Understanding transport behaviour and policies to increase walking and cycling

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This dissertation is submitted for the degree of

Doctor of Philosophy

Kellogg College

October 2021

Let’s begin with what you’re probably doing right now as you read these words - not moving - to explore more deeply the biggest myth of them all: that it’s normal to exercise.

- Daniel Lieberman, *Exercised: The Science of Physical Activity, Rest, and Health*

Give a man a fish and feed him for a day. Teach a man to fish and feed him for a lifetime. Teach a man to cycle and he will realize fishing is stupid and boring.

– Desmond Tutu

Offhand I had said it, to an author from Israel, seated beside me in a grand square at the Edinburgh Book Festival. I said that the bicycle seemed to bring out the best in people. I said that it cut through to something deeper and, in so doing, showed the truth of a place.

- Julian Sayarer, *Fifty Miles Wide*

I will begin with the proposition that in no other major area are pricing practices so irrational, so out of date, and so conducive to waste as in urban transportation.

- Vickrey, 1963

Why bad decisions
Cars carbon pollution death
Pathways must change now

- Jacqueline Klopp, Co-Director Center for Sustainable Urban Development at the Earth Institute, Columbia University

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 100,000 words including appendices, bibliography, footnotes, tables, and equations.

Covid-19 statement

The onset of the Covid-19 pandemic in March 2020 did not significantly affect my ability to carry out academic work, or any planned research opportunities. I had completed all my fieldwork in the spring of 2019, and was doing desk-based research throughout 2020. The vast majority of my resources are available online, so the closure of libraries and archives did not affect my research options. I spent 2020 analysing data collected in 2019 and other open-access data, writing up my research into publishable form, and writing my DPhil framing chapters. My plan remained unchanged after working-from-home rules were established. My personal circumstances were largely favourable since March 2020. I lived alone for a couple months when my international housemates moved back home, and I have been through several quarantines, as people around me e.g. my sister, tested positive for Covid-19. For the most part though, I have been lucky.

Simona Sulikova

October 2021

Acknowledgements

I would like to thank my supervisors, Christian Brand and Linus Mattauch, for taking on a student with a disparate project and only two years of funding, who helped mold my ideas into coherent research, and supported me throughout the way. I would also like to thank the community at the Transport Studies Unit and the Institute of New Economic Thinking, whose inclusive atmosphere made this a (mostly) enjoyable experience.

I would like to acknowledge the participants of my survey research in Vienna and Örebro, who spent their time and shared their opinions and travel patterns with me, without whom a significant part of this research would not have been possible.

Next, I would like to acknowledge my two funding sources: the Ministry of Education, Science, Research and Sport of the Slovak Republic for awarding me the Stipend of Martin Filko (and for giving me a job in the pandemic), and the Kellogg Progress Scholarship.

Thanks to Copestake, for his unwavering, unrelenting, all-encompassing trust in me. So many things would have been impossible without you.

To Katherine and Debbie, whose slow descent into madness during their DPhils made me appreciate my own, and whose Taylor Swift playlists and crazy car trips I cherish endlessly. Even more so, to their incredible work with ISARIC during the pandemic, and that I was able to feel like I contributed, ever so slightly, to their life-saving efforts.

Thanks to my two ECM MSc partners in crime - Lena, who lit up every day with her spark, passion, coffee, random food, booming laughter and rowing chat; and Mo, for always being willing to listen, to help when I broke down over some coding error, and for pushing me to strive for better. Thanks to Sergio, Marcel, Iqbal, Anna, Helen and Jenny, for brightening every day in the DPhil room and the department.

Finally, thanks to all the inspiring people out there working on mobility, cycling, walking, and physical activity. Cycling and movement are great. Let's make them more common.

Abstract

This thesis examined the factors affecting active mobility, walking and cycling, in urban environments using a multilevel perspective, from individual agency to built environment, to national-level policies. Understanding that health behaviour change is complex, and cannot be achieved through a single one-size-fits-all policy is the key premise of this thesis. In order to recognise the system-wide influences on walking and cycling, a socio-ecological framework was developed. This combines insights from psychological literature, transportation, and broader policy, and presents their relative roles and interactions in determining urban transport. Statistical analysis based on data from seven European cities showed the crucial role attitudes and psychosocial variables play in determining active travel. Based on the principles of realist evaluation, an analysis of interventions aimed at changing the psychosocial mindset of study participants in four of the seven cities revealed the short-term positive effects of such soft-measure interventions. However, the analysis also emphasised the need to change people's experiences for these measures to have a lasting effect. Finally, an economic analytical framework was developed to evaluate the potential effectiveness of a nation-wide policy (higher fuel taxes) to reduce car use and increase active travel. While including physical inactivity as a social cost greatly increases the optimal value of a fuel tax, limiting factors such as the psychosocial mindsets of people, or lack of suitable infrastructure, reduce the potential impact of such policies. Hence, working in an integrated, multidisciplinary manner is necessary for changing complex systems such as urban transport, physical activity-related health, and reducing carbon dioxide emissions.

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Chapter 1

Introduction

1.1 Motivation

Physical inactivity was declared a global pandemic in 2012 and is the fourth leading cause of death worldwide (Kohl et al., 2012). It contributes to cardiovascular disease, diabetes, depression, and several different types of cancer, among other diseases (Davies et al., 2019). It is therefore unsurprising that physical activity has been called a "miracle cure" for diseases (Davies et al., 2019). The situation in the global North has steadily become worse with time, with the proportion of the population that is inactive rising from 31.6% in 2001 to 36.8% in 2016 (Guthold et al., 2018). Policymakers still lack the tools and knowledge to be able to tackle population-level inactivity comprehensively, and the public still confuses the effects of a sedentary lifestyle with that of being obese (Stensel et al., 2016).

Transport sectors and systems of transportation in many Western countries are also coming under scrutiny due to climate change. In France (Lepoutre, 2018), the United Kingdom (Gabbatiss, 2018), and the United States (Hockstad and Hanel, 2018), the transport sector is currently the largest emitter of CO_2 emissions. To date, declarations of national climate emergencies or national net-zero carbon emissions legislation have not led to systematic changes in transport systems. In addition, road transport is responsible for congestion costs in the value of 1.75% of GDP in European countries. This increases to 1tn EUR, or 7% of the GDP of EU27 countries, once other social costs, such as air pollution and accidents, are included (van Essen et al., 2019).

As around 40-45% of all travel in Europe and the US is under 3 miles in length (DfT, 2018; NHTS, 2019; Götschi et al., 2015), a large potential for switching to active travel exists (Rabl and De Nazelle, 2012). Active travel is walking and cycling for transportation, including trips to and from public transit stops or train stations, shared bicycles and e-bikes, but not nascent types of micromobility such as e-scooters. Increasing cycling and walking rates has the potential to improve the rates of physical activity on a population level, as well as reduce carbon emissions and other social costs associated with vehicle-based transport. Active travel serves the dual purpose of both transportation and exercise. It is therefore more easily integrated into daily routines than sports activities, and provides an equitable and more economically affordable form of physical activity. It can also improve the physical activity levels of population groups that are not interested in other forms of leisure-based physical activity (Dons et al., 2015). For example, walking to public transport can provide up to 30% of daily physical activity needs (Besser and Dannenberg, 2005). Focussing on active travel therefore has the potential to increase physical activity levels within a population, deliver physical and mental health benefits of exercise in an equitable way, but also reduce transportation-based negative effects such as excess congestion, high air pollution levels, or carbon emissions.

This means that active travel is associated with large co-benefits that are not the main aim of a policy, if policies are implemented in order to increase physical movement (Wolkinger et al., 2018). Nonetheless, prevalence of cycling amongst the public remains astonishingly low in most developed economies, typically around 7% of urban trips, or less (Sahlqvist et al., 2012; NHTS, 2019). This is partly because, to date, transportation policies have failed to address the negative impact of car use on our societies, and establish appropriate prices for car use. There is still an overwhelming focus on efficiency, and hybrid and ultra-low emissions vehicles, and a neglect of exercise, air (and carbon) pollution, water pollution, and noise-related health, among other problems. Due to the pressure of climate change, increasingly radical changes are needed to transform transport, but these are not coming fast enough. For example, Anable (2019) predicts that to meet UK national emissions targets, reductions of vehicle use of up to 60% by 2030 might be necessary, even with a rapid scaling up of electric vehicle uptake.

The large benefits of active travel, and the lack of positive trends in active travel worldwide despite rising interest in the topic, are the inspiration for this thesis. This thesis explores the relationships between active travel and people's built environments, their attitudes, and the wider policy system, and evaluates the potential of two kinds of policies: one targeted, ex-post, and individualised; and one national, ex-ante, and financial, to shift urban travel towards more walking and cycling.

In order to recognise the system-wide influences on walking and cycling, this thesis develops a socio-ecological framework. This combines insights from psychological literature, transportation, and wider policy, and presents the relative roles of the built and social environments, and interactions between them, in determining urban transport. Statistical analysis based on data from seven European cities showed the crucial role attitudes and psychosocial variables play in determining active travel. Based on the principles of realist evaluation, an analysis of interventions aimed at changing the psychosocial mindset of study participants in four of the seven cities revealed the short-term positive effects of such soft-measure interventions. However, the analysis also emphasised the need for changing the experiences of people for these measures to have a lasting effect. Finally, an economic analytical framework was developed to evaluate the potential effectiveness of a nation-wide policy (higher fuel taxes) to reduce car use, and increase active travel. While including physical inactivity as a social cost greatly increases the optimal value of a fuel tax, limiting factors such as people's attitudes, or the lack of suitable infrastructure, reduce the potential impact of such policies. Hence, working in an interdisciplinary manner is a necessary strategy for changing complex systems such as urban transport, physical activity-related health, and reducing carbon dioxide emissions. The remainder of this introduction presents past research and policy efforts, in order to provide a motivation and background. Next, the aims of this thesis, and a summary of its findings, are presented.

1.2 Background in brief

A significant body of empirical research on interventions aimed at increasing active travel exists (see Kelly et al. (2020), Winters et al. (2017) and Stewart et al. (2015) for some of the recent reviews), but so far reports mixed results regarding effectiveness. In addition, many of these studies rely on self-reported travel, small sample sizes (Panter et al., 2016), lack of control groups (Yang et al., 2010) and short follow-up periods (Song et al., 2017), undermining the conclusions that can be drawn about long-term behavioural outcomes.

Policy-induced change towards healthier behaviours and habits is notoriously difficult to achieve, as the decades-long efforts to reduce alcohol overconsumption and smoking show. This is especially true for active travel, which traverses the domains of public health, behavioural psychology and economics, transportation, urban regeneration, and climate change mitigation efforts, to name a few. Efforts to increase active travel therefore often lack a coherent strategy. An understanding of, and cooperation within, all of the above domains is necessary in order to foster a supportive environment for people to become more active, healthier, and more environmentally friendly. This thesis takes a number of different approaches to the problem described above, and argues that there are many different actors involves, and interests that need to be met, in order to increase active travel.

Currently, a number of cities in Europe and North America have tried to step up and increase their efforts to become more sustainable. Many have air pollution limits and standards, and have set carbon emissions reductions targets, or are bound by national commitments. Few city-level or national-level active travel targets exist, however, meaning there is often no mandate to incorporate active travel into air pollution and carbon emissions-related policy, or vice-versa.

The COVID-19 pandemic has revealed two possible levers for increasing efforts in encouraging active travel. First, it has exposed the vulnerability of people suffering from chronic illness, and has led to a public awakening of people's interest in their own health. Second, due to the grave restrictions on movement and travelling that governments worldwide are imposing, old travel habits are being disrupted. This has provided city governments and civil society alike with the opportunity to implement walking- and cycling-friendly policies. Both urban transport, and the prevalence of sedentary lifestyles and physical inactivity, need to be tackled more consistently, and with greater nuance, in order to deliver results and noticeable changes in the physical health of people.

Perhaps, however, people simply prefer not to move. When asked, the majority of people report a lack of interest as one of the main reasons for their insufficient physical activity levels (Eurobarometer, 2018). Evolutionary and anthropological research suggests that the modern-day conception of exercise for exercise's sake is not a "natural" form of movement for humans (Lieberman, 2020), and that slogans such as "Just Do It" or simple information campaigns are not appropriate motivation tools. As walking and cycling can be seen as a means of transportation, not exercise, they can be a mentally easier form of movement to incorporate into daily life than dedicated exercise activity (Lieberman, 2020). Indeed, experts find that demand-side solutions in transport, in particular shifts to walking and cycling, do improve subjective wellbeing (Creutzig et al., 2021). However, it is undecided whether people would like the government to implement policies that improve their subjective wellbeing, or would rather have their preferences satisfied, e.g. in the form of faster roads (Mattauch et al., 2016). The chain of causality is also unclear: does improved health makes one happier? Or does improved happiness make one healthier (Veenhoven, 2008; Graham, 2008)? Due to these uncertainties, this thesis focusses on more objectively measured walking and cycling use as outcome variables of interest: mode choice, frequency of mode use, and distance travelled actively, rather than satisfaction by mode choice and use, value of travel time by mode, or wellbeing associated with mode use. Recognising personal vehicle use, whether diesel, petrol, or electricity fuelled, as a sub-optimal form of urban transportation due to its inefficiencies and harmful effects, this thesis explores the potential of walking and cycling as viable alternatives to personal car use.

1.3 Aims and research questions

The aim of this thesis is to investigate public policies, interventions, and environments that foster travel behaviour change, specifically away from car use towards active travel. In order to do so, it argues for a multilevel, multidisciplinary approach to identifying and addressing the barriers to active travel. This thesis has four main objectives:

1. to present a multilevel socio-ecological framework for active travel within which different theoretical frameworks dominate different levels, and interact with each other;
2. to identify the most significant factors affecting active travel behaviour in the 7 PASTA cities within a socio-ecological conceptual framework for individuals, helping identify policy levers in transport;
3. to examine the effectiveness of various information-based (soft) interventions aimed at increasing active travel using two case study cities in a 5 year case-control cohort study, in particular whether these interventions work, for whom, and when;
4. to identify all the major social costs of car travel, adding previously excluded health benefits from exercise using a theoretical economic framework that translated a well-

known problem in public health and transport into language relevant to economists, and thereby identify the potential of national policy to influence active travel.

In order to fulfil these aims, this thesis follows the paper format. The papers are:

1. "As you bike it: Investigating what makes people walk or cycle using a socio-ecological approach in seven European cities," addressing Objectives 1 and 2;

2. "Increasing active travel using information-based measures in the PASTA dataset: a longitudinal case-control study," addressing Objective 3;

3. "Healthy climate and healthy bodies: Optimal fuel taxes under suboptimal health choices," addressing Objective 4.

1.4 Summary of thesis findings

This thesis focusses on the global North, relying largely on secondary survey data collected in seven European cities as part of the Physical Activity Through Sustainable Transportation Approaches (PASTA) study looking at factors affecting active travel, attitudes, health, and travel patterns, which ran from 2014-2017. The thesis also uses primary follow-up survey data collected in 2019, open-access data available for these seven cities, and national-level data available for the UK and US, in order to provide a comprehensive analysis of the similarities and differences in active travel and transport patterns that prevail throughout the Western world.

First, Chapter 2 provides an overview of the literature that exists on the benefits of active travel, the correlates of different constructs and environments with active travel, and the different types of policies and policy mixes that can be used to encourage people to walk and cycle more.

Second, the methodology chapter, Chapter 3, describes the conceptual framework developed in order to improve understanding of the complex interactions between factors that help promote or impede walking and cycling in urban areas. Socio-ecological frameworks, theories explaining how the built and natural environments, and social, household and individual factors influence travel behaviour, are increasingly being utilised in travel behaviour research. Apart from several exceptions (Gascon et al., 2019; Ogilvie et al., 2011; Panter and Jones, 2010; Burbidge and Goulias, 2009), research remains limited to evaluating one specific part of the system or topical perspective (Götschi et al., 2017). Götschi et al. (2017) synthesise this literature and construct a comprehensive socio-ecological framework that this thesis builds on. The socio-ecological framework itself is not exhaustively complex; rather, it provides a space where new theories, or other fields of research not considered in this thesis, may slot in and interact with the system that encourages or inhibits active travel. By drawing explicit feedback loops, the socio-ecological framework highlights the need for policies and research at all levels of the framework to work with each other, rather than in a piecemeal fashion.

Third, Chapter 4 applies the conceptual framework presented in this thesis, and examines the relative importance of different factors in determining walking and cycling using quantitative methods. In line with Objective 2 specified in Section 1.3, the aim of this chapter is to identify where policy efforts should focus most in order to promote active travel. It tests the hypothesis that each domain of active travel is equally important in determining which mode of transport is used, with a specific focus on the relative importance of the built environment compared to the other domains. This chapter uses logistic regressions for the analysis, a common method in research examining the strength of built environment and attitudinal factors in determining mode choice.

The contributions of this chapter are threefold:

- providing an expansion to an existing state-of-the-art socio-ecological framework;
- identifying which aspects of the conceptual framework are the most important determinants of active travel in the PASTA dataset at work and home locations;

- by using novel spatial and accessibility data, it demonstrates the added value of making use of open source and big data.

This chapter rejects the hypothesis that all domains are equally important in determining active travel, but rather than psycho-social constructs influence behaviour slightly more than the built environment does, on a trip-by-trip basis. It provides evidence that social *distribution* - the socio-economic and demographic composition in the area of one's household - also influences transport decisions.

Fourth, many recent studies have reported significant levels of success in terms of increases in active travel following comprehensive and integrated policy interventions over multiple years (e.g. Chapman et al. (2018) and Aittasalo et al. (2019)). Evaluations of single infrastructure or information-based interventions report more mixed success (Song et al., 2017; Cairns et al., 2008), and are usually limited to one- or two-year follow-up periods (Panter et al., 2016; Goodman et al., 2013b). In addition, very few studies go beyond evaluating increases in physical activity to explore the putative causal pathways underpinning the effectiveness of the intervention, and the specific settings in which it does (Sahlqvist et al., 2015).

Chapter 5 aims to evaluate the effectiveness of interventions aimed at increasing walking and cycling employed during the PASTA study, as specified by Objective 3 of this thesis in Section 1.3. It tests the hypothesis that information-based interventions are effective in eliciting long-term behaviour change, taking advantage of PASTA's case-control study design. This chapter uses realist evaluation to study subgroups of individuals, and tests which hypothesised subgroups, contexts and causal mechanisms led to the greatest magnitudes of behaviour change in the group of individuals given the mostly information-based intervention. It therefore directly builds on the findings of Chapter 4, and aims to validate them further. For this purpose, a follow-up survey was conducted in 2019, and data from 2014-2019 were used in a quantitative longitudinal analysis of changes in travel patterns observed in the travel diary data, as well as self-reported travel habits and intentions recorded through the questionnaire survey.

This chapter therefore contributes to the literature in two ways:

- it conducts an evaluation of an intervention policy over a much longer (5-year) period than is typical in the literature;
- it proposes specific channels and subgroups for which this particular intervention was most and least effective, helping individualise and target similar interventions in the future.

The main finding was that the information-based intervention worked, but was significantly more effective for the first year after it was implemented than 3 years later. During the initial follow-up period (2016), walking, cycling, and e-biking were all significantly higher in the intervention affected group than the control group. However, this effect diminished for walking by 2019, ceased to exist for cycling, but was reinforced for e-biking.

Fifth, Chapter 6 proposes that active travel, and the associated health benefits foregone when someone chooses to travel by car, should be included in the cost of driving in economic analyses. It has a simple message: physical activity gained through daily transport is significant, and lack thereof has significant private and social costs. Although public health and transport experts are well aware of the benefits associated with higher active travel levels, the field of public economics has not engaged with this point.

Recognising that transport, infrastructure, and national-level tax decisions are overwhelmingly made by economists, this chapter makes use of economic utility theory and optimisation under a given set of constraints, Pigouvian externality taxation, health impact assessments, and public economics in order to address economists specifically. It did so in the form of an optimal fuel tax that accounted for the significant externalities of car travel - congestion, carbon emissions, air pollution, accidents, and physical inactivity. It builds on a seminal paper in the fuel tax literature by Parry and Small (2005), expanding on their framework and methods as examples of best-practice. In addition, the chapter recommends that the signal of an increased price of driving needs to be accompanied by an increase in public investment into dedicated cycling and walking infrastructure. It therefore focusses on the policy and built environment factors in the macro domain of the socio-ecological framework described in Chapter 3.2.

The chapter is therefore a novel contribution to the literature in at least four ways:

- it argues that physical (in)activity should be considered a social cost of car driving;
- it quantifies the economic value of this social cost for two example countries, the UK and US;
- it updates and expands on an existing framework of optimal fuel taxation present in environmental and public economics;
- and it combines the field of health impact assessments, formerly purely a domain of public health journals, with economics, providing new information in the field of economics and helping increase communication between these two fields.

The main finding is that the second-best optimal fuel tax needs to be adjusted by 49% in US and 36% in the UK, once physical inactivity is accounted for. Overall, the chapters demonstrate the strength of different disciplines, and how they can be applied in order to improve our understanding of the urban transport system. This thesis argues that omitting certain influences or actors within a system can lead to policies and recommendations that lead to counterproductive outcomes, as has been shown to be the case when people's motivations for action are misunderstood (see e.g. Bowles (2016)). The benefit of using a multi-level framework is that it explicitly recognises the impact of different levels of influences, and prevents the user from forgetting or omitting them in their own analysis.

Transport is one of the most ubiquitous aspects of daily life, and is often taken for granted, yet it is also one of the most inefficient sectors in the global economy. Focussing on the global

North, this thesis establishes connections between active travel and internal and external influences, evaluates the effectiveness of a series of soft measures aimed at reducing car dependency, and quantifies the social impacts of car-based transport and the fuel tax levels needed to reach optimal levels of vehicle-based and active travel.

1.5 Structure of this thesis

The thesis introduction set out the motivation for focussing on active travel as an important transport and health behaviour, and on the necessity of the multi-methods approach. Chapter 2 provides a brief overview of the evidence related to the ability of walking and cycling to increase physical activity and reduce carbon emissions, and past policies and research that aimed to understand and increase these two behaviours. The methodology explains the conceptual framework used for this thesis, and how it draws on different types of research within its different levels. It also explains the methods used within those levels. The methodology chapter then explains the PASTA study that much of the research in this thesis uses, and the broader geographical context. Next follow the three research chapters described above. The discussion and conclusion chapters summarise the findings, and explore the benefits and limitations of the multi-methods approach, as well as drawing conclusions for further research.

Chapter 2

Literature review

Road transportation policy has been considered insufficient for decades (Axsen et al., 2020; Vickrey and Sharp, 1968). Increasingly, recommendations are being made for integrated policy mixes, with commitments across all government levels to change transportation systems (Stephenson et al., 2018). In practice, transportation research integrates land-use planning (May et al., 2006), and more recently, climate change mitigation. However, broader concerns of equity and health do not usually enter analyses or evaluations of policy or investment decisions (Delbosc, 2012). This chapter first reviews evidence from public health and transportation research on the potential benefits of active travel. The chapter then explores factors affecting active travel, and looks at what kinds of policies have been found to be effective at increasing active travel. Finally, this chapter describes the various calls that have been made for a more integrated approach to transport policy, briefly followed by an explanation of how this can be done. More detail on certain parts of the literature is provided in Chapters 3 through 6.

2.1 Epidemiological and environmental evidence of active travel benefits

Increasing walking and cycling in urban areas is considered to be beneficial on two accounts: first, it is assumed that an increase in active travel leads to an overall increase in physical activity, not a displacement of exercise; and second, it is assumed that an increase in active travel leads to a decrease in the use of private motor vehicles for transportation, and thereby the negative effects associated with car use. This section explores the extent to which these two assumptions are true.

2.1.1 Physical activity and health effects

Any, even marginal, increases in physical activity would be highly beneficial to large parts of society (Haskell et al., 2007). It contributes to cognitive impairment and dementia (Loprinzi et al., 2018), depression (Catalan-Matamoros et al., 2016) (itself the leading cause of disability globally (James et al., 2018)), hypertension (Liu et al., 2017), type 2 diabetes (Smith et al., 2016), cardiovascular disease, low bone mineral density (Onambele-Pearson et al., 2019), and breast, colon, and lung cancer (Davies et al., 2019), as well as greater all-cause mortality. This remains true even when the increase in air pollution exposure is taken into account (Tainio et al., 2016; Woodward and Samet, 2016; Kelly et al., 2014).

Whether switching from car travel to active travel tends not to displace most other types of exercise, and leads to an overall improvement in health, has not been confirmed with certainty. In a longitudinal study, Laeremans et al. (2017) found an association between increased active travel and a reduction in BMI. Martin et al. (2015) report similar results for a nation-wide study of the British population. However, a systematic review by Wanner et al. (2012) did not find this association, and surveys of people who cycle for travel often show that people do cycle primarily for the exercise benefit (Useche et al., 2019), and that a substantial portion of regular cyclists believe they would do other forms of exercise if they did not cycle (Börjesson and Eliasson, 2012).

2.1.2 Physical activity and environmental impacts

In order for walking and cycling to be given priority in urban planning, active travel needs to contribute to improving the main determinants of whether an urban transport system is efficient and well-functioning. These measures are accidents, exposure to noise, time savings, air pollution (Nieuwenhuijsen et al., 2016; Santos, 2017; Montag, 2015), and increasingly carbon emissions (Givoni et al., 2013), noise, and water pollution (van Essen et al., 2019).

Car use contributes significantly to both carbon dioxide emissions and air pollution, and is one of the leading causes of city breaches of air pollution standards of PM_{10}, $PM_{2.5}$, NO_X, and SO_2 concentrations (Xia et al., 2015). In turn, air pollution is among the leading causes of death worldwide (Landrigan et al., 2017). Vehicle-related particulate matter (PM) emissions impact people's cardiovascular (Miller and Newby, 2020) and lung (Götschi et al., 2008) health. Efforts to reduce road transport air pollution are not straightforward, as neither switching away from fossil-fuel based cars, or investing into active travel infrastructure, are guaranteed ways of eliminating particulate matter emissions from transport. Switching away from fossil fuels to electric or hydrogen vehicles would remove some, but not the majority, of particulate matter emissions from transport (Brown et al., 2018). This is because up to a half of emissions from vehicles is from tyre and brake wear, and road abrasion.

Health impact assessments, conducted by public health researchers, are useful in assessing the health and environmental potential of shifts in travel patterns. Woodcock et al. (2009) show that ambitious climate mitigation scenarios through (1) the adoption of electric vehicles in New Delhi, India, and London, United Kingdom, and (2) a shift of urban transport largely to active modes, would lead to comparable reductions in air pollution concentrations, but slightly higher reductions in carbon emissions in case (2), and a much higher number of lives saved through increased physical activity in case (2). Maizlish et al. (2017) estimate the possible scenarios of increasing public transport use, moderately increasing active travel, or aggressively increasing cycling in California in order to achieve the state's carbon mitigation targets. They found that the largest potential decrease in carbon emissions growth stemmed from the aggressive cycling increase scenario, with large health co-benefits, as well. Similar health impact assessment-based studies were conducted by De Hartog et al. (2010), Dhondt et al. (2013), Gao et al. (2017), Götschi et al. (2015), Johansson et al. (2017), Rabl and De Nazelle (2012), Woodcock et al. (2013) and Woodcock et al. (2014) and reviewed by Mueller et al. (2015), including economic assessments by Fishman et al. (2015), Jarrett et al. (2012), Pérez et al. (2017), Rodrigues et al. (2020) and Zapata-Diomedi et al. (2018), among others. Health impact assessments, though useful in demonstrating the potential benefits of switching to active travel in cities, do not model how this shift to active travel can be achieved. Most of these studies also do not model the potential displacement of other types of exercise with higher active travel.

On the other hand, higher levels of multimodality or active travel may not automatically translate to lower carbon or air pollution emissions. For example, though people in the Netherlands cycle around 30% of all their journeys, their annual car mileage is higher than in many other countries, resulting in similar overall carbon emissions from transport (Heinen and Mattioli, 2019). Research into the emissions effect of investments into cycling infrastructure does not show a substantial change in air pollution or carbon emissions in the surrounding area, either. This was the case of small bicycle infrastructure improvements in the UK (Brand et al., 2014), as well as larger urban-wide policies that led to substantial increases in active travel (16% between 2010-2014) but only small reductions in carbon emissions (around 1.6%) in New Zealand (Keall et al., 2018). Nonetheless, dedicated infrastructure away from cars does move cyclists and pedestrians further away from car exhaust emissions, reducing their exposure to harmful pollutants (Isakov et al., 2017; Tong et al., 2016). On an individual level, if people switch from driving to active modes of travel, longitudinal evidence suggests that this might be a genuine substitution of car-based trips, rather than an additional trip, resulting in annual emissions savings of about 0.5 tonnes CO_2 per year for a 1 trip/day for 200 days of the year (Brand et al., 2021), with a potential reduction of up to 10% of car-based emissions (Neves and Brand, 2019). Similar results apply to walking, as well (Frank et al., 2010). Without active travel, transport emissions would be even higher than they are today. Hence, depending on what policy is being evaluated, there may or may not be a beneficial impact on air pollution and carbon emissions.

These studies help show that providing a pull measure towards active travel is not sufficient to initiate substantial active travel co-benefits, but that push measures discouraging car travel, such as higher fuel or parking prices, are also needed for a comprehensive change in the urban transportation system.

2.2 What correlates with higher rates of active travel?

The ingrained nature of car use in society, car-dependent practices, and how difficult it is to change them have long been recognised (Mattioli et al., 2016). Large amounts of literature have been dedicated to understanding the reasons for high levels of inertia in transport patterns (Panter et al., 2016; Heinen et al., 2017), and high prevalence of car use (Daramy-Williams et al., 2019). Research on mode choice can be broadly categorised along: the *micro* scale, pertaining to the individual and his/her attitudes and perceptions; the *meso scale*, referring to the routines, trip attributes, social cultures, and practices that shape people's use of transport modes; and the *macro* scale, the built environment and society as a whole (Mattioli et al., 2016). The micro-meso-macro understanding of the determinants of mode choice will be used throughout this thesis, on a subset of active travel decisions. This section provides a very short introduction to the literature on the factors affecting active travel, which will be extended in the methodology chapter and Chapter 4, which analyses the relative influence of each of these factors.

Factors affecting active travel have been explored in many different ways, with a specific focus on psychological and personal influences, and built environment influences. The relationships between active travel behaviour, and demography and age (Gao et al., 2017; Goodman and Aldred, 2018), cultural background (Gao et al., 2017; Götschi et al., 2015), weather (Børrestad et al., 2011), travel time (Frank et al., 2008; Strazdins et al., 2011) and thresholds (e.g. 20 minutes in a study by Bopp et al. (2012)) or transfers (Ha et al., 2020), or personality and driving affinity (Anable, 2005; Hunecke et al., 2010), have been researched. A substantial amount of attention has been paid to the roles of conscious decision-making as opposed to unreasoned action (Verplanken et al., 1998; Bamberg et al., 2003), the application of the (extended) theory of planned Behaviour to cycling and walking (Bird et al., 2018; Lois et al., 2015; Donald et al., 2014). Lanzini and Khan (2017) conduct a meta-analysis of 58 primary studies, finding that intentions, habits and past use are the most relevant predictor, followed by constructs consistent with the theory of planned behaviour and pro-environmental behaviour (consistent with the New Ecological Paradigm). The role of social practices and how the meanings, skills and competences associated with different modes of transport affect mode choice and use (Reckwitz, 2002; Schwanen et al., 2012; Spotswood et al., 2015) are also increasingly being examined.

The role of the built environment in general, specifically features of population density, diversity of services, design of the streets, and accessibility, and their ability to explain mode choice and transport behaviours have also been studied (Ewing and Cervero, 2010; Owen et al., 2004; den Braver et al., 2020; Handy et al., 2005; Lee et al., 2018; Cao et al., 2007; McCormack and Shiell, 2011; Zapata-Diomedi and Veerman, 2016; Panter et al., 2019). Overall, greater diversity and higher residential or building density consistently increase likelihood of active travel (Ewing and Cervero, 2010; Zapata-Diomedi and Veerman, 2016;

Durand et al., 2011; Kerr et al., 2016). In particular, connectivity, diversity of facilities and concentration of green spaces increase walking (Gascon et al., 2019; Christiansen et al., 2016; Cerin et al., 2017), as well as perceptions of a walking-friendly environment (Adams et al., 2016), but the effect of these factors is non-linear for cycling (Christiansen et al., 2016). However, den Braver et al. (2020) found that built environment and individual sociodemographic attributes explained only 2% and 3% of variance in car travel patterns in their study of five different urban areas in Europe, respectively.[1] Cerin et al. (2017) summarises the state of knowledge of the micro-environmental influences on active travel, accentuating the importance of perceived safety and features such as street lights and overall cleanliness. The importance of perceived safety and how the built environment may influence these has also been stressed by Brown et al. (2017) and Yang et al. (2017).

This is complemented by research on the strength of built environment vs. psychosocial variables (e.g. Dill et al. (2014), Lemieux and Godin (2009), Lanzini and Khan (2017) and Carlson et al. (2012)). These studies typically find that attitudes have a slightly stronger influence on travel behaviour, in particular with regards to driving, than the built environment (Cao et al., 2007; Hunecke et al., 2010; Dill et al., 2014). For example, interactions between the physical and social environments lead to significant increases in physical activity when encouraging conditions in both levels exist, but are far smaller than when only the physical environment is activity-friendly (Carlson et al., 2012; Josey and Moore, 2018). Local destination accessibility influences walking levels for people with positive attitudes towards walking, whereas higher connectivity influences people with less positive attitudes (Joh et al., 2012). Giles-Corti (2006) argues that both are needed for substantial levels of active travel to be achieved.

There are also strong interactions between different modes of travel. Based on expert interviews, de Nazelle et al. (2016) argue that encouraging cycling competes directly with

[1]Using data from the Sustainable Prevention of Obesity Through Integrated Strategies (SPOTLIGHT) study; 4258 respondents were included in the cited analysis.

public transport; Kager et al. (2016) argue these two modes are complements, not competitors. Walking is often conducted for more ad hoc, discretionary trips, while cycling is more common for repetitive, obligatory trips such as commuting (Song et al., 2013; Zhao et al., 2018). Furthermore, Dalton et al. (2013) found that low junction density, greater distance to a bus stop, lower bus stop frequency, and fewer bus services at home location were most strongly related to choosing to drive rather than walk or cycle to work. The authors argue that access to public transport, though not often a part of active travel analysis, should be included in studies and policies aimed at increasing active travel. Findings such as these support the argument that multilevel interventions are necessary to tackle physical inactivity, and change travel behaviour. This may, however, be due to self-selection into neighbourhoods of desirable environmental qualities (Cao et al., 2007; Schwanen and Mokhtarian, 2005), which occurs when individuals choose to move to a location that meets their preferences for transportation.

This diversity extends to different methods of research as well - from the use of mobility biographies (Sattlegger and Rau, 2016), different mobile method interviews to qualitative realist evaluation work (Sahlqvist et al., 2015) to statistical analysis, latent class analysis (Anable, 2005), choice modelling (Paulssen et al., 2014), and many others. It is not always easy to determine consistent relationships from these studies. Many are specific to a particular city or suburb (Cerin et al., 2017), or use slightly different measures of built environment factors, or spatial buffers, or objective and subjective measures of the built environment (for example, Dill et al. (2014) and Beenackers et al. (2012)).

It is also unclear whether outcome measures of interest commonly used provide realistic insights into what influences active travel and evaluate travel patterns and policy effectiveness. For example, total travel time is commonly used in transport (e.g. Götschi et al. (2015)), but is criticised due to the theory of constant travel budgets (Tanner, 1961; Van Wee et al., 2011; Delbosc, 2012) and sensitivity to time travel uncertainty (e.g. (Avineri and Prashker, 2003)).

These theories suggest that if a trip takes less time, that frees up minutes to spend on other travel, and that a person penalises potential waiting and delays more than the trip journey time itself. Consensus on modal split, trip frequency, or subjective measures such as enjoyment of mode choice does not exist, either (De Witte et al., 2013). Others use the same theory, for example the theory of planned behaviour, but measure the theoretical constructs in different ways (as is the case in Bird et al. (2018) and Donald et al. (2014)). In addition, interactions between different factors may lead to different conclusions in different studies. Finally, while most studies on the psychological determinants of active travel focus on walking and cycling for transport, studies evaluating the impact of the built environment on movement look both at exercise in general and walking and cycling for transport, two distinct forms of movement which may be influenced by different factors.

Nonetheless, in general both the attitudes of people, and their respective surroundings, influence their decisions to walk or cycle (Dill et al., 2014). It is likely that unconscious behaviours, habits, and the habitual behaviours of whole communities affect active travel substantially as well. This affects the potential effectiveness of policies aimed at increasing active travel, which the next section covers.

2.3 Policies aimed at increasing active travel

Interventions aimed at increasing active travel can be broadly categorised as pull and push policies, the former encouraging preferences to change by offering attractive alternatives and the latter using mechanisms that make polluting behaviours less attractive. The benefit of using pull measures is that they are seen as encouraging demand and removing barriers. Push measures, such as fuel taxes or congestion zones, can be seen as unjustified and coercive (Martens et al., 2020), particularly if no suitable alternatives exist. Pull measures, such as information campaigns, subsidies, and dedicated infrastructure, require public investment, for which there may not be any available funding. Hence, a combination of both is often advocated (Stephenson et al., 2018). The next section will explore popular pull measures, in particular information-based and infrastructure-based policies aimed at increasing active travel. The section after that will explore some of the potentials of push policies, specifically tools to increase the cost of car use.

2.3.1 Pull measures

A number of studies have looked at the ability of pull measures to change travel behaviour, either towards public transport, or to walking and cycling. The two most common pull measures are variations of information-based campaigns (soft measures), and improving cycling and walking infrastructure (hard measures). Soft measures meant to reduce car driving have been reviewed many times (Möser and Bamberg, 2008; Pucher et al., 2010; Ogilvie et al., 2004; Ogilvie et al., 2011; Stewart et al., 2015). Kelly et al. (2020) identified over 190 different schemes trying to increase cycling, particularly soft measures such as information campaigns, cycling training, reward schemes.

Nonetheless, travel-to-work plans have been shown to reduce car travel slightly (e.g. 4% in a review by Cairns et al. (2008)), and increase active travel (Song et al., 2017; Finkelstein et al., 2016). Martin et al. (2012) provide an overview of financial incentives to increase physical activity, finding that, compared to before the intervention, in most cases active travel rates increased significantly, even up to 3 years after the intervention occurred. Wardman et al. (2007) also evaluate the effect of a daily £2 payment for cycling to work, finding substantial increases in cycling while the payment continued. Tsirimpa et al. (2019) reported similar findings using an app-based reward system.

Infrastructure changes such as bike lanes (Aittasalo et al., 2019; Heinen et al., 2017; Prins et al., 2016; Wardlaw, 2014; Buehler and Pucher, 2012; Pucher et al., 2010; de Dios Ortuzar et al., 2000) have been found to have a high potential impact on increasing cycling. Mueller et al. (2018), for example, use correlation and statistical analysis of 167 cities and find that increasing cycling infrastructure alone may increase cycling in European cities up to 26% of the overall mode share. Visual improvements to routes may or may not increase active travel. Adams and Cavill (2015) found that, following environmental improvements to regular walking routes, walking decreased by around 19% in the first year after the intervention, but increased overall by around 15% 14-20 months after the intervention. Goodman et al. (2014) also found that uptake of new or improved infrastructure took longer than 1 year.

Overall, research has not consistently demonstrated a sustainable long-term increase in active travel following interventions aimed to increase active travel (Finkelstein et al., 2016; Song et al., 2017). In particular, if policies require time to become effective (Banister and Hickman, 2013), then evidence on the effectiveness of soft measure policies is particularly lacking. Many interventions in active travel are based on the idea of information provision inducing behaviour change. This approach has been criticised by many (Shove, 2010; Kelly and Barker, 2016; Watson, 2012), but remains the most frequently used intervention in active travel (Kelly et al., 2020). In addition, many of these studies only have short follow-up periods (Finkelstein et al., 2016; de Kruijf et al., 2018a), or focus on only two modes of transport (de Kruijf et al., 2018b), or bias their respondents by (unintentionally) increasing interest in certain active travel schemes (Rose and Marfurt, 2007).

Soft measures have been subject to strong critique (Kelly and Barker, 2016). Focussing on providing information simplifies the embedded nature of cars in urban transportation, and the discrimination that walking and cycling face in urban transport. By placing the "blame" on the individual and their lack of knowledge or laziness, such policies diminish the importance of providing road space (Szell, 2018) or green spaces (Christiansen et al., 2016), as well as push measures such as congestion charging (Eliasson et al., 2009), the lack of other appropriate motivation (Kelly and Barker, 2016), or institutional barriers to increasing active travel. This phenomenon is not unique to physical activity, and manifests itself in the narrative around carbon emissions and personal responsibility for them, as well.

2.3.2 Push measures

Urban policies, such as parking restrictions (Buehler et al., 2017; Pucher and Buehler, 2007), traffic calming (Brown et al., 2017), congestion pricing (Buehler et al., 2017; Brown et al., 2015), and low emissions zones (Grange and Carslaw, 2019) have been found to reduce driving. Reducing car road space (Cairns et al., 2002; Litman, 2015) in favour of other modes has been found to have a moderate effect on reducing driving rates. However, whether these policies increase active travel, and therefore physical activity levels in the community affected by the measures, has not been conclusively determined. In their review of 71 studies of traffic calming measures, Brown et al. (2017) find that only 9 of those report associations in the expected directions, and most use subjective measures of traffic calming and safety perceptions, not objective measures. None of these were in the field of economics, in which calculating elasticities - the relationship between a % change in a policy or price on the % change of a behaviour - of driving and public transport use are common, but not walking or cycling.[2]

In the national policy context, transport is currently mostly assessed with the aim of improving road conditions, congestion, and reducing carbon emissions. The overwhelming focus on these is on various pricing schemes (Cavallaro et al., 2018; Parry and Small, 2005; Bjertnæs, 2019) and vehicle regulation (Axsen et al., 2020), with active travel taking up only a small part of the literature focus (Axsen et al., 2020). In a Delphi study[3] of transport practitioners, rising fuel prices were considered to be the most likely trend to change transport business as usual, followed by built environment investments (Stephenson et al., 2018). Fuel taxes have been found to reduce overall levels of driving (Sterner, 2007; Montag, 2015; Li et al., 2014; Austin and Dinan, 2005). Sterner (2007), for example, estimates that vehicle mileage in Europe would be twice as high its current rates if US fuel tax rates existed

[2]A European transport modelling project, Hague Publishing et al. (1999), is the only exception I found.

[3]The Delphi method is used in small focus groups or interviews of a panel of experts, and is used to generate forecasts or predictions from them. It relies on expert rather than layman opinion.

in Europe. These results are similar to the study conducted by Banister and Hickman (2013) on the climate change mitigation potential in transport. In addition, popular transport evaluation tools rarely incorporate micromobility in the form of active travel, excluding its potential benefits from becoming a part of the conversation. This is true of cost-benefit analyses, mostly used on an investment-by-investment basis (Gössling and Choi, 2015), and transportation models, which often do not have the resolution or ability to simulate the underlying institutional and cultural principles to be able to incorporate micromobility (Twaddle et al., 2014).

Evidence of the effectiveness of pull or push measures aimed at increasing active travel or reducing car travel is inconsistent, and the literature offers no "silver bullet" solution for either.

2.4 Arguments for multi-level interventions

Achieving climate neutrality and acceptable levels of public health protection within transport will require a "sophisticated policy mix" (Eddington, 2006), multiple interventions, and coordination between different actors and institutions. In their Delphi study of transport researchers, Stephenson et al. (2018) conclude that "a consistent and integrated commitment is required at all levels of governance and across all parts of the transport system to transition away from automobility and towards sustainable mobility." Calls for more integration in transport policy have also come from Wolfram and Consult (2004), May et al. (2006), Buchan et al. (2012), Geels (2012), Mäkinen et al. (2015) and Savan et al. (2017).

An integrated policy mix would typically be cohesive across policy goals, be complementary, for example by considering land use planning and transport infrastructure investments in tandem, and additive, such as introducing traffic calming measures as well as improving public transport access (May et al., 2006). Banister (2008) argues that there are four main channels through which mobility can become more sustainable, specifically travel substitution, modal shift, distance reduction, and efficiency increases to reduce the negative social effects of transport. In other research, these are also known as avoid, shift, improve (Banister, 2011). Achieving synergy across these channels is necessary, though potentially still insufficient (Anable, 2019), to achieve a sizeable transformation of transport. Research has shown that integration of policy throughout levels in transport is incomplete (Corfee-Morlot et al., 2009; Givoni et al., 2013; Bhardwaj et al., 2020), and that often, using one or two approaches to understanding how policy or change happens across all levels are not sufficient. For example, neither a top-down or bottom-up perspective fully capture how climate change policy gets translated and enacted across government levels (Urwin and Jordan, 2008; Geels, 2005).

It is necessary to recognise that many Western societies are car dependent. Due to path dependence and feedback loops, individuals often do not have viable alternative transportation options to the car, or where they exist, they are far inferior to car-based transport. Emergent systems of ground transportation consist of car-based cultures (Mattioli et al., 2016) and car-dominant built environments (Szell, 2018). These negative feedback loops lead to behaviour that is primarily car-based, and difficult for an individual to break out of. In order to change this, professionals, policymakers, urban planners, public health officials and others, have tried to implement policies within their domain of expertise, focussing on changing one thing at a time (e.g. the studies evaluating reward schemes listed in Tsirimpa et al. (2019)). However, changing one level or factor within the system does not enable change, because other aspects of the system still work to lock in the dominant behaviour and prevent *structural* change.

Instead of siloed, one-off interventions, cohesive long-term policies influencing all aspects of the system - built environment, culture, pricing - must be put in place simultaneously to break down the negative feedback loops of car dependence, and introduce new positive feedback loops reinforcing active travel. This is called path creation (Mäkinen et al., 2015), and necessarily involves multi-level interventions, as advocated by Stephenson et al. (2018), Wolfram and Consult (2004) and Buchan et al. (2012).

This type of thinking is also embodied in social practice theory, which takes a holistic approach to understanding how behaviours develop and become enmeshed in society (Watson, 2012; Schwanen et al., 2012). For example, installing bicycle share programs may result in higher complexity of behaviour and greater multimodality, but not a straightforward switch from driving to cycling (Fuller et al., 2013). Changing cycling or walking infrastructure, for example, changes the material competences associated with the practice of cycling, but without cycling training and widespread promotion, the skills and capacity needed to be able to cycle safely may be missing, and the cultural meaning of cycling may remain that of a sport reserved for fit young men (Gatersleben and Appleton, 2007). This may be due to strong embedded social learning models, in which conformity is rewarded (de Dios Ortuzar et al., 2000; Fukuda and Morichi, 2007; Yip et al., 2016). If critical mass is reached, then the meaning of cycling may change, resulting in new emergent systems of travel (Jones and Sloman, 2003; Fukuda and Morichi, 2007; Sunstein, 2019). Uttley and Lovelace (2016) find that, over a 2-year period, a cycling challenge increases cycling among non-regular cyclists, but fails to attract new cyclists, and after the end of the challenge, many people revert back to their original commuting patterns. They call for more research into understanding how social practices of commuting form, and how active travel can be incorporated into a practice-based understanding of commuting. This could, for example, include active travel promotion that fits a salient cultural frame, instead of being a generic message about health, increasing its persuasive power (Uskul and Oyserman, 2010; Dolan et al., 2012).

This idea can also be visualised using a popular tool in the risk literature, and public health (particularly with regards to coronavirus prevention measures), the Swiss Cheese Model, 2.1. Removing one layer of cheese, or creating a hole in the barrier, for example through free public transport provision, does not remove the other layers of cheese, meaning that the dominant behaviour, car driving, prevails. This is indeed what the UK Cabinet concluded in its review of urban transport (Cabinet Office Strategy Unit, 2009).

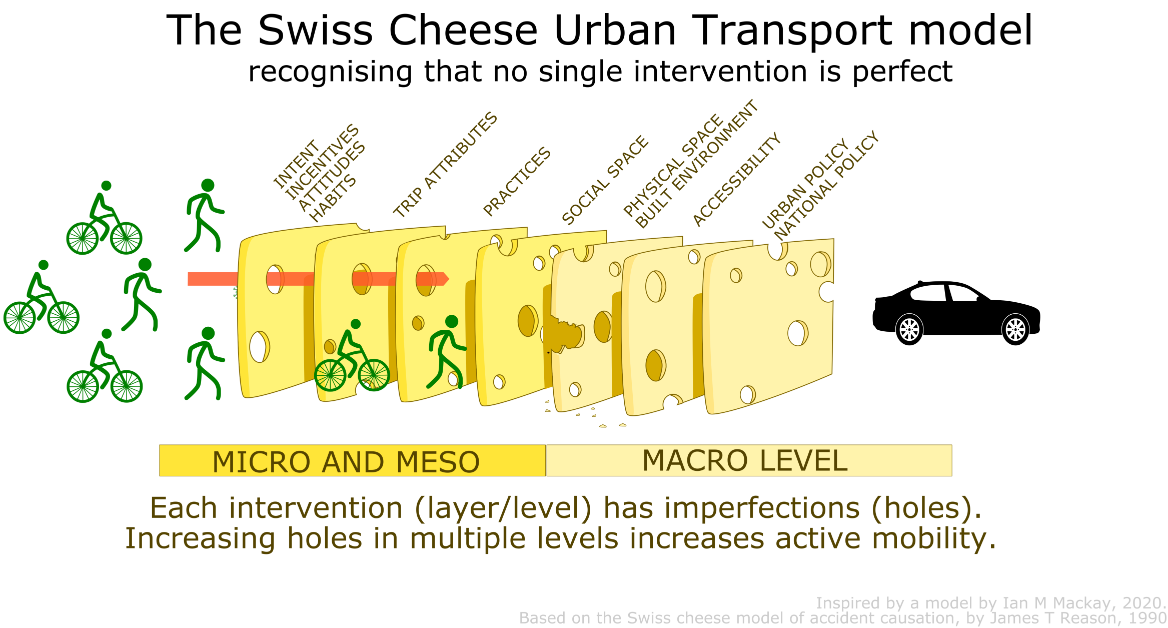

Figure 2.1 Adaptation of the Swiss Cheese Model to urban transport

Integrated policies, such as the UK's Cycling Demonstration Towns, or Cycling Cities and Towns projects, worked to remove multiple of these barriers - by investing in cycling infrastructure, widespread promotion aiming to change the culture around cycling, and other soft measures, such as cycling training - all at the same time. These efforts were found to significantly increase cycling relative to baseline, and relative to other similar towns not included in the initiative (Christensen et al., 2012; Goodman et al., 2013a). Similar results were found by Keall et al. (2018), who evaluated the Model Communities program in two cities in New Zealand. In these two cities, the program included both infrastructure investments and education, information, and training provision. The program helped increase cycling by 16% over a four-year period. Marqués et al. (2015) evaluated the impact a collaborative effort between the city of Sevilla and the civil society had on cycling, more than doubling cycling infrastructure and quadrupling cycling rates over four years. Cairns et al. (2008) found that targeted travel-to-work policies were twice as effective (4% vs. 10-15%

increase in active travel) with complementary measures. Pratt et al. (2012) argue for an increase in the use of information and communication technologies, such as mobile phones, alongside traditional transport and exercise interventions, to capture the full potential of all methods to increase physical activity.

2.5 Summary

Physical activity has great benefits for the majority of the adult population. When combined with a destination purpose to become a mode of travel, it has the potential to reduce the negative social impacts of car-based transportation systems - carbon emissions, air pollution, congestion, and accidents. Factors influencing the levels of active travel within a city can vary, but generally include a favourable built environment such as parks, cycling and walking space separated from motorised traffic, and dense settlements. A positive cycling culture, underpinned by government policies encouraging active travel, also helps further increase or maintain active travel rates. However, the main determinants of walking and cycling appear to be personal attitudes and beliefs, and destination accessibility.

Policies to increase walking and cycling, therefore, tend to target one of the three levels of influence identified above. This can either be through pull measures, such as improving infrastructure provision, information campaigns or financial rewards for physical activity, or push measures. Push measures discourage car driving, for example by increasing driving prices, or restricting parking. Research suggests that a combination of the two types of measures, including different actors in a concerted policy effort, works better than isolated policies when it comes to increasing active travel.

It is recognised that multiple actors and governance levels influence behaviour, policy, and demand and supply in most sectors of the economy. Recognising the importance of multiple levels of influence within a system manifests in certain socio-ecological and conceptual frameworks of active transport, as well, for example by Sallis et al. (2006) or by Ogilvie et al. (2011). The multi-level nature of such frameworks is discussed in greater detail in Chapter 3.

Chapter 3

Methodology

3.1 Summary

This chapter describes the main concepts used for the analysis of transport health behaviours, brings them into context with one another, provides an overview of the geographical context of the research, including country and city case study choice, and describes the process of primary data collection.

The relationships between the individual, the activities they carry out, and what influences their behaviour are complex and rarely orderly. In order to provide a structure for these relationships, a framework was designed, incorporating the various domains that may influence a person's travel behaviour. In transport and health behaviour, this ranges from the smallest, individual-level emotions and day-to-day activities and habits, all the way to larger-scale policy environment and physical structures within which a behaviour is set. The conceptual framework identifies the possible patterns relating to a behaviour. This is described in greater detail in Section 3.2.

In order to demonstrate the value of different ways of conducting research, two different epistemological approaches were applied to examine subsets of the conceptual framework in more detail, which function best in different timelines, purposes, and scope. Realist evaluation, developed by Pawson et al. (1997), is a useful and pragmatic approach for evaluating policies ex-post, dissecting what works in which context and for whom. It looks for the patterns within patterns. In contrast, public and environmental economic theory is useful in simplifying a complex problem, identifying the most important interactions within an (economic) sector, testing the influence of a policy on the (urban transport) system (ex-ante or ex-post), and determining what outcome would maximise social welfare. It is, therefore, inherently normative. Reasons for choosing realist evaluation are explained in more detail in Section 3.5, and the use of economic theory is explained in more detail in Sections 3.6 and 3.4.

The second part of the methodology focusses on the original Physical Activity Through Sustainable Transportation Approaches study (PASTA). Most of the data used in this thesis originates from PASTA. The follow-up survey that is the majority of the primary data collection carried out as part of this thesis is a follow-up on PASTA, as well. It was conducted in two of the original PASTA study cities that implemented information-based measures as their intervention. The chapter then describes the seven case study cities within PASTA in more detail, and describes additional open-access data collected in order to carry out more detailed accessibility analyses as part of this thesis. An overview of the geographical context of the research is provided in Section 3.8.

3.2 Conceptual framework

This section outlines the main conceptual framework designed and used for the analysis of active travel behaviour. As Chapter 2 shows, active travel is influenced by a complex set of factors from policy and organisation, the built and natural environments, community and interpersonal relationships, to intrapersonal motivations, as well as the interdependencies between them (Sallis et al., 2015). In order to accommodate these factors, a socio-ecological framework, a framework combining the physical or built environment (the ecological part) and the social environment (the socio- part) a person is surrounded by, was developed. According to Sallis et al. (2015), a socio-ecological framework should follow four principles:

1. The model should be behaviour-specific.
2. There are multiple levels of influence on a specific behaviour.
3. The influences interact across multiple levels.
4. Therefore, multi-level interventions should be most effective.

A general intuition of the factors influencing active travel has existed for a long time. Rietveld and Daniel (2004) developed a framework that included local authority policies such as infrastructure, pricing, the generalised cost of other modes of transport, the generalised cost and attitudes towards cycling, as well as individual and socio-cultural factors. The literature on attitudes towards active travel has expanded significantly since then, and other ecological frameworks such as Sallis et al. (2006) paid more attention to the built environment, but the basic premises remain.

For a long time, health behaviours and models describing them have been multi-causal, drawing on many different theories and empirical evidence, sometimes describing the entire system of a behaviour, while at other times only a specific context within which that behaviour may occur (Earp and Ennett, 1991). A framework is useful in guiding the design of research, understanding how change might be happening, and enables the testing of complex interventions in a theoretically driven way. The current framework therefore includes both well-tested ideas, and constructs that warrant more research in the future.

Second, and discussed in more detail below, transportation researchers accept that the physical space a person is in, or their sociodemographic characteristics, are significant but not the sole determinants of travel behaviour. A review by De Witte et al. (2013) identified:

- 7 sociodemographic factors (age, gender, education, employment, income, household size and composition, and car availability);

- 5 socio-psychological factors (attitudes and experiences, familiarity, habits, lifestyle);
- 9 journey characteristic indicators (purpose, distance, time, cost, departure time, trip chaining, weather, information, interchanges on public transport);
- and 5 spatial indicators (density, diversity, proximity to infrastructure, public transit frequency, and parking)

that the transport literature has identified as related to mode choice.

Hence, a framework that combines both the social and environmental factors that influence travel behaviour is needed. Finally, the socio-ecological framework makes central the premise of this thesis: health behaviour is complex, and changing it requires actions at multiple levels, with many different possible interventions. Due to the multi-level nature of a socio-ecological framework, it is capable of incorporating different theories at different levels, from different research fields.

The conceptual framework presented here and shown in Figure 4.1 builds on the socio-ecological framework developed by Sallis et al. (2006), extended by Götschi et al. (2017) who follow a structure covering the Individual, Community, the Physical Environment, Policy, and Society and Culture from one side of the framework to the other, and the macro-meso-micro structure identified by Mattioli et al. (2016). It is tested empirically in Chapter 4. The framework by Götschi et al. (2017) is based on a systematic review of socio-ecological frameworks published in transport and health research and thus can be considered state-of-the-art. It captures the nuance and detail of widely accepted thought on what influences active travel behaviour. The current framework simplifies Götschi et al.'s in order to appeal to a non-health or non-transport audience, instead accentuating only the main levels of influence. Second, it incorporates ideas from theories of social practice to account for the possibility that certain travel behaviour may be more difficult to move away from. Third, while Götschi et al. (2017) recognise that environmental factors affect active travel "on all sides", the present framework includes arrows to explicitly account for potential causal relationships and feedback effects within the different levels of the framework.

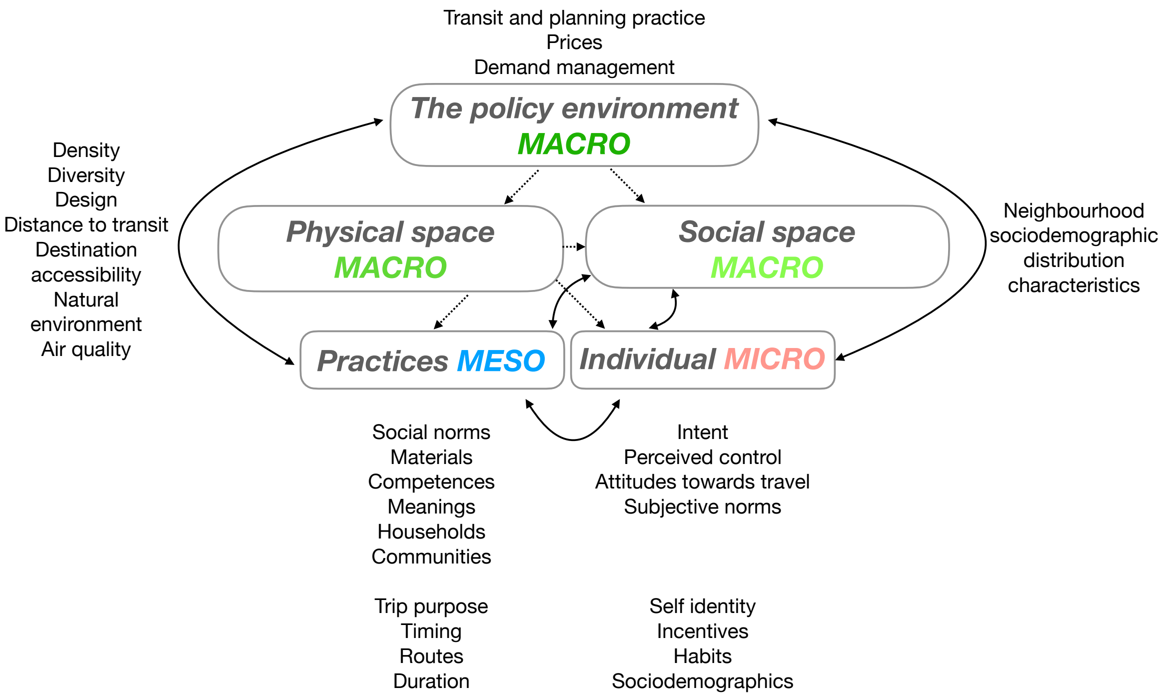

Figure 3.1 Conceptual framework developed as part of this thesis.

The colours represent the three levels of analysis: micro, meso, and macro. Next to each bubble is a list of constructs that comprise that level. Full, bi-directional arrows denote possible feedback effects, and single-headed dashed arrows denote a one-way effect.

The framework presented here also draws inspiration from frameworks presented by Saelens et al. (2003), Ogilvie et al. (2011), and De Witte et al. (2013). Most frameworks offer a comprehensive summary of the influences of both walking and cycling for travel, and separately for recreation, but do not offer a view on the interrelationships and causality between different factors in the framework. Ogilvie et al. (2011) added social environmental factors to their framework in order to denote the behaviour of a community as a whole. I include both the behaviour of the community, as well as the sociodemographic make-up of a community. De Witte et al. (2013) provides a very simple framework, which nonetheless captures the essence of travel behaviour influences: there are physical, social, and personal influences on travel decisions, and all interact with each other. Their work was useful in determining which variables to prioritise in empirical work.

The micro level includes the socio-demographic group membership of an individual, and their tastes, incentives, habits, and attitudes. The trip activity itself, including the distance, route, timing, purpose, and mode, are all included in the blue meso level, together with practices. Although people choose when, where and how they travel on a daily basis, travel behaviour is often repeated many times, becoming routinised and habitualised, mimicked by other household or community members. It thereby creates certain practices. However, the trip activity determinants can be decided separately for every trip, and so are separated by empty space to distinguish them from practices.

The macro (green) domain denotes aspects of the travel behaviour system that are most entrenched, slow to change, and most difficult to change. It is made up of three levels: the policy level, which is the most difficult to change, is coloured darkest; the built environment level, which includes natural environment and physical space; and the social distribution of the local area, which includes car ownership and income, and may be possible to change without external input over time, is coloured the lightest green. Nonetheless, all three of the green levels require substantial time and collective action to change.

The arrows in the framework are based on findings from the transport and health literature, and denote either a hypothesised causal direction (one-way arrow), or a bidirectional relationship (two-way) arrow. This also allows for feedback (also known as snowballing, self-reinforcing, or critical mass) effects within the framework, examples of which are provided in Section 3.3.4. However, these should be viewed as suggested, not confirmed relationships. Kroesen et al. (2017), for example, argue that it is nearly impossible to determine whether specific attitudes determine travel behaviour, or whether the behaviour is what determines attitudes. Rutter et al. (2020) also argue that including feedback and balancing loops with confirmed effects within a model may not be needed for policy recommendations, and may not be possible without years of review work. It may therefore omit important relationships that do not have sufficient evidence, and may further entrench previous policy mistakes.

3.3 Examining past research within the framework level

3.3.1 The micro level

At the micro - intrapersonal or individual - level of health behaviour, the framework follows two main strands of health behaviour literature: the extended theory of planned behaviour (TPB), and the literature on self-identity and environmental beliefs. Other theories that could have been chosen include the health belief model (Lee Champion, 1985), which explicitly includes health symptoms as behaviour motivators, the norm activation model (Schwartz, 1977), the transtheoretical model of stages of change (Prochaska et al., 2015), or the precaution adoption process model (Weinstein et al., 2020), or the PRIME theory of motivation (West and Michie, 2020), among others. Part of the motivation for incorporating the TPB into the framework used for this thesis was that questions collected as part of the original PASTA study, which I could not influence, were designed specifically to measure the strength of TPB constructs of intent, influenced by attitudes, subjective norms, and perceived behavioural control. Any further primary research had to ask the same questions, in order to assess changes in these constructs over time. It is based on the premise of believing that behaviour is the outcome of the expected value of an action (but does not assert that these expectations are rational or objective, see Ajzen (2015)), making it a useful tool to examine the relationship between beliefs and actions. The original PASTA study derived many of their questions using TPB because it has been tested empirically many times, and remains a very popular model of behaviour. The large number of constructs it includes enable the researcher to systematically assess what the strongest predictors of behaviour are, target interventions to change these, and then assess whether these predictors have changed with behaviour change.

Attitudes have repeatedly been found to have a significant role in determining cycling, specifically trip-based distance benefit, perception of safety, and awareness, (Damant-Sirois and El-Geneidy, 2015; Heinen et al., 2011), but also the health benefit of exercise (Useche et al., 2019; Börjesson and Eliasson, 2012), the environmental and mental relaxation benefits (Fernández-Heredia et al., 2014), or simply the activity being fun (Fu and Farber, 2017). A reason for including many more questions than simply direct attitudes about the travel mode of interest is that attitudes may have an effect on travel directly, but also manifest themselves through residential self-selection, and may mediate the effect of the built environment, or the built environment may mediate the effect attitudes would have had (Kroesen et al., 2017).

However, the TPB has also been extensively criticised - for example, Sniehotta et al. (2014)) argue it lacks predictive validity, is static rather than a model of behaviour change, includes the wrong constructs, and explains intention rather than behaviour. In order to account for these criticisms, the conceptual framework in this thesis incorporates an extended form of the theory, including self-control (Hagger et al., 2010), habits (Lanzini and Khan, 2017), and self-determination and self-identity constructs (as called by Whitmarsh and O'Neill (2010), but also for example "ego" in the MINDSPACE model Dolan et al. (2012)). Habits, automated behaviour, and behaviour based on environmental cues (such as that based on nudge theory) have all been recognised as important drivers of behaviour outside of "rational" thinking and behaviour motivation (Marteau et al., 2012; Kahneman and Tversky, 2013; Marteau et al., 2015).

3.3.2 The meso level

The meso level incorporates the concept of travel cultures and social influences on travel mode choice, and has been included for four main reasons. First, it is understood that a community-wide change in active travel culture is needed, for which city-wide information and cycling promotion campaigns are well suited. Practices and cultures influence general perceptions of a community on cycling (less so on walking) (Heinen et al., 2010), and in fact investing in cycling cultures has been called the "antithesis" to infrastructure investment in policy debates (Aldred and Jungnickel, 2014). Cultures may also be norm-setting, inhibiting or promoting behaviour because of the human desire to belong to a collective, as well as through the power of shame when defecting from that collective norm. These concepts have also been included in the MINDSPACE framework (Dolan et al., 2012), partly in the extended TPB as social norms, and partly in behavioural economics and law (e.g. Sunstein (2019)). Second, some of the concepts of practice theory have been acknowledged in transport in the theory of time geography for a long time. Including this level is an effort to recognise the similarities between practice theory and time geography, when applied to active travel. Specifically, the three constraints of time geography identified by Hägerstraand (1970) were capability (restrictions of transport mode, the needs of humans, their cognitive limitations), coupling (the materials used for travel or other activities, coordinating behaviour with other people), and authority/steering (the rules and norms of travel and activities). Third, these factors may be absent from models explaining car driving, because it is often the default mode of transport where social norms do not need to be overcome. Fourth, cultures may be considered in qualitative social studies, but as they lack an easily quantified measure, may be excluded from quantitative analyses.

3.3.3 The macro level

The macro level is separated into three domains: the social distribution domain (lightest green), which includes objectively measured sociodemographic characteristics of an area; the physical space domain, which includes objectively measured built and natural environment characteristics, as well as ambient measures such as air quality and weather; and the policy domain (darkest green), which includes district-, city-, or national-level policies affecting travel choices. The reason for including all three of these domains at the macro level is that changing the social or physical distribution of an area requires concerted long-term effort, most often achieved through a (deliberate) policy change.

The social distribution domain is not typically included in socio-ecological frameworks. This is understandable, as obtaining detailed, district-level or area-based measures of average income, education, or home ownership is often a complex task that requires the collation of multiple city-level datasets and combining them with GIS-based data, and may not always be available. Nonetheless, social distribution may be predictive of behaviour on a larger spatial scale, and may therefore influence both the meso level of practices, and the micro level of one's own attitudes and thus own travel behaviour (Kroesen et al., 2017; Van Wee et al., 2019). The phenomenon of "racial zipcodes" or specific inner-city population distributions, and the influences these may have on travel behaviour, the unequal health impacts of certain travel patterns (Jephcote et al., 2016), or policy making, also warrants greater research.

In this framework, the physical space domain consists of quantitatively obtained environmental measures. Frameworks on the influence of *subjective perceptions* of the built environment on travel behaviour have been developed elsewhere (e.g. the PENS framework by Adams et al. (2013)), but would be categorised as Attitudes or Perceived Behavioural Control constructs in the micro level of the framework in this thesis. Density, diversity and design were first identified as significant for the "life" of a city by the qualitative urban theorist Jane Jacobs (1961), and have since been confirmed as significant determinants of mode choice by Cao et al. (2007), Cerin et al. (2017) and Christiansen et al. (2016) among others. The extensions to include a further two Ds, distance to transit and destination accessibility, have also been confirmed as significant by many transport researchers (e.g. Ewing and Cervero (2010)).

Debates on the potential threshold effects at play with regards to the amount of green space, parks, and intersections are still ongoing (Kaczynski and Henderson, 2007; Koohsari et al., 2015; Christiansen et al., 2016). Air quality was included because the research on the influence of air quality on cycling is scarce, but what evidence exists suggests that commuting is less affected by changes in air quality, while leisure or personal business trips are taken by a different mode (Zhao et al., 2018; Saberian et al., 2017). Zijlema et al. (2018) argue that knowledge of people's perceptions of the natural environment, tree cover, and business of streets on a commute route is largely under-researched. Natural environment indicators are therefore included in the socio-ecological framework as a potential pathway to travel mode change.

Destination accessibility has been given more focus in the practical application of this framework than in many other studies that research the influence of the built environment on active travel. A greater focus on accessibility is warranted both due to the equity and justice aspects of transport systems (for a longer debate, see Martens (2016)), and because traditionally, policy has focussed on a person's travel-time budget, rather than changes in generalised travel costs, or perceptions (Van Wee et al., 2011). While the state-of-the-art in measuring accessibility is Transport for London's Public Transport Accessibility Level (PTAL) index, it was not used in this thesis. PTALs provide an index that reflects the reliability of the service used, the frequency of the service, the diversity of services offered at origin/destination, and walking time to/from the public transit stop (TfL, 2016). However, current open-access data on public transit schedules and stops available for the case study cities in this thesis was not sophisticated enough to enable the calculation of PTAL indices. Instead, the simpler, more easily understood, and more specific measures of time-to-destination or distance-to-destination by mode were used.

3.3.4 Examples of using the socio-ecological framework

This section provides examples of how the socio-ecological framework can be used to work through changes in variables affecting active transport. It is possible to specify how it applies:

- to sub-groups of individuals within the micro level.

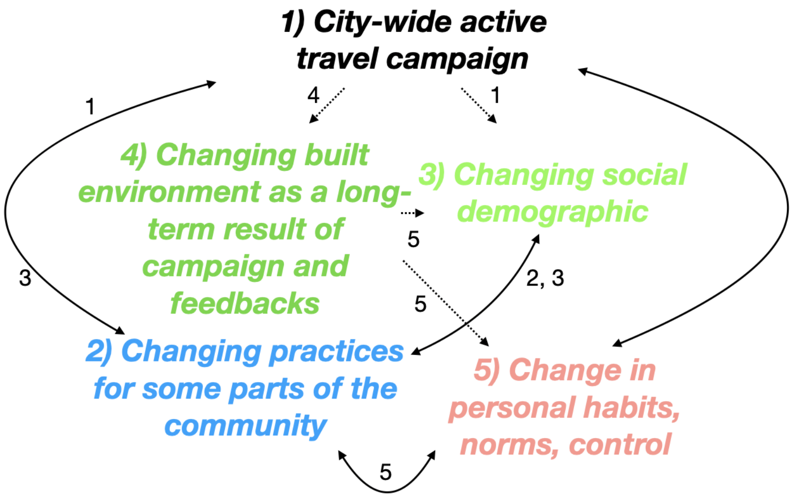

Figure 3.2 City-wide active travel information and training campaign applied to the socio-ecological framework.

- to particular trips such as commuting or shopping in the meso,
- and identify the circumstances within which a behaviour occurs, either an existing culture, built environment, or policy context.

Figure 3.2 shows the potential effects and feedback loops a city-wide campaign aimed at increasing active travel may have. This assumes the potential of initial marketing to snowball, as identified by Jones and Sloman (2003), into a much larger effect over time. Yip et al. (2016) find this effect for social interactions and the presence of a social environment and social groups in one's life, and Fukuda and Morichi (2007) find a similar effect. In other literatures, this may also be called a critical mass effect.

Figure 3.3 shows the possibility of reverse causality existing in active travel. In this particular case, a change in the built environment may affect routes and trip purposes first, with attitudes and conscious evaluations of behaviour changing second (Van Wee et al., 2019). The impact of life changing events in general (Kent et al., 2017), or as specific as childbirth (Lanzendorf, 2010), or a public transport workers' strike (Larcom et al., 2017), have been researched as potential catalysts for behaviour change. Also known as habit discontinuity,

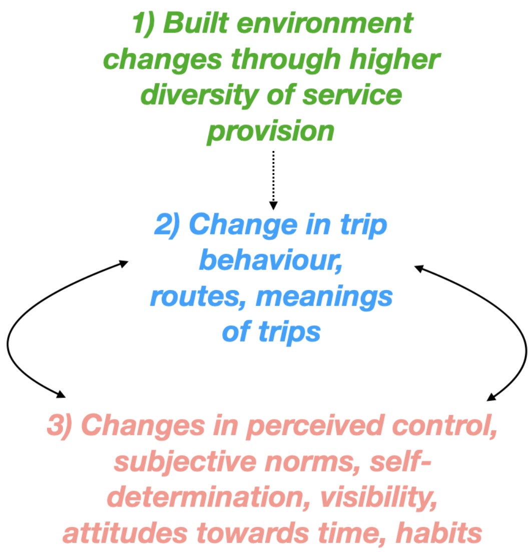

Figure 3.3 Reverse causality of preference change within the socio-ecological framework.

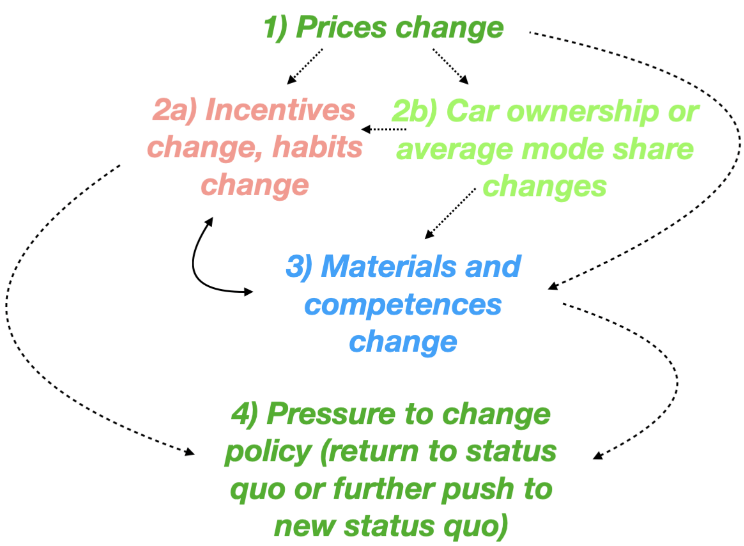

Figure 3.4 A nation-wide price change in driving applied to the socio-ecological framework.

a life-changing event is, much like a change in the built environment, a disruptor of habits, requiring the adoption of new sets of behaviours (Haggar et al., 2019).

Finally, the effect of a price change is described in Figure 3.4. A price change, particularly if a tax change rather than a price fluctuation (Li et al., 2014), is likely to influence the cognitive decision-making of individuals, leading to changes in attitudes, behaviours, the social environment, as well as potentially, future policy as feedback loops may exist.

The next sections describe the methods applied in Chapters 4-6, and the rationale for choosing these.

3.4 Factors affecting active travel: the benefits of choosing logistic regression analysis

Large numbers of factors in the socio-ecological framework lead to many variables whose relationship with the outcome variable of interest, walking and cycling, needs to be assessed. With the large amount of data, respondents, and close-ended answers to questions available as part of the PASTA study, quantitative statistical analysis of the relationship within and between the different levels of the socio-ecological framework was chosen as the primary research method, as opposed to a qualitative method. This research is presented in Chapter 4. Three main quantitative methods were identified as most useful in determining the strength of the different relationships between constructs in the conceptual framework: random forest machine learning, structural equation models, and logistic regression models. All three were tested, and logistic regression models were chosen as the best method.

SEMs are a combination of factor analysis and multiple regression, and are able to identify which variables “load” or contribute most to a latent, unobserved, construct, and in turn which constructs influence the outcome variable the most (Little, 2013). They therefore test a theorised causal relationship between observed and outcome variables, useful to test the relative strength of different TPB constructs, or the influence of the micro vs. the macro levels within the socio-ecological framework. They also deal with missing data well, have inequality constraints, and can be used with a mix of binary, categorical, and continuous data (Rosseel, 2017). However, a review of papers published on the subject of TPB or the built environment and transport found that virtually none of the SEMs published met the minimum goodness-of-fit tests that statisticians and mathematicians recommend for SEM-based analysis (Kline, 2015; Hoyle, 2012; Hooper et al., 2008), or do not investigate the underlying assumptions of the data well (Tarka, 2018). These include Dill et al. (2014), Van Acker et al. (2014), Vale and Pereira (2016), De Oña et al. (2013) and Zhang et al. (2019).[1] Indeed, in many fields this is true for the majority of all studies that use SEMs (Karakaya-Ozyer and Aksu-Dunya, 2018). Therefore, although theoretically appealing, SEMs were not used for the analysis.

Using recursive partitioning algorithms (random forest data mining) to establish which sub-groups of individuals, social and spatial characteristics influence people's decisions to travel by active mode was also an appealing option, which would allow me to uncover any new un-hypothesised relationships. They do not suffer from bias with a small number of observations and large numbers of variables (high dimensionality) of data (Hengl et al., 2018). However, as random forest results are averages of hundreds of different individual models (trees), it is impossible to uncover the different relationships within those trees, and makes interpreting random forests very difficult, both for the researcher and any reader of such a paper (Hengl et al., 2018). Second, while this kind of analysis could uncover new relationships, if not based upon theory, it is impossible to speculate on the reasons behind these relationships.

Logistic regressions are simpler to understand than both SEMs and random forests. Provided the same dataset, sample size, and outcome variable are used across models, results

[1]Exceptions are one of the two SEM models presented by Cao et al. (2007); Li et al. ("Healthy lifestyle and life expectancy free of cancer, cardiovascular disease, and type 2 diabetes: prospective cohort study"); and Neto et al. (2020).

from one regression are comparable with another. Finally, many studies in public health research and transportation planning that compare the relative influence of psychosocial constructs to those of the built environment also use logistic regressions (e.g. Keyes and Crawford-Brown (2018), Chan et al. (2019), Bird et al. (2018), Panter et al. (2013), Gascon et al. (2019), Dalton et al. (2013) and Carse et al. (2013)), meaning that a paper which uses the same method would be more likely to be accepted by both fields.

3.5 Micro level influences of active travel: why sub-group specific analysis is valuable

After determining which aspects of an individual's personal, social, and built environment spaces correlate with their decision to travel actively the most, the thesis then focusses on determining the effectiveness of policies to increase active travel. Realist evaluation was chosen as the theoretical underpinning of an evaluation of a micro-level, personalised travel-to-work plan campaign in two of the PASTA cities. This section describes realist evaluation.

Realist evaluation, developed by Pawson et al. (1997), can be summarised as the difference between asking "does it work?" and instead asking "what has worked? For whom? In what circumstances and respects? How?" (Pawson et al., 2004). It recognises that policies are always based on some kind of theory, which may or may not be appropriate, that policies may change or be subject to mistakes in implementation, that a policy is always embedded in wider society and social systems. A policy that is based on sharing information and educating people inherently relies on the active participation and volition of those participating in the policy, and so evaluating it requires understanding the interpretations of those educational messages (Pawson et al., 2004). Realist evaluation is based on understanding the context, the mechanism, and the outcome patterns in order to understand policies. More details on the theory itself, and a description of how it has been applied in this thesis, is available in Chapter 5.

Realist evaluation is a powerful way of thinking about policies that have been implemented in a well-defined, bounded space (such as a hospital or city), and look at the different ways in which every person involved has been affected. It is, therefore, mostly used as an ex-post method. It can be used to help uncover which aspects of the conceptual framework presented in this thesis are most relevant to a particular person or situation. It also aims to identify which individuals may have benefited most from the policy, have been affected most adversely, or have not been affected at all, examining people in different life stages and circumstances differently. It is highly granular, and therefore provides more nuanced analysis than standard policy evaluations conducted as part of randomised controlled trials or differences-in-differences statistical analyses, which usually treat data as binary (treatment/control and improved/not improved). The benefit of using realist evaluation is that it goes beyond typical public health, or even econometric analyses: rather than looking at whether a policy has influenced the outcome of interest, a common problem in institutional analyses (e.g. transport environmental impact assessments (Harris et al., 2018)), in this case walking and cycling, realist evaluation looks at what change in thinking or perceptions that policy has caused, and how those changes then influence the outcome (De Souza, 2013). This is useful for preparing theoretically grounded policies in the future that may not be identical to the ones tested in this study, but may want to instigate behaviour change using the same mechanisms as the current interventions.

Most research still focusses on whether an intervention has worked, but few strive to identify through which channels it has worked, or why. Exceptions include a mixed-methods study by Sahlqvist et al. (2015), and a study by Panter and Ogilvie (2015), who found that physical infrastructure interventions worked primarily by changing the nature of the environment, not by changing perceptions of it. Conversely, in their scoping review, Brown et al. (2017) argue that the main mechanism through which infrastructure changed transport were changes in perceived safety. However, neither proposition has been proven. It is, therefore, unsurprising that studies have admitted that knowledge of the specific mechanisms and relationships governing individual and social actions is insufficient in recommending policy and interventions (Kelly and Barker, 2016). Realist evaluation aims to identify exactly those contexts and mechanisms which have led to an intervention changing behaviour, and those that have not.

3.6 Macro influences of active travel: the usefulness of big-picture analyses

As Chapters 1 and 2 described, national-level policy is both important to encourage an increase of physical activity, and dominated by economic discourse and economic analyses. In order for active travel to enter the discourse on a level playing field, it is necessary to present it in economic terms. This section describes the economic theory and tools that can be used to conceptualise transport, people's health, and how policy tools can be evaluated, as well as the benefits of using an economic framework, at the macro level.

Public economics is a field that evaluates whether public intervention in a market is justified, and the implications of such a policy. It is often based on maximising individual utility in order to maximise social welfare (Piketty and Saez, 2013). When a market is not functioning at the efficient or equitable optimum, intervention is justified. Reasons for this inefficiency might be the existence of imperfect competition (e.g. modern tech companies, or fossil fuel companies concentrating market power in the energy and car sectors), public goods (goods that are non-excludable but rivalrous, e.g. one cannot be excluded from breathing air, but a vehicle or factory "consuming" and polluting air may detrimentally affect the quality of air consumed by everyone else), imperfect information (e.g. people not being fully aware of the negative effect of smoking or lack of physical activity on their and others' health, and the healthcare system), and externalities (e.g. the presence of carbon emissions from burning fossil fuels where the negative (or positive) impact is not fully borne by the producer or consumer, but by third parties). All of these inefficiencies distort prices and costs, both to consumers and firms, leading to the misallocation of goods and services, and overall welfare loss (Auerbach et al., 2013).

Policy schemes can be designed to correct these market failures. These may include regulations, such as car emissions standards (CAFE standards in the US or CO_2 emission performance standards in the EU), or information campaigns and requirements, such as warnings on cigarette packets or nutritional colour-coded information on food packaging in the UK. It can also include subsidies or taxes, in order to change relative prices, and thereby change behaviour.

Utility-based analysis treats the individual as having preferences - likes and dislikes - that are representative of a group within society, a so-called representative agent. Often, one abstracts from heterogeneous behaviour to build the simplest possible model of a specific economic effect of interest. Within expected utility theory, the individual maximises their own welfare through the consumption of certain goods and services, subject to a set of constraints (Varian, 2014). They have well-ordered preferences that do not exhibit idiosyncratic behaviour.[2] Expected utility theory is therefore a useful tool for analysing change at a larger scale, for example at the national or society-wide level, where higher granularity leads to a cumbersome and difficult-to-understand result, and is mostly unnecessary, provided people's behaviour concentrates around the mean in a normal distribution.

For example, if a person purchases a large SUV, the driver then may go on to contribute to externalities, such as high CO_2 emissions, or cause an accident because the car makes them feel falsely secure, or they did not see someone in a blind spot. Other possible externalities

[2]In choice theory, preferences are taken to be transitive (if A is preferred to B, and B to C, then A is preferred to C, and complete (on a continuous downward sloping curve, all points higher up, closer to point A, will always be preferred to all points lower down, closer to B).

include reducing the supply of the public good of air, causing (likely a child or an elderly person) an asthma attack (Goldizen et al., 2016). Alternatively, they may end up with higher fuel expenditure than expected due to inappropriately communicated information (Andor et al., 2020). They may cause themselves an internality - an un-priced effect that harms primarily the individual consuming the good, not third parties - because they no longer walk to pick up their children from school, and do not compensate (often due to lack of time) by engaging in other forms of movement. The government may intervene, primarily to compensate or prevent third party costs, and maximise social welfare. Government intervention in the presence of externalities is well established.

Pigouvian taxation, the idea of taxing harmful activities in order to re-establish an optimal price and therefore optimum consumption (Pigou, 1932), has been around for almost a century. An appropriately taxed good will have a higher price to the consumer, or a higher cost to the producer, thus leading to less demand or supply of the good. This is called an *internalisation* of the externality, and a return to an efficient allocation of resources in the market. In many situations, multiple externalities will be present. In such a context, the Tinbergen rule applies, namely that for every market failure there exists one policy or tax that should correct for that failure. In a first-best world, the government is operating in a setting where only one distortion on the market exists. However, this is unlikely to be true - income taxes or other market failures will probably already be distorting the market, meaning that the government will operate in a second-best world, and needs to take into account potential interactions between these failures and policy instruments. In environmental economics, this has given rise to the concept of the double dividend: levying a tax on a polluting activity raises revenues that can then be used to reduce other distortionary taxes that are welfare reducing and harm economic development, such as labour taxes (Fullerton and West, 1999).

Mathematically, the aim is then to optimise an individual's objective utility function subject to the relevant constraints they identify, and any other tax interactions necessary for a balanced government budget. Mathematically, this "balancing" is done by setting up an optimisation problem similar to the concept of optimisation in engineering. The representative agent's utility function (the objective function) is maximised subject to the constraint functions of air pollution, time, their budget including the price of fuel, etc., using the Lagrangian function. Taking partial derivatives of the components of the objective function within the Lagrangian and setting them to zero maximises their value. Taking partial derivatives of the variables in the constraint functions and setting them to zero ensures that the constraints are also satisfied. The responsiveness of markets to past changes in price are taken into consideration when writing these functions. Rewriting the resulting equations with appropriate substitutions then leads to a formula for the optimal policy instrument.

One of the benefits of using economic theory over a different framework is that it is normative. Where realist evaluation and the socio-ecological frameworks assess a behaviour and how it occurs, in public economics it is explicitly stated what an optimal outcome for an individual who values a specific set of things would be, and how it can be achieved. Instead of describing a cause-effect situation, normative statements make recommendations about what ought to be done within society. Problems arise when people deliberately choose a welfare-reducing option, for example alcohol over-consumption, smoking, or a large SUV car. If people are rational choice-makers, their revealed preference, in this case the purchase and use of that SUV, was a carefully considered choice, and the individual is optimising their utility function with their constraints - a family, which requires a larger car, or a fear of driving, which is compensated for with a bulkier car to increase the separation between the driver and the traffic, or time constraints. Typically, if revealed preferences are completely rational and the individual's best choice and the activity only affects themselves, then perhaps government intervention is not justified, and would obstruct free will. A common critique of health-related policies such as smoking bans, mandated types of health insurance, vegetarianonly food menus, or calorie-signs, is that they are paternalistic, aimed at preventing own harm or for one's own benefit, regardless of one's own desires.

Paternalism may be perceived in different ways: in philosophy, a ban is paternalistic, a tax or recommendation is not; in libertarian economics, even a tax is considered paternalistic in many cases, if it appears to correct a behaviour that is based on one's preferences or desires. In order to avoid a "paternalistic" approach to policy, perceived negatively in economics (Haybron and Alexandrova, 2013; Burrows, 1993), I and my co-authors took a preference-based approach to the modelling of health benefits in the optimal fuel tax calculation. This was achieved by introducing the variable omega, ω, which represents the extent to which the individual "internalises" the knowledge and the potential health gain they *could* achieve *if* they cycled. With values from 0 to 1, ω captures whether the individual is fully aware of all the health benefits of active travel (1) or completely unaware of these personal health benefits (0). This then affects the extent to which the health benefits per mile travelled enter the optimal fuel tax formula; for example higher awareness means that the individual already accounted for the opportunity cost of not doing exercise themselves, making the tax unnecessary and therefore lower. This preference-based modelling approach was chosen partly in order to fit in with the economic discourse. In contrast, a paternalistic approach would impose a fuel tax level such that every individual reaches the minimum health requirement of 150 minutes of exercise a week (WHO, 2010), regardless of their desires. As behavioural economics research progresses, more leeway is being given to some paternalistic approaches to policy, particularly "libertarian paternalism", which directs an individual towards the more welfare-enhancing option, but leaves open the possibility of choosing another option. Initial research showed that few people choose options with lower welfare outcomes (Thaler and Sunstein, 2003).

The most common approaches to pricing driving, not just car ownership, are tolls on roads, and fuel taxes. As toll roads are typically motorways or bridges, not urban areas, and taxes are a widely used, well-understood economic pricing tool through which policy-makers try to optimise the consumption of many goods, one can use a fuel tax to illustrate the importance of physical activity. In transport, fuel taxes are used to provide an appropriate price for the previously omitted externalities - carbon emissions, air pollution, too many people driving causing congesting problems for third parties, and accidents that cause harm for third parties. The signal conveyed in the higher fuel price reduces driving to the optimal level. Chapter 6 uses a fuel tax to consider the above-mentioned externalities, as well as the second-best setting where different tax schemes interact with each other. In addition, it considers the (internal) effect of a lack of physical activity (due to car driving) on one's health, in order to illustrate the size of the health effect relative to the other social costs people are familiar with within transport.

Using a fuel tax allowed me and my co-authors to build upon a paper widely known in environmental and public economics by Parry and Small (2005). The paper built an analytical framework that maximised consumer welfare subject to all the largest social costs in transport (congestion, accidents, carbon emissions, and air pollution), and formalised a congestion feedback and balancing of the government budget (through labour and fuel taxes). Using a familiar framework and updating their values of social costs, we could prove the relative size of the social cost of physical inactivity far outweighed other social costs, in a way that creating our own framework could not.

Using taxes to internalise externalities is well-established within economics. Externalities, by definition, involve the impact of one's actions on a third party. However, the health benefit from exercising is experienced by the individual only, not a third party, and not exercising incurs only an "internality", not an externality.[3] Traditional economics presumes a perfectly rational actor, who would not have any internalities. However, recent developments in behavioural economics have led to the development of modelling techniques that allow for

[3]Certain costs, such as public healthcare costs due to higher incidences of non-communicable diseases, may be considered external, but are very small compared to the internal costs. The healthcare system itself is a policy instrument, collectivising private risk, and therefore distorting the market.

imperfectly rational actors with internalities. Research is still predominantly focussed on proving that these internalities exist (Shogren and Taylor, 2008), rather than on providing examples of policies that can reduce them (exceptions do exist, see e.g. Allcott et al. (2019)). The paper in Chapter 6 therefore takes an important step in showing how internalities may be incorporated, in a relatively straightforward manner, to policy evaluations.

Economic theory also formalises any feedback effects within the system, and estimates their size. For example, within health behaviour, not only will more physically active travel improve health and reduce carbon emissions, it will change the government income from fuel taxes and people's productivity at work. This means that their choice of how much time to dedicate to labour or leisure may also change. By reducing the number of miles driven in the economy, congestion falls; this increases the speed of driving, incentivising people to drive again. By explicitly modelling these feedbacks, it is possible to compare the feedback effects different policies may have within the system. Thus, it can also be used ex-ante, unlike realist evaluation.

Another benefit of using economic theory is that it reduces different concepts, such as carbon emissions and personal health gains from physical activity, to "utils", or assigns a monetary (dollar) value to them. Given this common denominator, these concepts can then be compared and analysed, arriving at a policy that maximises their total value to society. Monetisation of social costs valued in Chapter 6 is always challenging, particularly with regard to health monetisation. Although estimates of per-mile costs of accidents, air pollution, and carbon emissions were available in the literature, no appropriate estimates of the per-mile costs of physical inactivity for the UK and US exist. Although Zapata-Diomedi et al. (2018) list a number of studies estimating the monetary value of health benefits per kilometre walked or cycled, the vast majority were grey literature, and no two estimates for the UK or US existed that used the same methodology. Hence, in order to quantify the health benefits of physical activity per mile actively travelled, I had to carry out a health impact assessment myself, choosing both a method for quantifying health, and a tool for this purpose.

As monetising health benefits involves the valuation of health, for which no competitive market exists, this is typically done using contingent valuation methods - stated or revealed preference methods. Revealed preference methods, such as analysing housing price correlations with air pollution concentrations, typically return lower values and may reflect current inefficiencies in the markets rather than true preferences (Keohane and Olmstead, 2016), values from studies using stated preference approaches were used in this thesis. In stated preference, an individual is required to make a trade-off between mortality risk and a change in monetary wealth (Ashenfelter, 2006). This can be used to calculate the Value of Statistical Life (VSL) for a general "value" of life, or for specific willigness-to-pay (WTP) estimates for a reduction in the risk of getting a specific disease, or gaining an extra quality-adjusted year of life (QALY). The VSL approach monetises only deaths avoided, while the latter two approaches also monetise reductions in morbidity. A mortality only approach reduces the likely value of physical activity health benefits, as it does not count the extra years of life gained, or their quality. A disease-specific WTP approach also considers the differences in the valuation of different diseases between cultures and countries, offering a more context-specific estimate of health benefits (Saarni et al., 2006). Alternatively, it is also possible to use a risk avoidance approach, monetising the value of reducing a certain number of deaths through a specific policy. Though criticised, it is used in some settings by the UK government, for example. Of all these approaches, the VSL is the only method used consistently in environment, transportation, and health research and practice (OECD, 2012), making it the most appropriate valuation method for multi-disciplinary research.

The two overriding principles in determining which tool to use for a health impact assessment were simplicity, and international respectability. The European World Health Organisation's Health Economic Assessment Tool (HEAT) (Kahlmeier et al., 2017) was used because of its low input requirements, dependence on default values collected by experts, and simple mortality-only monetisation of death calculated using the Statistical Value of Life. It also included a carbon reduction tool, useful for potential welfare analysis. It has been used in academic research, as well, for example by Gao et al. (2017), Fishman et al. (2015) and Pérez et al. (2017), among others. Thus, although the Integrated Transport Health Impact Model (ITHIM, Woodcock et al. (2013)) is more detailed and its outputs include both mortality and morbidity estimates, it is more input intensive, less widely known outside academia, and to be fully useful, would require separate estimates of the monetary value associated with every disease and age group. Although this modelling approach was taken in my MPhil dissertation (Sulikova, 2018), the greater level of detail provided by ITHIM was not necessary for the purposes of the research presented in Chapter 6.

Overall, the aim of the research in Chapter 6 is simple: to introduce physical activity as an important consideration in pricing and national policy-making into the public economic literature and transport policy considerations. It uses a framework that is well-established in the literature, a simple equation to represent the physical activity internality without any complex behavioural economic concepts, and an appropriately complex tool to calculate the health benefits.

3.7 The Physical Activity Through Sustainable Approaches study

3.7.1 The original study

The bulk of this thesis relies on data from the Physical Activity Through Sustainable Transportation Approaches (PASTA) study. PASTA is a multi-centre, European longitudinal research project, which collected data on people's travel and health behaviours in 2014-2017. The PASTA team incorporated insights from both transportation and public health research in its research design in order to investigate the correlates and interrelations of active travel, exercise, air pollution and crash risk, to improve the understanding of active travel and methodology of quantitative health impact assessments, and evaluate the effectiveness of interventions implemented in their case study cities (Dons et al., 2015). PASTA was delivered as a web-based survey. PASTA case study cities were Antwerp (Belgium), Barcelona (Spain), London (United Kingdom), Örebro (Sweden), Rome (Italy), Vienna (Austria), and Zürich (Switzerland). The remainder of this section describes the benefits of using the PASTA dataset, the recruitment process, survey delivery and contents, and the seven case study cities in the original PASTA dataset. This structure is repeated for the primary research I conducted on a subset of the PASTA dataset as part of this thesis.

There are several distinct advantages to using PASTA data for this thesis as opposed to collating data from several European studies, or relying on data collected entirely by me. PASTA uses the same research design in all seven cities, including a common recruitment strategy (Dons et al., 2015) and year of sampling (2014-2016), which few other studies are able to do. In their meta-analysis, Lanzini and Khan (2017) concluded that the year of study and recruitment were significant contributors to the heterogeneity of studies evaluating psychological and environmental variables influencing mode choice. The PASTA approach helped ensure a similar and more evenly distributed number of participants across cities, travel modes, and social groups, important in order to be able to analyse the effectiveness of interventions across cities. While many studies rely on cross-sectional data or self-reported data, which often results in failure in studies evaluating interventions (Gerike et al., 2016), PASTA is a longitudinal study, relies on a large sample size, and includes recruits who used activity, location, and air pollution trackers in order to validate and potentially correct for biases in self-reported data (Dons et al., 2015). For example, when cycling travel patterns were compared in the first PASTA questionnaire (effectively cross-sectional) and in the longitudinal repeated measures questionnaires, Branion-Calles et al. (2019) found that the cross-sectional approach under-estimated the number of respondents who cycled, but was more representative in terms of the sociodemographic make-up of a city, while the longitudinal questionnaires suffered from the drop-out of more frequent cyclists and other forms of participation bias. Finally, being able to perform primary data collection on a subset of the original PASTA respondents in 2019 meant that I had access to 5 years of longitudinal data for analysis, rather than one cross-sectional dataset.

3.7.2 Recruitment methods and sampling

A common recruitment guide was developed as part of the PASTA study, combining different opportunistic sampling methods. These were a press release and common visuals in all seven cities, including postcards and leaflets, other public notice, social media (e.g. a popular twitter account of the city of Rome), news outlets, on-street outreach activities, word of mouth, and work-place or other organisation-based promotion (Dons et al., 2015). The aim was to recruit 2000 participants in each city, 14,000 in total. As the survey was web-based, efforts to recruit older members of the population were made by, for example, contacting people who had recently completed computer courses. 10,691 participants were recruited, all over the age of 16, living/studying/regularly travelling in a PASTA city. 21.51% of participants found out about PASTA through their employer, 20.76% through outreach, and

17.39% through social media. Örebro, which also employed random sampling by contacting citizens by mail or phone, also experienced the greatest attrition rate of respondents (4.8 questionnaires completed per respondent as opposed to the average of 8.1 for the whole study) (Gaupp-Berghausen et al., 2019). This also helps show that the sample might be slightly biased towards people interested in physical activity, active travel, transport, or health in the first place. The sample was representative of car access, gender, employment, less so on education, and purposefully oversampled cyclists. A user engagement strategy was developed in order to reduce attrition, which included a lottery (other than in Sweden, due to legislation on rewards permissible for study participants), posting on social media, regular contact with the respondents, allowing people to open, save, and finish questionnaires at their leisure, and reminder emails were sent after the 3rd, 10th, and 20th day from the previous survey completion (Dons et al., 2015). More details on the study design protocol can be found in Dons et al. (2015) and Gerike et al. (2016), and recruitment methods and their relative strengths can be found in Gaupp-Berghausen et al. (2019).

3.7.3 Survey design and questionnaire content

Once survey participants were recruited, they gained access to their personal web-based survey account platform, where they could view their completed and open questionnaires, and see updates from the PASTA study. They had the option to withdraw themselves from the survey, provided they did not want to continue to participate (Gaupp-Berghausen et al., 2019). The web-based survey deployed follow-up questionnaires every 13 days through an automated platform. The first questionnaire took approximately 30 minutes to complete. This asked for the respondent's:

- sociodemographic characteristics,

- travel behaviour (based on a self-reported monthly frequency measure and a KONTIV design[4] one-day travel diary)
- physical activity (based on a frequency measure and the Global Physical Activity Questionnaire),
- traffic accidents (crashes and near misses),
- and attitudes.

The questionnaire asked about cycling- and walking-specific attitudes such as the extent to which it is time-efficient or healthy, what activity they were most likely to use either mode for, as well as whether they felt they had a supportive community around them, health issues, perceived proximity to public transport, and others. At least one, sometimes two or three questions targeted each of the original theory of planned behaviour constructs, while some questions followed the transtheoretical theory of behaviour change. The second was a short follow-up asking about physical activity and travel habits in the past seven days, taking about 5 minutes to complete, and the third took about 10 minutes, asking about accidents and requesting a one-day travel diary. More information on the questions included, as well as which constructs and levels of the socio-ecological framework and theory of planned behaviour they map on to, is included in Appendix B of Chapter 4. A subset of the original questions is available in Appendix A. In addition, the PASTA study also collected built and natural environment data for each participant home and study/work address, which they provided as part of the travel diary.

A benefit of using web-based methods for promoting, recruitment, and administration of the survey were both a wider audience reach, lower cost, and played into the rise of exclusive usage of mobile phones and email instead of landlines and mail (Batterham, 2014).

[4]The KONTIV travel diary design was pioneered by the German Ministry for Transport and Infrastructure Development, aiming to enable the logging of all trips, however short, and be easy and complete (SocialData, 2009).

A subsample of about 20% of the respondents was recruited to use the GPS tracking app Moves to validate self-reported travel data, and a total of 120 participants were recruited to use air pollution and health monitors (Dons et al., 2015). All content was created in English and translated into Swedish, Dutch, Catalan, Spanish, Italian, Swiss German, and Austrian German using the collaborative Pootle translation tool (http://pootle.translatehouse.org/) (Dons et al., 2015). Contextual data on population statistics was collected from publicly available sources. Ethics approval was obtained by the relevant institution from each survey country from their national or institutional boards.

3.7.4 Interventions within the PASTA study

The participants were also allocated into a top measure affected, control, or general population group. The top measure affected groups were given different policies or interventions that the control groups were not, and differed by city. These were primarily workplace mobility management plans, bicycle racks, promotion campaigns, and cycling bridge building, and are described in more detail in 3.7.5 and Chapter 5. The allocation was based either on their responses to the baseline questionnaire, by their workplace, or by their home/work distance to the built environment measure being implemented. The respondents in the top measure group answered a baseline and two short follow-up questionnaires, and then were put into a hibernation period, to prevent the survey from intervening in the implementation of the intervention. They then filled in a re-entry questionnaire, similar to a baseline questionnaire, and short follow-up questionnaires (Dons et al., 2015). Respondents in the control group did not enter a hibernation period, but were sent follow-up questionnaires.

3.7.5 The follow-up conducted for this thesis

Study design

The long-term follow-up survey was conducted in two cities where soft top measures were implemented: Vienna, Austria, (1.8m inhabitants) and Örebro, Sweden (100 000 inhabitants). In Vienna, the intervention was the provision of personalised travel planning. In Örebro, the intervention consisted of workplace campaigns accompanied by infrastructure upgrades (leasing of electric assist bicycles, installation of bicycle racks). The purpose of conducting a second follow-up was to gain an additional repeated measure to gauge the effectiveness of the intervention over a longer period of time than 12 months, as the original PASTA study allowed. Overall, the survey follows a pretreatment (baseline questionnaire), post-treatment (final survey of original study) and follow-up (my 2019 survey) (PPF) design most typically used for case-control cohort studies.

Recruitment method

The original PASTA survey was concluded at the beginning of 2017, and respondents were able to provide consent to be contacted in the future for further PASTA surveys, or similar surveys, and provided their emails for that purpose. A total of 714 people (482 from Vienna, 234 from Örebro) provided their consent. Asking participants who had already agreed to be contacted in the future is significantly easier than recruiting new participants using a promotional strategy I would have designed on my own. Increasing privacy concerns, higher numbers of surveys, expectations of monetary rewards, all make it more difficult to attain a sufficient and unbiased sample (Galea and Tracy, 2007).

On re-enrolment in the follow-up, participants provided the email address they were contacted with in order to link them to the original survey database and give informed consent before proceeding to the main survey. Prior to participation in the study subjects were informed of the study procedures and potential risks and were requested to give informed consent. To proceed, they needed to check the box “I agree with the conditions”. When the participant clicked on the word “conditions,” the information sheet appeared. The form gave detailed information about the research itself, the conduct, the rights of the participant, contact information etc. If the participant did not check the box, he/she were not be able to participate in the survey. The information sheet, as well as the entire survey, were available in English, German, and Swedish. The surveys were translated first by a native speaker, and then checked using the professional translation service Gengo.

Survey design and content

While the original PHP survey frontend and backend (survey website and data management platform) and encryption files were kindly provided to me by the original PASTA survey designers, it was first designed in 2014 and was therefore obsolete from a security standpoint by 2019. Therefore, I chose a professional survey platform with a user interface to make the survey design and data management easier and more secure. From the options of SurveyMonkey, LimeSurvey, and Qualtrics, or the university recommended BOS, I chose LimeSurvey. LimeSurvey offers a fully flexible platform with pre-coded options for different question types, and where I could insert my own code for certain questions needed for interactive map locations, something neither SurveyMonkey, Qualtrics, or BOS allowed. They offer a GDPR compatible German server for the storage of data, and allowed the customisation of the survey website with logos and colour schemes. Finished or closed questionnaires are stored, encrypted and backed up every 24 hours. The original team had considered LimeSurvey in 2014, but the platform was not mature or flexible enough for their needs at that time.

The benefit of providing an online questionnaire for participants to fill in is that they may do so in their own time, and return to it and finish or alter the answers at a later point for their own convenience. The questionnaire was designed to take no longer than 30 minutes to complete, although asking people to fill in a travel diary is an onerous task. In order to make this easier, an option of using a Google Maps plug-in to visually record a journey was provided in addition to asking for trip start point and end point location, trip start and end time, travel mode, trip purpose, and number of companions. Most questions were re-used from the original questionnaire, in order to ensure familiarity and reduce the burden on the participant. The entire follow-up survey is listed in Appendix A.

For data protection and confidentiality purposes, all responses were pseudonymised using code numbers, and their identifying information was stored separate from the survey response data. The data for analysis was stored on my personal (portable) computer and was password protected; data linking ID codes to participant names were stored in a different folder, protected by a different password. The whole laptop internal hard drive is encrypted using a built-in FileVault system. After the survey closed, personally identifiable data were stored by VITO (Flemish Institute of Technological Research, Belgium), which handled the original survey and stores personally identifiable data from the original survey, as well. My laptop did not hold a copy of this file after the completion of the survey and pseudonymisation of the data. One question in the survey asked whether the respondent was happy to be contacted by PASTA in the future; a file with contact information for people who responded positively to this question is stored by VITO for as long as the PASTA platform remains active, due to the possibility of future research. Otherwise, VITO will safely destroy the data.

In order to engage the respondents, basic email marketing skills were needed. I used the MailChimp platform to send and manage participant emails. MailChimp allowed me to design HTML-based emails with the PASTA and University of Oxford logo. In order to match previous trip diary data from the 2014-2017 study, each of the participants was asked to fill the travel diary for a specific day of the week. This day was their most frequently reported travel diary day over the 2014-2017 PASTA study. This is because travel by weekday is highly variable, and so could bias results if previous surveys were filled in on Wednesdays, and the 2019 follow-up was filled in on a Sunday. This process was made significantly easier using the MailChimp platform, in which I was able to group email addresses by day and city/language membership, in order for a personalised email to be sent out. In order to make survey responses easier, the survey consisted mostly of pre-set questions, and interactive Google Map-based maps for travel diary data input. A reminder email was sent 15 days after the first email, which increased participation rate by 27%. The final response rate for my survey was 47%.

Baseline information of the respondents of the original survey is available in Chapter 4, and on the follow-up survey is available in Chapter 5.

3.8 PASTA case study cities

Figure 3.5 Map of the seven case study cities in the PASTA study.

There were seven cities included in the PASTA study. These were Antwerp (Belgium), Barcelona (Spain), Newnham (London, United Kingdom), Örebro (Sweden), Rome (Italy), Vienna (Austria), and Zürich (Switzerland). Figure 5.3.1 shows the location of the seven PASTA case study cities. The case study cities are all located in Western Europe, and have a population higher than 100,000. Importantly, the PASTA consortium had contacts in these cities, and the planning authorities in each city had expressed a desire to increase active travel within the city, and presented plans in order to achieve this. This allowed PASTA researchers to be opportunistic with their choice of research locations. In addition, participants were recruited in the same way, for the same purpose, in each city.

The cities vary by size, climate, and travel patterns. These are summarised in Table 5.A.1, but each city has comparable travel patterns and bike cultures with another city in the sample. For example, Vienna, Zürich, and the London borough of Newnham all have well developed public transit networks, report high levels of walking and public transit use but low levels of cycling, and both Zürich and Vienna have a humid continental climate. London and Vienna also have a well-developed cycling network, but very low levels of cycling. They both face a different challenge to Zürich, Barcelona or Rome, where the cycling infrastructure is not well developed. Antwerp and Örebro share a Nordic culture, with developed cycling networks and very high levels of cycling, notwithstanding the low average temperatures. In contrast, Barcelona and Rome are both considered to have a Southern culture, both have more than 1 million inhabitants, and a small cycling network with very low levels of cycling. This classifies them as having an emerging cycling culture, rather than the mature cycling cultures of Antwerp and Örebro, and will therefore face different obstacles and challenges to the two Northern cities. Thus, although the cities look very different at first glance, they share important traits that allow comparisons between them to be made.

Variable	**Antwerp**	**Barcelona**	**Newnham (London)**	**Örebro**	**Rome**	**Vienna**	**Zürich**
Description	Second largest city in Belgium	Second largest city in Spain	South-east London Borough, United Kingdom	Regional centre, 200km west of Stockholm, Sweden	Largest city in Italy	Largest city in Austria	Largest city in Switzerland
Population*	510,610	1.6 million	265,688	140,000	2.9 million	1.8 million	400,000
Average monthly income per capita in EUR end 2019 exchange rate**	3749	3117	4333	4100	2824	5120	5980
Weather							
Average annual temperature, C***	10.1	16.5	11.1	6.1	15.7	9.9	9.3
Annual rainfall, mm***	778	612	621	633	798	623	1085
Koeppen-Geiger climate classification***	Temperate oceanic	Dry summer	Temperate oceanic	Humid continental	Dry summer	Humid continental	Humid continental
Mode share %							
Driving	41	26	38	55	54	27	30
Cycling	23	2	3	25	1	6	4
Public transport	16	40	29	9	29	39	39
Cycling network km (OSM)****	469.17	159.54	969.17	361.35	120.64	715.63	118.36

Table 3.1 PASTA city characteristics

* From worldpopulationreview.com
** Various sources
*** from climate-data.org
**** from Mueller et al. (2018)

3.8.1 Collection of primary accessibility data for the seven PASTA cities

The rise of commercial and open-access APIs for routing of trips, and open-access General Transit Feed Specifications (GTFS) on public transportation schedules and routes has greatly increased the potential of accessibility-based analyses in transport. Part of this thesis focussed on showing how this can be done, and provides the code for this on Github.[5] OpenStreetMap was used to identify the grocery store, school, and city centre closest to the respondent's home and work/study locations, and then a routing API from Openrouteservice was used to calculate the distance and time needed to travel from home/study/work to the destination of interest, for each mode of travel: walking, cycling, driving, and in some cases, public transport. In addition, the public transit (GTFS) data made available by the cities of Antwerp, Barcelona, Rome, London and Vienna was used, and nationwide public transit data available from Switzerland and Sweden were used to extract information on the nearest public transport stops to the respondents' home and work/study locations, the frequency of services stopping at that stop, and the number of different services operating at that stop, to serve as proxies for accessibility. This is not meant to be a perfect measure of accessibility; a more comprehensive analysis would take an average of all the public transit stops within walking distance range (800m (TfL, 2016)) of these locations, rather than just the nearest stop, or include destinations the respondents themselves were interested in. Examples of what public transport feeds look like can be found in Appendix B.

[5]Link: https://github.com/ssulikova/DPhil-online-material.

3.9 The geographical and research context of this thesis

Chapters 4 through 6 span a diverse set of geographical contexts and circumstances. If patterns and conclusions arise when using a very diverse set of contexts, then they have a greater likelihood of being applied to other geographical contexts and situations, as well.

Chapters 4 and 5 both use subsets of the PASTA dataset described above, and focus on the European setting. Although studying several cities instead of one increases the complexity of any analysis, a benefit of the PASTA study is the uniform recruitment strategy. This means that if there are biases in the respondents recruited, they are likely to be similar across all seven cities. If there are any generalisations or consistent patterns that arise for all seven, or a majority of, the PASTA cities, this marginally increases the likelihood that these conclusions can be applied to other contexts, as well, increasing the contribution of this research.

Chapter 6 does not use the PASTA dataset, instead focussing on national-level policy analysis for the UK and US. There are several reasons for this switch. First, better data, e.g. on elasticities with respect to fuel prices, are available for the UK and US than most other countries in the world. Second, the paper was inspired by a well-established optimal fuel taxation paper by Parry and Small (2005), who used the UK and US as their example countries. In order to make comparisons between their study and ours, the decision was made to use the same countries. Third, if patterns arise that can be generalised for both the UK and US, which have quite different fuel pricing strategies (Sterner, 2007), then it is possible to extrapolate those findings to other countries, as well.

3.10 Summary and next chapters

This chapter provided a description of the socio-ecological framework developed based on the literature summarised in Chapter 2, and the methods used in this thesis. The socio-ecological framework distinguishes three levels of influence within the active travel domain - the micro level, pertaining to the individual and their psychological attitudes and demographical membership; the meso level, comprising of trip-specific attributes and social practices of these trips and the culture the individual is embedded in; and the macro level, which includes the built and natural environments, the objectively measured social distribution of the neighbourhood the individual lives in, and the urban and national policy contexts.

The next three chapters, written in paper format originally, form the main research contents of this thesis. In Chapter 4, the relative influence of each of the constructs and levels of the socio-ecological framework are analysed using cross-sectional data from the PASTA study, providing evidence for hypotheses about whom these constructs may influence, and how. Having identified the micro level as the most significant determinant of travel mode choice on a day-to-day basis, and the differences in influences based on trip purpose, Chapter 5 then takes evaluates the impact of a soft, information-based measure on increasing active travel in a longitudinal study based on a 5-year follow-up version of the PASTA study. It focusses specifically on the micro level, the psychosocial attributes of an individual, and how demography and time affect the effectiveness of the intervention. Finally, Chapter 6 evaluates the potential effectiveness of a macro-level policy, a fuel tax, to change transport behaviour and achieve a socially optimal level of active travel.

Chapter 4

As you bike it: Investigating what makes people walk or cycle using a socio-ecological approach in seven European cities

Chapter 4 describes and evaluates the socio-ecological framework presented earlier in more detail. This chapter is co-authored with Christian Brand, who helped with conceptualisation, supervision, and writing and review. The paper was submitted to *Transportation Research Part F: Traffic Psychology and Behaviour* on 23/02/2021. A co-authorship statement is available in Appendix C.

As you bike it: Investigating what makes people walk or cycle using a socio-ecological approach in seven European cities

Simona Sulikova and Christian Brand, on behalf of the PASTA Consortium

Large efforts and investments have been made into public transport, walking, and cycling in cities around Europe. Yet, cars remain the most ubiquitous mode of travel in urban areas. Social scientists have focussed on using psychosocial theories such as the theory of planned behaviour to explain active travel, while transport practitioners have typically focussed on the built environment and costs of relative modes of transport. We develop a socio-ecological model that combines these competing levels, and use the Physical Activity Through Sustainable Transportation Approaches (PASTA) dataset on travel habits, behaviours and the built environments at home and work locations of people in seven different European cities to identify the constructs that correlate with active travel most. Using logistic regression, we find that psychosocial constructs influence the decision to take a trip by bicycle or walk more than built environment variables. We also find that psychosocial constructs link to intention and actual cycling/walking behaviour in different ways. The built environments at home and work locations have a very similar influence on active travel, but trip purpose does influence the importance of built environment and attitudinal variables in explaining active travel. These relationships do not vary significantly between cities.

Keywords: Transport mode choice; socio-ecological model; built environment; attitudes; active travel

4.1 Introduction

Walking and cycling for travel have long been recognised as practical means of reaching daily exercise targets (Gibson-Moore, 2019), improving mental wellbeing (Zijlema et al., 2018), reducing body mass index (Laeremans et al., 2017), decreasing overall mortality (De Hartog et al., 2010; Woodcock et al., 2009), as well as being environmentally beneficial, congestion-reducing and non-polluting modes of transport (Banister, 2008). 50-57% of all trips in the EU are shorter than 5km (Dekoster and Schollaert, 1999; Aher et al., 2013), and up to 75% are shorter than 10km (Aher et al., 2013), making car trips, particularly in well-connected urban areas, replaceable by public transport, walking, or cycling. Although significant efforts have already been employed to reduce car use in Europe, cars remain the most widely used transport mode in most European cities, and the transport sector is dominated by symbolic efforts to manage travel demand rather than observable mitigation (Bache et al., 2015).

Travel mode choice is determined by several factors: prices (Pucher and Buehler, 2007), proximity to destination and accessibility (Lee et al., 2018; Ewing and Cervero, 2010; Cao et al., 2007), seasons (Børrestad et al., 2011), trip purpose (Chan et al., 2019; Saberian et al., 2017; Mattioli et al., 2016), available infrastructure en route and at destination (Tilahun et al., 2007; Winters et al., 2011), the built environment (Cerin et al., 2017; Ewing and Cervero, 2010; Schwanen and Mokhtarian, 2005; Adams et al., 2013), travel patterns of others (Mattioli et al., 2016), own psychology and attributes (Arroyo et al., 2020; Bird et al., 2018; Lois et al., 2015; Dill et al., 2014), overall urban policy, and many other considerations. While researchers agree that each of these factors contributes to the decision whether to travel by active mode, there is a lack of consensus regarding which factors are most important in determining trip mode, and how these factors interact. Furthermore, while certain environmental variables have been found to predict car use reliably, the same level of confidence has not been established for active travel (Zijlema et al., 2018; Christiansen et al., 2016).

Dill et al. (2014) identify that the built environment impacts behaviour indirectly through influence on attitudes and behavioural control, but that attitudes have stronger predictive power. However, studies that evaluate the relative importance of both the built environment and personal attitudes on walking and cycling in detail remain uncommon (Götschi et al., 2017). When they do exist, they use survey and subjective data only (Cao et al., 2007), or a single location, such as the built environment at home (Dill et al., 2014; Van Acker et al., 2014), examine commuting trips only (Keyes and Crawford-Brown, 2018), or fail to assess the interactions between personal attributes and the built environment (Taube et al., 2018). Additionally, as Winters et al. (2017) point out, research is often spatially focussed within one neighbourhood or city, and assumes a homogenous collection of attitudes in the respondents, potentially limiting the applicability of research to other contexts. Meanwhile, price and car ownership fees, low emissions zones, and the planning context are all but excluded from the literature on attitudes and built environment with respect to mode choice, even though they have been shown to influence general patterns of travel behaviour significantly (Buehler et al., 2017; Duranton and Turner, 2018; Brand et al., 2013).

We aim to fill this gap in the literature by evaluating the relative importance of psychosocial factors and the built environment and accessibility in determining active travel mode choice and travel behaviours in people in 7 different European cities. We first developed a conceptual framework based on the socio-ecological models of Sallis et al. (2006), Sallis et al. (2015) and Götschi et al. (2017), the multi-level model by Mattioli et al. (2016), and attitudinal models of self-identity (Whitmarsh and O'Neill, 2010) and the extended theory of planned behaviour (eTPB) (Bird et al., 2018), as state of the art conceptual models of travel behaviour. We then present data from the multi-centre Physical Activity Through Sustainable Transportation Approaches (PASTA) study, which consists of transport and health behaviour surveys, trip-diaries, GPS and accessibility data from seven cities in Europe, Antwerp, Barcelona, London, Örebro, Rome, Vienna, and Zürich. We conducted multivariate logistic regressions to test the relative importance of the built and social environments as opposed to psychosocial and individual characteristics. We also carry out separate analyses for different trip purposes (work/study, home-related responsibilities, and leisure), and built environment characteristics for both home and work/study locations of the respondents.

We find that the built environment, while explaining a small degree of variance in our dataset, provided less explanatory power than individual sociodemographic attributes, attitudes, and social environment. For individual psychological constructs, perceived behavioural control had the greatest explanatory power of whether a trip was taken by active mode. Still, habit was the single most influential variable in determining mode choice. Intent to travel by active mode and whether a trip was actually taken by active mode are correlated with different eTPB constructs. Finally, the influence of psychosocial and built environment variables did not differ significantly between cities.

This paper provides an assessment of the varying degree to which the built environment and psychosocial factors affect daily travel behaviour, and may provide useful evidence for why a holistic and flexible policy approach is needed to encourage active travel in urban areas in Europe.

4.2 Theory and background

Socio-ecological models incorporate the environmental and policy context of a behaviour, as well as the psychological and social influences on it. There are several grounding principles of socio-ecological frameworks, namely that there are multiple levels of influence on a specific behaviour, these may interact with each other, and that such a framework should be behaviour-specific (Sallis et al., 2015). We take unifying principles from the active living framework by Sallis et al. (2006), the conceptual framework for active travel by Götschi et al. (2017) and the macro-meso-micro structure identified by Mattioli et al. (2016) for car-dependent behaviours, to develop a simpler tool to conceptualise active travel behaviour and feedback effects specifically, while retaining what we consider the core parts of these three frameworks. Both Sallis et al. (2006) and Götschi et al. (2017) roughly follow a socio-spatial structure covering the Individual/Intrapersonal, the Physical Environment, Policy, and the Community/Social/Cultural Environment. Mattioli et al. (2016) identify the built environment (macro), the individual and their agency (micro), and individual and social practices and trip-activity related behaviour (meso) as the three core levels of car-dependence. The socio-ecological framework in this paper, Figure 4.1, aims to balance determinants often found in socio-cognitive models, which accentuate conscious individual decision-making, with unreasoned determinants such as self-identity and habit, while also incorporating the social and environmental context.

We identify three distinct levels of influence, the macro, meso, and micro, and within each we identify several factors that observable variables map onto. The conceptual framework was designed specifically for a European setting.

The planning context, the built environment, and the social environment are assigned to the macro level. The main identified sources of built environment influences of travel behaviour are the *density* of population or building floor area, *diversity* of service provision, *design* of the urban street network and environment, *destination* accessibility measured as ease of reaching desired locations, and *distance* to transit, identified as the 5Ds by Cervero and Kockelman (1997) and Ewing and Cervero (2010). The natural environment in our framework is defined by greenness and pollution levels, whose importance was evidenced by, among others, Christiansen et al. (2016) and Koohsari et al. (2015).

Ewing and Cervero (2010) conduct a systematic review of the built environment literature and evidence supporting the existence of the 5Ds, finding that vehicle miles travelled are most closely linked to accessibility at destination, followed by street design and connectivity. In a

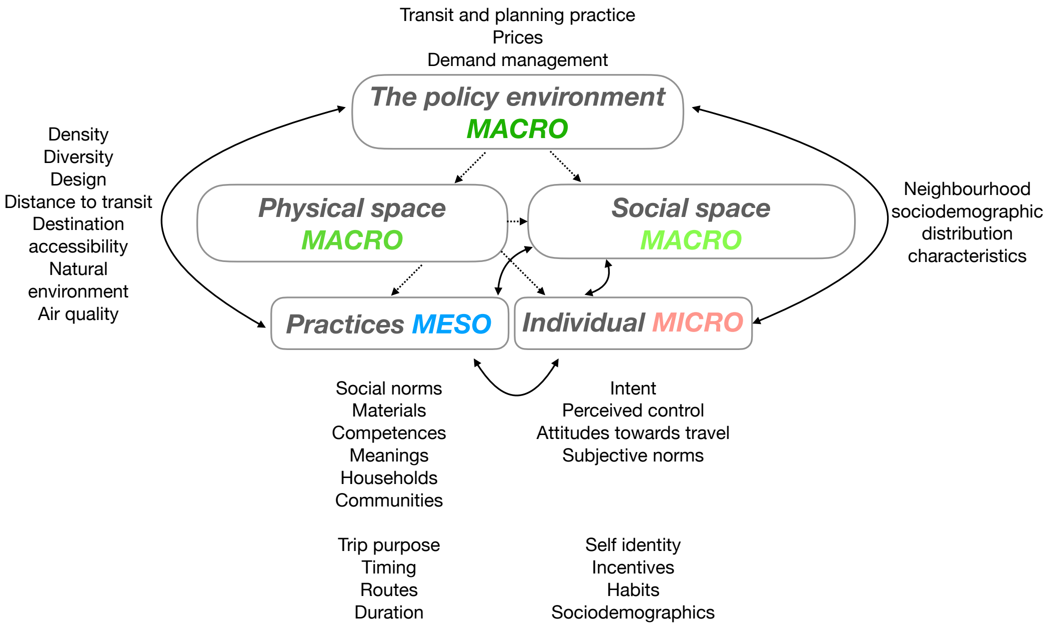

Figure 4.1 The conceptual framework.

The colours represent the three levels of analysis: micro, meso, and macro. Next to each bubble is a list of constructs that comprise that level. Full, bi-directional arrows denote possible feedback effects, and single-headed dashed arrows denote a one-way effect.

longitudinal study, Beenackers et al. (2012) found evidence that higher density, availability of destinations, and connectivity were all significant predictors of increases in active travel. Christiansen et al. (2016) also find that land use mix and residential density are associated with higher walking levels. However, accessibility may be the most influential built environment determinant of travel mode choice (Maria Kockelman, 1997; Ewing and Cervero, 2010; Handy et al., 2005), and more consistently significant than many other correlates of active transport (Christiansen et al., 2016). Daramy-Williams et al. (2019) also stress the importance of infrastructure and the provision of attractive alternatives to car use to determining modal choice. We therefore computed additional accessibility statistics not usually included in analyses of modal choice with respect to the built environment. In their systematic review of the effect of the built environment on travel, Fraser and Lock (2011) find that higher perceived safety, shorter trips, and proximity to green paths increase cycling. Pucher and Buehler (2006) argue that, absent of a difference in culture, higher urban densities and land-use mix increase cycling rates, while Winters et al. (2011) argue that cycling routes, and separation from traffic, are essential. However, the estimates of the influence of the built environment on active travel still vary significantly - from up to 86% of the walking frequency in Northern California (Cao, 2010), to only 3% of car driving in Belgium, France, Hungary, the Netherlands, and the UK (den Braver et al., 2020).

Structural barriers to driving through prices, such as average parking prices and supply, costs of public transport, and whether an area is covered by a low emissions zone or congestion charge were added as part of a policy and planning context factor (Duranton and Turner, 2018) as Demand management, or the sixth D (also proposed by den Braver et al. (2020)). For example, difficulty parking has been associated with higher levels of active commuting (Bopp et al., 2012; Panter et al., 2013). Pucher et al. (2010) review case study cities that have managed to reduce car dependency, and identify parking restrictions as one of the most important policies. Ease of parking exists in the frameworks by Götschi et al. (2017) and

Sallis et al. (2006), but is excluded in the review by Mattioli et al. (2016). As most studies that evaluate psychosocial and environmental reasons for behaviour are very context-specific, few consider city-wide planning context, and so it is often excluded. Our study examines the correlates of active travel in seven different cities, allowing us to control for city-level planning as well.

We also include objective measures of the social environment in an individual's home and work locations, called Social Distribution, the seventh D. This reflects the propensity of like-minded people to self-select into neighbourhoods with similar incomes, cultures and backgrounds, even where those neighbourhoods may be nearly identical in terms of their built environment. Similar variables were found to influence cycling and walking for work vs. leisure in the Netherlands (Rietveld and Daniel, 2004; Van den Heuvel et al., 2005). For Finland (Harms et al., 2014) and the Netherlands (Götschi et al., 2015), immigrant populations were significantly less likely to drive. However, these findings have not been consistently significant throughout the literature (Van Acker et al., 2010). Although these papers are country-specific, they point to cultural differences in active transport use, and potential shifts to or away from cars (Klein and Smart, 2017; McDonald, 2015; Hopkins and Stephenson, 2014). We therefore incorporate the proportion of foreign-born nationals in the respondents' neighbourhoods, car ownership, education levels, and incomes in our analyses.

The importance of the meso level of trip-specific practices and the purpose of the trip itself is stressed by Mattioli et al. (2016), and much of the literature on social practice theory (e.g. Sarrica et al. (2019), Watson (2012) and Schwanen et al. (2012)). Specific activities people carry out, such as shopping, going for walks in the park, or commuting, all have their specific needs and create new mobility patterns and practices (Watson, 2012). Different competences and skills, meanings associated with transport (e.g. public transport use being associated with bad parenting, or cycling being considered a low-income mode of transport (Aldred and Jungnickel, 2014)), timing (e.g. flexible working hours vs. morning rush hour trips (Shove, 2002), "image" (Haustein and Nielsen, 2016; Murtagh et al., 2012; Anable, 2005)), the support of the social environment (Carlson et al., 2012), may influence mode choice (Mattioli et al., 2016). Chan et al. (2019), for example, distinguish three trip purpose categories, and find that walking for work/study and household responsibilities is associated less strongly with the (perceived) built environment than leisure trips are. However, many studies focus on repetitive commuting trips only (e.g. Keyes and Crawford-Brown (2018) and Yang et al. (2017)).

The micro level defines an individual through their sociodemographic profile, and proxy measures of reasoned and unreasoned justifications for action. The influences of age, income, employment, and household composition on mode choice have been explored extensively in the past (Dawson et al., 2007; Filion et al., 2006), and are now routinely being incorporated into policy (DfT, 2018).

Widely used socio-cognitive models of behaviour include the theory of planned behaviour (TPB) (Ajzen et al., 1991), the theory of interpersonal behaviour (Triandis and Values, 1979; Anable, 2005), the transtheoretical model of behaviour change, the self-determination theory (Buchan et al., 2012), among others. TPB has been used extensively in transport behaviour (Armitage, 2015). We therefore base the reasoned action factors on TPB, in which *attitudes* (an individual's evaluative reaction to the behaviour), *perceived behavioural control* (beliefs about having the skills and ability to carry out a behaviour) and *subjective norms* (perception that others think the behaviour should or should not be performed) all impact the intention to carry out a behaviour, and Intention is seen as the main predictor of the behaviour itself. At its core is the belief that an individual makes conscious decisions about their actions. Empirical evidence suggests that the predominant predictors of behaviour in TPB are either attitudes (Lee and Shepley, 2012), perceived behavioural control (Beenackers et al., 2013), or a combination of the two (Dill et al., 2014; Bird et al., 2018). In the study by Bird et al.

(2018), subjective norms, and habit and visibility (proposed extensions to TPB), did not predict travel behaviour change in their study.

With a rise in literature criticising TPB (e.g. Sniehotta et al. (2014)) and increasing interest in heuristics-based decision-making, we add several measures indicating unreasoned action. Based on social practice theory, we extend TPB measures to include *habit*, *visibility* of travel behaviours, and *self-identity* as potential determinants of travel behaviour. As travel, e.g. commuting to work or school, and going shopping, is considered highly repetitive, almost unintentional activity that is embedded in the habits of others, habit as a measure of past and automatic behaviour is likely to be a significant predictor of mode choice (Lanzini and Khan, 2017; Spotswood et al., 2015; de Bruijn et al., 2009; Bamberg et al., 2003). Visibility may be an overlooked aspect of subjective norm (Bird et al., 2018), as perceived outside pressure to perform a behaviour may not only be injunctive and come from significant others, but may be descriptive in the form of visibility in the neighbourhood or local culture (Ball et al., 2010). Self-identity, such as a pro-environmental worldview or being a sports-car admirer, may also influence travel choices and styles in ways not encompassed by other attitudes. Developed extensively by Potoglou et al. (2020) and Whitmarsh and O'Neill (2010), it has been used in TPB-based studies by Anable (2005), Bamberg and Möser (2007) and Harland et al. (1999), finding for example that self-enhancement or openness to change (Hunecke et al., 2010; Pojani et al., 2018) influence mode choice.

Though a number of studies exist on the importance of psychological, or psychological and environmental variables in determining active travel, they typically involve a smaller sample size (130, Lemieux and Godin (2009); 404, Arroyo et al. (2020), 1698, Bird et al. (2018), 1159, Dill et al. (2014) compared to 4270 in this study), only one set of travel diary data or phone survey responses (Bird et al. (2018) being an exception), or look at land-use and key socio-demographic characteristics, but do not evaluate further reasoned and non-reasoned action motivators for mode choice (Convery and Williams, 2019). Conversely, Dill et al.

(2014) focus on the built environment and attitudes only, and overlook the importance of accessibility and public transport, while confirming that attitudes are often more important than the built environment. In their meta-analysis of studies evaluating attitudes towards transport using the theory of planned behaviour, habits, and value-belief-norm theory, Lanzini and Khan (2017) found 58 studies, but only seven looked at cycling, and none looked specifically at walking.

Four primary additions to the framework distinguish it from other such frameworks present in the literature. Self-identity was added to micro level influences, a factor not included in other studies evaluating behaviour using variations of the eTPB that included habit and visibility (e.g. Bird et al. (2018) and Neto et al. (2020)). Adding the visibility and habit factors at the micro level, and the social distribution factors at the meso level, allows us to incorporate insights from social practice theory made by Schwanen et al. (2012) and Spotswood et al. (2015). These variables go beyond the idea that travel patterns can change through the provision of information and reasoned action only (also criticised extensively by Kelly and Barker (2016)), and act as proxy measures for the mental environment of an individual and their surrounding society. Visibility and descriptive subjective norm also act as proxies for social capital and social network membership, which have been found to increase overall levels of physical activity (Legh-Jones and Moore, 2012; Josey and Moore, 2018). Our next two additions - the two D's Demand management and social Distribution - reflect the car-dependent nature of modern society, the social and mobility obligations that arise from participating in society in Western Europe, and recognise that emphasising individual attitudes and choice may obscure other, structural, reasons for choosing not to travel actively. Finally, although we cannot test for causality, we provide feedback loops and causal links between levels identified elsewhere in the literature. For example, Vienna, one of the PASTA case study cities, invested heavily into increasing public transit frequency, number of stops, reducing the cost of public transit and introducing parking demand management. At the macro level, this influenced the Policy environment, and improved destination accessibility and distance to transit in the Physical space. The change in accessibility and cost of parking can have a long-term effect on the Social space, reducing car ownership rates in an area, and these two factors can then change practices at the meso level through changes in routes, trip chaining or the skills required for travel. As the surroundings and behaviours of others around a person change, so can their attitudes, their habits, their beliefs of subjective norms, etc. This may, in turn, lead to more demand for further improvements in public transit, or alternatively pressures for changes in transportation provision, creating a feedback loop back to the macro level.

Overall, the framework combines the main psychological and environmental constructs common to most socio-ecological frameworks in the micro and macro level, while the meso level aims to emphasise aspects of urban transport that are harder to objectively observe - the cultures and sociology of everyday transport practices.

4.3 Materials and Methods

4.3.1 Study design and population

The Physical Activity Through Sustainable Transportation Approaches (PASTA) study[1] is a multi-centre longitudinal study of people's physical activity patterns and travel behaviours in seven different cities in Europe (Antwerp, Barcelona, London, Örebro, Rome, Vienna, and Zürich), covering different geographical regions, city size, travel culture, density. Details of the study design and protocol have been provided elsewhere (Dons et al., 2015; Gerike et al., 2016; Gaupp-Berghausen et al., 2019), and a map of the study locations and table of city-specific characteristics were included in Appendix 5.A. A standardised opportunistic sampling approach was used to recruit respondents in all seven cities. The respondents

[1] The original study and data collection were funded by the EC under FP7-HEALTH-2013-INNOVATION-1.

were representative of their city populations in terms of gender, but were over-educated and younger. In addition, due to the low prevalence of cycling in cities like Barcelona and Rome (2% and 1%, respectively, Mueller et al. (2018)), oversampling of cyclists was carried out on purpose. Respondents were asked to answer a web-based survey on a bi-weekly basis between November 2014 and October 2017[2]. The baseline questionnaire included questions about sociodemographic, individual, and household characteristics, and respondents' attitudes towards travel; physical activity, health, and mobility were gathered using the Global Physical Activity Questionnaire (GPAQ), in addition to a travel diary on a typical day. Attitudinal questions were developed in line with TPB (Ajzen et al., 1991) and the Transtheoretical model of behaviour change (Prochaska et al., 1998). 10,691 people answered the baseline questionnaire (Gaupp-Berghausen et al., 2019), but only 4503 included a valid trip diary and home address in the baseline. A further 233 participants were excluded because of missing sociodemographic data.

Baseline characteristics are shown in Table 4.1, incidence rate ratios (IRRs) and p-values from logistic bivariate regression. City was included as a random effect. The bivariate analysis indicated that while university educated people with access to a bicycle living in Antwerp were most likely to walk or cycle. Conversely, having children and employment status did not significantly affect travel patterns. Table 4.1 also demonstrates the significant influence on travel behaviour that living in Antwerp has, as opposed to the other cities. Comprehensive built environment characteristics were collected for the respondents' home and work locations using geographic information system (GIS) analysis (using Navteq (2012), Open Street Map (OSM), local layers (2015–2020), and census/neighborhood data (2011–2016)). Additional accessibility-based measures were calculated using the statistical software R 3.6.2 and packages *osmdata, openrouteservice, stplanr* and *tidytransit*. Map data from OpenStreetMap, General Transit Feed Specification (GTFS) data from city authorities, and routing services from GraphHopper, OpenRouteService and Google Maps APIs were

[2]http://pastaproject.eu/fileadmin/editor-upload/sitecontent/City_survey/PASTA-questionnaires.pdf

Variable	Description	Odds ratio	p-value
Age (mean, range)	38 (17-91)	1.00	0.574
Gender %			
Male	47	1	
Female	53	0.98	0.002
University level education %			
No	22	1	
Yes	78	1.06	<0.001
Employment status %			
Econ. inactive	19	1	
Econ. active	81	0.99	0.246
Access to a vehicle %			
No	12	1	
Yes	88	0.96	0.003
Access to a bicycle			
No	16	1	
Yes	84	1.27	<0.001
Household size			
With children	34	0.99	0.398
Without children	66	0.99	0.590
City %			
Antwerp	16	1	<0.001
Barcelona	16	0.86	<0.001
London	19	0.86	<0.001
Örebro	10	0.85	<0.001
Rome	14	0.73	<0.001
Vienna	13	0.80	<0.001
Zürich	12	0.80	<0.001

Table 4.1 Descriptive statistics for the variables included in the base model of the correlates between whether a trip was taken by active mode (number of respondents, N = 4270).

used. Kujala et al. (2018) describe the necessary steps to extract and validate GTFS public transport feeds. Here, we followed their steps, but executed our own code in R.

For each city, permission to collect, store, and process data was obtained from local ethics committees. On enrollment, participants registered on the PASTA website and gave informed consent.[3]

4.3.2 Outcome assessment

The primary outcome variable of interest was whether a trip was taken by active mode (Yes/No). This was obtained from the survey travel diary, for each trip stage, and could include walking, cycling, or e-bike.

4.3.3 Correlates of active travel

To characterise respondents who chose to walk or cycle, we considered individual (sociodemographic, attitudinal) indicators, social characteristics at the neighbourhood level, the built environment, and the larger policy context. All the variables used, and the way they map onto the socio-ecological framework, are described in Appendix 4.B. We include a set of sociodemographic attributes in every regression as control variables, called the minimally adjusted model. Our minimally adjusted model included sex, age, level of education, employment status, access to a car or van, and city as random effect. Income was excluded because respondents typically under- or over-report income, or do not supply the information (e.g. Bound and Krueger (1991)). Instead, employment status and car access were used as proxies for income levels. City membership was included to account for city-specific cycling and walking cultures and infrastructure. The following subsections explain which variables map onto which construct and level of the socio-ecological framework in our analysis, and the statistical approach.

[3] Available at http://pastaproject.eu/fileadmin/editor-upload/sitecontent/City_survey/PASTA-questionnaires.pdf

The micro level: individual attributes

Following eTPB, we included attitudes, perceived behavioural control, subjective norm, and extended TPB constructs. For attitudes, we included an individual's view of walking and cycling with respect to: air pollution, safety with respect to crime, contribution to overall health, comfort experienced during the activity, travel time, predictability, privacy, and flexibility. In most cases, the attitudinal variables were averages of two questions asking respondents to rank the importance of a specific attribute of the activity, one with regards to walking, and one to cycling, ranked from "not important" to "very important" on a 5-point Likert scale. Categorical variables can be treated as continuous without severe bias if there are at least 5 levels on the Likert Scale (Finney and DiStefano, 2006), and there is no severe kurtosis in the observations. Perceived behavioural control was measured by an individual's self-rated ability to control the process or outcome of the behaviour, namely whether a person finds it impossible to travel by foot or bicycle, is obliged to travel a lot due to work, cannot change travel habits due to work (similarly to Bird et al. (2018) and Neto et al. (2020)), and is not fit enough to travel by foot or bicycle. Following Bird et al. (2018), subjective norms were measured in two ways: injunctive ("I believe people around me think it is important I do X for travel") and descriptive ("People around me use mode X travel").

Habit was measured using some of the key components of Verplanken and Orbell's (2003) self-reported habit strength index, measuring automaticity of behaviour, and subjectively measured history of repetition ("daily or almost daily" to "less than once per month"). Visibility was measured as the perception of how common it is to walk and cycle in one's neighbourhood. Self-identity measured one's sense of moral responsibility to carry out environmentally-friendly behaviours, and own beliefs ("Regardless of what other people do, my own values and principles oblige me to walk 'for travel' whenever possible."), in line with definitions used by Whitmarsh and O'Neill (2010). These were also all measured on a 5-point Likert scale ("very much disagree" to "very much agree"). We also contrasted the results when the actual trip mode was the outcome variable of interest, and when intent to travel actively was the outcome variable of interest.

The meso level: trip attributes

We include trip purpose, time of trip, and trip distance as meso-scale determinants of active travel in our models. Our trip diary data classified trip purposes into ten categories, which we collapsed into three: commuting, including work/study and business trips, shopping and other household responsibilities, and leisure trips. This recognised that grocery and other shopping trips, and escort trips for other members of the family may have to be carried out using a car due to its cargo-carrying capacities. Some of the original 10 sub-categories, e.g. fitness, were too small to determine statistical significance of the explanatory variables with confidence.

The macro level: neighbourhood, social, and planning context

Variables measuring environmental characteristics have a number and a D before their name to denote what construct they belong to. Density, 1D, was measured by population, residential, and building density (in the number of inhabitants and metres squared per km sq., respectively). Diversity, 2D, was measured by the density and the richness of facilities (number of facilities and number of facility types per km sq.). Street design, 3D, was measured by the connectivity of streets (number of intersections per km sq.), street density and bike lane density (both in metres per km sq.). Distance to transit, 4D, consisted of a measure of public transport route density (number of stations per km sq.), and distance to the nearest public transport stop (in metres). Destination accessibility, 5D, was measured by the number of routes stopping at the nearest transit stop, average waiting time at the transit stop, distance and time (in metres and minutes) to city centre, nearest secondary school, and grocery store, by all four modes of transport, as well as the Euclidian distance between home and work/study address. The demand management construct, 6D, consisted of city-specific variables, and included a dummy variable for having a low emissions zone, average spending on public transport as a proportion of average income, and average price of on-street parking in the city. The social distribution variables, 7D, were car ownership, mean income, the proportion of foreign born nationals, and the proportion of people with higher education in a 500m^2 area. Based on Pearson's chi squared test and bivariate logistic regressions, we chose a subset of the available measures and buffer area size. All area-based measures used were for a 500m^2 area within the home/work/study location, apart from diversity, for which we only had data for a 300m^2 area. This distance is also easily walkable in less than 8 minutes, the time used in many public transport accessibility evaluations (TfL, 2016).

4.3.4 Statistical Analysis

In order to test the relative importance of each of the levels (micro, meso, and the three macro sub-levels) and obtain odds ratios for the correlates of active travel, we used a logistic regression set-up. Multinomial logistic regressions have been used by Panter et al. (2013), Bird et al. (2018), Keyes and Crawford-Brown (2018), Chan et al. (2019), Dalton et al. (2013) and Carse et al. (2013) and others in order to analyse the relationships between psychosocial constructs, the built environment, and travel mode choice in the past. We tested different levels of influence on mode choice:

- demographic variables (minimally adjusted model)
- the micro level, or agency (the influence of each construct of eTPB tested separately, and together)
- the meso level, or practices (trip-specific attributes)
- the macro level: (the influence of each of the seven D environments at home and at work, city-level influences to identify policy and cultural context)

City was included as a random effect to account for the influence of city-level clustering, as city membership explained about 3.7% of the variance in the PASTA sample. We carried out stepwise regressions to select the most parsimonious model, which included only the most influential variables in each level. We also interacted the variables with city membership to estimate any city-specific and universal relationships. Finally, we combined these separate models into a global model, and present parsimonious models derived using backwards step-wise elimination.

The built environment characteristics were standardised with standard deviation as the contrast. As attitudes, travel behaviours, and habits influence each other (Kroesen et al., 2017), we calculated the variance inflation factor (VIF) to estimate collinearity between variables in the base model, built environment characteristics, social norms, and transport habits. Logistic regression results are presented in the form of odds ratios; linear regression results for the Intent model are presented as standardised coefficients. Subtracting 1 from the odds ratio and multiplying by 100 provides the percentage change in the odds of choosing to take a trip by bicycle or walk for a one unit change in the independent variable. All analysis was conducted in the statistical software R v3.6.2.

4.4 Results

4.4.1 Study population characteristics

Summary statistics for our dataset are shown in Table 4.1. The final sample included 4270 respondents who reported 16 018 trips. The sample was balanced in terms of gender, and more than three-quarters of the study population had attained a university degree.[4] The average age was 38.3 years (17-91), 34% had at least one child in the household, and 81% were economically active. The trip diary data revealed an average of 3.40 $\pm$1.74 trips per

[4] This is partly due to the opportunistic sampling method, partly due to advertisement on social media, and partly due to the purposeful oversampling of cyclists.

person per day, with a total of 101 $\pm$57 minutes of travel per day. On average, people walked between 22 minutes (Vienna) and 31 minutes (Örebro) per trip; cycled between 23 minutes (Zürich) and 33 minutes (Rome) per trip; drove for between 32 minutes (Zürich) to 44 minutes (London); and were on public transport for between 46 minutes (Vienna) to 78 minutes (Örebro) per trip.

4.4.2 Micro level: individual characteristics

The parsimonious eTPB-based logistic regression results are presented in Figure 4.2. The Intent model shows the independent variable correlates with a person's stated intention to walk or cycle, "My intention to walk/cycle for travel is [weak-strong]", measured on a 5-point Likert-like scale. The Behaviour model shows the independent variable correlates with whether or not a trip the respondent took was actually made by active mode, i.e. their decision in reality. As Intent is a continuous variable but Behaviour is a binary variable, Figure 4.2 presents results as standardised coefficients, where for every standard deviation increase in the independent variable, the outcome variable increases by a proportion β of a standard deviation. However, in-text and in other figures, we present outcome likelihoods as odds ratios.

Variables that have effects in the same direction for both Intention and Behaviour models are employment status ("Economically active"); from PBC constructs whether a person considers it impossible to walk or cycle ("PBC_Impossible"); from Attitudes constructs the extent to which a person considers active modes comfortable ("ATT_Comfortable"); from the extended TPB the strength of own beliefs motivating active travel regardless of what others do or think ("OwnBeliefs"), the visibility of active modes ("Visible"), and habit ("Habit"). However, attitudes towards the comfort levels of active modes, as well as own beliefs, mattered more for Intent than Behaviour, while habit was more strongly associated

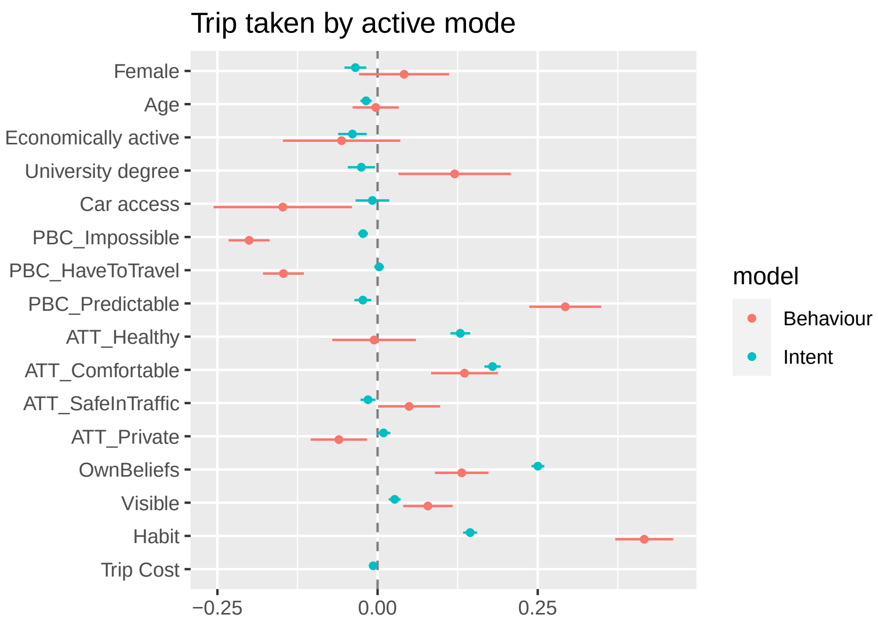

Figure 4.2 Micro level model determinants of active travel behaviour.

Note that for comparability, estimates in this Figure are presented as standardised coefficient estimates, not odds ratios. The first five variables are sociodemographic control variables; PBC_ variables belong to the TPB construct of perceived behavioural control, ATT_ variables belong to the attitudes construct; OwnBeliefs, Visible, and Habit are part of eTPB.

with Behaviour than Intent. Interestingly, car access was not associated with Intent, but did reduce the likelihood of taking a trip by active mode in reality (0.86, 95% CI 0.77-0.96).

It is notable that certain variables have opposite influences in the Intent and in the Behaviour models. Higher predictability of active modes ("PBC_Predictable") lowered Intent to walk or cycle, but increased the likelihood of carrying out the behaviour of walking or cycling (1.34, 95%CI 1.27-1.42). Conversely, positive attitudes about the healthiness of active travel ("ATT_Healthy") were associated with higher Intent to walk/cycle (for every standard deviation increase in strength of belief of how healthy active travel is Intent to travel actively increased by 12.9%), but this association did not exist when actual travel patterns were the outcome variable (0.99, 95% CI 0.93-1.06). Intent to carry out a behaviour, and whether the behaviour was carried out, are not synonymous, and using Intent as a proxy for action may result in inaccurate conclusions about what drives that behaviour. Conversely, it is also possible for behaviour to drive intention, instead.

Table results of both the full eTPB and the parsimonious models are presented in Appendix 4.C.1.

4.4.3 The macro level

The macro level consists of the built and social environments, and the planning context. We compare the importance of the built and social environments at home and work neighbourhood locations. Overall, McFadden's pseudo-R^2 was slightly higher for the model with work location built environment (0.13), than home environment (0.10).[5] Figure 4.3 shows the results for the parsimonious models with city as random effect. Appendix 4.C.2 contains the results for these two models in table format.

Built environment indicators at both home and work locations have a very similar influence on active travel. The most significant correlate of whether a trip was taken by active

[5]Typically, values for McFadden's pseudo-R^2 are much lower than those of OLS R^2.

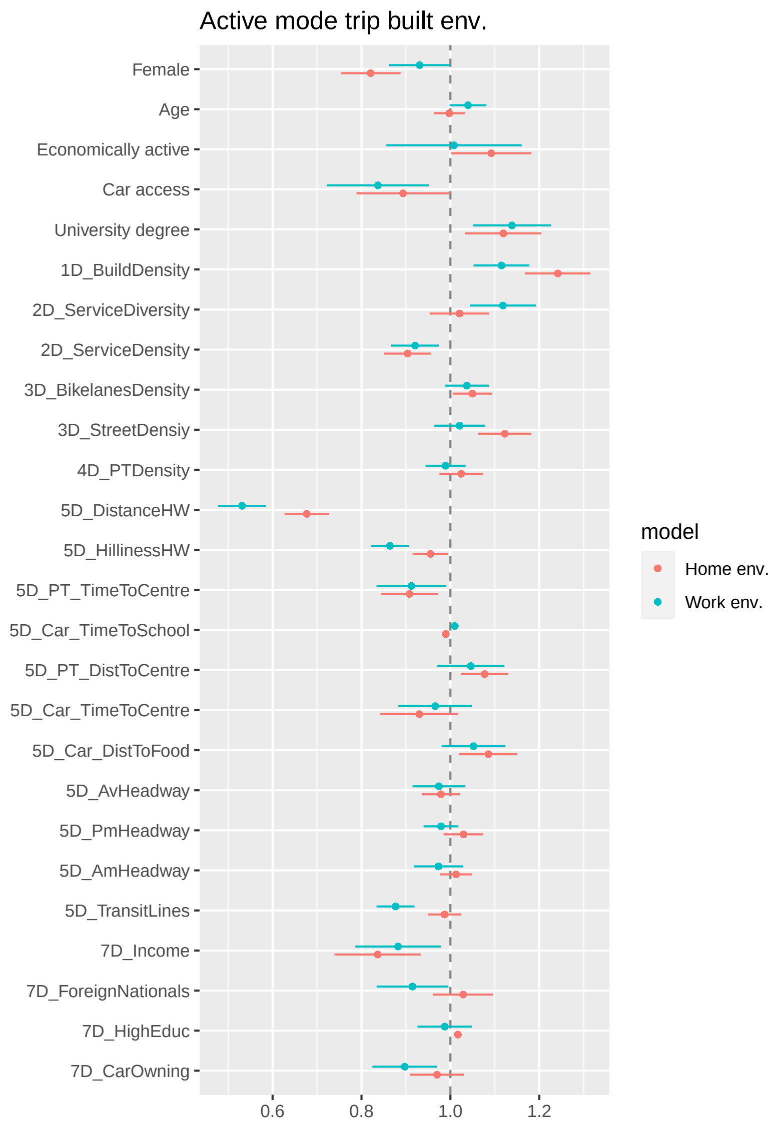

Figure 4.3 Correlates of an actively travelled trip, both at home and work locations.

Coefficients presented as odds ratios. Distances or Time to a location are taken to be from the respondent's home or work location to the nearest point of interest identified in OpenStreetMap. HW refers to Home to Work. The first five variables are sociodemographic control variables; 1D refers to measures of density, 2D measures of diversity, 3D measures of design, 4D measures of distance to transit, 5D measures of destination accessibility, 7D to measures of social distribution.

mode were the distance from home to work ("5D_DistanceHW"), and hilliness of the route ("5D_HillinessHW"). Longer distance from the home to the nearest grocery store (1.09, 95% CI 1.02-1.16)("5D_Car_DistToFood"), and the time taken by public transit to reach the city centre (0.91, 95% CI 0.85-0.97) ("5D_PT_TimeToCentre") from the home location were significant. A higher number of service lines from the nearest transit stop decrease likelihood of walking or cycling at work location (0.88, 95% CI 0.84-0.92)("5D_TransitLines") but not home location, which is likely due to the greater odds of using public transportation for commuting to and from work. Other accessibility measures, denoted with "5D_" in Figure 4.3, were not strongly associated with active travel.

Higher building density ("1D_BuildDensity") increases the likelihood of active travel (1.12, 95% CI 1.05-1.19 for work and 1.24, 95% CI 1.15-1.3 for home locations), while higher service density ("2D_ServiceDensity"), an indicator of an area that is economically more specialised, reduces the likelihood of active travel. In the social distribution construct, only average income levels in the area ("7D_Income") are significant for both locations. For both work and home locations, a standard deviation increase in the income levels decreases the odds of a trip being taken by active mode (0.88, 95% CI 0.80-0.97 and 0.84, 95% CI 0.76-0.92, respectively). The "6D_" demand management variables did not include enough variation to offer a realistic insight into their effects, and were dropped for the parsimonious models.

4.4.4 The meso level

We combined the macro and micro level models, and conducted backwards stepwise regression to eliminate the least influential variables. We stratified that model by trip purpose, in order to elicit whether different built environment and psychosocial variables impact decisions to travel differently depending on the reason for the trip. The results are presented in Figure 4.4, and Appendix 4.C.3.

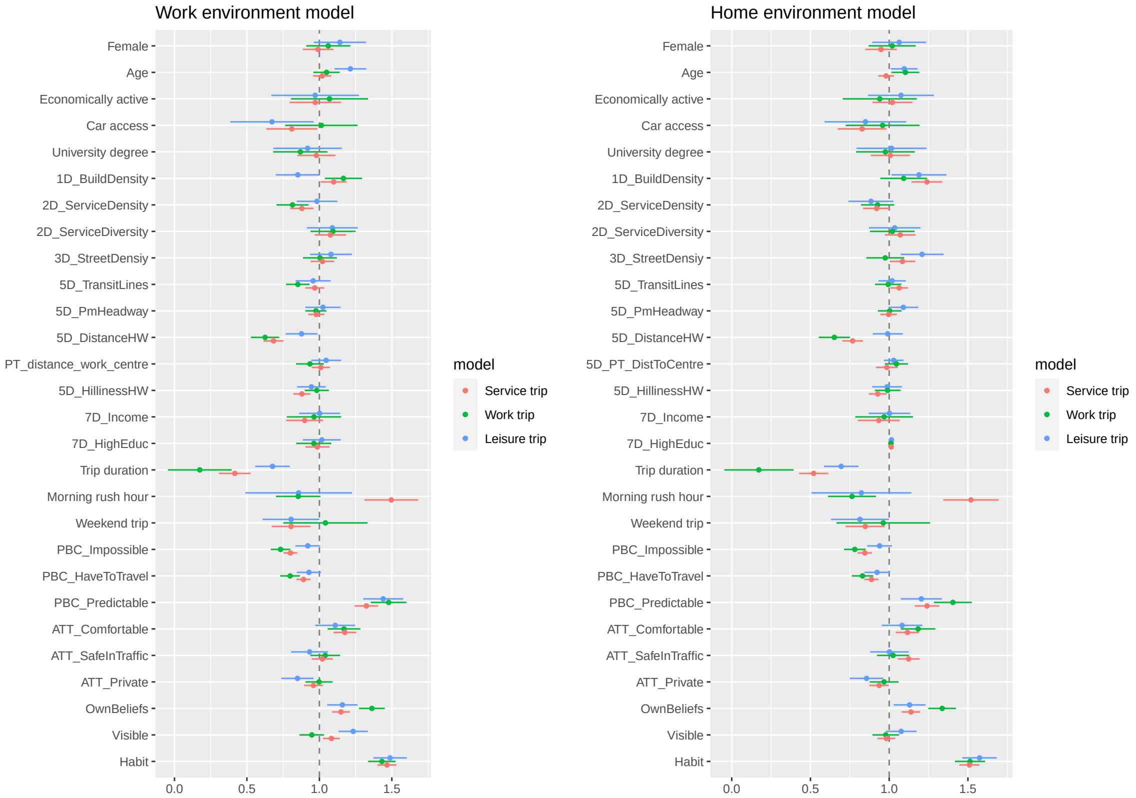

Figure 4.4 Correlates of an actively travelled trip by trip purpose, both at home and work locations and trip attributes.

Coefficients presented as odds ratios. Distances or Time to a location are taken to be from the respondent's home or work location to the nearest point of interest identified in OpenStreetMap. HW refers to Home to Work. The first five variables are sociodemographic control variables; 1D refers to measures of density, 2D measures of diversity, 3D measures of design, 4D measures of distance to transit, 5D measures of destination accessibility, 7D to measures of social distribution; PBC refers to the perceived behavioural construct within TPB; ATT referes to the attitudes construct within TPB; the final three variables are measures within the eTPB.

We find that meso level trip-specific attributes and trip purpose have a much larger influence on the decision to walk or cycle than the macro-level built and social environments do. When separated out by trip purpose, no built environment variable influenced mode choice significantly for all three trip purpose categories. As expected, longer trip duration reduced the likelihood of walking and cycling for all trip purposes. Although the distance between home and work locations ("5D_DistanceHW") remains highly significant for work and service trips, it is insignificant in determining transport mode for leisure trips. Taking a trip during the morning rush hour, between 7am and 10am ("Morning rush hour"), does not consistently influence the mode choice for work or leisure trips, but it does significantly increase the likelihood of walking and cycling if the purpose of the trip is service - for personal business, errands, or dropping off or picking up someone (1.52, 95% CI 1.28-1.82 for the home environment model). However, if a service trip was made during a weekend, e.g. for a large weekly shop, it was less likely to be taken by active mode (0.85, 95% CI 0.75-0.96 for the home environment model).

Measures that were significant and similar for all trip purposes at the micro level were habit ("Habit"), the strength of own beliefs that oblige people to walk to cycle ("OwnBeliefs"), and the degree to which walking or cycling for travel was considered predictable ("PBC_Predictable"). The strongest predictor that increased the likelihood of walking and cycling was habit (1.57, 95% CI 1.41-1.76 for the home environment model for leisure trips).

4.4.5 Variations by city

Finally, we estimate whether the influence of each of these factors varies significantly by city. This was done in order to determine whether each of the seven cities has a unique culture and built environment, or whether certain attributes and preferences are common to all seven of the cities. It also takes into account the correlation of responses from the same city, and that this was an incomplete selection of cities out of all possible cities. Visual results are available in Appendix 4.C.4. This analysis largely confirmed the results in previous sections. We have confidence, therefore, that many of our results are generalisable to other urban areas in Europe. Antwerp had the highest prevalence of active travel of the sample (23% of the modal share is walking, 20% cycling), so it was chosen as the reference city. Overall, micro level constructs do not vary significantly by city. Being female resulted in slightly less active travel than in Antwerp in all cities but Zürich. Habit was a slightly stronger predictor of active travel in all cities but Vienna, when compared to the influence habit had in Antwerp. Compared to people in Antwerp, those in other cities who expressed a strong sense of conviction that it is impossible for them to walk or cycle more, were nonetheless more likely to cycle or walk than people in Antwerp. These results imply that in most cities with moderate levels of walking and cycling, attitudes and self-identity influence active travel in similar ways. In a city such as Antwerp, where active travel is better established, the ability of eTPB constructs to determine (active) travel mode choice might be lower, as mode choice starts to be determined by perceived control and trip purpose, rather than attitudes and beliefs.

4.5 Discussion

4.5.1 Summary of results and comparison with previous studies

The PASTA study collected information on respondents' sociodemographics, attitudes, travel habits and activity data, and the built environment they are most exposed to at home and work locations. This study evaluated the individual, social, and built environment correlates of active travel. Using a socio-ecological framework that combined the extended theory of planned behaviour at the micro level, the concept of 7Ds at the macro level, and specific trip attributes at the meso level, this study found that the micro level consistently explained most of the variance in whether a trip was walked or cycled, followed by the meso level, with the macro level having variable explanatory power for active travel trips.

In their meta-analysis, Lanzini and Khan (2017) find that psychological variables consistently predict mode choice, in particular habits and intentions. They also find that although environmental variables predict intention, they do not predict actual mode choice, forming a “deep intention behaviour gap”. Our findings support those of the meta-analysis, with habits having the strongest association with choosing to cycle or walk, followed by most of the psychosocial variables, and the built environment having only a small role to play in travel mode choice. We also found that psychosocial variables were differently correlated with Intent than with actual behaviour, confirming the existence of the intention behaviour gap. This supports arguments made elsewhere (e.g. Schwanen et al. (2012), de Bruijn et al. (2009) and Verplanken et al. (1998)) about the strength of habit and practices, as opposed to conscious choices, in everyday travel behaviour. The outcome measure of interest does have a significant impact on the results of any study, and should be a topic of discussion in any policy intervention plan, as well.

We find strong support for the relevance of using theory of planned behaviour constructs in determining travel attitudes and behaviour, and the relevance of the micro level in general. As Bird et al. (2018) and Heinen et al. (2011) and others, we found that PBC explained (marginally) more of the variation in trip mode choice than attitudes (McFadden’s pseudo-R^2 0.11 vs 0.09), and almost double the variance that subjective norms did (McFadden’s pseudo-R^2 0.05). This contrasts the findings of Lois et al. (2015), who find that attitudes and subjective norms explain far more of the variation in bicycle commuting than self-efficacy did (their name for PBC). Similarly to Heinen et al. (2011) and De Souza et al. (2014), we find that perceived safety in traffic is positively associated with the decision to travel by active mode. Whitmarsh and O’Neill (2010) and Fekadu and Kraft (2001) find that self-identity is more important than other TPB factors in determining carbon off-setting behaviours, and we also find that self-identity was consistently found to be a strong predictor of active travel. However, this could also be due to the self-selection of people interested in active travel, health, and the environment into the PASTA study, and so should not be extrapolated to the general population. As Lanzini and Khan (2017) have identified, what often changes the findings of studies about the psychological and environmental influences of mode choice are recruitment methods and the year of study. The benefit of using PASTA data is that the project recruited respondents in a unified manner across all seven cities, over the same time period (2014-2016), ensuring that results between cities are comparable. Indeed, what we find is that psychosocial variables have a slightly different influence between cities, but that most influences are all in the same direction.

Finally, at the macro level, we tested the seven Ds: the relative importance of the work and home built environments, and social distribution. These were all measured by objectively measured variables, not subjective perceptions, as is sometimes done (Schneider, 2013; Panter et al., 2013; Adams et al., 2013). The meta-analysis by Cerin et al. (2017) found that density and diversity of facilities, and street connectivity at small scales have a significant effect on walking, but consistent evidence does not exist for the effects on cycling or total active travel. Gascon et al. (2019) identified that high-density areas with many facilities increase walking. We confirm the finding that high density increases active travel. However, we do not find such an effect for facility diversity or density, though the meta-analysis by Ewing and Cervero (2010) also find a strong effect of diversity on walking. Ewing and Cervero (2010) also emphasise that the accessibility of destinations influences mode choice, and we therefore included time and distance to the city centre, school, and shops from home and from work, as well as public transit frequency data. Similar to Ding and Cao (2019), we find that the frequency, and number of different services operating the nearest public transport stop to work decrease the likelihood of active travel (probably through increasing public transport), but most of the other accessibility indicators do not have a consistent and significant effect on active travel. Confirming the findings of Marquet and Miralles-Guasch (2015), we also find that neighbourhood income and socio-economic variables influence the decision to travel actively. In our study, the built environment played a secondary role in determining active travel.

In order to examine the meso level, we stratified our data by trip purpose (for work, home-related responsibilities, and leisure). Work-related trips were consistently more strongly associated with attitudes and built environment factors than home- and leisure-based trips, likely due to the repetitive nature of commuting trips. Unsurprisingly, from trip attributes, trip duration is the strongest deterrent of walking or cycling, confirming findings from Yang et al. (2018) and Handy et al. (2014) and Bopp et al. (2012), among others. Perceived behavioural control constructs were most strongly associated with mode choice for work trips, exemplifying the inflexible nature of most work.[6]

Overall, we find support for previous research findings suggesting that attitudes matter more than the built environment (Handy et al., 2005; Cao et al., 2007; Dill et al., 2014), and that out of built environment characteristics, accessibility matters most (Ding and Cao, 2019; Keyes and Crawford-Brown, 2018; Maria Kockelman, 1997).

4.5.2 Limitations of this study

This study has several limitations. The opportunistic recruitment methods of the original sample mean that PASTA respondents are not representative of the general population; the sample is younger, better educated, and regular cyclists in particular were purposefully oversampled (Gaupp-Berghausen et al., 2019). Nonetheless, our analysis shows that age and education are not correlated to driving in general, or when stratified by purpose or location. This is in contrast to Gascon et al. (2019), who find that higher education has a significant effect on walking for travel. This study is cross-sectional, making it difficult to control for

[6]In pre-Covid 19 pandemic times.

residential self-selection and rule out reverse causality observed between correlations of the built environment and travel behaviour. We also do not include questions asking people to rank why they decided to live where they did, the way e.g. Knuiman et al. (2014) have, which may have helped control for self-selection. Nonetheless, their evidence, specifically on destination accessibility, supports our findings.

We exclude information on the proportion and proximity of green and blue spaces, and noise and air pollution levels in neighbourhood areas in our analysis, as this information was not available for many respondents in our dataset and would reduce the sample size significantly. As the debate on green spaces has not been settled yet (e.g. Christiansen et al. (2016)), and noise in particular is increasingly recognised as a significant public health exposure (Basner et al., 2014), the addition of these variables would have been useful. In the future, micro-built environment factors such as road lighting, graffiti, and pedestrian traffic control should also be explored more (Cerin et al., 2017; Uttley et al., 2020; Ferrer et al., 2015).

We use 500m buffers in most cases, but only 300m buffers were available for land use data, meaning we mix different buffer areas in our analysis. In high density and diverse cities such as Barcelona, the 500m buffer may be too large and may not capture the minutiae of surrounding neighbourhoods accurately. However, when sensitivity analysis with 300m buffer areas was done, similar results were obtained.

In addition, transport has an impact on mental well-being and levels of distress experienced on a daily basis (St-Louis et al. (2014), Chng et al. (2016), de Nazelle et al. (2017)), but we do not include these considerations in our analysis. Evidence on the relationships between mental well-being and mode of transport using the PASTA study has, however, been published by Avila-Palencia et al. (2018). Cerin et al. (2017) also find that for different groups of people, different interactions between psychosocial, health and sociodemographic factors, as well as the built environment, matter. This implies that there are subgroups of people for whom different aspects of the socio-ecological model may be most relevant, but we did not carry out this type of analysis.

4.6 Conclusion

Due to the creeping urgency of climate change and carbon emissions reduction, rising congestion, air pollution and accident costs, our societies need to learn to decouple transport from economic activity, our mobility needs from economic activity (Waisman et al., 2013), and our travel needs from car use. This study evaluates the correlates of sociodemographic attributes, attitudes, the built and social environments, and trip purposes and characteristics with mode choice, specifically walking and cycling. Using data for 4270 respondents and over 16,000 trips from seven different European cities, this study highlights the importance of psychosocial variables in determining active travel relative to built environment influences, and the importance of considering specific trip attributes and purposes when planning interventions to increase walking and cycling. A socio-ecological framework is a useful tool to consider possible feedback loops, caveats for any effects between variables and the behaviour of interest found, and the wider system around the individual.

Author Statement

Simona Sulikova: Conceptualisation, Data curation, Software, Formal Analysis, Writing - Original Draft.

Christian Brand: Supervision, Data curation, Conceptualisation, Writing - Review Editing.

Research Data

Due to the sensitive nature of the questions asked in this study survey respondents were assured raw data would remain confidential and would not be shared.

Acknowledgements

This article was written on behalf of the PASTA consortium (http://pastaproject.eu; Albert Ambrós, Esther Anaya-Boig, Ione Avila-Palencia, Christian Brand, Evi Dons, Mailin Gaupp-Berghausen, Regine Gerike, Thomas Götschi, Esther Gracia, Francesco Iacorossi, Luc Int Panis, Sonja Kahlmeier, Michelle Laeremans, Oriol Marquet, Sandra Márquez, Audrey de Nazelle, Mark Nieuwenhuijsen, Elisabeth Raser, and Julian Sanchez). PASTA was supported by the European project Physical Activity through Sustainable Transportation Approaches (PASTA). PASTA was a four-year project funded by the European Union's Seventh Framework Program (EU FP7) under European Commission Grant Agreement No. 602624. Simona Sulikova was funded the Martin Filko Scholarship and the Kellogg Progress Scholarship. We thank the study participants, and Ersilia Verlighieri for pointing out the literature on self-identity to us.

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Appendix

Appendix 4.A Case study cities

Figure 5.3.1 shows the location of the seven PASTA case study cities.

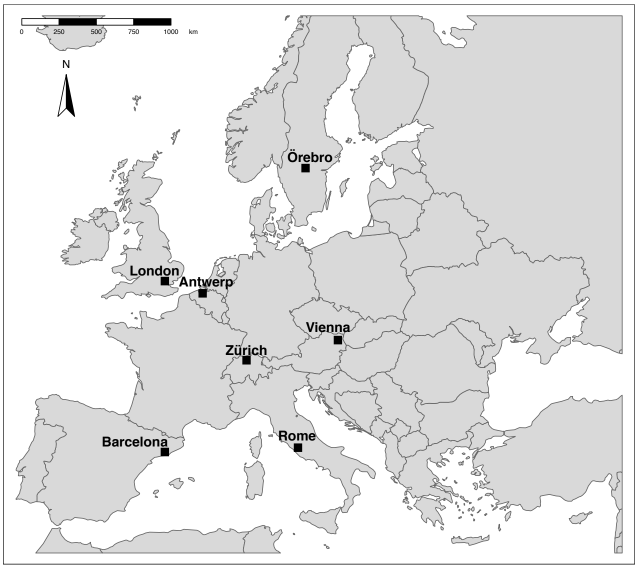

Figure 4.A.1 Map of the seven case study cities in the PASTA study.

The cities vary by size, climate, and travel patterns. These are summarised in Table 5.A.1.

Variable	**Antwerp**	**Barcelona**	**Newnham (London)**	**Örebro**	**Rome**	**Vienna**	**Zürich**
Description	Second largest city in Belgium	Second largest city in Spain	South-east London Borough, United Kingdom	Regional centre, 200km west of Stockholm, Sweden	Largest city in Italy	Largest city in Austria	Largest city in Switzerland
Population*	510,610	1.6 million	265,688	140,000	2.9 million	1.8 million	400,000
Average monthly income per capita in EUR end 2019 exchange rate**	3749	3117	4333	4100	2824	5120	5980
Weather							
Average annual temperature, C***	10.1	16.5	11.1	6.1	15.7	9.9	9.3
Annual rainfall, mm***	778	612	621	633	798	623	1085
Koeppen-Geiger climate classification***	Temperate oceanic	Dry summer	Temperate oceanic	Humid continental	Dry summer	Humid continental	Humid continental
Mode share %							
Driving	41	26	38	55	54	27	30
Cycling	23	2	3	25	1	6	4
Public transport	16	40	29	9	29	39	39
Cycling network km (OSM)****	469.17	159.54	969.17	361.35	120.64	715.63	118.36

Table 4.A.1 PASTA city characteristics

* From worldpopulationreview.com
** Various sources
*** from climate-data.org
**** from Mueller et al. (2018)

Appendix 4.B Variable details

Table 4.B.1 details how questions from the PASTA survey map onto eTPB constructs. Each statement was ranked by the respondents on a Likert-like scale with possible values from 1 to 5, the lowest value means lowest ranking or greatest disagreement. Where possible, responses from at least two different questions were averaged to create a TPB construct question. For each question on walking, a similar statement on cycling existed. Table 4.B.2 details the macro level variables, and how they were measured. Table 4.B.3 describes the meso level variables. Figure 4.B.1 shows how each of the variables that appear in the main text map onto each level within the framework.

Construct	Item	Question code
Attitude		
Instrumental	“Walking for travel saves time.”	ATT_Time
	“Walking for travel is unpleasant due to high levels of air pollution.”	ATT_Airpol
	“Walking for travel is offers personal health benefits.”	ATT_Healthy
Experiential	“Walking for travel is comfortable.”	ATT_Comfortable
	“Walking for travel is safe with regards to road traffic.”	ATT_SafeInTraffic
	“Walking for travel is safe with regards to crime.”	ATT_SafeCrime
	“Walking for travel offers privacy.”	ATT_Private
Subjective norm		
Injunctive	“Most people who are important to me think that I should walk ’for travel’.”	SN_INJ
Descriptive	“In my neighbourhood walking is well regarded.”	SN_Descript
Perceived behavioural control		
Self-efficacy	“Personal circumstances make it impossible for me to walk more (e.g. family or work commitments, carrying luggage, escorting children).”	PBC_Impossible
	“I am fit enough to walk.”	PBC_Fit
Controllability	“The organisation of my everyday life requires me to travel a lot.” “I have to travel all the time to meet my obligations.”	PBC_HaveToTravel
	“Walking for travel offers flexibility (e.g. with regards to departure time).”	PBC_Flexible
	“Walking for travel offers a predictable travel time.”	PBC_Predictable
	The cost of a trip by car or public transport in Euros	Trip_Cost
Extended TPB constructs		
Intention	“I intend to walk more ’for travel’ in the future.” “My intention to walk ’for travel’ is … strong/weak”	Intent
Self-Identity	“I feel morally responsible to walk in order to decrease the negative effects on the environment that motorized methods of travel have.”	Morals

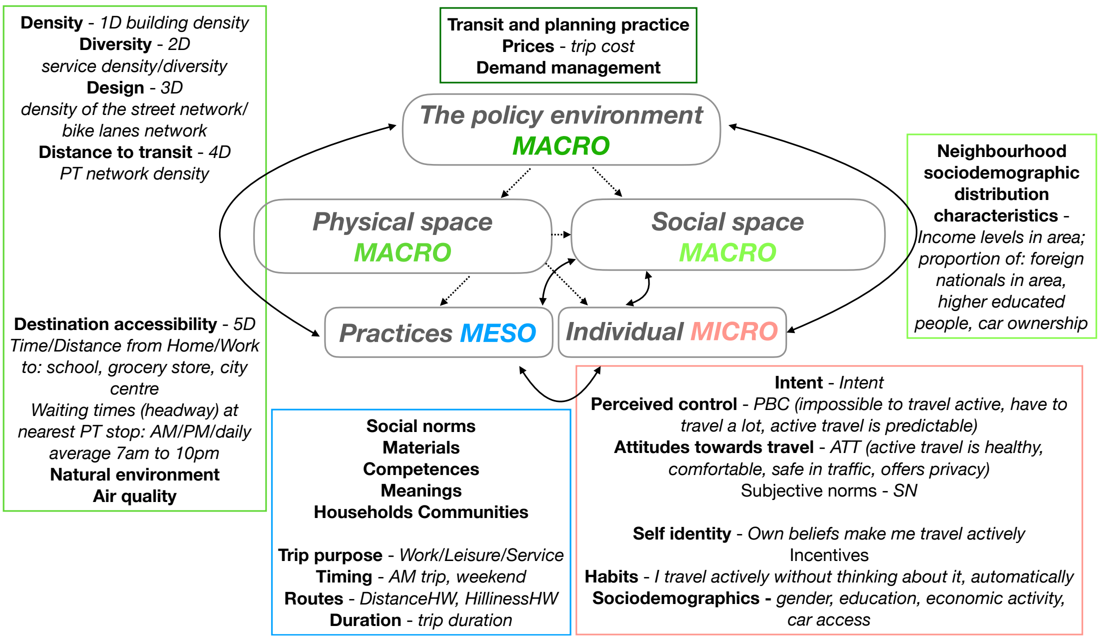

Figure 4.B.1 Variables and how they map onto each part of the socio-ecological framework.

Construct	Item	Question code
	"Regardless of what other people do, my own values and principles oblige me to walk 'for travel' whenever possible."	OwnBeliefs
Habit	"Walking 'for travel' is something I do automatically without really thinking about it."	Habit
	"I walk daily/almost daily; 1-3 days per week; 1-3 days per month; less than once per month; never."	MettravWalk
Visibility	"In my neighbourhood it is common for people to walk 'for travel'."	Visible

Table 4.B.1 PASTA survey questions and how they map onto the constructs of the extended theory of planned behaviour. The constructs follow the structure by Bird et al. (2018).

Measure	Variable
DENSITY	
Residential, 500m2	1D_ResDensity
Population, 500m2	1D_PopDensity
Building, 500m2	1D_BuildDensity
DIVERSITY	
Land use mix, 300m2	2D_ServiceDiversity
Service density, 300m2	2D_ServiceDensity
DESIGN	
Connectivity (intersection density) in 500m buffer, m/km^2	3D_Connectivity
Street density in 500m buffer, m/km^2	3D_StreetDensity
Bike lanes density in 500m buffer, m/km^2	3D_BikeLanesDensity
DISTANCE TO TRANSIT	
Distance to the nearest PT stop, in m	4D_pub_tr_dist
DESTINATION ACCESSIBILITY	
Euclidean distance from home to main work/study address	5D_DistanceHW
Height difference from home to work or study address.	5D_HillinessHW
Distance to school by car, km*	5D_Car_DistToSchool
Distance to city centre by car, km*	5D_Car_DistToCentre
Distance to nearest grocery store by car, km*	5D_Car_DistToFood
Time to school by car, km*	5D_Car_TimeToSchool
Time to city centre by car, km*	5D_Car_TimeToCentre
Time to nearest grocery store by car, km*	5D_Car_TimeToFood
Frequency of transit operation	5D_AvHeadway (also PM and AM)
Number of service lines of transit	5D_TransitLines
SOCIAL DISTRIBUTION	
Mean income in 500m buffer	7D_Income
Percentage of foreigners in 500m buffer	7D_ForeignNationals
Percentage of higher degree education in 500m buffer	7D_HighEduc
Car ownership in 500m buffer	7D_CarOwning

Table 4.B.2 Macro level variables included in full model.
*Variables exist for car, public transport, walking, and cycling.

Measure	Variable
Duration of trip, minutes	Trip duration
Trip was taken between 7 and 10am	Morning rush hour
Whether a trip was taken on a Saturday or Sunday	Weekend trip
Trip purpose	Service /Work /Leisure

Table 4.B.3 Meso level variables included in the full model

Appendix 4.C Model details

This sections shows the regression results used as inputs for the graphs in the main text. Note that since they either use a different regression method (Table 4.C.1), or different datasets (Table 4.C.2 or 4.C.3), so coefficients are not directly comparable.

4.C.1 Micro level model

Table 4.C.1 Micro level effects

	Dependent variable:	
	Behaviour	Intent
	(1)	(2)
Female	1.042	-0.035***
	(0.972,1.118)	(-0.052,-0.018)
Age	0.997	-0.018***
	(0.962,1.034)	(-0.027,-0.009)
Economically active	0.945	-0.039***
	(0.863,1.036)	(-0.062,-0.017)
University degree	1.128***	-0.025**
	(1.033,1.231)	(-0.047,-0.004)
Car access	0.863***	-0.008
	(0.774,0.961)	(-0.034,0.018)
PBC_Impossible	0.818***	-0.023***
	(0.793,0.845)	(-0.030,-0.015)
PBC_HaveToTravel	0.863***	0.003
	(0.836,0.891)	(-0.005,0.010)
PBC_Predictable	1.340***	-0.023***
	(1.267,1.418)	(-0.036,-0.010)
ATT_Healthy	0.995	0.129***
	(0.932,1.062)	(0.114,0.144)
ATT_Comfortable	1.145***	0.180***
	(1.087,1.207)	(0.167,0.192)

Table 4.C.1 Micro level effects

	Dependent variable:	
	Behaviour	Intent
	(1)	(2)
ATT_SafeInTraffic	1.050**	-0.015**
	(1.001,1.103)	(-0.027,-0.003)
ATT_Private	0.941***	0.009*
	(0.901,0.984)	(-0.001,0.020)
OwnBeliefs	1.140***	0.250***
	(1.094,1.189)	(0.240,0.260)
Visible	1.082***	0.027***
	(1.041,1.124)	(0.017,0.036)
Habit	1.516***	0.145***
	(1.041,1.124)	(0.134,0.155)
Trip Cost		-0.007**
		(-0.012,-0.001)
Intercept	0.060***	1.042***
	(0.039,0.092)	(0.872,1.212)
Akaike Inf. Crit.	19,610.740	25,112.170
Bayesian Inf. Crit.	19,741.320	25,258.120
Note:	*p<0.1; **p<0.05; ***p<0.01	

4.C.2 Macro level

Table 4.C.2 Macro level effects

	Dependent variable:	
	Work env.	Home env.
	(1)	(2)
Female	0.931**	0.821***
	(0.869,0.997)	(0.767,0.878)
Age	1.040*	0.997
	(0.997,1.084)	(0.963,1.033)
Economically active	1.008	1.092*
	(0.866,1.174)	(0.997,1.195)
Car access	0.837***	0.893**
	(0.747,0.938)	(0.804,0.992)
University degree	1.139***	1.119**
	(1.043,1.243)	(1.027,1.219)
1D Building density	1.115***	1.242***
	(1.047,1.187)	(1.154,1.336)
2D Service diversity	1.118***	1.020
	(1.038,1.204)	(0.954,1.091)
2D Service density	0.921***	0.904***
	(0.872,0.971)	(0.857,0.953)
3D Bikelane density	1.037	1.049**
	(0.987,1.090)	(1.004,1.097)
3D Street density	1.021	1.122***
	(0.963,1.081)	(1.057,1.192)
4D PT density	0.989	1.024
	(0.946,1.035)	(0.976,1.075)
5D Distance HW	0.531***	0.677***
	(0.504,0.561)	(0.644,0.712)

Table 4.C.2 Macro level effects

	Dependent variable:	
	Work env.	Home env.
	(1)	(2)
5D Hilliness HW	0.864***	0.955**
	(0.828,0.901)	(0.917,0.994)
5D PT time to centre	0.912**	0.908***
	(0.843,0.987)	(0.851,0.968)
5D Car time to school	1.010**	0.990***
	(1.001,1.018)	(0.984,0.996)
5D PT distance to centre	1.046	1.077***
	(0.970,1.128)	(1.021,1.136)
5D Car time to centre	0.966	0.930
	(0.889,1.049)	(0.852,1.015)
5D Car distance to grocery store	1.052	1.085**
	(0.979,1.130)	(1.017,1.158)
5D Average waiting time	0.974	0.979
	(0.918,1.034)	(0.937,1.022)
5D Afternoon waiting time	0.979	1.029
	(0.941,1.018)	(0.984,1.077)
5D Morning waiting time	0.973	1.013
	(0.920,1.029)	(0.976,1.050)
5D No. of transit lines	0.877***	0.987
	(0.840,0.915)	(0.951,1.025)
7D Income in area	0.882**	0.837***
	(0.801,0.971)	(0.759,0.922)
7D Foreign nat. in area	0.915**	1.029
	(0.844,0.992)	(0.961,1.101)
7D Higher education in area	0.987	1.017***
	(0.929,1.050)	(1.012,1.022)

Table 4.C.2 Macro level effects

	Dependent variable:	
	Work env.	Home env.
	(1)	(2)
7D Car ownership in area	0.897^{***}	0.970
	(0.834,0.965)	(0.913,1.030)
Akaike Inf. Crit.	19,779.750	20,508.430
Bayesian Inf. Crit.	19,994.020	20,723.420
Note:	*p<0.1; **p<0.05; ***p<0.01	

4.C.3 Meso level

Home environment

Table 4.C.3 Meso level effects

	Home environment, trip type:		
	Work	Leisure	Service
	(1)	(2)	(3)
Female	1.019	1.063	0.948
	(0.877,1.184)	(0.896,1.262)	(0.858,1.048)
Age	1.103**	1.096**	0.980
	(1.009,1.205)	(1.006,1.193)	(0.932,1.031)
Economically active	0.940	1.075	1.021
	(0.743,1.19)	(0.873,1.325)	(0.899,1.159)
Car access	0.958	0.849	0.828**
	(0.758,1.212)	(0.655,1.1)	(0.709,0.966)
University degree	0.976	1.015	1.007
	(0.81,1.176)	(0.813,1.268)	(0.89,1.14)
1D Building density	1.092	1.189*	1.240***
	(0.942,1.267)	(0.999,1.415)	(1.125,1.366)
2D Service density	0.926	0.884*	0.921*
	(0.834,1.029)	(0.766,1.02)	(0.844,1.004)
2D Service diversity	1.020	1.035	1.071
	(0.885,1.175)	(0.879,1.219)	(0.971,1.181)
3D Street density	0.975	1.209***	1.084*
	(0.864,1.1)	(1.055,1.385)	(0.999,1.177)
5D No. of transit lines	0.994	1.019	1.063**
	(0.914,1.08)	(0.934,1.111)	(1.006,1.124)
5D Afternoon waiting time	1.003	1.090*	0.996
	(0.93,1.082)	(0.991,1.198)	(0.945,1.051)
5D Distance HW	0.652***	0.991	0.768***
	(0.59,0.719)	(0.901,1.09)	(0.72,0.819)

Table 4.C.3 Meso level effects

	Home environment, trip type:		
	Work	Leisure	Service
	(1)	(2)	(3)
5D PT distance to centre	1.046	1.029	0.985
	(0.972,1.127)	(0.967,1.095)	(0.919,1.057)
5D Hilliness HW	0.990	0.986	0.928***
	(0.913,1.074)	(0.898,1.084)	(0.877,0.982)
7D Income in area	0.968	1.002	0.934
	(0.806,1.163)	(0.878,1.143)	(0.818,1.066)
7D Higher education in area	1.011**	1.014***	1.013***
	(1.002,1.021)	(1.005,1.024)	(1.006,1.019)
Trip duration	0.172***	0.695***	0.521***
	(0.138,0.215)	(0.623,0.776)	(0.474,0.571)
Morning rush hour	0.764***	0.823	1.519***
	(0.656,0.89)	(0.6,1.13)	(1.275,1.811)
Weekend trip	0.962	0.815**	0.848***
	(0.715,1.296)	(0.678,0.979)	(0.749,0.96)
PBC_Impossible	0.782***	0.939	0.845***
	(0.73,0.837)	(0.868,1.016)	(0.808,0.884)
PBC_HaveToTravel	0.831***	0.923*	0.887***
	(0.776,0.889)	(0.852,1.001)	(0.848,0.929)
PBC_Predictable	1.405***	1.204***	1.241***
	(1.245,1.585)	(1.057,1.372)	(1.148,1.34)
ATT_Comfortable	1.184***	1.082	1.116***
	(1.06,1.321)	(0.952,1.23)	(1.036,1.202)
ATT_SafeInTraffic	1.025	1.001	1.124***
	(0.925,1.135)	(0.886,1.132)	(1.048,1.205)
ATT_Private	0.968	0.856***	0.936**
	(0.883,1.061)	(0.77,0.953)	(0.879,0.996)

Table 4.C.3 Meso level effects

	Home environment, trip type:		
	Work	Leisure	Service
	(1)	(2)	(3)
OwnBeliefs	1.337***	1.130**	1.138***
	(1.224,1.46)	(1.021,1.25)	(1.073,1.208)
Visible	0.978	1.076	0.982
	(0.899,1.065)	(0.976,1.187)	(0.929,1.039)
Habit	1.513***	1.574***	1.510***
	(1.375,1.666)	(1.41,1.757)	(1.417,1.609)
Intercept	0.031***	0.085***	0.073***
	(0.013,0.076)	(0.036,0.203)	(0.042,0.128)
Akaike Inf. Crit.	4,689.499	3,338.618	10,020.550
Bayesian Inf. Crit.	4,882.526	3,515.448	10,232.620
Note:			*p<0.1; **p<0.05; ***p<0.01

Work environment

Table 4.C.4 Meso level effects

	Work environment, trip type:		
	Work	Leisure	Service
	(1)	(2)	(3)
Female	1.061	1.141	0.991
	(0.912,1.235)	(0.954,1.366)	(0.892,1.101)
Age	1.05	1.214***	1.019
	(0.959,1.149)	(1.088,1.355)	(0.957,1.086)
Economically active	1.07	0.971	0.972
	(0.82,1.396)	(0.717,1.313)	(0.814,1.161)
Car access	1.014	0.673***	0.81**
	(0.79,1.302)	(0.504,0.897)	(0.679,0.966)
University degree	0.869	0.919	0.979
	(0.72,1.048)	(0.725,1.164)	(0.859,1.117)
1D Building density	1.166	0.851	1.098
	(1.025,1.326)	(0.731,0.991)	(1.005,1.201)
2D Service density	0.814***	0.984	0.879***
	(0.729,0.909)	(0.855,1.132)	(0.811,0.953)
2D Service diversity	1.094	1.089	1.076
	(0.937,1.278)	(0.914,1.299)	(0.966,1.198)
3D Street density	1.004	1.08	1.021
	(0.893,1.129)	(0.935,1.247)	(0.941,1.107)
5D No. of transit lines	0.851***	0.957	0.969
	(0.785,0.923)	(0.848,1.08)	(0.907,1.034)
5D Afternoon waiting time	0.976	1.024	0.979
	(0.908,1.05)	(0.908,1.156)	(0.926,1.035)
5D Distance HW	0.625***	0.877**	0.683***
	(0.567,0.689)	(0.786,0.978)	(0.637,0.732)
5D PT distance to centre	0.935	1.047	1.01

Table 4.C.4 Meso level effects

	Work environment, trip type:		
	Work	Leisure	Service
	(1)	(2)	(3)
	(0.849,1.029)	(0.944,1.161)	(0.948,1.076)
5D Hilliness HW	0.982	0.945	0.879***
	(0.903,1.068)	(0.856,1.043)	(0.829,0.933)
7D Income in area	0.963	1.002	0.898*
	(0.798,1.161)	(0.869,1.155)	(0.791,1.02)
7D Higher education in area	0.961	1.017	0.986
	(0.851,1.085)	(0.892,1.159)	(0.908,1.072)
Trip duration	0.174***	0.676***	0.416***
	(0.14,0.217)	(0.6,0.762)	(0.373,0.464)
Morning rush hour	-0.158**	-0.155	0.403***
	(0.732,0.996)	(0.593,1.238)	(1.243,1.801)
Weekend trip	0.854	0.857**	1.496***
	(0.779,1.393)	(0.661,0.979)	(0.704,0.92)
PBC_Impossible	1.042***	0.805*	0.804***
	(0.684,0.783)	(0.845,1.001)	(0.763,0.839)
PBC_HaveToTravel	0.732***	0.92*	0.8***
	(0.745,0.855)	(0.854,1.009)	(0.849,0.934)
PBC_Predictable	1.478***	1.44***	1.324***
	(1.307,1.672)	(1.254,1.654)	(1.221,1.436)
ATT_Comfortable	1.17***	1.109	1.176***
	(1.044,1.31)	(0.967,1.272)	(1.087,1.272)
ATT_SafeInTraffic	1.04	0.933***	1.02
	(0.938,1.153)	(0.821,1.06)	(0.949,1.097)
ATT_Private	0.998	0.849	0.959
	(0.909,1.096)	(0.76,0.949)	(0.899,1.023)
OwnBeliefs	1.362***	1.159***	1.149***

Table 4.C.4 Meso level effects

	Work environment, trip type:		
	Work	Leisure	Service
	(1)	(2)	(3)
	(1.246,1.49)	(1.043,1.286)	(1.08,1.222)
Visible	0.948	1.234***	1.083***
	(0.87,1.031)	(1.115,1.365)	(1.022,1.148)
Habit	1.432***	1.488***	1.466***
	(1.302,1.575)	(1.325,1.67)	(1.373,1.565)
Intercept	0.041***	0.067***	0.068***
	(0.016,0.1)	(0.026,0.173)	(0.039,0.12)
Akaike Inf. Crit.	4,704.744	3,069.722	9,155.963
Bayesian Inf. Crit.	4,899.482	3,244.069	9,366.400

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

4.C.4 City specific effects

This section shows variation in micro and macro level variables by city, in graphic form for easier understanding. Antwerp has the highest rates of active travel, and therefore may be slightly different to the other 6 cities.

Micro level effects

Micro level constructs do not vary significantly between the 6 cities.

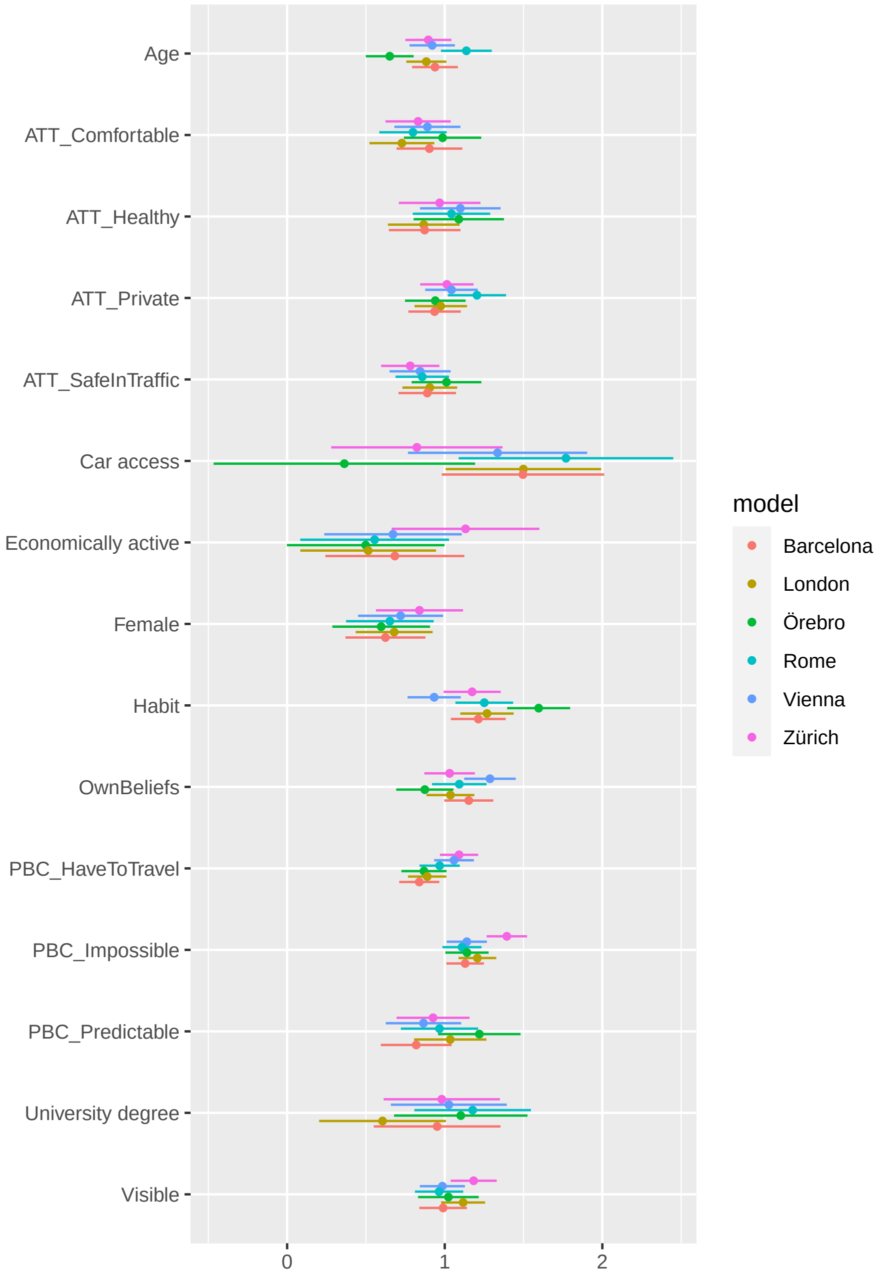

Figure 4.C.1 City-level effects for micro level variables.

Antwerp, with the highest active travel rates, is the reference city. Variations away from the average in Antwerp are shown in the graph. Age, being female, economically active, having a higher education and access to a car are sociodemographic control variables; PBC_ variables belong to the TPB construct of perceived behavioural control, ATT_ variables belong to the attitudes construct; OwnBeliefs, Visible, and Habit are part of eTPB.

Macro level effects

Largest variation between cities is within the destination accessibility construct of the macro level, in particular with regards to public transport accessibility and level of service. Although this study did not evaluate public transport use directly, research does exist suggesting that increased public transport access may increase both walking and cycling rates (e.g. Kager et al. (2016) and Dalton et al. (2013)), but this research is not conclusive.

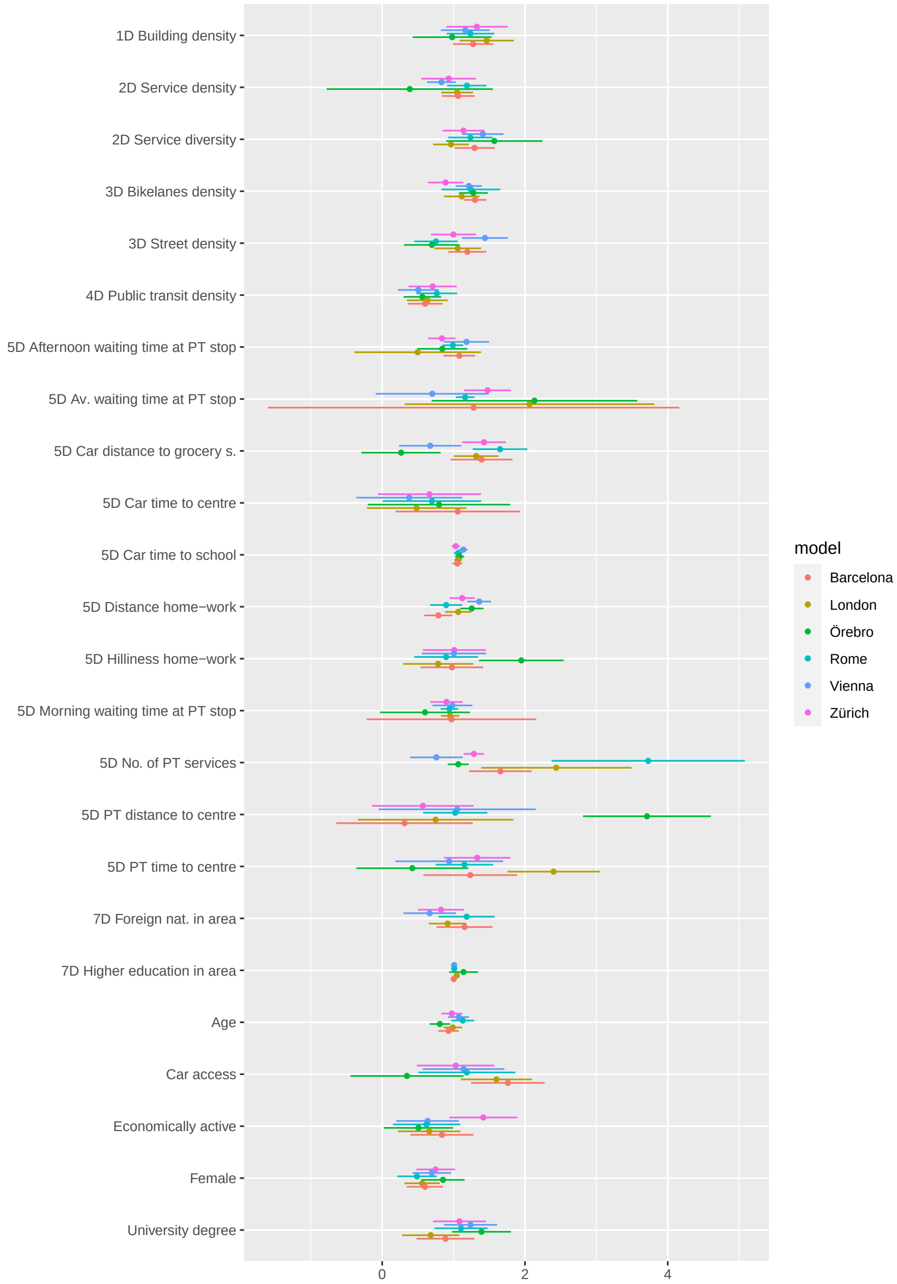

Figure 4.C.2 City-level effects for macro level variables.

Coefficients presented as odds ratios. Distances or Time to a location are taken to be from the respondent's home or work location to the nearest point of interest identified in OpenStreetMap. HW refers to Home to Work. The last five variables are sociodemographic control variables; 1D refers to measures of density, 2D measures of diversity, 3D measures of design, 4D measures of distance to transit, 5D measures of destination accessibility, 7D to measures of social distribution.

Chapter 5

Do information-based measures affect active travel, and if so, for whom, when and under what circumstances? Evidence from a longitudinal case-control study

Chapter 5 recognises the findings of Chapter 4, namely that psychological constructs influence day-to-day travel behaviour more significantly than the urban environment, and evaluates the long-term effectiveness of soft measures aimed at changing the psychosocial attitudes of people towards non-motorised travel options. This chapter is co-authored with Christian Brand. It was submitted in paper format to *Transportation Research Part A: Policy and Practice* on 02/01/2021. A co-authorship statement is available in Appendix C.

Do information-based measures affect active travel, and if so, for whom, when and under what circumstances? Evidence from a longitudinal case-control study

Simona Sulikova and Christian Brand, on behalf of the PASTA consortium

Soft, information-based measures to encourage walking and cycling for travel are increasingly being recommended alongside infrastructure investments. Using principles of realist evaluation, we evaluate measures implemented as part of the European Physical Activity Through Sustainable Transportation Approaches (PASTA) study in Vienna (Austria), Örebro (Sweden), Rome (Italy), and Antwerp (Belgium) over a 3-year longitudinal case-control study, and a further follow-up 2.5 years later in Vienna and Örebro. Increases in active modes of travel due to the interventions were most significant for walking, one year after the intervention, and for people in full-time employment. Increases in e-bike use were associated with changes in perceptions of cycling, while increases in walking were not associated with any changes in perceptions of walking. We find evidence supporting previous findings that information provision is unlikely to work as a standalone intervention in the longer run, but may be effective when combined with other policies.

Keywords: Active travel; Cycling; Realist evaluation; Intervention; Mechanism; Walking

5.1 Introduction

The health benefits of exercise are widely recognised. These include reduced risk of cognitive impairment and dementia (Loprinzi et al., 2018), hypertension (Liu et al., 2017), type 2 diabetes (Smith et al., 2016), cardiovascular disease, almost halving the risk of depression (Catalan-Matamoros et al., 2016), several types of cancer, and others (Davies et al., 2019). This is true even for exercise carried out in areas with elevated pollution levels (Tainio et al., 2016). Walking and cycling for travel has been recognised as an easy and feasible way of achieving the minimum daily recommended amounts of exercise (Gibson-Moore, 2019). A shift towards active travel (AT) can also reduce congestion, emissions, air pollution, and traffic accidents (Woodcock et al., 2007).

A significant body of empirical research on built-environment (hard) and psychosocial (soft) interventions aimed at increasing active travel exists ((Bird et al., 2013; Ogilvie et al., 2011; Ogilvie et al., 2007; Pucher et al., 2010; Yang et al., 2010) for reviews), but reports mixed, and sometimes conflicting, results regarding effectiveness (Panter et al., 2017). Organisational travel plans (OTPs) belong to the category of "soft measures", an umbrella term that includes personalised travel plans, information provision, car clubs and sharing facilities, or promotional activities (May et al., 2018), undertaken in order to encourage public and active transport use in the trip to work and study. (Kelly et al., 2020) identified 129 studies describing cycling promotion initiatives, and classified 93 unique action types. A meta-analysis of 141 travel plan single-group evaluations found a statistically significant, 11% decrease in car-based trips (Möser and Bamberg, 2008). Other meta-analyses and systematic reviews of personalised marketing found smaller but consistent changes (Fell and Kivinen, 2016; Yang et al., 2010), about 4% (Cairns et al., 2008) to 6% (Fujii et al., 2009). Others conclude there is not enough evidence to support their effectiveness (Hosking et al., 2010; Macmillan et al., 2013; Stewart et al., 2015; Winters et al., 2017). However, workplace travel plans have been found to be effective in some cases, and both Winters et al. (2017) and Fell and Kivinen (2016) argue that a mix of measures is most likely to be most effective.

In addition, many of these studies rely on self-reported travel, small sample sizes (Panter et al., 2016), short follow-up periods (Goodman et al., 2014; Kearns et al., 2019; Song et al., 2017) or lack a control group (Fujii et al., 2009; Yang et al., 2010), which undermines the conclusions that can be drawn about long-term behavioural outcomes, or may be insufficiently long for substantial behaviour change to have taken place. Studies with sufficient pre-treatment data and multi-year follow-up periods are rare, and do not always find consistent patterns of behaviour change (Heinen et al., 2017).

Even fewer studies examine the causal pathways through which an intervention has worked (examples for the built environment include the studies by Ogilvie et al. (2011) and Sahlqvist et al. (2015)). Richter et al. (2011) identify gaps in knowledge surrounding personalised travel plans and call for more research into the mechanisms explaining why customising information, goal setting, and plan formation are effective.

This study aims to fill these two gaps in the literature and evaluates whether the interventions implemented as part of the Physical Activity Through Sustainable Transportation Approaches (PASTA) study shift travel behaviour towards active modes, and whether this change is sustained more than 3 years after the intervention has ended. The PASTA study is a multi-centre cohort study of people's physical activity and travel behaviours in seven different cities in Europe during 2014-2016. Of the seven cities, four implemented interventions with top measure affected, and control groups. The interventions were primarily promotion and travel plan based, with some built environment improvements such as bicycle rack building. We also conduct subgroup analysis in order to explore the relationships between the context (setting), mechanisms (putative causal pathways), and outcomes using the principles of realist evaluation (Pawson et al., 1997). This approach is particularly useful in evaluating transport interventions, which are context-dependent by design (Craig et al., 2012). This study tracks the behaviour of people in two-week intervals for up to a year after the intervention, and again two and a half years later. The case-control study design allows us to control for city-wide campaigns and efforts to increase active travel, as well as control for wider trends.

The next section explains realist evaluation principles and our hypotheses of how behaviour change happens more closely; the Methods section describes the PASTA study, the study sites, interventions, sample characteristics, and statistical methods in more detail. This is followed by the results which include subgroup analyses, a discussion where we compare our results to previous studies and provide policy recommendations, and the conclusion.

5.2 Realist evaluation principles

Pawson and Tilley propose (Pawson et al., 1997) that evaluation of interventions should be context-specific and theory-driven, rather than aggregate. We follow the simple agenda set out by them, and ask "what works, how, in which conditions and for whom?" By applying realist evaluation, it is possible to identify levers that either mediate or moderate the effects of interventions aimed at increasing active mobility. We formulate a set of contexts, mechanisms, and outcomes which we then statistically test, in order to be able to draw conclusions about causal inferences on behaviour change in our dataset. Context may refer to the institutional, social, or physical setting in which an intervention was implemented, while mechanisms can be defined as the processes and structures that operate in particular contexts to inhibit or generate outcomes (Panter et al., 2017).

The contexts and mechanisms considered in this paper are described in brief in Table 5.2.1. We consider employment status, income, and education as primary mediating factors in information-based campaigns, as these factors have been found to influence travel behaviour; perceptions related to travel (Anable, 2005; Goodman et al., 2014) are classified as moderating factors. First, conscious behaviour change may occur as the result of a change in the meaning, and competency (or usefulness) of that activity. Second, the top measure may

Context	Mechanism	Outcome
Having a family/dependants	Less flexibility around transport mode choice and timing of travel	Greater reliance on car as a mode of transport
Economic status	Having a part time job increases flexibility of time use; having a higher income increases flexibility with regards to financial outlays for travel purposes	Higher multi-modal travel patterns; more cycling/e-biking
Access to a vehicle	Having access never/only sometimes encourages trying out different modes of travel	Higher multi-modal and variable travel patterns
Treatment	Perceived greater personal health benefit	Lower significance of health-related problems in determining mode choice
Treatment	Greater understanding of the other (environmental, congestion) benefits of switching to active travel	Higher self-rated beliefs for walking/cycling, and higher rated environmental reasons for walking/cycling
Treatment	Greater awareness of decision-making in transport	Higher self-rated intent to walk/cycle
Treatment	Decrease in influence of what other people think/do	Higher intention to walk/cycle and frequency of mode use, regardless of social norms
Social norms	A behaviour being common or important to people will influence a person?s choice	Higher rates of the common or socially desirable activity
Cultural meaning of transport mode	Owning a motorbike is associated with a culture and an image that travel plan provision and the intervention are unlikely to change	Maintenance of motorbike use

Table 5.2.1 Realist evaluation hypothesised context-mechanism-outcome configurations

reduce the influence of social norms on a behaviour. Third, we are interested in finding out whether the influence of social norms, and the influence of the intervention, attenuate over time, or become stronger.

Specifically, considering Bamberg and Möser (2007), Stern (2000) and Whitmarsh and O'Neill (2010), we ask whether two statements reflecting own environmental beliefs and own moral responsibility beliefs, are influenced by the intervention and link to changes in active travel behaviour. Changing the strength of descriptive subjective norms, the visibility and prevalence of walking and cycling in one's surroundings, are also an important mechanism through which behaviour change might be accomplished (Ball et al., 2010); hence we also include how common it is to walk or cycle in the neighbourhood as a moderating variable. Similarly, the influence of injunctive subjective norms (Bird et al., 2018), whether other people important to a person believe that person should walk or cycle, may change as a result of the intervention, and was included as a moderating variable. As motorcycling is associated with a particular image, we also hypothesise that regular motorcyclists will be unaffected by the top measure. We did not consider built environment changes in our analysis, as these are presumed to have been the same for both groups.

5.3 Methods

5.3.1 Interventions

The Physical Activity Through Sustainable Transportation Approaches (PASTA) study[1] is a multi-level longitudinal study of people's physical activity patterns and travel behaviours in seven different cities in Europe (Antwerp, Barcelona, London, Örebro, Rome, Vienna, Zürich), covering different geographical regions, as well as varying city sizes, transport provisions, mobility cultures, and built environments. They also vary from the inexperienced

[1]The study was funded by the EC under FP7-HEALTH-2013-INNOVATION-1.

in active travel promotion (Rome) to "mature" cycling cities (Antwerp), to cities with a strong political focus on public transport (Vienna, Zürich). Figure 5.3.1 shows their location in Europe. Details of the study design and protocol are provided elsewhere (Dons et al., 2015; Gaupp-Berghausen et al., 2019; Gerike et al., 2016). This study focusses on four cities: Rome, in Italy; Antwerp, in Belgium; Vienna, in Austria; and Örebro, in Sweden. Additional surveys were conducted in 2019 in Vienna and Örebro. Further details of the four cities are in Appendix 5.A.

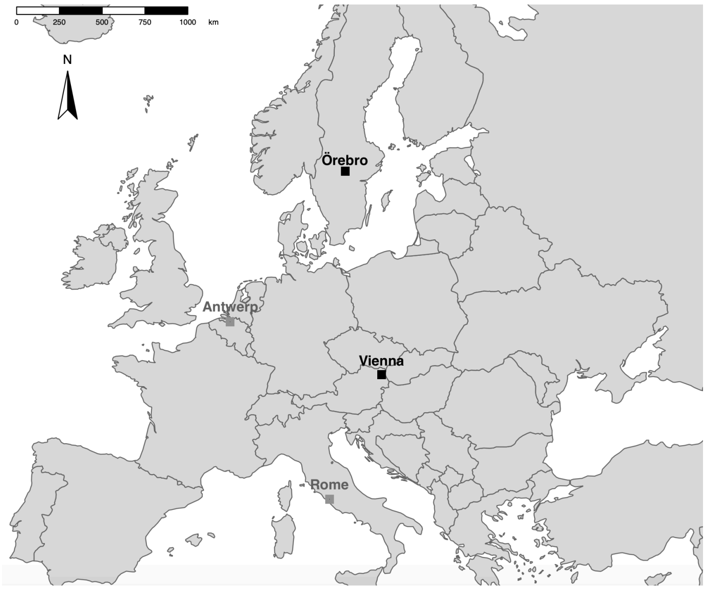

Figure 5.3.1 Map of the four case study cities.

Cities in grey were part of the study 2014-2017, cities in black 2014-2019.

The interventions implemented in the four cities were a mixture of built environment, city-wide promotional activities, and personalised individual travel plans. Rome and Antwerp, where only one phase of follow-up surveys was collected between end 2015 and end 2016, both planned a mixture of built environment and soft measures. In Rome, the intervention was a mixture of bike rack provision, and safety improvements, as well as information provision aimed at high school students, teachers, parents, and public office employees. In Antwerp, bicycle storage safety improvements and bicycle highways (Fietostrades) were part of the top measure, together with information campaigns, aimed at commuters and long-distance cyclists.

In Vienna, two local partners worked in close cooperation with the city and the Walking and cycling commissioner. Part of this cooperation was the implementation of a personalised mobility consultancy for people in life-changing circumstances, namely health problems for which they were recommended to undertake more exercise, or moving home (CORDIS, 2018). This consisted of information provision and mobile apps, which served as reminders and motivators for behaviour change in the top measure affected group. Coinciding with this the city implemented extensive improvements to the speed and frequency of public transport services. Festivals and initiatives encouraging kids and mothers to cycle, people to cycle to work, walk, initiatives to let people submit feedback about the cycling environment in Vienna were all part of the active mobility plan (Klimaaktiv) in Vienna. It is therefore expected that travel patterns have changed in Vienna overall.

In Örebro, several companies and public institutions participated in the intervention. The top measure consisted of workplace information campaigns and infrastructure upgrades (leasing of electric-assist bicycles, installation of bicycle racks) (Gerike et al., 2016) for the top measure affected group, with a specific focus on car driving employees. In addition, as part of the University of Örebro's experiment, employees at certain workplaces have pledged to cycle for at least a year, instead of taking the car or public transport (Åhlgren, 2013). Many other city-wide initiatives were also implemented. A safety "call a friend" number was set up, public transport became free, and a healthy cyclist campaign and a cycling map were published (PASTA, 2016).

5.3.2 Sample

Respondents were asked to answer a web-based survey on a bi-weekly basis between November 2014 and January 2017 [2]. The baseline questionnaire included questions about sociodemographic, individual, and household characteristics, and respondents' attitudes towards travel. Attitudinal questions were developed in line with the theory of planned behaviour (Ajzen et al., 1991), and the transtheoretical model of behaviour change (Prochaska et al., 1998).

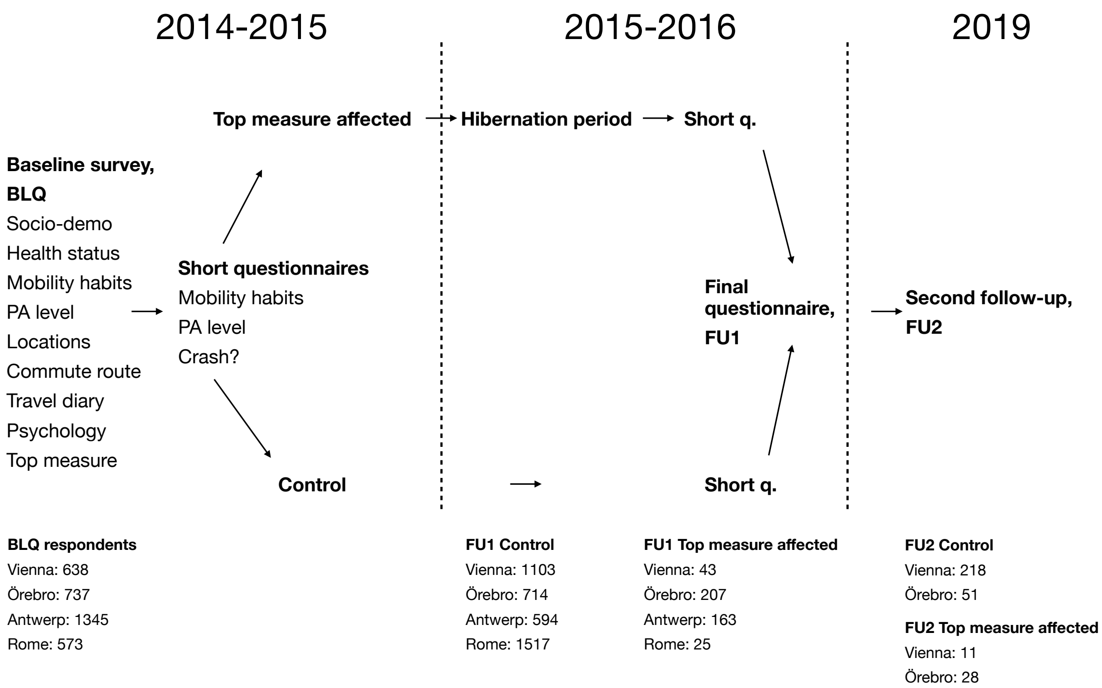

Figure 5.3.2 Flow diagram of surveys.

The survey followed a baseline pre-treatment (BLQ), post-treatment (FU1) and follow-up (FU2) case-control design most typically used for randomised controlled trials (also known as PPF). Participants were recruited throughout 2014-2016, and a slightly larger number of respondents answered questionnaires in the FU1 period than BLQ (4366 vs 3239). Figure 5.3.2 details the flow of survey sampling during the study. None of the interventions had

[2] http://pastaproject.eu/fileadmin/editor-upload/sitecontent/City_survey/PASTA-questionnaires.pdf

been implemented at baseline, and all participants were divided into general, control, and top measure affected groups, and post-treatment questionnaires were administered only after an approximately 6-month hibernation period had ended, during which the top measure was implemented (Gerike et al., 2016). For each city, permission to collect, store, and process data was obtained from local ethics committees. On enrolment, participants registered on the PASTA website and gave informed consent.[3]

1447 adults in Antwerp, 1849 adults in Rome, 1477 adults in Vienna, and 1404 adults in Örebro completed questionnaires between November 2014 and January 2017 (BLQ or FU1) about their travel patterns, preferences, motivations, and filled in travel diaries. 286 people in Vienna and 96 people in Örebro completed a follow-up survey and travel diary in June 2019, with 308 valid responses overall.

5.3.3 Baseline characteristics

Table 5.3.1 presents the characteristics of the respondents examined as predictors of behaviour change towards active mobility. We included respondents for whom information on sex, age, employment status, city of residence, access to a car, access to a bicycle, and top measure affected/control group assignment were available. 5.C presents the baseline characteristics for Vienna and Örebro only, and includes the second waves of follow-ups conducted in 2019. Information on the frequency of walking and cycling was based on self-reported frequency over the past week. All other values were also self-reported, apart from whether a respondent belonged to a top-measure affected, or control group.

[3] Available at http://pastaproject.eu/fileadmin/editor-upload/sitecontent/City_survey/PASTA-questionnaires.pdf

Variable	Level	N (%) Baseline N = 3239	N (%) Follow-up 1 N = 4366
City	Antwerp	1345 (41.5%)	757 (17.3%)
	Rome	573 (17.7%)	1542 (35.2%)
	Vienna	638 (19.7%)	1146 (26.2%)
	Örebro	737 (22.8%)	921 (21.1%)
Top measure affected	Yes	-	438 (10%)
	No	-	3928 (90%)
Sex	Female	1727 (53.3%)	2137 (48.9%)
	Male	1510 (46.6%)	2129 (48.8%)
Age (range) in years		41.5 (18.1 - 91.4)	41.8 (18.1 - 87.7)
Household, children <17	Yes	1141 (35.2%)	1329 (30.4%
	No	1808 (55.8%)	2252 (51.6%)
Education level	Tertiary or equivalent	2266 (70%)	2572 (58.9%)
	Secondary school	737 (22.8%)	1075 (24.6%)
	Primary or other	631 (19.5%)	719 (16.5%)
Employment status	Employed	2768 (85.5%)	3036 (69.5%)
	Student	353 (10.9%)	541 (12.4%)
	Retired or other	513 (15.8%)	660 (15.1%)
Access to a car	Always	2147 (66.3%)	2471 (56.6%)
	Sometimes	946 (29.2%)	1173 (26.9%)
	Never	531 (16.4%)	697 (16%)
Access to a bicycle	Yes	2889 (89.2%)	3653 (83.7%)
	No	350 (10.8%)	653 (15%)
Self-rated health	Excellent/good	2674 (82.6%)	3923 (89.9%)
	Fair/poor	401 (12.4%)	609 (13.9%)
Self-rated frequency of walking	Less than once a month	135 (4.2%	145 (3.3%)
	1-3 days per month	307 (9.5%)	300 (6.9%)
	1-3 days per week	739 (22.8%)	875 (20%)
	Daily or almost daily	2328 (71.9%)	2551 (58.4%)
Self-rated frequency of cycling	Less than once a month	379 (11.7%)	534 (12.2%)
	1-3 days per month	351 (10.8%)	462 (10.6%)
	1-3 days per week	626 (19.3%)	716 (16.4%)
	Daily or almost daily	1769 (54.6%)	1472 (33.7%)

Table 5.3.1 Baseline characteristics for all four cities, 2014-2016 waves

5.3.4 Statistical analyses

Exposure

The exposure was membership in the top measure affected (1) or control (0) group. Both groups were also exposed to the wider initiatives coordinated by both cities aimed at reducing car-based travel described in Subsection 5.3.1.

Outcome

Individual travel behaviour was measured bi-weekly through self-reported frequencies of walking, cycling, e-bike use, public transport use, driving, and motorcycling. Respondents were asked to summarise the frequency of different mode for the past seven days approximately every two weeks for the baseline period (BLQ), re-entry period (for top-measure affected respondents) and final 2016 period of questionnaires (FU1), and follow-up 2019 (FU2) questionnaires. Respondents only had to fill in one questionnaire in 2019.

Analysis

First, we calculated the average mode use frequency for each city. Then, we conducted statistical analysis (details in Appendix 5.B) that allowed us to evaluate the change in transport mode use frequency at baseline and follow-up 1, or baseline, follow-up 1 and follow-up 2. Using a differences-in-differences regression design allowed us to control for any city-wide trends in travel. Next, we conducted subgroup analyses to evaluate the role of contexts and mechanisms we hypothesised could influence the strength of the interventions. All coefficients reported are standardised β coefficients (mean 0, SD 1) and standard errors, and can be interpreted the following way: for every one point (standard deviation) increase in the values of the independent variable, the dependent variable of interest increases by the β coefficient standard deviation. For example, a standard deviation increase in age might increase the frequency of walking by 0.2 (the reported β coefficient) standard deviations.

The statistical analysis was carried out using the *plm* package in Rv3.6.2 (Croissant and Millo, 2008).

5.4 Results

5.4.1 Study population characteristics

3239 respondents filled in the baseline questionnaire in the 2014-2015 period. Due to the continuous recruitment of participants in PASTA, 4366 respondents filled in questionnaires during the post-treatment phase of PASTA. We included these to track general travel trends in all four cities. At the end of the 2014-2017 PASTA survey, 716 respondents (28 top measure affected and 454 control group respondents in Vienna, and 81 top measure affected and 153 control group respondents in Örebro) gave consent to being contacted for further research in the future. 373 respondents filled in the follow-up questionnaire sent in 2019; 308 were valid. A more detailed overview of the differences between cyclists and non-cyclists in the PASTA dataset specifically has been done by Raser et al. (2018).

Our sample was evenly split between Rome, Vienna, and Örebro during the first two waves of questionnaires, with a slight over-representation of Antwerp. Most respondents in the first follow-up came from Rome and Vienna. Vienna is significantly over-represented at the second follow-up in 2019, comprising 76.6% of the sample. As expected, the average age rose from 42 to 46 throughout the study. More females (53%) than males (46%) filled in the questionnaires during the first two waves. Overall, respondents were highly educated, with 70% having attained higher education degrees. Around half of the respondents always had access to a car, and over 80% had access to a bicycle. More than 80% of respondents rated their health as good, very good, or excellent. Comparisons with local authority and national data suggest that our respondents are representative in terms of age distribution, and particularly in the final wave of questionnaires in terms of gender, but are significantly over-educated for Austrian standards.[4]

5.4.2 Aggregate mode choice change

Mode use frequency

Mode use frequency for Rome and Antwerp, where data for 2014-2016 is available, are presented in Table 5.4.1. Mode use for Vienna and Örebro, where we conducted a follow-up in 2019 as well, presented in Table 5.4.2. The number of observations in each group is shown in Figure 5.3.2.

Rome	Top measure	Walk	Bike	E-bike	Public t.	Driving	Motorbike
BLQ	Yes	2.1 ±1.2	1.4 ±1.2	0.5 ±0.7	2.2 ±1.2	2.1 ±1.1	0.9 ±1.1
	No	2.5 ±1.1	1.6 ±1.1	0.8 ±0.6	2.3 ±1.1	2.1 ±0.9	1.1 ±0.9
FU1	Yes	3.1 ±1.1	1.4 ±0.7	1.0 ±0.2	2.6 ±1.3	2.1 ±0.8	1.4 ±0.9
	No	2.5 ±1.1	1.7 ±1.0	0.9 ±0.5	2.1 ±1.0	2.1 ±1.0	1.2 ±0.9
Antwerp							
BLQ	Yes	2.2 ±1.0	2.4 ±1.2	0.8 ±0.6	2.0 ±1.0	2.1 ±0.8	0.8 ±0.6
	No	2.1 ±0.9	2.6 ±1.1	1.0 ±0.6	1.7 ±0.9	2.1 ±0.8	0.9 ±0.4
FU1	Yes	2.4 ±0.9	3.0 ±1.0	1.0 ±0.3	1.6 ±0.8	2.0 ±0.7	1.0 ±0.2
	No	2.0 ±0.9	2.6 ±1.1	1.1 ±0.6	1.6 ±0.9	2.1 ±0.8	0.9 ±0.4

Table 5.4.1 Modal shift for Rome and Antwerp, baseline to follow-up one, 2014-2016

In Antwerp, large increases for walking and cycling frequency in the top measure affected group can be observed (increase in cycling by 0.6 days/week vs no change for the control group). This was, however, accompanied by decreases in public transport use (0.4 days/week less transit use in the top measure vs a 0.1day/week decrease in the control group). In Rome, similar increases in walking can be observed, but there is a marked increase in e-bike and public transit use in the top measure affected group as well (by 0.5 days/week for e-biking, and 0.4 days/week for public transit use). In both cities, the overall frequency of driving did not change.

[4]This may be due to the popularity of vocational training in Austria, which respondents may have classified as tertiary or equivalent education.

Örebro	Top measure	Walk	Bike	E-bike	Public t.	Driving	Motorbike
BLQ	Yes	2.0 ±1.0	2.0 ±1.2	0.6 ±0.7	2.0 ±1.4	2.2 ±1.0	0.6 ±0.7
	No	2.2 ±1.1	1.9 ±1.1	0.7 ±0.5	1.7 ±1.2	2.2 ±1	0.8 ±0.6
FU1	Yes	2.3 ±0.9	2.5 ±1.1	1.1 ±0.4	1.3 ±0.8	2.3 ±0.9	1.0 ±0.4
	No	2.1 ±1.0	1.9 ±1.1	0.8 ±0.5	1.7 ±1.1	2.2 ±1.0	0.8 ±0.5
FU2	Yes	3.2 ±0.9	2.4 ±1.7	0.9 ±1.6	1.6 ±1.1	2.5 ±1.1	0.2 ±0.7
	No	3.2 ±1.2	2.7 ±1.6	0.3 ±0.9	1.3 ±1.1	2.6 ±1.1	0.1 ±0.3
Vienna							
BLQ	Yes	2.4 ±1.3	1.9 ±1.1	0.6 ±0.6	2.4 ±1.2	2.1 ±1.1	0.7 ±0.8
	No	2.6 ±1.2	2.0 ±1.2	0.8 ±0.5	2.4 ±1.1	1.9 ±1.0	0.8 ±0.6
FU1	Yes	3.3 ±0.8	1.5 ±0.8	1.0 ±0.2	3.1 ±0.8	1.8 ±0.7	1.1 ±0.4
	No	2.8 ±1.1	1.9 ±1.1	0.9 ±0.4	2.4 ±1.0	1.9 ±0.9	1.0 ±0.5
FU2	Yes	3.9 ±0.3	1.9 ±1.6	0.3 ±0.6	3.3 ±0.9	2.0 ±0.9	0.4 ±0.8
	No	3.7 ±0.7	2.6 ±1.5	0.2 ±0.7	3.2 ±1.0	1.6 ±1.1	0.1 ±0.5

Table 5.4.2 Percentage change in average modal split for baseline to follow-up one and follow-up two by top-measure vs control, and by city

In Örebro, changes in walking frequency were similar for both the top measure and control groups, with a marked increase in walking during the 2019 questionnaire (an increase of more than 1 day/week for both groups). Cycling frequency increase for the top measure group between the baseline and first follow-up in 2016 by 0.5 days/week and remained unchanged for the control group. However, this trend was reversed in the second follow-up in 2019, when cycling in the top measure affected group remained stable and cycling in the control group increased by 0.8 days/week. However, e-bike use increased in the top measure affected group between baseline and the first follow-up, and remained high even in the second-follow-up in 2019. In the second follow-up, driving frequency increased for both groups.

In Vienna, the top measure affected group increased walking slightly more than the control group in the first follow-up. The increase in walking frequency was much more pronounced, and present for both groups, when a comparison between the baseline and second follow-up is made, with an increase of 1.5 days/week, and 1.1 days/week for the top measure and control groups, respectively. The top measure affected group reduced reported frequency of bicycle use, but increased the use of e-bikes from baseline to follow-up one.

However, this effect was lost by the second follow-up in 2019. Large increases in public transit use in the second follow-up can be observed for both groups, though no consistent pattern for driving exists.

Overall, it appears that walking is easier to influence and keep up after an intervention has finished than cycling. In Antwerp and Örebro, cycling, e-biking, and public transport use appear to be competing modes that people substitute for one another. Finally, driving patterns have not changed consistently in any of the cities.

Minimally adjusted model, all four cities

In order to determine whether these changes are significant, we conducted panel data analysis for each city. We control for sex (female 1/male 0), age (continuous variable), car access, and top measure/control group membership (control group being the reference category). The dependent variable is the self-reported frequency of mode use over the past seven days, and we conducted separate regressions for each of the six modes. Respondents were assigned into a pre-intervention (0) and a post-intervention (1) time-period, depending on when they filled out the questionnaires. The results are presented in the left-most column labelled "Full results" in Figure 5.4.2, and the full regression results are in Appendix 5.D. As expected, the increase in walking is significant for all four cities (0.23, 95% CI 0.15 - 0.31 for Antwerp; 0.70 95% CI 0.43 - 0.97 for Rome; 0.31, 95% CI 0.20 - 0.42 for Örebro; and 0.77, 95% CI 0.58 - 0.96 for Vienna), as is the increase for e-biking (0.22, 95% CI 0.17 - 0.27 for Antwerp; 0.36 95% CI 0.23 - 0.49 for Rome; 0.31, 95% CI 0.26 - 0.36 for Örebro; and 0.26, 95% CI 0.17- 0.34 for Vienna). The two northern cities, Antwerp and Örebro, both show a statistically significant increase in cycling (0.52, 95% CI 0.43 - 0.62 for Antwerp; 0.58, 95% CI 0.47 - 0.69 for Örebro), and decrease in public transit use (-0.33, 95% CI -0.41 - -0.24 for Antwerp; -0.57, 95% CI -0.69 - -0.46 for Örebro). In contrast, the increase in public transit use in Rome and Vienna (0.26, 95% CI 0.00 - 0.52 for Rome; 0.63, 95% CI 0.44 -

0.82 for Vienna) is counterbalanced by a decrease in cycling in those two cities (significant for Vienna only, -0.30, 95% CI -0.49 - -0.12), relative to their control groups. Furthermore, Vienna, which exhibits the largest increase in public transit use, is also the only city that shows a significant decrease in driving (-0.46, 95% CI -0.62 - -0.29). Likewise, it appears that regular cycling frequency fell due to a comparable increase in e-bike use. Motorcycle use was low in the sample overall, but increased for the top measure affected groups in all four cities.

5.4.3 Long-term influences in Örebro and Vienna

Follow-up questionnaires sent to respondents in Örebro and Vienna in 2019 were used to find the long-term effect of the soft-measure interventions. Figure 5.4.1 shows the treatment effects separately for the follow-up 1 and follow-up 2 periods for 308 people who were sampled for the entire 2014-2019 period. For some modes, the intervention effect decreased over time (walking, public transit, driving in Vienna; cycling and driving in Örebro), but for others, the effect became stronger in the second follow-up (notably e-bike use in Örebro, 0.11, 95% CI -0.08 - 0.30 in FU1, and 0.43, 95% CI 0.13 - 0.73 in FU2). This shows that while in many cases, an intervention may appear to be successful in the first year after implementation, the effectiveness of the intervention may fade after a longer period of time. Full regression results are in Appendix 5.E.

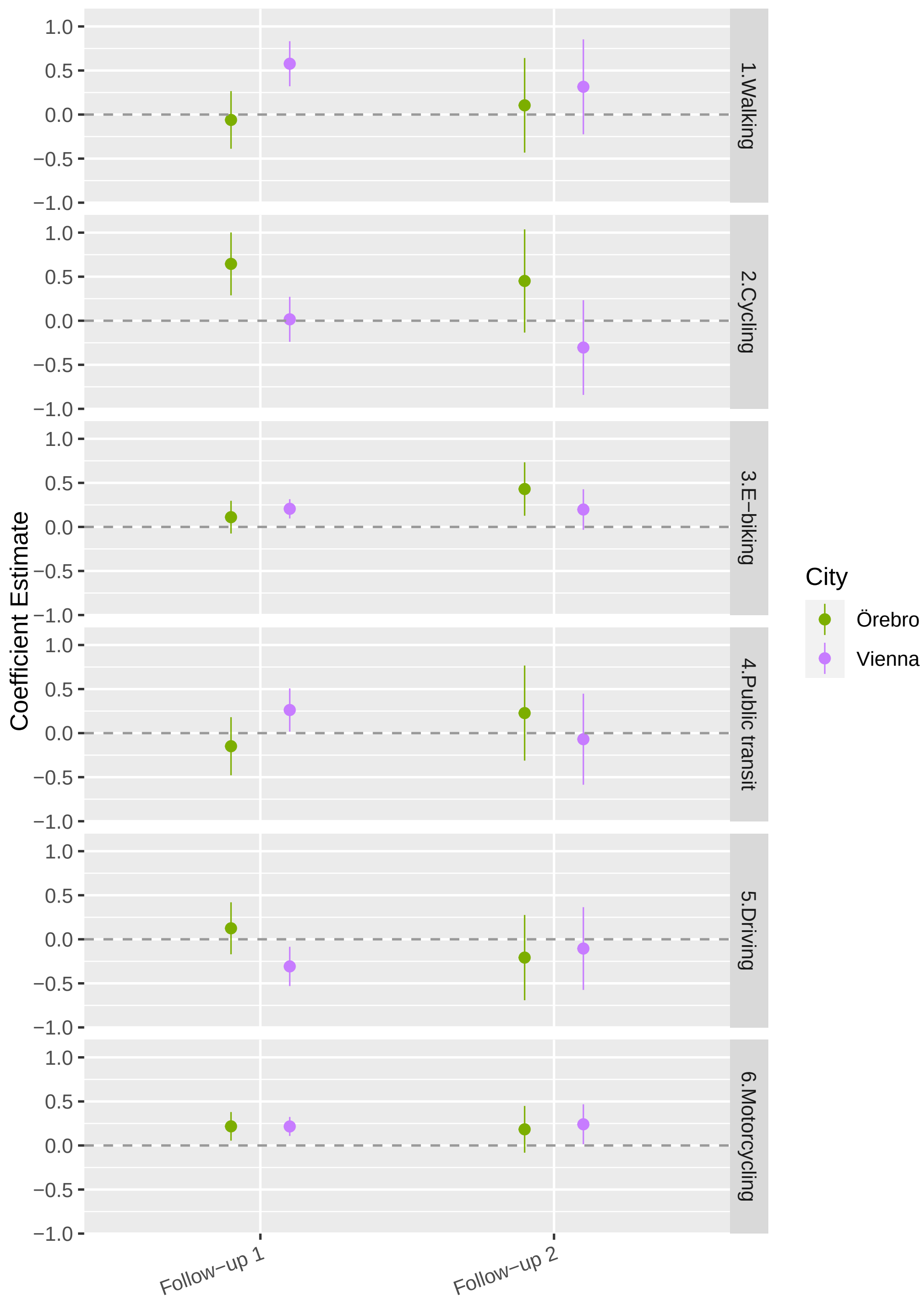

Figure 5.4.1 Treatment effect over time in selected cities

5.4.4 Contexts

In line with the contexts and mechanisms proposed in Section 5.2, we conducted subgroup analyses in order to determine the relative influence of different socio-economic, demographic, and personal factors on the effectiveness of the interventions.

Socio-economic groups

In order to evaluate the influence of socio-economic groups, we split the dataset into university educated and fully employed; university educated with other types of occupation; university educated and high income; non-university educated and fully employed; non-university educated with other types of occupation; and full sample results. Figure 5.4.2 shows coefficient results for socio-economic subgroup analysis for all modes of transport. Appendix 5.D includes regression results for each transport mode and socio-economic group.

Figure 5.4.2 shows the change in mode use frequency over time for the top measure affected group, relative to the control group. The top measure was most effective at influencing the behaviour of people in with a degree in full-time employment, specifically for walking (0.20, 95% CI 0.10 - 0.30 for Antwerp; 0.67 95% CI 0.36 - 0.99 for Rome; 0.14, 95% CI -0.00 - 0.29 for Örebro; and 0.51, 95% CI 0.18 - 0.85 for Vienna) and e-bike use (0.13, 95% CI 0.07 - 0.18 for Antwerp; 0.38 95% CI 0.15 - 0.61 for Rome; 0.24, 95% CI 0.16 - 0.31 for Örebro; and 0.37, 95% CI 0.23 - 0.51 for Vienna). Driving showed the least change overall, though people with tertiary education and in full-time employment exhibited slight decreases in driving relative to the control group across all four cities. Curiously, motorcycling frequency also increased consistently across most socio-economic groups and cities. Effects for other transport modes vary both by city, and socio-economic grouping. Relatively few people identified themselves as high income in Rome and Vienna, or as people not in full-time employment in Rome. This increased the standard errors for these groups,

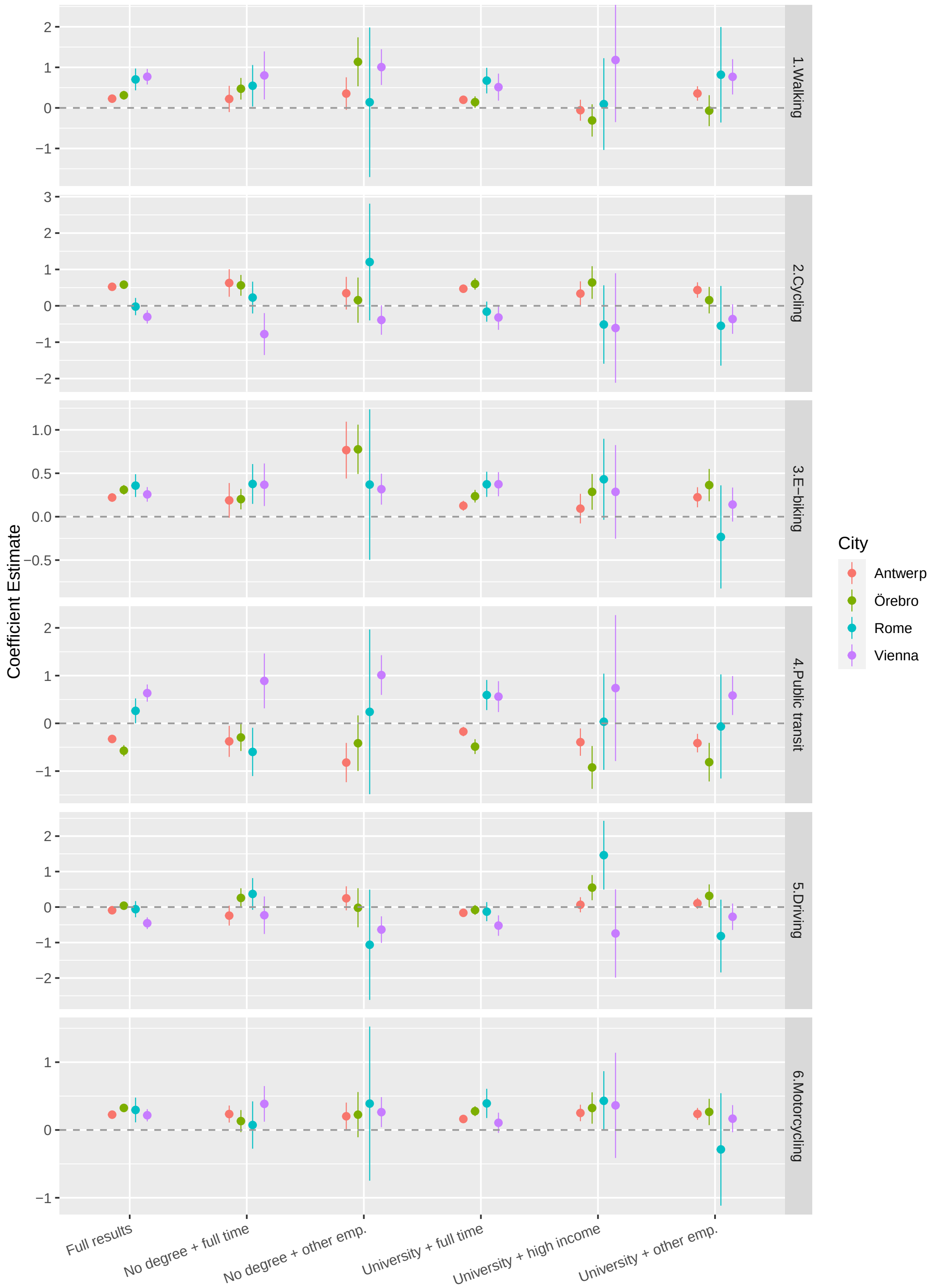

Figure 5.4.2 Top measure effect on transport mode use frequency by socio-economic group.

though variable influences were mostly in the same direction as all other socio-economic groups.

Respondents without a university degree in other occupations than full time employment were the least uniform, and often reacted to the interventions differently from city to city. For example, they increased public transit use in Vienna (1.01, 95% CI 0.60 - 1.43), but showed no consistent change in Rome or Örebro, and even decreased transit use in Antwerp (-0.82, 95% CI -1.23 - -0.41). Rome is the only city where the behaviour of fully employed individuals differed quite widely by the level of education attained. Public transit use increased (0.59, 95% CI 0.28 - 0.91) slightly for the tertiary-educated fully employed group, but the opposite change (-0.60, 95% CI -1.10 - -0.09) was observed for non-university educated fully employed individuals in Rome. Smaller, but still opposing, effects were observed for driving and cycling, as well.

Family and dependents

Having under-age or elderly family members is proposed as a context in which respondents have less flexibility with regards to their use of time and mode choice. Instead, they may be reliant on cars for escorting purposes, thus reducing the effect of the top measures on modal shift. Respondents were asked to list the number of household members under the age of 6, aged 6-17, 18+, and 65+. We estimated whether the top measure had significantly different effects over time, depending on household size and type.

Overall, living with children or with elderly did not change the effect of the intervention significantly, implying that behaviour change within the top measure affected group happened irrespective of household size or membership. Marginal effects were detected for some subgroups. E-bike (-0.19, 95% CI -0.38 - 0.00) and motorcycle use (-0.39, 95% CI -0.67 - -0.12) over time was significantly lower for top measure affected respondents with a child under 6 in Rome. Conversely, for the same group, e-bike use was increased (0.14, 95% CI

-0.01 - 0.29) in Vienna. Not enough people reported living with elderly members of the household to enable comparison across cities or control vs. top measure affected groups. Regression results are presented in Appendix 5.F.

5.4.5 Mechanisms

Following Section 5.2, where we proposed that some of the mechanisms through which travel behaviour can change is through a change in the relative strength of social and personal influences on travel, we analyse people's responses regarding their subjective views of walking and cycling. Respondents were asked: how common it is to walk/cycle in their neighbourhood; how strongly their sense of moral responsibility requires them to walk/cycle; how strong their own intent o walk/cycle is; how strongly their own values, regardless of what other people think, require them to walk/cycle; and how strongly people important to them think they should walk/cycle. In order to find whether changes in psychological indicators regarding active travel persisted through time, we focus only on Vienna and Örebro, where both the first and the second-follow up questionnaires were conducted. Due to the small sample size in the second follow-up wave, we pooled both cities together.

Influences of walking perceptions

Influences of walking perceptions on walking were minimal, and did not differ by time, or by top measure affected vs. control groups. The regression results are presented in Appendix 5.G. The influences of cycling perceptions on walking were also insignificant, and are shown in Figure 5.4.3.

Although walking frequency did increase significantly for the top measure affected group (see Figure 5.4.2), perceptions of walking, or their influences on walking, did not change as a result of the intervention. This implies that increasing the frequency of walking, a more mundane and ordinary activity among society, requires less conscious decision-making and careful deliberation than increasing cycling or e-biking use do. The increases in walking, when they occurred, also persisted through to the second follow-up wave of questionnaires in 2019.

Influences of cycling perceptions

The influences of cycling perceptions on mode use for both top measure affected and control group are presented in Figure 5.4.3. While mode use change was significantly different in the top measure group already in the first follow-up in 2016, a significant change in perceptions relative to the control group is only detectable three years after the intervention was implemented, during the second follow-up wave. The relative influence of the perception of social norms, specifically whether it is common to cycle, did not change for the control group. However, the top measure affected group was significantly more likely to e-bike when the respondent considered it common to cycle (0.08, 95% CI -0.04 - 0.19 in FU1; 0.34, 95% CI 0.16-0.53 in FU2). The intervention helped change perceptions of how common it is to cycle, and this change helped alter behaviour towards greater e-bike use over bicycle use, over the longer run. Similarly, the influence of one's own sense of moral responsibility towards travelling more sustainably increased significantly for the top measure affected group for cycling for the second follow-up period (0.29, 95% CI -0.02 - 0.60). This effect was not present for e-bike use, potentially because their consumption of electricity may be perceived as less sustainable. In fact, for e-biking a stronger sense of own values that would require a person to walk or cycle where possible, was negatively associated with e-bike use, and grew stronger in the second follow-up survey (-0.12, 95% CI -0.26 - 0.01 in FU1; -0.26, 95% CI -0.49 - -0.04 in FU2).

The strength of one's own intent to cycle in the future led to significantly higher cycling for the control than top measure affected group (0.44, 95% CI 0.30 - 0.59 in FU2 as opposed to 0.15, 95% CI -0.19 - 0.48 in FU2). Conversely, strong intent led to significantly higher

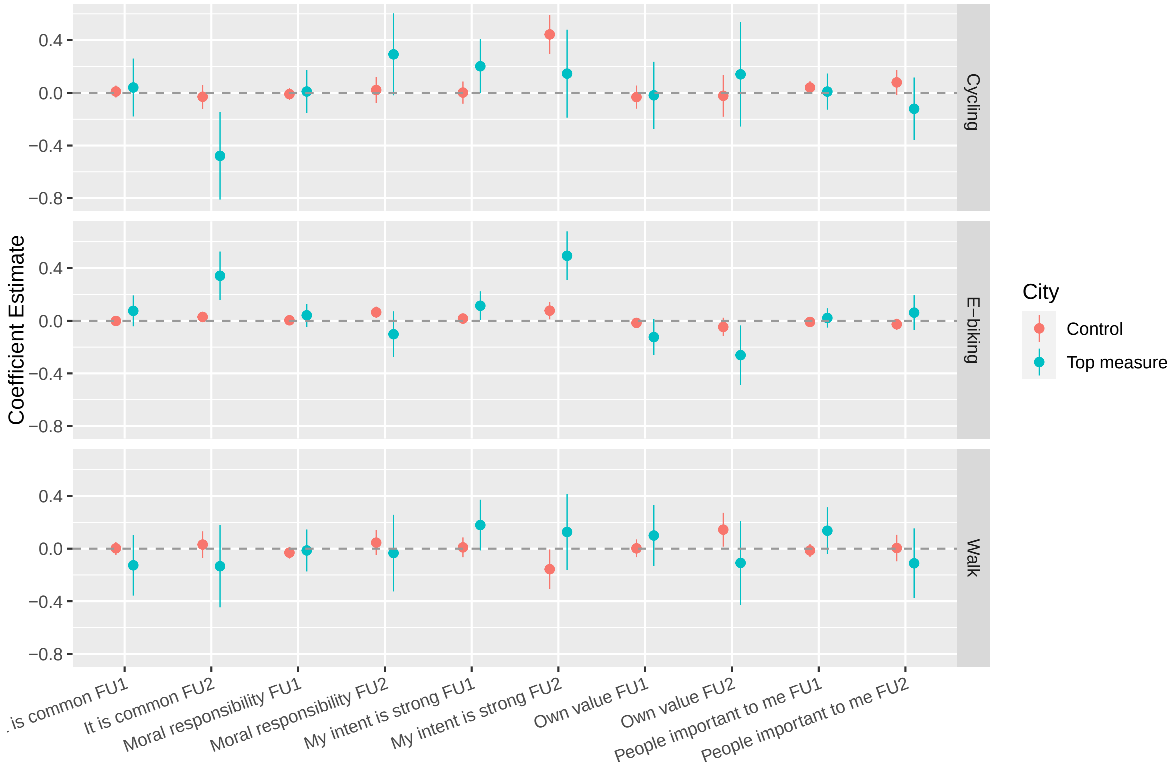

Figure 5.4.3 Influence of cycling-related perceptions on behaviour.

e-biking for the top measure affected than control groups (0.49, 95% CI 0.31 - 0.68 in FU2). It is possible that for the top measure affected group, cycling had become a normalised activity and e-biking was a new mode the respondents had to challenge themselves to choose. In contrast, the control group perceived the bicycle as their challenge. In both cases, these effects became stronger in the second follow-up wave.

The influence of the variable representing injunctive social norm, whether other people think a person *should* cycle, did not reduce significantly as a result of the intervention, contrary to what was hypothesised. Although not tested in this study, this could be because other people's opinions consistently matter to one's own decision-making process and in promoting behaviour change (Heath et al., 2012).

5.5 Discussion

5.5.1 Summary of results and comparison with previous research

The case-control cohort study design of the PASTA study allowed us to determine the effectiveness of largely information-based travel-to-work plan interventions in promoting walking and cycling. We conducted regression analyses to estimate the differences in transport mode use frequency over time between control and top-measure affected groups for four cities for 5460 participants, and conducted subgroup analyses to test specific contexts and mechanisms that may influence the effectiveness of the interventions. We tested different household size and socio-economic group membership as influencing contexts, and individual perceptions as moderating mechanisms of the interventions. In order to establish the duration and time over which the interventions work, we conducted additional follow-up surveys in two of the four cities 2.5 years after the initial study was completed, resulting in data spanning five years for 308 individuals.

The interventions were effective in increasing active travel in the 2014-2016 period, but this was not associated with equally large shifts away from car transport, but rather from public transport to walking, or from cycling to e-biking. Broadly in line with previous research (Brand et al., 2014; Goodman et al., 2014), our results highlight society's overall dependence on cars for transport. At an aggregate level, changing the outcome variable of interest to individual trips (obtained from trip diary data), or adding additional control variables, did not change the general trends. However, considerable variability in travel patterns between cities and groups indicates that the interventions were indeed highly dependent on local contexts, and provides support for the use of realist evaluation, in order to understand "what works, when, and for whom" (Pawson et al., 1997).

Regardless of socio-economic group membership, certain city-specific (and therefore intervention-specific) effects are evident. In Vienna, driving and cycling frequency fell slightly for most socio-economic groups; public transit, e-biking, and walking increased. In Antwerp and Örebro, more similar culturally, walking, cycling, and e-bike use increased for most socio-economic groups, while public transit use fell across all groups. In Rome, socio-economic group effects dominated city-wide effects. Rome is both larger, and so unequal in terms of social, income, and employment distribution, that it has been called “two cities” instead of one (Lelo et al., 2019). This may help explain why different socio-economic groups behave differently in Rome but not in the other three cities.

Our study is consistent with findings that high income/highly educated people may have higher senses of environmental moral responsibility, but may continue having less sustainable travel behaviour (Anable, 2005). We do not find a consistently different pattern of intervention effect among university educated and non-university educated respondents, contrasting the findings of Goodman et al. (2014). As interventions in all four cities included variants of travel-to-work plans, full-time employees were the most likely to benefit most from the interventions. Indeed, the results of regressions divided by socio-economic grouping confirm this hypothesis. On the other hand, the results could also imply that switching to active modes is not a viable alternative for non-university educated, flexibly employed people (Groth, 2019). We suggest that different policies need to be designed to suit the accessibility needs of every socio-economic group.

In Vienna, no consistent change in travel patterns across modes in the top measure affected group was observed over both follow-up periods. This may be due to the type of people the intervention targeted, namely people with health problems, and people who recently moved homes. However, *individualised* travel plans were found more likely to be effective (Yang et al., 2010), and large life changes were found to be critical enablers of travel-related behaviour change (Christensen et al., 2012; Marsden et al., 2020) in other studies. Finally, many studies cite lack of access to a bicycle as the main barrier to the adoption of cycling (Kelly et al., 2020; Savan et al., 2017), and in Örebro, part of the intervention included renting e-bikes to employees for free. It is thus perhaps not surprising that the largest relative increase in e-biking was observed in Örebro.

5.5.2 Policy recommendations

Policymakers need to identify whether their active mobility plans aim to increase the health of citizens, or reduce carbon emissions. The interventions were successful at increasing frequency of active travel, in particular walking. The effect on cycling and e-biking decreased over time. If the effects of a costly policy may be lost several years after the intervention has ended, it may be desirable to design repeated interventions, where people receive information to reinforcing their new behaviours for longer. Alternatively, it may be beneficial to phase in policies that target walking first (where behaviour can change without changes in perceptions), then followed by cycling, and followed finally by e-biking (which may be an option only for people who are comfortable cycling already).

None of the interventions studied reduced the frequency of driving significantly for both waves of the survey, and would thus not reduce carbon emissions from transport significantly. Furthermore, apart from Rome, increases in active travel were mostly accompanied by decreases in public transit use, not driving. Policymakers thus need to weigh whether it is worth using public funds for policies that may not achieve their desired goals, particularly if the goal is reducing vehicle-based traffic.

Finally, as the examples from Vienna and Örebro show, we recognise that information-based measures are unlikely to work on their own. In Vienna, where driving did fall during the first follow-up wave, the city also conducted a large-scale expansion of public transport services and frequency, making the switch away from cars more attainable. Örebro was the only city in which free renting out of e-bicycles for longer periods was part of the intervention. As a result, it is the only city where e-bike use had significantly increased for the top measure group for both the first, and the second follow-up waves of questionnaires. In their review of personalised travel planning measures, Cairns et al. (2008) conclude that standalone interventions have the potential to reduce car travel by only around 4-5%. However, when coupled with other interventions, effectiveness can increase up to 20%. Similarly, Song et al. (2017) argue that infrastructure investments alone may be necessary, but are not sufficient, in order to increase walking and cycling. Keall et al. (2015) argue that joining behaviour and infrastructure-focussed policies can almost double the impact on reducing carbon emissions. We support these findings and conclude that more integrated measures are needed in order to achieve a substantial shift away from car-based travel in urbanised areas in the future.

5.5.3 Limitations of this study

The original PASTA study used opportunistic recruitment methods to sample respondents. The sample is therefore not representative of the general population and oversampled regular cyclists, younger people, and more highly educated members of the public (Gaupp-Berghausen et al., 2019). The findings of this study can nonetheless be applied to tailor measures to particular subgroups within the general population. Due to the focus of the study on transport and active mobility in particular, the long-term nature of the study and time-consuming survey, people interested in walking and cycling may be more likely to remain in the study. This introduces the risk of selection bias. Attrition of survey participants was severe in the 2019 wave, with only 11 top-measure-affected respondents in Vienna participating. The study did not ask people specific questions about the top measure, and whether it influenced their opinions on active travel and hence only proxy measures for perception changes could be used, potentially not capturing the full effect of the interventions. However, in order to fully understand processes of behaviour change, full ethnographic studies may be necessary (Panter et al., 2017). Finally, the rise of shared mobility schemes such as Uber and Lyft were not considered in the design of this study, even though their rise could have changed mobility patterns (Graehler et al., 2019).

5.6 Conclusion

We analysed mode use change following the implementation of four different interventions in four cities in Europe in 2014-2016 as part of the PASTA longitudinal study. We conducted a further follow-up in 2019 in two of the cities to evaluate the long-term effects of the interventions. In the one-year follow-up, the interventions were effective at increasing walking and cycling. At the three year follow-up, levels of walking remained elevated among the top measure affected group, returned to previous levels for cycling, and increased significantly for e-biking. Driving frequency did not change. We used realist evaluation and subgroup analysis to analyse differences in modal shift within groups, based on socio-economic, demographic, and perception variables. Respondents in full-time employment were the most responsive to the interventions, with most inconsistent results for people in the high income group. Policies that take different approaches to people with different kinds of employment and time management requirements should be adopted. The findings also support the development of policies that combine built environment, accessibility, and information-based measures, rather than taking a siloed approach. In the future, more research on ways to reduce driving, not only increase active travel, should be conducted.

Author Statement

Simona Sulikova: Conceptualisation, Software, Formal Analysis, Writing - Original Draft.

Christian Brand: Supervision, Conceptualisation, Writing - Review Editing.

Research Data

Due to the sensitive nature of the questions asked in this study survey respondents were assured raw data would remain confidential and would not be shared.

Acknowledgements

This article was written on behalf of the PASTA consortium (http://pastaproject.eu; Albert Ambrós, Esther Anaya-Boig, Ione Avila-Palencia, Christian Brand, Evi Dons, Mailin Gaupp-Berghausen, Regine Gerike, Thomas Götschi, Esther Gracia, Francesco Iacorossi, Luc Int Panis, Sonja Kahlmeier, Michelle Laeremans, Oriol Marquet, Sandra Márquez, Audrey de Nazelle, Mark Nieuwenhuijsen, Elisabeth Raser, and Julian Sanchez). PASTA was supported by the European project Physical Activity through Sustainable Transportation Approaches (PASTA). PASTA was a four-year project funded by the European Union's Seventh Framework Program (EU FP7) under European Commission Grant Agreement No. 602624. Simona Sulikova was funded the Martin Filko Scholarship and the Kellogg Progress Scholarship. We thank the study participants, Ersilia Verlighieri for pointing out the literature on self-identity, and Moritz Schwarz and Anna Clark for guidance on phrasing emails in German and Swedish, respectively.

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Appendix

For Online Publication

Do information-based measures affect active travel, and if so, for whom, when and under what circumstances? Evidence froma longitudinal case-control study

Simona Sulikova: University of Oxford.

Christian Brand: University of Oxford.

Appendix 5.A Case study cities

The cities vary by size, climate, and travel patterns. These are summarised in Table 5.A.1.

Table 5.A.1 City characteristics

Variable	Antwerp	Örebro	Rome	Vienna
Description	Second largest city in Belgium	Regional centre, 200km west of Stockholm, Sweden	Largest city in Italy	Largest city in Austria
Population*	510,610	140,000	2.9 million	1.8 million
Average monthly income per capita in EUR end 2019 exchange rate**	1987	4100	1422	5120
Weather				
Average annual temperature, C***	10.1	6.1	15.7	9.9
Annual rainfall, mm***	778	633	798	623
Koeppen-Geiger climate classification***	Temperate oceanic	Humid continental	Dry summer	Humid continental
Mode share %				
Driving	41	55	54	27
Cycling	23	25	1	6
Public transport	16	9	29	39
Cycling network km (OSM)****	469.17	361.35	120.64	715.63

* From worldpopulationreview.com
** Various sources
*** from climate-data.org
**** from Mueller et al. (2018)

Appendix 5.B Description of statistical analysis

The *plm* package by Croissant and Millo (2008) is designed to deal specifically with panel data for econometric analysis, taking into account the serially correlated nature of repeated measures data. We used a differences-in-differences regression model set-up in order to compare the within-person change in mode use over time, and compare the average change in mode use between the control and the top measure affected group. This allowed us to control for wider city trends and the larger city-wide active travel initiatives that each city implemented at the same time, which we assumed affected both the control and top measure affected groups in the same way. This ensured that the only changes that occurred as a result of the intervention would be captured by our variables of interest. As none of the cities had the same exact sample size or number of people in the top measure affected vs. control groups, a direct comparison of beta coefficients is *not* equivalent to a direct comparison of effect strength between cities. Therefore, each beta coefficient can only be compared to other beta coefficients within that regression. Plots were created using the *dotwhisker* package by Solt and Hu (2015). Tables were created using the *stargazer* package by Hlavac (2015).

Appendix 5.C Baseline characteristics for Vienna and Örebro only

The 2014-2015 series of questionnaires measured baseline characteristics in Antwerp and Örebro; in Rome and Vienna the 2014-mid-year 2015 questionnaires measured baseline characteristics; the 2016-2017 questionnaires measured travel behaviour after the intervention was implemented in Antwerp and Örebro; in Rome and Vienna the November 2015-2017 questionnaires measured travel behaviour after the intervention.

Table 5.C.1 Baseline characteristics of respondents

Variable	N (%) at baseline N = 1375	N (%) at follow-up 1 N = 1999	N (%) at follow-up 2 N = 338
City			
Vienna	638 (46.4)	1106 (55.3)	259 (76.6)
Örebro	737 (53.6)	893 (44.7)	79 (23.4)
Top measure affected			
Yes	373 (27.1)	308 (15.4)	39 (11.5)
No	1002 (72.9)	1691 (84.6)	299 (88.5)
Sex			
Female	781 (56.8)	1155 (57.8)	177 (52.4)
Male	594 (43.2)	844 (42.2)	161 (47.6)
Age (range) in years	41.9 (18.1-83.7)	42.7 (18-87.7)	45.9 (22.4-78.7)
Household with children under 17			
Yes	432 (31.4)	358 (17.9)	95 (28.1)
No	943 (68.6)	1641 (82.1)	262 (77.5)
Education level			
Tertiary or equivalent	931 (67.7)	1122 (56.1)	218 (64.5)
Secondary school	407 (29.6)	503 (25.2)	108 (32)
Primary or other	37 (2.7)	50 (2.5)	12 (3.6)
Employment status			
Employed	994 (72.3)	1433 (71.7)	280 (82.8)
Student	225 (16.4)	301 (15.1)	25 (7.4)
Retired or other	156 (11.4)	265 (13.3)	47 (13.9)
Access to a car			
Always	776 (56.4)	1064 (53.2)	159 (47)
Sometimes	360 (26.2)	540 (27.0)	96 (28.4)
Never	239 (17.4)	395 (19.8)	84 (24.9)
Access to a bicycle			
Yes	1280 (93.1)	1850 (92.5)	309 (91.4)
No	95 (6.9)	149 (7.5)	29 (8.6)
Self-rated health			
Excellent/good	1198 (87.1)	1650 (82.5)	319 (94.4)
Fair/poor	168 (12.2)	210 (10.5)	30 (8.9)
Self-rated frequency of walking			
Less than once a month	66 (4.8)	62 (3.1)	9 (2.7)
1-3 days per month	68 (5)	87 (4.4)	15 (4.4)
1-3 days per week	216 (15.7)	268 (13.4)	53 (15.7)
Daily or almost daily	1014 (73.8)	1483 (74.2)	261 (77.2)
Self-rated frequency of cycling			
Less than once a month	350 (25.5)	527 (26.4)	102 (30.2)
1-3 days per month	169 (12.3)	239 (12)	28 (8.3)
1-3 days per week	263 (19.1)	337 (16.9)	67 (19.8)
Daily or almost daily	582 (42.3)	797 (39.9)	139 (41.1)

Appendix 5.D Minimally adjusted models, all four cities

5.D.1 Antwerp

Walking

Table 5.D.1 Minimally adjusted model, walking, Antwerp

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.011	0.310**	0.063
	(-0.078,0.055)	(0.074,0.546)	(-0.175,0.302)
Age	-0.0004	-0.001	-0.0002
	(-0.003,0.002)	(-0.012,0.010)	(-0.008,0.008)
Top measure	0.083*	-0.108	0.088
	(-0.010,0.175)	(-0.430,0.215)	(-0.292,0.469)
Time	-0.055***	0.003	0.084
	(-0.086,-0.024)	(-0.091,0.096)	(-0.066,0.233)
TM effect over time	0.228***	0.221	0.353*
	(0.150,0.306)	(-0.102,0.544)	(-0.049,0.754)
Observations	15,086	1,485	777
R^2	0.132	0.138	0.160
Adjusted R^2	0.132	0.135	0.154

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.2 Minimally adjusted model, walking, Antwerp

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.012	0.011	-0.022
	(-0.295,0.271)	(-0.083,0.104)	(-0.147,0.104)
Age	0.009	-0.001	0.008***
	(-0.007,0.025)	(-0.006,0.003)	(0.003,0.013)
Top measure	0.008	0.048	-0.004
	(-0.322,0.338)	(-0.070,0.166)	(-0.197,0.190)
Time	0.018	-0.035*	-0.138***
	(-0.122,0.158)	(-0.075,0.004)	(-0.204,-0.073)
TM effect over time	-0.057	0.200***	0.356***
	(-0.317,0.202)	(0.104,0.296)	(0.178,0.534)
Observations	825	9,004	3,388
R^2	0.121	0.132	0.188
Adjusted R^2	0.116	0.131	0.187
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

Cycling

Table 5.D.3 Minimally adjusted model, cycling, Antwerp

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.076*	0.109	0.116
	(-0.162,0.010)	(-0.215,0.433)	(-0.205,0.438)
Age	-0.008***	0.007	0.001
	(-0.012,-0.004)	(-0.008,0.022)	(-0.010,0.012)
Top measure	0.055	-0.121	0.109
	(-0.063,0.173)	(-0.549,0.308)	(-0.393,0.612)
Time	-0.094***	-0.057	-0.352***
	(-0.131,-0.057)	(-0.167,0.052)	(-0.518,-0.185)
TM effect over time	0.523***	0.628***	0.347
	(0.429,0.618)	(0.249,1.006)	(-0.103,0.796)
Observations	15,093	1,486	778
R^2	0.069	0.058	0.086
Adjusted R^2	0.069	0.055	0.080
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.4 Minimally adjusted model, cycling, Antwerp

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.052	-0.111*	0.271***
	(-0.423,0.320)	(-0.225,0.003)	(0.101,0.440)
Age	0.005	-0.001	0.0004
	(-0.015,0.026)	(-0.007,0.005)	(-0.006,0.007)
Top measure	-0.123	0.022	0.157
	(-0.556,0.309)	(-0.122,0.166)	(-0.102,0.415)
Time	0.007	0.042*	-0.174***
	(-0.175,0.188)	(-0.006,0.089)	(-0.253,-0.096)
TM effect over time	0.336*	0.470***	0.434***
	(-0.001,0.673)	(0.354,0.585)	(0.223,0.646)
Observations	825	9,005	3,391
R^2	0.055	0.084	0.064
Adjusted R^2	0.050	0.083	0.063

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

E-biking

Table 5.D.5 Minimally adjusted model, e-biking, Antwerp

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.011	-0.087	0.334**
	(-0.042,0.064)	(-0.268,0.093)	(0.071,0.598)
Age	0.003***	0.013***	0.005
	(0.001,0.005)	(0.005,0.021)	(-0.004,0.015)
Top measure	-0.102***	-0.368***	-0.213
	(-0.174,-0.031)	(-0.605,-0.132)	(-0.623,0.197)
Time	0.006	0.072**	-0.039
	(-0.013,0.026)	(0.014,0.129)	(-0.160,0.082)
TM effect over time	0.221***	0.188*	0.767***
	(0.171,0.271)	(-0.012,0.387)	(0.439,1.094)
Observations	15,085	1,487	778
R^2	0.017	0.059	0.023
Adjusted R^2	0.017	0.056	0.016

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.6 Minimally adjusted model, e-biking, Antwerp

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.151	0.084**	0.093*
	(-0.337,0.034)	(0.017,0.151)	(-0.016,0.201)
Age	0.005	0.006***	0.010***
	(-0.005,0.016)	(0.003,0.009)	(0.006,0.014)
Top measure	-0.179	-0.145***	-0.037
	(-0.395,0.038)	(-0.228,-0.062)	(-0.202,0.128)
Time	0.177***	0.083***	-0.064***
	(0.085,0.269)	(0.060,0.106)	(-0.108,-0.021)
TM effect over time	0.093	0.126***	0.224***
	(-0.078,0.264)	(0.070,0.183)	(0.108,0.341)
Observations	825	9,004	3,386
R^2	0.057	0.034	0.012
Adjusted R^2	0.051	0.034	0.011

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

Driving

Table 5.D.7 Minimally adjusted model, driving, Antwerp

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.002	-0.151	0.058
	(-0.060,0.065)	(-0.434,0.133)	(-0.180,0.296)
Age	-0.003**	-0.005	-0.004
	(-0.006,-0.0004)	(-0.018,0.008)	(-0.012,0.004)
Top measure	-0.050	0.144	-0.261
	(-0.136,0.036)	(-0.220,0.509)	(-0.633,0.111)
Time	-0.018	0.135***	0.015
	(-0.045,0.008)	(0.054,0.217)	(-0.111,0.141)
TM effect over time	-0.090***	-0.241*	0.247
	(-0.158,-0.022)	(-0.522,0.040)	(-0.093,0.586)
Observations	15,092	1,486	778
R^2	0.158	0.141	0.162
Adjusted R^2	0.158	0.138	0.157
Note:			*p<0.1; **p<0.05; ***p<0.01

s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.8 Minimally adjusted model, driving, Antwerp

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.080	-0.034	0.080
	(-0.312,0.153)	(-0.114,0.047)	(-0.040,0.199)
Age	0.005	-0.001	-0.001
	(-0.008,0.018)	(-0.005,0.003)	(-0.005,0.003)
Top measure	-0.017	-0.058	-0.123
	(-0.288,0.254)	(-0.160,0.043)	(-0.305,0.058)
Time	0.087	-0.044**	0.002
	(-0.028,0.202)	(-0.077,-0.010)	(-0.055,0.059)
TM effect over time	0.065	-0.162***	0.105
	(-0.148,0.278)	(-0.244,-0.080)	(-0.048,0.259)
Observations	825	9,005	3,390
R^2	0.148	0.156	0.260
Adjusted R^2	0.143	0.155	0.259
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

Public transit

Table 5.D.9 Minimally adjusted model, p. transit, Antwerp

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.088***	0.327***	-0.085
	(0.024,0.153)	(0.090,0.563)	(-0.357,0.188)
Age	-0.002*	-0.003	0.001
	(-0.005,0.0003)	(-0.014,0.008)	(-0.008,0.011)
Top measure	0.200***	0.455***	0.219
	(0.109,0.292)	(0.131,0.779)	(-0.210,0.648)
Time	0.001	-0.143***	0.222***
	(-0.032,0.033)	(-0.238,-0.048)	(0.070,0.375)
TM effect over time	-0.327***	-0.377**	-0.821***
	(-0.410,-0.244)	(-0.702,-0.052)	(-1.233,-0.409)
Observations	15,091	1,487	777
R^2	0.186	0.187	0.290
Adjusted R^2	0.186	0.184	0.285

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.10 Minimally adjusted model, p. transit, Antwerp

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.099	0.045	-0.183***
	(-0.181,0.379)	(-0.040,0.131)	(-0.323,-0.044)
Age	0.001	-0.007***	-0.013***
	(-0.015,0.017)	(-0.011,-0.003)	(-0.018,-0.008)
Top measure	0.184	0.234***	-0.048
	(-0.149,0.517)	(0.124,0.344)	(-0.263,0.166)
Time	0.026	-0.122***	0.140***
	(-0.128,0.180)	(-0.162,-0.082)	(0.068,0.212)
TM effect over time	-0.393***	-0.172***	-0.414***
	(-0.679,-0.107)	(-0.269,-0.075)	(-0.609,-0.220)
Observations	825	9,003	3,390
R^2	0.154	0.158	0.315
Adjusted R^2	0.149	0.158	0.314

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

Motorcycling

Table 5.D.11 Minimally adjusted model, motorcycling, Antwerp

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.032**	0.010	0.079
	(-0.062,-0.002)	(-0.067,0.087)	(-0.043,0.201)
Age	-0.001	-0.001	-0.002
	(-0.002,0.001)	(-0.004,0.003)	(-0.006,0.002)
Top measure	-0.034	-0.216***	0.153
	(-0.076,0.008)	(-0.327,-0.105)	(-0.041,0.347)
Time	-0.009	0.050***	-0.140***
	(-0.024,0.005)	(0.013,0.087)	(-0.215,-0.065)
TM effect over time	0.226***	0.235***	0.202**
	(0.188,0.264)	(0.110,0.360)	(0.001,0.404)
Observations	15,083	1,487	778
R^2	0.027	0.069	0.015
Adjusted R^2	0.027	0.065	0.009

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.12 Minimally adjusted model, motorcycling, Antwerp

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.068	-0.024	0.102^{***}
	(-0.171,0.034)	(-0.060,0.012)	(0.034,0.170)
Age	-0.0004	0.003^{***}	0.008^{***}
	(-0.006,0.005)	(0.001,0.005)	(0.005,0.010)
Top measure	-0.101	-0.101^{***}	0.137^{***}
	(-0.228,0.026)	(-0.148,-0.054)	(0.033,0.240)
Time	-0.016	0.069^{***}	-0.087^{***}
	(-0.081,0.049)	(0.051,0.087)	(-0.119,-0.054)
TM effect over time	0.251^{***}	0.162^{***}	0.237^{***}
	(0.129,0.373)	(0.118,0.205)	(0.150,0.325)
Observations	825	9,001	3,388
R^2	0.061	0.061	0.012
Adjusted R^2	0.056	0.061	0.011
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
			HI is high income
			FT is full time employed
			other is part-time, student, retired

5.D.2 Rome

Walking

Table 5.D.13 Minimally adjusted model, walking, Rome

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.074*	0.191*	0.178
	(-0.009,0.158)	(-0.020,0.402)	(-0.034,0.390)
Age	0.0003	-0.004	-0.011***
	(-0.003,0.004)	(-0.015,0.007)	(-0.018,-0.003)
Top measure	-0.067	-0.596*	-0.313
	(-0.322,0.187)	(-1.257,0.064)	(-1.280,0.655)
Time	0.053**	0.089*	-0.075
	(0.005,0.102)	(-0.014,0.193)	(-0.224,0.075)
TM effect over time	0.702***	0.546**	0.140
	(0.434,0.970)	(0.034,1.058)	(-1.705,1.985)
Observations	13,577	2,856	1,517
R^2	0.067	0.081	0.059
Adjusted R^2	0.067	0.079	0.056
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.14 Minimally adjusted model, walking, Rome

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.629	0.064	0.237**
	(-0.223,1.482)	(-0.069,0.197)	(0.053,0.421)
Age	-0.033*	0.006	-0.014***
	(-0.068,0.002)	(-0.001,0.013)	(-0.022,-0.006)
Top measure	-0.708	0.124	-0.400
	(-1.928,0.512)	(-0.192,0.439)	(-1.208,0.409)
Time	-0.220	0.167***	-0.141*
	(-0.600,0.160)	(0.100,0.233)	(-0.293,0.010)
TM effect over time	0.094	0.673***	0.818
	(-1.037,1.224)	(0.356,0.989)	(-0.360,1.996)
Observations	170	6,145	2,079
R^2	0.117	0.083	0.054
Adjusted R^2	0.090	0.082	0.052
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

Cycling

Table 5.D.15 Minimally adjusted model, cycling, Rome

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.238***	-0.270**	0.117
	(-0.323,-0.153)	(-0.484,-0.055)	(-0.115,0.349)
Age	0.002	0.0001	-0.0004
	(-0.001,0.006)	(-0.011,0.011)	(-0.009,0.008)
Top measure	-0.227*	0.344	-0.314
	(-0.478,0.024)	(-0.306,0.994)	(-1.342,0.714)
Time	0.021	-0.069	0.034
	(-0.023,0.064)	(-0.158,0.020)	(-0.100,0.167)
TM effect over time	-0.021	0.227	1.204
	(-0.259,0.217)	(-0.211,0.665)	(-0.401,2.809)
Observations	13,563	2,853	1,511
R^2	0.082	0.073	0.099
Adjusted R^2	0.081	0.072	0.096
Note:			*p<0.1; **p<0.05; ***p<0.01 *s-e* is socio-economic groups *FT* is full time employed *other* is part-time, student, retired.

Table 5.D.16 Minimally adjusted model, cycling, Rome

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.319	-0.324***	-0.208**
	(-1.270,0.632)	(-0.455,-0.194)	(-0.391,-0.025)
Age	-0.010	0.0004	0.003
	(-0.049,0.029)	(-0.006,0.007)	(-0.004,0.011)
Top measure	0.213	-0.361**	-0.389
	(-1.098,1.523)	(-0.662,-0.059)	(-1.174,0.397)
Time	0.076	0.075**	-0.047
	(-0.286,0.438)	(0.016,0.133)	(-0.187,0.093)
TM effect over time	-0.514	-0.160	-0.549
	(-1.592,0.564)	(-0.437,0.116)	(-1.645,0.547)
Observations	170	6,151	2,073
R^2	0.056	0.092	0.122
Adjusted R^2	0.027	0.092	0.120

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

E-biking

Table 5.D.17 Minimally adjusted model, e-biking, Rome

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.086***	-0.102**	0.051
	(-0.126,-0.046)	(-0.190,-0.013)	(-0.060,0.162)
Age	0.004***	0.004*	-0.005***
	(0.002,0.006)	(-0.0002,0.009)	(-0.009,-0.002)
Top measure	-0.138**	-0.283**	-0.167
	(-0.261,-0.014)	(-0.565,-0.002)	(-0.666,0.332)
Time	0.075***	0.073***	0.042
	(0.051,0.099)	(0.027,0.119)	(-0.029,0.114)
TM effect over time	0.358***	0.377***	0.370
	(0.227,0.488)	(0.147,0.606)	(-0.497,1.237)
Observations	13,584	2,855	1,518
R^2	0.009	0.026	0.0001
Adjusted R^2	0.009	0.024	-0.003
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.18 Minimally adjusted model, e-biking, Rome

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.158	-0.073**	0.054
	(-0.105,0.421)	(-0.133,-0.014)	(-0.044,0.151)
Age	-0.014**	0.004**	-0.007***
	(-0.025,-0.003)	(0.001,0.007)	(-0.011,-0.002)
Top measure	-0.314	-0.177**	0.108
	(-0.732,0.105)	(-0.319,-0.036)	(-0.314,0.529)
Time	0.099	0.104***	0.082**
	(-0.057,0.256)	(0.073,0.135)	(0.006,0.158)
TM effect over time	0.431*	0.373***	-0.233
	(-0.036,0.897)	(0.227,0.518)	(-0.828,0.361)
Observations	170	6,153	2,079
R^2	0.052	0.022	0.0004
Adjusted R^2	0.023	0.021	-0.002
Note:			*p<0.1; **p<0.05; ***p<0.01 *HI* is high income *FT* is full time employed *other* is part-time, student, retired

Driving

Table 5.D.19 Minimally adjusted model, driving, Rome

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.033	0.019	-0.160
	(-0.106,0.041)	(-0.182,0.221)	(-0.363,0.042)
Age	0.004**	-0.001	0.001
	(0.001,0.007)	(-0.012,0.009)	(-0.006,0.008)
Top measure	0.055	-0.125	-0.869*
	(-0.167,0.276)	(-0.744,0.495)	(-1.775,0.038)
Time	0.050**	0.021	0.027
	(0.009,0.092)	(-0.070,0.111)	(-0.100,0.155)
TM effect over time	-0.060	0.370	-1.063
	(-0.289,0.168)	(-0.076,0.816)	(-2.617,0.490)
Observations	13,585	2,856	1,515
R^2	0.142	0.101	0.182
Adjusted R^2	0.141	0.100	0.180

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.20 Minimally adjusted model, driving, Rome

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.004	-0.029	0.036
	(-0.863,0.856)	(-0.137,0.079)	(-0.128,0.201)
Age	-0.009	0.001	0.001
	(-0.045,0.026)	(-0.005,0.007)	(-0.006,0.008)
Top measure	-0.486	0.035	0.357
	(-1.668,0.697)	(-0.223,0.292)	(-0.361,1.075)
Time	-0.154	0.021	0.256***
	(-0.479,0.172)	(-0.035,0.078)	(0.125,0.387)
TM effect over time	1.463***	-0.129	-0.817
	(0.494,2.432)	(-0.397,0.139)	(-1.841,0.207)
Observations	170	6,154	2,080
R^2	0.197	0.153	0.226
Adjusted R^2	0.172	0.152	0.224

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

Public transit

Table 5.D.21 Minimally adjusted model, p. transit, Rome

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.078*	0.120	-0.135
	(-0.0002,0.155)	(-0.089,0.328)	(-0.331,0.060)
Age	-0.002	-0.006	-0.001
	(-0.005,0.002)	(-0.017,0.004)	(-0.008,0.005)
Top measure	-0.034	0.389	0.091
	(-0.273,0.205)	(-0.264,1.042)	(-0.802,0.985)
Time	-0.093***	0.065	-0.108
	(-0.140,-0.045)	(-0.037,0.168)	(-0.248,0.032)
TM effect over time	0.262**	-0.598**	0.241
	(0.002,0.522)	(-1.102,-0.093)	(-1.485,1.966)
Observations	13,588	2,856	1,517
R^2	0.133	0.096	0.191
Adjusted R^2	0.133	0.094	0.189

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.22 Minimally adjusted model, p. transit, Rome

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.551	0.062	0.004
	(-1.316,0.214)	(-0.066,0.190)	(-0.153,0.162)
Age	0.001	-0.004	0.002
	(-0.030,0.033)	(-0.011,0.003)	(-0.004,0.009)
Top measure	-0.280	-0.227	-0.275
	(-1.372,0.813)	(-0.532,0.079)	(-0.987,0.438)
Time	-0.254	-0.122***	-0.172**
	(-0.592,0.085)	(-0.188,-0.055)	(-0.312,-0.032)
TM effect over time	0.034	0.593***	-0.065
	(-0.973,1.042)	(0.278,0.908)	(-1.154,1.024)
Observations	170	6,155	2,082
R^2	0.228	0.127	0.188
Adjusted R^2	0.204	0.126	0.186

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

Motorcycling

Table 5.D.23 Minimally adjusted model, motorcycling, Rome

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.152***	-0.158	-0.043
	(-0.224,-0.079)	(-0.351,0.036)	(-0.218,0.131)
Age	0.003	0.013***	-0.002
	(-0.001,0.006)	(0.003,0.023)	(-0.008,0.004)
Top measure	-0.089	-0.484*	-0.469
	(-0.300,0.122)	(-1.061,0.093)	(-1.240,0.303)
Time	0.051***	0.061*	-0.002
	(0.017,0.084)	(-0.011,0.132)	(-0.097,0.093)
TM effect over time	0.295***	0.073	0.389
	(0.112,0.478)	(-0.277,0.422)	(-0.747,1.525)
Observations	13,585	2,857	1,518
R^2	0.023	0.027	0.019
Adjusted R^2	0.023	0.026	0.015
Note:			*p<0.1; **p<0.05; ***p<0.01 *s-e* is socio-economic groups *FT* is full time employed *other* is part-time, student, retired.

Table 5.D.24 Minimally adjusted model, motorcycling, Rome

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.271	-0.180***	0.024
	(-0.757,0.215)	(-0.295,-0.065)	(-0.129,0.177)
Age	-0.0003	-0.002	-0.007**
	(-0.020,0.020)	(-0.008,0.004)	(-0.014,-0.0004)
Top measure	-0.464	-0.117	-0.161
	(-1.108,0.181)	(-0.377,0.144)	(-0.801,0.479)
Time	0.121	0.104***	0.026
	(-0.026,0.268)	(0.059,0.150)	(-0.078,0.131)
TM effect over time	0.430*	0.392***	-0.287
	(-0.008,0.867)	(0.177,0.607)	(-1.117,0.542)
Observations	170	6,154	2,078
R^2	0.193	0.030	0.032
Adjusted R^2	0.169	0.030	0.030
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

5.D.3 Örebro

Walking

Table 5.D.25 Minimally adjusted model, walking, Örebro

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.019	-0.048	0.051
	(-0.104,0.067)	(-0.265,0.169)	(-0.184,0.285)
Age	0.005***	0.007	0.008***
	(0.002,0.008)	(-0.004,0.017)	(0.002,0.013)
Top measure	-0.004	-0.062	-0.630**
	(-0.113,0.105)	(-0.322,0.198)	(-1.196,-0.063)
Time	-0.038	-0.103	-0.275***
	(-0.095,0.019)	(-0.269,0.064)	(-0.412,-0.137)
TM effect over time	0.312***	0.472***	1.136***
	(0.204,0.419)	(0.206,0.737)	(0.532,1.740)
Observations	6,572	874	998
R^2	0.081	0.100	0.134
Adjusted R^2	0.080	0.095	0.129
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.26 Minimally adjusted model, walking, Örebro

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.102	-0.045	0.010
	(-0.196,0.399)	(-0.175,0.086)	(-0.201,0.221)
Age	-0.004	0.003	0.005
	(-0.018,0.010)	(-0.002,0.008)	(-0.001,0.012)
Top measure	0.130	-0.018	-0.090
	(-0.262,0.523)	(-0.167,0.131)	(-0.447,0.267)
Time	0.331^{**}	0.144^{***}	-0.085
	(0.052,0.611)	(0.049,0.238)	(-0.196,0.027)
TM effect over time	-0.309	0.142^{*}	-0.068
	(-0.707,0.090)	(-0.001,0.286)	(-0.450,0.314)
Observations	365	2,863	1,429
R^2	0.102	0.097	0.080
Adjusted R^2	0.090	0.096	0.076

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

Cycling

Table 5.D.27 Minimally adjusted model, cycling, Örebro

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.005	-0.062	0.012
	(-0.086,0.096)	(-0.342,0.218)	(-0.249,0.274)
Age	-0.002	0.0005	-0.001
	(-0.005,0.001)	(-0.013,0.014)	(-0.007,0.005)
Top measure	-0.011	-0.327**	0.181
	(-0.126,0.105)	(-0.650,-0.004)	(-0.425,0.786)
Time	-0.106***	-0.098	-0.172**
	(-0.167,-0.045)	(-0.279,0.083)	(-0.313,-0.032)
TM effect over time	0.581***	0.563***	0.156
	(0.467,0.694)	(0.277,0.849)	(-0.465,0.776)
Observations	6,569	871	997
R^2	0.134	0.105	0.143
Adjusted R^2	0.133	0.100	0.138

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.28 Minimally adjusted model, cycling, Örebro

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.428**	0.029	0.046
	(-0.760,-0.095)	(-0.108,0.167)	(-0.148,0.240)
Age	-0.006	0.001	-0.002
	(-0.021,0.009)	(-0.004,0.007)	(-0.008,0.004)
Top measure	0.153	-0.056	-0.112
	(-0.287,0.593)	(-0.216,0.103)	(-0.444,0.220)
Time	-0.175	-0.041	-0.144***
	(-0.490,0.139)	(-0.145,0.063)	(-0.251,-0.037)
TM effect over time	0.641***	0.602***	0.156
	(0.193,1.090)	(0.444,0.761)	(-0.208,0.521)
Observations	365	2,865	1,430
R^2	0.103	0.131	0.169
Adjusted R^2	0.091	0.130	0.166

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
HI is high income
FT is full time employed
other is part-time, student, retired

E-biking

Table 5.D.29 Minimally adjusted model, e-biking, Örebro

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.018	-0.076**	0.042
	(-0.062,0.026)	(-0.153,-0.0002)	(-0.076,0.161)
Age	0.002***	0.005***	0.004***
	(0.001,0.004)	(0.001,0.009)	(0.001,0.007)
Top measure	0.100***	-0.052	-0.174
	(0.045,0.155)	(-0.151,0.048)	(-0.449,0.102)
Time	0.078***	0.185***	0.008
	(0.050,0.107)	(0.113,0.258)	(-0.056,0.072)
TM effect over time	0.310***	0.202***	0.776***
	(0.256,0.364)	(0.085,0.318)	(0.491,1.060)
Observations	6,564	872	994
R^2	0.021	0.042	0.027
Adjusted R^2	0.020	0.036	0.023
Note:			*p<0.1; **p<0.05; ***p<0.01 *s-e* is socio-economic groups *FT* is full time employed *other* is part-time, student, retired.

Table 5.D.30 Minimally adjusted model, e-biking, Örebro

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.100	-0.011	-0.064
	(-0.226,0.026)	(-0.069,0.047)	(-0.181,0.052)
Age	0.005*	0.001	0.002
	(-0.001,0.011)	(-0.002,0.003)	(-0.002,0.006)
Top measure	0.051	-0.021	0.032
	(-0.132,0.234)	(-0.090,0.049)	(-0.157,0.222)
Time	-0.004	0.161***	-0.007
	(-0.147,0.139)	(0.113,0.209)	(-0.061,0.046)
TM effect over time	0.286***	0.236***	0.364***
	(0.079,0.492)	(0.163,0.308)	(0.178,0.551)
Observations	365	2,864	1,427
R^2	0.026	0.060	0.004
Adjusted R^2	0.012	0.059	0.001
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

Driving

Table 5.D.31 Minimally adjusted model, driving, Örebro

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.003	-0.020	0.161
	(-0.083,0.089)	(-0.275,0.235)	(-0.080,0.402)
Age	-0.005***	0.009	-0.010***
	(-0.008,-0.002)	(-0.003,0.021)	(-0.016,-0.005)
Top measure	0.029	-0.415***	-0.018
	(-0.078,0.136)	(-0.711,-0.119)	(-0.566,0.530)
Time	0.064**	0.121	0.079
	(0.010,0.118)	(-0.051,0.292)	(-0.046,0.203)
TM effect over time	0.038	0.257*	-0.020
	(-0.063,0.139)	(-0.015,0.528)	(-0.571,0.530)
Observations	6,572	875	993
R^2	0.147	0.098	0.233
Adjusted R^2	0.147	0.092	0.229
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.32 Minimally adjusted model, driving, Örebro

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.0001	0.032	0.122
	(-0.273,0.273)	(-0.090,0.153)	(-0.055,0.300)
Age	-0.002	-0.001	-0.003
	(-0.014,0.011)	(-0.007,0.004)	(-0.008,0.003)
Top measure	-0.254	0.023	-0.157
	(-0.610,0.102)	(-0.117,0.162)	(-0.457,0.144)
Time	-0.008	0.091^{**}	0.008
	(-0.257,0.241)	(0.001,0.181)	(-0.086,0.102)
TM effect over time	0.548^{***}	-0.081	0.316^{*}
	(0.193,0.902)	(-0.218,0.055)	(-0.007,0.640)
Observations	366	2,866	1,432
R^2	0.132	0.129	0.219
Adjusted R^2	0.120	0.128	0.216
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		
	HI is high income		
	FT is full time employed		
	other is part-time, student, retired		

Public transit

Table 5.D.33 Minimally adjusted model, p. transit, Örebro

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.053	-0.125	0.070
	(-0.041,0.148)	(-0.357,0.108)	(-0.182,0.323)
Age	-0.008***	-0.005	-0.008***
	(-0.011,-0.005)	(-0.016,0.006)	(-0.014,-0.003)
Top measure	-0.031	-0.033	0.168
	(-0.150,0.089)	(-0.312,0.246)	(-0.409,0.745)
Time	-0.083***	-0.160*	-0.058
	(-0.146,-0.020)	(-0.338,0.018)	(-0.189,0.074)
TM effect over time	-0.573***	-0.295**	-0.416
	(-0.691,-0.455)	(-0.580,-0.010)	(-0.998,0.166)
Observations	6,570	873	996
R^2	0.234	0.160	0.275
Adjusted R^2	0.234	0.156	0.272
Note:			*p<0.1; **p<0.05; ***p<0.01

s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.34 Minimally adjusted model, p. transit, Örebro

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.241	-0.001	0.253**
	(-0.055,0.536)	(-0.124,0.123)	(0.039,0.467)
Age	0.009	-0.007***	-0.009**
	(-0.005,0.022)	(-0.012,-0.002)	(-0.015,-0.002)
Top measure	0.229	0.086	-0.052
	(-0.184,0.641)	(-0.062,0.234)	(-0.419,0.315)
Time	0.279*	-0.216***	0.052
	(-0.033,0.591)	(-0.318,-0.113)	(-0.067,0.170)
TM effect over time	-0.923***	-0.487***	-0.813***
	(-1.372,-0.475)	(-0.642,-0.331)	(-1.217,-0.409)
Observations	366	2,865	1,429
R^2	0.202	0.210	0.277
Adjusted R^2	0.191	0.209	0.275
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

Motorcycling

Table 5.D.35 Minimally adjusted model, motorcycling, Örebro

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.128***	-0.085	-0.015
	(-0.178,-0.078)	(-0.241,0.070)	(-0.163,0.133)
Age	0.003***	0.011***	0.004**
	(0.002,0.005)	(0.004,0.019)	(0.0003,0.007)
Top measure	0.035	-0.030	-0.048
	(-0.027,0.097)	(-0.209,0.150)	(-0.383,0.286)
Time	0.043***	0.202***	-0.034
	(0.011,0.075)	(0.100,0.304)	(-0.108,0.041)
TM effect over time	0.325***	0.131	0.226
	(0.266,0.384)	(-0.031,0.292)	(-0.107,0.559)
Observations	6,561	873	993
R^2	0.021	0.044	0.008
Adjusted R^2	0.020	0.038	0.003
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.36 Minimally adjusted model, motorcycling, Örebro

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.333***	-0.111***	-0.198***
	(-0.515,-0.150)	(-0.171,-0.051)	(-0.303,-0.093)
Age	0.005	0.003**	0.001
	(-0.004,0.013)	(0.001,0.006)	(-0.002,0.004)
Top measure	0.075	-0.043	-0.167*
	(-0.160,0.311)	(-0.113,0.028)	(-0.346,0.011)
Time	-0.036	0.128***	-0.036
	(-0.199,0.126)	(0.081,0.175)	(-0.093,0.020)
TM effect over time	0.324***	0.277***	0.266***
	(0.093,0.555)	(0.205,0.349)	(0.072,0.460)
Observations	365	2,864	1,426
R^2	0.054	0.069	0.008
Adjusted R^2	0.041	0.067	0.005

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

5.D.4 Vienna

Walking

Table 5.D.37 Minimally adjusted model, walking, Vienna

	Dependent variable:		
	All s-e groups (1)	No degree + FT (2)	No degree + other (3)
Gender	0.068	0.135	0.166*
	(-0.019,0.155)	(-0.140,0.410)	(-0.031,0.363)
Age	0.001	0.019***	0.003
	(-0.002,0.004)	(0.006,0.031)	(-0.003,0.009)
Top measure	0.041	-0.194	-0.076
	(-0.180,0.261)	(-0.816,0.428)	(-0.571,0.419)
Time	0.175***	0.102*	0.149***
	(0.132,0.218)	(-0.008,0.212)	(0.044,0.255)
TM effect over time	0.769***	0.801***	1.006***
	(0.578,0.961)	(0.209,1.393)	(0.565,1.446)
Observations	14,731	1,902	2,858
R^2	0.053	0.061	0.062
Adjusted R^2	0.053	0.058	0.061

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.38 Minimally adjusted model, walking, Vienna

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.160	0.105	0.190**
	(-0.429,0.749)	(-0.052,0.263)	(0.041,0.340)
Age	-0.030**	0.009**	-0.010***
	(-0.054,-0.005)	(0.001,0.017)	(-0.016,-0.004)
Top measure	0.174	0.125	0.107
	(-1.230,1.579)	(-0.278,0.528)	(-0.226,0.440)
Time	0.317**	0.286***	0.071*
	(0.066,0.568)	(0.218,0.354)	(-0.007,0.149)
TM effect over time	1.181	0.512***	0.767***
	(-0.350,2.712)	(0.180,0.845)	(0.331,1.203)
Observations	464	4,993	4,445
R^2	0.078	0.069	0.054
Adjusted R^2	0.068	0.068	0.053

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

Cycling

Table 5.D.39 Minimally adjusted model, cycling, Vienna

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.161***	-0.227*	-0.042
	(-0.248,-0.073)	(-0.478,0.025)	(-0.235,0.152)
Age	-0.006***	-0.001	-0.009***
	(-0.009,-0.003)	(-0.013,0.010)	(-0.015,-0.003)
Top measure	-0.060	0.186	-0.061
	(-0.278,0.158)	(-0.393,0.764)	(-0.539,0.418)
Time	-0.087***	-0.091*	-0.064
	(-0.129,-0.046)	(-0.199,0.017)	(-0.161,0.033)
TM effect over time	-0.304***	-0.777***	-0.390*
	(-0.486,-0.121)	(-1.353,-0.202)	(-0.796,0.017)
Observations	14,725	1,901	2,857
R^2	0.085	0.063	0.124
Adjusted R^2	0.084	0.061	0.123
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.40 Minimally adjusted model, cycling, Vienna

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.391	-0.223^{***}	-0.096
	(-0.864,0.082)	(-0.386,-0.060)	(-0.248,0.056)
Age	0.006	0.001	-0.003
	(-0.013,0.026)	(-0.007,0.009)	(-0.009,0.003)
Top measure	-0.464	0.009	-0.134
	(-1.647,0.719)	(-0.407,0.425)	(-0.467,0.200)
Time	-0.328^{***}	-0.098^{***}	-0.085^{**}
	(-0.577,-0.079)	(-0.168,-0.029)	(-0.157,-0.013)
TM effect over time	-0.610	-0.321^{*}	-0.364^{*}
	(-2.114,0.895)	(-0.661,0.018)	(-0.771,0.042)
Observations	464	4,993	4,445
R^2	0.082	0.063	0.116
Adjusted R^2	0.072	0.062	0.115
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
			HI is high income
			FT is full time employed
			other is part-time, student, retired

E-biking

Table 5.D.41 Minimally adjusted model, e-biking, Vienna

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.033*	-0.050	-0.013
	(-0.068,0.002)	(-0.137,0.036)	(-0.086,0.060)
Age	0.001	0.008***	-0.0004
	(-0.0004,0.002)	(0.004,0.012)	(-0.003,0.002)
Top measure	-0.054	-0.201*	-0.101
	(-0.144,0.036)	(-0.418,0.016)	(-0.288,0.087)
Time	0.144***	0.174***	0.119***
	(0.125,0.163)	(0.126,0.222)	(0.076,0.162)
TM effect over time	0.257***	0.368***	0.317***
	(0.173,0.340)	(0.124,0.612)	(0.139,0.495)
Observations	14,727	1,902	2,859
R^2	0.016	0.044	0.014
Adjusted R^2	0.015	0.041	0.013
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.42 Minimally adjusted model, e-biking, Vienna

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.022	-0.026	0.087**
	(-0.165,0.120)	(-0.081,0.030)	(0.018,0.156)
Age	-0.003	0.006***	-0.002*
	(-0.009,0.003)	(0.004,0.009)	(-0.005,0.0004)
Top measure	-0.082	-0.176**	0.041
	(-0.462,0.298)	(-0.331,-0.022)	(-0.112,0.194)
Time	0.171***	0.149***	0.116***
	(0.081,0.261)	(0.121,0.178)	(0.081,0.151)
TM effect over time	0.286	0.374***	0.140
	(-0.252,0.825)	(0.234,0.513)	(-0.056,0.336)
Observations	462	4,990	4,443
R^2	0.030	0.043	0.009
Adjusted R^2	0.019	0.042	0.008

Note: *p<0.1; **p<0.05; ***p<0.01
HI is high income
FT is full time employed
other is part-time, student, retired

Driving

Table 5.D.43 Minimally adjusted model, driving, Vienna

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.094***	-0.090	-0.215***
	(-0.164,-0.024)	(-0.329,0.150)	(-0.371,-0.059)
Age	-0.002	-0.007	-0.007***
	(-0.005,0.001)	(-0.017,0.004)	(-0.011,-0.002)
Top measure	0.101	-0.021	-0.029
	(-0.079,0.281)	(-0.567,0.525)	(-0.428,0.370)
Time	-0.038**	0.020	-0.025
	(-0.076,-0.001)	(-0.079,0.119)	(-0.114,0.065)
TM effect over time	-0.455***	-0.230	-0.635***
	(-0.620,-0.289)	(-0.760,0.300)	(-1.010,-0.260)
Observations	14,721	1,902	2,856
R^2	0.147	0.114	0.173
Adjusted R^2	0.147	0.111	0.171

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.44 Minimally adjusted model, driving, Vienna

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.039	-0.020	-0.152**
	(-0.369,0.290)	(-0.134,0.095)	(-0.274,-0.030)
Age	-0.002	0.0003	0.003
	(-0.015,0.012)	(-0.005,0.006)	(-0.002,0.008)
Top measure	0.113	0.356**	-0.002
	(-0.765,0.990)	(0.038,0.674)	(-0.276,0.273)
Time	-0.075	-0.089***	-0.003
	(-0.283,0.133)	(-0.149,-0.029)	(-0.070,0.065)
TM effect over time	-0.744	-0.522***	-0.273
	(-1.990,0.501)	(-0.810,-0.233)	(-0.645,0.098)
Observations	464	4,990	4,442
R^2	0.150	0.146	0.215
Adjusted R^2	0.140	0.145	0.214
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

Public transit

Table 5.D.45 Minimally adjusted model, p. transit, Vienna

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	0.108***	0.176	0.066
	(0.030,0.187)	(-0.091,0.444)	(-0.114,0.246)
Age	0.001	0.009	0.002
	(-0.002,0.004)	(-0.003,0.021)	(-0.003,0.008)
Top measure	0.110	0.006	-0.091
	(-0.091,0.311)	(-0.597,0.610)	(-0.547,0.365)
Time	0.063***	0.016	0.061
	(0.022,0.104)	(-0.091,0.122)	(-0.039,0.160)
TM effect over time	0.634***	0.889***	1.012***
	(0.453,0.815)	(0.315,1.462)	(0.595,1.428)
Observations	14,733	1,902	2,860
R^2	0.094	0.091	0.113
Adjusted R^2	0.093	0.089	0.111

Note: *p<0.1; **p<0.05; ***p<0.01
s-e is socio-economic groups
FT is full time employed
other is part-time, student, retired.

Table 5.D.46 Minimally adjusted model, p. transit, Vienna

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	0.184	0.116	0.200***
	(-0.343,0.711)	(-0.032,0.263)	(0.068,0.331)
Age	-0.022**	0.001	-0.007***
	(-0.043,-0.0002)	(-0.006,0.009)	(-0.012,-0.002)
op measure	0.248	0.083	0.155
	(-1.037,1.533)	(-0.301,0.467)	(-0.142,0.452)
Time	0.111	0.087**	0.034
	(-0.140,0.363)	(0.020,0.153)	(-0.040,0.108)
TM effect over time	0.739	0.560***	0.583***
	(-0.789,2.268)	(0.235,0.884)	(0.176,0.991)
Observations	464	4,992	4,445
R^2	0.087	0.094	0.110
Adjusted R^2	0.077	0.093	0.109
Note:			*p<0.1; **p<0.05; ***p<0.01
			HI is high income
			FT is full time employed
			other is part-time, student, retired

Motorcycling

Table 5.D.47 Minimally adjusted model, motorcycling, Vienna

	Dependent variable:		
	All s-e groups	No degree + FT	No degree + other
	(1)	(2)	(3)
Gender	-0.125***	-0.187***	-0.092*
	(-0.167,-0.084)	(-0.300,-0.073)	(-0.190,0.005)
Age	0.001	0.009***	0.0003
	(-0.001,0.002)	(0.004,0.014)	(-0.003,0.003)
Top measure	0.025	-0.187	0.017
	(-0.080,0.129)	(-0.448,0.075)	(-0.228,0.262)
Time	0.119***	0.089***	0.095***
	(0.098,0.139)	(0.039,0.138)	(0.042,0.148)
TTM effect over time	0.217***	0.385***	0.263**
	(0.126,0.308)	(0.123,0.648)	(0.041,0.484)
Observations	14,723	1,901	2,859
R^2	0.022	0.057	0.016
Adjusted R^2	0.021	0.054	0.014
Note:			*p<0.1; **p<0.05; ***p<0.01
			s-e is socio-economic groups
			FT is full time employed
			other is part-time, student, retired.

Table 5.D.48 Minimally adjusted model, motorcycling, Vienna

	Dependent variable:		
	Degree + HI	Degree + FT	Degree + other
	(1)	(2)	(3)
Gender	-0.213*	-0.089**	0.012
	(-0.452,0.026)	(-0.158,-0.021)	(-0.058,0.082)
Age	0.0003	0.004**	-0.004***
	(-0.009,0.010)	(0.001,0.008)	(-0.007,-0.001)
Top measure	-0.278	0.168*	0.009
	(-0.879,0.323)	(-0.010,0.346)	(-0.147,0.165)
Time	0.089	0.152***	0.099***
	(-0.039,0.218)	(0.121,0.182)	(0.063,0.135)
TM effect over time	0.363	0.106	0.167
	(-0.413,1.140)	(-0.043,0.256)	(-0.034,0.367)
Observations	462	4,990	4,440
R^2	0.028	0.040	0.007
Adjusted R^2	0.017	0.039	0.006

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
HI is high income
FT is full time employed
other is part-time, student, retired

Appendix 5.E Long term effects, Vienna and Örebro

5.E.1 Örebro

Table 5.E.1 Long term influences Örebro

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Age	-0.202*	-0.011	-0.120**
	(-0.410,0.005)	(-0.237,0.216)	(-0.237,-0.002)
FU1	0.564***	-0.154	0.393***
	(0.256,0.872)	(-0.490,0.182)	(0.218,0.568)
FU2	2.002***	0.357	0.167
	(1.103,2.901)	(-0.624,1.338)	(-0.343,0.677)
Car sometimes	0.012	1.234*	-0.464
	(-1.131,1.155)	(-0.013,2.481)	(-1.109,0.181)
Car always	0.037	1.145*	-0.668**
	(-1.101,1.175)	(-0.096,2.387)	(-1.310,-0.026)
TM effect FU1	-0.061	0.645***	0.111
	(-0.388,0.266)	(0.288,1.002)	(-0.075,0.297)
TM effect FU2	0.105	0.452	0.430***
	(-0.432,0.642)	(-0.134,1.037)	(0.127,0.733)
Observations	783	783	779
R^2	0.111	0.039	0.118
Adjusted R^2	0.044	-0.033	0.051

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure
FU1 is the first, *FU2* the second follow-up

Table 5.E.2 Long term influences Örebro

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Age	0.053	0.391***	-0.195***
	(-0.134,0.240)	(0.182,0.600)	(-0.298,-0.092)
FU1	0.095	-0.808***	0.412***
	(-0.182,0.373)	(-1.119,-0.496)	(0.259,0.565)
FU2	0.380	-2.126***	0.118
	(-0.431,1.190)	(-3.033,-1.219)	(-0.328,0.564)
Car sometimes	-0.899*	0.037	0.058
	(-1.929,0.131)	(-1.111,1.185)	(-0.506,0.622)
Car always	-0.604	-0.238	0.052
	(-1.629,0.422)	(-1.380,0.905)	(-0.509,0.613)
TM effect FU1	0.125	-0.149	0.217***
	(-0.170,0.420)	(-0.478,0.181)	(0.055,0.380)
TM effect FU2	-0.208	0.227	0.183
	(-0.692,0.276)	(-0.312,0.767)	(-0.082,0.449)
Observations	781	781	779
R^2	0.035	0.059	0.273
Adjusted R^2	-0.038	-0.012	0.218

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure
FU1 is the first, *FU2* the second follow-up

5.E.2 Vienna

Table 5.E.3 Long term influences Vienna

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Age	-0.249***	0.074*	-0.096***
	(-0.334,-0.165)	(-0.010,0.158)	(-0.132,-0.059)
FU1	0.101**	-0.098**	0.085***
	(0.014,0.189)	(-0.186,-0.011)	(0.047,0.122)
FU2	1.710***	0.332*	-0.341***
	(1.365,2.054)	(-0.012,0.676)	(-0.488,-0.193)
Car sometimes	0.053	-0.277**	-0.004
	(-0.208,0.314)	(-0.538,-0.017)	(-0.115,0.108)
Car always	-0.166	-0.044	-0.146**
	(-0.474,0.143)	(-0.352,0.264)	(-0.277,-0.014)
TM effect FU1	0.577***	0.016	0.206***
	(0.321,0.833)	(-0.239,0.271)	(0.096,0.315)
TM effect FU2	0.315	-0.304	0.198*
	(-0.224,0.854)	(-0.842,0.233)	(-0.033,0.428)
Observations	5,305	5,305	5,301
R^2	0.050	0.025	0.143
Adjusted R^2	0.011	-0.014	0.108

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure
FU1 is the first, *FU2* the second follow-up

Table 5.E.4 Long term influences Vienna

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Age	0.113***	-0.106**	-0.070***
	(0.040,0.187)	(-0.187,-0.025)	(-0.105,-0.034)
FU1	-0.123***	0.078*	0.063***
	(-0.200,-0.047)	(-0.006,0.162)	(0.026,0.100)
FU2	-0.605***	1.103***	-0.567***
	(-0.905,-0.304)	(0.772,1.433)	(-0.713,-0.422)
Car sometimes	0.397***	-0.029	0.003
	(0.169,0.625)	(-0.279,0.222)	(-0.107,0.113)
Car always	0.744***	-0.462***	-0.094
	(0.475,1.012)	(-0.758,-0.166)	(-0.224,0.036)
TM effect FU1	-0.308***	0.262**	0.216***
	(-0.531,-0.085)	(0.017,0.508)	(0.108,0.324)
TM effect FU2	-0.105	-0.069	0.240**
	(-0.575,0.365)	(-0.586,0.447)	(0.013,0.467)
Observations	5,305	5,305	5,299
R^2	0.012	0.035	0.189
Adjusted R^2	-0.028	-0.005	0.155

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure
FU1 is the first, *FU2* the second follow-up

Appendix 5.F Family and dependants analysis

5.F.1 Antwerp

Table 5.F.1 Family, Antwerp

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Gender	-0.009	-0.069	0.041
	(-0.079,0.060)	(-0.159,0.021)	(-0.013,0.095)
Age	-0.00004	-0.008***	0.005***
	(-0.003,0.003)	(-0.012,-0.004)	(0.003,0.007)
Child un.6	-0.022	-0.073**	0.044**
	(-0.072,0.028)	(-0.138,-0.009)	(0.005,0.082)
Child 6-17	-0.033	0.025	0.009
	(-0.076,0.010)	(-0.030,0.080)	(-0.023,0.042)
Child un.6, TM over time	0.236***	0.051	-0.040
	(0.110,0.362)	(-0.102,0.204)	(-0.120,0.041)
Child 6-17, TM over time	0.083	0.041	0.004
	(-0.017,0.183)	(-0.079,0.161)	(-0.058,0.067)
Observations	14,586	14,592	14,587
R^2	0.134	0.073	0.028
Adjusted R^2	0.133	0.073	0.027

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure, *Child un.6* is child under the age of 6.

Table 5.F.2 Family, Antwerp

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Gender	-0.005	0.065**	-0.025*
	(-0.070,0.060)	(0.001,0.129)	(-0.053,0.002)
Age	-0.002	-0.003**	0.0005
	(-0.005,0.001)	(-0.006,-0.0004)	(-0.001,0.002)
Child un.6	0.059**	-0.020	-0.006
	(0.013,0.105)	(-0.066,0.027)	(-0.026,0.014)
Child 6-17	0.054***	-0.043**	0.006
	(0.015,0.094)	(-0.083,-0.003)	(-0.011,0.023)
Child un.6, TM over time	0.010	-0.038	-0.002
	(-0.099,0.120)	(-0.169,0.093)	(-0.061,0.057)
Child 6-17, TM over time	0.0004	-0.033	0.019
	(-0.085,0.086)	(-0.137,0.071)	(-0.028,0.066)
Observations	14,591	14,590	14,586
R^2	0.147	0.165	0.046
Adjusted R^2	0.146	0.164	0.045

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure, *Child un.6* is child under the age of 6.

5.F.2 Rome

Table 5.F.3 Family, Rome

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Gender	0.131***	-0.209***	-0.051**
	(0.040,0.222)	(-0.302,-0.117)	(-0.091,-0.010)
Age	0.002	0.004*	0.003***
	(-0.002,0.006)	(-0.001,0.008)	(0.002,0.005)
Child un.6	-0.047	-0.003	0.002
	(-0.130,0.035)	(-0.081,0.074)	(-0.036,0.040)
Child 6-17	-0.061	0.049	0.002
	(-0.146,0.025)	(-0.032,0.130)	(-0.037,0.041)
Child un.6, TM over time	-0.103	0.041	-0.189**
	(-0.503,0.297)	(-0.314,0.395)	(-0.377,-0.0002)
Child 6-17, TM over time	0.155	-0.220	-0.013
	(-0.219,0.529)	(-0.550,0.110)	(-0.190,0.164)
Observations	12,497	12,485	12,503
R^2	0.073	0.081	0.016
Adjusted R^2	0.072	0.080	0.015
Note:	*p<0.1; **p<0.05; ***p<0.01		

TM is top measure, *Child un.6* is child under the age of 6.

Table 5.F.4 Family, Rome

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Gender	0.010	0.085**	-0.106***
	(-0.070,0.090)	(0.001,0.170)	(-0.186,-0.026)
Age	0.004**	-0.001	0.004**
	(0.0003,0.007)	(-0.005,0.002)	(0.0002,0.007)
Child un.6	0.044	-0.016	-0.017
	(-0.027,0.115)	(-0.095,0.062)	(-0.081,0.046)
Child 6-17	0.095**	-0.089**	0.053
	(0.022,0.169)	(-0.170,-0.008)	(-0.015,0.120)
Child un.6, TM over time	0.001	-0.191	-0.392***
	(-0.340,0.341)	(-0.577,0.196)	(-0.668,-0.116)
Child 6-17, TM over time	0.041	-0.250	0.134
	(-0.277,0.359)	(-0.613,0.112)	(-0.122,0.390)
Observations	12,507	12,508	12,504
R^2	0.129	0.126	0.025
Adjusted R^2	0.128	0.125	0.024
Note:			*p<0.1; **p<0.05; ***p<0.01

TM is top measure, *Child un.6* is child under the age of 6.

5.F.3 Örebro

Table 5.F.5 Family, Örebro

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Gender	-0.024	0.014	-0.027
	(-0.118,0.070)	(-0.085,0.112)	(-0.070,0.016)
Age	0.005***	-0.002	0.002***
	(0.002,0.009)	(-0.005,0.001)	(0.001,0.004)
Child un.6	0.061	-0.055	-0.008
	(-0.042,0.164)	(-0.164,0.053)	(-0.057,0.041)
Child 6-17	-0.016	0.058	-0.004
	(-0.100,0.068)	(-0.031,0.146)	(-0.044,0.036)
Child un.6, TM over time	-0.185**	-0.091	-0.098**
	(-0.369,-0.002)	(-0.284,0.103)	(-0.188,-0.007)
Child 6-17, TM over time	0.072	-0.185**	-0.062*
	(-0.062,0.205)	(-0.326,-0.044)	(-0.129,0.004)
Observations	6,106	6,104	6,097
R^2	0.091	0.132	0.037
Adjusted R^2	0.089	0.130	0.035

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

TM is top measure, *Child un.6* is child under the age of 6.

Table 5.F.6 Family, Örebro

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Gender	0.035	0.070	-0.113***
	(-0.055,0.126)	(-0.020,0.160)	(-0.160,-0.065)
Age	-0.004**	-0.008***	0.003***
	(-0.007,-0.0005)	(-0.011,-0.005)	(0.001,0.005)
Child un.6	-0.023	0.031	-0.039
	(-0.121,0.075)	(-0.072,0.135)	(-0.092,0.015)
Child 6-17	0.016	-0.012	0.013
	(-0.064,0.096)	(-0.095,0.072)	(-0.030,0.057)
Child un.6, TM over time	0.024	0.016	-0.062
	(-0.147,0.195)	(-0.177,0.209)	(-0.159,0.035)
Child 6-17, TM over time	0.204***	0.172**	-0.026
	(0.080,0.328)	(0.030,0.313)	(-0.097,0.045)
Observations	6,107	6,104	6,096
R^2	0.146	0.202	0.036
Adjusted R^2	0.144	0.201	0.034

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure, *Child un.6* is child under the age of 6.

5.F.4 Vienna

Table 5.F.7 Family, Vienna

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Gender	0.105**	-0.181***	-0.023
	(0.014,0.196)	(-0.275,-0.088)	(-0.056,0.010)
Age	0.003	-0.005***	0.002***
	(-0.001,0.006)	(-0.009,-0.001)	(0.001,0.004)
Child un.6	-0.024	0.022	-0.041**
	(-0.124,0.075)	(-0.077,0.121)	(-0.080,-0.002)
Child 6-17	-0.069	0.070	-0.012
	(-0.159,0.021)	(-0.020,0.160)	(-0.047,0.023)
Child un.6, TM over time	0.010	-0.308*	0.140*
	(-0.337,0.357)	(-0.641,0.025)	(-0.007,0.286)
Child 6-17, TM over time	0.447	-0.492	0.044
	(-0.792,1.685)	(-1.690,0.707)	(-0.466,0.553)
Observations	14,077	14,073	14,075
R^2	0.066	0.071	0.030
Adjusted R^2	0.065	0.071	0.029

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

TM is top measure, *Child un.6* is child under the age of 6.

Table 5.F.8 Family, Vienna

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Gender	-0.073**	0.164***	-0.088***
	(-0.145,-0.002)	(0.080,0.248)	(-0.128,-0.049)
Age	-0.002	-0.001	0.001
	(-0.005,0.001)	(-0.004,0.002)	(-0.001,0.002)
Child un.6	0.017	-0.084*	-0.023
	(-0.064,0.098)	(-0.177,0.009)	(-0.067,0.022)
Child 6-17	0.025	-0.041	-0.012
	(-0.049,0.098)	(-0.125,0.043)	(-0.052,0.028)
Child un.6, TM over time	-0.027	-0.037	0.018
	(-0.323,0.270)	(-0.366,0.293)	(-0.142,0.178)
Child 6-17, TM over time	-0.832	0.864	0.021
	(-1.875,0.210)	(-0.305,2.033)	(-0.543,0.586)
Observations	14,069	14,078	14,071
R^2	0.119	0.092	0.030
Adjusted R^2	0.118	0.091	0.029

Note: *p<0.1; **p<0.05; ***p<0.01
TM is top measure, *Child un.6* is child under the age of 6.

Appendix 5.G Perceptions analysis

5.G.1 Control group

Table 5.G.1 Control group

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Gender	0.032	-0.182***	0.003
	(-0.142,0.205)	(-0.317,-0.048)	(-0.058,0.063)
Age	0.005	-0.005**	0.003**
	(-0.002,0.011)	(-0.010,-0.0003)	(0.001,0.005)
FU1 Own values	0.009	-0.032	-0.016
	(-0.082,0.100)	(-0.120,0.056)	(-0.055,0.023)
FU2 Own values	-0.195**	-0.022	-0.047
	(-0.362,-0.029)	(-0.181,0.136)	(-0.118,0.023)
FU1 It is common	-0.030	0.010	-0.002
	(-0.076,0.016)	(-0.035,0.055)	(-0.022,0.018)
FU2 It is common	-0.026	-0.030	0.029
	(-0.121,0.070)	(-0.121,0.062)	(-0.012,0.069)
FU1 Intent strong	-0.035	0.002	0.017
	(-0.122,0.052)	(-0.082,0.086)	(-0.021,0.054)
FU2 Intent strong	0.226***	0.444***	0.077**
	(0.070,0.382)	(0.295,0.593)	(0.010,0.143)
FU1 Moral resp.	-0.004	-0.009	0.004
	(-0.050,0.042)	(-0.054,0.035)	(-0.016,0.024)
FU2 Moral resp.	0.037	0.022	0.064***
	(-0.065,0.139)	(-0.076,0.119)	(0.021,0.108)
FU1 People imp.	-0.007	0.041*	-0.009
	(-0.056,0.041)	(-0.007,0.088)	(-0.030,0.012)
FU2 People imp.	0.096*	0.080*	-0.026
	(-0.003,0.195)	(-0.015,0.174)	(-0.069,0.016)
Observations	5,369	5,369	5,361
R^2	0.078	0.117	0.141
Adjusted R^2	0.075	0.114	0.138
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table 5.G.2 Control group

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Gender	-0.178**	0.190**	-0.082***
	(-0.314,-0.041)	(0.023,0.358)	(-0.141,-0.023)
Age	0.003	-0.008**	0.0004
	(-0.002,0.009)	(-0.014,-0.001)	(-0.002,0.003)
FU1 Own values	-0.039	0.082*	0.002
	(-0.118,0.039)	(-0.005,0.170)	(-0.036,0.040)
FU2 Own values	0.064	-0.061	-0.003
	(-0.079,0.207)	(-0.221,0.098)	(-0.071,0.065)
FU1 It is common	-0.011	-0.013	0.006
	(-0.051,0.029)	(-0.057,0.032)	(-0.014,0.025)
FU2 It is common	-0.043	-0.104**	-0.002
	(-0.125,0.039)	(-0.196,-0.012)	(-0.041,0.038)
FU1 Intent strong	0.032	-0.068	0.007
	(-0.043,0.108)	(-0.152,0.015)	(-0.030,0.043)
FU2 Intent strong	-0.042	-0.008	0.019
	(-0.176,0.092)	(-0.158,0.142)	(-0.045,0.083)
FU1 Moral resp.	0.051**	-0.022	-0.002
	(0.011,0.091)	(-0.066,0.022)	(-0.021,0.017)
FU2 Moral resp.	0.082*	0.016	-0.028
	(-0.006,0.170)	(-0.081,0.114)	(-0.070,0.014)
FU1 People imp.	-0.058***	0.027	-0.004
	(-0.100,-0.016)	(-0.020,0.073)	(-0.024,0.017)
FU2 People imp.	-0.116***	0.106**	-0.002
	(-0.202,-0.031)	(0.011,0.201)	(-0.043,0.039)
Observations	5,367	5,367	5,359
R^2	0.039	0.074	0.194
Adjusted R^2	0.035	0.070	0.191
Note:			*p<0.1; **p<0.05; ***p<0.01

5.G.2 Top measure affected group

Table 5.G.3 Top measure affected group

	Dependent variable:		
	Walking	Cycling	E-biking
	(1)	(2)	(3)
Gender	0.070	-0.169	0.223
	(-0.443,0.583)	(-0.705,0.368)	(-0.137,0.583)
Age	-0.004	0.018	0.008
	(-0.027,0.018)	(-0.005,0.042)	(-0.009,0.024)
FU1 Own values	0.078	-0.018	-0.124*
	(-0.173,0.329)	(-0.274,0.237)	(-0.260,0.012)
FU2 Own values	-0.017	0.141	-0.261**
	(-0.404,0.370)	(-0.256,0.538)	(-0.487,-0.035)
FU1 It is common	-0.117	0.041	0.075
	(-0.333,0.100)	(-0.179,0.261)	(-0.042,0.192)
FU2 It is common	0.100	-0.479***	0.342***
	(-0.225,0.424)	(-0.810,-0.147)	(0.157,0.526)
FU1 Intent strong	0.124	0.202*	0.114**
	(-0.078,0.327)	(-0.003,0.408)	(0.004,0.224)
FU2 Intent strong	0.164	0.146	0.493***
	(-0.163,0.491)	(-0.188,0.480)	(0.308,0.679)
FU1 Moral resp.	-0.122	0.010	0.041
	(-0.282,0.039)	(-0.153,0.173)	(-0.046,0.128)
FU2 Moral resp.	-0.035	0.293*	-0.102
	(-0.339,0.270)	(-0.019,0.604)	(-0.276,0.071)
FU1 People imp.	-0.035	0.010	0.021
	(-0.170,0.100)	(-0.127,0.147)	(-0.052,0.094)
FU2 People imp.	0.004	-0.121	0.062
	(-0.229,0.237)	(-0.359,0.117)	(-0.070,0.193)
Observations	505	505	505
R^2	0.146	0.163	0.229
Adjusted R^2	0.113	0.130	0.199
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.G.4 Top measure affected group

	Dependent variable:		
	Driving	P. Transit	Motorcycling
	(1)	(2)	(3)
Gender	0.091	-0.097	-0.139
	(-0.362,0.544)	(-0.446,0.252)	(-0.471,0.194)
Age	-0.001	-0.024^{***}	-0.005
	(-0.021,0.019)	(-0.039,-0.009)	(-0.019,0.010)
FU1 Own values	0.228^{*}	-0.099	-0.033
	(-0.014,0.469)	(-0.360,0.162)	(-0.180,0.114)
FU2 Own values	0.156	0.234	-0.095
	(-0.207,0.519)	(-0.121,0.590)	(-0.328,0.138)
FU1 It is common	0.152	-0.210^{*}	0.059
	(-0.057,0.360)	(-0.435,0.015)	(-0.068,0.186)
FU2 It is common	0.121	0.172	-0.012
	(-0.187,0.429)	(-0.145,0.489)	(-0.205,0.182)
FU1 Intent strong	-0.249^{**}	-0.010	0.043
	(-0.444,-0.055)	(-0.220,0.199)	(-0.076,0.161)
FU2 Intent strong	-0.137	-0.085	0.110
	(-0.447,0.172)	(-0.397,0.228)	(-0.085,0.305)
FU1 Moral resp.	0.053	-0.186^{**}	-0.005
	(-0.101,0.208)	(-0.352,-0.019)	(-0.098,0.089)
FU2 Moral resp.	-0.079	-0.381^{**}	-0.003
	(-0.367,0.210)	(-0.672,-0.090)	(-0.185,0.178)
FU1 People imp.	-0.050	-0.078	-0.006
	(-0.180,0.080)	(-0.218,0.063)	(-0.085,0.072)
FU2 People imp.	0.099	-0.190^{*}	0.043
	(-0.122,0.319)	(-0.416,0.036)	(-0.095,0.182)
Observations	505	505	505
R^2	0.069	0.108	0.231
Adjusted R^2	0.033	0.073	0.201

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

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Chapter 6

Healthy climate, healthy bodies: Optimal fuel taxation and physical activity

Chapter 6 focusses more closely on the potential of the policy domain and demand management, within the macro level of the socio-ecological framework. This chapter is co-authored with Linus Mattauch, Inge van den Bijgaart and David Klenert. Please note that in economics, paper authors are listed alphabetically, not by order of contribution. This paper was submitted to the *American Economic Review* on 30/10/2020. Co-authorship statements are available in Appendix C.

Healthy climate, healthy bodies: Optimal fuel taxation and physical activity

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Transport has significant externalities including carbon emissions and air pollution. Public health research has identified additional social gains from active travel, due to health benefits of physical exercise. Per mile, these benefits greatly exceed the external costs from car use. We introduce active travel into an optimal fuel taxation model and analytically characterise the optimal second-best fuel tax. We find that accounting for active travel benefits increases the optimal fuel tax by 49% in the US and 36% in the UK. Fuel taxes should be implemented jointly with other policies aimed at increasing the uptake of active travel.

Keywords: Transport Externalities; Congestion; Active travel; Fuel; Health Behaviour; Optimal Taxation

JEL Codes: H23, I12, Q53, Q54, Q58, R41, R48, Z28

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6.1 Introduction

Transport policies need to balance the economic gains from vehicle use with a large number of significant externalities, including air pollution, accidents, congestion, and climate change. For example, in the US and UK, the transport sector is now the largest contributor of greenhouse-gas emissions (Hockstad and Hanel, 2018; Gabbatiss, 2018). Increased active travel such as cycling and walking – even to the nearest public transport stop – can reduce these externalities, especially in urban areas. In addition, the physical exercise involved in active travel is beneficial for health, especially given high rates of inactivity and obesity in many populations. Previous scenario-based modelling in public health has indicated that these health benefits exceed the benefits from abating emissions and air pollution of private vehicles (Woodcock et al., 2009; De Hartog et al., 2010). For example, Woodcock et al. (2009) find that an increased active travel scenario would avoid 530 premature deaths per million population in London annually, while a lower-carbon-emission motor vehicles scenario would only save 17 through lower air pollution exposure.

Surprisingly, economists have yet to examine the significance of the health benefits from active travel for optimal regulation of urban transport. Many citizens are not aware of the full health benefits exercise provides (Fredriksson et al., 2018). For instance, the effectiveness of simple interventions such as reminders to go to the gym (Calzolari and Nardotto, 2017), initial payments (Charness and Gneezy, 2009), and evidence of overspending on gym contracts (DellaVigna and Malmendier, 2006) point to self-control problems and an underappreciation of the health benefits of exercise, especially before they materialise. Therefore, the health benefits of active travel make passenger transport an unexamined case of a "behavioural-environmental second-best problem" (Shogren and Taylor, 2008). It is, however, yet to be determined whether instruments such as fuel taxes are appropriate to reap these health benefits in addition to mitigating the externalities of car use.

In this article, we examine a novel economic effect by adding an active travel mode to a model of transport externalities from car use. Households respond to higher fuel taxes by buying more fuel-efficient cars and reducing car travel, and additionally shift to alternative models of travel that involve exercise, such as walking or cycling. However, they do not fully internalise that they get healthier by adopting such active modes of travel. We confirm that, on a per mile basis, the monetary value of the health benefits from active travel exceeds the social costs of unregulated externalities of carbon emissions, air pollution, congestion, and accidents by two orders of magnitude. Any first-best policy would thus involve a large subsidy to promote active travel. In the absence of such subsidies, we derive the optimal second-best fuel tax that corrects for the externalities and the unrealised health benefits. We examine the difference for the tax rule and quantify the appropriate tax rate both including, and excluding health benefits from active travel.

We find that the optimal tax increases by 49% in the US and 36% in the UK when health benefits from physical exercise are included. The second-best optimal fuel tax for the US is \$10.13/gal, and \$6.81/gal without physical inactivity costs, while the current rate in the US is \$0.55/gal (API, 2020). The optimal fuel tax for the UK is \$4.54/gal, which is somewhat higher than the current rate of \$4.06/gal (RAC, 2020). Without physical activity costs, the optimal second-best tax would be \$3.35/gal.

Previous work established that the external costs of transport are not fully reflected in fuel price; fuel taxes are inefficiently low in most European countries (Santos, 2017) and the US (Bento et al., 2009).[1] Accounting for the physical health benefits from active travel thus further increases the gap between actual and optimal fuel taxes. Our sensitivity analysis shows that the optimal second-best tax varies significantly within the range of realistic parameter values, from \$6/gal to \$13/gal for the US, and from \$3.75/gal to \$7/gal for the UK. Hence, neither the UK nor the US current fuel taxes likely exceed the optimal rate.

[1] An exception is Parry and Small (2005), who claim that UK fuel taxes are too high.

On a per mile basis, physical inactivity represents the largest social cost of motorised private transport. Nevertheless, the "active travel adjustment" of the optimal fuel tax is comparatively small. This is explained by the fact that a fuel tax is a fairly inefficient instrument to address these high costs because the uptake of active travel is not highly responsive to fuel price. A greater responsiveness of active travel to fuel taxation would increase the optimal tax adjustment. The broader insight from our article is therefore that, when it is acknowledged that individuals' health decisions are not always welfare-maximising, pricing car use should be complemented with infrastructure re-development. This mirrors results from urban planning and transportation research (Banister, 2008; Buehler et al., 2017).

This manuscript builds on three distinct strands of literature: First, a large body of literature studies optimal levels of fuel taxes, and which externalities should be addressed by them (van Essen et al., 2019). In addition to generating government revenue, fuel taxes are typically used for the purpose of reducing most forms of non-priced costs of transport, e.g. the externalities of carbon dioxide and particulate matter, or reducing congestion by raising the cost of driving. Parry and Small (2005) derive the optimal gasoline taxes for the US and Britain, accounting for congestion, accidents, carbon emissions and air pollution, and Antón-Sarabia and Hernández-Trillo (2014) apply this framework to Mexico. Sterner (2012) compares the optimality of fuel taxes in Europe and US, concluding that fuel taxes vary considerably between countries. In 2017, the fuel tax raised on a gallon of unleaded gasoline in the US was \$0.55, and \$3.75 in the UK (API, 2020; RAC, 2020).[2] Yet, the optimal fuel tax literature has so far not considered the health benefits from active travel.

Second, the field of public health, starting with Woodcock et al. (2009), has identified high social benefits from active travel over and above the benefits from abating emissions and air pollution of private vehicles (De Hartog et al., 2010; Wolkinger et al., 2018). To the majority of the population, increasing physical activity outweighs the negative impacts of

[2] For the UK, this is the sum of the fuel and the excise taxes. For the US this is the average over the different federal and state taxes.

increased exposure to air pollution (Tainio et al., 2016). This is due to the overwhelmingly sedentary lifestyles that people in both the UK and US lead, making physical inactivity a leading risk factor for 6 of the 10 largest causes of death worldwide (WHO, 2018). Most UK adults do not exercise regularly (37% never, 16% less than once a week, 57% admit they never do activity strenuous enough to be out of breath, Commission (2018)). This leads to significant costs including higher rates of disease incidence, lower quality of life, loss of income, excess healthcare costs, and productivity losses in the workplace. We build on the valuation methods in public health to quantify the welfare cost of travel that is inactive.

Third, behavioural public economics research has elaborated on the important role of "internalities" in various domains of public policy (Allcott and Sunstein, 2015). An "internality" occurs when an individual imposes a significant cost on herself due to behavioural failures. As these private costs are imposed only or mainly on oneself – which is true for lack of physical activity –, they fall outside the definition of an externality. Nonetheless, governments regulate internalities, in cases where scientific evidence substantiates it. Internality taxes have been applied to the market for smoking (Gruber and Kőszegi, 2004), gym memberships and exercise (in the form of subsidies, DellaVigna and Malmendier, 2006), sugary drinks (Allcott et al., 2019a; Allcott et al., 2019b) and the energy and automobile market (Allcott and Wozny, 2014; Allcott and Sunstein, 2015), where they also interact with environmental externalities. In the latter case, the interaction leads to a behavioural-environmental second-best problem (Shogren and Taylor, 2008). Chetty (2015), Bhargava and Loewenstein (2015), Allcott and Sunstein (2015), and Allcott et al. (2019b) all provide more extensive discussions of why regulating internalities is desirable, arguing that the complexity of choices people face, and large internal costs in e.g. health and energy efficiency, warrant the greater use of behavioural economics in regulation. Sin taxes, surcharges on prices of goods of which people consume too much because of internalities, have been modelled as either simple extensions of a Pigouvian tax (O'Donoghue and Rabin, 2006), or as complex interactions between taxes and individuals' heuristics and decisions, to achieve an optimal outcome in second-best settings (Allcott et al., 2014).

However, this body of literature has not considered the internality of physical inactivity in urban transport. Walking, cycling, and switching to public transport are considered ways in which people can achieve "appropriate" levels of physical activity as prescribed by public health guidelines (Gibson-Moore, 2019; US, 2015). Physical activity has been referred to as a "miracle cure" (Davies et al., 2019) in the UK Chief Medical Officers' 2019 Physical Activity Guidelines. Meeting the minimum recommendations of 150 minutes of moderate-intensity physical activity per week can reduce the risk of cognitive impairment and dementia, depression, hypertension, type 2 diabetes and cardiovascular disease, as well as increase bone mineral density (Davies et al., 2019). People generally under-value the contribution of physical exercise to their long-term health (Zamir and Teichman, 2014). There are two behavioural biases behind this under-valuation, which lead to insufficient levels of exercise and further health impacts: imperfect information and insufficient self-control (Allcott et al., 2019b). This reinforces the case for building active travel into commuting routines.

Our contribution to the literature is threefold: First, we introduce a physical activity-related health internality into an established framework of transport decisions (Parry and Small, 2005), and use this behavioural-environmental framework to provide an analytical solution for the optimal second-best fuel tax. Second, we provide an updated quantification of the external costs of travel provided by Parry and Small (2005), considering recent research and global climate policy goals, and complement this with a quantification of the health benefits of active travel. For example, updating the carbon price estimates increases the contribution of fuel pollution to the optimal fuel tax by an order of magnitude. Third, in terms of policy implications, we contribute to evaluating the potential use of a fuel tax as opposed to other policies. We confirm that raising the propensity of consumers to switch to active travel modes can greatly impact the appropriate fuel tax: the demand for vehicle miles travelled (VMT) is so inelastic that increasing appropriate elasticities to their upper bound found in the literature raises the fuel tax by up to 62% for the UK and 155% for the US.[3]

Fuel taxes have some distinct advantages over more specific transport policies such as congestion charges or emission zones. First, they can be implemented with relatively small administrative costs compared to other policies, since most countries already have fuel taxes in place and levels would only have to be adjusted accordingly. Second, fuel taxes have a proven track record of reducing carbon emissions (Bento et al., 2009; Bretschger and Grieg, 2020; OECD, 2019; Sterner, 2012). Third, they generate government revenue, which could be used either for green spending, for instance on low-carbon transport infrastructure, or for compensating households that are especially affected by the tax (Bento et al., 2009). Both measures could make the public more supportive of fuel taxation (Klenert et al., 2018).

The remainder of the paper is organised as follows. Section 6.2 describes the model, and our analytical result for the optimal fuel tax. Section 6.3 explains our choice of parametrisation. Section 6.4 presents the quantitative results and Section 6.5 discusses the policy implications. Section 6.6 concludes.

6.2 Analytical Framework

6.2.1 Model

To explore how the fuel tax might be optimally adjusted to account for health benefits of public transport, we extend Parry and Small (2005) to account for active travel decisions and associated health benefits. We take advantage of the fact that in certain settings, internalities can be treated as extensions of externalities (O'Donoghue and Rabin, 2006).

[3]It may be argued that, especially in the US case, realising such an increase is politically unrealistic in the foreseeable future. Still, our result indicates that current fuel tax rates are further below their preferred levels than previously thought, which, as we discuss in Subsection 6.4.2, implies fuel tax increases have greater benefits.

We consider a representative agent with the utility function

$$U = u(\psi(C, M, T^{in}, T^{ac}, G), N) - \varphi(P) - \delta(A) + \xi(Q), \tag{6.1}$$

where C is the quantity of numeraire consumption, M total distance travelled, T^{in} and T^{ac} is total time travelled using active and inactive modes respectively, G exogenous government spending, and N leisure, with $U_C, U_M, U_G, U_N > 0$, and $U_{T^{in}}$ and $U_{T^{ac}} < 0$, with the subscript denoting a partial derivative. The level of pollution is denoted by P, A captures accidents, and health is denoted by Q. As Parry and Small (2005), we assume $u(\cdot)$ and $\psi(\cdot)$ are quasi-concave, and $\varphi(\cdot)$ and $\delta(\cdot)$ are convex. The functions $\varphi(\cdot)$ and $\delta(\cdot)$ capture the dis-utility from pollution and accidents, respectively. We add the concave function $\xi(\cdot)$, which captures the positive utility from health Q.[4]

Total travel M can be separated into two components, inactive travel M^{in} and active travel M^{ac}.

$$M = M^{in} + M^{ac}. \tag{6.2}$$

Inactive travel denotes travel using modes that require very little physical activity, most importantly using the car. Active travel instead captures walking and cycling. We also consider public transport as an active mode of travel, as it typically requires the individual to walk or bike to the bus stop, tram stop, or train station, in some cases providing up to 30% of daily exercise recommendations (Besser and Dannenberg, 2005). As such, active travel requires spending S, which will be further specified below. Inactive travel distance M^{in} requires fuel F and other travel inputs H: $M^{in} = \chi(F, H)$. In line with Parry and Small (2005), we assume that M^{in} is homogeneous of degree one with respect to its inputs. This specification allows for multiple channels of substitution. For instance, as fuel prices increase, the consumer can decide to i) reduce total distance travelled, M, ii) spend more on other

[4]Equation (6.1) models the utility from health and leisure as separable. As a consequence, any improvement in health will leave the labour-leisure trade-off unaffected.

inactive travel inputs, H, such as purchasing a vehicle with higher fuel economy, or iii) increase active travel distance, M^{ac}.

The agent spends time T^{in} in inactive travel. For a given distance M^{in}, this time is increasing in the amount of congestion on roads, which we take as an increasing function of the population average inactive miles travelled, $\bar{M}^{in}$:

$$T^{in} = \pi^{in}(\bar{M}^{in})M^{in}, \tag{6.3}$$

where $\pi^{in}_{\bar{M}^{in}} > 0$. π^{in} is equal to the inverse of speed of inactive travel, which we assume the agent takes as exogenous. In equilibrium, $\bar{M}^{in} = M^{in}$. For active travel we abstract from congestion,[5] and model time travelled as directly proportional to distance:

$$T^{ac} = \pi^{ac}M^{ac}, \tag{6.4}$$

with π^{ac} the inverse of speed from active mobility. Only inactive travel contributes to pollution, both in the form of carbon dioxide emissions, and local air pollution. CO_2 emissions are directly proportional to fuel use. To capture local air pollution effects, inactive miles travelled offer a better proxy (Hitchcock et al., 2014).[6] This allows us to write

$$P = P^f(\bar{F}) + P^m(\bar{M}^{in}), \tag{6.5}$$

with $P^f_{\bar{F}} > 0$ and $P^m_{\bar{M}^{in}} > 0$. We also assume the agent will take pollution as given; she will not internalise the effect of travel decisions on the population averages $\bar{F}$ and $\bar{M}^{in}$.

Both active and inactive travel are subject to accident risk. We separate accident costs associated to active and inactive travel. For inactive travel, accident costs are increasing with

[5] Even though public transport can get congested, this does not typically increase travel time. Bicycle paths do not generally get congested to the extent that travel time increases.

[6] Substantial emissions of particulate matter from transport are due to tyre, brake, and road abrasion, rather than fuel consumption. Fuel emissions contribute mostly to noxious gas emissions such as NO_x and ozone.

the amount of travel. As travel increases, the agent also imposes an "accident externality" upon other users: the higher average travel, $\bar{M}^{in}$, the more likely a road user will be involved in an accident. For active travel, we similarly assume that higher travel increases the number of, and thereby costs of, accidents. Yet, roads that are busier with cars tend to be more dangerous to both cyclists and pedestrians. Conversely, there exists a so-called "safety in numbers" effect: more cyclists on the road tend to make cycling safer overall (Elvik and Bjørnskau (2017), Kahlmeier et al. (2017)). Hence, we assume that the accident costs associated with active travel are increasing in the average amount of inactive travel, $\bar{M}^{in}$, and decreasing in average active travel, $\bar{M}^{ac}$. This gives

$$A = A^{in}(M^{in}, \bar{M}^{in}) + A^{ac}(M^{ac}, \bar{M}^{in}, \bar{M}^{ac}), \tag{6.6}$$

with $A^{in}_{M^{in}} > 0$ and $A^{in}_{\bar{M}^{in}} > 0$. Likewise, $A^{ac}_{M^{ac}} > 0$, and $A^{ac}_{\bar{M}^{in}} > 0$, while $A^{ac}_{\bar{M}^{ac}} < 0$.

We assume active travel is conducive to health. To capture this we write health as a function of active travel:

$$Q = Q(M^{ac}, O), \tag{6.7}$$

where O are other forms of exercise,[7] with $Q_{M^{ac}} > 0$ and $Q_O > 0$. We assume that the agent considers only a constant share $\omega \in [0,1]$ of Q as relevant in her optimisation problem. Instead of considering actual health Q, she considers "perceived health", Q^{per}:

$$Q^{per} = \omega Q + \tilde{Q}, \tag{6.8}$$

where the agent considers $\tilde{Q}$ as outside of her control, while in reality, $\tilde{Q} = (1-\omega)Q$. Whenever $\omega < 1$, Equation (6.8) represents the notion that the individual underestimates the

[7] Note that any adverse effect of pollution on health is already subsumed in $\varphi(P)$.

effect of exercise on health. This underestimation is consistent with substantive evidence that individuals do not fully appreciate the positive effects of activity-related health.[8]

With Equation (6.8) we adopt a specification of limited attention proposed by DellaVigna (2009), which assumes that the benefit of completing travel (in active mode) is "visible", while the health benefit from active travel is "opaque". This seems justified as many citizens are largely unaware of the high health benefits of even short walks (Fredriksson et al., 2018; Bennett et al., 2009). Alternatively, the unrealised health benefits from active travel could represent a case of time-inconsistent preferences (Laibson, 1997; O'Donoghue and Rabin, 1999), where citizens highly value their health, but repeatedly postpone undertaking exercise (DellaVigna and Malmendier, 2006). This can be captured by an equivalent formulation of Equation (6.8) in our static model, as the assumption of time-inconsistent preferences implies an activity level less than desirable in the long term is pursued at any point in time. This holds in the absence of commitment devices, which arguably do not exist for active travel.

The agent's budget constraint is given by

$$C+(p^f+t^f)F+p^hH+p^oO+S=w\left(1-t^l\right)L, \tag{6.9}$$

where p^f+t^f is the consumer price of fuel, p^h is the price of other inactive travel inputs, and p^o is the price of other forms of exercise. In addition, active travel requires the consumer to spend on items such as a bicycle or public transport. We denote by S any such spending on active travel (with normalised price), with $S=S(M^{ac})$, $S(0)=0$ and $S_{M^{ac}}>0$. Finally, we denote the gross wage rate by w, and the labour tax rate by t^l. The total amount of time available is given by $\bar{L}$, which is allocated to labour L, leisure, N, and time spent travelling T^{in} and T^{ac}, such that

$$L+N+T^{in}+T^{ac}=\bar{L}. \tag{6.10}$$

[8]Additionally, publicly financed healthcare systems and moral hazard in health insurance imply that individuals may not bear the full cost of unhealthy decisions.

In the remainder of this paper, we assume that all prices are exogenous and constant. The fuel tax t^f, will be set by the policymaker. The proceeds of the fuel tax will be used to fund government spending G. The labour tax will in turn be set such that the government budget constraint is binding:

$$G = t^f F + t^l wL. \tag{6.11}$$

Throughout, we assume that there exists a unique and interior equilibrium, where the consumer chooses strictly positive levels of C, F, H, M^{ac}, O and L, and that G is such that $t^l > 0$.

6.2.2 Second-Best Fuel Tax

In the above setup, an increase in fuel use is associated with carbon emissions. Additionally, higher fuel use increases the number of miles travelled, which increases local pollution, as well as congestion, and accident risk. All these effects are not internalised by the representative consumer, who takes these factors as given. On their own, these externalities already justify the introduction of a positive "externality tax" on fuel. Such a tax will be welfare-improving, as it forces the agent to internalise (part of) the externality. In addition to the externalities, our framework also features an "internality": whenever $\omega < 1$, the agent underestimates the extent to which higher levels of active travel deliver positive health benefits. Consequently, the choices of M^{ac} and O, and resulting Q, may be suboptimally low.

Our aim is to quantify how the consideration of these health benefits of active travel affects the welfare-maximising (optimal) fuel tax. For this purpose, we derive the solution for the optimal fuel tax, t^{f*}, and calibrate its value. We present the full derivation of t^{f*} in

Appendix 6.A, where we obtain the following result:

$$t^{f*} = Z^{P_{\bar{F}}} + \left[Z^{P_{\bar{M}^{in}}} + Z^{C} + Z^{A_{\bar{M}^{in}}}\right]\left(\frac{-dM^{in}}{dt^{f}} / \frac{-dF}{dt^{f}}\right) + Z^{A_{\bar{M}^{ac}}}\left(\frac{-dM^{ac}}{dt^{f}} / \frac{-dF}{dt^{f}}\right)$$
$$- (1-\omega)\tilde{Z}^{Q}\left(\frac{-dQ}{dt^{f}} / \frac{-dF}{dt^{f}}\right) - wt^{l}\left(\frac{-dL}{dt^{f}} / \frac{-dF}{dt^{f}}\right). \quad (6.12)$$

Here we define

$$Z^{P_{\bar{F}}} \equiv \frac{\varphi_P}{\mu_I} P^{f}_{\bar{F}};\ Z^{P_{\bar{M}^{in}}} \equiv \frac{\varphi_P}{\mu_I} P^{m}_{\bar{M}^{in}};\ Z^{C} \equiv \Gamma^{in} \pi^{in}_{\bar{M}^{in}} M^{in},$$

and

$$Z^{A_{\bar{M}^{in}}} \equiv \frac{\delta_A}{\mu_I}\left[A^{in}_{\bar{M}^{in}} + A^{ac}_{\bar{M}^{in}}\right];\ Z^{A_{\bar{M}^{ac}}} \equiv \frac{\delta_A}{\mu_I} A^{ac}_{\bar{M}^{ac}};\ \tilde{Z}^{Q} \equiv \frac{\xi_Q}{\mu_I},$$

with $\Gamma^{in} \equiv w\left(1-t^{l}\right) - \frac{\psi_{T^{in}}}{\psi_C}$.

Equation (6.12) characterises the optimal fuel tax. This tax is equal to the sum of uninternalised costs associated with fuel use. The first term in (6.12), $Z^{P_{\bar{F}}}$, is the direct pollution externality of fuel use. It is equal to the marginal cost of pollution, φ_P, multiplied by the effect of additional fuel use on pollution, $P^{f}_{\bar{F}}$, and converted to consumption units using the shadow value of income, μ_I.

Next, higher fuel use is associated with more inactive miles travelled. The marginal externality cost of inactive miles travelled is captured by $Z^{P_{\bar{M}^{in}}} + Z^{C} + Z^{A_{\bar{M}^{in}}}$, the cost associated with increased air pollution, congestion, and accidents, respectively.[9] The contribution of these costs to the magnitude of the optimal fuel tax depends on the extent to which fuel taxes reduce miles travelled vis-à-vis fuel use. If the reduction in fuel use due to higher fuel taxes is associated with a small reduction in miles travelled (small $\left(\frac{-dM^{in}}{dt^{f}} / \frac{-dF}{dt^{f}}\right)$), then only a small portion of the externality costs associated with miles travelled can (implicitly) be attributed to fuel use.

[9]The term Γ^{in} in Z^{C} captures the notion that congestion is costly for two reasons: it creates a direct disutility (see (6.1)) and reduces time available to allocate to labour (see (6.10)).

Likewise, fuel taxes may lead to changes in active travel distance, which is associated with accident externalities, with cost $Z^{A_{\bar{M}^{ac}}}$. The contribution of those costs to the optimal fuel tax then depends on the relative response of active travel to fuel taxes: $\left(\frac{-d\bar{M}^{ac}}{dt^f} / \frac{-dF}{dt^f}\right)$.

Our main effect of interest is $(1-\omega)\tilde{Z}^Q\left(\frac{dQ}{dt^f} / \frac{-dF}{dt^f}\right)$: the adjustment of the optimal fuel tax to the health internality. $\tilde{Z}^Q$ is the marginal value of additional health, with $1-\omega$ the un-internalised portion, see Sections 6.3.1 and 6.3.1. As can be seen from (6.12), a high value of $\tilde{Z}^Q$ does not automatically imply that, once health internalities are accounted for, the optimal fuel tax is adjusted much; this is only the case if the fuel tax is an effective tool to increase health Q. Following (6.7), fuel taxes can affect health through two channels: by changing active travel M^{ac}, or through other forms of exercise O. In the remainder of this article, and consistent with the empirical literature (Martin et al., 2012), we will assume that the effect of fuel taxes on other forms of exercise O is negligible. This implies we set $dO/dt_f = 0$, and focus on changes in active travel as the primary channel through which fuel taxation affects health.

The interpretation of the final remaining term is similar. Fuel taxes may also affect labour supply. Even though the agent takes into account that higher labour supply increases income, she does not internalise the positive effect of increased labour on the government budget. This effect is equal to the wage, multiplied by the labour tax rate, wt^l. The contribution of this effect to the optimal fuel tax is larger the larger the increase in labour supply in response to higher fuel taxes.

In the next section we quantify the optimal t^f and the effect of considering the health benefits of active travel thereon. To facilitate this quantification, we further manipulate

Equation (6.12) to

$$t^{f*} = \frac{MEC}{1+MEB} + \frac{t^l\left(p^f+t^f\right)}{1-t^l}\frac{\varepsilon^c_{LL}\left(1-\eta^{M^{in}I}\right)}{-\eta^{FF}} + \frac{t^l}{1-t^l}\left[\varepsilon_{LL}-\varepsilon^c_{LL}\left(1-\eta^{M^{in}I}\right)\right]Z^C\beta^{M^{in}}\frac{M^{in}}{F}, \quad (6.13)$$

with ε^c_{LL} and ε_{LL} the compensated and uncompensated labour supply elasticity. Akin to Parry and Small (2005), this optimal tax is separated in three components. The first component is the "adjusted Pigouvian tax," equal to the marginal external cost associated to fuel use, corrected by the marginal excess burden of labour taxation. The marginal external cost of fuel use is given by

$$MEC \equiv Z^{P_{\bar{F}}} + \left[Z^C + Z^{A_{\bar{M}^{in}}} + Z^{P_{\bar{M}^{in}}}\right]\beta^{M^{in}}\frac{M^{in}}{F} + \left[Z^{A_{\bar{M}^{ac}}} - (1-\omega)Z^Q\right]\beta^{M^{ac}}\frac{M^{ac}}{F}, \quad (6.14)$$

with $Z^Q \equiv \frac{\xi_Q}{\mu_I}Q_{M^{ac}}$ the marginal value of active travel through induced changes in health. We use the following ratios of fuel and income price elasticities to capture the indirect benefits of fuel taxes through inactive and active distance travelled and health[10]:

$$\beta^{M^{in}} \equiv \frac{\eta^{M^{in}F}}{\eta^{FF}};\ \beta^{M^{ac}} \equiv \frac{\eta^{M^{ac}F}}{\eta^{FF}}, \quad (6.15)$$

with η^{XF} the fuel price elasticity of $X \in \left\{F, M^{in}, M^{ac}\right\}$, and $\eta^{M^{in}I}$ the income elasticity of inactive travel. The marginal excess burden MEB is commonly defined as

$$MEB \equiv \frac{\frac{t^l}{1-t^l}\varepsilon_{LL}}{1-\frac{t^l}{1-t^l}\varepsilon_{LL}}. \quad (6.16)$$

[10]The β's are equal to the response of miles travelled to fuel taxes relative to the response in fuel taxes. As such, they capture the relative effectiveness of fuel taxes in inducing changes in miles travelled, both active and inactive.

The second component is the "Ramsey tax": fuel taxes raise revenues, which are used to finance government spending. This component commands a positive tax on fuel even in the absence of external costs. The third component is the "congestion feedback": a reduction in travel due to fuel taxation reducing congestion, freeing up time for labour. This creates a positive welfare effect as long as labour is taxed at a positive rate ($t^l > 0$), and as such increases the optimal fuel tax.

6.3 Fuel tax components

In this section we explain how we choose the parameter values for the quantification of the optimal fuel tax. We specify a central value and a plausible range. Table 6.3.1 summarises the main parameter values, and Figure 6.3.1 provides a graphical representation of the costs Z. For comparability, where relevant, we adjust all values to year 2017 US dollar prices and US gallons. Finally, we state the implications for first-best policy. We base our values on the most recent publications, or official datasets, where possible.

Table 6.3.1 Parameter values used for optimal fuel tax calculation and sensitivity analyses

	US		UK	
Parameter	Central value	Range	Central value	Range
Baseline fuel efficiency, $M^{in,0}/F^0$	24		28	
Fuel pollution (CO_2), per gallon, $Z^{P_{\bar{F}}}$	91	[41, 405]	86	[38, 380]
Distance pollution (air), per mile, Z^{P_M}	4.5	[1, 9]	3.6	[1, 8]
Congestion, per mile, Z^C	10	[3, 14]	5	[0.1, 7.3]
Accidents, inactive, per mile, $Z^{A_{\tilde{M}^{in}}}$	6.4	[2, 18]	1.6	[1, 2.3]
Accidents, active, per mile, $Z^{A_{\tilde{M}^{ac}}}$	5.3	[1.5, 15]	1.6	[1.2, 2.6]
Inactivity, per mile, Z^Q	691	[403, 999]	244	[146, 683]
Rate of health internalisation, ω	0.5	[0.3, 0.7]	0.5	[0.3, 0.7]
Fuel price elasticity, η^{FF}	-0.36	[-0.21, -0.75]	-0.48	[-0.3, -0.9]
VMT-fuel price elasticity, $\eta^{M^{in}F}$	-0.25	[-0.05, -0.3]	-0.35	[-0.2, -0.5]
Income elasticity of inactive travel, $\eta^{M^{in}I}$	0.4	[0.02, 0.6]	0.605	[0.3, 0.8]
Cross-elasticity of active travel, $\eta^{M^{ac}F}$	0.18	[0.17, 0.25]	0.18	[0.17, 0.25]
Current tax rate on gasoline*, t_f^0	55	n.a.	406	n.a.

*Includes VAT for the UK but not US. All values are provided in USD cents using the end 2017 exchange rates 1 GBP = 1.351 USD. = 1.1251 EUR, and either per mile or per US gallon. $M^{in,0}$ and F^0 denote intensive miles travelled and fuel used at the initial gasoline tax rate. Justification for the social cost values is given in subsections 6.3.1 through 6.3.1.

In Figure 6.3.1, we converted CO_2 emissions pollution per gallon into per mile units using baseline fuel efficiency as presented in Table 6.3.1, such that all social costs are expressed in per mile units. It shows that the per mile benefits of using an active mode of travel are two orders of magnitude larger than most other social costs. This difference is partly due to the difference in travel time between motorised transport and walking or cycling.

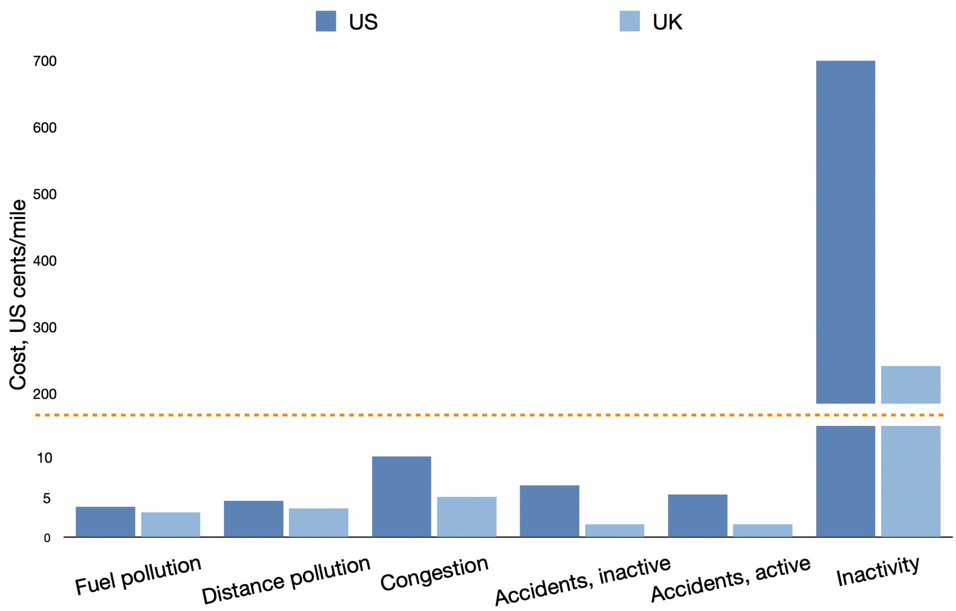

Figure 6.3.1 Social costs of personal car travel in US cents and on a per-mile basis.

6.3.1 Parametrisation

Baseline fuel efficiency and elasticities

Baseline fuel efficiency We set $M^{in,0}/F^0$ according to average fuel efficiency of the UK and US vehicle fleets. The US average was 24 miles/gallon in 2016 (Administration, 2018), the UK average 28 miles/gallon (DfT, 2018b; DfT, 2018c). The difference in fuel efficiency is due to a smaller average size of the UK private vehicle fleet, and a higher proportion of diesel cars, which have a higher average fuel economy. We account for this difference in diesel and gasoline personal vehicle fleet composition in the UK and US also in our carbon emissions and air pollution calculations.

Fuel price elasticities Based on Dieler et al. (2015) and Litman (2013), we choose a fuel price elasticity, η^{FF}, of -0.38 for the US as a central estimate. This is slightly less elastic than the UK value of -0.45, where wider public transit offers alternatives to car use. The elasticities of inactive miles travelled (VMT) with respect to fuel price, $\eta^{M^{in}F}$, are calibrated at -0.25 in US, and -0.35 in the UK.[11]

To our knowledge, few direct estimates of the cross-elasticity of active travel (walking and cycling) with respect to the fuel price, $\eta^{M^{ac}F}$, exist. Instead, we primarily utilise estimates of the cross-elasticity of public transport with respect to fuel price (Litman, 2019). The use of public transit requires getting to and from stations, often done on foot or by an alternative active mode, and certain public transit investments have been found to be an effective way of increasing active travel (Reis et al., 2016). We adopt a range of 0.17 - 0.25 for $\eta^{M^{ac}F}$, with a central value of 0.18 for both the US and the UK.

Income elasticity of inactive travel The elasticity of inactive travel demand with respect to income, $\eta^{M^{in}I}$, is calibrated at 0.4 (0.02-0.6) for the US, and 0.605 (0.3-0.8) in the UK. We use long-term elasticities where possible to allow for mode shifts and other behaviour changes. Further details and a full list of references on fuel price and income elasticities can be found in Appendix 6.B.2.

Labour supply elasticities For the compensated and uncompensated labour supply elasticities, ε^{c}_{LL} and ε_{LL}, we adopt the same values as Parry and Small (2005). These estimates fall in between the more recent estimates by e.g. Bargain et al. (2011) and Erosa et al. (2016).

[11] The lower elasticity of miles travelled vis-à-vis fuel use is explained by the fact that the most significant response of an increase in fuel price is typically not reduction in the distance travelled by people, but rather upgrading to a higher fuel economy car (Coglianese et al., 2017).

External cost of CO_2 emissions (fuel pollution), $Z^{P_{\bar{F}}}$

The external costs of fuel use are the cost of carbon emissions and associated climate damages. We derive our central estimate and range of plausible values from a large body of literature (see Appendix 6.B.3 for a full overview). We multiply the value of climate change costs per tonne of CO_2 emitted by the amount of CO_2 emitted per gallon of fuel burnt, weighted by fuel type consumption in both countries (diesel/gasoline) to derive an average value of fuel pollution costs per gallon of fuel.[12] With a social cost of carbon of \$90/tCO_2 and a range \$40 - 400/tCO_2, the central estimate for the US is 91 cents/gallon, with a range of 41-405 cents/gallon. The central estimate for the UK is 86 cents/gallon, with a range of 38-380 cents/gallon. Throughout, we abstract from any effects of fuel taxation on the cost of carbon.

External cost of air pollution (distance pollution), $Z^{P_{\bar{M}^{in}}}$

Local air pollution is caused by car tyre and break wear emissions of $PM_{2.5}$ and PM_{10}, which are approximately proportional to miles travelled, and by gases from incomplete fuel combustion processes.

For the US, estimates of the cost of air pollution per mile range from high values of \$0.089 (OECD, 2015) to extremely low values of \$0.007 (Muller et al., 2011), with several values in between: \$0.03 (Mashayekh et al., 2011), \$0.06/mile Parry et al. (2014).To reflect this uncertainty, we adopt values of \$0.01, \$0.045 and \$0.09 as the low, central, and high estimates for the US, respectively.

For the UK, national project evaluations use a value of \$0.036/mile (Hitchcock et al., 2014). OECD (2015) report a high value of \$0.08/mile travelled, while the average for a passenger car in the EU is estimated at \$0.009/mile for gasoline and \$0.033/mile for diesel cars. Reflecting the 55-45% split between gasoline and diesel cars in the UK and updated

[12] As fuel mix is almost exclusively gasoline in the US but approximately half and half gasoline and diesel in the UK, the marginal cost of climate damages per gallon of fuel is not the same in both countries.

costs of air pollution (Birchby et al., 2019), we adopt values of \$0.01, \$0.036 and \$0.08 as the low, central, and high estimates.

External cost of congestion, Z^C

Congestion is defined as the travel delay due to crowding of roads. For the US, we adopt the values by Inrix (2018), who provide a central value of \$0.1/mile, and a range of \$0.03-\$0.14/mile. In the UK, we follow Inrix (2019) and set the per-mile congestion costs at \$0.05/mile, with a lower and upper bound of \$0.001/mile and \$0.073/mile, respectively.[13]

External cost of accidents, $Z^{A_{\bar{M}^{in}}}$ and $Z^{A_{\bar{M}^{ac}}}$

There are two components to accident costs: the internalised cost of knowing and accounting for the risk of getting into a crash; and the external cost of the increased risk of causing an accident imposed on others by travelling. Hence, using the full cost of accidents per mile driven would overestimate the size of the accident externality. Instead, we adopt the approach by Lemp and Kockelman (2008), who estimate the external costs of transport in the US and assume that 50% of accident costs are external.[14]

Using accident data and cost estimates from the report by Blincoe et al. (2015), we find that accident costs attributable to inactive modes of transport, $Z^{A_{\bar{M}^{in}}}$, amount to \$0.064/mile, with a range of \$0.02-\$0.18/mile for the US. Accident costs attributable to active modes of transport, $Z^{A_{\bar{M}^{ac}}}$ amount to \$0.053/mile, with a range of \$0.015-\$0.15/mile. This is due to the proportionately higher death rate per accident and per mile travelled for active modes.

[13] Parry and Small (2005) already noted that the values available in empirical studies in transportation are VMT-weighted, but congestion costs enter the optimal fuel tax equation as being both VMT-weighted and fuel-price elasticity weighted. This is because demand for travel is more inelastic in more congested times and people internalise more of the waiting time cost. Adjusting for this reduces the marginal cost of congestion.

[14] To determine the external cost of accidents associated to inactive travel, we consider all costs associated to car-on-car and car-on-pedestrian accidents, as well as 50% of the car-on-cyclist accident costs. Similarly for active travel, we include pedestrian only and cyclist-on-pedestrian accident costs and the remaining half of the car-on-cyclist accident costs.

In the UK, $Z^{A_{\bar{M}^{in}}}$ amounts to \$0.015/mile, with a range of \$0.01-\$0.023/mile. Accident costs attributable to active modes of transport, $Z^{A_{\bar{M}^{ac}}}$, amount to \$0.016/mile as well, with a range of \$0.012-\$0.026/mile (DfT, 2018a).

Cost of inactivity, Z^Q

The health benefits of exercise are well-known to be the most substantial health-related impact of active travel, dwarfing air pollution or accident effects. For example, De Hartog et al. (2010) estimate that people shifting from car to bicycle for short trips lose 7 days of life due to traffic accidents, 21 days of life due to air pollution, but gain 8 months of life due to physical activity. Our analysis requires translating such benefits into monetary values.

First, health benefits comprise all mortality- and morbidity-reducing effects. Second, there may be productivity benefits, due to a reduction in absenteeism (taking sick leave), and presenteeism (being at work but having lower productivity due to illness). Third, greater health reduces the (public) health system costs. Depending on the characteristics of the health system (and the extent to which the individual bears the cost of absenteeism), the costs can be labelled as private or external. In the remainder of the analysis, we focus on the value of unrealised private health benefits only, as they are much larger than the direct productivity gains to the economy.

In order to calculate the marginal value of the private health benefits from physical activity for the UK and US, we used the Health Economic Assessment Tool (HEAT) developed by the World Health Organisation (Kahlmeier et al., 2017). HEAT calculates the value of the changes in mortality arising from a specified change in walking and cycling for travel purposes.[15] Further details regarding the HEAT model, inputs and corresponding data sources can be found in Appendix 6.B.4.

[15] HEAT is designed as a practitioner-oriented tool for health impact assessments. More complex assessments could quantify the effect of exercise on morbidity as well as mortality. Our results are therefore likely to be conservative estimates of the health benefits of physical activity.

We convert the HEAT output to an estimate of the health benefit per mile of active travel. We obtained a central Z^Q value of \$6.91/mile for the US, with a range of \$4.03-9.99/mile. For the UK, this value is \$2.44/mile, with a range of \$1.46-6.83/mile. The UK-US discrepancy has two sources: higher VSL estimates for the US, and higher US baseline mortality rates for younger members of the population.

Rate of health internalisation, ω

The extent to which individuals are aware of the health benefits of exercise and active travel are captured by the parameter ω. We base our estimates of health benefit internalisation on: stated preference surveys of cyclists/pedestrians and drivers on their reasoning for choosing that particular mode of transport; and surveys asking the general population about their knowledge of the health benefits of physical activity. High numbers of respondents (50-85%) in attitudinal transport surveys cite health reasons as one of their top three reasons for walking or cycling for travel (Börjesson and Eliasson, 2012; Useche et al., 2019). However, in general exercise knowledge surveys, only about half of respondents are knowledgeable of the amounts of physical activity required for health, and about 20-30% are capable of identifying the approximate odds of developing diseases without physical activity (Fredriksson et al., 2018; Bennett et al., 2009). We therefore chose a central value of 0.5 and a range of 0.3-0.7 for ω.

6.3.2 Implications for first-best policy

Table 6.3.1 already permits a quantitative conclusion about first-best policy. In a first-best world, there exist appropriate policy instruments to address all market failures, as well as non-distortive (e. g. lump-sum) taxes to generate government revenues. One can verify that under these assumptions, the optimal carbon (fuel) tax is equal to the cost of fuel pollution, $Z^{P_{\bar{F}}}$. Similarly, the socially optimal level of the price instruments for all other externalities (and internality, by analogy) are at their respective Pigouvian levels. For the internality, this Pigouvian level is equal to the social cost of inactivity, multiplied by the uninternalised share (1-ω). Importantly, this means that, on a per mile basis, a first-best subsidy paid to individuals for incentivising active travel modes would be at a much higher level than any of the tax levels for the externalities, or indeed, the sum of all other externality taxes.[16]

6.4 Quantitative Results

6.4.1 Optimal second-best fuel tax rates

We use Equations (6.13)-(6.15) and the parameter estimates provided in Table 6.3.1 to calculate the optimal fuel tax.[17] An increase in fuel taxation will reduce fuel use and inactive miles travelled, which will in turn affect the optimal tax through Equation (6.14). To account for this, we follow Parry and Small (2005), and endogenise F, M^{in}, and M^{ac} in our numerical solution. Further details can be found in Appendix 6.B.5.

We find an optimal fuel tax of $4.54/gallon of fuel in the UK, which is slightly higher than the current fuel tax.[18] In the US, the optimal fuel tax amounts to $10.13/gallon of fuel, which is more than ten times the current (population-weighted) average fuel tax across the fifty states. Table 6.4.1 lists the optimal tax levels and their decomposition. This decomposition shows that costs associated to congestion and physical inactivity are the main contributors to the fuel tax, albeit this is somewhat reduced due to the compensation for the marginal excess burden of labour taxation. Ramsey taxes are substantial, especially in the US; the congestion feedback does not significantly influence the optimal fuel tax rate.

[16]For comparison to second-best see Section 6.4, and for the policy implications of that comparison see Section 6.5.

[17]We used R for all computations. Code available from authors on request.

[18]The total tax on UK fuel includes VAT (110 cents/gallon) and fuel duty (296 cents/gallon). In the United States, value added or indirect taxes are not levied on fuel.

Table 6.4.1 Central calculations of the optimal fuel tax rate

Cost, USD cents/gallon	United States	United Kingdom
Fuel efficiency, M^{in}/F	28.6	28.3
Adjusted Pigouvian tax:		
Pollution, fuel-related, $Z^{P_{\bar{F}}}$	91	86
Pollution, distance-related, $Z^{P_{\bar{M}^{in}}}\beta^{M^{in}}M^{in}/F$	90	74
Congestion, $Z^{C}\beta^{M^{in}}M^{in}/F$	199	103
Accidents inactive, $Z^{A_{\bar{M}^{in}}}\beta^{M^{in}}M^{in}/F$	127	33
Accidents active, $Z^{A_{\bar{M}^{ac}}}\beta^{M^{ac}}M^{ac}/F$	-4	-1
Physical inactivity, $(1-\omega)\,\beta^{M^{ac}}M^{ac}/F$	256	109
Adjustment to MEC for excess burden	-71	-36
Ramsey tax	326	83
Congestion feedback	-1	3
Optimal fuel tax rate with physical activity, t_1^{f*}	**1013**	**454**
Optimal fuel tax rate without physical activity	681	335
Naïve fuel tax rate	593	372
Actual (2017) tax rate	55	406

Based on Equation (6.13) and (6.14), the optimal rate is the adjusted Pigouvian tax, adjustments for the excess burden, the Ramsey tax, and the congestion feedback, combined. The naïve rate is given by MEC_F (excluding the health internality) from Equation (6.14) with $M^{in}/F = M^{in,0}/F^0$ and all β's equal to 1.

Including physical activity increases the UK fuel tax by 36%, and the US fuel tax by 49%. Although this increase is significantly smaller than the pure per-mile social cost of physical inactivity, the inactivity component is still the largest contributor to the MEC part of the tax.

Consistent with both Parry and Small (2005) and Santos (2017), we find that the second largest externality component of the second-best optimal fuel tax for both countries is congestion. In London, congestion impacts are 28 times higher than the EU average (Cookson, 2016), which greatly influences the congestion costs for the UK, even though the value of travel time estimates for the US are higher than for the UK.

This is followed by inactive accidents in the United States. In the US, traffic accidents are associated with a far higher per-mile cost, even though the rates of traffic injuries are very similar in both countries. This is explained by a higher nominal value that is attached to human life in the US. Contrary to Parry and Small (2005), air pollution costs for both countries contribute less to the fuel tax than carbon emissions. This is the result of both increasingly stringent fuel air pollutant emissions standards,[19] and growing consensus that the social cost of carbon is higher (see Subsection 6.3.1).

In addition to the second-best optimal tax, we compute the "naïve" tax rate, which is based on three assumptions: first, all βs are equal to 1; i.e. both active and inactive miles travelled are equally responsive to fuel taxation as fuel use. Second, the feedback of tax-induced changes in fuel use and miles travelled to the tax rate is ignored. Third, interactions of the fuel tax with the labour tax, as well as the Ramsey component are abstracted from. Instead, the only relevant components to the tax are the external effects of car use. The naïve rate as such mimics common practice in transport and cost-benefit analysis evaluations. [20] In our central calculations $\beta^{M^{in}} = 0.69$ (US) or 0.73 (UK), and $\beta^{M^{ac}} = -0.50$ (US) and -0.38 (UK). The low $\eta^{M^{in}F}$ reflects the very inelastic demand for vehicle-miles travelled (VMT), meaning that most reduction in fuel use comes from increases in fuel economy of driving and the vehicle fleet, not reductions in distances covered in cars. Thus, mileage-related externalities (air pollution, congestion, and accidents) are all inflated in the naïve fuel tax calculation.

Treating fuel efficiency, fuel consumption and distance travelled as endogenous, rather than exogenous, in the second-best optimal fuel tax calculation causes fuel consumption to fall by 43.9% and 3.7% in the US and UK, respectively. Inactive travel M^{in} falls slightly less, by 33.1% in the US, and this is more than compensated for by an increase of 33.5% in active travel. In the UK, inactive travel also falls by less than fuel consumption, by 1.7%. However, as active travel increases only by 1.4%, total travel in the UK falls. The overall

[19]Such as Corporate Average Fuel Economy (CAFE) standards.

[20]In applied transportation research, the difference between the responsiveness of fuel consumption to fuel prices and miles travelled to fuel prices are often disregarded, and assumed to be unitary. Multiplying externalities only by fuel efficiency, and not by the responsiveness of VMT to fuel price, is considered the naïve approach in literature, and can sometimes lead to a doubling of the optimal fuel tax estimation (Newbery et al., 1995).

tax increases by 81.1% in the US and 3% in the UK. The change is more dramatic in the US because of the low fuel efficiency of motor vehicles, and higher contingent valuation of people's time and lives, resulting in a bigger Pigouvian tax. In the UK, the current tax level is very close to the optimal level. The fuel efficiency of motor vehicles in the UK therefore does not change much in response to moving to the optimal level, and the endogenous solution does not change the optimum level significantly.

6.4.2 Welfare Effects

The welfare gain of implementing the second-best optimal fuel tax is presented in Table 6.4.2. We use the current tax rate as a benchmark, and consider a fuel tax that does, and does not, take into account active travel benefits. All gains are expressed as a share of current fuel expenditure. The analytical derivation of the welfare benefit is discussed in Appendix 6.B.6. The welfare gain of implementing the second-best optimal tax that accounts for the health internality is 129% for the US, but only 0.16% for the UK. Contrary to the UK, in the US, any increase in the fuel tax yields significant welfare improvements. This difference is primarily due to the very low current US fuel tax, while the UK fuel tax is already close to the optimal rate.

We additionally present the changes in active and inactive miles travelled following the change in the fuel tax. In the UK, the small change in fuel taxes results in relatively small changes in distance travelled. In the US, however, the fuel price changes are large, and induce a substantial shift from inactive to active miles.[21]

Finally, we compute the effect of the tax increase on mortality through increased active travel using the HEAT tool, described in Section 6.3.1 and Appendix 6.B.4. Increases in active travel primarily save lives by improving health from increasing exercise. HEAT then

[21]However, as we used constant fuel price elasticities to calculate these changes, these results should be interpreted with caution. It is unlikely that a 20-fold increase in the fuel tax in the US would induce the same rate of response as a 20% increase in the tax.

Table 6.4.2 Welfare effects of fuel taxation

	US				
Fuel tax	Rate (c/gal)	Welfare change	M^{in} change	M^{ac} change	Annual lives
t^{f*}	1013	129%	-33.04%	33.47%	6266 saved
t^{f}, excluding health benefits	681	124%	-27.39%	25.92%	4701 saved
	UK				
Fuel tax type	Rate (c/gal)	Welfare change	M^{in} change	M^{ac} change	Annual lives
t^{f*}	454	0.16%	-2.67%	1.40%	39 saved
t^{f}, excluding health benefits	335	-0.99%	4.58%	-2.28%	120 lost

Calculated relative to the current rate, expressed as a percentage of current fuel expenditure (approximately \$1800 in the US and \$1500 per person per year in the UK, according to household expenditure surveys (BLS, 2019; ONS, 2019)). The current US fuel tax rate is \$0.55/gal, and the current UK fuel tax rate is \$4.06/gal.

corrects this value for the lives lost due to greater air pollution exposure, and increase in accident fatalities of pedestrians and cyclists (see also Appendix 6.B.7).[22] Due to a larger tax increase and larger population size, lives saved are greatest in the US: setting the fuel tax at its optimal level saves 6266 lives each year.

6.4.3 Sensitivity Analysis

In Figure 6.4.1, we illustrate the sensitivity of the optimal second-best fuel tax with respect to the elasticities and rate of health internalization, keeping all other parameters at their central values (denoted X in the graphs). Figure 6.B.2 presents additional results where we vary the cost parameters Z. Further details and figures can be found in Appendix 6.B.8.

For both the UK and US, the fuel tax is most sensitive to η^{FF}, the fuel price elasticity. This elasticity directly affects the optimal fuel tax through $\beta^{M^{in}}$ and $\beta^{M^{ac}}$ in the MEC component (see Equation (6.14)), and indirectly by governing the response of fuel use F to the introduction of the fuel tax. Jointly, as shown in the figure, this results in a positive relationship between the fuel price elasticity and the optimal fuel tax. Using the upper or

[22] HEAT only computes the lives saved due to an increase in active travel. Higher fuel taxation also reduces inactive miles travelled, which reduces air pollution and vehicle traffic fatalities. As we do not capture these effects, the values reported in Table 6.4.2 can be considered a lower bound for the lives saved due to the tax increase.

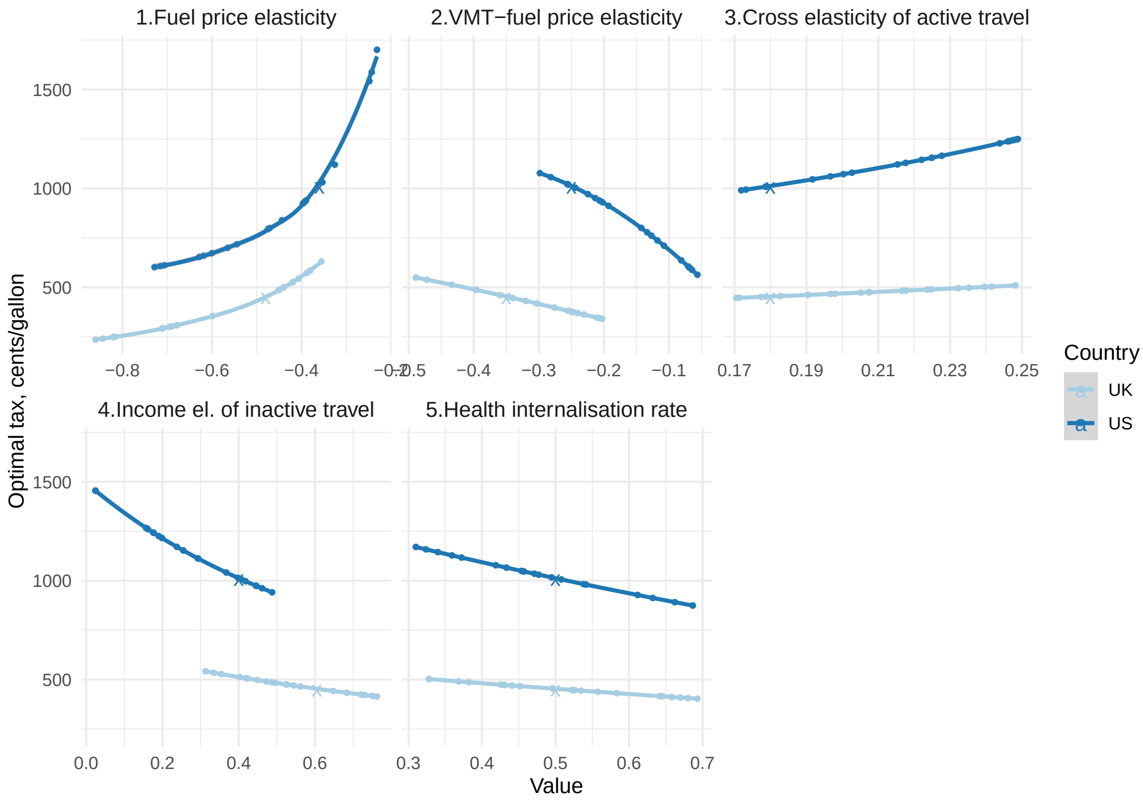

Figure 6.4.1 Sensitivity of the fuel tax to relevant elasticities and the rate of health internalisation

lower bound of the fuel price elasticity, as opposed to the central value, can either increase or decrease the fuel tax by as much as 50 percent. Conversely, the net effect of the elasticity of inactive travel (VMT) with respect to the fuel prices, $\eta^{M^{in}F}$, on the fuel tax is negative. Using the upper bound instead of the central value for $\eta^{M^{in}F}$, reduces the fuel tax by up to 50 percent; using the lower bound instead has a noticeably smaller effect. The fuel tax is relatively insensitive to the cross elasticity of active travel, $\eta^{M^{ac}F}$ and the rate of health internalisation. The income elasticity of inactive travel affects the fuel tax especially for the US. This effect materialises via the Ramsey tax component, which is comparatively large for the US to begin with (see Table 6.4.1).

The fuel tax in both the US and the UK increases approximately linearly with all social cost parameters and the cost of inactivity (that is $Z^{P_{\bar{F}}}$, $Z^{A_{\bar{M}^{in}}}$, $Z^{A_{\bar{M}^{ac}}}$, $Z^{P_{\bar{M}^{in}}}$, Z^{C}, and Z^{Q}), reacting most strongly to $Z^{P_{\bar{F}}}$, fuel pollution, i.e. the social cost of carbon. For more details see Appendix 6.B.8.

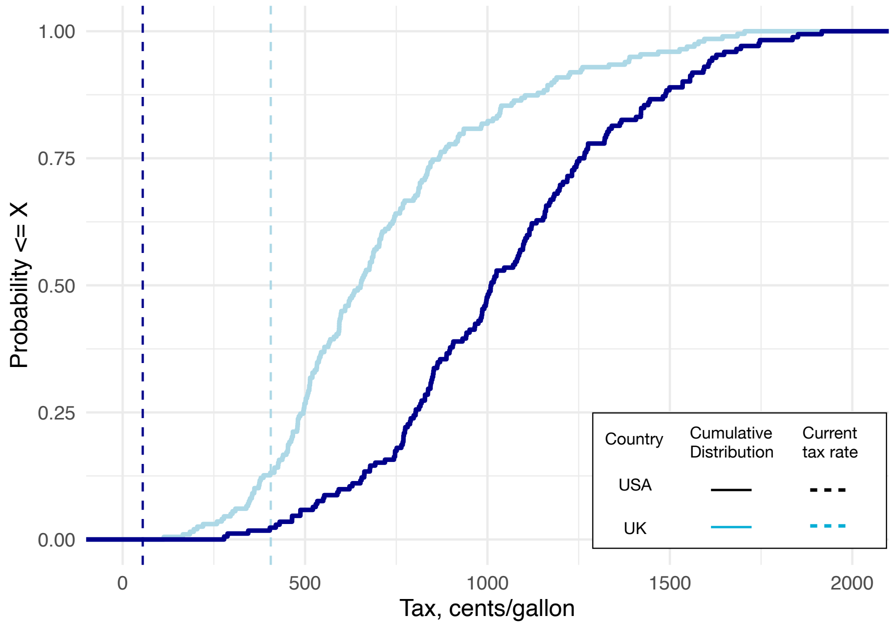

Figure 6.4.2 Cumulative distribution function of optimal fuel tax values for both US and UK.

Figure 6.4.2 presents the results of a Latin Hypercube parameter sensitivity analysis using the *pse* package in R (Chalom and de Prado, 2015). We varied parameters for external costs and the elasticities using 20 values drawn at random from a uniform distribution, and allowed fuel use and mileage to be generated endogenously. The function was run 200 times, with 50 bootstrap replicates. For the United States, the optimal fuel tax is less than 0.01% likely to be below the current 55 cents/gallon. For the UK, the optimal fuel tax is below current fuel tax of 406 cents/gallon with a 15% probability.

6.5 Discussion

This article shows that it may be very costly to societies not to reap the health benefits from choosing travel modes that lead to more physical activity. Including these benefits in an analysis of optimal fuel taxation shows that the optimal fuel tax increases significantly, although to a lesser extent than one might expect based on assessments of the benefits of active travel measured in public health. Here we discuss how our findings align with current thought on optimal transport policy, and subsequently discuss limitations of our approach.

Experts on urban transport policy have long argued for a mix of "push" and "pull" factors to efficiently reduce societal costs from car use (Pucher and Buehler, 2007; Creutzig and He, 2009). "Push measures" discourage car use and include fuel or road pricing and parking fees; "pull measures" encourage uptake of other forms of transport by making them more attractive. Our study only explicitly considers a fuel tax, but a number of conclusions about other policy instruments may be drawn. First, both active and inactive miles travelled are relatively inelastic to the fuel tax. This not only affects the second-best optimal level, but also implies that a fuel tax on its own is not an ideal instrument for reducing mileage-related externalities. Parry and Small (2005) suggest that using a VMT tax for all externalities other than carbon emissions would be preferable. Indeed, there is renewed academic interest in alternative road pricing mechanisms, such as congestion or GPS-based charging, cordon pricing, optimal toll pricing, or real time road pricing (see Guo et al., 2017; Cramton et al., 2018; Bjertnæs, 2019). However, ideal externality-correcting mechanisms have not been widely implemented and most plans to introduce congestion charging are advancing slowly. Still, the benefit of the fuel tax over a congestion charge is that a fuel tax can, at least indirectly, address all large externalities caused by driving concurrently, and be used to generate a broader revenue base for the government (Rietveld and van Woudenberg, 2005). It also encourages improvements in the fuel economy of the fleet by encouraging the purchase of more efficient new cars, and in some cases, more fuel efficient driving patterns (Dhondt et al., 2013; Bjertnæs, 2019).

Second, our study has further implications for policies encouraging active transport. Akin to congestion charges, a straightforward public finance approach could involve a direct subsidy for active modes of travel (Wardman et al., 2007; EBS, 2020) or indirect subsidies in the form of suitable cycling and washing facilities for employees that would improve comfort of cycling relative to driving (Useche et al., 2019).

Appropriate active travel infrastructure may however be a more important "pull" measure to make walking and cycling attractive.[23] Car-free city centres, bicycle lane networks and improvements in public transport provision will increase the mode share of active travel (Pucher and Buehler, 2007; Buehler and Pucher, 2012; Gössling, 2013). For example, in a study of 167 European cities, Mueller et al. (2018) find that increasing bicycle lane infrastructure in urban areas up to 315km/100,000 inhabitants increases the mode share of cycling up to 24.7%. Further, the lack of appropriate street lighting, and badly maintained roads and cycle lanes have all been identified as factors impeding active commuting (Yang et al., 2017; NHTS, 2019). Active travel infrastructure policies also create opportunities to adopt active travel modes to begin with, by making the demand for both active miles travelled, and miles by car more responsive to fuel prices. Investing in cycling infrastructure has not been considered a significant investment strategy until recently, and neither have infrastructure cost assessments been including it in their analyses (Van Essen et al., 2011). Due to the large differences in the effectiveness of cycling infrastructure investments, or alternatively soft, information-based measures, it is difficult to estimate their effectiveness relative to a fuel tax change.

Our optimal tax result signals that the extent to which an increase in fuel taxes is welfare enhancing is constrained by the presence of viable low-carbon alternatives (high β's). This result was also demonstrated by Martens (2016), and (in part) justifies the grievances of the Gilets Jaunes movement in France. Conversely, this implies that improvements in infrastructure designed for active travel and public transport as discussed above could further

[23] Standalone marginal increases in fuel taxes are unlikely to spur significant behaviour change in drivers, because the response to a fuel tax is to alter fuel consumption, but not to reduce the amount or distances travelled by car – the demand for VMT is more inelastic than the demand for fuel (Gillingham and Munk-Nielsen, 2019).

support increased fuel taxation.[24] While greater willingness of citizens to switch to active travel in particular would manifest itself in a higher responsiveness of active travel to fuel taxation, $\eta^{M^{ac}F}$, it would likely also result in higher active miles travelled M^{ac}, lower fuel use F, and higher (absolute) elasticities $\eta^{M^{in}F}$. From (6.13)-(6.15), all of these effects would justify higher fuel taxes.

A full characterisation of the "pull effect," would include the public good characteristics of infrastructure – everyone benefits from safer and more comfortable cycling infrastructure – which will lead individuals to derive more utility from active travel and therefore "pull" them into these modes. This channel is not considered in our model and yet could lead to either higher or lower second-best optimal fuel taxes (Siegmeier, 2016), once infrastructure changes are seen as an additional policy instrument rather than an exogenous change in elasticities (similar to Bovenberg and van der Ploeg, 1994). In other words, as improved public transport infrastructure moves active travel decisions closer to optimal decisions, it may reduce the need for and value of higher fuel taxes as captured through Z^Q. We believe this is a crucial area for further work.

We note a number of limitations to our study: health manifests itself only as an internality within the utility function, though there is evidence that health-labour feedback loops might exist, specifically between physical activity and productivity (Proper et al., 2006), and presenteeism (Pereira et al., 2015). We abstract from these effects in our analysis; if anything, including such effects would strengthen the case for including health benefits from active travel in transport policy assessments. Further, we do not consider distributional concerns of the policy instruments, especially related to income, location or race (see Bento et al., 2009 and Tessum et al., 2019, Creutzig et al., 2020). We further do not explicitly model pre-existing regulation such as fuel efficiency standards, which are an important element in current transport regulation (Greene, 2011). Finally, we combine public transport with

[24]Future research could investigate how cost-benefit analysis of public transport infrastructure project changes once health benefits are taking into account. Such an analysis should note that the health benefits are unevenly distributed across the population.

walking and cycling as an active mode of transport, and so omit recent trends in urban travel such as ride-hailing and sharing apps such as Uber, or the increasing popularity of e-scooters.

6.6 Conclusion

This article shows that optimal fuel tax rates increase significantly if the health benefits from increased active travel, such as reduced rates of diabetes, cardiovascular diseases, dementia, and depression are not fully internalised by citizens. Building on the established framework developed by Parry and Small (2005), we present an assessment of optimal fuel taxation when an internality through physical inactivity is also considered in the tax design.

We confirm the main conclusion of a large body of research in public health that, per mile travelled, the social costs of inactivity dominate the social costs from transport externalities by two orders of magnitude. We examine how this fact changes the appropriate second-best optimal fuel tax, which targets active travel health benefits only indirectly. We conclude that the second-best optimal fuel tax increases from \$3.35 to \$4.54/gallon in the UK and \$6.81 to \$10.13/gallon in the US. Due to the inelastic demand for vehicle miles travelled and cross-elasticity of active travel, the tax rate increases by less than the value of the per-mile internality.

In contrast to Parry and Small (2005), we find that the fuel tax rate in the United Kingdom is close to optimal when the health benefits from active travel are accounted for. We confirm that, even without these benefits, in the United States fuel is significantly undertaxed: it exceeds the current average fuel tax rate across the 50 states, as well as the previous estimate by Parry and Small (2005). Over the past two decades, the economic cost of damages to human health (air pollution and accident externalities) have risen significantly; more time is being spent in congestion on US roads, and the value of time has also risen faster than inflation. Further, the social cost of carbon estimates we derived from the literature (\$40-400/tCO_2) are now several times higher than the values Parry and Small used in 2005

(\$6.8/tCO_2, \$0.2-27/tCO_2). Whereas pollution linked to CO_2 emissions contributed the least to their Pigouvian tax component, it is the third largest component according to our estimates. It has the most significant influence on the fuel tax as the cost of carbon damages increases.

Including the significant health benefits from active travel means that fuel taxes should be increased, as they are an established instrument for addressing all social costs of transport. The modest relevance of a fuel tax on an individual's decision to walk or cycle indicates, however, that the fuel tax may not be the most appropriate policy instrument to encourage active travel. This is further reinforced as the optimal US fuel tax can be deemed politically unrealistic. Instead, more targeted measures to increase the relative price of car travel such as congestion charges, and measures aimed at reducing barriers to other modes of transport such as building better active travel infrastructure, will permit societies to reap the high health benefits. Congestion charging would be effective in both the UK and the US for this purpose (Cramton et al., 2018). The US specifically would benefit from more public transit infrastructure that would result in more active trips as people reach the transit stops by foot or bicycle. The UK, characterised by denser cities, would especially benefit from improved urban infrastructure for walking and cycling. Nonetheless, without an associated change in the price signal in the form of a fuel tax rise or congestion charge, infrastructure investment is unlikely to lead to sufficient changes in travel decisions on its own (Buehler et al., 2017; Pucher et al., 2010). Different policies at multiple levels are needed to realise meaningful change in transport.

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Appendix

For Online Publication

Healthy climate, healthy bodies: Optimal fuel taxation and physical activity

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Appendix 6.A Mathematical Appendix.

6.A.1 Derivation of the optimal fuel tax t^f

We derive the optimal fuel tax in two steps. First, we consider the consumer's optimisation problem. We define V as the consumer's maximised value function, and determine the first-order conditions corresponding to the solution of this value function. Next, we determine the optimal fuel tax by computing the total derivative of V with respect to the tax on fuel, dV/dt^f. Setting this term equal to zero then allows us to obtain Equation (6.13) as detailed below.

Consumer optimisation problem

The consumer maximises (6.1) with respect to (6.2)-(6.10). As described in the text, it takes pollution P, measures for congestion π and a large part of the accident risk as given. Instead of considering actual health (6.7), it considers perceived health (6.8). This allows us to define the following maximised value function:

$$\begin{aligned}
V \equiv Max_{C,F,H,M^{ac},O,L}\{&u(\psi(C,M,T^{in},T^{ac},G),N)-\varphi(P)-\delta(A)+\xi(Q^{per})\\
&+\mu_M\left[M^{in}+M^{ac}-M\right]+\mu_{M^{in}}\left[\chi(F,H)-M^{in}\right]+\mu_{T^{in}}\left[\pi^{in}(\bar{M}^{in})M^{in}-T^{in}\right]\\
&+\mu_{T^{ac}}\left[\pi^{ac}M^{ac}-T^{ac}\right]+\mu_A\left[A^{in}(\bar{M}^{in},M^{in})+A^{ac}(M^{ac},\bar{M}^{in},\bar{M}^{ac})-A\right]\\
&+\mu_{Q^{per}}\left[\omega Q(M^{ac},O)+\bar{Q}-Q^{per}\right]\\
&+\mu_I\left[w\left(1-t^l\right)L-C-(p^f+t^f)F-p^hH-p^oO-S^{ac}\right]\\
&+\mu_S\left[S(M^{ac})-S^{ac}\right]+\mu_L\left[\bar{L}-L-N-T^{in}-T^{ac}\right]\},
\end{aligned} \quad (6.17)$$

with corresponding first-order conditions

$$u_\psi \psi_C - \mu_I = 0, \tag{6.18}$$
$$u_\psi \psi_M - \mu_M = 0, \tag{6.19}$$
$$-\delta_A - \mu_A = 0, \tag{6.20}$$
$$\mu_M - \mu_{M^{in}} + \mu_{T^{in}} \pi^{in} + \mu_A A^{in}_{M^{in}} = 0, \tag{6.21}$$
$$\mu_M + \mu_{T^{ac}} \pi^{ac} + \mu_A A^{ac}_{M^{ac}} + \mu_Q \omega Q_{M^{ac}} + \mu_S S_{M^{ac}} = 0, \tag{6.22}$$
$$u_\psi \psi_{T^{in}} - \mu_{T^{in}} - \mu_L = 0, \tag{6.23}$$
$$u_\psi \psi_{T^{ac}} - \mu_{T^{ac}} - \mu_L = 0, \tag{6.24}$$
$$\mu_{M^{in}} \chi_F - \mu_I (p^f + t^f) = 0, \tag{6.25}$$
$$\mu_{M^{in}} \chi_H - \mu_I p^h = 0, \tag{6.26}$$
$$\xi_Q - \mu_Q = 0, \tag{6.27}$$
$$\mu_Q \omega Q_O - \mu_I p^o = 0, \tag{6.28}$$
$$-\mu_I - \mu_S = 0, \tag{6.29}$$
$$u_N - \mu_L = 0, \tag{6.30}$$
$$-\mu_L + \mu_I w \left(1 - t^l\right) = 0. \tag{6.31}$$

Optimal taxation

The optimal fuel tax is implicitly determined by $dV/dt^f = 0$, taking into account that t^l is determined through (6.11), and that in equilibrium $\bar{M}^{in} = M^{in}$, $\bar{M}^{ac} = M^{ac}$, $\bar{F} = F$, and $\tilde{Q} = (1-\omega)Q$. From (6.17) and (6.18)-(6.31) we then obtain

$$\begin{aligned}
\frac{dV}{dt^f} = \Big[\mu_{T^{in}} \pi^{in}_{\bar{M}^{in}} \chi_F M^{in} - \delta_A \left[A^{in}_{\bar{M}^{in}} + A^{ac}_{\bar{M}^{in}}\right] \chi_F - \\
\varphi_P \left[P^f_{\bar{F}} + P^m_{\bar{M}^{in}} \chi_F\right] + \mu_I t^f \Big] \frac{dF}{dt^f} \\
+ \left[\mu_{T^{in}} \pi^{in}_{\bar{M}^{in}} M^{in} \chi_H - \delta_A \left[A^{in}_{\bar{M}^{in}} + A^{ac}_{\bar{M}^{in}}\right] \chi_H - \varphi_P P^m_{\bar{M}^{in}} \chi_H\right] \frac{dH}{dt^f} \\
+ \left[-\delta_A A^{ac}_{\bar{M}^{ac}} + \xi_Q (1-\omega) Q_{M^{ac}}\right] \frac{dM^{ac}}{dt^f} + \xi_Q (1-\omega) Q_O \frac{dO}{dt^f} + \mu_I w t^l \frac{dL}{dt^f}.
\end{aligned}$$

Further rearranging this term and using $\frac{dM^{in}}{dt^f} = \chi_F \frac{dF}{dt^f} + \chi_H \frac{dH}{dt^f}$ and $\frac{dQ}{dt^f} = Q_{M^{ac}} \frac{dM^{ac}}{dt^f} + Q_O \frac{dO}{dt^f}$, we obtain

$$\begin{aligned}\frac{1}{\mu_I}\frac{dV}{dt^f} = \left[t^f - \frac{\varphi_P}{\mu_I} P^f_{\bar{F}}\right]\frac{dF}{dt^f} \\ + \left[\frac{\mu_{T^{in}}}{\mu_I}\pi^{in}_{\bar{M}^{in}} M^{in} - \frac{\delta_A}{\mu_I}\left[A^{in}_{\bar{M}^{in}} + A^{ac}_{\bar{M}^{in}}\right] - \frac{\varphi_P}{\mu_I} P^m_{\bar{M}^{in}}\right]\frac{dM^{in}}{dt^f} \\ + \left[-\frac{\delta_A}{\mu_I} A^{ac}_{\bar{M}^{ac}}\right]\frac{dM^{ac}}{dt^f} + (1-\omega)\frac{\xi_Q}{\mu_I}\frac{dQ}{dt^f} + wt^l \frac{dL}{dt^f}.\end{aligned} \tag{6.32}$$

Equation (6.32) is a generalisation of Equation (2.9) in Parry and Small (2004), taking into account active travel decisions. To find the optimal fuel tax we then set (6.32) equal to zero, and isolate t^f. We obtain

$$\begin{aligned}t^{f*} = Z^{P_{\bar{F}}} + \left[Z^C + Z^{A_{\bar{M}^{in}}} + Z^{P_{\bar{M}^{in}}}\right]\left(\frac{-dM^{in}}{dt^f} / \frac{-dF}{dt^f}\right) + Z^{A_{\bar{M}^{ac}}}\left(\frac{-dM^{ac}}{dt^f} / \frac{-dF}{dt^f}\right) \\ - (1-\omega)\tilde{Z}^Q\left(\frac{-dQ}{dt^f} / \frac{-dF}{dt^f}\right) - wt^l\left(\frac{-dL}{dt^f} / \frac{-dF}{dt^f}\right),\end{aligned} \tag{6.33}$$

where we define

$$Z^{P_{\bar{F}}} \equiv \frac{\varphi_P}{\mu_I} P^f_{\bar{F}};\ Z^{P_{\bar{M}^{in}}} \equiv \frac{\varphi_P}{\mu_I} P^m_{\bar{M}^{in}};\ Z^{A_{\bar{M}^{in}}} \equiv \frac{\delta_A}{\mu_I}\left[A^{in}_{\bar{M}^{in}} + A^{ac}_{\bar{M}^{in}}\right];$$

$$Z^{A_{\bar{M}^{ac}}} \equiv \frac{\delta_A}{\mu_I} A^{ac}_{\bar{M}^{ac}};\ \tilde{Z}^Q \equiv \frac{\xi_Q}{\mu_I}, \text{and } Z^C \equiv \Gamma^{in}\pi^{in}_{\bar{M}^{in}} M^{in}.$$

To obtain Z^C, we use (6.23) and (6.31), and define $\Gamma^{in} \equiv w\left(1-t^l\right) - \psi_{T^{in}}/\psi_C$. Equation (6.33) can in turn be expressed as

$$t^{f*} = MEC - wt^l\left(\frac{-dL}{dt^f} / \frac{-dF}{dt^f}\right), \tag{6.34}$$

with

$$MEC \equiv Z^{P_{\bar{F}}} + \left[Z^C + Z^{A_{\bar{M}^{in}}} + Z^{P_{\bar{M}^{in}}}\right]\beta^{M^{in}}\frac{M^{in}}{F}$$

$+ \left[Z^{A_{\bar{M}^{ac}}} - (1-\omega) Z^{Q}\right] \beta^{M^{ac}} \frac{M^{ac}}{F},$

$$\beta^{M^{in}} \equiv \frac{\eta^{M^{in}F}}{\eta^{FF}};\ \beta^{M^{ac}} \equiv \frac{\eta^{M^{ac}F}}{\eta^{FF}};\ Z^{Q} \equiv \frac{\xi_Q}{\mu_I} Q_{M^{ac}},$$

where η^{XF} is the fuel price elasticity of $X \in \left\{M^{in}, M^{ac}\right\}$, and we impose $dO/dt^f = 0$.

By linear homogeneity, $M^{in} = \chi_F F + \chi_H H$. Then, using (6.19)-(6.21), (6.23), (6.25), (6.26) and (6.31) we obtain

$$\frac{u_M}{\mu_I} = p^{M^{in}}, \tag{6.35}$$

with $u_M \equiv u_\psi \psi_M$, $p^{M^{in}} \equiv \left[(p^f + t^f)\alpha^F + p^h \alpha^H\right] + \Gamma^{in}\pi^{in} + \Lambda^{in}$, $\alpha^F \equiv F/M^{in}$, $\alpha^H \equiv H/M^{in}$, and $\Lambda^{in} \equiv \frac{\delta_A A^{in}_{M^{in}}}{u_\psi \psi_C}$. Similarly, from (6.18), (6.19), (6.20), (6.22), (6.24), (6.27), (6.29) and (6.31) we can write

$$\frac{u_M}{\mu_I} = p^{M^{ac}}, \tag{6.36}$$

with $p^{M^{ac}} \equiv S_{M^{ac}} + \Gamma^{ac}\pi^{ac} + \Lambda^{ac} - \Omega^{Q}$, $\Gamma^{ac} \equiv w\left(1 - t^l\right) - \frac{\psi_{T^{ac}}}{\psi_C}$, $\Lambda^{ac} \equiv \frac{\delta_A A^{ac}_{M^{ac}}}{u_\psi \psi_C}$, and $\Omega^{Q} \equiv \frac{\xi_Q}{u_\psi \psi_C} \omega Q_{M^{ac}}$. From the perspective of the consumer, $p^{M^{in}}$ and $p^{M^{ac}}$ denote the (minimised) effective price of inactive and active travel, respectively. As in Parry and Small (2004), the homogeneity assumption will ensure that we can write $\alpha^F(t^f)$ and $\alpha^H(t^f)$. Repeated substitutions using (6.3), (6.9), (6.10), the first order conditions and (6.35) and (6.36) then allow us to write the following demand functions

$$\begin{aligned}
C &= C(p^{M^{in}}, t^l); & L &= L(p^{M^{in}}, t^l);\\
M^{in} &= M^{in}(p^{M^{in}}, t^l); & M^{ac} &= M^{ac}(p^{M^{in}}, t^l);\\
F &= F\left(p^{M^{in}}, t^l, t^f\right) = \alpha^F\left(t^f\right) M^{in}(p^{M^{in}}, t^l); & &\\
H &= H\left(p^{M^{in}}, t^l, t^f\right) = \alpha^H\left(t^f\right) M^{in}(p^{M^{in}}, t^l). & &
\end{aligned} \tag{6.37}$$

where the last two follow from the definition of α^F and α^H. For prices we can similarly write

$$p^{M^{in}} = p^{M^{in}}\left(t^f, \pi^{in}, t^l\right);\ p^{M^{ac}} = p^{M^{ac}}\left(t^f, \pi^{in}, t^l\right). \tag{6.38}$$

The demand and price functions (6.37) and (6.38) are equivalent to expressions (B3a) and (B3b) in Parry and Small (2004). The remainder of the derivations then similarly follows Parry and Small (2004). First, from (6.37) and (6.38), we can write $L(t^f, \pi^{in}, t^l)$. Then

$$\frac{dL}{dt^f} = \frac{\partial L}{\partial t^f} + \frac{\partial L}{\partial \pi^{in}}\frac{d\pi^{in}}{dt^f} + \frac{\partial L}{\partial t^l}\frac{dt^l}{dt^f}. \tag{6.39}$$

Now from (6.11), we have $wLdt^l + wt^l dL + F dt^f + t^f dF = 0$, which gives

$$\frac{dt^l}{dt^f} = -\frac{F + t^f \frac{dF}{dt^f} + wt^l \frac{dL}{dt^f}}{wL}. \tag{6.40}$$

Combining (6.40) and (6.39) then allows us to write

$$\frac{dt^l}{dt^f} = -\frac{F + t^f \frac{dF}{dt^f} + wt^l \left[\frac{\partial L}{\partial t^f} + \frac{\partial L}{\partial \pi^{in}} \frac{d\pi^{in}}{dt^f}\right]}{w\left[L + t^l \frac{\partial L}{\partial t^l}\right]}. \tag{6.41}$$

Substituting (6.41) into (6.39) and multiplying by t^l then yields

$$t^l \frac{dL}{dt^f} = \frac{-t^l \frac{\partial L}{\partial t^l}}{w\left[L + t^l \frac{\partial L}{\partial t^l}\right]} \left[t^f \frac{dF}{dt^f}\right] + \frac{t^l}{w\left[L + t^l \frac{\partial L}{\partial t^l}\right]} \left[w\frac{\partial L}{\partial t^f} L - \frac{\partial L}{\partial t^l} F + wL \frac{\partial L}{\partial \pi^{in}} \frac{d\pi^{in}}{dt^f}\right]. \tag{6.42}$$

Now define $MEB \equiv \frac{-\frac{\partial L}{\partial t^l}\frac{t^l}{L}}{1 + \frac{\partial L}{\partial t^l}\frac{t^l}{L}}$, and let ε_{LL} denote the uncompensated labour supply elasticity: $\varepsilon_{LL} \equiv \frac{\partial L}{\partial\left[(1-t^l)w\right]} \frac{(1-t^l)w}{L} = \frac{\partial L}{\partial t^l} \frac{\partial t^l}{\partial (1-t^l)w} \frac{(1-t^l)w}{L}$. Then $MEB_L = \frac{\frac{t^l}{1-t^l}\varepsilon_{LL}}{1 - \frac{t^l}{1-t^l}\varepsilon_{LL}}$, which we use in (6.42) to obtain

$$wt^l \frac{dL}{dt^f} = MEB\left[t^f \frac{dF}{dt^f}\right] - \frac{MEB}{\partial L/\partial t^l} \left[w\frac{\partial L}{\partial t^f} L - \frac{\partial L}{\partial t^l} F + wL \frac{\partial L}{\partial \pi^{in}} \frac{d\pi^{in}}{dt^f}\right]. \tag{6.43}$$

Next consider the second term in brackets in (6.43). Then t^f and π only affect L through $p^{M^{in}}$ (consider (6.37) and (6.38)). So

$$\frac{\partial L}{\partial t^f} = \frac{\partial L}{\partial p^{M^{in}}} \frac{\partial p^{M^{in}}}{\partial t^f} = \frac{\partial L}{\partial p^{M^{in}}} \alpha^F, \tag{6.44}$$

and

$$\frac{\partial L}{\partial \pi^{in}} = \frac{\partial L}{\partial p^{M^{in}}} \frac{\partial p^{M^{in}}}{\partial \pi^{in}} = \frac{\partial L}{\partial p^{M^{in}}} \Gamma^{in}. \tag{6.45}$$

Next, from (6.3),

$$\frac{d\pi^{in}}{dt^f} = \frac{\partial \pi^{in}}{\partial M^{in}} \frac{dM^{in}}{dt^f}. \tag{6.46}$$

In turn, $\frac{\partial L^c}{\partial p^{M^{in}}} = \frac{\partial L}{\partial p^{M^{in}}} + \frac{\partial L}{\partial I}\frac{\partial I}{\partial p^{M^{in}}}$, where $I = w(1-t^l)L$ denotes income and the superscript c denotes a compensated coefficient. Then we obtain from (6.37):

$$\frac{\partial L}{\partial p^{M^{in}}} = \frac{\partial L^c}{\partial p^{M^{in}}} - \frac{\partial L}{\partial I}M^{in};\ \frac{\partial L}{\partial t^l} = \frac{\partial L^c}{\partial t^l} - \frac{\partial L}{\partial I}wL. \tag{6.47}$$

The Slutsky symmetry property gives $\frac{\partial L^c}{\partial p^{M^{in}}} = -\frac{\partial M^{in,c}}{\partial\left(1-t^l\right)w}$. Note again that $\frac{\partial M^{in,c}}{\partial\left(1-t^l\right)w} = \frac{\partial M^{in,c}}{\partial t^l}\frac{\partial t^l}{\partial\left(1-t^l\right)w} = -\frac{\partial M^{in,c}}{\partial t^l}w^{-1}$, so

$$\frac{\partial L^c}{\partial p^{M^{in}}} = \frac{\partial M^{in,c}}{\partial t^l}w^{-1}. \tag{6.48}$$

Next, leisure is weakly separable in utility. So when t^l changes, it affects consumption and demand only through disposable income. This gives

$$\frac{\partial M^{in,c}}{\partial t^l} = \frac{\partial M^{in,c}}{\partial I}w\left(1-t^l\right)\frac{\partial L^c}{\partial t^l}, \tag{6.49}$$

where $w\left(1-t^l\right)\partial L^c/\partial t^l$ is the change in disposable income following a compensated increase in the labour tax. Then we can use (6.44)-(6.49) to find

$$w\frac{\partial L}{\partial t^f}L - \frac{\partial L}{\partial t^l}F = \left(\eta^{MI}-1\right)\frac{\partial L^c}{\partial t^l}F, \tag{6.50}$$

and

$$wL\frac{\partial L}{\partial \pi^{in}}\frac{d\pi^{in}}{dt^f} = \left[\eta^{M^{in}I}\frac{\partial L^c}{\partial t^l} - wL\frac{\partial L}{\partial I}\right]Z^C\frac{dM^{in}}{dt^f}, \tag{6.51}$$

with $\eta^{MI} \equiv \frac{\partial M^{in,c}}{\partial I}\frac{I}{M^{in}}$. Substituting (6.50) and (6.51) back in (6.43) then gives

$$\begin{aligned} wt^l\frac{dL}{dt^f} = MEB\left[t^f\frac{dF}{dt^f}\right] - \frac{MEB}{\varepsilon_{LL}}&\left[\varepsilon^c_{LL}\left(\eta^{M^{in}I}-1\right)F\right. \\ &\left.+\left[\varepsilon_{LL} - \varepsilon^c_{LL}\left(1-\eta^{M^{in}I}\right)\right]Z^C\frac{dM^{in}}{dt^f}\right], \end{aligned}$$

to

(6.53)

where we use the compensated labour elasticity $\varepsilon^c_{LL} = -\frac{\partial L^c}{\partial t^l}\frac{1-t^l}{L} = -\frac{\partial L^c}{\partial t^l}\frac{t^l}{L}\frac{1-t^l}{t^l}$, and, from the Slutsky equation, $\varepsilon_{LL} = \varepsilon^c_{LL} + \eta_{LI}$. We then substitute (6.52) into (6.34) to obtain (6.13).

Appendix 6.B Parametrisation, further details

6.B.1 Additional parameters

Table 6.B.1 lists additional values used in our calculations of Equation (6.13), but not previously specified in Table 6.3.1.

Table 6.B.1 Remaining parameter values

Parameter	US Central value	UK Central value
Number of active miles travelled per person per year, M^{ac}	267	740
Number of vehicle miles travelled per person per year, M^{in}	10,307	9124
Uncompensated labour supply, ε_{LL}	0.2	0.2
Compensated labour supply, ε^c_{LL}	0.35	0.35
Producer price of gasoline, p^f	186	186
Tax on labour, t_L	0.318	0.31

6.B.2 Elasticities

Tables 6.B.2, 6.B.3 and 6.B.4 provide an overview of the elasticity of fuel, inactive, and active miles travelled with respect to the fuel price established in the literature. These elasticities capture the extent to which fuel consumption, inactive miles travelled (VMT), and active miles travelled change in response to fuel prices. We use these values to parametrise our model as explained in Section 6.3.1. Similarly, Table 6.B.5 lists the literature estimates for the income elasticity of inactive travel, which captures the response of inactive miles travelled to income changes.

The only direct estimate of a cross-elasticity of active modes of travel (walking and cycling) with respect to fuel price, $\eta^{M^{ac}F}$, we identified is a 1999 report summarising the research of several European studies (Hague Publishing et al., 1999). To our knowledge, no cross-elasticity estimates for the US exist in the literature. This poses two problems: first, the data on cross-elasticities is old, and cultural differences may mean that people's behaviour is more (less) elastic towards other modes of travel, including bike sharing, ride-hailing services such as Uber, or electric non-active modes such as e-scooters (see e.g. Hollingsworth et al. (2019)). Second, the data is context-specific to higher density European cities.

To adjust for this gap in the literature, we additionally consider the cross-elasticity of public transport with respect to the fuel price. Although we recognise that the relationship

Table 6.B.2 Fuel price elasticity, η^{FF}

Country	Value	Range	Notes	Source
OECD	-0.3	-0.6 to -0.8	short run and long run, resp.	Graham and Glaister (2002)
UK and US	-0.55	-0.3 to -0.9		Parry and Small (2005)
US	-0.21	-0.21 to -0.75	short run	Hughes et al. (2006)
US	-0.43			Small and Van Dender (2007)
US	-0.46	-0.1		Davis and Kilian (2011)
US	-0.3			Dahl (2012)
UK	-0.33			Dahl (2012)
UK	-0.6			Fouquet (2012)
US	-0.31			Havranek et al. (2012)
Europe	-0.82		response to change in tax size	Dieler et al. (2015)
US	-0.37			Coglianese et al. (2017)
US	-0.27	-0.27 to -0.35		Levin et al. (2017)
Denmark	-0.3	up to -0.87		Gillingham and Munk-Nielsen (2019)

Table 6.B.3 Fuel price elasticity of inactive miles travelled (VMT), $\eta^{M^{in}F}$

Country	Value	Range	Notes	Source
OECD	-0.3	-0.15 to -0.3	short run and long run, resp.	Graham and Glaister (2002)
UK and US	-0.4	0.2-0.6		Parry and Small (2005)
US	-0.1			Small and Van Dender (2007)
Germany	-0.45			Frondel and Vance (2013)
California	-0.147	0.041 to -0.288		Knittel and Sandler (2018)
Denmark	-0.32	-0.32 to -0.45		De Borger et al. (2016)
UK	-0.301	-0.1803 to -0.417		Cerruti et al. ("Charging Drivers by the Pound: How Does the UK Vehicle Tax System Affect CO_2 Emissions?")
US	-0.3	-0.05 to -0.3		Gillingham and Munk-Nielsen (2019)

between active travel, public transport, and car use is likely to be different in the UK and US, we use the same values of $\eta^{M^{ac}F}$ for both countries. This is because of the limited number of studies estimating this value.

For the income elasticity of inactive travel, $\eta^{M^{in}I}$, we consider the following. Direct estimates of $\eta^{M^{in}I}$ can be found in Small and Van Dender (2007), Santos and Catchesides (2005) and Fouquet (2012). Additionally, and akin to Parry and Small (2005), we consider estimates for the income elasticity of fuel use (Mattioli et al., 2018; West and Williams III, 2007). This approach is justified by Johansson and Schipper (1997), who found that the income elasticity of fuel use and miles travelled were approximately equal.

Table 6.B.4 Cross-elasticity of active travel and public transport (PT) use, $\eta^{M^{ac}F}$

Type	Country	Value	Notes	Source
PT	Australia	0.104 to 0.291		Hensher and King (1998)
Walking and cycling	Europe	0.13		Hague Publishing et al. (1999)
PT	Europe	0.14		Hague Publishing et al. (1999)
PT - transit general	US	0.12		Currie and Phung (2007)
PT - light rail	US	0.27 to 0.38		Currie and Phung (2007)
PT - buses	US	0.04		Currie and Phung (2007)
PT	US	0.24		Haire and Machemehl (2007)
PT	US	0.4	short term	Holmgren (2007)
PT	Australia	0.22		Currie and Phung (2008)
PT	US	0.366	Upward trend in elasticities	Lane (2008)
PT	US	0.08 to 0.16	(medium-)small cities only	Mattson (2008)
PT	South Korea	0.32		Lee et al. (2009)
PT - rail, regional	US	0.27 to 0.38		Maley and Weinberger (2009)
PT - local, bus	US	0.15 to 0.23		Maley and Weinberger (2009)
PT - commuter rail	218 US cities	-0.012 to 0.213	Upward trend in elasticities 2002-2008	Blanchard (2009)
PT - light rail	218 US cities	-0.103 to 0.507	elasticities increased 2002-2008	Blanchard (2009)
PT		0.116		Iseki, Ali et al. (2014)

Table 6.B.5 Income elasticity of inactive travel, $\eta^{M^{in}I}$

Country	Value	Range	Source
UK	0.8	0.4-1.2	Parry and Small (2005)
US	0.6	0.3-0.9	Parry and Small (2005)
UK	0.4	0.0681 to 0.6335	Santos and Catchesides (2005)
US	0.02		West and Williams III (2007)
US	0.53		Small and Van Dender (2007)
UK	0.8		Fouquet (2012)
UK high income	0.62	0.54 to 0.7	Mattioli et al. (2018)
UK low income	0.56	0.36 to 0.75	Mattioli et al. (2018)

6.B.3 External cost of fuel (CO_2) pollution, $Z^{P_{\bar{F}}}$

Table 6.B.6 provides an overview of literature estimates for the social cost of carbon. We assign the greatest weight to the recent studies by Pindyck (2019) and Hänsel et al. (2020), which both rely on interviews conducted with experts in the field and their view regarding the appropriate value of the SCC.

Table 6.B.6 Social cost of carbon estimates literature overview

USD 2017, per tonne CO_2	Plausible SCC range	Source
91.8	2.6 - 367	Parry and Small (2005)
78.8	0 - 297.6	Tol (2011)
900	up to 1500	Ackerman and Stanton (2012)
49.7	14.2 - 73.3	Environmental Protection Agency (2016)
40	17 - 84	van den Bijgaart et al. (2016) and DICE as calculated by OECD (2018)
517	5274.4	Adler et al. (2017)
92.4	46.2 - 140	BEIS (2018)
41.3	25.4-157.5	Nordhaus (2018)
417	177 - 805	Ricke et al. (2018)
319.3	253.2 - 385.4	Cai and Lontzek (2019)
90	80 - 100	Pindyck (2019)
96	16.2 - 494.4	Hänsel et al. (2020)

A selection of the social cost of carbon estimates found in the literature. BEIS (2018) is a UK specific value.

To obtain the externality cost per gallon of fuel used, we need to account for the different fuel CO_2 emission intensities, as well as the country-specific average fuel composition. The average emissions intensity of diesel is 8.7 kgCO_2/gallon, and 10.1 kgCO_2/gallon for gasoline. The US fuel mix is 98.5% gasoline, while the UK fuel mix is 55% gasoline and 45% diesel. Using a central value for the social cost of carbon of 90 \$/tCO_2, and a low (high) value of 40 (400) \$/tCO_2, we obtain the estimates for $Z^{P_{\bar{F}}}$ as specified in Table 6.3.1.

6.B.4 Marginal value of health through active travel Z^Q (HEAT)

To determine the marginal value of health through active travel increases, Z^Q, we use estimates from the WHO Health Economic Assessment Tool (HEAT). HEAT is an open-access online tool for conducting economic assessments of active transport (changes) and their impact on health benefits from physical activity, air pollution, accidents, and effects on carbon emissions.[25] Importantly, the tool relies on international expert consensus and

[25]The tool is available on www.heatwalkingcycling.org.

the methodology is regularly updated to reflect new research evidence and data. The tool can be used for cost-benefit analysis, and requires inputs on baseline levels of active travel, the assessed change in active travel, the time needed to achieve those changes, as well as assumptions regarding substitution away from other forms of exercise. Other (optional) inputs are the discount rate, the value of statistical life (VSL), and the source the information supplied to the model comes from (count data, population survey, modelled data, hypothetical scenario). In its computations, HEAT assumes a linear relationship between active travel increases and health benefits. More details can be found in Section 3.4 of Kahlmeier et al. (2017).[26]

While the tool is not designed for use outside of Europe,[27] it has been applied to US settings. Examples are Colorado (BBC Consulting, 2017), Arkansas (BBC Consulting, 2018) and Boston (James et al., 2014). We therefore used HEAT for both the UK and the US, and used country-specific values to calibrate the model.

Further details regarding the data inputs we used are given below. Baseline average levels of walking and cycling of 4.8 and 1.2 minutes per day in the UK, and 5.6 and 0.4 for the US. We consider an increase of 5 minutes of activity per person per day for the population aged 20-74, split between the walking and cycling according to current proportions of the two modes. We assume changes materialize over a three year adjustment period, and denote an average of lives saved per year over a 10 year period as our outcome variable of interest. We use 2017 population data from Murphy et al. (2018) for the US, and Patel (2017) for the UK. HEAT requires the user to specify the degree to which increases in active travel crowd out other forms of activity. As evidence suggests that exercise through active travel is additive, rather than crowding out other forms of exercise (Foley et al., 2015; Laeremans et al., 2017; Dons et al., 2018; Castro et al., 2019), we assume that all increases in physical activity are additional. Finally, we maintain the HEAT default parameter values for "mortality relative risk reductions" associated with walking (0.89) and cycling (0.90), which affect the number of lives saved due to a given increase in active travel.

HEAT focusses on mortality reductions due to active travel. A more accurate representation of the health effects of active travel would also account for quality of life effects. Adopting a healthy lifestyle can, for instance, increase the disease-free lifetime of an adult by up to 10 years ("Healthy lifestyle and life expectancy free of cancer, cardiovascular disease,

[26]Discussions of the strengths and limitations of HEAT, and the best methods for economic evaluations of active travel, can be found in Fishman et al. (2015) and Deenihan and Caulfield (2014).

[27]US cities are less dense and have too small shares of walking and cycling (about 0.2% of total travel) to make a country-wide assessment about the impact of active travel on health. Conversely, Asian cities, though often high-density, have such elevated levels of air pollution exposure that the physical activity relative risk reduction coefficients HEAT uses are not appropriate.

and type 2 diabetes: prospective cohort study"). As HEAT does not include such benefits, we consider it a conservative estimate of the overall health benefits of active travel per mile travelled.

The main output from HEAT is the number of deaths saved through the specified increase in active travel. We use the VSL, which reflects the value society places on a life and is commonly used in cost-benefit analyses, to convert these lives saved to $ amounts. The central value of VSL used for the US is $9.26 million, with a range of $5.4m-13.4 million (Moran and Monje, 2016). The central value of VSL for the UK is more conservative, $4.36 million (WHO 2015), with a range of $2.2m-12.6 million (Thomas, 2020). HEAT assumes a linear relationship between exercise and health benefits for sedentary societies (Kahlmeier et al., 2017). This approach gives the value of the total number of lives saved due to an increase in active travel by 5 minutes. We finally convert this value to the value of health gained per additional mile of active travel, by dividing by the total increase in active travel, assuming a speed of 15 minutes per mile. This gives a central value of Z^Q of $6.91 for the US, and $2.44 for the UK.

6.B.5 Obtaining the numerical results

Our quantification of the optimal fuel tax takes into account that the fuel consumption F and miles travelled M^{in} and M^{ac} depend on the fuel tax level. In other words, we approximate Z/F in (6.14) by

$$\frac{Y}{F} = \frac{Z^0}{F^0}\left(\frac{p^f + t_1^{f*}}{p^f + t^{f0}}\right)^{\eta^{ZF} - \eta^{FF}},$$

with $Y \in \{M^{in}, M^{ac}\}$, and where t^{f0} and Y^0 denote the baseline level of t^f and Y.[28] We take labour supply L and labour taxes t^l as constant throughout the quantification. While through Equations (6.10) and (6.11), changes in time spent travelling and fuel tax revenues may affect labour supply and taxes, this effect is likely minor, and abstracting from this interaction substantially simplifies computations.

[28] See also Parry and Small (2005).

6.B.6 Quantifying welfare effects

We follow Parry and Small (2005) and Parry and Small (2004) to obtain a formula for the welfare gain of a marginal tax increase. First, we use the definitions for Z to rewrite (6.32) as

$$\frac{1}{\mu_I}\frac{dV}{dt^f} = \left[Z^{P_{\bar{F}}} - t^f\right]\frac{-dF}{dt^f} + \left[Z^C + Z^{A_{\bar{M}^{in}}} + Z^{P_{\bar{M}^{in}}}\right]\frac{-dM^{in}}{dt^f} + \left[Z^{A_{\bar{M}^{ac}}}\right]\frac{-dM^{ac}}{dt^f} - (1-\omega)\tilde{Z}^Q\frac{-dQ}{dt^f} - wt^l\frac{-dL}{dt^f}.$$

Next, assuming that the effect of t^f on Q runs through M^{ac} alone, we can write

$$\frac{1}{\mu_I}\frac{dV}{dt^f} = \left[Z^{P_{\bar{M}^{in}}} - t^f\right]\frac{-dF}{dt^f} + \left[Z^C + Z^{A_{\bar{M}^{in}}} + Z^{P_{\bar{M}^{in}}}\right]\frac{-dM^{in}}{dt^f} + \left[Z^{A_{\bar{M}^{ac}}} - (1-\omega)Z^Q\right]\frac{-dM^{ac}}{dt^f} - wt^l\frac{-dL}{dt^f}.$$

Now use the the definitions of $\eta^{FF} \equiv \frac{dF}{dp_F}\frac{p_F}{F}$, $\eta^{M^{in}F} \equiv \frac{dM^{in}}{dp_F}\frac{p_F}{M^{in}}$, $\eta^{M^{ac}F} \equiv \frac{dM^{ac}}{dp_F}\frac{p_F}{M^{ac}}$, $\beta^{M^{in}} = \eta^{M^{in}F}/\eta^{FF}$ and $\beta^{M^{ac}} = \eta^{M^{ac}F}/\eta^{FF}$. Then $\frac{-dF}{dt^f} = -\frac{dF}{dp_F}\frac{p_F}{F}\frac{F}{p_F} = -\eta_{FF}\frac{F}{p_F}$ and, using a similar approach for $\frac{-dM^{in}}{dt^f}$, we can write

$$\begin{aligned}\frac{1}{\mu_I}\frac{dV}{dt^f} &= \left[Z^{P_{\bar{M}^{in}}} - t^f\right]\left(-\eta^{FF}\frac{F}{p^f+t^f}\right)\\ &\quad + \left[Z^C + Z^{A_{\bar{M}^{in}}} + Z^{P_{\bar{M}^{in}}}\right]\left(-\eta^{M^{in}F}\frac{M^{in}}{p^f+t^f}\right)\\ &\quad + \left[Z^{A_{\bar{M}^{ac}}} - (1-\omega)Z^Q\right]\left(-\eta^{M^{ac}F}\frac{M^{ac}}{p^f+t^f}\right) - wt^l\frac{-dL}{dt^f}.\end{aligned}$$

Next use (6.14) to find

$$\frac{1}{\mu_I}\frac{dV}{dt^f} = \left[MEC - t^f\right]\left(-\frac{F\eta^{FF}}{p^f+t^f}\right) + wt^l\frac{dL}{dt^f}. \tag{6.54}$$

Note that in Parry and Small (2005), wages w are normalised to 1. In addition, the (negative) value of η^{FF} is expressed in absolute terms. Finally, they define p^F as the tax-inclusive fuel price, which in our setting is given by $p^f + t^f$. In sum, this means that Equation (D1) in Parry and Small (2004) and (6.54) and all subsequent expressions in the derivations are equivalent solutions.

Finally, further substitutions along the lines suggested in Appendix D in Parry and Small (2004) allow us to further rewrite (6.54), as

$$\frac{1}{\mu_I}\frac{dV}{dt^f} = \left(-\frac{F\eta^{ff}}{p^f + t^f}\right)(1 + MEB_L)\left[t^{f*} - t^f\right].$$

6.B.7 Quantifying changes in mortality

To quantify the number of lives lost or gained as discussed in Section 6.4, we used HEAT and followed instructions by Kahlmeier et al. (2017). We parameterise HEAT as described in Section 6.B.4. Further conditions that were specifically calibrated to the US and UK contexts are listed in Table 6.B.7 below.

Table 6.B.7 Country-specific HEAT inputs into welfare change analysis

	US		UK	
Input	Value	Source	Value	Source
Traffic conditions	35km/h	HEAT def., some congestion	32km/h	HEAT def., EU av.
Air quality, $PM_{2.5}$ μg/m^3	7.5	EPA (2017)	10.5	HEAT def., UK av.
Fatalities/100m km, walking	4.7	Buehler and Pucher (2017)	2.2945	HEAT def., UK av.
Fatalities/100m km, cycling	9.7	Buehler and Pucher (2017)	2.1377	HEAT def., UK av.

Additional inputs that calibrate the calculations HEAT does to the context of the US and UK. Values labelled "HEAT def." are default values provided by the HEAT tool and are average values that apply specifically to the UK or European context.

HEAT provides risk-specific mortality changes, which we aggregated in to a single value in the main text. Table 6.B.8 shows the disaggregation of this value for the change from the current tax levels to the second-best optimal fuel tax levels for both countries.

Table 6.B.8 Country and cause-specific mortality changes, as provided by HEAT

	US	UK
Cause of death	Value	Value
Physical activity	-6457	-40
Air pollution exposure	83	0.9
Crash risk	108	0.3

Number of lives gained (negative value) or lost (positive value) per country per year, following a change from current to second-best optimal fuel tax levels, t^f.

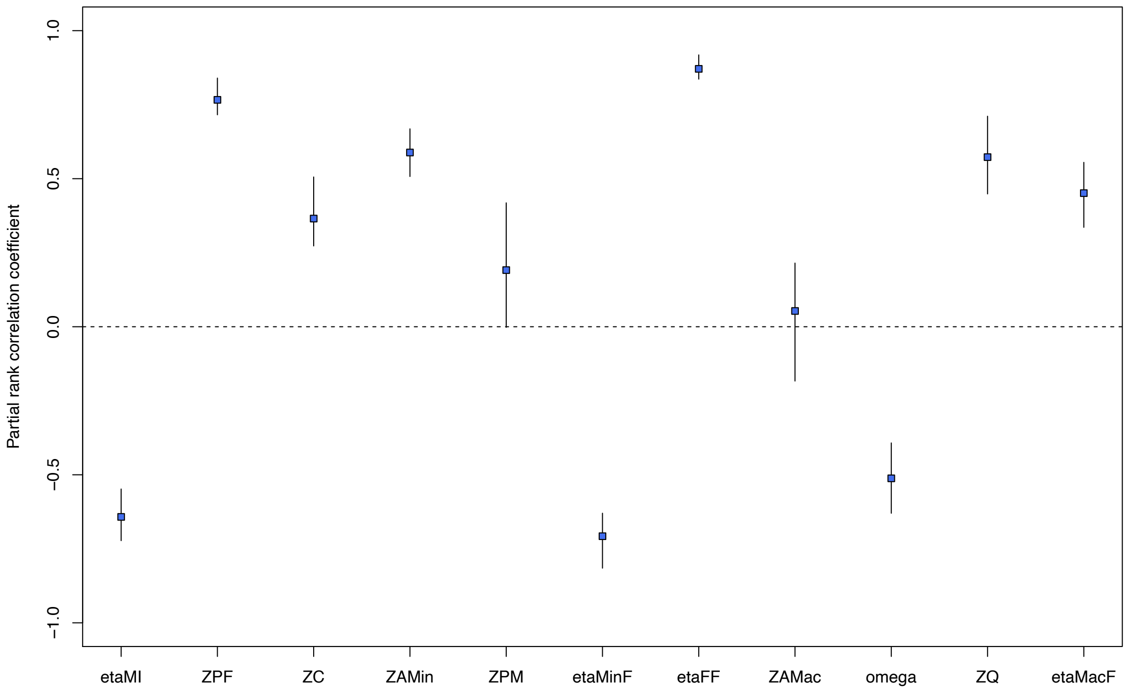
6.B.8 Sensitivity analysis

The sensitivity analysis was done by applying Latin Hypercube algorithms, implemented by the *pse* package in R (Chalom and de Prado, 2015). Latin Hypercube sampling is a method of parameter space exploration and optimisation, and is described in more detail (and compared against other methods, such as individual parameter disturbance and Monte Carlo) in Chalom and de Prado (2015). The results are depicted in Figure 6.4.2, which specifies the probabilities that the second-best optimal fuel taxes lie below a pre-specified value.

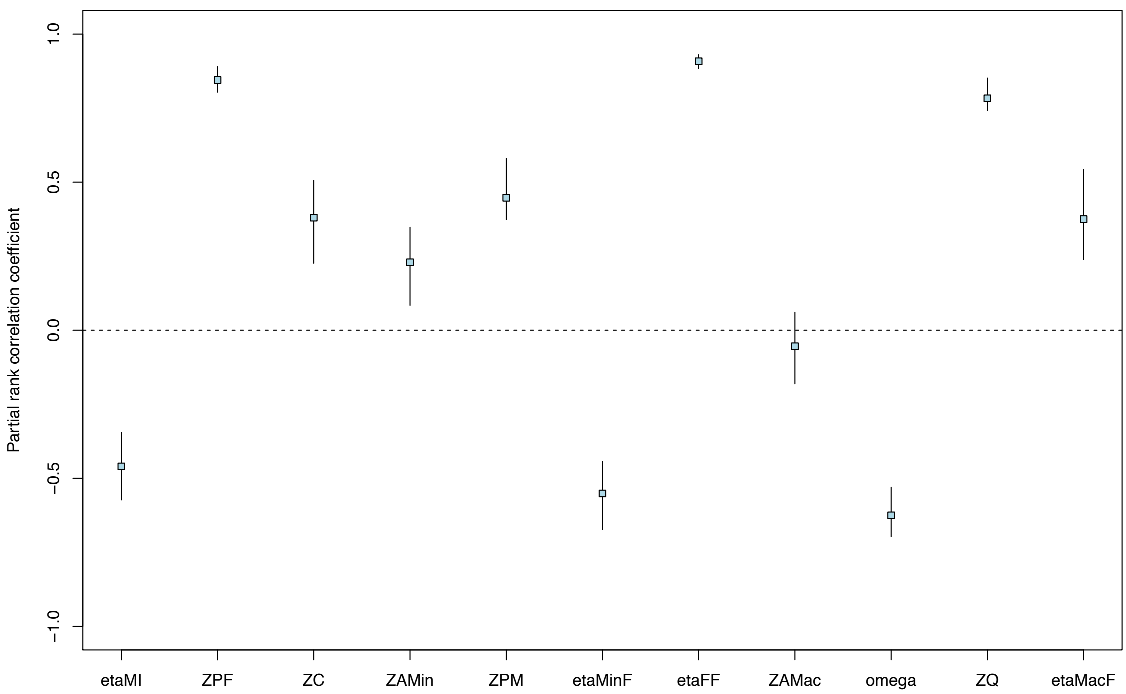
Figures 6.B.1a and 6.B.1b additionally show the relative influence of each parameter on the optimal fuel tax. More specifically, each Figure shows the partial rank correlation coefficient, defined as the effect of changing one parameter, ceteris paribus, relative to changing any other parameter, ceteris paribus, on the fuel tax. A negative value means that a larger parameter value reduces the size of the optimal fuel tax, and vice versa. From the figure, the external cost of CO_2, $Z^{P_{\bar{F}}}$ and the fuel price elasticity, η^{FF} have the greatest effect on the optimal tax, both for the US and the UK. The effect of the external cost of accidents is comparatively small.

Regarding social costs, the fuel tax is most sensitive to $Z^{P_{\bar{F}}}$, fuel pollution, i.e. the social cost of carbon. This is attributed to the fact that $Z^{P_{\bar{F}}}$ has a very high right-hand tail, which follows from high estimates for the social cost of carbon under a business-as-usual scenario for global carbon emissions in the relevant literature (see also Table 6.B.6 in Appendix 6.B.3). Increasing $Z^{P_{\bar{F}}}$ to this upper bound increases the optimal fuel taxes by more than \$4/gal for both the UK and US. We find a similar sensitivity of the fuel tax to the calibration of $Z^{A_{\bar{M}^{in}}}$ for the US, while the UK fuel tax increases by only a little when moving from the central value to the upper bound for $Z^{A_{\bar{M}^{in}}}$.

Finally, the fuel tax shows similarly strong sensitivity to the remaining social cost parameters, with the exception of active accident costs, $Z^{A_{\bar{M}^{ac}}}$. Higher social costs Z^{Q}, $Z^{P_{\bar{M}^{in}}}$ and Z^{C} result in higher levels of optimal fuel taxation, with the upper (lower) bound increasing the optimal fuel tax by around \$1.50-2.50/gal.



(a) PRCC plot for the US.



(b) PRCC plot for the UK.

Figure 6.B.1 Partial rank correlation coefficient (PRCC) plots showing the relative influence of each parameter on the optimal fuel tax, obtained using Latin Hypercube sensitivity analysis.

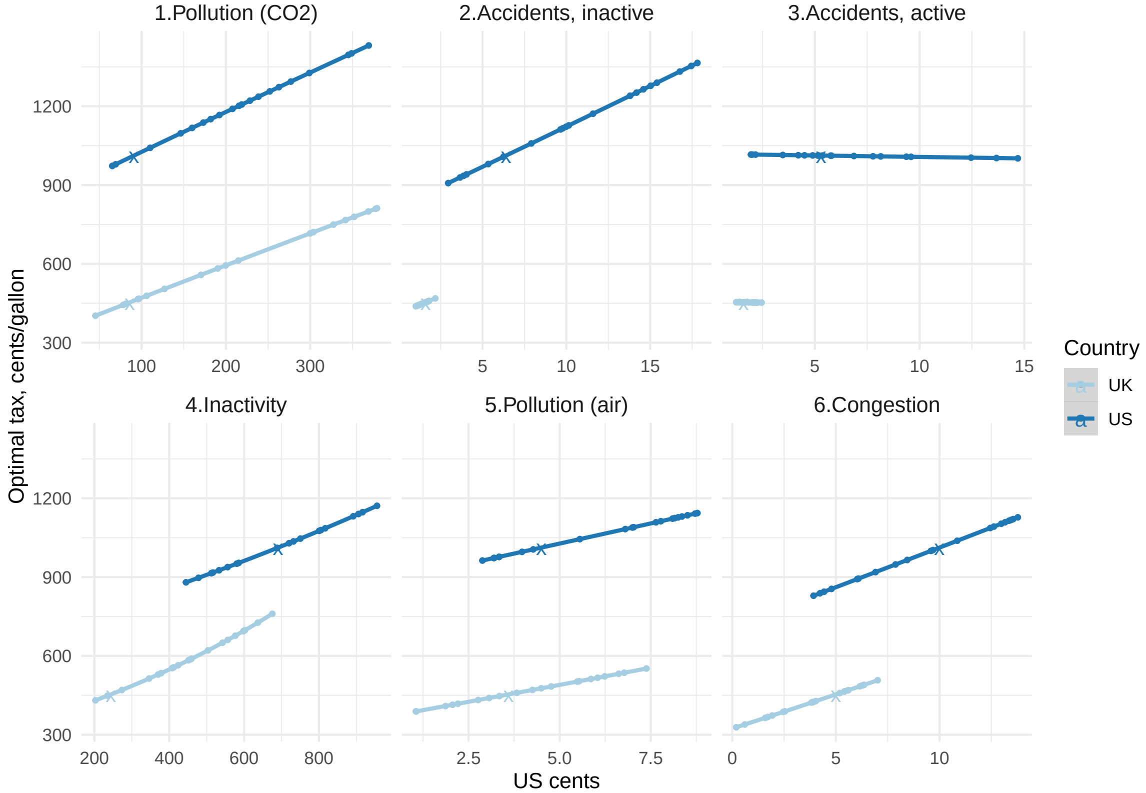


Figure 6.B.2 The sensitivity of the fuel tax to the social cost parameters.

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Chapter 7

Discussion

7.1 Summary

This thesis aimed to take a broader look at active travel and how it can become more widespread. It did so in Chapter 4, where it examined the relative influences of an individual's attitudes, practices, the social and physical space, and the policy environment, in Chapter 5, which examined how, when, and for whom information-based measures work to increase active travel, as well as Chapter 6, which compared the effects of physical activity from travel to other harmful effects of transport, also within the larger context of the economy and taxation.

This thesis highlights the importance of socio-ecological frameworks, and recognises the limitations of any specific theory. The socio-ecological framework was useful because it ties many different theories and helps illustrate where a particular theory or concept might contribute the most to knowledge. Each theory is useful in a separate setting - while realist evaluation is very useful for uncovering the way individuals act and that is needed for the evaluation of targeted, individualised policies, the evaluation of larger-scale policies will often not be possible with such a granular approach. For example, in many cases, the only data available to evaluate a nation-wide policy will be revealed-preference data, data of actual fuel consumption or car/bicycle purchases, or public transit passenger miles. Revealed preference data shows what an individual chose to do, but not whether they would have preferred to, and whether they had the *capability* to choose a different option. The latter type of data may be necessary to uncover what changes within a system are needed. The usefulness of the different theories used in this thesis is thus constrained by: the scale of the policy, the type of data available, and the target audience of the researcher.

The remainder of this chapter first briefly summarises and evaluates the contributions of each of the analytical chapters, and then explores several themes that arose from this research, but may not have been included in any of the previous chapters.

7.1.1 Chapter 4: factors affecting active travel

Chapter 4 tests the relative influence of different factors affecting the decision to walk or cycle. Within the micro level and the theory of planned behaviour, the construct of perceived behaviour control has the strongest influence on whether or not a trip will be taken by active mode. Attitudes and constructs from the extended TPB also matter, but subjective norm constructs were not significantly associated with daily travel. Interestingly, the intent to carry out a behaviour and the action itself were associated with different variables; for example, whether a mode is perceived as being predictable did not influence the intention to travel actively by a large amount, but it did significantly increase the likelihood of actually travelling actively. Within the meso level, the morning rush hour mostly affected the decision to take service (personal business, visiting friends) trips by active travel mode. Within the macro level, the built environment influenced active travel only marginally, and the distance travelled was the greatest determinant of transport mode choice. This did not vary significantly by work or home location, or city.

This paper also included a socio-ecological framework as a guiding principle for future research in order to enable people to look for context-specific relationships in their environment, instead of relying on the relationships uncovered in this chapter. Comparisons between the built environment and attitudes towards active travel are relatively common (as shown in Chapter 2). This chapter helped demonstrate that walkable neighbourhoods need to be implemented in conjunction with plans to increase destination accessibility within the entire city, not just a neighbourhood. The paper also highlighted the strength of attitudes relative to the built environment in terms of their correlation with active travel. This may, however, be due to the aggregated nature of built environment variables used in the analysis; people may be much more sensitive to micro-built environment variation that is averaged out in larger area-based measures.

The research only applies to the European context, and is geographically limited as a result. Smaller towns and villages will also exhibit different travel patterns, with less diversity in terms of density, service provision, or distance from green space. Attitudes will always be context-specific, as norms of what behaviour is acceptable, and what constitutes proper infrastructure enabling active travel, will differ from location to location. As it was a cross-sectional analysis, feedback effects could not be directly tested. Nonetheless, it provides a useful examination of the similarities and differences between PASTA cities.

7.1.2 Chapter 5: long-term effectiveness of information-based interventions

Chapter 5 used realist evaluation principles, analysing the effectiveness of soft measures (primarily travel-to-work programs) in four cities of the PASTA study, Rome, Antwerp, Örebro, and Vienna. It demonstrated the importance of long-term evaluations of targeted projects in transport, as the effectiveness of the measures differed by time period and mode of transport. In the first follow-up one year after the intervention, walking and cycling increased in all four cities of the PASTA study, with some of the increases for cycling being dampened by an increase in public transport, for example in Vienna. Three years after the intervention, most travel patterns returned back to their pre-intervention levels in Örebro and Vienna, apart from e-bicycling. One of the main findings of this research was the extent of uptake of e-bicycling among the top measure affected group. This uptake was, however, largely limited to people who were already cyclists, rather than car drivers. The intervention worked in a mature cycling city, Örebro, and may not have worked that well in a place where cycling is not popular or common. Other policies and evaluation strategies may be needed there.

Realist evaluation, while more demanding of time and resources, has the benefit of explicitly examining contradictory results for different socio-demographic groups, forms of activity or reverse causality. This helps reduce the likelihood of overestimating the effectiveness of a policy or reaching inappropriate conclusions (van Wee and Ettema, 2016).

7.1.3 Chapter 6: optimal fuel taxes when physical activity is considered

Research presented in Chapter 6 calculated the second-best optimal fuel tax, when all major social costs of personal vehicle use are accounted for. It incorporated a public health modelling exercise - the health impact assessment - into an economic framework, showing how cooperation between these two fields could work. It also helps provide monetary arguments in one of the systematic problems within physical activity policy-making: the lack of money and consistent investments, as highlighted recently by Sallis (2020). By writing to economists and emphasising the size of the costs to society from inadequate physical activity, relative to issues that have caught widespread public attention, such as carbon emissions and air pollution, this chapter provided an additional motive for expanding physical activity budgets in public health bodies. The main finding of the paper is that the relative size of the health benefits from cycling or walking a mile are an order of magnitude larger than the value of the carbon dioxide or air pollutants avoided by not driving. When the physical activity benefits are added to a second-best fuel tax calculation, the optimal fuel tax increases by 49% in the US and 36% in the UK.

This kind of research faces several challenges. First, whether it is possible to work with a model that relies on an unobservable variable (ω, the extent to which the representative agent is aware of the benefits of exercise and internalises them - likely to be high for a regular cyclist, likely low for someone who thinks physical activity is a redundant activity). Second, as discussed in Chapter 3, using the term "internality" may alienate many researchers within the field of economics itself. This was somewhat counteracted by using a well-known framework, the analytical detail of which lent the research more credibility.

It would have been useful to add another constraint to the model to take into account more of the findings in Chapter 4, specifically adding a built environment constraint - the amount of designated cycling infrastructure - to the model, to make US results more realistic. However, the aim of Chapter 6 was to illustrate the potential that including physical activity in transportation policy on a national scale could have, rather than advocating for the specific tax size calculated in the paper. Hence, an archetypal tool for externality correction, the fuel tax, was used instead of congestion charges or mileage-based fees. Second, no accepted methodology exists in the literature for including a built environment- or cycling infrastructure-elasticity, meaning that any attempts conducted as part of Chapter 6 would have likely been approached with scepticism, and distract from the primary results of that chapter.

7.2 Themes arising from the research

7.2.1 Use of frameworks

Insights from these chapters help support the Swiss Cheese Urban Transport model presented in Chapter 2, Figure 2.1. For example, from Chapter 4, the micro and meso levels are the primary barriers to active travel, with some holes that represent positive attitudes. Trip attributes, particularly trip distance, are a further barrier to active travel. However, certain types of trips, such as morning rush hour trips, increase active travel - these are the holes in the barrier, or the cheese layer. Similarly, in the majority of western cities, urban road space is dedicated overwhelmingly to cars, with public transport, walking, and cycling having little to no dedicated space (Gössling et al., 2016; Szell, 2018). Holes in this barrier include higher connectivity of roads in dense inner-city areas in Europe, protected sidewalks for pedestrians, and cycle paths separate from motorised traffic.

Chapter 5 also demonstrated how the interventions implemented as part of the PASTA study, personalised travel-to-work programmes and lending of e-bikes at workplaces in Örebro, help create holes in the first two layers of the Swiss Cheese model - they create new incentives, and change the perception of trip attributes, helping change the intent a person has. City-specific mode changes, in particular the increase in public transport use accompanied by a decrease in car driving in Vienna in the top measure group, show that the built environment and accessibility can create a barrier to certain modes - public transit use did not increase in similar ways in the other cities.

Chapter 6 examined the opposite direction of influence within the urban transport system, examining car travel and what intervention can plug more holes for car travel in the layer of national policy, inhibiting car travel. Increasing the fuel tax, and providing a signal to the market by including physical inactivity in the fuel tax both serve this function.

Considerations for the future

The socio-ecological framework that forms part of this thesis, shown initially as Figure 4.1 can be used in a similar way, as it includes all the components that the Swiss Cheese model does, with the added complexity of feedback effects, jargon, and more comprehensive lists of influences within each level. The socio-ecological framework is more descriptive and informative, while the Swiss Cheese model, with its use of humour, is likely to serve a wider audience. Both frameworks offer visual cues for the audience, increasing memorability, and ease of use, thereby increasing the amount of knowledge they communicate to the reader. Science communication is becoming more important every day due to the rise of misinformation, and multiplicity of opinions; opportunities for such communication are also increasing steadily, with the rise of platforms like Twitter, and websites such as Our World In Data. Having the ability to convey the same ideas in different ways, in order to target different audiences within the wider public, is a competitive advantage. The example given with the socio-ecological and Swiss Cheese models demonstrates the benefits of using colour, and symbolic and metaphorical aides in communicating knowledge in different ways.

7.2.2 Use of data

In the individual research chapters, the thesis used several novel sources of data. Using open-access data on public transport and routing APIs, Chapter 4 included a more detailed analysis of mode choice accessibility than many other studies were able to (examples include Dill et al. (2014), Keyes and Crawford-Brown (2018) and Vale and Pereira (2016)). Most of this type of data has only recently become available, so future research is likely to make increasing use of accessibility data. Second, in order to write the analysis presented in Chapter 5, a survey was conducted, asking several hundred respondents to answer a follow-up questionnaire two years after the original study had ended, and 3 years after a soft measure was implemented in one of the study groups. This provided unique long-term data on over 300 individuals and their travel habits and perceptions. Long-term follow-up studies are rare in projects that focus specifically on physical activity and transport patterns (Song et al., 2017), partly because of the narrow focus of such studies and, therefore, more likely short-term funding periods.

Some data constraints existed that I could not influence. One such constraint was the design of the original PASTA study. While best-practice guidelines suggest that there should be two to three questions targeting the measure of a construct within the theory of planned behaviour (Ajzen, 2020), there were typically only one to two questions mapping onto a particular TPB construct in the PASTA survey. This was done in part to reduce the burden on the respondent, as the baseline survey was approximately 25 minutes long. Furthermore, in a quest to keep the follow-up questionnaire to a reasonable length, I excluded certain questions that existed in some of the original PASTA short follow-up questionnaires, but not their baseline one. In the email address created by the University of Oxford specifically for the purpose of this questionnaire, I then received several complaints about missing the crash risk questionnaire, because the participants had had near misses, or been in an accident while walking or cycling. This shows that accident risk and experiences are clearly more important to the general public than I, as a researcher, anticipated, and by not including an option for them to provide this information, rid them of their voice. Within my position as principal investigator, I could have easily created an optional section for them to fill in about crashes, but I did not anticipate gaining enough responses on this section for statistical power, and therefore excluded it. This shows that careful and inclusive research needs to be enabled, with flexible approaches even to pre-formatted surveys, and that researchers should, at all times, question their position of power in relation to their study participants.

Considerations for the future

Increased connectivity and interest of academics, as well as professionals, in (urban) transport will likely help accelerate the move to open source and non-proprietary transport analysis tools, data, and models. Lovelace (2021) summarised the open-source tools available on different platforms for quantitative transport analysis, identifying 3 modelling softwares, and 25 packages or tools. Open-access data such as the public transit feeds used in this thesis, or forms of citizen-led science are also becoming more ubiquitous, a welcome trend in transportation. A potential positive effect of this could be an increased focus on accessibility in transport planning, as geographic tools provide new insights into urban-rural areas cut off from transport options other than the car, among other benefits.

7.2.3 Outcome measures of interest

This thesis used several different outcomes of interest to measure mobility: whether a trip was taken by an active mode, frequency of active travel, and distance actively travelled as opposed to the distance driven. However, and together with the majority of quantitative transportation research, it was concerned with mobility. It is possible that accessibility and justice (Martens, 2016), or rather well-being or happiness (Stanley and Stanley, 2007; Mattauch et al., 2016), or freedom from air and noise pollution (Jephcote et al., 2016) should be aims in transport policy, rather than simply levels of active travel. As this thesis shows, however, that active travel typically contributes to all of the above, it is, at least for the time being, an acceptable outcome measure of interest.

Nonetheless, both Chapters 5 and 6 show that car use is fairly inflexible or inelastic, which means that policies aiming to reduce car use through higher active travel may achieve their aim to increase active travel, but perhaps not to reduce driving itself.[1] Future research therefore also needs to focus not only on policies that would increase active travel, but actively search for policies that would make car driving redundant.

Considerations for the future

The rise of new forms of mobility, namely e-scooters, share bikes, ride-hailing apps and automated and shared vehicles, were not explicitly considered in this thesis. Wadud et al. (2016) demonstrate that widespread adoption of automated vehicles could either halve or double greenhouse gas emissions of transport. The rise of cheap ride-hailing apps such as Uber and Lyft, in particular, have already led to a change in urban transport patterns. Schaller (2021) estimates that uptake of such apps has indeed doubled urban vehicle miles in certain large cities in the US. Using user experience data, Schaller (2021) predicts that this trend will continue with the introduction of automated vehicles on roads, and stresses the importance

[1] Recent research by Brand et al. (2021) shows, however, that an increase in active travel is often associated with a switch away from car travel.

of focussing on space-saving modes of transport - public transport, walking, and cycling - to maintain functioning urban transport systems and liveable inner-city areas.

7.2.4 Academic audience

In academic research, deciding on the target audience necessarily alters the contents of the research. The research in this thesis therefore had to fulfil the standards of rigour for more than one discipline, but also recognise the limitations of any one paper and compromise within a field.

For example, as the aim of Chapter 6 on optimal fuel taxation in transport was to communicate rigorously researched insights between research fields, this meant writing a paper using language and tools commonly used in economics, and sacrificing the complexity of doing an in-depth health economic assessment, a survey of infrastructure-related elasticities between driving and cycling/walking, and the influence of infrastructure relative to a change in the monetary cost of driving. The aim of that chapter was not necessarily to provide an in-depth analysis, but to convey a simple message that many other researchers in the fields of public health and transport have already accepted: that walking and cycling and the health benefits associated with the exercise should be included in transport cost-benefit analyses and other appraisals. In order to meet the demands for analytical rigour within applied microeconomics, a number of co-authors were invited to collaborate on this research.

However, the paper did include a simple health impact assessment. It was there for two reasons: to prove to any public health researcher that the dollar values in the paper were derived using an accepted method, to provide an example on how to frame health-related research as "welfare effects" to economists, and to illustrate to economists what the dollar values mean in terms of lives gained or lost, and to provide an easier-to-understand figure to policymakers.

In the case of Chapter 5 on the long-term impacts of a soft measure aimed at increasing active travel, communicating insights with the field of economics would have been achieved using econometric methods and, for example, specifying equations that describe the statistical analysis carried out for the research, carrying out robustness checks and describing them in detail. However, as the aim of Chapter 5 was to convey highly specialised information in a field where conclusive evidence is not available, the decision was made to write the manuscript in the style typical of a transportation journal article on quantitative assessments of modal shift, with a focus on public health. This meant, for example, excluding details of the statistical methods and robustness checks used, in order to prevent alienation or disinterest in the target reader group, and including odds ratios and confidence intervals in the main text. Crossing boundaries between research fields is always difficult, and as fields become more specialised, this may become more true.

7.2.5 Policy

Within urban transport, several problems are competing for public interest and funding: carbon emissions and climate change, air pollution, accidents, travel time, comfort, accessibility, and physical activity. Popular outcries over air pollution-related health recently (e.g. the *Stop Killing Londoners* and *Cittadini per l'aria* movements) have built up momentum and personal concern over the environmentally unsustainable nature of urban transport. This has led to the exploration of more radical policies such as ultra-low emissions zones (London), congestion charges (debated in Edinburgh, Leeds, Moscow, New York, among others), pedestrianised super-blocks (Barcelona), or outright bans on diesel-fuelled cars (Bristol) and cars in general (Paris). However, such vocal and inclusive citizen-led campaigns are absent from the discussion on increasing population levels of physical activity. In addition, when popular movements lead to increased cycling infrastructure, it is often with mixed results (Combs and Pardo, 2021). For example, the recent South Kensington bicycle lane in London, United Kingdom, was closed down after several weeks due to vocal opposition from local businesses, and residents (Walker, 2020), capturing national interest in the process. More concerted efforts are needed to increase public acceptance of cycling and walking, and being able to do so safely.

Many cities are adapting to these changes, implementing cycling and walking campaigns, investing in segregated infrastructure for active travel, and much more. However, there is a significant difference between what incremental change can achieve, and what a radical shift in policy, population-backed, can achieve. For example, isolated cycling infrastructure policies may increase cycling by about 10% for every km of infrastructure (Mueller et al., 2018), whereas coordinated policies may increase cycling by 400% for every km of infrastructure built, as happened in Sevilla, Spain (Marqués et al., 2015). While by no means a representative sample, these examples demonstrate the potential difference that different levels of "dedication" can make to a city's mobility culture. Notwithstanding some positive examples in travel, past policies aimed at improving population-level health behaviours also report limited success for a long time before population-level behaviour change occurred. It took decades for alcohol consumption and driving to become frowned upon (Fell and Voas, 2006), or for smoking prevalence to fall (Mendez and Warner, 2000), and may take a similarly long amount of time with physical activity and reducing sedentary lifestyles.

From the above examples, three conclusions are clear:

1. both research, and the wider public in many countries around the world believe the urban environment and urban practices have to change to be liveable;

2. research has not identified a "silver bullet" solution to increasing physical activity and improving liveability of urban environments, and there likely is none;

3. efforts for change are often siloed and fragmented, with mixed reactions from the public, and with limited results.

Considerations for the future

The examples cited above, and many other reasons, have led to various calls from researchers and practitioners alike: for policies to increase physical activity to be prioritised and scaled up (Guthold et al., 2018), for a complete overhaul of how we think about health interventions and policies (Kelly and Barker, 2016), for multi-level interventions (Young et al., 2020), or simply for increases in funding for physical activity and public health bodies (Sallis, 2020). In order to effect change on a population-wide, city-wide, or community-wide level, closer collaboration with practitioners and stakeholder parties will be necessary.

First, greater agreement on what type of policies to recommend is needed. It would be useful to conduct a meta-analysis or review synthesising the evidence available on the impact that individual policies or investments have on active travel in urban areas, compared to the effect that combined, complex initiatives have. Second, knowledge gained from meta-analyses and studies assessing different schemes (e.g. games and apps, reward schemes, information campaigns) such as the paper by Kelly et al. (2020) needs to be communicated clearly, if the purpose of the research was to improve the effectiveness of future policies. In light of evidence from this thesis, particularly Chapter 5, and evidence from previous studies, perhaps the aim of interventions should not be their longevity in terms of effects. Rather, the aim could be to implement many short-term projects in short succession after one another to offer repeated incentives to people to be active, rather than relying on a one-off input. A larger systemic change is also needed, rather than personally-targeted interventions, as those will not be able to change the behaviour of an entire city or country population due to their resource-intensive nature.

Third, interventions and policies need to be evaluated on a longer-term basis, as research in this thesis and in the past (e.g. Goodman et al. (2014) and Song et al. (2017)) shows that the effects of policies are highly variable with time.

Finally, I advocate for more collaboration between research fields, both between climate scientists, transport engineers, and public health researchers, but also beyond these three fields, for example anthropology. As the recent book by Lieberman, *Exercised*, examines, current motivation methods and slogans for exercise are at odds with the genetically ingrained, fundamental motivations for physical activity and movement that humans possess - for food, shelter, out of necessity rather than opportunity or desire. He argues that by targeting the prefrontal cortex and "active thinking", most public health campaigns and simple slogans do not work for a large portion of the adult population. Understanding instead what can drive human beings to physical movement, and incorporating this into policies to improve health behaviours, is crucial for the success of these policies. More pragmatically, the rise of economic health impact assessment tools of changes in active travel, such as the WHO's HEAT tool (Kahlmeier et al., 2017; Lozzi and Monachino, 2021), provides necessary information for cost-benefit or cost-effectiveness analyses that many infrastructure investment proposals have to include prior to approval.

Chapters 4 to 6 each provide a significant contribution to the efforts to make research more interdisciplinary and increase collaborations between researchers and policymakers. This chapter discussed their relative contributions, and the role that communicating information plays in the development of knowledge and frameworks itself, the availability of high-quality data, the intended academic audience, and policy, while providing thoughts on policy and research needs into the future.

Chapter 8

Conclusion

Active travel, walking and cycling for the purpose of transportation, is recognised for its potential to alleviate many of the problems urban areas around the world are facing: congestion, the climate change damage associated with carbon emissions, accidents, or the air pollution associated with motorised vehicle traffic. Together with an increase in physical inactivity, depression, obesity, and associated diseases around the world, active transportation modes that incorporate bodily movement have the potential to contribute significantly to the solutions to a large number of problems urbanised areas face.

Objective 1 of this thesis was to present a multilevel socio-ecological framework for active travel within which different theoretical frameworks dominate different levels and interact. This thesis therefore first identified the main drivers and barriers to adopting walking and cycling, and then formally presented the relationships between them in a socio-ecological framework. This consisted of several levels, the micro (individual-focussed), meso (behaviour-focussed), and macro (environment-, society- and institution-focussed), providing space for other theories, worldviews, methods or data types to slot into different levels of the framework, as they are devised or matured.

Objective 2 of this thesis was to identify the most significant correlates of active travel behaviour in the seven PASTA cities within a socio- ecological conceptual framework for individuals, helping identify policy levers in transport. Chapter 4 evaluated the relative strength of relationships between these factors and the likelihood of a trip being taken by active mode or not. The following order of influence on mode choice of the different levels of the socio-ecological framework was identified:

1. At the micro level:
   (a) extended TPB constructs (habit)
   (b) perceived behavioural control
   (c) attitudes
   (d) subjective norms
2. At the meso level:
   (a) morning/evening rush hour
   (b) trip purpose
   (c) weekend/weekday trip
3. At the macro level:
   (a) the built environment, particularly accessibility and building density
   (b) the social environment, particularly average income in the area

It found that psychosocial constructs influence mode choice most significantly within the PASTA study dataset, relative to the built environment, and variations due to trip purpose. Variations between home and work locations were mostly insignificant. The chapter identified that the socio-demographic distribution of an individual's neighbourhood is relevant to mode choice, and found that it was significantly associated with active travel. Practices, the natural environment, and the policy environment were not included in the statistical analyses, though they all may play a significant role in active travel mode choice.

Objective 3 of this thesis was to examine the effectiveness of various information-based (soft) interventions aimed at increasing active mobility using two case study cities in a 5-year case-control cohort study, in particular whether they work, for whom, and when. The interventions were personalised travel-to-work plans providing alternatives to car driving, general information provision on the benefits of movement, and the lending of e-bikes at workplaces in Örebro. Acknowledging that individual-level perceptions are more strongly correlated with active travel, but that the world is indeed “messy” and many factors affect travel behaviours, Chapter 5 applied the concepts of realist evaluation to examine the long-term effectiveness of a number of soft measure policies in several of the PASTA cities. This chapter looked at the micro level within which policies operate, at subgroups of individuals in different life stages, health levels, economic activity, and education. It evaluated how their perceptions may have changed as a result of the intervention. Although outcomes differed by group, some results were general:

- walking was easiest to increase within the first year of the intervention,
- cycling increased in cities where public transit use had not increased,
- car travel did not decrease significantly.

However, this change in walking had not been maintained three years later, in the second follow-up wave. The longest-lasting behaviour changes, without any noticeable changes in perceptions of travel modes, were following an e-bike lending scheme in certain workplaces in Örebro, which likely led to a change in the experience of cycling initially, and subsequent habituation of the new mode of travel. Full-time employees were most likely to change their behaviour as a result of the intervention, while the high-income group behaved in the most heterogenous way of all the socioeconomic groups.

Finally, Objective 4 of this thesis was to identify all the major social costs of car travel, adding previously excluded health benefits from exercise using a theoretical economic framework that translated a well- known problem in public health and transport into language relevant to economists, and thereby identify the potential of national policy to influence active travel. Chapter 6 examined policy potential to increase active travel at the macro level, through an optimal fuel tax. The chapter:

1. Developed a micro-economic framework to calculate a fuel tax that optimises the utility of driving and active travel with respect to the social costs of driving, the tax interactions within the national taxation system, and a congestion feedback,
2. Identified the main social costs of driving, by order of magnitude:
   (a) physical inactivity
   (b) congestion
   (c) accidents
   (d) carbon emissions
   (e) air pollution,
3. Calculated the size of a second-best optimal fuel tax with and without physical inactivity costs,
4. Used a health impact assessment to carry out a welfare analysis, demonstrating at which levels of tax the greatest benefits to society exist,
5. Carried out a sensitivity analysis to identify which aspects of the tax were most likely to become policy levers.

A fuel tax increases by 49% in the US and 36% in the UK, when physical inactivity costs are added. Particularly because a fuel tax is an indirect instrument to target physical activity, this large increase demonstrates the potential for improving social welfare, if more attention was paid to active travel. Without physical activity, the current fuel tax in the UK is close to optimal, while the US fuel tax is more than an order of magnitude too low. However, the welfare analysis showed that the greatest improvement to health would be achieved from a very slight increase in fuel taxes from current levels. This is partly due to the inelastic nature of travel demand, and the sensitivity analysis also showed that the elasticities within the framework influence fuel tax levels the most. Using an economic framework, and being explicit about the normative beliefs associated with a particular theoretical set-up, can be a powerful way of providing clarity to complex problems.

One strand of thought binds all of these chapters together, namely that one single policy is unlikely to increase active travel effectively on its own. The socio-ecological framework evaluated in Chapter 4 demonstrated some of the complex interactions that exist in active travel, and showed that while soft measures are important, certain built environment interventions are also necessary for active travel to increase. Chapter 5 showed both how incomplete the effect of a well-targeted policy can be, as well as the potential power of combining policies, in this particular case travel-to-work plans, basic bicycle parking infrastructure at workplaces, and lending of e-bikes to employees. Chapter 6 showed that while theoretically increasing fuel tax rates should lead to an increase in walking and cycling, it argues that this should only be done in conjunction with associated pull measures such as infrastructure building for cyclists and pedestrians, to provide people with viable alternatives for travel. Concerted efforts are needed to change the inefficient pricing within the transportation and parking sectors, to change the built and natural environments to encourage active travel and enable safe travel without the use of cars, to inform and make people truly aware of the health, happiness, and carbon-reducing benefits that active travel brings.

In general, the transport system remains guided by the principle of travel time savings and increasing the speed of traffic and comfort, and does not reflect the ethos of justice demonstrated by European governments in many other sectors, such as water supplies, or energy access (Martens et al., 2020). This has been demonstrated by significant outcries around the world - the uprisings in Santiago, Chile following public transport price increases; the repeated closures of bridges and streets by Extinction Rebellion in the UK; the closure of bridges by cab drivers protesting the congestion charge hikes in London; and perhaps most famously, the *gilets jaunes* movement in France.

The public health system also does not have the capacity of political influence to push for a significant structural change in physical activity and transportation approaches. Sallis (2020) offers a particularly scathing review of the current state of affairs in the United States, writing that "the CDC's Physical Activity and Health Branch probably has the smallest budget and staff it has ever had. There is no person or office at the NIH to provide leadership for physical activity research. Many state health departments do not have a physical activity coordinator. Physical education programs, teachers, and requirements are decreasing. Most of these statements were true in 2009 when Preventive Medicine published a special issue on the priority of physical activity in public health. And little has changed for the better."

The accumulation of crises and emergencies within the transportation and public health systems demonstrates that systems developed in the 1950s are slowly becoming inadequate in providing for the needs of a rapidly changing modern society. New policies that understand the motivation behind people's actions are needed. Widespread campaigns that focus on positive messaging of physical movement instead of negative, body-shaming messaging, need to be created. These should target reducing sedentary lifestyles rather than body weight, a common risk factor to a range of other diseases, more influenced through diet choices than physical activity. Policies that consist of both a carrot and a stick - pull and push measures - have to work together, rather than against each other, in order for policies aiming to increase physical activity also managing to reduce car driving. A range of actors need to be brought into the debate on being active. Finally, mandates for including physical activity within transportation need to be given on a national, regional, and city level, in order for siloes between organisations and departments to be broken down.

People have many different reasons why they choose not to walk or cycle in certain or all circumstances, and removing these reasons one-by-one requires specific action targeted at each of these attitudes, norms, or barriers. Therefore, this thesis ends with an appeal to the wider scientific and public community: increase the attention, funding, and creativity being paid to movement behaviour and transport, in order to improve the wellbeing of people living in urban areas.

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Appendix A

PASTA Questionnaire

A.1 Original PASTA study selected questions

A.1.1 Person questionnaire

The full PASTA questionnaire is not included in this thesis, as many of the questions were not used in any of the initial exploratory, or final analysis. Instead, a selection of relevant variables is listed in Table A.1.1. Table 4.B.1 in Appendix 4.B specifically details the final questions used for analysis. The columns BLQ, FU1, FUS, FUR, FUL, and FIN list whether the question was included in the baseline, first follow-up, follow-up short, follow-up re-entry questionnaire (post-hibernation period), follow-up long, or final questionnaire of the original survey conducted 2014-2017. Figure 5.3.2 in Chapter 5 shows the way in which the administration of the questionnaires was organised.

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
c_id	city.name	Antwerp, Barcelona, London, Oerebro, Rome, Vienna, Zuerich
p_id		
sex		M, F
bday		
driverlicence	Do you have a driver's licence for a car or van?	Yes, No
driverlicence		
caraccess	Do you have access to a car or van?	Always, Sometimes, Never
carsharing	Are you a member of an official car sharing system or car club?	Y/N
useptlastyear	Have you used public transport at least once in the last year?	Y/N
ridebi	Do you know how to ride a bicycle?	Y/N
accessbi	Do you have access to a bicycle (private, or through a bike sharing system)?	Y/N

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
mettravwalk	How often do you currently use each of the following methods of travel to get to and from places? Walk	Daily or almost daily / on 1-3 days per week / on 1-3 days per month / Less than once per month / Never / Don’t know
mettravbi	How often do you currently use each of the following methods of travel to get to and from places? Bicycle	-
mettravebike	How often do you currently use each of the following methods of travel to get to and from places? Electric bicycle	-
mettravmot	How often do you currently use each of the following methods of travel to get to and from places? Motorcycle or moped	-
mettravpt	How often do you currently use each of the following methods of travel to get to and from places? Public transport	-
mettravcar	How often do you currently use each of the following methods of travel to get to and from places? Car or van	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
impcritshort	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Shorter travel time	1-5 Not important - Very important
impcritcost	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Lower travel cost	-
impcritcom	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Higher travel comfort	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
impcritsaftraf	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Saver travel (with regards to traffic)	-
impcritsafcrim	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Saver travel (with regards to crime)	-
impcritairpol	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Lower exposure to air pollution	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
impcritpriv	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Privacy	-
impcrithealth	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Personal health benefit	-
impcritenv	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Low environmental impact	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
impcritflex	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: Flexible departure time	-
impcritpred	For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel: More predictable travel time and journey reliability	-
walktravtim	With your day-to-day travel needs in mind would you say that walking ’for travel’ àIt saves time.	1-4 Very much disagree to very much agree
walktravcom	With your day-to-day travel needs in mind would you say that walking ’for travel’ à It is comportable.	-
walktravsaftraf	With your day-to-day travel needs in mind would you say that walking ’for travel’ à is safe (with regards to traffic)	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
walktravsaftcrim	With your day-to-day travel needs in mind would you say that walking 'for travel' à It is safe (with regards to crime).	-
walktravairpol	With your day-to-day travel needs in mind would you say that walking 'for travel' à It is unpleasant due to high levels of air pollution.	-
walktravpriv	With your day-to-day travel needs in mind would you say that walking 'for travel' à It offers privacy.	-
walktravhealth	With your day-to-day travel needs in mind would you say that walking 'for travel' à It offers personal health benefits.	-
walktravflex	With your day-to-day travel needs in mind would you say that walking 'for travel' à It offers flexibility (e.g. with regards to departure time).	-
walktravpred	With your day-to-day travel needs in mind would you say that walking 'for travel' à It offers a predictable travel time.	-
cycltravtim	With your day-to-day travel needs in mind would you say that cycling 'for travel' àIt saves time.	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
cycltravcom	With your day-to-day travel needs in mind would you say that cycling ’for travel’ à It is comportable.	-
cycltravsaftraf	With your day-to-day travel needs in mind would you say that cycling ’for travel’ à is safe (with regards to traffic)	-
cycltravsaftcrim	With your day-to-day travel needs in mind would you say that cycling ’for travel’ à It is safe (with regards to crime).	-
cycltravairpol	With your day-to-day travel needs in mind would you say that cycling ’for travel’ à It is unpleasant due to high levels of air pollution.	-
cycltravpriv	With your day-to-day travel needs in mind would you say that cycling ’for travel’ à It offers privacy.	-
cycltravhealth	With your day-to-day travel needs in mind would you say that cycling ’for travel’ à It offers personal health benefits.	-
cycltravflex	With your day-to-day travel needs in mind would you say that cycling ’for travel’ à It offers flexibility (e.g. with regards to departure time).	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
cycltravpred	With your day-to-day travel needs in mind would you say that cycling 'for travel' à It offers a predictable travel time.	-
statgenwalk	Do you agree with the following statements Ça In general, I try to walk for my day-to-day travel whenever possible.	-
statgencycl	Do you agree with the following statements Ça In general, I try to cycle for my day-to-day travel whenever possible.	-
homead_bl	Where do you live? Please be as accurate as possible.	
empstat	What is your current employment status?	Full-time employed / Part-time employed, or casual work / Student or in training / Home duties, Unemployed, Retired, Sickness leave, Parental leave / Don't know or Prefer not to answer
workad	What is the location of your main place of work? Please be as accurate as possible.	

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
studad	Where is your main place of study located? Please be as accurate as possible.	
daysofwalk	In a typical week, on how many days do you walk for at least 10 minutes continuously to get to and from places?	
dayscycle	In a typical week, on how many days do you cycle for at least 10 minutes continuously to get to and from places?	
daysebic	In a typical week, on how many days do you use an electric bike for at least 10 minutes continuously to get to and from places?	
tall	How tall are you?	
weigh	How much do you weigh?	
health	In general, how would you say your health is?	1-5 poor to excellent / 99 Don't know or prefer not to answer
smoke	Do you smoke?	Yes / No, but I used to smoke / No, I have never smoked
alcohol	How many glasses of alcohol do you drink in a typical week?	
sufferdiz	In the past week, how often have you suffered from: Dizziness/light-headedness	1-5 Never to very often / 99 don't know

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
sufferback	In the past week, how often have you suffered from: Back and/or shoulder pain	-
sufferhead	In the past week, how often have you suffered from: Headache	-
suffermusc	In the past week, how often have you suffered from: Painful muscles	-
sufferchest	In the past week, how often have you suffered from: Chest pain	-
suffernausea	In the past week, how often have you suffered from: Nausea	-
sufferstom	In the past week, how often have you suffered from: Pain in stomach or abdomen	-
sufferfat	In the past week, how often have you suffered from: Fatigue	-
peoimpwalk	Most people who are important to me think that I should walk 'for travel'.	1-4 Very much disagree to very much agree
peoimpcycle	Most people who are important to me think that I should cycle 'for travel' (that is, getting from place to place).	-
moralrespwalk	I feel morally responsible to walk in order to decrease the negative effects on the environment that motorized methods of travel have.	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
moralrespcycle	I feel morally responsible to use a bicycle in order to decrease the negative effects on the environment that motorized methods of travel have.	-
neighwalk	In my neighbourhood walking is well regarded.	-
neighcycle	In my neighbourhood cycling is well regarded.	-
walkdifficult	For me, walking would be difficult in everyday life.	-
bicycledifficult	For me, using a bicycle would be difficult in everyday life.	-
walkautom	Walking 'for travel' is something I do automatically without really thinking about it.	-
cyclingautom	Cycling 'for travel' is something I do automatically without really thinking about it.	-
fitwalk	I am fit enough to walk.	-
fitcycle	I am fit enough to cycle.	-
persimpwalk	Personal circumstances make it impossible for me to walk more (e.g. family or work commitments, carrying luggage, escorting children).	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
persimpcycle	Personal circumstances make it impossible for me to cycle more (e.g. family or work commitments, carrying luggage, escorting children).	-
inadpark	Inadequate parking for my bike at home and at my destinations make it impossible for me to cycle more.	-
orglife	The organisation of my everyday life requires me to travel a lot.	-
travelobl	I have to travel all the time to meet my obligations.	-
ownvalwalk	Regardless of what other people do, my own values and principles oblige me to walk 'for travel' whenever possible.	-
ownvalcycle	Regardless of what other people do, my own values and principles oblige me to cycle 'for travel' whenever possible.	-
commoncycle	In my neighbourhood it is common for people to cycle 'for travel'.	-
intwalk	My intention to walk 'for travel' is ...	1-5 Very weak to very strong
intcycle	My intention to cycle 'for travel' is ...	-
child6	How many children under 6 years of age	

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
child17	How many children aged 6-17 years	
adult18	How many adults aged 18-65 years	
adult65	How many adults aged over 65 years	
national	What nationality are you?	
fatnatio	What was your father's nationality when you were born?	
mothnatio	What was your mother's nationality when you were born?	
leveduc	What is your highest level of completed education?	No degree / Primary education / Secondary education or Further education / Higher education or University education / Don't know or Prefer not to answer
income	What was your total household income after taxes during the past 12 months?	Scale 1-7
lifechmove	In the past 12 months, have any of the following life changing events happened to you? Moved house	Y/N

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
lifechmed	In the past 12 months, have any of the following life changing events happened to you? I received medical advice to increase my physical activity	-
lifechoth	In the past 12 months, have any of the following life changing events happened to you? Other life changing event or events	-
lifechno	In the past 12 months, have any of the following life changing events happened to you? No life changing event	-
dayswalk	In the last 7 days, on how many days did you use each of the following methods of travel to get to and from places? Walk	Did not use it / on 1-3 days per week / on 4-5 days per week / on 6-7 days per week
daysbic	In the last 7 days, on how many days did you use each of the following methods of travel to get to and from places? Bicycle	-
dayebic	In the last 7 days, on how many days did you use each of the following methods of travel to get to and from places? Electric bicycle	-
daymoto	In the last 7 days, on how many days did you use each of the following methods of travel to get to and from places? Motorcycle or moped	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
daypt	In the last 7 days, on how many days did you use each of the following methods of travel to get to and from places? Public transport	-
daycar	In the last 7 days, on how many days did you use each of the following methods of travel to get to and from places? Car or van	-
eventstopwork	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Stopped working / retired	Y/N
eventstartuni	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Started university	-
eventfinishuni	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Finished university	-
eventmarried	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Got married	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
eventbirth	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Birth / adoption of a child in the household	-
eventchildstartschool	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Child starts at school / a new school	-
eventlefthome	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Child / someone has left the household	-
eventlicence	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Obtained a driving licence for a car or a van	-
eventlostlicence	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Lost my driving licence for a car or a van	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
eventaccesscar	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Got access to a car or a van	-
eventlostcar	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Lost access to a car or a van	-
eventmembercarsharing	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Became a member of an official car sharing system or car club	-
eventptfirsttime	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Have used public transport for the first time in a long time	-
eventaccessbike	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Got access to a bike (private or bike sharing system)	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
eventlostbike	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Lost access to a bike (private or bike sharing system)	-
eventebike	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Started to ride an electric bike	-
eventstopebike	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Stopped to ride an electric bike	-
eventbettercyclecon	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Cycling conditions have noticeably improved in my area	-
eventdetcyclecon	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Cycling conditions have noticeable deteriorated in my area	-

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
eventbetterwalkcon	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Walking conditions have noticeably improved in my area	-
eventdetwalkcon	Please select which of the following events have taken place in your life since you started your participation in the PASTA survey: Walking conditions have noticeably deteriorated in my area	-
movehomesincepasta	Did you move home since you started your participation in the PASTA survey?	-
homead_fin	Where do you live? Please be as accurate as possible.	
startnewjob	Did you start a new job or change location of employment, work/school since you started your participation in the PASTA survey?	Y/N
newworklocation	What is the location of your new main place of work/study? Please be as accurate as possible.	

Table A.1.1 Selected questions from the original PASTA person questionnaire. Adapted from consortium material.

Variable_name	Description	Value
lifestylesincepasta	Since you started in PASTA, would you say your lifestyle (like levels of physical activity, diet) got healthier?	Yes, improved a lot / Yes, improved a little / Stayed the same / No, got worse / No, got a lot worse
sufferdiseases	Do you suffer from one or more chronic diseases?	Y/N
preventact	To what extent does this prevent you from performing your daily activities?	Strongly / Moderately / Not at all
moneysit	Thinking about your total available money situation, would you say:	You cannot make ends meet / You just have enough to get along / You are comfortable / Don't know or prefer not to answer
contactfutureproj	Upon completion of this questionnaire your participation in our project will have finished, although our research will continue. Would you be willing to be contacted by us with regards to future research projects?	Y/N

A.1.2 Travel diary

The travel diary variables are listed in Table A.1.2.

Table A.1.2 Travel diary question variables from original PASTA dataset. Adapted from consortium material.

Variable_name	Description
p_id	person id
d_id	day id
pd_id	person day id
tripdate	trip date
tripdate_ad	
weekdays	transformed date in weekday
t_id	trip id
t_nr	trip number (as new and accurate trip number)
jrn_new	dummy variable for trips which starts a new journey (1 == new journey; 0 = not new journey)
jrn_nr	journey number
t_last	trip last (last trip of the day)
t_cnt	total number of trips per person-day
tripstarttime	start time of trip
tripendtime	end time of trip
tripstartpoint	trip start point
st_x	x-coordinate of start point
st_y	y-coordinate of start point
tripendpoint	trip endpoint
ds_x	x-coordinate of endpoint (destination)
ds_y	y-coordinate of endpoint (destination)
tripmode4	main mode of trip (1 = walking, 2 = cycling, 3 = car, 4 = pt)
tripmode4char	character vector of modes with renamed labels for trip mode

Table A.1.2 Travel diary question variables from original PASTA dataset. Adapted from consortium material.

Variable_name	Description
trippurpose	trip purpose (1 = Return home, 2 = To work (commuting), 3 = For business / in the course of work, 4 = To school or place of study, 5 = Shopping, 6 = For personal business/errands, 7 = Pick up/drop off/accompanying or escorting others, 8 = Walk or bike for recreation, fitness or health, 9 = Social/leisure, 99 = Other)
trippurposechar	character vector of modes with renamed labels for trip purpose
tripduration	reported trip duration by participants
tripwaittime	waiting time for public transport
tripstages	nummer of stages per trip
dur_calc	duration calculated (end time - start time) in minutes
dist_air	calculated air distance (derived from start- and endpoint)
speed	calculated speed (dist_air / dur_calc) in km/h
g_1_duration	google duration with route alternative 0
g_1_distance	google distance with route alternative 0
g_1_speed	calculated speed (g_1_distance/g_1_duration) in km/h
g_2_duration	google duration with route alternative with shortest duration
g_2_distance	google distance with route alternative with shortest duration
g_2_speed	calculated speed (g_2_distance/g_2_duration) in km/h
g_3_duration	google duration with mean duration from all alternatives
g_3_distance	google distance with mean distance from all alternatives
g_3_speed	calculated speed (g_3_distance/g_3_duration) in km/h
homead_bl	geo-codes of home address (reported in baseline questionnaire)
ho_x	x-coordinate of home address

Table A.1.2 Travel diary question variables from original PASTA dataset. Adapted from consortium material.

Variable_name	Description
ho_y	y-coordinate of home address
workad	geo-codes of work address
wo_x	x-coordinate work address
wo_y	y-coordinate work address
studad	geo-codes of education address
ed_x	x-coordinate education address
ed_y	y-coordinate education address
imputation	dummy variable for supplement return trip:0 = not last trip of day - not supplemented, 1 = last trip of day, but does not fulfil the imputation conditions - not supplemented, 2 = start-coordinates of "previous" trip “home”- supplemented; 3 = start-coordinates of "previous" trip “not home”- supplemented; 4 = previous imputation = 2, after supplementing an additional return home trip the dummy variable imputation will be set to 4; 5 = previous imputation = 3, after supplementing an additional return home trip the dummy variable imputation will be set to 5)
valid_trip	dummy variable indicating if a trip is valid (=1) or not (= 0)
valid_pd	dummy variable indicating if a person day is valid (=1) or not (=0)
pdj_id	person_day_id - Journey_id

A.1.3 Additional spatial data

Additional spatial data was collected by the original team in 2014 based on available administrative and demographic data. Although questions that made were included in the final analysis in this thesis are listed in Appendix 4.B, Table 4.B.2, Table A.1.3 shows all the variables available, for reference.

Table A.1.3 GIS data collected by the original PASTA team in 2014. Adapted from consortium material.

Variable_name	Description
gidl	gis id, unique. Created for GIS analysis
user_id	user id
question_id	question id, # 10 Home address from Baseline questionnaire # 33 Work address from Baseline questionnaire # 43 Study address from Baseline questionnaire # 444 Home address from re-entry questionnaire # 448 Home address from final questionnaire # 450 New Work address from final questionnaire
questionnaire	questionnaire code
city	city name
street_den_100	street density within 100m buffer, m/km2. No calculation of inter_street has been done, as streets cover all places.
street_den_300	street density within 300m buffer, m/km2
street_den_500	street density within 500m buffer, m/km2

Table A.1.3 GIS data collected by the original PASTA team in 2014. Adapted from consortium material.

Variable_name	Description
bikelanes_den_100	bike lanes density within 100m buffer, m/km2
perc_bik_str_100	proportion of bikelanes from total number of streets. From 0 to 1
bikelanes_den_300	bike lanes density within 300m buffer, m/km2
perc_bik_str_300	proportion of bikelanes from total number of streets. From 0 to 1
bikelanes_den_500	bike lanes density within 500m buffer, m/km2
perc_bik_str_500	proportion of bikelanes from total number of streets. From 0 to 1
inter_bike	locations are within the area enclosed by bike lanes layer, yes / no. This is useful to distinguish between 0 (home address is in the bike lanes covering area, but no bike lanes were close) or missing (address is outside of bike lanes covering area, usuallty outside the city)
bikelane_dist	distance to first bike lane, meters
conn_den_100	connectivity is the intersection density within 100m buffer, number/km2. No calculation of inter_conn has been done, as streets from were come from the intersection cover all places.
conn_den_300	connectivity is the intersection density within 300m buffer, m/km2
conn_den_500	connectivity is the intersection density within 500m buffer, m/km2
pub_tr_den_100	public transport stations density within 100m buffer, number/km2
bike_st_den_100	bike stations density within 100m buffer, number/km2
pub_tr_den_300	public transport stations density within 300m buffer, number/km2
bike_st_den_300	bike stations density within 300m buffer, number/km2
pub_tr_den_500	public transport stations density within 500m buffer, number/km2
bike_st_den_500	bike stations density within 500m buffer, number/km2
inter_pubtr	locations within public transport layer, yes / no

Table A.1.3 GIS data collected by the original PASTA team in 2014. Adapted from consortium material.

Variable_name	Description
inter_bikest	locations within bike stations layer, yes / no
pub_tr_dist	distance to first public transport station, meters
bike_st_dist	distance to first bike station, meters
build_den_100	building density density within 100m buffer, m2/km2
build_den_300	building density density within 300m buffer, m2/km2
build_den_500	building density density within 500m buffer, m2/km2
inter_build	locations within building layer, yes / no
fac_nav_den_300	number of facilities (points of interest) present, divided by buffer area results in Facility density index. Using Navteq POI data
fac_nav_rich_300	number of different facility types (points of interest) present, divided by the maximum potential number of facility types specified in a buffer of 300m, results in Facility richness index. Using Navteq POI data
inter_fac	locations within facilities layer, yes / no
grn_gid	gis id from urban atlas layer. Identify the green polygon in case appears the need to calculate something else in the future.
d	distance in meters from location to the closer major green space (higher than 0.5Ha), from urban atlas layer
grn_areasqm	area in square meters of the closer green space polygon, from urban atlas layer
blu_gid	gis id from urban atlas layer. Identify the blue polygon in case appears the need to calculate something else in the future, from urban atlas layer

Table A.1.3 GIS data collected by the original PASTA team in 2014. Adapted from consortium material.

Variable_name	Description
blu_distm	distance in meters from location to the closer major blue space (higher than 0.5Ha), from urban atlas layer
blu_areasqm	area in square meters of the closer blue space polygon, from urban atlas layer
gs_300m	location is within 300 meters of a major green space, y/n, from urban atlas layer
bs_300m	location is within 300 meters of a major blue space, y/n, from urban atlas layer
grn_gid_cor	gis id from CORINE layer. Identify the green polygon in case appears the need to calculate something else in the future.
grn_distm_cor	distance in meters from location to the closer major green space (higher than 0.5Ha), from corine layer
grn_areasqm_cor	area in square meters of the closer green space polygon, from corine layer
blu_gid_cor	gis id from urban atlas layer. Identify the blue polygon in case appears the need to calculate something else in the future, from corine layer
blu_distm_cor	distance in meters from location to the closer major blue space (higher than 0.5Ha), from corine layer
blu_areasqm_cor	area in square meters of the closer blue space polygon, from corine layer
gs_300m_cor	location is within 300 meters of a major green space, y/n, from corine layer

Table A.1.3 GIS data collected by the original PASTA team in 2014. Adapted from consortium material.

Variable_name	Description
bs_300m_cor	location is within 300 meters of a major blue space, y/n, from corine layer
shannonind	shannon index, or entropy measure. Minus the sum, across all land use types, of the proportional abundance of each land use type multiplied by that proportion, divided by the logarithm of the number of land use types, in a buffer of 300 meters
lden	Noise nearest value on lden to each geocoded location
dist_noise	Distance which noise value was considered at geocoded location
inter_noise	geocoded locations within noise layer, yes / no
popden_100	population density within 100m buffer
popden_300	population density within 300m buffer
popden_500	population density within 500m buffer
inter_pop	geocoded locations within population layer, yes / no
educ_100	percentage of education at lower degrees within 100m buffer
educ_h_100	percentage of education at higher degrees within 100m buffer
educ_300	percentage of education at lower degrees within 300m buffer
educ_h_300	percentage of education at higher degrees within 300m buffer
educ_500	percentage of education at lower degrees within 500m buffer
educ_h_500	percentage of education at higher degrees within 500m buffer
inter_edu	geocoded locations within education layer, yes / no
nat_100	percentage of foreigners within 100m buffer
nat_300	percentage of foreigners within 300m buffer
nat_500	percentage of foreigners within 500m buffer

Table A.1.3 GIS data collected by the original PASTA team in 2014. Adapted from consortium material.

Variable_name	Description
inter_nat	geocoded locations within foreigners layer, yes / no
inc_100	mean income within 100m buffer
inc_300	mean income within 300m buffer
inc_500	mean income within 500m buffer
inter_inc	geocoded locations within income layer, yes / no
car_100	car ownership within 100m buffer
car_300	car ownership within 300m buffer
car_500	car ownership within 500m buffer
inter_car	geocoded locations within car layer, yes / no
res_100	residential density within 100m buffer
res_300	residential density within 300m buffer
res_500	residential density within 500m buffer
inter_res	geocoded locations within residential layer, yes / no
dem_gc	elevation from DEM at geocoded address
distanceHW	euclidean distance from home to main work/study address
difeleHW	height difference from home to work or study address. If both are present, it takes work address. From Baseline Questionnaire.
slopeHW	slope from home to work location (height/distance*100)
dem_MN_50	average of elevation from DEM within 50m buffer, meters
dem_MN_100	average of elevation from DEM within 100m buffer, meters
dem_MN_300	average of elevation from DEM within 300m buffer, meters
dem_MN_500	average of elevation from DEM within 500m buffer, meters
pm25_MN_100	average of pm2.5 within 100m buffer, meters

Table A.1.3 GIS data collected by the original PASTA team in 2014. Adapted from consortium material.

Variable_name	Description
pm25_MN_300	average of pm2.5 within 300m buffer, meters
pm25_MN_500	average of pm2.5 within 500m buffer, µg/m3
no2_MN_100	average of NO2 within 100m buffer, meters
no2_MN_300	average of NO2 within 300m buffer, meters
no2_MN_500	average of NO2 within 500m buffer, meters
ndvi_MN_50	average of NDVI within 50m buffer, meters
ndvi_MN_100	average of NDVI within 100m buffer, meters
ndvi_MN_300	average of NDVI within 300m buffer, meters
ndvi_MN_500	average of NDVI within 500m buffer

A.2 Accessibility data collected for the PASTA case study cities

Table A.2.1 lists the variables that were extracted from open source data for each participant in the original PASTA study. Code to create this type of data is available on Github, https://github.com/ssulikova/DPhil-online-material.

Table A.2.1 Accessibility variables extracted from open-source data for PASTA participants.

Variable_name	Description	Scale
home_school_time	Time to travel by car from home to nearest secondary school	min
home_school_distance	Distance to travel by car from home to nearest secondary school	km

Table A.2.1 Accessibility variables extracted from open-source data for PASTA participants.

Variable_name	Description	Scale
home_school_time_cycle	Time to travel by bike from home to nearest secondary school	min
home_school_distance_cycle	Distance to travel by bike from home to nearest secondary school	km
home_school_time_walk	Time to travel on foot from home to nearest secondary school	min
home_school_distance_walk	Distance to travel on foot from home to nearest secondary school	km
p_id	unique respondent ID.	factor
work_school_time	Time to travel by car from work to nearest secondary school	min
work_school_distance	Distance to travel by car from work to nearest secondary school	km
work_school_time_cycle	Time to travel by bike from work to nearest secondary school	min
work_school_distance_cycle	Distance to travel by bike from work to nearest secondary school	km
work_school_time_walk	Time to travel on foot from work to nearest secondary school	min
work_school_distance_walk	Distance to travel on foot from work to nearest secondary school	km
c_id	city id (1 = Antwerp, 2 = Barcelona, 3 = London, 4 = Oerebro, 5 = Rome, 6 = Vienna, 7 = Zurich)	factor

Table A.2.1 Accessibility variables extracted from open-source data for PASTA participants.

Variable_name	Description	Scale
PT_distance_home_centre	Distance to travel by public transport from home to city centre	km
PT_time_home_centre	Time to travel by public transport from home to city centre	min
ho_x	home x coordinate	coordinate
ho_y	home y coordinate	coordinate
PT_distance_work_centre	Distance to travel by public transport from work to city centre	km
PT_time_work_centre	Time to travel by public transport from work to city centre	min
wo_x	work x coordinate	coordinate
wo_y	work y coordinate	coordinate
PT_distance_study_centre	Distance to travel by public transport from place of study to city centre	km
PT_time_study_centre	Time to travel by public transport from place of study to city centre	min
ed_x	study place x coordinate	coordinate
ed_y	study place y coordinate	coordinate
centre_time_home	Time to travel by car from home to city centre	min
centre_distance_home	Distance to travel by car from home to city centre	km
centre_time_cycle_home	Time to travel by bike from home to city centre	min
centre_distance_cycle_home	Distance to travel by bike from home to city centre	km
centre_time_walk_home	Time to travel on foot from home to city centre	min
centre_distance_walk_home	Distance to travel on foot from home to city centre	km

Table A.2.1 Accessibility variables extracted from open-source data for PASTA participants.

Variable_name	Description	Scale
centre_time_work	Time to travel by car from work to city centre	min
centre_distance_work	Distance to travel by car from work to city centre	km
centre_time_cycle_work	Time to travel by bike from work to city centre	min
centre_distance_cycle_work	Distance to travel by bike from work to city centre	km
centre_time_walk_work	Time to travel on foot from work to city centre	min
centre_distance_walk_work	Distance to travel on foot from work to city centre	km
centre_time_study	Time to travel by car from place of study to city centre	min
centre_distance_study	Distance to travel by car from place of study to city centre	km
centre_time_cycle_study	Time to travel by bike from place of study to city centre	min
centre_distance_cycle_study	Distance to travel by bike from place of study to city centre	km
centre_time_walk_study	Time to travel on foot from place of study to city centre	min
centre_distance_walk_study	Distance to travel on foot from place of study to city centre	km
food_time_home	Time to travel by car from home to nearest food store	min
food_distance_home	Distance to travel by car from home to nearest food store	km
food_time_cycle_home	Time to travel by bike from home to nearest food store	min

Table A.2.1 Accessibility variables extracted from open-source data for PASTA participants.

Variable_name	Description	Scale
food_distance_cycle_home	Distance to travel by bike from home to nearest food store	km
food_time_walk_home	Time to travel on foot from home to nearest food store	min
food_distance_walk_home	Distance to travel on foot from home to nearest food store	km
food_time_work	Time to travel by car from work to nearest food store	min
food_distance_work	Distance to travel by car from work to nearest food store	km
food_time_cycle_work	Time to travel by bike from work to nearest food store	min
food_distance_cycle_work	Distance to travel by bike from work to nearest food store	km
food_time_walk_work	Time to travel on foot from work to nearest food store	min
food_distance_walk_work	Distance to travel on foot from work to nearest food store	km
food_time_study	Time to travel by car from place of study to nearest food store	min
food_distance_study	Distance to travel by car from place of study to nearest food store	km
food_time_cycle_study	Time to travel by bike from place of study to nearest food store	min

Table A.2.1 Accessibility variables extracted from open-source data for PASTA participants.

Variable_name	Description	Scale
food_distance_cycle_study	Distance to travel by bike from place of study to nearest food store	km
food_time_walk_study	Time to travel on foot from place of study to nearest food store	min
food_distance_walk_study	Distance to travel on foot from place of study to nearest food store	km
ho_av_headway	Average waiting time at nearest public transit stop to home over 23 hours of a day	min
ho_pm_headway	Average waiting time at nearest public transit stop to home during the evening peak 4-7pm	min
ho_am_headway	Average waiting time at nearest public transit stop to home during the morning peak 6-10am	min
ho_n	number of different services and routes stopping at nearest public transit stop to home	numeric
wo_av_headway	Average waiting time at nearest public transit stop to work over 23 hours of a day	min
wo_pm_headway	Average waiting time at nearest public transit stop to work during the evening peak 4-7pm	min
wo_am_headway	Average waiting time at nearest public transit stop to work during the morning peak 6-10am	min
wo_n	number of different services and routes stopping at nearest public transit stop to work	numeric
ed_av_headway	Average waiting time at nearest public transit stop to place of study over 23 hours of a day	min

Table A.2.1 Accessibility variables extracted from open-source data for PASTA participants.

Variable_name	Description	Scale
ed_pm_headway	Average waiting time at nearest public transit stop to place of study during the evening peak 4-7pm	min
ed_am_headway	Average waiting time at nearest public transit stop to place of study during the morning peak 6-10am	min
ed_n	number of different services and routes stopping at nearest public transit stop to place of study	numeric

A.3 Follow-up study full questionnaire

As part of a follow-up study conducted in 2019, I designed and administered a survey to over 700 people. Below is the full questionnaire. White blank spaces denote where an interactive map would have allowed respondents to pinpoint a location. The full set of options for the travel diary is not provided, and the introduction page was also not included.

Section A: General

We have a few questions about you and your household.

A1. Please enter the email address you received the invitation to participate to.

A2. Did you move home since you started your participation in the PASTA survey?

Yes ☐

No ☐

A3. Where do you live? Please provide an address.

A4. **You can also use the map to pinpoint the location.**

A5. **How many people live in your household? Please include yourself, and include the exact number for each.**

How many children under 6 years of age

How many children aged 6 -17 years

How many adults aged 18-65 years

How many adults aged over 65 years

A6. **Did you start a new job or change employment, work/school since you started your participation in the PASTA survey?**

Yes

No

A7. What is your current employment status?

- [ ] Full-time employed
- [ ] Part-time employed, or casual work
- [ ] Student / In training
- [ ] Home duties / Unemployed / Retired / Sickness leave / Parental leave

A8. On average, how many hours do you work per week?

A9. Where do you work/study? Please provide an address.

A10. You can also use the map.

A11. Thinking about your total available money situation, would you say:

- You cannot make ends meet ☐
- You just have enough to get along ☐
- You are comfortable ☐

A12. Please select which of the following events have taken place in your life since you started your participation in the PASTA survey:

- Moved home ☐
- Changed job ☐
- Started working ☐
- Stopped working/retired ☐
- Started university ☐
- Finished university ☐
- Got married ☐
- Birth/adoption of a child in the household ☐
- Child starts at school/ a new school ☐
- Child/ someone has left the household ☐
- Obtained a driving license for a car or a van ☐
- Lost my driving license for a car or a van ☐
- Got access to a car or a van ☐
- Lost access to a car or a van ☐
- Became a member of an official car sharing system or car club ☐
- Have used public transport for the first time in a long time ☐
- Got access to a bike (private or a bike sharing system) ☐
- Lost access to a bike (private or a bike sharing system) ☐
- Started to ride an electric bike ☐

Section B: Health

We now have some questions about you and your health.

B1. In general, how would you say your health is?

- Excellent ☐
- Very good ☐
- Good ☐
- Fair ☐
- Poor ☐

B2. How tall are you?

B3. How much do you weigh?

B4. Do you smoke?

- Yes ☐
- No, but I used to smoke ☐
- No, I have never smoked ☐

B5. How many glasses of alcohol do you drink in a typical week?

B6. Do you have any physical constraint or condition that restricts your mobility?

- Yes ☐
- No ☐

B7. Do you suffer from one or more chronic diseases?

- Yes ☐
- No ☐

B8. To what extent does this prevent you from performing your daily activities?

- Strongly ☐
- Moderately ☐
- Not at all ☐

B9. Since you started in PASTA, would you say your lifestyle (like levels of physical activity, diet) got healthier?

- Yes, improved a lot ☐
- Yes, improved a little ☐
- Stayed the same ☐
- No, got worse ☐
- No, got a lot worse ☐

Section C: Norms

Next, we would like to learn about some of your attitudes, beliefs and opinions.

C1. Do you agree with the following statements

	Very much disagree	Disagree	Neither agree nor disagree	Agree	Very much agree
Most people who are important to me think that I should walk for travel.	☐	☐	☐	☐	☐
Most people who are important to me think that I should cycle for travel (that is, getting from place to place).	☐	☐	☐	☐	☐
I feel morally responsible to walk in order to decrease the negative effects on the environment that motorized methods of travel have.	☐	☐	☐	☐	☐
I feel morally responsible to use a bicycle in order to decrease the negative effects on the environment that motorized methods of travel have.	☐	☐	☐	☐	☐
In my neighbourhood walking is well regarded.	☐	☐	☐	☐	☐
In my neighbourhood cycling is well regarded.	☐	☐	☐	☐	☐

C2. Do you agree with the following statements

	Very much disagree	Disagree	Neither agree nor disagree	Agree	Very much agree
For me, walking would be difficult in everyday Iife.	☐	☐	☐	☐	☐
For me, using a bicycle would be difficult in everyday Iife.	☐	☐	☐	☐	☐
Walking 'for, travel' is something I do automatically without really thinking about it.	☐	☐	☐	☐	☐
Cycling 'for travel' is something I do automatically without really thinking about it.	☐	☐	☐	☐	☐
I am fit enough to walk.	☐	☐	☐	☐	☐
I am fit enough to cycle.	☐	☐	☐	☐	☐

C3. Do you agree with the following statements

	Very much disagree	Disagree	Neither agree nor disagree	Agree	Very much agree
Regardless of what other people do, my own values and principles oblige me to walk 'for travel' whenever possible.	☐	☐	☐	☐	☐
Regardless of what other people do, my own values and principles oblige me to cycle 'for travel' whenever possible.	☐	☐	☐	☐	☐
In my neighbourhood It is common for people to walk 'for travel'.	☐	☐	☐	☐	☐
In my neighbourhood It is common for people to cycle 'for travel'.	☐	☐	☐	☐	☐

C4. Rate the following statements

	Very weak	Weak	Neutral	Strong	Very strong
My intention to walk 'for travel' is	☐	☐	☐	☐	☐
My intention to cycle 'for travel' is	☐	☐	☐	☐	☐

C5. Do you agree with the following statements

	Very much disagree	Disagree	Neither agree nor disagree	Agree	Very much agree
I intend to walk more 'for travel' in the future	☐	☐	☐	☐	☐
I intend to cycle more 'for travel' in the future	☐	☐	☐	☐	☐
Over the past 12 months I have done more walking 'for travel' than in previous years.	☐	☐	☐	☐	☐
Over the past 12 months I have done more cycling 'for travel' than in previous years.	☐	☐	☐	☐	☐
In general, I try to walk for my day-to-day travel whenever possible.	☐	☐	☐	☐	☐
In general, I try to cycle for my day-to-day travel whenever possible.	☐	☐	☐	☐	☐

Section D: Travel

Next, we would like to ask you about your mobility habits.

D1. Do you have a driver's license for a car or van?

Yes ☐

No ☐

D2. Do you have access to a van or car?

Always ☐

Sometimes ☐

Never ☐

D3. **Are you a member of an official car sharing system or club?**

- Yes ☐
- No ☐

D4. **Do you know how to ride a bicycle?**

- Yes ☐
- No ☐

D5. **Do you have access to a bicycle (private, or through a bike sharing system)?**

- Yes ☐
- No ☐

D6. **What type of bicycle do you use?**

- City-bike, road bike, mountainbike ☐
- Bike from bike sharing system ☐
- Pedal assisted electric bike (pedelec) for which motor cuts out at speeds over 25 kph (15 mph) ☐
- Pedal-assisted electric bike (Speed pedelec) for which motor continues to assist for speeds greater than 25 kph (15 mph) and up to 45 kph (27 mph). ☐
- Other ☐

D7. **How often do you currently use each of the following methods of travel to get to and from places?**

	Daily or almost daily	on 1-3 days per week	on 1-3 days per month	Less than once per month	Never
Walk	☐	☐	☐	☐	☐
Bicycle	☐	☐	☐	☐	☐
Electric bicycle	☐	☐	☐	☐	☐
Motorcycle or moped	☐	☐	☐	☐	☐
Public transport	☐	☐	☐	☐	☐
Car or van	☐	☐	☐	☐	☐

D8. **Listed below are potential activities that you may engage in in your daily life. Which method of travel would you be most likely to use?**

	Walk	Bicycle	Motorcycle or moped	Public transport	Car or van	Other
Visiting friends or family in your city	☐	☐	☐	☐	☐	☐
Shopping for groceries	☐	☐	☐	☐	☐	☐
Going to a restaurant	☐	☐	☐	☐	☐	☐

	Walk	Bicycle	Motorcycle or moped	Public transport	Car or van	Other
Taking a weekend excursion to a site/event in the city on a nice day	☐	☐	☐	☐	☐	☐
Engaging in sports	☐	☐	☐	☐	☐	☐

D9. **For certain journeys that you take as part of your day-to-day travel you may have more than one method of travel available (e.g. car, bus, train, bicycle, walking). In general, how important are the following criteria for you when choosing a method of travel:**

	Not important	Less important	Neutral	Important	Very important
Shorter travel time	☐	☐	☐	☐	☐
Lower travel cost	☐	☐	☐	☐	☐
Higher travel comfort	☐	☐	☐	☐	☐
Safer travel (with regards to traffic)	☐	☐	☐	☐	☐
Safer travel (with regards to crime)	☐	☐	☐	☐	☐
Lower exposure to air pollution	☐	☐	☐	☐	☐
Privacy	☐	☐	☐	☐	☐
Personal health benefits	☐	☐	☐	☐	☐
Low environmental impact	☐	☐	☐	☐	☐
Flexible departure time	☐	☐	☐	☐	☐
More predictable travel time and journey reliability	☐	☐	☐	☐	☐
It's a greener route	☐	☐	☐	☐	☐

D10.

With your day-to-day travel needs in mind would you say that walking 'for travel' ...

	Very much disagree	Disagree	Neither agree nor disagree	Agree	Very much agree
It saves time.	☐	☐	☐	☐	☐
It is comfortable.	☐	☐	☐	☐	☐
is safe (with regards to traffic)	☐	☐	☐	☐	☐

	Very much disagree	Disagree	Neither agree nor disagree	Agree	Very much agree
is safe (with regards to crime)	☐	☐	☐	☐	☐
It is unpleasant due to high levels of air pollution.	☐	☐	☐	☐	☐
It offers privacy	☐	☐	☐	☐	☐
It offers personal health benefits.	☐	☐	☐	☐	☐
It offers flexibility (e.g. with regards to departure time).	☐	☐	☐	☐	☐
It offers a predictable travel time.	☐	☐	☐	☐	☐

D11. With your day-to-day travel needs in mind would you say that cycling 'for travel'...

	Very much disagree	Disagree	Neither agree nor disagree	Agree	Very much agree
It saves time.	☐	☐	☐	☐	☐
It is comfortable.	☐	☐	☐	☐	☐
is safe (with regards to traffic)	☐	☐	☐	☐	☐
is safe (with regards to crime)	☐	☐	☐	☐	☐
It is unpleasant due to high levels of air pollution.	☐	☐	☐	☐	☐
It offers privacy	☐	☐	☐	☐	☐
It offers personal health benefits.	☐	☐	☐	☐	☐
It offers flexibility (e.g. with regards to departure time).	☐	☐	☐	☐	☐
It offers a predictable travel time.	☐	☐	☐	☐	☐

D12. Since the last time you filled out a questionnaire for the PASTA study, have you experienced any safety relevant incidents (i.e. a collision, fall, or near miss as a pedestrian, cyclist, in public transport, or driving)? Note that we are interested in all incidents, whatever the purpose of your journey.

Yes ☐

No ☐

Section E: City specific

We have some questions for people from specific cities.

E1. Where do you live?

Vienna ☐

Örebro ☐

Section F: Travel, Örebro

F1. We have one more question specifically for the inhabitants of (the wider region of) Örebro.

Part of this study is specifcally addressed at employees at certain workplaces. Do you currently work at any of these workplaces?

Region Örebro Iän: Regionservice Eklundavägen (Eklundavägen 1, 2 eller 11, Örebro) ☐

Region Örebro Iän: Regionservice på USÖ (Södra Grev Rosengatan, Örebro) ☐

Region Örebro Iän: avdelningarna: Special kemi, öppna akut+lab, Hornhinnenbanken på USÖ (Södra Grev Rosengatan, Örebro) ☐

Region Örebro Iän: avdelningarna: Strategisk samordning, Utveckling och säkerhet, Sterilcentralen, Arbets- och mijlömedicin, Specialkemi, Kardiologiska kliniken, Reumatologiska kliniken pä USÖ (Södra Grev Rosengatan, Örebro) ☐

Axfood (Handelsgatan 5. Örebro) ☐

Örebro Kommun Stadsbyggnadshusen (Äbylundsgatan 8 A-Beller Tomtagatan 9. Örebro) ☐

Örebro Kommun Socialförvaltningen (Ribbingsgatan 1-3, Örebro) ☐

None of the above ☐

F2. Has your workplace been promoting cycling and walking?

Yes ☐

No ☐

F3. Have you adopted some of the recommendations your workplace has presented?

Yes ☐

No ☐

F4.

Here is a map of high quality cycle roads (current (purple) and planned (orange)) in Örebro.

Have you been informed of them?

- Yes - through general publicity by the city ☐
- Yes - through my workplace ☐
- No ☐

F5. **Do you use any of these routes for cycling?**

- Yes ☐
- No ☐

F6. **Do you use any of these routes for walking?**

- Yes ☐
- No ☐

Section G: Travel, Vienna

We have some questions specifically for the inhabitants of Vienna.

G1. **Have you received material about the cycling and walking opportunities in Vienna?**

- Yes ☐
- No ☐

G2. **Have you adopted any of the suggestions provided in these materials?**

- Yes ☐
- No ☐

Section H: Travel diary

Please report all journeys you did in the order they occurred. A journey is defined by a journey purpose (e.g. commuting, shopping, bringing kids to school, business travel, visiting friends or family). Once the purpose changes, a new journey begins. For each journey you may have used multiple methods of travel (for example, walking to the train station, taking the train, and walking to your final destination). Please enter every part of your journey for which something changes as a new row. **After filling in the travel diary, you can also use a map to enter start and end points of journeys.**

Example

Jamie escorted kids to school in a car (journey 1, leaving at 07:40 and arriving at 07:55, travelling with 2), then went to work (journey 2, from 07:55 to 08:20, travelling alone). At lunchtime, he walked to a sandwich shop (journey 3) and back to work (journey 4). In the evening, he travelled back home (journey 5).

H1. Please select the day for which you filled in the travel diary.

H2.

At what time did you begin your trip? HH:MM

What is the purpose of the trip?

What is your destination? Please provide your address as precisely as possible.

How did you travel there?

Have you travelled with someone else?

How far would you say it is, in km?

When did you arrive at your destination? HH:MM

H12. **Would you like to use a map to select the start and end points of your travels instead?**

Yes ☐

No ☐

H13. **Please choose a starting point for Trip 1.**

H32. **Please choose an end point for Trip 10.**

Section I: Final

I1. **Thank you for completing the survey!**

We take this opportunity to express our gratitude for your interest and participation in our project.

Best wishes from the PASTA team.

Upon completion of this questionnaire your participation in our project will have finished, although our research will continue.

Would you be willing to be contacted by us with regards to future research projects?

Yes ☐

No ☐

Thank you for participating! If you would like to check the results of our research to date, please go to pastaproject.eu.

Appendix B

PASTA case study cities public transit feeds

This appendix provides examples of how public transit system data can be visualised and checked, before using the data for further analysis. For example, knowing the number of services on any given or over the study period helps determine average waiting times between services. The code to validate GTFS feeds and create this type of visualisation is included on Github, https://github.com/ssulikova/DPhil-online-material.

The calendars, Figures B.0.1 to B.0.7 visualise the number of stops that were serviced and the number of services for any given day by all public transport providers in the city.

The charts in Figures B.0.8- B.0.14 depict the public transit patterns and frequency of services in the seven PASTA cities. The London data only includes Tube service stations and select bus stations that were included in the transit feed publicly available. Figures B.0.9 and B.0.14 shows the service feeds for one chosen provider within Barcelona and Zürich. This is to help show the difference between a city-wide operation, and a smaller provider who operates within only a part of a city. The charts depict the predictability of the overall public transit system; more unique patterns indicates more variable services per route or stop

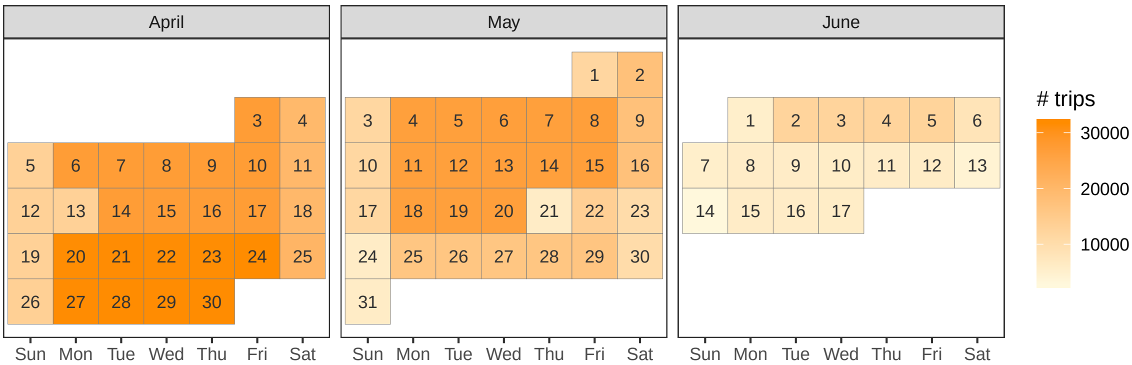

Figure B.0.1 Public transport feeds in Antwerp.

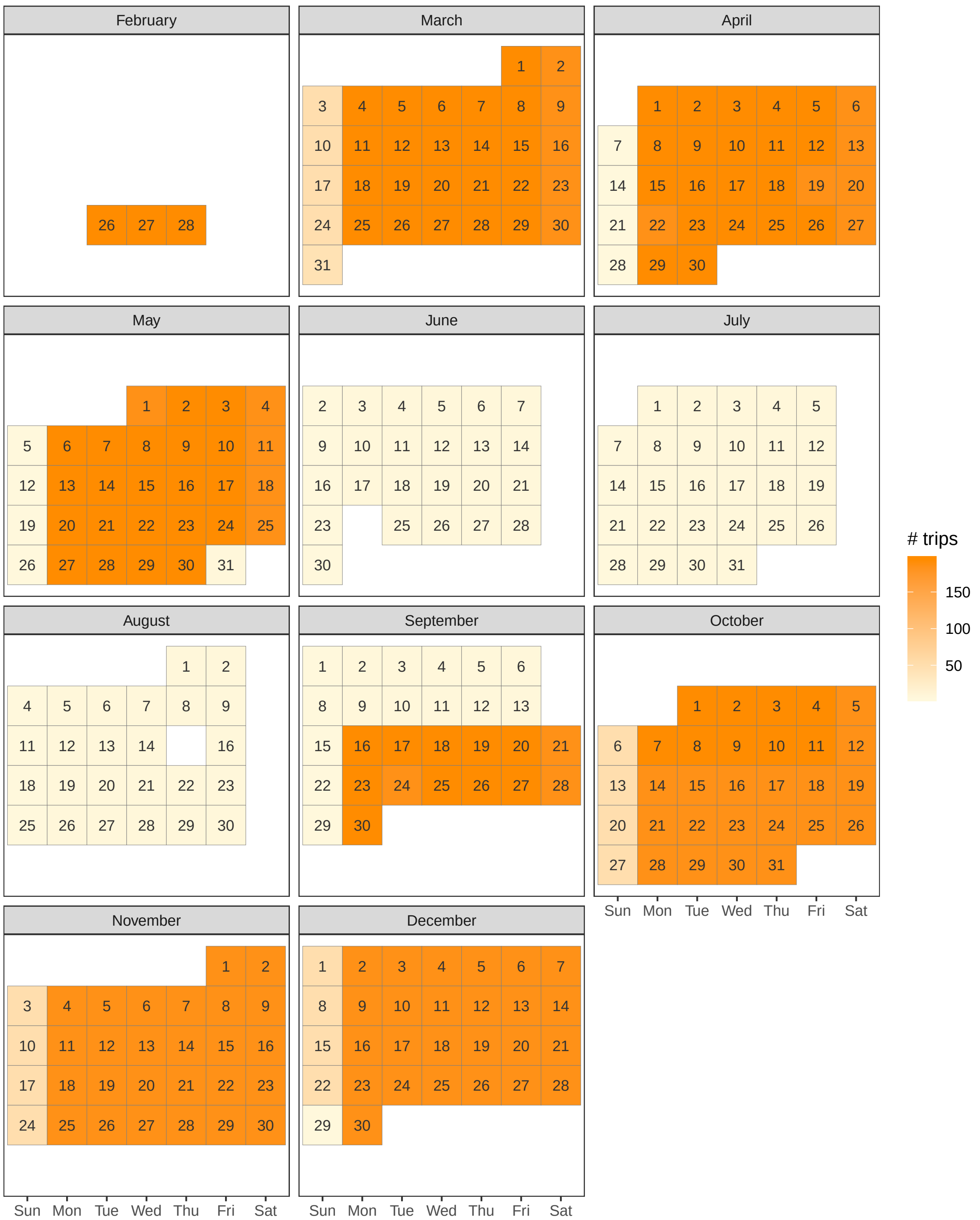

Figure B.0.2 Public transport feeds in Barcelona.

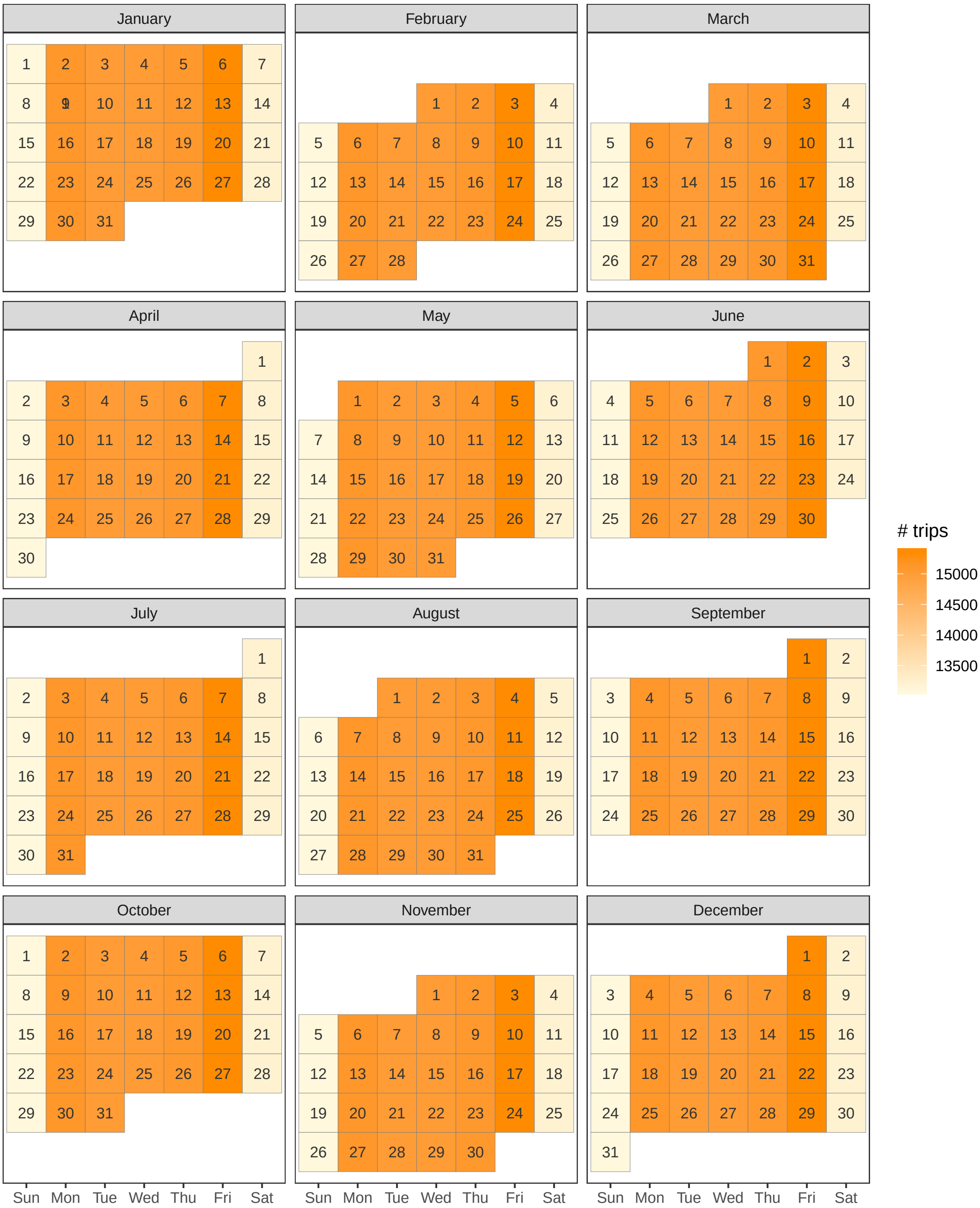

Figure B.0.3 Public transport feeds in London.

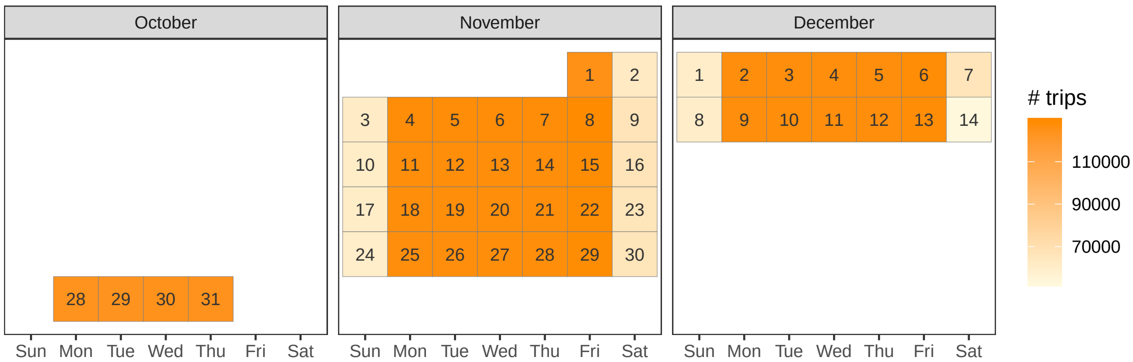

Figure B.0.4 Public transport feeds in Örebro.

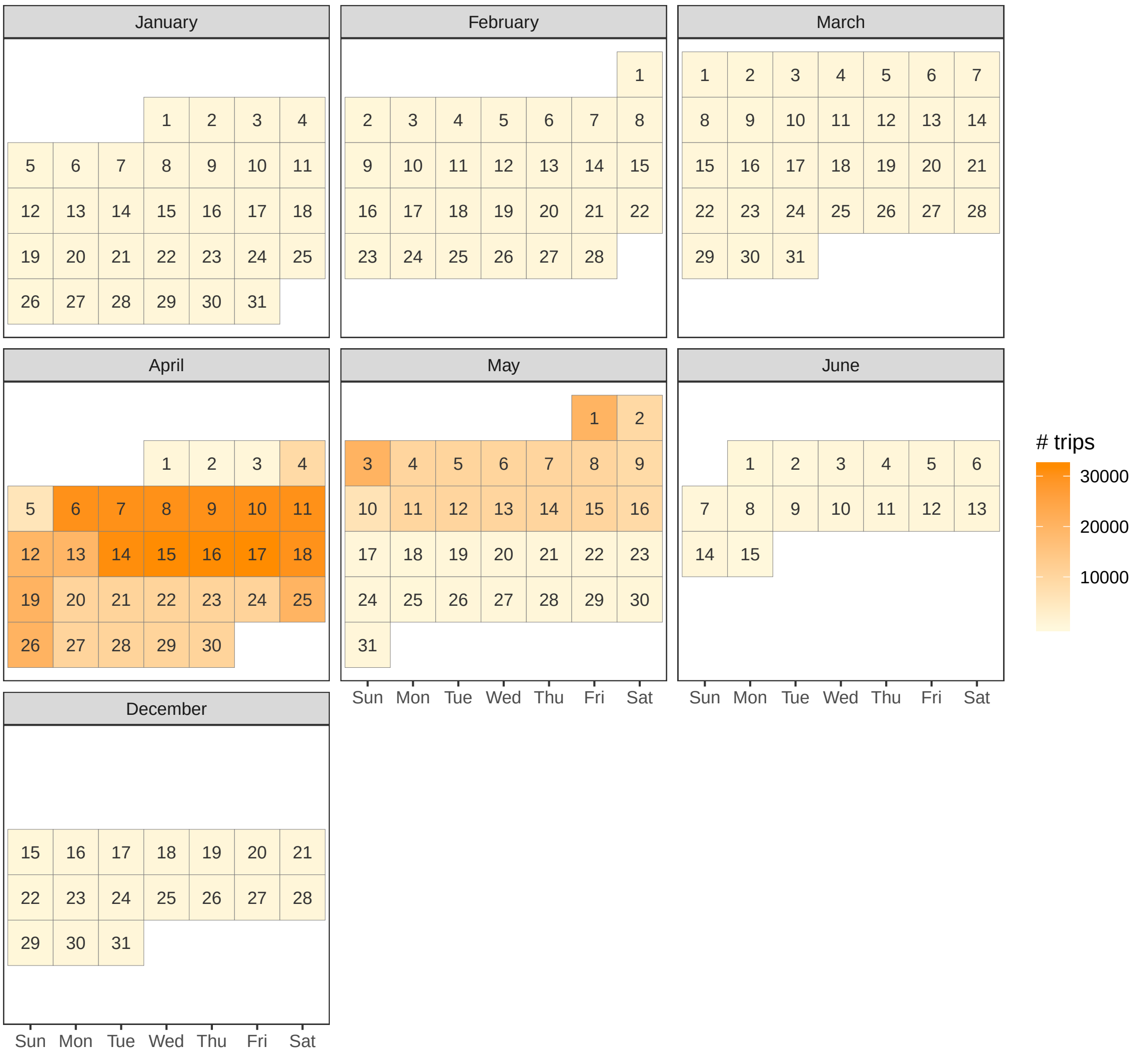

Figure B.0.5 Public transport feeds in Rome.

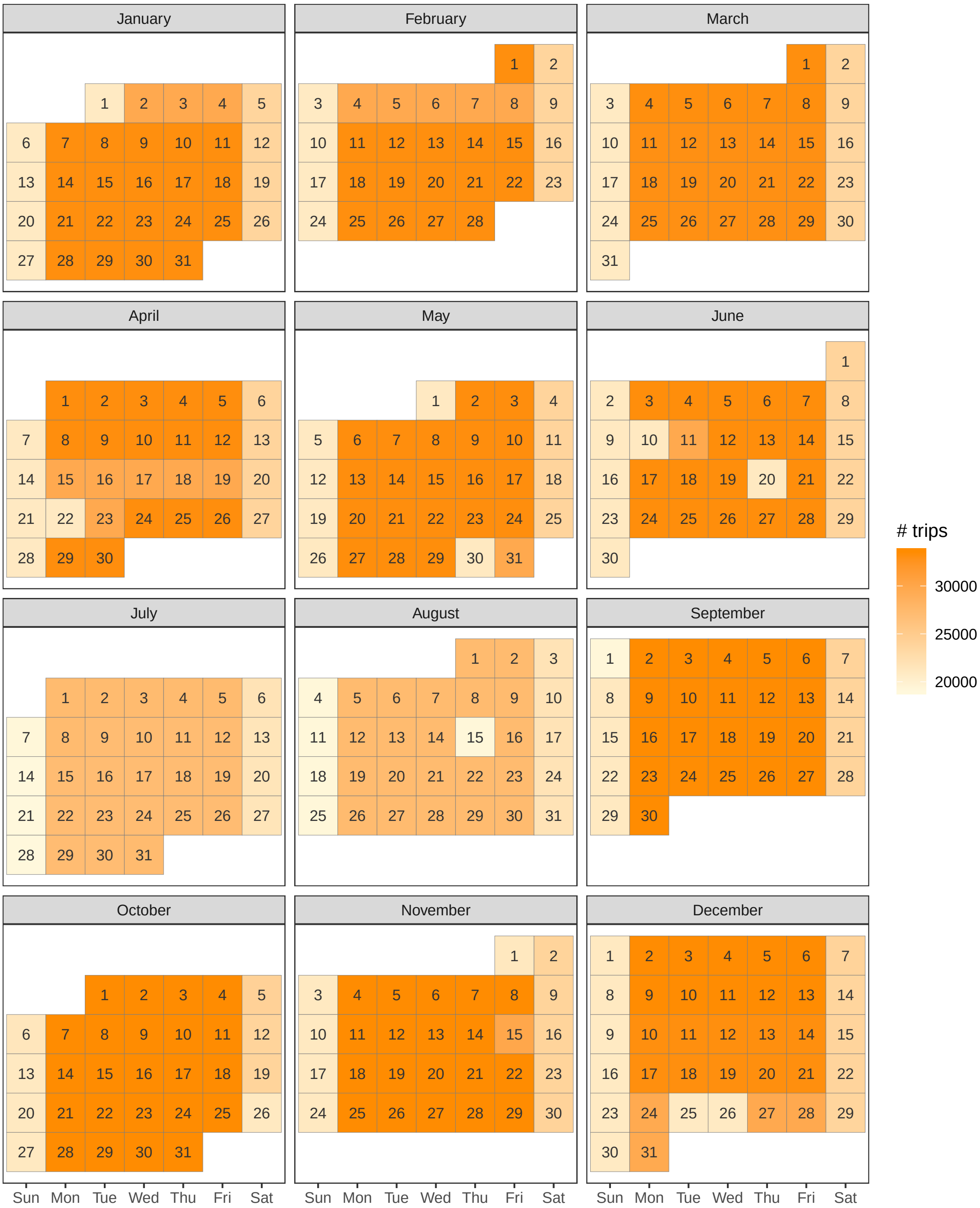

Figure B.0.6 Public transport feeds in Vienna.

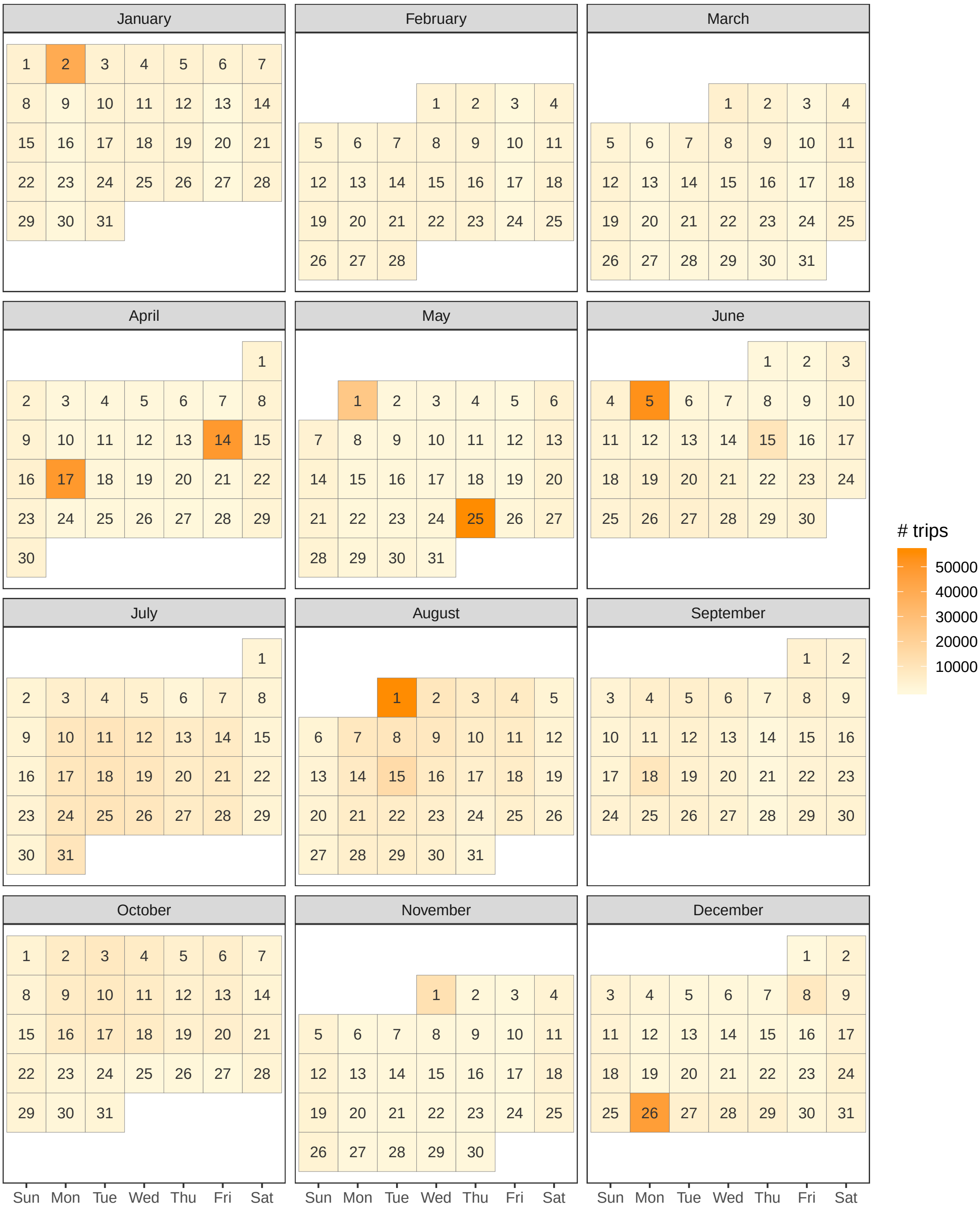

Figure B.0.7 Public transport feeds in Zürich.

than fewer unique patterns. For example, the consistency of London's underground system, Figure B.0.10, leads to fewer unique service patterns in London than e.g. in Rome.

It is also possible to visualise general serviceability within a city. Figure B.0.15 shows the public transit routes that service the city overall, stops with a high number of services in the morning peak are highlighted with a black circle. Home and work locations of study participants can then be superimposed on this type of map, identifying potential "dead zones" or highly accessible zones within a city. This was not done here to maintain the privacy of the participants.

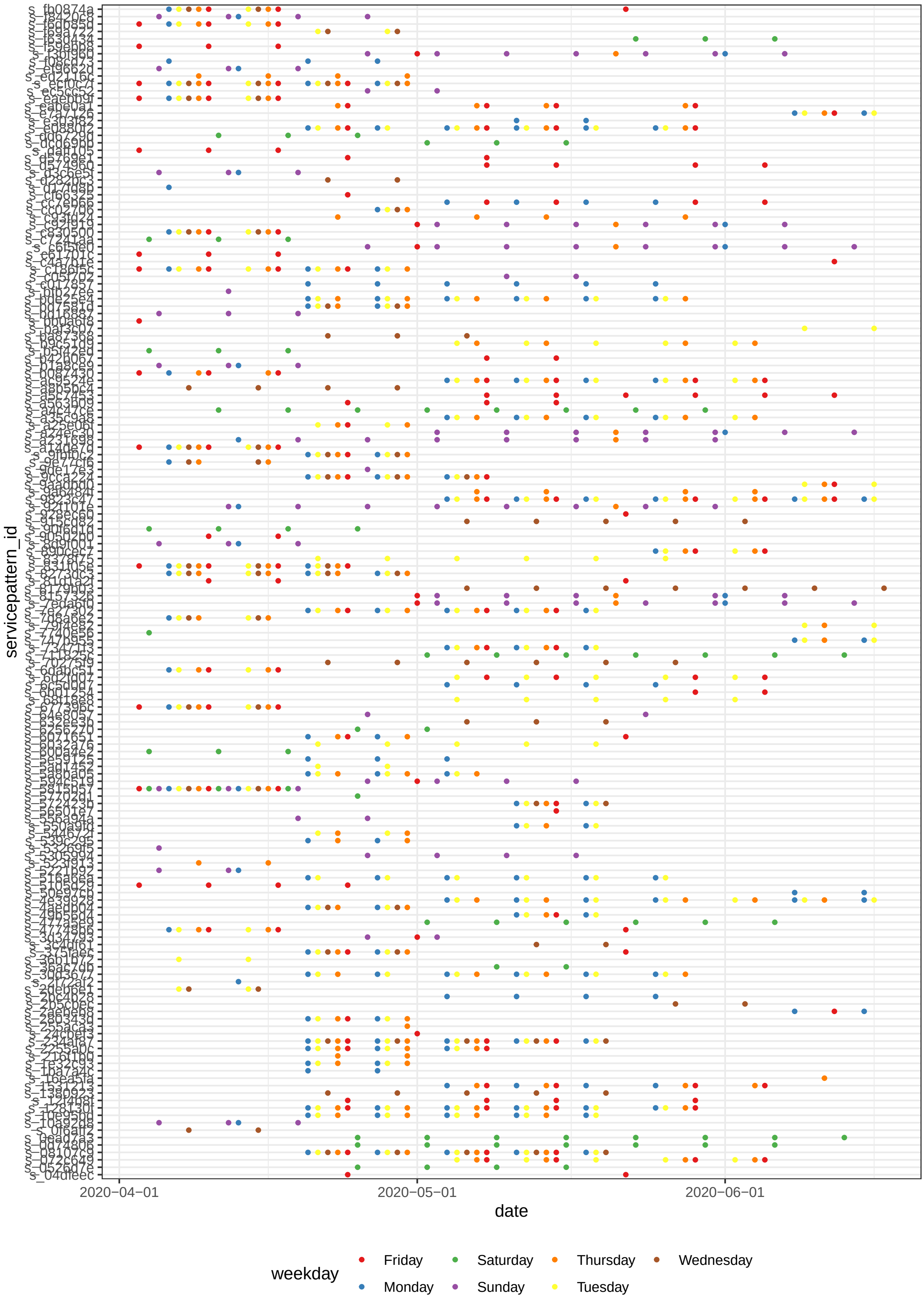

Figure B.0.8 Service patterns and frequency overview, Antwerp.

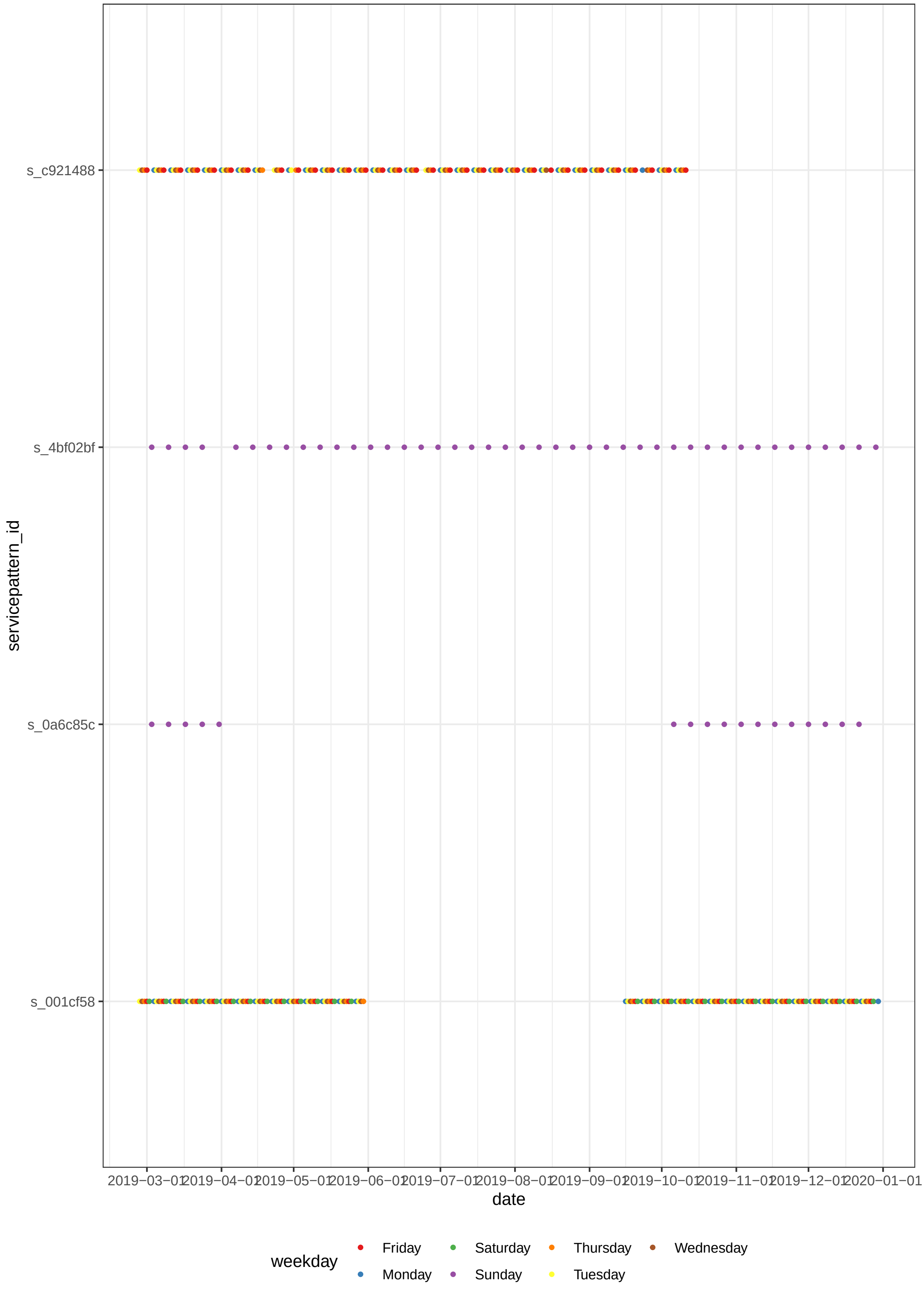

Figure B.0.9 Service patterns and frequency overview, Barcelona.

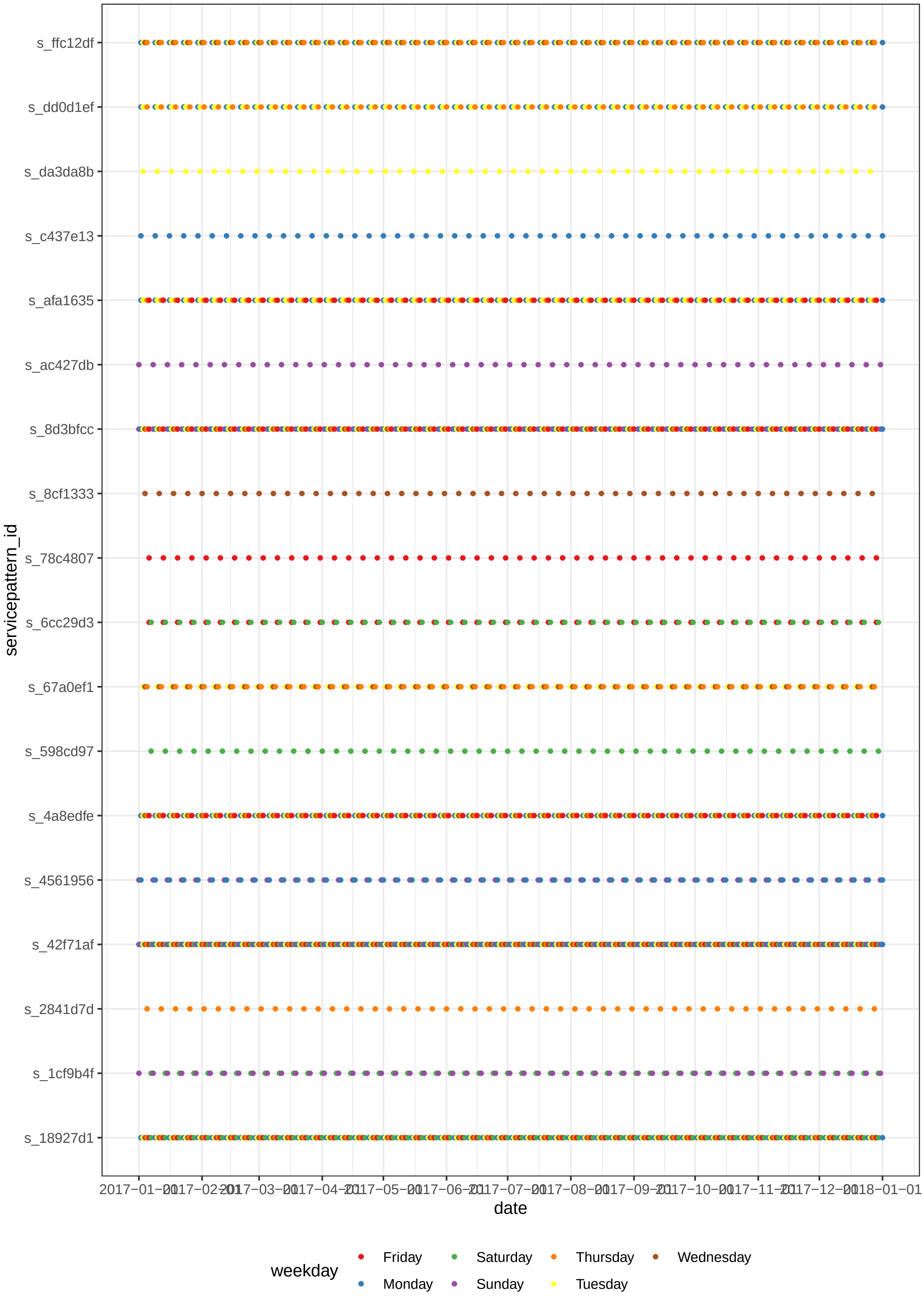

Figure B.0.10 Service patterns and frequency overview, London.

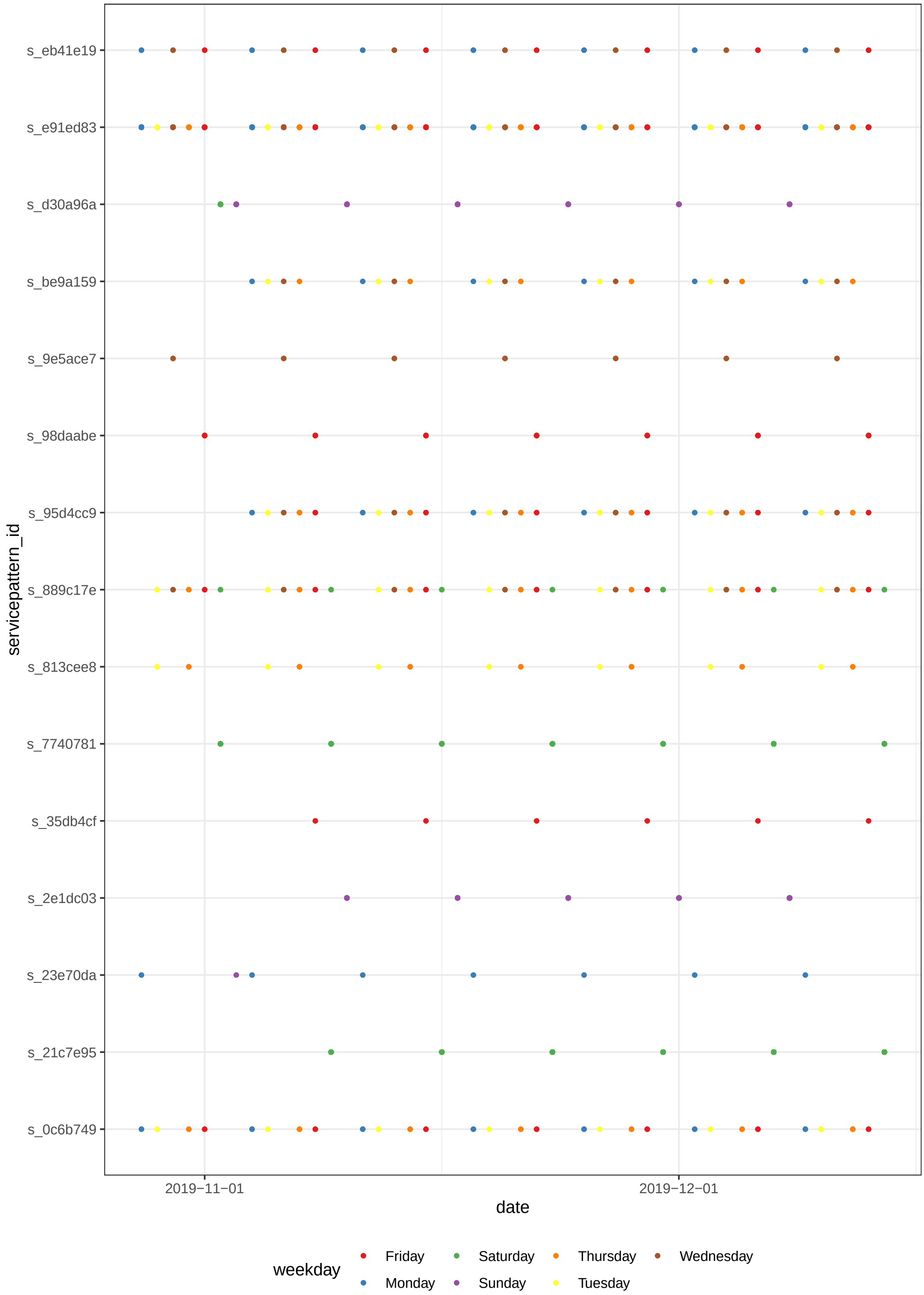

Figure B.0.11 Service patterns and frequency overview, Örebro.

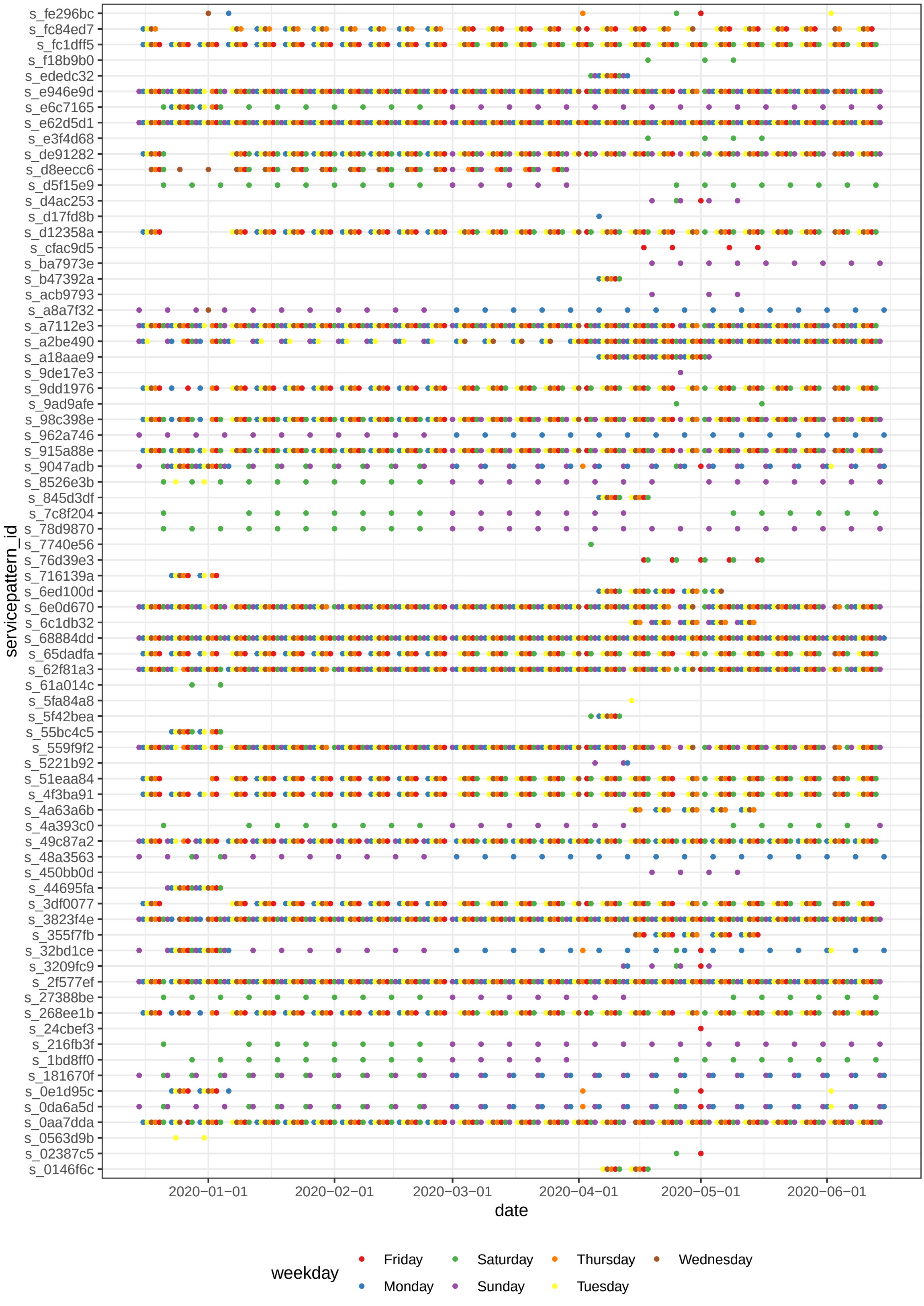

Figure B.0.12 Service patterns and frequency overview, Rome.

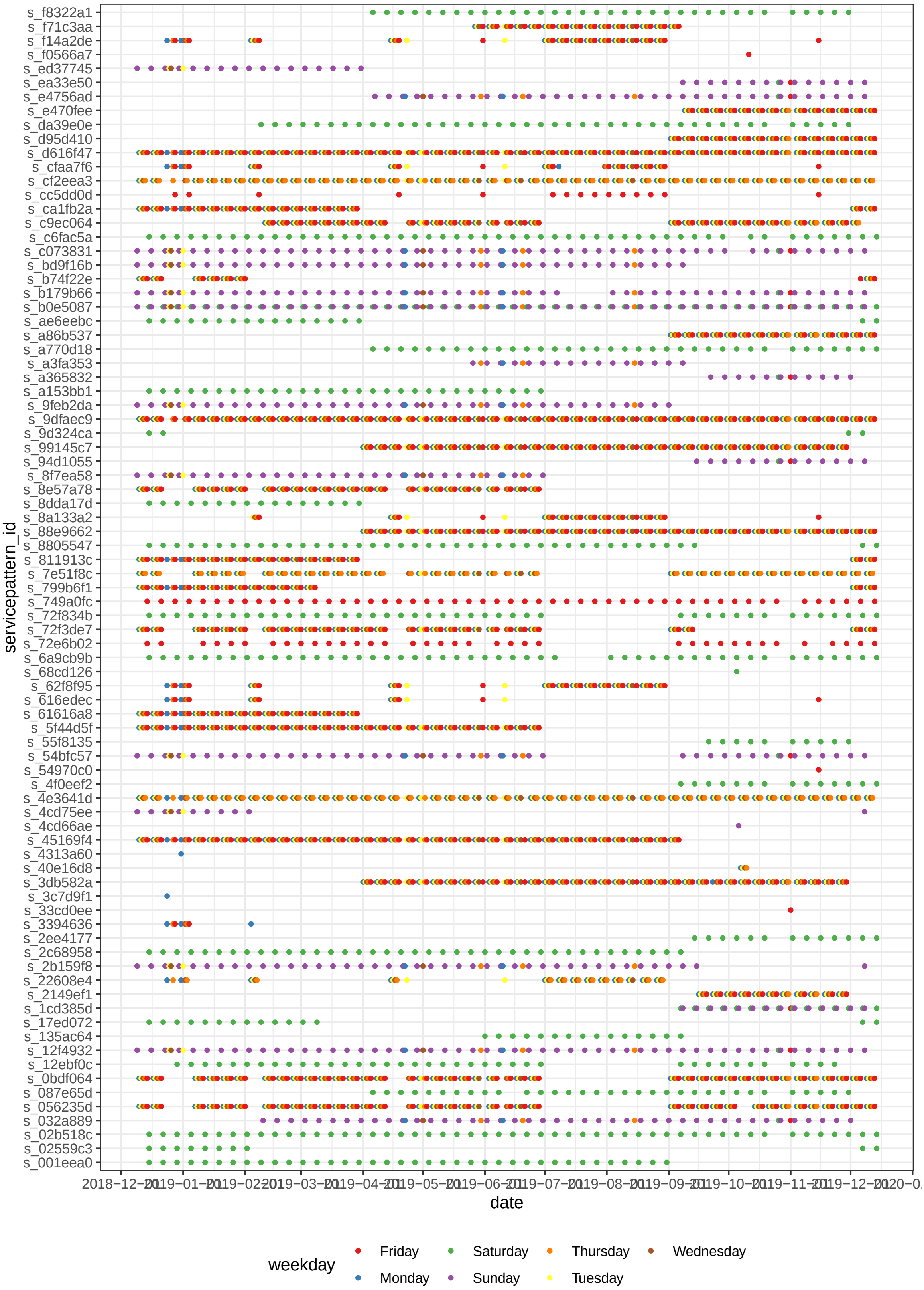

Figure B.0.13 Service patterns and frequency overview, Vienna.

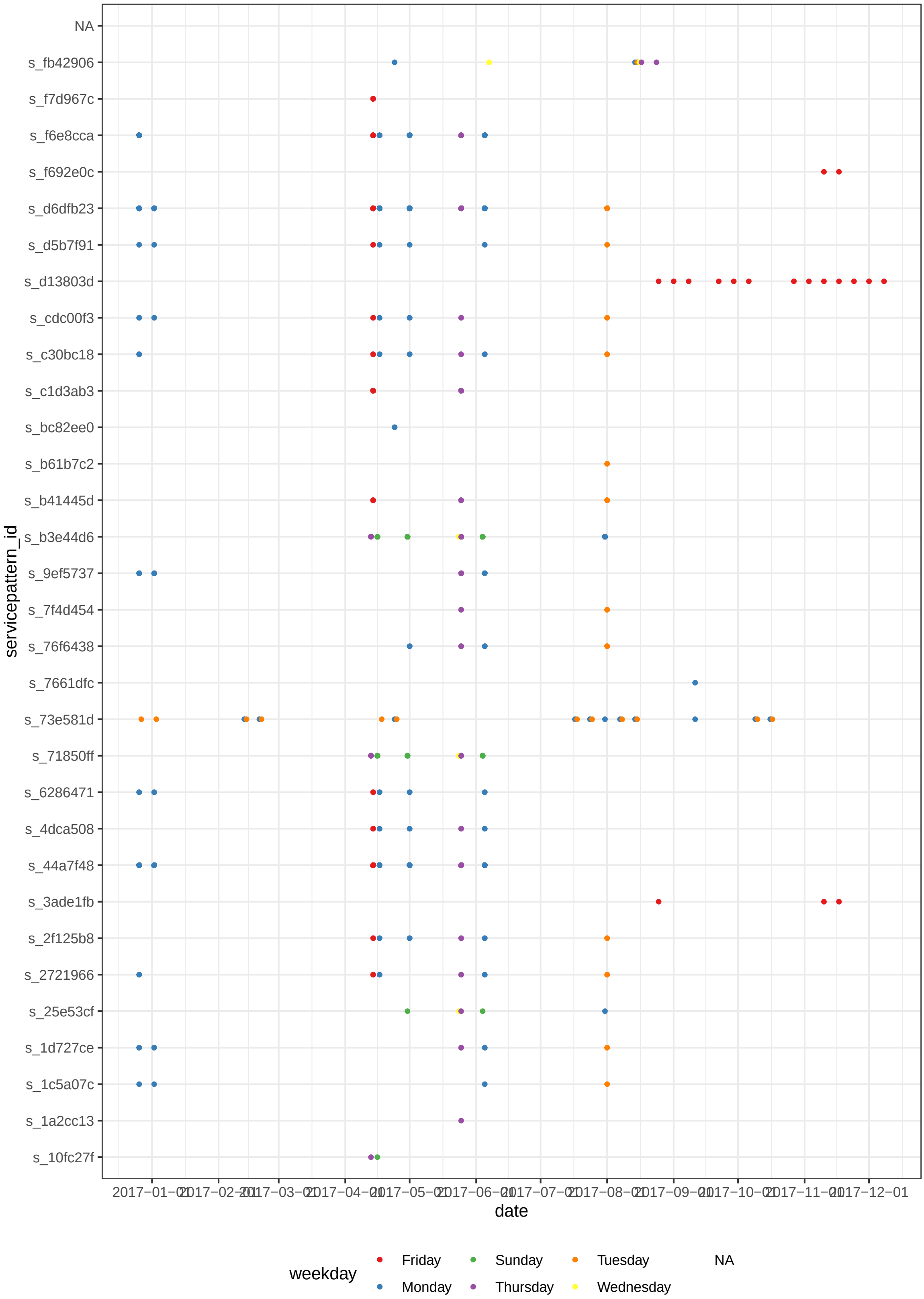

Figure B.0.14 Service patterns and frequency overview, Zürich.

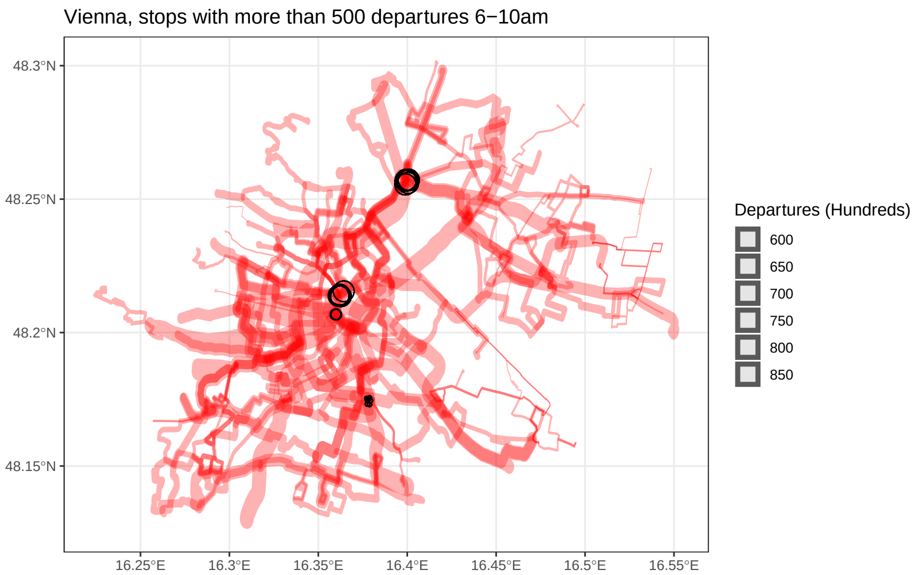

Figure B.0.15 All routes are highlighted in red; more overlaps, and therefore more services at any given public transport stop, are given a darker shade of red.

Appendix C

Co-authorship statements

This appendix includes all the co-authorship statements for chapters included in this thesis.

To Whom It May Concern,

Candidate section:

Name of Candidate: Simona Sulikova

Thesis Title: Understanding transport behaviour and policies to increase walking and cycling

Title of co-authored chapters: As you bike it: Investigating what makes people walk or cycle using a socio-ecological approach in seven European cities

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Candidate's contribution to the paper chapter: conceptualisation, data curation, formal analysis, project administration, validation, visualisation, writing - original draft, writing - review and editing.

CHRISTIAN BRAND | Oxford, 15 February 2021

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Christian Brand

CHRISTIAN BRAND | Oxford, 15 February 2021

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Candidate's contribution to the paper chapter: conceptualisation, data curation, formal analysis, project administration, validation, visualisation, writing - original draft, writing - review and editing.

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February, 2, 2021

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Thesis Title: Understanding transport behaviour and policies to increase walking and cycling

Title of co-authored chapters: Healthy climate, healthy bodies: Optimal fuel taxation and physical activity

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My contribution to the paper chapter: conceptualisation, methodology, project administration, writing - original draft, writing - review and editing.

Candidate's contribution to the paper chapter: conceptualisation, data curation, formal analysis, project administration, validation, visualisation, writing - original draft, writing - review and editing.

Yours faithfully,

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