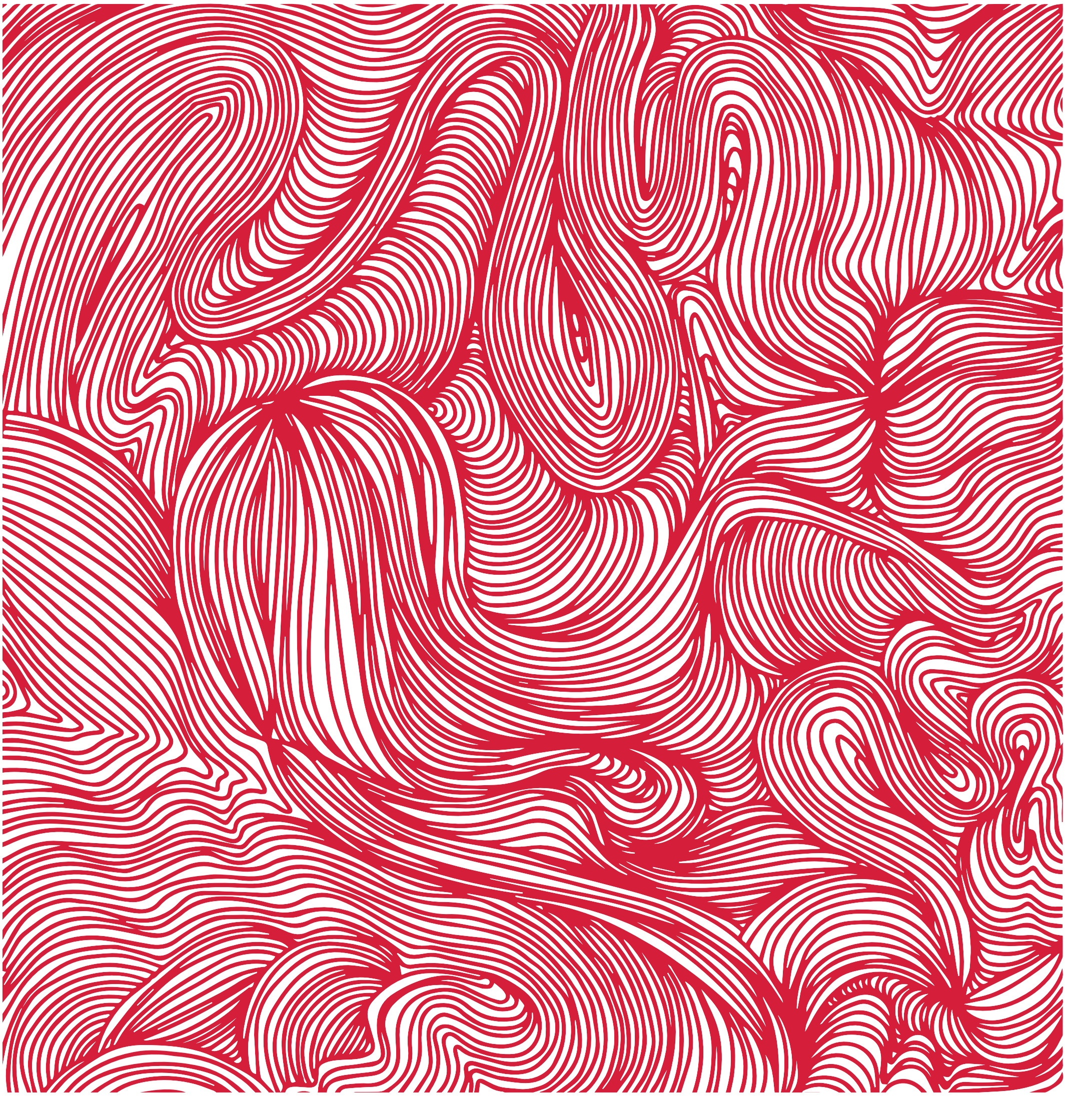
Build, *Move*, Repeat

Strengthening the Causal Links between the Built Environment and Active Travel



Institute for
Management Research

Francisco Edson Macedo Filho

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Francisco Edson Macedo Filho

Radboud University

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Build, *Move*, Repeat

Strengthening the Causal Links between the Built Environment and Active Travel

Proefschrift ter verkrijging van de graad van doctor

aan de Radboud Universiteit Nijmegen

op gezag van de rector magnificus prof. dr. J.M. Sanders,

volgens besluit van het college voor promoties

in het openbaar te verdedigen op

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door

Francisco Edson Macedo Filho

geboren op 16 januari 1992

te Fortaleza (Brazilië)

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from Radboud University Nijmegen

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according to the decision of the Doctorate Board

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Thursday, February 5, 2026

at 12.30 pm

by

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Dedicated to Cami, Mazé, Kamilla, Macedo and Meg.

Acknowledgements

As I write this, I'm struck by how fast time has flown. I've never been so close to completing such a beautiful and transformative cycle. Five years ago, I had just finished my second master's in Spatial Planning in Nijmegen. I was thinking about moving back to my beloved Fortaleza — right in the middle of COVID, when everything felt uncertain. I had almost no money left in the bank (true story), I missed Brazil a lot, and I didn't have a strong support network around me. But then, two life-changing things happened...

First, I received two incredible opportunities. One was to pursue this PhD under the guidance of Erwin van der Krabben, Kevin Raaphorst, and Huub Ploegmakers. The other was to become a "Rebel" with Jeroen Kok and a team of great colleagues. Thanks to the support of Jeroen and Erwin, I was able to do both. (Though I'll admit, filling my tax return forms has been bit confusing ever since). Still, I believe it was one of the best decisions I've ever made. On one side, the PhD gave me the space to dive deep into a topic I genuinely care about. On the other, Rebel allowed me to apply part of what I was learning to real-world projects. As someone who is (by nature) super risk-averse, this combination offered the stability I needed while consistently pushing me beyond my comfort zone and encouraging creative thinking.

The second big thing? I met Camila. Her partnership has been a pillar through this entire journey. I truly don't think I could have completed this cycle without her emotional and intellectual support. (We even managed to publish a paper together!) Thank you, Cami, for being there through everything—for listening to my complaints ("this PhD is taking forever!", "am I really making an impact?", "juggling two jobs is exhausting!"), and for helping me see solutions to problems that were often right in front of me.

I also want to thank my parents, who have always been there for me—especially my mom, who has been a solid source of support and a true safe haven during hard times.

To Kevin, Huub, and Erwin: thank you for your guidance and the many engaging conversations we've had. I know I haven't been around the office as much as I would've liked, but I've really enjoyed working with you. I hope we'll continue to collaborate on research that makes a difference.

To some of my colleagues at Rebel—this is not goodbye, just a "see you soon." A special thank you to Chrétienne Hoek and Clemens Nauta, with whom I've

worked closely. I’ve truly valued the chance to collaborate with such a committed team, and I’m proud of the meaningful solutions and data insights we developed together.

Finally, to the members of my PhD committee—thank you for taking the time to read and evaluate my thesis. I genuinely hope you have fun reading it!

Francisco Macedo

May 2025

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Chapter 1

Introduction

1.1. The role of the built environment in promoting health through daily movement

Over the past century, technological advances have increasingly built sedentary behaviour into our daily routines. Defined as low-energy expenditure while sitting, reclining, or lying down, sedentary behaviour has become pervasive during work, transportation, and at home (Tremblay et al., 2017). In the Netherlands, for example, adults now spend an average of 9 hours per day sitting, making it the "sitting champion" in Europe[1] [2] (Schurink-van 't Klooster et al., 2023; Renaud et al., 2024). This sedentary lifestyle poses significant health risks, including an increased likelihood of developing non-communicable diseases such as cardiovascular disease, type 2 diabetes and certain types of cancer (Ekelund et al., 2016; Hartman et al., 2017; Healy et al., 2015).

Growing evidence suggests that even small amounts of physical activity (PA), such as walking for 10 minutes daily, can lead to substantial health benefits (Chomistek et al., 2013; Ekelund et al., 2016). Studies confirm physical activity's role in reducing morbidity and mortality from chronic disease (Aune et al., 2015, 2016; Cloostermans et al., 2015; Huai et al., 2013; Kyu et al., 2016; Li and Siegrist, 2012; Schmid and Leitzmann, 2014). Walking and cycling, especially when incorporated into daily travel routines, can be a simple way to integrate movement into sedentary lifestyles and increase overall physical activity levels (Fairnie et al., 2016), not necessarily replacing other forms of exercise (Panik et al., 2019; Sahlqvist et al., 2013). Rather than relying on separate fitness activities, public health authorities increasingly emphasize the importance of including Active Travel (AT) into everyday transportation as a practical solution to combat physical inactivity (Aldred, 2019).

A key way through which physical activity can be encouraged through AT is by changing the Built Environment (BE) around us (Frank et al., 2019). When activity-supportive built environments and sufficient travel opportunities are available, exposed individuals tend to engage in more active transportation (Smith et al., 2017; Sallis et al., 2020), thus increasing physical activity levels ('behavioural response'), improving 'biological response' (e.g., lower obesity

1. According to data from the Eurobarometer on Sport and Physical Activity (2018) the European Union average for time spent sitting is approximately **5 to 6 hours per day** for adults.
2. Europe's champion sitters: even the sporty Dutch are falling victim to 'chair-use disorder' (The Guardian, 2024)

levels or stress levels), and finally decreasing the risk of disease and death (see Fig. 1.1). Land use patterns in combination with infrastructure can shape one's activity spaces and his/ her level of access to opportunities in cities (Ewing and Cervero, 2010), by making walking and cycling more attractive than driving, through shorter travel times and distances between origins and destinations (Frank et al., 2019). Environments can also discourage active travel. Sprawled urban developments are often car oriented because it is not convenient to access key destinations by foot or bicycle. These land use patterns are characterized by little diversity, low density, and poor destination accessibility. Environments with low walkability and/ or bikeability, such as those lacking safe sidewalks, bike lanes, or secure routes, reduce the likelihood of active travel. Poor aesthetics, low security, and unsafe intersections further discourage walking and cycling (Wang et al., 2016; Shaer et al., 2021; Rahman et al., 2023).

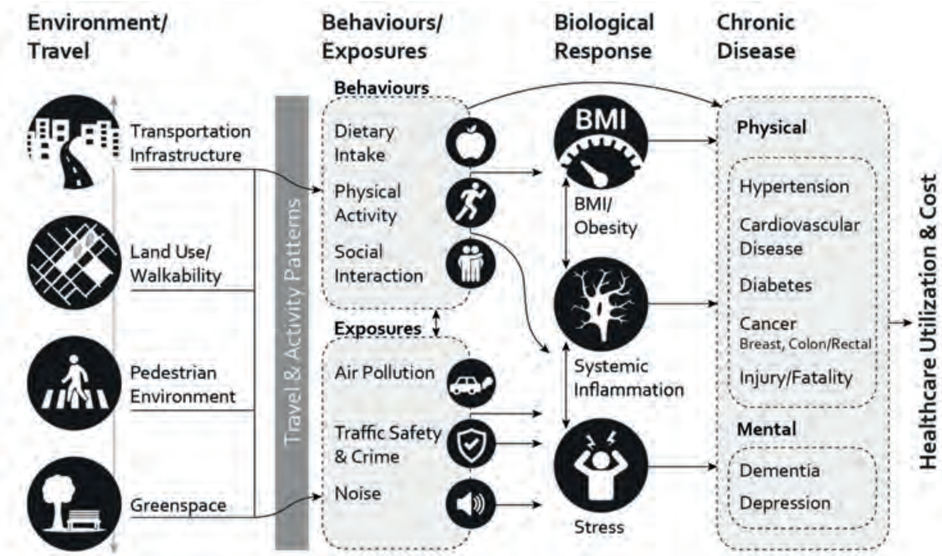

Fig. 1.1. Causal scheme linking built environment, behavioural response and health. Adapted from Frank et al. (2019).

1.2. Built environment and travel behaviour: beyond correlations toward causal understanding

There is a prevailing assumption—if not a consensus—that the built environment plays a <u>deterministic role</u> in shaping travel behaviour. A common idea is that, if the BE did not exert any influence on people's well-being, the economy, the natural environment, etc, there would be no point in trying to shape built structures around us (Næss, 2015). This assumption has been reinforced by the consolidation of a *neo positivist* tradition[3] in transport research, where correlational analyses have dominated the literature (Næss, 2015; Scheiner et al., 2024), and explicit discussions on how interventions benefit target users, or how the characteristics of a place or the affected residents can also amplify or attenuate the impact of those interventions, have been left in the second plane (Panter et al., 2019).

Many studies have drawn conclusions based on estimated coefficients—typically representing associations—under the assumption that if key confounding variables (such as sociodemographic factors and individual attitudes) are controlled for, causal relationships between the built environment (BE) and travel behaviour (TB) can be inferred. However, this assumption is increasingly questioned within the scientific community. Even when the temporal sequence between intervention and outcomes is clear—for instance, when changes in the built environment precede changes in travel behaviour—scholars have challenged the idea that the built environment alone deterministically shapes travel choices (Handy et al., 2005; Cao et al., 2009; Næss, 2015; Panter et al., 2019; van de Coevering, 2021). This critique has gained traction among transport and spatial planners, as the limitations of relying solely on correlational models become more evident. The issue of causality in travel demand modelling is being increasingly discussed, yet it remains far from fully resolved or understood (Brathwaite and Walker, 2018).

Given the complexity of studying active travel behaviour and the inherent risks of bias in statistical modelling, several scholars have emphasized the importance of understanding the logical reasons that drive transport demand—making causality a central focus of debate (Handy et al., 2005; Mokhtarian and Cao, 2008; Næss, 2015). Estimating causal effects can be particularly challenging due not only to the complexity of the behavioural mechanisms involved—which ideally should be specified in advance—but also to data limitations and methodological choices made during study design.

3. In transport planning research, the neopositivist paradigm is characterized by a strong emphasis on quantitative methods, empirical observation, and hypothesis testing to explain travel behaviour and transport systems. Rooted in logical positivism, it assumes that reality can be objectively measured, modelled, and predicted through statistical analysis and data-driven approaches.

While the body of evidence on the BE–TB relationship continues to grow, important gaps remain—particularly regarding the quantity and quality of causal studies.

1.3. The need for more (and better) causal evidence in transport research

Systematic reviews suggest that active travel interventions, particularly at scale, are often associated with increasing levels of walking and cycling (see Ogilvie et al., 2004, 2007; Handy et al., 2005; Yang et al., 2010; Pucher et al., 2010; Saunders et al., 2013; Mölenberg et al., 2019; Xiao et al., 2022). People may say they would like public parks, wide footways, protected bike routes, and so on, and even that such changes would encourage them to be active. But a critical question remains: will actual behavioural change follow when we implement these changes?

As most of the evidence is primarily cross-sectional (Buehler and Dill, 2016; Mölenberg et al., 2019), analysing correlations between infrastructure provision and active travel behaviour at a single point in time might lack the analytical basis for causal inference. While cross-sectional studies often show strong associations between the BE, AT, and PA—suggesting possible causal links (Naess, 2015)—these studies are exploratory in nature. They cannot assess how changes in the BE over time affect individuals, since they do not capture the temporal sequence between exposure to structural changes and behavioural outcomes (Hogendorf et al., 2020).

Even studies that use multi-period data often fall short. Many lack control or comparison sites, or fail to satisfactorily correct for potential confounders—for instance, the possibility that a change in travel behaviour might be partly explained by an external factor outside the control of the researcher, or that people who already prefer a certain mode choose to live in neighbourhoods that support their preferences (Buehler and Dill, 2016). Researchers in the field of causal inference have applied several identification techniques to address these challenges and answer different research questions—such as difference-in-differences (DiD), fixed effects (FE) models, or structural equation modelling (SEM)—which require robust, longitudinal datasets to isolate and identify the true impact of interventions (Brathwaite and Walker, 2018). For example, while FE models rely on the elimination of time-invariant confounders by looking at the same units at different periods of time, SEM requires all relevant '*back-doors*' that would influence outcomes to be explicitly identified. Such causal studies are rare, because, independently of the framework or technique used, collecting high-quality data can be expensive, logistically demanding, and politically sensitive.

Political resistance can complicate the implementation of active travel policies. In light of the confrontational political contexts that can arise with such built environment interventions (e.g., financially burdensome pro-cycling interventions in low-cycling highly-contested areas, expensive pro-cycling interventions in already cycling-rich contexts), there has been a rise in the number of intervention studies and longitudinal designs, and systematic reviews assessing those (Xiao et al., 2022), however there is a general consensus that more is needed (Naess, 2015; Buehler and Dill, 2015; Frank et al., 2019; Aldred, 2019; Mölenberg et al., 2019; Scheiner et al., 2024).

This issue matters greatly. In practice, many transportation professionals and decision-makers do not fully trust the results of travel demand models used for *ex-ante* evaluations (e.g., cost-benefit analyses). These models are often viewed as "black boxes" with outputs that are difficult to interpret or verify. In contrast, evidence based on real-world interventions carries far more weight, offering tangible insights into what works, for whom, and under what conditions (Brathwaite and Walker, 2018).

1.4. Empirical focus and research questions

Cities are constantly evolving, shaped by new infrastructure and land-use reforms that influence how people live and move. Urban planners and policymakers constantly seek robust evidence to determine whether interventions such as new bike lanes, transit expansions, densification strategies, and mixed-use zoning effectively reduce car dependency and encourage active travel. Changes in BE characteristics, either due to land use and infrastructural changes (or residential relocation) provide unique context for these interventions because they motivate people to reconsider their behaviour and attitudes.

At the core of these transformations lies the fundamental interaction between land use and transport infrastructure, and how they influence travel behaviour. Transport infrastructure design, capacity and connectivity shape accessibility to different locations. Differences in accessibility levels generate changes in land-use patterns by influencing the location of new activities, densification and where people choose to live and work. Conversely, land-use changes—such as zoning policies, housing developments, and commercial planning, even a lockdown—impact how and why people travel, thereby influencing transport demand. As a result of built environment changes, trip patterns may change in a number of ways, such as in terms of the number of trips, the timing of trips, their origin or destination, the mode, and trip chaining. Then, this change in demand shapes the planning, maintenance, and upgrade of transportation infrastructure and services such as roads and public transit. Again, these changes further impact accessibility into a new interactive cycle.

For instance, a new high-quality cycle route may increase accessibility to important destinations, leading to new residential developments, which then generate additional demand for transportation services. Similarly, high-density, mixed-use developments can promote walkability and reduce reliance on private vehicles, while low-density, car-oriented developments reinforce automobile dependency. Understanding and modelling these effects is critical for designing urban environments that support sustainable mobility and high-quality urban living.

In light of the growing interest among planners on causal effects of transport infrastructure and land use reforms on active travel—their potential impact of the latter on people's health, and the fact that causality is still far from being widely understood given the need for more evidence — this thesis aims to contribute to the current understanding of the causal relationship between the built environment (BE) and active travel (AT). Specifically, it focuses on how improving transport infrastructure and changing access to land use affects the uptake of cycling and walking. Fig. 1.2. shows the relationships between BE-TB studied, and major confounders considered in this research. Achieving this thesis aim means establishing meaningful theoretical and statistical associations between changes in built environments of travellers' origins / destinations [1] while mitigating the impact of confounders/ third variables arising from uncontrolled common causes [2, 3].

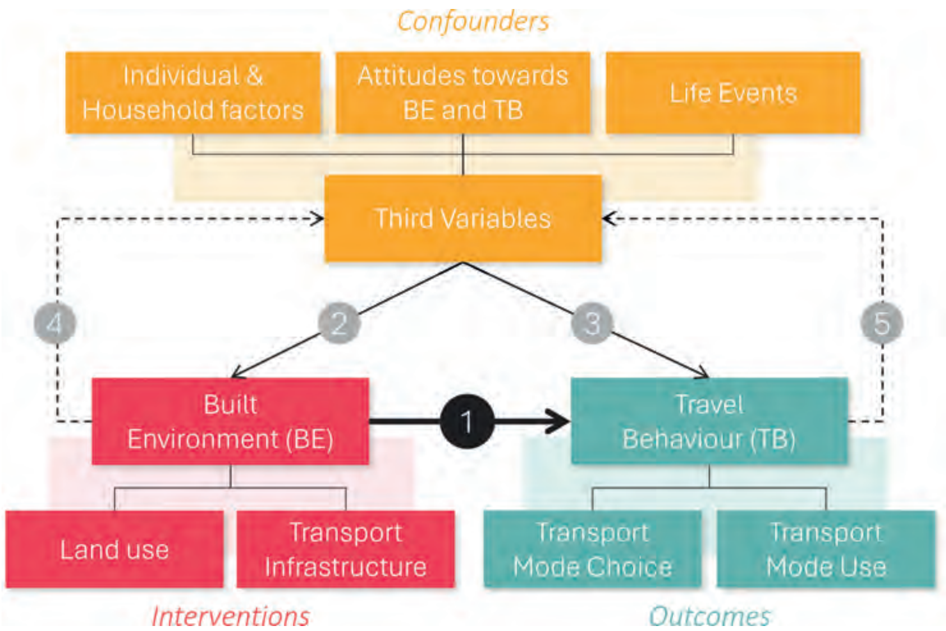

Fig. 1.2. Graphical representation of thesis' aim.

In this context, this thesis focuses on two central research questions. First, ***how and to what extent does active travel infrastructure influence travel behaviour? Second, how and to what extent do density, access to destinations and land-use diversity affect active travel behaviour?***

The first question focuses on the role of physical infrastructure improvements, such as the expansion of bicycle networks, which improve connectivity and reduce the time and effort required to travel between origins and destinations. The second question looks at how shifts in the spatial distribution of activities—driven by policy interventions or residential relocation—change people's proximity to key destinations, thereby influencing active travel demand, particularly in terms of mode choice and frequency of use. By distinguishing between these two dimensions of the built environment, this research seeks to understand their distinct effects on active travel: while infrastructure enhances accessibility by improving network connectivity and reducing travel costs, land use changes improve accessibility by bringing destinations closer to where people live and work.

1.5. Conceptual research design & sub-questions

To guide my research efforts towards answering the main research questions, I propose a research design that draws on a post-positivist paradigm, as it aligns with the view that reality—such as the influence of the BE on TB—exists independently but can only be partially captured through observation. Ontologically, this means that the existence of causal relationships between policy making and mobility choices, while recognizing that these relationships are complex, context-dependent, and influenced by a range of individual and structural factors. Epistemologically, this perspective supports the use of empirical methods—including both experimental and observational designs—to identify causality. Accordingly, the research is structured on four empirical studies, which are divided among 2 distinct foci - transport infrastructure and access to land use.

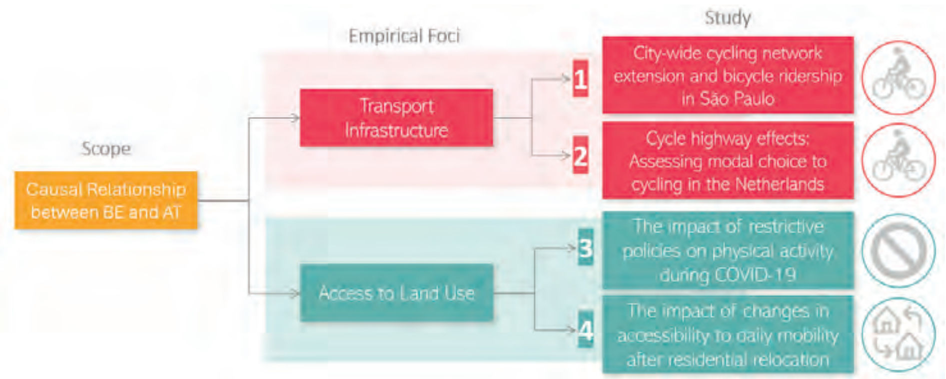

Fig. 1.3. Graphical overview of empirical studies and their foci.

Focus 1: Assessing the impact of exposure to pro-cycling policies in cycling-poor and -rich areas.

Given the highlighted need for more causal evidence—particularly through high-quality intervention studies (Aldred, 2019)—this research addresses both low-cycling contexts, where political resistance can hinder implementation, and high-cycling contexts, where the marginal benefits of new infrastructure remain uncertain (Buehler and Dill, 2016). The following research questions and studies are proposed:

Study 1:	City-wide cycling network extension and bicycle ridership in São Paulo: A causal analysis.
Study 2:	Cycle highway effects: Assessing modal choice to cycling in the Netherlands.
RQ1a.	How has the implementation of a large network of cycle routes impacted modal choice and encouraged shifts from other modes to cycling?
RQ1b.	How to develop exposure-to-treatment measures that are well integrated with travelers' routines and explicitly operationalize intervention benefits?
RQ1c.	How does exposure of treated groups to new cycle routes influence modal shift to cycling?
RQ1d.	How has the new cycle network affected different subgroups' mode choice?

To answer the research questions in either contexts, two natural-experiments using multiple cross-sections of household travel surveys are designed and executed - the first one in the Metropolitan Area of São Paulo (low-cycling context), and the other using the Netherlands (high-cycling context). In the first case, I look at the effect of implementing an extensive network of urban cycle routes across São Paulo, to serve its more than 20 million inhabitants. In the second case, I estimate the impact of introducing a large network of ambitious/ high-quality facilities across the Netherlands. In both cases I adopt robust and 'dynamic' approaches (Humphreys et al., 2016) to defining levels of exposure, which take into consideration routine mobility and operationalize the benefits promoted by the interventions through the application of routing algorithms and geospatial techniques, therefore establishing a more direct connection with causal mechanisms behind behavioural change.

To further address causal mechanisms, in both cases, I explore how the impact of exposure varies across different traveller segments based on their demographics and household characteristics. While those two studies may not fully resolve all mentioned gaps individually, they contribute to strengthening causal evidence in quantity and quality, refining exposure assessment methodologies, uncovering intervention benefits, and expanding the empirical focus to underexplored cycling infrastructure typologies.

Focus 2a: Assessing the role of context on the impact of restrictive policies on physical activity during COVID-19.

Beyond analysing subgroup differences, researchers can strengthen causal links between the BE and AT by estimating how exposure to different environments influences movement and physical activity outcomes. During the COVID-19 pandemic in the Netherlands, restrictive government measures limited public access to important destinations. However, despite nationwide movement restrictions, the extent of reduced access to amenities and sports facilities varied across neighbourhoods—leading to uneven impacts on physical activity levels. The built environment plays a key role in shaping these disparities. Some communities may have been disproportionately affected by declines in physical activity due to the way their surrounding land use is organized. While several studies have examined factors such as urban greenery or population density during pandemic-related restrictions, other aspects of the built environment remain underexplored. In particular, there is limited understanding of how different neighbourhood types and declines in access to key destinations due to movement restrictions, contributed to the decline in physical activity during COVID-19. Considering the exposed, the following question and study are proposed:

Study 3:	Investigating the Amplifying and Attenuating Role of Neighbourhood Environments on Physical Inactivity during COVID-19 Movement Restrictions.
RQ2a1.	Under which BE conditions movement restrictions adopted by governments produced the strongest or weakest effect on physical inactivity?

In this study, I examined short-term changes in leisure- and work-related active mobility (cycling and walking) in the Netherlands before and after the first COVID-19 lockdown (2020) and explored how exposure to different BE characteristics and typologies are associated with these changes. Unlike the previous 2 studies, which focused on the impact of supportive interventions for active travel, this study considers COVID-19 restrictions as an unsupportive 'extreme event'—one that limited residents' access to exercise opportunities rather than facilitating them.

Focus 2b: Assessing the impact of changes in accessibility to daily mobility after residential relocation.

Efforts to influence travel behaviour through land-use and transport planning often assume a causal link between the built environment (BE) and how people travel (Naess, 2015, 2016). While this may hold to some extent, the relationship has been increasingly questioned due to the role of self-selection —where individual preferences and demographics shape both residential choice and travel behaviour (Cao et al., 2009; van de Coevering et al., 2018). Scholars have since called for more nuanced approaches that consider contextual factors and mechanisms through which the BE affects behaviour (Panter et al., 2019), and for the recognition of multiple causal structures (Van Wee and Cao, 2020).

Despite these conceptual advances, longitudinal studies that test such frameworks remain scarce, in part because BE changes occur slowly and are hard to observe over time. A useful alternative is to study residential relocation, where people experience a more immediate change in accessibility and infrastructure. This setting allows researchers to assess how behaviour and attitudes shift in response to a new environment, provided the causal relationships are clearly defined (Scheiner et al., 2024).

Still, longitudinal evidence on the effects of relocation remains limited—especially studies that account for self-selection and reverse causality (e.g., Tao, 2024; Tao et al., 2023; De Vos et al., 2018). Most research in this field is composed by cross-sectional or quasi-longitudinal studies that have discussed the extent to which travel behaviour changes as the result of changes in residential BE after relocation (residential determinism) (Cao and Ermagun, 2017; Cao et al., 2009). Less longitudinally investigated is whether attitudes change over time after relocation (reverse causality), to what extent are travel attitudes endogenous to the relationships between BE and travel behaviours (self-selection), and to what extent is mode use affected by changes in built environment as a major life event while considering both self-selection and reverse causality into account in the same framework. In this sense, the following research questions and study are proposed:

Study 4:	Short-term changes in daily mobility due to residential relocation: A cross-lagged panel analysis
RQ2b1.	How does a change in urban density and proximity to daily amenities through residential relocation influence daily cycling, car use, and travel preferences in the short term?
RQ2b2.	To what extent do pre-relocation travel preferences affect changes in accessibility levels during relocation?

To explore these questions, we use data from four waves of the Netherlands Mobility Panel (MPN) to assess how changes in neighbourhood environments influence daily cycling and car use among relocated residents between 2013 and 2016. These environmental changes are measured through urban density and proximity to daily amenities, while also accounting for pre-relocation travel preferences.

1.6. Research methodology

To answer the proposed research questions, I focus on quantitative observational research designs, where travel behaviour data is collected across multiple time periods—before and after significant changes to the built environment. While cross-sectional data can provide valuable insights, multi-period designs provide the opportunity to assess changes in travel behaviour resulting from BE changes over time (van de Coevering et al., 2015). Compared to qualitative approaches, these quantitative designs still do less well in explaining the mechanisms that trigger these effects, that is, provide causal explanations. Detailed discussions of qualitative approaches is not part of this research's scope, but can be found in the work of Peter Næss (2015) and Scheiner et al. (2024). The choice for the research designs of this thesis were influenced by the type of intervention under study, the specific research questions of each study, the data available to my PhD project, and the mechanisms that different statistical methods offered to mitigate the impact of confounders.

1.6.1. Causal inference frameworks used in transport research

Causality is an important concept in many fields, but there is no single universally accepted definition, and the notion of causality in human behaviour is not always accepted (Naess, 2016; Parascandola and Weed, 2001). Two important causal inference (CI) frameworks, which are dominant in studies examining the relationship between the built environment (BE) and travel behaviour (TB) (Imbens, 2020), are useful in this thesis to develop the proposed studies.

The first is the Potential Outcomes (PO) framework, also known as the "Rubin Causal Model" (Holland, 1986), which was developed by Donald Rubin and collaborators. This framework builds upon randomized controlled trials (RCTs) and is widely used in experimental and observational settings to evaluate the impact of policies and assess causal relations in economics, epidemiology, social sciences and transport research. The second framework is the graphical approach using Directed Acyclic Graphs (DAGs), also widely adopted in transport research, but also in computer science (Imbens, 2020), is associated with the work of Judea Pearl and collaborators and is often implemented in Structural Equation Models (SEMs).

In simplified terms, the PO framework defines causality through counterfactual comparisons, meaning that for each unit—whether an individual or household—multiple potential outcomes exist, each corresponding to a different treatment condition. Formally, we denote the potential outcome under treatment level x as Y(x). However, for any given unit, we can observe only one of these potential outcomes, depending on the treatment actually received. In the simplest case with a binary treatment there are two potential outcomes, Y (0) and Y (1), but in other cases there can be more. Only one of these potential outcomes can be observed, namely the one corresponding to the treatment received:

$$Y^{\mathrm{obs}} = Y(X) = \sum_{x} Y(x) 1_{X=x}$$

Where:

- Y^{obs} is the observed outcome.
- X is the treatment received.
- $1_{X=x}$ is an indicator function equal to 1 if X = x, and 0 otherwise.

This formulation highlights the fundamental problem of causal inference in POs (Holland, 1986): we can never observe the counterfactual outcome $Y(x\text{'}) \text{ for } x\text{'} \neq X$ - the outcome that would have occurred under a different treatment. Estimating this unobserved counterfactual is at the heart of PO. Much of the literature has concentrated on the case with just a single binary treatment, with the focus on estimating the average treatment effect of this binary treatment for the entire population or some subpopulation.

$$\tau = E\left[Yi(1) - Yi(0)\right]$$

Where $Yi(1)$ and $Yi(0)$ are potential outcomes under treatment and control conditions.

The DAGs framework often provides accessible ways to express visually causal assumptions, allowing researchers to map causal links and explicitly identify confounders. Unlike PO, DAGs explicitly define causal directionalities and help assess whether certain variables should or should not be controlled for in statistical models. DAGs require the researcher to visualize the common causes of an exposure and outcome and the common causes among all variables already in the DAG that might affect estimation of the target causal effect. Although less commonly used than the PO framework in BE-TB research, they have gained traction in relocation studies, where researchers have structural equation modelling techniques (SEM) as "algebraic systems" of causal DAGs (Kunicki et al., 2023) to understand if whether travel behaviour is influenced by the built environment itself or whether individuals self-select into environments that match their travel preferences (e.g., De Vos et al., 2018; van de Coevering, 2018, 2021; Cao et al., 2009). These two frameworks are complementary, each with advantages and challenges, making them more suitable for different types of research questions and settings (Imbens, 2020).

1.6.2. Selecting research designs and causal identification techniques

In transport research using the potential outcomes (PO) framework with multi-period data, experimental designs—typically randomized or quasi-experiments—are preferred. These designs allow researchers to control where and when interventions occur, minimizing bias in treatment assignment and strengthening causal claims when outcomes differ. Because treatment assignment (D_i) is independent of participant characteristics X_i, individuals are randomly allocated to treatment and control groups. This helps eliminate the influence of both observed and unobserved confounders, thereby reducing the risk of third-variable bias or spuriousness (Shadish et al., 2012).

When it comes to BE interventions, it is often hard to apply experimental designs, given that it would be impractical and unethical to randomly assign residents to different residential areas, or implement random changes in the BE. Additionally, BE interventions have a highly localized nature and are highly influenced by participant characteristics, often suffering from small sample sizes.

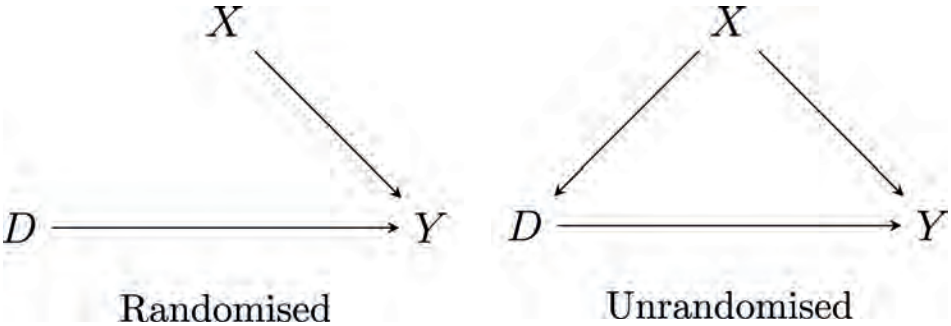

Fig. 1.4. Directed acyclic graph of randomized (left) and non-randomized (right) treatment assignment.

Regardless of the causal inference framework employed, a central challenge in observational research is to determine whether observed changes in an outcome variable—such as travel behaviour—can genuinely be attributed to a specific treatment or intervention—such as the introduction of a new cycle route—rather than to underlying confounding factors like pre-existing attitudes toward cycling. In the absence of randomized treatment assignment, researchers must approximate the conditions of randomization by employing identification strategies that eliminate or control for confounding variables—those that influence both the treatment and the outcome and may therefore bias causal estimates. This principle, introduced by Singleton and Straits (1993) and adopted by transport researchers as the condition of non-spuriousness, has been formalized by Graham (2014, 2025) as the Conditional Independence (or exchangeability). If all relevant confounders (X) are adequately accounted for (or conditioned), treatment assignment can be considered 'as good as random', even in observational settings (Rubin, 1974; Imbens, 2020). That condition could be stated as:

$$Y(0), Y(1) \perp\!\!\!\perp D \mid X$$

Where:

- $Yi(0)$ is the outcome that would occur if the unit did not receive the treatment (control condition).
- $Yi(1)$ is the outcome that would occur if the unit did receive the treatment.
- D is the treatment indicator;
- X a vector of observed covariates or pretreatment characteristics to be controlled for (e.g., age, income, prior behaviour).

Under these conditions, differences in outcomes between treated and untreated groups may be credibly interpreted as the causal effect of the treatment, rather than the result of omitted variable bias.

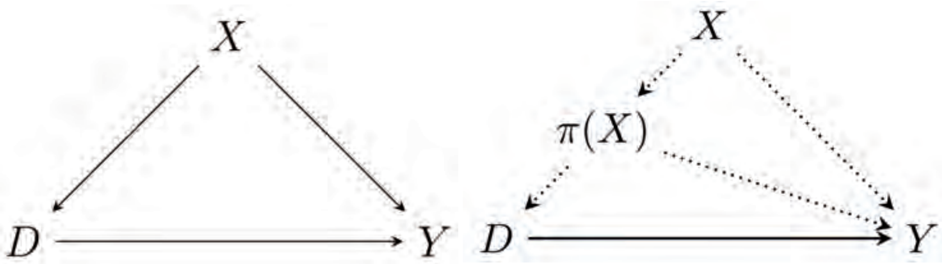

Fig. 1.5. Confounded treatment assignment (left). Addressing Conditional independence of Y and D given X or $\pi(X)$ (right).

To address the limitations inherent in observational research, this thesis considers naturally occurring, non-randomized interventions—as shown in the first two empirical studies (Studies 1 and 2)—to assess the impact of cycling infrastructure on mode choice. Among observational designs, natural experiments are considered particularly well-suited for causal inference, as they enable researchers to exploit these developments as exogenous events that arise independently of the subjects' characteristics or behaviour (Krizek et al., 2009; Van de Coevering et al., 2015). The degree to which cycling interventions events are 'exogenous' to residents can be debatable, as it depends on the specific context and how the interventions were planned and implemented.

In the absence of randomized treatment assignment, establishing conditional independence becomes essential for robust causal identification. To approximate this condition, both Studies 1 and 2 adopt the Parallel Trends

Assumption (PTA), which serves as a central identifying assumption in Difference-in-Differences (DiD) designs and helps to approximate the exchangeability condition from the potential outcomes framework. The PTA posits that, had the treatment not occurred, outcome trends for both treated and control groups would have evolved in parallel over time. Under this assumption, any divergence in outcomes observed after the intervention can be attributed to the treatment, provided that the groups were on similar trajectories before the intervention and that time-varying confounding is minimal or properly controlled for.

In practice, DiD compares changes in outcomes (e.g., cycling rates) before and after the intervention between groups that were exposed to new infrastructure and those that were not. To strengthen the plausibility of the PTA, studies 1 and 2 also include control variables for time-varying confounders. Figure 03 illustrates the PTA in a DiD setting. If the assumption holds, the trends in mode choice for both the treatment and control groups would have remained parallel over time in the absence of the intervention. Any divergence observed after the intervention can thus, in theory, be attributed to the treatment itself.

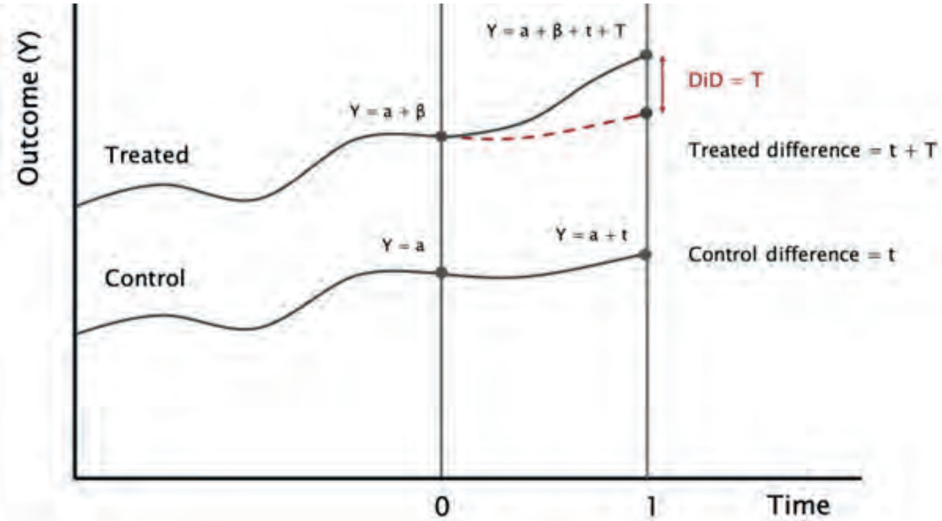

Fig. 1.6. Graphical representation of the PTA in DiD (Adapted from Gertler et al., 2010)

Land use changes present unique challenges for causal inference, as they tend to occur gradually and are often hard to observe or measure due to limited longitudinal data (Scheiner et al., 2024). Nonetheless, interesting exceptions exist—sudden shifts in land use can sometimes be documented and used in intervention studies. Disruptive events, in particular, are significant because they create moments when established routines are re-evaluated and mobility choices are more likely to change (Verplanken et al., 2008).

One such case is the disruption brought on by the COVID-19 pandemic assessed in Study 3, which drastically changed residents' level of access to daily amenities in the very short-term due to lockdown policies. Within the Potential Outcomes framework, longitudinal designs are useful in contexts like these, where defining a traditional control group is difficult, since the whole population is affected by the same policy, but with different intensity—such as during a nationwide lockdown. In such case, Fixed Effects (FE) models provide a useful causal identification alternative by comparing individuals to themselves over time. By exploiting within-person variation, FE models can isolate the effect of a change in exposure (e.g., to COVID-related movement restrictions under certain built environment conditions) on outcomes like travel behaviour or physical activity. FE methods partially satisfy the exchangeability condition by controlling for all time-invariant unobserved confounders (Hogendorf et al., 2020)—such as key demographics—thus narrowing the set of variables that must be explicitly observed and adjusted for. Provided that changes are observed, the FE model is able to capture to what extent the forced change in access to amenities (through lockdown) between time-points is related to changes in active travel between time-points under different built environment conditions.

Another example of disruptive events happens in the context of residential relocation, explored in Study 4, where individuals are self-motivated (or forced) to experience a shift in their residential built environment, which can in turn affect their travel behaviour and attitudes. Residential relocations represent such an event in the context of travel behaviour because it is of crucial importance for daily mobility as it defines a fixed point individuals need to return to (usually) daily. Thus, it largely defines the range of accessible destinations in everyday life (Hägerstrand, 1970). After a residential relocation, movers might reconsider their travel choices in response to BE changes at the residential location or changed travel distances (Stanbridge, 2016). In the case of relocation, longitudinal designs are also useful, as they enable us to assess the impact of BE on TB in the occurrence of potentially endogenous (self-selected) changes in household circumstances, as it can happen that people self-select to match the built environment with their preferences. The latter is a major concern for this type of study since personal preferences influence the ‘intensity’ of BE change during the move.

An alternative approach to partially deal with the confounder bias is to explicitly (and graphically) estimate the influence of third variables in the analysis through the adoption of the Directed Acyclic Graphs (DAGs) framework. Though with fewer empirical examples in other fields (e.g., policy evaluation, economics), DAGs have connected well with Structural Equation Models (SEM), helping transport researchers explore causal BE-TB relationships and control for relevant back-doors. In the past 5 years, quite a few interesting relocation studies have adopted DAG to understand the reciprocal relations between built environment change, attitudes and travel behaviour (see e.g., Schimohr et al., 2025; Scheiner et al., 2024; Tao, 2024; De Vos et al., 2018).

As an identification strategy in Study 4, I propose the use of Random Intercept Cross-Lagged Panel Models (RI-CLPM) to explore the influence of changes in the residential built environment of movers on travel behaviour. RI-CLPM is a SEM method for applicable for longitudinal data. This approach deals with exchangeability by separating stable between-person traits from within-person variation over time (Mulder and Hamaker, 2021; Hamaker et al., 2015). For example, changes in travel mode use are composed of variations in the frequency of mode use for different individuals with specific trait-like features and for the same individuals who change mode use over time. Similarly to FEs, by focusing on within-individual changes of travel behaviour, RI-CLPM partly addresses the bias from unobserved time-invariant confounders.

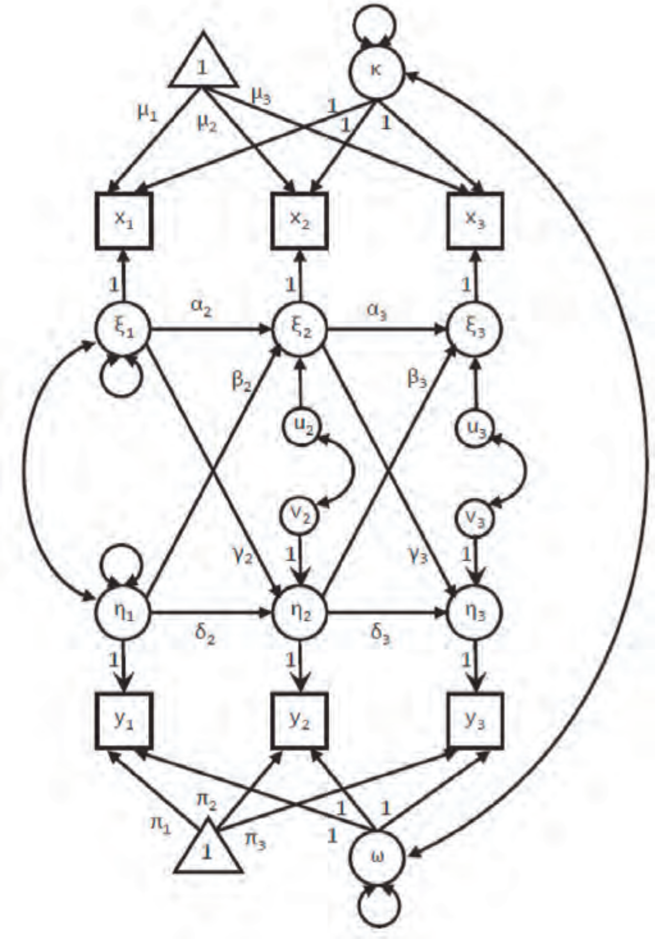

Fig. 1.7. Model structure three-wave Random Intercept Cross-Lagged Panel Model (Hamaker et al., 2015).

Fig. 1.7. shows the model structure of the RI-CLPM proposed by Hamaker et al. (2015). For each of the observed variables (xt and yt, mode use and mode-specific attitudes in study 4) a latent variable is estimated (ξt and ηt) with the paths linking the observed and latent variables set to 1. Temporal group means are represented by μt and πt. The random intercepts ω and κ capture the individual's stable score over all measurements and represent between-person differences. These random intercepts capture the individual's time invariant deviations from the temporal means. With these temporal means and random intercepts, the latent variables ξt and ηt represent an individual's deviation from his expected score based on the combination of the temporal group mean and the random intercept.

The RI-CLPM approach has been particularly useful in Dutch studies using panel data to study travel behaviour (e.g., Faber et al., 2024; Tao et al., 2023; De Haas et al., 2021; Olde Kalter et al., 2021), as it can integrate different phenomena (e.g., residential determinism, residential self-selection, reverse causality) in a single model.

The chart below summarizes the two types of built environment changes examined in this research, along with their respective research design, causal inference frameworks, and causal identification technique.

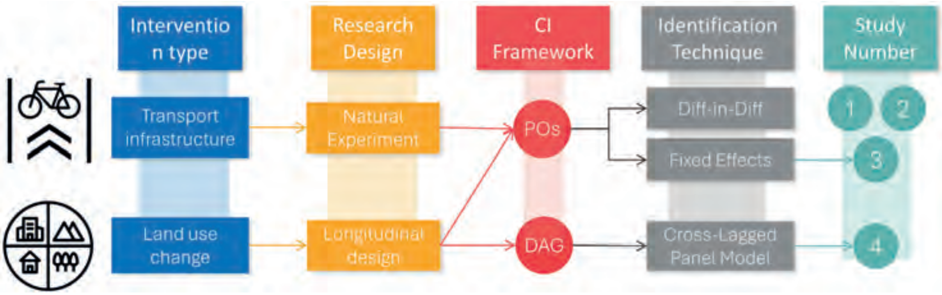

Fig. 1.8. Overview methodological decisions - from intervention type to causal identification technique.

1.6.3. Geospatial data analysis and indicators

Geographic Information Systems (GIS) were essential to the thesis, enabling the processing and analysis of different spatial data layers across all papers. The geospatial work began with the use of geocoding algorithms to locate respondents' residential addresses (Studies 1 to 4) and to locate the origins and destinations of their trips (Studies 1 and 2). In Paper 4, this approach was also essential to track respondents who had relocated, providing a spatial dimension to residential mobility. Building on these geolocated points, a range of built environment (BE) indicators were calculated or directly applied to characterize the areas surrounding home addresses (Studies 1 to 4), trip origins, and destinations (Studies 1 and 2). These indicators were derived from a combination of openly available spatial datasets—such as OpenStreetMap (OSM) and Overture Maps—as well as governmental sources like CBS, Atlas Leefomgeving, and PDOK. The data is composed of both vector and raster formats, and were processed to extract meaningful information about urban form and infrastructure.

In all 4 studies, core ‘D’ measures of the built environment recognized in the literature as influential for promoting walking and cycling were systematically included (Cervero and Kockelman, 1997; Handy et al., 2002; Ewing and Cervero, 2010). Among these, Density stands out as an important “D” indicator (Cervero and Kockelman, 1997) and is employed across all 4 studies. Following the work of Cervero and colleagues, higher population or address density is consistently associated with increased levels of active travel. In this thesis, density is operationalized as either the number of inhabitants or addresses per unit of area, depending on the study. Another important indicator was Destination Accessibility, which captures the ease with which individuals can reach activity locations. In Studies 1 through 4, accessibility is measured in two ways: (i) as the distance from origins to destinations, calculated either as the straight-line (Euclidean) or network distance, and (ii) as the number of destinations (e.g., daily shops, supermarkets) reachable within a defined time or distance threshold. Another ‘D’ measure used was Diversity (or land-use mix), which was implemented in Study 4. This measure pertains to the number of different land uses in a given area and their proportional representation (Ewing and Cervero, 2010). I quantified it as the ratio of residential floor area to total floor area.

In specific cases, more elaborate indicators were developed by combining multiple spatial layers. For example, in Study 3, a K-means clustering algorithm was applied to a set of BE indicators to identify distinct typologies of the built environment. In Studies 1 and 2, to capture individuals’ exposure to transport infrastructure interventions, advanced geoprocessing routines were developed. These routines spatially intersected respondents' locations and travel behaviour with the spatial footprint of interventions.

A combination of tools supported these geospatial analyses. QGIS and ArcGIS were used for visualizing and manually processing spatial layers, while more advanced and automated routines were implemented using PostGIS and R packages such as r5r and sf. Additionally, proprietary APIs like Here and *GoogleAPI* were employed to run predefined algorithms for routing and geocoding tasks.

1.6.4. Research outline and main characteristics

This following table outlines how I went about each of the overarching research questions, their respective studies and characteristics:

Table 1.1. Overview of studies and their respective characteristics.

Intervention	Transport Infrastructure (RQ1)		Access to Land use (RQ2)	
RQ	1-a1, 1-a2, 1-a3, 1-a4	1-b1, 1-b2, 1-b3, 1-b4	2-a1	2-b1, 2-b2
Study #	Study 1	Study 2	Study 3	Study 4
Status	Published at Latin American Transport Studies	Published at Transportation Research Part A: Policy and Practice	Ready for submission	Under review at Transportation
Theme	City-wide cycling network extension and bicycle ridership in São Paulo	Cycle highway effects: Assessing modal choice to cycling in the Netherlands	The impact of restrictive policies on physical activity during COVID-19	The impact of changes in accessibility to daily mobility after residential relocation
Behavioural response	Transport mode choice for multiple travel purposes	Transport mode choice for commuting and multiple travel purposes	Work- and leisure-related walking and cycling minutes/ week (min/ week)	Self-stated cycling and driving frequency for multiple purposes (Ordinal)
BE change	City-wide cycling network	Country-wide cycle highway network	Reduction in the accessibility to facilities and amenities (movement-restrictions)	Residential Relocation
Travel Data	Multiple Cross-Sections / São Paulo's Household Travel Survey (2007; 2017);	Multiple Cross-Sections / The Netherlands Household Travel Survey (2010 to 2021)	The Nijmegen Exercise Study (NES) (2020)	Longitudinal Data / The Netherlands Mobility Panel (MPN) (2013:2016)
Causal Approach	Rudy's Potential Outcomes (POs)	Rudy's Potential Outcomes (POs)	Rudy's Potential Outcomes (POs)	Directed Acyclic Graphs (DAGs)
Causal Identification Technique	Dif-in-Dif / Logit regressions	Dif-in-Dif (Two Way Fixed Effects) / Logit regressions	Fixed Effects Regressions with Interactions	Structural Equation Modelling / (Random-Intercept) Cross-Lagged Panel Modelling

1.7. Relevance

1.7.1. Scientific contributions

Besides providing evidence to support the deterministic role of BE on active travel demand, this research provides additional contributions to causal inference literature, which are related to how intervention exposure is defined in observational research (when treated, when not), the current scope of intervention studies, the influence of physical and socioeconomic contexts when assessing the impact of interventions, and the small body of work investigating changes in mode choice after relocation using a panel study In this section these contributions are then discussed.

a) When treated, when not

In much of the causal inference literature, particularly in natural experiments, exposure to interventions is often poorly defined, with unclear geographic boundaries. As a result, studies typically compare individuals based on residential proximity to an intervention (see Mölenberg et al., 2019), often using simple distance-based measures such as straight-line distances or buffers (e.g., Goodman et al., 2014; Heinen et al., 2015; Rodriguez-Valencia et al., 2019). These static definitions can be attractive due to the relatively low analytical effort required to apply (Humphreys et al., 2016) but assume that exposure is determined solely by how close someone lives to the intervention. In transport policy, however, responses to interventions depend on how much individuals actually interact with them (Brathwaite and Walker, 2018). Proximity alone may not capture this—some people may live near new infrastructure but never use it due to their routines, while others living farther away may use it regularly if it aligns with their travel patterns (Humphreys et al., 2016; Aldred, 2019). More dynamic exposure measures, which consider activity spaces and routine mobility, have been recommended to address this issue (e.g., Humphreys et al., 2016; Hirsch et al., 2017; Aldred et al., 2019). Although more data-intensive, these approaches rely on fewer assumptions and may better reflect actual exposure.

Some work has already been done in this direction (e.g., Humphreys et al., 2016; Hirsch et al., 2017; Aldred et al., 2019; Karpinski, 2021). While these analyses provide valuable contributions, there is still room for improvement (Humphreys et al., 2016), both terms of quantity of studies testing different levels of exposure, but also in quality - exposure could be better expressed in terms of benefits. In this context, this thesis contributes to this challenge in Studies 1 and 2 by testing the impact of multiple exposure definitions using advanced geospatial techniques and sensitivity analyses, ensuring estimated causal effects are robust, and measuring how travel behaviour changes against different exposure levels.

b) Diversifying the scope of intervention studies

Most studies on active travel interventions have been conducted in the USA, Canada, or the UK—countries with low cycling levels, high car dependency, and fragmented infrastructure compared to much of Europe (Buehler and Dill, 2016). This geographic bias has been highlighted in systematic reviews (Mölenberg et al., 2019; Xiao et al., 2022). For instance, over half of the 121 studies reviewed by Xiao et al. were from North America, with limited representation from Europe (30%), Asia (9%), Latin America (1%), and Oceania (8%). Similarly, Mölenberg's review focused almost entirely on urban areas in high-income, English-speaking countries. This concentration limits the generalizability of findings. Countries with strong cycling cultures and infrastructure—like the Netherlands, Belgium, or Denmark—remain underrepresented, as do regions where cycling is growing but still emerging and car-reliance is still very much present, such as Eastern Europe, Latin America, or parts of Asia (Buehler and Dill, 2016; Aldred, 2019). In addition to geographic bias, many studies focus on isolated infrastructure elements (e.g., single bike lanes) rather than broader, network-level interventions. Evaluations of city-scale expansions or ambitious/ high-quality facilities like cycle highways remain limited, despite their potentially greater impact on mode shift (Aldred et al., 2019; Piras et al., 2022; Skov-Petersen et al., 2017).

This thesis addresses these challenges by estimating the causal effects of large-scale cycling infrastructure in two demographically comparable but contextually different urban regions: the Netherlands (~18 million people) and the São Paulo Metropolitan Region in Brazil (~20 million). Despite contrasting cycling cultures—one mature, the other emerging—both implemented expansive networks within a similar period (São Paulo: 2007–2017; Netherlands: 2010–2020). By examining interventions at the network level across these settings, the thesis contributes to understanding how high-quality cycling infrastructure affects travel behaviour and supports active travel uptake.

c) Exploring the role of sociodemographic and physical contexts

An important challenge in causal research, as noted by Aldred (2019) and Panter et al. (2019), is the limited attention to how local socioeconomic and environmental contexts influence the effectiveness of active travel interventions. Aldred highlights the need to examine how subgroup characteristics interact with specific design features—for instance, protected cycling infrastructure is often preferred by women, children, and older adults, but may be less relevant for confident cyclists who prioritize speed and directness (Buehler and Dill, 2016). Panter et al. further argue that the success of interventions depends not only on their design but also on how they interact with physical and social environments. Interventions may trigger different outcomes depending on whether the context enables or constrains their mechanisms of action.

This thesis responds to these concerns in two ways. Studies 1 and 2 analyse how the effects of cycling infrastructure vary across traveller subgroups, considering characteristics such as gender, age, car ownership, education, and occupation—thereby examining heterogeneous treatment effects. Furthermore, Study 3 explores how the impact of COVID-19 mobility restrictions on active travel differs across built environment typologies. By interacting policy exposure with local context, the study assesses whether built environment characteristics amplify or attenuate behavioural responses to the same intervention.

d) Jointly modelling built environment impacts, self-selection and reverse causality using panel data

Despite growing interest in how residential relocation affects travel behaviour, there remains limited longitudinal evidence on the causal relationships between the built environment (BE), travel behaviour, and travel-related attitudes—particularly among movers. Two core challenges in this field are self-selection and reverse causality (e.g., Tao, 2024; Tao et al., 2023; De Vos et al., 2018). Specifically, it is still unclear whether attitudes change after relocation (reverse causality), to what extent travel attitudes are endogenous to the relationship between BE and behaviour (self-selection), and how changes in BE during major life events like moving influence mode use when both self-selection and reverse causality are considered within a unified analytical framework.

Moreover, while relocations can disrupt habits and prompt a reassessment of travel choices—even when moving between neighbourhoods with similar BE characteristics (Haque et al., 2019; Scheiner and Holz-Rau, 2013)—few studies have used true panel data collected before and after the move to explore these dynamics (e.g., Giles-Corti et al., 2013; Wang and Lin, 2019; Tao et al., 2023).

With Study 4, I contribute to addressing these challenges by explicitly (graphically) modelling residential relocation as a disruptive event that may lead to changes in both mode use and mode-related preferences. By incorporating individuals' pre-relocation attitudes, the study tries to capture how changes in the built environment influence travel behaviour directly, and are influenced by self-selection. This approach offers a more comprehensive understanding of the reciprocal relationships between BE, attitudes, and behaviour within the context of relocation. It also adds to a small but growing body of longitudinal research that examines how mobility decisions evolve in response to residential change.

1.7.2. Practical contribution

A key societal contribution of this thesis lies in providing informative empirical insights for policy-makers, urban planners, designers, and public health professionals, which can be used to support built environment interventions able to increase accessibility and connectivity of active mobility users. By doing so, the findings can support more persuasive arguments in infrastructure/ policy design and implementation—especially when engaging with stakeholders who may be less convinced by ex-ante evidence alone. This translational approach aligns with a growing need in both planning and public health fields for ex-post evidence. Ultimately, by promoting walking and cycling as integrated components of daily transportation—rather than as separate—this thesis can enhance physical activity through the very structure of everyday mobility. This makes the debate around causal relationships between the BE and behaviour central to transport research. Indirectly, the adoption of more active travel routines could bring substantial public health and economic benefits, particularly in light of the global costs of physical inactivity, which are estimated to exceed $50 billion annually (Ding et al., 2016).

1.8. Embedding of this thesis

This research contributed to the objectives of three wider research projects - Space2Move, REAL (Radboud Ecosystem for Active Living) and IPAL (Innovation Program Active Living). These interfaculty consortia of researchers consisted of academics and consultants from a diverse range of disciplines working in synergy, including: health care (Radboudumc, Primary care, GGD, VGZ); spatial planning, mobility, housing (School of Management at Radboud University); public governance and policy (Dutch municipalities); and practical expertise on urban development, neighbourhood revitalization by design and citizen engagement (Bureau UUM and others).

Working on these projects offered a valuable opportunity to collaborate with highly interdisciplinary teams. While very enriching, it was somewhat challenging to develop my own PhD-project in light of so many different interests, ways of working and thinking. In this context, periodic meetings together with the core team members ensured good performance at the organisational level of the project and a nice insertion of my research within the projects.

1.9. Thesis outline

Aside from the Introduction (Chapter 1), this thesis is composed of the 4 proposed empirical studies (Chapters 2 to 5); and the Conclusions and Recommendations section (Chapter 6). The organization of the articles follows the order of the research questions described in section 1.4. The first 2 papers have been published, and the remaining two papers have been either submitted to a peer reviewed journal and/ or are ready for submission. In the conclusion chapter, I reflect on the main findings, discuss the policy implications of those findings, and make recommendations for future research.

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Chapter 2

City-wide cycling network extension and bicycle ridership in São Paulo: a causal analysis

Abstract

Over the past 15 years, São Paulo, a megacity in Southeastern Brazil, has tackled its enduring mobility challenges by constructing over 500 km of bike routes and supporting various cycling initiatives, including recreational cycling programs, mobility strategies and bikeshare. Despite the generally positive impacts of these initiatives, the absence of robust causal evidence on their benefits can pose serious challenges for future investments in light of the existing social dynamic favouring the use of automobiles. Driven by the need to reduce motorized transport in Brazilian cities, we investigate the causal effects of bicycle routes on ridership between 2007 and 2017, focusing on travellers highly exposed to bike routes developed between 2008 and 2015. Using Difference-in-Differences models alongside Household Travel Surveys conducted before and after the interventions, we observed a modest but positive increase in cycling mode choice probability, ranging from 0.60% to 1.37%, among the highly exposed treatment groups. Our results also indicate distinct intervention effects across different groups of travellers. This study provides policymakers with valuable insights to support future cycling infrastructure planning and investment, demonstrating their potential net benefits even in car-dependent urban areas. By integrating these results into existing economic appraisal tools, policymakers can further assess additional benefits related to physical activity, health, and emissions reduction.

Keywords: mode choice; difference-in-differences; causal effects; cycling infrastructure.

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2.1. Introduction

Promoting urban cycling has emerged as a key strategy in cities worldwide to address contemporary mobility challenges, given its multifaceted benefits and cost-effectiveness. Research across environmental, economic and health domains has consistently highlighted the advantages of cycling on public health and emissions. Consequently, urban cycling is progressively gaining prominence in public policy agendas as a promising transportation alternative, given its documented benefits. This trend extends to megacities in upper-middle income countries like Brazil or Colombia, where there currently are strong efforts to expand bicycle infrastructures and support cycling.

São Paulo, located in Southeastern Brazil, serves as a compelling case in point. Since the 2010s, the city has invested in creating a more cyclable city, including the implementation of a network of dedicated cycle paths or lanes, the launch and support one of Brazil's largest bikeshare schemes, and the development of the (http://www.cetsp.com.br/media/1100812/Plano-Ciclovia%CC%81rio_2020.pdf)Municipal Bicycle Master Plan (2019-2028)[4]. Most of these achievements have unfolded within a highly confrontational political context, where, in the absence of proper *ex-post* causal evidence, financially burdensome investments in contested urban areas—such as dedicated cycle infrastructure—can be questioned by residents and policymakers.

In recent years the number of research studies investigating which factors can boost cycling levels has dramatically increased (Piras et al., 2022) leading to a consensus that "planners know what to do to promote cycling in the real world" (Nello-Deakin, 2020). Several studies have demonstrated positive correlations between bicycle usage and the implementation of dedicated cycling infrastructure (Heesch et al., 2016; Félix et al., 2020; Kraus & Koch, 2021; Karpinski, 2021). Moreover, authors have emphasized the preference of users for comprehensive and well-connected networks of cycle paths or lanes

4. The official designation "Plano Cicloviário do Município de São Paulo (2019-2028)" can be translated as Municipal Bicycle Master Plan (2019-2028). Strategically, the Plan aims to define the city's cycling network and its supporting elements oriented towards structuring an integrated network. It also aims to promote intermodality and connection with the main public transport facilities, ensure the safety of cycling on the city's road network and promote actions that encourage the use of bicycles. The plan also envisaged that, by 2024, 1,350 km of cycling network would have been implemented, 2,000 bike parking spots would have been built, 60% of the territory would be covered by bike-sharing, and several bridges, tunnels, and other exclusive infrastructures for cyclists and pedestrians would have been constructed. Despite being far from reaching the stated goals, São Paulo has achieved more than 700 km of bicycle lanes and paths by 2024.

in urban areas (Aldred et al., 2019; Piras et al., 2022; Rodriguez-Valencia et al., 2019). However, to date, only a few researchers have assessed how these large-scale cycling policies have effectively increased bicycle usage in Latin American cities comparable in scale to São Paulo. From a policymaker's point of view, addressing these gaps can be highly valuable, given that these insights can help them justify the benefits of prior investments, justify future projects and make active mobility more inclusive.

Motivated by the need to reduce the reliance on motorized transport in low-cycling contexts and increase cycling's share in the modal split of Latin American cities, this paper investigates whether the emerging network of cycle routes in São Paulo influenced cycling levels between 2007 and 2017. We develop Difference-in-Differences (DiD) models to analyse the impact of the new network of routes on mode choice, particularly for people whose trips geographically overlap with the interventions. The analysis considers varying levels of travellers' 'exposure' to the new routes and their effect on the probability to cycle before and after the interventions. We hypothesize that individuals will benefit from new routes if a portion of their Origin-Destination (O-D) pairs geographically intersect the interventions. Considering that cycling policies are strategically implemented by policymakers rather than at random, and recognizing that factors such as demographics, trip characteristics, and the built environment significantly influence modal choices, these variables have been incorporated as controls in our analysis. Our study uses a comprehensive inventory of routes inaugurated between 2008 and 2015 in São Paulo, alongside two years of cross-sectional origin-destination survey data (2007 and 2017). Furthermore, we investigate heterogeneity in the effects of interventions across different demographic characteristics to assess the extent to which different traveller groups value and respond to such interventions.

This paper starts with a literature review of the cycling interventions, highlighting underexplored gaps. This is followed by the explanation of the data, variables and empirical strategy. Then, the main results are presented, and the effects of new cycle routes on mode choice in São Paulo are estimated. Finally, the paper discusses its main strengths and limitations, potential policy implications and conclusions.

2.2. Literature review

Extensive reviews by Buehler and Dill (2016), Mölenberg et al. (2019), and Xiao et al. (2022) have shown positive relationships between the presence of bicycle infrastructure and increased cycling activity, both in terms of infrastructure use (e.g., cyclist counts) and individual behaviour (e.g., modal share). However, assessing cycling behaviour before and after infrastructure installation presents challenges, which are further discussed below.

Buehler and Dill (2016) found that studies relating characteristics specific to a bicycle network with cycling levels are less common than those examining individual links of a network (see e.g., Heesch et al., 2016; Kraus & Koch, 2021; Karpinski, 2021). Both stated and revealed preference studies have consistently highlighted users' preference for comprehensive and interconnected cycling networks. This unbalance has been partly addressed in recent research, which has examined the expansion of bicycle networks at the neighbourhood or city level, as seen in studies by Aldred et al. (2019); Piras et al. (2022); Félix et al. (2020); and Rodriguez-Valencia et al. (2019). In a multi-year assessment of cycling and walking interventions implemented between 2014 and 2020 in Cagliari, Piras et al. (2022) found a general increase in the probability of cycling over time following city-wide actions undertaken by local policymakers. They also found that individuals living in areas with cycling facilities were more likely to use bicycles than the rest of the city’s residents. In Lisbon, which has improved its network of cycle paths and bikeshare in the 2010s, results by Felix and colleagues suggest that implementing “hard” measures (e.g., cycling networks and bike-sharing systems) to promote cycling can significantly increase bicycle modal share in cities with low cycling maturity.

Up to this point, only a small number of cycling studies have investigated the causal effects of city-wide cycling policies in Latin American cities, and even fewer in urban areas of similar scale to São Paulo. Xiao et al. (2022) confirm this, noting that after a global review of stick and carrot interventions aimed at improving active travel and health, there are still limitations to the generalizability of their findings regarding the effect of interventions due to the very limited number of studies from low- and middle-income countries, such as those in South America. Of the 121 papers assessed in their review, only one came from South America in the last five years. The before-and-after study by Rodriguez-Valencia et al. (2019) is the only example mentioned in

Xiao's report. Other reviews, such as the one by Mölenberg et al. (2019), only provide evidence from urban areas in high-income countries. The discussion above underscores the pressing need for more causal studies examining the impact of city-wide cycling policies in Latin America.

As most of the evidence is primarily cross-sectional in nature (Buehler and Dill, 2016; Mölenberg et al., 2019), analysing correlations between bike route provision and cycling behaviour at a single point in time might lack the analytical basis for causal inference. The challenge of providing causal evidence has been addressed by other researchers, which, through quasi-experiments, have assessed the evolution of cycling behaviour before and after the installation of new cycling infrastructures or implementation of cycling policies across treatment and control groups (e.g., Dill et al., 2014; Frank et al., 2021; Karpinski et al., 2021).

Among existing quasi-experiments, it is often unclear who is exposed to interventions or where the boundaries of exposure are located. Given this lack of consensus, many studies have frequently relied on simple distance-based measures (or proximity thresholds), which use straight-line distances or buffers from interventions to the 'treated' individuals (see Goodman et al., 2014; Heinen et al., 2015; Rodriguez-Valencia et al., 2019; Frank et al., 2021). These static exposure definitions can be attractive due to the relatively low analytical effort required (Humphreys et al., 2016). The impact of proximity can, however, be strongly dependent on individual behaviour and habits, as well as key origins and destinations (Aldred, 2019). For example, some individuals might have new cycle routes close to their home address, but outside their daily activity space (e.g., commuting origins and destinations). With additional information about participants' pre-existing self-reported behaviour (e.g., travel diaries, home and work locations), it may be possible to generate 'activity' or 'exposure' spaces that better determine whether exposure to a particular built environment change is likely to occur (Humphreys et al., 2016).

The paper by Hirsch et al. (2017) is one of the few that partly addresses this challenge by applying a 'projection-based' approach, which calculates the proportion of O-D pairs that potentially benefit from new cycling infrastructure investment. In their analysis, trips were only included if the straight-line connection between the origin and destination tract centroids intersected the new infrastructure. While Hirsch's analysis offers an indication of potential use, we suggest that it could be further enhanced by incorporating multiple levels of exposure.

Considering the discussion above, we believe that our paper contributes to the expanding body of research on the causal effects of implementing city-wide bicycle networks on ridership. In specific, this can be achieved by:

i. Developing a quasi-experiment that uses repeated cross-sectional data to estimate the probability of cycling for treatment and control groups before and after the studied interventions;
ii. Testing the robustness of our estimation methodology against varying levels of traveller exposure to treatment.

2.3. Policy background

São Paulo is a megalopolis that experienced significant expansion during the 20th century, driven by a road-based development model and the interests of the automotive industry. Despite numerous investments in alternative forms of transportation since the 1970s, state interventions have failed to promote a shift to a new mobility paradigm (Rolnik and Klintowitz, 2011).

During Mayor Fernando Haddad's tenure (Workers' Party — PT, 2013 to 2016), there was a notable shift in the city's mobility agenda (Leite et al., 2018). The formulation and implementation of public policies for active mobility gained importance, following the discussion and realisation of the Strategic Master Plan (PDE — Law 16.050/2014). The municipal government significantly expanded cycling infrastructure by creating dedicated lanes, increased the number and length of bus corridors, lowered speed limits at main city routes, and established recreational cycle routes on major avenues during weekends and holidays. Notable examples of the latter are the “Leisure Cycle Routes” (in Portuguese, Ciclofaixa de Lazer)[5] and the “Open Streets” (Ruas Abertas)[6] programs. These initiatives were adopted by the municipal administration as

5. The Leisure Cycle Routes initiative is composed by temporary bike routes spanning approximately 100km. When operational, one or more lanes on various streets and avenues are separated by signalling devices, creating a safe environment for cyclists. The scheme is operated by a private company and is active on Sundays and national holidays from 7 AM to 4 PM.
6. Through the Open Streets program, which has been active since 2016, areas are closed to vehicle traffic, with markings installed by the Traffic Engineering Company (CET), and dedicated to pedestrians and cyclists. The goal is to expand public spaces, offering more options for leisure, social interaction, and activities for the population.

operational measures to encourage cycling and walking among the population and to raise awareness about the potential use of active modes for purposes beyond recreation. Since the inception of its first cycling masterplan in 1981, São Paulo introduced approximately 572 km of permanent and 120 recreational bike routes by 2020 (see Fig. 2.1). By 2024, the city has more than 731 km of bike routes, consisting of 699 km of dedicated bike lanes, and 32 km of shared routes[7]. Furthermore, the city developed an additional four cycling masterplans and operationalized its first bikeshare program (CET, 2020), which remains active today with more than 3,700 bicycles.

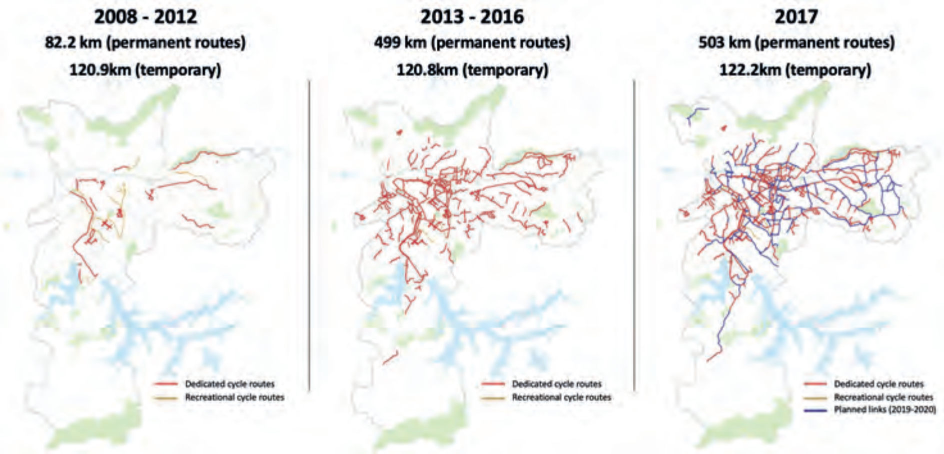

Fig. 2.1. Evolution of cycling routes implemented between 2008 and 2020 in São Paulo.

São Paulo's recent cycling infrastructure and policies have been developed within a highly confrontational political context, facing a historically articulated resistance coalition (involving the media) and a social dynamic that idolizes the use of the automobile as "private, individual and mobile property" (Schor, 1999), the political process of developing and implementing the policy of bicycle lanes was anything but trivial and faced a lot of friction. In such a confrontational environment, robust causal evidence can contribute to diminishing the influence of ideology or cultural biases surrounding the implementation and effectiveness of cycling routes.

7. According to the CET, additionally to the 731 km of cycle routes, the city has 7,309 bicycle parking spaces across in 70 bike parking facilities and 1,221 spaces in 51 locations with bike racks, integrated into the public transportation system.

2.4. Material and methods

2.4.1. Data sources

The Household Travel Survey (HTS) was the primary source of travel data in order to investigate whether people are more or less likely to take the bicycle for trips that benefited from the construction of new cycling routes. To this end, a representative (stratified) sample is drawn in which each respondent is asked to provide detailed information for every trip made on a certain predetermined working day of the year[8]. For each individual trip, information is provided on the trip origin (O) and destination (D) (specified at the traffic zone level), the purpose of the trip and the (main) modes of travel. In addition to the reported travel behaviour, details are collected about various socioeconomic characteristics, such as income, education, place of residence, and others. We use two annual O-D surveys - 2007 and 2017.

The final sample used in the analyses was also affected by some exclusion heuristics. Firstly, we limit our examination to journeys where the self-reported distances between origin and destinations were up to 10 km, which represent 30 to 40 min by bicycle at a moderate pace of 15 to 20 km/h. This choice is influenced by the consideration that urban cycle routes primarily target trips within the urban area, or last-mile travel. Secondly, we exclude respondents with missing values for mode choice, key demographics and trip characteristics. After applying these heuristics and merging the 2 years of HTS, an O-D matrix of 167,651 unique trips was obtained. It should be noted that individuals do not necessarily participate in consecutive survey rounds, and as a result, they could not be tracked over time in a longitudinal fashion.

Data on completed bicycle routes were used to determine whether a given route led to any changes in modal choice between 2007 and 2017. To this end, an inventory of cycle routes maintained by São Paulo's Traffic Engineering Company (CET) was used. This inventory tracked all routes that have already been completed between 2008 and 2015, and contains information about the type of route, inauguration year and length. By 2015 (the last inauguration year of this inventory), a total of 181 links were completed, corresponding to more than 400 km of new routes compared to 2007. It is important to notice that this inventory contains only permanent routes, therefore the "Leisure Cycle

8. According to the HTS manual, the collected travel information relates to the day before the first visit to a respondent's household and should refer to a typical working day (Monday to Friday).

Routes" mentioned earlier were not included in our analyses given their temporary character.

2.4.2. Defining treatment and control groups

Defining control and treatment groups can be challenging for built environment interventions (Aldred, 2019). Even in situations in which cycling interventions can be easily identified, the broader challenge of geographically defining populations exposed to interventions still exists.

In this study, we assume that the effect of new infrastructures depends mainly on the proximity of an intervention to the intended target residents and how they travel, including their origins, destinations and potential exposure to new cycling routes. Considering the outlined challenges and seeking to comprehensively address the mentioned aspects when quantifying travellers' exposure to cycling routes, we employ different geographic approaches to combine our two primary datasets - i) Origin- and destination-zones from São Paulo's HTS; and ii) the municipal inventory of cycle routes maintained by the *CET-SP*. In a first approach, we integrate the catchment area of the bicycle routes with the HTS traffic zones to calculate a buffer zone measure. We then construct mode choice regression models based on this measure. In a second approach, we create projection lines from trip origins and destinations, overlapping them with the new cycle routes to assess the level of exposure of travellers to the latter. Regression models are also developed using the second approach. The subsequent sections provide a more detailed description of both approaches.

Buffer zone approach: Treatment groups are defined as those individuals from a given traffic zone with at least 50% of its total area falling within a 500m straight line distance buffer from the cycling routes. Control groups were defined as the complement, namely travellers of a traffic zone with less than half of its total surface within the buffer (see Fig. 2.2). Some impact evaluation studies have adopted this distance approach as reference for cyclists' willingness to divert their routes in order to use newly built cycling infrastructure (e.g., Rodriguez-Valencia et al., 2019; Hirsch et al., 2017; Larsen and El-Geneidy, 2011; Winters et al., 2010).

For the *buffer zone* approach, treatment and control groups can be defined as follows:

T = 1; for people living in an origin TAZ> 50% within a 500 m buffer from bicycle route;

T = 0; for people living in an origin TAZ< 50% within a 500 m buffer from bicycle route.

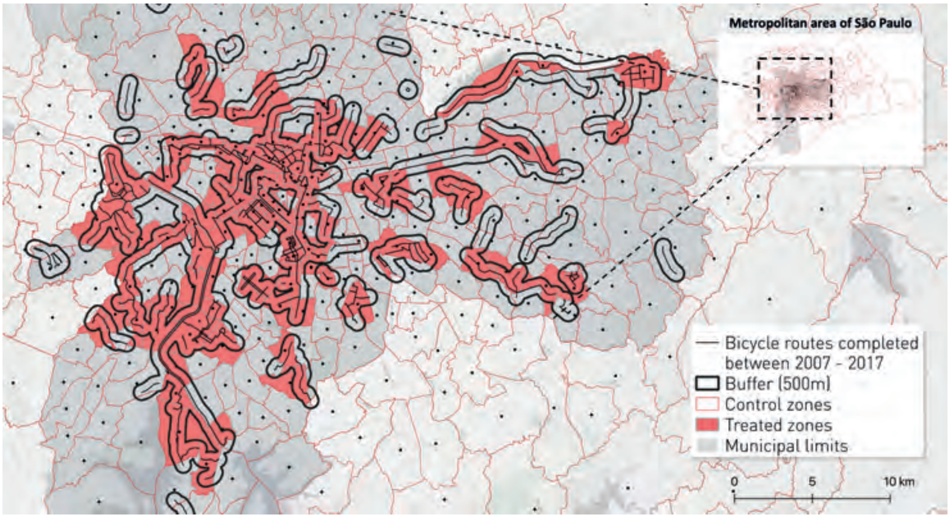

Fig. 2.2. Cycling routes implemented between 2007 and 2017; and OD zones classified as treatment and control groups (*buffer zone* approach).

Projection line approach: In the second approach, we assume that individuals would benefit from these routes if any part of a given O-D projection line intersects the 500m buffer zones (areas of influence) generated from their central axis. Fig. 2.6 (Appendix), illustrates which O-Ds intersect the 500m buffers and which do not. It also highlights the intended spatial mismatch between treatment and control O-D lines for cycling, as well as for motorized trips. Fig. 2.3 shows the exposure levels of each O-D line, considering they intersected the buffer zones and have at least part of their length within the cycle routes' area of influence.

Our hypothesis is that the larger the proportional intersection of O-Ds with cycling routes, the higher the exposure, thus resulting in a stronger effect on modal split. Given the novel character of this approach and, as highlighted by Humphreys et al. (2016), the broader lack of consensus on defining treatment groups for built environment interventions, we performed sensitivity analyses for 9 different exposure definitions, ranging from 10% to 90%, in intervals of

10%. To our knowledge, few studies in the field of transportation (see Hirsch et al., 2017) have so far used a similar 'projection-based' approach combined with a sensitivity analysis to measure exposure level of origin-destination lines to newly built interventions. Both treatment and control groups can be defined as follows:

For the *projection line* approach, treatment and control groups can be defined as follows:

T = 1; for an O-D line with its length > x % within a 500 m buffer from bicycle route;

T = 0; for an O-D line with its length< x % within a 500 m buffer from bicycle route.

Whereas 'x' is the level of exposure of a given O-D line varying from 0 to 100%.

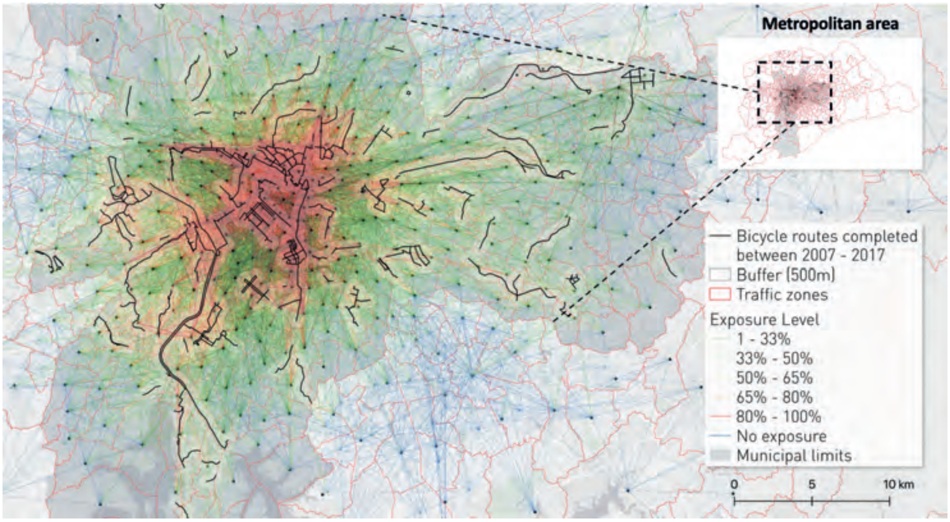

Fig. 2.3. O-D lines coloured according to their exposure level to the implemented cycling routes.

2.4.3. Empirical approach

We employ a Difference-in-Differences (DiD) estimation integrated with a binomial logit regression to assess the effect of the implementation of cycle routes. In its classical "(two groups) x (two time periods)" setting, DiD compares changes in the outcome variable in the treatment group with a control group of similar areas or individuals and allows for unobserved time-varying as well as time-invariant differences between treatment and control groups, thus eliminating potentially strong sources of bias when estimating effects. As one of the most widely applicable research designs to evaluate causal effects of policy interventions (Callaway & Sant'Anna, 2021), DiD has been previously utilized in quasi-experimental studies to examine the impact of new bikeway facilities (Mölenberg et al., 2019; and Xiao et al., 2022). Moreover, DiD has been extensively applied in intervention studies across a variety of transportation problems, such as assessing the impact of new or improved transit infrastructure on home prices (e.g., Beaudoin & Tyndall, 2023; Dubé et al., 2024), analysing how congestion charging has affected traffic and road safety (e.g., Green et al., 2016), or assessing the health effects of low emission zones (e.g., Margaryan et al., 2021).

In this study, the outcome of interest is the commuting bicycle mode choice vs other modes (binary). While DiD is commonly applied with continuous outcomes it can also be used in analyses with a binary outcome (see Karaca-Mandic et al., 2012) in combination with logistic regressions. Dealing with a binary outcome (cycling or not) implies the use of a nonlinear function that describes the probability of choosing the bicycle in terms of the explanatory variables of the model presented. A binary logit model is used to estimate the parameters of the explanatory variables including the DiD coefficient and to study how the explanatory variables affect the probability of choosing the bicycle as a main mode of transportation. We use the following equation to estimate the effect of implemented cycle routes:

$$\ln\left(\frac{\mathrm{Pcycle}_{ijt}}{1-\mathrm{Pcycle}_{ijt}}\right) = \beta_0 + \beta_1 T_{ij} + \beta_2 P_t + \beta_3 (P_t * T_{ij}) + \beta_n X_{ijt} + e_{ijt} \tag{1}$$

where Pcycle_{ijt} is the outcome of interest, which takes a value of one if respondent i had decided to use the bicycle as the main mode of transport to make trip j in year t. This binary variable equals zero for all other modes of transport. The term T_{ij} is a treatment group dummy, which designates O-D pairs exposed to the intervention. To be more precise, this variable identifies trips where the construction of paths and lanes would result in improved connectivity and comfort for cyclists of São Paulo. Time is captured by the term P_t, which takes the value of zero for the period before the interventions (2007), and one for the period after interventions (2017). This variable captures factors that would cause changes in the modal split, even in the absence of a policy change. The term $(P_t * T_{ij})$ takes a value of one for trips between O-D pairs in the years after the construction of a cycle route that resulted in an improvement (exposed), and the value of zero for trips after the intervention that did not benefit from it (not exposed). This variable represents the 'treatment × period' interaction term in the DiD model.

The term X_{ijt} represents a set of characteristics of the person, the journey, and the built environment of the traffic zones. The factors that compose X_{ijt} were selected based on two extensive strains of literature: i) studies that operationalize the effect of the built environment on active travel using well-known dimensions such as population and employment density, land use mix, street design, destination accessibility, distance to transit, and demographics (e.g., Cervero and Kockelman, 1997; Ewing and Cervero, 2010); and ii) related cycling studies that examine the before-and-after impact of cycling infrastructure (e.g., Piras et al., 2022; Yang et al., 2021; Rodriguez-Valencia et al., 2019; Zahabi et al., 2016). More specifically, we consider the influence of respondents' socio-demographics (age, income, background, education, and car ownership), trip distance (measured the self-reported distance between O-Ds), population density (as the concentration of inhabitants per square kilometre), and the proximity of traffic zones to metro and regional train stations alongside intervention impacts.

Although frequently used in the built environment literature, the influence (significance, magnitude, and direction) of these factors can vary greatly across different geographies, resulting in a lack of generalizability (Aldred, 2019). For instance, gender and age can be quite relevant for explaining cycling behaviour in car-reliant countries (e.g., Piras et al., 2022; Rodriguez-Valencia et al., 2019), but are not strong explanatory variables in cycling-rich countries like the Netherlands (Ton et al., 2019). Other examples include population density and land use mix, which can generate conflicting behavioural responses among different target groups (Macedo et al., 2023). For example, dense and diverse neighbourhoods can nurture active school transport (AST) by offering accessible recreational facilities, and bringing activities closer together (Saelens and Handy, 2008). However, they can also discourage cycling and walking among youngsters (Broberg and Sarjala, 2015; Mitra et al., 2010) when routes consist of large traffic attractors and busy intersections. By including these factors in the analyses, we address part of the generalizability issue by bringing context to the estimated effects, making them comparable to other urban or demographic contexts.

While we may observe significant average effects of São Paulo's cycling policy on transportation choices, it is reasonable to assume that socio-demographics might trigger distinct intervention effects. For instance, a bike route could be more appealing between O-D pairs with high commuter rates. Such groups might value cycling infrastructure more than O-D pairs where utilitarian travel—like running errands or school commutes—is dominant. Consequently, the impact of the same bike route can vary across different demographic groups. To study these variations, we also estimate treatment effects at fixed values of key demographic covariates and across 'traveller groups' (or clusters), which are an intuitive, policy-relevant blend of travellers' sociodemographics. The R package '*ggeffects*' was used to compute the predicted values for our dependent variable - Pcycle_{ijt} across different values of age, gender, car ownership, trip purpose and the composite traveler group we proposed.

Multicollinearity between independent variables used in the presented models was also tested (see Table 2.6 in the Appendix), assuming a conditional Variance Inflation Factors (VIF) from regression outputs to be <10 (but preferably <5) (Tabachnick et al., 2001). The statistical analyses were performed using R ('*mlogit*', '*mfx*'). After constructing the models, the estimated coefficients were interpreted and compared with results of related studies.

2.4.4. Defining clusters of travellers

The covariates gender, age, car ownership, level of education, and type of occupation were used as inputs for a Latent Class Cluster Analysis (LCCA) to identify distinct groups of travellers with similar socio-demographic profiles. Individuals were assigned to clusters based on a latent nominal variable that explains their responses across a set of observed indicators (Molin et al., 2016). The aim of LCCA is to maximize homogeneity within clusters and heterogeneity between them (Sasidharan et al., 2015). A key feature of this method is that it is person-oriented (Weller et al., 2020): rather than analysing associations between variables, it identifies patterns across individuals, enabling a more behaviourally meaningful classification. This approach can be particularly valuable in transportation research, as it allows for a more comprehensive and interpretable representation of variation in travel behaviour, beyond looking at single attributes like age or occupation. It thus offers better insight into how policy outcomes may vary across different traveller segments. Furthermore, LCCA make it well-suited for our study given that: (1) it operates on categorical indicator variables, aligning well with data from household travel surveys such as São Paulo's HTS; and (2) it infers class structure directly from the data, without requiring strong prior assumptions (Weller et al., 2020).

In our analysis, the number of latent classes was determined by comparing models with 1 to 5 classes and selecting the specification that provided the best balance between model fit and interpretability. Fit was assessed using the AIC and BIC indicators (results not shown). Based on these criteria, we identified and interpreted five distinct and intuitive traveller clusters (see Table 2.7 in the Appendix): i) Highly educated and motorized workers; ii) Low-education workers; iii) Retired and elderly (60+); iv) Incomeless housewives; v) Incomeless students. The LCCA model was estimated using the '*poLCA*' R package.

2.5. Results

We begin this section by presenting descriptive statistics for participants in the treatment and control groups across different years. Next, we visualize the results of the logistic regression models, focusing on the impact of new cycle routes on modal choice under the various exposure calculation methods. Finally, we illustrate the treatment effects across key socio-demographic variables and across different traveller groups.

2.5.1. Descriptive statistics

Tables 2.1, 2.8 (Appendix) and 2.2 present descriptive statistics regarding mode choice, demographics, trip characteristics, and built environment features around trip origins. Table 2.1 details statistics for trips utilizing the *buffer zone* approach, whereas Table 2.8 provides descriptives for incremental exposure levels (10%, 50%, 90%) using the *projection line* approach. Table 2.2 provides an overview of mode choice distribution before and after the studied interventions. All variables were grouped by year and treatment group. In 2007, a total of 90,445 trips were analysed, compared to 77,206 trips in 2017, making the overall sample size 167,651 trips.

Although both HTS samples are not entirely comparable due to methodological and sample differences between the two databases, the presented statistics provide an overview of São Paulo's cyclists' characteristics before and after the introduction of the analysed cycling routes. As seen in Tables 2.1 and 2.8, the composition of both treatment and control samples develop similarly between HTS cross-sections despite the different proportions between those two groups regarding some of the explanatory variables (e.g., car ownership, education levels, trip purpose, population density). Relative to the control group, participants in the treatment group are more inclined to be car owners, have higher levels of education, engage in more work-related travel, and reside in denser areas of São Paulo.

We recognize that variables such as education level, income, and proximity to public transit develop differently across treatment and control groups. However, considering our study's extensive geographic scope, which spans across multiple parts of a megalopolis such as São Paulo, along with the large size of the population studied, the decade-long period of analysis, and the strategic rather than random placement of interventions to influence travel behaviour, we find it reasonable to expect some degree of compositional change, thus, to assume the Parallel Trends assumption, and continue with the analysis.

Regarding the dependent variable (bicycle choice), Table 2.2 shows that while there is no significant shift in bicycle proportions among the control group (1.2%), the probability of cycling for the treatment groups nearly doubled between 2007 and 2017 (from 0.7% to 1.3%), which can be interpreted as an initial indication of significant behavioural changes between the different groups.

Table 2.1 . Descriptive statistics of control and treatment groups by year (*buffer zone* approach).

	HTS 2007		HTS 2017		Difference (2017-2007)	
	Control	**Treatment**	**Control**	**Treatment**	**Control**	**Treatment**
Socioeconomics	%		%		%	%
Age group						
under 18	20.06	12.42	19.76	11.22	-0.29	-1.21
18-24 years	13.35	13.87	10.84	10.75	-2.51	-3.12
25-44 years	35.44	35.74	33.14	35.74	-2.30	0.00
45-64 years	24.65	27.62	27.14	29.49	2.49	1.87
65 or older	6.50	10.35	9.11	12.81	2.61	2.46
Gender						
Male	50.13	48.38	50.93	48.87	0.80	0.49
Female	49.87	51.62	49.07	51.13	-0.80	-0.49
Car ownership						
No	32.92	25.12	31.91	26.26	-1.01	1.14
Yes	67.08	74.88	68.09	73.74	1.01	-1.14
Income Status						
Income	45.11	44.79	35.90	33.62	-9.21	-11.18
No income	27.87	20.71	28.06	18.08	0.20	-2.62
No Answer	27.02	34.50	36.04	48.30	9.01	13.80
Education Level						
Incomplete Primary education	13.06	6.99	14.17	7.04	1.11	0.05
Primary education	16.51	9.70	12.08	5.97	-4.43	-3.73
Incomplete High School	16.30	10.91	13.83	7.41	-2.47	-3.50
Incomplete Bachelor	31.83	31.18	35.68	28.44	3.85	-2.74
Undergraduate degree	22.30	41.22	24.24	51.14	1.94	9.92
Trip characteristics	%		%		%	%

Table 2.1 . (continued)

	HTS 2007		HTS 2017		Difference (2017-2007)	
	Control	Treatment	Control	Treatment	Control	Treatment
Socioeconomics	%		%		%	%
Trip Distance						
1.0-2.5km	38.17	35.36	38.76	35.06	0.59	-0.29
2.5-5.0km	30.08	32.93	30.56	32.28	0.49	-0.65
5-10km	31.75	31.72	30.68	32.66	-1.08	0.94
Trip Purpose						
Work	24.45	36.49	24.87	35.46	0.43	-1.02
Education	14.18	6.73	13.85	8.52	-0.33	1.79
Leisure	3.81	3.53	3.30	2.88	-0.51	-0.66
Home	43.89	46.86	46.01	47.28	2.12	0.42
Other	13.67	6.39	11.97	5.86	-1.70	-0.53
Built Environment	%		%		%	%
Density						
0 -1000 inhab./ km2	6.58	0.42	9.10	0.44	2.52	0.02
1.000-5.000 inhab./ km2	21.31	17.08	20.89	16.14	-0.42	-0.93
5.000-7.500 inhab./km2	41.75	32.58	40.86	33.87	-0.89	1.28
7.500-10.000 inhab./km2	11.97	13.56	11.38	13.11	-0.60	-0.45
10.000-20.000 inhab./km2	16.13	16.56	14.97	16.81	-1.17	0.25
>20.000 inhab./km2	2.26	19.80	2.81	19.63	0.55	-0.17
PT proximity	%		%		%	%
Regional Train (1km buffer)						
No	52.57	56.54	55.19	55.29	2.62	-1.25
Yes	47.43	43.46	44.81	44.71	-2.62	1.25

Table 2.1 . (continued)

	HTS 2007		HTS 2017		Difference (2017-2007)	
	Control	**Treatment**	**Control**	**Treatment**	**Control**	**Treatment**
Socioeconomics	%		%		%	%
Regional Train (2km buffer)						
No	35.58	36.11	38.54	35.91	2.96	-0.20
Yes	64.42	63.89	61.46	64.09	-2.96	0.20
Metro (500m buffer)						
No	64.56	18.30	73.09	19.07	8.53	0.77
Yes	35.44	81.70	26.91	80.93	-8.53	-0.77
Metro (1km buffer)						
No	75.15	27.59	79.84	28.41	4.69	0.82
Yes	24.85	72.41	20.16	71.59	-4.69	-0.82
Observations	**51,263**	**39,182**	**48,005**	**29,201**	**-**	**-**

Table 2.2 . Mode choice distribution of control and treatment groups by year (*buffer-zone approach*).

	2007			2017		
	Control	**Treatment**	**Observations**	**Control**	**Treatment**	**Observations**
Mode of Transport	%		#	%		#
Auto	43.3%	51.4%	42.,71	43.5%	47.0%	34,610
Public Transport	31.1%	32.6%	28,693	35.1%	38.7%	28,132
Other	7.3%	3.5%	5,108	6.9%	2.7%	4,101
Bicycle	1.2%	0.7%	877	1.2%	1.3%	939
Walk	15.2%	10.4%	11,868	10.7%	8.1%	7,502
Motorcycle	1.9%	1.4%	1,528	2.7%	2.1%	1,922
Observations	**51,263**	**39,182**	**90,445**	**48,005**	**29,201**	**77,206**

2.5.2. Main results

In tables 2.3 and 2.4, we provide our findings regarding the effects of São Paulo's cycling infrastructure considering the *buffer zone* approach using Eq. (1). Table 2.5 presents results of our *projection line* approach by increasing the exposure in increments of 10% with levels ranging from 10% to 90%. As described in the previous chapter, the regressions exclude trips longer than 10km. At each of those tables, we introduced 3 model categories (A, B and C). Model A reports the estimates of a standard DiD model, which controls for time (after) and travel distance effects. In Model B, we add respondent characteristics and travel motives. In Model C, we include controls for population density and proximity of traffic zone centroids to public transit hubs (train and metro stations). To enhance the interpretation of the results, we also provide marginal effects estimations. In the context of our DiD models, these effects represent the additional probability of cycling in the treated areas compared to their counterfactuals (assuming they had not been exposed to any treatment). We follow the procedure outlined by Karaca-Mandic et al. (2012) to calculate the marginal effects.

Across all treatment definitions, we find mild but positive intervention effects. The probability of using a bicycle is higher after the implementation of cycling infrastructures between 2007 and 2017, when comparing treatment groups to control groups.

The results of models A, B and C in Table 2.3 (*buffer approach*) suggest a positive correlation between treatment and cycling probability after the construction of new routes (0.75), as depicted by the *Treatment * After* coefficients. In models B and C, the treatment effects exhibit slight variations but remain statistically significant (0.70 and 0.73, respectively). The corresponding marginal effects in Table 2.4 suggest that the completion of new routes increases the probability of cycling by 0.38% to 0.94% across all the three models if treated and compared to their counterfactual (if the same O-D pair would not have been exposed to new routes). Furthermore, the *Treatment Group* effects in model A, B and C indicate that, prior the intervention, groups defined as treatment had slightly (but significantly) lower cycling levels compared to control groups (-0.55% to -0.11%). The *After Treatment* coefficients being statistically insignificant, very small and close to zero across all models (-0.051% to -0.008%) suggest that there is little to no change in cycling mode choice in the post-treatment period within the control group.

As depicted in Table 2.5, our estimations reveal that O-D pairs with a minimum exposure level of 10% to a new cycle route exhibit a cycling probability increase ranging from 0.41% to 1.05% following the intervention. Further incrementing exposure levels suggests a mild increase in cycling uptake, reaching its peak at a 60% to 80% exposure level, where the cycling probability sees an increase between 0.60% to 1.37% post-intervention. However, at the 90% exposure level, the marginal effects show a slight decline in strength and significance, which we attribute to reductions in the size of treated samples (see Fig. 2.7 in the Appendix). The pattern of incremental exposure leading to a rise in treatment effects indicates that enhancing traveller exposure to bike networks can promote behavioural changes, albeit at modest rates.

The *Treatment Group* and *After Treatment* coefficients of the *projection line* approach developed similarly to the *buffer zone* approach coefficients. As depicted in Table 2.9 (Appendix), the *Treatment Group* coefficients in model A, B and C indicate that the treatment group was less likely to cycle compared to the control group prior treatment; and that there is little to no change in the probability to cycle in the post-treatment within the control group.

While the positive effects align with previous findings from studies that used DiD to examine the impact of city-wide cycling interventions on the proportion of cycling trips (Rodriguez-Valencia et al., 2019; Hirsch et al., 2017), there are variations in their magnitude. Furthermore, the marginal effects of our study can be considered qualitatively modest when compared to the very few similar studies. For example, in Bogotá, a Latin American city of comparable scale to São Paulo, Rodriguez-Valencia (2019) estimated an average probability increase of 7% between 1995 and 2011. In Minneapolis, Hirsch et al. (2017) reported an increase ranging from 1% to 3% in the proportion of commuters cycling to work when exposed to new off-road bicycle trails between 2000 and 2010.

After comparing the results of the two exposure calculation approaches (*buffer zone* and *projection line*) presented in Tables 2.4 and 2.5, we observed small differences in treatment effects across all 10 treatment definitions. While we observed a modest degree of sensitivity of mode choice to varying levels of exposure, with larger marginal effects observed at mid to high exposure levels (e.g., 60 to 80%), the marginal effects of the *projection line* approach differed only by 0.2% (Model C) and 0.43% (Model A) compared to the *buffer zone* approach. This stability in effects provides evidence for the robustness of our results across different exposure definitions and supports the causal influence of bike network implementation on mode choice in São Paulo. The low sensitivity of mode shift to highly distinct exposure levels, as visualized in Figure 2.4, suggests that additional cycling can be encouraged even with small overlap between new bike routes and pre-existing travel behaviours.

Table 2.3. Logistic regression model results (*buffer zone* approach).

	Model A **Estimate** **(Std. Error)**	**Model B** **Estimate** **(Std. Error)**	**Model C** **Estimate** **(Std. Error)**
Treatment Effects			
Treatment Group	-0.59***	-0.48***	-0.28***
	(0.07)	(0.08)	(0.08)
After treatment (2017)	-0.05	0.005	-0.02
	(0.06)	(0.06)	(0.06)
*Treatment * After (2017)*	0.75***	0.70***	0.73***
	(0.10)	(0.10)	(0.10)
Socioeconomics			
Sex (Ref. Category: male)			
Female	-	-2.11***	-2.10***
		(0.08)	(0.08)
Age Group (Ref. Category: Under 18)			
18-24 years	-	-0.23*	-0.27**
		(0.12)	(0.12)
25-44 years	-	0.17**	0.19**
		(0.08)	(0.08)
45-64 years	-	-0.33***	-0.31***
		(0.09)	(0.09)
65 or older	-	-2.08***	-2.02***
		(0.21)	(0.21)

Table 2.3. (continued)

	Model A Estimate (Std. Error)	Model B Estimate (Std. Error)	Model C Estimate (Std. Error)
Income level (Ref. Category: Income)			
No income	-	-0.80***	-0.77***
		(0.11)	(0.11)
Not available	-	-0.09*	-0.09
		(0.05)	(0.05)
Car ownership (Ref. category: Yes)			
	-	-1.10***	-1.09***
		(0.05)	(0.05)
Trip Characteristics			
Trip Distance (km)	-0.17***	-0.22***	-0.22***
	(0.01)	(0.01)	(0.01)
Trip Purpose (Ref. category: Education)			
Home	-	0.50***	0.52***
		(0.10)	(0.10)
Leisure	-	0.61***	0.64***
		(0.16)	(0.16)
Work	-	0.61***	0.63***
		(0.10)	(0.10)
Other	-	0.04	0.07
		(0.13)	(0.14)

Table 2.3. (continued)

	Model A Estimate (Std. Error)	**Model B Estimate (Std. Error)**	**Model C Estimate (Std. Error)**
Built Environment			
Density (Ref. category: 0 -1000 inhab./ km2)			
1.000-5.000 inhab./ km2	-	-	-0.47***
			(0.09)
5.000-7.500 inhab./km2	-	-	-0.67***
			(0.11)
7.500-10.000 inhab./km2	-	-	-1.02***
			(0.11)
10.000-20.000 inhab./km2	-	-	-0.98***
			(0.09)
>20.000 inhab./km2	-	-	-1.06***
			(0.13)
Public Transit Integration			
Regional Train (2km buffer)	-	-	0.13**
			(0.05)
Metro (1km buffer)	-	-	-0.18***
			(0.06)
Constant	-3.80***	-2.58***	-2.98***
	(0.05)	(0.12)	(0.16)
Observations	**167,651**	**164,469**	**164,469**
Log Likelihood	**-9,848.22**	**-8,499.43**	**-8,402.93**
Akaike Inf. Crit.	**19,706.44**	**17,032.86**	**16,853.87**
McFadden's R2	**0.017**	**0.144**	**0.154**

Notes: Significant at .10%, *5%, **0,1%, ***0.

Table 2.4. Marginal effects (*buffer zone approach*).

Variable	**Average Marginal Effects (%)**		
	(Std. Error)		
	Model A	**Model B**	**Model C**
Treatment Effects			
Treatment Group	-0.548%***	-0.196%***	-0.108%***
	(0.001)	(0.000)	(0.000)
After treatment (2017)	-0.051%	0.002%	-0.008%
	(0.001)	(0.000)	(0.000)
*Treatment * After (2017)*	0.944%***	0.377%***	0.380%***
	(0.002)	(0.001)	(0.001)
Travel Distance Effects	Y	Y	Y
Socioeconomic Effects	N	Y	Y
Travel Motive Effects	N	Y	Y
Density Effects	N	N	Y
Public Transit Proximity Effects	N	N	Y

Notes: Significant at .10%, *5%, **0,1%, ***0.

Table 2.5. Marginal Effects of different exposure approaches (*projection line* approach).

	Average marginal effects (%)					
	Model A		Model B		Model C	
Exposure Level	**AME**	**Std. Error**	**AME**	**Std. Error**	**AME**	**Std. Error**
> 10%	1.05%***	0.001	0.41%***	0.001	0.41%***	0.001
> 20%	1.10%***	0.001	0.43%***	0.001	0.43%***	0.001
> 30%	1.13%***	0.002	0.44%***	0.001	0.44%***	0.001
> 40%	1.19%***	0.002	0.48%***	0.001	0.47%***	0.001
> 50%	1.16%***	0.002	0.46%***	0.001	0.45%***	0.001
> 60%	1.29%***	0.002	0.51%***	0.001	0.51%***	0.001
> 70%	1.37%***	0.002	0.59%***	0.001	0.59%***	0.001
> 80%	1.28%***	0.003	0.56%***	0.001	0.56%***	0.001
> 90%	0.98%***	0.003	0.41%***	0.001	0.41%***	0.001
Travel Distance Effects	Y		Y		Y	
Socioeconomic Effects	N		Y		Y	
Travel Motive Effects	N		Y		Y	
Density Effects	N		N		Y	
Public Transit Proximity Effects	N		N		Y	

Notes: Significant at .10%, *5%, **0,1%, ***0.

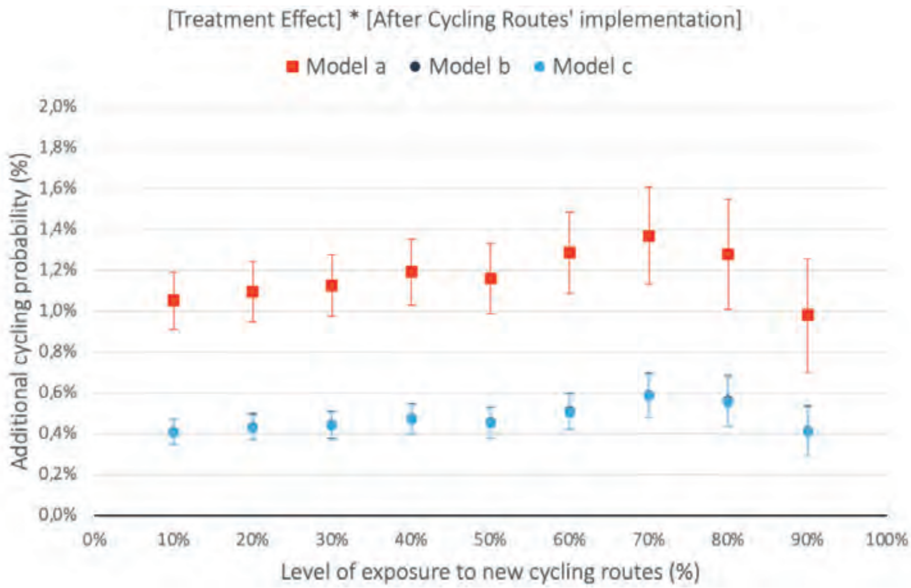

Fig. 2.4. Estimated intervention effects of different exposure levels and controlled covariates (*projection line* approach).

2.5.3. The effect of covariates

The calibrated models B and C in Table 2.3 and Table 2.9 (see Appendix) indicate how different covariates correlate with the decision to cycle. Overall, the effect size and direction of the covariates have remained consistent and similar across models.

The variables car ownership and gender had strong correlations with the individuals' choice to travel by bicycle. People who have access to at least one car are less prone to use a bicycle in comparison with the people who do not. As expected, and also found in previous cycling studies done in car-reliant urban areas (e.g.. Dill et al., 2014; Zahabi et al., 2016; Song et al., 2017; Rodriguez-Valencia., 2019; Frank et al., 2021), all our models indicate that gender is very relevant in explaining bicycle mode choice, with female travellers being less likely to cycle than males on average. This gap between man and women cyclists stems from, among other factors, (personal) safety concerns, inadequate infrastructure, or household responsibilities (Aldred et al., 2016). On the latter, Aldred and colleagues also mention escort trips and/ or multi-purpose as journeys that women are particularly likely to make, which are all less suited for bicycle travel than trips by ‘typical commuters’ travelling alone and unencumbered from A to B. Despite this general trend regarding the influence of gender, Heinen et al. (2010) highlights that these insights on gender cannot be generalized, since they are area-specific. In countries with low cycling rates, men tend to cycle more; while in countries with high cycling rates, such as the Netherlands and Belgium, cycling is also very popular among women (Garrard et al., 2008).

Other individual factors, such as age and income demonstrated significant correlations with cycling. Our results indicate that individuals older than 44 or younger than 18 exhibited lower odds of cycling compared to adults at working age (18 to 44 years old). Not only in this study, but in several others, cycling levels fall with older age (e.g., Aldred et al., 2016; Zahabi et al., 2016; Felix et al., 2020; Piras et al., 2022), particularly in low-cycling regions. In London, for instance, cycling levels peak between 30 and 39 years of age, with a decline at 55+ years (Aldred et al., 2016). In Denmark and the Netherlands, two cycling-rich countries, bike share also declines with age, however at a much slower pace than in other places (Pucher & Buehler, 2008).

Regression results suggest that trip characteristics are important covariates to consider for bicycle mode choice. Consistent with previous literature (Heinen et al., 2015; Ton et al., 2019), the probability of choosing the bicycle varies significantly depending on the distance and the purpose of the trip. For instance, trips for work and leisure are more likely to be associated with cycling than trips for education or purposes within the category 'other' (e.g., shopping, errands, health). One possible explanation for the lower probability of education trips compared to others relate to key mode choice factors that influence levels of active school travel. These factors include parental concerns about stranger danger, road safety, and traffic speeds (Pont et al., 2009; Carver et al., 2014). Another possible explanation for the different correlations of trip purposes with cycling is the imbalance in proximity and exposure of O-D pairs to the implemented cycle routes. In Table 2.10 (Appendix), we show that education trips, for instance, have the lowest exposure levels, with only 36% of the analysed trips exposed to new cycle routes, compared to other purposes such as work (39%) or leisure (49%) travel. The higher exposure for work and leisure trips may partly explain the highest regression coefficient observed among trip purposes. Other purposes, such as errands and shopping trips often involve multiple stops (trip chaining), making them less convenient to be done by bicycle.

The final set of correlations is composed by built environment characteristics surrounding the centroid of trip origin zones. These factors encompassed population density (inhabitants per km2) and the proximity to public transit hubs. Specifically, we considered a 1-km buffer around metro stations and a 2-km buffer around regional train stations. Interestingly, contrary to findings in comparable cycling studies, higher population densities around trip origins were linked to lower probabilities of cycling. The proximity of trip origins to regional train stations exhibited consistently positive and significant associations with cycling likelihood across most models. This suggests a correlation with bike-and-ride trips. On the other hand, the negative association between cycling and the 1-km proximity to metro stations implies competition with cycling from public transit options in those areas. The latter pattern is compatible to findings from previous studies examining bicycle mode choice (Zhao, 2014; Cole-Hunter et al., 2015).

2.5.4. Subgroup effects

Fig. 2.5 shows the predicted probabilities[9] of cycling before (2007) and after (2017) the implementation of the cycling network, for treatment and control groups across different socio-demographics. Solid lines represent the treatment group; dashed lines represent the control group. Arrows indicate the direction and magnitude of change. Each panel shows interactions between treatment, time, and a specific subgroup: sex, age group, income group, car ownership, trip purpose, and traveller cluster (from the LCCA).

In line with previous findings in this paper, all panels show that the treatment group experienced consistently larger increases in the probability of cycling after the intervention, while the control group remained relatively stable. However, the results also point to heterogeneous treatment effects that reflect underlying socio-demographic disparities among travellers. The intervention had the strongest impact on men, young adults (18–44 years), and individuals with income or without access to a car. Among the proposed traveller clusters, “incomeless housewives,” “incomeless students,” and the “retired” displayed only modest gains, especially when compared to various categories of workers. While the infrastructure appears to have had a generally positive effect on modal choice, these unequal impacts suggest missed opportunities to reduce pre-existing gaps in cycling uptake across São Paulo. Women, for instance—already underrepresented in cycling in low-cycling contexts—responded only marginally to the improvements, potentially

9. These predicted probabilities are derived from the calibrated logistic regression models using the ‘*ggeffects*’ R package.

widening the gender gap even further. The limited uptake among socially disadvantaged groups, such as the elderly and incomeless housewives, raises concerns about how effectively the infrastructure was designed to promote equitable access to cycling infrastructure. These patterns underscore the need to critically assess whether the planning and design of the new routes were sufficiently inclusive to make cycling a viable and attractive option for all segments of the population.

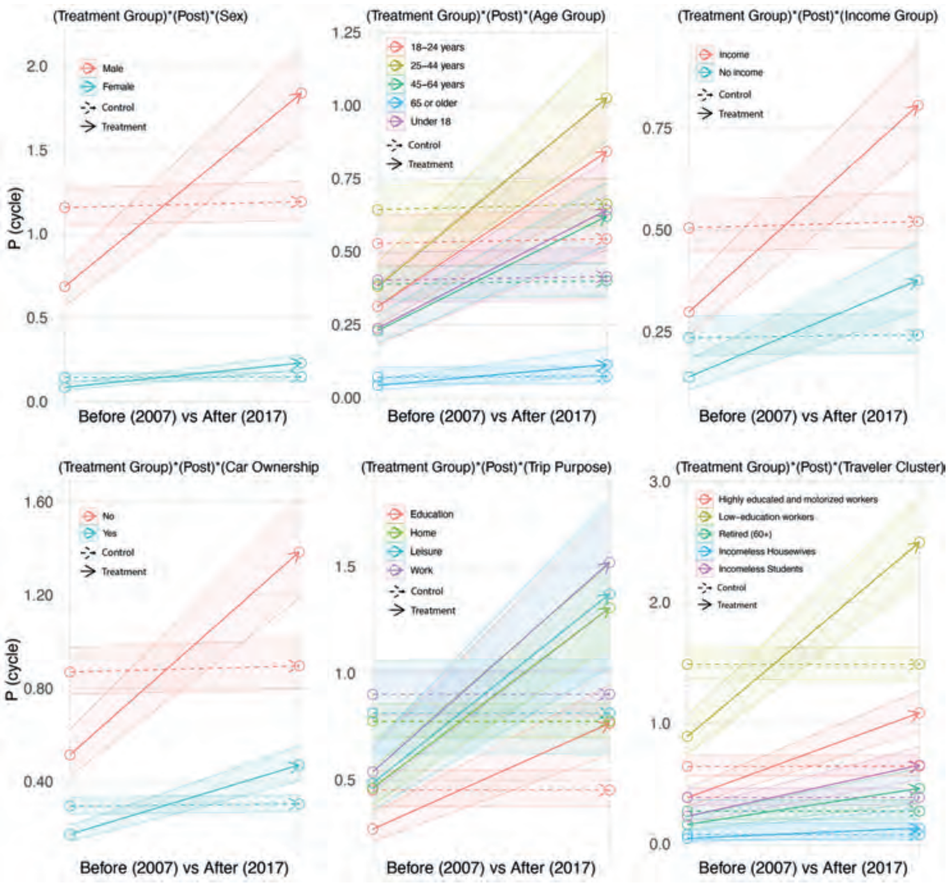

Fig. 2.5. Subgroup effects of cycling infrastructure implementation on the probability of cycling (P(cycle)).

2.6. Strengths, limitations and future research

This study is one of the relatively few quasi-experiments that examine changes in bicycle mode share over time after the construction of city-wide cycling networks in large scale Latin-American cities, achieved through the development of different exposure calculation methods. This paper adds to the existing body of evidence on the mode choice impacts of building such extensive networks, and supports future decision making about routes of similar characteristics. The empirical approach was applied under a sufficiently wide time window (from 2007 to 2017), which can be a reasonable period to take into account the lagged impact of infrastructure provision on modal shift (Song et al., 2017), given the latest route in the database was inaugurated in 2015, and the O-D survey was completed 2 years later. Increasing the coverage of the bicycle network can bring modest benefits in terms of total bicycle ridership.

Beyond the positive results, important limitations and potential improvements are recognized. Firstly, despite the successful implementation of the DiD method, the Parallel Trends assumption for periods before 2007 could not be robustly verified. Analysing the evolution of covariates before 2007 could help better verify if the treated unit's counterfactual trend (e.g., trend without intervention) and control unit's actual trend are parallel. We also recognize that the composition of specific variables—namely education level, income, and proximity to public transit—evolved differently across treatment and control groups till 2017. Although we found no evidence that these compositional changes would significantly impact our results, we recommend that future studies conduct more rigorous tests to either confirm or ensure that relaxing this assumption does not introduce bias into the regression outcomes.

While this is one of the few studies (e.g., Hirsch et al., 2017), to our knowledge, to calculate treatment exposure using O-D lines, the accuracy of our exposure measurements could be improved in at least two ways. Firstly, by refining the representation of O-D pairs used to delineate treated trips by incorporating the accurate locations of trip origins and destinations, thereby achieving more precise exposure measurements. Secondly, by improving exposure level calculations by simulating more realistic itineraries through the utilisation of shortest- or fastest-routing algorithms (see Karpinski, 2021).

Regarding the universe of trips analysed, we only captured journeys made by individuals on the last working day before the O-D survey. Trips taken on weekends and holidays were not included in our sample. By excluding these trips, which likely have a high participation in recreational cycling (encouraged by the Leisure Cycle Routes and Open Streets programs), we may have missed a significant portion of cyclists.

Future work could also consider heterogeneity in the effects of different cycling facility design features (e.g., width, directness, signalling, lighting, attractiveness), the moderating role of built environment characteristics (e.g., land-use mix, access to destinations), and how different target groups (e.g., women with children, elderly, children commuting to school) respond to new cycle routes. These considerations can be especially useful for cycling infrastructure planning and design decision-making, as previous studies suggest that a hierarchy of cyclist and non-cyclist preferences exists, with risk-averse riders, for instance, prioritizing separate paths and/or lanes over cycling in roadways with motorized traffic (Buehler and Dill, 2016).

Finally, while our estimate of the average effect of cycle routes is based on two cross-sectional data waves about trips that were made at least 2 years after the completion of the infrastructural improvements, effects on mode choice change across time was not assessed. An exploration of the dynamics over a longer time period would also provide more explicit insights into non-compositional change and parallel trend assumptions.

2.7. Policy implications

Our study suggests that improving the coverage with the provision of more than 400km of cycling routes between 2007 and 2017 represented mild (but statistically positive) benefits in terms of behavioural change, with roughly 1.0% of the exposed travellers to these infrastructures shifting to cycling. Considering São Paulo's population of 12.33 million, where up to 70% of the trips reported in the HTS are shorter than 10km, and the average resident makes 2.3 daily journeys[10], a city-wide cycling policy could result in nearly 200,000 additional cycling trips daily, assuming the entire population had some exposure to bike routes. Moreover, these estimated effects are likely to be sustained if network maintenance levels are consistent or improved.

Policymakers can use our results to support future cycling investments by building the case for new cycle routes as facilities that, when targeted at pre-existing travel behaviour (e.g., key origin-destination pairs, specific target demographics or trip purposes), could produce net benefits even in car-reliant areas. For instance, if increasing daily levels of active school travel is an important goal for municipal policymakers, future cycling plans could investigate how to maximize the exposure of major education origin-destination pairs to new bike routes. Furthermore, the mentioned benefits can also be used to feed existing economic appraisal tools, for example, the Health Economic Assessment Tool (HEAT)[11] and the Integrated Transport and Health Impact Model (ITHIM)[12] to monetize the health (all-cause mortality and morbidity) costs and benefits from additional exposures to physical activity, air pollution, traffic collisions, and the reduction of carbon transport emissions.

2.8. Conclusion

This study is one of the few (natural-)experiments able to examine changes in bicycle mode choice over time as a result of the construction of large-scale cycling networks in large South American cities such as São Paulo. Given the lack of consensus regarding the determination of boundaries of populations effectively exposed to new infrastructures, we operationalized distinct exposure calculation methods on a classical DiD framework. After comparing the results of different exposure calculation approaches (buffer zone and projection line), we observed stability in the treatment effect sizes. This suggests exposing travellers (and incrementing their exposure) to bike networks can promote behavioural change, although at modest rates. Furthermore, modest, positive and significant effects (+0.60%-+1.37%) on the probability of cycling were found after the implementation of new routes at treatment areas benefiting from mid to high exposure to new cycle routes, compared to their counterfactual (without intervention). In practice, these

10. On average, a São Paulo resident makes approximately 2.3 journeys per day. This typically involves travelling twice between origins and destinations (for instance, from home to work or school and back). We calculated this figure using data from the HTS (2007; 2017). The same figure was further confirmed by the Centro Brasileiro de Análise e Planejamento (CEBRAP) in a recent report on the Social Impacts of Bicycle in São Paulo.
11. HEAT is a tool used to assess the economic benefits of policies promoting physical activity through activities like walking and cycling. It helps calculate health gains and economic savings resulting from such initiatives, aiding decision-making for policymakers and health professionals. HEAT was developed within the Transport, Health and Environment Pan-European Programme (THE PEP), a joint initiative of WHO/Europe and the United Nations Economic Commission for Europe.
12. The Integrated Transport Health Impact Model (ITHIM) is a mathematical model that integrates data on travel patterns, physical activity, fine particulate matter, GHG emissions, and disease and injuries based on population and travel scenarios. The model was pioneered by Dr. James Woodcock at Cambridge University's Centre for Diet and Activity Research (CEDAR). It has been used to evaluate the health benefits of transport-related technology and behaviours changes in the UK, and some cities in the United States (Bay Area and Nashville).

effects could represent roughly 200 thousand cycling trips considering the scale of São Paulo. Enhancing our analysis with considerations for route design and target group heterogeneity, refining exposure calculations, and conducting more robust assessments of DiD assumptions could further elucidate the causal impact of new cycle routes. Policymakers can use our results to better support future cycling investments by building the value-case for cycling routes as facilities that can produce net benefits even in cities that are highly car-reliant.

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Declarations of interest

None.

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APPENDIX

Table 2.6. Variance Inflation Factor (VIF) verification.

Variable	GVIF	Df	GVIF^(1/(2*Df))
Treatment group	1.43	1.0	1.19
Year (200:2017)	1.03	1.0	1.01
Gender	1.02	1.0	1.01
Age group	2.50	4.0	1.12
Income level	2.46	2.0	1.25
Car ownership	1.03	1.0	1.02
Trip distance (km)	1.07	1.0	1.04
Trip purpose	1.37	3.0	1.05
Density (inhab./ km2)	1.27	5.0	1.02
Regional train (2km buffer)	1.09	1.0	1.04
Metro (1km buffer)	1.41	1.0	1.19

Table 2.7. Cluster sizes and profiles.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
N = 73,466 unique respondents	**Highly educated and motorized workers**	**Low-education workers**	**Retired and Elderly (60+)**	**Incomeless Housewives**	**Incomeless Students**
Proportion (%)	27.00%	38.61%	10.21%	4.55%	19.65%
Gender					
Male	49.26%	55.36%	44.30%	0.25%	51.08%
Female	50.74%	44.64%	55.70%	99.75%	48.92%
Age group					
Under 18 years	0.00%	1.74%	0.00%	0.39%	87.25%
18-24 years	3.63%	21.91%	0.00%	3.04%	12.75%
25-60 years	84.73%	70.79%	17.91%	69.13%	0.00%
> 61 years	11.64%	5.55%	82.09%	27.43%	0.00%

Table 2.7. (continued)

N = 73,466 unique respondents	Cluster 1 Highly educated and motorized workers	Cluster 2 Low-education workers	Cluster 3 Retired and Elderly (60+)	Cluster 4 Incomeless Housewives	Cluster 5 Incomeless Students
Car Ownership					
No	12.91%	41.84%	34.46%	27.36%	31.93%
Yes	84.69%	56.44%	63.79%	70.64%	66.19%
Education level					
Not educated	0.00%	4.47%	16.12%	10.87%	41.31%
High-school	0.00%	95.27%	50.35%	71.17%	58.69%
Bachelor/ Masters	100.00%	0.26%	33.53%	17.95%	0.00%
Occupation					
Employed	95.37%	90.23%	4.20%	0.00%	0.00%
Not employed	3.88%	8.65%	0.00%	3.65%	17.77%
Retired	0.02%	0.06%	95.65%	0.00%	0.02%
Housewife	0.02%	0.00%	0.16%	96.21%	0.03%
Student	0.72%	1.05%	0.00%	0.14%	82.18%

Notes: This table presents the five traveller classes identified through Latent Class Cluster Analysis (LCCA). Class sizes range from 4.55% to 38.61% of the total sample (N = 73,466). The first row reports class proportions, while subsequent rows show the posterior probabilities of individuals within each class belonging to specific socio-demographic categories. Class 1 (27%) – Highly Educated and Motorized Workers: Balanced gender distribution, mostly aged 25–60, all with tertiary education, high household car ownership(84.69%), and predominantly employed (95.37%). Class 2 (38.61%) – Low-Education Workers: Majority male, younger age skew (18–24), lower household car ownership (56.44%), and mainly high-school educated and employed. Class 3 (10.21%) – Retired and Elderly: Mostly aged 60+, majority female, moderate household car ownership, mixed education levels, and primarily retired (95.65%). Class 4 (4.55%) – Incomeless Housewives: Almost entirely female (99.75%), mainly aged 25–60, low income and household car ownership, high-school educated, and not in the labour force. Class 5 (19.65%) – Incomeless Students: Predominantly under 18, balanced gender, low household car ownership (31.93%), and primarily students (82.18%) with incomplete education levels.

Table 2.8. Descriptive statistics of control and treatment groups by year and exposure level (projection line approach).

	10% Exposure				50% Exposure				90% Exposure			
	2007		2017		2007		2017		2007		2017	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Socioeconomics		%		%		%		%		%		%
Age group												
under 18	25.41	12.49	23.49	11.67	20.8	11.62	20.02	10.86	17.23	13.73	17.04	12.68
18-24 years	13.01	13.85	10.84	10.78	13.17	14.09	10.83	10.77	13.7	12.77	10.91	10
25-44 years	33.82	36.43	31.88	35.7	35.41	35.77	33.35	35.39	35.79	34.2	34.25	33.17
45-64 years	22.46	27.65	25.67	29.68	24.22	28.12	26.82	30	25.71	27.36	27.84	29.5
65 or older	5.3	9.58	8.13	12.17	6.41	10.4	8.99	12.98	7.57	11.94	9.97	14.65
Gender												
Male	50.25	48.94	50.86	49.65	50.02	48.55	50.58	49.45	49.69	47.39	50.36	48.51
Female	49.75	51.06	49.14	50.35	49.98	51.45	49.42	50.55	50.31	52.61	49.64	51.49
Car ownership												
No	37.19	25.76	34.34	26.58	33.47	24.56	32.19	25.85	30.08	26.11	29.96	28.33
Yes	62.81	74.24	65.66	73.42	66.53	75.44	67.81	74.15	69.92	73.89	70.04	71.67
Income Status												
Income	43.66	45.62	35.93	34.41	45.21	44.67	36.24	33.09	45.11	44.07	35.26	33.34
No income	32.9	20.76	31.97	18.92	28.35	20.22	28.3	17.76	25.34	21.07	24.92	19.46
No Answer	23.43	33.63	32.1	46.67	26.44	35.11	35.46	49.15	29.54	34.85	39.82	47.2

Table 2.8. (continued)

	10% Exposure				50% Exposure				90% Exposure			
	2007		2017		2007		2017		2007		2017	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Education Level												
Incomplete Primary education	16.39	7.5	16.68	7.84	13.53	6.5	14.43	6.68	10.9	7.48	12.03	7.21
Primary education												
Incomplete High School	19.74	10.52	13.99	6.82	17	9.2	12.23	5.78	14.29	8.94	10.26	6.02
Incomplete Bachelor	18.29	11.84	15.56	8.5	16.43	10.85	13.93	7.29	14.53	10.38	12.02	6.68
Undergraduate degree												
Incomplete Primary education	30.72	31.95	36.26	30.62	31.73	31.32	35.62	28.58	31.87	29.51	33.88	25.74
Primary education												
Incomplete High School	14.87	38.19	17.51	46.22	21.31	42.13	23.79	51.67	28.42	43.69	31.81	54.35
Trip characteristics	%		%		%		%		%		%	
Trip Distance												
1.0-2.5km	51.94	29.57	48.34	29.69	40.5	32.46	39.92	33.2	33.93	56.19	34.91	56.15
2.5-5.0km	27.52	33.18	29.75	32.24	29.75	33.3	30.23	32.8	31.26	31.66	31.14	31.77
5-10km	20.54	37.25	21.91	38.07	29.76	34.25	29.84	33.99	34.81	12.15	33.95	12.08

Table 2.8. (continued)

	10% Exposure				50% Exposure				90% Exposure			
	2007		2017		2007		2017		2007		2017	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Trip Purpose												
Work	22.19	25.73	22.37	26.84	23.84	25.49	23.85	26.88	24.84	22.81	25.13	24.02
Education	17.29	12.53	15.85	12.34	15.28	12.61	14.62	12.43	14.16	13.75	13.78	13.81
Leisure	2.66	4.38	2.78	3.65	3.25	4.52	2.97	3.81	3.6	5.15	3.09	4.89
Home	45.99	42.9	47.12	45.25	45.27	42.21	46.75	44.84	44.36	41.11	46.32	43.74
Other	11.87	14.46	11.88	11.91	12.37	15.17	11.81	12.04	13.04	17.17	11.68	13.54
Built Environment	%		%		%		%		%		%	
Density												
0 -1000 inhab./km	8.61	1.59	11.57	1.81	5.85	1.46	8.35	1.72	4.44	0.57	6.49	0.72
1.000-5.000 inhab./km	26.54	16	25.31	14.75	22.06	16.19	21.68	14.89	20.06	15.77	19.7	14.44
5.000-7.500 inhab./km	35.06	39.12	34.73	40.65	39.04	36.17	38.6	37.59	39.02	29.85	39.27	30.13
7.500-10.000 inhab./km	13.37	12.31	12.85	11.46	12.66	12.66	12.06	11.98	12.45	14.01	11.83	13.61
10.000-20.000 inhab./km	14.61	17.16	13.04	17.5	16.51	16.07	15.26	16.32	16.52	15.02	15.58	16.31
>20.000 inhab./km	1.81	13.83	2.49	13.84	3.88	17.45	4.05	17.49	7.52	24.78	7.13	24.8

Table 2.8. (continued)

	10% Exposure				50% Exposure				90% Exposure			
	2007		2017		2007		2017		2007		2017	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
PT Proximity	%		%		%		%		%		%	
Regional Train												
(1km buffer)												
No	52.37	55.23	55.1	55.32	53.82	54.88	55.48	54.81	54.47	53.16	55.59	52.46
Yes	47.63	44.77	44.9	44.68	46.18	45.12	44.52	45.19	45.53	46.84	44.41	47.54
Regional Train												
(2km buffer)												
No	36.48	35.48	39.96	35.85	35.96	35.62	38.71	35.66	35.88	35.38	37.86	35.13
Yes	63.52	64.52	60.04	64.15	64.04	64.38	61.29	64.34	64.12	64.62	62.14	64.87
Metro												
(500m buffer)												
No	85.55	39.27	89.02	40.38	72.75	31.45	77.83	32.05	59.28	24.4	65.07	24.52
Yes	14.45	60.73	10.98	59.62	27.25	68.55	22.17	67.95	40.72	75.6	34.93	75.48
Metro												
(1km buffer)												
No	80.16	26.96	85.78	29.51	64.62	19.03	72.23	20.86	49.74	11.28	57.99	11.81
Yes	19.84	73.04	14.22	70.49	35.38	80.97	27.77	79.14	50.26	88.72	42.01	88.19
Observations	29,853	60,592	31,758	45,448	50,572	39,873	47,788	29,418	78,165	12,280	68,285	8,921

Table 2.9. Logistic regression model results (projection line approach).

Variable	> 70% exposure		
	Model A	**Model B**	**Model C**
	Estimate (Std. Error)	**Estimate (Std. Error)**	**Estimate (Std. Error)**
Treatment Effects			
Treatment Group	-0.736***	-0.687***	-0.528***
	(0.093)	(0.095)	(0.099)
After treatment (2017)	0.011	0.050	0.030
	(0.054)	(0.055)	(0.055)
Treatment * After (2017)	0.954***	0.947***	0.969***
	(0.119)	(0.121)	(0.121)
Socioeconomics			
Sex (Ref. Category: male)			
Female	-	-2.111***	-2.096***
		(0.076)	(0.076)
Age Group (Ref. Category: Under 18)			
18-24 years	-	0.233*	0.273**
		(0.123)	(0.124)
25-44 years	-	0.409***	0.472***
		(0.116)	(0.116)
45-64 years	-	-0.103	-0.035
		(0.123)	(0.124)
65 or older	-	-1.842***	-1.742***
		(0.225)	(0.226)
Income level (Ref. Category: Income)			
No income	-	-0.796***	-0.766***
		(0.110)	(0.110)
Not available	-	-0.093*	-0.087
		(0.053)	(0.053)
Car ownership (Ref. category: Yes)			
	-	-1.105***	-1.087***
		(0.049)	(0.049)

Table 2.9. (continued)

Variable	Model A	> 70% exposure Model B	Model C
	Estimate (Std. Error)	Estimate (Std. Error)	Estimate (Std. Error)
Trip Characterstics			
Trip Distance (km)	-0.173***	-0.219***	-0.223***
	(0.011)	(0.012)	(0.012)
Trip Purpose (Ref. category: Education)			
Home	-	0.491***	0.509***
		(0.098)	(0.098)
Leisure	-	0.598***	0.635***
		(0.162)	(0.163)
Work	-	0.608***	0.629***
		(0.104)	(0.105)
Other	-	0.038	0.065
		(0.135)	(0.135)
Built Environment			
Density (Ref. category: 0 -1000 inhab./ km2)			
1.000-5.000 inhab./ km2	-	-	-0.444***
			(0.093)
5.000-7.500 inhab./km2	-	-	-0.634***
			(0.105)
7.500-10.000 inhab./km2	-	-	-0.991***
			(0.106)
10.000-20.000 inhab./km2	-	-	-0.956***
			(0.091)
>20.000 inhab./km2	-	-	-1.009***
			(0.126)

Table 2.9. (continued)

Variable	> 70% exposure Model A Estimate (Std. Error)	Model B Estimate (Std. Error)	Model C Estimate (Std. Error)
Public Transit Integration			
Regional Train (2km buffer)	-	-	0.131**
			(0.054)
Metro (1km buffer)	-	-	-0.130**
			(0.057)
Constant			
	-3.853***	-2.832***	-2.233***
	(0.052)	(0.141)	(0.158)
Observations	167,651	164,469	164,469
Log Likelihood	-9,844.159	-8,489.988	-8,397.008
Akaike Inf. Crit.	19,698.320	17,013.980	16,842.020
McFadden's R2	0.018	0.145	0.154

Notes: Significant at *10%, **5%, ***1%.

Table 2.10. Exposure to cycle routes by trip purpose (buffer zone and projection Line approach).

Trip purpose	Buffer zone approach Exposed Trips (%)	Projection line approach Mean Exposure (%)	Std. Dev	Observations
Education	36.0%	35.5%	0.37	23,398
Home	42.2%	38.1%	0.36	75,255
Leisure	48.9%	46.7%	0.37	5,988
Other	41.6%	42.3%	0.37	21,490
Work	39.4%	41.1%	0.35	41,520
All trip purposes	40.8%	39.3%	0.36	167,651

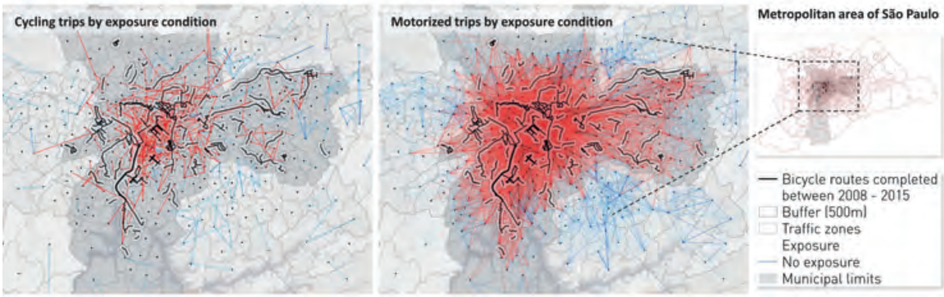

Fig. 2.6. O-D lines categorized by exposure condition for cycling and motorized trips.

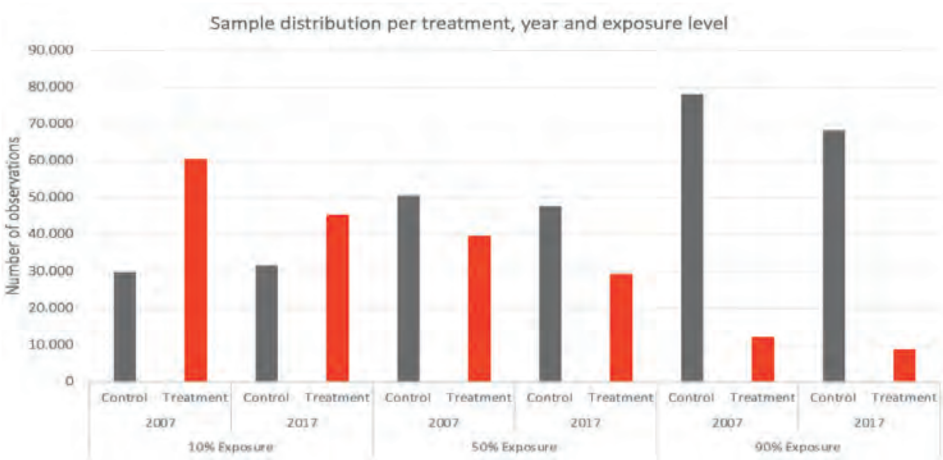

Fig. 2.7. Number of observations per treatment group, year and exposure le

Chapter 3

Cycle highway effects: Assessing modal shift to cycling in the Netherlands

Abstract

Cycle highways are regarded as a promising new type of infrastructure because they promote longer-distance cycling between (sub)urban residential areas and work and study centres. This study examines whether the emerging network of regional cycle highways in the Netherlands has contributed to a modal shift from car to bicycle. More specifically, we investigate the effect of these routes on commuting bicycle mode choice. Our main data sources are a national travel survey covering commuting journeys that were made between 2010 and 2021 and a comprehensive dataset we have compiled to document the exact timing and status of all cycle highways in the Netherlands. We employ a difference-in-differences approach with a binary logit model, comparing bicycle mode choice versus the car for trips that benefited from a new cycle highway, before and after the introduction of the new infrastructure, with a control group of trips that were not affected by the construction of a new route. We present results from a novel routing-based approach to measuring exposure to this new cycling facility, which allows us to establish the extent to which the fastest route to work traverses a newly constructed cycle highway. After controlling for relevant covariates, our main results indicate that the introduction of cycle highways has contributed to a shift in commuting behaviour toward cycling, with an increase of approximately 10% in cycling probability post-intervention for trips highly exposed to cycle highways. The results also indicate some heterogeneity in the effects of cycle highways across different groups of individuals. The findings of this study are especially important in the context of the Netherlands (or similar biking countries, such as Denmark). Although these countries have well-established cycling infrastructure, they can still derive benefits from new cycling routes and can support decision-makers in other countries who want to invest in cycling in the near future.

Keywords: cycle highways; mode choice; difference-in-differences; cycling infrastructure.

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3.1. Introduction

The emergence of cycling as a promising alternative to driving has attracted considerable policy attention, largely due to the potential for active travel to bring about transformative health benefits through increased physical activity (Pucher and Buehler, 2008; Krizek, Handy, and Forsyth, 2009; Handy, Van Wee, and Kroesen, 2014). This is particularly notable when integrated into daily commuting travel (Heinen, Van Wee, and Maat, 2010). Globally, cities have implemented various policy initiatives and actions aimed at increasing the role of cycling in urban transportation. Among the most important are investments in the expansion and improvement of cycling infrastructure. Literature suggests that infrastructural interventions have varying degrees of attractiveness and impact on cycling uptake, with users apparently preferring to cycle on physically separated, protected cycling paths with ample space and clear signalling (Buehler and Dill, 2016; Furth, 2021).

In light of this evidence, cycle highways or express bikeways are frequently identified as a promising development (see e.g. Buehler and Pucher, 2021). These types of routes facilitate safe, comfortable and continuous (uninterrupted) travel by providing separate bike paths with minimal road crossings. Consequently, cycle highways serve longer-distance bike commuters traveling between (sub)urban residential areas and nodes of work and study. By enabling increased cycling speeds, they not only accommodate conventional bicycles but also cater to faster e-bikes, which are witnessing a substantial rise in their market share. The concept, introduced by the Dutch about 15 years ago, has sparked the development of similar initiatives across the world, particularly in Europe (Liu et al., 2019; Cabral Dias and Gomes Ribeiro, 2021). While cycle highways show promise in comparison to conventional bike route facilities, they can be financially demanding, especially if robust features like tunnels or bridges compose their final design. Therefore, gaining a better understanding of their success in promoting cycling is crucial for the development of future cycling programs and investments.

The aim of this study is to assess whether the emerging network of regional cycle highways in the Netherlands has contributed to a shift in travel behaviour from driving to cycling. To achieve this, a difference-in-difference (DiD) research design is employed, comparing the choice of bicycle versus car for commute trips that benefited from a new cycle highway, before and after the introduction of the new infrastructure, with a control group of trips that were not affected by the construction of a new route. We focus on commute trips, as cycle highways are primarily designed to facilitate this type of travel.[13] Our analysis exploits a comprehensive dataset that we have compiled to document the exact timing and status of all cycle highways in the Netherlands. We employ annual data from a cross-sectional origin–destination travel survey for the period 2010-2021 to investigate mode choice for trips that potentially benefitted from the construction of these routes. Trips are assigned to the control and intervention groups using a routing-based approach, which allows us to establish the extent to which the fastest route to work traverses a newly constructed cycle highway. We perform several sensitivity analyses to examine the robustness of our findings to different ways of defining exposure, and to using a different outcome variable, where we compare commuting bicycle choice to *all* other modes. In addition, we investigate heterogeneity in the effects of cycle highways across different groups of individuals to assess the value these groups attach to such interventions.

The article makes three main contributions to the existing literature. It represents one of the first systematic evaluations of how the construction of cycle highways might affect cycling behaviour. Existing studies have evaluated the effectiveness of cycle highways and other routes of similar scale and design in terms of infrastructure usage. This typically involves the use of automated counting stations or mobile app data to measure the number of bikes on the new or improved route (Heesch et al., 2016; Skov-Petersen et al., 2017; Hong, McArthur, and Livingston, 2020). While this type of research yields valuable insights regarding how many people are using the new infrastructure, it is important to note that due to the inherent nature of count data, it is not possible to discern whether observed changes can be attributed to an increase in the overall number of cyclists or simply to existing riders shifting to the new routes. Nevertheless, cycle highways are, at least in the Netherlands, designed to encourage people who primarily use cars to switch to cycling. This study seeks to establish the extent to which they are successful in doing so.

Second, we make a methodological contribution to the growing body of literature evaluating the effectiveness of cycling infrastructure using so-

13. Another reason for limiting the analysis to commute trips is that they are relatively stable over time, which reduces the potential for biases to arise from the generation of new trips (Wardman, Tight, & Page, 2007; Zahabi et al., 2016).

called 'natural experiments' where variation in accessibility to new cycling facilities is exploited to assign intervention and control groups. Existing studies have typically relied on 'distance-based measures' that define exposure in terms of the proximity of an individual's home address to the intervention (see, for example, Dill et al., 2014; Goodman, Sahlqvist, and Ogilvie, 2014; Aldred, Croft, and Goodman, 2019; Rodriguez-Valencia et al., 2019). However, such measures of exposure may not necessarily yield valid estimates of intervention effects, because the impact of proximity to new cycling facilities will be strongly dependent on individual behaviour and habits. As Aldred (2019) previously noted, travel is typically to 'somewhere' and that 'somewhere' can potentially change for many types of trip (also see Humphreys et al. (2016) for an extensive treatment of this challenge in the context of built environment interventions). In this context, we propose a routing-based approach that addresses this challenge by utilizing information on both the home and work locations of individuals in determining the degree to which they are exposed to new cycling facilities.

Finally, this article presents evidence on the effectiveness of new cycling facilities in a context where a mature and complete bikeway network already exists. The majority of studies evaluating the impact of cycling infrastructure are from the United Kingdom, North America and Australia, where cycling levels are low and cycling networks fragmented (see Mölenberg et al. (2019) and Xiao et al. (2022) for an overview of existing studies). Buehler and Dill (2016) have previously proposed that more evaluations should be conducted in cities and regions with robust cycling networks. This is because they assumed that the benefits of providing additional infrastructure may diminish once a basic level of cycling facility provision is reached.

The paper starts with a literature review of the cycling interventions literature, including underexplored gaps that have been highlighted in past reviews. This is followed by the explanation of the data, variables and modelling approaches adopted for the research. Then, the results are presented, and the effects of new cycle highways on mode choice are estimated, including the use of heterogeneous effect analyses. Finally, the paper discusses its main strengths and limitations, practical implications and conclusions.

3.2. Literature review

Our research builds on a growing body of literature that examines the impact of cycling infrastructure on travel behaviour. Most studies have revealed a positive empirical association between the availability of bicycle infrastructure and cycling levels, either in terms of infrastructure usage or cycling behaviour.[14]

A first strand of literature has investigated individual-level preferences for different bicycle facility types. The majority of these studies have relied on stated-preference surveys to examine how the likelihood to cycle changes under various bicycle infrastructure scenarios (see e.g. Tilahun, Levinson, and Krizek, 2007; Winters and Teschke, 2010; Griswold et al., 2018; Clark et al., 2019). Increasingly, revealed-preference techniques, such as GPS units to track cyclists' routes, have been employed to examine the relative attractiveness of different types of facilities on route choice (Menghini et al., 2010; Broach, Dill, and Gliebe, 2012; Ton et al., 2017). Within this body of research, a discernible hierarchy of preferences has emerged depending on the specific type of infrastructure under analysis, with cyclists favouring separate paths over sharing lanes with motorized traffic. Studies have also found a preference specifically for infrastructure that facilitates continuous travel without the need to dismount at each intersection (Caulfield, Brick, and McCarthy, 2012; Ton et al., 2017).

A second line of research has relied on travel surveys or censuses to establish a relationship between bicycle ridership and the availability of bikeway facilities. Most of the work in this area has examined levels of cycling at a more aggregated level, such as individual cities (see e.g. Dill and Carr, 2003; Buehler and Pucher, 2012; Schoner and Levinson, 2014; Yang et al., 2021). However, some studies have exploited these data sources to conduct individual-level analyses, examining the influence of bikeway facilities and other built environment characteristics on bicycle mode choice. Examples of such studies include Cervero and Duncan (2003), Winters et al. (2010), Braun et al. (2016) and Zahabi et al. (2016). Both aggregate- and individual-level studies have examined the influence of individual network components, such as bicycle lanes, tracks and paths or some combined measure of their total provision. Consequently, there is limited evidence on the impact of overall

14. Buehler and Dill (2016) and Mölenberg et al. (2019) provide extensive reviews.

network connectivity, which encompasses factors such as directness, and accessibility (exceptions are Schoner and Levinson, 2014; Zahabi et al., 2016). Moreover, as these studies are primarily cross-sectional in nature, analysing correlations between bike infrastructure and cycling behaviour at a single point in time, they provide only limited evidence to support causal inference.

The challenge of establishing a stronger causal link between bikeway infrastructure and cycling levels has been addressed in a third stream of literature, which includes research that compares cycling behaviour before and after the installation of new bikeway facilities (reviewed in Mölenberg et al., 2019). However, important challenges remain in this strand of literature, which we seek to address in this paper. A first challenge arises from the necessity of ensuring that observed effects do not solely reflect underlying time trends in cycling in the wider area. In order to capture the effect of these broader cycling trends, the use of controlled designs is recommended. Indeed, there is a growing body of natural experimental studies that exploit variation in accessibility to new cycling facilities to establish which members of the study population potentially benefit from the new infrastructure and which do not (see, for example, the evaluations included in the systematic review by Xiao et al. (2022) that consider the effectiveness of cycling infrastructure).

Secondly, the majority of these studies tend to focus on singular or a limited number of infrastructural interventions, whereas stated and revealed preference studies have found a preference specifically for continuous and connected bicycle facilities. This limitation is partially mitigated in more recent investigations, which have assessed the expansion of bicycle networks at the neighbourhood or city-level (e.g. Aldred et al., 2019; Rodriguez-Valencia et al., 2019; Félix, Cambra, and Moura, 2020; Piras, Scappini, and Meloni, 2022). However, these expansions frequently only involve investments in small-scale cycling links, like (segregated) cycle paths or tracks. In contrast, research that has examined major bike routes, such as cycle highways, specifically designed to facilitate continuous and long-distance travel has primarily assessed usage of the new or improved infrastructure.[15] As we already indicated, this type of analysis provides a less credible research design to assess actual behavioural change. Indeed, intercept surveys suggest that the proportion of users who would not have engaged in cycling had these improvements not occurred, was much smaller than the increase in bike counts (Heesch et al., 2016; Skov-Petersen et al., 2017).

A third methodological challenge in the use of natural experimental studies to evaluate cycling infrastructure, and indeed many other interventions that alter the physical environment, is the identification of the exposed population. A comparison is typically made within the study population between people who live closer to an intervention and those who live further away (see Mölenberg et al., 2019). Such approaches for characterizing exposure must rely on the rather strong assumption that exposure to cycling infrastructure is solely dependent on the proximity of the home location to the intervention site. However, the extent to which individuals living close to a new cycling facility actually benefit from this infrastructure will depend in large part on their (pre-existing) behaviour and habits (see Humphreys et al., 2016; Aldred, 2019). For example, some individuals may reside in close proximity to a new bicycle route, yet rarely utilize it due to their daily routines and activities (e.g., commuting origins and destinations) taking them to other areas. Conversely, other individuals may reside far from the new infrastructure, yet their regular activities (such as commute route) may bring them close to it, increasing the likelihood of its use. Humphreys et al. (2016) therefore recommend the use of more 'dynamic' measures of exposure that take into consideration routine mobility and activity spaces. While such measures may require greater technical sophistication, they require less restrictive assumptions about who may be exposed to an intervention.

Some work has already been done in this direction. In their evaluation of an area-based program to create pedestrian and cycling-friendly street environments in London, Aldred et al. (2019) combine distance thresholds with context-based knowledge from officials involved in the implementation

15. Exceptions are studies by Merom et al. (2003) and Hirsch et al. (2017), which evaluated changes in cycling behaviour rather than infrastructure usage for the 16.5 km long Rail Trail cycleway in Sydney and two off-road paths with a combined length of 16.4 km in the city of Minneapolis, respectively. In addition, several studies have examined how the 25 km long Cambridgeshire guided busway, which involved the construction of an adjacent parallel walking and cycling path, changed travel behavior (see e.g. Heinen et al., 2015b; Panter et al., 2016). The current study extends this research by providing an estimate of the *average* treatment effect of major bicycle routes, as we consider the effect of multiple routes of similar design across different regions. This may be important because the impact of new cycling facilities may vary across locations (see Mölenberg et al., 2019).

process to define exposure. This knowledge pertained to the visibility of the interventions and the key destinations they might serve. Hirsch et al. (2017) identify commuting trips that could potentially benefit from the cycling infrastructure under consideration by establishing whether the straight-line connection between the origin and destination tract centroids intersects the new infrastructure. The measure that arguably best approximates the dynamic exposure measure proposed by Humphreys et al. (2016), and which is most similar to our own, was developed for the evaluation of a new busway in the Cambridge area, which also entailed the construction of a parallel pathway for walking and cycling (reported in Heinen et al., 2015a; Heinen et al., 2015b). As one of the exposure measures, this study calculated the change in cycling (and walking) distance to work induced by this new transport infrastructure using a routing analysis.

3.3. Cycle highways in the Netherlands

Due to the expansion of urban living spaces in the Netherlands, transport networks of different metropolitan areas (notably in the Randstad) are beginning to overlap. It is precisely in these “corridors” that an important task for the further development of more efficient infrastructures can be found. With more people cycling longer distances, robust and efficient cycling infrastructures are important to encourage motorists to cycle to work, school, and/or other regional destinations. Cycle highways are specifically designed to promote regional cycling. It is difficult to pinpoint the first cycle highway in the Netherlands[16], but the “cycle highway” concept really gained traction with a national program launched in 2007 that became known as “Met de Fiets Minder File” (With the Bicycle Less Congestion). As part of this program, five pilot routes were constructed in areas in which motorized commuter traffic experienced congestion.

The 'Met-de-fiets-minder-file' program only made funds available for project management, and additional funds were required to meet the costs of physical improvements. In light of the success of these pilot projects, the national government has encouraged the construction of cycle highways

16. Already in the 1970s, two demonstration routes were built in the cities of Tilburg and the Hague that shared many of the elements currently associated with a cycle highway. However, these routes were built within one city. The first route to connect two cities was inaugurated in 2004 as a 7 km-long path between the cities of Breda and Etten-Leur. See Lagendijk and Ploegmakers (2021) and Bruno and Nikolaeva (2020) for a further discussion of the origin and evolution of the concept in the Netherlands.

through several rounds of funding, which could be used to (partially) cover the engineering and construction costs. Similarly, provincial governments (as second-tier governments) have also established grant programs for the physical construction of bicycle highways. As a result, the number of cycle highway initiatives has expanded greatly over time, from approximately 20 projects in 2010 to over 300 currently. To date, approximately 50 projects have been fully completed in the Netherlands. The concept is now more commonly referred to as non-stop bikeways (in Dutch, "doorfietsroutes"), although other terms are also in use, such as fast cycle routes (in Dutch, "snelfietsroutes").

Fig. 3.1. Cycle Highway examples. Left: Section of the Arnhem-Nijmegen cycle highway (Source: www.gelderlander.nl); middle: cycling bridge over the Maas River in Nijmegen (Source: https://mapio.net/); right: cycling tunnel in Nijmegen (Source: www.hetccv.nl/).

Among the most common cycle highway design standards in the Netherlands (see examples in Fig. 3.1), several can be mentioned: (i) having wide lanes (3–4m), (ii) being separated from motorized traffic and pedestrians, (iii) having gradual curbs and overall mild gradients, (iv) road surfaces of "flat and non-slip" asphalt or concrete (v) designed for high cycling speeds (25–30 km/h), and (vi) avoiding frequent stops and having priority at crossings to enable higher cycling speeds (CROW, 2014, 2016). It should be emphasized that these criteria are indicative and allow for adaptation to local contexts. In addition, provincial governments[17] have designed policy frameworks and grant programs for cycle highways that establish specific requirements (Lagendijk and Ploegmakers, 2021).

In terms of design and implementation costs, cycle highways can quickly become more expensive than the usual bicycle paths. Calculations based on a national inventory of cycle highway initiatives in the Netherlands reveal that average expenditure amounts to 500.000 Euros per km. This figure relates to more than 30 projects that had been fully completed as of 2020.[18] Substantial variations in costs exist. Five projects have costs of over a million euros per km, while four projects required expenditure of less than 100.000 Euros per km. The lack of previous road infrastructure and the need to build fixed links, such as bridges and tunnels, strongly influences the cost of infrastructure delivery.

3.4. Materials and methods

3.4.1. Data collection

The Dutch Travel Survey (DTS) is our source of travel data in order to investigate whether people are more or less likely take the bicycle for trips that benefited from the construction of a cycle highway.[19] This origin–destination (O-D) survey takes place every year and provides travel information for an average day in the week for all residents in the Netherlands. To this end, a representative (stratified) sample is drawn in which each respondent is asked to provide detailed information for every trip made on a certain pre-determined day of the year. For each individual trip, information is provided on the trip origin and destination (specified at the four-digit postcode level), the purpose of the trip and the (main) modes of travel. This means that our analyses are based on the self-reported mode choice of respondents and the DTS does now allow us to examine changes in travel frequency. In addition to the reported travel behaviour, details are collected about various socioeconomic characteristics, such as income, education, place of residence, and others. We use the annual O-D surveys for the period 2010-2021. After merging the datasets and cleaning the data, we have information on 423,689 respondents who have made almost 1.4 million

17. Since cycle highways normally span several municipal boundaries, provincial governments are actively involved in the planning and construction of cycle highways. A recent survey among provincial officials reveals that 9 out of 12 provinces provide co-funding for cycle highways (Tour de Force, 2017). One of the three remaining provinces takes responsibility for the entire project from plan development to implementation, including all funding. In other cases, municipalities are responsible.
18. For some 15 projects that have also been built no such financial information is available, but most of these projects were implemented before 2010.
19. The official designation "Onderweg in Nederland" (ODiN) can be translated as "On the Road in the Netherland". Prior to 2017, it was referred to as "Onderzoek Verplaatsingen in Nederland" (OViN), which translates to "Travel Survey in the Netherlands". Some survey questions were added or reformulated during the transition from OviN to ODiN. We implemented alterations to the original codes to ensure comparability of data gathered from the distinct surveys. The ODiN sample was also restricted to persons aged 6 years or older, but this does not affect our results because the analysis pertains to work-related journeys made by individuals aged 18 or older.

different trips. It should be noted that individuals do not necessarily participate in consecutive rounds of the survey and therefore are not followed over time.

The final sample used in the analyses is based on several exclusion criteria. First, only trips made for commuting purposes are retained, as this study assesses the impact of bicycle highways on the mode of travel to work. As a commuting journey will typically involve one outward and one return trip, only respondents who made a maximum of two commute trips are included in the analysis. Furthermore, our analysis is confined to commuting journeys where the shortest network distance between origin and destination postcodes ranged from 5 to 15 km. This decision is influenced by the fact that officials involved in the planning of cycle highways typically assume that their potential is greatest within this particular distance range.[20] The upper range of 15 km is motivated by the assertion that the (electric) bicycle is a cheap and convenient mode of transport for distances up to 15 kilometres. The sample is further limited to respondents in possession of a driving license who are aged 18 and older, as individuals aged 16 to 17 are not permitted to drive unaccompanied in the Netherlands. Respondents with missing values for demographic and socioeconomic variables are excluded from the study. Finally, for the main analysis of this paper, only trips made by car or bicycle are selected. As a result of these choices, our main results are based on a sample of 28,829 respondents, who undertook a total of 49,732 unique commuting trips.

3.4.2. Defining treatment and control groups

In order to ascertain whether a particular origin-destination pair was affected by the construction of a cycle highway during the study period, we exploit detailed information from a comprehensive dataset of routes in the Netherlands. The dataset is compiled by *Tour de Force* through an annual inventory of cycle highways, which records all routes that have been completed, are currently under planning or implementation, or may be constructed in the future (see Fig. 3.2). Part of this inventory is a detailed geographic information system (GIS) map that delineates the precise routes of completed cycle highways and those for which the future course is known

20. This view is reflected in in a number of national policy documents and visions on cycling promotion, including those produced by the Fietsersbond & the Ministry of Infrastructure and the Environment (2015) and Tour de Force (2017, 2021). Tour de Force is a collaboration between national and regional governments, interest groups, and knowledge institutes aimed at the promotion of cycling and the facilitation of knowledge exchange.

because they are in or near the implementation stage. The information in the dataset on the routes listed as completed has been augmented by adding the specific year that construction works began and the year that all construction was concluded. This information was obtained from various sources, including available project documents and media coverage.

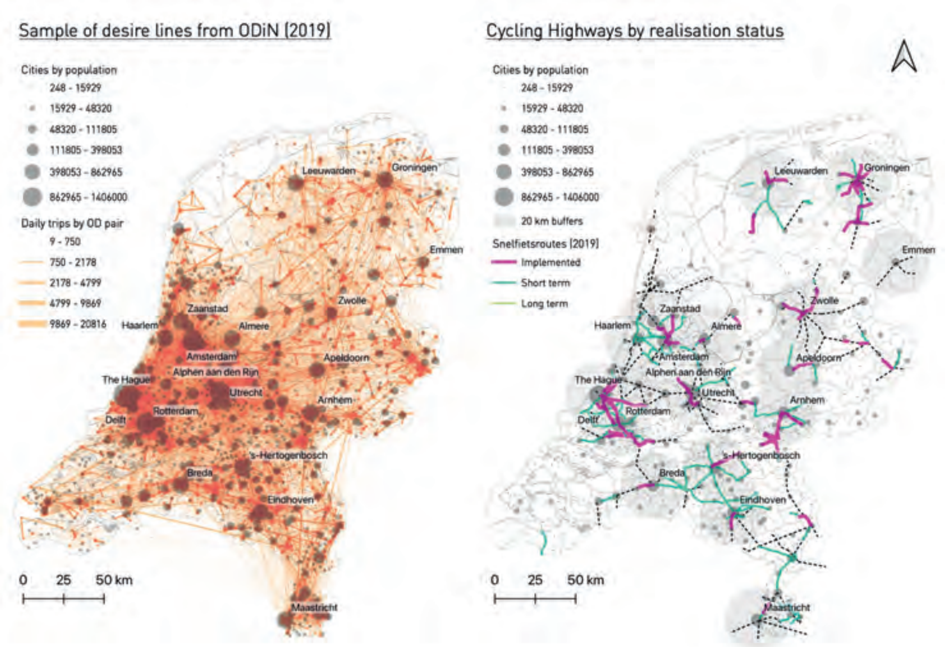

Fig. 3.2. ODiN sample of origin-destination OD pairs (left); Cycle highways by completion status (right).

The database indicates that 40 regional bicycle routes were completed by 2018, corresponding to more than 400 km of new infrastructure. However, we only utilize a subset of these routes in the empirical analyses for two main reasons. The first reason for this is that we lack access to pre-intervention travel data for 10 routes that were completed in 2009 or earlier, given that we our DTS sample is for the period 2010-2021. A second reason is that not all routes in the dataset qualify as a cycle highway in terms of design. The dataset records a wide variety of bikeway initiatives that facilitate longer-distance commutes between residential areas and locations of work and study, under the label "regional routes". However, not all of these meet the minimum design standards for a cycle highway. To determine which routes meet these design criteria, we use information from a user test conducted by the Royal Dutch Touring Club (ANWB) in 2019, which assessed several routes completed at that time. For the routes not included in this assessment, we employ information from individual project evaluations in which routes are scored based on user intercept surveys. This selection was discussed with responsible government officials that participate in the Tour de Force. As a result, a further 15 routes are excluded from the analysis.[21]

In this study, we follow the recommendation by Humphreys et al. (2016) and create a "dynamic" exposure measure that explicitly takes into account the routine commute mobility of the research participants.[22] As the DTS records home and workplace postcodes for each commute trip, we calculate the portion of the commuting route (in terms of distance in km) traversing a new cycle highway. The underlying assumption is that when a larger section of the commute trip can be traversed over a cycle highway, the potential benefits of this route will be greater, resulting in a higher level of exposure. We prefer this measure to the change in travel time or distance to work induced by the new infrastructure for each respondent. This is because cycle highways are designed not only to provide more direct connections, thereby reducing travel time and distance, but also to increase the safety, comfort, and convenience of cycling (CROW, 2014, 2016). In the Netherlands, these benefits may be of greater importance, as the bikeway network is already quite complete. Indeed, nearly all sections of the new routes under consideration involve the improvement of existing cycle infrastructure rather than the addition of new links.

The exposure measures were calculated using geographic information system (GIS) software QGIS. The basis for this calculation was the OpenStreetMap (OSM) network, to which GPS data on actual bicycle speeds was added. These data were obtained during a nationwide initiative in the Netherlands called the 'Bicycle Counting Week' (see Van de Coevering, De Kruijf, and Bussche, 2014). For this initiative, the cycling movements of participants were tracked using a smartphone application, resulting in the most comprehensive dataset of cycling speeds in the Netherlands. However, the data only cover part of the study period, as the initiative only took place annually between 2015 and

21. The following routes are included in the analysis: Amsterdam – Purmerend; Amsterdam – Zaandam; Apeldoorn – Deventer;
22. Interestingly, the authors illustrate this type of measure with the case of a bicycle superhighway. In this regard, they propose a measure that is similar to ours, which is based on the modelling of commute distances and times, taking into account the new bicycle infrastructure as well as the home and work locations of individuals.

2017.[23] We therefore assume that cycling speeds have not significantly changed on the majority of network connections in the remaining years of the study period. As the exposure measure is not defined in terms of reduced distance or travel time to work, it is unlikely that this will significantly affect the validity of the results. For road sections with a minimum of four observations, the measured speed from the 'Bicycle Counting Week' data was utilized, ensuring it ranged between 4 km/h and a maximum of 25 km/h. In instances, where there were fewer than four observations, a deliberately low speed of 12 km/h was applied. This approach allows for the inclusion of these connections, while acknowledging that unmeasured road sections are often less significant, as they involve forest paths, park roads, or parking lots.

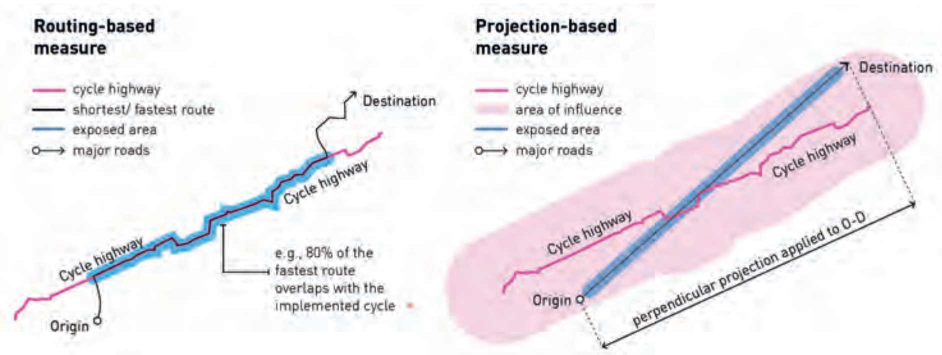

Fig. 3.3. Comparison of different exposure calculation methods used in this study.

In order to capture all commuting trips where the route over the cycle highway might present an attractive alternative, even if it is not the fastest one between the origin and destination, the speed on cycle highways was artificially raised to 30 km/h. To assess the sensitivity of our findings for this choice, we also calculated a measure where the speed on cycle highways was raised to 25 km/h and a measure based route with the shortest distance over the network. Furthermore, we also calibrated exposure measures using a complementary approach, where the road geometry of the cycle highways was perpendicularly projected onto each O-D pair. This complementary projection-based approach assumes that individuals would benefit from a cycle highway if the straight-line (Euclidean) connection between each O-D pair runs parallel to a route and (ii) if both the origin and destination postcode centroids are located within a maximum area of influence (buffer) from a given cycle

23. The total number of participations was approximately 38,000, 30,000, and 15,000 in the years 2015, 2016, and 2017, respectively.

highway. Since there is no strong a priori evidence regarding the potential zone of influence of a cycle highway, we have calculated projections using buffers of 2km and 3km. Fig. 3.3 illustrates how both the routing- and projection-based measures were calculated. In Fig. 3.4 we show results for our three main exposure measures based on the fastest route, shortest route and perpendicular projection.

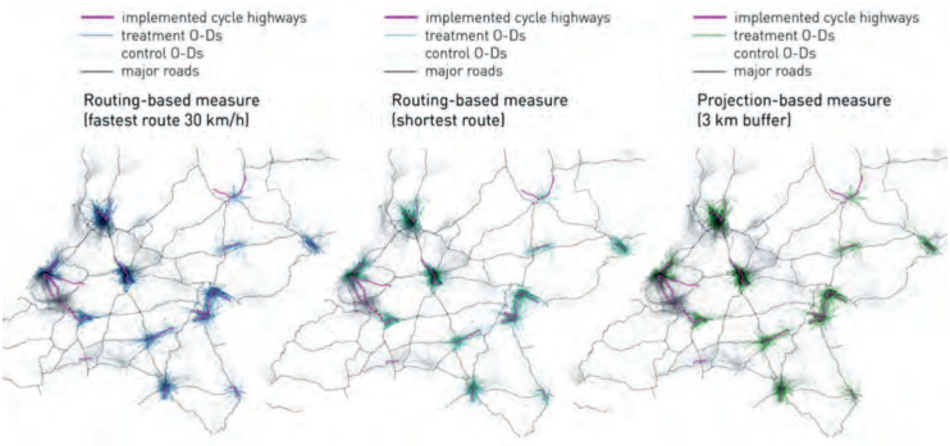

Fig. 3.4. Distribution of control and treatment groups across different exposure calculations.

3.4.3. Empirical strategy

We use a difference-in-differences (DiD) design to compare commuting bicycle mode choice for trips that benefited from a cycle highway, before and after its implementation, to trips that did not experience an improvement. This approach has previously been utilized to examine the impact of infrastructure improvements by comparing bicycling behaviour in areas with and without new bikeway facilities, before and after their installation (e.g. Dill et al., 2014; Rodriguez-Valencia et al., 2019). Our application of the approach differs in three important ways from the "classical" DiD design, which is based on two groups (treatment and control) and two periods (before and after). Firstly, in our case, as in many others, the treatment occurs at different times, since the 15 routes considered in this study were completed in different years. Such variation in the timing of treatment can be accounted for by a generalization of the DiD in which time and group fixed effects are included in the model (see, for example, Wing, Simon, and Bello-Gomez, 2018).

Secondly, we employ DiD estimation with a binary logit model, given that the outcome of interest – bicycle mode choice for commuting – is of a binary nature. Although DiD is typically applied with continuous dependent variables, it can also be used in nonlinear models such as a logit (Karaca-Mandic, Norton, and Dowd, 2012; Puhani, 2012). Thirdly, treatment is not defined by a binary variable but rather is measured on a continuous scale, specifically, the distance that can potentially be cycled on a cycle highway for each OD-pair. Here, we adopt the approach proposed by Humphreys et al. (2016), who argue that when it is unclear at what level individuals are actually exposed to an intervention, it is preferable to use a 'graded' measure of exposure to capture the intensity of influence of an environmental change.

The outcome of interest in the binary logit model is the choice of bicycle versus the car for commuting trips. Although our measure of exposure is continuous, to avoid making parametric assumptions, we group trips into discrete bands for different distance ranges that can potentially be cycled on a bicycle highway. There are many trips with a modelled distance of zero, indicating that no part of fastest the route between the specific origin and destination postcodes traverses any of the bicycle highways considered in this study. These trips will not be affected by the construction of a cycle highway and therefore serve as the control group. The following equation is used to estimate the probability to cycle:

$$ln\left(\frac{\mathrm{Pcycle}_{it}}{1-\mathrm{Pcycle}_{it}}\right) = a_{ij} + \sum_{z} a_z dist_{itz} + \sum_{z} \gamma_z dist_{itz}\mathrm{PC}_{it} + b_t + \beta\mathrm{X}_{it} + \varepsilon_{it}$$

where $\mathrm{Pcycle}_{\mathrm{ijt}}$ is the outcome of interest, which takes a value of 1 if a respondent decides to use the bicycle as the main mode of transport to make commuting trip i in year t. This binary variable equals zero if the car is chosen. The term b_t indicates year and month fixed effects, which allow for the possibility that bicycle mode choice may differ in each year and month. These *time* fixed effects control for autonomous trends in bicycle use and seasonal influences.

The term $dist_{ijtz}$ denotes the various distance bands that are employed to define exposure status and, thus, represents the *group* fixed effect. Four distance bands are defined: no traverse, less than 2.5 kilometers, 2.5 to 5.0 kilometers, and over 5.0 kilometers. The term PC_{ijt} is an indicator variable for the post-treatment period and does not need to be included separately because it is absorbed by the year fixed effects. The interaction $dist_{ijtz}\mathrm{PC}_{ijt}$ indicates trips within the z-th distance band after the construction of the bicycle highway. This variable is comparable with the treatment x post interaction in the 'classical' two-group x two-period DiD. The coefficients for the exposure measures can be interpreted as follows: $a_z$captures the pre-treatment difference in the probability to cycle for each distance band relative to trips that do not have the potential to traverse a cycle highway, γ_z is our main coefficient of interest and represents the mean effect of a cycle highway on bicycle mode choice for each distance band. Specifically, it indicates how the probability of cycling changes for each distance band after the construction of a cycle highway.

We include several sets of controls, denoted by X_{it}, to account for the demographic and socioeconomic characteristics of the commuters and the characteristics of each trip. These variables correct for any differences in the composition of the control and treatment groups that might influence the choice of transport mode. Variables representing individual-level characteristics include gender, age and educational attainment, and we also add three household-level characteristics that capture household income, household composition and car ownership. We also control for trip distance measured as the shortest cycling distance between each OD pair, and an indicator variable for the degree of urbanization of each respondent's home postcode (measured as the number of addresses per square kilometer). These variables have been used in related studies (see, for example, Heinen et al., 2015a; Zahabi et al., 2016; Rodriguez-Valencia et al., 2019; Piras et al., 2022). Finally, ε_{it} is the error term.

Because each observation represents a discrete trip and that a typical commute journey comprises both an outward and a return trip, it is evident that the observations are not independent. One potential solution to address this issue would be to allow for clustering of the standard errors at the respondent level. Nevertheless, this approach may still result in biased standard errors, given that there are repeated observations for a considerable number of two-way OD pairs, with different individuals in the sample undertaking the same commute journey. We therefore cluster the standard errors at the level of the two-way OD pair. This is deemed the most appropriate level of clustering given that exposure to the intervention will also vary at this level. In DiD settings, cluster-robust standard errors are considered valid (although potentially conservative) if the clustering is done at the level at which the treatment varies (Angrist and Pischke, 2009).

It is important to note that our DiD design makes use of repeated cross-sectional data, as the DTS does not permit the same individuals to be followed over time. Repeated cross-sectional designs have been commonly employed in natural experimental evaluations of cycling interventions. (see, for example, Chang et al., 2017; Hosford et al., 2018; Rodriguez-Valencia et al., 2019; Karpinski, 2021; Piras et al., 2022). The broader (economic) literature concerned with identifying and estimating causal effects with observational data also maintains that DiD methods can accommodate repeated cross-sectional data. In such cases, this literature commonly imposes the so-called no-compositional change assumption. This assumption could be violated when there is a substantial change in the composition of the treatment group over time, which results in a growing imbalance between the treatment and control group across time. While there may be some plausible scenarios where this occurs, we do not expect it to be the case in this study, given that the observations are drawn from the same population across time periods. Nevertheless, we have examined the possibility of compositional changes and discuss the results in Section 5.

3.5. Results

3.5.1. Descriptive statistics

Table 3.1 (see Tables section) presents descriptive statistics for the DTS sample, organized period and by exposure status, with sample totals included. Exposure is defined as the portion of the fastest route between each O-D pair that traverses a newly constructed bicycle highway. The control group comprises respondents who made one or more trips that were not affected by the construction of a cycle highway as of 2018. The treatment group includes all respondents who made at least one trip that would, by 2018, traverse a new bicycle highway for some part of the commute route. The share of respondents who drove to work decreased gradually during the study period, while the share who cycled to work demonstrated a corresponding increase. The respondents were between the ages of 18 and 89 (with a mean age of 43.4). 46% were women, 42% had either completed secondary or higher education (42% and 38%, respectively). Furthermore, the majority live as couples (with or without children) and have at least one car in their household (92 %). The respondents in the treatment group exhibit slightly higher levels of education, tend to have higher incomes and are more likely to have only one or no cars in their household. In addition, they tend to live in more urbanized areas and make longer commute trips.

Table 3.1 also indicates that the composition of the sample has slightly changed over time in terms of demographic and socioeconomic characteristics. However, the observed changes over time are largely comparable for the control and treatment groups. Consequently, any potential effect of these changes on the likelihood of taking the bike will be captured by the year fixed effects. This also suggests that the assumption of no compositional change is not likely to be violated. It is important to note that there appear to be some minor imbalances over time regarding household composition and income levels between the control and treatment groups. Specifically, the share of respondents in the higher income category increased slightly more in the treatment group between 2010 and 2021, while the share of respondents in the middle-income category experienced a corresponding decline. The treatment group also experienced a more pronounced increase in terms of the share of respondents living as a couple without children over time. To test whether the trend for the different income and household categories indeed differs between the control and treatment groups, we estimated separate logistic regressions for each category. Our findings indicate that there are no statistically significant differences in the trend between the exposed and unexposed groups, a finding that is consistent across the other demographic or socioeconomic characteristics.

3.5.2. Main results

Table 3.2 presents our main findings on the effect of bicycle highways on the probability of bike mode choice versus the car on commuting trips within a 5 to 15 kilometre range. We report results for three different specifications. Model 1 reports the estimates of a DiD model, which controls for year (and month) fixed effects. In Model 2, we add respondent characteristics, urban density and trip distance as additional control variables. In Model 3, we restrict the control group to only home postcodes that are part of at least one O-D pair affected by the construction of a new route. These postcodes provide a plausibly more credible counterfactual as residents living in the same postcode are more likely to face similar (unobserved) local trends affecting cycling levels and to experience common shocks (e.g., the COVID-19 pandemic) at around the same time. The exposure measure used in all three specifications establishes the portion (in kilometres) of the fastest route between the origin and destination of each trip traversing a new cycle highway (imposing a speed of 30 km/h on cycle highways). To facilitate the interpretation of the results, both odds ratios (OR) and marginal effects are presented.[24] When ORs are greater than 1, an increase in the independent variables is associated with an increase in the odds of commuting by bicycle.

The first set of coefficients measures the difference in bicycle mode choice between the different distance bands relative to the 0 km distance band, which encompasses all trips where the commute route would not traverse a bicycle highway. These coefficients capture the effect of the different distance bands *prior* to the construction of a bikeway, as all models incorporate an interaction term between these distance band indicator variables and a post-construction variable, which represents our DiD estimator.[25] All models indicate that commuters were less likely to choose a bicycle instead of a car for trips where the commute route could potentially traverse a future bicycle highway for 5 km or more. For example, Model 1 indicates that the odds of using a bicycle for such trips decrease by 46% compared to trips on routes that did not benefit from the construction of a bicycle highway. The probability of cycling to work does not differ significantly for the other, shorter distance bands. This finding implies that prior to its implementation, commuters were less likely to use the bike for trips that would benefit significantly from a bicycle highway.

The second set of coefficients for the distance bands is of primary interest to this paper as they represent the DiD estimates. More specifically, they capture the estimated effect of the construction of a bicycle highway for each distance band. The coefficients for the first distance band, which indicates trips made by individuals that could potentially traverse a cycle highway for up to 2.5 km, are positive and significant at the 5% level in Models 1 and 2. The point estimates indicate that the odds of commuters choosing a bicycle for these trips are, respectively 1.33 and 1.37 times higher. The corresponding marginal effects imply that the completion of a cycle highway increases the probability of cycling by 5 % points. In contrast, the coefficients for the 2.5–5 km distance band are not statistically significant and in Models 2 and 3, they are even below zero. It can be reasonably assumed that this distance band represents the highest level of exposure, as it indicates trips where the

24. Marginal effects are calculated at the means of the covariates using Stata's margins command. We follow the procedure outlined by Karaca-Mandic et al. (2012) to calculate the marginal effect of the coefficients representing the DiD estimate, as they involve an interaction between the distance bands and a post-completion variable.
25. As previously noted, the main effect of the post-completion variable is absorbed by the year fixed effects.

section of the commute route that can be potentially traversed on a cycle highway is largest. As a result, these trips are likely to benefit most from the construction of a bicycle highway. The coefficients for this distance band are positive and statistically significant at the 1% level in Models 1 and 2 and the 5% level in Model 3. The estimated odds of using the bicycle for these trips are between 1.73 and 2 times higher after the construction of a cycle highway. If we interpret these results in terms of marginal effects, the probability to cycle increases by 8.3 to 11.9 % points after the construction of a bicycle highway.

The observed positive effects for the shortest distance band are somewhat unexpected, as one would particularly expect trips in the 2.5–5 km and the >5 km distance bands to benefit more from the construction of a bicycle highway. One possible explanation is that our estimates for this distance band do not reflect the effect of a new bicycle highway, but are driven by an idiosyncratic trend in cycling levels specific to this group. Indeed, trips in this distance band appear to be concentrated in urban areas, where cycling levels have steadily grown over the study period.[26] It is, however, reassuring to note that when the control group is confined to postcodes that are part of at least one O-D pair affected by the construction of a bicycle highway, the effect for the <2.5 km distance band is no longer statistically significant at the 5% level, while the coefficient for the > 5km distance band remains significant and the implied marginal effect becomes even larger. As previously stated, these postcodes provide a better counterfactual for trips that benefited from the construction of a bicycle highway.

Most of the other covariates in Models 2 and 3 have statistically significant coefficients, with the estimates being largely similar across both models. There is a negative association between the likelihood of cycling and being female, with the probability decreasing by approximately 3.4 % points for females. This finding is not consistent with the suggestion by Heinen et al. (2010) that in countries with high cycling rates, such as the Netherlands, women cycle more frequently than men. This may be attributed to the fact that we restrict the sample to longer travel distances (5 km to 15 km). Age also influences cycling levels, with individuals aged between 45 and 54 and, in particular, those aged between 55 and 64 being more likely to cycle compared

26. The imposition of an artificially high speed of 30 km per hour on all sections of the cycle highways may result in routes traversing this infrastructure being identified as the fastest alternative, while in fact they represent a significant detour from the fastest route, based on real speeds. This is especially likely to occur in urban areas with a more dense bikeway network.

to individuals aged between 18 and 24 years. Similar to findings in other studies (see Ton et al., 2019), the probability to choose the bicycle decreases by 11.6 to 14.1 % points for individuals with a non-Western background compared to Dutch natives. Educational attainment is also a significant predictor of the choice to cycle to work, with especially individuals who have completed higher education demonstrating a higher probability of choosing the bicycle. The likelihood of cycling increases by 10.9 to 15.7 % points for this group compared to individuals with only primary education.

With regard to household-level characteristics, our findings indicate that individuals living in middle and high-income groups are more likely to commute by bicycle compared to individuals in low-income households. Individuals who are part of couples with or without children are also more likely to choose to bicycle. The point estimates in Model 3 indicate that the probability increases by 14.4 % points for couples without children and 17.9 % points for couples with children compared to single-person households. Finally, individuals that live in a household with at least one car have a reduced likelihood of cycling to work compared to those living in a household with no private vehicles. This is in consistent with previous mode choice studies, which have demonstrated a strong association between car ownership and a reduced likelihood of cycling (Zahabi et al., 2016; Rodriguez-Valencia et al., 2019; Ton et al., 2019).

3.5.3. Sensitivity analyses

As a robustness check of our main results, we have estimated models with different 'dynamic' measures of exposure to test the sensitivity of our findings to alternative ways of measuring exposure. Table 3.3 (in Tables section) presents the results of this analysis, using the specification that includes time fixed effects and the full set of control variables. Models 1 and 2 report estimates for an exposure measure where a projection-based approach was used to establish the portion of the commute route (in km) that could be potentially traversed over a bicycle highway. In this case, a 2 km buffer was used to define the maximum area of influence of the new route. Models 3 and 4 present results for a similar exposure measure but using a 3 km buffer instead. The exposure measures in Models 5 and 6 were calculated using the shortest route between each OD-pair. Finally, the exposure measure employed in Models 7 and 8 is similar to that used in Table 3.2, but with an imposed speed of 25 km/h instead of 30 km/h on bicycle highways. In Models 2, 4, 6, and 8 the control and exposed groups are more similar to each other because we restrict the sample to commuting trips originating from postcodes that are part of at least one O-D pair affected by the construction of a bicycle highway. We report only the coefficients representing the DiD estimates.

The estimated effects of a new bicycle highway for the >5 km distance band are positive across all models. The point estimates are qualitatively similar to the main results presented in Table 3.2, except for Models 5 and 6, and indicate that the odds of using a bicycle for trips within this distance band are 1.4 to 2.1 times higher after the construction of a cycle highway. In Models 5 and 6, where the exposure measure is calculated using the shortest route, the estimated odds are considerably higher. This difference in effect size may be attributed to the fact that this exposure measure only identifies trips where the new bicycle highway provides a realistic alternative, given that the shortest route traverses the new infrastructure for more than five kilometres. However, the estimated standard errors are also large, and as a result, we cannot precisely identify the effect of a bicycle highway for the exposure measure based on the shortest distance.[27] In the other models, the estimates for this distance band are statistically significant at the 5% level, even in specifications where a control group is used that is more similar to the exposure groups. This finding provides further evidence to rule out the presence of unobserved trends specific to our exposure groups that might confound the estimates of the effect of a new bicycle highway. It is also noteworthy that the estimated effects for the <2.5 km distance band are smaller in magnitude and not statistically significant for the models where the exposure measure is most similar to the one used for the main results, except that a lower (more realistic) speed of 25 km/h is imposed on bicycle highways.

Our main results focus on the decision to use either a bicycle or a car for a commuting trip. One potential concern is that the observed increase in the probability of cycling is not due to an increase in the number of individuals choosing the bicycle for these trips, but rather to a decrease in the number of car drivers who have switched to other modes such as public transport. As a further test, we therefore estimate binary logistic regression models where the outcome of interest is the choice of cycling over all other modes. Table 3.4 (in Tables section) displays the results of these analyses, using similar specifications as in Table 3.3, except for Models 7 and 8 where the exposure measure based on the fastest route, is now calculated assuming a speed of 30

27. It is possible that this is due to the relatively small number of observations for this exposure measure, with only 124 trips for the >5 km distance band.

km/h on bicycle highways instead of 25 km/h. As a result, the specifications are similar to those used for our main analyses reported in Table 3.2. Comparing these results with the estimates in Tables 3.2 (for Models 7 and 8) and 3 (Models 1 to 6), we find them to be largely similar. The estimates for the >5 distance band calculated using the shortest route are smaller though and more precisely identified in Model 5.

As we explained in section 3.4, our main results focus on trips between 5 and 15 km, because bicycle highways are primarily designed to facilitate commuting over these distances. We have also checked our main results using two extended trip distance intervals of 4-16 km and 2-18 km. The results are presented in Table 3.A1 in Appendix A. The estimated effects of the completion of a bicycle highway for the >5 km distance band are always positive, but smaller in magnitude compared to the estimates presented in Table 3.2. The coefficients are statistically significant at the 5% level for the models that include the full set of controls. In the models where the control and exposed groups are more similar, the estimates are significant at the 5% and 10% level for the for the 4-16 km and 2-18 km samples, respectively. In Table 3.A2 in Appendix A, we report estimates for models similar to Table 3.4, where the distance bands are based on 2 km intervals. We find that the effects of the construction of a bicycle highway are less pronounced and not always statistically significant for the >4 km distance band, which represents trips where the longest distance can be travelled on a bicycle highway. The estimates for the other distance bands are qualitatively similar. Overall, the robustness of our estimated effects to the use of alternative exposure measures and a different outcome variable provides additional internal validity to our research design.

3.5.4. Heterogeneity in the effects of bicycle highways

The estimates that have been presented thus far have assumed that the effects of a new cycle highway are similar for all individuals. However, it is reasonable to assume that not all individuals attach the same value to the benefits of new cycling infrastructure, such as comfort, safety, and directness. To examine this possibility, we estimate logistic regressions where the exposed group is restricted to trips in the >5 km distance band only and where we include an additional interaction between the >5 km distance band x post-completion term and a given characteristic of the individual undertaking the trip. The following individual-level characteristics are considered: gender, age, and educational attainment. We also investigate whether the impact of a new route differs between individuals living in households within the high and low income groups and those in households with or without access to private vehicles. Finally, we investigate whether the impact of a new cycle highway differs between individuals in households with one or more e-bikes and individuals who do not have access to an e-bike in their household. These estimates are presented in Table 3.5.

The estimates in Model 1 indicate that after the construction of a bicycle highway, females are more likely to choose the bicycle than males. Female commuters, who were previously found to be less likely to cycle compared to males, may attach greater value to comfortable and safe routes. Nevertheless, the coefficient is only statistically significant at the 10% level. Model 2 suggests that individuals aged between 35 and 54 or 55 and older are less likely to use the bicycle highway for their daily commute than individuals aged between 18 and 34. The estimated effects in Model 3 indicate that individuals with a secondary or higher level of education have a lower probability to use the bicycle when a new route is completed. However, these odds are not found to be significantly different from those observed for individuals with only primary education. Model 4 indicates that the impact of a new bicycle highway does not vary significantly across income groups. The estimates in Model 6 suggest that individuals living in households with one or more cars have a lower probability to use the bike for commute trips compared to individuals without a car in their household. Finally, Model 7 suggests that individuals with access to an e-bike in their household are more likely to cycle to work after the construction of a bicycle highway, but the estimate is statistically indistinguishable from zero. It is important to note that the (pre-intervention) sample for this model is smaller than for the other models, as the information on e-bike ownership by household is only available from 2013.

3.6. Discussion

3.6.1. Strengths, limitations, and future research

This study represents one of the first systematic evaluations of the impact of cycle highways on the mode of travel to work. However, the validity of our results depends on three key assumptions. First, our DiD design is based on the assumption that the change in outcome between the pre- and post-intervention periods in the unexposed control group represents a good approximation for the counterfactual change in the exposed group. To assess the validity of this assumption, we have estimated several specifications in which the control group is restricted to postcodes that are part of at least one O-D pair affected by the construction of a bicycle highway, which provide a more credible counterfactual because individuals living in the same postcode are generally affected by similar local trends and shocks that might affect cycling levels. The fact that the estimated effects for these models are quite similar suggests that our results are not primarily driven by unobserved trends specific to the exposed groups.

Second, the use of repeated cross-sectional data for our DiD approach, requires the assumption of no-compositional change. In this particular case, this assumption is unlikely to be violated, as the observations are sampled from the same population over time. Indeed, there is no evidence to suggest that the observed changes over time in terms of demographic and socio-economic characteristics differ between the control and treatment groups. Third, although our approach to defining exposure represents an improvement on the more static distance-based measures used in the majority of existing evaluations, it crucially depends on the assumption that, at least in the Netherlands, the primary benefits of this type of cycling facility are increased safety, comfort and convenience of cycling. While new cycling infrastructure may also result in significant reductions in travel time or cycling distance to work, this is not explicitly accounted for with our exposure measure. This is because the bicycle network in the Netherlands is already complete, and because the bicycle highways considered in the analyses have not resulted in the removal of major physical barriers, such as large rivers or highways (i.e. by building a bridge), that would lead to substantial changes in travel time or distance to work.

While the results of this study are encouraging, it is important to acknowledge the limitations of the study. There is potential for improvement in the approach used to measure exposure, as information on the location of the origin and destination of each trip was available at the 4-digit postcode level. The use of exact locations would result in more precise exposure measurements. Furthermore, future evaluations of bicycle highways and other infrastructure of similar scale and design could also define exposure in terms of the reductions in travel time or cycling distance to work induced by this type of infrastructure. This could now even be relevant in the context of bicycle highways in the Netherlands, where recent projects have involved the removal of major physical barriers.

In this study, we have examined heterogeneity in the effects across different groups of individuals. However, the impact of cycling facilities may also vary according to their specific design and the characteristics of the route environment (e.g., land-use mix, access to destinations). As Aldred (2019) already observed, facilities developed under the same broad label are often somewhat amorphous and may represent very different route environments or designs. This is certainly the case for cycle highways in the Netherlands. Although designed to be high-quality routes reserved for fast and direct commuting and to follow specific design standards, these bikeways can have quite different physical qualities in practice (ANWB, 2019). Nevertheless, few evaluations of new cycling infrastructure have examined the role of the quality of the facility (such as pavement), exact design (such as colour, width, and/or type of separation), and/or specific location (such as left- or right-side positioning on one-way streets). Finally, future work should assess the evolution of the effects of cycle highways on cycling levels over time.

3.6.2. Practical implications of this study

The estimated marginal effects presented in our main results indicate that the probability to cycle can increase by 10% after the construction of cycle highways for trips highly exposed by these infrastructures. This shift towards cycling is slightly larger, but qualitatively similar in scale to the effects established in an earlier Dutch stated preference experiment study, which was carried out earlier, predicted that the maximum effect on the percentage of cyclists for this group would up to 9% for various selected routes (MuConsult, 2007). Another study by the same firm (MuConsult (2010), an ex-post evaluation of the first five pilot routes constructed within the earlier mentioned “Met de Fiets Minder File” program, found the effect of cycle highways on cycling probability to range between 1% and 3% for different routes. It should be noted, however, that this calculation was done for a larger target group, including people traveling more than 20 km.

Policymakers can use our results to support future cycling investments by building the case for cycle highways as facilities that will produce net benefits even in countries already well-equipped with transport infrastructure. More specifically, our findings can inform existing economic appraisal tools, such as the Health Economic Assessment Tool (HEAT)[28] and the Integrated Transport and Health Impact Model (ITHIM)[29], to monetize the health (all-cause mortality and morbidity) costs and benefits from additional exposure to physical activity, air pollution, traffic collisions, and the reduction of carbon transport emissions.

3.7 Conclusions

While cycle highways are considered promising developments due to their additional safety and comfort, they can be financially demanding, especially if their design includes robust features like tunnels or bridges. Therefore, gaining a better understanding of their success in promoting cycling is crucial for the development of future cycling programs and investments. In this context, our main goal was to assess whether the emerging network of regional cycle highways in the Netherlands has contributed to a shift in travel behaviour from driving to cycling. To achieve this, a DiD research design was employed with a binary logistic model, comparing the choice of bicycle versus car for commute trips that benefited from a new cycle highway, before and after the introduction of the new infrastructure, with a control group of trips that were not affected by the construction of a new route. As one of our main contributions, we use information on both the home and work locations of travellers to determine the degree to which they are exposed to cycle highways and test the sensitivity of our effect estimates against a variety of treatment definitions.

Overall, our results point in the same direction of other cycling studies – new and high quality infrastructure have a positive effect on travel behaviour, increasing the demand for cycling (Mölenberg et al., 2019; Xiao et al., 2022). Specifically, our effect estimates have remained stable across treatment specifications, indicating that the introduction of cycle highways has contributed to a shift in commuting behaviour toward cycling, with an increase of approximately 10% in cycling probability post-intervention for trips highly exposed to cycle highways. Covariates' effects have been found to be generally aligned with previous cycling studies.

28. HEAT is a tool used to assess the economic benefits of policies promoting physical activity through activities like walking and cycling. It helps calculate health gains and economic savings resulting from such initiatives, aiding decision-making for policymakers and health professionals.
29. The Integrated Transport Health Impact Model (ITHIM) is a mathematical model that integrates data on travel patterns, physical activity, fine particulate matter, GHG emissions, and disease and injuries based on population and travel scenarios.

It is also important to emphasize that the effects presented in this study are contingent upon on key assumptions: the change in the outcomes for the unexposed control group between the pre- and post-intervention periods approximates the counterfactual change for the exposed group; there are no significant demographic or socio-economic compositional change in the sampled population over time; and the estimated effects primarily depend on the additional comfort, safety and convenience provided by these infrastructures. Assumptions assured, our study provide policymakers with valuable insights to support future cycle highway planning and investment, demonstrating their potential benefits, even in countries with consolidated cycling networks such as the Netherlands. By integrating these results into existing economic appraisal tools, policymakers can further assess additional benefits related to physical activity, health, and emissions reduction.

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Declarations of interest

None.

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Tables

Table 3.1. Descriptive statistics for the control and the treatment group by period

	2010-2012		2013-2015		2016-2018		2019-2021		2010-2021		
	Control	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Total**
Transport mode											
Car	0.78	0.79	0.78	0.79	0.74	0.72	0.72	0.66	0.75	0.73	0.75
Bicycle	0.22	0.21	0.22	0.21	0.26	0.28	0.28	0.34	0.25	0.27	0.25
Gender											
Male	0.54	0.53	0.54	0.53	0.54	0.58	0.54	0.53	0.54	0.54	0.54
Female	0.46	0.47	0.46	0.47	0.46	0.42	0.46	0.47	0.46	0.46	0.46
Age											
18-24 years	0.08	0.06	0.07	0.08	0.08	0.05	0.08	0.06	0.08	0.06	0.08
25-34 years	0.18	0.20	0.16	0.17	0.20	0.20	0.19	0.20	0.18	0.20	0.18
35-44 years	0.26	0.29	0.24	0.21	0.19	0.20	0.20	0.21	0.22	0.22	0.22
45-54 years	0.30	0.29	0.29	0.29	0.28	0.30	0.27	0.27	0.29	0.29	0.29
55-64 years	0.17	0.14	0.20	0.22	0.21	0.21	0.21	0.22	0.20	0.20	0.20
65 or older	0.02	0.02	0.03	0.03	0.04	0.04	0.06	0.04	0.04	0.03	0.04
Background											
Dutch native	0.89	0.85	0.88	0.84	0.88	0.84	0.85	0.80	0.87	0.83	0.87
Western immigrant	0.07	0.09	0.07	0.08	0.07	0.06	0.07	0.10	0.07	0.08	0.07
Non-western immigrant	0.04	0.06	0.05	0.08	0.06	0.10	0.08	0.11	0.06	0.09	0.06

Table 3.1. (continued)

	2010-2012		2013-2015		2016-2018		2019-2021		2010-2021		
	Control	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Total**
Education level											
Primary education	0.20	0.15	0.18	0.18	0.15	0.15	0.14	0.10	0.17	0.14	0.17
Secondary education	0.44	0.36	0.45	0.38	0.43	0.35	0.41	0.35	0.43	0.36	0.42
Higher education	0.34	0.45	0.36	0.42	0.40	0.49	0.43	0.53	0.38	0.48	0.39
No or other	0.02	0.03	0.01	0.01	0.02	0.02	0.02	0.03	0.02	0.02	0.02
Income											
Lowest income group	0.27	0.29	0.27	0.25	0.20	0.19	0.17	0.17	0.23	0.22	0.22
Middle income group	0.48	0.44	0.47	0.47	0.48	0.51	0.50	0.45	0.48	0.47	0.48
Highest income group	0.24	0.27	0.26	0.28	0.31	0.30	0.33	0.38	0.29	0.32	0.29
Household composition											
Single person	0.12	0.12	0.13	0.15	0.14	0.19	0.15	0.14	0.14	0.15	0.14
Couple without child(ren)	0.28	0.23	0.28	0.32	0.29	0.26	0.29	0.32	0.29	0.29	0.29
Couple with child(ren)	0.54	0.59	0.53	0.46	0.50	0.49	0.50	0.48	0.52	0.50	0.51
Parent with child(ren)	0.05	0.05	0.05	0.07	0.06	0.04	0.05	0.05	0.05	0.05	0.05
Other composition	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Car ownership											
no car	0.02	0.04	0.02	0.03	0.04	0.06	0.05	0.05	0.04	0.05	0.04
1 car	0.46	0.48	0.47	0.52	0.45	0.50	0.43	0.49	0.45	0.50	0.45
2 or more cars	0.52	0.48	0.51	0.45	0.50	0.43	0.52	0.45	0.51	0.45	0.51

Table 3.1. (continued)

	2010-2012		2013-2015		2016-2018		2019-2021		2010-2021		
	Control	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Total**
Trip distance											
5.0 to 7.5 km	0.35	0.27	0.36	0.27	0.37	0.29	0.38	0.31	0.37	0.29	0.36
7.5 to 10.0 km	0.28	0.30	0.25	0.30	0.26	0.30	0.26	0.27	0.26	0.29	0.27
10.0 to 12.5 km	0.20	0.22	0.21	0.24	0.20	0.22	0.20	0.23	0.20	0.23	0.21
12.5 to 15.0 km	0.16	0.20	0.17	0.20	0.16	0.20	0.16	0.19	0.17	0.20	0.17
Degree of urbanization											
Extremely urbanized	0.10	0.16	0.12	0.18	0.15	0.19	0.16	0.21	0.14	0.19	0.14
Strongly urbanized	0.20	0.36	0.22	0.38	0.22	0.37	0.25	0.33	0.22	0.36	0.24
Moderately urbanized	0.18	0.24	0.18	0.24	0.20	0.26	0.20	0.25	0.19	0.25	0.20
Hardly urbanized	0.22	0.13	0.22	0.12	0.21	0.12	0.20	0.13	0.21	0.12	0.21
Not urbanized	0.29	0.10	0.26	0.08	0.21	0.06	0.19	0.08	0.24	0.08	0.22
Observations	**10,937**	**929**	**9,614**	**956**	**11,078**	**1,296**	**13,443**	**1,675**	**45,072**	**4,856**	**49,928**

Note. Results are organized by period and exposure status. Sample totals are also reported. Exposure is defined as the portion of the fastest route between each O-D pair that traverses a newly constructed bicycle highway (imposing a speed of 30 km/h on this infrastructure). The treated group refers to trips that, by 2018, would potentially traverse a new bicycle highway for some portion of the commuting route. The control group refers to trips that were not affected by the construction of a cycle highway as of 2018. Trip distance is measured by the shortest route over the cycling network. The degree of urbanization is established at the postcode of the home address.

Table 3.2. Effects of new bicycle highways on mode of travel to work (bicycle x car).

	Model 1		Model 2		Model 3	
	Odds Ratio (Z-value)	Marginal Effect	Odds Ratio (Z-value)	Odds Ratio (Z-value)	Marginal Effect	Odds Ratio (Z-value)
Potential use (ref. no traverse)						
less than 2.5 km	0.998	-0.000	0.852	-0.025	0.778*	-0.046
	(-0.018)		(-1.346)		(-1.949)	
2.5 to 5.0 km	1.248*	0.044	1.185	0.029	1.101	0.019
	(1.752)		(1.150)		(0.617)	
over 5.0 km	0.539***	-0.097	0.667**	-0.057	0.631**	-0.079
	(-3.479)		(-1.963)		(-2.131)	
Potential use * Completed						
less than 2.5 km	1.331**	0.057	1.371**	0.050	1.332*	0.051
	(2.040)		(2.147)		(1.814)	
2.5 to 5.0 km	1.036	0.007	0.971	-0.005	0.922	-0.016
	(0.217)		(-0.150)		(-0.400)	
over 5.0 km	1.726**	0.083	1.999***	0.106	1.959**	0.119
	(2.460)		(2.707)		(2.529)	
Gender (ref. Male)						
Female			0.807***	-0.034	0.835***	-0.034
			(-6.563)		(-3.201)	
Age (ref. 18-24 years)						
25-34 years			0.665***	-0.057	0.661***	-0.071
			(-5.454)		(-3.098)	
35-44 years			0.792***	-0.034	0.757**	-0.050
			(-3.193)		(-2.101)	
45-54 years			1.267***	0.040	1.262*	0.047
			(3.363)		(1.814)	
55-64 years			1.492***	0.071	1.373**	0.065
			(5.357)		(2.316)	
65 or older			0.798**	-0.033	0.653**	-0.073
			(-2.078)		(-2.230)	

Table 3.2. (continued)

	Model 1		Model 2		Model 3	
	Odds Ratio (Z-value)	**Marginal Effect**	**Odds Ratio (Z-value)**	**Odds Ratio (Z-value)**	**Marginal Effect**	**Odds Ratio (Z-value)**
Background (ref. Dutch native)						
Western immigrant			0.738***	-0.046	0.747***	-0.054
			(-4.644)		(-2.828)	
Non-western immigrant			0.396***	-0.116	0.400***	-0.141
			(-11.547)		(-7.735)	
Education level (ref. Primary)						
Secondary education			1.173***	0.022	1.264**	0.035
			(3.245)		(2.453)	
Higher education			1.980***	0.109	2.392***	0.157
			(13.586)		(9.205)	
No or other			1.242	0.030	1.484	0.062
			(1.559)		(1.623)	
Income (ref. Lowest income)						
Middle income group			1.246***	0.033	1.125	0.021
			(5.030)		(1.564)	
Highest income group			1.497***	0.064	1.351***	0.056
			(7.872)		(3.483)	
Household composition (ref. Singe Person)						
Couple without child(ren)			2.560***	0.112	2.568***	0.144
			(16.306)		(9.872)	
Couple with child(ren)			3.429***	0.163	3.052***	0.179
			(21.711)		(11.629)	
Parent with child(ren)			1.159	0.013	1.180	0.019
			(1.621)		(1.105)	
Other composition			2.449***	0.105	2.839***	0.164
			(5.216)		(3.977)	

Table 3.2. (continued)

	Model 1		Model 2		Model 3	
	Odds Ratio (Z-value)	**Marginal Effect**	**Odds Ratio (Z-value)**	**Odds Ratio (Z-value)**	**Marginal Effect**	**Odds Ratio (Z-value)**
Car ownership (ref. No car)						
1 car			0.075***	-0.542	0.067***	-0.540
			(-26.523)		(-17.975)	
2 or more cars			0.018***	-0.762	0.016***	-0.778
			(-38.165)		(-24.801)	
Constant	0.215***		2.532***		3.179***	
	(-21.282)		(6.568)		(4.815)	
Year fixed effects	Yes	No	Yes	No	Yes	No
Month fixed effects	Yes	No	Yes	No	Yes	No
Cycling distance	No	No	Yes	No	Yes	No
Degree of urbanization	No	No	Yes	Yes	Yes	Yes
Only trips originating from affected postcodes	No	No	No	No	Yes	Yes
Observations	49,928		49,928		15,710	
Pseudo R^2	0.009		0.193		0.224	
LR Chi^2	272.2		4,089.0		1,499.2	

Notes. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010-2021. All models include fixed effects for year and month. For each model, odds ratios and marginal effects are reported alongside each other. Z-values are reported in brackets and are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10%, **5%, ***1%.

Table 3.3. Effects of bicycle highways: sensitivity to different approaches to measuring exposure **(bicycle x car).**

	Projection (2km buffer)		**Projection (3km buffer)**		**Shortest route**		**Fastest route (new routes: 25 km/h)**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Potential use x Completed								
less than 2.5 km	1.154	1.194	1.234*	1.290*	1.106	1.068	1.234	1.153
	(1.242)	(1.425)	(1.673)	(1.895)	(0.715)	(0.423)	(1.447)	(0.904)
2.5 to 5.0 km	1.333*	1.330*	1.132	1.152	1.704	1.657	1.030	0.962
	(1.811)	(1.710)	(0.820)	(0.889)	(1.550)	(1.436)	(0.134)	(-0.169)
over 5.0 km	1.558**	1.573**	1.415**	1.454**	8.137*	7.466*	2.164**	2.019**
	(2.149)	(2.108)	(2.245)	(2.287)	(1.742)	(1.646)	(2.285)	(2.035)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Only trips from affected postcodes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,928	18,524	49,928	18,726	49,928	12,540	49,928	15,059
Pseudo R^2	0.194	0.216	0.194	0.216	0.193	0.225	0.193	0.223
LR Chi^2	4,073.3	1,707.0	4,077.2	1,729.1	4,070.6	1,132.7	4,077.5	1,416.5

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010-2021. The fastest route is calculated imposing a speed of 25 km/h on bicycle highways. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 2, 4, 6 and 8 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10%, **5%, ***1%.

Table 3.4. Effects of bicycle highways: sensitivity to using a different outcome variable (bicycle x all other modes).

	Projection (2km buffer)		**Projection (3km buffer)**		**Shortest route**		**Fastest route (new routes: 30 km/h)**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Potential use x Completed								
less than 2.5 km	1.100	1.118	1.182	1.212	1.071	1.004	1.283*	1.222
	(0.889)	(0.965)	(1.397)	(1.512)	(0.522)	(0.026)	(1.749)	(1.318)
2.5 to 5.0 km	1.332*	1.299*	1.110	1.112	1.423	1.322	0.995	0.917
	(1.917)	(1.678)	(0.751)	(0.723)	(1.103)	(0.852)	(-0.028)	(-0.462)
over 5.0 km	1.536**	1.509**	1.416**	1.413**	7.461*	6.847*	1.929***	1.840**
	(2.329)	(2.146)	(2.451)	(2.311)	(1.787)	(1.689)	(2.848)	(2.551)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Only trips from affected postcodes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,928	18,524	49,928	18,726	49,928	12,540	49,928	15,059
Pseudo R^2	0.194	0.216	0.194	0.216	0.193	0.225	0.193	0.223
LR Chi^2	4,073.3	1,707.0	4,077.2	1,729.1	4,070.6	1,132.7	4,077.5	1,416.5

Note. Each observation represents an unique trip. The outcome variable is bicycle mode choice versus all other modes. Data cover the period 2010-2021. The fastest route is calculated imposing a speed of 30 km/h on bicycle highways. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 2, 4, 6 and 8 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10%, **5%, ***1%.

Table 3.5. Heterogeneity in the effect of new bicycle highways.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Gender	**Age**	**Education level**	**Income group**	**Car ownership**	**E-bike ownership**
Potential use x Completed	1.573					
	(1.627)					
… x Female	1.732**					
	(1.964)					
Potential use x Completed		2.108**				
		(2.240)				
… x 35 to 54 years		0.919				
		(-0.269)				
… x over 54 years		0.863				
		(-0.397)				
Potential use x Completed			2.362*			
			(1.673)			
… x Secondary education			0.824			
			(-0.363)			
… x Higher education			0.818			
			(-0.403)			
Potential use x Completed				1.794		
				(1.314)		
… x Middle income group				1.092		
				(0.202)		
… x Highest income group				1.142		
				(0.294)		
Potential use x Completed					4.067*	

Table 3.5. (continued)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Gender	**Age**	**Education level**	**Income group**	**Car ownership**	**E-bike ownership**
					(1.700)	
... x 1 car					0.448	
					(-1.041)	
... x 2 or more cars					0.529	
					(-0.821)	
Potential use x Completed						1.348
						(1.021)
... x 1 or more e-bikes						1.477
						(1.299)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	No
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,928	49,928	49,928	49,928	49,928	38,060
Pseudo R^2	0.193	0.187	0.193	0.193	0.193	0.206
LR Chi^2	4,078.9	3,954.7	4,084.4	4,081.8	4,086.4	3,443.2

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010-2021. The exposed group is confined to trips made within the >5 km distance band. An additional interaction is included between the >5 km distance band x post-completion term and the individual characteristics of interest. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10%, **5%, ***1%.

Appendix A

Table 3.A1. Effects of bicycle highways: sensitivity to using different trip distance ranges

	Trip distance range: 4–16 km			Trip distance range: 2–18 km		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
*Potential use * Completed*						
less than 2.5 km	1.215	1.260*	1.213	1.251**	1.268**	1.198
	(1.607)	(1.757)	(1.371)	(2.243)	(2.081)	(1.505)
2.5 to 5.0 km	0.957	0.903	0.851	1.000	0.914	0.848
	(-0.287)	(-0.573)	(-0.863)	(-0.001)	(-0.528)	(-0.934)
over 5.0 km	1.493**	1.683**	1.626**	1.480**	1.606**	1.520*
	(1.971)	(2.184)	(1.976)	(2.067)	(2.131)	(1.838)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes
Only trips from affected postcodes	No	No	Yes	No	No	Yes
Observations	80,364	80,364	28,459	86,003	86,003	32,649
Pseudo R^2	0.008	0.243	0.272	0.008	0.257	0.282
LR Chi^2	420.1	8,334.7	3,282.3	449.2	9,035.4	3,751.7

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010-2021. The fastest route is calculated imposing a speed of 30 km/h on bicycle highways. All models include fixed effects for year and month and models 2, 3, 5 and 6 add a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 3 and 5 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10%, **5%, ***1%.

Table 3.A2. Effects of bicycle highways: sensitivity to using a different outcome variable (bicycle x all other modes).

	Projection (2km buffer)		**Projection (3km buffer)**		**Shortest route**		**Fastest route (new routes: 30 km/h)**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
*Potential use * Completed*								
less than 2 km	1.258*	1.301*	1.225	1.282*	1.176	1.140	1.423**	1.376*
	(1.780)	(1.916)	(1.469)	(1.699)	(1.114)	(0.825)	(2.210)	(1.870)
2 to 4 km	1.193	1.199	1.314*	1.352*	1.021	0.971	0.968	0.922
	(1.078)	(1.052)	(1.796)	(1.878)	(0.062)	(-0.086)	(-0.165)	(-0.393)
over 4 km	1.382**	1.398**	1.235	1.262	2.922*	2.825*	1.596**	1.560**
	(2.026)	(1.988)	(1.582)	(1.629)	(1.908)	(1.814)	(2.302)	(2.091)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Only trips from exposed postcodes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,928	18,524	49,928	18,726	49,928	12,540	49,928	15,710
Pseudo R^2	0.193	0.216	0.194	0.216	0.193	0.225	0.193	0.224
LR Chi^2	4,074.1	1,708.9	4,075.4	1,726.3	4,082.2	1,145.2	4,086.2	1,495.2

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010-2021. The fastest route is calculated imposing a speed of 30 km/h on bicycle highways. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 2, 4, 6 and 8 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10%, **5%, ***1%.

Chapter 4

Safe to Move? A study of built environment moderation effects on mobility-related physical activity during COVID19 movement restrictions in the Netherlands.

Abstract

This study assesses the impact of COVID-19 movement restrictions on the mobility-related physical activity of Dutch adults, focusing on leisure and transportation. Using data from 3.829 participants, we explored how various built environment characteristics, namely neighbourhood typologies, moderated short-term effects of these policies. Neighbourhood typologies were derived through unsupervised *k-means* clustering. Our findings indicate that pre-pandemic neighbourhood characteristics promoting physical activity were significantly disrupted during the pandemic, with highly urban neighbourhoods experiencing greater reductions in activity. Conversely, rural and less densely populated areas showed lesser absolute declines. This research underscores the pivotal role of neighbourhood characteristics in either mitigating or catalysing the effects of movement restrictions on active mobility. Identifying which neighbourhood typologies are most vulnerable to such measures can provide valuable insights for policymakers aimed at enhancing the resilience of physical activity in the face of health crises alike.

Keywords: Coronavirus; Lockdown; Built Environment; Physical activity; Active Mobility.

This chapter is ready to be submitted to a peer-reviewed journal.

4.1. Introduction

As an attempt to mitigate the human-to-human transmission amid COVID-19, various restrictive social distancing measures have been temporarily implemented by governments worldwide. Through those measures citizens have been urged to practice social distancing in public spaces and to avoid any crowded or unnecessary gatherings (Honey-Roses et al., 2020). The pandemic-induced social distancing measures can be regarded as a 'disruptive event' in daily mobility patterns. Such events, which are known to have both short-term effects and long-term effects, offer unique opportunities to study physical activity (PA) behaviour and the conditions under which this behaviour emerges (Marsden et al., 2020; Delbosc et al, 2022).

Although successfully decreasing infection rates, social distancing policies caused negative effects on people's PA levels (Sallis et al., 2020). Empirical studies produced in the last 3 years indicate a significant decrease in PA levels due to lockdown and quarantine measures (e.g., closure of indoor sports and recreational facilities) (Constandt et al., 2020; Lesser and Nienhuis, 2020). These policies led to negative effects on both mental and physical health of communities that suffered from physical inactivity (PI) as adverse effects of social-distancing (Lesser and Nienhuis, 2020; Sallis and Pratt, 2020; Sallis et al., 2020).

Physical activity is recognized as an important determinant of health, as it reduces the risk of obesity, type 2 diabetes, cardiovascular diseases, dementia and depression (Pedersen and Saltin, 2015; Reiner et al., 2013). Regular PA, such as walking or cycling for work (active mobility), is associated with higher life expectancy (Reimers et al., 2012) and lower costs with healthcare (de Boer et al., 2021). Accordingly, walking and cycling for transport are particular behaviours of interest for researchers and policy-makers, as they can be directly influenced by living environments (Smith et al., 2017).

Recent studies suggest that COVID-19 restrictions have affected residents' total or domain-specific physical activity unequally (De Boer et al., 2021; Schoofs et al., 2022; Yang et al., 2021), with socioeconomic status (SES) and neighbourhood characteristics significantly influencing behavioural responses to policy. Using the Dutch Lifelines Covid-19 cohort study (*n* = 17,749) to measure PA at 15 time-points between March and December 2020, De Boer et al., 2021 observed a strong socioeconomic gradient in the changed moderate to vigorous PA behaviour, with persons of low SES (e.g., low education, low income) having significantly higher odds for decreasing PA, than high SES. In another Dutch cohort study, Schoofs et al., 2022 observed that factors like unemployment, COVID-19-related occupational changes, Body Mass Index (BMI), and living in an apartment or semi-detached/terraced house were significantly related to larger decreases in total and domain-specific PA.

It is widely accepted that in pre-pandemic times certain neighbourhood characteristics could encourage or hamper mobility-related PA and health outcomes across individuals (Cervero and Kockelman, 1997; Handy et al., 2002; Cervero et al., 2009; Ewing and Cervero, 2010). As the pandemic started and movement restrictions were imposed, a small number of authors explored the role of urban green and density in encouraging movement and maintaining the health of residents during the pandemic (Gu et al., 2022; Heo et al., 2020; Lu et al., 2021; Wang et al., 2021; Yang et al., 2021; Xie et al., 2020; Li et al., 2022). For example, a study developed by Wang and colleagues (2021) in Hong-Kong showed that, during the COVID19 pandemic, residents living in low-density areas had a smaller decrease in physical activity when compared to residents living in high-density areas. Furthermore, a nationwide study conducted in the USA revealed that the racial disparities in SARS-CoV-2 infection rate were significantly smaller in counties with a higher ratio of green spaces (Lu et al., 2021). This is in line with findings of Yang et al., (2021), who found that urban green has served as refuge for the public during COVID-19 restrictions.

Despite the growing body of evidence mentioned above, little is still known about how residents in different neighbourhood types respond to social distancing policies, and if different neighbourhood qualities were able to attenuate or amplify the decline in PA during movement restrictions. The main research question of this study is: what built environments are most sensitive to policy restrictions in terms of mobility-related PA? To answer this question, we evaluate the changes in total and domain-specific mobility-related PA, focusing on leisure- and transportation-time, of Dutch adults against different degrees of movement restrictions, and identify neighbourhood typologies that were able to either attenuate or catalyse their activity levels as consequence of those restrictions in the short-term. This analysis is conducted using data from the Nijmegen Exercise Study cohort, whereby we were able to collect information of residents of the Netherlands across 8 measurement-points (one each week) from weeks 16 (pre-restrictions) to 38 (during restrictions) of 2020.

Firstly, we introduce a methodology for categorizing built environments into neighbourhood typologies based on three primary domains: i) average neighbourhood levels of physical activity and obesity, ii) availability of sports facilities, and iii) building morphology. Secondly, we examine active mobility patterns within different neighbourhood typologies concerning varying levels of social distancing policies. Lastly, we conclude our study by exploring the neighbourhood typologies and their key built environment features that exhibit moderation effects on movement during periods of social distancing policies.

4.2. Methods

4.2.1. Study area and population

The study presented in this paper was conducted in the Netherlands. It uses responses from the NES (Maessen et al., 2016), a large longitudinal study with more than 23,000 unique participants (18,500 unique postal codes) that examines the impact of PA on health, quality of life and the development and progression of chronic diseases (Schoofs et al., 2022) (Fig. 4.1). A subgroup of the study population (*n* = 9,118) who completed an annual follow-up questionnaire in 2017-2019 was invited to this additional questionnaire applied between weeks 17 and 38 of 2020 (first and last measurements, respectively). Of those previously 9,118 invited individuals, a total of 3,829 participants that completed the online questionnaire were used in this study. All methods were performed in accordance with the relevant guidelines and regulations (Declaration of Helsinki). The Local Ethics Committee on Research Involving Human Subjects (CMO) of the region Arnhem and Nijmegen approved the study and all subjects gave their informed consent before participation.

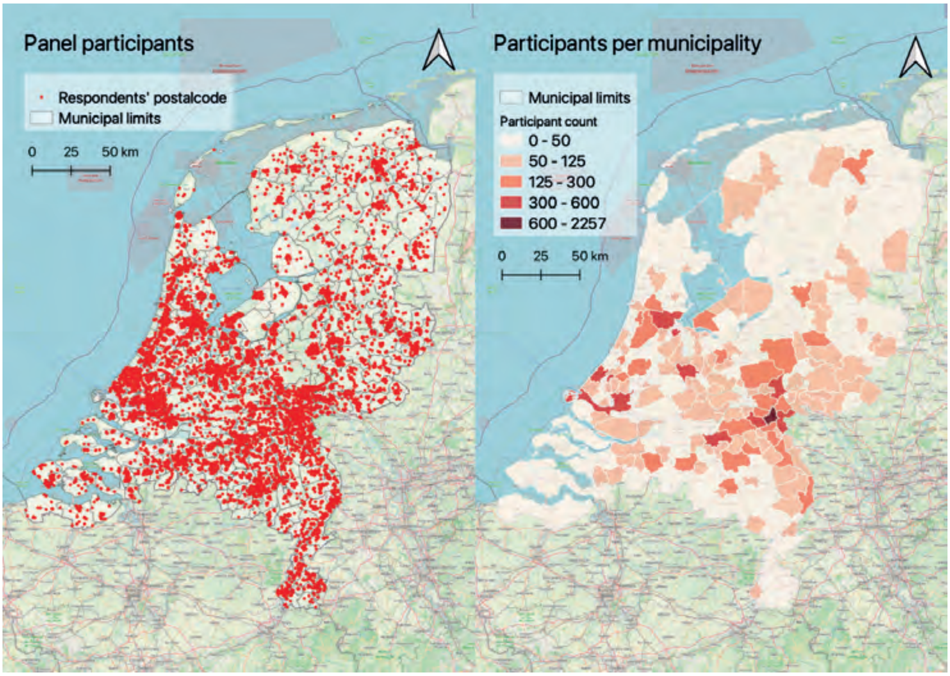

Fig. 4.1. Postcode locations of NES participants and participant count per municipality.

4.2.2. Questionnaires

During the data collection waves distributed across the first and last measurements, the participants answered identical questions about key demographic characteristics, living environment, physiological characteristics, and self-reported physical activity. Demographic characteristics included age, gender, occupation, education level, marital status. Living environment included the degree of urbanization (urban, sub-urban, rural), housing typology (detached house, semi-detached/terraced house, or apartment) and postal code (PC6) information, which enabled the calculation of several spatial indicators to compose neighbourhood typologies. Psychological characteristics included resilience, outcome expectations, vitality, and mental health.

PA differences before (week 16) and during (weeks 17 to 38) restrictive policies (e.g., lockdown) were assessed via the Short Questionnaire to Assess Health-enhancing physical activity (SQUASH) (Wendel-Vos, 2003). From that questionnaire, we selected questions addressing the number of minutes that people used to cycle and walk with the purpose of leisure and commuting (work or education) transportation before and during COVID-19: a) *"Do you cycle for leisure in your free-time?"*; b) *"How many times a week do you cycle for leisure?"*; c) *"How much time per day do you cycle for leisure?"* .

4.2.3. Spatial indicators and neighbourhood typologies

In the survey, participants reported their residential location using their six-digit postal code (PC6). Dutch postal codes represent small geographical areas with an average of 20 addresses per postal code. The locations were then overlayed with objectively measured spatial and demographic indicators of varying geographic scales and grouped in neighbourhood typologies.

Different spatial indicators were used to describe living environments around participants' postal codes and to compose neighbourhood typologies. Given the diversity of living environment factors with potential influence on active mobility and the difficulty to isolate effects of single factors, we focused on creating clusters of attributes (or typologies) by analysing participants' postal codes according to 3 key domains: i) PA activity habits and obesity levels of the population residing in the same neighbourhood of the participants; ii) the amount and proximity to sports/ exercise facilities (distance to parks and gyms, proportion of green space); iii)) the morphology of buildings within the postal code (floor area index, open space ratio, year of construction, amount of green space). Data were obtained from openly available sources and aggregated at the postal code level. Pre-pandemic evidence about the influence of neighbourhood environments on exercise and mobility shaped the delineation of domains and the choice for their respective variables (Cervero and Kockelman, 1997; Handy et al., 2002; Cervero et al., 2009; Ewing and Cervero, 2010).

PA compliance and obesity levels were readily available, at the neighbourhood level, by the National Institute for Health and Environment (RIVM) and date from 2020. Both datasets are part of the Health Monitor for Adults and the Elderly of GGD, CBS and RIVM. The former is expressed as the % of adults who do at least 150 min of moderate-intensity exercise per week; and obesity levels, as the % of adults with BMI levels above 25kg/ m2.

The distance to sports facilities and parks, and the proportion of green were obtained from both Open Street Maps (OSM) and the most recent 'Green map' (or '*Groenkaart van Nederland*') from the Dutch National Georegister. Distances were measured as the distance from the centroid of postal codes to the centroid of facilities. Green coverage was measured within 500m circular buffers around each postal code centroid as the percentage (%) of the area completely covered by agricultural (i.e. pastures) and natural areas, man-made greenery.

Building morphology data were obtained from the openly available *RUDIFUN* dataset (PBL, 2022), which provides information about spatial densities of the entire country. *RUDIFUN* express density as a multi-variable phenomenon, using measures such as *Floor Space Index (FSI)*, and *Open Space Ratio (OSR)* to correlate population density with built masses (urban form). FSI reflects the building intensity independently of the programmatic composition; OSR demonstrates the amount of open space occupying a lot, expressed as a percentage of the total floor area on the zoning lot. These indices are often used to empirically support spatial research with regard to mobility, quality of life, health, real estate values and energy, among other things (Berghauser Pont and Haupt, 2020). Building age data was obtained from the *Basis Registratie Addressen* (*BAG*), a national database about different characteristics of addresses, such as type of use, area, building age, number of addresses, etc.

Using an unsupervised K-means clustering algorithm (Hartigan and Wong, 1979), we organized the variables of each domain (Table 4.1) to create distinct typologies that enabled the estimation of attenuating and amplifying effects of policy. We used this clustering technique to maximize inter-cluster variation while minimizing intra-cluster variation. *K-means* organized postal codes into K clusters so that each observation belongs to the cluster with the nearest mean. The algorithm does so by randomly picking a set of centroids of spatial indicators, which are used as the starting point for each cluster, and then performing iterative calculations to optimize the selection of the centroids. The selection of K was defined by the 'Elbow' approach, a method that eases the selection of the optimal K. The clustering process was performed in R, using the '*cluster*' and '*factorextra*' libraries, and visually confirmed via *Google Street View*.

Table 4.1. Framework of clusters and covariates used to compose neighborhood typologies.

Cluster domain	Name	Description	Source
Building morphology	**Proxy for density: Floor Space Index**	The ratio of total floor area of a building (built-up area) to the total plot area (land).	Planbureau voor de Leefomgeving (2019); Berghauser Pont and Haupt, 2020
	Proxy for density: Open Space Ratio	The amount of open space occupying a lot, expressed as a percentage of the total floor area on the zoning lot.	Planbureau voor de Leefomgeving (2019); Berghauser Pont and Haupt, 2020
	Building age	Average building age for all buildings within a given postcode.	Basisregistraties Adressen en Gebouwen (BAG)
	Proportion of green (postcode)	Proportion of green within a given postcode.	Rijksinstituut voor Volksgezondheid en Milieu (2020)
Sports opportunities (in- and outdoors)	**Distance to nearest parks**	Straight-line distance from the centroid of a given postcode to the 'x' nearest parks.	Open Street Maps (OSM)
	Distance to nearest sport clubs	Straight-line distance from the centroid of a given postcode to the 'x' in-door sports facilities (gym, sports clubs, swimming pools, etc).	Open Street Maps (OSM)
	Proportion of green (500m)	Proportion of green within a 500 meters buffer.	Rijksinstituut voor Volksgezondheid en Milieu (2020)
Neighborhood habits	**Physical activity compliance**	The % of adults residing in each neighborhood who do at least 150 min of moderate-intensity exercise per week.	Rijksinstituut voor Volksgezondheid en Milieu (2020)
	Obesity levels	The % of adults in neighborhoods with BMI levels above 25kg/ m2.	Rijksinstituut voor Volksgezondheid en Milieu (2020)

4.2.4. Movement restrictions

Movement restrictions were operationalized though the 'Stringency Index', which was first introduced by Wenham and colleagues in 2020. This index is a composite measure scaled from 0 to 100, based on a group of response indicators that track policy responses adopted by governments to tackle COVID-19: school closures, workplace closures, cancel public events, restrictions on gatherings, public transport closures, public information campaigns, stay-at-home restrictions on internal movement, and international travel controls (Wenham et al., 2023). A higher index level indicates more restrictions. Stringency data were obtained at the "Covid-19 Government Response Tracker" website (Covid-19 Government Response Tracker, 2020) and connected to the PA questionnaire. Although reported daily, in order to match the format of latter, we averaged the stringency on a weekly basis (Fig. 4.2).

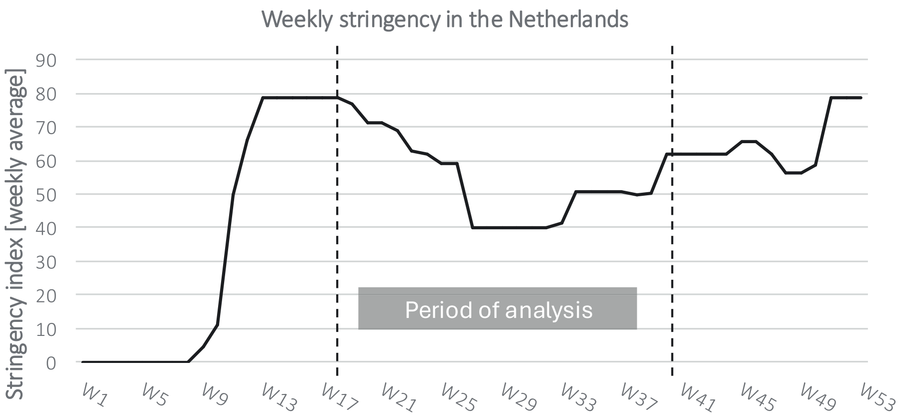

Fig. 4.2. Stringency index and PA questionnaire waves.

4.2.5. Data analysis

To examine the relationship between mobility-related PA, movement restrictions, and neighbourhood types, we began by analysing pre-pandemic associations between the BE and weekly PA using linear regression models. We then employed Fixed Effects (FE) models to analyse the data in a longitudinal design at the within-person level. This approach controls for individual characteristics that remain stable over time—such as gender or education level—but vary between individuals (Hogendorf et al., 2020). Provided there is sufficient variation in policy stringency over the study period, the FE models can assess the extent to which changes in mobility restrictions are associated with changes in leisure and transport-related PA, and whether these associations differ across neighbourhood types.

We operationalize the attenuating or amplifying effect of neighbourhood typologies on movement before and during policy restrictions using moderation analyses. In this study, moderations were useful to understand the extent to which the relationship between the COVID-related movement restrictions and PA is influenced by the third variables – in this case, living environment characteristics. In essence, a moderator is the third variable that modifies the strength or direction of the effect (Wu and Zumbo, 2008). The operationalization is conceptually compatible with the framework proposed by McLaren and Hawe (2005), which suggests that, besides its direct impact on physical activity, the built environment can act as a moderator between other determinants and physical activity (Fig. 4.3).

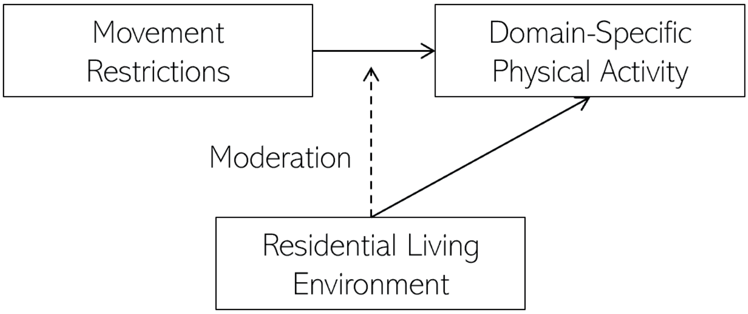

Fig. 4.3. Conceptual scheme of built environment as moderator of policy.

In our case, we consider the **Built Environment** (BE) as a moderator in the FE analysis. The model can be specified as:

$$Y_{it} = \beta_1\,(Policy_t) + \beta_2\,(BE_i) + \beta_3\,(Policy_t * BE_i) + \beta_4\,(X_i) + u_t + \propto_t + e$$

where Y_{it} is the mobility outcome observed for participant i (in minutes per week) at time period t, $Neighborhood_i$ is the indicator of participant i living in different types of built environments, and $Policy_t$ represents the different policy stringencies applied by the Dutch government. To answer our research question, for each modelled interaction, we add parameters β_1 and β_3, as we want to understand the adverse effect of policy on PA in different neighborhood typologies. X_i indicates a vector of other individual and neighborhood covariates not considered in a given interaction (namely, age, gender, housing type, urbanization levels and neighborhood typologies) and self-reported active mobility before the introduction of restrictive policies. u_t accounts for time effects that are fixed for all individuals, while $\propto_t$ controls for time invariant personal characteristics. All analyses were conducted using ***R*** and ***QGIS***. Specifically, **fixed effects models** were estimated with the '*plm*' package in R.

To facilitate the interpretation of the models developed, we present regression outputs in the form of Average Marginal Effects (*AMEs*) in minutes/week, which show how a dependent variable (e.g., leisure active mobility) changes in response to alterations in a specific independent variable, for instance, a neighborhood typology compared to a reference. Other covariates are assumed to be held constant (e.g., policy restrictions). We follow the procedure outlined by Karaca-Mandic et al. (2012) to calculate the marginal effects.

Multicollinearity between independent variables used in the presented models was also verified (see Table 4.7 in the Appendix), assuming a conditional Variance Inflation Factors (VIF) from regression outputs to be <10 (but preferably <5) (Tabachnick et al., 2001). The statistical analyses were performed using R ('*mlogit*', '*mfx*'). After constructing the models, the estimated coefficients were interpreted and compared with results of related studies.

4.3. Results

4.3.1. Study population

Table 4.2 shows basic descriptive statistics of the 3,829 participants that answered the questionnaire. In terms of age, adults aged 40 and older are predominant in the sample (90%), from which older adults (≥40 and <65 years) have a large share (50%). The majority of the participants were men (57%). Most of the participants live in areas considered 'urban' (over 42%), being followed by sub-urban (34%) and rural (23%). 3652 unique postcodes were reported by respondents, from which 57 were excluded since they had no compatible format with the Dutch PC6 format.

Table 4.2. Basic statistics of participants' characteristics.

Variables	**Mean (SD)**
Active Travel (min/ week)	
Walking for Transport	3.33 (28.64)
Cycling for Transport	26.16 (76.46)
Walking for Leisure	6.85 (53.70)
Cycling for Leisure	19.54 (75.20)
Total Active Travel for Transport	29.49 (81.97)
Total Active Travel for Leisure	26.39 (93.47)
Time Fixed Effects	
Age	**N(%)**
18-25	25 (0.65%)
25-40	356 (9.30%)
40-65	1,885 (49.23%)
65-80	1,475 (38.52%)
>80	88 (2.30%)
Gender	**N(%)**
Male	1,657 (57%)
Female	2,172 (43%)
Housing type	**N(%)**
Apartment with garden/ balcony	550 (14.39%)
Apartment without garden/ balcony	74 (1.94%)
Corner house	512 (13.40%)
Detached housed	954 (24.96%)
Semi-detached house	761 (19.91%)
Terraced house	971 (25.41%)
Degree of urbanization	**N(%)**
Urban	1,630 (42.65%)
Sub-urban	1,315 (34.41%)
Rural	877 (22.95%)
Included respondents	N = 3,829
Unique postcodes	N = 3,652 (3,595 valid-PC6)

4.3.2. Mobility-related physical activity

Overall, there was a decrease in self-reported domain-specific active mobility (minutes per week) at all measurement points from Week 17 to Week 38 of 2020 (see Table 4.3). Before the lockdown, participants reported an average of 35.6 minutes per week of school/work (transport) active mobility and 34.8 minutes per week of leisure active mobility across all residential areas. Following the start of the lockdown, a sharp decline was observed, particularly in school/work-related mobility. In Week 17, transport active mobility dropped by approximately 56% (from 35.6 min to 15.5 min), while leisure active mobility decreased by about 56% as well (from 34.8 min to 15.3 min). The larger decline in school/work mobility was likely influenced by closures of workplaces, schools, and the expansion of remote working and studying. Between Weeks 17 and 38, as restrictions gradually loosened, levels of self-reported mobility improved but did not fully return to pre-lockdown values. By Week 38, participants reported 23.2 minutes of school/work active mobility and 20.8 minutes of leisure active mobility per week, still considerably lower than pre-pandemic levels. Before the lockdown, urban residents reported higher levels of active mobility compared to rural and sub-urban residents in both domains. For instance, urban participants averaged 57.5 minutes of school/work active mobility and 40.0 minutes of leisure active mobility per week. However, they also experienced the steepest losses: by Week 17, urban transport and leisure mobility had decreased to 24.3 minutes and 21.5 minutes, representing approximately 42% and 54% of their pre-lockdown levels, respectively. In contrast, rural residents showed a smaller decline, with school/work and leisure mobility falling to around 59% and 81% of their pre-lockdown levels, respectively.

Table 4.3 . Changes in self-reported active mobility minutes per week.

	School/ work active mobility (min/ week)				Leisure active mobility (min/ week)			
Week (2020)	**Rural**	**Sub-urban**	**Urban**	**Total**	**Rural**	**Sub-urban**	**Urban**	**Total**
Pre-Lockdown	28.8	40.2	57.5	35.6	22.7	33.6	40.0	34.8
Week 17	17.1	20.7	24.3	15.5	18.5	21.1	21.5	15.3
Week 19	19.4	20.4	23.2	24.5	16.5	19.7	24.6	15.2
Week 20	19.6	26.5	29.0	27.5	17.4	24.8	29.5	17.9
Week 22	23.0	26.9	30.1	24.4	25.2	23.1	30.0	19.6
Week 24	25.2	30.3	32.7	26.4	21.8	27.7	34.8	21.1
Week 26	23.9	23.3	28.4	23.3	20.8	20.2	24.8	16.4
Week 30	23.2	23.2	27.4	24.6	24.3	19.1	27.2	23.5
Week 34	27.8	26.8	32.7	21.8	23.1	21.7	33.4	19.6
Week 38	26.3	26.5	39.8	23.2	25.4	20.4	37.6	20.8

4.3.3. Neighbourhood typologies

The K-means analysis segmented the unique 18,500 postcodes from the whole NES study into a limited number of neighbourhood typologies for each of the proposed domains: *i) physical activity and obesity, ii) sports opportunities, and iii) building morphology* (see Fig. 4.4).

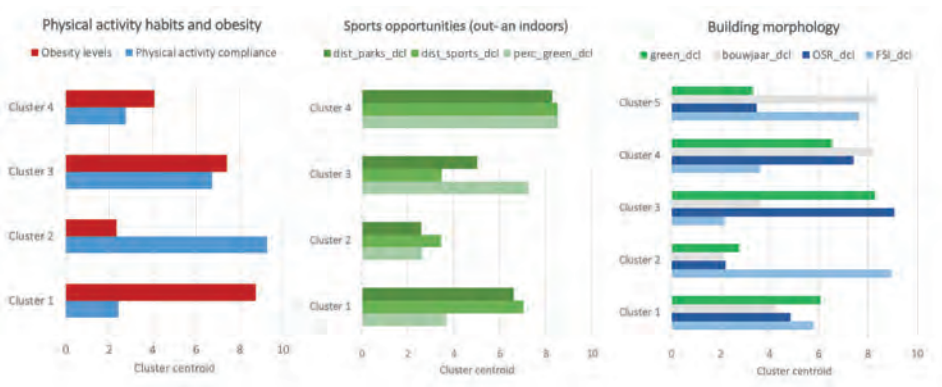

Fig. 4.4. Proposed domains and neighborhood typologies.

The first domain, Physical Activity Habits and Obesity, consists of four clusters. Cluster 1 (19.0%) includes residents with high levels of obesity and low compliance with PA, while cluster 2 (39.1%) includes residents with low obesity and high physical activity compliance. Clusters 3 (37.8%) and 4 (0.41%) consist of residents with low and high levels of both dimensions, respectively.

The dimensions that make up the second domain, Sports Opportunities, are organized into four distinct clusters. Cluster 1 (21.4%) includes postcodes located far from parks and sports facilities, with intermediate levels of green. Postcodes in cluster 2 (27.9%) are located near sports facilities and parks but are not well served by green. Cluster 3 (25.0%) consists of postcodes with intermediate levels of each dimension, while cluster 4 (25.6%) contains postcodes that are not well served by parks or sports facilities but are filled with green infrastructure.

The final domain, Building Morphology, is grouped into five distinct clusters (see examples in Fig. 4.5). Cluster 1 (23.0%) holds intermediate levels for all domains, while cluster 2 (15.7%) is composed of old and dense building blocks with low open space ratio (OSR) and high floor space index (FSI), which have very little green space in non-built areas. Clusters 3 (19.3%) and 4 (21.3%) are similar in terms of block density, but the latter consists mostly of older buildings. Cluster 5 (20.1%) is formed by dense and relatively new building blocks that have little green space.

Fig. 4.5. Typologies within 'Building Morphology' domain.

Table 4.4. Summary of typologies

Cluster	Physical Activity and Obesity	Sports Opportunities	Building Morphology
1	19.0% (3518)	21.4% (3961)	23.0% (4120)
2	39.1% (7230)	27.9% (5169)	15.7% (2809)
3	37.8% (7000)	25.0% (4631)	19.3% (3454)
4	0.04% (754)	25.6% (4741)	21.3% (3830)
5	-	-	20.1% (3728)

4.3.4. Cross-sectional analysis of pre-pandemic conditions

Linear regression models applied to pre-lockdown cross-sectional data revealed significant associations between BE characteristics and weekly totals of mobility-related physical activity, both for transport and leisure purposes (see Table 4.8 in the Appendix). Compared to rural areas, residents of urban neighbourhoods were, on average, 10 to 16 minutes more active per week for both leisure and transport before COVID-19. Within the sports opportunity clusters, Cluster 2, which is characterized by better access to parks and indoor sports facilities, was associated with 14 to 15 additional minutes of physical activity per week for both purposes, compared to the reference group. When it comes to building morphology, significant differences emerged in relation to transport-related activity. Residents of clusters with less compact and lower-density built forms reported up to 20 fewer minutes of weekly transport-related activity compared to those in the denser reference cluster (2). However, no significant differences were observed across morphology clusters in terms of leisure-related activity.

4.3.5. Effect of Policy Stringency on Mobility-Related Physical Activity

Table 4.5 shows the impact of varying levels of government stringency on domain-specific active mobility (leisure- and transport-related), measured in minutes per week, at the within-person level. We classified policy stringency into four levels: no stringency (index = 0), low stringency (>0 and <40), mid stringency (>40 and <70), and high stringency (>70). The no-stringency period, reflecting pre-restriction weeks, is used as the reference category. The results show a clear negative association between the level of government restrictions and active mobility. Compared to no-stringency periods, under low stringency, total transport-related active travel declined by 20.1 minutes per week, and leisure-related active travel by 9.8 minutes per week. Under mid stringency, transport-related active travel decreased by 16.6 minutes and leisure-related active travel by 7.0 minutes. The strongest declines were observed under high stringency, with transport-related active travel falling by 22.5 minutes per week and leisure-related active travel by 12.4 minutes per week.

Cycling, particularly for transport, experienced greater declines compared to walking. Leisure walking and cycling also saw significant but comparatively smaller reductions. Mean weekly temperature was positively associated with active travel, particularly cycling, where increases in temperature corresponded to increases of approximately 0.5 minutes per week. Although the models show relatively low R^2 values, all models are statistically significant based on their F-statistics. Beyond movement restrictions, all FE control for mean weekly temperature as a time-varying variable.

Table 4.5. Effect of restrictive policy on leisure Active Mobility.

	Total and Domain-Specific Active Travel					
Effect of COVID Policy	**Total AT for Transport**	**Total AT for Leisure**	**Cycling for Transport**	**Cycling for Leisure**	**Walking for Transport**	**Walking for Leisure**
(Ref. Cat: No Stringency(0))	**Beta**	**Beta**	**Beta**	**Beta**	**Beta**	**Beta**
	(SE)	**(SE)**	**(SE)**	**(SE)**	**(SE)**	**(SE)**
Low Stringency (>0 and <40)	-20.13***	-9.77***	-16.27***	-5.82***	-3.86***	-3.95***
	-1.85	-2.32	-1.65	-1.88	-0.83	-1.32
Mid Stringency (>40 and <70)	-16.61***	-7.00***	-13.30***	-3.54**	-3.30***	-3.46***
	-1.36	-1.7	-1.21	-1.38	-0.61	-0.97
High Stringency (>70)	-22.53***	-12.37***	-17.95***	-7.57***	-4.58***	-4.79***
	-1.14	-1.42	-1.01	-1.15	-0.51	-0.81
Mean Temperature (C)	0.51***	0.42**	0.54***	0.46***	-0.03	-0.04
	-0.16	-0.2	-0.14	-0.16	-0.07	-0.11
Observations	19,950	19,950	19,950	19,950	19,950	19,950
R^2	0.02	0.01	0.02	0.004	0.01	0.002
F Statistic (df = 4; 16128)	100.92***	21.24***	81.70***	16.22***	21.80***	9.50***

*Notes: Reference category – No stringency (0). Significant at *10%, **5%, ***1%. All models control for mean weekly temperature.*

4.3.6. Built environment moderations

In Tables 4.6, and 4.9 to 4.11 (Appendix), we examined how different degrees of policy stringency impacted leisure and transport active mobility across various neighbourhood characteristics. After adjusting for relevant time-varying and personal fixed effects, we provide a detailed summary of the findings, highlighting the moderating role of different residential living environments on active mobility after the implementation of restrictive measures. In Fig. 4.6 to 4.9, we also present a summary of all marginal effects calculated.

Table 4.6. Impact of movement restrictions under different residential BE conditions (Urbanization)

	Movement Restrictions under different Urbanization Levels:					
	Total AT for Transport	**Total AT for Leisure**	**Cycling for Transport**	**Cycling for Leisure**	**Walking for Transport**	**Walking for Leisure**
	Beta	**Beta**	**Beta**	**Beta**	**Beta**	**Beta**
	(SE)	**(SE)**	**(SE)**	**(SE)**	**(SE)**	**(SE)**
Effect of COVID Policy (Ref. Cat: No Stringency)						
Low Stringency (>0 and <40)	-9.15**	-1.98	-9.26***	-0.87	0.11	-1.11
	-3.59	-4.53	-3.22	-3.76	-1.55	-2.42
Mid Stringency (>40 and <70)	-6.37**	-3.46	-6.53***	-2.37	0.16	-1.09
	-2.53	-3.19	-2.26	-2.65	-1.09	-1.7
High Stringency (>70)	-8.74***	-4.07	-8.28***	-3.71	-0.46	-0.36
	-2.5	-3.16	-2.24	-2.63	-1.08	-1.69
Effect of interactions (Ref. Cat: No Stringency * Rural)						
*Low Stringency * Sub-urban*	-7.56*	-10.92**	-4.38	-9.67**	-3.17*	-1.25
	-4.37	-5.53	-3.92	-4.59	-1.89	-2.95
*Mid Stringency * Sub-urban*	-7.32**	-4.25	-4.37	-3.4	-2.95**	-0.85
	-3.05	-3.85	-2.73	-3.2	-1.32	-2.05
*High Stringency * Sub-urban*	-10.01***	-7.13*	-6.61**	-4.22	-3.40**	-2.92
	-3.21	-4.06	-2.88	-3.37	-1.39	-2.16
*Low Stringency * Urban*	-18.87***	-11.04**	-13.79***	-5.81	-5.08***	-5.22*
	-4.26	-5.38	-3.82	-4.47	-1.84	-2.87
*Mid Stringency * Urban*	-16.27***	-6.44*	-11.60***	-0.77	-4.67***	-5.67***
	-2.96	-3.74	-2.65	-3.11	-1.28	-1.99

Table 4.6. (continued)

	Movement Restrictions under different Urbanization Levels:					
	Total AT for Transport	**Total AT for Leisure**	**Cycling for Transport**	**Cycling for Leisure**	**Walking for Transport**	**Walking for Leisure**
	Beta	**Beta**	**Beta**	**Beta**	**Beta**	**Beta**
	(SE)	**(SE)**	**(SE)**	**(SE)**	**(SE)**	**(SE)**
*High Stringency * Urban*	-22.08***	-13.21***	-16.54***	-5.43*	-5.54***	-7.78***
	-3.14	-3.96	-2.81	-3.29	-1.36	-2.11
Mean Temperature (C)	0.48***	0.53**	0.53***	0.55***	-0.06	-0.02
	-0.16	-0.21	-0.15	-0.17	-0.07	-0.11
Observations	16,969	16,969	16,969	16,969	16,969	16,969
R^2	0.03	0.01	0.02	0.005	0.01	0.004
F Statistic (df = 10; 13750)	37.55***	8.44***	30.86***	6.42***	8.16***	5.22***

*Notes: Reference category – No stringency in Rural Areas. Significant at *10%, **5%, ***1%. All models control for mean weekly temperature.*

In high stringency periods, active mobility declined sharply across all urbanization levels, with urban areas showing the greatest reductions compared to rural areas. Specifically, under high stringency, urban residents experienced a decrease of approximately -30.8 minutes per week in total transport-related mobility, compared to -18.7 minutes for suburban residents and -8.7 minutes for rural residents. Similar trends were observed for leisure-related activities, where urban areas showed a reduction of -17.3 minutes, suburban areas -11.2 minutes, and rural areas -4.07 minutes per week.

In low stringency periods, reductions were less pronounced but still evident. Urban residents showed a decrease of approximately -28 minutes in transport mobility, compared to -16.7 minutes for suburban and -9.1 minutes for rural residents. Leisure activity followed the same pattern, with urban areas experiencing around -13 minutes, suburban areas -12.9 minutes, and rural areas -2 minutes of reduction per week. The patterns differed slightly when focusing on specific modes of active travel. In absolute terms, cycling activities were substantially more affected by restrictions than walking. Under high stringency, cycling for transport dropped by approximately -24.8 minutes per week among urban residents, compared to -14.9 minutes for suburban and -8.3 minutes for rural areas. Leisure cycling also showed notable declines, particularly in suburban and urban areas (approximately -8 minutes and -9.1 minutes respectively. Reductions in walking for transport were modest even under high stringency, reaching -6 minutes in urban areas. Walking for leisure showed slightly greater declines in urban areas (around -8 minutes) but remained less sensitive overall compared to cycling. Figure 4.6 illustrates these patterns, demonstrating that reductions in active mobility during restrictive periods were consistently steeper for residents of urban and suburban neighbourhoods compared to those living in rural areas, particularly for cycling and transport-related activities.

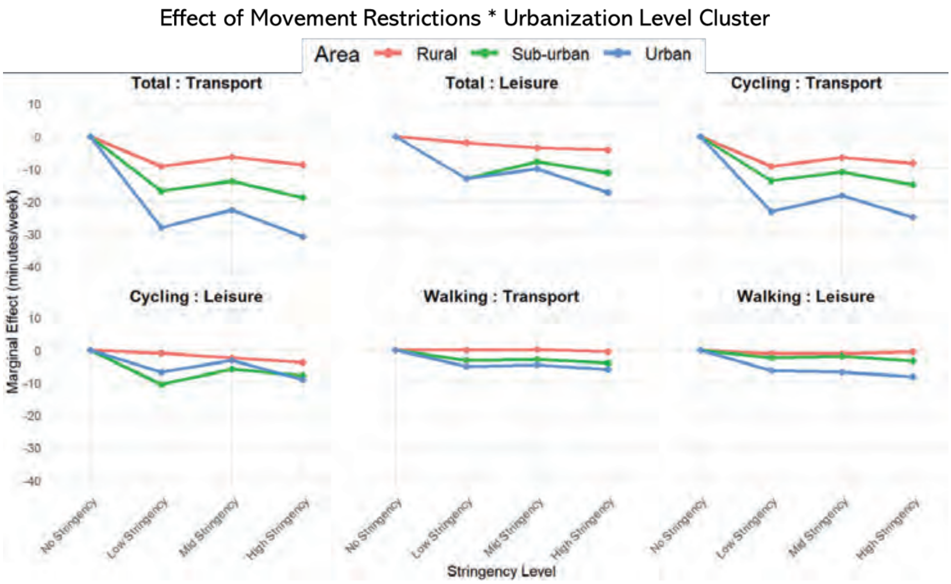

Fig. 4.6. Interaction between urbanization level and different stringency levels.

The moderation analysis also suggests significant differences among neighbourhood types in all three domains that were studied (Fig. 4.7, 4.8 and 4.9): i) neighbourhood PA and obesity, ii) sports opportunities, and iii) building morphology.

The analysis of marginal effects across PA and Obesity Clusters (Fig. 4.7) suggests that COVID-19 policy stringency was associated with substantial reductions in active mobility across all clusters, albeit with important variations. Neighbourhoods within *Cluster 2*, characterized by high pre-pandemic activity levels and low obesity rates, exhibited the most pronounced declines, particularly in transport-related activities, where losses approached -30 minutes per week under high stringency. However, notably, *Cluster 1*, composed of neighbourhoods with higher obesity prevalence and lower baseline activity, also experienced reductions of a similar magnitude, which is a concerning result. This finding highlights that mobility losses were not confined to highly active areas, but also might have affected populations already at greater risk of inactivity-related health problems, potentially deteriorating their physical health even further.

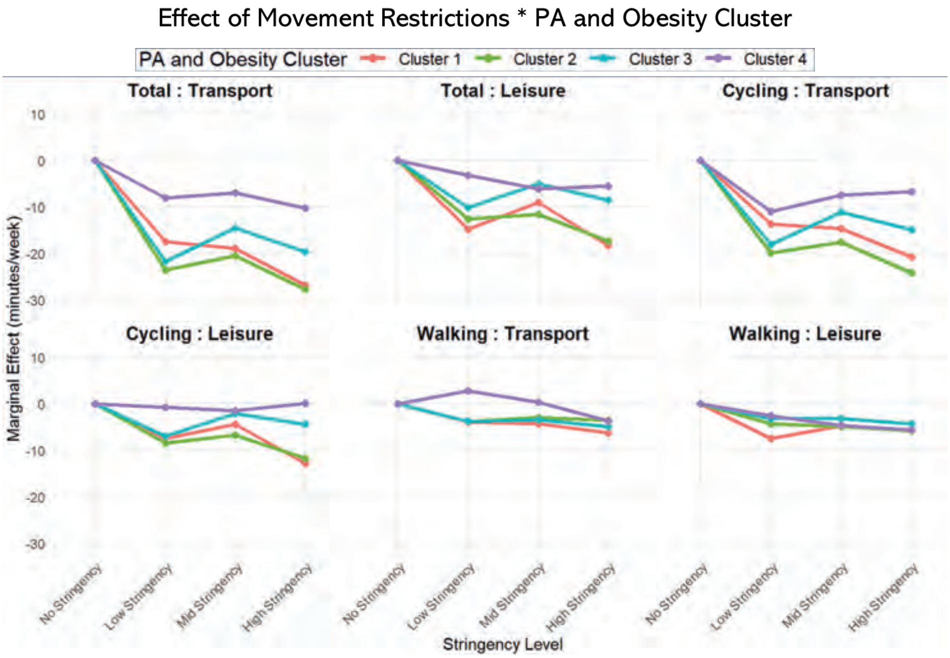

Fig. 4.7. Interaction between urbanization and different stringency levels.

Regarding the sports opportunities dimension, the marginal analysis shows that neighbourhoods in *Cluster 2*, typically characterized by better access to urban parks and indoor sports facilities, experienced the sharpest declines in active mobility during periods of high policy stringency. Specifically, reductions in Cluster 2 reached approximately -35 to -40 minutes per week for transport-related activities and about -10 to -15 minutes for leisure activities. *Cluster 3* followed a similar pattern, with substantial but somewhat smaller declines across both transport and leisure domains. These trends suggest that neighbourhoods more reliant on indoor sports opportunities were significantly affected by restrictive measures (e.g., *Cluster 2*) compared to areas surrounded by nature (e.g., *Cluster 4*). Interestingly, under movement restrictions, *Cluster 4* exhibited a distinct pattern: maintaining relatively stable leisure-related active mobility levels while showing only moderate reductions in transport-related active mobility.

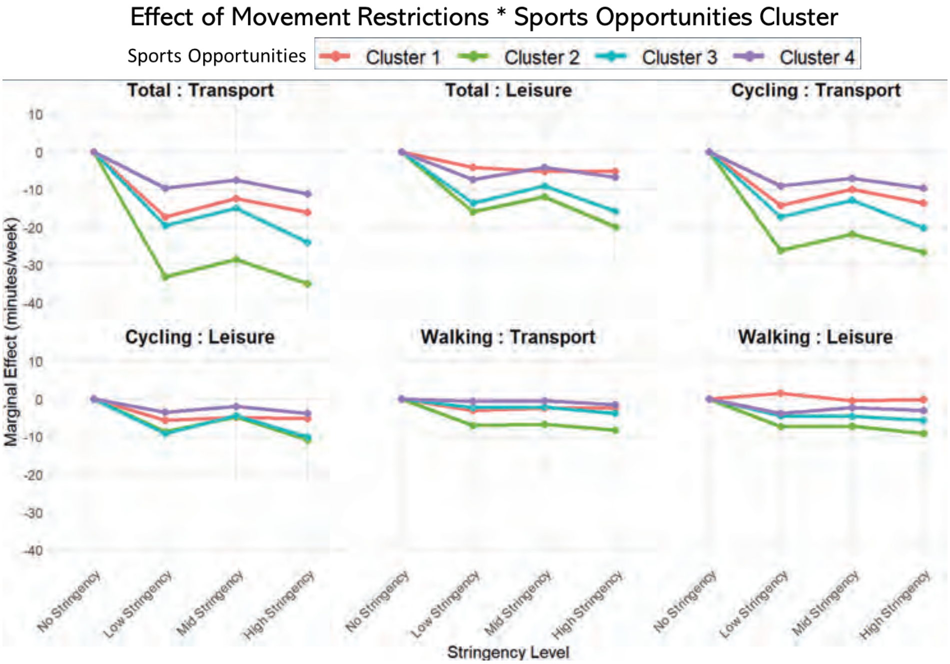

Fig. 4.8. Interaction between sports opportunities and different stringency levels.

Building morphology significantly influenced the response of neighbourhoods to varying levels of policy stringency. Clusters 1 and 2, characterized by older and mid- and high-density blocks, exhibited the largest decreases in active mobility across all categories — particularly during high stringency phases, with reductions exceeding -70 minutes per week in transport-related activities and nearly -40 minutes in leisure-related mobility. In contrast, clusters 4, and 5, which have newer building stocks and higher residential densities (as seen in the morphology profile), demonstrated smaller reductions in active mobility.

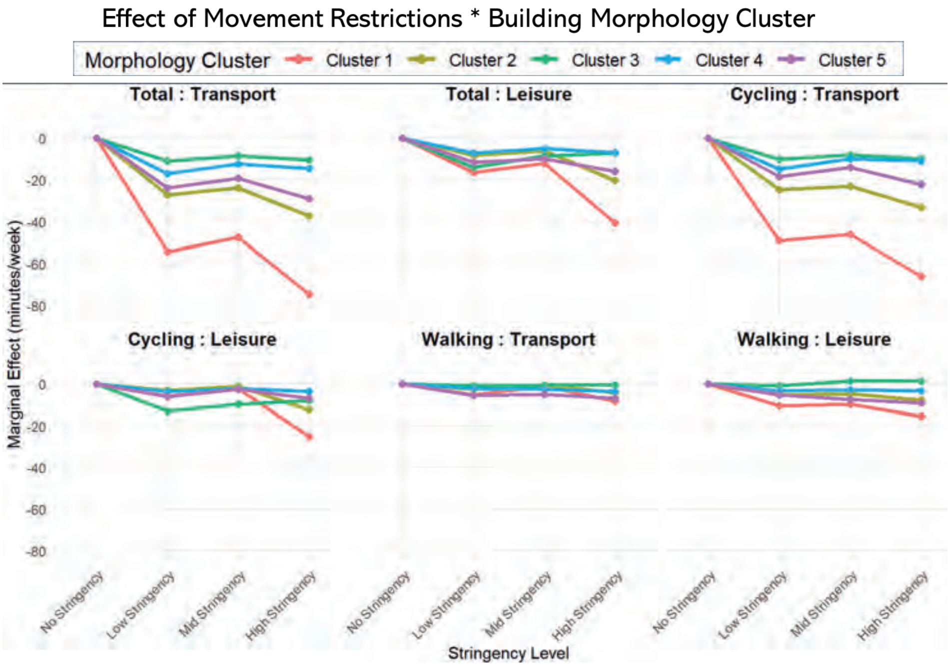

Fig. 4.9. Interaction between building morphology and different stringency levels.

4.4. Discussion

4.4.1. Main findings

Our Fixed Effects and moderation analyses yielded important findings. Firstly, regressions indicate that built environments, as represented by neighbourhood typologies, play a crucial role in moderating the effects of restrictive policies on active behaviour. They can either attenuate or amplify the spillover effects of these policies on mobility-related PA. Secondly, our research found that, during strict movement restrictions, more urbanized, dense, and accessible neighbourhoods were more likely to experience a significant decrease in leisure and transportation time compared to the latter low-density types.

The second key finding of our study may initially seem contradictory (Fig. 4.6 to 4.9) when compared to prior research on the association between built environment characteristics and physical activity (Ewing and Cervero, 2010; Handy et al., 2002; Yang et al., 2021). Previous studies have consistently pointed towards a positive relationship between living in neighbourhoods that are conducive to movement and being more physically active. Though it is important to mention that those studies have looked at BE-AT correlations in situations under no extreme event such as COVID. During lockdown, we observed that neighbourhoods deemed as conducive to active mobility also experienced a stronger reduction in the latter. This suggests that despite their positive association with active living, these neighbourhoods are also particularly sensitive to movement restrictions.

Those findings are aligned with recent studies focusing on the role of built environments during COVID-19 state of emergency (Mitra et al., 2020; Hino and Asami, 2021). In a study about healthy movement behaviours among children during COVID-19, Mitra and colleagues found that neighbourhoods with low dwelling density, those that located further from major roads and those with higher access to green were associated with increased outdoor PA. In Japan, Hino and Asami (2021), after modelling the moderating effects of BE on the association between the pandemic and PA, found that the existence of spacious outdoor open spaces (e.g., large parks) has become more important for mitigating the negative effects of COVID-19 on exercise. Population density may be associated with an increased risk of virus transmission, therefore, people living in high-density neighbourhoods may not be willing to expose themselves to a crowded neighbourhood environment to travel or exercise (Wang et al., 2021). On the other hand, low density may create a perception of greater ease to physical distance because there may be fewer people outside (Mitra et al., 2020). Residents of more urbanized neighbourhoods, although more physically active, may rely more heavily on indoor PA facilities, which were closed during lockdown.

A final important finding emerges from the analysis of the physical activity and obesity clusters. Although the cluster that exhibited the greatest decline in active travel compared to pre-COVID levels consisted of individuals who were the most physically active before the pandemic, a second cluster — characterized by high obesity levels and low physical activity standards — also showed comparable reductions in both leisure and transport-related activities. This latter result is particularly concerning, as it suggests that groups already vulnerable to negative health outcomes experienced further declines in physical activity and an increase in sedentary behaviour during the pandemic, potentially deteriorating existing health conditions.

4.4.2. Contributions and limitations

This study stands out as one of the few to shed light on the moderating effects of neighbourhood environments on within-person changes in active mobility following COVID-19 movement restrictions. A major strength of the study is the large panel dataset, which increases statistical power and enhances the reliability of the findings. Moreover, a wide range of built environment correlates was used to construct neighbourhood typologies, making the results more robust and informative. It is also noteworthy that the study explored domain-specific activity, offering a more comprehensive picture of active mobility patterns.

The use of fixed effects modelling further strengthens the analysis by controlling for individual-specific, time-invariant unobserved heterogeneity — such as baseline neighbourhood characteristics or socioeconomic status — which were assumed stable during the initial months of the pandemic. By comparing each individual to themselves over time, the design helps mitigate the influence of confounders that could not be directly observed.

Several limitations must be acknowledged. First, response bias may have affected the results, as the sample primarily consisted of physically active adults over 40 years old, potentially limiting the generalizability of the findings to the broader Dutch population. Second, reliance on self-reported data introduces the risk of recall bias (Hogendorf et al., 2020), which could reduce the precision of the estimates. A specific concern here is the retrospective reporting of pre-lockdown active mobility, which may be prone to both recall and reporting biases (Duncan et al., 2001).

Third, the geographical concentration of respondents in the eastern Netherlands and larger cities could introduce location bias, further limiting the generalizability to other regions. Fourth, although fixed effects models control for time-invariant unobserved confounders, they cannot address time-varying unobserved factors that may influence both exposure and outcome. For instance, individuals' perceived risk of infection — not measured in this study — likely varied over time and across locations, especially as COVID-19 case numbers and media coverage fluctuated. Similarly, changes in employment status during the pandemic, such as job loss or shifts to remote work, could have affected mobility needs and active travel behaviour, potentially confounding the estimated effects of policy stringency changes. Finally, this analysis focuses solely on short-term effects. Caution should therefore be exercised when extrapolating these findings to the long term, as residents' sensitivity to policy stringencies may have evolved across different phases of the pandemic.

4.4.3. Policy implications

The results of this study could offer valuable insights for urban planners and policy-makers. This study can help to better understand how residents in different neighbourhoods respond to movement restrictions in the short-term, and what the consequences of these behavioural responses are for PA levels. By connecting these findings to other relevant research conducted in the Netherlands during the same period (De Boer et al., 2021; Schoofs et al., 2022), policymakers can identify neighbourhoods that are particularly vulnerable to physical inactivity due to movement restrictions, and investigate potential long-term effects of past restrictions on physical activity levels. Furthermore, the knowledge gained from this study can be used to design future interventions aimed at increasing the resilience of neighbourhoods in case of new pandemic events. For instance, this information can be used to identify neighbourhoods that are heavily dependent on indoor sports facilities and provide them with better access to outdoor spaces for physical activity, or with more flexible public spaces to accommodate different user types in highly sensitive neighbourhoods. Overall, these strategies can help promote physical activity levels and enhance the overall well-being of communities, particularly in disadvantaged neighbourhoods that may be disproportionately impacted by movement restrictions.

4.5. Conclusions

Recent research suggests that COVID-19 restrictions have impacted on the physical activity of residents in various ways. Socioeconomic status and neighbourhood characteristics have played a significant role in influencing how people respond to these restrictive policies. Our study highlights the substantial role of built environments in moderating the effects of these policies, either mitigating or exacerbating their impact on mobility-related physical activity (walking and cycling). When strict movement restrictions were in place, densely populated, mixed, and well-connected neighbourhoods are more likely to experience a greater decline in the number of minutes spent walking or cycling compared to lower density, sprawled, and monofunctional neighbourhoods. Potential explanations for this trend are proposed. First, higher population density may deter individuals from outdoor activities due to an elevated risk of virus transmission in crowded areas, a concern mentioned by Wang et al., 2021. Second, urban residents, who are more likely to walk or cycle to their destinations, faced significant disruptions due to the closure of indoor physical activity facilities. These residents typically have more "minutes to lose" when it comes to daily exercise, relying heavily on such facilities for their physical activity, which were closed during lockdown. This analysis helps explain why those in urban settings might have experienced greater disruptions to their routine physical activities compared to those in less urbanized areas. Despite some limitations discussed in our study, it stands out as one of the few longitudinal analyses that provides valuable insights into how neighbourhood environments moderate changes in mobility-related physical activity during and after COVID-19 movement restrictions. By combining our findings with other relevant research conducted in the Netherlands during the same period (De Boer et al., 2021; Schoofs et al., 2022), policymakers can pinpoint neighbourhoods that are especially at risk of increased physical inactivity due to these restrictions. Additionally, this research opens the door to exploring potential long-term effects of past restrictions on overall physical inactivity levels.

Declaration of competing interests

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX

Table 4.7. Variance inflation factors for modelling leisure and transport active mobility (min/ week).

Variable	Leisure Active Mobility VIF	Transport Active Mobility VIF
COVID Policy	1.04	1.05
Building Morphology	2.67	2.71
Active Mobility (pre-COVID)	1.53	1.26
Mean temperature	1.03	1.04
Age	1.27	1.26
Gender	1.16	1.12
Housing type	2.22	2.19
Urbanization degree	1.84	1.95
Opportunity to sports	2.02	2.28
Physical Activity habits	1.49	1.26

Notes: For both leisure and transport active mobility models, the variables used had VIF > 1 and < 5, which suggest low to moderate multicollinearity.

Table 4.8. Linear regression models regressing mobility-related physical activity (leisure and transport) in minutes per week on different neighbourhood typologies using cross-sectional data pre-lockdown.

	Transport Total PA				Leisure Total PA			
	Sports Opportunities	**PA and Obesity**	**Building Morphology**	**Urbanization Level**	**Sports Opportunities**	**PA and Obesity**	**Building Morphology**	**Urbanization Level**
Sports Opportunities Cluster (ref. Cat: Cluster 1)								
Sports Cluster 2	14.04***				15.10***			
	(5.32)				(5.81)			
Sports Cluster 3	6.45				10.50*			
	(5.05)				(5.52)			
Sports Cluster 4	-0.63				2.87			
	(5.09)				(5.56)			
Physical Activity and Obesity Cluster (ref. Cat: Cluster 1)								
PA Cluster 2		8.23*			7.42			
		(4.86)			(5.32)			
PA Cluster 3		4.77			2.25			
		(4.88)			(5.34)			
PA Cluster 4		-17.49*			-7.28			
		(9.42)			(10.30)			

Table 4.8. (continued)

	Transport Total PA				Leisure Total PA			
	Sports Opportunities	**PA and Obesity**	**Building Morphology**	**Urbanization Level**	**Sports Opportunities**	**PA and Obesity**	**Building Morphology**	**Urbanization Level**
Building Morphology Cluster (ref. Cat: Cluster 2)								
Morphology Cluster 1			-12.23*			1.53		
			(6.52)			(7.13)		
Morphology Cluster 3			-19.71***			-1.02		
			(7.30)			(7.99)		
Morphology Cluster 4			-11.79*			-2.43		
			(6.86)			(7.50)		
Morphology Cluster 5			-1.40			4.63		
			(6.53)			(7.15)		

Table 4.8. (continued)

	Transport Total PA				Leisure Total PA			
	Sports Opportunities	**PA and Obesity**	**Building Morphology**	**Urbanization Level**	**Sports Opportunities**	**PA and Obesity**	**Building Morphology**	**Urbanization Level**
Urbanization Level Cluster (ref. Cat: Rural)								
Sub-urban				5.45				7.18
				(4.45)				(4.86)
Urban				16.13^{***}				10.38^{**}
				(4.72)				(5.16)
Observations	3,007	3,007	2,927	3,493	3,007	3,007	2,927	3,493
R^2	0.06	0.06	0.06	0.06	0.02	0.02	0.02	0.01
Adjusted R^2	0.06	0.06	0.06	0.06	0.02	0.01	0.01	0.01

Note: Models adjusted for basic demographics (age, sex and type of house). $^{*}p^{**}p^{***}p<0.01$

Table 4.9. Impact of movement restrictions under different residential BE conditions (Physical Activity and Obesity Levels)

	Movement Restrictions * Physical Activity and Obesity Cluster					
	Transport Total	**Leisure Total**	**Transport Cycling**	**Leisure Cycling**	**Transport Walking**	**Leisure Walking**
	Beta (SE)	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**
Effect of COVID Policy						
Low Stringency (>0 and <40)	−8.742*	−7.413	−6.836+	−3.721	−1.907	−3.692
	(3.935)	(4.969)	(3.524)	(4.125)	(1.703)	(2.649)
Mid Stringency (>40 and <70)	−9.443***	−4.544	−7.335**	−2.181	−2.108+	−2.363
	(2.796)	(3.530)	(2.504)	(2.931)	(1.210)	(1.882)
High Stringency (>70)	−13.447***	−9.154**	−10.353***	−6.384*	−3.094*	−2.770
	(2.803)	(3.539)	(2.510)	(2.938)	(1.213)	(1.887)
Effect of interactions (Ref. Cat: No Stringency * Rural)						
*Low Stringency * PA Cluster 2*	−11.039***	−7.003+	−10.206***	−4.505	−0.833	−2.499
	(3.225)	(4.072)	(2.889)	(3.381)	(1.396)	(2.172)
*Mid Stringency * Cluster 2*	−14.805**	−5.200	−13.021**	−4.612	−1.783	−0.588
	(4.612)	(5.824)	(4.131)	(4.835)	(1.996)	(3.105)
*High Stringency * Cluster 2*	−14.265***	−8.148+	−13.850***	−5.247	−0.415	−2.901
	(3.399)	(4.292)	(3.044)	(3.563)	(1.471)	(2.289)
*Low Stringency * Cluster 3*	−13.035**	−2.738	−11.208**	−3.249	−1.827	0.511
	(4.596)	(5.803)	(4.116)	(4.818)	(1.989)	(3.094)
*Mid Stringency * Cluster 3*	−5.075	−0.530	−3.809	0.204	−1.266	−0.734
	(3.234)	(4.084)	(2.897)	(3.391)	(1.400)	(2.178)
*High Stringency * Cluster 3*	−6.260+	0.577	−4.511	2.032	−1.749	−1.455
	(3.422)	(4.321)	(3.065)	(3.588)	(1.481)	(2.304)

Table 4.9. (continued)

	Movement Restrictions * Physical Activity and Obesity Cluster					
	Transport Total	**Leisure Total**	**Transport Cycling**	**Leisure Cycling**	**Transport Walking**	**Leisure Walking**
	Beta (SE)	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**
*Low Stringency * Cluster 4*	0.627	4.227	−4.150	3.047	4.777	1.180
	(9.232)	(11.657)	(8.268)	(9.678)	(3.995)	(6.216)
*Mid Stringency * Cluster 4*	2.500	−1.510	−0.063	0.758	2.563	−2.268
	(6.254)	(7.897)	(5.602)	(6.557)	(2.707)	(4.211)
*High Stringency * Cluster 4*	3.153	3.683	3.677	6.509	−0.524	−2.826
	(6.714)	(8.477)	(6.013)	(7.038)	(2.905)	(4.520)
Mean Temperature (C)	0.477**	0.526*	0.533***	0.548**	−0.057	−0.022
	(0.165)	(0.208)	(0.147)	(0.173)	(0.071)	(0.111)
Observations	16969	16969	16969	16969	16969	16969
R2	0.025	0.006	0.022	0.005	0.005	0.003

*Notes: Reference category – No stringency (0). Significant at: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.*

Table 4.10. Impact of movement restrictions under different residential BE conditions (Sports Opportunities Cluster)

	Movement Restrictions * Sports Opportunities Cluster					
	Transport Total	**Leisure Total**	**Transport Cycling**	**Leisure Cycling**	**Transport Walking**	**Leisure Walking**
	Beta (SE)	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**
Effect of COVID Policy						
Low Stringency (>0 and <40)	−17.372***	−4.119	−14.297***	−5.649	−3.075+	1.531
	(3.722)	(4.704)	(3.337)	(3.907)	(1.611)	(2.508)
Mid Stringency (>40 and <70)	−12.424***	−5.328	−10.047***	−4.845+	−2.377*	−0.483
	(2.632)	(3.327)	(2.360)	(2.763)	(1.139)	(1.773)
High Stringency (>70)	−16.102***	−5.249	−13.636***	−5.122+	−2.466*	−0.127
	(2.613)	(3.303)	(2.343)	(2.744)	(1.132)	(1.761)
Effect of interactions (Ref. Cat: No Stringency * Rural)						
*Low Stringency * Sports Cluster 2*	−15.780**	−11.869+	−11.800**	−3.031	−3.979+	−8.838**
	(4.865)	(6.149)	(4.362)	(5.107)	(2.106)	(3.278)
*Mid Stringency * Sports Cluster 2*	−16.185***	−6.684	−11.878***	0.038	−4.307**	−6.722**
	(3.405)	(4.305)	(3.053)	(3.575)	(1.474)	(2.295)
*High Stringency * Sports Cluster 2*	−18.864***	−14.698**	−13.044***	−5.664	−5.820***	−9.034***
	(3.602)	(4.553)	(3.229)	(3.781)	(1.560)	(2.427)
*Low Stringency * Sports Cluster 3*	−2.159	−9.536	−2.945	−3.525	0.786	−6.011+
	(4.730)	(5.979)	(4.241)	(4.966)	(2.048)	(3.188)
*Mid Stringency * Sports Cluster 3*	−2.659	−3.685	−2.862	0.478	0.203	−4.163+
	(3.315)	(4.190)	(2.972)	(3.480)	(1.435)	(2.234)
*High Stringency * Sports Cluster 3*	−7.907*	−10.503*	−6.571*	−4.934	−1.336	−5.569*
	(3.498)	(4.422)	(3.137)	(3.673)	(1.515)	(2.357)

Table 4.10. (continued)

	Movement Restrictions * Sports Opportunities Cluster					
	Transport Total	**Leisure Total**	**Transport Cycling**	**Leisure Cycling**	**Transport Walking**	**Leisure Walking**
	Beta (SE)	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**
*Low Stringency * Sports Cluster 4*	7.671	−3.229	5.171	2.147	2.499	−5.376+
	(4.733)	(5.982)	(4.243)	(4.968)	(2.049)	(3.189)
*Mid Stringency * Sports Cluster 4*	4.850	1.095	2.909	2.915	1.941	−1.820
	(3.291)	(4.160)	(2.951)	(3.455)	(1.425)	(2.218)
*High Stringency * Sports Cluster 4*	4.952	−1.596	3.991	1.297	0.961	−2.893
	(3.472)	(4.389)	(3.113)	(3.645)	(1.503)	(2.340)
Mean Temperature (C)	0.480**	0.530*	0.535***	0.551**	−0.056	−0.022
	(0.164)	(0.208)	(0.147)	(0.173)	(0.071)	(0.111)
Observations	16,969	16,969	16,969	16,969	16,969	16,969
R^2	0.027	0.006	0.022	0.005	0.007	0.004

*Notes: Reference category – No stringency (0). Significant at: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.00*

Table 4.11. Impact of movement restrictions under different residential BE conditions (Building Morphology Cluster)

	Movement Restrictions * *Building Morphology* Cluster					
	Transport Total	**Leisure Total**	**Transport Cycling**	**Leisure Cycling**	**Transport Walking**	**Leisure Walking**
	Beta (SE)	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**	**Beta (SE)**
Effect of COVID Policy						
High Stringency (>70)	−37.272***	−20.224***	−33.092***	−12.492***	−4.180**	−7.732**
	(3.523)	(4.451)	(3.157)	(3.696)	(1.525)	(2.372)
Low Stringency (>0 and <40)	−27.164***	−8.227	−24.590***	−2.939	−2.574	−5.288
	(5.017)	(6.339)	(4.495)	(5.263)	(2.172)	(3.378)
Mid Stringency (>40 and <70)	−23.677***	−5.976	−23.059***	−1.171	−0.618	−4.805*
	(3.517)	(4.444)	(3.152)	(3.690)	(1.523)	(2.369)
Effect of interactions (Ref. Cat: No Stringency * Rural)						
*High Stringency * Morphology Cluster 1*	13.982**	5.859	14.500***	3.746	−0.517	2.113
	(4.314)	(5.450)	(3.865)	(4.525)	(1.867)	(2.905)
*Low Stringency * Morphology Cluster 1*	4.976	−2.932	6.635	−3.817	−1.660	0.885
	(5.903)	(7.459)	(5.290)	(6.193)	(2.556)	(3.976)
*Mid Stringency * Morphology Cluster 1*	5.396	−2.310	8.971*	−1.944	−3.575*	−0.366
	(4.135)	(5.225)	(3.705)	(4.338)	(1.790)	(2.785)
*High Stringency * Morphology Cluster 3*	26.839***	13.298*	23.183***	4.368	3.655+	8.931**
	(4.427)	(5.594)	(3.967)	(4.644)	(1.917)	(2.981)
*Low Stringency * Morphology Cluster 3*	16.254**	−5.597	14.442**	−10.056	1.812	4.458
	(6.131)	(7.747)	(5.494)	(6.432)	(2.654)	(4.129)
*Mid Stringency * Morphology Cluster 3*	15.367***	−2.487	15.211***	−8.527+	0.156	6.040*
	(4.258)	(5.381)	(3.816)	(4.467)	(1.844)	(2.868)
*High Stringency * Morphology Cluster 4*	22.753***	13.349*	22.120***	8.867*	0.634	4.481

Table 4.11. (continued)

	Movement Restrictions * *Building Morphology* Cluster					
	Transport Total	Leisure Total	Transport Cycling	Leisure Cycling	Transport Walking	Leisure Walking
	Beta (SE)	Beta (SE)	Beta (SE)	Beta (SE)	Beta (SE)	Beta (SE)
	(4.290)	(5.420)	(3.844)	(4.500)	(1.857)	(2.889)
*Low Stringency * Morphology Cluster 4*	10.215+	1.137	9.762+	−0.806	0.453	1.942
	(5.911)	(7.469)	(5.297)	(6.201)	(2.559)	(3.981)
*Mid Stringency * Morphology Cluster 4*	11.342**	1.039	13.182***	−1.013	−1.841	2.052
	(4.115)	(5.200)	(3.688)	(4.317)	(1.782)	(2.772)
*High Stringency * Morphology Cluster 5*	8.249+	4.352	10.927**	5.607	−2.678	−1.255
	(4.441)	(5.611)	(3.979)	(4.659)	(1.923)	(2.991)
*Low Stringency * Morphology Cluster 5*	3.285	−3.240	6.311	−3.238	−3.026	−0.002
	(6.084)	(7.688)	(5.452)	(6.383)	(2.634)	(4.097)
*Mid Stringency * Morphology Cluster 5*	4.555	−3.882	9.048*	−1.298	−4.492*	−2.583
	(4.245)	(5.364)	(3.804)	(4.454)	(1.838)	(2.859)
Mean Temperature (C)	0.478**	0.528*	0.534***	0.551**	−0.057	−0.023
	(0.164)	(0.208)	(0.147)	(0.173)	(0.071)	(0.111)
Observations	16,969	16,969	16,969	16,969	16,969	16,969
R2	0.027	0.006	0.023	0.005	0.006	0.004

*Notes: Reference category – No stringency (0). Significant at: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.*

Chapter 5

Short-term changes in daily mobility after residential move: A longitudinal analysis

Abstract

Reducing car dependency and promoting active travel are key objectives for urban planners and policymakers. While land-use policies that enhance accessibility are expected to foster sustainable travel modes, the understanding of causal relationship between built environment (BE) changes, travel behaviour, and travel attitudes remains limited, particularly when considering events such as self-selection and reverse causality. This study examines how residential relocation, a major life event disrupting mobility routines, influences daily cycling, car use, and travel preferences in the Netherlands. Using four waves (2013–2016) of the Netherlands Mobility Panel (MPN), we analyse nearly 1000 relocated individuals through Random-Intercept Cross-Lagged Panel Models (RI-CLPM) to capture the dynamic interrelations between BE change, mode use, and preferences while accounting for life events and sociodemographic factors. Built environment changes are measured through shifts in density, proximity to daily amenities, and land-use mix after relocation. Results suggest that moving to denser, more accessible neighbourhoods encourages cycling and reduces car use and car preference, whereas relocation to less accessible areas increase car reliance. No evidence is found that pre-relocation preferences significantly influence built environment change. Important life events, particularly childbirth, can also shape mobility patterns post-relocation. These insights highlight the importance of land-use policies that promote compact and accessible urban developments as effective interventions for encouraging sustainable travel behaviours. This can be particularly relevant to the Dutch context, where the development of new neighbourhoods has become a national priority in the last decade.

Keywords: built environment, travel behaviour, travel preferences, residential relocation, causal inference, active mobility.

This chapter is currently under review at Transportation.

5.1. Introduction

Reducing car dependency and promoting active, multimodal travel behaviour are key priorities for policymakers and planners worldwide. Achieving these goals requires land-use policies and infrastructure investments that enhance accessibility, providing individuals with more opportunities to adopt sustainable travel modes (Ewing and Cervero, 2010; van de Coevering et al., 2021; Litman, 2023). A core assumption in urban planning is that people are more likely to choose sustainable transport when they live in dense, mixed-use environments with well-developed infrastructure for walking, cycling, and public transit (Ewing and Cervero, 2010; Aldred, 2019). These environments shorten the distance between origins and destinations, bringing travellers closer to desired amenities and, in turn, fostering active travel and increasing physical activity (Xiao et al., 2022).

The rationale for such policy interventions usually rests on assumed causal relationships between the built environment and travel behaviour (Graham, 2025). Although there is growing interest in understanding the causal effects of land-use policies on travel demand, studying these effects presents unique challenges. Land-use changes tend to occur gradually and are often difficult to observe or measure due to limited longitudinal data (Scheiner et al., 2024). Though there are interesting exceptions—sudden shifts in land use can sometimes be captured and analysed through intervention studies. Disruptive events, in particular, are important because they create moments when established routines are re-evaluated, and mobility choices are more likely to change (Verplanken et al., 2008).

One key example is residential relocation. Relocation offers a valuable opportunity to study travel behaviour changes, as individuals consciously reassess their mobility options when exposed to a new environment that may support (or not) different modes of transportation (Verplanken et al., 2008; Tao, 2023a). While passive 'changes in the built environment (BE) typically occur too slowly for clear longitudinal study, relocation represents an immediate and measurable shift. It is a critical event for changes in mode choice and use (Schimohr et al., 2025), as movers experience sudden changes in their accessibility levels, allowing researchers to observe how travel behaviour and attitudes adjust. This study focuses on relocation as a key trigger for behavioural and attitudinal change.

There is, however, limited longitudinal evidence on the causal relationship between BE, travel behaviour and travel-related attitudes of movers, with considerations to two important phenomena – self-selection and reverse causality (e.g., Tao, 2024; Tao et al., 2023; De Vos et al., 2018). Because of this, it is under investigated whether attitudes change over time after relocation (reverse causality), to what extent travel attitudes are endogenous to the relationships between BE and travel behaviours (self-selection), and to what extent mode use is affected by changes in built environment as a major life event while taking both self-selection and reverse causality into account in the same framework.

Our study, set in the Netherlands, aims to add to the small body of work focusing on the implications of changes in mode use and preferences after relocation using panel data (Schimohr et al., 2025). We therefore address the following 2 research questions:

1. How does a change in urban density and proximity to daily amenities through residential relocation influence daily cycling, car use, and travel preferences in the short-term after relocation?
2. To what extent do pre-relocation travel preferences affect changes in accessibility levels during relocation?

To explore these questions, we use data from four waves of the Netherlands Mobility Panel (MPN) to assess the implications of built environment change among 996 relocated residents. These changes are measured through urban density and proximity to daily amenities, while also accounting for pre-relocation travel preferences. We regard relocation as a major life event that disrupts people's routines and that involves high transaction costs, affecting travel behaviour and attitudes (Scheiner et al., 2024). To explicitly model causal relationships and their directionality, we employ Random-Intercept Cross-Lagged Panel Models (RI-CLPM), which are estimated using the three aforementioned MPN waves.

In the remainder of the paper, findings from previous studies are discussed first, followed by a description of the applied methods and data and the results of the analyses.

5.2. Literature Review

5.2.1. Mode use, mode preferences and built environment change

There is a prevailing view —if not a consensus—that the built environment plays a deterministic role in shaping travel behaviour (Naess, 2015). While this may hold true to some extent, this relationship has been increasingly questioned over the past two decades with discussions about self-selection. Notable scholars argue for a more nuanced approach to causal structures, emphasizing the influence of demographics and personal preferences (self-selection) (e.g., Cao et al., 2009; van de Coevering et al., 2018), as well as the need to understand the context and mechanisms through which the built environment affects travel behaviour (Panter et al., 2019). In this view, the built environment is not the sole determinant of travel behaviour. People's attitudes toward transport modes and their residential preferences also play a significant role, often leading them to choose living environments that reinforce their pre-existing preferences. In this context, self-selection becomes a major challenge for planners (Cao and Chatman, 2016; Kroesen and Chorus, 2018). Ignoring self-selection in policy design and transport research can result in biased estimates of intervention impacts. If changes in travel behaviour are partly driven by individuals' pre-existing preferences rather than by the built environment itself, the independent effect of built environment interventions is likely to be either under- or overestimated (van Wee and Cao, 2022).

Fruitful discussions have emerged to explore this topic (Tao, 2024; Olde Kalter et al., 2021; De Vos et al., 2018), with the proposition of multiple causal structures rather than a single best framework (Van Wee and Cao, 2020). Tao (2024) suggests that these discussions have led to three main arguments regarding the causal relationship between the built environment and travel behaviour: residential determinism, residential self-selection, and reverse causality (Tao, 2024). The first one - residential determinism - asserts that the residential built environment independently influences residents' travel mode choices (Lin et al., 2017). For instance, relocating from a city centre to a suburban neighbourhood—where daily destinations such as shops and leisure activities are farther away—may increase car use due to the reduced practicality of walking or cycling.

In contrast, the residential self-selection argument suggests that socioeconomic characteristics and pre-existing preferences shape daily mobility choices (Cao et al., 2009). For example, those who value walking or cycling may be more likely to move to dense, mixed-use neighbourhoods with good infrastructure for active travel. This selective sorting complicates the analysis of causal relationships between the built environment and travel behaviour, as observed behaviours may reflect individual preferences rather than the effects of the environment itself. The third argument, reverse causality, relates to the dynamic nature of travel attitudes, which can either adapt to a new situational context (e.g., following residential relocation) or persist despite environmental changes. An example of the latter occurs when a built environment restricts or discourages the use of certain travel modes—such as a neighbourhood lacking cycling infrastructure—leading residents to adjust their preferences to align with their available travel options (De Vos et al., 2018). In the case of residential relocation, a new environment may not only encourage the use of certain travel modes but also foster a preference for them (Tao et al., 2023).

Changes in travel attitudes and mode use are empirically understudied due the difficulty to collect information on both travel attitudes and behaviour at pre- and post-relocation moments. Some longitudinal studies have looked at the bidirectional relationships between mode use and preferences of residents (e.g., Olde Kalter et al., 2021), with results supporting the argument that attitudes may change over time, however less longitudinally investigated is how people adjust their attitudes and behaviour in an unstable context, for example, after moving house, with just a few examples out there (e.g., Tao, 2024; Tao et al., 2023; De Vos et al., 2018).

Besides relocation, the influence of other life events, such as the birth of a child, or becoming employed, is also another important perspective in relocation studies, since they can trigger changes in travel behaviour and attitudes (e.g., Schimohr et al., 2025; Olde Kalter et al., 2021). These life events often lead to an imbalance between people's preferences and existing resources (Tao, 2024), which stimulate relocation decision-making. For instance, residents may develop a preference for more accessibility to public transit after finding a new job, or look for neighbourhoods that offer easy parking opportunities after a having a child, and subsequently buying a car. As suggested by Panter et al. (2019) and Scheiner et al. (2024), travel behaviour changes after an intervention (in this case, relocation) should be understood considering individual contexts (e.g., characteristics and life events that might be intertwined with relocation decisions). To this end, a structural causal approach is required to investigate how life events affect relocation decisions, travel behaviour and preferences.

5.3. Data and methods

5.3.1. Sample selection

For our analysis, we use four waves (2013, 2014, 2015, 2016) from the Netherlands Mobility Panel (MPN). The MPN is an annual household panel that started in 2013 and consists of approximately 2,000 complete households and 6.000 individuals aged 12 and older. The MPN was set up with the goal to study the short-run and long-run dynamics in travel behaviour of Dutch individuals and households and to assess how changes in personal- and household characteristics correlate with changes in travel behaviour. Respondents, which are randomly selected and recruited nationwide, are asked about their mobility-related (e.g., mode use and preferences) and household-related characteristics through online questionnaires. Respondents are also asked about important life events (e.g., changing jobs, childbirth, residential relocation). All respondents have postcode (PC6) information attached, which enables for the calculation of built environment indicators. This unique combination of information allows us to longitudinally examine the relationship between travel behaviour, preferences, built environment change and life events. A more detailed description of the MPN can be found in Hoogendoorn-Lanser et al. (2015).

The total MPN sample for the 2013 – 2016 period consists of 12,348 respondents (see Fig. 5.1). From this group, we selected only respondents that relocated, and that provide valid answers on their travel behaviour and mode preferences for at least two consecutive waves. Our final sample comprised of 996 respondents. Including only participants who responded to at least 2 consecutive waves might lead to attrition bias. To examine the non-random dropout of the respondents between survey waves, we compared the mode use and preferences of the studied respondents (2-consecutive wave relocated; N = 996), with those of the MPN (N = 12,348), respondents for the same time period. After a qualitative inspection, we did not find significant differences between those two groups. This suggests no major attribution biases in our sample (analysis not shown in this study).

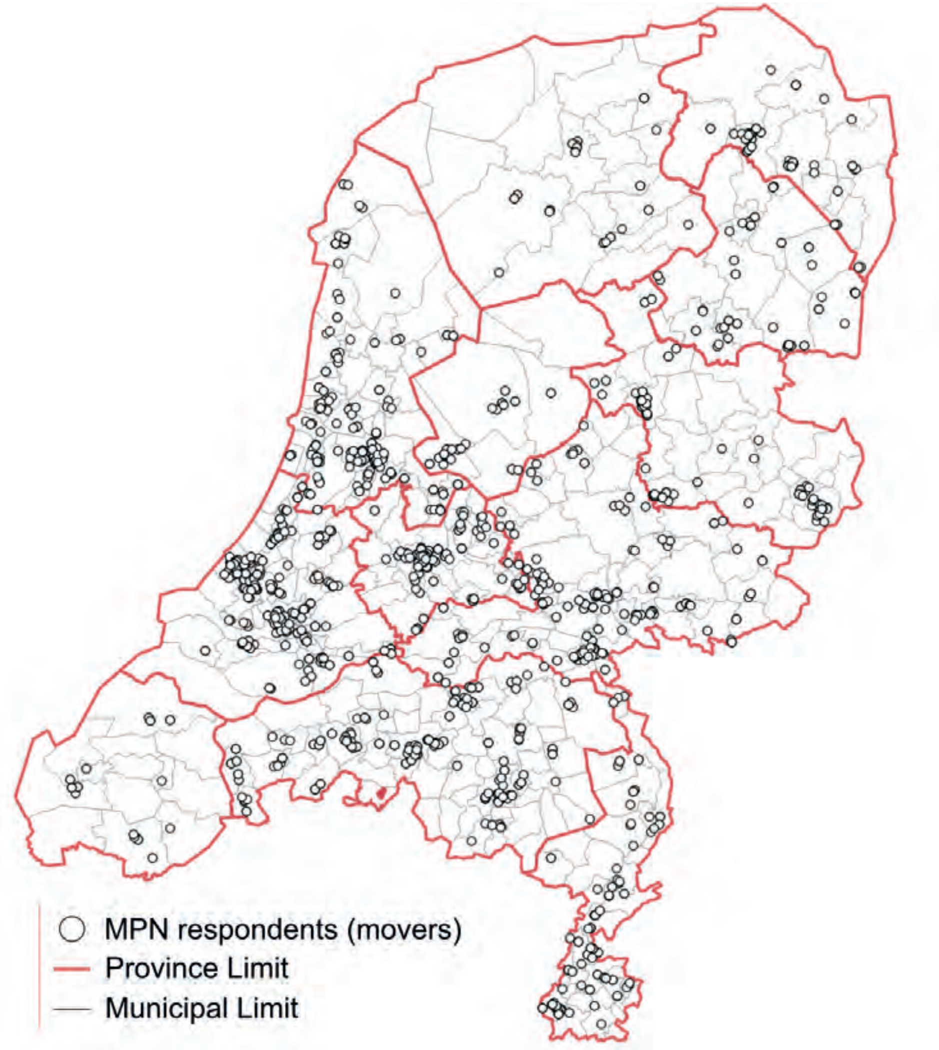

Fig. 5.1. Postcode locations of MPN respondents that moved between 2013 and 2016 within the Netherlands.

5.3.2. Variables

We divide the variables in 3 subsets, which include travel behaviours and attitudes, residential built environment and exogenous variables (socioeconomics and life events). These variables of interest are introduced in Table 5.1 and explained in detail below.

Table 5.1 . Description of used variables.

Table 5.1 . (continued)

Variable	Description	Type	Source
Behaviour and preferences			
Mode use	Frequency of mode use for all-purpose daily travel.	Ordinal (6-scale score)[30]	Netherlands Mobility Panel (MPN)
Mode-specific preference	Score from 0-1 representing respondents' mode preference for all-purpose daily travel.	Continuous (0-1 score)	MPN
Built Environment			
Address Density (add./ km2)	Number of addresses per square kilometre, showing the concentration of diverse human activities (residential, working, going to school, shopping, going out).	Continuous	Derived from the Dutch Central Bureau of Statistics (CBS)[31]
Proximity to daily amenities (km)	The average distance from residential locations to the nearest daily amenities (supermarkets, daily shops, cafes, restaurants, intercity train stations, hospitals and pharmacies) before and after relocation.	Continuous	Derived from CBS
Number of amenities within 15min reach	Count of key daily amenities within 15min in-network reach from respondents' residential locations by bicycle and by car.	Continuous	Derived from Overture Maps Foundation[32]
Land-use mix Index (MXI)	Gross floor area dedicated to residential use divided by the total floor area in a region. The higher the MXI, the less diverse is the location.	Continuous	Derived from RUDIFUN[33]

30. 1 (almost never or never); 2 (1 to 5 days per year); 3 (6 to 11 days per year); 4 (1 to 3 days per month); 5 (1 to 3 days per week); 6 (4 or more days per week).
31. In Dutch "Omgevingsadressendichtheid van een adres" or "OAD".
32. Overture is a collaborative open-data initiative led by software developers, data experts, cartographic engineers, and product managers from dozens of Overture Maps Foundation member companies. Since our launch in December 2022, Overture members have been working toward a shared vision: to create reliable, user-friendly, and interoperable open map data that supports both current and future map products. We envision a world where shared, open base layers drive collaboration and innovation across industries and communities.
33. RUDIFUN stands for "Spatial Densities and Function Mixing in the Netherlands". These indexes not only provide a basis for numerical spatial densities but also insight into the physical morphological properties of the living environment.

Table 5.1 . (continued)

Variable	Description	Type	Source
Exogenous variables			
Life events	Family- and job-related life events. The occurrence of childbirth, cohabitation, separation, job changes and income changes in the same year of relocation	Categorical and continuous	MPN
Socio-economic characteristics	Gender, educational attainment, age in category, and baseline household income at pre-relocation.	Categorical and continuous	MPN

5.3.3. Mode use and preferences

The main variables of interest are travel mode use, mode-specific preferences and changes in built environment characteristics after relocation. Travel mode use is measured by asking respondents the frequency of using the car and bicycle[34] for their daily trips. Answers were coded on a 7-levels scale, ranging from 1 (almost never or never) to 6 (four or more days a week).

Regarding mode preferences, MPN respondents are asked about their preferred transport mode for eight different purposes (i.e. work, business, education, daily groceries, shopping, visiting family or friends, going out, recreational trips and sports activities). Using the approach proposed by Olde Kalter et al. (2021) and further tested by Tao (2024), mode-specific preferences for cycling and the car were calculated by dividing the number of trip purposes where each mode was identified as the preferred option by the total number of trip purposes. That calculation resulted in scores from 0 (the least preferred) to 1 (the most preferred) for each transport mode and participant.

5.3.4. Measuring Built Environment changes

Building on the 'Ds framework' proposed by Cervero and Kockelman (1997) and later refined by Ewing and Cervero (2001; 2010), three key built environment characteristics were analysed before and after residential relocation: i) Destination Accessibility, ii) Density, and iii) Diversity. Cervero's and colleagues' research has shown that compact, mixed-use developments are generally associated with higher shares of sustainable travel modes and lower vehicle miles travelled (VMT) (Ewing and Cervero, 2010). Among the three factors, destination accessibility has the strongest correlation with both motorized (VMT) and non-motorized travel, while density and diversity also show significant, though weaker, associations.

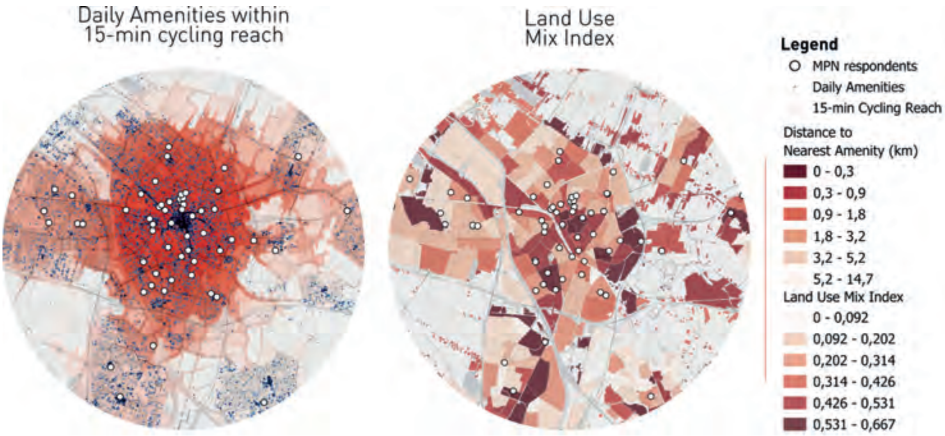

Fig. 5.2. Example of destination accessibility and diversity measures.

Destination Accessibility reflects ease of access to key trip destinations at the local level. In this study, it was assessed in two ways. Firstly, as the average distance from residential locations to the nearest daily amenities (supermarkets, daily shops, cafes, restaurants, intercity train stations, hospitals and pharmacies), which are compatible with the travel purposes used to build the mode-specific preferences. Secondly, as the number of key daily amenities within a 15-min reach from respondents' residential location, by car and cycling. This 15-min reach was calculated using the '*r5r*' network routing algorithm in *R*[35].

Density was measured as the number of addresses per square kilometre within the 4-digit postal code areas of the residence. Unlike many other

34. Our initial intention was to include walking; however, due to sample size issues, this was not possible. There were too many empty cells in the data.
35. **r5r** is an R package for rapid realistic routing on multimodal transport networks (walk, bike, public transport and car). It provides a simple and friendly interface to R[5], the Rapid Realistic Routing on Real-world and Reimagined networks, the routing engine developed independently by Conveyal.

studies that focus on residential or population density (e.g., Ewing and Cervero, 2010; Cervero and Kockelman, 1997), our approach defines density as the concentration of multi-purpose human activity, including living, working, education, shopping, and leisure[36]. Diversity (or land-use mix) refers to the variety of land uses within a given area and their proportional representation (Ewing and Cervero, 2010). We quantified it as the ratio of residential floor area to total floor area. To assess changes in the built environment, the study calculated the difference in these variables before and after relocation, capturing the impact of moving as a major life event.

5.3.5. Exogenous variables

The exogenous covariates are baseline socioeconomics at the first year and life events. Job-related life events include becoming employed, job/school address changes and retiring from work, while family-related life events include giving birth to a child. Baseline socio-economic characteristics are composed of gender, age and car ownership at pre-relocation.

5.3.6. Analytical Framework

To investigate the extent to which changes in residential built environments after relocation correlate with driving and cycling, we developed 16 random-intercept cross-lagged panel models (RI-CLPM), - 8 for cycling, 8 for driving. RI-CLPM is a structural equation modelling (SEM) method for analysing relationships between variables in a longitudinal fashion. Compared to CLPM, which was used in a similar study to investigate the interrelations between attitudes, built environment and VMT (see van de Coevering et al., 2021), RI-CLPM decomposes observed variables into stable between-individual traits and time-varying within-individual dynamics (Hamaker et al., 2015).

In panel analysis, it is essential to consider the correlation between repeated observations of the same individual (Zager and Liang, 1992). It is likely that variations in the frequency of mode use for the same individual will be less than the variation in the frequency of mode use for different individuals. The traditional CLPM method is not able to consider these intrapersonal correlations. By making this separation, a less biased estimation of the mode use-preference interrelations can be estimated at the within-individual level.

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36. We consider the same definition of Density used by Dutch Bureau of Statistics (CBS). It translates as 'Omgevingsadressendichtheid van een adres'.

The RI-CLPM model separates stable between-person differences (K, W) and within-person variations over time (P_t, Q_t) as:

$$X_{\mathrm{it}} = K_i + \delta_t + P_{\mathrm{it}} \tag{1}$$

$$Y_{\mathrm{it}} = W_i + \omega_t + Q_{\mathrm{it}} \tag{2}$$

and

$$P_{\mathrm{it}} = \alpha_i P_{i,t-1} + \mu_t Q_{i,t-1} + \pi_{\mathrm{it}} \tag{3}$$

$$Q_{\mathrm{it}} = \beta_i Q_{i,t-1} + \theta_t P_{i,t-1} + v_{\mathrm{it}} \tag{4}$$

Where:

- K and W are the random intercepts (stable individual differences).
- X_{it} = mode-specific preferences of individual i at time t
- Y_{it} = mode-specific use of individual i at time t
- δ_{it} and ω_{it} capture temporal group means for mode preference and use
- P_{it} and Q_{it}capture the individual temporal deviation terms
- π_{it} and v_{it} are the within individual time-varying error terms.

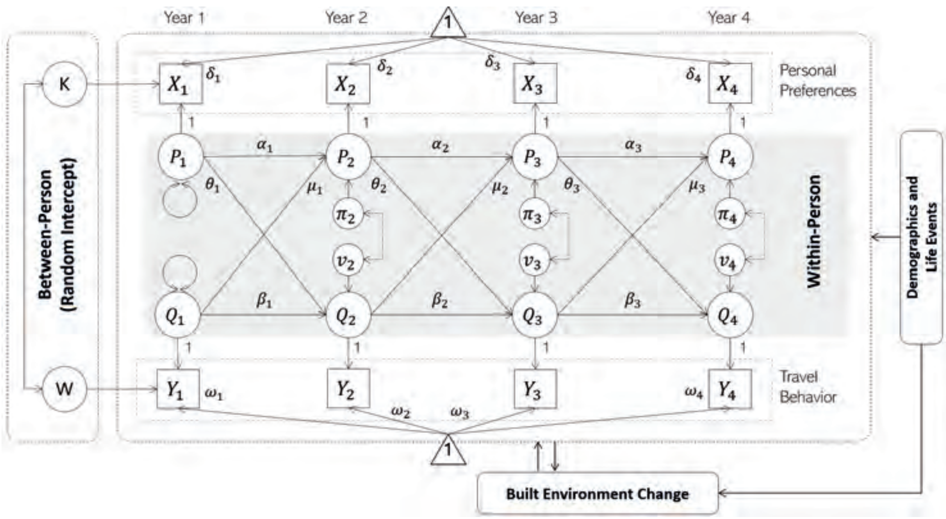

Fig. 5.3. Simplified schematic view of the RI-CLPM.

The analytical framework of this study (see Fig. 5.3) uses a 4-wave Random Intercept Cross-Lagged Panel Model (RI-CLPM) to analyse travel mode preferences (X_t) and travel mode use (Y_{it}) over time. The model separates between-person differences (K, W) from within-person variations (P_t, Q_t). The **between-person component** captures stable individual differences. The random intercepts K and W allow for correlations between mode preference and use at the interpersonal level, showing how stable between-person differences in mode preference are associated with between-person differences in frequency of mode use

The **within-person component** focuses on temporal dynamics. Autoregressive paths (α_t and β_t) indicate the degree of intrapersonal stability: a positive coefficient indicates that higher-than-average use or preference at time $t-1$ predicts higher-than-average values at t. Cross-lagged effects (μ_t and θ_t) capture the influence of past mode use on future preferences and vice versa, representing causal dynamics over time. Note that BE change, represented by the difference pre- and post-relocation, is modelled as a life event that explains changes in preferences and mode use, and which is endogenous to demographics and other life events (pre-relocation self-selection). Residential relocation can be understood as a life event in mobility biographies (Schimohr et al., 2025), as they are often connected to other key events in the life course, such as leaving the parental home, moving in with/separating from a partner, childbirth, or starting a job (Lanzendorf, 2003).

RI-CLPMs were developed and fitted using the *R* package *lavaan*[37], and the estimators of maximum likelihood with robust standard errors (MLR) were used to address the non-normal distribution of variables.

5.4. Results

5.4.1. Sample characteristics

Table 5.2 presents the means and standard deviations for time-varying variables related to mode use, personal preferences, and built environment characteristics.

37. The lavaan package is developed to provide users, researchers and teachers a free open-source package for latent variable modelling. Lavaan is used to estimate a large variety of multivariate statistical models, including path analysis, confirmatory factor analysis, structural equation modelling and growth curve models.

Regarding travel behaviour, respondents showed a gradual increase in car use and a corresponding decline in bicycle use between 2013 and 2016. This shift in mobility patterns aligns with changes in personal preferences, as respondents progressively reported a lower preference for cycling. Simultaneously, the built environment of the respondents' home locations evolved in ways that support increased car use. Over time, movers transitioned to less compact, mixed, and accessible neighbourhoods. This is reflected in a growing distance to daily amenities, a decline in the number of amenities reachable within a 15-minute cycling radius, and a slight decrease in density levels. These trends suggest a shift toward more car-dependent environments.

Table 5.2. Sample characteristics – travel behaviour, personal preferences and the built environment of home locations (N = 996).

Variable	**2013**		**2014**		**2015**		**2016**	
	Mean (SD)		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**	
Travel Behaviour (score 1 to 7)								
Cycling Frequency	4.80	1.62	4.77	1.55	4.69	1.57	4.71	1.54
Car Frequency	4.98	1.25	4.97	1.24	5.01	1.24	4.98	1.31
Personal Preferences (0 to 1)								
Cycle Preference	0.47	0.25	0.48	0.26	0.48	0.26	0.47	0.28
Car Preference	0.53	0.29	0.55	0.29	0.59	0.29	0.58	0.30
Built Environment								
Dist. To Amenities (km)	1.89	1.30	2.05	1.42	2.19	1.51	2.23	1.40
Amenities within 15min Cycling (Count)	1823.0	1853.9	1680.9	1856.8	1500.2	1696.0	1398.9	1589.4
Amenities within 15min Driving (Count)	3236.6	2209.2	3035.5	2217.3	2816.0	2164.6	2769.2	2021.0
Land Use Mix Index (0 to 1)	0.78	0.20	0.80	0.18	0.81	0.18	0.79	0.20
Density (add/ km2)	2,310.4	1,758.9	2,192.7	1,704.0	2,053.0	1,653.5	1,978.2	1,624.9

Tables 5.3 and 5.4 present the descriptive statistics for the exogenous variables related to socioeconomics and life events. Percentages were calculated for each wave and compared with those of all MPN respondents from the same periods. A comparison of the two samples shown in Table 5.3—movers and the full MPN dataset—suggests similar socioeconomic characteristics. This suggests that non-random dropouts are not a significant concern. Similar findings were reported in recent MPN studies by Tao (2024) and Olde Kalter et al. (2021).

Table 5.3. Sample characteristics – demographics (N = 996).

Variable	2013	2014	2015	2016
		%		
Sex				
Male	39.7	40.6	40.8	39.5
Female	60.3	59.4	59.2	60.5
Age Category				
18-24 years	16.3	18.3	14.6	11.8
25-49 years	59	60	63.1	62.6
50-59 years	8.1	9.6	10.1	13.9
> 60 years	16.5	12	12.2	11.6
Car Ownership (Household)				
No	37.2	33.2	30.9	27.9
Yes	62.8	66.8	69.1	72.1
Occupation				
employed	51.9	58	57.6	58.2
not employed	17	13.6	12.7	12.1
occupational disability/unfit to work	6.1	4.7	4.6	5
other	9.9	6.6	6	5.4
school	10.9	11.7	7.9	5.4
self-employed entrepreneur	4.1	5.4	6.5	6.1
not available	0	0	4.6	7.8

Table 5.3. (continued)

Variable	2013	2014	2015	2016
			%	
Education Level				
MBO	24.2	23.4	21.8	17.3
bachelor	27.7	25.8	27.4	25.3
jr. high school	3.6	4.6	4.5	5
masters / phd	19.6	18.3	21.1	23.4
no education/ primary	2.3	3.6	3.8	5.4
Sr. high school	15.3	16	13.2	15.1
vocational	7.4	8.4	8.2	8.5

Table 5.4. Sample characteristics – life events (N = 996).

Life event	2013	2014	2015	2016
		% of total		
Child born	6.5	6.3	7.7	5.4
Retired	10.9	4.1	4.9	3.3
Changed Work Address	11.9	14.8	12.6	14.1
Changed School Address	10.6	7.6	4.9	4.6

5.4.2. Model fits

Two separate sets of cross-lagged panel models are estimated to examine how changes in the built environment after relocation influence mode use and mode preferences. The first set of 8 models (A1 to H1) focuses on cycling behaviour, while the second set (A2 to H2) analyses driving behaviour. Within each set, different built environment characteristics are tested sequentially, starting with density (A1, B1, A2 and B2), destination accessibility (C1, D1, C2 and D2), followed by the number of daily amenities within 15min cycling or driving (E1, F1, E2 and F2), and finally land use mix (G1, H1, G2 and H2).

Tables 5.5 and 5.6 present the fit measures for the estimated SEM models examining bicycle and car use. All models demonstrate a good or acceptable fit[38], as indicated by the high *CFI* (Comparative Fit Index) and *GFI* (Goodness-of-Fit Index) values, along with low *RMSEA* (Root Mean Square Error of Approximation) and *SRMR* (Standardized Root Mean Square Residual) scores. Models incorporating demographics and life event controls (A1-2, C1-2, E1-2, G1-2) tend to exhibit lower *AIC* and *BIC* values, suggesting better parsimony compared to those without these controls. However, these models also tend to show slightly higher *RMSEA* and *SRMR*, indicating potential trade-offs between parsimony and fit precision. Despite these variations, all models meet the minimum criteria for valid and satisfactory model fit, reinforcing the robustness of the estimated relationships.

Table 5.5 . Measures of fit for the SEMs; recommended values shown in brackets (Bicycle Use and Preferences).

Fit Measure	Bicycle Use and Preferences							
	Density		Dist. to amenities		Amenities 15min		Land Use Mix	
	Model A1	Model B1	Model C1	Model D1	Model E1	Model F1	Model G1	Model H1
AIC	2510.77	5354.10	3202.13	6617.02	3442.74	6776.54	3286.20	5989.48
BIC	2697.67	5543.17	3389.03	6806.10	3629.65	6965.62	3473.10	6178.55
CFI (>0.90)	1.00	1.00	1.00	1.00	0.97	0.98	1.00	1.00
Df	153.00	33.00	153.00	33.00	153.00	33.00	153.00	33.00
GFI (>0.90)	0.92	0.95	0.93	0.95	0.92	0.95	0.92	0.96
SRMR (< 0.08)	0.06	0.05	0.06	0.04	0.08	0.09	0.07	0.05
RMSEA (< 0.08)	0.00	0.01	0.00	0.00	0.03	0.04	0.00	0.00
Observations	208	543	208	543	208	543	208	543
Demographics and Life Events	Y	N	Y	N	Y	N	Y	N

Notes: Models A1, C1, E1, G1 are controlled for demographics and life events.

38. Comparative Fit Index (CFI): Values above **0.90** indicate an acceptable fit, while values above 0.95 suggest a good fit (Hu & Bentler, 1999). Goodness-of-Fit Index (GFI): Values close to **1.0** indicate a well-fitting model (Jöreskog & Sörbom, 1993). Root Mean Square Error of Approximation (RMSEA): Values below **0.08** indicate an acceptable fit, while values below **0.05** suggest a good fit (Steiger, 1990). Akaike Information Criterion (AIC) & Bayesian Information Criterion (BIC): Lower values indicate better model parsimony and comparative fit (Burnham & Anderson, 2004).

Table 5.6. Measures of fit for the SEMs; recommended values shown in brackets (Car Use and Preferences).

	Car Use and Preferences							
	Density		Dist. to amenities		Amenities 15min		Land Use Mix	
Fit Measure	**Model A2**	**Model B2**	**Model C2**	**Model D2**	**Model E2**	**Model F2**	**Model G2**	**Model H2**
AIC	2619.69	5400.52	3184.75	6703.77	2130.72	4688.27	3131.32	6046.01
BIC	2796.58	5589.59	3371.65	6901.44	2317.62	4877.35	3318.22	6235.08
CFI (>0.90)	0.76	0.99	0.95	0.97	0.91	0.98	0.96	1.00
Df	156.00	33.00	153.00	31.00	153.00	33.00	153.00	33.00
GFI (>0.90)	0.96	0.99	0.98	0.99	0.98	0.98	0.98	0.99
SRMR (< 0.08)	0.11	0.06	0.06	0.06	0.08	0.10	0.06	0.04
RMSEA (< 0.08)	0.07	0.02	0.03	0.04	0.05	0.04	0.03	0.00
Observations	208	543	208	543	208	543	208	543
Demographics and Life Events	Y	N	Y	N	Y	N	Y	N

Notes: Models A2, C2, E2, G2 are controlled for demographics and life events.

5.4.3. Built Environment change effects

Table 5.7 examines how changes in the built environment due to residential relocation influence preferences and mode use for both cycling and driving over time at the intrapersonal level (within-person analysis). Built environment changes are represented by four key factors: density increase, distance to daily amenities, number of amenities within a 15-minute travel range, and land use mix (MXI). These elements influence travel behaviour and preferences in different ways. Positive estimates indicate that an increase in a built environment factor is associated with above-average levels of mode use and preferences in the following year.

Our results indicate that increased density and improved accessibility to amenities significantly shape transportation choices and attitudes post-relocation. Specifically, moving to denser neighbourhoods encourages cycling ($\beta =$ 0.177 to 0.230, $p < 0.05$) and discourages car use ($\beta =$-0.251, $p < 0.05$)

and preference ($\beta =$ -0.071, $p < 0.05$). Individuals who relocate to compact environments exhibit higher-than-average cycling levels while reducing car use (Models A1, B1, B2). Preferences also follow this trend, suggesting that relocating to high-density areas fosters positive attitudes toward active mobility ($\beta =$0.049 to 0.067, $p < 0.10$).

Increasing the distance to daily amenities has a negative impact on cycling, reducing both preference (β = -0.05, $p < 0.10$) and usage (β = -0.17 to -0.21, $p < 0.05$) and. This suggests that when essential services and facilities are farther away, individuals are less likely to cycle, likely due to longer trip distances and reduced convenience. For car users, however, greater distance to amenities does not significantly change driving frequency but does show a positive correlation with car use (0.10, $p < 0.05$), suggesting that individuals may compensate for reduced accessibility by increasing their reliance on automobiles.

A higher number of amenities within a 15-minute range has a weak positive effect on cycling preferences (β = 0.02 to 0.04, $p < 0.01$) and use (β = 0.05 to 0.09, $p < 0.05$. This suggests that access to a greater variety of destinations within a short travel distance supports cycling behaviour. However, the number of amenities does not significantly affect car use, indicating that car users might be less sensitive to local accessibility and more influenced by other factors such as parking availability or congestion levels.

Changes in land use mix do not exhibit strong associations with either cycling or driving behaviours. Neither cycling frequency nor preference is significantly influenced by mixed land use after relocation, suggesting that simply change land use diversity through relocation may not be sufficient to alter travel patterns. Similarly, car use remains largely unaffected by changes in land use mix.

Overall, the results indicate that density increases and improved accessibility to amenities are the most influential built environment factors affecting transportation choices post-relocation. Cycling preferences and behaviour, however, are more reactive to environmental changes than car preferences and behaviour. Direct exposure to environmental conditions can play a significant role in this difference. Safety concerns are a major barrier to cycling (Handy et al., 2014), as cyclists are more sensitive to changes in infrastructure, safety, and traffic conditions than car users. For example, increasing traffic volume or reducing cycling infrastructure can directly reduce the perceived safety and comfort of cycling, making individuals less likely to cycle. In contrast, car users remain relatively insulated from such environmental changes.

Models that control for demographics and life events (A, C, E, G) show different effects compared to those that do not, reinforcing the idea that individual characteristics (age, household composition, employment status) also shape transportation choices. This suggests that while built environment changes are important, they interact with personal circumstances to determine travel behaviour outcomes.

Table 5.7. Summary of Built Environment Change Effects as a Result of Residential Relocation.

	Bicycle Use and Preferences				**Car Use and Preferences**			
BE Effects	***coeff.***	***SE***	***coeff.***	***SE***	***coeff.***	***SE***	***coeff.***	***SE***
Effect of density	***Model A1***		***Model B1***		***Model A2***		***Model B2***	
Density Increase -> Mode Use	0.177**	0.088	0.230***	0.072	-0.159	0.113	-0.251**	0.101
Density Increase -> Mode Preference	0.067**	0.028	0.049*	0.027	-0.053	0.038	-0.071**	0.029
Effect of Distance to Amenities	***Model C1***		***Model D1***		***Model C2***		***Model D2***	
Distance Increase -> Mode Use	-0.169**	0.068	-0.207***	0.051	0.058	0.060	0.095**	0.046
Distance Increase -> Mode Preference	-0.052*	0.029	-0.053***	0.019	0.013	0.017	0.010	0.012

Table 5.7. (continued)

	Bicycle Use and Preferences				Car Use and Preferences			
BE Effects	***coeff.***	***SE***	***coeff.***	***SE***	***coeff.***	***SE***	***coeff.***	***SE***
Effect of Number of Amenities	***Model E1***		***Model F1***		***Model E2***		***Model F2***	
Amenities Increase -> Mode Use	0.050	0.044	0.085**	0.033	0.040	0.106	-0.032	0.099
Amenities Increase -> Mode Preference	0.022	0.023	0.039***	0.012	0.002	0.029	-0.003	0.023
Effect of Land Use Mix	***Model G1***		***Model H1***		***Model G2***		***Model H2***	
MXI increase -> Mode Use	0.016	0.023	0.014	0.017	-0.013	0.030	-0.026	0.022
MXI increase -> Mode Preference	0.001	0.007	-0.002	0.007	0.009	0.013	0.005	0.008
Demographics and Life Events	Y		N		Y		N	

Notes: ***p < 0.00; **p < 0.05; *p < 0.10.

5.4.4. Interrelations between mode use and preferences

Here we also discuss 2 additional aspects of the RI-CLPMs developed: (1) the relationship between random-intercept factors, showing how stable, between-person differences in mode use are linked to differences in personal preferences (see Table 5.8); (2) the endogenous structure of the RI-CLPMs, capturing the interrelations between mode use and preferences for the bicycle and car; and the effects of pre-relocation preferences on changes in the built environment (Tables 5.11 and 5.12, in the Appendix).

Strong correlations were found between individual preferences and mode use for both cycling (β =0.132 to 0.234, $p < 0.01$) and driving (β =0.064 to 0.141, $p < 0.01$). This suggests that individuals who consistently express a stronger preference for cycling over time are also more likely to cycle more frequently, with a similar pattern observed for driving. These findings further indicate that bicycle users may have an inherent preference for cycling due to shared values or exposure to favourable environments before and after relocation (Tao, 2024).

Table 5.8. Correlation Between Individuals (Random Intercepts).

Cycling Models			***Driving Models***		
Model	***coeff***	***SE***	***Model***	***coeff***	***SE***
Model A1	0.166***	0.117	*Model A2*	0.056	0.047
Model B1	0.230***	0.056	*Model B2*	0.141***	0.029
Model C1	0.132***	0.143	*Model C2*	0.070**	0.030
Model D1	0.229***	0.056	*Model D2*	0.141***	0.030
Model E1	0.180***	0.143	*Model E2*	0.064**	0.025
Model F1	0.234***	0.056	*Model F2*	0.132***	0.027
Model G1	0.185***	0.058	*Model G2*	0.069**	0.029
Model H1	0.231***	0.033	*Model H2*	0.139***	0.029

Notes: ***p < 0.00; **p < 0.05; *p < 0.10.

Despite the strong stable-trait effects, some significant autoregressive paths (Tables 5.11 and 5.12 in Appendix) persist in our models. Specifically, for mode use, respondents that reported above-average levels of cycling and driving in one year at the individual level, also reported above-average levels of mode use in the following year. For attitudes, this trend did not hold, neither for car nor bicycle, which indicates that, among movers, above-average preferences towards a certain mode of transport did not exert influence on their preferences in the following year. Furthermore, the weak or non-existent cross-lagged effects between mode use and preferences indicate that an increase in mode preference at time *t* does not necessarily translate into greater mode use in the following year. For instance, a mover who exhibits an above-average positive attitude toward cycling is not necessarily more likely to start cycling in the next year. This finding challenges the assumption that attitudinal shifts directly drive behavioural changes in mode choice over time.

Surprisingly, not supporting the residential self-selection argument, we found that pre-move travel preferences have no significant effect on built environment change (Tables 5.11 and 5.12 in Appendix) for our sample. Part of the reason for that result could be that the personal preferences reported in MPN are more directly related to modes of transport, and not to specific types of residential living environments. Additionally, we did not have complete information about the access of residents to the housing market (e.g., personal budget, housing supply), or about the main drivers for the move (e.g., if the move was mandatory or voluntary).

5.4.5. Life Events and Demographics

Here we discuss the effects of life events and demographics on mode use and preferences for bicycle (Table 5.9) and car (Table 5.10). While some patterns are similar for both modes, key differences emerge in how movers adjust their mobility choices following events such as childbirth, retirement, and workplace relocation.

The birth of a child is associated with a significant decline in cycling frequency and preferences (Table 5.9, β = -0.34 to -0.36 for frequency, β = -0.09 to -0.11 for preference, $p < 0.05$). This suggests that new parents face increased mobility constraints that make cycling less practical, possibly due to safety concerns, the need for child transport, or time constraints. On the other hand, car use increases following childbirth (Table 5.10, β = 0.27 to 0.30, $p < 0.05$), reinforcing the idea that parents shift towards more convenient and flexible transport options. This trend reflects the well-documented "car dependence" that emerges when families expand (e.g., Olde Kalter et al., 2021).

Similarly, changing work address negatively impacts cycling preferences (Table 5.9, β = -0.07 to -0.08, $p < 0.05$), indicating that relocating workplaces may lead to less favorable cycling conditions, due to, for instance, longer commuting times. This effect does not hold for car use (Table 5.10), suggesting that individuals do not necessarily rely more on cars following job relocations. Retirement did not significantly influence cycling or driving frequency or preferences in our sample of movers.

Sociodemographic characteristics are significantly correlated with car use frequency and cycling frequency. Car ownership plays a decisive role in shaping transport behaviour in both modes. In Table 5.9, owning a car negatively correlates with cycling frequency (β = -0.67 to -0.76, $p < 0.01$) and preference (β = -0.15 to -0.16, $p < 0.01$). This suggests that having access to a private vehicle significantly discourages active travel. Conversely, in Table 5.10, car ownership is, as expected, positively associated with higher car use (β = 0.81 to 0.85, $p < 0.01$) and stronger preferences for driving (β = 0.23 to 0.25, $p < 0.01$). Age differences also play a role in travel behavior. Older individuals show greater cycling preference over time (β = 0.07, $p < 0.01$, Table 5.9), but this does not significantly impact how often they cycle. The same trend appears for car use, where older individuals report higher car preference (β = 0.07 to 0.08, $p < 0.01$, Table 10) but without a significant effect on frequency.

In most cases, gender did not exhibit a significant correlation with mode use. However, when differences were observed, females demonstrated a stronger preference for cycling than males (β = 0.10, $p < 0.01$, Table 5.9), whereas males showed a higher preference for driving compared to females (β = 0.10 to 0.12, $p < 0.01$, Table 5.10), though these differences did not translate into significantly different mode use. These findings highlight that while sociodemographic factors influence travel behaviour, their effects vary across individuals and transport modes.

Table 5.9. Summary of the Effects of Life Events and Demographics on Relocation decision, Travel Behaviour and Preferences (Bicycle).

	Bicycle Use and Preferences							
	Model A1		**Model C1**		**Model E1**		**Model G1**	
	coeff	***SE***	***coeff***	***SE***	***coeff***	***SE***	***coeff***	***SE***
Life Events								
Child is born -> Mode Use	-0.34*	0.20	-0.36*	0.20	-0.35	0.22	-0.35	0.22
Is retired -> Mode Use	0.07	0.14	0.07	0.13	0.09	0.17	0.06	0.16
Changed work address -> Mode Use	-0.16	0.12	-0.18	0.12	-0.19	0.14	-0.19	0.14
Child is born -> Preference	-0.10**	0.05	-0.09*	0.05	-0.09*	0.05	-0.11**	0.06
Is retired -> Preference	0.03	0.05	0.04	0.06	0.04	0.05	0.05	0.07
Changed work address -> Preference	-0.08**	0.04	-0.08**	0.04	-0.07*	0.04	-0.08**	0.04
Demographics								
Car Ownership -> *Mode Use*	-0.76***	0.24	-0.74***	0.25	-0.67**	0.27	-0.68**	0.27
Gender (ref: Male) -> *Mode Use*	0.03	0.22	0.01	0.21	0.04	0.23	0.03	0.23
Age Cat (Ordinal) -> *Mode Use*	0.00	0.13	0.00	0.13	0.00	0.15	-0.02	0.15
Car Ownership -> *Preference*	-0.16***	0.04	-0.16***	0.04	-0.16***	0.04	-0.15***	0.04
Gender (ref: Men) -> *Preference*	0.10***	0.04	0.10**	0.04	0.10***	0.04	0.10***	0.04
Age Cat (Ordinal) -> *Preference*	0.07***	0.02	0.07***	0.02	0.07***	0.02	0.07***	0.02

Notes: ***p < 0.00; **p < 0.05; *p < 0.10.

Table 5.10 . Summary of the Effects of Life Events and Demographics on Relocation decision, Travel Behaviour and Preferences (Car).

	Car Use and Preferences							
	Model A2		**Model C2**		**Model E2**		**Model G2**	
	coeff	***SE***	***coeff***	***SE***	***coeff***	***SE***	***coeff***	***SE***
Life Events								
Child is born -> Mode Use	0.36***	0.12	0.26**	0.12	0.24**	0.11	0.26**	0.12
Is retired -> Mode Use	-0.10	0.15	-0.04	0.16	-0.06	0.15	-0.05	0.16
Changed work address -> Mode Use	0.13	0.09	0.26**	0.12	0.08	0.08	0.08	0.09
Child is born -> Preference	0.04	0.05	0.04	0.05	0.04	0.05	0.04	0.05
Is retired -> Preference	-0.03	0.07	-0.04	0.07	-0.03	0.07	-0.03	0.07
Changed work address -> Preference	-0.04	0.03	0.04	0.05	-0.04	0.03	-0.04	0.03
Demographics								
Car Ownership -> *Mode Use*	0.30***	0.06	1.80***	0.16	1.72***	0.14	1.80***	0.16
Gender (ref: Male) -> *Mode Use*	-0.04	0.04	0.14	0.11	0.12	0.10	0.14	0.11
Age Cat (Ordinal) -> *Mode Use*	-0.08***	0.02	-0.23***	0.07	-0.22***	0.07	-0.22***	0.07
Car Ownership -> *Preference*	0.30***	0.06	0.29***	0.05	0.29***	0.05	0.29***	0.05
Gender (ref: Men) -> *Preference*	-0.04	0.04	-0.04	0.04	-0.04	0.04	-0.04	0.04
Age Cat (Ordinal) -> *Preference*	-0.08***	0.02	-0.09***	0.02	-0.09***	0.02	-0.09***	0.02

Notes: ***p < 0.00; **p < 0.05; *p < 0.10.

5.5. Discussion and implications

5.5.1. Discussion

In our study, we find that moving to more urban-like neighbourhoods with greater accessibility to daily destinations results in less use of cars over time with a stronger preference towards cycling and greater use of the bicycle, while relocating to less compact living environments encourages more car use and positive preferences towards driving. This effect of behaviour and attitudes by the BE, referred as “environmental determinism” by Ewing et al. (2015) and Lin et al. (2017), has been tested recently by a few researchers (e.g., Tao, 2024; Tao et al., 2023; De Vos et al., 2018; Wang and Lin, 2019), which arrived at findings aligned with ours. This study found no evidence, however, of personal self-selection pre-relocation to affect built changes. This insignificance in self-selection effects, also found in Wang and Lin (2019), does not mean that this effect is inexistent, but possibly relates to a lack of complete information on the context of the move (e.g., housing stock availability, financial context of the movers, if that was a voluntary move or not). Residential self-selection studies should acknowledge the multi-faceted nature of residential choice (Cao and Chatman 2016; Chatman 2009), and that may help explain the insignificance concerning the influence of pre-move travel preference on post-move built environment observed here.

Within the deterministic bit of the built environment, we found that cycling may be more sensitive to built environment changes than car use. What can explain this difference is that cycling is a more environmentally dependent mode of transport—it requires safe, connected, and convenient infrastructure, as well as short travel distances, to remain a viable option. When density increases, cyclists benefit from shorter trip distances and more mixed land uses, making cycling more attractive. Conversely, when accessibility decreases—such as when the distance to amenities increases—cycling becomes significantly less convenient than driving, leading to lower use.

The significant and positive between-individual correlations (random intercepts) of mode use and attitudes align with findings from previous studies (Qi et al., 2024; Tao, 2024; Olde Kalter et al., 2021). If these random intercepts had not been separated from the within-person effects, our models would have overestimated the size of both effects, as demonstrated by Qi et al. (2024). Regarding within-individual effects, previous studies have reported surprisingly stronger autoregressive and cross-lagged effects (e.g., Qi et al., 2024; Olde Kalter et al., 2021) compared to our findings. Because our sample consists primarily of movers, it is likely to exhibit lower behavioural and attitudinal stability over time due to the influence of changing built environments. The observed discrepancy may be due to differences in sample definitions. Our study focuses on adults (aged 18 and older) who relocated between 2013 and 2016 and participated in at least two consecutive waves of the panel. In contrast, Olde Kalter's study included all young adults (aged 18–39) who participated in all three waves between 2014 and 2016.

Though interesting and important results are reported, this study has several data-related limitations and suggests directions for future research. Firstly, the amount of longitudinal data on attitudes and travel behaviour that we could effectively use were lower than we expected. This issue has been highlighted by active authors in the field (e.g., van Wee and Cao, 2022) as one of the main hindering factors for the current 'lack of understanding' of causal relationships between built environments and travel behaviour. Secondly, neither the personal or contextual circumstances of the move were fully understood in this study (e.g., housing market availability, person budget, mismatch between personal preferences and existing mobility options available). As recommended by Naess (2015), van Wee and Cao (2022) and Scheiner et al. (2024), a better integration between the quantitative analysis with in-depth qualitative insights from interviews would further help researchers understand the causal mechanisms behind relocation decisions, including changes in residential built environment conditions. Thirdly, to reach acceptable goodness-of-fit measures for most models, we treated some socioeconomic variables and life-events as completely exogenous, which may not always be the case. Take car ownership for instance, which in our study was used as one of the exogenous causes for car use and preference, however, over time, it could also be influenced the latter (e.g., pre-existing car preferences leading to movers buying a car).

5.5.2. Policy implications

These results emphasize the importance of urban planning strategies that enhance local accessibility, support compact development, and prioritize cycling infrastructure to facilitate more sustainable travel behaviours. This can be regarded as an extra motivation for urban planners and policy makers to stimulate people to live/relocate to urban areas, or to create more urbanstyle neighbourhoods (by creating new compact neighbourhoods, or by increasing the proximity of daily amenities to existing households).

5.6. Conclusions

In this paper, we study the relationship between changes in residential built environments, mode preferences, and frequency of mode use over time for movers in the Netherlands, with focus on cycling and driving. Using a cross-lagged panel approach (RI-CLPM) on approximately 1000 movers between 2013 and 2016, we find that changes in mode-specific attitudes can be affected by changes in people's residential living environment, albeit differently according to travel mode and built environment indicator. We also find significant correlations between mode use and preferences at the inter-personal level. The validity of the RI-CLPM models developed in this study is demonstrated via Goodness-of-Fit measures. Main results from this study indicate that moving to more urban and accessible neighbourhoods does not only stimulate active bicycle use but can also improve attitudes toward this travel mode, though the opposite partially holds for car use. As a result, relocating to compact and accessible urban areas can create a positive reinforcement effect between attitudes and the usage of active travel modes. This suggests that the built environment plays a crucial role in shaping travel behaviour beyond immediate adjustments, potentially contributing to habit formation. Additionally, while changes in built environments are key drivers of mobility shifts, personal characteristics and life events also play a role in shaping transport preferences and behaviour. Factors such as car ownership, household composition, and major life events—including childbirth and changes in employment—were also found to influence mode choice over time. These findings suggest that built environment interventions may be more effective when complemented by policies that consider household circumstances and individual travel needs. Altogether, this study provides further evidence that urban planning and transport policies aimed at promoting active travel should not only focus on infrastructure but also consider how residential relocations and life transitions influence mode choice.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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APPENDIX

Table 5.11. Table 5.11 Autoregressive and cross-lagged effects (Cycling).

	Cycling Model							
	Model A1		**Model C1**		**Model E1**		**Model H1**	
	coeff	***SE***	***coeff***	***SE***	***coeff***	***SE***	***coeff***	***SE***
Autoregressive Effects								
Mode Use (2013) -> Mode use (2014)	0.14	0.18	-0.02	0.19	-0.01	0.32	0.08	0.33
Mode Use (2014) -> Mode use (2015)	0.12	0.44	0.01	0.57	0.04	0.55	0.09	0.58
Mode Use (2015) -> Mode use (2016)	-0.22	0.61	0.06	0.46	0.08	0.50	-0.01	0.61
Preference (2013) -> Preference (2014)	-0.33	0.31	-0.45	0.60	-0.43	0.45	-0.37	0.40
Preference (2014) -> Preference (2015)	-0.09	0.26	-0.10	0.30	-0.01	0.33	0.03	0.26
Preference (2015) -> Preference (2016)	-0.15	0.26	-0.01	0.18	-0.10	0.18	-0.11	0.21
Cross-lagged Effects								
Mode Use (2013) -> Preference (2014)	0.03	0.03	0.01	0.05	0.01	0.08	0.03	0.05
Mode Use (2014) -> Preference (2015)	-0.07	0.07	0.14	0.24	-0.02	0.24	-0.06	0.16
Mode Use (2015) -> Preference (2016)	0.05	0.07	0.05	0.06	0.06	0.07	0.05	0.06
Preference (2013) -> Mode Use (2014)	-1.12	1.14	-0.76	3.27	-1.93	2.11	-1.67	1.70
Preference (2014) -> Mode Use (2015)	0.20	1.19	0.49	1.67	0.41	1.41	0.41	1.57
Preference (2015) -> Mode Use (2016)	-2.91	3.10	0.53	2.32	-1.31	3.28	-2.19	3.89

Table 5.11. (continued)

	Cycling Model							
	Model A1		Model C1		Model E1		Model H1	
	coeff	***SE***	***coeff***	***SE***	***coeff***	***SE***	***coeff***	***SE***
Self-selection Effects								
Preference to cycle -> Density Increase	0.16	0.12	-	-	-	-	-	-
Preference to cycle -> Distance Increase	-	-	0.28	0.35	-	-	-	-
Preference to cycle -> Amenities Increase	-	-	-	-	0.08	0.37	-	-
Preference to cycle -> Mix Increase	-	-	-	-	-	-	0.06	0.25

Notes: ***p < 0.00; **p < 0.05; *p < 0.10.

Table 5.12. Autoregressive and cross-lagged effects (Driving).

	Driving Model							
	Model A2		Model C2		Model E2		Model H2	
	coeff	***SE***	***coeff***	***SE***	***coeff***	***SE***	***coeff***	***SE***
Autoregressive Effects								
Mode Use (2013) -> Mode use (2014)	0.46**	0.19	0.45***	0.16	0.41***	0.15	0.44***	0.17
Mode Use (2014) -> Mode use (2015)	0.37*	0.22	0.31**	0.16	0.29**	0.14	0.32**	0.16
Mode Use (2015) -> Mode use (2016)	0.41***	0.13	0.42***	0.14	0.39***	0.13	0.42***	0.14
Preference (2013) -> Preference (2014)	0.07	0.20	0.06	0.21	0.10	0.22	0.06	0.21
Preference (2014) -> Preference (2015)	0.12	0.31	0.21	0.23	0.19	0.23	0.22	0.22
Preference (2015) -> Preference (2016)	-0.27	0.50	0.20	0.18	0.18	0.19	0.20	0.19

Table 5.12. (continued)

	Driving Model							
	Model A2		Model C2		Model E2		Model H2	
	coeff	***SE***	***coeff***	***SE***	***coeff***	***SE***	***coeff***	***SE***
Cross-lagged Effects								
Mode Use (2013) -> Preference (2014)	-0.02	0.08	-0.05	0.05	-0.04	0.05	-0.05	0.05
Mode Use (2014) -> Preference (2015)	0.06	0.08	0.02	0.06	0.02	0.06	0.02	0.06
Mode Use (2015) -> Preference (2016)	-0.03	0.03	-0.03	0.03	-0.03	0.03	-0.03	0.03
Preference (2013) -> Mode Use (2014)	0.28	0.70	0.17	0.61	0.30	0.53	0.23	0.59
Preference (2014) -> Mode Use (2015)	-1.45	1.00	-1.66**	0.71	-1.37**	0.55	-1.57**	0.69
Preference (2015) -> Mode Use (2016)	-0.27	0.50	-0.60	0.50	-0.57	0.46	-0.66	0.49
Self-selection Effects								
Preference to drive -> Density Increase	0.03	0.10	-	-	-	-	-	-
Preference to drive -> Distance Increase	-	-	-0.09	0.30	-	-	-	-
Preference to drive -> Amenities Increase	-	-	-	-	-0.01	0.02	-	-
Preference to drive -> Mix Increase	-	-	-	-	-	-	0.06	0.18

Notes: ***p < 0.00; **p < 0.05; *p < 0.10.

Chapter 6

Conclusions and Recommendations

This final chapter looks back at the whole research to synthesize and discuss the main findings of the thesis. It begins by answering the two main overarching research questions (see section 1.4), followed by a discussion of how these findings contribute to the existing literature on causal inference in active travel research. Next, I offer recommendations for future research. Finally, I outline the policy implications that can emerge from this study.

6.1. Providing answers to the research questions

This section presents the main conclusions derived from this research, addressing the overarching research questions (refer to section 1.4).

This research reinforces the deterministic role of the built environment in shaping travel behaviour and attitudes over time while revealing how these effects can vary across different traveller groups and local characteristics. Across 4 empirical studies, the findings consistently demonstrate that changes the built environment, and particularly transport infrastructure and land use have a measurable impact on active mobility (mode choice and use, minutes cycling and walking), even when mitigating the influence of potential confounders. This aligns with previous research (e.g., Ewing and Cervero, 2010; Cao et al., 2009), and suggests that interventions, such as increasing neighbourhood compactness/ destination accessibility or expanding cycling infrastructure, can encourage higher levels of walking and cycling. However, these results also highlight that the effects of such interventions depend on local conditions, the intensity of prior active mobility use, and socio-demographic factors, which means that some groups show a larger uptake more than others. Those differences also emphasize the challenge that is to establish causality in this type of research.

The first main research question (RQ1) of this thesis was: How and to what extent does active travel infrastructure influence travel behaviour?

Specifically, the findings from the natural experiments presented in Chapters 2 and 3 consistently show that the construction of high-quality, pro-cycling infrastructure positively influences travel behaviour, leading to increased levels of cycling. After accounting for potential confounders, both studies confirm that the introduction of cycling networks effectively shifts travel patterns toward cycling, with consistently positive effects across different treatment definitions. In São Paulo, the infrastructure had a broad impact across all travel purposes, with commuting showing the largest increase. In the Netherlands, where the analysis focused solely on commuting trips, the effect was quite positive. In both cases, the success of the intervention was strongly linked to how well exposure to the infrastructure aligned with existing travel habits. Higher treatment exposure—measured by the extent to which origin-destination pairs were affected—saw more substantial increases in cycling than areas with limited exposure. This pattern held true across different definitions of exposure, highlighting that the effectiveness of cycling infrastructure depends not just on its presence, but on how it integrates with actual travel behaviour. The magnitude of the effects was relatively stable across treatment exposure definitions: in São Paulo, cycling trips for all purposes increased by around 1%, while in the Netherlands, the share of commuting cycling rose by about 10%. Both studies also identified important subgroup differences. In São Paulo, socially vulnerable groups—such as students and income-less housewives—showed the lowest increases in cycling, suggesting that infrastructure alone may not be sufficient to change travel behaviour in these populations. In the Netherlands, cycle highways had stronger effects on women, younger individuals, and people without access to a car. These findings suggest that the comfort and safety of high-quality infrastructure are especially influential for groups that traditionally cycle less—particularly women. In contrast, car owners were generally less responsive to the improvements, which aligns with previous research on cycling behavior (e.g., Rodriguez-Valencia et al., 2019).

The second main research question (RQ2) of this thesis was: How and to what extent do density, access to destinations and land-use diversity affect active travel behaviour?

Sudden changes in land use around residential areas have been shown to significantly influence active travel demand. As demonstrated in Studies 3 and 4, shifts in density and accessibility—whether prompted by emergency restrictive policies or residential relocation—can lead to marked changes in walking, cycling and driving. In Study 3, physical activity levels in regions that experienced a significant decrease in access to amenities and sports facilities during the COVID-19 pandemic were compared to areas where access to these services was already limited. This decline in access can be attributed to the implementation of movement restrictions, which led to the temporary closure of amenities and indoor/outdoor sports facilities, which limited accessibility to opportunities for physical activity. The restrictions were particularly impactful for residents exposed to high urban density, compact layouts, and good access to sports facilities. While walking and cycling decreased across the Netherlands overall, the decline was more pronounced in areas where access to facilities was substantially reduced. This suggests that, although residents in high-density areas were, on average, more active pre-COVID—thanks to better overall accessibility—they also relied more heavily on organized and indoor sports facilities to maintain their physical activity levels beyond commuting to work or to school. When access to these facilities was taken away, they appeared to have fewer (or perhaps perceived fewer) alternative options for leisure-time physical activity. These findings highlight a potential vulnerability in how built environments are structured: even in areas with high accessibility, a lack of adaptable or diverse physical activity opportunities can undermine physical activity resilience in case of extreme events. Study 4, by contrast, focused on residential relocation and found that moving to areas with higher density and better access to daily amenities was correlated with greater bicycle use, while relocating from such areas to lower-density neighbourhoods was associated with a decrease in cycling. These environments support shorter travel distances and a greater mix of land uses, making cycling a more appealing alternative to driving. Importantly, these improvements in density and accessibility were also associated with positive shifts in travel attitudes, highlighting the role of the built environment in fostering behavioural change and habit formation.

6.2. Discussion

In this section, I revisit the key research gap identified earlier (Section 1.3) and discuss the contribution and limitations of my thesis in addressing the challenge of causal inference in built environment and active travel research. Specifically, I reflect on how the four studies employed different causal methods—within the Potential Outcomes (PO) and Directed Acyclic Graphs (DAG) frameworks—to generate more credible causal evidence. Furthermore, as recommended by Pearl (2009) and Graham (2025), I articulate the validity of the conclusions considering the assumptions upon which the models rest.

The 4 studies developed in this thesis contribute to the growing body of causal evidence on how changes in the built environment, and more specifically, active travel infrastructure and changes in accessibility to destinations influence active travel behaviour. All studies are based on multi-period observational designs, which offer a more robust basis for causal inference compared to cross-sectional designs (Heinen et al., 2018; Cao et al., 2009). The basic condition of "no unmeasured confounders" (or conditional *exchangeability*) (Graham, 2025) is shared by the causal approaches used in this research, e.g.,- Potential Outcomes and DAGs, but each causal approach addresses this issue differently. Within each approach, the different studies employ identification techniques aimed at minimizing the influence of confounders and isolating the influence of BE. These identification techniques included Difference-in-Differences (DiD) (Studies 1 and 2), Fixed Effects (FEs) (Study 3), and Random Intercept Cross-Lagged Panel Models (RI-CLPM) (Study 4). Each technique was tailored to the specific research context, research questions and data available. Although the exchangeability condition cannot be completely fulfilled, the influence of confounders can be partly addressed by (unprovable) assumptions underlying each causal identification mechanism. Below, I discuss each of the assumptions made for both approaches and identification methods.

Using the Potential Outcomes Framework (Studies 1, 2 and 3)

In studies 1 and 2, conducted within the Potential Outcomes (PO) framework, I used Difference-in-Differences (DiD) models to estimate the effects of new cycling infrastructure in São Paulo and the Netherlands. This method allows for control of time-varying confounders by using a comparison group of individuals not exposed to the new infrastructure to approximate the counterfactual trend for the treated group. To approximate the conditional *exchangeability*, I relied on key assumptions, including the Parallel Trends Assumption (PTA), consistency, non-interference, and common support (Graham, 2025). The PTA assumes that, in the absence of the intervention, treated and control groups would have followed parallel outcome trends. I believe this assumption is plausible, though not fully verifiable. To address this and relax (to some extent) the PTA, measures were taken. In both studies, we included a rich set of confounding covariates. Additionally, in Study 2, we refined the control group by limiting the analysis to postal codes where at least one origin-destination pair experienced the intervention, making it more comparable to the treatment group.

While no major compositional changes were observed across treatment and control groups (based on qualitative inspection), some differences inevitably remain. This is largely due to the localized nature of cycling infrastructure, which also tends to be explained by demographic characteristics and travel behaviour. The large geographic scope of the study areas also introduces pre-existing differences in built environments—such as density, land use mix, and accessibility—which are often associated with specific population traits like income, occupation, and family composition.

Another important condition for the two DiDs used in this thesis is the *consistency* (see Graham, 2025), which requires that exposure is sufficiently well defined, and as specific as possible (Imbens and Rubin, 2015; Rosenbaum and Rubin, 1983). I believe that this condition has been addressed in two ways. Firstly, by following recommendations of Humphreys et al. (2016), I used more dynamic measures of exposure to account for travellers' routine mobility patterns—such as information on origin and destination locations and shortest travel routes. Secondly, I tested the sensitivity of outcomes to multiple definitions of exposure. For instance, by testing the sensitivity of modal choice to varying exposure levels in São Paulo, the analysis showed consistent positive intervention impacts. This consistency adds confidence that the intervention had a meaningful effect. While these methods required more technical sophistication—such as developing geospatial routines and applying routing algorithms—they offered a more accurate approximation of the real benefits of cycling interventions, including improved connectivity and reduced travel times. While very little work has been done in this direction (e.g., Hirsch et al., 2017; Aldred et al., 2019; Karpinski, 2021), this thesis contributes to advancing the use of more robust definitions of treatment exposure in intervention studies.

One can also use Rachel Aldred's research to bring arguments for not addressing the consistency condition – due to the prevalence of abstract terminology, such as "cycle highways", "network of cycle routes" or even "complete streets", "traffic calming". Nevertheless, different versions of exposure can still be defined (Aldred, 2019). For instance, looking at urban cycle routes, a basic difference exists between typologies of cyclable routes (e.g., physically-separated lanes vs unseparated lanes), which has been regarded in cycling literature as of big influence on cycling uptake (Buehler and Dill, 2016). Aldred identifies this as a recurring issue in intervention studies: interventions are often defined using vague or broad terms, leading to inconsistencies in what is actually being evaluated. In practice, perfect consistency is rarely achievable because planning interventions are inherently multifaceted. The key question, then, is whether the variation in exposure is small enough to be considered ignorable—thus allowing for a meaningful estimate of the average causal effect—or whether these differences are significant enough that they require the research design to define multiple, more precise categories of exposure.

Two additional conditions important for the validity of Difference-in-Differences (DiD) models—also highlighted by Graham—are non-interference and common support. The non-interference condition, often referred to as the Stable Unit Treatment Value Assumption (SUTVA) (Rubin, 1980), is particularly challenging in built environment interventions, where spillover effects are common. For instance, the construction of cycling infrastructure in one neighbourhood may influence cycling behaviour in adjacent neighbourhoods, alter traffic patterns, or shift perceptions and demand citywide. In this study, I could not verify the non-interference condition, though it remains desirable for causal inference (Graham, 2025). The second condition, common support, requires that each 'unit', which in the case of studies 1 and 2 were origin-destination pairs, has a positive probability of receiving treatment (Heckman et al., 1997). This assumption may be violated in practice, as some areas—due to geography, planning priorities, zoning restrictions, or political factors—might never be considered for cycling infrastructure. At the same time, central or highly urbanized areas are often systematically prioritized, meaning there may be no completely comparable "untreated" group with similar covariate profiles, which can limit the validity of the counterfactual comparison.

In study 3, although no explicit treatment and control groups could be defined, given that the same COVID restrictions were applied country-wide by the Dutch Government, the FE method employed partially addresses the *exchangeability* condition by examining residents' active travel behaviour as a response to the temporary loss of access to amenities and facilities. FE controlled individual-specific unobserved heterogeneity (unit-specific fixed effects), driven by differences of the neighbourhood or respondents or their socioeconomic characteristics. These characteristics can be reasonably assumed time-invariant over the study time (since the study happens during initial COVID months). By comparing each unit to itself over time, this design helps mitigate the influence of confounders that cannot be directly observed.

The validity of the FE developed in this thesis relied on the additional assumption of *no omitted time-varying confounders* (see Angrist and Pischke, 2008). For many causal questions—such as the one explored in Study 3—the assumption that the most important omitted variables are time-invariant is not entirely plausible. Although the analysis assumes no unobserved time-varying confounders, this assumption does not fully hold in this case. For example, individuals' perceived risk of infection—though not directly measured—can influence their likelihood of walking or cycling and is likely correlated with their living environment. This perception likely varied over time and across locations, especially as COVID-19 case numbers fluctuated or media coverage intensified. People living in higher-density areas, for instance, may have perceived a greater risk of infection compared to those in lower-density areas (Wag et al., 2021). Another example is employment status, which may have changed during the pandemic (e.g., job loss, remote work), influencing both mobility needs and active travel behaviour. If these employment changes are correlated with the timing of more or less stringent policies, this could violate the assumption and bias the estimated effect.

Using Directed Acyclic Graphs (Study 4)

In Study 4, I adopted a different approach to address *exchangeability* by using random intercept cross-lagged panel models (RI-CLPM) to investigate the reciprocal relationships between the built environment, active travel, and individual travel preferences. This method—often referred to as longitudinal structural equation modelling (SEM)—is considered conceptually robust for causal inference in transport planning research (Cao et al., 2009; Næss, 2015; Van Wee & Cao, 2022). It explicitly measures individual attitudes, allows for bidirectional causality, and uses panel data to address within-unit changes over time. Additionally, at a higher level, in what is essentially a didactic component, the formulation of the critical assumptions is intended to capture the way researchers think of causal relationships (Imbens, 2020).

Study 4 incorporates individuals' pre-relocation attitudes to analyse within-person changes in travel behaviour and attitudes following a move. The RI-CLPM approach allows for a dynamic examination of how the built environment influences travel behaviour over time, while also accounting for the potential role of self-selection—that is, how pre-existing preferences may influence relocation decisions. The findings support the notion that changes in the residential built environment can structurally reshape both travel mode choices and mode-specific attitudes, capturing reverse causality in the relocation process and accounting for other relevant common causes of travel behaviour. In particular, individuals who moved to more urban, compact, and accessible neighbourhoods tended to increase their use of bicycles and developed more favourable attitudes toward cycling, while individuals moving to less dense and accessible areas tended to decrease their cycling behaviour.

By explicitly modelling reciprocal relationships, this method assumes the absence of any other unmeasured common causes of variables, since all important relationships are already represented through the paths. Although three dominant arguments regarding the causal relationship between the built environment and travel behaviour have been included in the modelling of study 4: residential determinism, residential self-selection, and reverse causality (see Tao, 2024). However, one has to make a strong assumption: that all relevant variables affecting travel behaviour, built environment and attitudes are included in the model. It is highly unlikely that this is actually the case and this limits possibilities for causal inference. Simply assuming that one can consistently learn how all variables behave together is not always helpful (Imbens, 2020).

Not competing, but complementary approaches to causal inference

It is important to acknowledge that no single approach can fully overcome the inherent challenges associated with estimating causal effects between the built environment (BE) and active travel (AT). All methods employed in this thesis necessarily rely on identifying assumptions or causal mechanisms that are not always directly testable or verifiable, but can nevertheless be reasonably justified and partially addressed, as discussed above. Rather than viewing them as competing paradigms, the two causal inference frameworks applied here—Potential Outcomes (PO) and Directed Acyclic Graphs (DAGs)—are better understood as complementary to one another (Imbens, 2020). Each framework offers distinct advantages: DAGs emphasize the explicit representation and critical evaluation of causal assumptions, while the Potential Outcomes approach provides a formal framework for defining and estimating treatment effects. A combined use of DAGs and POs can offer a more comprehensive strategy for approximating observational studies to randomized experiments, offering stronger basis against bias and facilitating the identification of critical assumptions necessary for causal identification in transport research.

6.3. Recommendations for future research

Despite the evidence produced in this research, I argue that a strong need for more natural experiments and high-quality causal studies remains, particularly on the impacts of pro-walking interventions on walking levels and physical activity, which are particularly few compared to cycling studies (Xiao et al., 2022; Aldred, 2019). While conducting the research for this thesis, several new research directions arose, and which are not completely addressed in this research. Based on the research findings, 7 key recommendations for further research are proposed.

6.3.1. Towards a more comprehensive causal approach

After applying different causal approaches, a central recommendation for future research is to advocate for a more integrated use of Directed Acyclic Graphs and Potential Outcomes frameworks in transport intervention studies. The use of DAGs during the initial stages of research would allow for the systematic and conceptual structuring of causal relationships between the built environment and active travel. By explicitly mapping these relationships, DAGs support both the identification of relevant common causes of treatment assignment and outcomes, and the clarification of underlying causal pathways (Pearl, 2009; Imbens, 2020). These clarified causal relations can then be formally estimated using the Potential Outcomes framework, selecting appropriate causal identification strategies (e.g., DiD, FEs, etc.) based on the structure revealed by the DAG and possibilities offered by the data (e.g., prospective longitudinal, retrospective longitudinal, multiple cross-sections, etc.). Relying solely on the identification assumptions of the PO framework may be insufficient to fully address potential confounders (Pearl, 2009). While DAGs, on their own, cannot guarantee that the assumptions underpinning PO-based methods—such as no omitted time-varying confounders—are fully satisfied, they play a critical role in reducing the risk of unobserved confounding. Additionally, by systematically identifying which variables must be controlled for, DAGs improve the internal validity of causal estimates (see this very recent example by Brito-Filho and Oliveira-Neto, 2025). Combining these two approaches would enable a more robust causal analysis by linking assumption diagnosis with formal effect estimation.

6.3.2. The call for more (and better) multi-period data

A major limitation in current transport research is the scarcity of multi-period study designs compared to cross-sectional designs, which hinders a deeper understanding of causal relationships between the built environment and travel behaviour (Van de Coevering, 2021). Although the implementation of multi-period studies often faces challenges—such as keeping contact with respondents between measurement points and managing the complexity of questionnaire design—their broader and more systematic adoption is strongly recommended in intervention studies. Multi-period designs, which can involve repeated observations of the same participants (panels) or geographic units over time (repeated cross-sections), offer substantial advantages for causal inference. They are better equipped to address common issues such as confounding, reverse causality, and residential self-selection, leading to more robust and credible findings. Recent advances in data collection methods, including online questionnaires and GPS-based surveys, have made it easier than ever to conduct large-scale longitudinal studies with adequate sample sizes. As a result, the opportunities for generating extensive multi-period mobility datasets—such as those exploited in my own research—have increased. These datasets are particularly valuable for assessing the impacts of policy interventions on active travel and physical activity over time. In addition to expanding the use of multi-period designs, further efforts could focus on integrating transport-related data into existing large-scale biobanks. Mobility behaviour, travel attitudes, and perceptions of the built environment, for instance, could be systematically incorporated into major initiatives such as Lifelines[39] or the Netherlands Epidemiology Study (NES), enhancing their utility for transport research and policy-making (Aldred, 2019). During my research, I explored the possibility of using the Lifelines dataset. However, I ultimately decided against it because it missed important attitudinal variables, making it difficult to conduct relocation studies that adequately address the self-selection issue.

6.3.3. Moving beyond average treatment effects

While many studies evaluate broad policy impacts, it is equally important to consider traveller-specific effects. My findings on intervention effect heterogeneity suggest that the same intervention can yield significantly different outcomes depending on the traveller group affected and the environmental context in which it is implemented. This raises additional research questions regarding the equity and diversity considerations, for instance, which types of traveller groups benefit the most from the installed policy? And how is that reflected in their demand uptake? Future studies should also go beyond assessing the overall impact of interventions and examine the design features that may either enhance or diminish their impact. This is particularly relevant for multifaceted and costly interventions such as 'transit-oriented developments (TODs)', 'complete streets', 'bicycle boulevards', 'traffic calming zones', 'green corridors', 'Car-free neighbourhoods', which are defined by general terms, but actually combine both positive ("carrots") and negative ("sticks") strategies to encourage sustainable behaviour, while discouraging car use (Xiao et al., 2022).

39. Lifelines is a large-scale, longitudinal cohort study in the Netherlands following over 167000 participants across three generations to investigate the biological, behavioural, and environmental factors influencing health and disease.

6.3.4. Rethinking exposure in intervention studies

While observational studies offer valuable opportunities to generate causal evidence when high-quality data is available, they often face significant conceptual and methodological challenges, particularly in defining exposure. As discussed, many intervention studies rely on simply identifying 'exposed' and 'unexposed' populations based on fixed spatial boundaries—such as zip codes, census tracts, or distance buffers. However, this research suggests that it may be more effective to complement these traditional definitions with more dynamic approaches. Rather than relying solely on static spatial categories, exposure could be more accurately defined as the actual benefit derived from a given intervention, and linked directly to existing travel behaviour (e.g., origin-destination pairs, simulated routes, or GPS-observed routes). This approach better captures the real-world impacts of interventions on mobility patterns. Recent advancements in secondary data sources—such as Cellular Network Data, Mobility-as-a-Service (MaaS) apps, location-based fitness apps (Strava), and shared mobility platforms—have made it increasingly feasible to apply such dynamic methods. These technologies significantly reduce study costs and allow for the collection of much larger datasets compared to launching new longitudinal studies. As a result, they offer powerful tools for monitoring travellers' spatial exposure to changes in the built environment. Although obtaining individual-level data may still be challenging due to potential GDPR[40]limitations, working with higher levels of aggregation (e.g., origin-destination pairs, neighbourhoods) can nonetheless enable the development of robust and informative intervention studies.

6.3.5. The potential contribution of qualitative insights

Whereas the determination of correct effect size estimates requires quantitative models, complementary qualitative research can help to further disentangle the relationships between moving, attitudes, the built environment, and travel behaviour. To strengthen empirical research on causality, residential self-selection, and travel behaviour, Scheiner et al.

40. Under the General Data Protection Regulation (GDPR), personal mobility data collected in Europe—such as GPS traces or app-based travel records—must be anonymized or aggregated to protect individual privacy. Researchers often work with higher aggregation levels (e.g., trip origins and destinations, neighbourhood-level data) to comply with GDPR requirements while still enabling meaningful analysis.

(2024, p.2) recommend the development of more comprehensive survey designs. Specifically, they suggest that surveys should capture:

a. *travel behaviour before and after changes in the built environment (e.g., residential relocation),*
b. *residential and travel preferences before and after such changes,*
c. *the characteristics of the built environment itself before and after the change, and*
d. *individuals' underlying rationales for their residential and travel decisions (i.e., the causal mechanisms).*

The first three elements enable a before-and-after analysis, allowing researchers to estimate changes not only in behaviour but also in preferences, while addressing potential confounders. The fourth element, rooted in the assumption that individuals can articulate the reasons for their actions (Giddens, 1984; Næss, 2005, 2013), provides additional insight into whether shifts in circumstances or preferences drive changes in travel behaviour from the respondents' perspective. While standardized longitudinal surveys (e.g., MPN) effectively capture the first three elements, qualitative methods are arguably better suited for exploring personal rationales since they are able to get detailed understanding of the mechanisms by which people adapt their behaviour to the opportunities and restrictions provided by various types of BE characteristics. The fourth element also contributes to greater certainty about the nature of the studied relationships. It may also show other relationships between the constructs, which may inform future quantitative research. A qualitative study of movers may also be useful in understanding the causal relationships, more fully capturing the intervention effects including medium- and long-term impacts, and informing future research designs and statistical analyses. (Heinen et al., 2018).

This underscores the need for a mixed-methods approach (Næss, 2015; Scheiner et al., 2024). While either approach (qualitative and quantitative) can be valuable on its own, incorporating insights from the other could strengthen the analysis. Quantitative researchers should draw on qualitative findings, and vice versa. However, since studies on built environment influences on travel are context-dependent, the most effective integration of methods occurs when both are applied within the same research framework. This enables researchers to leverage first-hand evidence from multiple perspectives, leading to a more comprehensive understanding.

6.3.6. Including alternative measures of the built environment

Expanding on the variables used to measure the built environment can enhance our understanding of how urban form influences travel behaviour. Traditional metrics such as the *'3Ds'* (density, design, diversity) provide valuable insights, but they often fail to capture human perceptions. Incorporating measurements of perceptions, self-efficacy, and social norms would offer a more comprehensive picture of the causal mechanisms driving mobility choices (e.g., Panter and Ogilvie, 2015). For instance, certain individuals may regard an area as more walkable due to its perceived safety and quietness, even if objective measures such as density or diversity suggest that area as 'compact' and 'accessible'. Researchers can also leverage emerging computational techniques to directly measure human perception or derive proxies that correlate with perception-based factors. Advances in object detection and image segmentation techniques applied to street-level images (e.g., Google Street View or crowdsourced imagery, such as Mapillary), for example, can help quantify features such as textures and identify certain objects that would otherwise have been captured differently by traditional GIS techniques (see e.g., Biljecki and Ito, 2021; Li et al., 2022). These metrics can then be linked to survey-based measures of perception or behavioural data from location-based apps like Strava or GPS tracking tools to examine their influence on travel behaviour.

6.3.7. Establishing a more direct link between active travel investments and health outcomes

Additional daily physical activity can significantly reduce the risk of several health conditions, including coronary heart disease, hypertension, Type 2 diabetes, certain types of cancer, depression, and all-cause mortality (Garcia et al., 2023; Kraus et al., 2019; Kelly et al., 2014; Sattelmair et al., 2011). Walkable and cyclable neighbourhoods have also been associated with improved health indicators, such as lower BMI and healthier blood pressure levels. Conversely, prolonged time spent in vehicles is linked to higher rates of obesity, diabetes, and a greater risk of premature death (Sugiyama et al., 2020; Ding et al., 2014; McCormack and Virk, 2014; Goncalves et al., 2014; Hoehner et al., 2013; Nunez-Cordoba et al., 2013; Sugiyama et al., 2013). To better understand these relationships, future intervention studies should explore how changes in infrastructure and land use that promote walking and cycling lead to measurable health outcomes beyond increased physical activity alone.

6.4. Implications for practice

The empirical insights produced in this research support the initial assumption presented at the beginning: changes in the built environment—whether through land use policies or infrastructure —play a decisive role in shaping travel (Naess, 2015). While place characteristics and individual factors, such as residents' attitudes and travel habits, and external factors, also influence mobility patterns (Panter et al., 2019), the built environment remains a key determinant of behavioural change.

In this sense, how can we best apply the methodological and empirical contributions of this thesis to ensure the success of policy and support future investments on active mobility infrastructure? I propose 3 main strategies to address this question:

Fig. 6.1. Strategies to maximize success of policy design.

Strategy 1 | Leveraging local context to maximize policy impact

We learned that the impact of built environment interventions can vary significantly depending on the characteristics of different traveller groups, neighbourhood contexts, and the level of exposure to those interventions. Policymakers can use these insights to better inform future investments by emphasizing the importance of targeting interventions so they better align with established travel behaviours. New cycle routes, for instance, when strategically aligned with key origin-destination patterns, specific demographics, or trip purposes, can yield substantial benefits. This targeted approach can strengthen the case for investment by enhancing the likelihood of positive behavioural shifts and broader policy impact.

Strategy 2 | Supporting future investment with ex-post insights

Cost-benefit analysis is commonly used to assess mobility projects before implementation (ex-ante evaluation). However, post-implementation evaluations (ex-post assessments) are rarely conducted, even though they provide valuable insights for future investments. These retrospective analyses are crucial for understanding whether projects delivered the expected outcomes, especially given the frequent cost overruns and benefit shortfalls in CBAs. Ex-post evaluations also help explain why certain projects outperform or underperform expectations (Jong et al., 2019). By leveraging empirical insights from ex-post assessments, such as those generated in my thesis, policymakers can make more informed investment decisions and design more effective policies for active mobility. And as previously learned, when tailored to the right target groups, these policies can maximize benefits.

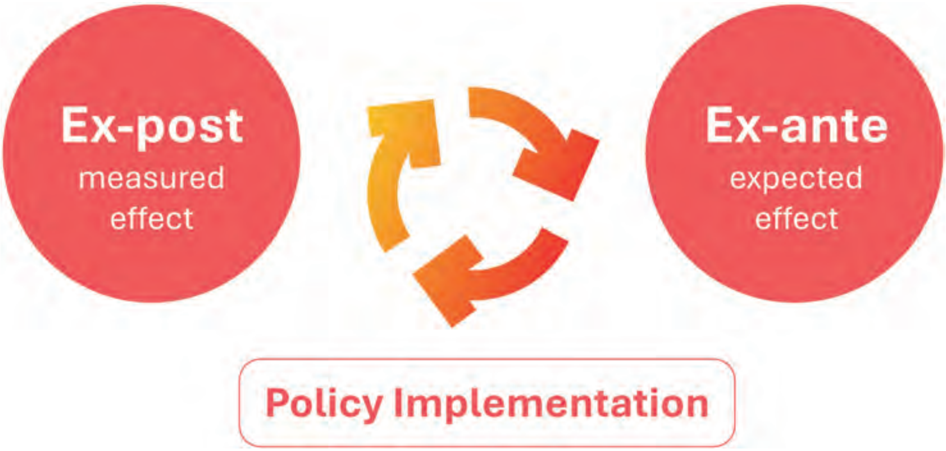

Fig. 6.2. Ex-post and Ex-ante relationship framework.

Moreover, the empirical evidence presented here reinforces confidence in predictive models and ex-ante analyses, enhancing their reliability. Given the scepticism often surrounding transport models—particularly when predicting disruptive changes—ex-post evaluations can also help build public and political support for future interventions (Brathwaite and Walker, 2018). This is especially valuable in contexts of high political friction and opinionated stakeholders, where empirical evidence can facilitate discussions by partly eliminating subjectivity.

The example below, from our cycle highways study (paper 3), is a simplified demonstration how ex-post findings can enhance ex-ante analysis when planning new cycling infrastructure, such as cycle highways. The analysis considers different levels of traveller "exposure" to the new infrastructure, which refers to how directly a new cycle highway influences commuting routes. In areas where commuters will have a significant interaction with the new cycle highway, a shift of up to 12% from car to bicycle is estimated. In areas with less direct access to the cycle highway, the expected behavioural shift is smaller, with up to 6% of car trips converting to bicycle trips. These values can be used as reference to forecast additional cycling demand, taking into account the future interaction of residents with the new infrastructure.

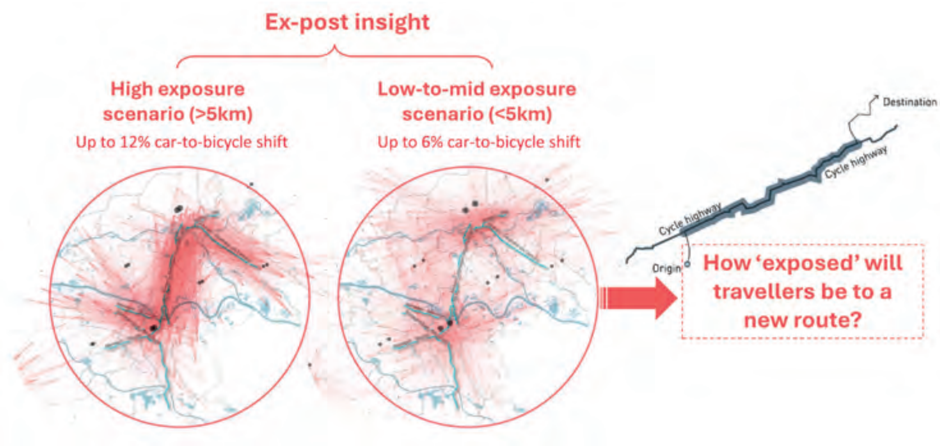

Fig. 6.3. Example of using ex-post finding on ex-ante analysis.

Strategy 3 | Showcasing ex-post social benefits

The ex-post findings of this thesis can strengthen the links between active travel investment and public health by feeding existing economic appraisal tools and frameworks, such as the Health Economic Assessment Tool (HEAT)[41] and the Integrated Transport and Health Impact Model (ITHIM)[42], which

41. HEAT is a tool used to assess the economic benefits of policies promoting physical activity through activities like walking and cycling. It helps calculate health gains and economic savings resulting from such initiatives, aiding decision-making for policymakers and health professionals. HEAT was developed within the Transport, Health and Environment Pan-European Programme (THE PEP), a joint initiative of WHO/Europe and the United Nations Economic Commission for Europe.
42. The Integrated Transport Health Impact Model (ITHIM) is a mathematical model that integrates data on travel patterns, physical activity, fine particulate matter, GHG emissions, and disease and injuries based on population and travel scenarios. The model was pioneered by Dr. James Woodcock at Cambridge University's Centre for Diet and Activity Research (CEDAR). It has been used to evaluate the health benefits of transport-related technology and behaviors changes in the UK, and some cities in the United States (Bay Area and Nashville).

monetize the health improvements (in terms of, for example, all-cause mortality and morbidity) from additional physical activity levels, decreasing exposure to air pollution, changes in traffic collisions, and the reduction of carbon transport emissions promoted by those investments. For example, if a study shows that a new cycle highway in the Netherlands, on average, leads to a 10% increase in commuting by bike, this behavioural change can be input into HEAT to estimate how many premature deaths are avoided due to increased physical activity. These health outcomes can then be translated into monetary values, providing estimates of the intervention's societal benefits, and helping finance pro-cycling infrastructures. Regardless of the approach used to evaluate active travel interventions, the foundation lies in empirical knowledge of behavioural change, thus making causal inference extremely important for future infrastructure investment.

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Summary

Over the past century, city dwellers have become more sedentary due to advances in technology and the way our environments are designed. People now spend long hours sitting at work, during commutes, and at home—especially in higher-income countries. This shift has serious health implications, as low levels of physical activity are linked to chronic conditions like heart disease and diabetes. Encouraging even small amounts of physical movement, such as walking or cycling as part of daily travel, can significantly improve public health. As a result, integrating active travel into everyday routines is increasingly seen as a practical and efficient way to reduce sedentary behaviour.

The built environment plays a key role in shaping how people travel. Neighbourhoods that are walkable, bike-friendly, and offer easy access to daily destinations tend to support more active travel behaviour, thus more physical activity. In contrast, sprawling, car-dependent areas with poor infrastructure discourage walking and cycling. Although it is widely assumed by planners and policymakers that changing the built environment leads to changes in travel behaviour, much of the research to date has focused on correlations rather than proven cause-and-effect relationships. Scholars are now calling for more careful thinking about what really triggers behaviour and how different urban environments affect different groups of people.

While there is growing interest in studying the impact of infrastructure and urban design on travel habits, solid causal evidence remains limited. Many studies rely on snapshots in time rather than measuring long-term changes, and few account for factors like self-selection or local political resistance to active travel investments. Research methods—such as longitudinal studies and natural experiments—can offer stronger insights, but they require better data and are often costly or difficult to carry out. Still, building this kind of evidence is essential. It can give policymakers and planners greater confidence in making decisions that genuinely improve health, sustainability, and mobility for everyone.

Scope of this thesis

In light of the growing interest among planners and researchers on causal effects of transport infrastructure and land use reforms on active travel—their potential impact of the latter on people's health, and the fact that causality is still far from being widely understood given the need for more evidence — this thesis aims to contribute to the current understanding of the causal relationship between the built environment (BE) and active travel (AT). Specifically, it focuses on how improving transport infrastructure and changing access to land use affects the uptake of cycling and walking.

This thesis focuses on two central research questions. First, *how and to what extent does active travel infrastructure influence travel behaviour? Second, how and to what extent do density, access to destinations and land-use diversity affect active travel behaviour?*

To answer these two overarching questions, 4 empirical studies are proposed:

- Study 1**:** City-wide cycling network extension and bicycle ridership in São Paulo: A causal analysis.
- Study 2: Cycle highway effects: Assessing modal choice to cycling in the Netherlands.
- Study 3: Safe to Move? Investigating the Amplifying and Attenuating Role of Neighbourhood Environments on Physical Inactivity during COVID-19 Movement Restrictions.
- Study 4: Short-term changes in daily mobility due to residential relocation: A cross-lagged panel analysis.

The first two studies are large-scale natural-experiments using multiple cross-sections of household travel surveys - the first one in the Metropolitan Area of São Paulo (a low-cycling context), and the other using the Netherlands (a high-cycling context). In the first case, I look at the effect of implementing an extensive network of urban cycle routes across São Paulo, to serve its more than 20 million inhabitants. In the second case, I estimate the impact of introducing a large network of ambitious/ high-quality facilities across the Netherlands. In both cases I adopt robust and 'dynamic' approaches (Humphreys et al., 2016) to defining levels of exposure, which take into consideration routine mobility and operationalize the benefits promoted by the interventions through the application of routing algorithms and geospatial techniques, therefore establishing a more direct connection with causal mechanisms behind behavioural change. In the third study, I investigate how different neighbourhood environments triggered changes in active mobility during the first COVID-19 lockdown in the Netherlands, which drastically decrease accessibility of people to amenities and sports opportunities. While restrictions were applied uniformly across the country, changes in walking and cycling for leisure and work varied depending on built environment characteristics. The research explores whether certain neighbourhood types amplified or mitigated the decline in physical activity caused by limited access to public spaces and facilities. Unlike earlier studies in the thesis that analysed supportive infrastructure interventions, this study treats COVID-19 restrictions as an unsupportive "event" that constrained accessibility, thus physical activity. In the fourth study I examine how changes in the residential built environment relates with shifts in travel attitudes and mode use among individuals who relocated in the Netherlands. By using longitudinal data from about 1,000 movers between 2013 and 2016, and applying a cross-lagged panel model (RI-CLPM), I investigate how relocation influences cycling and car use, the evolution of travel attitudes, and how built environment changes and life events interact with travel behaviour. The analysis accounts for self-selection and reverse causality within a single framework.

Main Findings

Study 1

1. Exposure to interconnected cycling networks can attract new cyclists. The probability of choosing cycling for multiple trips purposes has increased by a modest yet statistically significant margin (+0.60% to +1.4%) in areas where new routes were implemented, particularly for travellers experiencing moderate to high exposure to new routes, compared to a counterfactual scenario without intervention.

2. After testing multiple exposure definitions, results show relatively stable intervention effects. This consistency strengthens both the robustness of our treatment definitions and the validity of the intervention’s effectiveness. At the same time, it highlights the importance of testing multiple exposure definitions to obtain a more comprehensive understanding of the intervention’s impact.

3. After the introduction of the network in São Paulo, the insignificant marginal effects suggest that no significant developments happened with control groups in terms of cycling probability, which reinforce the positive effects of the intervention on exposed groups in comparison to the rest of the metropolitan area.

4. A subgroup-level analysis revealed significant differences in cycling uptake among traveler clusters (types). Low-educated workers showed the highest marginal increase in cycling, followed by highly educated workers, predominantly men. However, socially vulnerable groups, such as housewives without income and students, exhibited the lowest uptake after exposure to new cycling routes. These disparities in treatment effects raise important questions about the design and planning of cycling infrastructure, which may not be sufficiently adaptable to accommodate the diverse needs of different user groups.

Study 2

1. High-quality, new infrastructure positively influences travel behaviour, leading to increased cycling demand. Effect estimates remain consistent across different treatment specifications, confirming that the introduction of cycle highways has shifted commuting patterns toward cycling.

2. Highly exposed travellers, those who frequently use the new infrastructure —experience up to a 12% increase in cycling probability post-intervention. This effect specifically applies to commute trips between 5 and 15 km made by individuals over 18 years old. For travellers with lower exposure levels, the increase is estimated at 5%, which remains a significant improvement.

3. Prior to the introduction of cycle highways, treatment groups were 6% to 9% less likely to commute by bike compared to control groups. The fact that these groups exceeded expected cycling increases following the intervention strongly indicates the positive impact of the new infrastructure.

4. Similar to the findings in Chapter 2, our results show relatively stable intervention effects across different exposure methodologies. This consistency strengthens both the robustness of our treatment definitions and the validity of our intervention's effectiveness. At the same time, it highlights

the importance of testing multiple exposure definitions to obtain a more comprehensive understanding of the intervention's impact.

5. The effects of cycle highways are not uniform across all demographic groups. Individuals value benefits such as comfort, safety, and directness differently. Our findings indicate that the infrastructure had a stronger impact on women, younger cyclists, and individuals without a car in their household. The improved comfort and safety of high-quality routes may explain why they appeal more to women, who, as past studies show, tend to cycle less than men. Meanwhile, car owners displayed lower sensitivity to the new infrastructure—an expected outcome that aligns with findings from Chapter 3 and other cycling studies.

Study 3

1. In the absence of strong restrictions, as also shown in other studies, neighbourhoods that are highly urbanized, compact, well-served by sports facilities, and inhabited by physically active individuals tend to be associated with higher levels of active mobility than low-density, peripheral, and less physically active neighbourhood types.

2. Local context, as represented by neighbourhood typologies in or study, play a crucial role in moderating the effects of restrictive policies on active behaviour. They can either attenuate or amplify the spillover effects of these policies on mobility-related PA.

3. During strict movement measures, the former compact type of neighbourhoods (deemed as conducive of active mobility) was more likely to experience a significant decrease in leisure and transportation time compared to the latter low-density type. This suggests that despite their pre-pandemic positive association with active living, these neighbourhoods are also particularly sensitive to movement restrictions. Interestingly, a group of residents living neighbourhoods with higher obesity prevalence and lower baseline activity, also experienced significant reductions, which is concerning. This finding highlights that mobility losses were not confined to highly accessible areas, but also might have affected populations already at greater risk of inactivity-related health problems, potentially deteriorating their physical health even further.

Study 4

1. Moving to more accessible neighbourhoods not only encourages cycling use but also improves attitudes toward cycling. However, the opposite effect is only partially observed for car use. Higher density and accessibility provide shorter travel distances and more mixed land uses, making cycling a more attractive option compared to driving.

2. Among driving and cycling, the latter behaviour appears to be more sensitive to built environment changes than car behaviour. Unlike driving, cycling depends heavily on a well-designed environment, requiring safe, connected, and convenient infrastructure as well as short travel distances to remain a practical and attractive option.

3. Changes in density and accessibility that lead to shifts in attitudes suggest that the built environment plays a crucial role in shaping travel behaviour beyond immediate changes caused by relocation. This process may contribute to long-term habit formation. The argument that behaviour and attitudes are shaped by the built environment—often referred to as "environmental determinism"—has also been supported in recent studies. As a result, relocating to compact and accessible urban areas can create a positive reinforcement effect, strengthening both cycling attitudes and usage.

4. Consistent with classical built environment-travel behaviour research, destination accessibility and density significantly influence travel behaviour and attitudes. However, in our study, land-use mix did not show a significant effect. This may be partly due to how these factors were measured. Density in our study was measured not only in terms of residential address density but also by the concentration of different activities around each respondent's residence. This measure likely correlates with destination accessibility, leading to similar effects. However, our diversity measure focused only on the contribution of residential surface to the total land use, which may not fully capture an area's overall diversity.

Implications of this thesis

The findings of this research confirm that improvements in pro-Active Travel infrastructure and accessibility lead to measurable increases in walking and cycling, even when reasonably mitigating the influence of potential confounders. However, the effects are not uniform across all populations or locations. Factors such as socio-demographics, local context, and existing travel habits moderate the impact of interventions, with some traveller groups—like women, younger people, or car-free households—responding more positively than others. To strengthen causal inference, the thesis applies causal identification methods, including Difference-in-Differences, Fixed Effects, and Random Intercept Cross-Lagged Panel Models, framed within both the Potential Outcomes and Directed Acyclic Graphs frameworks of Causal Inference. Each method addresses specific sources of bias, with their respective assumptions and limitations explicitly acknowledged. A key contribution of this thesis is the development of more "behaviour-based" definitions of intervention exposure, allowing for more accurate estimations of impact based on actual travel patterns. The research also emphasizes the importance of multi-period data for identifying changes over time and recommends combining different causal approaches (DAG + PO) for better understanding of causal relationships between transport interventions and travel behaviour.

In terms of transport policy, the thesis proposes three main implications. First, based on the previous findings, it is imperative that interventions should be designed to interact with local travel habits and user groups to maximize their effectiveness. Second, as transport intervention studies (*ex-post*) grow, they should be better integrated into the practice of policymakers and consultants, to support traditional *ex-ante* models that assess the impact of future investments and policy changes. Third, empirical findings on travel behaviour shifts of this thesis can be directly integrated into health and environmental appraisal tools to quantify broader societal benefits of pro-active mobility policies. Together, these insights contribute to both the academic literature on causal inference in transport research and to practical decision-making for more sustainable and equitable urban mobility planning.

In the following table, I present an overview of the 4 studies:

Table 6.1 . Summary of all studies produced during my PhD journey.

Study	What we did	Findings and Discussion	Future Research	Policy implications
Paper 1: City-wide cycling network extension and bicycle ridership in São Paulo	Natural-experiment (2x2 DiD + Logit) with 2 cross-sections to compare the impact of a cycling policy on treatment and control groups. Tested treatment robustness against 2 treatment-group definitions and varying exposure degrees. Tested treatment heterogeneity.	Intervention increases cycling probability in +0.60% to +1.4% for treated groups compared to control. Relatively stable intervention effects across multiple treatment definitions (robustness). No change observed in control group. Important differences in uptake among traveller groups (e.g., housewives less responsive than working men). Improved link between exposure and causal mechanism associated with stronger treatment effects,	PTA before 2007 could not be verified. Accuracy of exposure measure could be improved (more precise OD locations, or simulating more realistic itineraries). Excluding weekends might have affected leisure cycling. Effect heterogeneity of design features could further elucidate potential impacts.	Insights support future cycling investments by building the case for new cycle routes. New designs should consider causal context and mechanisms. Effects can be used to feed ex-ante analysis..
Paper 2: Cycle highway effects	Natural-experiment (TWFE + Logit) with multiple cross-sections to compare the impact of a cycling policy on treatment and control groups. Tested treatment robustness against several treatment-group definitions and varying exposure degrees. Tested treatment heterogeneity.	Intervention increases cycling probability in +8% to +12% for highly exposed traveller groups. Relatively stable intervention effects across multiple treatment definitions (robustness). Significant differences in uptake among traveller groups (e.g., uptake among women stronger than among men). Improved link between exposure and causal mechanism associated with stronger treatment effects,	Accuracy of exposure measure could be improved (more precise OD locations). Effect heterogeneity of design features (quality) could further elucidate potential impacts.	Insights support future cycling investments by building the case for new cycle routes. New designs should consider causal context and mechanisms. Effects can be used to feed ex-ante analysis.

Table 6.1 . (continued)

Study	What we did	Findings and Discussion	Future Research	Policy implications
Paper 3: Moderating role of BE between COVID policy and physical activity	Fixed Effects regressions (with min/ week) with moderation analyses (BE type * Intervention) to estimate policy effects on physical activity. Used K-means to create neighbourhood typologies.	BE plays a crucial role in moderating policy effects. Dense type of neighbourhoods more likely to experience a significant decrease in leisure and transportation time compared to the latter low-density ones. A group of residents living neighbourhoods with higher obesity levels and lower baseline activity, also experienced significant reductions, which is concerning.	Response bias, as most respondents were > 40 y.o. and reside in the east of NL. Self-reported retrospective data prone to measurement error. Likely to have omitted time-varying factors.	By linking findings to other relevant research conducted in the NL during COVID, policymakers can identify neighbourhoods particularly vulnerable to physical inactivity due to movement restrictions (e.g., high reliance on indoor PA).
Paper 4: Relocation, travel behaviour and attitudes	Estimated within-person effects of changing BE (relocation) on travel behaviour and attitudes using a RI-CLPM approach and a 4-wave panel.	Moving to more accessible and compact BEs not only encourages cycling use but also improves attitudes toward cycling ("environmental determinism" reinforced). Opposite effect (partially) observed for car usage. Cycling behaviour more sensitive to BE changes than car behaviour. Diversity had no significant effect likely due to how it was measured.	Limited longitudinal data on attitudes and travel behaviour. Neither personal or contextual circumstances of the move fully understood. Qualitative insights from interviews would help understand causal mechanisms.	Creating more compact and accessible BEs can change residents' travel behaviour in the short term and perhaps change attitudes in the long term.

Samenvatting

Gedurende de afgelopen eeuw zijn stadsbewoners steeds minder gaan bewegen, als gevolg van technologische vooruitgang en de manier waarop onze omgevingen zijn ontworpen. Mensen brengen tegenwoordig lange uren zittend door op het werk, tijdens het forenzen en thuis — vooral in landen met hogere inkomens. Deze verschuiving heeft ernstige gezondheidsgevolgen, aangezien lage niveaus van fysieke activiteit in verband worden gebracht met chronische ziekten zoals hartaandoeningen en diabetes. Het stimuleren van zelfs kleine hoeveelheden fysieke beweging, zoals wandelen of fietsen als onderdeel van dagelijkse verplaatsingen, kan de volksgezondheid aanzienlijk verbeteren. Als gevolg hiervan wordt het integreren van actieve mobiliteit in dagelijkse routines steeds meer gezien als een praktische en efficiënte manier om sedentair gedrag terug te dringen.

De gebouwde omgeving speelt een sleutelrol in de manier waarop mensen zich verplaatsen. Wijken die beloopbaar, fietsvriendelijk zijn en gemakkelijke toegang bieden tot dagelijkse bestemmingen, bevorderen doorgaans actiever verplaatsingsgedrag en dus meer fysieke activiteit. In tegenstelling daarmee ontmoedigen uitgestrekte, autogerichte gebieden met gebrekkige infrastructuur het wandelen en fietsen. Hoewel het onder planners en beleidsmakers breed wordt aangenomen dat verandering in de gebouwde omgeving leidt tot verandering in verplaatsingsgedrag, heeft veel onderzoek tot nu toe vooral gekeken naar correlaties in plaats van naar bewezen oorzaak-gevolgrelaties. Wetenschappers pleiten nu voor een zorgvuldiger benadering van de vraag wat gedrag werkelijk triggert en hoe verschillende stedelijke omgevingen verschillende groepen mensen beïnvloeden.

Hoewel er groeiende belangstelling is voor het bestuderen van de impact van infrastructuur en stedenbouwkundig ontwerp op verplaatsingsgedrag, blijft robuust causaal bewijs beperkt. Veel studies zijn gebaseerd op momentopnamen in plaats van het meten van langetermijnveranderingen, en slechts weinigen houden rekening met factoren zoals zelfselectie of lokale politieke weerstand tegen investeringen in actieve mobiliteit. Onderzoeksmethoden zoals longitudinale studies en “natuurlijke”

experimenten kunnen sterkere inzichten bieden, maar vereisen betere gegevens en zijn vaak kostbaar of moeilijk uit te voeren. Toch is het opbouwen van dit soort bewijs essentieel. Het kan beleidsmakers en planners meer vertrouwen geven bij het nemen van beslissingen die daadwerkelijk bijdragen aan gezondheid, duurzaamheid en mobiliteit voor iedereen.

Focus van dit proefschrift

In het licht van de groeiende belangstelling onder planners en onderzoekers voor de causale effecten van transportinfrastructuur en ruimtelijke ordening op actieve mobiliteit — hun potentiële impact op de volksgezondheid, en het feit dat causaliteit nog verre van breed begrepen wordt vanwege de noodzaak aan meer bewijs — beoogt dit proefschrift bij te dragen aan het huidige begrip van de causale relatie tussen de leefomgeving en actieve mobiliteit. Specifiek richt het zich op hoe verbeteringen in transportinfrastructuur en veranderingen in toegang tot landgebruik een toe- of afname van fietsen en wandelen beïnvloeden.

Dit proefschrift richt zich op twee centrale onderzoeksvragen. Ten eerste: hoe en in welke mate beïnvloedt infrastructuur voor actieve mobiliteit het verplaatsingsgedrag? Ten tweede: hoe en in welke mate beïnvloeden dichtheid, toegang tot bestemmingen en functiemenging het gedrag ten aanzien van actieve mobiliteit?

Om deze twee overkoepelende vragen te beantwoorden, worden vier empirische studies voorgesteld:

Studie 1: Uitbreiding van het fietsinfrastructuurnetwerk op stadsniveau en fietsgebruik in São Paulo: een causale analyse.

Studie 2: Effecten van fietssnelwegen: beoordeling van de modale keuze voor fietsen in Nederland.

Studie 3: "Safe to Move?" Onderzoek naar de versterkende en verzwakkende rol van wijkomgevingen op fysieke inactiviteit tijdens COVID-19-bewegingsbeperkingen.

Studie 4: Korte termijn veranderingen in dagelijkse mobiliteit als gevolg van verhuizing: een cross-lagged panelanalyse.

De eerste twee studies zijn grootschalige "natuurlijke" experimenten die gebruik maken van meerdere dwarsdoorsneden van huishoudelijke verplaatsingsenquêtes — de eerste in de metropoolregio São Paulo (een context met laag fietsgebruik), en de tweede in Nederland (een context met hoog fietsgebruik). In het eerste geval bekijk ik het effect van de implementatie van een uitgebreid netwerk van stedelijke fietsroutes in São Paulo, bedoeld voor meer dan 20 miljoen inwoners. In het tweede geval schat ik de impact van de introductie van een uitgebreid netwerk van hoogwaardige voorzieningen in Nederland. In beide gevallen pas ik robuuste en 'dynamische' benaderingen toe (Humphreys et al., 2016) voor het definiëren van blootstellingsniveaus, waarbij routineuze mobiliteit wordt meegenomen en de voordelen van de interventies worden geoperationaliseerd via routeringsalgoritmen en geospatiale technieken. Op die manier wordt een directere koppeling gelegd met de causale mechanismen achter gedragsverandering.

In de derde studie onderzoek ik hoe verschillende wijkomgevingen veranderingen in actieve mobiliteit teweegbrachten tijdens de eerste COVID-19-lockdown in Nederland, waarin de toegankelijkheid tot voorzieningen en sportmogelijkheden sterk werd beperkt. Hoewel de restricties uniform werden toegepast in het hele land, verschilden de veranderingen in wandelen en fietsen voor werk en vrije tijd afhankelijk van kenmerken van de gebouwde omgeving. Het onderzoek verkent of bepaalde wijktypes de daling in fysieke activiteit versterkten of juist afzwakten, veroorzaakt door beperkte toegang tot openbare ruimten en faciliteiten. In tegenstelling tot eerdere studies in het proefschrift die ondersteunende infrastructuurinterventies analyseerden, beschouwt deze studie de COVID-19-beperkingen als een niet-ondersteunende 'gebeurtenis' die de toegankelijkheid en dus fysieke activiteit beperkte.

In de vierde studie onderzoek ik hoe veranderingen in de woon leefomgeving samenhangen met verschuivingen in mobiliteitsattitudes en vervoerswijzen bij personen die verhuisden binnen Nederland. Met behulp van longitudinale gegevens van circa 1.000 verhuizers tussen 2013 en 2016, en toepassing van een cross-lagged panelmodel (RI-CLPM), onderzoek ik hoe verhuizing fietsen en autogebruik beïnvloedt, hoe mobiliteitsattitudes zich ontwikkelen, en hoe veranderingen in de gebouwde omgeving en levensgebeurtenissen interageren met verplaatsingsgedrag. De analyse houdt rekening met zelfselectie en omgekeerde causaliteit binnen één enkel analytisch kader.

Belangrijkste bevindingen

Studie 1

1. Blootstelling aan onderling verbonden fietsroutes kan nieuwe fietsers aantrekken. De kans om de fiets te kiezen voor meerdere verplaatsingsdoeleinden nam met een bescheiden maar statistisch significant percentage toe (+0,6% tot +1,4%) in gebieden waar nieuwe routes werden aangelegd, met name bij reizigers met middelmatige tot hoge blootstelling aan de nieuwe routes, vergeleken met een contrafeitelijk scenario zonder interventie.

1. Na het testen van meerdere blootstellingsdefinities blijken de interventie-effecten relatief stabiel. Deze consistentie versterkt zowel de robuustheid van onze behandelingsdefinities als de geldigheid van de effectiviteit van de interventie. Tegelijkertijd onderstreept het het belang van het testen van meerdere blootstellingsdefinities voor een vollediger begrip van de impact van de interventie.

1. Na de introductie van het netwerk in São Paulo suggereren niet-significante marginale effecten dat er geen significante ontwikkelingen plaatsvonden bij controlegroepen qua fietsgebruik, wat de positieve effecten van de interventie op blootgestelde groepen ten opzichte van de rest van het metropoolgebied versterkt.

1. Een subgroepanalyse toonde significante verschillen in fietsgebruik onder reizigerstypes. Laagopgeleide werknemers vertoonden de grootste marginale stijging in fietsen, gevolgd door hoogopgeleide werknemers, voornamelijk mannen. Daarentegen vertoonden sociaal kwetsbare groepen, zoals huisvrouwen zonder inkomen en studenten, de minste stijging na blootstelling aan de nieuwe fietsroutes. Deze verschillen in behandelingseffecten roepen belangrijke vragen op over het ontwerp en de planning van fietsinfrastructuur, die mogelijk onvoldoende flexibel is om in te spelen op de diverse behoeften van verschillende gebruikersgroepen.

Studie 2

1. Hoogwaardige, nieuwe infrastructuur beïnvloedt het verplaatsingsgedrag positief en leidt tot een toename van de vraag naar fietsen. Effectschattingen blijven consistent over verschillende behandelingsspecificaties, wat bevestigt dat de introductie van fietssnelwegen de woon-werkpatronen richting fietsen heeft verschoven.
2. Reizigers met hoge blootstelling aan de nieuwe infrastructuur — zij die deze regelmatig gebruiken — ervaren tot een stijging van 12% in de kans op fietsgebruik na de interventie. Dit effect geldt specifiek voor woon-werkverplaatsingen tussen 5 en 15 km door personen ouder dan 18 jaar. Voor reizigers met lagere blootstellingsniveaus wordt een toename van 5% geschat, wat nog steeds een significante verbetering is.
3. Vóór de introductie van de fietssnelwegen waren de behandelingsgroepen 6% tot 9% minder geneigd om met de fiets naar het werk te gaan dan de controlegroepen. Het feit dat deze groepen na de interventie boven de verwachte toename uitstegen, wijst sterk op de positieve impact van de nieuwe infrastructuur.
4. Net als in hoofdstuk 2 blijven de interventie-effecten relatief stabiel over verschillende blootstellingsmethodologieën. Deze consistentie versterkt opnieuw de robuustheid van onze behandelingsdefinities en de geldigheid van de effectiviteit van de interventie. Tegelijkertijd benadrukt dit het belang van het testen van meerdere blootstellingsdefinities.
5. De effecten van fietssnelwegen zijn niet uniform verdeeld over demografische groepen. Individuen waarderen aspecten als comfort, veiligheid en directheid op verschillende wijze. Onze bevindingen tonen aan dat de infrastructuur een sterker effect had op vrouwen, jongere fietsers en mensen zonder auto in het huishouden. Het verbeterde comfort en de veiligheid van hoogwaardige routes verklaren wellicht waarom deze groepen er meer door worden aangetrokken. Ondertussen vertoonden autobezitters een lagere gevoeligheid voor de nieuwe infrastructuur — een verwachte uitkomst die aansluit bij hoofdstuk 3 en andere fietsstudies.

Studie 3

1. In de afwezigheid van strenge restricties, zoals ook in andere studies is aangetoond, worden sterk verstedelijkte, compacte buurten met goede toegang tot sportfaciliteiten en bewoond door fysiek actieve individuen doorgaans geassocieerd met hogere niveaus van actieve mobiliteit dan laag-dichte, perifere buurten met minder actieve bewoners.

1. De lokale context, zoals gerepresenteerd door de wijktypologieën in deze studie, speelt een cruciale rol in het modereren van de effecten van beperkende beleidsmaatregelen op actief gedrag. Deze context kan de neveneffecten van dergelijk beleid op mobiliteitsgerelateerde fysieke activiteit versterken of afzwakken.

1. Tijdens strikte bewegingsbeperkingen hadden compacte buurten (die doorgaans bevorderlijk zijn voor actieve mobiliteit) een grotere kans op significante afname van tijd besteed aan verplaatsing en vrijetijdsbesteding, vergeleken met laag-dichte buurten. Dit suggereert dat deze buurten, ondanks hun positieve associatie met actief leven vóór de pandemie, ook bijzonder gevoelig zijn voor bewegingsrestricties. Opmerkelijk is dat ook bewoners van buurten met een hogere obesitasprevalentie en lagere basisniveaus van activiteit significante afnames in fysieke activiteit ervaarden. Dit is zorgwekkend, aangezien het verlies aan mobiliteit dus niet beperkt bleef tot goed toegankelijke gebieden, maar ook populaties trof die reeds een verhoogd risico liepen op gezondheidsproblemen gerelateerd aan inactiviteit.

Studie 4

1. Verhuizen naar beter toegankelijke buurten stimuleert niet alleen het fietsgebruik, maar verbetert ook de houding ten opzichte van fietsen. Het omgekeerde effect voor autogebruik wordt slechts gedeeltelijk waargenomen. Hogere dichtheid en toegankelijkheid leiden tot kortere reisafstanden en meer functiemenging, wat fietsen aantrekkelijker maakt dan autorijden.

1. Van de gedragingen autorijden en fietsen, blijkt vooral fietsen gevoeliger voor veranderingen in de gebouwde omgeving. Fietsen

vereist een goed ontworpen omgeving met veilige, verbonden en handige infrastructuur en korte afstanden om praktisch en aantrekkelijk te blijven.

1. Veranderingen in dichtheid en toegankelijkheid die attitudeveranderingen teweegbrengen, suggereren dat de gebouwde omgeving een sleutelrol speelt in het vormgeven van verplaatsingsgedrag, voorbij de directe veranderingen door verhuizing. Dit proces kan bijdragen aan langetermijngewoontevorming. Het argument dat gedrag en attitudes gevormd worden door de fysieke omgeving—vaak aangeduid als "omgevingsdeterminisme"—wordt ook ondersteund door recente studies. Verhuizen naar compacte en toegankelijke stedelijke gebieden kan zo een positieve terugkoppelingslus creëren die zowel fietshoudingen als gebruik versterkt.

1. In lijn met klassiek onderzoek naar de relatie tussen gebouwde omgeving en verplaatsingsgedrag beïnvloeden bestemmingsbereikbaarheid en dichtheid het gedrag en de houding ten aanzien van mobiliteit significant. In deze studie bleek functiemix echter geen significant effect te hebben. Dit kan deels te maken hebben met de wijze waarop deze factor gemeten is. Dichtheid werd niet alleen gedefinieerd als het aantal woonadressen, maar ook als de concentratie van verschillende activiteiten rondom de woning van respondenten. Deze maat overlapt waarschijnlijk met bestemmingsbereikbaarheid, wat leidt tot vergelijkbare effecten. Onze maat voor functiemix richtte zich daarentegen alleen op het aandeel woonoppervlak in het totale ruimtegebruik, wat mogelijk niet de volledige diversiteit van een gebied weergeeft.

Implicaties van dit proefschrift

De bevindingen van dit onderzoek bevestigen dat verbeteringen in infrastructuur en bereikbaarheid ten gunste van actieve mobiliteit leiden tot meetbare toenames in wandelen en fietsen. De effecten zijn echter niet uniform verdeeld over alle populaties of locaties. Sociaaldemografische factoren, lokale context en bestaande verplaatsingsgewoonten modereren de impact van interventies, waarbij sommige groepen—zoals vrouwen, jongeren of huishoudens zonder auto—positiever reageren dan anderen.

Om causale inferentie te versterken, past dit proefschrift methoden toe voor causale identificatie, waaronder Difference-in-Differences, Fixed Effects en Random Intercept Cross-Lagged Panel Models, binnen zowel het Potential Outcomes-framework als het raamwerk van Directed Acyclic Graphs. Elke methode adresseert specifieke bronnen van vertekening, met expliciete erkenning van hun respectieve aannames en beperkingen. Een belangrijke bijdrage van dit proefschrift is de ontwikkeling van meer "gedragsgerichte" definities van blootstelling aan interventies, waarmee nauwkeurigere inschattingen kunnen worden gemaakt op basis van feitelijke verplaatsingspatronen. Het onderzoek benadrukt ook het belang van gegevens over meerdere tijdsperioden om veranderingen in de tijd vast te stellen, en beveelt aan om verschillende causale benaderingen (DAG + PO) te combineren voor een beter begrip van de causale relaties tussen transportinterventies en verplaatsingsgedrag.

Wat betreft mobiliteitsbeleid doet dit proefschrift drie belangrijke aanbevelingen. Ten eerste, op basis van de bevindingen, is het van essentieel belang dat interventies ontworpen worden in samenhang met lokale verplaatsingsgewoonten en gebruikersgroepen om hun effectiviteit te maximaliseren. Ten tweede, naarmate studies naar transportinterventies (ex-post) toenemen, zouden deze beter geïntegreerd moeten worden in de praktijk van beleidsmakers en adviseurs, ter ondersteuning van traditionele ex-ante modellen die de impact van toekomstige investeringen en beleidswijzigingen beoordelen. Ten derde kunnen de empirische bevindingen over gedragsveranderingen in dit proefschrift direct worden opgenomen in gezondheids- en milieubeoordelingsinstrumenten om bredere maatschappelijke baten van beleid voor actieve mobiliteit te kwantificeren. Samen dragen deze inzichten bij aan zowel de wetenschappelijke literatuur over causale inferentie in mobiliteitsonderzoek als aan de praktische besluitvorming voor duurzamere en rechtvaardigere stedelijke mobiliteitsplanning.

Resumo

Ao longo do último século, a vida cotidiana se tornou cada vez mais sedentária, impulsionada pelos avanços tecnológicos e pelo modo como nossos ambientes urbanos foram sendo organizados. Hoje, as pessoas passam muitas horas sentadas — no trabalho, no transporte e em casa — o que tem gerado impactos sérios na saúde, como o aumento de doenças crônicas, incluindo problemas cardiovasculares e diabetes. Pequenas mudanças, como caminhar ou pedalar diariamente, já podem trazer benefícios significativos. Por isso, incluir o deslocamento ativo no dia a dia tem sido cada vez mais defendido como uma forma prática de combater o sedentarismo.

O ambiente construído tem um papel central em como as pessoas se deslocam. Áreas com boa infraestrutura para pedestres e ciclistas, uso misto do solo e fácil acesso a destinos cotidianos tendem a incentivar mais deslocamentos ativos. Já bairros espalhados, voltados ao uso do carro e com pouca infraestrutura, acabam desestimulando caminhar ou pedalar. Embora exista uma crença comum de que mudanças no ambiente urbano levam diretamente a mudanças no comportamento de viagem, a maioria das pesquisas até hoje se baseia em correlações, não em relações de causa e efeito comprovadas. Há um movimento crescente na academia para entender melhor o que realmente influencia o comportamento das pessoas e como diferentes tipos de ambiente impactam grupos distintos.

Apesar do interesse crescente nesse tema, ainda faltam evidências robustas sobre os efeitos causais do ambiente urbano sobre o comportamento de viagem. Muitas pesquisas utilizam dados de apenas um momento no tempo e não conseguem capturar mudanças ao longo dos anos. Além disso, questões como a autoseleção residencial e resistências políticas locais dificultam a avaliação real do impacto das intervenções. Métodos mais avançados, como estudos longitudinais e experimentos naturais, podem oferecer respostas mais confiáveis — mas exigem dados de alta qualidade e investimentos maiores. Ainda assim, construir esse tipo de evidência é fundamental para

que gestores e planejadores possam tomar decisões mais seguras, com impactos reais na saúde, sustentabilidade e mobilidade das cidades.

Escopo desta tese

Diante do crescente interesse de planejadores e pesquisadores nos efeitos causais de intervenções em infraestrutura de transporte e mudanças no uso do solo sobre os deslocamentos ativos — e do reconhecimento de que a relação causal ainda é pouco compreendida devido à falta de evidências robustas — esta tese busca contribuir para o entendimento da relação causal entre o ambiente construído (BE) e os deslocamentos ativos (AT). Especificamente, ela se concentra em como melhorias em infraestrutura de transporte e mudanças no acesso ao uso do solo afetam a adoção da bicicleta e da caminhada.

A tese está estruturada em torno de duas perguntas centrais de pesquisa. Primeiramente, como e em que medida melhorias na infraestrutura de transporte influenciam a mudanca nos padrões de mobilidade ativa dos residentes beneficiados por essas intervenções? Segundo, como e em que medida mudanças no acesso a destinos diários— impulsionadas por transformações nos padrões de uso do solo — afetam os padrões de mobilidade ativa?

Com o objetivo de responder a essas perguntas, foram desenvolvidos quatro estudos empíricos:

Estudo 1: Expansão da rede cicloviária e o uso da bicicleta na cidade de São Paulo: Uma análise causal.

Estudo 2: Efeitos das ciclovias regionais: Avaliando a escolha modal na Holanda.

Estudo 3: Seguro para exercitar-se? Investigando o papel amplificador e atenuador do ambiente construído sobre a (in) atividade física durante as restrições de mobilidade impostas pela COVID-19.

Estudo 4: Mudanças de curto prazo na mobilidade diária causadas por relocação residencial: Uma análise cross-lagged com dados longitudinais.

Os dois primeiros estudos são experimentos naturais de larga escala, baseados em múltiplas seções transversais de dados domiciliares de mobilidade — o primeiro na Região Metropolitana de São Paulo (contexto de baixa demanda cicloviária), e o segundo na Holanda (contexto de alta demanda cicloviária). O Estudo 1 avalia os efeitos da implementação de uma extensa rede de ciclovias urbanas em São Paulo, cidade com mais de 20 milhões de habitantes. Já o Estudo 2 estima o impacto da criação de uma rede nacional de ciclovias de alta qualidade na Holanda. Em ambos os casos, foram adotadas abordagens robustas e "dinâmicas" para definição de exposição de residentes aos tratamentos, considerando os padrões de mobilidade rotineiros e operacionalizando os benefícios gerados pelas intervenções por meio de algoritmos de rotas e técnicas geoespaciais — estabelecendo, assim, uma ligação mais direta com os mecanismos causais de mudança comportamental.

No Estudo 3, investigam-se os impactos das restrições de mobilidade da COVID-19 sobre a mobilidade ativa em diferentes bairros da Holanda. Embora as medidas tenham sido aplicadas nacionalmente, os efeitos sobre caminhada e uso da bicicleta variaram de acordo com as características do ambiente construído. Diferente dos dois primeiros estudos, que avaliaram intervenções de suporte à mobilidade ativa, este estudo trata a pandemia como um "evento não favorável", que reduziu o acesso das pessoas a oportunidades de atividade física.

O Estudo 4 examina como mudanças no ambiente construído residencial se relacionam com mudanças nas atitudes e modos de deslocamento de indivíduos que se mudaram de casa na Holanda. Usando dados longitudinais de cerca de 1.000 pessoas (entre 2013 e 2016) e aplicando o modelo cross-lagged com interceptos aleatórios (RI-CLPM), o estudo analisa como a relocação influencia o uso da bicicleta e do carro, a evolução das atitudes em relação ao transporte e como eventos de vida interagem com o comportamento de deslocamento. A análise considera efeitos de 'self-selection' e causalidade reversa dentro de um mesmo arcabouço.

Resultados principais

Estudo 1

1. A exposição a redes cicloviárias interconectadas de São Paulo aumentou a probabilidade de uso da bicicleta entre 0,6% e 1,4%, especialmente entre indivíduos com exposição moderada ou alta à nova infraestrutura.
2. Os efeitos da intervenção foram consistentes mesmo com diferentes definições de exposição, reforçando a robustez metodológica do cáculo da exposicao.
3. Não foram observadas mudanças significativas nos grupos de controle, o que reforça a atribuição dos efeitos positivos aos grupos tratados.
4. Residentes do sexo masculino com menor nível educacional tiveram os maiores aumentos marginais, seguidos por homens com maior escolaridade. Por outro lado, grupos vulneráveis, como donas de casa sem renda e estudantes, apresentaram os menores aumentos — evidenciando desigualdades no alcance das intervenções.

Estudo 2

1. Infraestruturas de alta qualidade influenciaram positivamente o comportamento de mobilidade, aumentando a demanda por bicicleta.
2. Viajantes altamente expostos à nova infraestrutura apresentaram aumento de até 12% na probabilidade de usar bicicleta para deslocamentos entre 5 e 15 km. Para exposições menores, o aumento foi de 5%.
3. Antes da intervenção, os grupos tratados tinham entre 6% e 9% menos chance de usar a bicicleta, o que torna os efeitos pós-intervenção ainda mais relevantes.
4. Os efeitos foram estáveis entre diferentes definições de exposição, reforçando sua validade.
5. A infraestrutura teve maior impacto sobre mulheres, jovens e pessoas sem carro, sugerindo que conforto e segurança são fatores-chave. Donos de carro mostraram menor sensibilidade à nova infraestrutura.

Estudo 3

1. Em contextos sem fortes restrições, bairros compactos, urbanizados e com boa oferta de instalações esportivas tendem a apresentar maiores níveis de mobilidade ativa.
2. Tipologias de bairro atuam como moderadores importantes: podem amplificar ou atenuar os efeitos das políticas restritivas sobre a atividade física.
3. Durante o lockdown, bairros compactos — geralmente favoráveis à mobilidade ativa — foram os que mais sofreram quedas na mobilidade de lazer e transporte. Bairros com alta prevalência de obesidade e baixa atividade também tiveram quedas significativas, o que é preocupante dado o risco de agravamento das condições de saúde dessas populações.

Estudo 4

1. Mudar-se para bairros mais acessíveis aumenta o uso da bicicleta e melhora as atitudes em relação a esse modo, embora efeitos sobre o uso do carro sejam mais limitados.
2. O comportamento de ciclismo é mais sensível às mudanças no ambiente construído do que o uso do carro, exigindo infraestrutura segura, conectada e distâncias curtas.
3. Alterações no ambiente residencial podem gerar mudanças duradouras no comportamento e nas atitudes, contribuindo para a formação de novos hábitos.
4. A acessibilidade e a densidade foram significativamente associadas ao comportamento e atitudes de mobilidade, mas a diversidade de uso do solo não mostrou efeito significativo — possivelmente devido às limitações na forma como foi medida.

Implicações prãticas desta Tese

Os resultados desta tese confirmam que melhorias na infraestrutura e acessibilidade favorecem aumentos mensuráveis nos níveis de caminhada e uso da bicicleta, mesmo quando considerados possíveis variáveis de confusão. No entanto, os efeitos variam conforme grupo socioeconômico, contexto local e hábitos prévios. Para fortalecer as inferências causais, foram utilizados métodos como Diferenças em Diferenças, Efeitos Fixos e Modelos

Cross-Lagged, dentro dos marcos teóricos de 'Resultados Potenciais' e 'Grafos Acíclicos Dirigidos'. Um dos principais avanços metodológicos é a introdução de definições mais comportamentais de exposição ao tratamento, baseadas em padrões reais de deslocamento. Além disso, a tese destaca a importância de dados com múltiplos períodos de observação para detectar mudanças ao longo do tempo e recomenda a combinação entre DAGs e PO para melhorar a compreensão dos mecanismos causais entre intervenções e comportamento de transporte.

Do ponto de vista de políticas públicas de mobilidade, três implicações principais são propostas: As intervenções devem ser projetadas considerando os hábitos e perfis locais de deslocamento, para maximizar sua efetividade. Estudos ex-post devem ser melhor integrados ao processo de planejamento, servindo como complemento às avaliações ex-ante tradicionais. Os resultados empíricos desta tese podem alimentar ferramentas de avaliação de impacto em saúde e meio ambiente, quantificando os benefícios sociais mais amplos das políticas de mobilidade ativa. Essas contribuições fortalecem tanto a literatura acadêmica sobre inferência causal em transportes quanto o planejamento prático de políticas urbanas mais sustentáveis e equitativas.

About the Author

Francisco Macedo was born in Fortaleza on January 16, 1992. After completing high school, he enrolled in the Federal University of Ceará (UFC), where he earned a bachelor's degree in architecture and urban design. It was during this time that he developed a strong interest in transportation, which led him to pursue a master's degree in Transport Engineering, also at UFC.

In 2019, after working for two years as a transport planner in Brazil, Francisco moved to the Netherlands to complete a second master's degree in Spatial Planning, specializing in Urban Mobility at Radboud University. During this period, he worked as a research assistant under Kevin Raaphorst and as a trainee at the Rebel Group. After graduating, he continued working with both organizations for five years, combining his roles as an urban mobility consultant and PhD candidate. Currently, he works as a senior consultant at Ecorys.

His work and research are driven by a deep interest in infrastructure and policies with potential to improve accessibility, and promote sustainable and equitable mobility.

List of publications

Journal articles

Macedo, F. E., Raaphorst, K. M. C., Bevelander, K. E., & van der Krabben, E. (2023). The influence of the built environment on active school travel in the Netherlands: A mode choice analysis. Multimodal Transportation, 2, 100103. https://doi.org/10.1016/j.multra.2023.100103

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Macedo Filho, F. E., & Cunquero, C. (2024). City-wide cycling network extension and bicycle ridership in São Paulo: A causal analysis - Presented at the mobil.TUM - The Future of Mobility and Urban Space conference, April 2024, Munich – Germany.

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Macedo Filho, F. E. and M.C. Raaphorst, K. M. C., Ploegmakers, H., van der Krabben, E., Schoofs, M., Safe to Move? A Study of Built Environment Moderation Effects on Mobility-Related Physical Activity During Covid19 Movement Restrictions in the Netherlands. Available at SSRN: https://ssrn.com/abstract=5018611 or http://dx.doi.org/10.2139/ssrn.5018611 (https://dx.doi.org/10.2139/ssrn.5018611) (Under Review)

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