Built-Environment Interventions and Urban Sustainability: Evidence on Energy Use, Travel Behaviour, and Traffic Safety

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Abstract

Urban areas are complex socio-economic and ecological systems in which political, economic, social, natural, and built components are tightly interlinked. As growing hubs of population and activity, cities concentrate energy use and greenhouse gas emissions, particularly in the building and transport sectors, while also facing local sustainability challenges such as heat exposure, congestion, and traffic risk. Improving urban sustainability and decarbonizing cities therefore depends critically on managing energy demand and consumption patterns in transport and building sector. Physical components of urban areas including land use patterns, buildings and open spaces, and road and transportation network play an integral role in urban carbon emissions as they form the long-lasting skeletons of the city with the ability to lock in energy consumption patterns of everyday lives. This dissertation examines how changes to urban form and infrastructure influence residents' energy consumption and travel behaviour, and what these changes imply for urban decarbonization and well-being.

The first paper studies the microclimatic role of urban tree canopy in moderating ambient temperatures and the extent to which this translates into reduced residential cooling demand. It also assesses how cooling benefits depend on canopy configuration relative to buildings and on weather conditions, highlighting when and where urban greening yields the largest energy savings.

Shifting to the transport sector, the second paper evaluates how urban design, particularly the provision and expansion of cycling infrastructure, affects commute mode choice and the transition from motorized travel to more sustainable alternatives. The analysis further examines heterogeneity across socio-economic groups to identify which populations benefit most from increased exposure to cycling infrastructure along their commuting environments.

The third paper investigates whether promoting cycling through infrastructure expansion delivers safety gains or whether changes in road design risk increasing collisions. It assesses safety outcomes for cyclists and for all road users and compares effects across facility types with different levels of physical separation from motor-vehicle traffic to inform design choices.

Together, the three papers provide causal, policy-relevant evidence on how built-environment interventions can advance climate and sustainability goals while addressing heat mitigation, travel behaviour, and traffic safety.

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I would like to dedicate this work to Iranian girls and women who, despite systemic restrictions, have always found a way to pursue education, independence, and a life free from gendered oppressions. This journey continues. Those of us outside Iran will keep using our voices in solidarity with those inside the country, and we will keep working toward the advancement of women's rights.

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Preface

This thesis consists of three stand-alone papers that have been prepared for publication in academic journals. Although the papers relate conceptually, they are not necessarily meant to be read in order, and they do not directly build onto another. They use distinct research methods and theoretical frameworks.

Chapter 1, “Quasi-Experimental Evidence that Urban Tree Canopy Reduces Residential Energy Consumption”, is co-authored with Dr. Nicholas Rivers. who provided overall conceptual and methodological guidance, access to resources and data, and validation of the research design and results. Writing and visualization were iterative and collaborative, with both authors contributing to revisions, interpretation, and refinement of the final narrative. At the time of submitting this dissertation, the paper has been published in the journal of Energy and Buildings (Volume 344, October 1, 2025). I presented this work at the World Sustainable Energy Days conference (March 2025, Austria), where it received the award for Best Young Energy Efficiency Researcher. I would also like to thank Blair MacPherson at Hydro Ottawa, and Nick Stowe and Martha Copestake at the City of Ottawa, for their assistance and for providing the data on electricity consumption and urban tree canopy used in this research.

Chapter 2, “Causal Impacts of Cycling Infrastructure on Commuting Mode Choice: A Quasi-Experimental Evidence”, is another collaborative project between Fatima Ravazdezh and Dr. Nicholas Rivers. The project idea and overall research design were proposed by Dr. Rivers. I was responsible for preparing and assembling the datasets, conducting the empirical and statistical analyses, producing the visualizations, and leading the literature review. I also drafted the manuscript and coordinated revisions. Dr. Rivers provided supervision throughout the project and validated the research design and results.

Chapter 3, “Does Cycling Infrastructure Improve Urban Traffic Safety? Evidence from a Quasi-Experimental Design”, is my sole-authored work. Dr. Rivers provided supervisory guidance throughout the project, including advice on the research approach and validated the empirical strategy and results.

Chapter 2 and a part of chapter 3 were conducted at University of Ottawa, a part of the Canadian Research Data Centre Network (CRDCN). This service is provided through the support of the Canada Foundation for Innovation, the Canadian Institutes of Health Research, the Social Sciences and Humanities Research Council, and Statistics Canada, and through the support of University of Ottawa. All views expressed in this work are our own.

Introduction

1.Urban Systems and Climate Mitigation

The reality of climate change is undeniable and is the defining feature of the present century. Urban areas play an integral role in climate change. As places that provide various services, facilities, and living accommodation, cities are the main areas in which carbon emissions are generated (Huang et al., 2022) and urban land use is one of the most intensive human impacts on the planet (Pouyat et al., 2007; Grimm et al., 2008). Cities consume approximately 75% of the world's resources (Madlener and Sunak, 2011). In 2015, urban emissions were estimated to be about 62% of the global share, and in 2020 this share increased to 67-72% (Lwasa et al., 2022). Making cities low-carbonized and more sustainable serves as one of the key mitigation strategies to tackle climate change since more than half of the world population lives in urban areas, and by mid-century, 7 out of 10 people on the planet will live in a town or a city (United Nations, 2019).

The drivers of urban energy demand and greenhouse gas (GHG) emissions are complex. Transportation, as an indispensable part of urban residents' daily lives for moving goods and accessing services, is one of the primary sources (Huang et al., 2022). In 2019, direct GHG emissions from the transport sector accounted for about 23% of global energy-related CO_2 emissions, and urban transport is responsible for about 8% of global CO_2 emissions (Jaramillo et al., 2022). While urban transportation is not the biggest emitter of GHGs in cities, since 2010, the sector's emissions have increased faster than any other end-use sector (Jaramillo et al., 2022). The building sector forms the core physical setting of urban life and, because people spend much of their time in buildings, it is a major energy-consuming sector in urban areas (Cheng et al., 2024). According to the latest IPCC report, total GHG emissions in the building sector reached 21% of global GHG emissions in 2019 (Lwasa et al., 2022). Mitigation in the urban sector, particularly in buildings and transport, is vital yet challenging. Cities function as interconnected systems (Lwasa et al., 2022; Purwar et al., 2024), and urban form and the built environment including land-use patterns, transportation networks, and building design shape both mobility demand and building energy needs (Jaramillo et al., 2022). Moreover, the transport system and building sector are long-lived urban infrastructures that can lock in energy use and emissions trajectories over time (Cabeza et al., 2022).

1.1. Drivers of Energy Use and Emissions in Transport and Buildings

While emissions from urban transportation are also shaped by vehicle efficiency and the carbon intensity of fuels, urban form and land-use patterns form key determinants of transportation emissions by shaping the trip distances, accessibility, and the feasibility of different modes, thereby influencing both mode choice and vehicle kilometers traveled (VKT) (Transportation Research Board and National Research Council, 2009). In many North American cities, low-density, single-use development, the separation of housing from jobs and services, and limited access to high-quality public transit have contributed to long travel distances and strong dependence on cars (Transportation Research Board and National Research Council, 2009). These car-dependent patterns, often described as urban sprawl, are associated with higher VKT and higher transport emissions per capita than more compact, mixed-use, and transit-oriented development (Ewing and Cervero, 2017). At the same time, limited provision of safe, continuous infrastructure for walking, cycling, and other micromobility modes (small, low-speed devices such as e-bikes, e-scooters, and mopeds that are typically used for short trips) (Zhang et al., 2023) can further constrain modal shift away from cars and reinforce high-carbon travel behaviour. These car-dependent urban forms can also lock cities into a strategy of expanding road capacity to accommodate rising car ownership, population growth, and recurring congestion. Evidence suggests that more car-oriented cities tend to provide more road infrastructure per capita and face higher ongoing spending burdens for road construction and maintenance than less car-oriented cities (Litman, 1995; Kenworthy and Laube, 1999). Life-cycle assessment research further shows that road construction and maintenance are material- and energy-intensive and can contribute substantially to the environmental impacts of road infrastructure (Jiang and Wu, 2019). Moreover, literature finds that increases in highway capacity are often absorbed by additional traffic: lane additions can lead to increases in VKT, so congestion and associated emissions tend to rebound over time (Duranton and Turner, 2011; Hymel, 2019). As a result, road expansion is both fiscally and environmentally costly and is unlikely to keep pace with growth in car use in highly car-dependent urban forms, fortifying a self-reinforcing cycle of car dependence and infrastructure expansion.

In the building sector, space heating and cooling are among the largest end uses of energy. Globally, buildings account for around 30-36% of final energy consumption, with space and water heating representing about half of building energy demand and space cooling a smaller but rapidly growing share (Delmastro and Chen, 2023). Because heating and cooling are often supplied by fossil fuel-based systems or by electricity generated from fossil fuels, these end uses are major contributors to building-related GHG emissions. Regardless of the generation mix, they can also increase peak electricity demand, particularly during periods of extreme temperature (Delmastro and Chen, 2023). Urbanization further amplifies cooling needs through the urban heat island (UHI) effect. As cities expand, vegetated and permeable surfaces are replaced by darker, impervious materials (e.g., asphalt and concrete), which store heat and reduce evaporative cooling, making urban areas warmer than their rural surroundings (Hibbard et al., 2017). Higher ambient temperatures increase cooling loads needed to maintain indoor thermal comfort. Reviews suggest that UHI conditions increase building cooling energy consumption by a median of around 10-20% and can substantially raise peak electricity demand, even if they slightly reduce heating demand in some climates (Li et al., 2019). Climate change is projected to increase the frequency and intensity of heat waves, further increasing electricity use for air conditioning and placing additional strain on power systems, especially during summer peaks (Xu et al., 2012).

As heat exposure increases, cooling is becoming a central adaptation need in cities. However, adaptation strategies that rely primarily on technology-driven cooling can increase electricity demand and, depending on the generation mix, raise GHG emissions and peak loads. They can also worsen local heat through waste heat release (Dodman et al., 2022). This creates a mitigation-adaptation trade-off. Improving thermal comfort is essential, but meeting that need through energy-intensive cooling can reinforce carbon-intensive pathways from buildings in urban areas (Cabeza et al., 2022).

2. Urban Mitigation Strategies

Designing low-carbon urban transport and building systems is essential for achieving low-carbon cities, and it requires supportive urban mitigation policies and instruments. The literature often distinguishes between two broad approaches to urban mitigation. The first focuses on technological improvements that reduce emissions per unit of service (e.g., cleaner vehicle technologies and more efficient engines, high-performance HVAC systems, and low-carbon electricity), thereby lowering the carbon intensity of energy use. The second approach targets changes in energy-use behaviours and demand patterns. Within this approach, behaviour-oriented policies are commonly divided into hard and soft measures. Hard policies rely on physical and regulatory changes to the built environment to reshape energy-use behaviour (e.g., land-use regulation and infrastructure provision). Soft policies, in contrast, use psychological and informational strategies to encourage voluntary behavioural change (Bamberg et al., 2011).

While technology-focused policies receive substantial attention in efforts to decarbonize cities, they have important limitations. They are often politically and socially attractive because they allow people to maintain existing patterns of travel and energy use with minimal disruption to comfort or convenience (Banister, 2011). However, efficiency improvements in vehicles and buildings, if not accompanied by demand-side measures, can generate rebound effects that erode expected energy and emissions savings (Chan and Gillingham, 2015). In addition, technology-centred transitions can raise equity concerns because many of these options depend on private adoption and upfront investment (e.g., purchasing electric vehicles or high-efficiency equipment). As a result, benefits can increase disproportionately for higher-income households, while lower-income groups face affordability and access barriers (Sultana et al., 2019). More broadly, the feasibility and pace of technology-based transitions are shaped by fiscal capacity. Without adequate support, lower-income and developing countries may face greater barriers to adopting low-carbon technologies (Bashmakov et al., 2022)

In contrast, behaviour-oriented policies that reshape the urban built environment operate at the population level and target the demand side by changing the spatial conditions under which everyday energy-related practices occur. Such interventions can provide long-term demand management because they influence travel needs, mode choice, and building energy requirements through durable changes in urban form and infrastructure. These built-environment measures can also offer relatively low operating costs once implemented (Creutzig et al., 2015; Seto et al., 2016). Importantly, built-environment policy instruments can be adapted by cities at different stages of urbanisation and economic development, whether rapidly growing, intermediate, or mature. Although the appropriate mix and sequencing of measures will differ across city types (Seto et al., 2016).

2.1. Built Environment Strategies for Reducing Energy Demand

A large body of research summarizes the influence of the built environment on travel behaviour. Exploration of the implications of urban form and the built environment on travel behavior led to a popular framework of measures known as 3Ds or density, diversity, and design. (Ewing & Cervero, 2001). Higher residential and employment densities, a greater mix of land uses, and pedestrian and cycling friendly urban design are generally associated with lower car use and higher levels of walking, cycling, and public transport use (Leck, 2006). Subsequent work has expanded this to 5Ds, adding dimensions such as destination accessibility and distance to transit, but the core idea remains that land-use patterns help shape travel distances, mode choice, and VKT. (Peng et al., 2024).

Within this framework, the design dimension captures how street networks and facilities make different modes more or less attractive in practice. Urban design includes indicators such as intersection density, street connectivity, and the presence and quality of infrastructure for alternative modes such as walking and cycling (Ewing and Cervero, 2010). Literature suggests that while compact, mixed-use development can reduce the need for travel and shorten trip distances, a substantial shift from car use to more sustainable alternatives including walking, cycling and transit access also depends on the provision of safe, connected and comfortable infrastructure for these modes. Evidence from the literature shows that the built environment and infrastructure are associated with higher walking, including evidence linking pedestrian-supportive features (e.g., sidewalks, connectivity, and walkable land-use patterns) to walking behaviour (Saelens and Handy, 2008). Similarly, studies and reviews find consistent evidence that cycling infrastructure, particularly connected networks and separate protected facilities, is associated with higher cycling levels and can increase cycling when new facilities are added (Yang et al., 2019). Active modes are also important as micromobility modes that improve access to and extend the catchment area of public transit. Bicycle-transit integration can expand effective station access distances, improve home-destination connectivity, and increase the accessibility of transit services (Kosmidis and Müller-Eie, 2024). Beyond supporting transit, walking and cycling provide low-carbon alternatives to motorized travel and generate co-benefits at both individual and community levels, including improved physical and mental health, reduced emissions and air pollution, and broader economic benefits through avoided health costs and more efficient use of urban space (Ding et al., 2024).

Beyond technological upgrades to heating and cooling systems, built-environment design measures can reduce building energy demand by limiting heat gains. At the building scale, design measures such as improved insulation, external shading devices, reflective roofs, green roofs, and climate-responsive building orientation can substantially lower cooling loads and peak electricity demand (Cabeza et al., 2022). At the neighborhood scale the deployment of urban green infrastructure which includes street trees and urban forests, parks, and green roofs, can mitigate the UHI effect, moderate outdoor air and surface temperatures, and thereby reduce the need for indoor cooling demand (Lwasa et al., 2022). In a warming climate with rapidly rising global cooling demand, these demand-side measures are an essential complement to technology-focused efficiency improvements (Cabeza et al., 2022).

Within this built environment measures, urban trees and vegetation are particularly important because they act simultaneously as adaptation and mitigation options. Trees cool urban environments through shading and evapotranspiration, which lowers air and surface temperatures, improves outdoor thermal comfort, and reduces the cooling energy required to maintain indoor comfort in adjacent buildings (Wang et al., 2018). Where electricity generation remains fossil-fuel intensive, these reductions in cooling demand translate into lower operational emissions, making urban greening a demand-side mitigation strategy as well as an adaptation measure (Cabeza et al., 2022). Reduced cooling demand lowers pressure on the power grid, particularly during peak electricity demand hours. In addition, urban vegetation delivers co-benefits such as improved air quality, noise reduction and stormwater management, strengthening its role as a multifunctional built-environment intervention (Burden, 2006).

3. Evaluating the Effects of Built-Environment Interventions

Policies and policy instruments are designed to change specific outcomes. Assessing whether these intended changes are achieved is a central question in public policy and a core objective of policy impact evaluation (Gertler et al., 2016). Impact evaluation seeks to estimate the impact, or causal effect, of an intervention on an outcome of interest (Gertler et al., 2016). When carefully designed and implemented, impact evaluations can provide convincing and comprehensive evidence to guide policy decisions, from curtailing inefficient programs to scaling up effective interventions, adjusting program benefits, choosing among alternative designs, shaping public opinion, and improving program operations (Gertler et al., 2016).

To be able to estimate the causal effect or impact of a program, any impact evaluation method must estimate the counterfactual, or the outcome of interest in the absence of the policy instruments. The core difficulty is that, for the same unit at the same time, we can only observe one realized outcome which is either the outcome under the policy or the outcome without it, but not both. This implies that the "world without the policy" or the counterfactual must be estimated using explicit research designs (Holland, 1986). Counterfactual estimation is the main challenge of impact evaluation and inferring causality (Huntington-Klein, 2022). There are different strategies to estimate the causal effect of a program, with the main logic embedded in them being provision of a valid counterfactual estimate.

Investigation of the relationship between a policy and an outcome, and the evaluation of the impact of policy interventions, is commonly carried out using empirical studies based on direct observation, experimentation, and the collection of measurable data (empirical evidence) (Harwell, 2011). Empirical studies are often divided into experimental and observational designs, but both share the same core challenge of counterfactual estimation. The difference is that experiments use controlled (often randomized) assignment to create a credible comparison group, whereas observational studies must justify the counterfactual using research designs and identifying assumptions about selection into treatment. (Cook et al., 2002; Athey and Imbens, 2017).

Experimental studies are often considered the gold standard for impact evaluation (Bernal et al., 2017) because the researcher controls the assignment of units to the intervention. The core premise is that units have an equal chance of being assigned to treatment or control through randomization (Aussems et al., 2011). Random assignment makes the treated and control groups comparable, on average, in both observed and unobserved characteristics prior to the intervention; therefore, under standard assumptions such as no interference between units (perfect compliance) and consistent implementation, the post-intervention outcomes in the control group provide a valid estimate of what would have happened to treated units in the absence of the intervention (Cook et al., 2002). Under conditions with perfect compliance, differences in average outcomes between the assigned groups identify the causal effect of the intervention.

Although experimental studies in the context of the built environment and urban sustainability exist (e.g., Fujii and Kitamura, 2003; Laband and Sophocleus, 2009; South et al., 2018; Bull et al., 2021; Ek et al., 2020), several factors limit the use of such designs. First, in real-world settings, the assumption of perfect compliance is difficult to maintain (Lagarde, 2012). Second, experiments are often highly localized. As noted by Cook et al. (2002), experiments are almost always conducted in a restricted range of settings. This creates tension between the localized nature of experiments and the broader and generalizable causal claims that research aims to make (Cook et al., 2002). Third, economic constraints (pure experiments can be costly and labor-intensive) and political or ethical concerns (it may not be acceptable to deliberately allocate some communities to receive an innovation while others do not) can also hinder the implementation of experimental designs (Lagarde, 2012) in the context of urban built-environment interventions. As a result, when experimental designs are infeasible or limited, researchers often turn to observational approaches to assess the impacts of built-environment interventions in real-world settings.

Observational studies lack random assignment of units to treated and control groups therefore exposure to the treatment is observed rather than assigned (Hernán and Robins, 2010). Observational studies can be further divided into quasi-experimental designs and non-experimental designs. Quasi-experiments attempt to use the logic and language of experiments in observational settings (Morgan and

Winship, 2014). In quasi-experiments, outcomes are investigated by comparing groups, so control groups are still used to estimate the counterfactual (Aussems et al., 2011). However, assignment to treatment or control is not random. It may occur through self-selection, where units choose treatment for themselves, or through administrator selection, where an evaluator or policymaker decides which units are exposed to the treatment (Cook et al., 2002). Quasi-experiments try to find (or construct) a comparison group using specific identification strategies that makes treatment variation "as-if random" under certain conditions and assumptions (Cook et al., 2002; Angrist and Pischke, 2009). Common examples of quasi-experimental designs include instrumental variables, regression discontinuity, and difference-in-differences (DiD), which use features of policy implementation, external sources of variation, thresholds, locations, or timing to approximate random assignment and divide units into treated and control groups.

While quasi-experiments can estimate the impact of a policy under clearly stated identifying assumptions, non-experimental observational studies, including cross-sectional analyses, simple pre-post comparisons without a control group, or conventional panel regressions that rely primarily on statistical adjustment for observed covariates, typically offer weaker leverage for causal inference. These approaches often do not embed a design-based mechanism that makes the comparison group a credible approximation of the treated units' counterfactual. As a result, findings from these designs are often best interpreted as associations that can motivate causal hypotheses rather than as estimates of policy impacts. (Cook et al., 2002; Hernán and Robins, 2010). Much of the built-environment literature has historically relied on cross-sectional analyses and reviews have highlighted the resulting limitations for causal inference (Aldred, 2019; Yang et al., 2019). More recent work has increasingly emphasized quasi-experimental approaches to generate more policy-relevant causal evidence.

4. Dissertation Overview

With a focus on energy-demand management and decarbonization in the transport and building sectors, this dissertation examines how changes in the built environment shape energy use, travel behaviour, and traffic safety in North American cities. This focus is especially policy-relevant because many cities in the region are characterized by low-density, automobile-oriented urban forms, where the externalities of sprawl including high energy use, greenhouse-gas emissions, and road safety risks, have intensified the need for practical interventions that support urban sustainability and climate goals. Across three papers, the dissertation evaluates policy-relevant built-environment strategies, including urban tree canopy and cycling infrastructure, and uses quantitative methods to estimate their impacts on households and road users. A unifying theme in all papers is the importance and challenges of bringing a causal lens to questions about built-environment effects. Because cities rarely implement interventions at random, observational associations can be confounded by pre-existing trends, selective investment, and other concurrent changes, limiting their value for decision-making. To address this challenge, each paper applies quasi-experimental designs that leverage temporal and spatial variation in built-environment interventions to strengthen causal inference and provide more credible evidence on how real-world policy changes translate into changes in urban outcomes.

The first paper investigates how urban tree canopy influences residential electricity consumption for cooling. Using high-resolution hourly electricity data linked to detailed measures of street tree canopy cover for residential dwellings in Ottawa, the study estimates how shading and evapotranspiration provided by trees reduce cooling demand during the warm seasons. The analysis uses difference-in-differences models that compare the same dwelling over time and across seasonal conditions, isolating the contribution of tree canopy from other factors that affect energy use. Study further examines whether the effects of urban tree cover vary with the spatial configuration of trees around buildings. To assess how trees' effects are moderated by weather conditions, study combines the quasi-experimental framework with machine learning analysis. This paper highlights the role of nature-based built-environment solutions in improving indoor thermal comfort and reducing residential energy demand.

In the second paper, we shift to the transportation sector and examine how street-network design and the provision of cycling facilities can support a shift in commuting from motorized modes to lower-carbon alternatives such as cycling. Using Census of Population travel behavior microdata spanning 15 years for the two major Canadian cities of Vancouver and Toronto, combined with detailed measures of cycling infrastructure around both home and workplace locations, the study assesses whether the provision and expansion of cycling infrastructure increases the likelihood of cycling to work. Focusing on home-to-work commuting routes, we use a quasi-experimental approach that exploits within-route changes in cycling infrastructure over time, while controlling for fixed features of these routes. The study also examines heterogeneity in the effects of cycling infrastructure on commute choice by gender, age, education, income, and mobility status to identify which groups benefit most from cycling infrastructure expansion.

The third paper evaluates the effects of cycling infrastructure on traffic safety outcomes for all road users. Cycling infrastructure is widely promoted as a key policy instrument to support a shift from motorized travel to active modes such as cycling. However, cycling involves higher exposure and vulnerability in mixed traffic, raising concerns that increases in cycling could come at the cost of greater traffic risk if safety does not improve. Given the growing emphasis on cycling as a sustainable transport option, it is important to assess whether public investments in cycling infrastructure enable mode shift while maintaining or improving traffic safety for cyclists and other road users. Drawing on longitudinal spatial data on traffic collisions at the census tract level in four Canadian cities (Toronto, Ottawa, Vancouver, and Victoria), combined with longitudinal measures of cycling infrastructure, this study estimates how changes in infrastructure are associated with changes in total collisions and cyclist-involved collisions. The empirical strategy uses difference-in-differences model that compare collision trends in areas that receive new or expanded infrastructure with trends in areas that do not, while controlling for time-invariant tract characteristics and common time shocks. We further examine whether safety effects differ across types of cycling infrastructure that provide varying levels of separation from mixed traffic. Overall, the paper assesses whether promoting cycling through infrastructure expansion can be achieved without increasing, and ideally while reducing, traffic risk for cyclists and other road users.

Taken together, the three papers provide an integrated view of how built-environment interventions can contribute to climate and transport policy goals. They show how changes to urban greenery and street design influence energy consumption, travel behaviour, and safety, and they illustrate the value of quasi-experimental methods for estimating the impacts of real-world urban policies. By translating infrastructure and urban-greening changes into measurable effects on outcomes that matter to households and road users, the findings provide policy-relevant evidence to support decisions about where, when, and for whom these interventions deliver the greatest benefits. Since the analyses span multiple Canadian cities with different climates, policy direction, and baseline cultural and socio-economic conditions, the results are informative for other North American cities with similar characteristics. More broadly, the empirical frameworks developed can be adapted to other settings where comparable longitudinal data exist, offering a general approach for evaluating built-environment policies in diverse contexts worldwide.

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Chapter 1

Quasi-Experimental Evidence that Urban Tree Canopy Reduces Residential Energy Consumption

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Abstract

The relationship between the urban tree canopy (UTC) and residential space-conditioning electricity use has been explored over the past decades, but depending on the methods and assumptions, there is a wide disparity in the estimated energy savings. Using a quasi-experimental research design, we combine aerial imagery of the UTC with high-frequency electricity consumption data for 1,968 houses in Ottawa, Canada, to revisit the causal links between the UTC and residential electricity demand. We estimate that a 10-percentage point increase in the UTC within the 12.5-meter buffer of a house corresponds to a 2.9% reduction in electricity consumption during the period that trees are in leaf. For the average house in our sample, UTC covers 25% of the area within 12.5-metres from the house, and results in 3.0% reduction in annual average electricity consumption. The effect of tree coverage varies by the spatial configuration of trees relative to buildings: UTC closer to the building reduces electricity consumption by a larger amount than UTC farther from the building, and UTC to the west of the house has a larger effect compared to coverage in other directions. To understand how the effects of UTC on electricity consumption are moderated by weather variables we combine a causal quasi-experimental framework with machine learning. We find that UTC has a larger impact on electricity consumption at higher temperatures, lower wind speeds, and lower relative humidity. Savings from UTC reach 15% of residential electricity consumption on hot summer afternoons and the peak residential load is 17.9% lower as a result of the UTC.

Keywords: Urban tree canopy, Natural climate solutions, Climate change, Urban heat island, Energy consumption, Energy efficiency

1.Introduction

Cities occupy only 2% of the earth's surface but support more than half of the world's population (Madlener and Sunak, 2011) and by mid-century, 7 out of 10 people will live in a town or city (United Nations, 2019). The concentration of such a large number of dwellers and their activities leads to the release of heat in urban areas (Gago et al., 2013; Wang et al., 2020). The rising global temperature and increasing urbanization will lead to the continuous aggravation of thermal problems in urban environments (Yin et al., 2024) since climate model projections indicate that tropospheric temperatures will continue to rise, with an increase in the frequency and intensity of heat waves (Hartmann et al., 2013). Moreover, warming is a particular concern for urban areas due to urban densification and the urban heat island effect (Skelhorn et al., 2016), a phenomenon in which air temperatures in urban areas are significantly higher compared to nearby rural areas (Oke, 1982; Arnfield, 2003).

High air temperatures are associated with increases in mortality and morbidity (Wu et al., 2014; Gasparrini et al., 2015; Gasparrini et al., 2016; Son et al., 2016, Carleton et al., 2022). High temperatures in urban areas also increase the time spent indoors and escalate the need to regulate indoor temperatures, resulting in increasing electricity demand and building energy consumption for cooling (Santamouris et al., 2015; Rivers and Shaffer, 2020). Higher cooling energy use can lead to higher emissions if the electricity is generated from fossil fuels (IEA 2018; Biardeau et al., 2020). Regardless of the source of the electricity, this surge in cooling demand can have broader systemic effects, potentially impacting peak electricity demands during extreme heat periods (IEA, 2018).

Increasing urban vegetation, especially the urban tree canopy (UTC), is proposed as an effective means for urban heat mitigation and adaptation due to its effects on the urban microclimate (Akbari and Konopacki, 2004; Morakinyo et al., 2016; Wang and Akbari, 2016; Wang et al., 2016; Liu et al., 2020; Meli et al., 2021; Zhou et al., 2021; Gough and Anderson, 2022; Errel and Zhou, 2022; Yin et al., 2024). Despite widespread recognition of the cooling benefits of urban trees, little is known about their real-world impact on household electricity use for cooling, particularly during periods of peak summer electricity demand. We focus on this research gap in this study.

UTC may affect household energy consumption through two possible mechanisms. The first and primary mechanism is by affecting indoor thermal conditions. Trees affect thermal comfort through 1) shading, which reduces the amount of radiant energy absorbed and stored by built surfaces 2) evapotranspiration, which converts liquid water in plants to vapor, thereby cooling the air, and 3) wind speed reduction, which reduces the infiltration of outside air into interior spaces and impacts convective heat transfer (Heisler 1986). The second mechanism in which UTC affects building energy consumption is by affecting the time spent indoors. UTC can motivate people to spend more time outdoors due the improvements in local air quality also associations between recreational purposes of UTC and outdoor leisure (Ugolini et al., 2020; Venter et al., 2020; Feng et al., 2021). In contrast, in areas with low UTC, increased local pollution or extreme heat can lead to more time spent indoors to avoid poor air quality and discomfort (Zivin and Neidell, 2009; Sexton, 2012; He et al., 2021; Salvo, 2020). Since building operations account for a large share of global energy-related greenhouse gas emissions (22% in 2020) (Cabeza et al., 2022), examining alternatives like tree planting to reduce their energy use is critical for the decarbonization of cities and climate mitigation efforts.

The effects of UTC on indoor thermal conditions and electricity consumption have been explored in the literature, with studies generally falling into two main categories: simulations and empirical estimations. Many studies rely on simulation models to assess the impact of UTC on building energy use, consistently reporting increased energy savings due to the evapotranspiration and shading effects of trees (Akbari and Taha, 1992; Simpson and McPherson, 1996; Akbari et al., 2001; McPherson and Simpson, 2003; Nikoofard et al., 2011 ; Abdel-Aziz et al., 2015; Hwang et al., 2016; Skelhorn et al., 2016; Wang et al., 2016; Hwang et al., 2017; Nowak et al., 2017; Hsieh et al., 2018; Moss et al., 2019; Aboelata and Sodoudi, 2020; Tsoka et al., 2021; Dong et al., 2023). Simulations allow researchers to control various factors such as climate, building condition, heating, ventilation and air conditioning system efficiency, thermostat setting, tree configuration and tree size (Ko, 2013). On the other hand, simulations can be extremely sophisticated but still incomplete and simplified portrayals of the complex processes of radiative exchange in real urban environments. Simulation models also struggle to incorporate how human behavioral responses may mediate the impact of UTC on energy consumption.

Empirical approaches address the limitations of simulation studies by evaluating real-world cases and showing the actual outcomes influenced by biophysical and behavioral factors (Ko, 2018). Empirical investigation into the effects of UTC on household energy consumption have been conducted through experimental and observational approaches. Experimental settings typically involve small samples of buildings and compare electricity savings between identical buildings with and without UTC (Akbari et al., 1997; Laband and Sophocleus, 2009). These buildings are usually not real-world structures with real human occupants, and the measurements often focus on extreme scenarios, such as full shade coverage or no shade at all (Ko, 2018).

Observational studies relate real-world household energy consumption data to the UTC. Many observational studies have investigated household energy consumption primarily in relation to urban form, lifestyle and occupant behavior, household demographics, and building characteristics such as size, age, features like pools, and heating and cooling systems. In these studies, UTC is typically included as a control variable, with findings suggesting that UTC is only weakly associated with building energy consumption and of relatively small impact compared to other factors like building condition (e.g., house size, insulation) and occupants' lifestyle (Nelson et al., 2012; Wilson, 2013; Ko and Radke, 2014). Studies focused on estimating the impact of UTC on residential electricity consumption typically include a more detailed estimate of UTC for each building in the sample and use a cross-sectional approach (comparing one building to another) to estimate the impact of UTC on building energy consumption (Abbot and Meentemeyer, 2005). These cross-sectional studies require strong assumptions about un-confoundedness to be interpreted as causal (Greenstone and Gayer, 2009) and report mixed findings about the impact of UTC on residential energy consumption. Studies aiming to assess a causal estimate of UTC on energy consumption, of which there are few, typically use a relatively small sample of buildings (Donovan and Butry, 2009; Pandit and Laband, 2010).

In this study, we aim to contribute to the observational literature that evaluates how the UTC affects residential electricity consumption for cooling. We build on the literature in several ways. First, we contribute by assembling a data set with high spatial and temporal resolution compared to prior studies. We obtain household-level electricity consumption data at hourly intervals, compared to prior studies in this literature which mostly use monthly data. Our high-resolution data allows us to make more precise inference as well as better isolate how the UTC affects electricity consumption. We also obtain high-resolution spatial data on the UTC based on a recent survey of the UTC that combines aerial imagery with light detection and ranging (LiDAR). Second, our data set is relatively large compared to prior studies. We obtain data from nearly 2,000 single-family homes. We deliberately selected house-pairs on the same side of a street with differing levels of UTC to maximize our ability to measure the effect of interest as well as control for confounding factors. We supplement this sample with a data set of houses chosen completely at random to allow us to predict impacts of the UTC on energy consumption for the population. Third, we use a modern quasi-experimental design to isolate the impact of UTC on energy consumption. Our strategy consists of comparing electricity consumption within a home at a given hour of the day and day of the week when trees are in leaf compared to when they are not, and to compare this difference in electricity consumption for houses on the same side of the same street with different levels of UTC. In addition, we build on this approach by using a machine learning approach to estimate how weather conditions mediate the impact of UTC on electricity consumption. We are not aware of other studies that take a similar approach. We also use our approach to estimate the value of energy savings from the UTC and to evaluate how planting in different areas relative to a house affects how UTC impacts electricity savings.

We find substantial electricity savings from the UTC. Increasing the UTC coverage at a house by 10 percentage points reduces electricity demand by 2.9% on average during periods when trees are in leaf.

Put another way, a house with full UTC coverage would have about 29% lower summer electricity consumption than an identical house with no trees. On an annual basis, the current level of UTC reduces residential electricity consumption by about 3% on average. The impacts of UTC are concentrated on hot summer afternoons; we find that in afternoons in June through August, UTC reduces average residential electricity demand by as much as 15%. These periods are coincident with system electricity peaks, and so there is high value in these reductions. From a household perspective, our results suggest that the current UTC for a typical house saves approximately $450 in lifetime electricity costs. Savings are highest for trees planted to the west and not too far from a house.

The next section describes the study region, how we construct the data set, and the approach we use to estimate the causal effect of UTC on electricity consumption. We then detail the results in Section 3, and provide a discussion and conclusion in Sections 4 and 5.

2.Methods and Materials

2.1. Study Area

We conduct our study in Ottawa, Canada, a city of 1,017,449 people (Statistics Canada Census of Population, 2021). Ottawa has a humid continental climate, characterized by warm summers and cold winters, and features a mix of low, medium, and high-density housing along with significant green spaces. This diversity in urban form and climate type is common in North American urban areas, making Ottawa representative of many midsize Midwest cities. The annual temperature averages 6.9 °C with an approximate 1,068 mm of annual precipitation (Environment Canada, 2024). With an average temperature of 21.1 °C, July is the warmest month and has the highest amount of daily sunshine hours at 10.63 (Environment Canada, 2024).

Ottawa has 10 classes of zoning within urbanized areas. Some of the major zones are demonstrated in fig. 1.1. (A). Environmental protection and open space classes contain the vast amount of Ottawa's tree canopy (over 40%) but nearly 25% of the tree canopy is on land zoned as residential (Tree Canopy Assessment, 2019). UTC is not evenly distributed in the residential class and there are wide-ranging differences in the percentage of UTC in the various neighbourhoods; some of this variation is due to the degree of urbanization and the current land use, but other factors such as housing age also play a role (Tree Canopy Assessment, 2019). About 63% of households in the Ottawa-Gatineau Census Metropolitan Area owned a central air conditioner, while nearly 21% had a window or room air conditioner (Natural Recourses Canada, 2019).

2.2. Urban Tree Canopy Data

In this study, an urban tree is considered as woody perennial plants growing in towns and cities, typically having a single stem or trunk − and usually a distinct crown − growing to a considerable height and bearing lateral branches at some height from the ground (Roy et al., 2012). Urban trees include individual trees as well as those occurring in stands, patches, and groups (Roy et al., 2012). In our analysis, the urban tree canopy is defined as the layer of tree leaves, branches and stems that provide tree coverage of the ground when viewed from above (Tree Canopy Assessment, 2019). The high-resolution (visually detectable) data on UTC was acquired by the City of Ottawa in 2018 using remotely sensed data in the form of aerial imagery, and light detection and ranging (LiDAR). As trees and shrubs can appear spectrally similar, or obscured by shadow, LiDAR, which consists of 3D height information, enhances the accuracy of the mapping (Tree Canopy Assessment, 2019). The height cut-off used for separating tree canopy from other vegetation was two meters (Tree Canopy Assessment, 2019). 167 different tree species are represented in this data. The most frequent species are deciduous trees, including Sugar Maple (Acer saccharum), Norway Maple (Acer platanoides), and Red Maple (Acer rubrum).

To develop the sample, we began with a dataset of all residential addresses in Ottawa, filtering to include only those zoned “R1” for single-family houses (see fig. 1.1A). We further filtered the data to include only addresses within the Hydro Ottawa electricity service territory. By focusing on single-family houses, the study benefits from uniform zoning regulations and similar land-use characteristics, providing a more homogenous sample for analysis. Single-family homes are the dominant form of urban development in North America, and so evaluating impacts in this context is relevant. Focusing on single-family homes also allows us to avoid issues associated with attributing energy demand to particular units in multi-unit buildings.

Then a list of all unique streets containing these properties was generated and approximately 900 of these streets were randomly selected. On each of the randomly-selected streets, we randomly selected one side of the street (odd or even house numbers), and then selected the homes with the highest and lowest UTC on each street for inclusion in our sample, to ensure substantial variation in UTC in our sample (Huang et al., 2024). This resulted in a list of about 1,800 unique addresses forming our sample used to estimate the effect of UTC on cooling electricity consumption (the estimation sample). Additionally, we selected about 200 homes from all the R1-zoned properties in the City completely at random to form a prediction sample that accurately reflects the broader population. This sample was used to make predictions of electricity savings resulting from UTC (the prediction sample) and not used for estimation. Summary statistics for all variables in both estimation and prediction sample data sets are provided in table. 1.1S and fig. 1.8S in the Supplementary Information (SI).

To analyze the spatial configuration of UTC in relation to houses, we measured tree canopy within a series of buffers (5, 12.5, and 20 meters) and in four directions (North, South, East, West) surrounding each house. A more detailed description of the UTC measurements for each address and the estimation configuration can be found in SI section 1. By measuring tree canopy within different buffers, we analyze how proximity to UTC affects electricity consumption. We chose buffers to capture UTC close to the home (within 5 meters) compared to more distant UTC (within 20 meters), with 12.5 meters chosen as an intermediate buffer. Nearby trees might have a stronger effect on cooling and shading benefits compared to those more distant from a home. Analysis of the effects of UTC within different buffer distances also allows for the examination of the gradient effect of UTC and whether there is a threshold distance beyond which tree canopy has a diminished effect on electricity consumption. Analyzing tree canopy in different directions allows for insights on how orientation and placement of trees can affect energy consumption.

2.3. Electricity Consumption Data

In Ontario, Canada, electricity consumption is measured using standard digital meters or smart meters. Most residential customers face Time of Use (TOU) prices, which vary throughout the day (Hydro Ottawa, 2024). For our study, we obtained hourly electricity consumption data matched to each of the 2,000 households in our estimation and prediction samples, covering the period from January 1 to December 31, 2018. This timeframe was chosen as it is the closest to when the UTC measurements were collected. This provided us with 8,760 observations per household for the year, offering a uniquely high resolution in electricity consumption data compared to other studies. Any address with problematic billing data—either more than or fewer than 8,760 observations throughout the year—was excluded from our analysis to maintain data integrity. Additionally, any observation with zero electricity consumption, often due to property vacancy, was also excluded from the sample. The estimation and prediction sample addresses selected from R1-zoned properties were matched with the electricity consumption data.

2.4. Weather Data

To analyze how climatic conditions modify the effect of UTC on electricity consumption, we included several weather variables in our final dataset: wind speed, temperature, relative humidity, and sun position. Wind speed can influence the cooling effect of tree canopy by enhancing natural ventilation. Research has shown that wind-driven natural ventilation can significantly impact indoor thermal conditions (Chen et al., 2023). The cooling effect of tree canopy may be more pronounced at higher temperatures when the demand for air conditioning increases (Akbari et al., 2001). However, the relationship between temperature and electricity consumption is non-linear. This non-linear relationship arises because the electricity demand for heating and cooling is not a direct function of temperature. Instead, it depends on how far the temperature deviates from a balance-point temperature (18 °C) and on the behavior of heating, ventilation, and air conditioning (HVAC) systems. When temperature is close to this balance-point the heating or cooling system may not operate at all, resulting in negligible electricity use. Electricity demand increases only when temperatures move significantly above or below this threshold, creating a non-linear response. Cooling degree hours (CDH) and heating degree hours (HDH) quantify the electricity needed for cooling and heating, respectively and HVAC systems are often designed and operated based on degree hours. In our analysis, CDHs and HDHs were used instead of temperature data to capture potential non-linearities. CDHs and HDHs are calculated in each hour as the difference between actual temperature and 18 ℃. UTC can influence microclimate conditions by affecting humidity levels. The interaction between humidity and tree canopy might reveal how trees impact perceived temperature and cooling needs, especially in humid conditions where cooling systems work harder (Heisler, 1986). With regards to sun elevation, the shading effect of trees is dependent on the position of the sun. Interacting sun elevation with UTC can show how the effectiveness of tree shade varies throughout the day, impacting electricity consumption differently at various times. We obtained the historical weather data from Environment and Climate Change Canada (ECCC) (ECCC Historical Climate Data, 2024). We identified Ottawa international Airport (YOW) as the relevant weather station near our study area in Ottawa. The data was obtained for hourly intervals and then merged with our electricity consumption and UTC dataset to provide a comprehensive analysis of how climatic conditions affect UTC effects on electricity usage. Fig. 1.10S illustrates the relationship between weather variables and average electricity consumption and fig. 1.11S highlights how this relationship varies between houses with different levels of UTC coverage.

2.5. Research Methods

2.5.1. Average Effect of Tree Coverage on Electricity Demand

Previous studies on the effects of UTC on urban temperatures (Huang et al., 1987; Scholz et al., 2018; Liu et al., 2020; He et al., 2021; Meili et al., 2021) highlight the role of shading, evapotranspiration, and wind modification, all of which depend on the presence of leaves. Leaves reduce solar heat gain by shading windows, walls, and roofs, thereby lowering radiant heat from surrounding surfaces. Through evapotranspiration, tree leaves absorb ambient heat and release water vapor, effectively cooling the surrounding air. Additionally, leaves reduce wind speeds, limiting the infiltration of outdoor air into buildings. Developing on these temperature-regulating mechanisms, this study assumes that UTC impacts electricity consumption only during the in-leaf period, defined as the start of May to end of September. Existing literature supports this choice and indicates that the leafing period for many deciduous trees begins in late spring and extends through summer until early autumn (Hoffmann, 1995; Jach and Ceulemans, 1999; Inouye et al., 2002).

By creating a binary variable for the leafing period and interacting it with the UTC, we can isolate the effect of the UTC during periods when trees are likely to provide the cooling benefits. Since our study is based on this assumption and the precise start date of the in-leaf period is uncertain, we conduct sensitivity analyses by testing our results with alternative dates for the in-leaf period. We estimate the average causal effect of the UTC on residential electricity demand using a difference-in-difference approach (Greenstone and Gayer, 2009). Our approach compares electricity consumption at a residential address during the in-leaf period to electricity consumption at the same address when trees are not in-leaf and compares this difference to that of other houses with different tree canopy coverage. Unlike most other observational studies of the impact of UTC on energy consumption, our approach does not rely on cross-sectional comparisons but instead focuses on within-address comparisons. This approach ensures that we can hold fixed potential address-level confounding variables, and more reliably identify the impact of UTC on energy consumption.

We implement the difference-in-difference model by estimating:

$$\mathrm{log(elec)_{it}} = \beta \times \mathrm{tree\_percent_i} \times \mathrm{in\_leaf_t} + \alpha_\mathrm{i} + \delta_\mathrm{t} + \epsilon_\mathrm{it} \qquad (1)$$

Where i indexes residential addresses, t indexes hours of the year (1:8760), $\mathrm{tree\_percent_i}$ is a variable with range of 0 to 1 that captures the share of area within 12.5m of the building that is covered by the tree canopy (later in the paper we explore alternative buffers), $\mathrm{in\_leaf_t}$ is a binary variable that captures the in-leaf period (May to September). α_i is an address fixed effect that captures unobserved heterogeneity across houses that persists across the whole year (e.g., house size, orientation, equipment, and number of occupants). δ_t is a time fixed effect that captures unobserved heterogeneity across hours that affects all addresses (e.g., holidays and special events, electricity prices, weather, diurnal, daily, and monthly variation in activity levels). ϵ_it is an error term. The coefficient β is the main estimated coefficient and reflects the estimated causal effect of tree coverage during the in-leaf period on residential electricity demand.

The coefficient β reflects an unbiased estimate of the effect of interest if, conditional on fixed effects, the interacted variable $\mathrm{tree\_percent_i} \times \mathrm{in\_leaf_t}$ is uncorrelated with the error term. One plausible violation of this assumption is that houses built in different eras, and subject to different building codes, have different summer-winter relative electricity demands and also systematically different levels of UTC. To control for this, we add street-time fixed effects δ_{st} in place of time fixed effects. These impose flexible time trends for each combination of houses located on the same side of the same street (address pair). Since houses on a street often share characteristics (e.g., built at similar times using similar construction practices, similar size), these fixed effects address potential violation of the assumption above. We also modify the equation above to replace address fixed effects with address-by-hour fixed effects α_{ih}, where h indexes the 24 hours in a day, and address-by-weekday fixed effects α_{id}, where d is a binary variable denoting weekdays (1) or weekends (0). These restrict within-house comparisons of electricity demand to same-hour and same-weekday type to improve precision of estimates of β. The preferred estimating equation is thus:

$$\log(\text{elec})_{it} = \beta \times \text{tree\_percent}_i \times \text{in\_leaf}_t + \alpha_{ih} + \alpha_{id} + \delta_{st} + \epsilon_{it} \qquad (2)$$

In all cases, we two-way cluster on address and hour of the year to account for arbitrary serial correlation within a house as well as cross-sectional correlation across houses within an hour (Abadie et al., 2023).

2.5.2. Average Effect of Tree Coverage by Distance and Direction

We estimate how the effect of UTC differs depending on how far from the structure it is and which side of the structure it is located. We measure tree coverage using three buffers (b) around each residential address: 5m, 12.5m, and 20m. To ensure we do not double-count, we define the variable $\overline{\text{tree\_percent}}_{bi}$ as the net tree coverage in buffer b (excluding buffer $b - 1$). We estimate:

$$\log(\text{elec})_{it} = \sum_b \beta_b \times \overline{\text{tree\_percent}}_{bi} \times \text{in\_leaf}_t + \alpha_{ih} + \alpha_{id} + \delta_{st} + \epsilon_{it} \qquad (3)$$

We measure tree coverage using four cardinal directions (c) – North, South, East, and West. We estimate the heterogeneous effect of tree coverage on electricity demand by direction using:

$$\log(\text{elec})_{it} = \sum_c \beta_c \times \overline{\text{tree\_percent}}_{ci} \times \text{in\_leaf}_t + \alpha_{ih} + \alpha_{id} + \delta_{st} + \epsilon_{it} \qquad (4)$$

In Eq. (3), the coefficients from different buffers are not directly comparable to each other, nor to the main preferred coefficient from Eq. (2). This issue arises because the percentage of canopy coverage within each buffer is calculated as the ratio of canopy area to the total buffer area. As the buffer distance increases, the total area grows significantly, which reduces the calculated canopy percentage for the same absolute amount of canopy. This discrepancy can lead to misleading comparisons if not accounted for. Similarly, the coefficients from Eq. (4) are not comparable to the main preferred coefficient as the canopy effect within each direction (quadrant) around a house is calculated for an area that is one-fourth (1/4) of the total area around the house. Therefore, we conduct the analysis of Eq. (3) with square meter of UTC within buffers instead of the ratios. Moreover, a normalization process is applied to the results of Eq. (4), to enable meaningful comparisons across different directions and the main estimate (Eq. (2)). More details on the rationale for normalization and the methodology used to perform it can be found in the SI, section 1.

2.5.3. Conditional Average Effect of Tree Coverage on Electricity Demand

We combine analysis of causal effects with machine learning to estimate the conditional average treatment effect of UTC on residential electricity demand (Wager and Athey, 2018; James et al., 2013). We are interested in determining how electricity savings from the UTC vary according to weather conditions. We define W_t as a vector of weather variables including CDH, HDH, relative humidity, wind speed, sun elevation, the cosine and sine of sun azimuth, and dummy variables for daylight and weekend. Table. 1.1S. provides descriptive statistics of weather variables included in the vector W_t, which are measured at the Ottawa International Airport monitoring station. Our aim is to estimate coefficients β_W that reflect the causal effect of in-leaf UTC conditional on weather:

$$\log(\text{elec})_{it} = \beta_W \times \text{tree\_percent}_i \times \text{in\_leaf}_t \times W_t + \alpha_{ih} + \alpha_{id} + \delta_{st} + \epsilon_{it} \quad (5)$$

We include all weather variables linearly, and also include squares of all the weather variables, and all possible two-way interactions of weather variables. The vector W_t thus includes a total of 54 weather variables (with 9 weather variables plus a constant, we have 45 unique combinations plus 9 quadratic terms).

We implement this regression using Least Absolute Shrinkage and Selection Operator (LASSO). LASSO is a penalized regression that performs variable selection. To obtain a causal interpretation, we first demean both the left-hand- and right-hand-side variables to eliminate fixed effects using the Frisch-Waugh-Lovell theorem by regressing each variable on all fixed effects and retaining residuals. LASSO, which is a linear model, can be estimated on residualized data and estimated coefficients can be used for prediction on non-residualized data (unlike classification tree approaches, which are non-linear). Using this approach, we remove house-by-hour of day fixed effects, house-by-weekday fixed effects, and street-by-hour of sample fixed effects, such that the causal interpretation of the results is identical to the main regression estimates. We then implement the LASSO regression on demeaned variables. We use five-fold cross-validation to select the shrinkage parameter (λ) that minimizes cross-validation mean squared error (James et al., 2013).

2.5.4. Valuation of Electricity Savings

We determine the annual value of electricity savings resulting from the urban tree canopy using the following equation:

$$\text{dollar\_savings}_i = \sum_{t=1}^{8760} \widehat{s_{it}} \times p_t \quad (6)$$

Where $\widehat{s_{it}} = \exp\,(\widehat{\log(\text{elec})}_{it} - 1)$ are electricity savings in kWh from the urban tree canopy predicted using the coefficients from the LASSO regression, and p_t are retail electricity prices. The LASSO model is estimated using the estimation sample, and predictions are made using the prediction sample, as defined above. Electricity prices in Ontario follow a time-of-use schedule, with on-peak, mid-peak, and off-peak prices defined over winter and summer seasons. We use 2018 electricity prices of 0.049, 0.071, and 0.1 USD/kWh for the low, mid-peak, and off-peak periods.[1]

[1] Prices are obtained from the Ontario Electricity Board: https://www.oeb.ca/consumer-information-and-protection/electricity-rates/historical-electricity-rates (accessed June 24, 2024). Values are based on 2018 retail prices in CAD, converted to USD using an exchange rate of 0.76, applicable for the period from May to November 2018.

3.Results

3.1. Graphical Evidence

We begin by providing a simple visualization to highlight the impact of UTC on energy consumption in Figure 1.2. The figure shows the average electricity consumption of households in the estimation dataset during the in-leaf (May to September) and off-leaf (October to April) periods. We plot average electricity consumption for two groups of homes: those with minimal UTC coverage (0%–25% of the area within 12.5m of the home is covered by UTC) and those with higher UTC coverage (25%–100%). We choose 25% UTC as the dividing line because this is roughly the median UTC in our sample.

During the off-leaf period, electricity consumption patterns are nearly identical between the two UTC groups. This similarity reflects the limited role of trees in influencing electricity consumption when they are not in leaf. In contrast, during the in-leaf period, homes with larger UTC exhibit significantly reduced electricity consumption, particularly during peak cooling hours in the afternoon and evening (12:00 PM to 8:00 PM).

In the following sections, we build on this intuition by leveraging the detailed house-level observations to estimate the impact of UTC on electricity consumption using a more formal regression approach. In the following sections, we assume electricity consumption varies linearly with UTC rather than simply binning houses into two groups as was done in this section (for visualization purposes only).

3.2. Average Impact of UTC on Electricity Consumption

Table. 1.2S shows the result of estimating Eq.(1) in Model 1. In this analysis, the dependent variable is log of hourly electricity consumption. In Eq.(1), a standard two-way fixed effect regression, the main coefficient of interest is β, the effect of the in-leaf UTC on electricity consumption. As expected, the results suggest that a negative and statistically significant relationship exists between in-leaf UTC and electricity consumption. A 10 percentage point increase in UTC within 12.5 meter buffer of the houses causes a 3.56% reduction in electricity consumption during the in-leaf period and this finding is statistically significant ($p < 0.01$).

We expand our analysis using several models to explore how different aspects of electricity consumption patterns and building characteristics influence the causal effects of UTC. In table. 1.2S, Models 2 and 3 add address-by-hour and address-by-weekend fixed effects, respectively, while Model 4 adds both sets of fixed effects simultaneously. Address-by-hour fixed effects account for within-house diurnal patterns in energy consumption, and address-by-weekend fixed effects account for within-house weekly patters in energy consumption. These additions increase the precision of coefficient estimates without affecting the point estimate. Model 5 adds street-by-time fixed effects which accounts for heterogeneity in street-varying building characteristics that might affect seasonal electricity demand. The model presents a smaller statistically significant coefficient of -2.9% for a 10-percentage point change in UTC ($p < 0.01$) compared to the baseline model (Model 1). Model 6 (Eq.(2)) accounts for both heterogeneity in building characteristics and persistent diurnal and weekly electricity consumption patterns. The estimated coefficient of this model (which is similar to Model 5) presents a smaller statistically significant coefficient of -2.9% ($p < 0.01$) for the tree canopy effect compared to Model 1. This implies that building characteristics including differences in insulation quality, building age, or construction materials, which are often similar among houses on the same street, can influence how buildings respond to seasonal temperature changes. It also indicates that the effectiveness of UTC on electricity use might be overestimated when building-specific influences are not sufficiently accounted for. We consider this our preferred estimate of the effect of in-leaf UTC on electricity consumption.

To assess the robustness of our findings to the assumed in-leaf period, we conducted a sensitivity analysis using an extended in-leaf period from start of April to end of October. According to Model 2 in table. 1.3S, the estimated effect size of a 10-percentage point increase in UTC within 12.5 meters of a house decreased slightly to -2.1% (compared to -2.9% for the May to September period). This suggests that trees have the strongest impact on energy consumption during peak leaf coverage months, with a weaker effect in early spring and late fall. The reduced effect in April and October may be due to leaves not being fully developed in April or losing effectiveness in October. These findings provide empirical support for our assumption that May to September represents the optimal in-leaf period for energy reduction.

We replicate the analysis using Model 6 (the preferred regression model) and included a full set of buffer distances and directions (Eq.(3), (4)). To ensure that the effects estimated for different buffer sizes are directly comparable to each other and to the main effect (overall UTC effect), UTC is measured using square meters of canopy cover within each buffer instead of ratios (Model 7, table. 1.2S). Moreover, a normalization process is applied so the estimates of the effect of UTC within different directions are directly comparable to the main effect (Model 8, table. 1.2S). Findings show that the magnitude and direction of the effect depends upon the relative position of the UTC. Within designated buffers, effect of UTC was most profound and statically significant when UTC is located within 5 to 12.5-meter of the house. The effect of UTC becomes statistically insignificant within 20-meter buffer. The electricity saving effects of UTC are most pronounced in the west quadrant. A 10-percentage point increase in UTC within this direction reduces electricity consumption during the in-leaf period by 4.6%, followed by the north (-3.6%) and east (-3.4%) quadrant. Trees on the south side have the smallest effect (-2.4%). East-quadrant trees cast shade during morning hours. Closer to the afternoon, shadows lengthen towards the east and temperatures peak, resulting in a greater reduction in electricity use from trees located in the west quadrants. In addition, this is the time of day when many people return home and use their air conditioning systems.

3.3. Mediating Impact of Weather on Effect of UTC on Electricity Consumption

Eq.(5) provides the foundation for modeling the hypothesis that UTC causally affects electricity consumption, conditional on weather conditions. The regression framework is implemented using LASSO, a machine learning method that combines variable selection and regularization (Saini et al., 2023). The final LASSO model includes coefficients for the base interaction term between UTC and the leafing period, along with interactions between this term and key weather variables such as temperature, relative humidity, and wind speed as described in the prior section. These interactions help capture how weather conditions modify the effect of UTC on electricity consumption. Using the trained LASSO model, we predicted electricity savings associated with existing UTC levels, applying the model to the prediction sample dataset.

We further examine the influence of each weather variable on electricity savings from UTC during the in-leaf period. To ensure that the predicted savings are specifically attributable to the weather variable of interest and not confounded by variations in other variables, the estimated LASSO model was employed while all variables were held constant at their mean values, with only the weather variable of interest allowed to vary. Results are shown in fig. 1.3. Panel (A) indicates that as temperatures rise, the effect of UTC on electricity savings increases but above the balance-point temperature (18℃), this relationship exhibits a steeper behavior. This indicates that as temperatures rise significantly above the balance-point temperature and the heat load on buildings increases, the benefits of UTC become more pronounced. Panel (B) shows that higher relative humidity levels are associated with lower electricity savings from in-leaf UTC. UTC contribute to cooling primarily through shade and evapotranspiration (ET). ET is most effective in reducing air temperatures when the surrounding air has lower humidity levels, allowing for more efficient moisture release and cooling. However, when relative humidity is high, the air is already saturated with moisture, limiting the tree's ability to cool the environment through ET (Shashua-Bar et al., 2009). This could result in lower energy savings from UTC at higher humidity levels. Panel (C) suggests that as wind speed increases, the effects of UTC in reducing electricity consumption diminish. This reduction in energy savings from UTC can be attributed to various environmental and physical dynamics, with one key explanation being that higher wind speeds enhance convective heat transfer between the air and the built environment. This increased convection disperses the cool air that typically accumulates under tree canopies more rapidly. As a result, the localized cooling effect provided by tree shade is weakened, reducing its impact on energy savings.

3.3.1. Predicted Electricity Savings

The left panel of fig. 1.4 illustrates the average predicted electricity savings from UTC during the in-leaf period, based on the LASSO model. Predictions are made using the randomly-sampled prediction sample and thus reflect our best estimate of average electricity savings from the UTC for single-family homes in Ottawa. The dashed line in the figure represents the average estimated annual electricity savings from the existing average UTC in the prediction sample (2.97%), as derived from our preferred regression model (Eq.(2)). As shown in the figure the peak savings of 16.2% occurs in the hour with the largest savings in July, coinciding with the period of highest cooling demand.

Fig. 1.5 presents two panels illustrating the predicted electricity savings from UTC during the in-leaf period, estimated using the LASSO model, alongside average hourly 2018 retail electricity prices on summer weekdays. Panel A shows significant variability in diurnal electricity savings across the months of the in-leaf period. The highest average hourly savings during the in-leaf period occur between 3:00 PM and 8:00 PM (ranging from -8.5% to -9.6%), with peak savings reaching -9.9% at 6:00 PM. This peak aligns with the period of highest cooling demand, as temperatures tend to be elevated in the late afternoon and early evening. In terms of monthly averages during the in-leaf period, the greatest electricity savings occur in July (-9.5%), followed by August (-7.9%) and June (-7.3%). The highest average hourly savings within each month also peak at 6:00 PM, with July exhibiting the largest savings of -13%. Panel B presents average hourly retail electricity prices, showing that the highest prices (on-peak) occur between 10:00 AM and 4:00 PM, corresponding to increased electricity demand during these hours. Together, these panels highlight that maximum electricity savings from UTC closely align with periods of higher retail electricity prices, particularly during on-peak and mid-peak hours. This alignment underscores the economic and environmental benefits of UTC, as it provides the greatest savings when cooling demand and electricity costs are at their highest.

Fig. 1.6 presents the predicted electricity consumption under two different scenarios: current UTC and zero UTC, using a load duration curve. The graph shows that during lower consumption hours, electricity demand is similar across both scenarios. The steep part of the load duration curve represents the peak hours when demand is highest. The current UTC scenario results in a lower peak electricity demand compared to the zero UTC scenario during the peak demand hours**.** At the peak hour, predicted average single-family electricity consumption with current UTC is 3.01 kWh/h; without the influence of the urban tree canopy predicted electricity consumption is 3.54 kW/h (17.9% higher). In the top 1% of hours (approximately the 88 highest-consumption hours of the year), electricity consumption with zero UTC reaches an average of 2.74 kW/h, compared to 2.37 kW/h under current UTC. This represents a 15.6% reduction in peak demand. We observe a 8.1% reduction in peak demand between zero UTC and current UTC in the top 10% of highest consumption hours. These findings indicate the importance of UTC in reducing the highest electricity loads, which is crucial for minimizing grid stress and improving energy system resilience.

Our results so far have been for existing UTC. However, we can also explore the benefits of an increase in UTC. Two panels of fig. 1.4 illustrate the predicted electricity savings from UTC under two different scenarios: current UTC and an adjusted scenario where tree coverage is increased by 25% of the remaining amount needed to reach 100% coverage. The rationale for forming this scenario is to provide a realistic augmentation without exceeding physical or practical limits (i.e., not exceeding 100% coverage). As demonstrated in the figure, during in-leaf period, the average annual predicted electricity savings from current UTC is 2.97%. This number increases to 5.02% in adjusted UTC scenario.

3.3.2. Valuation of Electricity Savings

As illustrated in fig. 1.7, our findings on annual electricity savings attributed to UTC reveal a clear and consistent increase in cost savings as UTC levels rise. As noted by Pandit and Laband (2010), one effective way to encourage individuals to adopt energy-conserving practices is to provide them with data demonstrating the financial savings they can achieve through tree shade management on their properties. The trend line in our analysis highlights the economic benefits of increased tree coverage, emphasizing the potential for significant cost reductions in urban energy expenditures through strategic urban forestry efforts. In our sample, based on the predicted savings obtained from the LASSO model, we estimated that a house with average tree cover (25% UTC) saves about $9 on electricity annually. Houses with high levels of UTC (>60%) can save up to $76 on electricity annually. To highlight the long-term economic benefits of UTC, we can incorporate the concept of lifetime value into the discussion of electricity savings. This calculation implies that the total value of electricity savings from an average tree cover (25%) is $450 over the tree canopy's lifespan, assuming the savings continue indefinitely and are discounted at 2% annually.

4.Discussion

Our study builds on the literature that estimates the effect of UTC on building energy consumption both by using higher resolution data and by using a methodology with higher internal validity. We leverage high-resolution energy consumption data from nearly 2,000 houses in Ottawa as well as measurement of UTC from a tree canopy assessment. We isolate the causal effect of UTC on electricity consumption using a difference-in-difference approach by comparing energy consumption in a house during periods with full leaf coverage to a similar period when leaves are not on trees, and we contrast this difference with that of a matched house on the same side of the same street with a different tree canopy coverage. Our findings reveal a statistically significant 2.9% reduction in electricity consumption attributable to 10 percentage point increase in UTC within a 12.5-meter buffer from the house during in-leaf period. Averaged over the entire year, our results suggest that with current canopy coverage, urban trees reduce electricity consumption by about 3%.

We extend the analysis to examine whether the magnitude of this effect varies based on the distance of UTC from the house and its directional orientation relative to the building structure. Consistent with the results of Donovan and Butry (2009) and Pandit and Laband (2010), our study demonstrates that UTC located in the west quadrant has the most substantial impact on electricity consumption. We find smaller impacts from UTC in the north and east quadrant, and no statistically significant impacts from UTC to the south of a house. We also find that UTC located closer to the building (within 12.5 meters) has a greater impact on electricity consumption compared to UTC situated farther away (up to 20 meters).

To examine how the effects of UTC on energy consumption vary by weather conditions, we combined causal inference with machine learning. We aim for causal identification with a difference-in-difference approach that compares household energy consumption during the in-leaf period to energy consumption in the same house in winter when leaves are not on trees and contrasts this difference with that of a matched house on the same street with different UTC. We use a LASSO-based approach to determine which weather covariates affect estimates of UTC on energy consumption identified in the difference-in-difference regressions. Estimates from the LASSO model show that UTC is more effective at increasing the electricity savings during periods of higher temperatures. In contrast, higher wind speeds and higher relative humidity diminish the effectiveness of UTC in achieving electricity savings. We use the estimated LASSO model to predict electricity savings and find that savings from UTC are most pronounced during July followed by August and June and are highest in early afternoon and evening. Electricity savings from the current tree canopy peak at over 15% of load on hot summer afternoons, and are coincident with system peaks.

Our findings underscore the potential of UTC to reduce electricity consumption. However, without a clear understanding of the value provided by the natural cooling effects of UTC, individuals and urban planners may lack the incentive to strategically plant and maintain trees to minimize electricity use during hot summer months (Pandit and Laband, 2010). By quantifying the cost of savings, we estimate that a house with average canopy cover (25%) saves approximately $450 over the canopy's lifespan. This highlights the economic benefits of increased tree coverage. Examining the variation in the magnitude of UTC effects based on its distance and direction relative to the house highlights the critical role of strategic urban forestry initiatives in reducing urban energy expenditures. Furthermore, targeted tree planting not only reduces electricity consumption but also contributes to broader environmental objectives, such as mitigating urban heat islands, improving air quality, and promoting biodiversity.

While Ottawa can serve as a representative city for Midwest with regard to climatic conditions and urban form development features, we acknowledge that the results obtained from this specific geographic or climatic area might not be applicable to other areas with different environmental conditions, housing structures, or consumer behaviors. In particular, our focus on single-family homes means that our results are unlikely to be reflective of impacts of the urban tree canopy on energy consumption in multi-unit residential buildings, or in commercial or industrial zones.

5.Conclusion

This study uses high-frequency electricity consumption data at the household level, matched with high-resolution estimates of urban tree canopy coverage, along with a difference-in-difference strategy, to estimate the impact of the urban tree canopy on residential electricity consumption. Our findings are both practical and theoretical.

On the practical side, we have detailed and internally valid findings about the impact of urban greening on cooling electricity demand. We find that the current urban tree canopy on average reduces the annual electricity load from single family dwellings in Ottawa by about 3%. During the summer period, we find that a house with complete urban tree canopy coverage consumes about 29% less electricity than an identical house with no trees nearby. Effects of the urban tree canopy are largest for trees planted within 12.5 m and to the West of a home. We find that the largest reduction in electricity consumption from trees occurs on hot summer afternoons and reaches over 15% of residential load. This period coincides with electricity system peaks and suggests that urban trees play a significant role in limiting peak period demands.

On the theoretical side, we make methodological advancements that can be replicated in other contexts. Most importantly, we demonstrate a new approach to using machine learning for uncover heterogeneous causal impacts in a difference-in-difference context. This approach allows us to understand how the electricity savings from the urban tree canopy vary with weather and sun conditions.

Overall, the study's results suggest that the urban tree canopy exerts a large influence on electricity demands. This finding suggests that maintaining and increasing urban tree canopy can be an important part of the strategy for managing future electricity load.

Figures

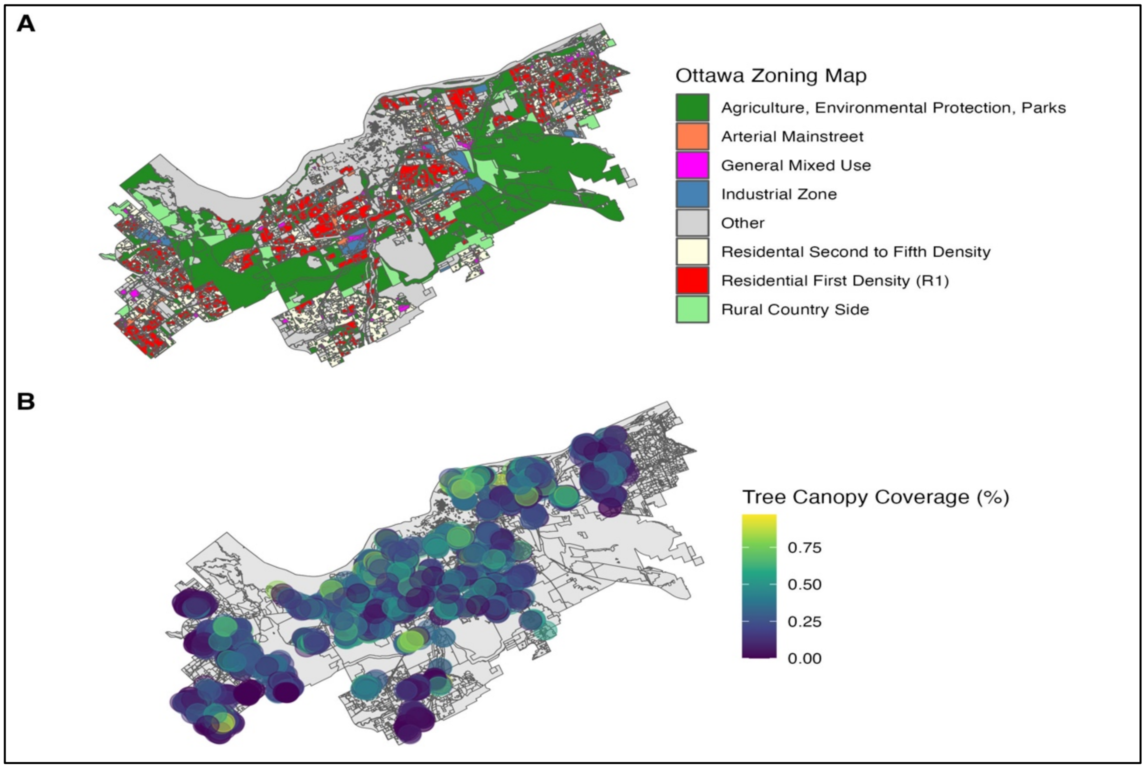

Figure 1.1. (A) Major land use zones in Ottawa; (B) Urban tree canopy coverage within 12.5-meter buffer of building structures in the R1 zoned houses in both the prediction and estimation data sets (N=1968). Geographic coordinates in B have been jittered to preserve confidentiality

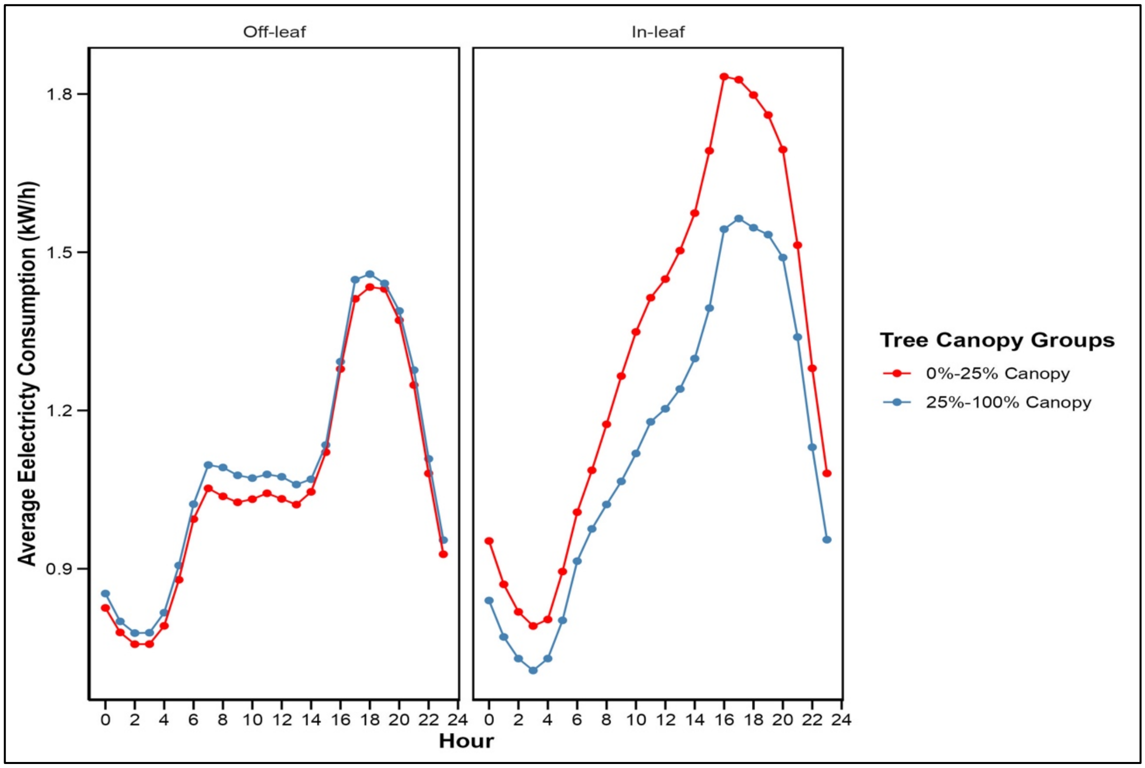

Figure 1.2. Average electricity consumption per hour within different canopy sizes during in-leaf (May to September) and off-leaf (October to April) period. During in-leaf period, houses with larger UTC within their 12.5-meter buffer consume less electricity, especially during daylight hours when outdoor temperature is elevated. A total of 977 houses in the estimation sample have 0%-25% UTC within their 12.5-meter buffer, while 842 houses have 25%-100% UTC within the same buffer.

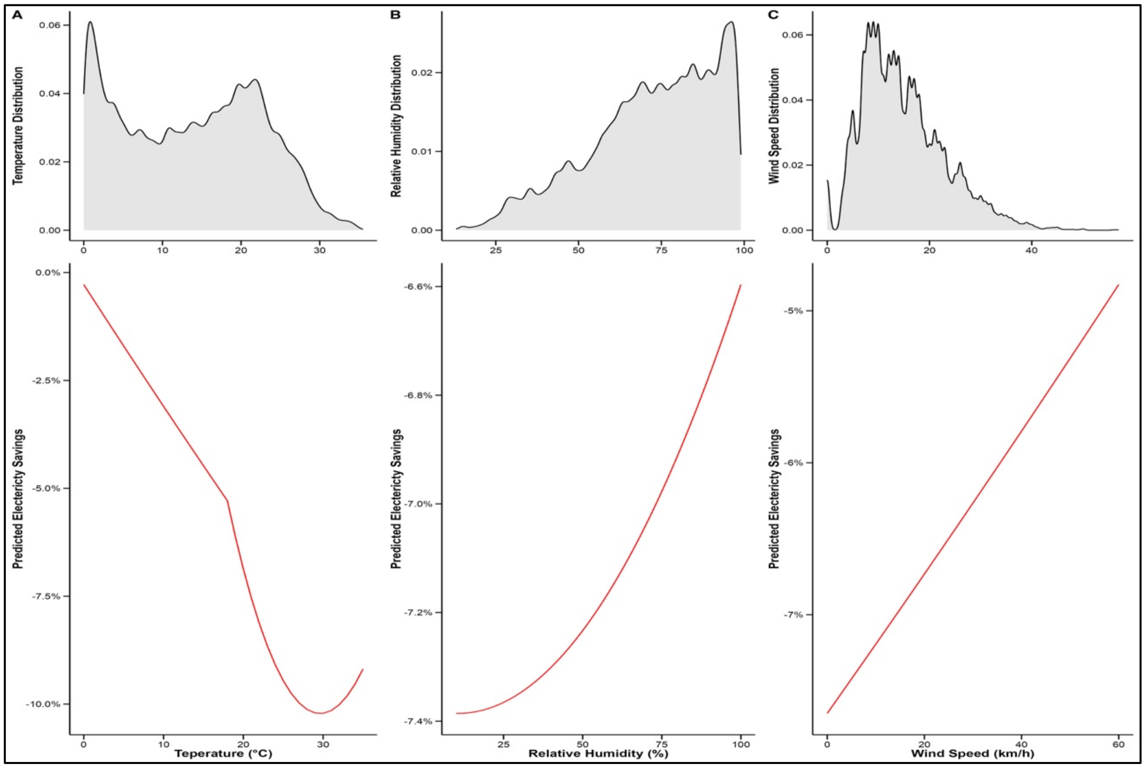

Figure 1.3. Density plot of weather variables in the prediction sample and predicted average electricity savings from the LASSO model. (A) Temperature is the only variable that varies while all other variables are held constant at their average values; (B) Relative Humidity is the only variable that varies while all other variables are held constant at their average values; (C) Wind Speed is the only variable that varies while all other variables are held constant at their average values.

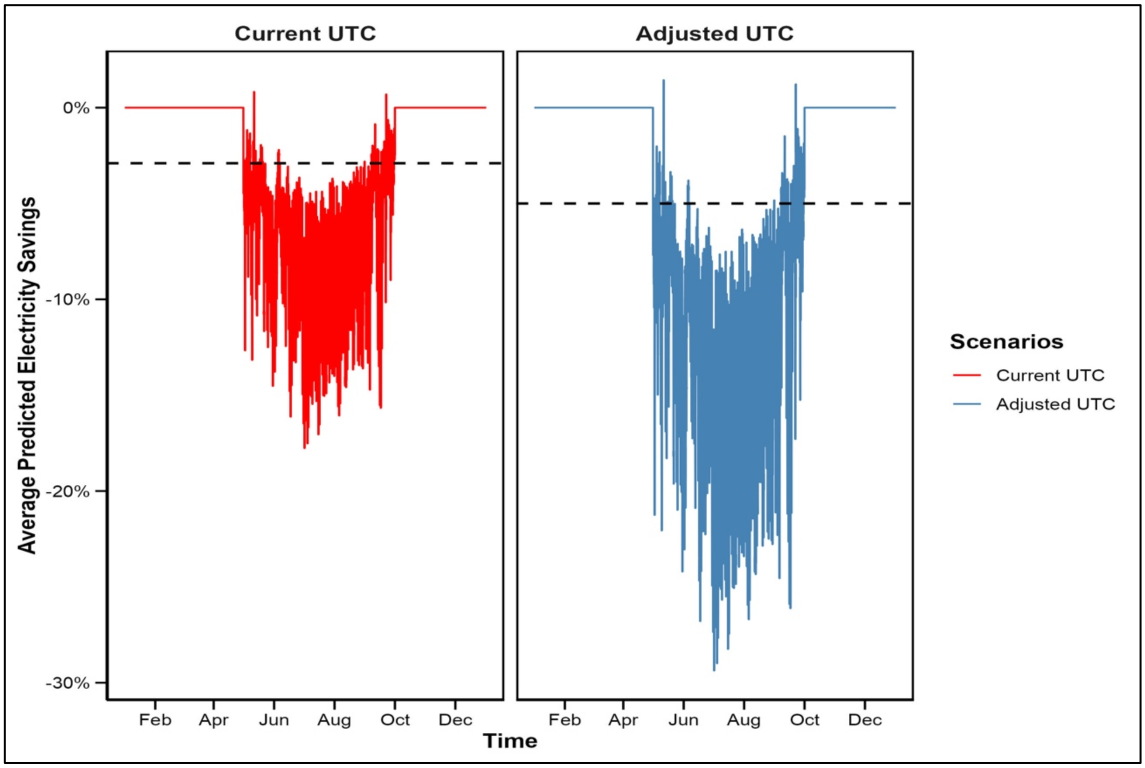

Figure 1.4. The average predicted electricity savings from UTC during the in-leaf period estimated by the LASSO model. Dashed lines depict average annual savings from current UTC (-2.97%) and adjusted UTC (-5.02%).

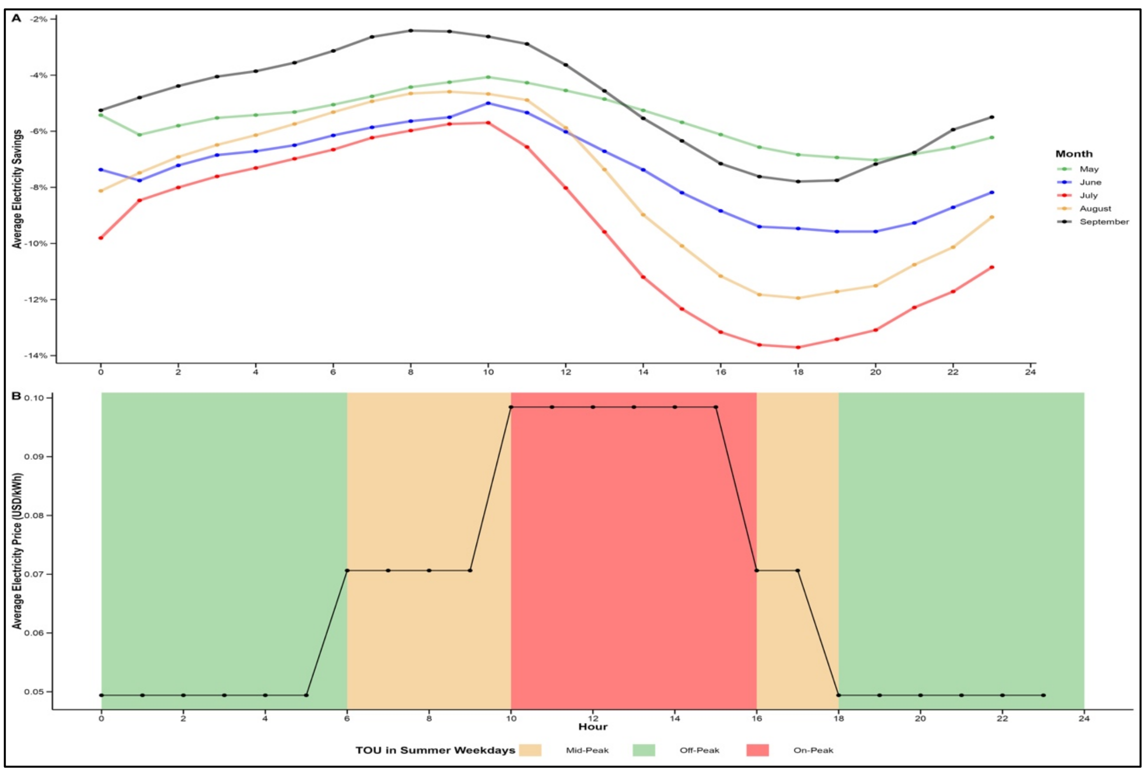

Figure 1.5. (A) Predicted electricity savings from UTC during the in-leaf period estimated by the LASSO model; (B) Average hourly 2018 retail electricity prices on summer weekdays obtained from the Ontario Energy Board.

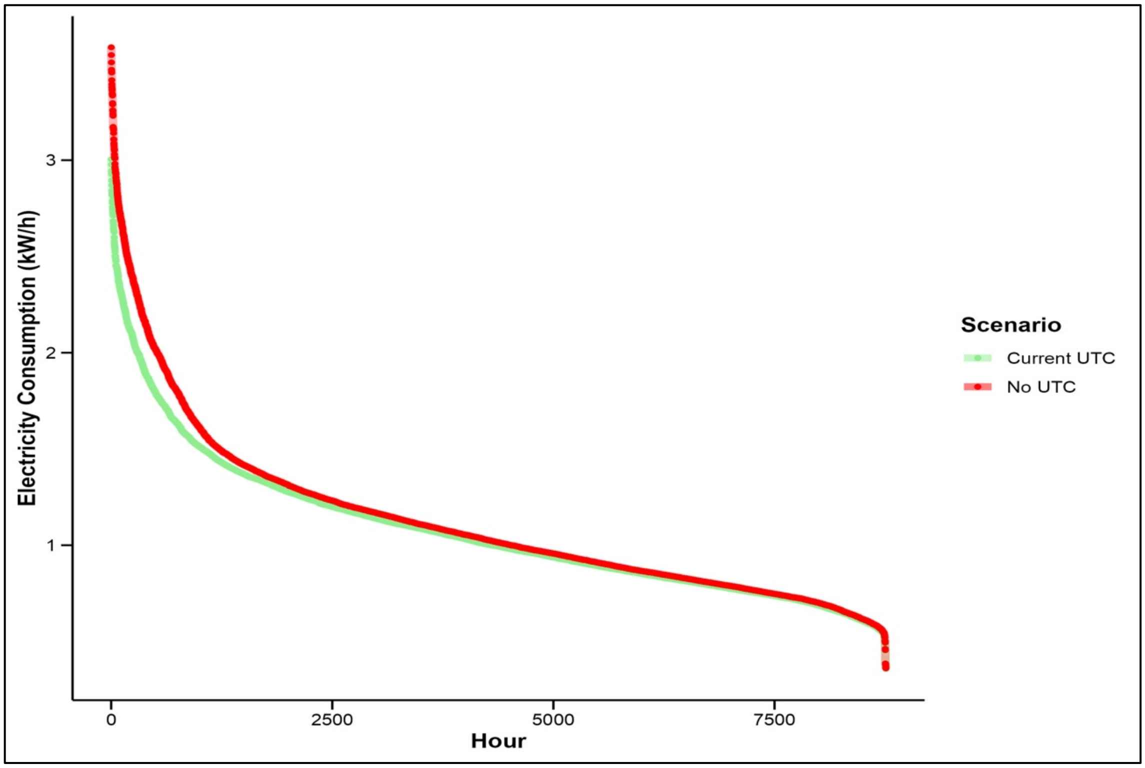

Figure 1.6. Load duration curve and predicted electricity consumption under two scenarios: current and zero UTC

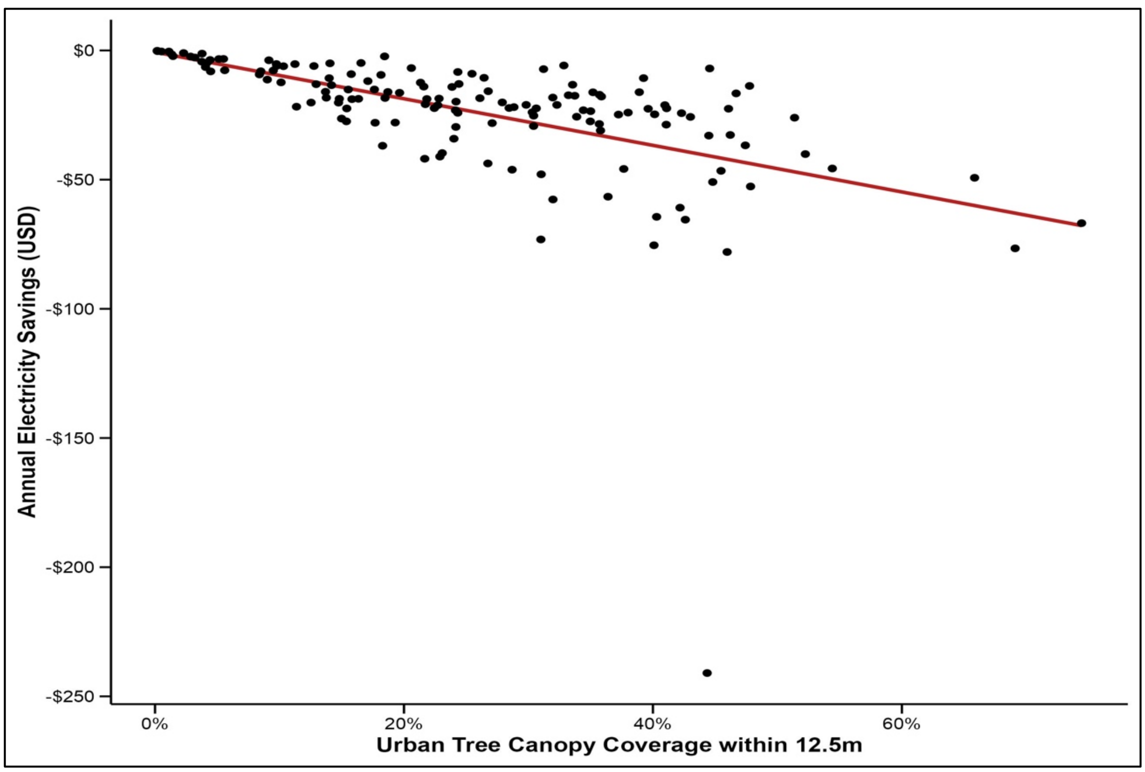

Figure 1.7. Annual cost of electricity savings by UTC coverage within 12.5-meter buffer. Each point represents one of the houses in the prediction sample.

Appendix A: Supplementary Information of Chapter 1

Section 1: Data Preparations and Modifications

Urban Tree Canopy Estimation

To estimate tree canopy coverage for each house in the sample dataset, we created buffers of 5, 12.5, and 20 meters around the centroid of each building structure. Additionally, four directional quadrants, North, East, South, and West, were defined to represent the different sides of the building (Fig. 1.8S). The percentage of tree canopy coverage was measured within each buffer and direction. For the main estimate of the effects of UTC on energy consumption (regardless of proximity and direction of the UTC relative to the buildings) the sum of tree canopy coverage within 12.5-meter buffer was utilized in the analysis.

Buffer Effect

The percentage of canopy coverage within each buffer is calculated as the ratio of canopy area to the total buffer area. As the buffer distance increases, the total area grows significantly, which reduces the calculated canopy percentage for the same absolute amount of canopy. This discrepancy can lead to misleading comparisons if not accounted for. To address this, we can either normalize the effects of canopy coverage within the larger buffers (12.5 meters and 20 meters) by dividing their effects by the ratios of their respective areas to the area of the 5-meter buffer. Another solution to this issue is to conduct Eq. (3) with UTC within each buffer measured in square meter rather than ratios. Hence, no normalization process is required for the interpretation of the results.

Direction Effect

The canopy effect within each direction (quadrant) around a house is calculated for an area that is one-fourth (1/4) of the total area around the house. Since the main effect represents the canopy impact for the entire area around the house, the effects calculated within each quadrant are effectively weakend by the smaller area. To make these effects comparable to the main effect, we need to scale up the effects of each direction by multiplying them by 4.

Figures

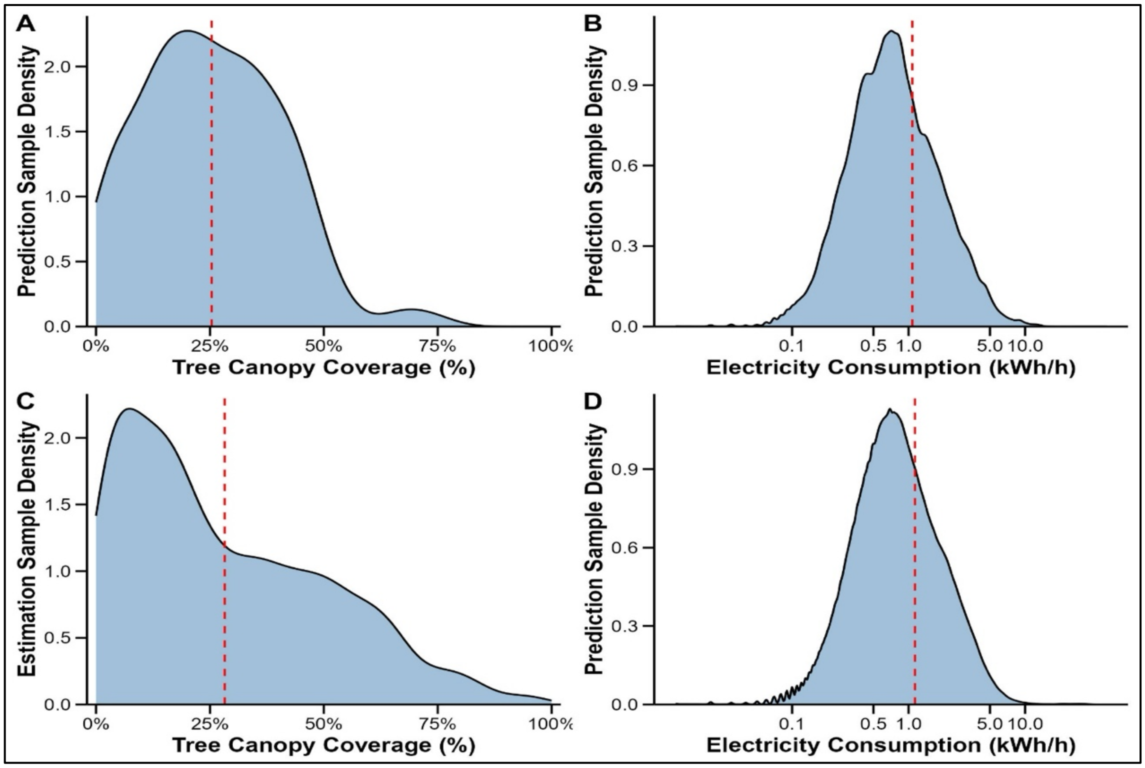

Figure 1.8S. UTC and electricity consumption density in estimation and prediction sample. Red dashed line depicts the mean in the sample.

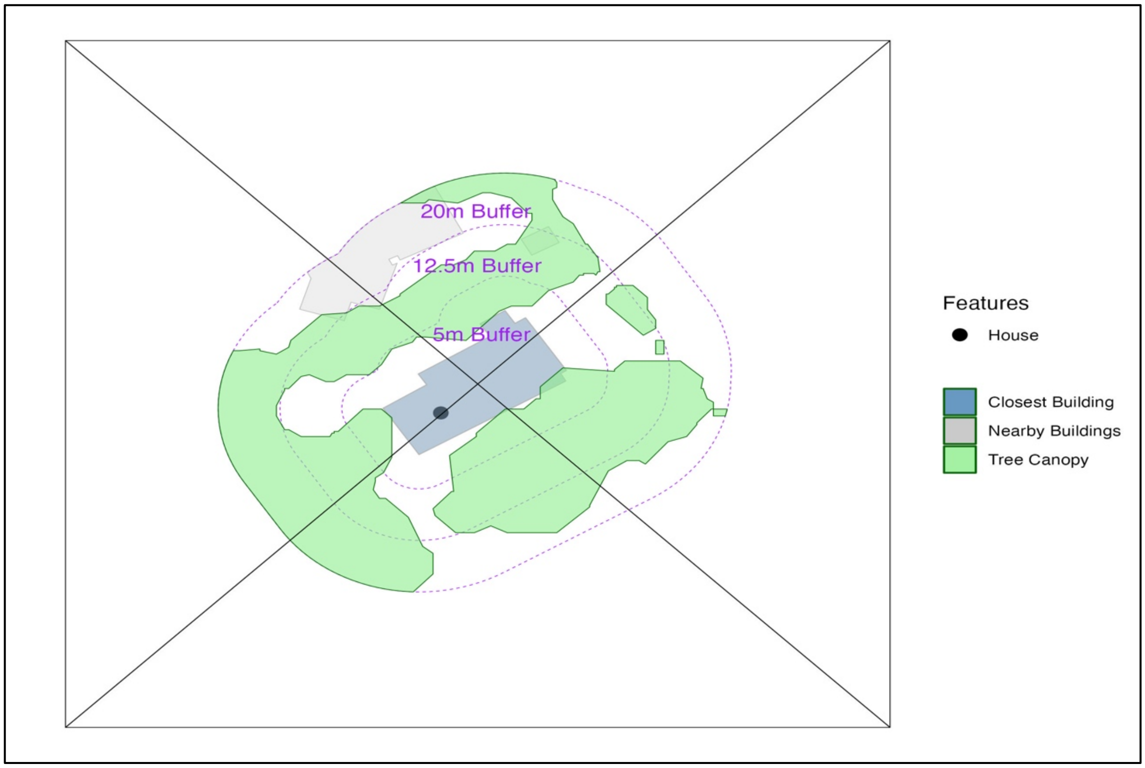

Figure 1.9S. UTC estimation configuration for buildings in the R1 zone. Four cardinal directions (North, East, South, and West) are shown as quadrants relative to the building.

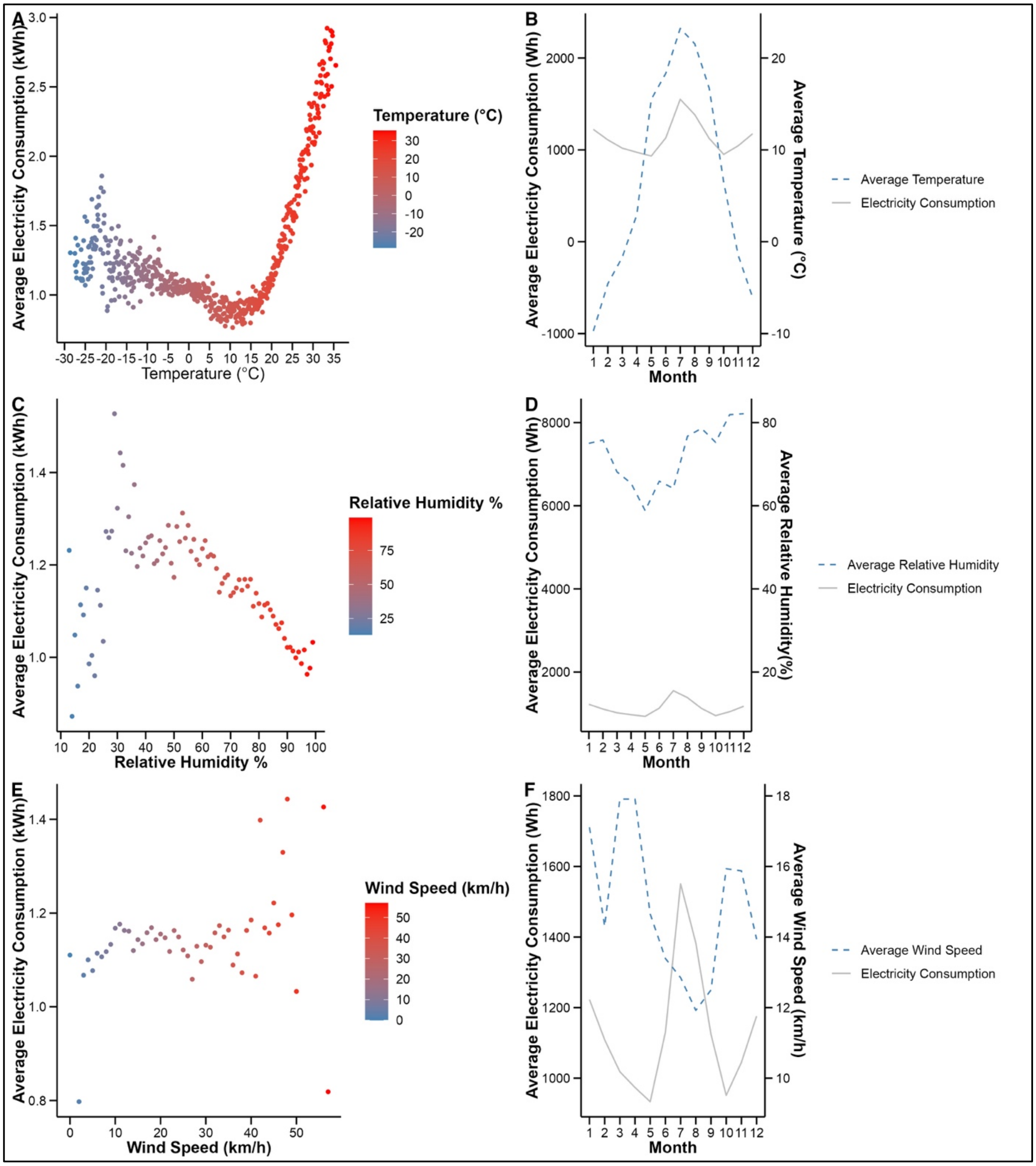

Figure 1.10S. (A, B) Average electricity consumption associated with temperature; (C, D) Average electricity consumption associated with relative humidity; (E, F) Average electricity consumption associated with wind speed.

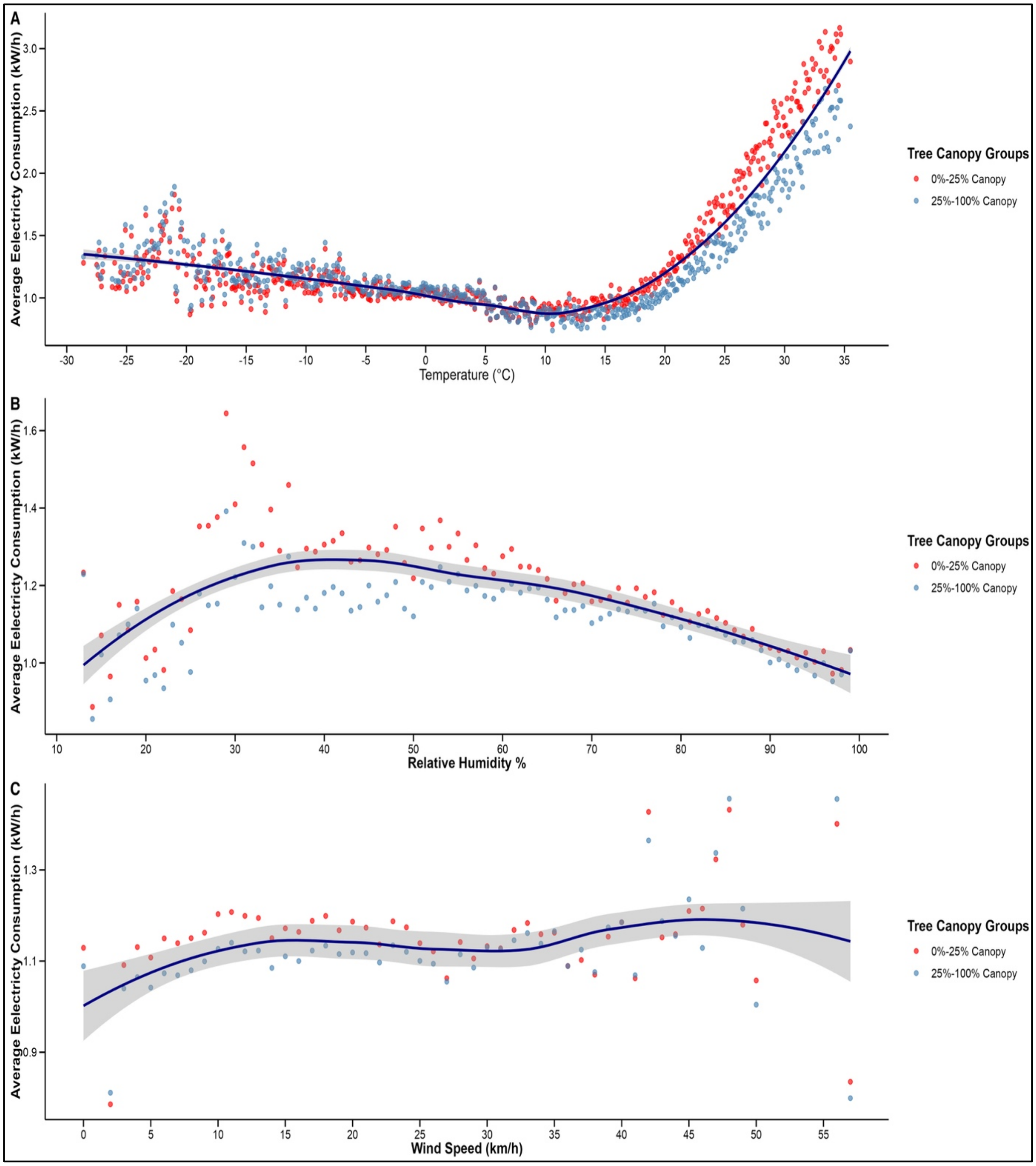

Figure 1.11S. (A) Average electricity consumption associated with temperature and variation between houses with different levels of UTC density; (B) Average electricity consumption associated with relative humidity and variation between houses with different levels of UTC density; (C) Average electricity consumption associated with wind speed and variation between houses with different levels of UTC density.

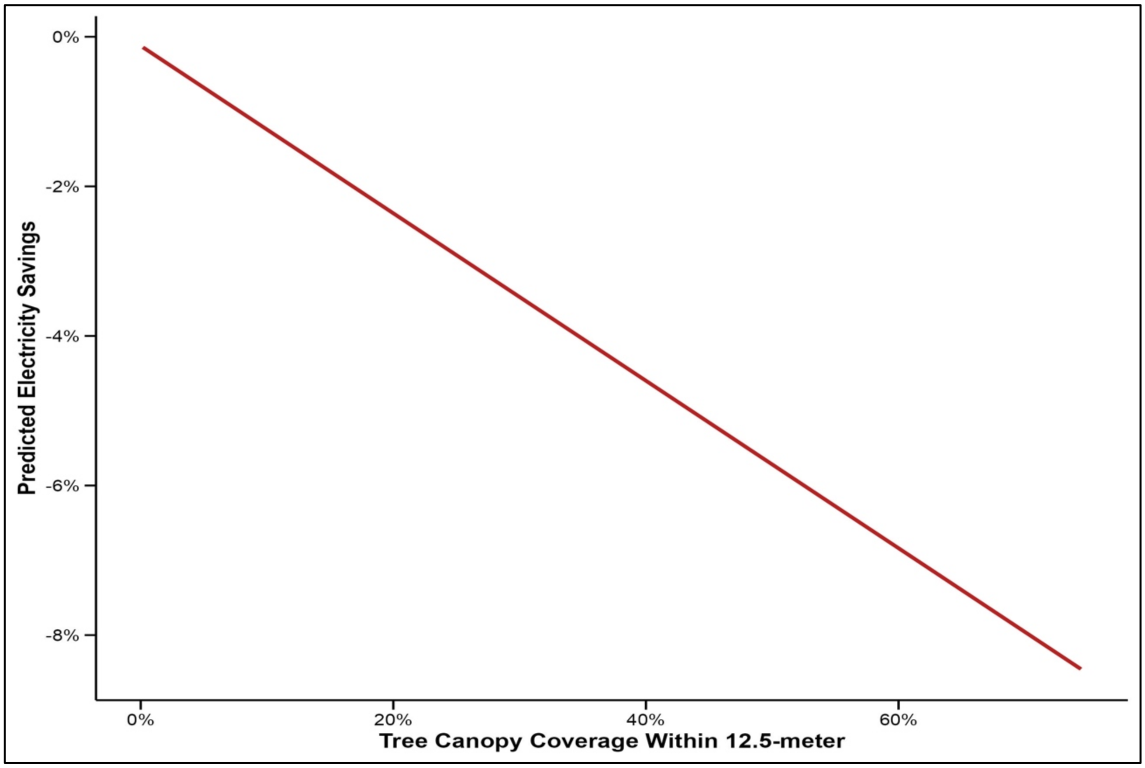

Figure 1.12S. Annual predicted electricity saving from UTC within 12.5 meter from the LASSO model. Larger UTC is associated with greater predicted electricity savings

Tables

Table 1.1S. Descriptive statistics of continuous variables (n=15901948) in the estimation sample

Variables	Mean	Max	Min	Standard deviation
Electricity (kW/h)	1.13	44.52	0.0000005	1.25
Urban Tree Coverage (%)	0.28	0.97	0	0.22
Relative humidity (%)	72.28	99	13	18.75
Temperature ℃	6.82	35.5	-28.6	12.68
Wind speed (km/h)	14.86	57	0	8.09
Azimuth	181.55	359.99	0.019	101.61
Elevation	0.37	68	-68.01	33.36
Heating degree days ℃	12.47	46.6	0	10.96
Cooling degree days ℃	1.29	17.5	0	2.87

Table 1.1S. Descriptive Statistics for binary variables (n=15901948) in the estimation sample

Variables	Count	Proportion
Weekend	11380255	0.28
In-leaf period	6658162	0.41
Daylight	8047956	0.50

Table 1.1S. Descriptive statistics of continuous variables (n=1277137) in the prediction sample

Variables	Mean	Max	Min	Standard deviation
Electricity (kW/h)	1.08	24.32	0.000099	1.16
Urban Tree Coverage (%)	0.25	0.74	0.74	0.15
Relative humidity (%)	72.29	99.00	13.00	18.76
Temperature ℃	6.83	35.50	-28.60	12.68
Wind speed (km/h)	14.86	57.00	0.00	8.10
Azimuth	181.56	359.99	0.02	101.62
Elevation	0.39	68.00	-68.01	33.36
Heating degree days ℃	12.47	46.60	0.00	10.96
Cooling degree days ℃	1.30	17.50	0.00	2.87

Table 1.1S. Descriptive Statistics for binary variables (n=1277137) in the prediction sample

Variables	Count	Proportion
Weekend	363292	0.28
In-leaf period	534888	0.42
Daylight	646465	0.51

Table 1.2S. In Model 1-6 and 8, Tree-percent refers to the percentage of UTC within 5 to 12.5 meter around the building structure. In model 7 Tree-area refers to 1,000 square meters of UTC within each buffer around the building. In-leaf refers to the period (May to September) in which we assume UTC affects electricity consumption. Models 2 and 3 control for seasonal and daily effects at a finer temporal scale using Address by Hour and Weekday fixed effects, respectively, instead of Address fixed effects. Model 4 shows the estimates with Address by Hour and Weekday fixed effect used simultaneously in the model instead of Address fixed effect. Model 5 excludes finer temporal scale from the model and uses Time by Street to control for heterogeneity in consumption patterns due to building age and construction practices. Model 6 includes both finer temporal scales and building characteristics fixed effects. The Standard errors presented in the brackets are two-way clustered by time and address.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8 (Normalized)**
				Dependent Variable Log (electricity consumption)				

Tree-percent*in-leaf		-0.356***	-0.356***	-0.356***	-0.356***	-0.297***	-0.297***		
		(-0.039)	(-0.039)	(-0.039)	(-0.039)	(-0.037)	(-0.037)		
Tree-area-5 + Tree-area-12.5*in-leaf								-0.261***	
								(-0.038)	
Tree-area-20*in-leaf								0.082	
								(-0.084)	
Tree-percent*in-leaf*north									-0.36*
									(-0.049)
Tree-percent*in-leaf*east									-0.34*
									(-0.046)
Tree-percent*in-leaf*west									-0.46**
									(-0.048)
Tree-percent*in-leaf*south									-0.24
									(-0.049)
Number of Observations		15903765	15903765	1.6E+07	1.6E+07	1.6E+07	1.6E+07	1.6E+07	15901948
R-sq		0.495	0.537	0.497	0.539	0.775	0.797	0.797	0.797
Adjusted R-Sq		0.494	0.535	0.497	0.538	0.531	0.573	0.573	0.573
Std.Errors		Address and Time							
Fixed Effects	Address by Hour		X		X		X	X	X
	Address by Weekday			X	X		X	X	X
	Time by Street					X	X	X	X
	Address	X				X			
	Time	X	X	X	X				
The significance at the 0.05, 0.01 and 0.001 levels is marked by *, ** and *, respectively**									

Table 1.3S. Tree-percent refers to the percentage of UTC within 5 to 12.5 meter around the building structure. In-leaf refers to the start of April to the end of October in which we assume UTC affects electricity consumption. Model 2 includes both finer temporal

scales and building characteristics fixed effects. The Standard errors presented in the brackets are two-way clustered by time and address.

		Model 1	Model 2
Dependent Variable Log (electricity consumption)			
Tree-percent × in-leaf		-0.277***	-0.214***
		(-0.035)	(-0.033)
Number of Observations		15903765	1.6E+07
R-Sq		0.494	0.796
Adjusted R-Sq		0.494	0.572
Std.Errors		Address and Time	
Fixed Effects	Address	X	
	Time	X	
	Address by Weekday		X
	Address by Hour		X
	Time by Street		X
The significance at the 0.05, 0.01 and 0.001 levels is marked by *, ** and *, respectively**			

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Chapter 2

Causal Impacts of Cycling Infrastructure on Commuting Mode Choice: A Quasi-Experimental Evidence

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Abstract

This paper examines the causal impact of cycling infrastructure on commuting behavior using a quasi-experimental research design. Drawing on four waves of the Canadian Census of Population and National Household Survey data from 2001 to 2016, we assess changes in cycling to work in Toronto and Vancouver, two major metropolitan areas that differ in climate, demographics, cycling culture, policy and investment towards cycling infrastructure. We construct a panel of individual commuters with origin and destination (O-D) information at the census tract (CT) level and develop five measures of exposure to cycling infrastructure, including proximity-based measures (within CTs and surrounding buffers) and projection-based measures (cycling infrastructure near or along the shortest O-D route). Our difference-in-differences design leverages variation in infrastructure expansion across O-D pairs to estimate the effect of infrastructure construction and expansion on cycling mode choice. In a pooled sample of both cities our results show that a 1 km increase in cycling infrastructure raises the odds of cycling to work by 1.6 to 4.1%. An analysis of heterogeneity of the effects across socioeconomic groups and trip characteristics reveals that individuals aged 15 to 35, those living within 5 km of their workplace, individuals with no formal education, those earning below the median income, and recent immigrants (i.e., those living outside Canada prior to the census wave) are the most responsive to improvements in cycling infrastructure.

Keywords: Cycling Infrastructure, Causal Effects, Commuting Behaviour, Sustainable Transportation, Urban Emission Mitigation

1.Introduction

Reducing emissions from the transport sector is an essential part of achieving net-zero economy-wide. Cycling, one of the most common forms of active transport, has gained increasing attention from policymakers as a sustainable alternative to attain environmental, social, and economic benefits. An increase in cycling rates contributes to lower energy consumption by reducing reliance on motor vehicles and fossil fuels (Lovelace et al., 2011), improved air quality, and reduced noise pollution (De Nazelle et al., 2011). Moreover, shifting from car-based transport to cycling can improve public health by promoting physical activity and reducing the risks of obesity, cardiovascular diseases, certain cancers, and type 2 diabetes (McCormack et al., 2004). Cycling also supports local economies, as cyclists and pedestrians are more likely to spend money at local businesses (Arancibia et al., 2019), and the development of cycling infrastructure is less costly and space-consuming than road infrastructure for automobiles (Börjesson and Eliasson, 2012).

A wide range of factors influence cycling uptake, including the historical development of cities (Lanzendorf and Busch-Geertsema, 2014), cultural attitudes toward cycling (Rietveld and Daniel, 2004; Pucher and Buehler, 2008), socio-economic conditions (Santos et al., 2013; Whalen et al., 2013), climate (Bergström et al., 2003; Böcker et al., 2013), topography (Parkin et al., 2008; Vandenbulcke et al., 2011), city size (Handy et al., 2012), and urban form (Kitamura et al., 1997). While these structural and contextual factors matter, the role of national and local policies in shaping cycling behavior is equally critical (Rietveld and Daniel, 2004; Bonham and Suh, 2008). Among various policy tools such as educational campaigns, car-restrictive policies, and land-use planning, investment in safe, connected, and accessible cycling infrastructure is often cited as the most influential factor, particularly in North American cities with lower shares of cycling (Krizek et al., 2009; Mitra et al., 2017; Mitra et al., 2021). Cycling infrastructure serves two interconnected functions affecting the decision to bike: accessibility and safety. Enhancing accessibility through the provision of cycling infrastructure increases the convenience and viability of cycling, and supports multimodal transport (Panter et al., 2019). Accessibility also includes improvements in connectivity, continuity, and the directness of cycling routes (Panter et al., 2019). Simultaneously, cycling infrastructure influences perceived safety. This is especially important in contexts with low cycling rates. Research shows that perception of safety varies among different groups. Women report higher discomfort levels when cycling without dedicated infrastructure, a greater perception of risk (Prati et al., 2019), and stronger preferences for separation from motor traffic (Aldred et al., 2019). Inexperienced cyclists, the primary target group of cycling promotion policies, tend to express greater concern about the perceived hazards of cycling in mixed traffic conditions compared to experienced cyclists (Bill et al., 2015).

Despite a broad consensus about the positive role of cycling infrastructure, there remains considerable variation in the estimated effects across studies, often due to variation in study methods and designs (Stappers et al., 2018; Mölenberg et al., 2019; Panter et al., 2019). A majority of studies estimate the association between cycling infrastructure and cycling participation. Causal interpretation of such studies is hampered by potential for reverse causality and un-measured confounders. A subset of observational studies explicitly aim for causal inference, but issues such as the absence of control groups, failure to control for time-varying confounders and reverse causality, measurement of cyclist volume on the specific infrastructure rather than changes in cycling behavior resulting from mode substitution, short exposure windows to intervention (Mölenberg et al., 2019), and imprecise measurement of exposure to cycling infrastructure (Macedo Filho et al., 2024a,b) limit the reliability of the findings.

Motivated by the need to strengthen generalizable causal inference in observational studies on the effects of cycling infrastructure (Panter et al., 2019), this study examines the impact of cycling infrastructure construction and expansion on cycling to work behavior over a 15-year period in two major Canadian metropolitan areas: Toronto and Vancouver. We leverage detailed, restricted-access microdata on commuting behavior from the Canadian Research Data Centre (CRDC) and adopt a Difference-in-Differences (DiD) design to control for unobserved time-constant and time-varying factors affecting the decision to bike during the study period. While most existing studies define exposure based solely on residential proximity to cycling infrastructure, we propose that the availability of infrastructure within the origin and destination areas of a trip plays a more significant role in influencing cycling behavior. In this regard, we identify the origin and destination (O-D) of each commute trip and compare changes in cycling over time for commutes between O-D pairs that received no new infrastructure and those with substantial infrastructure addition. Our O-D-based exposure measures account not only for infrastructure within varying spatial proximities to O-D pairs, but also for infrastructure located near the shortest commute route and infrastructure that is spatially aligned with it. We consider all possible O-D pairs across both cities, allowing for a generalizable estimate of the causal effect of infrastructure on commuting behavior.

Canada's recent increases in cycling investment at all government levels (Assunçao-Denis & Pinder, 2023; Tremblay-Racicot et al., 2023) underscore the need for robust, city-level evidence on the effectiveness of such investments. Strengthening the evidence base is crucial for informing infrastructure spending decisions and sustaining public and political support for cycling initiatives (Handy et al., 2014). While this study focuses on two Canadian cities, the methods and insights are applicable to urban areas in North America and other contexts with similar urban development forms and socio-economic features.

The remainder of this paper proceeds as follows: Section 2 reviews the relevant literature; Section 3 outlines the data and methodology; Section 4 presents the results; and Section 5 and 6 form the discussion, limitations, and the conclusion.

2.Literature Review

A growing body of cross-sectional research has found that the availability of high-quality and separated cycling facilities, such as bike lanes and dedicated paths, is positively associated with higher rates of cycling (Nelson & Allen, 1997; Shafizadeh & Niemeier, 1997; Dill & Carr, 2003; Evenson et al., 2005; Larsen and El-Geneidy, 2011; Buehler & Pucher, 2012; Mitra et al., 2017; Standen et al., 2017; Cervero et al., 2019), while some studies have found that cycling occurs regardless of infrastructure changes (Dill & Voros, 2007; Ma & Dill, 2015; Moudon et al., 2005). However, cross-sectional observational studies are limited in their ability to capture behavioral change and are limited in their ability establish causal relationships (Kitamura, 1990), since they do not adequately address confounding variables, reverse causality, or self-selection as key biases to causal inference.

In response to these limitations, a second strand of research has used natural experiments to assess the causal impact of cycling infrastructure. Many studies adopt a before-and-after design using direct observations of cycling counts (Fitzhugh et al., 2010; Parker et al., 2011, 2013; Fields et al., 2022; Xiao et al., 2022; Shahriari et al., 2024). Others use survey data to compare changes among cyclists who use new routes (Heesch et al., 2016) or combine crowdsourced data like Strava with cycling counter data (Garber et al., 2022). While these studies help assess responses to infrastructure changes, they often fail to distinguish between route substitution and true modal shifts from other modes to cycling (Rissel et al., 2015; Pritchard et al., 2019).

Focusing on changes in travel behavior rather than route substitution, some studies examine localized effects by analyzing specific components of the cycling network at smaller spatial scales (Pritchard et al., 2019; Vasilev et al., 2018; Burbidge et al., 2009; Rissel et al., 2015; Crane et al., 2017; Frank et al., 2021). These studies offer valuable insights into how small-scale infrastructure changes influence travel behavior within targeted areas. To capture population-level shifts and provide a more comprehensive understanding of how cycling infrastructure development influences overall travel patterns, some studies adopt a city-level perspective, analyzing changes in travel behavior by accounting for all improvements and expansions of the cycling network over time (Krizek et al., 2009; Goodman et al., 2013; Goodman et al., 2014; Dill et al 2014; Winters et al., 2018; Aldred et al., 2019; Rodriguez-Valencia et al., 2019; Eldeeb et al., 2021; Mitra et al., 2021; Macedo Filho et al., 2024a,b).

Several methodological challenges limit the strength of causal inference in natural experiment designs. First, studies that lack control groups such as before-after research designs are unable to account for broader contextual factors that may influence cycling behavior, such as economic fluctuations, changes in fuel prices, public awareness campaigns, or other concurrent cycling-related interventions. Moreover, the construction and expansion of cycling infrastructure may be a response to increased cycling demand rather than its cause, introducing the risk of reverse causality, an issue that many studies are unable to adequately address due to lack of proper control groups (Mölenberg et al., 2019). Second, short follow-up periods may underestimate the time needed for behavioral change. Changes in travel behavior and the uptake of cycling may require more than a year to develop (Goodman et al., 2014) and in a review of the studies that assessed changes in cycling behavior, Mölenberg et al (2019) found that the changes were larger when exposure time was longer than 1 year. The third challenge is accurately identifying the exposed population or the population who benefits from the cycling infrastructure. A majority of the existing natural experiments rely on distance-based measures of proximity, often defined as straight-line distances or buffers from the intervention to place of residence of the individuals (Mölenberg et al., 2019; Macedo Filho et al., 2024 a, b). The exposed population is typically defined as those living in close proximity to the intervention (Krizek et al., 2009). This measure of exposure assumes that the impact of a cycling infrastructure is solely determined by the proximity of residents to the infrastructure, disregarding the influence of trip's route in utilizing the intervention (Krizek et al., 2009; Humphreys et al., 2016; Aldred et al.,2019; Macedo Filho et al., 2024 a, b). Therefore, an exposure measurement which takes daily routes and regular activity spaces shaped by origin and destination patterns into account is required to evaluate the impacts of cycling infrastructure with less restrictive assumptions about the exposed population (Humphreys et al., 2016). Recognizing the importance of O-D routes in determining actual exposure to cycling infrastructure, Macedo Filho et al. (2024a, 2024b) and Hirsch et al. (2017) adopted a more behaviorally grounded definition of exposure. This approach, referred to as a projection-based measure, defines exposure as the proportion of the shortest O-D route that intersects with cycling infrastructure.

Building on the existing body of knowledge, our study contributes to the literature in four ways: (1) To account for the influence of cycling infrastructure within activity spaces shaped by O-D routes on cycling behavior, we implement an O-D-based exposure measure. (2) Using a DiD design, we compare cycling behavior on O-D pairs over time with and without new cycling infrastructure to address unobserved time-invariant confounders and city-level time-varying shocks. (3) We use individual-level census data spanning 15 years in five-year intervals to observe long-term trends in commuting behavior. (4) We assess equity effects of cycling infrastructure by examining heterogeneous impacts across gender, income, education, and commute distance, as an important dimension in the cycling literature.

3.Methods and Materials

We aim to estimate the causal impact of cycling infrastructure on travel behaviour using a longitudinal research design.

3.1. Data

3.1.1. Travel Behavior

For measuring travel behavior, the outcome of interest in this study is the prevalence of cycling for commuting. Several reasons support this choice. First, commute mode data has shown to serve as a reasonable proxy for the overall proportion of cycling in a population (Goodman et al., 2013). Second, commuting is typically fixed in time and location for most individuals, making it a relatively stable and structured component of daily travel patterns (Heinen et al., 2015). Third, commuting occurs during peak hours, when the externalities associated with private vehicle use such as congestion, emissions, and noise are most severe (Wardman et al., 2007; Caulfield, 2014). Lastly, since 1996, Statistics Canada has consistently collected information on the primary mode of transportation to work, categorizing cycling as an active mode of transport. This source provides an accessible and comparable dataset on cycling behavior available across multiple census waves in Canada.

This study uses microdata from four waves of the Canadian Census of Population (2001, 2006, 2016) and the 2011 National Household Survey (NHS), at five-year intervals. Restriction of the analysis to the 2001 census wave onward stems from the differences in census tract (CT) coding across waves. Beginning in 2001, Statistics Canada adopted a nine-digit CT coding system (with minor variations such as the inclusion of decimal points in some years), which allowed for consistent identification of CTs over time. The 1996 CT coding system differed substantially from later waves, making it infeasible to unify it with subsequent waves. The 2021 census wave is excluded from our analysis due to major disruptions caused by the COVID-19 pandemic, which significantly altered commuting patterns and led to approximately 2.8 million fewer commuters relative to 2016, including a reported decline of 289,000 individuals walking or cycling to work (Statistics Canada, 2022).

The primary variable used is the respondent's Main Mode of Commute, drawn from the "Journey to Work" questionnaire of the long-form census (and NHS in 2011). This question applies to the working population aged 15 to 64 in private households who worked for pay or were self-employed during the reference week (typically in early May of the census year). For those not working during that week but employed at any time since January 1 of the same year, responses reflect the job held longest during that period. Individuals who reported "working from home," "working outside Canada," or having "no fixed workplace address" (e.g., mobile workers like truck drivers) are excluded from the commuting population in our analysis. We exclude respondents whose workplace is located in a different Census Metropolitan Area (CMA) than their residence. Our sample is restricted to working individuals aged 15 to 64 who reside and work within the Toronto and Vancouver Census Subdivisions (CSDs). This geographic restriction is due to data availability. The cycling infrastructure data obtained from municipal sources cover only the CSDs, not the entire Toronto and Vancouver CMAs. With regard to students commuting to school or university, they are included in our sample only if they held a paid job at any time since January 1 of the corresponding census (or NHS) year. Otherwise, they fall outside the scope of our sample.

Data on the Main Mode of Commute is obtained from the response to the question "How did this person [the respondent] usually get to work?" and possible responses include private vehicle (as driver or passenger), public transit (bus, rail, ferry, etc.), walking, bicycling, or other mode. For each individual, information is provided for trip origin (place of residence) and destination (workplace) at CT level. The Distance to Work variable is derived from the same questionnaire and calculated by Statistics Canada as the straight-line distance between a respondent's home and workplace in kilometers (Statistics Canada, 2021). In addition to data on commute, we make use of demographic related variables, including, gender, age, income, education level, and mobility status that refers to whether a person's usual residence on census day is the same as their usual residence five years prior.

3.1.2. Geographic Level of Analysis

Both the census and NHS record the CMA and CT of the respondent's residence and workplace providing unique O-D commuting pairs. CTs are small, relatively stable geographic areas that usually have a population between 2,500 and 8,000 people (Statistics Canada, 2016). CTs in the central business districts, major commercial and industrial zones, or peripheral areas may have populations outside this range. CTs are as homogeneous as possible in terms of socioeconomic characteristics, such as similar economic status and social living conditions at the time of their creation (Statistics Canada, 2018).

Although alterations to CT boundaries are generally discouraged to ensure data comparability across census waves, revisions to these boundaries may still be made in each wave to reflect population shifts. Consequently, this leads to the fact that census data is more readily analyzed cross-sectionally than longitudinally, due to these boundary changes. To account for changes in CT boundaries over time, we harmonized all waves of census data to the 2001 CT boundaries. This was achieved using the concordance tables developed by Allen and Taylor (2018), which facilitate the allocation of data from multiple census years to a consistent set of boundaries for analysis.

3.1.3. Cycling Infrastructure

This study focuses on the cities of Vancouver and Toronto, both of which provide publicly accessible, longitudinal data on cycling infrastructure through open data portals maintained by their respective municipal governments. These datasets include detailed information on the location, type, and year of construction of cycling infrastructure at the CSD level, enabling a multi-year spatial analysis of infrastructure development. Each city features a diverse cycling network. Vancouver's infrastructure includes local street bikeways, painted lanes, shared lanes, and protected bike lanes. Toronto's network comprises cycle tracks, signed routes, park roads, multi-use trails, and bike lanes. Fig. 2.21S and 2.22S demonstrate the cycling network expansion over the years in Vancouver and Toronto CSD. While cycling infrastructure types vary in terms of safety performance and user comfort (Winters et al., 2020), this study does not differentiate between them. Instead, all types are treated equivalently in the analysis, with a focus on the overall expansion and spatial coverage of cycling infrastructure.

For Vancouver, we use cycling infrastructure data covering the period 1984-2022, matched to four census and NHS waves: 2001, 2006, 2011, and 2016. We assume that cycling infrastructure built within a given inter-census period only affects commuters in the subsequent wave, ensuring that the infrastructure had sufficient time to influence travel behavior. For instance, lanes built in 2001 are considered to potentially influence commuting decisions in the 2006 (and subsequent) census wave. For Toronto, the cycling infrastructure dataset includes a limitation. All cycling infrastructure constructed before 2001 is uniformly coded as being constructed in 2001, with no breakdown by earlier years. As a result, we cannot reliably distinguish infrastructure built in 2001 from that built much earlier. Hence, we exclude the 2001 census wave for Toronto and only use data from 2006, 2011, and 2016 to ensure consistency in exposure timing.

3.2. Research Design

We aim to identify the causal impact of cycling infrastructure investments on cycling behavior. Due to the non-random assignment of cycling infrastructure, various factors encompassing geography, demography, already existing shares of cycling, and the political environment influence decisions regarding where to construct new lanes or improve existing cycling networks. These factors may simultaneously affect cycling behavior. In addition, individuals with a strong preference for cycling may choose to live in areas with better cycling infrastructure, and the residential self-selection bias further complicates the estimation of causal effects. We cannot control for these factors directly, but instead we seek to make our evaluation more robust to reverse causality, omitted confounding variables, and residential self-selection by applying a difference-in-differences approach to evaluate the effect of cycling infrastructure investments. The DiD method combines insights from cross-sectional treatment-control comparisons and before-after studies for a more robust identification of the effects (Huntington-Klein, 2021). The DiD estimate of an intervention's impact is equivalent to calculating the before-after difference in outcomes in the treatment group (which receives new cycling infrastructure) and subtracting from this difference the before-after difference in the control group (which receives no cycling infrastructure upgrades) (Huntington-Klein, 2021). In our case, this approach amounts to comparing the difference in odds of cycling from a given origin to destination before and after a cycling infrastructure upgrade to the difference in odds of cycling in other O-D pairs which did not receive infrastructure upgrades over the same time period.

In many practical DiD applications the treatment is not a binary variable but has a dose or operates with varying intensity. In this study, we observe transport decisions following gradual increases to an already-existing cycling network. Hence, we assess the effect using a DiD-style estimator that accounts for continuous treatment effects.

3.2.1. Treatment and Control Groups

While many natural experiment evaluations rely on distinguishing between treated and control or exposed and unexposed populations, clearly identifying these groups is particularly challenging in the context of built environment interventions. As Humphreys et al. (2016) note, large-scale infrastructure changes often raise fundamental questions such as: "What does exposure mean or consist of?" (p. 941). In such cases, the conventional use of binary treatment conditions classifying individuals as either treated or untreated based on proximity to the intervention may be inadequate.

Existing proximity-based approaches typically define treatment based on residential distance to cycling infrastructure, assuming that individuals living within a specified buffer are exposed. However, this approach has a key limitation: it disregards the travel patterns which play a crucial role in determining whether infrastructure is actually used (Krizek et al., 2009; Humphreys et al., 2016; Aldred et al., 2019; Macedo Filho et al., 2024a, b). For instance, an individual living near a bike lane may not benefit from it if their daily commute does not intersect with that facility. Conversely, an individual classified as unexposed may regularly use the infrastructure if it aligns with their commute route, despite living farther away, a situation that introduces spillover bias and undermines the accuracy of causal estimates. To address this limitation, we use a proximity-based measure around O-D activity space associated with commuting, complemented with a projection-based approach. Our projection-based approach defines exposure based on the available cycling infrastructure within and spatially aligned with the shortest O-D commuting route.

3.2.1.1. Proximity-Based Exposure Measures

We construct three proximity-based measures. While they do not simulate actual commute routes, they reflect infrastructure available within the spatial context of an individual's place of residence and work (or origin and destination). Fig. 2.13-15 demonstrate each of our proximity-based measures. Measure 1 is the total km of cycling infrastructure within the CT of residence and workplace and captures local infrastructure. Measure 2 is the total km of cycling infrastructure within 1.6 km buffer[2] around CT of residence and workplace and captures larger zone of influence around where people live and work. Measure 3 is the total km of cycling infrastructure within 1.6 km of the centroid of both CTs to capture exposure near the geometric center of residence and workplace. Having three measures of exposure is beneficial because if all three show consistent positive associations with cycling, it strengthens the robustness of the findings to alternative definitions of exposure. Additionally, it allows us to assess the spatial scale at which the cycling infrastructure within the O-D vicinity most effectively influences behavior, and to better capture potential spatial spillover effects.

3.2.1.2. Projection-Based Exposure Measures

The total length of cycling infrastructure within the CT of residence and workplace (or nearby buffers) does not account for whether that infrastructure is within or aligned with a commuter's shortest route. In the projection-based approach we hypothesize that the provision and expansion of cycling infrastructure along the shortest commuting route has a stronger effect on cycling uptake. We develop two measures for this exposure (Fig. 2.16 and 17). Measure 4 is the total km of cycling infrastructure within a 1 km buffer of the shortest O-D route and captures the infrastructure within the immediate vicinity of the shortest commute route. Measure 5 captures the total length of cycling infrastructure within a 1 km buffer of the shortest O-D route that are spatially aligned with the commute route. To operationalize spatial alignment, we calculate the angle between each cycling infrastructure segment in the 1 km buffer and the line connecting the centroids of the origin and destination CTs. We retain only those segments that are approximately parallel to the O-D route, specifically those forming an angle less than 30 degrees or greater than 150 degrees. This approach assumes that cycling infrastructure is more likely to influence commuting behavior when it is not only spatially proximate, but also spatially aligned with the shortest commute route. To our knowledge, this is the first study to utilize the cycling infrastructure aligned with the shortest commuting route as the measure of exposure.

3.3. Research Method

We conduct the continuous DiD-style regression with a two-way fixed effects (TWFE) regression model as follows:

$$\ln\left(\frac{P(Y_{ijt})}{1-P(Y_{ijt})}\right) = \alpha_0 + \beta D_{jt} + \delta X_{it} + \mu_j + \theta_t + \epsilon_{ijt} \qquad (1)$$

Our analysis focuses on the CT level O-D pairs, denoted as level j. Although our data consist of repeated cross-sections of individuals from the census and NHS, our research design adopts a longitudinal approach by leveraging fixed effects at CT level. Y_{ijt} represents the binary outcome variable denoting cycling for commute for individual i, in O-D pair j, and at census year t. This binary variable equals zero for any modes of transportation other than cycling. $P(Y_{ijt})$ thus captures the probability that individual i travelling on the O-D route j at time t will choose to cycle to work. We implement a logistic regression model to estimate coefficient (β), which is the effect of cycling infrastructure on the odds of commuting by bike. For individuals within O-D pair j during census year t, the exposure measure (D_{jt}), derived from one of the five exposure definitions, is a continuous variable that can take any positive real value in kilometers.

[2] This distance follows Krizek et al. (2009).

We also include time-varying control variables for individuals and their journey in our equation as (X_{it}) including age, gender, education, income, mobility status in last 5 years, and distance from place of residence to workplace.

The equation includes unit fixed effects (μ_j) that control for all unobserved, time-invariant characteristics specific to each O-D pair, including pre-existing cycling infrastructure and underlying cycling culture or preferences. These fixed effects allow us to isolate the effect of newly constructed cycling infrastructure on changes in commuting behavior by netting out baseline differences across O-D pairs. Time fixed effect (θ_t) controls for all the time-varying variables affecting O-D pairs uniformly over time. These include changes in fuel prices, vehicle ownership costs, public transit fares, economic shocks, public attitudes toward cycling, and government investments in active transportation promotion, and any temporal variation that affects all O-D pairs uniformly.

One of the key threats to the internal validity of our estimate is the reverse causality, the possibility that cycling infrastructure is more likely to be constructed in O-D pairs that already have high levels of cycling. To address this concern, our research design leverages the timing of infrastructure construction relative to the census waves. We estimate the effects of infrastructure built during an inter-census period (e.g., between 2001 and 2006) on commuting behavior observed in the subsequent census wave (e.g., 2006). Because exposure is assigned based on infrastructure constructed before the commuting behavior is measured, we eliminate the possibility that observed behavior is influencing the infrastructure construction.

The identification strategy in DiD framework relies on the parallel trend assumption. Adopting from Callaway et al. (2024), the definition of parallel trend assumption for continuous DiD implies that the outcome trajectories of O-D pairs receiving lower doses of cycling infrastructure must represent a valid counterfactual for how higher-dose O-D pairs would have evolved in the absence of additional treatment. In other words, differences in cycling behavior across O-D pairs can be attributed to differences in infrastructure exposure only if, in the absence of treatment, their trends would have followed similar paths. A potential challenge to the parallel trends assumption in our study is the presence of other policies or programs, independent of cycling infrastructure, that may influence cycling behavior. Such interventions are plausible and could complicate causal attribution. However, as long as these factors do not differentially affect O-D pairs over time in a way that is correlated with cycling infrastructure investments, their influence will be absorbed by the time fixed effects in our model.

Assessing parallel trend assumption is less straightforward in the present setting. Cycling infrastructure changes continuously, units may receive different doses of increase, treatment timing varies across units, and some units experience multiple increases over the study period. Under these conditions, a simple comparison of treated and untreated groups is not conceptually appropriate, since exposure occurs in doses and accumulates over time. To assess pre-treatment trends, we use a cohort-specific, dose-based comparison that reflects how cycling infrastructure is introduced in practice. Additional details on the method are provided in the SI. We also plot the difference between dose groups at each pre-treatment time point. A difference that remains relatively stable provides visual support for parallel pre-trends, whereas systematic divergence would suggest caution.

Another potential threat to the validity of the estimates is residential self-selection bias, where individuals with a strong preference for cycling may relocate during the study period to CTs with higher length of infrastructure within their O-D route. To test robustness of our findings to this potential source of bias, we conduct a sensitivity analysis restricted to individuals who reported living at the same address for at least five years (i.e., non-movers). This subsample helps reduce bias arising from short-term residential mobility driven by unobserved cycling preferences.

We estimate the main regression equation (Eq. 1) separately for each of the five exposure measures (3 proximity and 2 projection-based), where D_{jt} represents the total kilometers of cycling infrastructure. Our regression analysis proceeds in two stages. First, we estimate the model using five measures of exposure on the pooled sample of Vancouver and Toronto and separately for each city. Second, we conduct subgroup analyses to examine heterogeneous effects across demographic and socioeconomic groups. These subgroup regressions are restricted to measure 5, cycling infrastructure kilometers spatially aligned with the shortest O-D route, as it most closely captures likely infrastructure use during commutes.

4.Results

Table 2.5S-7S provide an overview of the descriptive statistics focused on respondents' demographics and commute characteristics by year. Due to confidentiality requirements of the CRDCN, all descriptive statistics are rounded to the nearest multiple of five. Additionally, both the descriptive analyses and regression models are weighted using Statistics Canada's survey weights. As shown in Table 2.5S, cycling has the lowest share among all commuting modes in the pooled sample. Across all census waves, the highest shares of individuals in the pooled sample are between 15-35 years old, those with a college degree, individuals who have lived in the same dwelling for the past five years, and those whose commuting distance is less than 5 kilometers. Table 2.8S demonstrates the total number of unique origin and destination pairs in each sample by year. Table 2.9S-11S provide details on cycling infrastructure and cycling share for the pooled sample and each city. As shown in Table 2.9S, the share of cycling for commuting in the pooled sample increased by 63.6% between 2001 and 2016, while the cumulative length of cycling infrastructure grew by 7.25% over the same period. Table 2.12S indicates the average length of cycling infrastructure for each measure of exposure at O-D level. Fig. 2.23-25S demonstrate changes in cycling share along with average length of cycling infrastructure within O-D pairs in exposure measures 1-5 over the study period. As demonstrated in Table 2.12S and Fig. 2.23S (B), exposure measure 2 has the highest, and exposure measure 1 the lowest average length of cycling infrastructure within O-D pairs in the pooled sample.

4.1. Main Results

Results for our main coefficient of interest (β) from Eq. (1) are shown in Table 2.4, 2.13S, and 2.14S for exposure measure 1 to 5. The standard errors are two-way clustered on O-D pairs and census year. The TWFE logistic regression model is estimated using the "feglm" function from the "fixest" package in R. The model returns coefficients in log-odds, but to facilitate interpretation in the text, we report the results as odds ratios, calculated by exponentiating the log-odds estimates[3]. In the pooled sample (Table. 2.4), across exposure measure 1 to 5, we find a positive and statistically significant effect of new cycling infrastructure on the odds of cycling. Among exposure measure 1 to 3 (proximity-based exposure measures), the largest effect is observed for measure 1, cycling infrastructure located within the boundaries

[3] Exp(log-odds)=Odd-Ratios

of the origin and destination CTs. The estimated coefficient corresponds to a 4.1%[4] increase in the odds of cycling to work for each additional kilometer of infrastructure within the CT origin and destination boundary[5]. It suggests that infrastructure situated directly within residential and workplace tracts may offer better functional connectivity, whereas infrastructure in surrounding areas may be less relevant or frequently used for commuting purposes. Measure 4 and 5 (projection-based exposure measures) yield identical coefficients, corresponding to a 1.6% increase in the odds of cycling per each kilometer increase in the cycling infrastructure.

The consistent and significant results across all five exposure measures suggest that the relationship between infrastructure and cycling behavior is robust to the method of exposure measurement. Contrary to our initial hypothesis, projection-based exposure measures do not exhibit stronger impacts on cycling compared to proximity-based measures. These findings suggest that cycling infrastructure within the origin and destination census tracts may serve as a broader indicator of accessibility, even if it is not located near or spatially aligned with the shortest commute route. It may also suggest that actual commuting routes may differ from the shortest routes in our measure.

In Vancouver (Table 2.13S), Measure 1 to 5 show positive and statistically significant effects on cycling odds. Consistent with the pooled sample results, the largest effect among proximity-based measures is found for measure 1 and the estimated coefficient corresponds to a 4.29% increase in the odds of cycling to work for each additional kilometer of infrastructure. Among the projection-based measures, measure 5 exhibits a stronger effect with increasing the odds of cycling by 2.74%. Vancouver has a more mature cycling network and a stronger cycling culture than many North American cities (StatsCan Plus, 2024). In such contexts, people may be more likely to bike when the infrastructures not only exist but align with the anticipated shortest O-D route. In Toronto (Table. 2.14S), among the proximity-based measures, measure 3 yields the largest effect, corresponding to a 1.82% increase in the odds of cycling to work for each additional kilometer of cycling infrastructure. Among the projection-based measures, the largest effect is found for measure 4 that demonstrates an increase in the odds of cycling by 1.92%. This may suggest that in Toronto's context, access to cycling infrastructure along a broader corridor, rather than spatial alignment with the shortest path, is more influential.

DiD identification relies on a parallel-trends assumption; in the absence of treatment, units exposed to different treatment dose would have followed similar outcome trajectories over time. To assess pre-treatment trends, we use a cohort-specific, dose-based comparison for O-D pairs first receiving any dose of treatment in 2011. As shown in Fig. 2.18, in the pooled sample of Toronto and Vancouver, the low-dose and high-dose groups within the 2011 cohort display similar pre-treatment trend in the outcome prior to 2011. A difference line that remains stable provides visual support for parallel pre-trends.

To assess the robustness of our estimates to residential self-selection bias, we conducted a sensitivity analysis by re-estimating measure 5 on a restricted subsample of non-movers, individuals who reported residing at the same address for at least five years. The results (Fig. 2.19 and 2.26S, 2.27S), presented for the pooled sample as well as for Vancouver and Toronto separately, continue to show positive and statistically significant associations between cycling infrastructure and the odds of cycling to work.

[4] Exp(0.04)= 1.04 Odd-Ratios. The percentage increase in odds: (1.040−1)×100=4.1%

[5] The increase in odd ratio does not directly translate into changes in probabilities of cycling. For details on how odd ratios can be interpreted in terms of probability changes, refer to the SI.

This consistency in estimates strengthens confidence that the observed relationships are not driven by short-term residential relocation motivated by cycling preferences and our estimates are robust to the residential self-selection bias.

4.2. Effects of Covariates

Across all measures, most of the coefficients of the covariates in Eq. (1) (δ) are statistically significant and largely consistent with findings from previous studies, with some variation between the pooled sample, Vancouver, and Toronto. In the pooled sample (Table 2.4), men have higher odds of cycling to work compared to women. This finding is consistent with previous research showing lower shares of cycling among women in car-reliant contexts (Heinen et al., 2010; Dill et al., 2014; Aldred et al., 2019; Frank et al., 2021). Similarly, individuals with higher educational attainment, particularly those with a graduate degree, are more likely to commute by bike than those with no formal education, confirming findings from other studies (Carroll et al., 2020; Macedo Filho et al., 2014a). Age is negatively associated with the odds of cycling to work, a pattern that aligns with earlier research showing a decline in cycling participation with increasing age (Aldred et al., 2019; Piras et al., 2022). Commuting distance is also negatively associated with cycling to work. As a physical environmental factor, distance plays a key role in shaping travel mode choice and is widely recognized as a barrier to cycling (Rietveld, 2000). Longer commuting distances demand more time and physical effort, which can deter individuals from cycling. Prior studies have also documented the inverse relationship between travel distance and cycling mode share (Cervero, 1996; Pucher & Buehler, 2006). There is no statistically significant difference in cycling odds between higher-income individuals (above the median) and those with lower incomes. With respect to mobility status over the five years preceding the census year, individuals who have changed dwellings within the same CSD, those who have moved from a different CSD, and those who immigrated to Canada during the census year all exhibit higher odds of cycling to work compared to individuals who have lived at the same address for the past five years. A detailed interpretation of the covariate effects for Toronto and Vancouver is provided in the SI.

4.3. Heterogeneity of the Effects

To examine whether the benefits of increased cycling infrastructure are distributed evenly across socio-economic groups and trip characteristics, and to identify which groups gain most from infrastructure along their commute routes, we re-estimated the model using measure 5 separately for the pooled sample, as well as for each city individually (Fig. 2.19 and 2.26S, 2.27S). Subgroup analyses were conducted by gender, age group, educational attainment, income level, commuting distance, and residential mobility status.

In the pooled sample, male commuters exhibit higher odds of cycling to work in response to 1 km increase in direct cycling infrastructure, suggesting that this group derives greater benefit from improved infrastructure. Similarly, commuters between 15-35, those with shorter commute distance (less than 5 km), and individuals who have changed addresses in the past five years all show a greater increase in cycling odds with additional infrastructure. These groups also have higher odds of cycling to work (as shown in Table 2.4), indicating that they are both more likely to cycle and more responsive to infrastructure improvements.

However, this pattern does not hold across all subgroups. For example, while measure 5 (Table. 2.4) shows that individuals with graduate degrees have higher odds of cycling, the subgroup analysis reveals that those with no formal education or only a high school diploma are more responsive to infrastructure improvements, exhibiting greater increases in the odds of cycling per additional kilometer of direct infrastructure along their commute route. A similar divergence is observed for income. While the main model does not find a statistically significant difference in cycling odds between lower- and higher-income individuals, the subgroup regressions indicate that lower-income commuters are more responsive to infrastructure expansion[6].

4.4. Predictions of Cycling Probability

To assess the potential behavioral impact of changes in cycling infrastructure, we use measure 5, our most behaviorally grounded exposure measure, to generate predicted probabilities of commuting by bicycle under three scenarios: (1) the existing cycling network, (2) a hypothetical doubling of the cycling network in each year, and (3) keeping the cycling infrastructure at 2001 levels. These predictions are generated for each census wave (2001, 2006, 2011, and 2016).

As shown in Fig. 2.20 in the pooled sample, actual cycling prevalence increased from 5.2% in 2001 to 6.6% in 2016. Comparing actual cycling prevalence to a scenario in which cycling infrastructure was frozen at 2001 levels allows us to evaluate the impact of recent increases in cycling infrastructure on cycling behavior. Had cycling infrastructure remained frozen at 2001 levels, we estimate that cycling prevalence in 2016 would have been 5.3%, implying that recent cycling infrastructure expansion has resulted in a 1.3 percentage point, or 25 percent, increase in cycling propensity. We also use the model to project cycling prevalence with an expanded cycling network, double its current density. This scenario results in a cycling prevalence of 8.0%, 1.4 percentage points or 21 percent higher than today's level and suggests significant potential for further transformation in commuting patterns. These patterns are observed consistently in Vancouver and Toronto separately (Fig. 2.28S and 2.29S). The predicted probabilities offer a more intuitive interpretation of the model results and serve as a practical tool for policy implications. While odds ratios from Model 1-5 communicate the direction and causal strength of associations, predicted probabilities allow for a better understanding of behavioral change under different infrastructure scenarios.

5. Discussion

As a sustainable mode of transport, cycling offers significant environmental, social, and economic benefits at both individual and community levels. Despite a broad consensus about the positive role of cycling infrastructure, there remains considerable variation in the estimated effects across studies and ungeneralizable causal inference often due to variation in study methods and designs (Mölenberg et al., 2019). This study contributes to the existing literature in several ways. With focus on isolation of the causal impact of cycling infrastructure on commuting behavior, we employ a continuous DiD framework with unit (O-D pair) and time (census year) fixed effects, focusing on within-unit variation attributable to changes in cycling infrastructure and behavior over time. Time fixed-effects control for unobserved time-varying confounders affecting cycling behavior as long as they affect units uniformly over time. Unit fixed-effects control for pre-existing trends in cycling behavior and cycling infrastructure that might vary between units.

[6] Detailed results and interpretation of the city-specific subgroup analysis are available in the SI.

The long observational window of our study, spanning 15 years in five-year intervals using the Canadian census and NHS for two major metropolitans of Vancouver and Toronto, allows sufficient time for changes in travel behavior to develop (Goodman et al., 2014). We implement proximity-based metrics with varying spatial scope across the O-D activity space. Having multiple measures of exposure is beneficial since it strengthens the robustness of the findings to alternative definitions of exposure. Additionally, it allows to assess the spatial scale at which cycling infrastructure most effectively influences cycling behavior. The projection-based measures capture the extent and alignment of infrastructure along the shortest commute route. This dual approach enables us to assess not only the presence of cycling infrastructure within the shortest O-D route, but also whether the spatial alignment of the infrastructure to the commute route is able to provide a better functional connectivity between origin and destination. To account for the heterogeneity of the cycling infrastructure effects and to identify which populations are most responsive to infrastructure improvements, we estimate the model across socio-economic subgroups.

In the pooled sample, cycling infrastructure located within the census tract of residence and workplace (Measure 1) shows the strongest association with commuting by bicycle. Specifically, each additional kilometer of bike lanes in these tracts increases the odds of cycling by approximately 4.1%. In comparison, both cycling infrastructure within a 1 km buffer of the shortest O-D route (Measure 4) and infrastructure that is spatially aligned with the O-D route (Measure 5) yield smaller but identical effects, each associated with a 1.6% increase in the odds of cycling per additional kilometer of infrastructure. Our findings are consistent with the limited number of studies that define exposure to cycling infrastructure based on O-D) routes. On this point, Macedo Filho et al. (2024a) define exposure as any part of the O-D route intersecting a 500-meter buffer around cycling infrastructure, while Macedo Filho et al. (2024a, b) consider the proportion of the fastest O-D route traversing newly constructed cycling highways. Similarly, Hirsch et al. (2017) measure exposure based on the share of commute trips that pass through a newly developed cycling trail network. While the magnitude of the estimated effects varies across these studies, all report positive associations between O-D-based infrastructure exposure and cycling behavior, reinforcing the robustness of our results.

With regards to heterogeneity of the effects in the pooled sample, men are more responsive to increases in cycling infrastructure. This is contrary to the findings of studies showing stronger preferences for separation from motor traffic among women (Aldred et al., 2019). Individuals residing within 5 km of their workplace exhibit greater responsiveness to changes in cycling infrastructure along their commute route. This finding underscores the influence of land use patterns on transportation choices, as higher density, mixed-use development, improved connectivity, and greater accessibility have been shown to reduce reliance on private vehicles and support active modes of transportation such as cycling (Litman & Steele, 2017). Individuals between 15 to 35 years old, with no formal education, those earning below the median income, and recent immigrants (i.e., individuals who lived outside Canada prior to the census wave) exhibit greater responsiveness to improvements in direct cycling infrastructure along their commute route. These findings offer important insights for targeting investment in cycling infrastructure, particularly in areas where underserved populations are likely to benefit most. As noted by Firth et al. (2021), disparities in access to cycling infrastructure persist across visible minority groups, educational attainment levels, and age groups, further underscoring the need for equitable planning and infrastructure provision.

5.1. Limitations

This study focuses exclusively on commuting trips as the primary outcome, and as such does not account for cycling undertaken for other purposes (e.g., leisure, errands, or school commute) or on weekends. While commute-focused analysis provides a clear and policy-relevant lens, this approach inevitably excludes a large share of cycling for purposes other than commute. In addition, in examining the impact of cycling infrastructure, all facility types are treated uniformly, despite known differences in safety performance and user comfort across infrastructure categories. Future research could take advantage of the comfort and safety classification systems (Winters et al., 2020), to better capture the differential impacts of infrastructure design on cycling behavior. While our exposure measures incorporate origin and destination information at the CT level, the data do not include the actual routes taken by cyclists or the precise geocoded locations of trip origins and destinations. Future research could provide more accurate insights by integrating geocoded O-D data with information on actual commuting routes when measuring the exposure to the cycling infrastructure.

6. Conclusion

This study offers valuable policy insights by isolating the causal effect of cycling infrastructure on commuting behavior using a robust quasi-experimental design. By employing exposure measures that reflect the full origin-destination activity space, the analysis identifies the spatial areas where infrastructure expansion is most effective in encouraging cycling. Moreover, the heterogeneity analysis reveals which socio-economic groups benefit most from increased infrastructure, informing equitable and targeted planning efforts. Vancouver and Toronto differ in climate, socio-economic composition, cycling culture, and investments in cycling infrastructure. A positive association between infrastructure provision and cycling to work in both cities offers insightful evidence in support of expanding investment in cycling infrastructure and highlights the importance of integrating safe and connected bike networks into future urban development plans. While grounded in the Canadian context, the findings are relevant for other (North American) cities with comparable urban form and socio-economic profiles. The methodological approach is broadly applicable and can support infrastructure investment decisions in diverse urban settings.

Figures

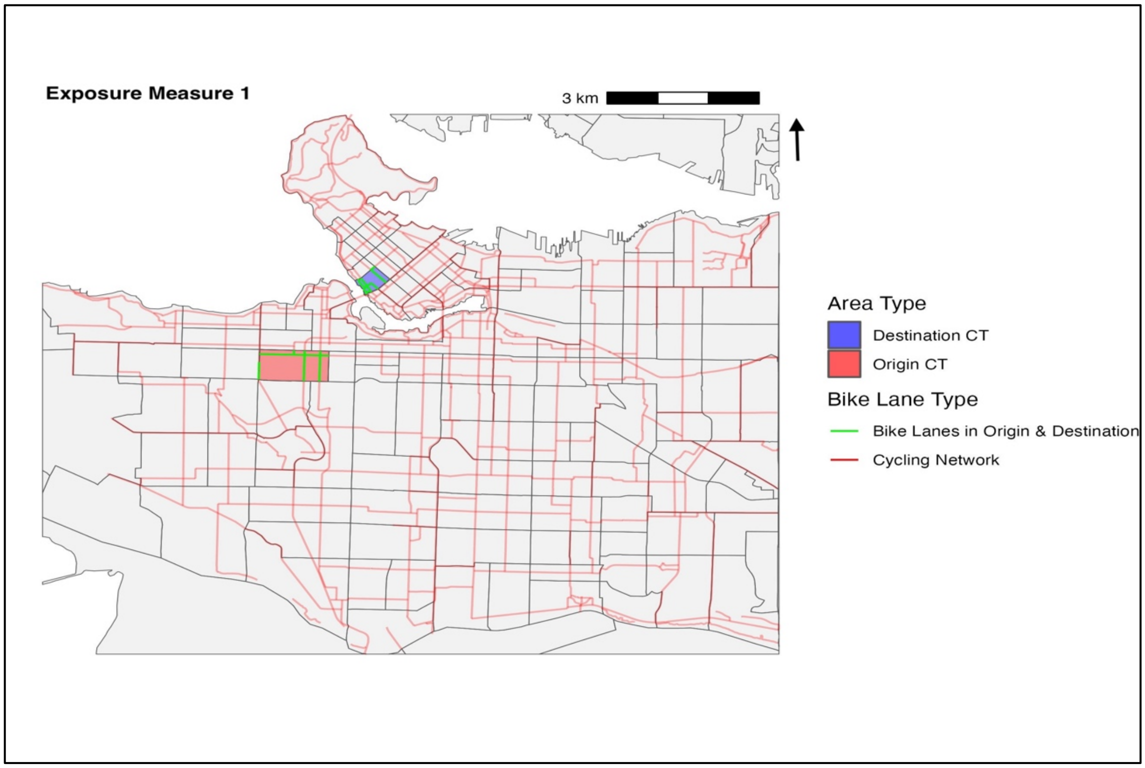


Figure. 2.13. Demonstration of exposure measure 1: total km of cycling infrastructure within the CT of origin and destination. The selected census tracts in Vancouver CSD are arbitrary and used solely for illustrating the method.

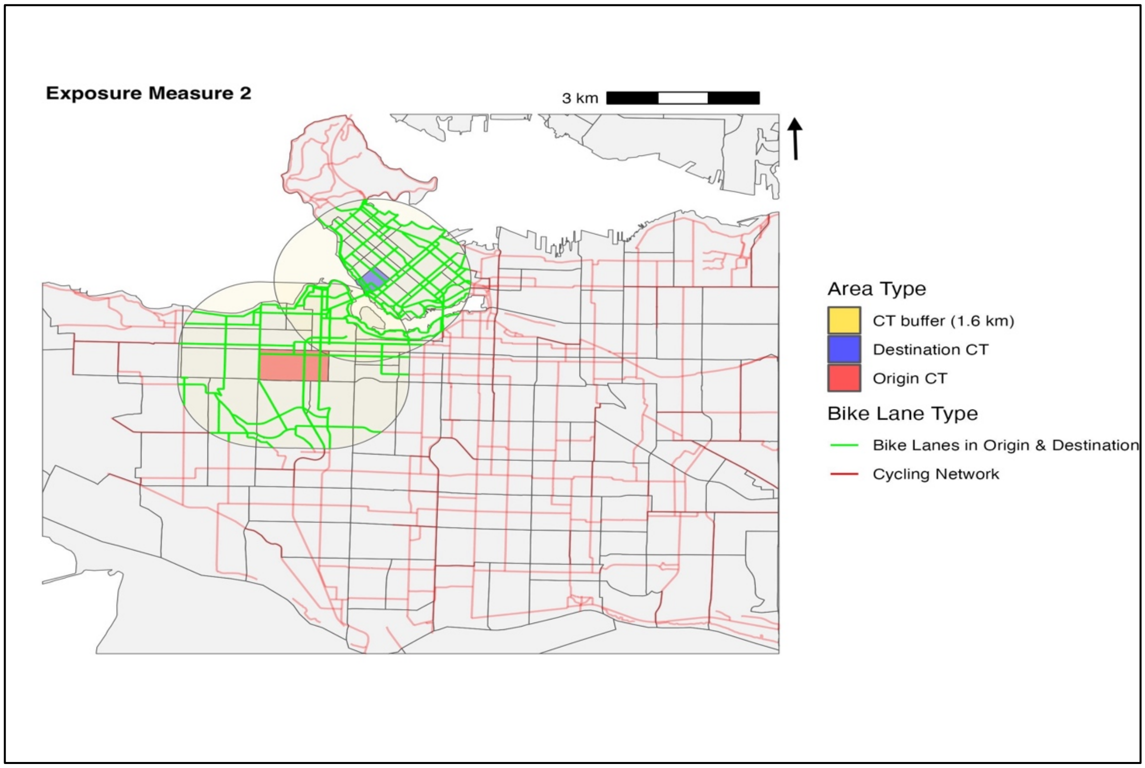


Figure. 2.14. Demonstration of exposure measure 2: total km of Cycling infrastructure within the 1.6km buffer of CT of origin and destination. The selected census tracts in Vancouver CSD are arbitrary and used solely for illustrating the method.

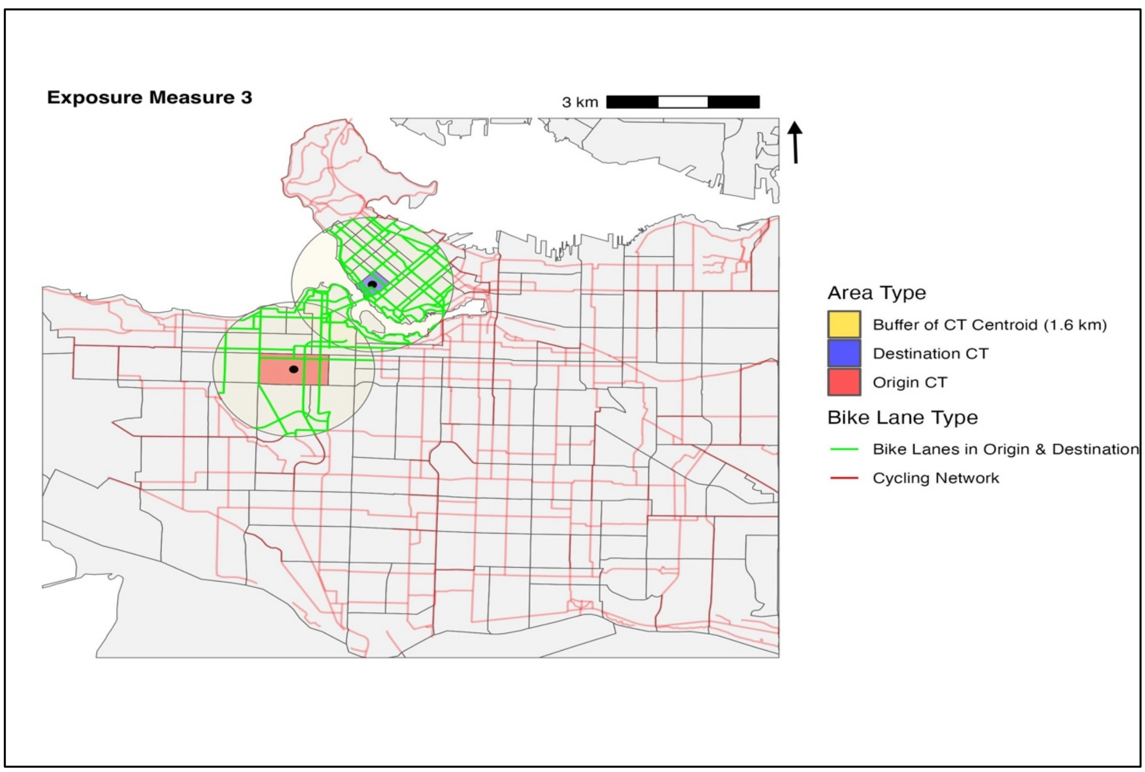


Figure. 2.15. Demonstration of exposure measure 3: total km of cycling infrastructure within the 1.6 km buffer of the centroid of CT of origin and destination. The selected census tracts in Vancouver CSD are arbitrary and used solely for illustrating the method.

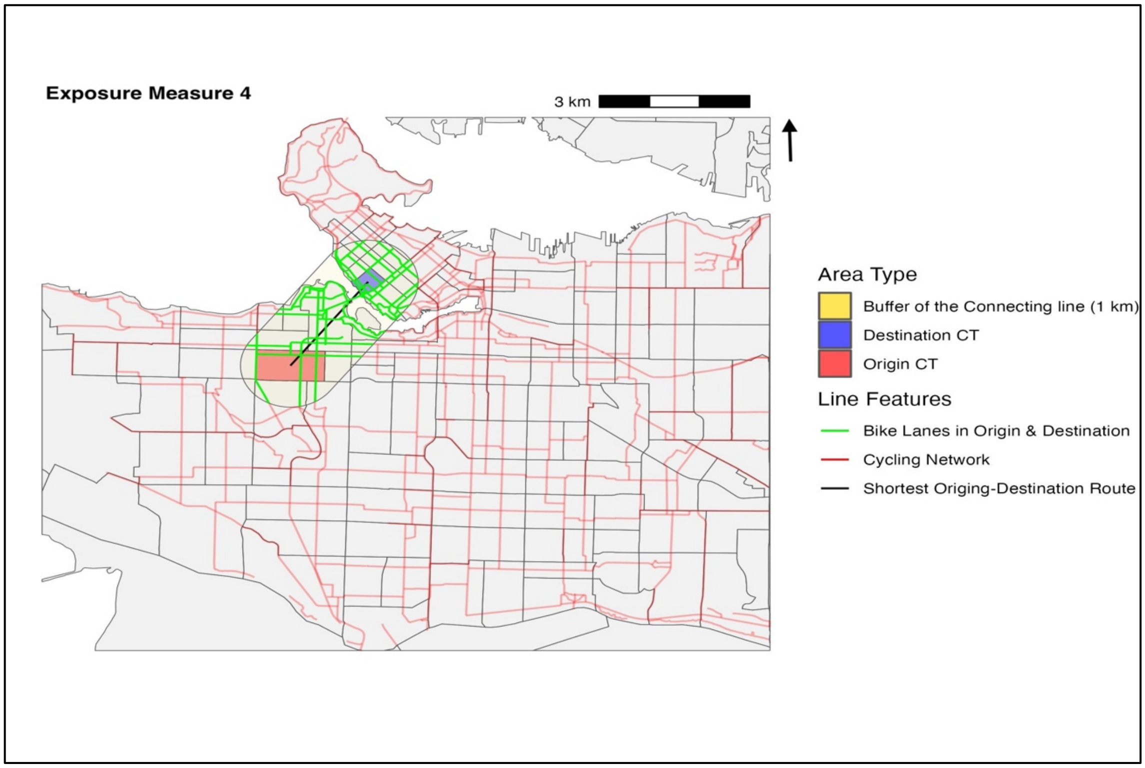


Figure. 2.16. Demonstration of Exposure measure 4: total km of cycling infrastructure within the 1 km buffer of the shortest route between origin and destination. The selected census tracts in Vancouver CSD are arbitrary and used solely for illustrating the method.

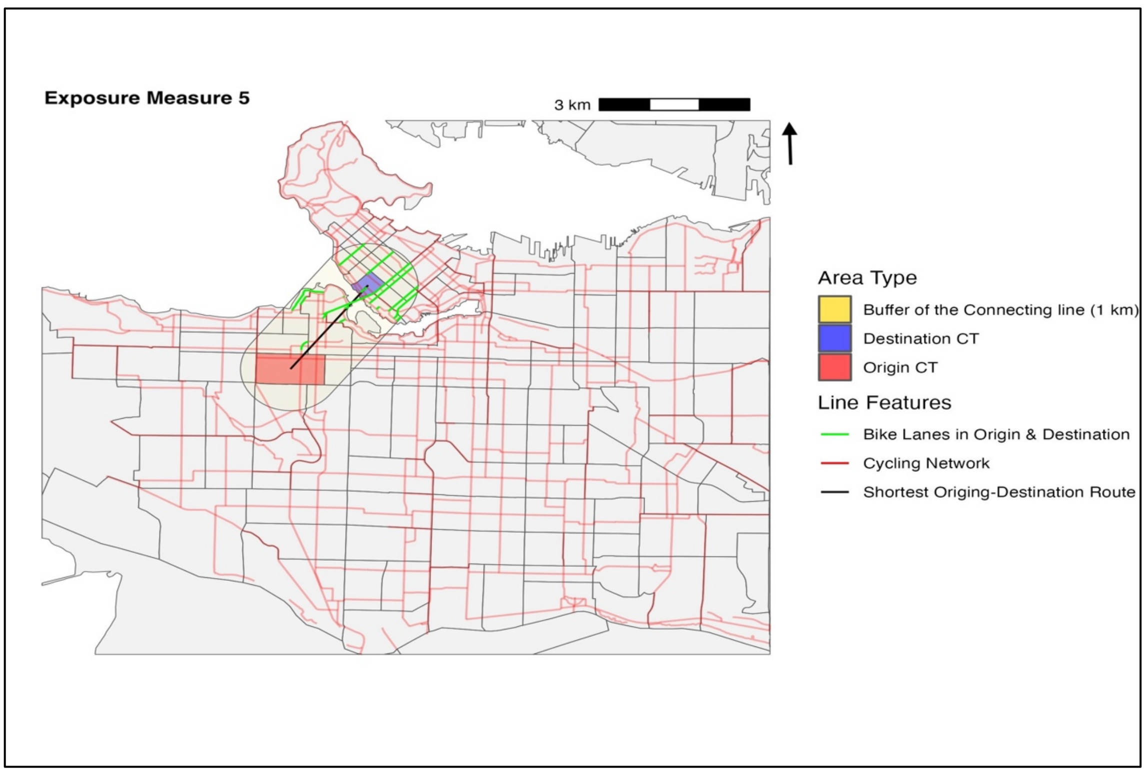


Figure. 2.17. Demonstration of Exposure measure 5: cycling infrastructure within 1 km of the shortest O-D route, with only segments that are spatially aligned with the O-D route (angle <30° or >150°) included in the measure. This measure emphasizes

infrastructure that is both proximate and spatially aligned with the shortest commute path. The selected census tracts in Vancouver CSD are arbitrary and used solely for illustrating the method.

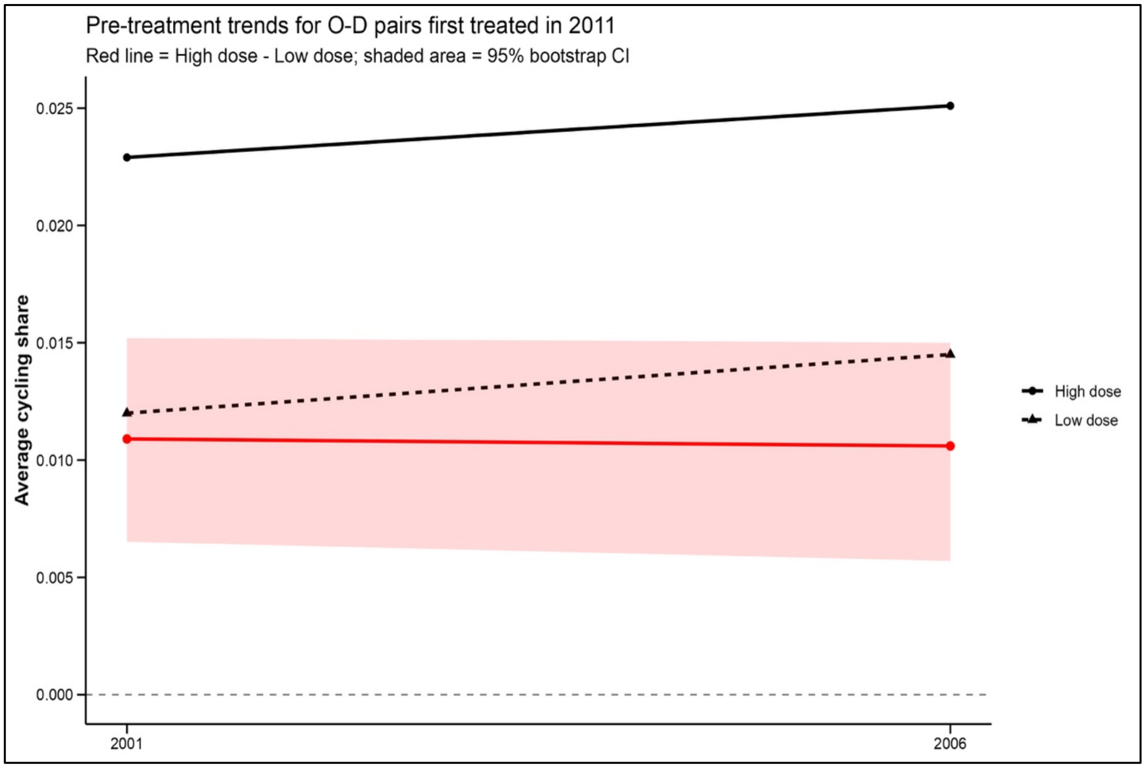


Figure 2.18. Pre-trend test for O-D pairs first treated in 2011, pooled sample.

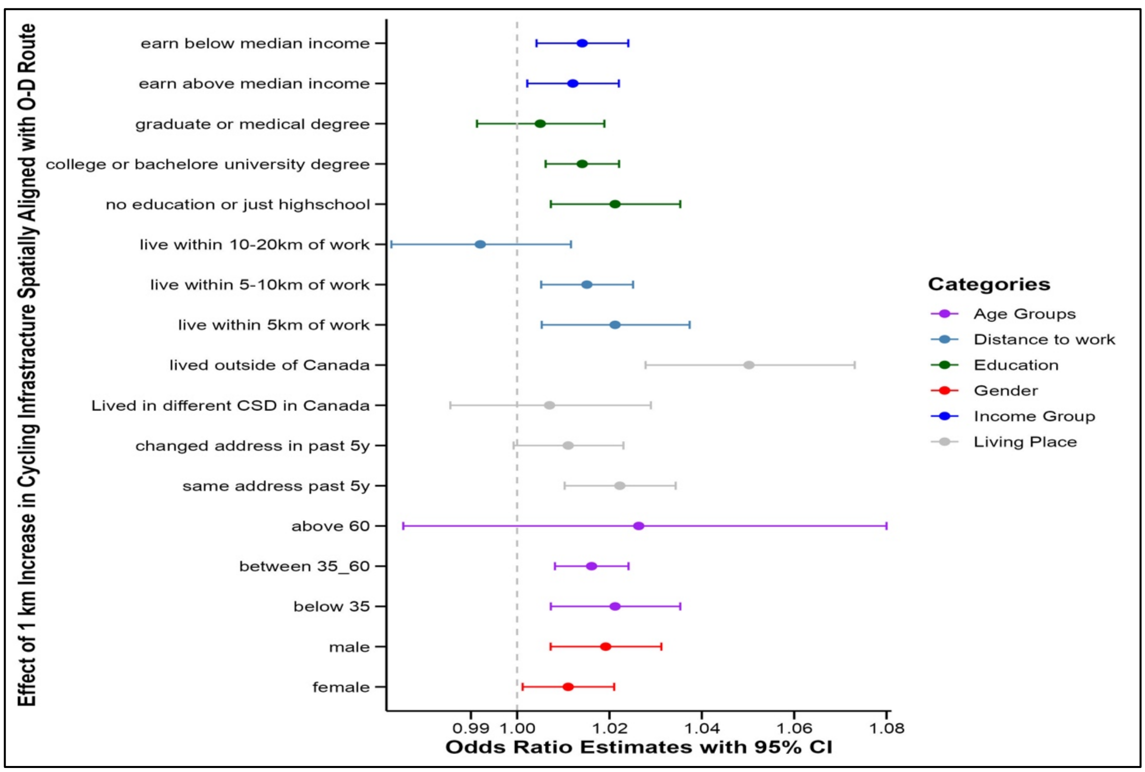


Figure. 2.19. Regression Coefficients of Measure 5 on socio-economic and trip characteristics subgroups in the pooled sample.

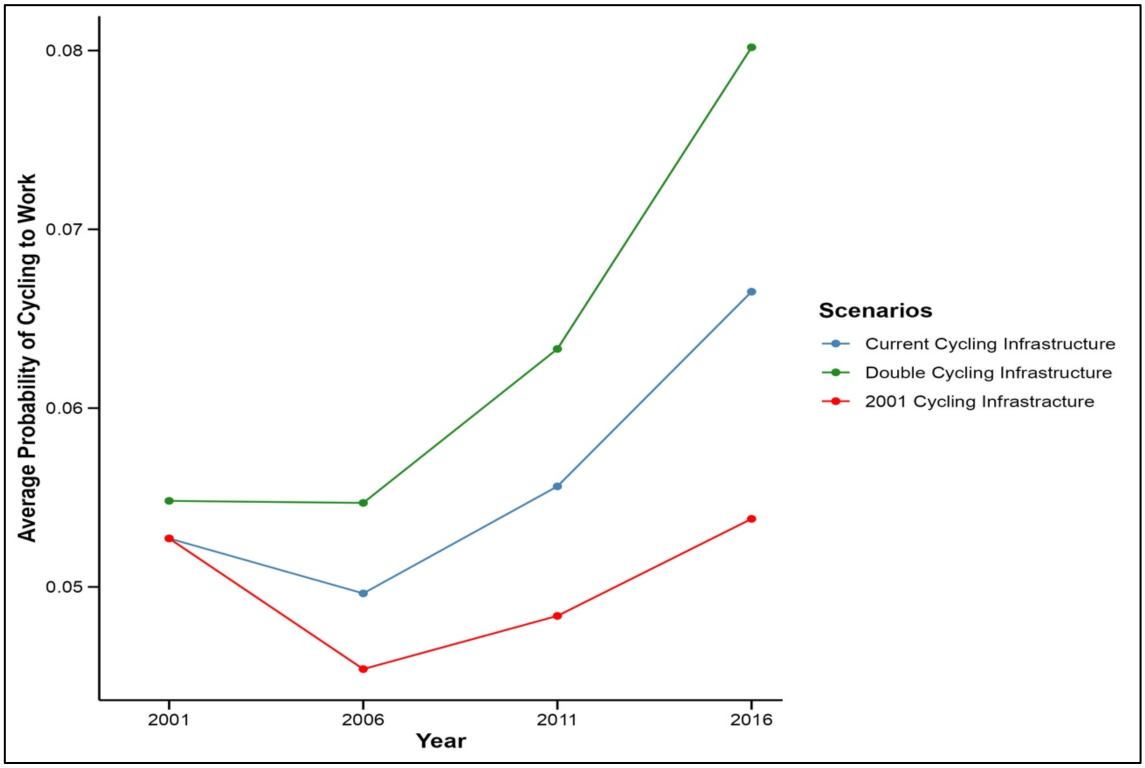


Figure 2.20. Predicted average probability of cycling to work under three scenarios, pooled sample

Tables

Table 2.4. Logistic regression model result (in log-odds). Model 1-5 present exposure measure 1-5 in the pooled sample. Measure 1: Total km of cycling infrastructure within the CT of residence and workplace. Measure 2: Total km of cycling infrastructure within 1.6 km buffer[7] around CT of residence and workplace. Measure 3: Total km of cycling infrastructure within 1.6 km of the centroid of both CTs. Measure 4: total km of cycling infrastructure within a 1 km buffer of the shortest O–D route to capture the infrastructure within the immediate vicinity of the shortest commute path. Measure 5: Total length of bike lanes within a 1 km buffer that align with the shortest O-D route. Standard Errors are clusters over O-D and year. The number of observations is not reported due to CRDCN data confidentiality

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	(std.Error)	(std.Error)	(std.Error)	(std.Error)	(std.Error)
Treatment Effect					
New Cycling Infrastructure	0.040***	0.010***	0.017***	0.016***	0.016***
(km)	(0.008)	(0.001)	(0.002)	(0.002)	(0.004)
Socioeconomics					
Sex (Ref. Category: Female)					
Male	0.952***	0.953***	0.952***	0.952***	0.952***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)

[7] This distance follows Krizek et al. (2009).

Education Groups (Ref. Category: No Education)					
High school diploma, no diploma or certificate	-0.120 (0.103)	-0.097 (0.102)	-0.099 (0.101)	-0.111 (0.099)	-0.122 (0.099)
College, trade, non-trade, other degrees	-0.106 (0.110)	-0.086 (0.110)	-0.087 (0.109)	-0.098 (0.106)	-0.108 (0.107)
University degree(below, above bachelor)	0.139 (0.105)	0.159 (0.107)	0.157 (0.106)	0.147 (0.103)	0.137 (0.102)
Medicine, dentistry, veterinary	0.186+ (0.109)	0.205+ (0.114)	0.204+ (0.114)	0.194+ (0.109)	0.183+ (0.107)
Graduate degree	0.508*** (0.124)	0.526*** (0.128)	0.525*** (0.127)	0.515*** (0.123)	0.506*** (0.121)
Age Groups (Ref. Category: 15-35)					
Age 35-60	-0.236*** (0.026)	-0.234*** (0.026)	-0.235*** (0.026)	-0.236*** (0.026)	-0.237*** (0.026)
Age above 60	-0.963*** (0.056)	-0.960*** (0.056)	-0.960*** (0.056)	-0.962*** (0.056)	-0.963*** (0.056)
Distance to workplace (Ref. Category: Below 5km)					
Distance between 5km to 10km	-0.310*** (0.055)	-0.310*** (0.055)	-0.310*** (0.055)	-0.309*** (0.055)	-0.310*** (0.055)
Distance between 10km to 20km	-0.578*** (0.089)	-0.578*** (0.090)	-0.578*** (0.090)	-0.577*** (0.091)	-0.578*** (0.091)
Distance above 20km	-1.175** (0.360)	-1.174** (0.358)	-1.175** (0.359)	-1.174** (0.359)	-1.175** (0.359)
Income (Ref. Category: Below median income)					
Above median income	-0.001 (0.035)	-0.004 (0.036)	-0.003 (0.036)	-0.002 (0.036)	0.000 (0.035)
Mobility Status (Ref. Category: Same dwelling address)					
Same CSD, different dwelling	0.136** (0.045)	0.136** (0.045)	0.136** (0.045)	0.136** (0.045)	0.136** (0.045)
Different CSD in Canada	0.161* (0.079)	0.161* (0.079)	0.161* (0.079)	0.162* (0.079)	0.161* (0.079)
Outside of Canada	0.116*** (0.020)	0.115*** (0.019)	0.114*** (0.019)	0.117*** (0.020)	0.118*** (0.020)
R2	0.209	0.210	0.210	0.209	0.209

R2 Adj.	0.183	0.183	0.183	0.183	0.183
Std.Errors	Origin-Destination and Year				
Fixed Effects	Origin-Destination and Year				

The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively

Appendix B: Supplementary Information of Chapter 2

Odd Ratio to Probability

To interpret changes in the odds ratio as changes in the probability of cycling, we use the following steps:

1. Start with the baseline probability of cycling in the pooled sample (e.g., 2%). Convert this to odds:

$$\text{Odds} = \frac{\text{p}}{1-\text{p}} = \frac{0.02}{0.98} = 0.02. \qquad \text{(A.1)}$$

2. Apply the odds ratio (estimated coefficient) associated with a 1 km increase in cycling infrastructure (e.g., 1.04):

$$\text{New odds} = 0.02\ \times\ 1.04 = 0.021 \qquad \text{(A.2)}$$

3. Convert the new odds back to probability

$$\text{New probability} = \frac{\text{New odds}}{1+\text{New odds}} = 0.0205\ \text{(or 2.05\%)} \qquad \text{(A.3)}$$

Thus, a 1 km increase in cycling infrastructure increases the predicted probability of cycling from 2% to 2.05%.

Parallel Trend Assumption Test

As a visual diagnostic of the parallel trend assumption, we compare pre-treatment outcome trajectories across units (O-D pairs) that were first exposed to a treatment increase in the same treatment cohort but received different treatment intensities. Because cycling infrastructure is introduced in varying amounts rather than through a simple treated-versus-untreated distinction, we divide O-D pairs within each first-treatment cohort into low-dose and high-dose groups based on the median size of their first observed increase in bike-lane exposure. We then plot the average outcome for each group over the pre-treatment period only. If the identifying assumption is plausible, the two groups should display similar movement before treatment, even if their outcome levels differ. We construct these figures for O-D pairs that first receive a positive increase in bike-lane exposure in 2006, 2011, and 2016. Although the 2006 cohort includes a larger number of O-D pairs, it offers only one pre-treatment observation (2001), which is insufficient for evaluating trends. The 2016 cohort provides a longer pre-treatment window (2001, 2006, and 2011), but it contains fewer treated units. We therefore focus on O-D pairs first treated in 2011, which provide the most balanced case for visual comparison.

To further assess pre-treatment similarity between dose groups, we plot a difference line with 95% confidence intervals. For each pre-treatment year, we calculate the weighted average cycling share separately for the high-dose and low-dose O-D pairs and define the difference line as the high-dose mean minus the low-dose mean. This line shows whether the gap between the two groups remains stable before treatment; under the parallel-trends assumption, no systematic pre-treatment divergence should be observed. To have a measure of uncertainty around the visual pre-trend comparison, confidence intervals are estimated using a nonparametric bootstrap, in which O-D pairs are repeatedly resampled with replacement within each dose group and the difference in weighted means is recalculated in each replication. The 95% confidence interval is then constructed from the empirical distribution of these bootstrap differences.

City-Specific Effects of Covariates

In Vancouver (Table 2.13S), across all models, most of the coefficients of the covariates in Eq. (1) (δX_{it}) are statistically significant and largely consistent with findings from previous studies. Men have higher odds of cycling to work compared to women. Similarly, individuals with higher educational attainment, particularly those with a graduate degree, are more likely to commute by bike than those with no formal education. Age is negatively associated with the odds of cycling to work. Commuting distance is also negatively associated with cycling to work. Individuals with higher income have higher odds of cycling compared to lower-income commuters.

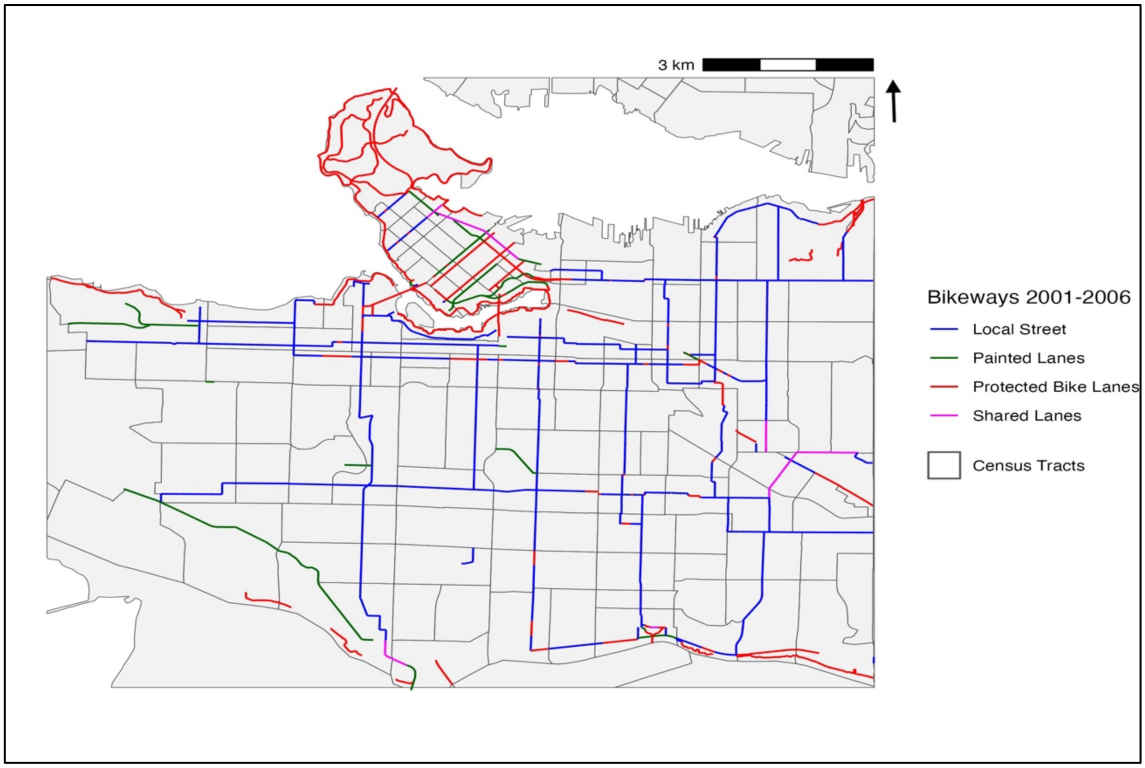
The pattern is slightly different in Toronto for some of the covariates (Table 2.14S). Individuals with no formal education have higher odds of cycling than those with any level of higher educational attainment, and commuters earning below the median income are more likely to cycle to work than their higher-income counterparts. Individuals who have changed dwellings within the same CSD have higher odds of cycling to work compared to those living in the same address for the past five years. These differences provide valuable insights into within-city variations in the socio-economic composition of commuters.

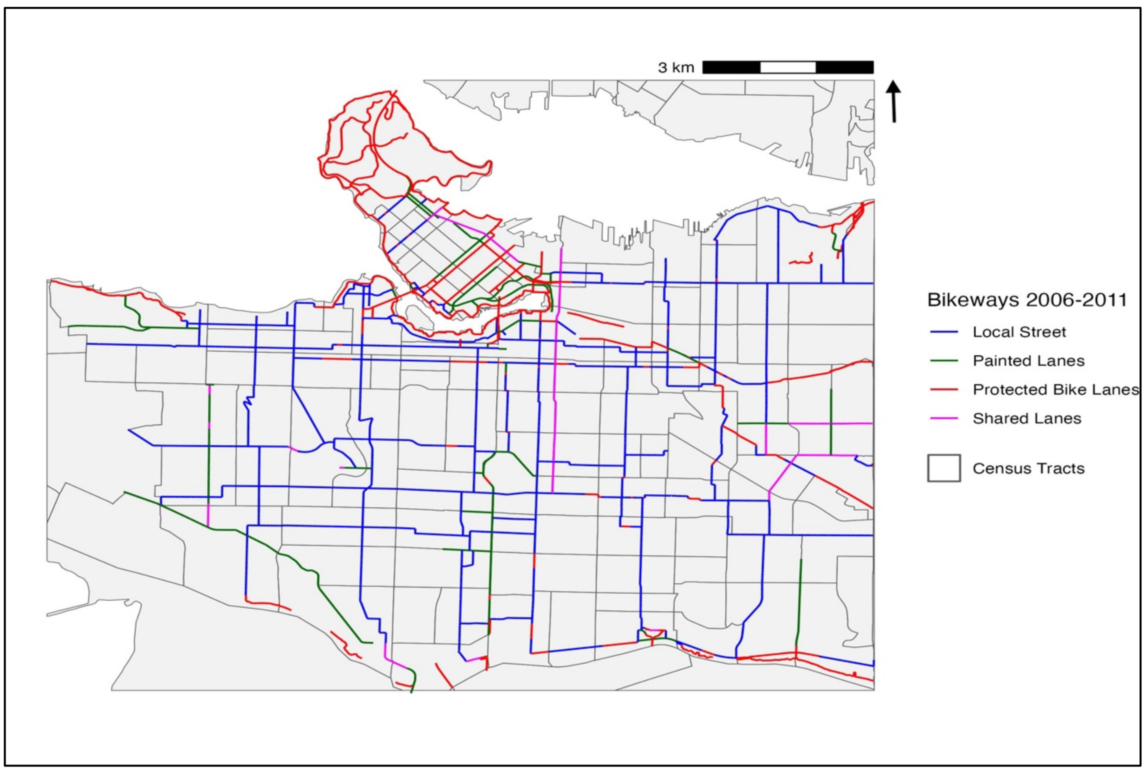
City-Specific Analysis of Heterogeneity of the Effects

A similar pattern to the polled sample emerges in both Toronto and Vancouver, though with slight variations across subgroups. In Vancouver (Fig. 2.26S), while commuters under age 35 have higher odds of cycling to work, the subgroup analysis reveals that commuters aged 60 and above show higher responsiveness to additional infrastructure. Specifically, for each additional kilometer of direct cycling infrastructure along the shortest O-D route, older commuters experience a larger increase in the odds of cycling.

In Toronto, although individuals living within 5 km of their workplace are more likely to cycle to work, the subgroup analysis by commute distance shows that those living 5-10 km from work demonstrate higher responsiveness to infrastructure expansion with a higher increase in the odds of cycling per kilometer of added infrastructure. Further, while individuals with no formal education or only a high school diploma and those with below-median income have higher odds of cycling to work in Toronto, the subgroup regressions show that it is commuters with a college or bachelor’s degree and those earning above the median income who benefit more from each additional kilometer of direct infrastructure along their commute route (Fig. 2.27S).

Figures


3 km
Bikeways 2001-2006
Local Street
Painted Lanes
Protected Bike Lanes
Shared Lanes
Census Tracts


3 km
Bikeways 2006-2011
Local Street
Painted Lanes
Protected Bike Lanes
Shared Lanes
Census Tracts

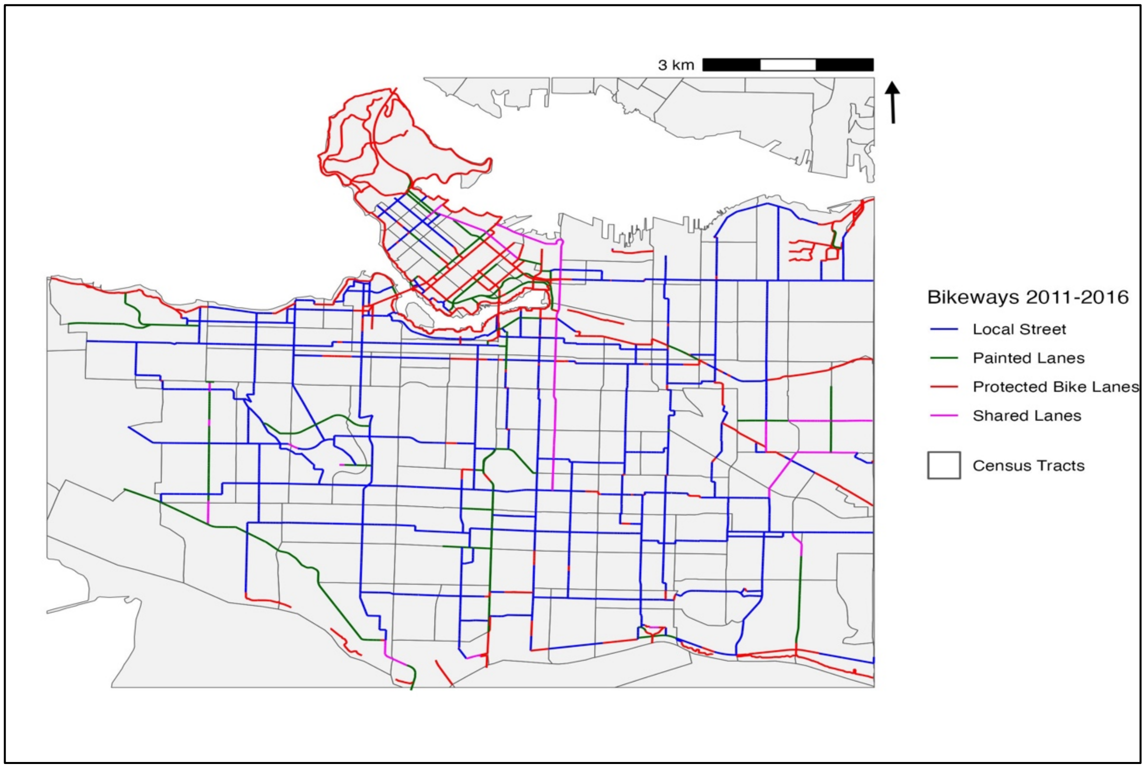
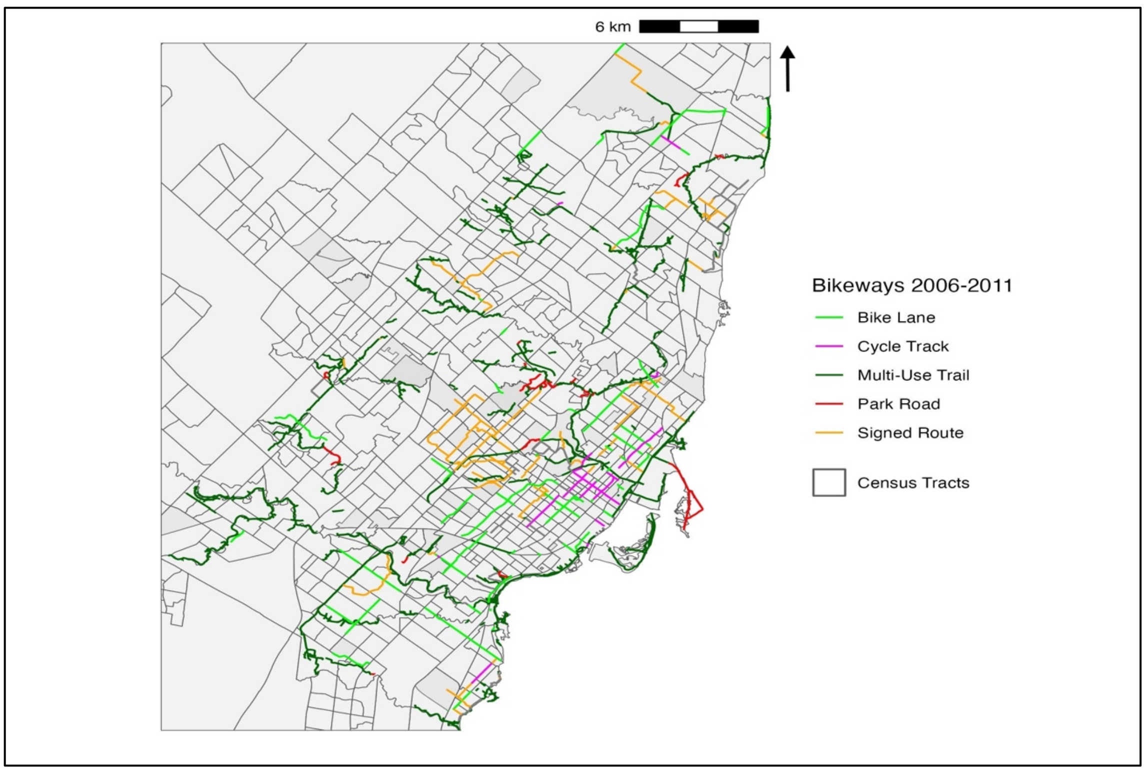


Figure 2.21S. Evolution of cycling infrastructure in Vancouver CSD by infrastructure type across census waves 2001–2016



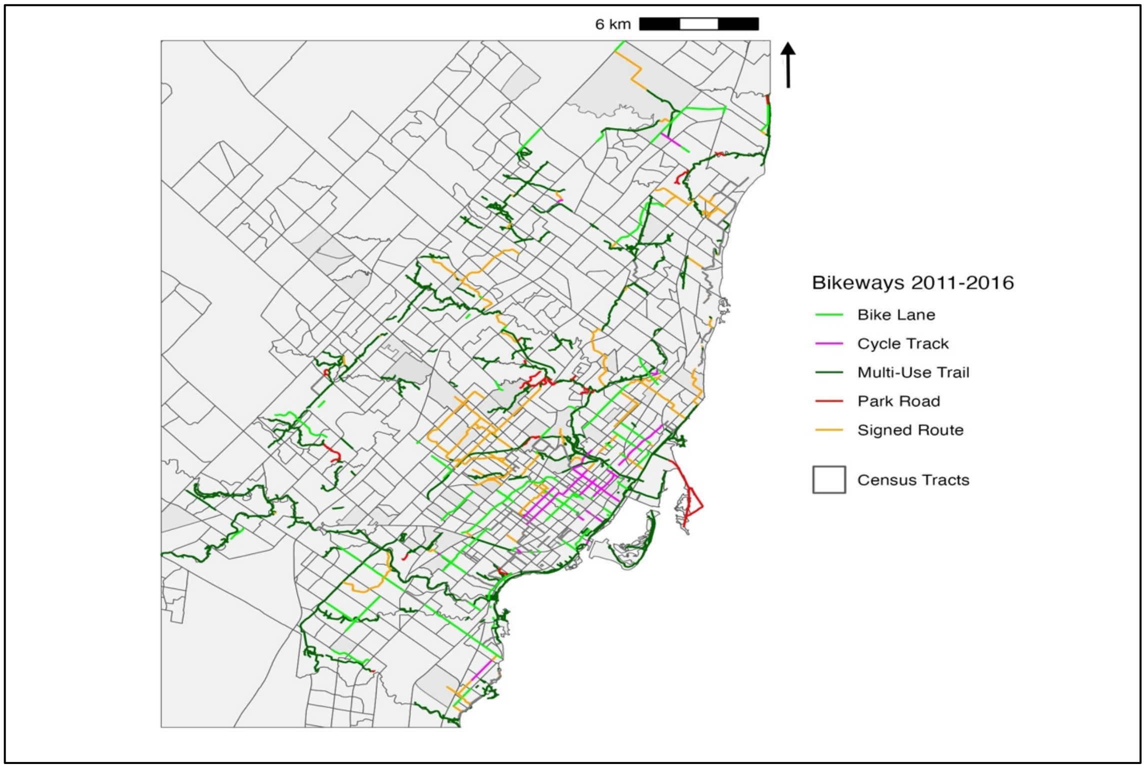


Figure 2.22S. Evolution of cycling infrastructure in Toronto CSD by infrastructure type across census waves 2006–2016

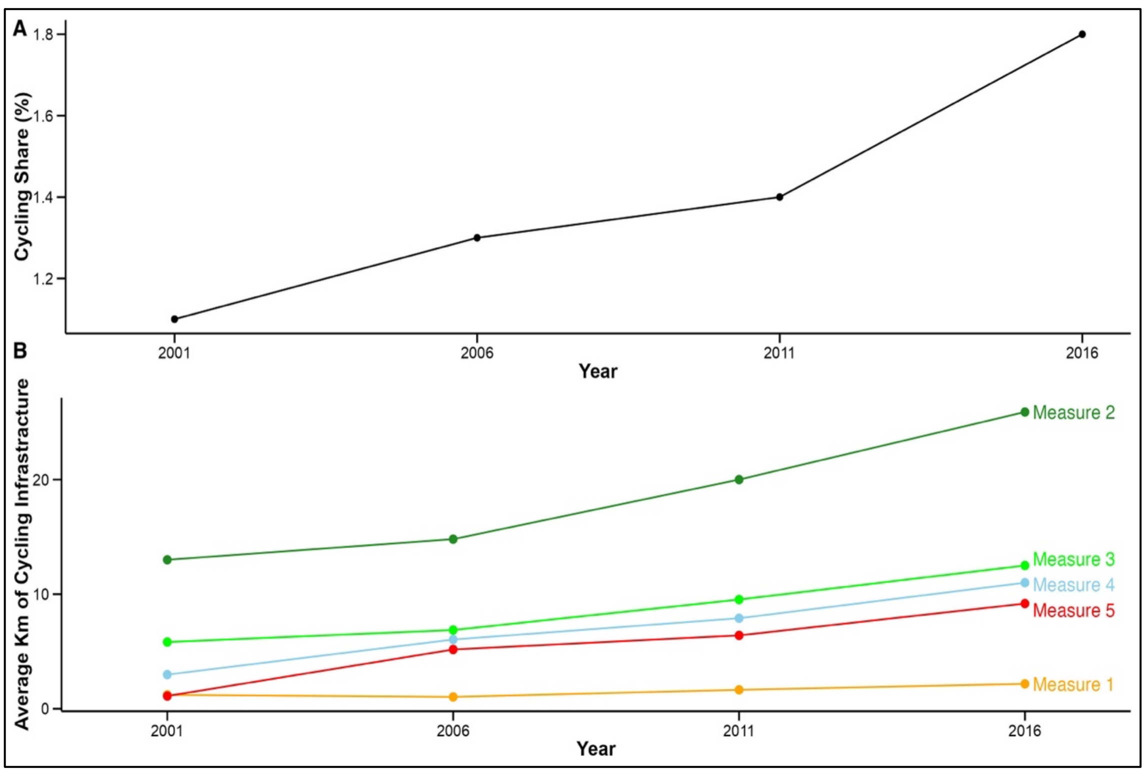


Figure 2.23S. (A) Cycling mode share across census waves. (B) Average length of cycling infrastructure (km) within O-D pairs in exposure measures 1-5, by census wave, pooled sample

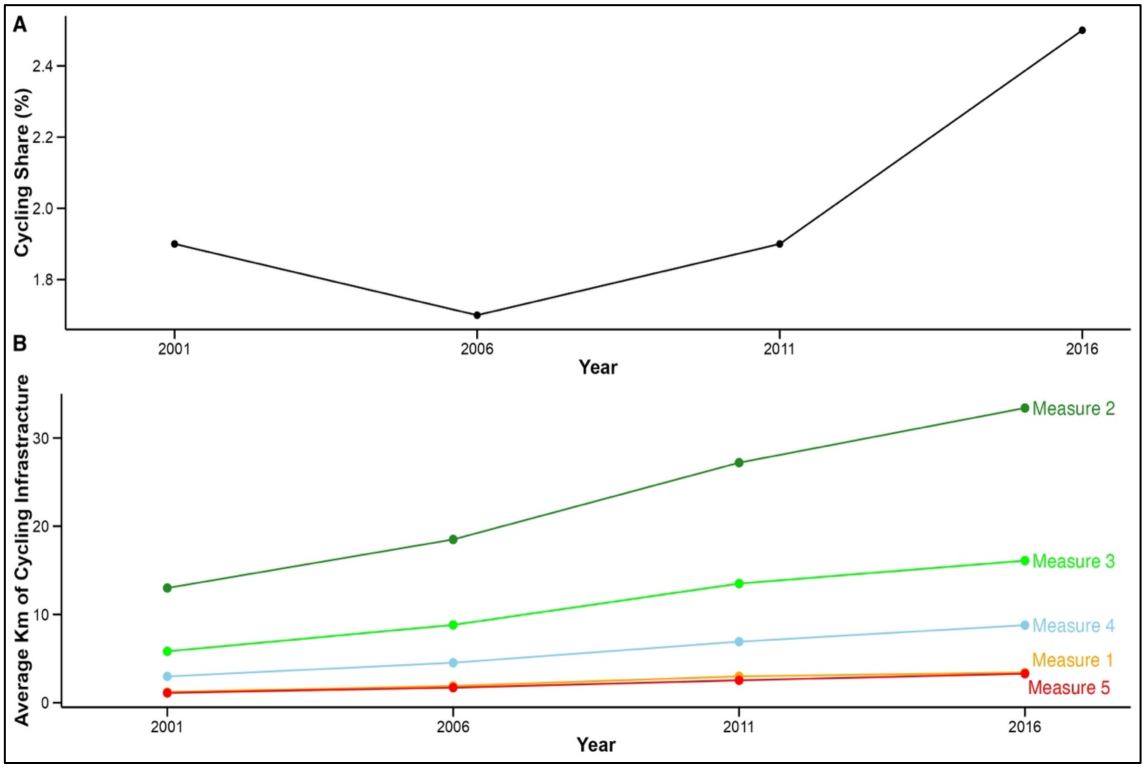


Figure 2.24S. (A) Cycling mode share across census waves. (B) Total length of cycling infrastructure (km) for exposure measures 1–5, by census wave, Vancouver

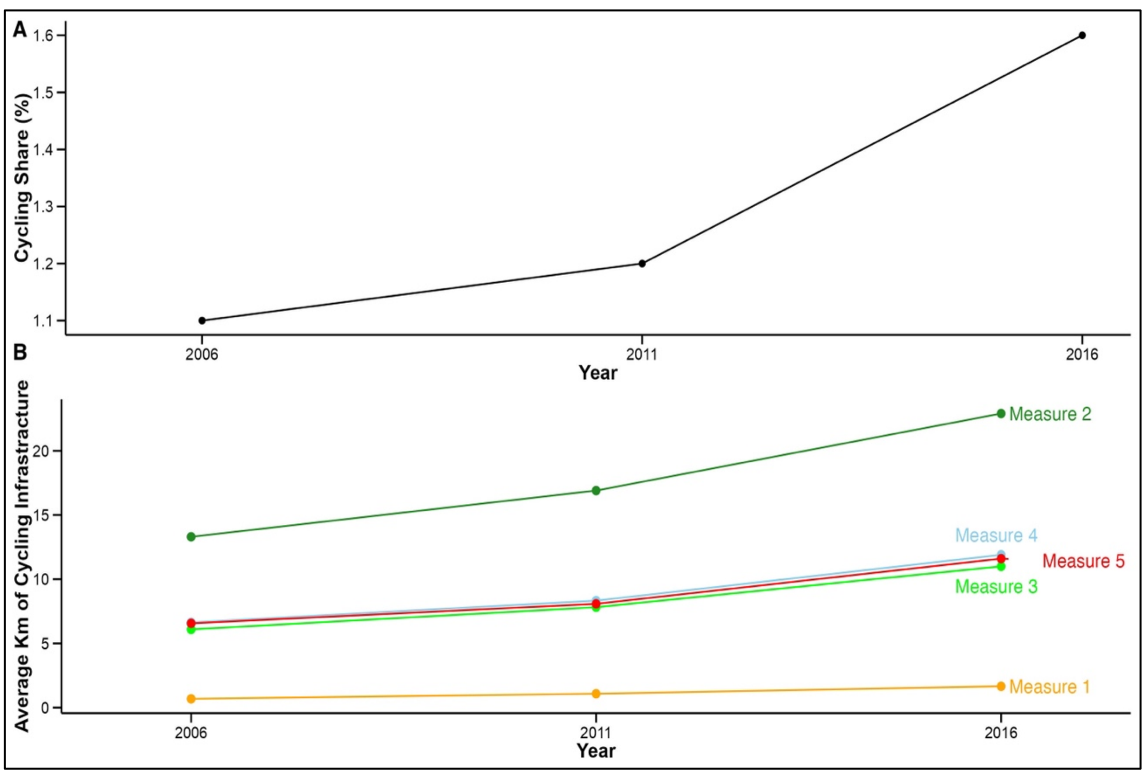


Figure 2.25S. (A) Cycling mode share across census waves. (B) Total length of cycling infrastructure (km) for exposure measures 1–5, by census wave, Toronto

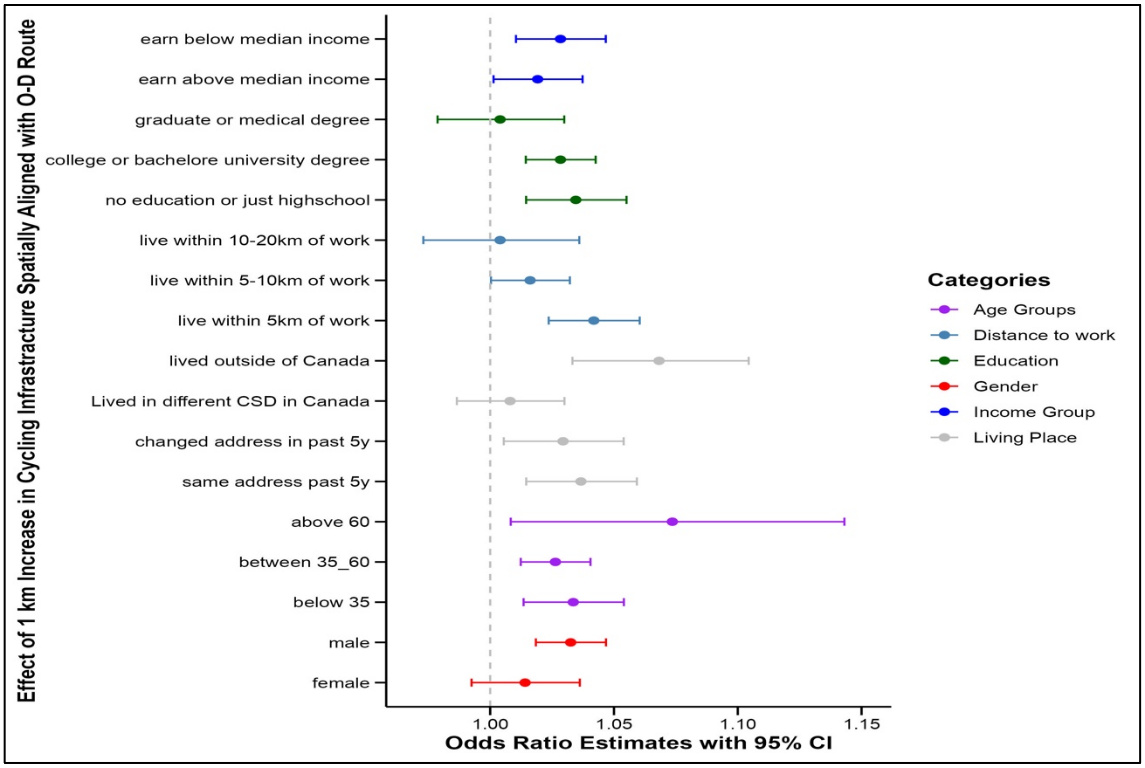


Figure 2.26S. Regression Coefficients of Model 5 on subgroups, Vancouver

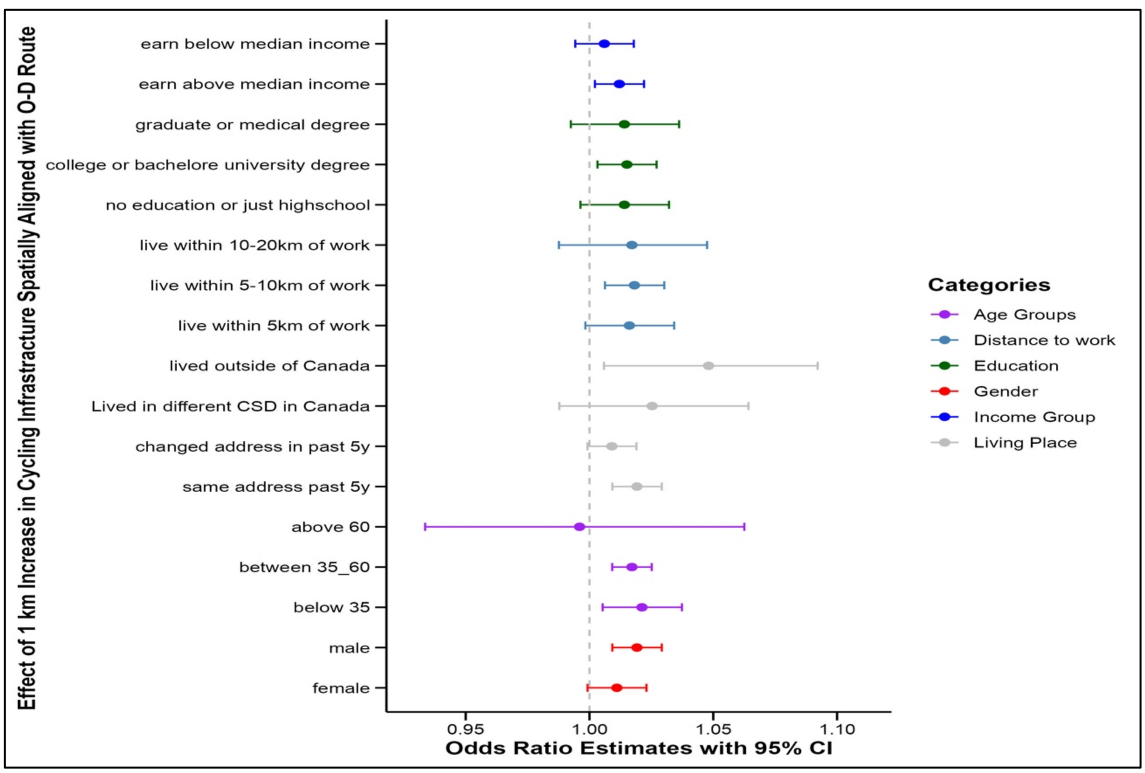


Figure 2.27S. Regression Coefficients of Model 5 on subgroups, Toronto

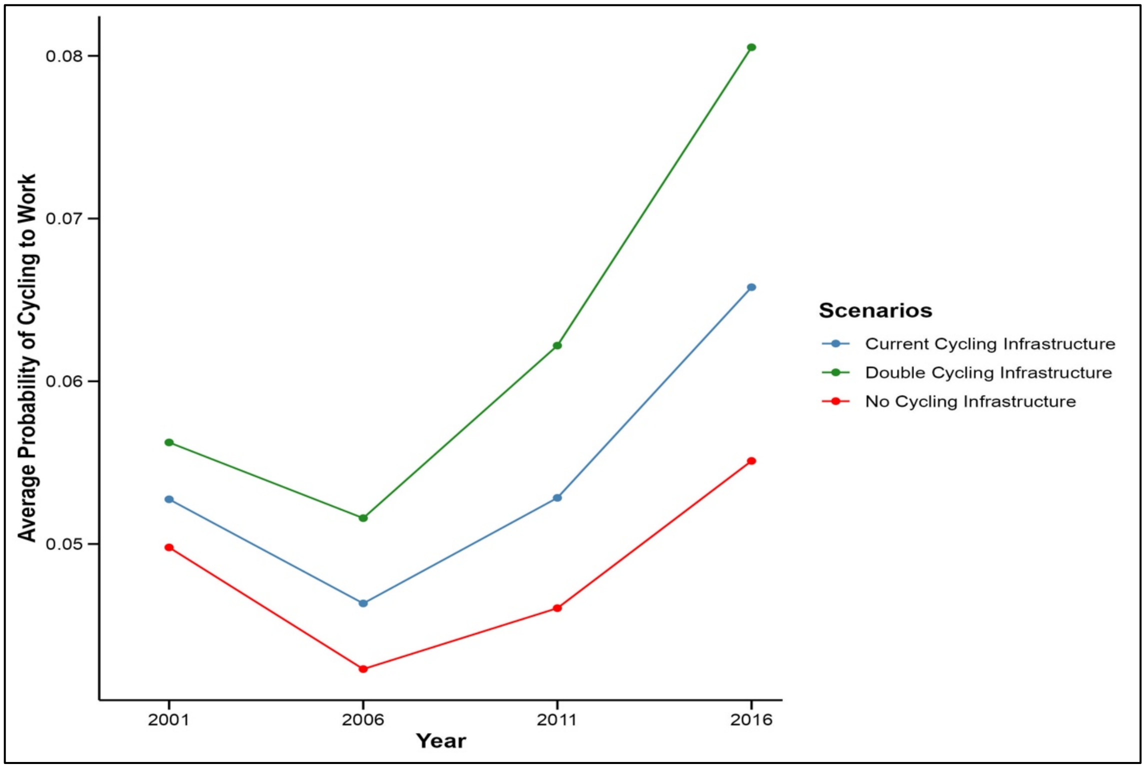


Figure 2.28S. Predicted average probability of cycling to work under three scenarios, Vancouver CSD

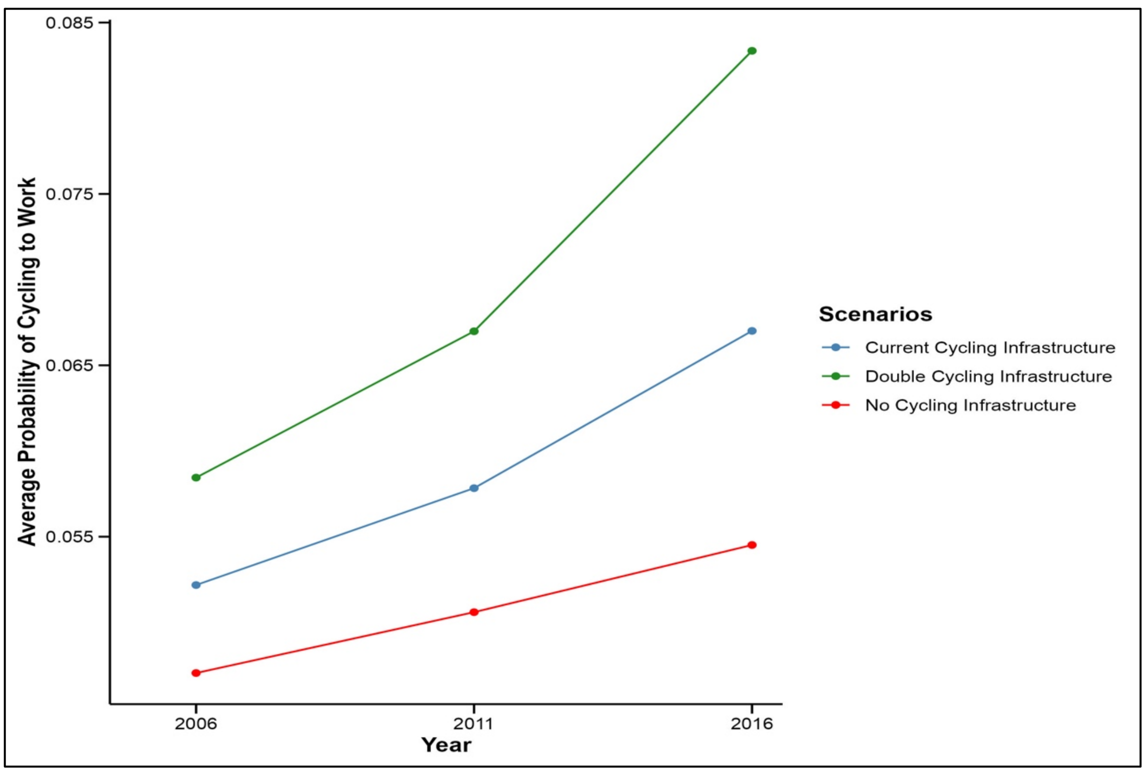


Figure 2.29S. Predicted average probability of cycling to work under three scenarios, Toronto CSD

Tables

Table 2.5S. Descriptive statistics of the pooled sample consisting of working individuals in Toronto and Vancouver CSD.

Number of observations: 13,672,440	**2001**	**2006**	**2011**	**2016**
Gender				
Female	0.50	0.51	0.51	0.51
Male	0.49	0.48	0.48	0.48
Main Mode of Commute				
Bike	0.01	0.01	0.01	0.01
Car as driver	0.69	0.61	0.61	0.59
Car as passenger	0.07	0.07	0.05	0.05
Motorcycle	0.001	0.001	0.001	0.001
Other modes	0.005	0.006	0.01	0.008
Public transit	0.13	0.22		
Taxi	0.001	0.001		
Walked	0.07	0.05	0.05	0.06
Bus			0.12	0.12
Light rail			0.02	0.03
Passenger ferry			0.00	0.00
Subway			0.08	0.09
Age Group				
15-35	0.54	0.55	0.55	0.52
35-60	0.40	0.37	0.35	0.36
Above 60	0.05	0.06	0.09	0.10
Education Group				
No education	0.19	0.11		
High school diploma, no diploma or certificate	0.24	0.26	0.32	0.33
College, trade, non-trade, other degrees	0.26	0.25	0.25	0.24
University degree(below, above bachelor)[8]	0.23	0.29	0.32	0.32
Medicine, dentistry, veterinary	0.008	0.008	0.009	0.01
Graduate degree	0.05	0.07	0.08	0.09
Mobility Status in last 5 Years				

[8] Statistics Canada Language in categorizing educational groups

Different CSD in Canada	0.15	0.14	0.13	0.12
Outside Canada	0.07	0.07	0.05	0.05
Same CSD, different dwelling	0.26	0.25	0.23	0.23
Same address (dwelling)	0.50	0.51	0.56	0.57
Distance to Workplace				
Below 5km	0.31	0.31	0.31	0.32
Between 5km to 10km	0.24	0.24	0.24	0.24
Between 10km to 20km	0.26	0.26	0.26	0.26
Above 20km	0.16	0.17	0.17	0.17
Income Group				
Below median income	0.55	0.55	0.47	0.43
Above median income	0.45	0.45	0.53	0.57

Table 2.6S. Descriptive statistics of working population in Vancouver CSD.

Number of Observations: 3,955,305	**2001**	**2006**	**2011**	**2016**
Gender				
Female	0.51	0.52	0.52	0.52
Male	0.49	0.48	0.48	0.48
Main Mode of Commute				
Bike	0.019	0.017	0.019	0.02
Car as driver	0.69	0.64	0.62	0.60
Car as passenger	0.07	0.07	0.05	0.05
Motorcycle	0.001	0.002	0.002	0.002
Other modes	0.005	0.006	0.01	0.008
Public transit	0.13	0.18		
Taxi	0.001	0.00		
Walked	0.07	0.07	0.07	0.07
Bus			0.14	0.14
Light rail			0.01	0.01
Passenger ferry			0.001	0.001
Subway			0.05	0.06
Age Groups				
15-35	0.40	0.37	0.36	0.37

35-60	0.55	0.56	0.55	0.51
Above 60	0.05	0.07	0.09	0.11
Education Level				
No education	0.18	0.10		
High school diploma, no diploma or certificate	0.25	0.27	0.33	0.35
College, trade, non-trade, other degrees	0.29	0.27	0.26	0.25
University degree(below, above bachelor)	0.22	0.28	0.32	0.31
Medicine, dentistry, veterinary	0.01	0.01	0.01	0.01
Graduate degree	0.05	0.07	0.08	0.09
Mobility Status in Last 5 Years				
Different CSD in Canada	0.18	0.17	0.16	0.16
Outside Canada	0.07	0.07	0.07	0.07
Same CSD, different dwelling	0.26	0.26	0.24	0.24
Same address (dwelling)	0.49	0.50	0.53	0.54
Distance to Workplace				
Below 5m	0.36	0.36	0.37	0.37
Between 5m to 10m	0.26	0.27	0.26	0.26
Between 10m to 20m	0.26	0.25	0.25	0.25
Above 20m	0.12	0.12	0.12	0.12
Income Groups				
Below median income	0.56	0.55	0.47	0.46
Above median income	0.44	0.45	0.53	0.54

Table 2.7S. Descriptive statistics of working population in Toronto CSD.

Number of Observations: 9,717,135	**2001**	**2006**	**2011**	**2016**
Gender				
Female	0.50	0.51	0.51	0.52
Male	0.50	0.49	0.49	0.48
Main Mode of Commute				
Bike	0.01	0.01	0.01	0.01
Car as driver	0.62	0.60	0.61	0.58
Car as passenger	0.07	0.08	0.05	0.06
Motorcycle	0.00	0.00	0.00	0.001

Other modes	0.01	0.006	0.01	0.009
Public transit	0.24	0.24		
Taxi	0.001	0.001		
Walked	0.05	0.05	0.05	0.05
Bus			0.11	0.11
Light rail			0.03	0.04
Passenger ferry			0.00	0.00
Subway			0.10	0.10
Age Groups				
15-35	0.40	0.37	0.35	0.36
35-60	0.53	0.55	0.55	0.53
Above 60	0.05	0.06	0.09	0.10
Education Level				
No education	0.19	0.11		
High school diploma, no diploma or certificate	0.24	0.25	0.32	0.32
College, trade, non-trade, other degrees	0.24	0.24	0.24	0.23
University degree (below, above bachelor)	0.23	0.29	0.33	0.32
Medicine, dentistry, veterinary	0.008	0.008	0.009	0.01
Graduate degree	0.05	0.07	0.08	0.09
Mobility Status in Last 5 Years				
Different CSD in Canada	0.14	0.14	0.12	0.11
Outside Canada	0.07	0.07	0.05	0.05
Same CSD, different dwelling	0.26	0.25	0.23	0.23
Same address (dwelling)	0.51	0.52	0.57	0.59
Distance to Workplace				
Below 5m	0.29	0.29	0.29	0.30
Between 5m to 10m	0.24	0.23	0.23	0.23
Between 10m to 20m	0.27	0.27	0.26	0.26
Above 20m	0.18	0.19	0.20	0.19
Income Groups				
Below median income	0.56	0.54	0.47	0.45
Above median income	0.44	0.46	0.53	0.55

Table 2.8S. Total number of unique origin and destination (O-D) pairs in each sample by year.

Year	Pooled Sample	Vancouver CSD	Toronto CSD
2001	178,255	43,235	135,020
2006	179,920	43,970	135,950
2011	187,665	47,980	139,685
2016	212,840	49,980	162,860

Table 2.9S. Bike share and cycling infrastructure for each census wave, Pooled sample.

Year	Cycling Share (%)	New cycling infrastructure constructed since last census wave (km)	Cumulative Cycling infrastructure (km)
2001	1.1	152.86	152.86
2006	1.3	635.22	788.12
2011	1.4	272.04	1060.161
2016	1.8	202	1262.18

Table 2.10S. Bike share and cycling infrastructure length for each census wave, Vancouver.

Year	Cycling Share (%)	New cycling infrastructure constructed since last census wave (km)	Cumulative Cycling infrastructure (km)
2001	1.9	152.86	152.86
2006	1.7	43.77	196.67
2011	1.9	86.58	283.251
2016	2.5	57.63	340.89

Table 2.11S. Bike share and cycling infrastructure length for each census wave, Toronto.

Year	Cycling Share (%)	New cycling infrastructure constructed since last census wave (km)	Cumulative Cycling infrastructure (km)
2006	1.1	591.45	591.45
2011	1.2	185.46	776.91
2016	1.6	144.37	921.29

Table 2.12S. Table A.8. Average length of cycling infrastructure (km) within O-D pairs in exposure measures 1-5. Measure 1: Total km of cycling infrastructure within the CT of residence and workplace. Measure 2: Total km of cycling infrastructure within 1.6 km buffer[9] around CT of residence and workplace. Measure 3: Total km of cycling infrastructure within 1.6 km of the centroid of both CTs. Measure 4: total km of cycling infrastructure within a 1 km buffer of the shortest O–D route to capture the infrastructure within the immediate vicinity of the shortest commute path. Measure 5: Total length of bike lanes within a 1 km buffer that align with the shortest O-D route.

Exposure Measure 1	**2001**	**2006**	**2011**	**2016**
Pooled sample	1.21	1.03	1.65	2.17
Toronto		0.68	1.08	1.66
Vancouver	1.21	1.9	2.99	3.42
Exposure Measure 2				
Pooled sample	13	14.8	20	25.9
Toronto		13.3	16.9	22.9
Vancouver	13	18.5	27.2	33.4
Exposure Measure 3				
Pooled sample	5.82	6.87	9.53	12.5
Toronto		6.09	7.82	11
Vancouver	5.82	8.82	13.5	16.1
Exposure Measure 4				
Pooled sample	2.98	6.04	7.9	11
Toronto		6.64	8.33	11.9
Vancouver	2.98	4.53	6.92	8.79
Exposure Measure 5				
Pooled sample	1.11	5.17	6.4	9.18
Toronto		6.56	8.08	11.6
Vancouver	1.11	1.71	2.54	3.29

Table 2.13S. Logistic regression model results in log-odds. Model 1-5 present exposure measure 1-5 in Vancouver. Measure 1: Total km of cycling infrastructure within the CT of residence and workplace. Measure 2: Total km of cycling infrastructure within 1.6 km buffer[10] around CT of residence and workplace. Measure 3: Total km of cycling infrastructure within 1.6 km of the centroid of both CTs. Measure 4: total km of cycling infrastructure within a 1 km buffer of the shortest O–D route to capture the infrastructure within the immediate vicinity of the shortest commute path. Measure 5: Total length of bike lanes within a 1 km buffer that align with the shortest O-D route.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	(std.Error)	(std.Error)	(std.Error)	(std.Error)	(std.Error)
Treatment Effect					

[9] This distance follows Krizek et al. (2009).
[10] This distance follows Krizek et al. (2009).

Cumulative Cycling Infrastructure (km)	0.043*** (0.009)	0.010*** (0.001)	0.017*** (0.002)	0.015*** (0.002)	0.027*** (0.007)
Socioeconomics					
Sex (Ref. Category: Female)					
Male	0.913*** (0.038)	0.914*** (0.038)	0.913*** (0.038)	0.914*** (0.038)	0.913*** (0.038)
Education Groups (Ref. Category: No Education)					
High school diploma, no diploma or certificate	-0.025 (0.053)	-0.008 (0.047)	-0.008 (0.047)	-0.025 (0.053)	-0.029 (0.053)
College, trade, non-trade, other degrees	0.127*** (0.038)	0.142*** (0.037)	0.142*** (0.038)	0.128** (0.039)	0.124** (0.039)
University degree(below, above bachelor)	0.364*** (0.053)	0.378*** (0.056)	0.378*** (0.058)	0.366*** (0.054)	0.362*** (0.053)
Medicine, dentistry, veterinary	0.385*** (0.104)	0.399*** (0.107)	0.401*** (0.107)	0.387*** (0.105)	0.384*** (0.105)
Graduate degree	0.821*** (0.080)	0.833*** (0.086)	0.834*** (0.087)	0.823*** (0.081)	0.819*** (0.081)
Age Groups (Ref. Category: 15-35)					
Age 35-60	-0.230*** (0.050)	-0.228*** (0.049)	-0.229*** (0.050)	-0.231*** (0.050)	-0.231*** (0.051)
Age above 60	-0.936*** (0.079)	-0.932*** (0.078)	-0.933*** (0.078)	-0.936*** (0.078)	-0.938*** (0.079)
Distance to workplace (Ref. Category: Below 5km)					
Distance between 5km to 10km	-0.234*** (0.037)	-0.234*** (0.037)	-0.233*** (0.037)	-0.233*** (0.037)	-0.233*** (0.038)
Distance between 10km to 20km	-0.540*** (0.113)	-0.540*** (0.114)	-0.539*** (0.114)	-0.540*** (0.112)	-0.540*** (0.113)
Distance above 20m	-1.056** (0.344)	-1.052** (0.341)	-1.053** (0.340)	-1.055** (0.340)	-1.056** (0.341)

Income (Ref. Category: Below median income)					
Above median income	0.120*** (0.032)	0.117*** (0.032)	0.119*** (0.032)	0.120*** (0.032)	0.121*** (0.031)
Mobility Status (Ref. Category: Same dwelling address)					
Same CSD, different dwelling	0.172** (0.055)	0.173** (0.056)	0.173** (0.055)	0.172** (0.055)	0.173** (0.055)
Different CSD in Canada	0.262** (0.096)	0.263** (0.096)	0.263** (0.096)	0.263** (0.096)	0.264** (0.096)
Outside Canada	0.212*** (0.039)	0.212*** (0.038)	0.211*** (0.039)	0.214*** (0.039)	0.214*** (0.039)
R2	0.182	0.182	0.182	0.182	0.182
R2 Adj.	0.158	0.159	0.159	0.158	0.158
Std.Errors	Origin-Destination and Year				
Fixed Effects	Origin-Destination and Year				
The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively					

Table 2.14S. Logistic regression model results in log-odds. Model 1-5 present exposure measure 1-5 in Toronto. Measure 1: Total km of cycling infrastructure within the CT of residence and workplace. Measure 2: Total km of cycling infrastructure within 1.6 km buffer[11] around CT of residence and workplace. Measure 3: Total km of cycling infrastructure within 1.6 km of the centroid of both CTs. Measure 4: total km of cycling infrastructure within a 1 km buffer of the shortest O–D route to capture the infrastructure within the immediate vicinity of the shortest commute path. Measure 5: Total length of bike lanes within a 1 km buffer that align with the shortest O-D route.

	Model 1	Model 2	Model 3	Model 4	Model 5
	(std.Error)	(std.Error)	(std.Error)	(std.Error)	(std.Error)
Treatment Effect					
Cumulative Cycling Infrastructure (km)	0.016 (0.012)	0.014*** (0.003)	0.018*** (0.005)	0.019*** (0.004)	0.016*** (0.004)
Socioeconomics					
Sex (Ref. Category: Female)					
Male	0.984***	0.984***	0.984***	0.984***	0.983***

[11] This distance follows Krizek et al. (2009).

	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Education Groups (Ref. Category: No Education)					
High school diploma, no diploma or certificate	-0.288*** (0.044)	-0.253*** (0.042)	-0.259*** (0.041)	-0.264*** (0.043)	-0.269*** (0.042)
College, trade, non-trade, other degrees	-0.404*** (0.038)	-0.373*** (0.041)	-0.378*** (0.040)	-0.382*** (0.041)	-0.387*** (0.039)
University degree (below, above bachelor)	-0.142*** (0.037)	-0.112* (0.046)	-0.117** (0.044)	-0.121** (0.043)	-0.125** (0.042)
Medicine, dentistry, veterinary	-0.056 (0.097)	-0.027 (0.104)	-0.031 (0.102)	-0.035 (0.102)	-0.039 (0.101)
Graduate degree	0.146* (0.066)	0.175* (0.078)	0.169* (0.076)	0.166* (0.074)	0.162* (0.073)
Age Groups (Ref. Category: 15-35)					
Age 35-60	-0.244*** (0.030)	-0.243*** (0.031)	-0.243*** (0.031)	-0.244*** (0.030)	-0.244*** (0.031)
Age above 60	-0.992*** (0.048)	-0.988*** (0.048)	-0.987*** (0.049)	-0.989*** (0.048)	-0.989*** (0.048)
Distance to workplace (Ref. Category: Below 5km)					
Distance 5km to 10km	-0.419*** (0.090)	-0.421*** (0.091)	-0.420*** (0.091)	-0.420*** (0.090)	-0.420*** (0.090)
Distance 10km to 20km	-0.636* (0.264)	-0.639* (0.263)	-0.638* (0.263)	-0.635* (0.265)	-0.635* (0.264)
Distance 20km	-1.332+ (0.689)	-1.337+ (0.683)	-1.337+ (0.687)	-1.333+ (0.686)	-1.333+ (0.687)
Income (Ref. Category: Below median income)					
Above Median Income	-0.123* (0.051)	-0.127* (0.053)	-0.126* (0.053)	-0.125* (0.052)	-0.125* (0.052)

Mobility Status (Ref. Category: Same dwelling address)					
Same CSD, different dwelling	0.106* (0.049)	0.105* (0.049)	0.105* (0.049)	0.106* (0.049)	0.106* (0.049)
Different CSD in Canada	0.056 (0.065)	0.052 (0.063)	0.053 (0.063)	0.054 (0.064)	0.055 (0.064)
Outside Canada	0.014 (0.058)	0.012 (0.057)	0.012 (0.057)	0.013 (0.057)	0.014 (0.058)
Num.Obs.	322775	322775	322775	322775	322775
R2	0.236	0.236	0.236	0.236	0.236
R2 Adj.	0.207	0.207	0.207	0.207	0.207
Std.Errors	Origin-Destination and Year				
Fixed Effects	Origin-Destination and Year				
The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively					

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Chapter 3

Does Cycling Infrastructure Improve Urban Traffic Safety? Evidence from a Quasi-Experimental Design

Fatima Ravazdezh

Abstract

This paper examines the causal impact of cycling infrastructure on the safety of cyclists and all road users using a quasi-experimental research design. Drawing on longitudinal spatial data on cycling infrastructure and collisions for four major Canadian cities of Toronto, Ottawa, Vancouver, and Victoria, that differ in climate, demographics, cycling culture, traffic safety, and policy investments, we assess how changes in cycling infrastructure relate to cyclist-involved and all-user collisions. To investigate the safety effects of specific infrastructure types, we evaluate facilities with different levels of physical separation from traffic, providing evidence on whether fully separated or traffic-integrated designs are more effective at reducing harmful interactions between cyclists and motor vehicles. Our results indicate that, in a pooled sample of Ottawa and Toronto, a 1 km increase in cycling infrastructure is associated with a 2.43% and 5.34% increase in fatal and injury collisions for all road users and cyclists, respectively. In contrast, in a pooled sample of Vancouver and Victoria, a 1 km increase in cycling infrastructure is associated with an 8.76% reduction in fatal and injury collisions for all road users, while no statistically significant relationship is observed for cyclist-involved collisions. Infrastructure that provides higher physical separation from traffic is associated with increased casualty collisions for cyclists and all road users in Toronto and Ottawa, whereas it reduces all-user collisions in Vancouver and Victoria by 12.3%. Overall, the mixed findings across the four cities suggest that the safety effects of cycling infrastructure are highly context-dependent, reflecting differences in roadway and network design, environmental conditions, and cycling patterns. This underscores the importance of designing cycling infrastructure to fit a city's specific network and risk context, rather than focusing solely on expanding lane kilometres.

Keywords: Cycling infrastructure, Cyclists safety, All road users' safety, Quasi-experimental evaluation

1.Introduction

Cycling has gained increasing attention from policymakers as a sustainable alternative to motorized transport, particularly for substituting short-distance trips. Governments, cities, and communities increasingly encourage citizens to cycle (Wegman et al., 2012). Cycling offers several health benefits, including improved physical health (McCormack et al., 2004) and enhanced psychological well-being, such as reductions in depressive symptoms (Cooney et al., 2013). While individual cyclists benefit directly from increased physical activity (Oja et al., 2011), the broader public also benefits from fewer car journeys through reduced emissions (Lindsay et al., 2011), decreased traffic congestion (McClintock, 2002), and support for local economies (Arancibia et al., 2019). Cycling is also a relatively inexpensive mode of transport and may therefore be more accessible to socially disadvantaged populations who are less likely to have access to a car (Mulvaney et al., 2015).

Safety is one of the key determinants of cycling uptake. Improving safety is essential for enabling a shift from motorized transportation to active transportation (Prati et al., 2018). Cyclists' collisions can result in severe injuries (Rivara et al., 1997; Sikic et al., 2009; Cripton et al., 2015), and the fear of being involved in a crash also discourages both current and potential cyclists from riding (Bauman et al., 2008;

Kingham et al., 2011). Most governments have therefore prioritized improving cycling safety to reduce the substantial health burden associated with bicycle crashes (Schepers et al., 2017) and to encourage more people to adopt cycling as a mode of transport (Fishman et al., 2012; Horton et al., 2016).

Cycling infrastructure has been implemented worldwide to promote bicycle use (Rietveld and Daniel, 2004; Winters et al., 2010) and to reduce collision and injury risk (Reynolds et al., 2009). The literature provides considerable evidence of a positive correlation between the provision of cycling infrastructure and higher cycling rates (Dill & Carr, 2003; Evenson et al., 2005; Larsen and El-Geneidy, 2011; Buehler & Pucher, 2012; Mitra et al., 2017; Cervero et al., 2019). However, it is essential to ensure that the increased cycling levels do not come at the cost of higher numbers of injuries and fatalities (Thompson et al., 2017).

In European countries with higher cycling shares, a stronger perception of safety toward cycling is associated with the availability of better cycling infrastructure (Teschke et al., 2012). Many northern European cities have extensive systems of separated bikeways, both on-road and off-road (Pucher and Buehler, 2008; Lanzendorf et al., 2014), which facilitate safe and convenient cycling (Buehler and Pucher, 2017). However, the effects of cycling infrastructure on cyclist safety continue to generate debate (Phillips et al., 2011). In North American (NA) cities, cycling infrastructure has a more recent history compared to European contexts, and the broader transition toward safe cycling lags behind. Recent evaluations in North America report inconsistent safety outcomes: some studies find that cycling infrastructure is associated with reductions in cyclist crashes or injuries (Teschke et al., 2012; Bhatia et al., 2016; Wall et al., 2016), while others report no change or even increases in collisions (Chen et al., 2012; Wei and Lovegrove, 2013; Raihan et al., 2019). Despite the mixed evidence on safety, the implementation of cycling infrastructure has expanded rapidly in North American cities (Tremblay-Racicot et al., 2023). These contrasting findings highlight the need for a comprehensive evaluation of the overall safety effects of cycling infrastructure (Götschi et al., 2018).

Moreover, most existing studies focus solely on cyclist safety, even though it is conceivable that safety mechanisms provided by cycling infrastructure may also influence the overall safety of other road users (Marshall and Garrick, 2011). Considering the importance of road space allocation, budget constraints, and the need for effective policies to address broader transportation challenges, evidence on whether cycling infrastructure enhances the safety of all road users is essential. Such evidence can strengthen the case for cycling infrastructure as a competitive, publicly acceptable policy instrument for improving transportation system performance.

In this paper, we investigate the effectiveness of cycling infrastructure in improving safety for cyclists as well as for all road users. With application of a quasi-experimental design, we use longitudinal spatial data on cycling infrastructure and collisions at the census tract level for four Canadian cities of Ottawa and Toronto (from 2013 to 2024), and Vancouver and Victoria (from 2020 to 2024), which differ in cycling levels, cycling policies, cycling culture, road network characteristics, demographic characteristics, and climate conditions. We adopt a Difference-in-Differences (DiD) approach to control for unobserved time-constant and time-varying factors that affect cyclists and all road users-involved collisions during the study period. Different types of cycling infrastructure provide varying levels of safety and comfort (Winters et al., 2022), yet studies that evaluate the safety effects of all infrastructure types across an entire road network remain limited (Götschi et al., 2018), and debates continue regarding the safety of various infrastructure types (Teschke et al., 2012). To address this gap, we further investigate the safety effects provided by all cycling infrastructure types within the networks of the selected cities.

The remainder of this paper proceeds as follows: Section 2 provides a theory background on the traffic safety and reviews the relevant literature; Section 3 outlines the data and methodology; Section 4 presents the results; and Section 5 forms the discussion, limitations, and the conclusion.

2.Background and Literature Review

2.1. Theory Background

The World Health Organization (WHO) has identified traffic injuries and fatalities as among the world's five most important causes of unnatural death, with predictions that they will become the leading cause by 2030 (World Health Organization, 2019). Improved traffic safety for road users and specially pedestrians and cyclists is an important goal of public health policies in countries throughout the world (International Transport Forum, 2016). According to the Vision Zero proposed by Cushing et al., (2016), traffic fatalities and injuries can and should be reduced far below current levels and should not be accepted as an inevitable component of travel. Enhancing safety is also essential for encouraging a shift from motorized transportation to cycling and for enabling more people to choose this mode without facing elevated risks (Prati et al., 2018).

To reduce traffic and cyclists' safety risks, we must understand the determinants of traffic safety (Teschke et al., 2012). Road users' behavior, vehicle type, and road infrastructure form the three pillars of road safety (Schepers et al., 2017). Socio-demographic characteristics (Park et al., 2015), traffic safety education (Pucher and Buehler, 2016), speed choice (Schepers et al., 2017), errors, violations, and substance use (Prati et al., 2018) are factors that shape road users' behavior and contribute to traffic safety outcomes. Experience is another important component of user behavior; being an experienced cyclist influences crash risk both when cycling and when driving (Schepers et al., 2017). The vehicle category encompasses the characteristics of the vehicle itself and the potential malfunctions, failures, or inadequacies of its equipment (Prati et al., 2018). With respect to vehicle type, cyclists are classified as vulnerable road users (VRU). A defining criterion for VRUs is the lack of external protection (Kemp and Productions, 2009). Cyclists cannot protect themselves from the speed and mass of other road users in a crash (Torfs and Meesmann, 2019) and therefore suffer the most severe consequences in collisions (Van Kampen, 2000). While extensive research has examined the relationship between road user behavior, vehicle type, and traffic safety (Prati et al., 2018), policy instruments that target changes in road infrastructure, the third pillar, are considered more promising for two reasons. Infrastructure interventions are population-based and can reach large numbers of users (Reynolds et al., 2009), and once implemented, changes to the built environment generally require little to no reinforcement over time (Reynolds et al., 2009).

Investigation of the safety effects of cycling infrastructure, as one of the main road-infrastructure tools used by governments to shift travel from motorized modes to cycling, is the central focus of this study. Provision of cycling infrastructure influences travel safety through two interconnected mechanisms: traffic separation and travel behavior. Cycling infrastructure separates cyclists from other modes in space or time (Wegman et al., 2012), and the basic mechanism through which it operates is the reduction of opportunities for interactions between cyclists and motor traffic (Thompson et al., 2017). In this regard, different infrastructure types provide varying levels of safety and comfort depending on the degree of physical separation they offer. Cycle tracks, bike paths, and multi-use trails provide higher levels of separation from traffic, whereas painted bike lanes and local streets offer lighter separation and greater integration between cyclists and motor vehicles.

In the second mechanism, cycling infrastructure affects traffic safety by influencing travel behavior and cycling uptake, as these facilities attract more cyclists (DiGioia et al., 2017). An increase in the number of cyclists leads to the concept known as "safety in numbers" (SiN). The main idea of SiN is that individual cyclist risk is not constant; rather, the likelihood of injury appears to decline as the number of cyclists increases. In other words, cyclists may experience greater safety when more people are cycling (Marshall and Garrick, 2011). According to this explanation, drivers adjust their expectations based on the perceived probability of encountering a cyclist. When cyclist volumes increase to the point where drivers anticipate frequent interactions, drivers' awareness and behavior may improve (Marshall and Garrick, 2011). The effect of SiN in reducing cyclist injury risk has been widely examined (Ekman, 1996; Jensen, 2002; Jacobsen, 2003; Jacobsen et al., 2015; Nordback and Marshall, 2010; Nordback et al., 2014). However, there is no evidence that lower risk can be attributed to cyclist numbers alone. Studies indicate that SiN effects are closely linked with the expansion of cycling infrastructure. While SiN is often discussed as a function of cycling infrastructure, the relationship between the two is complex. Increases in cycling volumes may arise because new infrastructure attracts more cyclists, but it is also possible that higher numbers of cyclists motivate further investment in cycling facilities and safer cycling conditions in turn. Untangling these shared pathways is beyond the scope of this study. Our goal is not to identify whether the safety benefits of cycling infrastructure arise from traffic separation, from SiN, or from their interaction. Instead, we focus on estimating the overall effect of cycling infrastructure on traffic safety, acknowledging that both mechanisms may operate simultaneously and may have synergistic effect.

Cycling infrastructure can affect travel safety through other mechanisms as well. First, vehicle speed is strongly associated with both the risk and severity of collisions (Rosenfield et al., 2024). The implementation of cycling infrastructure can influence safety by narrowing vehicle lane widths and reducing traffic speeds (Macbeth, 1999; Allen-Munley et al., 2004). Second, with respect to the SiN mechanism, it is also possible that higher numbers of cyclists' function as a form of traffic calming, lowering vehicle speeds and reducing safety risks (Marshall and Ferenchak, 2019). Third, increased cyclist volumes may enhance driver awareness. While SiN primarily focuses on changes in driver expectations toward cyclists, greater overall awareness may also improve safety outcomes for other road users (Marshall and Ferenchak, 2019).

2.2. Literature

While there are literature reviews on the relationship between cycling infrastructure and cycling safety (Reynolds et al., 2009; Thomas & DeRobertis, 2013; Mulvaney et al., 2015; DiGioia et al., 2017; Prati et al., 2018), the findings remain inconsistent in the North American context. Evidence from North American cities shows that studies examining cycle tracks, bike paths, multi-use trails, and painted bike lanes report conflicting results regarding whether these facilities improve or worsen safety outcomes (DiGioia et al., 2017). Some studies find reduced cyclist injury risk on streets treated with cycle tracks (Lusk et al., 2011; Teschke et al., 2012), physically protected bike paths (Wall et al., 2016), and off-street bike paths (Teschke et al., 2012). Multi-use trails appear to be associated with higher cyclist crash rates, possibly due to limited space shared with other trail users (Aultman-Hall and Kaltenecker, 1999), although other studies report no statistically significant relationship (Wilson, 2010; Teschke et al., 2012). Studies of on-road bike lanes with lighter separation from traffic also show mixed outcomes. Some studies report lower safety risks following the implementation of painted bike lanes (Chen et al., 2012; Teschke et al., 2012; Park et al., 2015; Pulugurtha and Thakur, 2015; Kondo et al., 2018), while others find increased risk (Wei and Lovegrove, 2013;Chen et al., 2013; Cicchino et al., 2020) or no statistically significant relationship (Helak et al., 2013; Bhatia et al., 2016)

Findings from North American cities are inconsistent, and much of this variation stems from differences in research design, sample size, control variables, and exposure measures (DiGioia et al., 2017). Another major limitation is the lack of spatially and temporally comprehensive cyclist collision data. Most studies rely on police-reported collision records, which substantially underrepresent true collision counts. Crashes involving cyclists tend to have low reporting rates compared with other transport modes (Bhatia et al., 2016; Prati et al., 2018), and even collisions that result in serious injury are often not reported to police. Hospital admission data are sometimes used to complement police records, but medical data often lack detailed information on collision circumstances, location, and contributing factors (Prati et al., 2018). Additionally, there is no consistent definition of what constitutes a collision across cities or over time (Derriks and Mak, 2007). These data limitations imply that study findings may differ solely because of the underlying data quality, further contributing to the inconsistency of results in the literature.

In the literature, fewer studies investigate the safety effects of cycling infrastructure for all road users (Marshal and Garrick, 2011; Wegman et al., 2012). Focusing on cities with high cycling shares, Marshal and Garrick (2011), Marshal and Ferenchak (2019), Ferenchak and Marshall (2024) show that these cities tend to experience better overall road safety and identify several contributors to these outcomes. Their results suggest that while SiN plays an important role in high-cycling cities, improved road safety is also associated with a greater prevalence of cycling infrastructure, particularly protected and separated facilities. Despite these findings, scholars emphasize the need for more evidence on how cycling infrastructure affects the safety of all road users (Park et al., 2015; Pulugurtha and Thakur, 2015). Suggesting this gap, Pulugurtha and Thakur (2015) highlight possible negative effects of bike lanes on overall road safety when road space is insufficient. They argue that motorists may encroach or shift toward the adjacent lane to maintain distance from cyclists, which, together with increased driver attention toward cyclists, can elevate the risk of collisions with vehicles to their left. Similarly, Liu et al. (1995) suggest that roads with insufficient capacity may experience higher collision risks because they cannot adequately accommodate both bicycles and motor vehicles during peak travel times.

2.3. Objective

Overall, the literature highlights three key gaps. First, findings on the safety effects of cycling infrastructure in the North American context remain inconsistent, particularly across different facility types. Second, most studies focus on cyclist safety alone, providing limited evidence on how cycling infrastructure affects the safety of all road users. Third, existing research rarely evaluates cycling networks across multiple cities, even though safety impacts may differ by infrastructure design, road network characteristics, and local context. Building on this evidence, our study contributes in several ways. To address the inconsistent findings in the North American context, we estimate the effects of cycling infrastructure on cyclist safety and on the safety of all road users using a difference in differences design with longitudinal spatial data on cycling infrastructure and collisions, allowing us to isolate the potential causal relationships involved. To account for under-representation of collisions in the data we use two definitions of traffic safety outcomes. One measure includes only casualty collisions (fatal and injury collisions), which are more consistently reported and linked to hospital admission data. The second measure includes both casualty and property-damage-only collisions, reflecting overall traffic safety. Secondly, to examine whether safety effects vary by the level of physical separation from traffic, we analyze two categories of cycling infrastructure: facilities with higher separation (cycle tracks, bike paths, multi-use trails) and facilities with lighter separation and more integration with traffic (painted bike lanes and local streets). Lastly, using a large sample of four Canadian cities, we provide insight into how safety effects may vary across contexts and how the heterogeneity of effects may be attributable to city-specific roadway, demographic, and environmental characteristics.

3.Methods and Materials

We aim to estimate the impact of cycling infrastructure on traffic safety of cyclists and other road users using a longitudinal research design.

3.1. City Selection

While we aimed to explore the safety outcomes of cycling infrastructure in as many Canadian cities as possible, data availability was a key criterion. The selection of cities was determined by the availability of longitudinal spatial data on both cycling infrastructure and safety outcomes, which narrowed our study to Vancouver and Victoria in British Columbia (BC) and Ottawa and Toronto in Ontario (ON).

3.2. Data

3.2.1. Cycling Infrastructure

The selected cities provide publicly accessible longitudinal spatial data on cycling infrastructure through open data portals maintained by their respective municipal governments. These datasets include detailed information on the location, type, and year of construction of cycling infrastructure, enabling multi-year spatial analysis of infrastructure development. Each city features a diverse cycling network. While a common nomenclature for cycling infrastructure is needed for traffic safety surveillance efforts (Winters et al., 2022), cycling infrastructure data obtained from Canadian municipalities does not have a standard naming convention. Drawing on transportation engineering design guides and public health guidance, Winters et al (2022) developed the Canadian Bikeway Comfort and Safety (Can-BICS), which groups cycling infrastructure into five types (Cycle Tracks, Bike Paths, Local Streets, Multi-Use Trails, and Painted Bike Lanes) based on safety performance and user comfort. Following this categorization, we classified each infrastructure segment in our data so that its naming corresponds to one of the five Can-BIC types (e.g., path categorized as Bike Path, segregated bike lane categorized as Cycle Track). Some cycling infrastructure in the municipal datasets of each city was excluded from the analysis because they are considered as nonconforming bikeways, as they do not meet safety and comfort criteria or conform to design guidance standards (Winters et al., 2022) (e.g., sharrows, suggested routes). Fig. 3.30-33 illustrate the cycling network for each city and the cities' census subdivisions (CSD) boundaries.

3.2.2. Traffic Safety

Traffic safety data, the main dependent variable of this study, consists of cyclists-involved and all road users-involved collision data. For Toronto and Ottawa, the data is provided through the City of Toronto (2014-2024)[12] and City of Ottawa (2013-2022)[13] open data portals, respectively. These datasets include police-reported, geocoded collisions, with information on occurrence date, severity level, weather conditions, individuals' age, and other location and cause-related details (Toronto Open Data, 2025). Collisions are categorized as property damage only (PDO) collisions (collisions resulting in material damage with no injury or fatality) or as injury collisions and fatalities. In both cities, fatal collisions refer to cases in which an individual dies within 30 days of injuries sustained in a collision and exclude occurrences where the individual dies more than 30 days after the incident. Injury collisions include cases in which an individual was either treated in the emergency room or admitted to the hospital.

For Vancouver and Victoria, collision data was sourced from the Insurance Corporation of British Columbia (ICBC) (2020-2024), the provincial insurance provider that supplies mandatory coverage to all motor vehicles in BC (Boss et al., 2018). ICBC crash data is compiled from reports made to ICBC by insured registered vehicle owners, drivers, pedestrians, and cyclists. The dataset is available for casualty collisions (including fatal and injury collisions) and PDO collisions. A separate dataset exists for collisions involving cyclists, although this dataset does not distinguish between casualty and PDO collisions. In the ICBC data, collision locations are reported as street addresses or intersections. All data was geocoded using the longitude and latitude fields associated with each collision event.

ICBC crash data includes more collisions than police collision data, for two main reasons. First, basic insurance coverage through ICBC is mandatory, which increases the likelihood that crash occurrences are reported. Second, police do not attend all collisions; typically, they respond only to more serious incidents involving injury or fatality. In addition, the number of reports submitted directly to police is low because reporting crashes to police is not mandatory. Since the sources of collision data differ between Vancouver and Victoria in BC and Ottawa and Toronto in ON, we decided not to pool all four cities together. Instead, we construct two separate pooled samples to conduct the analysis: one combining Vancouver and Victoria (the BC pooled sample) and one combining Ottawa and Toronto (the ON pooled sample).

3.2.3. Spatial Unit of Analysis

Cycling infrastructure and collision data were mapped to the cities' CSD and Census Tract (CT) boundaries provided by Statistics Canada. Total collisions were summed annually at the CT level, and the total cycling infrastructure built in each year, as well as the cumulative length, was measured annually in kilometers for each CT. CTs are small, relatively stable geographic units that typically contain between 2,500 and 8,000 residents (Statistics Canada, 2016), although CTs in central business districts, major commercial or industrial zones, or peripheral areas may fall outside this range (Statistics Canada, 2018). Traffic safety analyses can be conducted at multiple spatial scales, including road segments, census blocks, traffic analysis zones, or larger regional units (Winters et al., 2022). Because collisions are spatially correlated, the roadway environment, traffic volumes, and socio-demographic characteristics of the area in

[12] https://open.toronto.ca/dataset/police-annual-statistical-report-traffic-collisions/
[13] https://open.ottawa.ca/search?q=collision

which collisions occur influence collision patterns. We conduct the analysis at the CT level because CTs offer a harmonized spatial unit that captures both the roadway and travel context and the socio-demographic characteristics that shape traffic safety. CTs are designed to be relatively homogeneous in population and socio-economic conditions (Statistics Canada, 2016), which helps reduce within-unit variation in factors that may affect collision patterns. For these reasons, the CT level provides an appropriate and comparable spatial scale for evaluating the safety effects of cycling infrastructure.

Although changes to CT boundaries are generally discouraged to maintain comparability across census waves, Statistics Canada periodically revises CT boundaries to reflect population growth and redistribution. To ensure consistent spatial units over time, we harmonized all CT boundaries to the 2001 CT definitions using the concordance tables developed by Allen and Taylor (2018). We selected the 2001 boundaries to obtain the most aggregated configuration of CTs, reducing the likelihood of small-area splits or reconfigurations that complicate longitudinal analysis. In this study, the concordance is used solely to impose a consistent set of physical CT boundaries over time; we do not apply any apportionment or weighting to reallocate collision counts or cycling infrastructure variables across tracts. Using the most aggregated boundary system therefore minimizes inconsistencies in CT definitions across years and reduces the potential for boundary-related misclassification of collision locations, an issue discussed further in Section 3.2.3.2.

3.2.3.1. Exposure

When working with collision count data, larger or smaller counts may be observed simply because of the size differences of observational units (Parry, 2018). CTs vary in area, population size, and travel activity, and larger units with more people or higher travel volumes tend to experience more collisions even if they are not inherently less safe. This motivates the use of an exposure variable in traffic safety analysis. Exposure represents the amount of opportunity for a collision to occur and depends on the size and activity level of the unit of analysis (Parry, 2018; Ferenchak and Marshall, 2024). The exposure variable allows us to roll out collisions' differences driven by the size of the spatial unit. Exposure can be measured using population-based or travel-based indicators. Population-based exposure measures, such as the number of residents in a spatial unit, capture the number of people who may interact with the road network and therefore the potential for collision occurrence. Travel-based exposure measures include the number of trips, vehicle-kilometers travelled, hours of travel, or the number of roadway crossings (DiGioia et al., 2017; Ferenchak and Marshall, 2024). These measures represent the amount of movement taking place in an area and thus the extent of opportunities for collisions to occur (McAndrews et al., 2013; Ferenchak and Marshall, 2020).

There is no consistent longitudinal and spatial travel-based exposure measure across the chosen cities and over the years hence, we use the total number of commuters at CT level over the years using the Journey to work question in the Canadian Census of Population (waves 2006, 2016, and 2021) and National household survey (wave 2011). Total number of commuters serves as a rough estimate of the number of people traveling in each CT and to gain a better understanding of how safe it is to travel. Jacobsen (2003), Marshal and Ferenchak (2019), and Ferenchak and Marshall (2024) have also used this exposure measure. Jacobsen suggests that even though journey to work trips represent a small percentage of total trips, the percentage of each mode for commuters is proportional to the percentage for all trips. In this method, total number of commuters of a CT in each year is shared by the roads and infrastructure of that unit.

For the longitudinal analysis, total commuters were estimated annually at the CT level. Because Census data are available only every five years, we interpolated commuter counts for the years between census waves using a linear least squares regression in RStudio. For years after the 2021 Census wave (2022-2024), we extended the same linear trend to produce extrapolated values of total commuters at CT level. This variable applies to the working population aged 15 and above in private households who worked for pay or were self-employed during the reference week (typically in early May of the census year). For those not working during that week but employed at any time since January 1 of the same year, responses reflect the job held longest during that period. Individuals who reported "working from home," "working outside Canada," or having "no fixed workplace address" (e.g., mobile workers like truck drivers) are excluded from the commuting population in our analysis. We exclude respondents whose workplace is located in a different Census Metropolitan Area (CMA) than their residence. Our sample is restricted to working individuals who reside and work within the chosen cities CSD boundaries.

3.2.3.2. Boundary Crashes

As CT boundaries are often defined by roadways, where collisions commonly occur, boundary collisions can represent a substantial share of total collisions (Siddiqui and Abdel-Aty, 2012; Wang et al., 2012; Lee et al., 2014). However, identifying boundary collisions in practice is challenging. CT boundary lines and the mapped road network do not always align precisely, meaning that a collision occurring along a boundary road may not fall exactly on the mapped border (Cui et al., 2015). In such cases, the collision is often arbitrarily assigned to one of the adjacent CTs. Additionally, roads vary in width, and mapping procedures may place a collision point slightly to one side of the roadway, resulting in an arbitrary assignment to either CT that shares the road as the boundary (Cui et al., 2015). This arbitrary allocation is problematic because crashes are spatially correlated (Huang and Abdel-Aty, 2010), and collisions occurring near boundaries may be jointly influenced by the characteristics of neighboring spatial units (Zhia et al., 2018). In other words, boundary collisions may exhibit inter-unit effects, and failing to account for these influences may lead to biased estimates of safety outcomes. Studies using census blocks, census tracts, or traffic analysis zones have proposed several approaches to address this issue (Ziakopoulos and Yannis, 2020). One commonly used solution is to identify boundary collisions by creating a buffer around CT boundaries and separating collisions into boundary and interior groups, where interior collisions are assumed to be influenced only by characteristics of the CT in which they occur (Siddiqui and Abdel-Aty, 2012).

In our analysis, no collisions fell exactly on CT boundaries after mapping. However, mapping discrepancies may still cause boundary collisions to be arbitrarily assigned to one CT or another. To assess whether this issue biases our results, we create 5-meter buffers[14] around CT boundaries to identify collisions that occur sufficiently within the interior of each CT. We then re-estimate our models using only these interior collisions as a sensitivity test. If the estimates based on interior collisions are consistent with the main results, this indicates that our findings are not driven by boundary-related misallocation or by inter-unit influences on collisions near CT borders.

[14] 5-meter buffer length was chosen following the work of Cui et al. (2015).

3.2.3.3. Boundary Cycling Infrastructure

Infrastructure data were linked to CTs using spatial intersection in R, assigning each cycling facility segment to the CT polygon that it geometrically intersects. For cycling infrastructure that lies along CT borders, segments are assigned arbitrarily to one of the adjoining CTs, introducing a spatial misclassification. Boundary segments that plausibly serve both neighboring CTs are counted only in one. This misclassification is non-systematic, as the direction of assignment (to one CT or the other) is driven by minor geometric offsets between the road and CT boundary layers rather than by collision patterns or other outcome-related factors. Moreover, since boundary infrastructure run along roads shared by two neighboring CTs, residents of both tracts have access to these segments. As a result, even when a boundary facility is assigned entirely to one CT in the data mapping process, the true difference in cycling infrastructure exposure between the two CTs is small, and any resulting measurement error is unlikely to bias our estimates.

3.3. Research Design

We aim to identify the impact of cycling infrastructure on traffic collisions. Different factors can affect both traffic collisions and cycling infrastructure construction and expansion at CT level. These include land use and roadway characteristics, baseline traffic conditions such as existing safety levels and traffic or cycling volumes, and demographic characteristics. For instance, CTs with lower-income or minority populations are often underserved by cycling infrastructure, and residents may be less able to afford high-quality vehicles or bicycles (Lee et al., 2014, Park et al., 2015). In addition, unobserved factors such as local economic changes may affect both the development of cycling infrastructure and traffic safety (for instance, through changes in mode choice).

We seek to make our evaluation more robust to confounding variables by applying a difference-in-differences approach to evaluate the effect of cycling infrastructure investments on traffic safety. The DiD method combines insights from cross-sectional treatment-control comparisons and before-after studies for a more robust identification of the effects (Huntington-Klein, 2021). The DiD estimate of an intervention's impact is equivalent to calculating the before-after difference in outcomes in the treatment group (which receives new cycling infrastructure) and subtracting from this difference the before-after difference in the control group (which receives no cycling infrastructure upgrades) (Huntington-Klein, 2021). In our case, this approach amounts to comparing the difference in collisions before and after a cycling infrastructure upgrade to the difference in collisions in other CTs which did not receive infrastructure upgrades over the study period. This design provides insight into the potential causal factors underlying changes in transportation safety outcomes of cycling infrastructure.

In many practical DiD applications the treatment is not a binary variable but has a dose or operates with varying intensity. In this study, we observe total collisions that follow the gradual increases to an already-existing cycling network. Hence, we assess the effect using a DiD-style estimator that accounts for continuous treatment effects.

3.4. Statistical Methods

Given that our dependent variable is count-based collision data, a linear regression model may not be appropriate because of the requirement that the dependent response variable be normally distributed

(Scott Long, 1997). Researchers apply generalized linear models (GLM) when analyzing collision data because they can account for a non-normal distribution using a link function that relates the linear portion of the model to the mean of the dependent variable. Link functions allow the response variable to relate to the explanatory variables in a nonlinear way (Scott Long, 1997). Since our dependent variable is count data, we use a Poisson distribution (which is a discrete probability distribution intended to measure the rate of occurrence of some event).

We estimate a two-way fixed effect Poisson model. $\text{Total\_Collisions}_{it}$ denotes the number of collisions occurring in CT (i) in year (t):

$$\log(\text{Total\_Collisions}_{it}) = \beta_0 + \beta_1 \text{Cycling\_Facility}_{it} + \beta_2 \log(\text{Exposure}_{it}) + \theta_i + \delta_t \qquad (1)$$

Where $\text{Cycling\_Facility}_{it}$ represents the length of new cycling infrastructure (km) in CT (i) and year (t). The coefficient (β_1) is the exponentiated coefficient of the predictor variable and estimates how much the expected collision counts changes for a one unit increase in the predictor variable (Parry, 2018). θ_i captures time-invariant CT fixed effects which include pre-existing cycling infrastructure, baseline traffic volume, underlying cycling and traffic safety, network characteristics, and CT demographics. These fixed effects allow to isolate the effect of cycling infrastructure construction and expansion on changes in collisions by netting out baseline differences across CTs. δ_t captures year fixed effects that are common to all census tracts. These fixed effects absorb any temporal shocks that affect all CTs uniformly, including economic conditions, changes in public attitudes toward traffic and cycling safety, and government investments in cycling promotion or safety initiatives. We account for exposure (Exposure_{it}) in our model with total number of commuters in CT (i) and year (t) rather than the number of cycling commuters. Conceptually, cycling infrastructure influences both collision risk and the number of cyclists by making cycling more attractive and safer. Using the number of cyclists as an exposure variable would therefore condition on an outcome that is itself affected by the treatment (cycling infrastructure). In causal terms, this creates a bad control, because it blocks part of the causal pathway from infrastructure to safety and can induce bias in the estimated effects (Angrist and Pischke, 2009). By using total commuters instead, we avoid conditioning on a post-treatment variable and maintain an exposure measure that is determined primarily by broader travel demand and population, rather than by the infrastructure changes that are the focus of our analysis.

One potential threat to the internal validity of our estimates is reverse causality, the possibility that cycling infrastructure is more likely to be constructed in CTs that already experience higher levels of collisions. CT fixed effects address this concern to the extent that CTs with higher baseline collisions differ from CTs with lower baseline collisions in ways that are time-invariant, while year fixed effects absorb temporal shocks. However, the model cannot fully rule out dynamic policy responses where recent (e.g., previous year) spikes in collisions lead to subsequent infrastructure investment.

The identification strategy in DiD framework which compares CTs with varying levels of cycling infrastructure over the years relies on the parallel trend assumption. According to Callaway et al. (2024), the definition of parallel trend assumption for continuous DiD (where units receive different dose or intensity of treatment) implies that the outcome trajectories of CTs receiving lower doses of cycling infrastructure must represent a valid counterfactual for how higher-dose CTs would have evolved in the absence of additional treatment. In other words, differences in total collisions across CTs can be attributed to differences in infrastructure only if, in the absence of treatment, their trends would have followed similar paths. A potential challenge to the parallel trends assumption in our study is the presence of other policies or interventions, independent of cycling infrastructure, that may influence collisions. Such interventions are plausible (e.g. construction of a traffic calming measure) and could complicate causal attribution. However, as long as these factors do not differentially affect CTs over time in a way that is correlated with cycling infrastructure investments, their influence will be absorbed by the time fixed effects in our model. Assessing this assumption is challenging in the present setting where treatment is not binary. Cycling infrastructure changes continuously, units may receive different magnitudes of increase, treatment timing varies across units, and some units experience multiple increases over the study period. Under these conditions, a simple comparison of treated and untreated groups is not conceptually plausible. As a visual diagnostic of the parallel trend assumption, we compare pre-treatment outcome trajectories across units (CTs) that were first exposed to a treatment increase in the same treatment cohort but received different treatment intensities. Because cycling infrastructure is introduced in varying amounts rather than through a simple treated-versus-untreated distinction, we divide CTs within each first-treatment cohort into low-dose and high-dose groups based on the median size of their first observed increase in cycling infrastructure. We then plot the average outcome for each group over the pre-treatment period only. If the identifying assumption is plausible, the two groups should display similar trends before treatment, even if their outcome levels differ. We construct these figures for CTs that first receive an increase in cycling infrastructure exposure between 2014 and 2025 in the pooled ON sample and between 2021 and 2024 in the pooled BC sample. In the ON sample, although the 2014 cohort includes a larger number of CTs, it provides only one pre-treatment observation (2013), which is insufficient for assessing trends. We therefore focus on CTs first treated in 2024, as this cohort offers a longer pre-treatment window. In the pooled BC sample, where the study period covers 2020 to 2024, the number of CTs first treated in each year is very small. Although we again focus on CTs first treated in 2024 because they provide the longest pre-treatment period, the small cohort size limits the representativeness and interpretability of the visual trends. To further assess pre-treatment similarity between dose groups, we plot a difference line with 95% confidence intervals.

Our regression analysis proceeds in two stages. First, we estimate the main regression equation (Eq. 1), or Model 1, separately for the ON pooled sample and the BC pooled sample. We consider different measures of the outcome variable ($\text{Total\_Collisions}_{it}$) With a focus on all road users-involved collisions, the first measure includes casualty collisions (injury and fatal collisions), while second category includes casualty and PDO collisions. Casualty collisions in the first measure capture more severe safety outcomes and are generally reported more consistently across jurisdictions (corresponding with hospital records) whereas including PDO collisions in the second measure provides a broader measure of overall traffic safety by incorporating less severe incidents. Estimating the effects of cycling infrastructure using both measures allows us to assess whether the results are sensitive to the definition of safety and to compare how infrastructure relates to changes in severe versus total collision outcomes. In the second stage, Model 1 only considers the cyclists-involved collisions and applies the same two outcome ($\text{Total\_Collisions}_{it}$) measures 1 and 2 for ON pooled sample. However, in the BC pooled sample, cyclist-involved collision data do not distinguish between PDO and casualty collisions. Therefore, for cyclist-involved outcomes in BC, we estimate the model using measure 2.

To investigate the safety effects associated with each type of cycling infrastructure, we use Model 2 (Eq. 2):

$$\log(\text{Total\_Collisions}_{it}) = \beta_0 + \beta_1 \text{Separated}_{it} + \beta_2 \text{ Not\_Separated}_{it} + \beta_3 \log(\text{Exposure}_{it}) + \theta_i + \delta_t \quad (2)$$

Each city includes a different set of facility types, and we classify them into two broader categories. Separated_{it} is the cycling infrastructure (Km) with physical separation from motor-vehicle traffic (Cycle Tracks, Bike Paths, and Multi-use trails) in each CT and year. $\text{Not\_Separated}_{it}$ is the cycling infrastructure (Km) with lighter physical separation and where cyclists travel in mixed traffic environments (Local streets and Painted bike lanes) in each CT and year. This aggregation allows us to examine whether facilities with higher levels of physical protection and separation from traffic are associated with better safety benefits, or whether facilities with lighter separation where expectations for encountering cyclists may be higher provide comparable or stronger safety outcomes. This classification is consistent with evidence that physically separated or off-street facilities are associated with lower cycling injury risk than riding in mixed traffic or on major streets without dedicated infrastructure or only paint delineation (Reynolds et al., 2009; Lusk et al., 2011; Teschke et al., 2012). Grouping facilities this way allows us to test whether infrastructure with higher levels of physical protection is associated with greater safety benefits than lighter-separation facilities, where cyclists remain more exposed to motor-vehicle traffic. As with the main analysis in Model 1, we estimate effects using two measures of the outcome ($\text{Total\_Collisions}_{it}$) for all user-involved and cyclists-involved collisions.

4.Results

Fig. 3.34-46 illustrate all road users-involved and cyclist-involved collisions for Measure 1 (casualty collisions including injuries and fatalities) and Measure 2 (casualty and PDO collisions) across all cities. Table 3.15 provides descriptive statistics for collisions, cycling infrastructure, and total commuters over the study period at census tract level. Due to CRDCN confidentiality requirements, descriptive statistics for commuter measures derived from the Census of Population and the NHS are rounded and weighted using Statistics Canada's survey weights[15].

Across the study period, the analysis includes 178 census tracts (CTs) in Ottawa (2013-2022), 541 CTs in Toronto (2014-2024), and 115 and 24 CTs in Vancouver and Victoria, respectively (2020-2024). As shown in Table 3.15, Vancouver records the highest average CT-level collision counts in British Columbia for both all-user collisions and cyclist-involved collisions, and it also exhibits higher minimum and maximum values. Average collision counts (for both Measure 1 and Measure 2) are higher in Vancouver and Victoria than in the Ontario cities, which may reflect differences in data sources: collision records from ICBC in British Columbia are more comprehensive than police-reported collision data used for Ottawa and Toronto.

In terms of annual cycling infrastructure expansion, Ottawa has the highest average length of new infrastructure constructed per CT (1.71 km). Ottawa also leads in the cumulative (existing) length of cycling infrastructure, with an average of 8.27 km per CT, followed by Vancouver and Victoria. Toronto has the lowest average levels of both new construction and existing cycling infrastructure across its CTs. Finally, Ottawa and Victoria show the highest average CT-level lengths of physically separated facilities (0.08 km), and they also have the largest average lengths of non-separated facilities (0.15 km in Ottawa and 0.10 km

[15] Weight variable used is the "Compw2" in the Census of Population and National Household Survey of Canada

in Victoria), with Vancouver and Toronto ranking next. Further descriptive statistics on total number of commuters at CT level is demonstrated in Table 3.15.

In the descriptive statistics, some census tracts show a minimum value of zero commuters. This results from the interpolation procedure used to estimate commuter counts for years after 2021, the most recent Census year. The 2021 Census was conducted during the COVID-19 pandemic, a period in which commuting patterns changed substantially due to widespread remote work and reduced labour force mobility. As a result, several CTs reported very low commuter counts in 2021. When linear interpolation is applied to project commuter numbers forward from this unusually low base year, some CTs interpolate to zero commuters in subsequent years. These zeros therefore reflect pandemic-related anomalies in the underlying Census data rather than true absence of commuting activity and should be interpreted as artefacts of the interpolation process.

4.1. Main Results

Results for our main coefficient of interest (β) from Model 1 (Eq. 1) estimates the effect of 1 km change in cycling infrastructure length in a census tract and its effect on cyclists and all road users-involved collisions and are presented in Tables 3.16 and 3.17. These tables report estimates for all-user-involved collisions and cyclist-involved collisions, using both definitions of the outcome variable (casualty collisions; and casualty and PDO collisions). The standard errors are two-way clustered on CTs and year. Since Poisson models use a log link function, the coefficients represent log differences in the expected number of collisions (Cameron and Trivedi, 2013). For interpretation, we exponentiate the coefficients, which converts them into multiplicative effects on the expected collision rate (Long and Freese, 2006). For the first collision measure (casualty collisions), results for the ON pooled sample show a positive and statistically significant relationship between new cycling infrastructure and all users-involved collisions at the CT level. The exponentiated coefficient of 1.024 indicates that a 1 km increase in new cycling infrastructure in a census tract is associated with a 2.43% increase[16] in the expected number of casualty collisions among all road users in that census tract. In contrast, in the BC pooled sample we observe a negative and statistically significant relationship: a 1 km increase in new cycling infrastructure in a census tract is associated with an 8.76% decrease in the expected number of casualty collisions among all road users in that census tract.

For the second collision measure (casualty and PDO collisions), the same overall pattern holds for all users-involved collisions. In the ON pooled sample, the coefficient remains positive, but it is not statistically significant, indicating that changes in cycling infrastructure at the CT level do not have a detectable effect on the combined measure of casualty and PDO collisions for all road users. In contrast, in the BC pooled sample, a 1 km increase in new cycling infrastructure is associated with a 6.08% reduction in casualty and PDO collisions of all road users in the census tract where the new infrastructure is built.

As a sensitivity analysis, we re-estimate Model 1 using only interior collisions, defined as collisions located more than 5 meters from CT boundaries, to assess whether the arbitrary allocation of boundary crashes, potentially influenced by characteristics of adjacent CTs, affects our results. Tables 3.20S and 3.21S in the supplementary information present the regression estimates based on interior collisions only.

[16] Exp(0.024)=1.024, and 1.0243−1=0.0243

The coefficients are similar to those in the main specification, indicating that our findings are not biased by the allocation of boundary crashes or by inter-unit spatial influences near CT borders.

With respect to cyclist-involved casualty collisions (Table 3.16), in the ON pooled sample a 1 km increase in cycling infrastructure is associated with a 5.34% increase in the expected number of cyclist casualty collisions. For the second collision measure (casualty and PDO) (Table 3.17), a similar pattern is observed: in the ON pooled sample, a 1 km increase in cycling infrastructure is associated with an increase of 3.98% in cyclist-involved collisions. In contrast, results for the BC pooled sample indicate a negative and statistically insignificant relationship between cycling infrastructure and cyclist-involved collisions.

Figure 3.48 presents a visual pre-trend diagnostic for the ON pooled sample casualty and PDO collisions, comparing CTs that were first exposed to an increase in cycling infrastructure in 2024. Within this cohort, CTs are divided into low-dose and high-dose groups according to the size of their first observed increase in cycling infrastructure. The two series show broadly similar movement over the pre-treatment period. This similarity in the overall shape of the trajectories provides visual support for the parallel trend assumption, in the sense that low-dose and high-dose CTs do not appear to follow clearly divergent pre-treatment paths. The red line plots the difference between the high-dose and low-dose groups at each pre-treatment year, measured as the average change from baseline in the high-dose group minus that in the low-dose group. A difference line that remains close to zero would indicate nearly identical pre-treatment movement across the two groups. In this figure, the difference line is generally positive, suggesting that the high-dose CTs experienced somewhat larger increases, or smaller declines, in collisions relative to baseline than the low-dose CTs at most pre-treatment time points. However, the 95% confidence intervals around this line are wide and include zero throughout the pre-treatment period, indicating that these differences are imprecisely estimated and may reflect sampling variability rather than systematic divergence. This is consistent with the small size of the 2024 cohort, which includes only 11 CTs. The figure should therefore be interpreted as providing suggestive, but not definitive, visual support for parallel pre-treatment trends in the ON pooled sample.

Figure 3.49 presents the visual pre-trend diagnostic for the pooled BC sample, focusing on CTs that were first exposed to a positive increase in cycling infrastructure in 2024. Low-dose and high-dose groups do not show the same degree of similarity as in the ON sample. Relative to the 2020 baseline, collisions in the low-dose group rise more sharply over the pre-treatment period, while the high-dose group shows a more modest increase and then remains comparatively stable. This pattern suggests some difference in pre-treatment movement between the two groups, although the evidence should be interpreted with considerable caution given the very small cohort size.[17] In this figure, the difference line is negative throughout the pre-treatment period after 2020, indicating that the high-dose group experienced smaller increases in collisions from baseline than the low-dose group. However, the 95% confidence intervals around this line are extremely wide and include zero at all pre-treatment time points, indicating that the estimated differences are highly imprecise. This can stem from small number of CTs first treated in 2024 cohort, also the overall study period provides only a short pre-treatment window (2020-2023). The figure therefore provides noisy evidence on pre-treatment comparability and should not be taken as a strong test of the parallel-trends assumption.

[17] This cohort only includes 5 CTs.

4.2. Effect of Cycling Infrastructure by Level of Separation

Model 2 estimates the effect of cycling infrastructure with different levels of physical separation from motor-vehicle traffic using Eq.2. β_1 is the coefficient of cycling infrastructure with physical separation from traffic in ON and BC sample. β_2 is the coefficient estimating the effect of cycling infrastructure with low to no separation from traffic. Results for all road users-involved casualty collisions (Table 3.18) indicate that in the ON pooled sample, the safety effects provided by physically separated and mixed cycling infrastructure are equal and both show a positive relationship between cycling infrastructure construction and casualty collisions. 1 km increase in cycling infrastructure in the census tract is associated with 2.43% increase in collisions. However, in BC pooled sample, cycling infrastructure with physical separation from traffic have a larger effect on casualty collisions and 1 km increase in them reduces the collision by 12.30% in the census tract. Regarding the second measure of collisions (Table 3.19), there is no statistically significant relationship between cycling infrastructure with and without physical separation from traffic in the ON pooled sample. In the BC pooled sample, cycling infrastructure without physical separation has a more profound effect on all users' traffic safety and 1 km increase in infrastructure length reduces the collisions by 7.14%.

With a focus on cyclist-involved casualty collisions (Table 3.18), we find that in the ON pooled sample, a 1 km increase in cycling infrastructure that provides physical separation from motor traffic in a census tract is associated with a 7.36% increase in expected cyclist casualty collisions in that census tract. No statistically significant relationship is found for cycling infrastructure with lighter or no physical separation. Regarding casualty and PDO collisions (Table 3.19), separated and non-separated infrastructure in the ON pooled sample continue to show the same direction and significance as in the casualty-only model, while results for the BC pooled sample remain statistically insignificant.

5.Discussion

As a sustainable mode of transport, cycling provides environmental, social, and economic benefits at both individual and community levels. In many North American cities, cycling infrastructure is the primary policy instrument used to encourage cycling uptake (Mitra et al., 2021). However, cyclists are vulnerable road users, and the safety risks associated with cycling are relatively high compared with other modes of transport (Wegman et al., 2012). It is therefore essential to examine whether promoting cycling through the construction and expansion of cycling infrastructure leads to increases in collisions, injuries, or fatalities as more people begin to cycle (Wegman et al., 2012), or whether a more extensive infrastructure network contributes to safer cycling. Given limited physical space and financial resources, given that safety policies should apply to the entire network and to all road users (Wegman et al., 2012) and considering that other transportation challenges also require investments and plannings, it is important to evaluate whether cycling infrastructure improves not only cyclist safety but also the safety of other road users. Evidence on the safety effects of cycling infrastructure for both cyclists and all road users, and on how these effects differ across infrastructure types within a network, can support more strategic investment decisions, help maximize returns on investment (Götschi et al., 2018), and provide the evidence needed for public acceptance of cycling facilities.

North American evaluations of the effects of cycling infrastructure have produced inconsistent results (Cicchino et al., 2020), largely due to differences in study designs, exposure measures, controls, and limitations in collision data. To contribute to this literature, we employ a continuous DiD framework with CT and year fixed effects, focusing on within-unit variation attributable to changes in cycling infrastructure and traffic safety over time. Year fixed effects control for unobserved time-varying factors that influence traffic safety uniformly across CTs, while CT fixed effects account for pre-existing, time-invariant differences in cycling infrastructure, roadway conditions, and baseline traffic safety. We estimate effects using two measures of traffic safety, casualty collisions and all collisions, to distinguish the impact of cycling infrastructure on severe injuries versus overall collision occurrence. Casualty collisions, which include fatal collisions (death within 30 days of the event) and injury collisions requiring hospital admission or emergency room treatment, provide a more reliable and representative indicator of traffic and cyclists safety. To assess whether different levels of physical separation from traffic yield different safety outcomes, we compare facilities that physically separate cyclists from motor-vehicle traffic (Cycle Tracks, Bike Paths, and Multi-Use Trails) with those that provide lighter separation and greater mixing with traffic (Local Streets, Painted Bike Lanes). Conducting separate analyses for the Ontario and British Columbia pooled samples allows us to investigate whether safety effects vary based on differences in roadway design, travel patterns, and socio-demographic characteristics across provinces.

Our results indicate that, in the ON pooled sample, new cycling infrastructure is associated with higher casualty collisions for both cyclists and other road users. When using the broader measure that includes both PDO and casualty collisions, there is no statistically significant relationship between changes in cycling infrastructure and all-users collisions; however, a 1 km increase in cycling infrastructure is associated with a 3.98% increase in cyclist-involved collisions under this measure. The same pattern holds when cycling infrastructure is examined by its level of physical separation from traffic and for two safety measures of casualty collisions and all collisions. On the contrary, in the BC pooled sample, construction and expansion of cycling infrastructure at the CT level is associated with a decrease in all-users collisions under both casualty and all-collisions measures. However, there is no statistical evidence that cycling infrastructure affects cyclists-involved collisions. The same pattern is observed when examining infrastructure types with different levels of separation from traffic. While neither separated nor non-separated facilities show a statistically significant relationship with cyclists-involved collisions, non-separated infrastructure exhibits a stronger negative association with all-users collisions compared to separated facilities.

Our findings on cyclist safety in both the ON and BC pooled samples align with North American studies reporting negative effects or no statistically significant relationship between cycling infrastructure expansion and cyclist safety. Wei and Lovegrove (2013) find an increase in bicycle-motor vehicle collisions associated with an increase in bicycle lane kilometers. Bhatia et al (2016) reports no statistically significant change in cyclists' collisions before and after the implementation of painted cycle lanes, alongside a statistically significant increase in collisions that resulted in no injuries in Toronto. A cross-sectional study by Helak et al. (2013) found no statistically significant differences in injury severity of cyclists' collisions occurring on cycle lanes to those occurring on roads without cycle lanes. Cicchino et al (2020) also show that bike lanes with lighter separation from traffic had similar risk levels for cyclists to major roads.

Regarding the safety of all road users, the existing evidence is limited, as most studies focus exclusively on cyclist safety. Among the few studies that investigate the determinants of higher safety levels in high-cycling cities, our findings for the BC pooled sample align with those reporting positive safety effects for all road users associated with greater availability of cycling infrastructure (Marshall and Garrick, 2011; Marshall and Ferenchak, 2019; Ferenchak and Marshall, 2024).

Different findings for the ON and BC pooled samples, for both cyclist-involved and all-users collisions, suggests that cycling infrastructure does not have uniform safety effects across contexts and highlights the need for further investigation. Several factors may explain the disparity in results between the two provinces. A first explanation is that the effectiveness of cycling infrastructure varies across locations and depends on roadway characteristics (Pulugurtha and Thakur, 2015). As noted by Ziakopoulos and Yannis (2020) the relationship between spatial variables and safety outcomes is not constant across locations, and the strength and direction of coefficients may differ depending on local context. There is limited research on the heterogeneous safety effects of cycling infrastructure across sites with different roadway conditions (Park et al., 2015) and how route characteristics other than the cycling facility itself are also associated with risk reductions (Teschke., et al., 2012). In this vein studies indicate network characteristics such as the number of adjacent intersections, intersection configuration, and roadway width are network factors that influence the safety performance of cycling infrastructure (Wei and Lovegrove, 2013; Park et al., 2015; Kondo et al., 2018). These roadway features, which are shaped by differences in urban design and planning approaches across the two provinces, may help explain part of the disparity in our findings for Ontario and British Columbia.

A second explanation relates to the design of the cycling infrastructure network. Several design features of cycling facilities can influence the level of safety and comfort they provide. These include lane width (Park et al., 2015), the presence and design of entrances and exits (i.e., how cyclists merge with or diverge from motor traffic), discontinuities in the cycling network (Kim and Kim, 2015), surface quality, and lighting conditions. These design-related factors can vary systematically across jurisdictions. Differences in how cycling facilities are designed, constructed, and maintained in Ontario and British Columbia may therefore contribute to the contrasting safety outcomes observed in the two pooled samples. Environmental factors such as weather conditions, which influence roadway surface conditions and overall travel safety, also differ substantially between the two provinces and may contribute to the observed differences in safety outcomes.

Lastly, safety in numbers as a function of cycling infrastructure plays an important role in traffic safety, as higher numbers of cyclists increase drivers' expectations and awareness, thereby reducing collision risk. Vancouver and Victoria have some of the highest cycling mode shares and cyclist commuter shares in Canada (Statistics Canada, 2025). These baseline differences in cycling prevalence may contribute to the greater safety benefits associated with cycling infrastructure observed in the BC pooled sample. All the factors proposed, differences in roadway characteristics, cycling infrastructure design, environmental conditions, and baseline cycling levels, are potential explanations for the divergent findings between the ON and BC pooled samples. These mechanisms demand further investigation in future research, conditional on the availability of consistent longitudinal spatial data.

5.1. Limitations

In this study, cyclist-involved collisions are limited to events in which a collision between a cyclist and another road user occurs. Our analysis does not include single-bicycle crashes, such as falls or collisions with fixed objects. Although such crashes can lead to serious injuries, they are rarely recorded in a systematic manner, and reliable longitudinal datasets suitable for comparison or evaluation are unavailable (Schepers et al., 2015). As a result, studies of single-bicycle crashes are limited, and these events cannot be incorporated into our analysis.

In addition, our analysis focuses exclusively on cycling infrastructure installed along road segments. We do not account for intersection-level treatments such as bike boxes, roundabouts, traffic calming measure, or other time-varying intersection infrastructure features that may also influence traffic safety at the CT level. The primary reason for such exclusion is lack of consistent longitudinal spatial data on such interventions across the cities an area which future research could further explore.

5.2. Conclusion

This study provides policy-relevant evidence on whether investments in cycling infrastructure improve traffic safety, using a quasi-experimental design that strengthens causal interpretation. The findings matter because many North American cities are expanding cycling networks to meet climate, congestion, and public-health goals, yet decision-makers still face a central trade-off question: can cycling grow without increasing traffic risk for cyclists or for the broader road system? By estimating impacts on cyclist-involved collisions as well as collisions for all road users, the analysis informs whether cycling infrastructure functions as a safety intervention for the whole network, not only as a mode-shift instrument.

Two features of the approach are particularly important for policy. First, defining two safety measures based on severity helps address limitations of police-reported collision data and clarifies whether infrastructure affects severe outcomes differently from overall collision counts. Second, distinguishing facilities by physical separation provides actionable guidance about design choices, not only whether more cycling infrastructure matters. Overall, the evidence indicates that safety effects are context-dependent and can vary across cities, potentially consistent with differences in road network characteristics including street design, network connectivity, intersection density, baseline speeds, and cycling patterns. This implies that "one-size-fits-all" expectations about safety benefits are not well supported; instead, impacts depend on how and where infrastructure is implemented.

The inclusion of both Ontario (Ottawa and Toronto) and British Columbia (Vancouver and Victoria) strengthens the contribution in two ways. These provinces represent distinct institutional and urban contexts, large metropolitan regions with different network maturity, cycling culture, and implementation styles, making the analysis informative for a wider range of Canadian and North American cities. In addition, evaluating cities where collision reporting systems differ highlights the practical importance of measurement choices (including severity-based outcomes) for making robust safety inferences. Together, these settings provide a credible test of whether estimated impacts generalize across Canadian jurisdictions rather than reflecting a single city's implementation or data environment.

Several recommendations follow for policy and infrastructure investment. First, cycling infrastructure programs should prioritize safety-oriented designs rather than focusing only on network expansion targets. Second, because the effectiveness of infrastructure depends on local context, cities should pair corridor-level investments with complementary measures that address common conflict points. Third, governments should institutionalize harmonized collision outcome measures, using consistent severity definitions across jurisdictions to ensure results are comparable over time and between cities and provinces. Improving comparability across provinces and cities through more harmonized reporting standards (and, where possible, linkage across police, insurance, and hospital records) would increase confidence in cross-jurisdictional policy learning.

Taken together, the study supports a practical message that cycling infrastructure can influence traffic safety, but impacts are shaped by design choices and local conditions. The most defensible path forward is to treat cycling infrastructure as part of a broader safety strategy so that climate and mode-shift objectives are advanced without compromising safety for cyclists or other road users.

Figures

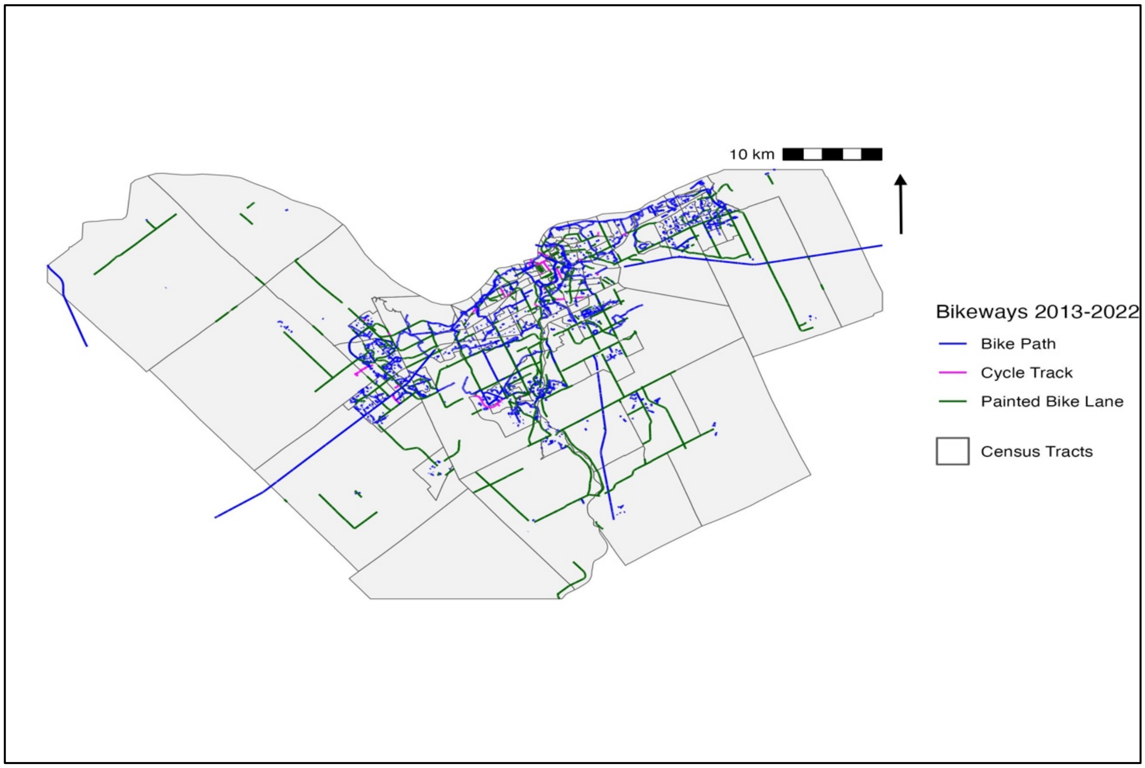

Figure 3.30. Cycling infrastructure in Ottawa CSD (2013-2022)

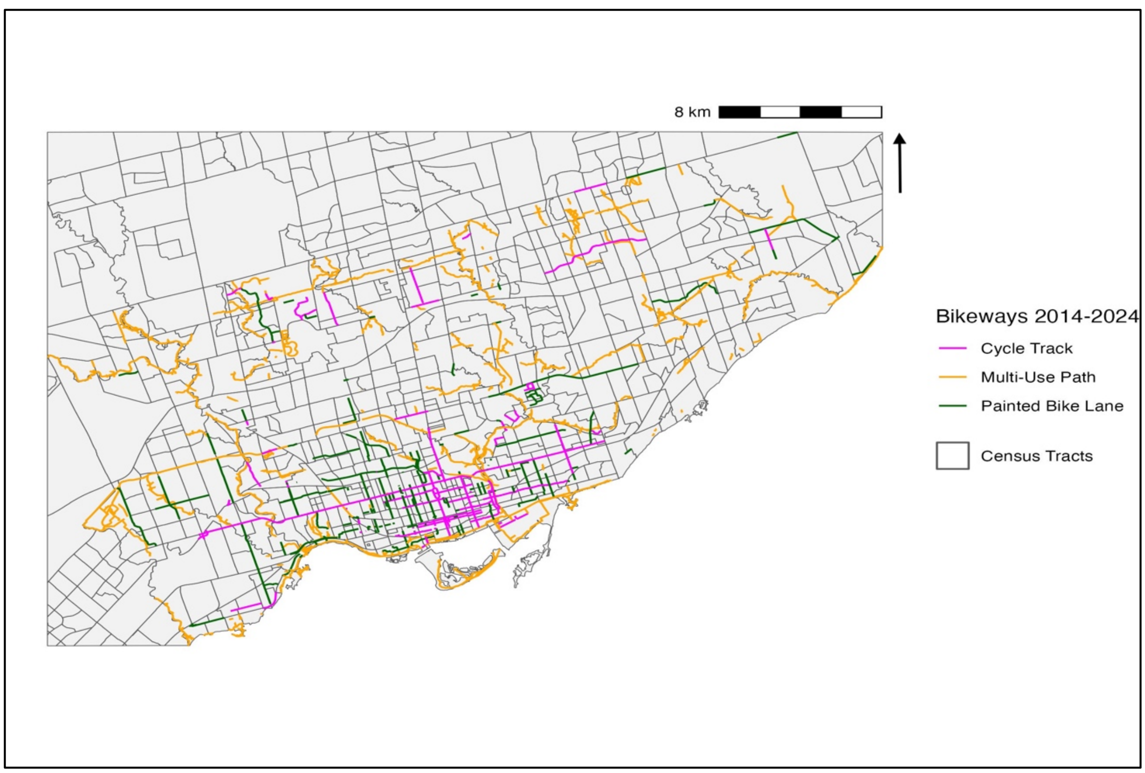

Figure 3.31. Cycling infrastructure in Toronto CSD (2014-2024)

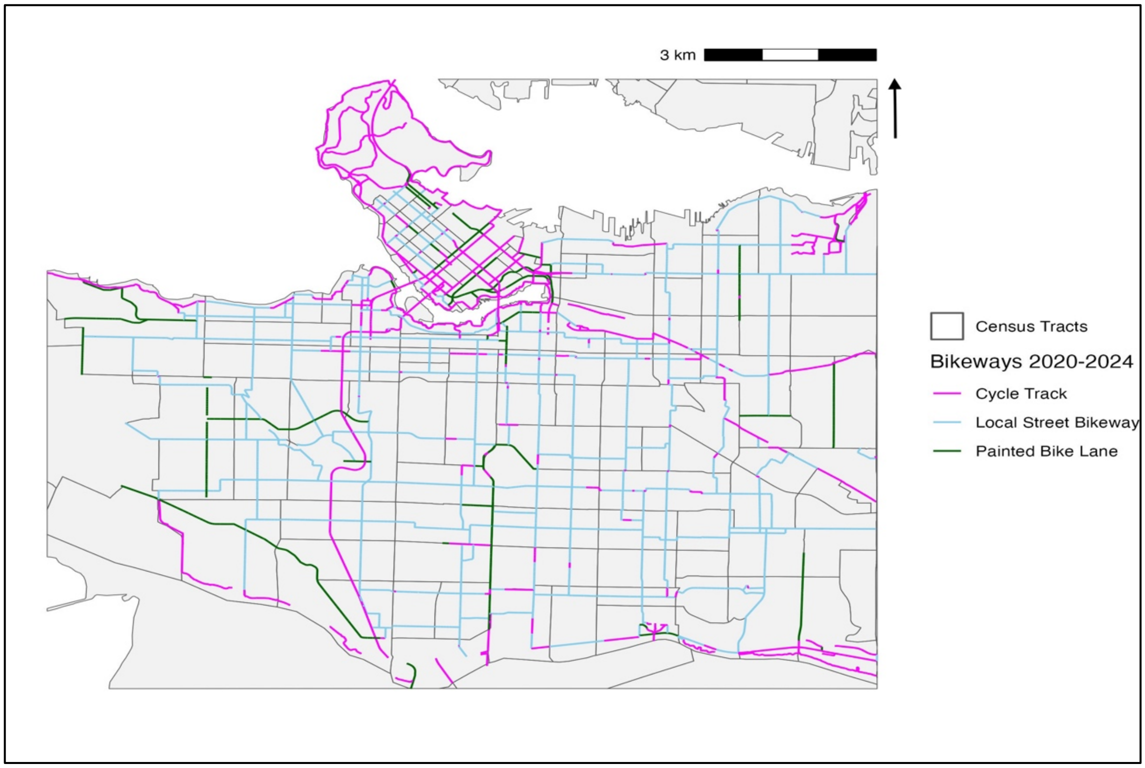

Figure 3.32. Cycling infrastructure in Vancouver CSD (2020-2024)

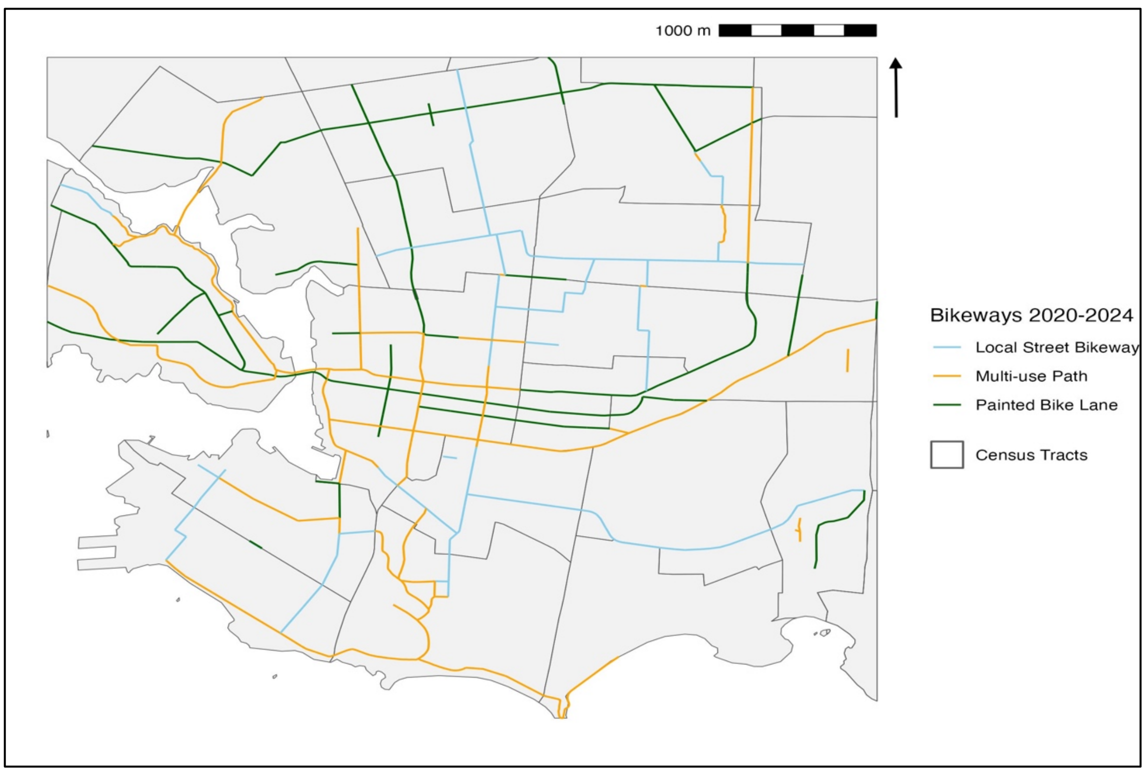

Figure 3.33. Cycling infrastructure in Victoria CSD (2020-2024)

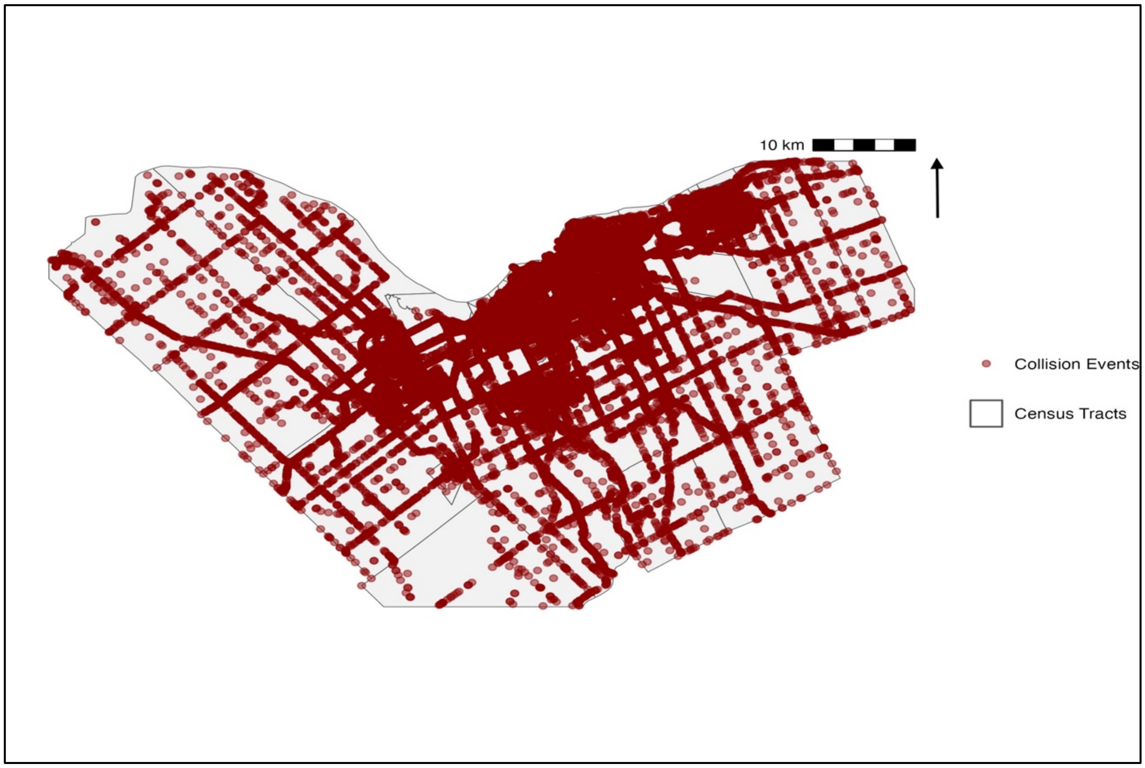

Figure 3.34. All road users-involved casualty (fatality and injury) and PDO collisions in Ottawa CSD (2013-2022)

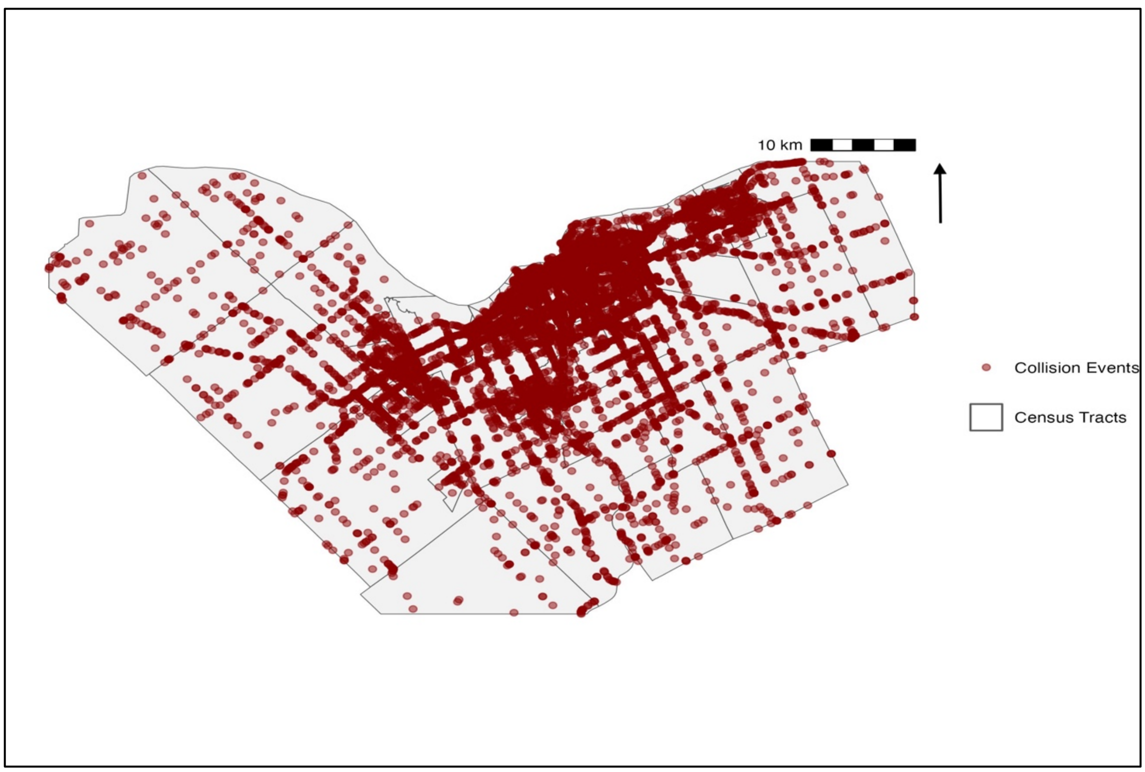

Figure 3.35. All road users-involved casualty (fatality and injury) collisions in Ottawa CSD (2013-2022)

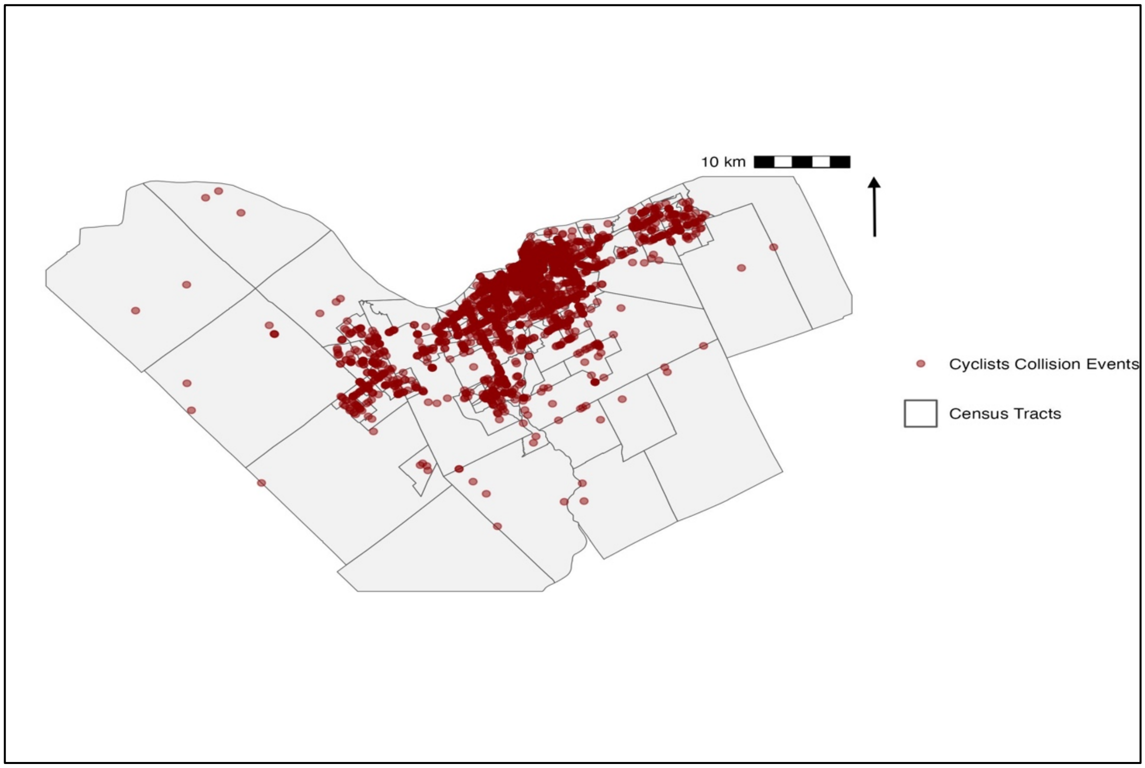

Figure 3.36. Cyclists-involved casualty (fatality and injury) and PDO collisions in Ottawa CSD (2013-2022)

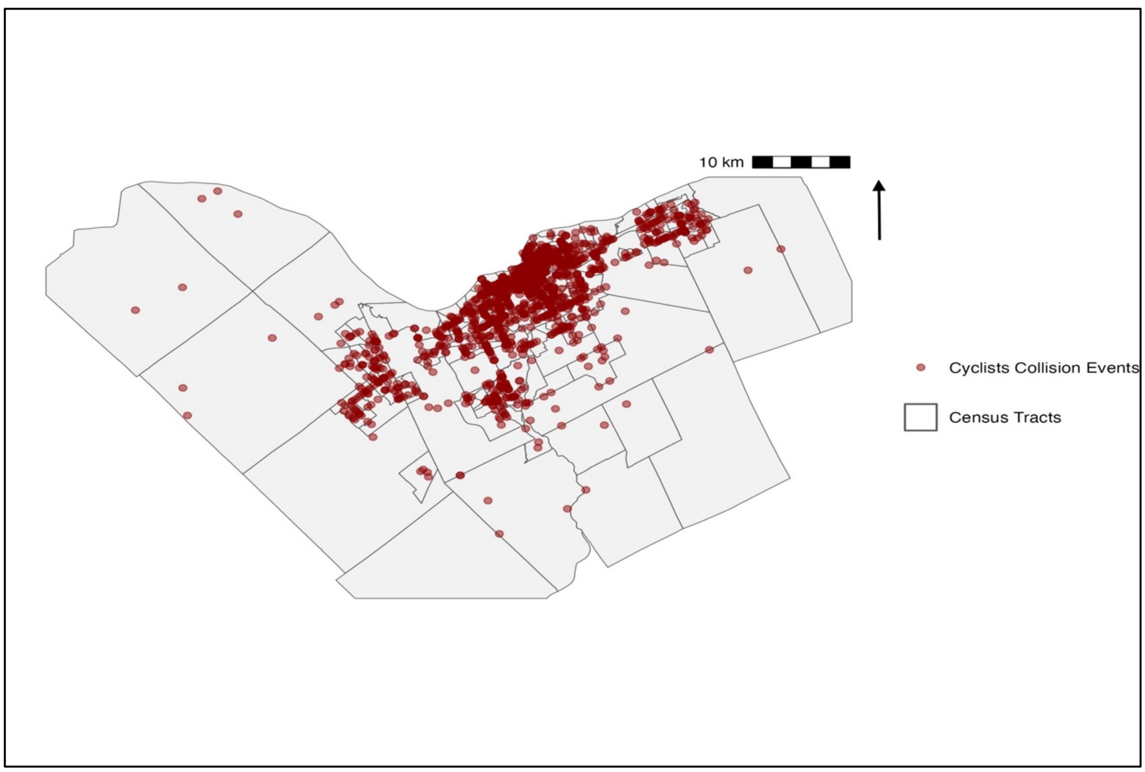

Figure 3.37. Cyclists-involved casualty (fatality and injury) collisions in Ottawa CSD (2013-2022)

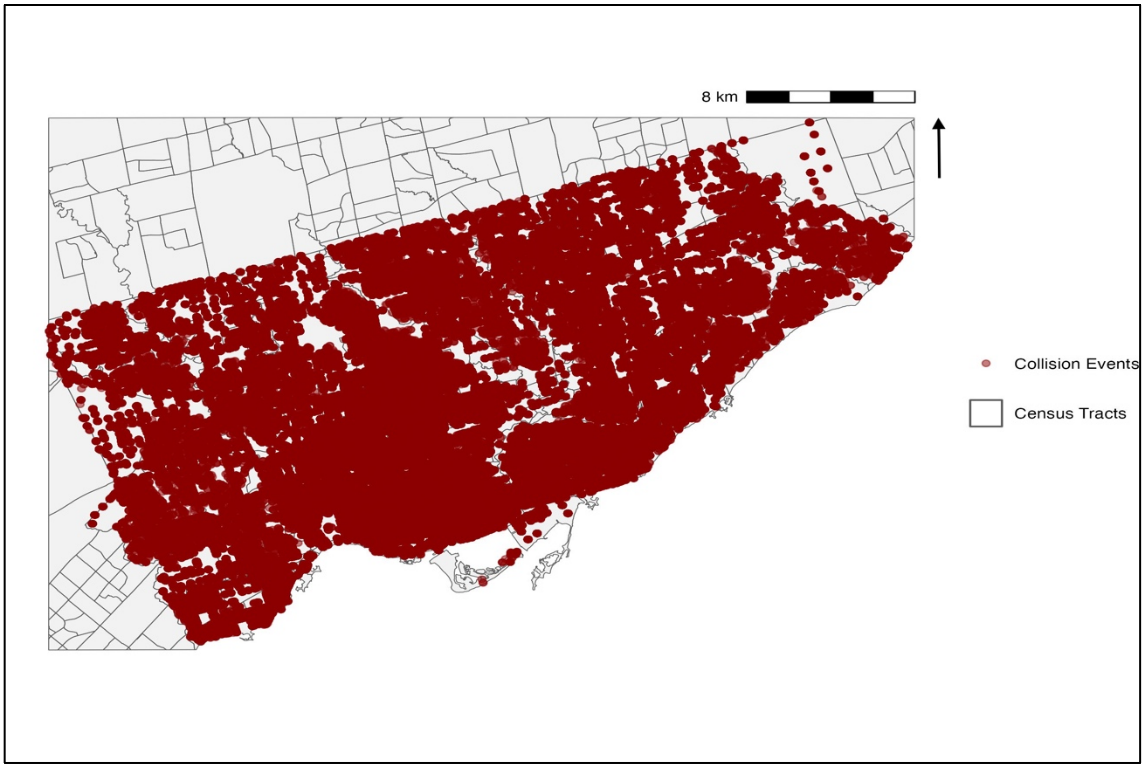

Figure 3.38. All road users-involved casualty (fatality and injury) and PDO collisions in Toronto CSD (2014-2024)

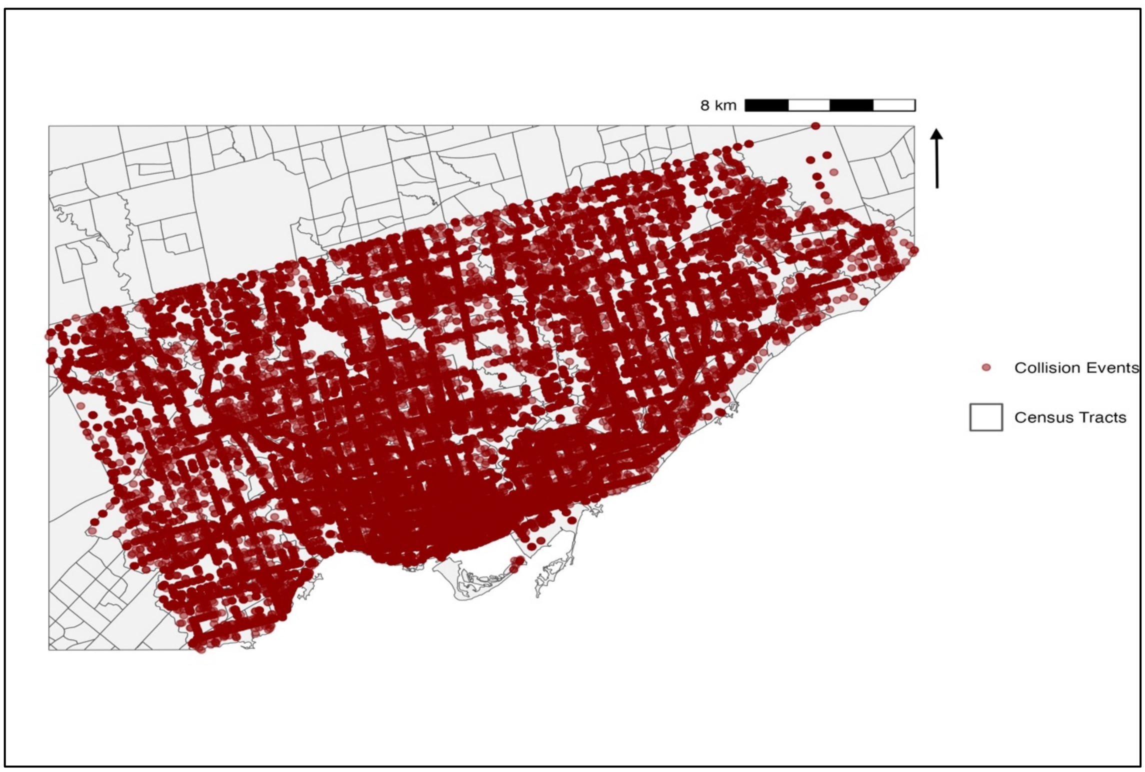

Figure 3.39. All road users-involved casualty (fatality and injury) collisions in Toronto CSD (2014-2024)

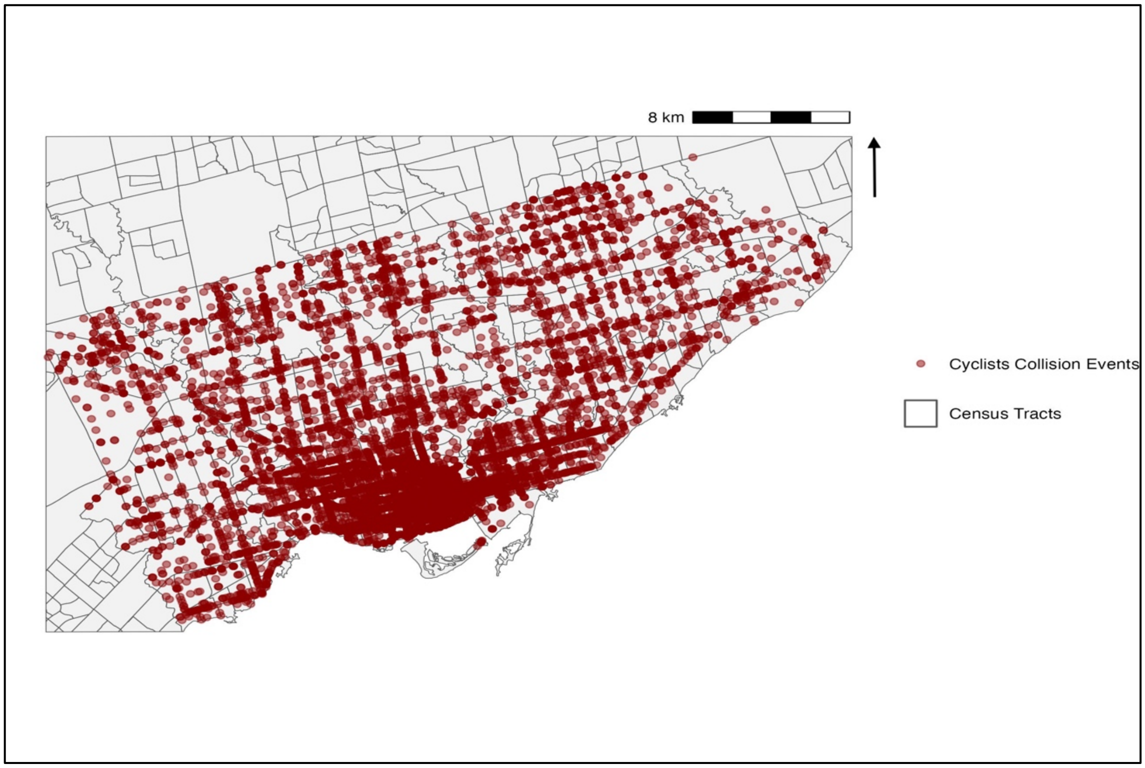

Figure 3.40. Cyclists-involved casualty (fatality and injury) and PDO collisions in Toronto CSD (2014-2024)

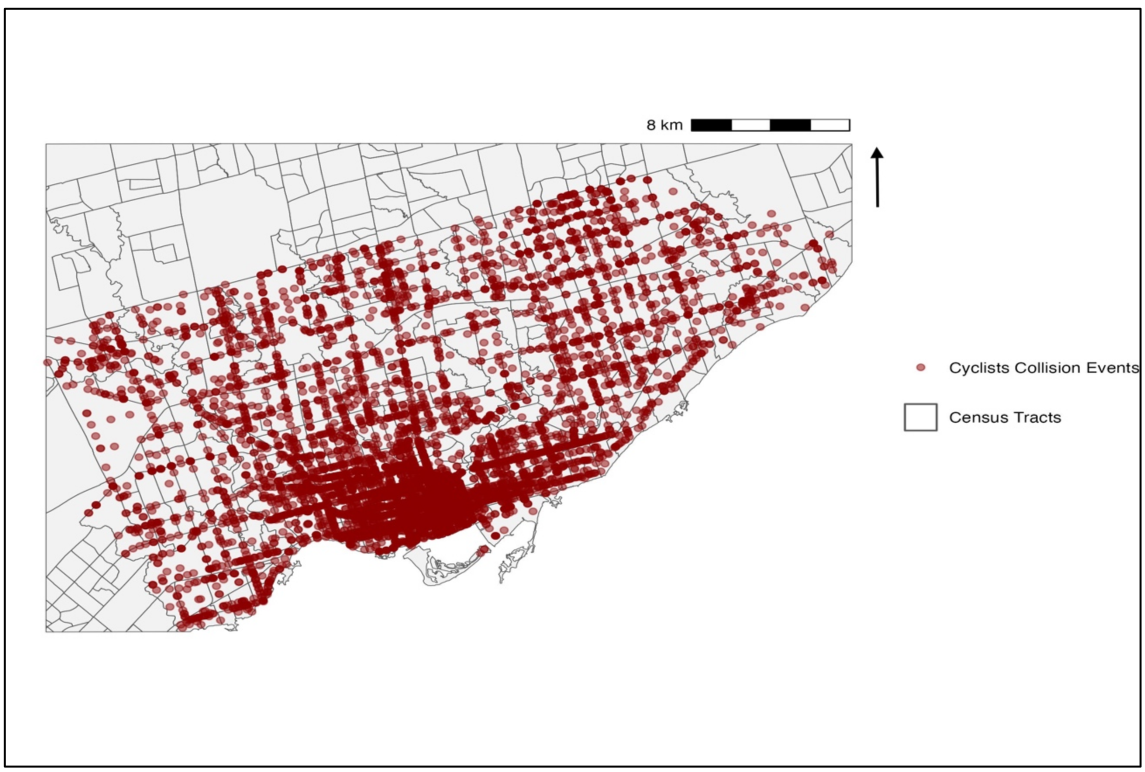

Figure 3.41. Cyclists-involved casualty (fatality and injury) collisions in Toronto CSD (2014-2024)

Figure 3.42. All road users-involved casualty (fatality and injury) and PDO collisions in Vancouver CSD (2020-2024)

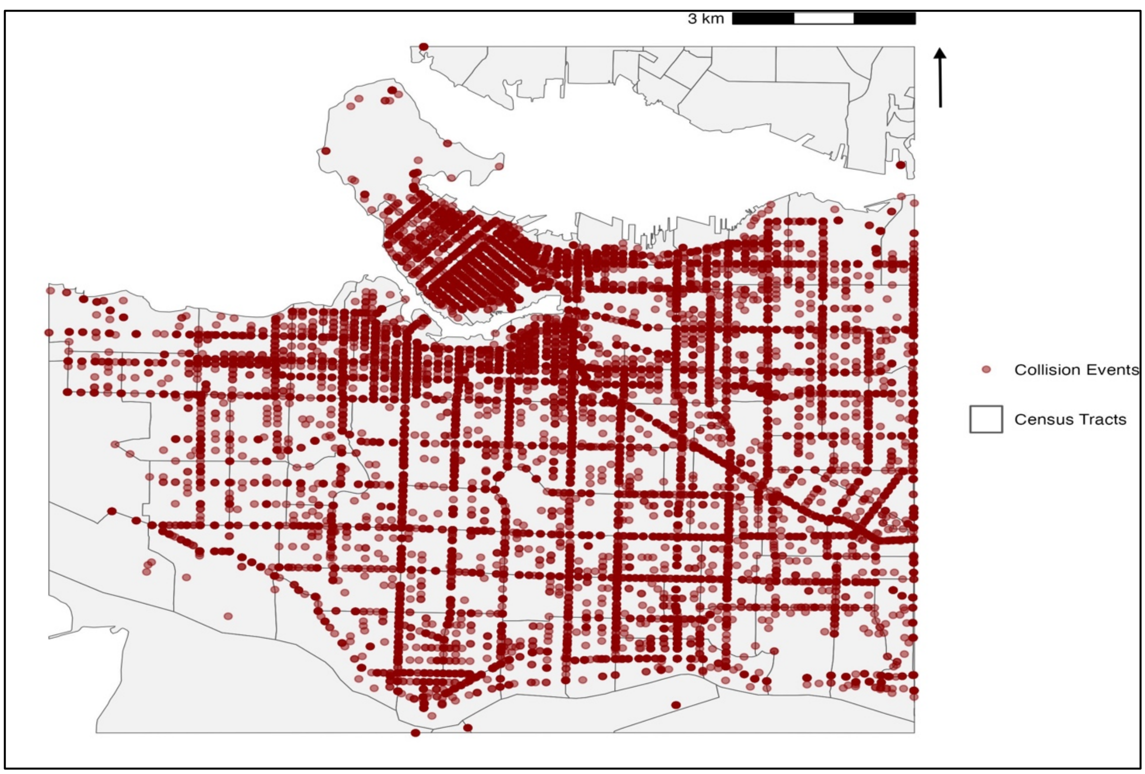

Figure 3.43. All road users-involved casualty (fatality and injury) collisions in Vancouver CSD (2020-2024)

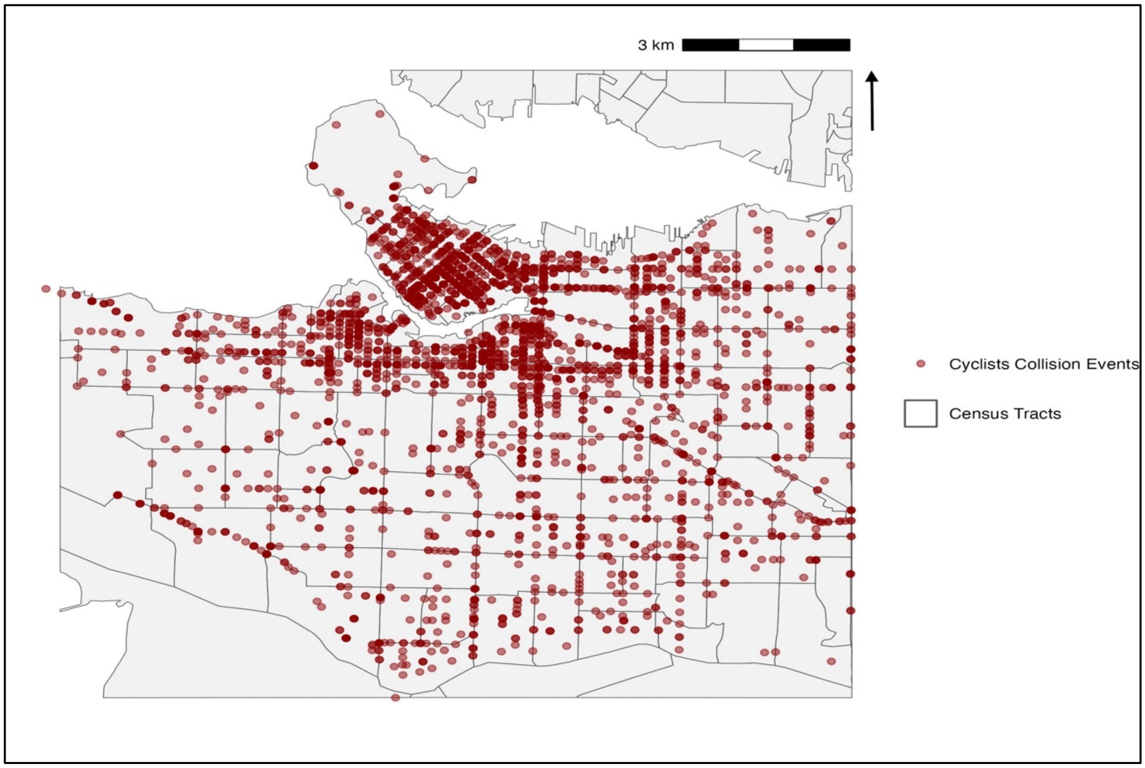

Figure 3.44. Cyclists-involved collisions in Vancouver CSD (2020-2024)

Figure 3.45. All road users-involved casualty (fatality and injury) and PDO collisions in Victoria CSD (2020-2024)

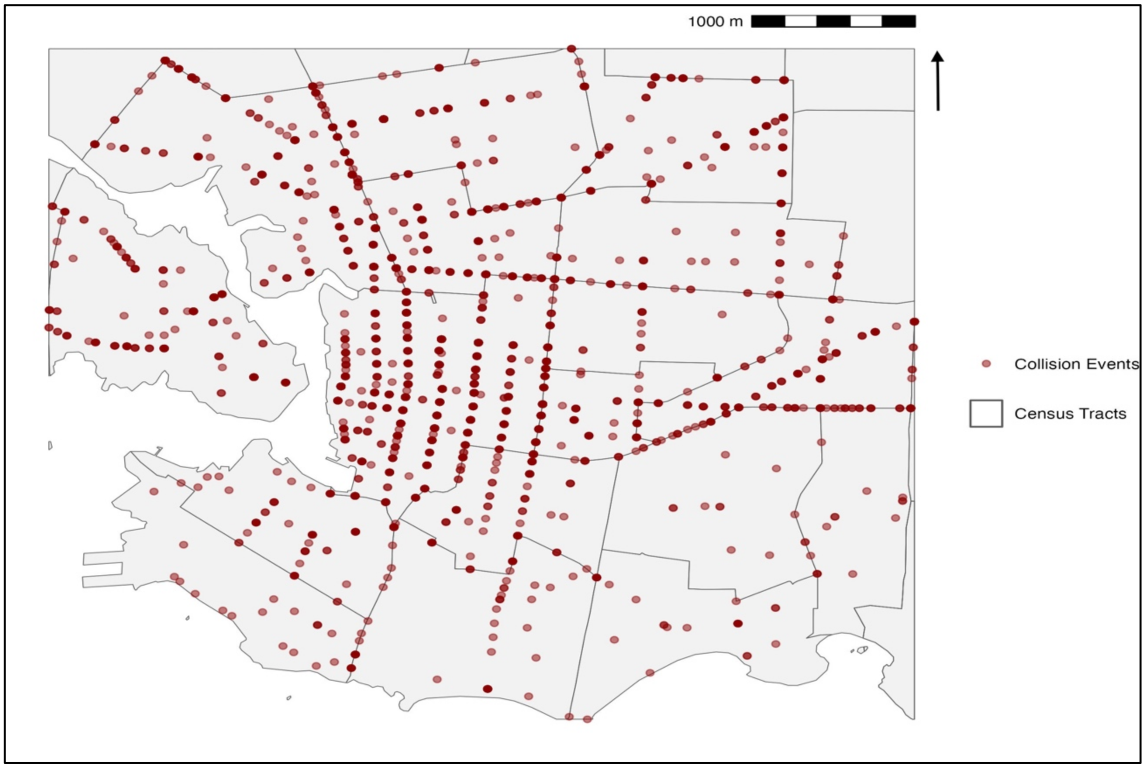

Figure 3.46. All road users-involved casualty (fatality and injury) collisions in Victoria CSD (2020-2024)

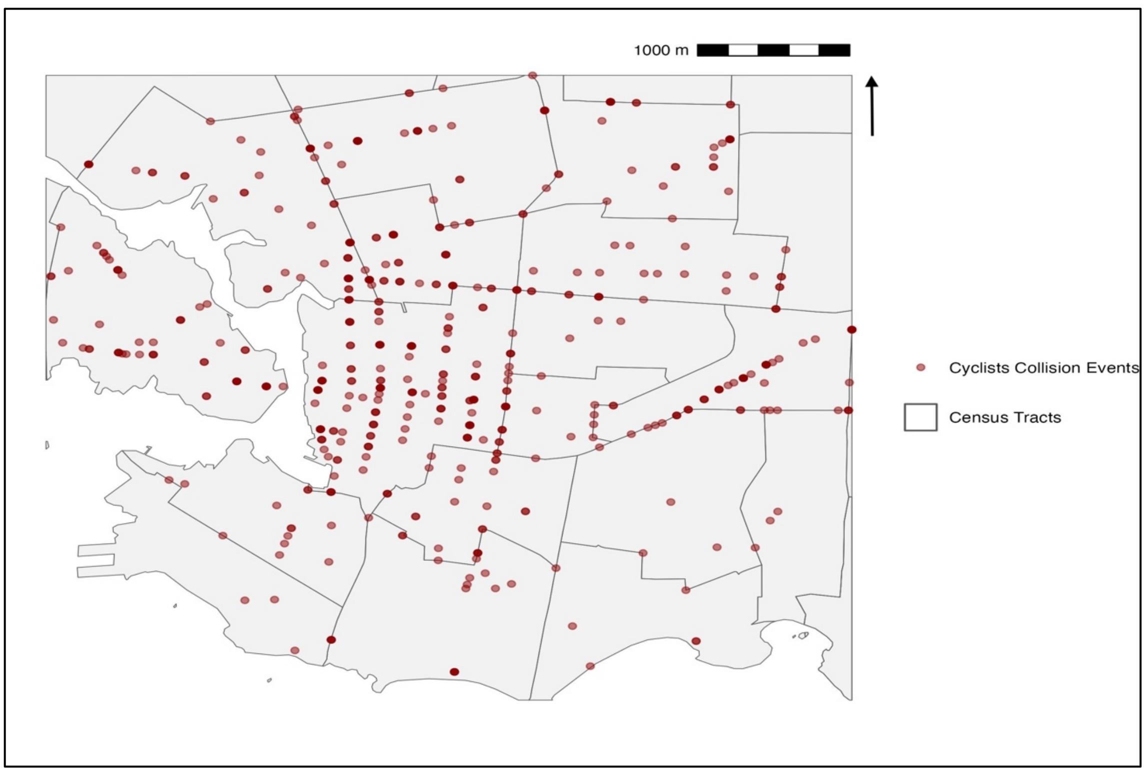

Figure 3.47. Cyclists-involved collisions in Victoria CSD (2020-2024)

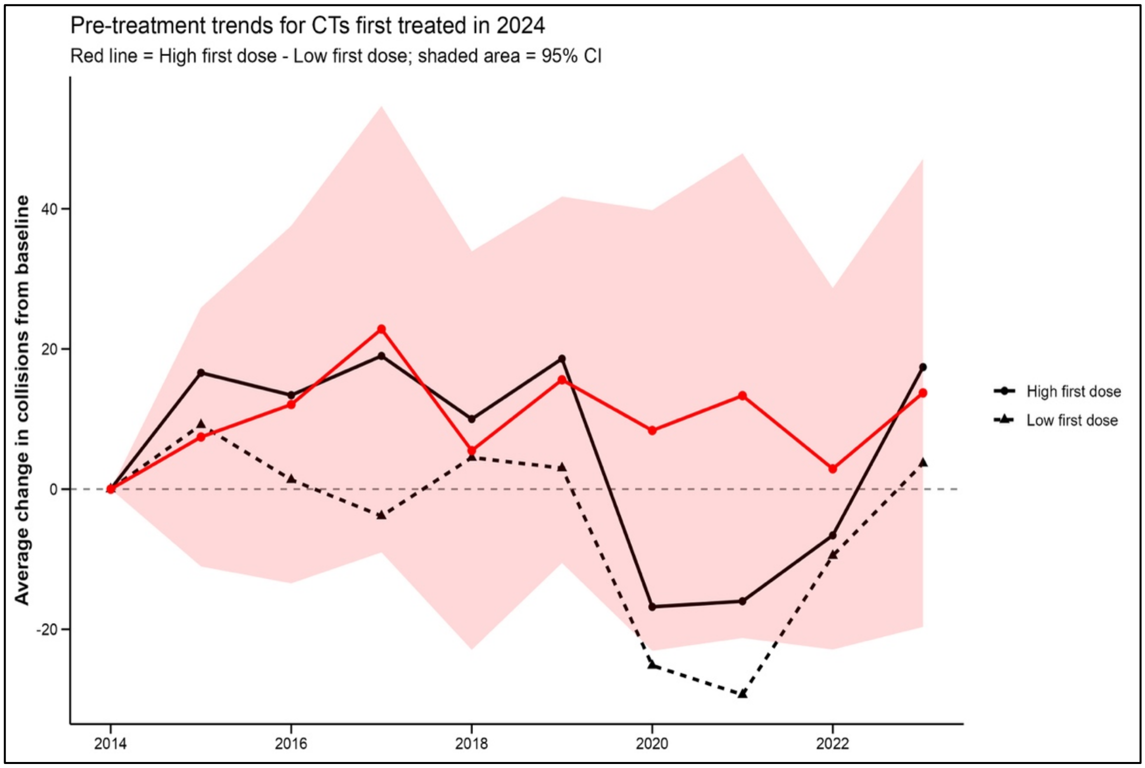

Figure 3.48. Pre-trend test for CTs first treated in 2024, ON pooled sample.

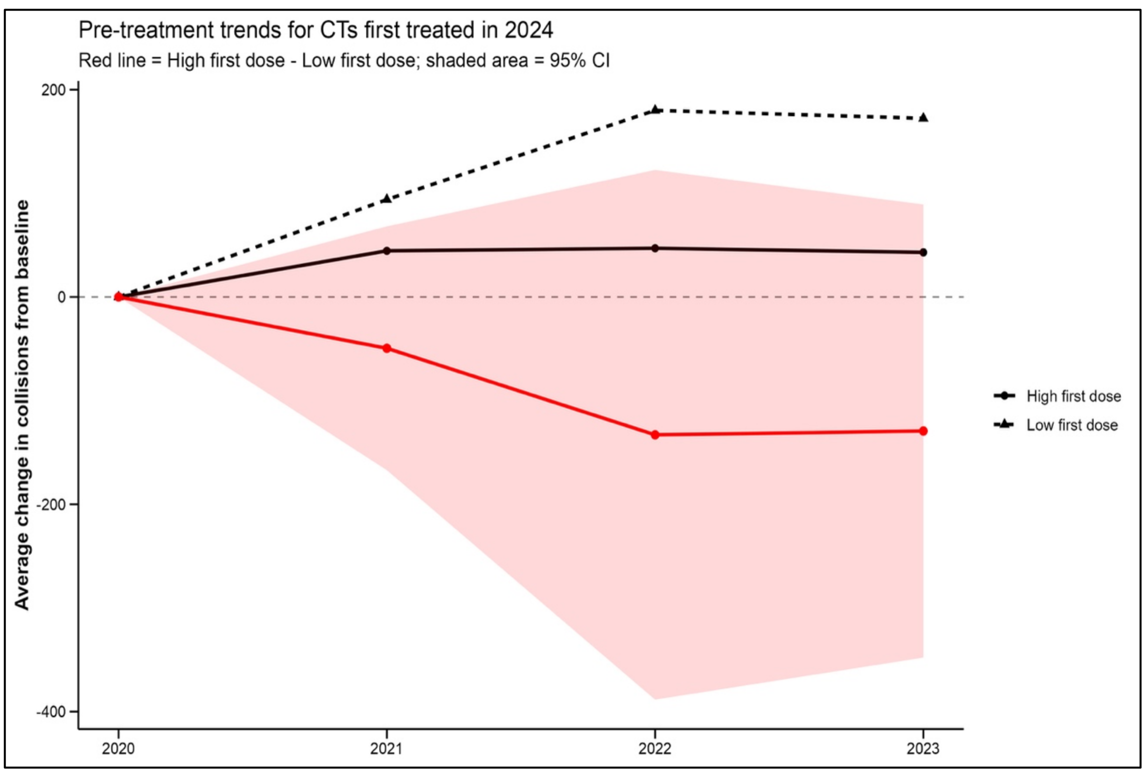

Figure 3.49. Pre-trend test for CTs first treated in 2024, BC pooled sample.

Tables

Table 3.15. Descriptive statistics at census tract (CT) level for cities of Ottawa, Toronto, Vancouver, and Victoria. Number of observations in each city represents the number of CTs multiplied by the years of observation for each city

City	Variables	Mean	Sd	Min	Max
Ottawa (2013-2022)	n= 1750 (number of CTs × Years)				
	All Road Users-Involved Casualty Collisions	14.60	15.30	1.00	108.00
	All Road Users-Involved PDO and Casualty Collisions	76.40	82.50	1.00	660.00
	Cyclists-involved Casualty Collisions	1.29	1.96	0.00	22.00
	Cyclists-involved PDO and Casualty Collisions	1.46	2.26	0.00	24.00
	Total Commuters	1945	1705	0.00	20865
	New Cycling Infrastructure (km)	1.71	3.11	0.01	39.90
	Cumulative Cycling Infrastructure (km)	8.27	13.10	0.02	77.10
	New Cycling Infrastructure with Physical Separation (km)	0.08	0.37	0.00	4.77
	Cumulative Cycling Infrastructure with Physical Separation (km)	4.31	5.63	0.00	40.99
	New Cycling Infrastructure without Physical Separation (km)	0.15	0.77	0.00	12.10
	Cumulative Cycling Infrastructure without Physical Separation (km)	28.41	57.00	0.00	364.02
Toronto (2014-2024)	n= 6468 (number of CTs × Years)				
	All Road Users-Involved Casualty Collisions	14.80	16.40	1.00	172.00

	All Road Users-Involved PDO and Casualty Collisions	99.20	114.00	1.00	1060.00
	Cyclists-involved Casualty Collisions	1.40	2.40	0.00	43.00
	Cyclists-involved PDO and Casualty Collisions	1.80	3.21	0.00	55.00
	Total Commuters	1705	2151	0.00	36785
	New Cycling Infrastructure (km)	0.63	0.92	0.00	10.00
	Cumulative Cycling Infrastructure (km)	1.49	2.21	0.00	15.00
	New Cycling Infrastructure with Physical Separation (km)	0.01	0.11	0.00	3.44
	Cumulative Cycling Infrastructure with Physical Separation (km)	0.44	1.14	0.00	14.81
	New Cycling Infrastructure without Physical Separation (km)	0.003	0.04	0.00	1.62
	Cumulative Cycling Infrastructure without Physical Separation (km)	0.11	0.35	0.00	2.77
Vancouver (2020-2024)	n= 575 (number of CTs × Years)				
	All Road Users-Involved Casualty Collisions	63.20	57.40	1.00	394.00
	All Road Users-Involved PDO and Casualty Collisions	200.00	188.00	1.00	1523.00
	Cyclists-involved PDO and Casualty Collisions	6.14	9.16	0.00	92.00
	Total Commuters	1825	1503	0	13655
	New Cycling Infrastructure (km)	0.71	0.82	0.00	8.10

	Cumulative Cycling Infrastructure (km)	2.85	3.24	0.00	23.00
	New Cycling Infrastructure with Physical Separation (km)	0.006	0.04	0.00	0.56
	Cumulative Cycling Infrastructure with Physical Separation (km)	0.82	2.22	0.00	21.14
	New Cycling Infrastructure without Physical Separation (km)	0.01	0.10	0.00	1.59
	Cumulative Cycling Infrastructure without Physical Separation (km)	1.75	1.46	0.00	7.40
Victoria (2020-2024)	n=118 (number of CTs × Years)				
	All Road Users-Involved Casualty Collisions	31.40	42.70	1.00	221.00
	All Road Users-Involved PDO and Casualty Collisions	95.40	136.00	1.00	694.00
	Cyclists-involved PDO and Casualty Collisions	5.45	7.35	0.00	45.00
	Total Commuters	1310	536	305	2970
	New Cycling Infrastructure (km)	0.58	0.48	0.00	2.45
	Cumulative Cycling Infrastructure (km)	2.25	2.15	0.00	9.92
	New Cycling Infrastructure with Physical Separation (km)	0.08	0.24	0.00	1.19
	Cumulative Cycling Infrastructure with Physical Separation (km)	0.62	1.06	0.00	5.34
	New Cycling Infrastructure without Physical Separation (km)	0.10	0.29	0.00	2.08

Cumulative Cycling Infrastructure without Physical Separation (km)	1.08	1.17	0.00	4.35

Table 3.16. Model 1- Effect of cycling infrastructure at CT level on casualty collisions (Measure 1) of all road users-involved and cyclists-involved collisions

	All Road Users-Involved Collisions		**Cyclists-Involved Collisions**
Treatment Effect	ON Pooled Sample	BC Pooled Sample	ON Pooled Sample
New Cycling Infrastructure (km)	0.024** (0.008)	-0.084*** (0.000)	0.052** (0.019)
Number of Observations	7875	681	7673
R2	0.684	0.880	0.389
R2 Adj.	0.673	0.872	0.343
Std.Errors	Census Tract and Year		
Fixed Effects	Census Tract and Year		
The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively			

Table 3.17. Model 1- Effect of cycling infrastructure at CT level on casualty and PDO collisions (Measure 2) of all road users-involved and cyclists-involved collisions

	All Road Users-Involved Collisions		**Cyclists-Involved Collisions**	
Treatment Effect	ON Pooled Sample	BC Pooled Sample	ON Pooled Sample	BC Pooled Sample
New Cycling Infrastructure (km)	0.008 (0.006)	-0.059*** (0.000)	0.039* (0.019)	-0.048 (0.046)
Number of Observations	8212	693	7927	585
R2	0.907	0.950	0.452	0.592
R2 Adj.	0.905	0.947	0.415	0.547
Std.Errors	Census Tract and Year			
Fixed Effects	Census Tract and Year			

The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively

Table 3.18. Model 1- Effect of each type of cycling infrastructure at CT level on casualty collisions (Measure 1) of all road users-involved and cyclists-involved collisions

	All Road Users-Involved Collisions		Cyclists-Involved Collisions
Treatment Effect	ON Pooled Sample	BC Pooled Sample	ON Pooled Sample
New Cycling Infrastructure with Physical Separation (km)	0.023* (0.012)	-0.116*** (0.028)	0.071* (0.029)
New Cycling Infrastructure without Physical Separation	0.024* (0.010)	-0.048 (0.061)	0.027 (0.025)
Number of Observations	7875	681	7673
R2	0.684	0.880	0.389
R2 Adj.	0.673	0.872	0.343
Std.Errors	Census Tract and Year		
Fixed effects	Census Tract and Year		
The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively			

Table 3.19. Model 1- Effect of each type of cycling infrastructure at CT level on casualty and PDO collisions (Measure 2) of all road users-involved and cyclists-involved collisions

	All Road Users-Involved Collisions		Cyclists-Involved Collisions	
	ON Pooled Sample	BC Pooled Sample	ON Pooled Sample	BC Pooled Sample
New Cycling Infrastructure with Physical Separation (km)	0.007 (0.005)	-0.049*** (0.006)	0.058* (0.027)	-0.074+ (0.044)
New Cycling Infrastructure without Physical Separation (km)	0.010 (0.009)	-0.069** (0.027)	0.015 (0.022)	-0.012 (0.090)
Number of Observations	8212	693	7927	585

R2	0.907	0.950	0.452	0.592
R2 Adj.	0.905	0.947	0.415	0.546
Std.Errors	Census Tract and Year			
Fixed effects	Census Tract and Year			
The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively				

Appendix C: Supplementary Information of Chapter 3

Sensitivity test table of results

Table 3.20S. Interior Collisions Sensitivity Test. Model 1- Effect of cycling infrastructure at CT level on interior casualty collisions (Measure 1) of all road users-involved collisions

	All Road Users-Involved Collisions	
	ON Pooled Sample	BC Pooled Sample
New Cycling Infrastructure (km)	0.015+ (0.008)	-0.111*** (0.000)
Number of Observations	6232	611
R2	0.699	0.849
R2 Adj.	0.683	0.837
Std.Errors	Census Tract and Year	
Fixed effects	Census Tract and Year	
The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively		

Table 3.21S. Interior Collisions Sensitivity Test. Model 1- Effect of cycling infrastructure at CT level on interior casualty and PDO collisions (Measure 2) of all road users-involved collisions

	All Road Users-Involved Collisions	
	ON Pooled Sample	BC Pooled Sample
New Cycling Infrastructure (km)	-0.001 (0.007)	-0.074*** (0.000)
Number of Observations	7787	615
R2	0.902	0.930
R2 Adj.	0.900	0.925
Std.Errors	Census Tract and Year	
Fixed effects	Census Tract and Year	
The significance at the 0.05, 0.01and 0.001 levels is marked by *, ** and ***, respectively		

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Conclusions

Decarbonizing cities is central to climate change mitigation because urban systems concentrate both energy use and greenhouse gas emissions. Within urban systems, transport and buildings are two of the largest emitters. In 2019, the transport sector accounted for roughly 15% of total global greenhouse gas emissions, while the building sector accounted for about 21% when direct emissions, emissions from purchased electricity and heat, and major construction materials are considered (Lwasa et al, 2022). Meaningful urban decarbonization therefore depends not only on cleaner end use energy supply, but also on reducing energy demand in everyday mobility and in residential life.

The built environment sits at the center of urban climate mitigation. Urban form, land use, transport infrastructure, street design, and green infrastructure shape key dimensions of everyday energy-related behaviour, including trip frequency, travel distance, mode choice, and the heating and cooling demands of buildings. A substantial body of research has documented links between the built environment and travel behaviour (Cao et al., 2009; Ewing and Cervero, 2001; Ewing and Cervero, 2010), and review studies similarly show that urban form influences building energy use (Ko, 2013; Sliva et al., 2017; Quan and Li, 2021); however, these relationships often vary across study settings, measures, and empirical strategies. More importantly, much of the existing literature identifies associations rather than causal effects. This distinction matters for policy. Built environment policy instruments are designed to change specific outcomes. Assessing whether these intended changes are achieved is a central question in public policy and a core objective of policy impact evaluation (Gertler et al., 2016). Moreover, identifying the causal effects of built environment change is especially important because these interventions are typically long-lived, capital-intensive, and difficult to reverse. Urban form, buildings, and infrastructure can lock in behaviour, energy demand, and emissions for decades. Considering cities as urban systems, the different components of the built environment interact with one another, and changes to one component do not operate in isolation. As a result, built environment interventions can generate cascading effects across multiple urban outcomes, including travel, health, safety, and environmental performance, while also shaping everyday routines and choices at the population level. For these reasons, built environment policy should rely as much as possible on causal evidence rather than associations alone.

Establishing causality in this field is complex. Experimental studies are often considered the gold standard for impact evaluation as the researcher controls the assignment of units to the intervention and creates a credible comparison group (counterfactual). Although experimental studies in the context of the built environment and urban sustainability exist, multiple methodological and ethical factors limit the use of such designs. When experimental designs are infeasible or limited, researchers often turn to observational approaches to assess the impacts of built environment interventions in real-world settings that are rarely assigned randomly. Built environment interventions are typically introduced in places that already differ in density, demand, land values, infrastructure quality, political attention, or pre-existing behavioural trends. Quasi-experiments attempt to use the logic and language of experiments in observational settings and try to find (or construct) a comparison group using specific identification strategies that makes treatment variation "as-if random" under certain conditions and assumptions (Cook et al., 2002; Angrist and Pischke, 2009). Due to lack of random assignment, in quasi-experiments exposure to the treatment is observed rather than assigned (Hernán and Robins, 2010). However, a challenge in built environment interventions is that treatment is not naturally clear-cut. Unlike many policy settings in which units can be more readily classified as treated or untreated, built environment interventions often affect entire communities while influencing individuals to different degrees depending on their daily routines, perceptions, and needs. As a result, defining clear-cut treatment and control groups is often neither realistic nor conceptually appropriate. Robust identification of built environment effects therefore requires more innovative and context-sensitive ways of defining the exposed population, ones that account for the complex and multi-faceted ways in which people interact with the built environment.

This dissertation responds to that challenge by bringing a causal lens to the study of built environment and energy-related behaviour in the transport and residential building sectors. Across the chapters, the central empirical strategy is difference-in-differences (DiD), used to compare changes over time between groups with different intensity of the intervention. DiD is particularly well suited to the evaluation of built environment policies in real-world contexts. It can accommodate multiple time periods and staggered treatment timing, which is common in policy implementation. It is also appropriate for assessing interventions intended to influence population-level outcomes, as it identifies average group effects rather than narrowly local effects. Importantly, the design is grounded in explicit identifying assumptions, allowing for transparent causal interpretation when those assumptions are plausible to hold. Overall, the dissertation has two significant contributions. First, it proposes causal evidence on how built environment change shapes energy-relevant behaviour. Second, it proposes innovative ways of exposure observation in quasi-experimental methods adapted to the complexities of urban built environment policy interventions. These contributions are important for planners and policymakers because they provide stronger guidance on whether such interventions work, for whom they matter most, and how they should be evaluated in practice.

Chapter one uses high-frequency electricity consumption data at the household level, matched with high-resolution estimates of urban tree canopy coverage, along with a DiD design, to estimate the impact of the urban tree canopy as a nature-based built environment intervention on residential electricity consumption. Our findings are both practical and theoretical. On the practical side, we have detailed and internally valid findings about the impact of urban greening on cooling electricity demand. We find that the current urban tree canopy on average reduces the annual electricity load from single family dwellings in Ottawa by about 3%. During the summer period, we find that a house with complete urban tree canopy coverage consumes about 29% less electricity than an identical house with no trees nearby. Effects of the urban tree canopy are largest for trees planted within 12.5 m and to the West of a home. We find that the largest reduction in electricity consumption from trees occurs on hot summer afternoons and reaches over 15% of residential load. This period coincides with electricity system peaks and suggests that urban trees play a significant role in limiting peak period demands. On the theoretical side, we make methodological advancements that can be replicated in other contexts. Most importantly, we demonstrate a new approach to using machine learning to uncover heterogeneous causal impacts in a DiD context. This approach allows us to understand how the electricity savings from the urban tree canopy vary with weather and sun conditions.

Overall, the study's results suggest that the urban tree canopy exerts a large influence on electricity demands. This finding suggests that maintaining and increasing urban tree canopy can be an important part of the strategy for managing future electricity load. Although this chapter focuses on one private benefit of urban trees (lower residential cooling demand), the value of urban trees extends well beyond household energy savings. A large body of research shows that urban trees and other forms of green infrastructure can provide multiple ecosystem services and co-benefits, including stormwater management, carbon storage and sequestration, and in many contexts, improvements in air quality and thermal comfort (Livesley et al., 2016). The literature also suggests that urban trees can support broader dimensions of human well-being, including mental and physical health (Wolf et al., 2020). Taken together, these wider benefits strengthen the case for nature-based built environment strategies. Even when a study identifies only one service such as reduced cooling energy use, urban trees should be understood as multi-functional infrastructure that can contribute simultaneously to building efficiency, climate adaptation, and the broader sustainability and livability of urban communities.

In the second chapter, we examine how built environment design, and particularly supportive cycling infrastructure, shapes commuting behaviour and cycling uptake. Cycling is an important mode in urban sustainability transitions because it can reduce transport emissions while also generating broader health, social, and economic co-benefits. This chapter contributes to the literature in several ways. First, it estimates the causal effect of cycling infrastructure on commuting behaviour using a continuous DiD framework, allowing identification to come from within-pair changes in infrastructure and behaviour over time. Second, it moves beyond conventional proximity-based measures of exposure that classify treatment mainly by proximity to infrastructure. Instead, it conceptualizes exposure through the daily home-to-work activity space of individuals and the intensity of cycling infrastructure within that space. By comparing multiple spatial definitions of exposure, including infrastructure within home-to-work activity space, buffers of activity space, and infrastructure located near or spatially aligned with the shortest home-to-work route, the chapter evaluates not only whether cycling infrastructure exists, but also whether it is functionally aligned with everyday travel needs. This is an important methodological contribution because prior research suggests that cyclists respond not simply to the total quantity of infrastructure, but to the availability of routes that are direct, connected, and lower stress between origins and destinations. Finally, the chapter examines heterogeneity across socio-economic groups, recognizing that the effects of cycling infrastructure are unlikely to be uniform across the population and that equity remains a central concern in active transportation planning.

The findings from the pooled sample of Toronto and Vancouver indicate that each additional kilometre of cycling infrastructure within home to work census tracts increases the odds of cycling to work by approximately 4.1%. The heterogeneity analysis further shows that responsiveness to cycling infrastructure is greater among men, individuals living within 5 km of their workplace, those aged 15 to 35, those with no formal education, and those earning below the median income when infrastructure is measured along their shortest commute route.

A key planning lesson from the findings is that the success of cycling infrastructure should not be evaluated only by the length built. What appears to matter is whether infrastructure forms a network that connects homes to workplaces and other daily destinations through routes that are reasonably direct and comfortable. Our findings align with research on cycling route choice and network performance that show cyclists value infrastructure that improves continuity between origins and destinations, and that connectivity and directness are central dimensions of a functional cycling network (Lowry et al., 2016). For planners, this means that investment decisions should move beyond simple infrastructure totals and instead prioritize networks that improve practical accessibility for everyday trips.

A second implication is that cycling planning should be explicitly equity-oriented. The heterogeneity results in this chapter show that infrastructure effects are not evenly distributed across social groups, which means that average treatment effects can conceal important differences in who benefits most from investment. This aligns with a growing literature showing that the benefits of cycling and cycling infrastructure are not always equitably shared, and that barriers related to safety, comfort, social conditions, and everyday travel responsibilities can shape who cycles and who does not. For planners, this suggests that cycling investment should be paired with an equity lens in corridor selection, network design, and evaluation, with particular attention to groups and neighbourhoods that may be less able to benefit under current conditions.

Cyclists are widely recognized as vulnerable road users, which makes it essential to ask whether expanding cycling infrastructure can promote cycling without increasing collisions, injuries, or fatalities. Chapter 3 addresses this question by examining the safety effects of cycling infrastructure for both cyclists and all road users, and by assessing whether those effects vary across infrastructure types. A key contribution of this chapter is that it moves beyond the local effects of individual facility upgrades and instead asks whether cycling infrastructure can improve safety at the level of the surrounding urban area. This broader perspective is important because previous research has shown that the safety benefits of cycling infrastructure depend not only on the facility itself, but also on route design, network context, and the degree of physical separation from motor traffic.

To examine these questions, the chapter applies a continuous DiD framework, identifying safety effects from within-unit changes in cycling infrastructure and collision outcomes over time. The analysis uses pooled samples from Toronto and Ottawa in Ontario, and Vancouver and Victoria in British Columbia, and estimates impacts separately for casualty collisions and all collisions to distinguish changes in severe safety outcomes from changes in overall collision occurrence. The chapter also compares infrastructure types that provide stronger physical separation from motor vehicles, such as cycle tracks, bike paths, and multi-use trails, with facilities that involve lighter separation or greater mixing with traffic, such as local streets and painted bike lanes. This distinction is substantively important because the literature suggests that physical separation is often a key mechanism through which cycling infrastructure improves safety.

The findings show that safety effects are not uniform across contexts. In the pooled Ontario sample, increase in cycling infrastructure is associated with higher safety risks for cyclists at the census-tract level, whereas in the pooled British Columbia sample, infrastructure improvements are associated with lower risks for all road users. These contrasting results, observed across both cyclist-involved and all-user collision measures, suggest that cycling infrastructure does not have a single, context-independent safety effect. Instead, its impacts appear to depend on broader urban and roadway conditions that this chapter does not directly model. This is consistent with prior research showing that safety outcomes vary across roadway environments, socio-spatial settings, and route characteristics. The chapter therefore highlights an important policy lesson: infrastructure expansion alone is not enough to guarantee safer cycling. The design, placement, and network context of facilities matter greatly in determining whether cycling infrastructure functions as a safety intervention.

These findings are important for planning because many cities are expanding cycling networks in pursuit of climate, congestion, and public-health goals, and policymakers need to know whether such investments improve safety for cyclists and for the wider road system. By estimating effects for cyclist-involved collisions as well as collisions affecting all road users, this chapter shows that cycling infrastructure should be evaluated not only as a tool for mode shift, but also as a network-level safety intervention. More broadly, the results suggest that urban sustainability planning should pay closer attention to context-specific design. The one type of infrastructure may not deliver the same safety outcomes across different cities or even across different parts of the same city. For planners, the implication is clear. Expanding cycling infrastructure is important, but safer and more sustainable outcomes are more likely when network design, physical separation, surrounding road conditions, and local context are considered together rather than in isolation. Cycling is increasingly recognized as part of urban mitigation and public-health strategy, but its success depends on whether infrastructure is designed as an integrated and context-sensitive system.

Collectively, this dissertation aims to emphasize that the built environment is not simply the setting in which urban life unfolds, but an active policy tool for climate mitigation and urban sustainability. Across the residential building and transport sectors, the findings demonstrate that changes in urban form, green infrastructure, and cycling infrastructure can shape everyday energy-related behaviour, but that these relationships must be examined with a causal lens. By applying quasi-experimental methods to complex, real-world urban interventions, this dissertation contributes both substantive evidence and methodological insight. Overall, it argues that more sustainable cities will depend not only on technological change, but also on careful, evidence-based planning of the environments in which people live, travel, and consume energy.

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