)**	**85 (60-115)**	**126 (92-170)**	**128 (95-164)**	**106 (79-138)**	211 (160-269)
Men	**89 (61-123)**	**82 (54-117)**	**103 (72-141)**	**115 (82-154)**	**95 (67-130)**	183 (137-237)
All	**95 (69-126)**	**84 (58-115)**	**115 (83-153)**	**115 (83-153)**	**101 (74-133)**	198 (162-236)
Change in total incidence cases (%)						
IHD	**-4.6 (-7.6 to -2.4)**	**-4.7 (-7.7 to -2.5)**	**-4.8 (-8.0 to -2.4)**	**-6.0 (-9.3 to -3.2)**	**-4.5 (-7.6 to -2.3)**	**-3.3 (-6.6 to -0.9)**
Stroke	**-4.6 (-7.9 to -2.1)**	**-4.7 (-8.1 to -2.2)**	**-4.8 (-8.3 to -2.0)**	**-6.0 (-9.7 to -2.8)**	**-4.5 (-7.8 to -1.9)**	**-3.1 (-6.7 to -0.3)**
Type 2 Diabetes	**-2.5 (-4.4 to -1.1)**	**-2.6 (-4.4 to -1.1)**	**-2.8 (-4.7 to -1.2)**	**-4.0 (-6.6 to -1.9)**	**-2.5 (-4.3 to -1.1)**	**-2.3 (-4.2 to -0.9)**
Dementia	-0.4 (-3.6 to 1.9)	-0.7 (-3.9 to 1.6)	-2.2 (-7.2 to 1.2)	-0.8 (-4.9 to 2.0)	-0.2 (-3.4 to 2.1)	3.3 (-0.9 to 6.4)
Breast Cancer	-0.8 (-2.0 to 0.0)	-0.8 (-2.1 to 0.0)	**-1.6 (-3.3 to -0.3)**	**-1.6 (-3.3 to -0.3)**	-0.7 (-2.0 to 0.1)	0.9 (-1.1 to 2.3)
Colon Cancer	-0.6 (-2.5 to 0.8)	-0.7 (-2.5 to 0.7)	-1.7 (-4.6 to 0.5)	-1.3 (-4.0 to 0.7)	-0.5 (-2.4 to 0.9)	0.0 (-1.3 to 0.8)
Lung Cancer	**1.5 (1.1 to 2.0)**	**1.1 (0.8 to 1.5)**	**1.9 (1.3 to 2.5)**	**1.9 (1.4 to 2.5)**	-0.7 (-1.8 to 0.3)	**2.6 (2.1 to 3.1)**
Prostate Cancer	**1.3 (0.9 to 1.7)**	**1.4 (0.9 to 1.9)**	**1.5 (1.1 to 2.1)**	**1.6 (1.2 to 2.1)**	0.5 (-0.3 to 1.2)	**3.1 (2.6 to 3.7)**
Pancreatic Cancer	**1.7 (1.2 to 2.2)**	**1.5 (1.0 to 2.1)**	**2.1 (1.5 to 2.7)**	**2.1 (1.6 to 2.8)**	-2.0 (-8.1 to 1.4)	**3.4 (2.8 to 4)**
Change in person-years with disease (%)						
IHD	-1.2 (-4.2 to 1.4)	-1.3 (-4.5 to 1.3)	-1.1 (-4.5 to 1.6)	-2.5 (-6.1 to 0.7)	-1.0 (-4.3 to 1.5)	0.3 (-3.0 to 2.9)
Stroke	**-3.1 (-6.0 to -1.1)**	**-3.2 (-6.1 to -1.2)**	**-3.1 (-6.3 to -1.0)**	**-4.7 (-8.1 to -2.0)**	**-3.0 (-5.9 to -1.0)**	-1.6 (-4.9 to 0.5)
Type 2 Diabetes	**-1.5 (-3.2 to -0.2)**	**-1.6 (-3.3 to -0.3)**	**-1.5 (-3.3 to -0.1)**	**-2.8 (-5.2 to -0.8)**	**-1.4 (-3.1 to -0.1)**	-0.6 (-2.3 to 0.7)
Dementia	-0.6 (-3.7 to 1.6)	-0.9 (-4.1 to 1.3)	-2.5 (-7.4 to 0.9)	**-1.3 (-5.5 to 1.6)**	-0.4 (-3.6 to 1.8)	2.8 (-1.3 to 5.9)
Breast Cancer	0.8 (-0.50 to 1.7)	-0.1 (-1.3 to 0.6)	0.5 (-1.2 to 1.8)	0.3 (-1.5 to 1.8)	0.8 (-0.4 to 1.8)	**2.1 (0.7 to 3.2)**
Colon Cancer	**4.4 (1.1 to 10.3)**	0.3 (-1.4 to 1.6)	4.1 (-0.1 to 10.2)	**4.9 (0.4 to 11.4)**	**4.6 (1.1 to 10.4)**	**6.8 (3.2 to 12.6)**
Lung Cancer	**1.8 (1.3 to 2.4)**	**1.6 (1.1 to 2.2)**	**2.2 (1.5 to 3.0)**	**2.3 (1.7 to 3.0)**	-0.3 (-1.4 to 0.7)	**3.7 (2.8 to 4.7)**
Prostate Cancer	**1.9 (1.3 to 2.6)**	**1.7 (1.2 to 2.5)**	**2.2 (1.6 to 2.9)**	**2.4 (1.7 to 3.2)**	**1.3 (0.5 to 2.2)**	**3.6 (3.0 to 4.3)**
Pancreatic Cancer	**1.5 (1.1 to 2.0)**	**1.4 (0.9 to 1.9)**	**1.8 (1.3 to 2.4)**	**1.9 (1.4 to 2.5)**	-1.9 (-7.7 to 1.3)	**3.1 (2.5 to 3.7)**
Change in person-years with disease (life expectancy unchanged) (%)						
IHD	**-5.1 (-8.2 to -2.9)**	**-5.1 (-8.2 to -2.9)**	**-5.1 (-8.2 to -2.9)**	**-6.8 (-10.4 to -4.0)**	**-5.1 (-8.2 to -2.9)**	**-5.1 (-8.2 to -2.9)**
Stroke	**-5.2 (-8.3 to -2.9)**	**-5.2 (-8.3 to -2.9)**	**-5.2 (-8.3 to -2.9)**	**-6.9 (-10.4 to -4.0)**	**-5.2 (-8.3 to -2.9)**	**-5.2 (-8.3 to -2.9)**
Type 2 Diabetes	**-3.8 (-6.1 to -1.8)**	**-3.8 (-6.1 to -1.8)**	**-3.8 (-6.1 to -1.8)**	**-5.1 (-8.0 to -2.5)**	**-3.8 (-6.1 to -1.8)**	**-3.8 (-6.1 to -1.8)**
Dementia	**-4.0 (-7.5 to -1.6)**	**-4.0 (-7.5 to -1.6)**	**-4.0 (-7.5 to -1.6)**	**-5.3 (-9.9 to -2.2)**	**-4.0 (-7.5 to -1.6)**	**-4.0 (-7.5 to -1.6)**
Breast Cancer	**-2.4 (-4.0 to -1.2)**	**-2.4 (-4.0 to -1.2)**	**-2.4 (-4.0 to -1.2)**	**-3.2 (-5.2 to -1.7)**	**-2.4 (-4.0 to -1.2)**	**-2.4 (-4.0 to -1.2)**
Colon Cancer	**-2.2 (-4.2 to -0.8)**	**-2.2 (-4.2 to -0.8)**	**-2.2 (-4.2 to -0.8)**	**-3.1 (-5.7 to -1.1)**	**-2.2 (-4.2 to -0.8)**	**-2.2 (-4.2 to -0.8)**
Lung Cancer	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	-2.5 (-3.7 to -1.6)	0 (0 to 0)
Prostate Cancer	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	-1.0 (-0.4 to -2.0)	0 (0 to 0)
Pancreatic Cancer	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	-3.9 (-0.5 to -10.0)	0 (0 to 0)

All adults meeting PA guidelines scenario assumes that all adults who are not presently doing 5.75 marginal MET-hours of physical activity (equivalent to 150 minutes of walking per week) increase their physical activity to 5.75 marginal MET-hours, the physical activity level of adults who are doing more than 5.75 marginal MET-hours per week is unchanged; IHD = ischaemic heart disease; bold type indicates that the uncertainty intervals do not include zero; Outcomes for lung cancer, prostate cancer and pancreatic cancer are included under all variants of the model for comparison. Physical activity only affects the incidence of lung cancer, prostate cancer or pancreatic cancer in the third model described as 'PA effects incidence of other cancers'. In all other models physical activity does not affect the incidence of lung cancer, prostate cancer or pancreatic cancer.

6.7 Chapter summary

This chapter has presented the modelling results for two principle outcomes (change in person-years with disease and change in total incident cases), considering six diseases and two scenarios (all adults meeting PA guidelines and all adults increase PA). Sensitivity analyses (tornado plots and structural changes to the model) have also been presented. A summary of the results is included at the start of the next chapter that discusses the results.

7 Discussion of findings from the modelling study

7.1 Chapter outline

The chapter discusses the modelling results. It begins with a summary of important findings. It then considers study limitations, model validity and draws comparisons with other studies, before offering an interpretation of the findings (including considering why the pattern of results is different for different diseases). Next it considers the implications of the findings for practice and policy. It finishes with some suggestions for future research specific to the work presented. Overarching suggestions for practice, policy and future research are discussed in the final chapter.

7.2 Summary of main findings

Increases in physical activity were associated with improvements in health, namely reduced risk of disease onset, prevention or delay in onset of disease, improved disease-specific survival and increased life expectancy.

Generally, increases in physical activity were associated with decreases in indices of healthcare need for the six diseases considered, for which physical activity is protective. Increases in physical activity were associated with decreases in the number of incident cases for the six diseases considered (under the scenarios considered), although some of these decreases were small and approached zero (e.g. dementia). Increases in physical activity were associated with decreases in the person-years lived with diseases for four diseases (ischaemic heart disease, stroke, dementia and type 2 diabetes, with uncertainty intervals that included zero for ischaemic heart disease and dementia) and increases in the person years lived with colon cancer and breast cancer. In other words, increases in physical activity led to an increase in person-years lived with disease for some diseases, decreases for some diseases and small changes that were close to zero for others.

Estimates of increases in physical activity on decrease in need, using a life table method which made allowance for change in survival, were smaller than similar estimates made using comparative risk assessment methods that did not make allowance for changes in survival. For some diseases these differences were relatively small (e.g. stroke, type 2 diabetes), but for other diseases these differences were relatively large (e.g. dementia) or led to estimates in the opposite direction (e.g. colon cancer).

The pattern of findings, comparing the different indices and comparing between diseases, was broadly similar under different sensitivity analyses, with the exception of the 'mortality model', which effectively modelled a much greater effect of physical activity on all-cause survival. Under these assumptions estimates of change in indices of healthcare need tended to be pulled in the positive direction (i.e. estimates that were negative changed to be less negative or became positive, estimates that were positive changed to be more positive). The sensitivity analyses also confirmed that the direction of change (i.e. increase or decrease) was uncertain for change parameters that were estimated to be close to zero.

7.3 Strengths and limitations

7.3.1 Strengths

The strengths of this study include: the explicit modelling of ageing, modelling the effect of physical activity on mortality through a set of diseases, use of different indices to describe need for healthcare, long period of follow-up, and making allowance for a lag between physical activity and its effect on disease risk. I have also sought to draw explicit comparisons between modelling techniques (life table vs comparative risk assessment).

7.3.2 Limitations

I consider limitations with life table modelling, in the measurement of physical activity in epidemiological studies, in the choice of scenarios considered, in the outcome measures (indices of healthcare need), that affect the diseases considered (cancer, type 2 diabetes), modelling effects in old age, and in assessment of background incidence of disease.

7.3.2.1 Life table model

The principle limitation of the life table modelling that pertains to this work is the assumption of independence (See Chapter Five, section 5.3.2.2).[303] A strict interpretation would suggest that the independence assumptions are violated. All six diseases share a common cause, physical activity, so their incidence is not independent. Moreover, four of the diseases (ischaemic heart disease, stroke, type 2 diabetes and dementia) share the same cardio-metabolic risk factors.

The extent to which violation of this assumption can be tolerated is unclear and is not discussed more widely in the literature.[301–303,326] Other authors have developed similar life table models to the one described here.[301,302,326] The original paper that described the proportional multi-state life table model included an example model with both heart disease and stroke, which shared common risk factors so could not strictly be considered independent.[303] Cross-sectional data shows that, despite sharing common risk factors, the extent to which chronic diseases co-occur above that expected if their probabilities of incidence were truly independent may be relatively slight particularly below the age of 70 years. For example, observed data suggests the combined prevalence of diabetes and acute myocardial infarction is one percentage point higher than suggested by independent probabilities. For other disease pairings such as stroke and acute myocardial infarction the excess is less than half a percentage point.[327]

The excess risk associated with co-occurrence of risk factors or conditions (e.g. excess risk of cardio-vascular mortality for an individual with type 2 diabetes and cardiovascular disease) is implicitly considered within the model. As the estimates of risk are derived for the English population whose underlying risk reflects the distribution, including co-occurrence, of risk factors in the population, small deviations from this are unlikely to be important, but larger deviations may be. For example, if increases in physical activity resulted in the prevalence of diabetes halving, then estimates for cardiovascular case fatality may not be valid as they were estimated on the assumption of a much higher prevalence of diabetes (and consequently of cardiovascular disease co-morbid with diabetes) in the population.

I have modelled a birth cohort from birth to death. I chose to do this partly for simplicity but also partly to consider the full effect of changes in physical activity throughout life. An alternative approach would have been to model a cohort representative of the English population through to death or for a fixed period of time. This might give a different perspective, as well as consider the effect on healthcare need in the short to medium term, which may be a more relevant timeframe for decision makers.

7.3.2.2 Measurement of physical activity

The model depends on quantification of physical activity, both to characterise the simulated population and to describe the relationship between physical activity and disease (based on epidemiological studies). Physical activity dose was quantified using information from questionnaires. However, physical activity questionnaires are subjective, typically biased towards recreational and leisure activities, do not adequately account for intra- and inter-participant variation in intensity and incompletely measure duration of activity. Existing epidemiological studies have tended to treat physical activity as a categorical variable. Translating estimates based on different categories or scales to a continuous measure may have introduced error. Further error may be introduced by comparing across populations if questions were interpreted differently in different settings. Consequently, the quantification of dose of physical activity is likely to be poor. The sensitivity and uncertainty analyses have not considered the effect of these error on the outcomes.

7.3.2.3 Assessment of baseline physical activity levels

I used questionnaire data from the Health Survey for England 2012.[98] I chose to include all forms of physical activity (i.e. leisure, transport, occupation and domestic) when estimating baseline levels of physical activity, in order to consider all physical activity energy expenditure. However, this may have led to relatively high estimates of physical activity levels compared to estimates reported in cohort

studies (and from which estimates of relative risk were derived). This effectively moved some individuals further along the dose-response curve, such that increases in physical activity had less effect on disease reduction.

One of the sensitivity analyses (labelled 'leisure only' and reported Table 6.3) used different estimates of physical activity levels, derived using estimates of leisure-time physical activity reported in the Health Survey for England. Under this assumption the effect of physical activity on the reported outcomes was greater (most estimates being 10-30% greater), although the overall pattern of finding persisted. This scenario may give a more realistic estimate of the effect of increases in physical activity as the estimates of physical activity levels are more consistent with the measurement of physical activity in the studies that have been used to describe the association between physical activity and disease risk. This scenario also serves as an example of how the effect of increases in physical activity might be different if background levels of physical activity were lower.

7.3.2.4 Estimating the relationship between physical activity and disease

Using questionnaires to estimate doses of physical activity will result in measurement error (as discussed above, section 7.3.2.3). In addition, other factors may lead to errors in the estimate of the relationship between physical activity and disease. First the physical activity level that the relative risk corresponded to was estimated from the single largest study contributing to the meta-analysis, rather than a weighted average across all studies.

Second following the approach used in the Integrated Health and Transport Impact Model, I assumed the relationship between physical activity and relative risk was a log linear relationship with a power transformation between 0.25 and 1.0. Whilst this relationship may be broadly consistent with other described relationships, it is different from those used in published meta-analyses for mortality[43,299] and for cardiovascular disease.[44] The tornado plots suggest the magnitude of the power transformation did not have much influence on the observed outcomes, so the modelled relationship may equate to a log linear relationship. A recently published meta-analysis for five of the six diseases (dementia was not included) broadly suggests that modelling the relationship between physical activity and relative risk as log linear was reasonable for colon cancer, breast cancer, ischaemic heart disease, type 2 diabetes and stroke.[110]

At a more fundamental level, there is uncertainty about the true relationship between physical activity and health. I have assumed the relationship between physical activity and health outcomes is dependent on the product of duration and intensity of activities above a certain energy level (3.0 MET). However other facets of physical activity may be important: frequency, type of activity,

context of activity and associated risk, relative (rather than absolute) intensity, low intensity (<3.0 MET) and sedentary activity.

Using the product of duration and intensity implies that doubling the time of physical activity is equivalent to doubling the intensity. If energy expenditure is what drives the association between physical activity and health such a relationship is appropriate. Whilst it seems possible to suggest other relationships, such as product of duration and energy square root, I am not aware that any have been explicitly tested.

I chose to use marginal MET-hours, rather than MET-hours, because it appeared inappropriate to give 'credit' for baseline energy consumption. However I note that MET-hours is increasingly being used.[44,110,299] Using marginal MET-hours effectively gave more weight to high intensity activity over lower intensity activity. For example, using MET-hours, an hour at 6.0 MET is 2 times as much physical activity as an hour at 3.0 MET, but using marginal MET-hours an hour at 6.0 MET becomes an hour at 5.0 marginal MET-hours, and an hour at 3.0 MET and hour at 2.0 marginal MET-hours, which is 2.5 times as much physical activity.

7.3.2.5 Scenarios

I have only explored a small number of scenarios. Whilst the pattern of results for these scenarios was similar some small differences in outcomes between the scenarios were noted. I have not explored other scenarios (e.g. around increases in physical activity during particular life stages such as mid-life), as others have done.[311] I have also assumed uniform increases across the population, which is unlikely to reflect the effect of real interventions, for which uptake and changes in physical activity (both duration and intensity) might be expected to show variability between individuals.

7.3.2.6 Assessment of outcome

I have considered only some measures of healthcare need. I have not considered severity or co-morbid illness, nor have I attempted to translate these epidemiological measures of need into demand for healthcare (e.g. presentations, referrals, procedures, prescriptions) or better indicators of need for social care (e.g. disability). Consideration of disease severity may be particularly important for some diseases, such as colon cancer and ischaemic heart disease. For these diseases increases in physical activity were associated with improved disease-specific survival, which might suggestive the severity of the underlying disease process was also reduced.

I have not considered costs. A full economic appraisal would require decisions to be made about the cost perspective (e.g. healthcare costs or societal costs) and consequently whether to include wider

costs and benefits (e.g. sickness absence and productivity, pension costs, changes in the size of the tax base attributed to a larger population).

Estimates of changes in the mean age of onset only account for those individuals who develop disease. If disease is prevented the estimates of age of onset are calculated for two different groups. One group consisting of those who develop disease under the baseline scenario and a second those who develop disease under the test scenario. The latter group will consist of fewer people because cases of disease were prevented, so is not comparable to the former group. As noted in the results, it is possible for the mean age of onset to fall when graph representing the number of people living with disease by age suggests that disease events are being pushed later into life.

7.3.2.7 Cancer

I have modelled cancer as a chronic disease, and not explicitly modelled recovery or remission. The increase in the person-years lived with colon cancer and breast cancer should thus be treated with some caution. Some of these person-years would be lived free of cancer with limited or no need for cancer related healthcare, although some of those years for some people will be lived in disability. Whilst not the usual metric of cancer burden, cancer prevalence is reported and is based on incident disease and does not account for recovery.[328] Cancer is increasingly seen as a chronic disease because the number of cancer survivors is increasing (around one in two live ten years or longer after diagnosis in the UK) and because many are left with residual symptoms and/or disability after surgical treatment or treatment with radiotherapy or chemotherapy.[329,330]

Data on cancer incidence is taken from cancer registries and given the nature of the reporting systems should be accurate.[279,331] Estimates of incidence are based on "new registrations" of cancer. Generally, events of cancer recurrence are coded as such and linked to the initial registration, although incident cancers in the same organ in cancer survivors can occur and would be counted as a new registration (Personal correspondence with John Broggio, National Cancer Registration and Analysis Service, Public Health England). Consequently the estimates of cancer incidence and prevalence may be slightly over-estimated.

I was also concerned that the assumption that physical activity affected cancer survival might not be realistic. The modelled effect of physical activity on cancer survival came from observational studies,[67,68] and may be prone to bias. Of particular concern in these studies, studying cohorts of patients after a diagnosis of cancer, was confounding by cancer severity. Cancer severity may determine how active people are and how likely they are to die of cancer, a form of confounding by indication.[332] In other words the improved survival reported in observation studies might be

attributable to a less aggressive cancer rather than physical activity. This was handled by undertaking sensitivity analyses where no survival effect was assumed, which markedly reduced the magnitude of the increase in person-years lived with colon cancer and resulted in a small increase in person-years lived with breast cancer changing to a small decrease.

7.3.2.8 Type 2 diabetes

The incidence data and prevalence of type 2 diabetes were inconsistent when entered into DisMod. At older ages, either the estimated incidences produced by DisMod were too low compared to those reported, or the estimated prevalence at older ages was too high. This discrepancy is most likely due to recent changes in the reported incidence of type 2 diabetes, partly reflecting changes in diagnostic practice.

The standardised incidence ratio of type 2 diabetes has risen nearly three-fold in the twenty years since 1990, because of changes in diagnostic practice and a true increase in the underlying incidence of type 2 diabetes.[333] The prevalence in published data reflects historical incidence, which was much lower than current incidence. However, the prevalence in DisMod reflects the current (relatively high) incidence rates, which leads to a high estimate of prevalence. Consequently, the estimates from DisMod and published data were discordant. Alternatively, DisMod could be set to preferentially track the prevalence, but this could only be achieved by estimating lower incidence rates.

If some of the rise in type 2 diabetes incidence is explained by a shift towards earlier diagnosis (or identification of undiagnosed type 2 diabetes), the reported incidence rates may be artificially inflated for a short period of time, i.e. they would appear higher than the true underlying incidence. Reported incidence rates at that level (in the absence of changes in the underlying incidence) would not be sustained. Using such rates would lead to an overestimate of the prevalence (i.e. higher than the underlying disease epidemiology would allow).

Given this and because prevalence rather than incidence is the more usual measure of healthcare need for type 2 diabetes, I chose to bias DisMod towards re-creating the prevalence of type 2 diabetes, accepting that this resulted in a very low (zero) estimate of incidence at older ages. In reality the incidence will be higher than zero, although in contrast to other diseases it does genuinely appear to reduce in old age.[333] The net effect of these assumptions is to bias the model towards to modelling type 2 diabetes as a disease for which physical activity leads to prevention rather than delay in its onset, because there are so few cases in old age. The epidemiology of diabetes (i.e. marked decline in incidence with age) does suggest that type 2 diabetes may be prevented rather

than just be delayed in onset, but the extent to which this happens may be overestimated in the model.

Type 2 diabetes was also modelled differently to other diseases. Type 2 diabetes and cardiovascular disease are not independent, as diabetes is a risk factor for the development of cardiovascular disease.[303] As others have done,[301] I did not model changes in diabetes incidence (from the disease model) through into changes in mortality in the general model (i.e. changes in the incidence of diabetes do not directly result in changes in mortality within the model). This may have underestimated the extent to which physical activity could contribute to changes in mortality. However, the extent of this underestimation may be small. Much excess mortality from type 2 diabetes is explained by cardiovascular disease[334] so may, in part, be modelled through changes in ischaemic heart disease and stroke that arise from changes in physical activity.

I also assumed that physical activity did not affect survival after a diagnosis of type 2 diabetes, and did not model remission from type 2 diabetes. Physical activity may have a role in inducing remission, amongst some patients.[335,336] Modelling different assumptions for these relationships may have altered the magnitude of changes observed for type 2 diabetes, and whilst the pattern observed for type 2 diabetes may be illustrative of how physical activity may affect a disease, one should be cautious about making strong conclusions about the association between changes in physical activity and type 2 diabetes specifically.

7.3.2.9 Lags

The lag between physical activity and development or progression of disease is poorly described, particularly for cancer and dementia. If the lag is much shorter than the lag I modelled this will have implications for the effect of physical activity on the disease burden. If the lag is shorter the influence of physical activity appears to be greater, probably because physical activity declines with age and similar absolute increases in physical activity have a greater effect on relative risk (given the nature of the dose response curve) at older ages when the absolute risk of disease, and disease burden, is greatest.

7.3.2.10 Effect on other diseases

I have primarily focused on the diseases for which physical activity is protective. The effect of increases in physical activity (and resultant increases in life expectancy) on other diseases for which physical activity is not protective will be different. The sensitivity analyses highlight this. For example, both incident cases and person-years lived with prostate cancer, pancreatic and lung cancer are

estimated to increase assuming that physical activity is not associated with incidence of these cancers (Chapter 6, Table 6.3).

Generally, for diseases that are not affected by physical activity if incident cases occur in older age (and particularly if incidence increases with age), then one would expect that as physical activity increases the number of incident cases should increase, because people are living longer. Similarly, the person-years with disease should also increase, partly due to more incident cases but also because of increased all-cause survival amongst those diagnosed with the disease. However, my focus was on considering diseases for which physical activity was protective.

7.3.2.11 Old age

The results should be treated with caution amongst those aged 80 years and over for several reasons. First, there is relatively limited data on disease parameters (incidence and prevalence) beyond age 90 years. Second whilst mortality data is complete to 100 years, the coding of deaths in older age may be less reliable.[337,338] Third, I have assumed that the effect of physical activity on disease incidence is similar (on a relative scale) throughout life, although its effect is much less studied in older age. Fourth, the increases in physical activity modelled in later life may be less achievable, either because of co-morbidities or limited cardiovascular reserve. It is noticeable that measures of physical activity intensity for walking are described in terms of absolute parameters, relating to walking speed, incline or surface. Whilst such parameters may be unattainable for some older people, it is unclear how failure to obtain these levels of intensity affects benefit. I note that physiological responses of the body (e.g. fat burning vs glucose metabolism) to activity depend on relative intensity rather than absolute intensity.[339] Whilst absolute measures of physical activity may be less achievable for older people, it seems conceivable that benefits may not wholly be explained by absolute intensity of activity. Fifth, co-morbidities are more common in older age, and the effect of physical activity on disease risk when there are co-morbidities is not explicitly represented in a proportional life-table model.

7.3.2.12 Background incidence of disease

The model has not accounted for future changes in disease incidence, disease survival or all-cause survival. Background incidence of these parameters has effectively been frozen at the values currently estimated for England. Historical trends suggest some or all of these parameters are likely to change. For example ischaemic heart disease incidence and case fatality have decreased, [340] and life expectancy increased over the past fifty years.[340,341] However, the extent to which past patterns continue in future trends is far from certain. Future changes in risk factors prevalence (e.g. smoking, obesity) and treatment will lead to changes in model parameters, such as ischaemic heart disease

incidence and case fatality. If the decrease in ischaemic heart disease incidence were to continue the effect of physical activity on population ageing might be less, which would affect the life table results.

Consequently, I suggest the results should not read as forecasts as to what would happen from increases in physical activity in England in the future, but rather one should see the work as an exploration of the effect of increases in physical activity on indices of healthcare need (or illumination of how increases in physical activity may affect need for healthcare).[342]

7.4 Model validity: comparisons with other estimates

Alongside limitations one should consider the model's validity, before interpretation of the findings. Although it has been suggested that health impact models should be systematically and explicitly tested for validity, in practice this does not happen.[138] Moreover, I am not aware of any guidance about how such testing should take place.

Validation is not straightforward. Comparison with empirical data may be one approach, but often health impact models are seeking to estimate the effects of interventions that are not empirically observable. Comparisons with other models may appear sensible, but this may result in models replicating mistakes and depends on the comparison model being validated.

My working approach, here, is first to compare model outputs (where possible) with empirical data, which effectively only validates part of the model. Second, I draw comparisons with other models, particularly those which have been validated.

In practice this has meant doing three things. First I have compared model estimates of incidence and prevalence with existing epidemiological parameters. Second I have compared estimates of changes in life expectancy from the model with other published estimates attributed to changes in physical activity. Third I have compared model outputs for changes in population attributable fraction (PAF) or population impact fraction (PIF).

7.4.1 Comparisons of incidence and prevalence

Comparisons of simulated epidemiological parameters (incidence for cancers, prevalence for cardio-metabolic disease) for the six diseases are shown below (Tables 7.1-7.4). Broadly these estimates show good agreement. There are some areas of divergence, e.g. the very high prevalence of dementia above age of 90 years (35.0% in observational data vs 28.4% in simulated data; Table 7.4) and a relatively shallow decline in type 2 diabetes prevalence at ages above 85 years (Table 7.2). These may reflect measurement error (e.g. the 95% confidence for the estimate of dementia prevalence was 28.4% to 42.3%) or it may reflect genuine differences in reconciling epidemiological parameters when underlying disease parameters are changing (e.g. type 2 diabetes, see section 7.3.2.8).

The good agreement, whilst reassuring, is expected as the comparison values were used as inputs to generate incidence and case fatality estimates by age. Given the primary focus of the work is to

explore the effect of changes in physical activity on indices of healthcare need, rather than forecast actual healthcare need, discrepancies between observed and simulated estimates are less important.

Table 7.1 Comparison of observational (Health Survey for England) and simulated estimates of cardiovascular prevalence

Observational Data					Simulated Data				
	Prevalence (%)					Prevalence (%)			
	Ischaemic Heart Disease		Stroke		Age (years)	Ischaemic Heart Disease		Stroke	
Age band (years)	Male	Female	Male	Female		Male	Female	Male	Female
45-54	3.6	1.6	1.5	1.3	**45**	2.4	0.4	1.2	0.4
					50	3.8	0.9	1.9	0.8
55-64	8.6	4.1	4.1	2.4	**55**	6.1	2.0	2.9	1.5
					60	9.2	3.9	4.3	2.6
65-74	15.1	7.5	7.2	4.4	**65**	13.3	7.0	6.1	4.2
					70	18.1	10.7	8.3	6.1
75-84	25.2	17.3	10.9	9.4	**75**	23.0	13.8	10.8	8.0
					80	27.2	15.8	13.2	9.4
85+	31.6	14.4	16.6	9.5	**85**	30.4	16.6	15.3	10.3

Table 7.2 Comparison of observational (National Audit of Primary Care) and simulated estimates of diabetes prevalence

Observational Data			Simulated Data		
	Prevalence (%)			Prevalence (%)	
Age band (years)	Male	Female	Age	Male	Female
30-34	0.6	0.6	30	0.5	0.5
35-39	1.3	0.8	35	1.0	0.8
40-44	2.4	1.4	40	2.0	1.2
45-49	4.2	2.5	45	3.5	2.1
50-54	6.4	4.0	50	5.5	3.5
55-59	8.9	5.6	55	7.9	5.0
60-64	10.7	6.9	60	10.2	6.5
65-69	13.9	9.2	65	12.5	8.4
70-74	16.3	11.8	70	15.2	10.8
75-79	17.5	13.3	75	16.9	12.7
80-84	16.3	12.5	80	16.9	12.8
85-89	13.1	10.3	85	15.5	11.5
90+	9.4	7.5	90	13.3	9.7

Table 7.3 Comparison of observational (cancer registry) and simulated estimates of cancer incidence by age

Observational data				**Simulated data used within model**			
	Incidence (per 100,000 population)				**Incidence (per 100,000 population)**		
Age band (years)	**Colon cancer (females)**	**Colon cancer (males)**	**Breast cancer (females)**	**Age (years)**	**Colon cancer (females)**	**Colon cancer (males)**	**Breast cancer (females)**
40-44	7.5	6.9	119.4	40	10	0	100
45-49	11.7	12.0	214.5	45	10	10	150
50-54	21.9	23.1	273.6	50	20	20	210
55-59	37.6	42.5	270.0	55	40	30	270
60-64	65.9	91.7	343.9	60	70	60	320
65-69	95.2	137.0	399.9	65	120	110	360
70-74	137.2	199.5	330.1	70	160	170	390
75-79	181	260.8	379.6	75	200	230	400
80-84	239.1	314.6	409.6	80	220	280	410
85 and over	245.6	342.9	441.5	85	240	320	420

Table 7.4 Comparison of observational (Cognitive Functioning and Ageing Study II) and simulated estimates of dementia prevalence

Observational data			Simulated data		
	Prevalence (%)			Prevalence (%)	
Age band (years)	Male	Female	Age (years)	Male	Female
65-69	1.2	1.8	65	0.9	0.4
70-74	3	2.5	70	2.1	1.1
75-79	5.2	6.2	75	4.7	3.3
80-84	10.6	9.5	80	8.6	8.5
85-90	12.8	18.1	85	13.1	18.1
≥ 90	17.1	35.0	90	16.8	28.4

7.4.2 Comparisons of life expectancy estimates

Table 7.5 compares estimates of the effect of increased physical activity on life expectancy. Comparisons should primarily be made with the first section of the table ('Population based scenarios') as these scenarios describe changes occurring in a population with a range of baseline levels of activity (rather than the effect arising from an individual, or a population with a narrow range of physical activity levels, changing).

The estimated increase in life expectancy from the standard model is noticeably less than other estimates. The estimates from the 'mortality variant' are compatible with the other estimates, within the limits of error. The other estimates, as with the mortality variant of the model, are made using a life table model parameterised with estimates, from observational studies, describing the association between physical activity and mortality. The relatively good agreement between the mortality variant of the model and the other estimates suggests that the primary model may not be

Table 7.5 Comparison of estimates of increase in life expectancy attributable to increases in physical activity

Study	Scenario	Population	Method	Estimated increase in life expectancy (years)
Population based scenarios				
Mytton, 2016 (Thesis)	Everyone in England meeting physical activity guidelines	England	Standard model (multi-state life table model: effect of physical activity on mortality modelled indirectly through five diseases)	0.26
Mytton, 2016 (Thesis)	Everyone in England meeting physical activity guidelines	England	Mortality variant of the model: i.e. effect of physical activity on mortality modelled directly	0.54
Baal et al, 2016[311]	Everyone in England, between the ages of 40 and 65 years of age, meets physical activity recommendations	England	Life table based model, physical activity has a direct effect on mortality	0.46
Ekelund et al, 2015[196]	Everyone in the UK undertook at least 20 minutes of brisk walking	UK	Large European cohort study to estimate RR of mortality and UK life table	0.70
Lee et al, 2012[107]	Elimination of physical inactivity globally, i.e. everybody meets physical activity guidelines (≥ 150 minutes of MVPA per week)	World	Life table (country specific)	0.68
Individual based scenarios				
Janssen et al, 2014[343]	An individual becoming "active" (8.33 MET-hours of leisure time physical i.e. 150 minutes of MVPA leisure activity per week) relative to inactive (no leisure time PA, 0 MET-hours per week)	USA	Survey data linked to death certification to estimate RR of mortality and US life table	2.4 (for men) and 3.0 (for women)
Moore et al, 2010[344]	A physical activity level of 0.1-3.74 MET-hour per week equivalent to brisk walking for up to 75 min per week relative to no leisure time activity (0 MET-hours per week)	USA	Six US based cohort studies to estimate relative risk of death and survival curves (i.e. life table method)	1.8 (95% CI: 1.6-2.0) y in life expectancy
Nusselder et al, 2008[294]	An individual becoming "active" (>33 MET-hours per day) relative to inactive (<30 MET-hours per day)	Framingham, USA	Life table based model, physical activity has a direct effect on mortality	3.5 (for men) and 3.4 (for women)

adequately describing how physical activity affects mortality (e.g. physical activity may affect other diseases that are important causes of mortality or physical activity may have an effect on survival of other diseases). I note that the sensitivity analyses suggest that the inclusion of other diseases (e.g. assuming physical activity affects risk of lung cancer, prostate cancer and pancreatic cancer) may have a relatively small effect on changes in life expectancy, however disease survival effects (e.g. demonstrated by the sensitivity analysis that assumed physical activity did not affect breast cancer and colon cancer case fatality) may be more important. Model specific issues, notably around co-morbid illness (see section 7.3.2.1) may also be a factor, but it seems unlikely that they could fully explain the observed discrepancy.

Issues with the epidemiological studies may also contribute to the discrepant estimates. It is noticeable that estimates of the association between physical activity and mortality tend to be of a similar magnitude to estimates of the association between physical activity and cardiovascular disease (e.g. 16-30% mortality reduction associated with changing from inactive to moderately

active; 17% incidence reduction and 23% mortality reduction in cardiovascular disease associated with change from inactive to all adults meeting PA guidelines).[44,196] This appears implausible because cardiovascular disease only contributes to around a quarter of all deaths in England[322] and would appear to be the important disease that mediates the relationship between physical activity and mortality. The findings may point to issues with the epidemiological studies, e.g. that the epidemiological studies overestimate the effect of physical activity on mortality and/or underestimate the effect of physical activity on other diseases.

Some other model specific factors may contribute to the lower estimates, but alone are insufficient to explain the differences given the marked discrepancy between the standard model and the mortality variant. For example, over estimating baseline physical activity levels (by including all forms of physical activity) relative to cohort studies, may contribute (section 7.3.2.3) although this issue is common to both the standard model and the mortality variant.

It is possible that a combination of these issues (e.g. that physical activity affects the risk of other cancers, that physical activity affects survival from other diseases, that baseline physical activity is modelled using leisure-time physical activity) might account for the differences between the mortality model and the standard model.

7.4.3 Comparison of estimates of population attributable fraction

Table 7.6 compares estimates of the population attributable fraction. The estimates from Lee et al are most relevant as they are UK specific and produced more recently,[107] although the relatively high estimates for breast, and to a lesser extent colon cancer, should be treated with caution. Lee's estimates of the population attributable fraction are about two to three fold greater for cardio-metabolic disease, although the reported intervals overlap for ischaemic heart disease.

These differences may be explained by differences in the data sources or how that data was used. Of note they may be explained by differences in the definition of baseline physical activity. My study had a broad definition of physical activity, including travel, recreational and work-related physical activity. This effectively inflated the proportion of the population who were meeting guidelines. The Lee study was based on older data where it was more common to use less flexible definitions of

Table 7.6 Comparison of population attributable fractions for physical activity and selected diseases

Model	Mytton et al (Thesis)	Lee et al, 2012	WHO, 2002
Scenario	All adults meet public health guidelines (UK)	All adults meet public health guidelines (UK)	All adults meet public health guidelines ('typical' developed country)
Ischaemic Heart Disease	5.1 (2.9-8.2)	10.5 (4.0-17.3)	22
Stroke	5.2 (2.9-8.3)	-	13
Type 2 Diabetes	3.8 (1.8-6.1)	13.0 (6.4 to 20.2)	15
Colon Cancer	2.4 (1.2-4.0)	17.9 (8.5-27.8)	17
Breast Cancer	2.2 (0.8-4.2)	18.7 (10.5 to 27.1)	11

bouts of physical activity (see section 1.3.2) and to define meeting guidelines based principally on leisure-time physical activity. This effectively meant the proportion of the population classified as inactive may be greater in these other studies, and hence there is more scope for physical activity to increase and effect health. The figures, in part, are thus estimating different things, my data refers to all adults meeting physical activity guidelines (by undertaking a range of activities) under the assumption that a relatively large proportion already are (through doing short bouts of activity and non-leisure activity), whereas the Lee figures refer to all adults undertaking at least 150 minutes of leisure-time physical activity (i.e. meeting guidelines primarily through undertaking leisure-time activity).

They may also reflect differences in the interpretation of 'all adults meeting PA guidelines'. I took a conservative interpretation of 'all adults meeting PA guidelines', undertaking 5.75 marginal MET-hours of physical activity, very close to the minimum threshold for meeting the guidelines (150 minutes at 3.0 MET, i.e. 5.0 marginal MET-hours). While the MET assumptions used by these authors were not explicitly stated,[107] I note that other authors when defining 'meeting guidelines' assume an intensity of 4.5 METs (i.e. 8.75 marginal MET-hours).[299] Moreover these authors based their estimates on measures of relative risk that used studies that effectively compared inactive people with active people. The latter group includes those who both just meet guidelines and also those who exceed the guidelines. Thus, the estimates are effectively calculating an attributable fraction under the assumption that inactive people adopt the physical activity distribution of active people, rather than minimal levels of physical activity.

Given the changes observed under some of the sensitivity analyses (e.g. 'leisure only' variant) and different scenarios (e.g. increase of 225 minutes per person, equivalent to 8.6 marginal MET-hour increase), it seems likely that estimates of the population impact fraction made using my model could be comparable with Lee's estimates, at least for cardio-metabolic disease.

However, my estimates and those of Lee's suggest a different ordering or relative magnitude of population attributable fraction for the different diseases. Lee suggests that the effect of physical activity on breast and colon cancer is greater than its effect on cardio-metabolic disease. My model suggests the opposite. A recent meta-analysis of the dose response relationship between physical activity and different diseases that suggested the effect of physical activity was less on breast and colon cancer risk than cardio-metabolic riks,[110] consistent with my model.

7.4.4 Implications for interpretation

Taken together these comparisons suggest that the model is under estimating the effect of physical activity on disease. This may relate to structural factors (e.g. not fully capturing all the pathways through which physical activity affects mortality) or differences in how the data has been used (e.g. modelling relationship between physical activity and disease, including non-leisure related activity in the assessment of baseline levels of activity). Differences in the interpretation of the scenario (e.g. the dose of physical activity used to simulate 'all adults meeting PA guidelines') may also have contributed to the appearance that the model is under-estimating the effect of physical activity. It warrants further investigation.

As the model is not primarily being used to estimate absolute health benefits, but rather to illustrate how physical activity through its effect on longevity may influence indices of healthcare need, possible under-estimation attributed to scenarios or data differences is less of a concern. However, a failure to model all of the pathways through which physical activity affects mortality (and hence life expectancy), as suggested by the differences in life expectancy between the 'standard' and 'mortality' models, may be more problematic. Nonetheless the overall findings that increases in physical activity may not be associated with decreases in indices of need for some diseases and that estimates of change in need are more conservative when making allowance for increased survival is likely to be robust. This general pattern of finding was observed for both the standard and mortality model.

The 'mortality' model suggests that if the ageing effect was greater, then in general estimates of change in indices of healthcare need would change (positive changes would be greater, negative changes would be smaller or become positive changes). However, such changes could only be explained by changes in the underlying disease processes (e.g. greater effect of physical activity on disease incidence; physical activity affecting more diseases; or physical activity affecting survival of other diseases). These changes would also likely alter other aspects of the model and outcomes from the model. For example, if physical activity improved dementia-specific survival, then one might expect that physical activity would be associated with an increase in person-years lived with

dementia rather than no change or a small decrease. Conversely if the effect of physical activity on dementia incidence was greater this would result in larger reductions in incident cases of dementia and person-years lived with dementia (although it would still tend to push estimates of person-years lived with other diseases in a positive direction).

7.5 Comparison with previous work: indices of healthcare need

I am not aware of any work that has sought to do what I have done (either for physical activity or for other behavioural risk factors, e.g. smoking). Nevertheless, some aspects of my work can be compared to other pieces of work. I have arranged these under four groups of studies:

- first studies describing the association of changes in physical activity with all-cause disability (an indicator of healthcare need);
- second studies describing the association of changes in physical activity with changes in the burden of several diseases;
- third life table modelling studies describing the association of changes in physical activity with changes in the burden of a single disease;
- and fourth life table modelling studies describing the association between other risk factors and change in indices of need.

Most of the modelling studies have used a different set of metrics to the metrics I have presented here, and I first discuss the comparability of these other metrics with the metrics I have presented.

7.5.1 Comparing across modelling studies with different metrics

The modelling studies with which I draw comparisons have estimated the mean number of years an individual would live with a particular disease (e.g. estimated years lived with a particular disease).[291–293]

I think changes in years lived with disease are equivalent to changes in person-years lived with disease.[xxviii] Change in mean years lived with disease for the average individual is estimated by dividing the total number of person-years lived with disease by the total population (at the start of the period of observation). In my study the population size at the start of observation (birth) was fixed in all scenarios. Thus increases in the person-years lived with disease will result in an increase in the average number of years lived with disease. Similarly decreases in the person-years lived with disease will result in a decrease in the average number of years lived with disease. One shortcoming of the approach that only reports individual expectation of years lived with disease is that it depends both on the likelihood of developing disease and duration of disease. Using only this metric, one

[xxviii] Whilst the two measures may be equivalent, the implied focus of each is different. One is an expression of the amount of disease in a population (and thus need for healthcare) and the other is an indicator of individual expectation of years lived with disease. Many of these studies use the terms disease expansion and disease compression (section 5.2.4.1). Disease expansion is an absolute increase in the average number of years lived with disease, so is equivalent to an increase in the person-years lived with disease. Disease compression is an absolute decrease in the average years lived with disease, so is equivalent to a decrease in person years lived with disease.

cannot distinguish between changes that result in more people living with disease (i.e. changes in the total incident cases) and the same number of people living with disease for a longer duration. The complementary indicators of healthcare need that I used (person-years with disease, total incident cases) allows these two effects to be distinguished.

7.5.2 Studies of physical activity and disability

Studies, whether using life table methods[294,301] or comparative risk assessment methods,[125,141] conclude that increases in physical activity are associated with a reduction in disability, expressed either as years lived with disability or disability-adjusted life years (DALYs).[xxix,125,141,294,301] Whilst I have not estimated all-cause disability, I note that the general trend (for the diseases considered) was for the person-years lived with disease to decrease.

The exception to this trend were colon cancer and breast cancer, although the increase observed for breast cancer were small and the burden of disability attributed to these two diseases relative to the other diseases is small. In the UK, the burden of disease as measured by Disability Adjusted Life Years (DALYs) for other diseases (for which indices of need decreased) was much greater (DALYs for ischaemic heart disease: 1,454,000; ischaemic stroke: 392,000; diabetes: 208,000; and Alzheimer's dementia: 387,000; vs DALYS for breast cancer: 295,000 and for colorectal cancer:[xxx] 325,000).[106] Moreover ischaemic heart disease, stroke, diabetes and Alzheimer's disease are in the top 25 causes of years lived with disability, whereas colon and breast cancer are not.[106] The contribution of colon and breast cancer to DALYS is predominantly through premature mortality rather than disability (i.e. the increases in person-years lived with colon cancer are likely to contribute little to disability).

7.5.3 Studies of physical activity and several individual diseases

Woodcock et al estimated that an increase in active travel (mean of 7 minutes per day) would reduce the disease burden (percentage change in DALYs) using comparative risk assessment modelling by 7.6% for ischaemic heart disease, 7.0% for stroke, 7.2% for type 2 diabetes, 5.3% for dementia, 2.2% for colon cancer and 1.8% for breast cancer.[140] The increases in this modelled scenario were largely attributable to increased cycling (at a mean of 6.8 MET), which together with walking may equate to a mean shift of around four to five marginal MET-hours. This is similar to the scenario 'all adults increase PA (150 minutes of walking)', which modelled an increase of 5.75 marginal MET-hours, so

[xxix] Disability adjusted life years includes two components, years of life lost (to premature death) and years lived with disability, so reflects more than disability.

[xxx] Approximately half of colorectal cancer is attributable to colon cancer.[279]

drawing comparisons between the outcome for this scenario and the Woodcock paper appears reasonable

As one would expect given parts of the underlying models are similar, when using comparative risk assessment estimates, the estimates from my model (estimates of the change in person-years lived with disease, unchanged life expectancy) are similar (slightly higher) to those of Woodcock et al.[140] However when comparing with the life table estimates, the results of the two studies no longer look similar. This underscores how consideration of changes in survival affects estimates of burden of disease and indices of healthcare need.

I am only aware of one published study that has used methods that allow for changes in life expectancy and has made estimates of the effect of changes in physical activity on a set of diseases.[301] However this study did not publish estimates for change at the level of individual diseases, instead pooling across diseases and describing changes in estimated DALYs. Consequently, no comparisons are possible for changes in individual diseases.

7.5.4 Life table studies of physical activity and single diseases

Several life table studies have been published that describe the effect of increases in physical on a single disease. In these studies, a direct effect of physical activity on mortality is modelled, such that these studies make allowance for changes in life expectancy attributable to changes in physical activity.

Two similar studies reported that increases in physical activity (during mid-life) were associated with small non-significant increases in average years lived with cardiovascular disease.[293,294] Their finding of a small increase may appear to contrast with my finding of a small decrease for ischaemic heart disease (assuming the direction of change for average years lived with disease and person-years lived with disease are comparable; see section 7.5.1). Both estimates might be best interpreted as being close to zero and have uncertainty intervals that overlap, so could be considered similar. I also note that the equivalent estimate for the 'mortality' model was a small increase.

A third study, using a similar model, but by a different set of authors, reported that increases in physical activity (inactive to low active; inactive to some activity; inactive to meets recommendations) was associated with a significant decrease in average years lived with dementia.[345] However other increases in physical activity (low active to some activity; low activity to meeting recommendations; and some activity to meeting recommendations) were associated with

very small changes in the average years lived with dementia. The study reported using a conservative estimate of the association between physical activity and all-cause mortality, when using estimates that modelled a larger effect size it was estimated that dementia related costs increased.[xxxi] Direct comparisons with my work are not possible as I explored scenarios around the population distribution of physical activity changing, whereas this paper described scenarios around individuals with specified activity levels changing. However broadly this study does provide some evidence that increases in physical activity (principally among people who are already active) may not be associated with reductions in need for care.

7.5.5 Life table studies of other risk factors

Life table modelling has also been used to describe the effect of changes in other risk factors on years lived with cardiovascular disease.[291,292,295] Smoking cessation was associated with an increase in the average number of years lived with cardiovascular disease (equivalent to an increase in the person-years lived with disease).[292] In contrast reductions in body weight were associated with a reduction in the average number of years lived with cardiovascular disease.[292,295] These findings are consistent with my general observation that an 'improvement' in a risk factor can be associated with either an increase or a decrease in person-years lived with those diseases for which it is a risk factor.

[xxxi] For this sensitivity analysis years lived with dementia were not reported, as healthcare costs were fixed per person-year and not discounted, changes in healthcare costs may be a proxy for changes in years lived with dementia.

7.6 Interpretation

Whilst it is possible that the model has not captured all of the pathways by which physical activity affects life expectancy and may also for other reasons underestimate the effect of changes in physical activity on individual diseases, the value of this work is its comparative analysis that draws out the differences from additionally modelling the effect of physical activity on survival. This shows that when modelling the effect on some diseases, it is important to make allowance for changes in survival and that for some diseases increases in physical activity that reduce risk may be associated with only small changes in indices of need for healthcare. Whilst other studies have not explicitly asked the same question, elements of other work would appear to underscore these findings.

7.6.1 Understanding patterns of change at a disease level

The effects of physical activity on changes in disease epidemiology show marked variation between the different diseases. The patterns of change in the disease epidemiology (indices of healthcare need) relate to the three effects I described in Chapter 5 and to the underlying epidemiology of that disease.

Type 2 diabetes and stroke show a similar pattern (decrease in incident cases, decrease in person-years lived with disease, and both these estimates are not too discordant from estimates made using comparative risk assessment methods). For these diseases the incidence effect is dominant. This reflects a relatively strong effect of physical activity on relative risk of incidence and the absence of a disease survival effect (i.e. physical activity does not affect disease case fatality). For type 2 diabetes, the fall in incidence rate with age also means that population ageing is less important.

Dementia is different (small decreases in incident cases and person-years lived with disease that are close to zero and much less than estimates made using comparative risk assessment methods). The incidence of dementia increases sharply with age, such that the population ageing effect is important. Whilst a few cases of dementia were prevented, more commonly the onset of dementia was postponed.

Ischaemic heart disease is different again (large decrease in incident cases but relatively small decrease in person-years lived with disease). The disease survival effect is important, whilst cases of disease are prevented those with disease are living longer. For colon and breast cancer the disease survival effect is also important. In addition, few cases of colon and breast cancer are prevented, which may be attributed to population ageing and a rise in incidence with age and/or a relatively

weak effect of physical activity on incidence. For colon cancer the combination of these effects meant that increases in physical activity were associated with an increase in person-years with colon cancer.

7.6.2 Extrapolation to other risk factors

Whilst I have only considered physical activity, the conclusions may extend to other risk factors for non-communicable diseases. The underlying epidemiological factors (e.g. an increase in incidence with age) and the multiple pathways between physical activity and disease (i.e. the three different effects outlined in Chapter 5, section 5.2.1) are common to other risk factors and diseases. I also note that the literature for other risk factors (considered briefly under section 7.5.5) appears consistent with the idea that changes in risk factor distribution resulting in risk reduction may only be associated with small change in indices of need for healthcare.

7.6.3 Mean age of disease onset

For some diseases, increases in physical activity were associated with decreases in the mean age of onset. Whilst this may appear counter-intuitive, particularly given that the curves for incident cases and people (Figures 6.6 and 6.7) shifted to the right suggesting later onset, one should remember that the estimates reflect the mean age *for those who develop* disease. Thus it is possible for the mean age of onset to decrease, whilst the age of onset is delayed if cases of disease are prevented predominantly in those who would have developed the disease at old age (i.e. this group is no longer part of the denominator).

Theoretically this also seems possible. One could imagine a scenario in which a disease is caused by a combination of genetic and environmental factors. A strong genetic predisposition combined with environmental factors results in early onset, and the absence of those environmental factors results in onset in mid-life. A weak genetic predisposition only results in disease when combined with environmental risk and onset is late in life. Most individuals in the population have a weak genetic predisposition. Elimination of the environmental cause will prevent disease amongst those with a weak genetic predisposition and shift the age of onset amongst those with a strong genetic predisposition to later in life. Thus disease cases will be prevented, disease onset amongst those who develop the disease is later, but (because of elimination of cases in old age) the mean age of onset could still decrease.

7.7 Implications

Broadly my work suggests that changes in life expectancy are important when evaluating or formally estimating the effect of changes in physical activity (and likely changes in other non-communicable disease risk factors) on indices of need for health or social care. Whilst beneficial changes in the distribution of a risk factor will be associated with improvements in health, need for health or social care for some diseases may be postponed rather than reduced. For some diseases for which physical activity is protective, need for health or social care could increase, although this is unlikely and any increases are likely to be small.

7.7.1 Implications for public health practice

7.7.1.1 Expectation that public health interventions will reduce need for health or social care

My findings suggest that public health officials and policy makers should be more cautious about claiming that interventions designed to increase physical activity or reduce other risk factors for non-communicable disease will lead to large reductions in need for health and social care in the long run. Whilst it may be reasonable to expect need to decrease for some diseases, such as type 2 diabetes, or to be postponed, in the long run it may not be a reasonable expectation for some diseases, such as dementia. Simply extrapolating estimates of risk reduction to reduction in indices of need will lead to overly optimistic estimates of the benefits of an intervention on reduction in need.

7.7.1.2 Appropriate language for risk reduction interventions

"Prevention" is a commonly used word within public health discourse. However, my work shows how risk reduction may result in little or no prevention of incident cases of disease, and I suggest that the word "prevention" should be used with caution. For some diseases (e.g. type 2 diabetes) prevention may be the appropriate term, but when it is not appropriate or it is unclear the phrase "risk reduction that may prevent or delay onset" may be more appropriate. This reflects the language in some recent publications concerning dementia risk reduction.[346,347]

7.7.1.3 Expectation that population ageing leads to increased need for health and social care

It is commonly assumed that an ageing population leads to increased need for health and social care, because the incidence of disease increases with age.[286,348] There have, for example, been forecasts that population ageing will lead to a significant rise in burden of dementia.[349,350] Whilst this assumption may sometimes be reasonable, my work shows that if changes occur in a risk factor, which is a risk factor for both mortality and for disease incidence, then it is possible for the

population to age whilst the need for healthcare (at least for some diseases) is relatively unchanged. Consistent with this, I note that recent research suggests that the number of people living with dementia is largely unchanged in the last 10-20 years, despite population ageing.[278,351]

7.7.1.4 Estimates of population attributable fraction and physical activity guidelines

Whilst not the focus of my study, my work suggests that estimates of the population attributable fraction for physical activity may be very different if different assumptions are made about either habitual (baseline) levels of physical activity (i.e. what physical activity is 'counted' as contributing to achieving physical activity guidelines) or about the intensity of physical activity undertaken to achieve physical activity guidelines. Whilst changing physical activity guidelines (see section 1.3.2) to include the incorporation of small bouts of physical activity may be important in recognising the value of these small bouts and encouraging more people, particularly less active people, to undertake some physical activity, it does result in a higher estimate of the proportion of the population who are physically active. This results in a smaller estimate of population attributable fraction for physical activity. Similarly, whilst an emphasis on activity at lower intensity (e.g. walking) may be an appropriate means to engage the least active in being active, the population health gains (measured as a population impact fraction) will be lower (perhaps markedly lower) if only this minimum level of activity is achieved and care should be taken in extrapolating the health gains from studies that assume greater increases in physical activity (intensity or duration).

The discrepancy between the estimates of the population attributable fraction and changes in indices of need for healthcare underscores the importance of remembering that the population attributable fraction is estimated under the assumption of all other factors, including mortality, being fixed.[352] Whilst the population attributable fraction may be interpreted as the proportion of disease attributable to a given risk factor, it does not necessarily follow that that proportion of disease may be eradicated by removal of the risk factor.

7.7.1.5 Use of public health models

Public health practitioners should consider what type of model has been used and whether it is appropriate to address the question being considered. Where disease events may realistically be prevented then comparative risk assessment (or similar) models are appropriate, if disease events may be postponed and particularly where one wants to consider the implications of interventions for need for health or social care, then a form of longitudinal modelling (e.g. life table or microsimulation) that makes allowance for changes in life expectancy and delay in events will be more appropriate. Modelling work that tries to answer these latter questions but does not use appropriate techniques should be treated with caution.

7.7.2 Implications for public health modelling

7.7.2.1 Modelling methods

Much of the work that considers the benefits of physical activity (or costs of physical inactivity) and other behaviours uses comparative risk assessment modelling.[106,107,141,353] This work suggests that researchers should consider using life table models or other tools to make allowance for increased life expectancy and the delay in onset of the disease. Whether it is necessary to use more complicated tools (e.g. microsimulation or life table models) may depend on the nature of the research question. When older age groups are being studied mortality is more important, which may suggest methods that account for changes in longevity are more important. It may also depend on the disease being studied, estimates of change in indices of healthcare need arising from different models were particularly discordant for dementia, but much less so for type 2 diabetes.

The discrepancy between the 'mortality' model and standard model warrants further investigation to understand the sources of the discrepancy. This is important not only for interpreting results but also building future health impact models. The standard model by modelling the known pathways through which physical activity is thought to affect health appears more plausible and is more internally consistent. For these reasons and for now, it appears the more appropriate model to use.

7.7.2.2 Disability adjusted life years

Disability Adjusted Life Years (DALYs) have been used extensively with comparative risk assessment models, notably the Global Burden of Disease project,[106,354] as well as with life table based models.[301,302] However, comparative risk assessment models assume that the effect of a risk factor change is the same on Years of Life Lost (YLL)[xxxii] and Years Lived with Disability (YLD). My life table work suggests this is inappropriate. Disease events can be delayed (which might result in a decrease in YLL) whilst the number of years lived with diseases (or YLD) may not change. Using a life table based model it is possible to calculate different effects of physical activity on YLL and YLD.[301] Moreover the relative contribution of YLL and YLD to DALYS varies between diseases, which may further exacerbate errors caused by assuming that the effect on changes in physical activity on YLD and YLL is the same.[106] Multistate life table models and microsimulation open the possibility of more

[xxxii] Years of life lost are estimated relative to life expectancy. They are estimated by summing the different between age of death and life expectancy for all deaths that occur before estimated life expectancy. Only premature deaths are counted.

realistically reflecting changes in disease onset (and premature mortality) to estimate YLL as well as estimating changes in YLD.

7.7.2.3 Appropriate metrics

There may be a need to develop better metrics and set clear expectations about what metrics should be reported, when using life table models (or similar) to capture improvements in health. My simple measure of mean age of disease onset did not reflect the delay in disease events when a large number of events were prevented (particularly amongst older people). Using a measure of adjusted age of onset, adjusting for cases prevented, may be more appropriate.

7.8 Chapter summary

This chapter began by summarising the key findings, notably that when allowance is made for increases in life expectancy estimates of reduction in need for healthcare are smaller and for some diseases are close to zero. Whilst need may decrease for some disease (e.g. type 2 diabetes), for other diseases onset of disease may be delayed (e.g. dementia) and the absolute amount of disease (measured either in person-years with disease or incident cases) may change very little. Other diseases may experience a more mixed pattern, where the period of morbidity is prolonged (e.g. colon cancer or ischaemic heart diseases) and the amount of disease may fall for some indices (e.g. incident cases) but change little or increase for other (e.g. person-years lived with disease).

A number of limitations were discussed. Some of these (e.g. measurement of physical activity) may affect absolute estimates of effect. Comparisons with empirical data and other models suggest that the model may be underestimating the effect of physical activity on health and disease. However, the primary contribution of this work is to illustrate the effect of considering increased survival on indices of healthcare need, rather than making explicit forecasts about the future or estimates of the effect of discrete interventions.

This analysis has principally considered diseases for which physical activity is protective. For other age-dependent diseases (e.g. some cancers) indices of need are likely to increase as a result of increases in physical activity. Whilst not explicitly explored it is likely that similar patterns may emerge for other risk factors. This is important for public health practitioners and policy makers. They should be wary of promising or expecting large reductions in need for healthcare as a result of investment in risk reduction or preventive interventions. Similarly, when formal estimates, using public health modelling techniques, of the health impacts of 'preventive' or risk reduction interventions are made, consideration should be made of need to make allowance for changes in life expectancy that will also result from the intervention.

8 Discussion

8.1 Chapter Outline

This chapter begins by summarising the key findings from the epidemiological studies (Chapters Two-Four) and the modelling research (Chapters Five-Seven). It presents an overarching discussion of my thesis, focusing around core themes (population approach, complementary methods, and measurement of physical activity). It then discusses implications for public health policy and practice and outlines future directions for public health and physical activity research, before reflecting on how my approach to public health research and practice has changed during the course of the PhD.

8.2 Summary of key findings

8.2.1 Associations of active commuting with sickness absence and well-being

I found that maintenance of cycling to work, relative to maintenance of not cycling to work, was associated with reduced sickness absence after adjustment for covariates and baseline sickness absence. Looking at the direction, magnitude, consistency and significance of associations across both the maintenance and changes analyses, there was some evidence that cycling to work was important for both mental and physical well-being, although few of these associations reached the recognised threshold of significance ($p<0.05$). I found no significant associations between walking to work and any of the three outcomes, either before or after adjustment for cycling to work.

8.2.2 Associations of active commuting with body mass index

I found that maintenance of cycling to work was associated with decreased body mass index (BMI) at one year follow-up, relative to maintenance of not cycling to work, after adjustment for covariates, but this association was markedly attenuated and no longer significant after conditioning on baseline BMI. The association for maintenance of walking to work, after adjustment for covariates, was of similar magnitude to that estimated for cycling to work (walking: 0.8 kg/m^2 vs cycling: 1.1 kg/m^2), but was marginally non-significant. An increase in weekly time walking to work was associated with a decrease in BMI, after adjusting for covariate and restricting to those who did not change home or work location. Other changes analyses were non-significant, although the direction of the findings was generally in keeping with an inverse association between active commuting and BMI.

8.2.3 Associations of active commuting with adiposity

Amongst participants living within five miles of work, participants (both men and women) who reported regularly cycling to work had decreased adiposity (both visceral adipose tissue and percentage body fat) compared to participants who reported always using the car. I also observed a dose-response relationship between distance to work and percentage body fat, amongst participants who reported only cycling to work. Associations for regular walking were not significant.

Amongst participants living five miles or further from work, participants who reported combining car use with active travel, or car/public transport use with cycling had reduced adiposity. There was some evidence that walking or cycling, as usual modes of travel, were also associated with decreased adiposity.

8.2.4 Modelling an increase in physical activity levels and need for healthcare

A shift increase in physical activity was associated with improvements in the following range of health indices: reduced risk of disease onset, improved disease-specific survival and increased life expectancy. Generally, increases in physical activity were associated with decreases in indices of healthcare need for diseases for which physical activity is protective. Increases in physical activity were associated with decreases in the number of incident cases, although some of these decreases were small and close to zero (e.g. dementia). Increases in physical activity were associated with decreases in the person-years lived with some diseases (e.g. stroke and type 2 diabetes) and increases for other diseases (e.g. breast and colon cancer). There were marked differences in estimates of healthcare need using life table modelling, compared to comparative risk assessment modelling, which did not make allowance for changes in life expectancy.

8.3 Themes

There are a number of themes that run through this thesis, which I discuss below.

8.3.1 Population perspective

Throughout my thesis I have tried to draw a distinction between estimates as they apply to an individual and estimates as they apply to populations.

In the early chapters the estimates of effect size (derived from epidemiological studies) were typically conceptualised as applying to an 'average' individual in the study, comparing somebody who commutes actively with somebody who does not commute actively, after holding covariates constant. Some of the observed effect sizes may appear relatively small, for example 1 unit for physical well-being (PCS-8) compared to suggested thresholds for clinical significance (typically 3 or more units).[157,184] In Chapter One I suggested that promoting active travel is a population-level approach, and so the observed differences, whilst they may be conceptualised as 'average' individual-level differences, could also be seen as the differences one could expect between a population who commute actively and a population who commute by car. Conceived in this way the 'small' difference is more likely to be important.

In order to better contextualise the observed differences, I drew comparisons between populations from within the cohort. In Chapter Two, I compared the differences in well-being between participants in their 20s and participants in their 50s. In Chapter Three I compared the differences in BMI to secular changes in BMI observed in the population of the USA. I also argued in Chapter Two (section 2.4.4.1), that 'acceptable' effect sizes for individual level interventions targeted at those at highest risk are larger than an 'acceptable' shift in the population mean for a population-level intervention. Thus drawing comparison with clinical thresholds for significance is not appropriate.

Public health modelling often seeks to culminate the estimated effect of multiple, and often small, individual changes to estimate population-level impacts.[xxxiii,138] Within Part II of my thesis, I tried to draw a distinction between, and contrast, the estimated effect of physical activity for a typical individual (which was beneficial) and the estimated impact on need for healthcare considered at the

[xxxiii] Sometime public health modelling may be used to estimate changes expressed at the individual level. These may relate to 'population scenarios', e.g. mean changes in life expectancy if everybody became more active or 'individual scenarios', e.g. estimated change in life expectancy for somebody who changes from being inactive to becoming active.

population-level (for which 'benefit' was less clear-cut). I also drew a distinction between my work, which used measures that were explicitly reported at the population-level (e.g. person years with disease, incident cases), with previous work that has expressed such measures at the individual-level (e.g. mean years lived with disease).

Besides a shift in focus away from individuals towards populations, there are other ways that thesis has taken a public health perspective. For example, taking a pragmatic approach to the classification of commuting (e.g. Chapter Four), which reflects the limitations imposed on commuting by distance, rather than creating biologically 'pure' categories of physical activity (i.e. comparing only car use with only walking or only cycling). The choice of alternative health indices, sickness absence and well-being, was motivated in part by a desire to provide evidence that may enable public health practitioners (and others) to engage other stakeholders, such as employers, in promoting active commuting by creating a broader 'health case' for its promotion. I chose to focus on adiposity (Chapters Three and Four) because of the strong focus on obesity within public health practice in the UK.[106,226,227,355] One of the modelling scenarios was based on meeting public health guidelines, and the other on increases in walking (an accessible form of physical activity for most of the UK population). The modelling part of my thesis also bridged two areas of public health practice, namely health improvement and health services public health.

8.3.2 Complementary approaches

Throughout my thesis I have tried to use complementary approaches to confirm findings or address related questions.

8.3.2.1 Epidemiological methods vs modelling methods

My thesis used two complementary methods for estimating and understanding the health impact of physical activity (epidemiological measures of association and health impact modelling). The epidemiological studies were used to estimate the association between active commuting and indices of health for an individual. The modelling studies were used to estimate changes in health (assuming a causal relationship between physical activity and health) or disease at a population-level, by culminating evidence from multiple epidemiological studies, and simulating scenarios of increased levels of physical activity.

Modelling is underpinned by epidemiology. My epidemiological analyses were not used to directly underpin the modelling I undertook. However, the epidemiological work did partially support the modelling work. The epidemiological analyses reported in Chapter Three and Four, did provide some

evidence linking active travel, and physical activity, via reduced adiposity with diabetes, stroke and ischaemic heart disease, which were outcomes in the modelling study.[150,356,357] Choosing a different set of outcomes for the modelling study, relative to the epidemiological analyses, resulted in my thesis, as a whole, covering a broader set of health indices and diseases.

The modelling work also used complementary methods (life table and comparative risk assessment) and complementary outcomes (person-years lived with disease, and incident cases). The complementary indices of healthcare need are important as single measure is unlikely to capture different aspects of healthcare demand, such as acute admissions and routine care.

8.3.2.2 Longitudinal vs cross-sectional methods

The first part of my thesis used both longitudinal (the Commuting and Health in Cambridge dataset) and cross-sectional (the Fenland Study) data. The second part of my thesis used life table modelling, which as it explicitly models time could be conceived as longitudinal, and comparative risk assessment, which as it does not model time could be conceived as cross-sectional.

I have argued that longitudinal methods tend to be superior. Longitudinal epidemiological studies can demonstrate temporality (the risk factor preceding the outcome) or specificity (e.g. linking changes in a risk factor with changes in an outcome), both of which may support causal inference.[35] An important strength of the work reported in Chapters Two and Three, relative to previous work, is that it used longitudinal data. Similarly, the modelling work demonstrates that explicitly modelling time (thus allowing the consideration of survival effects) offers a different, more realistic, perspective of the estimated effect of changes in physical activity on need for healthcare, compared to 'cross-sectional models' or comparative risk assessment methods. An important strength of the modelling work, compared to previous work, is its 'longitudinal' element.

The overall thrust of my thesis represented a movement away from cross-sectional methods towards longitudinal methods. The notable exception to this was Chapter Four (cross-sectional analyses using the Fenland dataset). Other important strengths of the Fenland Study (large size, detailed characterisation of physical activity and dietary behaviour, objective measurement of adiposity) justified its use. Similarly, there is still a role for comparative risk assessment modelling. It is easier to undertake and there may be circumstances when considering survival effects is less important (e.g. when studying younger adults).

8.3.2.3 Epidemiological analyses

The epidemiological analyses also used complementary approaches. In Chapter Two and Chapter Three, I used complementary longitudinal approaches (maintenance and change analyses). The different analyses addressed slightly different questions. For example, with respect to BMI, the maintenance analyses offered a better indication of the long-term difference in BMI attributable to active commuting, as many of the commuters are likely to have maintained their commuting behaviour for longer than one year. In contrast the change analyses offered an indication of the short-term changes in BMI that may occur on starting or stopping active commuting (the average change would have occurred half a year before repeat measurement). I also argued that a consistent pattern of findings across both maintenance and change analyses (even in the absence of statistical association) provided greater evidence of association than observing associations within just one of these analyses, as well as strengthening causal inference by demonstrating both temporality and specificity.

The conditional analysis also complemented the unconditional analysis. For example, a strong association was observed between maintenance of cycling to work and BMI at follow-up, after adjustment for co-variates, but not after conditioning on baseline BMI. This suggested that the differences observed in the unconditional analysis were largely attributed to differences in BMI at baseline between those who maintained cycling to work and those who maintained not cycling to work. Whilst such differences may be due to other systematic differences between the groups that were not adjusted for, such as diet, they might also be attributed to differences in behaviour prior to baseline. Rate of change of BMI, comparing those who cycle and those who do not, may be relatively small, such that absolute differences in BMI may only be apparent over a period of years. The complementary analyses, using the Fenland dataset more fully considered confounding factors (other physical activity, diet). As strong associations between active commuting and adiposity were observed after adjustment for confounding, unmeasured dietary or non-travel related physical activity confounding appears less likely to be explain the differences in BMI observed in the Commuting and Health in Cambridge dataset.

The Fenland analyses also complemented the BMI analyses, undertaken in the Commuting and Health in Cambridge dataset, in other ways. They used a different approach to categorisation of commuting, included a more socially diverse sample, considered non-commuting travel, and used different, more biologically relevant, measures of adiposity. They also tested for a dose-response relationship. Across the two studies more robust causal inference was possible (e.g. specificity, dose-response relationship, consistency, adjustment for a range of confounders) than across either single study alone.[35]

8.3.3 Measurement of physical activity

The importance of accurate measurement of physical activity was another theme. In the early chapters I primarily used self-reported measures of physical activity and active commuting. I argued that some self-reported measures of active commuting were more accurate than others, such as the seven-day travel diaries, which in theory is a more sensitive than other means for capturing any active commuting, such as asking about 'usual' travel mode for commuting. Better tools for measuring the exposure, such as the travel diary, may reduce measurement error and so improve power and reduce bias (random measurement error tends to bias results towards the null).[147,358]

Taking repeated measures is another way to reduce measurement error (e.g. to reduce regression dilution).[189] By restricting the maintenance analyses to those individuals who maintained commuting behaviour (e.g. maintained cycling to work and maintained not cycling to work) I sought to reduce the potential misclassification of individuals who started or stopped cycling between baseline and follow-up. Had the classification been made only on cycling at baseline (i.e. cycling to work at baseline vs not cycling to work at baseline), changing of commute modes between baseline and follow-up, would have resulted in two groups who became more alike (effectively 'regressing to the mean') during the year of follow-up, and biased the result towards the null. Similarly excluding movers from change analyses and BMI (Chapter Three), strengthened the association between change in walking and change in BMI, such that the association became significant[xxxiv].

Objective measurement of physical activity may be another way to reduce measurement error. I used objective measurement of physical activity energy expenditure as a co-variate in the adiposity analyses (the Fenland Study). The modelling work relied on an understanding of the dose-response relationship between physical activity and disease outcomes, and was limited by a lack of objective measurement of physical activity. Although not directly shown in the uncertainty analyses, there was considerable uncertainty about the actual dose of physical activity in the epidemiological studies (measured using questionnaires), and thus of the dose-response relationships between physical activity and relative risk used in the model.

[xxxiv] The rationale to exclude movers was that those who moved might be experiencing many other changes that might result in a change in BMI (of uncertain direction, i.e. an increase or a decrease), rather than misclassification. However, its effect may have been similar as it resulted in a 'purer' group of changers and non-changers, whose behaviour was not influenced by moving.

8.3.3.1 Dose of physical activity

Different definitions of 'dose' of physical activity have been used or implied throughout this thesis, although most definitions related to duration and/or intensity. For example, the epidemiological analyses defined dose in several ways: time (or change in time) cycling or walking to work, distance cycled to work, leisure time physical activity measured in MET-hours and objectively measured physical activity energy expenditure. The modelling analyses principally used a product of dose and intensity (marginal MET-hours).

Dose is not the only dimension of physical activity that may be important.[359] Other dimensions of physical activity, such as context, were also discussed in Chapter Two as a possible explanation for differences in well-being observed between different walking studies. Chapter Seven discussed issues with measuring absolute dose rather than relative dose. Type of physical activity is also relevant for some health outcomes, for example weight bearing activity for osteoporosis prevention.[79,360]

8.4 Overall Interpretation

Taken together the epidemiological analyses suggest that active commuting, particularly cycling to work, may be valuable for improving well-being, reducing sickness absence and reducing (or maintaining) adiposity amongst adults of working age. Given that sickness absence and visceral adipose tissue are associated with 'hard' outcomes (e.g. mortality and cardio-metabolic disease respectively),[149,150,175,176] these findings support previous observations of associations between active travel and these outcomes.[127,129,132]

Given the exposures used (stratified by distance in the Fenland analyses, and including any walking or cycling in the Commuting and Health in Cambridge dataset analyses) as well as other aspects of the findings, such as effect modification by distance for BMI (Chapter Three), a stronger case can be made that the inclusion of some active travel, as part of commuting to work, for people who live too far to only cycle or walk to work, is beneficial for health. However, it is unclear how much and how often active commuting must be undertaken to experience benefit, particularly for those who include some walking or cycling as part of a longer commute.

The associations for cycling tended to be stronger, than the associations for walking, across all of the outcomes studied. This may be attributed to the low duration of walking to work (relative to cycling, and relative to other studies). It may also be attributable to the lower intensity of walking relative to cycling. There may also be some Cambridge specific factors, related to socio-economic differences, between those cycling to and walking to work. Despite this, across the different analyses there was evidence that walking for travel, including walking to work, is valuable for health.

Increases in the levels of physical activity within a population, which could come about from shifts in travel behaviour (e.g. away from car-use towards walking and cycling), are likely to be associated with improvements in a range of health indices. For some diseases these improvements will result in a decrease in healthcare need. However, because of improved survival for some diseases, indices of healthcare need may change little or (rarely) increase.

8.5 Implications for practice and policy

I am defining practice as the "carrying out or exercise of a profession," and policy as "a course or principle of action adopted or proposed by an organization or individual".[361] Alternatively the practice of public health is what public health professionals do, with much of the professional activity taking place at a local level. Government policies, whether intended to effect health or not, are predominantly (but not solely) instituted at a national level.

8.5.1.1 Implications for public health practice

The findings reaffirm the value of active travel, including active commuting, for improving or maintaining health amongst adults of working age. This is an important message to communicate to individuals when choosing how to commute (or undertake other regular travel). Just as there is a recommendation to reduce sedentary time, within public health guidelines,[88] there could be an explicit recommendation to replace car travel with walking, cycling or public transport, when practical.

The findings should also be communicated to those who can influence the determinants of active travel (e.g. major employers, transport planners and officials, elected representatives). Of particular note, this thesis has strengthened the evidence base associating active commuting with reduced sickness absence and improved well-being. Both these outcomes are important to employers and may be associated with greater productivity and financial savings. Shifting the distribution of active commuting is likely to require changing the underlying environmental determinants of commuting behaviour, some of which are under control of employers, such as (car or bicycle) parking, financial incentives (to use the car, bicycle or public transport), access routes (by foot, bicycle, car or public transport).[112,113]

My thesis has also strengthened the evidence supporting the inclusion of active commuting within long commutes (as opposed to only commuting by foot or bicycle, which is not practical for many commuters). This is also an important message to convey to commuters, as some might assume that walking or cycling to work is not practical if they live too far from work. However, facilitating this type of commuting may require investment in new infrastructure, such as park and ride facilities and public transport, or ensuring that urban planning (e.g. the siting of homes and offices) makes best use of existing infrastructure.[198]

Whilst those with long commutes may have relatively more to gain from active commuting, my thesis also suggests that other groups, such as those who are obese (Chapter Three) and those who are

relatively inactive (implied within the modelling of the dose-response curves, Chapter Five), may also have relatively more to gain from active commuting. It might be appropriate to target active travel interventions at these groups.

My thesis did suggest that cycling tends to be more beneficial than walking, although the reasons for this are not well understood and may relate to intensity, duration or other factors. One implication might be to facilitate, encourage and normalise longer walking journeys. Another implication might be to make cycling more widely accessible in other parts of the UK.[362] Walking and cycling are complementary, may fill different travel needs and may appeal to different groups. It is important to promote both activities rather than focus on one activity.

The modelling work suggested that public health officials should be more circumspect about suggesting that increases in physical activity will reduce need for healthcare in the long run. Whilst need may decrease for some diseases, it may not decrease as much as simple calculations may suggest and it may not decrease for other diseases. Instead it may be more appropriate to put the emphasis on improvements in health and a delay in onset of disability or death. It may be possible to 'monetise' some of the benefits to health by considering wider societal benefits, for example through reduced sickness absence, rather than focusing on savings and costs within the healthcare sector.

Similarly, it is common to suggest that physical activity interventions are "preventative", whilst this may be reasonable for some outcomes, like diabetes, it may not be for others, like dementia. If it is not clear that prevention will occur, it may be appropriate to use the term "risk reduction, which may delay or prevent" onset of disease, reflecting the language used in some recent publications on dementia.[346,347] A strong case for investment in such interventions can still be made, focusing on health benefits.

Similarly, public health practitioners should be cautious in their interpretation and use of findings from modelling studies that have not made allowance for the effect of physical activity on survival. Some major studies have estimated the burden of disease (measured in disability adjusted life years), and consequent costs, attributable to lack of physical activity.[106,107,109,354] These models have not explicitly modelled changes in survival and consequently have not modelled possible delay in onset of disease and associated costs. Their estimates of burden and cost, attributable to lack of physical activity, assume that all other factors, including mortality are fixed.[352] Thus one should be careful about assuming that the relevant increases in physical activity will result in decreases in the burden of diseases, principally Years Lived with Disability (YLD), and consequent cost savings, that these figures appear to suggest. Some of the cost and some of the burden of disease, that attributable to

YLD, will be postponed. Similar caveats are likely to apply to the modelling of the effect of other risk factors on non-communicable diseases.

8.5.1.2 Clinical implications

The estimated association between maintenance of cycling to work and BMI was 1.2 kg/m^2. This equated to a difference of 3kg for a person of height 1.6m in a cohort with a relatively low prevalence of obesity. Whilst there remains uncertainty about the size of the effect, and whether the relationship between active travel and adiposity is causal, the reported effect size for active commuting is similar to that observed in weight loss interventions (4 to 6kg)[xxxv]. Given that there are good grounds to assume that the relationship is causal and a favourable assessment of benefits against risk,[142] clinicians may consider recommending active commuting to suitable patients. A benefit of adopting active commuting, compared to standard weight loss interventions (which are typically offered for a short period), may be long-term maintenance of weight loss, if the behaviour is sustained.

8.5.1.3 Implications for government policy

The implications for policy reflect the implications for practice, i.e. that governments seeking to improve health and well-being should encourage, support and facilitate walking and cycling as forms of travel, most likely (given limited resources and space constraints) at the expense of car-use. Whilst I have not specifically tested the effectiveness of different approaches to promoting active travel, in Chapter One I argued that advice alone is unlikely to be sufficient to achieve population 'shift'. Changing the social, environmental and economic determinants of active travel is likely to be necessary, and if this is to be done at scale, this requires a significant shift in government policy towards walking, cycling and public transport and away from car-use. The need for this is under-scored by my finding that suggest inclusion of walking or cycling within long commutes (or as part of a pattern of commuting) is beneficial. Undertaking this type of commuting is likely to depend on the development and maintenance of appropriate infrastructure (i.e. public transport, park and ride facilities).

The benefits of physical activity for health are much broader than its effect on obesity,[26] as this thesis has demonstrated. However, obesity can be an important driver for policy change in the UK, and there is a risk that policies to reduce or prevent obesity, primarily or solely, focus on diet and largely

[xxxv] Trials of weight loss interventions (where most participants are obese) are associated with an initial weight loss of the order of four to six kilograms (followed by regain).[368–370]

exclude physical activity including active travel.[xxxvi] My findings suggests that physical activity, particularly active commuting, given the estimated effect sizes and improved causal inference, could be a valuable component of any strategy to reduce obesity.

[xxxvi] Some commentators dismiss the role of physical activity in preventing obesity.[255] The recently released childhood obesity action plan did not discuss active travel, and physical activity (sport or physical education) only featured in two of the 14 recommendations.

8.6 Future research

8.6.1 Measurement of physical activity

A limitation of both the epidemiological and modelling work has been measurement of physical activity.

Future studies of physical activity and health should seek to quantify the dose of physical activity. This will facilitate a better description of dose-response relationship between physical activity (and active travel) and health, important both for informing public health guidelines (how long? how hard? how often?) and developing better public health models. Whilst it is possible to quantify physical activity using self-reported questionnaires, this has limitations and consequently objective measurement of physical activity should be encouraged.

Much of the discussion on 'dose' throughout this thesis has focused on measures of intensity and duration. Whilst these dimensions of physical activity are important, future research should also measure other dimensions, such as frequency, type of activity and context, as well as evaluating the importance of relative intensity (rather than absolute intensity).

A limitation of the modelling work was uncertainty about how to apply findings for a single domain of physical activity, such as leisure time physical activity, to a population that is undertaking activity across multiple domains. Future work should also consider how to 'integrate' measures of physical activity across different domains of physical activity.

8.6.1.1 Active travel

Whilst methods to objectively measure active travel exist,[205,206,363] they have not yet been used in a large datasets and need further development to enable their use in such studies. Objective measurement of active travel may require the retrospective identification of active travel from objective records of physical activity (e.g. based on signal pattern, time of activity or supplementary Global Positioning System data). This may be possible using the Fenland Study or other studies that have measured physical activity objectively, such as UK Biobank. However, studies that have measured physical activity objectively are relatively new and the length of follow-up short, so it may be several years before their potential can be realised.

Another potential direction is to develop methods to measure active travel using mobile phones. Mobile phones are ubiquitous and offer the possibility of frequent (or even continuous) data collection from large groups of individuals. However mobile phone data may have other limitations, such as comparability across multiple devices and generalisability of findings.

Accurate measurement of intensity and duration of walking and cycling, may contribute to a better understanding of the different associations for walking and cycling with indices of health.

8.6.2 Development and evaluation of interventions to promote active travel

Given the strength of the overall evidence suggesting active travel can improve or maintain health and well-being, future research should develop and/or evaluate interventions that aim to promote active travel. The 'radical' population approach to promoting active travel, as well as some of my findings suggests that interventions to promote active travel should seek to modify the underlying social, economic and physical environmental determinants of active travel. There needs to be more empirical evaluation of real interventions, such as the study of the Cambridge guided busway,[145] as well as health impact assessments of actual or proposed interventions, such as the London cycle hire scheme.[142]

There may also be scope for individually focused interventions. In the previous section on implications for practice and policy (section 8.5.1.2, under clinical implications), I suggested that clinicians might want to recommend the adoption of active commuting to suitable patients and that adopting active travel might support long-term maintenance of weight loss. These approaches may be best incorporated into existing interventions to promote physical activity (e.g. exercise on prescription) or weight loss maintenance. The acceptability and efficacy of such approaches should be tested.

8.6.3 Effect of physical activity on mortality and life expectancy

The life table modelling has highlighted a discrepancy in estimates of the effect of increases in physical activity on changes in life expectancy. Estimates of changes in life expectancy modelled through disease pathways are less than when the effect of physical activity on mortality is modelled directly. This may relate to issues with the model (e.g. around modelling all the pathways between physical activity and mortality) or may be an indication of issues with some of the epidemiological studies describing the association of physical activity with disease and mortality. This has not been an explicit focus of my work and warrants further exploration. Until this is resolved, I do not think it is

possible to make strong inference about the effects of physical activity on life expectancy from multi state life table modelling.

Given that epidemiological analyses themselves may appear inconsistent (e.g. recent estimates of comparable increases in physical activity were associated with a reduction in mortality of 16-30% and a reduction in cardiovascular incidence of 17%; see Chapter 7, section 7.4.2), resoultion may require both an exploration of issues with epidemiological studies as well as consideration of the (modelled) pathways by which physical activity affects mortality.

8.6.4 Effect of changes in physical activity on healthcare utilisation

This work only partially answers the question about the extent to which increases in physical activity, when considering its effect on survival, affect the disease burden and consequent need for healthcare. Future work could estimate the effect of increases in physical activity on all-cause disability and on other diseases (including those whose incidence increases with age, but is independent of physical activity). It could also explore different scenarios, for example the effect of a population with mixed ages (rather than a birth cohort), look over a different time horizon that is more prescient for decision makers (e.g. five to 20 years) or restrict the changes in physical activity to particular phases of life, such as mid-life.

A full economic appraisal should be undertaken to understand the economic implications. This should consider which economic costs or benefits (e.g. the increased tax base from an increased population, productivity of a working age population that is healthier, increased pension costs from an older population) are in or out of scope.

8.6.5 Use of longitudinal methods for epidemiological analyses

Future analyses of the association of active travel and health should principally focus on using longitudinal data, although many of the existing cohort studies will not have objective measurement of active travel. Of note, EPIC-Norfolk (and related EPIC studies) and UK Biobank include the same question on mode and frequency of travel to work which I made use of in my analyses reported in Chapter Four. This underscores the need to validate the frequency of travel question on the Recent Physical Activity Questionnaire. Both EPIC-Norfolk and Biobank have a rich set of health indices

including measures of well-being and objective measures of adiposity, such as BMI, total and regional adiposity[xxxvii].

Sickness absence is not commonly reported despite being relatively easy to capture with a single question. Given its wider importance it should be routinely included within cohort studies.

Appropriate longitudinal methods should be used. Traditional cohort studies test the association between an exposure at baseline and an outcome at follow-up. This design, which implicitly assumes that the baseline exposure is relatively constant, may be less applicable for active commuting if, as was observed in the Commuting and Health in Cambridge dataset, switching to or from active commuting is relatively common. Maintenance and change analyses may thus be more appropriate. Different approach to data collection, such as using mobile phone data, that could more accurately capture the timing of changes in travel patterns or enable collection of data at multiple time-points, may facilitate more informative longitudinal analysis.

8.6.6 Development and use of public health modelling methods

8.6.6.1 Appropriate models

The modelling work suggests that the effect of physical activity on increased survival will, at least in some circumstances, affect indices of healthcare need. When undertaking public health modelling the extent to which this process may influence the results should be considered, and an appropriate choice of public health model should be made. A shift towards greater use of longitudinal models within public health modelling may be appropriate.

Much existing work, both of physical activity and other risk factors, makes use of comparative risk assessment models. The work I have presented has highlighted the limitation of not considering the effect of a risk factor, such as physical activity, on survival. Further work should explore when findings from comparative risk assessment models may not be valid, and whether it may be possible to make simple adjustments to correct findings under those circumstances.

However my work (the discrepant life expectancy estimates) highlights potential issues with multistate life table models, principally that they may not consider all the pathways (and thus the full impact) of physical activity on health. Whilst I argue for greater use of these and other longitudinal

[xxxvii] In the UK Biobank, the cross-sectional associations or active commuting with BMI and percentage body fat have already been reported.[130]

models because they make allowance for delay in disease onset, greater use should be accompanied by an awareness of the model limitations. It is also important for further comparative modelling, between different types of models, to be undertaken in order to better understand differences between models and facilitate improvement in modelling methods.

8.6.6.2 Measures of disease

As an important outcome in longitudinal models is the delay in onset of disease, appropriate metrics to report delay may need to be developed (change in mean age of onset in the context of a reduction of cases may be misleading). Future work could also explore likely discrepancies in estimates in the change in DALYS (Disability Adjusted Life Years), using comparative risk assessment models and longitudinal models.

8.7 Personal reflections

When I began preparation for this thesis I thought I wanted to identify practical solutions to promote active travel that might be applied at the local or national level. I expected to focus a significant part of my thesis on the associations between the environment and active travel. This was because I saw lack of action in this sphere as a greater challenge for public health practice, than understanding the importance of physical activity for population health. I had assumed questions concerning physical activity and health were largely answered.

Shifting attention towards describing the associations between physical activity and health was partly driven by wanting to connect explicitly with health and disease, reflecting my background in medicine. It was also partly because during the process of preparing for and undertaking the PhD, I have come to recognise that there is greater uncertainty concerning the associations between physical activity (including active travel) and health than I had previously appreciated.

I now think that measurement of physical activity is a critical issue for the field of physical activity and public health. Improvements in measurement are necessary to improve public health models and refine public health guidelines. Improved measurement may also make it possible to detect, small but important, changes associated with real interventions. It may also help to formulate solutions by understanding the respective importance of walking for health, and how much is needed to improve health and well-being. I also think dose-response questions are important in terms of whether a public mandate for widespread environmental change (and restrictions on car use) is given. There is still considerable uncertainty for example concerning the effect size associated with active travel. If large increases in active travel were only associated with 'small' changes in obesity prevalence, of the order of one or two percentage points, then such change might not have widespread support. However, if the effect was much larger, such as ten percentage points with other improvements in other aspects of health and well-being, then such changes might receive wider support.

Work that describes the relationship between physical active and health, particularly from a population perspective, is important to help people formulate or advocate for solutions. Also work identifying, developing and evaluating interventions is necessary to change practice and policy.

Initially the second part of the thesis felt uncomfortable because it was challenging a line of argument used within public health practice to advocate for investment in or legislation for public

health interventions. It could be seen as undermining, rather than supporting, public health practice, particularly advocacy. Initially I justified the work because, I think public health should adhere to high standards of evidence and that failure to do so, in the long-run, risks undermining trust in public health and public health practice. As the thesis progressed, I came to recognise that a valuable role of academia, within society, is critical unbiased analysis. Academic public health should not provide evidence to support a particular approach but should offer critical unbiased analysis.

This is one example of a tension between public health advocacy (which involves putting a favourable case for health interventions often to audiences who use evidence differently to medical researchers) and adherence to evidence. I have seen some academics respond to this challenge by simply describing their findings and making no recommendations for policy or practice. I do not think this is appropriate, but I do recognise there is a risk of brining bias or prejudice to the analysis and interpretation of the results. The approach I have arrived at, during my PhD, is to strive for the analysis and interpretation to be impartial and then to frame the implications in terms of what they mean for improving health.

Whilst theoretically a population approach to improving health, by shifting the curve, may realise large health gains, it remains a theory. From observing other work during the course of my thesis, I have come to realise that even apparently modest shifts in behaviour at the population-level (e.g. an extra 10 minutes walking per day) are likely to be very hard to achieve in the UK, in part reflecting limited political and public support, and in part reflecting the observed effect sizes associated with studied interventions. Nonetheless I am sure there will be large changes in health behaviours and health, during my career. Some of these changes may be driven by factors outside of public health, and indeed outside of government, so called 'megatrends',[123] for example mobile phones or the use of electric cars, which will be important to study and to document. There will still be opportunities for academic public health to act as a catalyst for change, but identifying those points of leverage will be a challenge and may be as much an art as a science.

8.8 Conclusions

Active commuting is associated with improved well-being, reduced sickness absence and reduced adiposity amongst adults of working age. Increases in physical activity, because they are associated with improved survival, are not necessarily associated with reductions in need for healthcare for diseases for which physical activity is protective. When allowance is made for increased survival, estimates of reduction in the need for healthcare tend to be smaller and may be negligible.

Active travel should be promoted as a means to improve health. Its importance for health should be conveyed to individuals, choosing how to travel, as well as to governments and other stakeholders who can influence the determinants of travel.

Shifting the distribution of active travel, and ultimately physical activity, is likely to require facilitating and enabling active travel by changing those underlying determinants (e.g. normalising walking and cycling, reducing subsidies for car-use, investment in walking and cycling infrastructure). Whilst shifting the distribution of physical activity will improve health and reduce the incidence of certain disease, policy makers and public health practitioners should be cautious about how such changes are extrapolated to changes in need for health, and by implication costs for healthcare, as disease events may be postponed rather than prevented.

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Appendix

Commuting and Health in Cambridge seven-day travel record

About your travel to and from work in the last seven days

In this section, we are interested in **how you travelled to and from work on each of the last seven days**.

39 **For each of the last seven days, please tell us what time you started and finished work and tick all the modes of transport you used on the journey to and from work.** If you did not travel to work on a particular day (either because it was a day off or because you worked at home), please tick the box 'Did not travel to work'. If your journey to and from work was the same on more than one day, you can tick the box 'Same as previous' instead of repeating the information again. *We have given you an example for one day in the first row of the table.*

Which modes of transport did you use on this journey? *Tick all that apply*

Day of the week	Time started work	Time finished work	Did not travel to work		Same as previous	Bus or coach	Train or underground	Car, taxi or van	Motorcycle or moped	Bicycle	Walking	Other
Thu	7.30 am	3.30 pm	☐	**To work**		☑	☐	☐	☐	☐	☑	☐
				From work		☑	☐	☐	☐	☐	☑	☐
			☐	**To work**		☐	☐	☐	☐	☐	☐	☐
				From work		☐	☐	☐	☐	☐	☐	☐
			☐	**To work**	☐	☐	☐	☐	☐	☐	☐	☐
				From work	☐	☐	☐	☐	☐	☐	☐	☐
			☐	**To work**	☐	☐	☐	☐	☐	☐	☐	☐
				From work	☐	☐	☐	☐	☐	☐	☐	☐
			☐	**To work**	☐	☐	☐	☐	☐	☐	☐	☐
				From work	☐	☐	☐	☐	☐	☐	☐	☐
			☐	**To work**	☐	☐	☐	☐	☐	☐	☐	☐
				From work	☐	☐	☐	☐	☐	☐	☐	☐
			☐	**To work**	☐	☐	☐	☐	☐	☐	☐	☐
				From work	☐	☐	☐	☐	☐	☐	☐	☐
			☐	**To work**	☐	☐	☐	☐	☐	☐	☐	☐
				From work	☐	☐	☐	☐	☐	☐	☐	☐

Section B Activity at work

Travel to and from work in the last 4 weeks

What is the approximate distance from your home to your work?

☐☐☐ Miles *or* ☐☐☐ Kilometers

How many times a week did you travel from home to your main work? ☐☐
Count outward journeys only

Please tick (✓) one box **only** per line

How did you normally travel to work?	Always	Usually	Occasionally	Never or rarely
By car/motor vehicle				
By works or public transport				
By bicycle				
Walking				

What is the postcode for your main place of work during the last 4 weeks?

Postcode ☐☐☐☐☐☐☐

If not known please give your work address
Work address - _____
_____
_____

What is the postcode for your home address?

Postcode ☐☐☐☐☐☐☐