SEPARATED CYCLING INFRASTRUCTURE AND BIKE SHARE RIDERSHIP: FURTHERING CAUSALITY THROUGH GPS DATA

SEPARATED CYCLING INFRASTRUCTURE AND BIKE SHARE RIDERSHIP:

FURTHERING CAUSALITY THROUGH GPS DATA

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ABSTRACT

Cycling, and micromobility tools like bike share, have increasingly been recognized for their health, economic and environmental benefits, and municipalities have recently made encouraging the use of these modes of urban transportation both a policy and a financial priority. Many studies, using varying methods, have identified and confirmed an association between an increased presence and connectivity of cycling infrastructure (bike lanes, cycle tracks, etc.) and cycling or bike share ridership. Determining a more explicit causal link between infrastructure and ridership, however, often proves challenging to researchers, due to data limitations and a variety of simultaneous, exogenous, factors that abound within complex urban transportation systems. Given the financial impacts of capital investment in infrastructure, more closely establishing this causal link, and identifying infrastructure's ability to generate cycling and bike share traffic, is of growing importance to municipal governments and taxpayers. Using Hamilton Bike Share (HBS) trip logs and GPS trajectories occurring between January, 2019 and August, 2022 (n = 741,369 and 609,746, respectively), this thesis constructs individual shapefiles of each HBS trip for GIS analysis through Dalumpines and Scott's (2011) *GIS-Based Map-Matching Algorithm*. It investigates the impact of ten separated cycling infrastructure projects in Hamilton, constructed between 2019 and 2022, on HBS ridership along the respective intervention segments. The thesis also holistically analyzes the spatial and ridership impacts of one infrastructure intervention, the Victoria Avenue cycle track, on the distribution of riders using the segment of interest, a more precise classification of post-intervention trip natures ('induced' or 'diverted') using a novel categorization process, and maps the impact of the segment on trip diversion to use the cycle track. Results indicate that five of the ten interventions have had significant, positive, impacts on monthly HBS ridership along their respective segments, with others having nearly statistically significant results as well. Moreover, the Victoria Avenue cycle track lessened the cost of distance associated with using Victoria Avenue, and 46.9% of trips along the cycle track post-intervention, were determined to be ‘induced’ trips. Finally, of the streets in the Victoria Avenue cycle track’s neighborhood, the cycle track segments were the only segments to experience ridership increases post-intervention, which indicates a significant level of trip diversion and funneling of trips to use the cycle track. These results enhance findings from the literature and more concretely quantify the direct impacts of infrastructure investments. Investments in infrastructure appear to make a significant difference in increasing ridership and serve to benefit more than just existing riders. This thesis can have an important impact on municipal active transportation planning, policy, and financing, through its results and by providing a methodological foundation for future research into infrastructure’s impacts on a variety of users.

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PREFACE

This thesis consists of four chapters, including an introduction (Chapter 1), two research papers (Chapters 2 and 3, respectively), and a conclusion (Chapter 4). The introduction provides context and gaps in the research that this thesis aims to fill. Chapter 2 is a journal submission to *Travel Behaviour and Society* and accepted as a peer-reviewed conference presentation for the *2023 Annual Meeting of the Transportation Research Board*. It quantifies the impacts of ten cycling infrastructure investments on Hamilton Bike Share Bicycle Kilometers Traveled (BKT) per month, along the intervention segments. The second paper (Chapter 3) has been submitted to *Journal of Transport Geography*. It more closely, and holistically, investigates the spatial and 'induced' ridership effects of the Victoria Avenue Cycle Track on Hamilton Bike Share. The two papers are a combination of results-based and methodological contributions to the literature.

Regarding author contributions, the first author on both papers was responsible in part for the project conception, and fully responsible for the literature review, model estimation/data analysis, and manuscript writing. Dr. Darren Scott, as project supervisor and second author on both papers, contributed to the project conception, analysis, and interpretations of results, as well as manuscript revision and journal submission.

The two research papers of which this thesis is comprised are detailed below:

Chapter 2:

Van Veghel, D. and Scott, D.M. (2022). Are All Bike Lanes Built Equal? Using Bike Share GPS Data to Quantify Cycling Infrastructure Investments' Ridership Effects in Hamilton, Ontario. *Travel Behaviour and Society.* Submitted.

Chapter 3:

Van Veghel, D. and Scott, D.M. (2023). Investigating the Impacts of Bike Lanes on Bike Share Ridership: A Holistic Approach and Demonstration. *Journal of Transport Geography.* Submitted.

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1. INTRODUCTION

1.1. The Research Problem in Context

Cycling is increasingly recognized as an environmentally sustainable, fiscally responsible, economically beneficial means of urban travel, with additional significant health benefits for the individual user (Pucher and Buehler, 2017; Pucher and Buehler, 2012). Urban areas are working to promote cycling and increase its mode share through a variety of means, including the construction of dedicated cycling infrastructure (such as bike lanes or cycle tracks), and the establishment of Bike Share Systems (BSSs), which are increasingly seen as key investments in urban transport due to their wide array of societal and individual benefits (Morton, 2018; Shaheen et al., 2010). BSSs, many of which allow users or members to rent out a bike from a designated docking station, ride the bike, and dock the bike at another station within the system's service area, have exploded in popularity in the past decade, with nearly 2000 cities having systems in August 2022, and 11% of those existing in North America (Meddin et al., 2022).

Despite these developments, safety, or a perceived lack of safety when riding, is a major barrier to cycling privately, or to the use of bike share systems (Fishman et al., 2012; Sanders and Judelman, 2018; Swiers et al., 2017). The majority of individuals in urban environments have been found to be interested in cycling, but still affected by safety concerns (Dill and McNeil, 2013; Geller, 2006), and bike share members, while more confident than non-bike share members, often experience a lack of confidence cycling and a strong desire to use dedicated cycling infrastructure (Burmester and Lamondia, 2022; Fishman et al., 2015). Separated cycling infrastructure, where the rider is physically separated from automobile traffic, has been found to alleviate this perceived lack of safety in private cyclists and bike share members, and is generally rated favorably by cyclists (Bateman et al., 2021; Fishman et al., 2015; Guo et al., 2023; Monsere et al., 2012; Sanders and Judelman, 2018). Additionally, an increase in cycling levels within an area has been found to increase the objective safety – decreasing cycling injury rates – of those using the mode (Elvik, 2009; Jacobsen, 2003).

As a result, governments of all levels in Canada are committing to policy and financial channels to promote urban cycling levels. This includes changes in policy, such as at the provincial level, promoting multi-modal transportation networks and encouraging modal shift toward active transportation (e.g., *A Place to Grow* – Ontario Ministry of Municipal Affairs and Housing, 2019), and at the local level, including the City of Hamilton's 2018 Updated Cycling Master Plan, in which the City commits to improving its cycling levels in accordance with provincial direction (City of Hamilton, 2018). Moreover, and perhaps more directly of relevance to the average taxpayer, there are significant financial commitments to active transportation, and cycling specifically. This includes federal funding for local active transportation projects, like trail and bike lane construction via the Active Transportation Fund (Infrastructure Canada, 2021), and the City of Hamilton's recent capital budgets, which have made building cycling infrastructure like separated cycle tracks a major financial priority, including $1.4 million in 2022 cycling infrastructure spending, and $3.3 million in planned capital budget spending for 2023 (City of Hamilton Cycling Infrastructure Report, 2023).

Many studies have examined the influence of cycling infrastructure on ridership levels and have found a positive correlation between the two (Eren and Uz, 2020). This said, causal inferencing – determining the specific impacts of separated cycling infrastructure on cycling and bike share ridership – presents significant challenges to active transportation researchers due to the need for "association, nonspuriousness, and time order" (Krizek et al., 2009; Singleton and Straits, 2005). Addressing causality, and therefore more directly quantifying the impacts of separated cycling infrastructure on cycling, through bike share system data, can inform planners and policy makers on the efficacy of policy and financial investment and can guide future municipal decision making.

1.2. Objectives

This thesis seeks to quantify, categorize, and visualize the 'induced' ridership impacts of separated cycling infrastructure, on bike share in a mid-sized Canadian city (Hamilton, Ontario) more precisely and directly than previous works in the literature. The individual research objectives addressed in the following chapters include:

I. Quantify the impacts of various separated cycling 'interventions' on Hamilton Bike Share ridership, controlling for confounding factors.

II. Using longitudinal, and empirical revealed preference data, develop a methodology that more reliably establishes a causal link between cycling infrastructure and increased ridership.

III. Evaluate the heterogeneity in intervention success in generating HBS ridership across the cycling network and examine potential factors behind any heterogeneity.

IV. Evaluate the impacts of separated cycling infrastructure projects on the spatial distribution of bike share rides, and the cost of distance associated with use of a street segment with or without separated cycling infrastructure.

V. Evaluate the nature of bike share rides, to further a causal link between infrastructure and ridership, by parsing apart 'induced' ridership from 'diverted' ridership.

1.3. Addressing Gaps in the Literature

The objectives, outlined above, address several existing gaps in the literature. For one, whereas the majority of the studies in this field have used stated-preference survey data (Panter et al., 2016), count data (such as Félix et al., 2020), cross-sectional or panel checkout data (Buck and Buehler, 2012; Faghih-Imani et al., 2014, e.g.), or artificially generated route data (Karpinski et al., 2021 e.g.), this thesis uses empirical GPS route data over several years, to examine more directly the impact of infrastructure on the system-wide bike share ridership for a select time period, analyzing where users actually go and when they do so. This enhances the study's ability to determine, beyond an association, a causal link between infrastructure and ridership change, identified as a need by Buehler and Dill (2016), Krizek et al. (2009), and Pucher et al. (2010).

With regards to study scale, the research combines both a network-wide analysis of bike share ridership, focusing on all trips within the Hamilton Bike Share Service Area, as well as a more detailed single-case study of one infrastructure intervention, simultaneously building off network-wide analyses like Xu and Chow (2019), while also providing more localized investigations. The research also provides a holistic analysis of infrastructure's effects on ridership, with a variety of combined methodologies, as recommended by Mölenberg et al. (2019).

In conjunction, the work provides greater controls for temporal and non-temporal externalities, as well as further evaluation of the specific nature of trips, to better account for the variety of potential travel behavioral impacts of infrastructure interventions, including induced and diverted (pre-existing) traffic. Buehler and Dill (2016), in their review of the literature on cycling networks and ridership, recommended for future research that: “Longitudinal research designs need to include controls or other methods to assess the possible explanations for changes in observed ridership — existing bicyclists changing routes, regular bicyclists cycling more often, or people starting to bicycle who had not before.” This research seeks to address this recommendation through the combination of established methods of treatment and control group (quasi-experimental) methods to examine trip diversion from an infrastructure intervention, and it also introduces a novel classification method for parsing apart induced and diverted trips. Moreover, through classifying trips by new and existing members and induced or diverted, a more detailed evaluation of who is most benefitting from infrastructure interventions can be achieved (Mölenberg et al., 2019).

This thesis is focused specifically on infrastructure’s effects on bike share ridership, and it is important to note that the primary demographics and experience levels of bike share riders have been found to differ from those of private cyclists. For one, bike share riders have been found to be more likely young and female (Buck et al., 2013; Crossa et al., 2021). They are more likely to be individuals with lower incomes, are less likely to own bikes or cars, and bike share “super-users” are less likely to own bikes than regular members (Buck et al., 2013; Reilly et al., 2020; Winters et al., 2019). Moreover, there are indications that, in conjunction with demographic differences, bike share riders may differ from private cyclists in terms of their experience with cycling, as well as their confidence and potential desire for infrastructure (Martin et al., 2016). All of these potential differences emphasize the need to explore the influence of infrastructure on bike share ridership, as bike share riders potentially represent a different segment of the cycling population, who may especially benefit from these separated infrastructure investments.

1.4. Thesis Structure

This thesis is comprised of four chapters, including an introduction, two complete research papers (chapters 2 and 3), and a conclusion chapter.

Chapter 2 of this thesis models the potential impacts of ten separated cycling infrastructure projects, constructed between 2019 and 2022, on monthly Bicycle Kilometers Traveled (BKT) by Hamilton Bike Share users, along the segments which received the treatments or interventions. Using Fixed Effects Regression, a panel-style model with demonstrated uses in automobile 'induced demand' studies, controlling for a variety of time-variant and invariant properties, to isolate the interventions' specific impacts more closely. Moreover, it examines the heterogeneity in ridership impacts across the ten interventions, and discusses potential explanatory differences between the projects, to account for these impact discrepancies. This chapter serves as a network-wide, aggregate-level investigation in intervention impacts – focusing specifically on ridership levels.

Chapter 3, however, provides a much smaller-scale, case study examination on the holistic impacts of the Victoria Avenue Cycle Track. It analyzes changes in the origins of routes using Victoria Avenue, post-construction and models the cost of distance to Victoria Avenue pre- and post-intervention. Additionally, it posits a novel classification method, using both route and membership data, to more precisely categorize the nature of trips using the cycle track post-intervention. This provides a tool for planners to further parse apart trips considered 'induced traffic' and 'diverted traffic' (combined, the total 'generated traffic') likely attributable to the construction of an infrastructure project. Finally, it also uses Geographic Information Systems (GIS) to investigate changes in route patterns, including neighborhood street usage around the cycle track pre- and post-construction to determine potential trip diversion brought on by the construction of the cycle track.

Chapter 4 discusses the topics addressed by the preceding chapters, outlines the primary limitations of the research presented in this thesis, and presents several intriguing future avenues of research, based off the methodological foundations and the limitations determined in this work. Each chapter's respective references are found immediately after the body of the chapter, except for this introductory chapter and the conclusion. Combined references for this chapter, and Chapter 4, can be found immediately after the conclusion in Chapter 4.

2. ARE ALL BIKE LANES BUILT EQUAL? USING BIKE SHARE GPS DATA TO QUANTIFY CYCLING INFRASTRUCTURE INVESTMENTS' RIDERSHIP EFFECTS IN HAMILTON, ONTARIO

2.1. Introduction

Planners and policymakers across North America are emphasizing the importance of multi-modal urban transportation systems (Southworth, 2005). Within these systems, cycling plays an important role, and it is increasingly seen as an environmentally and economically beneficial means of urban travel (Pucher and Buehler, 2017; 2008). Governments at all levels are working to promote cycling as a viable means of urban transportation, through investments in urban cycling networks, to improve their connectivity and reduce safety concerns (Pucher et al., 2011; Wilson and Mitra, 2020). Further encouraged by the pandemic, cities around the world have rapidly expanded their cycling networks, including temporary 'pop-up' lanes during the height of the pandemic, to investments in large-scale permanent infrastructure (Buehler and Pucher, 2023). London, for example, has constructed six 'cycle superhighways' of mostly or entirely-separated cycle tracks connecting the central city, with indications of substantial impacts from these separated infrastructure projects on cycling levels (Li et al., 2018). In Canada specifically, the growing investment in cycling infrastructure can be broken down into policy, research, and financial investments. In Ontario, new provincial growth policy encourages active transportation and bike-ability, specifically (e.g., A Place to Grow, 2019). There has also been growth in research, for policy, on the conduciveness of the surrounding environment and transportation network for cycling in Canada, including the recent development of Can-

BICS (the Canadian Bikeway Comfort and Safety metrics), which provide a standard measure of cycling infrastructure prevalence, at the census dissemination area level (Winters et al., 2022). Monetarily, millions of dollars in funding, from all levels of government have been recently directed toward funding infrastructure projects aimed to aid and increase ridership levels in cities (e.g., Government of Canada Active Transportation Fund, 2021).

Alongside infrastructure investments, micromobility interventions such as the introduction of Bike Share Systems (BSSs) are another way in which governments, globally, are working to increase cycling levels. Many of these systems, including Hamilton Bike Share's system, generally enable users to check out a rental bike from designated docking stations, ride within the BSS's service area, and return the bike at different stations across the service area for either regular membership or pay-as-you-go rates. BSSs provide a wide range of benefits to the community (Bauman et al., 2017). While research has shown that BSS trips do not generally serve as modal replacements for automobile trips (Fishman et al., 2016; Fishman et al., 2015; Zhu et al., 2013), one of BSSs' main benefits is its noted potential to "normalize" cycling as a modal choice (Goodman et al., 2014). As such, BSSs serve an important role in diversifying urban transportation networks. These systems have recently exploded in popularity amongst municipalities around the world, as a means of encouraging cycling, and the number of active systems globally has grown exponentially since 2004 (Fishman, 2015; Meddin et al., 2021). There are systems on every continent (apart from Antarctica); North America, with 205 recorded BSSs, is third globally, behind Europe (897) and Asia (720) (O'Brien et al., 2022). While many BSSs saw large decreases in ridership due to COVID-19, bike share has recovered better and more quickly from the pandemic than other modes of transport (Buehler and Pucher, 2023; Sangveraphunsiri et al., 2022). Since August, 2021, 187 BSSs began operation, and North America is second only to Europe in terms of systems launched in this recent timeframe (O'Brien et al., 2022).

BSSs also serve as a planning tool. With many modern BSSs using GPS-enabled bicycles, bike share systems can play a crucial role in researching cyclist travel behavior, and thus informing planning and policy directions, to better suit the apparent wants and needs of users (Brown et al., 2022; Davis, 2014). Moreover, as previously implied, bike share can play an increasingly important role in urban transportation in the post-COVID-19 pandemic era, having been found to be less negatively impacted by the early-onset of the pandemic and its associated restrictions (Teixeira and Lopes, 2020; Bucksy, 2020). Subsequently, they are viewed as a useful tool for cities in the long-term (Kim, 2021).

With BSSs and infrastructure investments being major planning and policy avenues for municipalities to increase cycling trip rates, the ability to examine infrastructure's direct impact on bike share ridership over long-term periods is critical to determine the over or under-funding of these interventions in transportation networks. While the Background section of this paper establishes the known association between infrastructure and ridership, isolating the specific project impacts is a significant challenge. Research methods on this have varied, from specific case-studies (e.g., Karpinski, 2021), to more macro, network-wide approaches (e.g., Xu and Chow, 2019).

This work has several research goals. For one, it seeks to use empirical bike share route GPS data and an established modeling methodology in the automobile induced-demand literature, to quantify the ridership effects of ten separated cycling infrastructure interventions in Hamilton, Ontario, as well as to develop a more reliable causal link between infrastructure investments and bike share ridership. In addition, it examines intervention impacts network-wide, providing a middle ground between single intervention case studies and aggregated city-wide analyses. Finally, it also examines the potential heterogeneity of interventions' effects across the varying projects – exploring segment-specific and neighborhood characteristics. The proceeding section outlines background works that informed this study. Next, the Methods of the study, including the data, tests run, and modeling techniques used, describes the processes used to investigate the interventions' impacts. The Results section outlines the model outcomes and the effect of the various explanatory variables on Hamilton Bike Share demand. How these results relate to the relevant literature and situational context, as well as the limitations and future research avenues, are outlined in the Discussion and Conclusion sections.

2.2. Background

2.2.1. Safety and Cycling

With rising installations and use of public municipal bike share systems in the past decade, significant research has been done on the determinants – including cycling infrastructure – of BSS ridership levels, as well as users' route choices (Buehler and Dill, 2016; Eren and Uz, 2020; Scott et al., 2021). Most studies have identified an association between dedicated bike infrastructure and cycling ridership, including for BSSs (Brown et al., 2022; Eren and Uz, 2020), with some notable exceptions (Scott and Ciuro, 2019). Various survey studies have shown that real and perceived cyclist safety is a major barrier to using the mode: a barrier that dedicated infrastructure helps mitigate (Bateman et al., 2021; Dill and McNeil, 2013; Sanders and Judelman, 2018). Real and perceived safety also impact the route choice of cyclists (Ding et al., 2021). Regarding on-the-ground safety, research conducted with London's Santander bike sharing system has shown cycleways and bicycle superhighways to have a positive (lessening) effect on bicycle crash frequency (Ding et al., 2020). Dedicated infrastructure has also been found to influence bicycle crash exposure (bicycle distance traveled) (Ding et al., 2021). In particular, separated cycling infrastructure such as cycle tracks, keeping the cyclist on the road but with a barrier between them and automobile traffic, have been found to greatly decrease the hesitancy to cycle (Coughenouor et al., 2015). Buehler and Dill (2016) recommended more quantitative, longitudinal studies to help determine the direct impact, or causality, behind infrastructure and inducing cycling ridership. However, the determination of causality – that an intervention adding separated cycling infrastructure to the cycling network directly induces ridership – has been shown to be a challenge, as it is difficult to control for all environmental and societal/cultural factors at play (Krizek et al., 2009).

2.2.2. Infrastructure and Increased Cycling/Bike Share Ridership

Despite the inherent challenges, various studies have looked to prove this causality. Methodologies vary from qualitative and descriptive (e.g., Marqués et al., 2015) to quantitative modeling efforts. Many induced demand-focused studies use stated-preference surveys to assess cycling from an individual's perspective prior to, and after, an infrastructure intervention (Buehler and Dill, 2016). Some of these surveys were repeated, cross-sectional surveys over several years (e.g., Goodman et al., 2013; Panter et al., 2016), single-instance surveys incorporating participants' recall (e.g., Mitra et al., 2021), or on-location street-intercept surveys (e.g., Mitra et al., 2017; Piatkowski et al., 2015). These methodologies are often subject to self-selection biases, participant recollection issues, attrition, or the surveys themselves were conducted in established cycling communities, such as Cambridge, UK (e.g., Panter et al., 2016).

Studies using revealed-preference or longitudinal data to quantify causality, however, are more limited (Buehler and Dill, 2016). Manual count data has been found to be an effective way to capture gains in traffic longitudinally for individual network links of interest (Parker et al., 2013), and for wider regions of interest, such as the city of Lisbon (Félix et al., 2020) or Cambridge, MA (Gehrke and Reardon, 2021). Félix et al. (2020) examined the combined effects of two "hard" interventions – the construction of cycling infrastructure over the study period, as well as the development of a city-wide bike share system. They counted cycling traffic across the city of Lisbon in several key areas, and found that between their baseline year, 2016, and 2018, areas of the city which received most of the infrastructure investments over the study period more than quadrupled their cycling volume, while areas where infrastructure remained largely unchanged saw little growth.

Studies have also used docking station usage data, including Li et al. (2018) to examine the influence of cycling infrastructure, and notably, cycling superhighways in London, on London Cycle Hire ridership levels. Li et al. (2018) analyzed five years of

Cycle Hire data for 762 docking stations, and determined docking stations within 300m of the superhighways can attract significantly higher ridership rates than docking stations outside of this buffer area.

Other studies have coupled revealed-preference (GPS) and big data to address the causal effect of dedicated infrastructure on cycling. Hong et al. (2020) utilized a combination of manual count and data from the cycling tracking app *Strava* to inform Poisson fixed effects regressions and examine the effectiveness of several infrastructure investments in Glasgow. Several of the projects examined in their work show an estimated 12-18% increase in cycling logged by *Strava* after the introduction of the interventions.

Various studies have leveraged the revealed-preference data provided by bike share systems to investigate the impacts of cycling infrastructure on these systems specifically. Brown et al. (2022) used Hamilton Bike Share GPS route data, infrastructure locations, and accessibility measures to predict Annual Bike Share Traffic Volume along cycling network links, with a linear regression model that incorporated eigenvector spatial filtering to remove spatial autocorrelation. They found dedicated infrastructure was the strongest predictor of increased volume, but they did not distinguish between physically separated or painted lanes and did not examine pre- and post-construction effects.

As a longitudinal study, Xu and Chow (2019) used Citi Bike ridership data from New York City between 2013 and 2018, as well as city-wide cycling infrastructure lengths over the same period, to conduct a time-series analysis (ARCH model). Their modeling predicted an additional mile of cycling infrastructure led to an increase of 102 additional bike share trips in the city.

Mixing cross-sectional and time series analysis, Karpinski (2021), in a quasi-revealed preference case study, used panel-style OLS modeling and artificially generated Boston bike share routes between station pairs from 2011 to 2019, to examine differences-in-differences of ridership before, during and after a separated bike lane intervention on Boston's Commonwealth Avenue. They found station pairs with their determined 'dominant' route including the intervention network link, had an additional 960 monthly trips not explained by the baseline ridership. Kraus and Koch (2021) used a similar panel difference-in-difference approach in analyzing the impact of COVID-19-related infrastructure investments in 106 European city cycling networks, with more than 700 bicycle counters. They found the creation of these infrastructure investments, on average, brought on between 11-48% increases in cycling levels.

While these studies show a time-varying relationship between infrastructure interventions and bike share ridership or cycling at large, they do not answer at least one of two important questions: 1) When looking across the entire cycling network, does the introduction of new separated cycling infrastructure increase traffic along the associated network links? 2) Are the effects of the interventions consistent across the various projects, or are they heterogeneous?

2.3. Methods

2.3.1. Study Location

Located on the southwestern end of Lake Ontario and at the edge of the Greater Toronto and Hamilton region, Hamilton is a mid-sized Canadian city with an estimated 2021 population of 569,355 (City of Hamilton, 2022). It is geographically divided by the Niagara Escarpment, which runs through the middle of the city and provides a sharp elevation change. The city's docked bike share system, Hamilton Bike Share (HBS), was established in 2015 and currently services 141 bike docking stations across ~25 km^2 below the Niagara Escarpment, supplying more than 800 GPS-equipped rentable bicycles (Hamilton Bike Share, 2020). HBS offers service year-round to individuals 16 years of age or older.

2.3.2. Hamilton Bike Share Trip and Route Data

Trip logs for each Hamilton Bike Share (HBS) trip from January 1st, 2019, and March 31st, 2022, were obtained from HBS. These records contained information on trip start and end docking locations, trip dates and times, durations, and overall distances of the trips in kilometers. Additionally, each of the HBS bikes are GPS equipped and produce GPS trajectories for each trip by a user from origin station to destination station. During the study period, HBS logged 628,844 trips, with 608,099 being valid trips[1]. Each GPS trajectory was map-matched using Dalumpines and Scott's (2018) GIS-based Episode Reconstruction Toolkit (GERT), and Dalumpines and Scott's (2011) map-matching

[1] Valid trips were distinguished as those with durations between 1 and 480 minutes, distances between 0.1 and 100 KM, and speeds between 1 and 35 KM/H.

algorithm: which converted the trajectories into route shapefiles for analysis in a GIS. The process used by GERT is explained in greater detail in Lu et al. (2018), and further information on the construction of the cycling Network Dataset used by GERT in the map-matching process can be found in Brown et al. (2022). Of the 628,844 trips logged, 516,102 trips had valid GPS trajectories, and 495,084 trips were successfully map-matched; those lost had trajectories which could not be matched with the cycling network dataset, due to point dispersion or use of routes not included in the network, like alleyways (see Brown et al. (2022) for further explanations). Thus, the final dataset of routes included represented ~96% of all valid trajectories, and ~81% of all valid trips.

2.3.3. Infrastructure Data

Using information from City of Hamilton staff, the City's Cycling Master Plan, and its Open Data portal, a feature class of all separated cycling infrastructure projects built between January 2019 and March 2022 was constructed using ArcGIS Pro®. Information included in the shapefile were infrastructure type (bike lane with painted buffer, cycle track with soft barrier, and cycle track with concrete barrier), as well as the month and year the project opened for public use. Two Painted Buffer Lanes, though not providing cyclists a physical barrier, are included in this analysis to provide a more heterogeneous sample of projects, and to examine potential differences in intervention impact across the types of separation. Projects included in this study can be seen in Table 2.1. Figure 2.1 displays these projects spatially, in relation to HBS Stations and the overarching HBS Service Area. Photographs of each of the 10 interventions can be found in the Appendix. Cycling trails, multi-use paths and other off-road separated cycling infrastructure were not included in this analysis, as Scott et al. (2021) determined a preference of HBS users to avoid these, outside of university campus trails. Moreover, of the few that were constructed during the study period, these trails almost exclusively occurred outside of the HBS Service Area.

Table 2.1. Separated Cycling Infrastructure Improvements from January 2019 through March 2022, their associated lengths, and months of completion (n = 10).

Project Name	**Infrastructure Type**	**From Street**	**To Street**	**Length (Km)**	**Completed**
Locke St.	Painted Buffer	King St.	Hunter St.	0.401	2020-05
Hunter St.[a]	Concrete Barrier	Queen St.	Park St.	0.563	2021-04
Hunter St.[a]	Concrete Barrier	Park St.	Catherine St.	0.608	2021-08
Hunter St.[a]	Concrete Barrier	Catherine St.	Liberty St.	0.374	2021-04
Hunter St.[a]	Painted Buffer	Liberty St.	Keddy Access Trail (KAT)	0.295	2021-04
King St.	Concrete Barrier	Paradise Rd.	Dundurn St.	0.916	2021-07
Hatt St.	Concrete Barrier	John St.	Baldwin St.	0.743	2021-08
York Blvd. (Eastbound)	Plastic Barrier	Dundurn St.	Hess St.	1.034	2021-12
York Blvd. (Westbound)	Plastic Barrier	Dundurn St.	Hess St.	1.019	2021-12
Victoria Ave.	Concrete Barrier	Cannon St.	Copeland Ave.	0.522	2021-12

[a] Despite being consecutive sections of Hunter St., these investments were treated as separate interventions, as they were constructed at different times, or they were different types of infrastructure

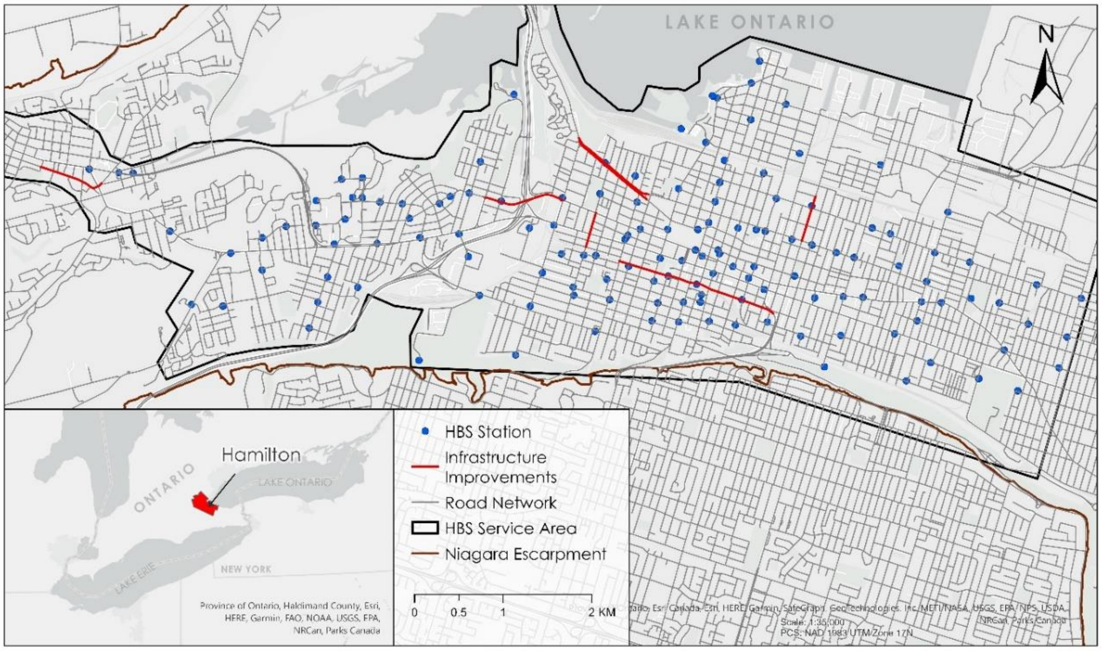


Figure 2.1. The study area. Cycling infrastructure investments of interest can be seen in red, as well as locations of HBS Stations.

2.3.4. GIS Processing

Route shapefiles were imported into ArcGIS Pro® and intersected with the infrastructure feature class. Outputs of this process were feature classes representing the overlap between HBS routes and the infrastructure, with each of the records capturing the infrastructure used, and the length of overlap in meters. Each intersection’s attribute information was then associated with the trip and route records discussed previously in a one-to-many join, where each trip now included information on any of the infrastructure locations used during the trip, and for how many meters.

2.3.5. Dependent Variable and Data Specification

The dependent variable used in the analysis is the natural logarithm of Monthly Bicycle Kilometers Traveled (BKT) along infrastructure links of interest. Monthly Trip Counts along the links were considered for use as the dependent variable, however, their nature as non-negative count data limited modeling distributions (e.g., Poisson Regression, Negative Binomial Regression) (Greene, 1997). Additionally, these counts would not take into consideration the level of use on the intervention geographically. Some trips may only use a small section of the infrastructure, while others would use the entire segment. Using a trip count dependent variable, these trips would be equivalent, whereas using BKT, their level of use differences are considered. BKT was used as a cycling equivalent to Vehicle Kilometers Traveled (VKT) or Vehicle Miles Traveled (VMT) – popular metrics used in induced demand research for automobile traffic (e.g., Fulton et al., 2000; Kang et. al., 2009; Noland and Cowart, 2000).

Monthly BKT for each infrastructure link, like trip counts, were also non-negative and had a cyclical seasonal pattern each year. These issues were rectified by using a Natural Logarithmic transformation of the dependent variable, and the inclusion of year-specific dummy variables, as well as temperature and precipitation control variables as regressors.

2.3.6. Independent Variables

Various other explanatory variables were considered in the modeling process. Weather and temperature have been found to be significant determinants of daily bike share ridership in Canada (El-Assi et al., 2017; Faghih-Imani, 2014; Scott and Ciuro, 2019). We use two climatological factors: Average Temperature and Average Daily Precipitation. In addition to having been found a significant BSS ridership determinant, the use of a temperature variable, which follows a cyclical seasonal pattern (as shown in Figure 2.2), controls for the seasonality of HBS ridership, while only slightly decreasing the model's degrees of freedom; a suite of month-specific dummy variables would capture this cyclic pattern but at a large cost to model degrees of freedom. Climate and weather information was assembled from Environment Canada daily recordings measured at the John C. Munro Hamilton International Airport.

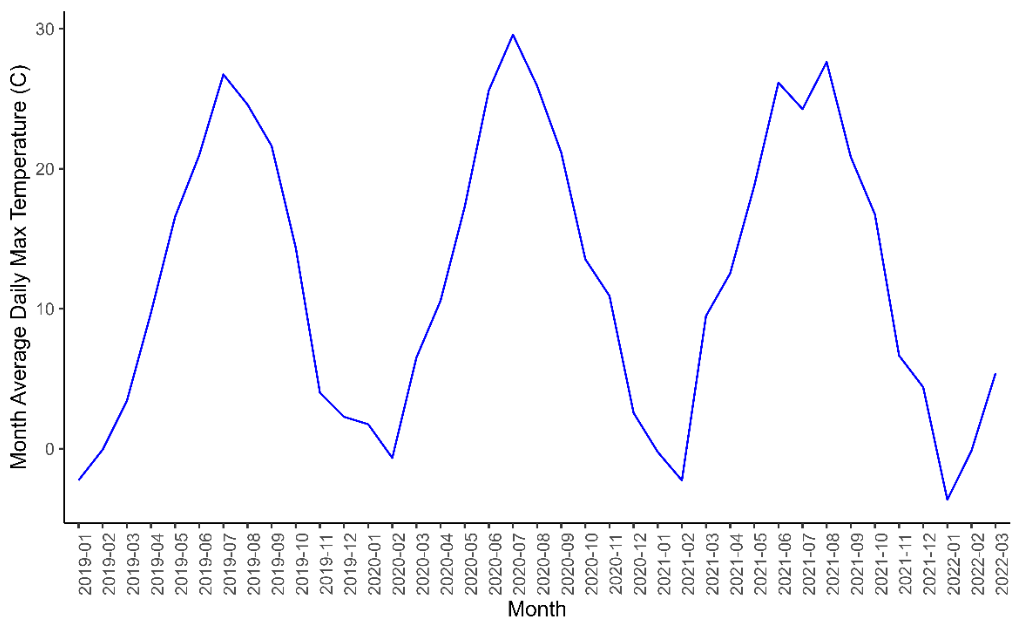


Figure 2.2. Average Daily Maximum Temperature in °C, for each month during the study period.

COVID-19 lockdowns had a significant impact on cycling and bike share levels across the globe (Buehler and Pucher, 2021; Jobe and Griffin, 2021). Thus, additional explanatory variables include dummy variables which account for any presence of COVID-

19 lockdowns during the study's time period, and a dummy variable to account for the June 2020 Hamilton Bike Share shutdown during the first COVID-19-related lockdown. All explanatory variable descriptive statistics can be found in Table 2.3.[2]

2.3.7 Monthly Station-Trip Distance Accessibility

Bike share stations near cycling infrastructure have been found to have higher traffic, and bike share traffic is affected by proximity of docking stations (Li et al., 2019; Zhang et al., 2017). To control for both variations in intervention segments' proximities to HBS traffic, as well as time-related fluctuations in system-wide traffic levels, monthly station-trip distance accessibility, an expansion upon a time-invariant version of the variable developed by Brown et al. (2022) was developed:

$$A_{i,t} = \left(\sum_j R_{j,t} f\left(C_{ij}\right)\right) \cdot 10^{-3} \qquad \textbf{(1)}$$

where $A_{i,t}$ is the monthly station-trip distance accessibility of intervention *i* at month *t*, $R_{j,t}$ is the total ridership (trip starts and ends) at station *j* during month *t*, C_{ij} is the cost of travel between intervention *i* and bike share station *j*, and $f(C_{ij})$ is an impedance function for travel between intervention *i* and bike share station *j*. The monthly station-trip distance accessibility values were scaled by 1000, for consistent reporting in the fixed effects modeling process, described in Section 2.3.8. Scott and Horner's (2008) approach was used

[2] Regarding independent variable multicollinearity, Variance Inflation Factors (VIF) for continuous variables ranged from 1.26 to 4.92, which are acceptable (Kim, 2019). Generalized Variance Inflation Factors (GVIF) (Fox and Monette, 1992), accounting for degrees of freedom differences, ranged from 1.12 to 2.22. These values indicate acceptable levels of multicollinearity.

to develop the impedance function, which was a negative exponential distance decay function:

$$f(C_{ij}) = e^{\beta_t C_{ij}} \qquad \textbf{(2)}$$

where β_t is the annual distance decay parameter, calculated for each year of the study period using the methods described in Brown et al. (2022), and C_{ij} is the cost of travel (distance). The annual parameters are shown in Table 2.2.

Table 2.2. Annual distance decay parameters, derived from station-to-station trip distances, system-wide each year of the study period.

Year	**β_t**
2019	-0.26
2020	-0.21
2021	-0.24
2022	-0.27

Finally, the remaining independent variables are a suite of dummy variables representing the various interventions, which are time-location interactions. This means that they only take the value of 1 for BKT values in the data set belonging to the segment of interest, for months on or after the construction of the intervention. For example, the Hatt St. intervention dummy variable would only take the value of 1 if the monthly BKT logged for a particular month was on Hatt St. specifically and it took place after the intervention on Hatt St. These explanatory variables seek to showcase the individual effects of the interventions, with respect to time, on their respective road links' monthly BKT, and are crucial to analyzing the heterogeneity in intervention effectiveness, across the various segments in the study area. They allow for all ten interventions to be considered separately within the model, rather than being aggregated by common characteristics.

Table 2.3. Descriptive statistics of variables used in the analysis.

Variable	Definition	Type	Mean (SD)
ACCESSIBILITY	Monthly Station-Trip Distance Accessibility	Metric (Continuous)	12.68 (8.96)
MAXTEMP	Month's average daily max temperature (°C)	Metric (Continuous)	12.29 (10.33)
AVG_PRECIP	Month's average daily precipitation (mm)	Metric (Continuous)	2.56 (1.12)
COVID	Dummy variable representing the presence of COVID-19 lockdowns in Ontario	Binary (Dummy)	

JUNE2020	Dummy variable representing the presence of the HBS Shutdown in June 2020	Binary (Dummy)
YEAR	Variable representing the calendar year	Categorical (Dummy)

2.3.8. Fixed Effects Regression

Fixed effects regression, or a more explicitly formatted least squares dummy variable (LSDV) model, is a multivariate modeling method using panel data, prevalent in causality investigations (Greene, 1997). In causality research, the proverbial ‘chicken or the egg’ debate, including the potential risks of ‘reverse causality,’ present significant challenges to the researcher (Leszczensky and Wolbring, 2019). In the case of BKT and infrastructure investments, do time-invariant characteristics of these segments lead to differing impacts of infrastructure investments, or vice versa? Entity-specific effects that do not change with time, such as the segment’s length, for example, are captured in the segment-specific dummy variables included in the model specification. Moreover, year-specific effects, which account for potential idiosyncrasies across the different years of the study, as in Karpinski (2021), are also captured as dummy variables in this method. By removing entity-specific and year-specific effects, the model can more closely isolate the specific impacts of the suite of infrastructure intervention dummy variables. One of the model’s key benefits is its ability to control for confounding factors that vary by time or location, without a substantial compromise on model parsimony or degrees of freedom.

While many confounding factors may not be explicitly defined in the model, the model's primary goal is to provide a more accurate estimation of intervention effects, in the most parsimonious way possible.

The set-up of the regression equations used in this analysis is based on automobile induced demand works by Noland and Cowart (2000) and Noland (2001), and similar model setups have also been used in cycling-related studies, such as Karpinski (2021) and Kraus and Koch (2021). The equations follow:

$$\ln\left(\mathrm{BKT}_{i,t}\right) = \mathrm{c} + \alpha_i + \tau_t + \sum_n \gamma_n \, \mathrm{INT}_i + \sum \beta_k \, \mathrm{X}_{i,t}^k + \epsilon_{it} \qquad \textbf{(3)}$$

where:

$\ln\left(\mathrm{BKT}_{i,t}\right)$	=	The natural logarithm of monthly Bicycle Kilometers Traveled for intervention *i*, at time-period *t*.
c	=	The equation's constant term.
α_i	=	The entity-specific dummy variable for segment *i*.
τ_t	=	Year-specific dummy variables.
γ_n	=	The coefficients representing the impact of intervention *i*.
INT_i	=	Dummy variables representing whether intervention *i* has occurred.
β_k	=	Coefficients for other explanatory variables.
$X_{i,t}^k$	=	Other explanatory variables for intervention *i*, at time period *t*.
ϵ_{it}	=	The error term; assumed to be i.i.d. and normally distributed.

2.4. Results

The 495,084 map-matched routes were intersected with the 10 interventions, with a total 135,132 intersections found. The lengths of the intersections were computed in kilometers and aggregated by month. Table 2.4, below, presents the descriptive statistics of the segment's monthly BKT (the natural logarithm of monthly BKT was used as the dependent variable). In terms of monthly BKT rates, the King St. segment has the highest rates across the study period, with an average of 573.13 BKT per month. Hatt St. has the lowest average rates across the study period (5.88 BKT per month). Figures 2.3 and 2.4 show the monthly BKT rates for all intervention segment, as well as boxplots, respectively. Table 2.4 presents descriptive statistics of Monthly BKT rates for all segments of interest. 2019 shows the highest BKT on the interventions; mean monthly BKT across all segments in 2019 was 22.11. The onset of the COVID-19 pandemic in March of 2020 drastically reduced monthly BKT across all the segments (averages in 2020, 2021, and 2022 were 8.89, 9.02, and 3.52 BKT per month, respectively).

An LSDV regression was run for all segment's monthly BKT from 2019 to March, 2022, following the format denoted in equation (3). Table 2.5 presents the results. The model includes a dummy variable for each specific intervention (n = 10).

Table 2.4. Descriptive Statistics of Monthly BKT, grouped by intervention.

Intervention	**N Intersections**	**Mean Monthly BKT (SD)**
Hatt St, John to Baldwin	974	5.88 (6.69)
Hunter St, Catherine to Liberty	16,017	86.04 (63.04)
Hunter St, Liberty to Keddy Access Trail	5,550	21.31 (13.75)
Hunter St, Park to Catherine	23,791	129.39 (97.06)
Hunter St, Queen to Park	17,120	118.82 (90.44)
King, Paradise to Dundurn	32,473	573.13 (468.21)
Locke, King to Hunter	5,012	29.96 (15.71)
Victoria, Cannon to Copeland	8,950	39.27 (22.97)
York, Dundurn to Hess (East)	11,157	85.61 (78.36)
York, Dundurn to Hess (West)	14,088	98.54 (71.87)

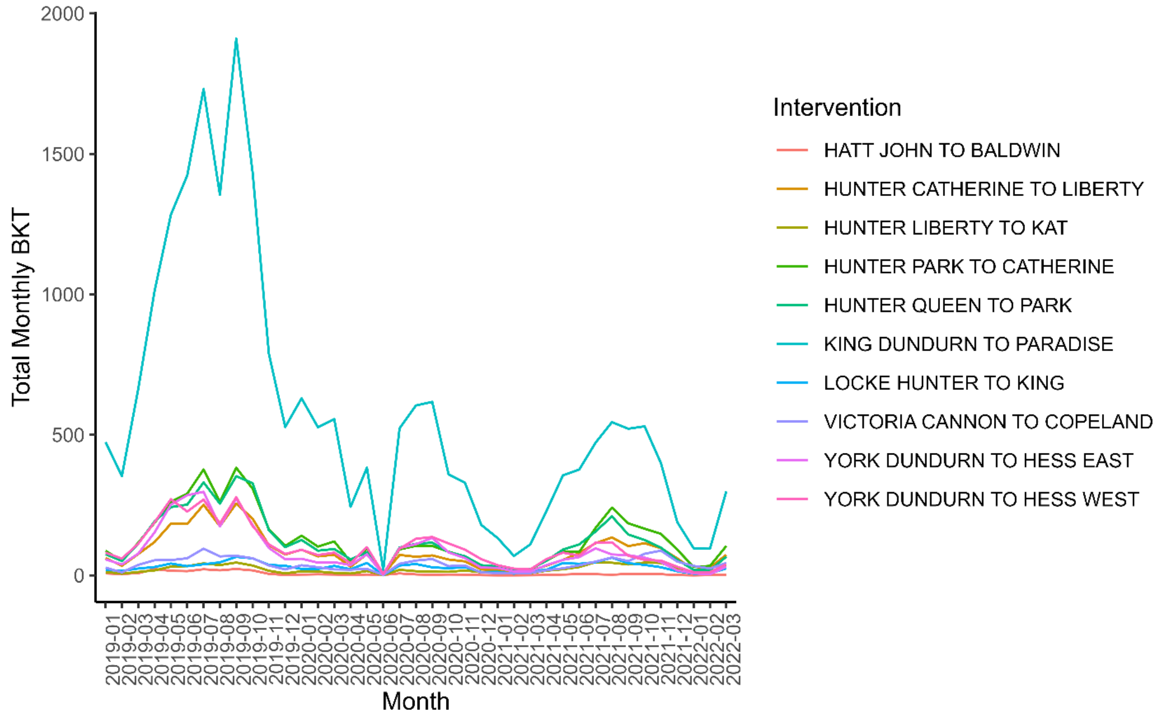


Figure 2.3. Infrastructure segments' monthly BKT rates, over the study period.

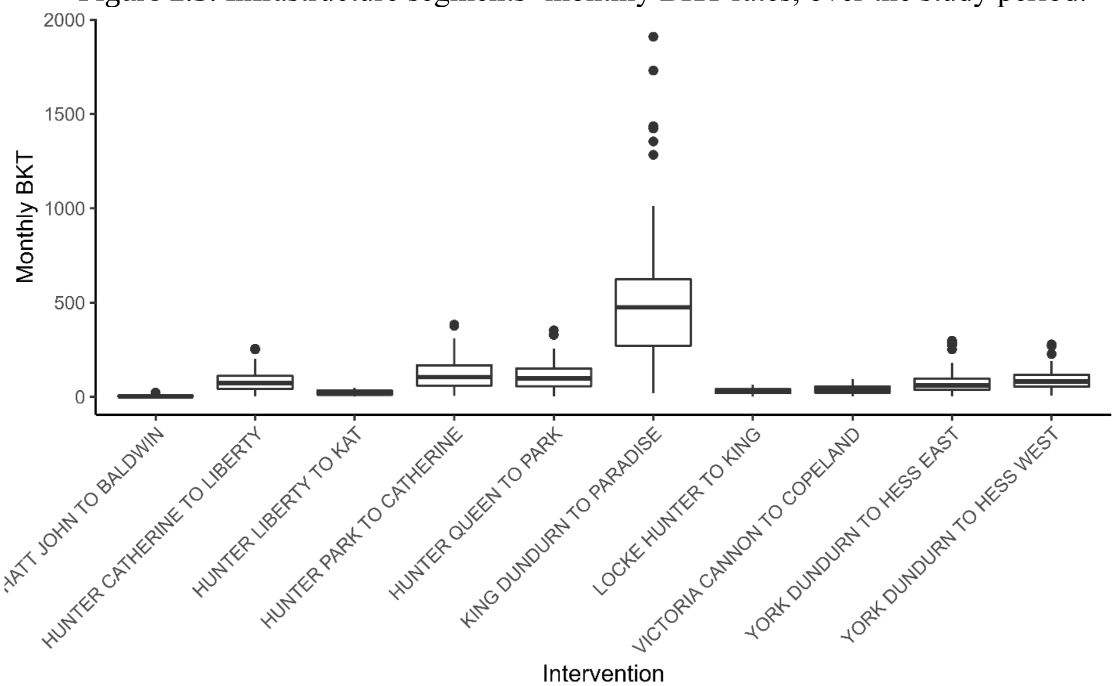


Figure 2.4. Boxplots of Monthly BKT for each intervention.

Table 2.5. Fixed Effects Regression for all cycling segments of interest, from 2019 to March, 2022.

	Dependent Variable: Ln(BKT)	
Variable	**β**	**t-value**
Intercept	0.94	5.07***
Segment Fixed Effects		
Hatt St. *(reference)*		
Hunter St. (Catherine to Liberty)	2.74	13.25***
Hunter St. (Liberty to KAT)	1.22	5.97***
Hunter St. (Park to Catherine)	3.16	15.64***
Hunter St. (Queen to Park)	3.08	14.75***
King St.	4.79	24.19***
Locke St.	1.65	6.74***
Victoria St.	2.09	11.02***
York Blvd. (Eastbound)	2.84	14.61***
York Blvd. (Westbound)	3.09	15.89***
Contextual Variables		
COVID	-0.41	-3.89***
June 2020	-2.77	-9.50***
2019 (reference)		

2020	-0.25	-1.95
2021	-0.93	-3.87***
2022	-1.11	-4.33***
Monthly Station-Trip Distance Accessibility	0.03	2.73**
MAX_TEMP	0.03	4.62***
AVG_PRECIP	0.07	1.91
Interventions		
Hatt St.	-1.18	-3.84***
Hunter St., Catherine to Liberty	0.67	2.46*
Hunter St., Liberty to Keddy Access Trail (KAT)	1.30	4.77***
Hunter St., Queen to Park	0.47	1.73
Hunter St., Park to Catherine	0.83	2.68**
Locke St.	0.54	2.15*
King St.	0.17	0.58
Victoria Ave.	1.69	4.14***
York Blvd. Eastbound	-0.27	-0.67
York Blvd. Westbound	0.08	0.20
Obs:	390	
R^2 (Adj. R^2):	0.840 (0.828)	
F-Statistic:	70.19***	
DF:	27; 362	

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

The model explains approximately 84.0% of the variance present in the data (R^2 = 0.840), with an adjusted R^2 of 0.828. The model's Durbin-Watson test value was 1.78, which is within the prevailing 'acceptable' range of 1.5-2.5, indicating low residual autocorrelation. 390 Observations were used in informing the model (39 months for each of the 10 segments of interest). As the model's dependent variable is the natural logarithm of monthly segment BKT, explanatory variables' increases by one variable unit either increase or decrease the dependent variable by $[e^{\beta} - 1] \cdot 100\%$. This same formula is used for the effects of a dummy variable, when the variable takes the value 1. All fixed effects, contextual variables, and more than half of the intervention dummy variables are statistically significant at the $p < 0.05$ level, and most are significant at the $p < 0.001$ level.

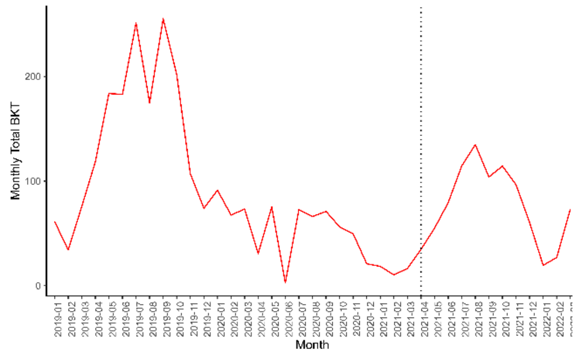
2.5. Discussion

All Fixed-Effects coefficients, or segment-specific constants – given in relation to the reference Hatt St. segment – are positive and highly significant ($p < 0.001$). The Hatt St. segment is in the community of Dundas, in Hamilton, and it can be seen as the intervention on the far left of the map in Figure 1. While Hatt St. is in the HBS Service Area, it has few HBS stations present nearby and experiences the lowest ridership of any of the segments of interest. The Hunter St. segment from Liberty to the Keddy Access Trail's (KAT's) fixed effects have the smallest positive impact on monthly BKT with reference to Hatt St. (+238.72%), and King St.'s fixed effects have the highest positive influence on monthly BKT (+11,930.14%).

Monthly station-trip distance accessibility, as a measure of interventions' proximities to system traffic, as well as overall system traffic fluctuations over time, was positive and significant ($p < 0.01$). A unit increase in this measure results in a 3.05% increase in monthly BKT. As a study segment's station-trip distance accessibility increases – that meaning, as system traffic increases, and study segments are closer in proximity to the traffic (high traffic nearby stations), the segments' monthly BKT increases. This is in agreement with findings from Brown et al. (2022), who developed a time-invariant version of the variable, and could indicate the presence of a feedback loop, as stations with nearby well-developed cycling infrastructure have been found to have higher rates of use (Buck and Buehler, 2012; El Assi et al., 2017).

Regarding the other contextual variables, as expected, the presence of a COVID-19 lockdown has a negative impact on the monthly HBS BKT on all intervention segments (-33.63%) – as does the HBS' June 2020 shutdown (-93.73%). Two of the three year-specific dummy variables, 2021 and 2022, were associated with significant percentage declines in monthly BKT (-60.54% and 67.04%, respectively), in relation to the base year, 2019. 2019 had the highest overall monthly BKT rates of the four years in the study – the remaining years took place in the context of the COVID-19 pandemic. 2022 is associated with the greatest decrease in segments' monthly BKT, with respect to 2019. This is likely because the only months in 2022 included in the analysis were the first three winter months, which are generally low-traffic months (as evidenced by Figure 3). As for climatological factors, a 1°C increase in Monthly Average Daily Maximum Temperature was associated with a 3.05% increase in the study segments' monthly BKT. Interestingly, while falling just short of the 5% significance threshold, a 1 mm increase in a month's average daily precipitation resulted in an 7.25% increase in monthly BKT along the study segments. This contradicts findings from the literature, for example Scott and Ciuro (2019), and El-Assi et al., (2017), and could be the result of the data's coarseness – i.e., the use of a monthly average – and the resulting susceptibility to outliers. For example, late spring and summer months, such as June and July, are often the months of highest ridership (as shown in Figure 3), but they also are often subject to summer storms with high rainfall totals. Looking specifically at July during the study period, only 39.8% of July days between 2019 and 2021 had precipitation, with many of these days including substantial portions of the total July rainfall. As the data are aggregated monthly, the days with substantial rainfall – while potentially having relatively less traffic than the July days without rainfall – greatly influence the July totals, and could likely cause this positive rainfall influence on ridership.

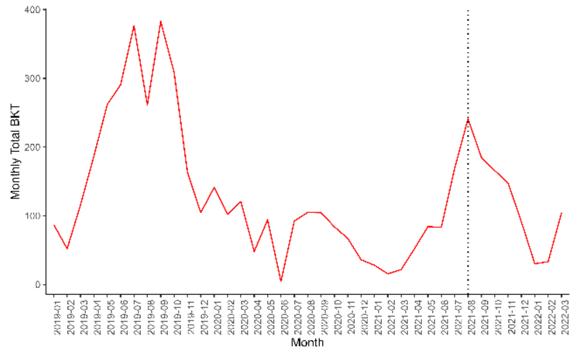
Of the ten intervention dummy variables, six had coefficients with a significance of $p < 0.05$. The model estimates that the construction of the separated cycle track along Victoria Ave. resulted in a 441.95% increase in HBS monthly BKT along the segment. It is important to note that this segment connects with another popular cycle track along Cannon St. which was Hamilton's first dedicated on-street cycle track (City of Hamilton, 2022). The presence of the painted buffer along Hunter St., from Liberty to the Keddy Access Trail resulted in an increase in the segment's monthly BKT by an estimated 366.93%. The construction of cycle tracks along Hunter, from Catherine to Liberty, and from Park to Catherine (both concrete barriers) were estimated to increase HBS monthly BKT by 95.42% and 129.33%, respectively. Both these segments exist around a major transit station in downtown Hamilton and are adjacent to one another. The Locke Street intervention resulted in an increase of monthly BKT by 71.60%. This segment also exists near downtown Hamilton, in between two major east-west arteries of the city (Hunter St. and King St.). Finally, the Hatt St. improvement is estimated to have decreased monthly BKT on the segment by an estimated 69.58%. As previously stated, this segment occurs outside of the main urban area of Hamilton and the HBS service area, and as such, it receives very little ridership in general, compared with many of the other segments, as evidenced by its low monthly station-trip distance accessibility ranking. Additionally, having been completed in August 2021, the post-intervention months for Hatt St. are in the fall of 2021 and winter of 2022. The model estimates the remaining five segments as not having statistically significant impacts on their monthly BKT rates. For the two segments of York Blvd., it is possible this is due to the completion date (December 2021) which was near the end of the study period. As such, only three months of data were recorded post-intervention, and they were winter months with low ridership. Hunter Street, from Queen to Park was within a 10% significance level, and does have a positive coefficient, which implies the intervention had a positive impact on monthly BKT along its segment. The distributions of monthly BKT for segments determined to have significantly positive interventions, based on the model in Table 2.5, are presented in Figure 2.5.


Monthly Total BKT
Month
0
100
200

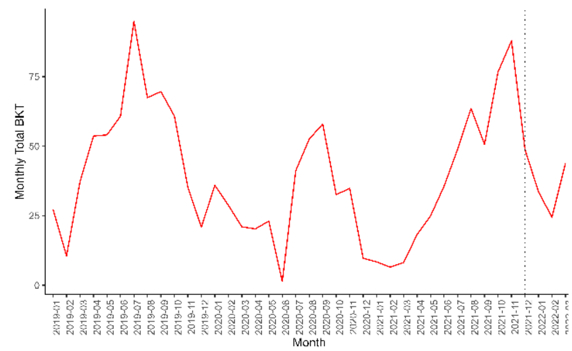
(A)


Monthly Total BKT
Month
0
10
20
30
40

(B)


Monthly Total BKT
Month
0
100
200
300
400

(C)


Monthly Total BKT
Month
0
25
50
75

(D)


Monthly Total BKT
Month
0
20
40
60

(E)

Figure 2.5. Monthly BKT rates on all segments with significant, positive, coefficients as determined by the LSDV regression in Table 2.5. The segment's intervention's completion month is shown as the black vertical dotted line in each chart. A) Hunter St., Catherine to Liberty; B) Hunter St., Liberty to Keddy Access Trail; C) Hunter St., Park to Catherine; D) Victoria Ave., Cannon to Copeland; E) Locke St., Hunter to King

Potential factors in the positive outcomes for all interventions are shown in Table 2.6. These factors include: infrastructure type, whether the infrastructure neighbors more separated infrastructure, whether the segment generally experiences relatively high traffic (that being, higher than the median monthly BKT of 3.49 km for all 10 segments of interest), and segment gradient. The data in the table is used to investigate, descriptively, potential factors in the homogeneity of intervention effectiveness. Looking at these characteristics, 3 of the 5 significantly positive interventions were the addition of a concrete barrier cycle track to the segment. This aligns with findings by Coughenouor et al. (2015), who found barrier-separated infrastructure was most likely to be chosen for a cycling trip by typical bus riders, cyclists, and drivers. It also aligns with Dill and McNeil (2013), who found that barrier-separated infrastructure greatly improved the comfort of moderately experienced/confident cyclists. While none of the segments with positive interventions had flexible barriers, it should be noted that only one of the study segments had this type of barrier. Again, 3 of the 5 positively impactful interventions bordered another cycle track segment in the study, and one other intervention bordered a cycle track constructed prior to the study period. This emphasizes the importance of connectivity in the cycling network, and complements previous bike share work by Lu et al., (2018), who found that Hamilton Bike Share users likely select routes between stations including dedicated cycling facilities – even diverting their trips to include the facilities. In addition, only 2 of the 5 positive interventions were on segments that on average had higher traffic than the median value for all the segments of interest – indicating that these facilities might not necessarily have to be located on traditionally the busiest segments to be impactful. All the positively impactful interventions occurred on segments that had an overall slope less than 2%, which is in agreement with Lu et al. (2018), who found 65% of HBS users' dominant routes were on gradients less than 2%. Several of the segments without significant intervention impact on BKT had greater slopes, and this could be a factor in their lesser impact on monthly BKT. Finally, the segments with significant positive impacts on monthly BKT varied in their rankings of average monthly station-trip distance accessibility, but 3 of the 5 segments were in the top 5 in terms of their average monthly accessibility metric, interventions on highly accessible segments were more successful, generally speaking.

Table 2.6. Summary of characteristics of interventions included in this study. Interventions listed in green were those whose intervention variables had statistically significant, positive, impacts on monthly BKT in the fixed effects regression. Red rows' intervention variables had a statistically significant, negative impact on monthly BKT. Black rows' intervention variables were not found to have an impact on monthly BKT.

Intervention	**Type is Painted Buffer**	**Type is Flexible Barrier**	**Type is Concrete Barrier**	**Neighbors another segment in study**	**High Traffic?**	**Average Percent Slope < 2%**	**Monthly Station-Trip Distance Accessibility Ranking**
Hunter St. Catherine to Liberty			✓	✓	✓	✓	4
Hunter St. Liberty to KAT	✓			✓		✓	7

Intervention	Type is Painted Buffer	Type is Flexible Barrier	Type is Concrete Barrier	Neighbors another segment in study	High Traffic?	Average Percent Slope < 2%	Monthly Station-Trip Distance Accessibility Ranking
Hunter St. Park to Catherine			✓	✓	✓	✓	2
Victoria Ave. Cannon to Copeland[a]			✓			✓	9
Locke St. King to Hunter	✓					✓	3
Hatt St. John to Baldwin			✓			✓	10

Intervention	Type is Painted Buffer	Type is Flexible Barrier	Type is Concrete Barrier	Neighbors another segment in study	High Traffic?	Average Percent Slope < 2%	Monthly Station-Trip Distance Accessibility Ranking
Hunter St. Queen to Park			✓	✓	✓		1
King St. Paradise to Dundurn			✓		✓		8
York Blvd. Dundurn to Hess (Eastbound)		✓			✓		5

Intervention	**Type is Painted Buffer**	**Type is Flexible Barrier**	**Type is Concrete Barrier**	**Neighbors another segment in study**	**High Traffic?**	**Average Percent Slope < 2%**	**Monthly Station-Trip Distance Accessibility Ranking**
York Blvd. Dundurn to Hess (Westbound)		✓			✓		6

[a] While the cycle track does not connect with another cycle track examined in this study, it does connect with the pre-existing Cannon St. cycle track in Hamilton, which was built several years prior to the study period.

2.6. Conclusion

There is a growing consensus among planners and policy makers that encouraging cycling as a modal choice for urban transportation is beneficial both environmentally and socially, and bike share systems like Hamilton Bike Share play an important role in the availability and normalization of cycling in cities (Goodman et al., 2014; Pucher and Buehler, 2017). Most revealed-preference research investigating cycling facilities' impacts on bike share ridership specifically have used non-empirical methods or have been subject to very coarse or very fine-scale subject areas (i.e. either aggregated city-wide methods using generalized metrics for cycling facilities like total length present, or single-case studies of individual interventions) (e.g. Karpinski, 2021; Xu and Chow, 2020). This work sought to provide middle-ground to the study scales – examining the impacts of several individual projects but accounting for the remainder of the cycling network – while also addressing the lack of empirical data in studies of this nature, by using actual Hamilton Bike Share GPS route data. The study successfully leveraged this data, along with other established determinants of bike share ridership, to estimate the individual intervention impacts of ten recent projects constructed in Hamilton. Several of the projects had significant positive results in increasing HBS traffic, indicating that separated cycling lanes can be a useful tool to encourage bike share traffic increases; however, the levels of impact varied drastically, from negative, to highly positive (+441.95% %).

This work is subject to several limitations. For one, data loss presents a significant issue. 19% of valid trips logged by the HBS system did not have valid GPS trajectories or were not successfully map-matched. These missing routes could have influenced the impacts of the various interventions. Subsequently, the study period contained only three full years of data (two of which were impacted by recurring pandemic lockdowns). More months of data would allow more interventions from before the current study period to be investigated and would have provided more data to inform the model. Additionally, the 2022 data included was only for the first three months of the year, and as mentioned in the Discussion section, several segments of interests' interventions only took place near the study period's end. As such, because the post-intervention periods were more limited and included only winter months, the impacts of some of these interventions could be inadequately estimated. Finally, the limited post-intervention data for these ten projects means that largely only the short-term effects of the interventions can be examined. More months of bike share trip logs and corresponding map-matched routes could allow for greater investigation of the medium and longer-term effects of these interventions, and they could give greater insight into the more lasting impacts, or heterogeneity of longer-term impacts, of these projects.

Similarly, the project also presents other intriguing research paths forward, in investigating the nature of the increases and decreases in bike share traffic across these different infrastructure interventions. For example, several of the interventions have been found to have a net positive effect on monthly Bicycle Kilometers Traveled by Hamilton Bike Share users along certain road segments; however, the model does not parse apart the increases in traffic, to characterize the types of increases. Is the increased traffic a result of newly generated (induced) trips, or is there a stronger presence of existing HBS users diverting their trips? Methodologies to unpack the underlying causes of the traffic increases, or decreases, will not only provide bases for future studies in other cities of this nature, but they will also provide important information to planners and policy makers about who is most benefitting from the infrastructure investments. Moreover, this research focused on bike share; future research should examine differences in interventions' impacts on private cyclists, to examine whether these effects differ across types of cyclists.

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Appendix

Photos of the 10 study interventions.

1. Hatt Street, from John to Baldwin

2. King Street, Paradise to Dundurn

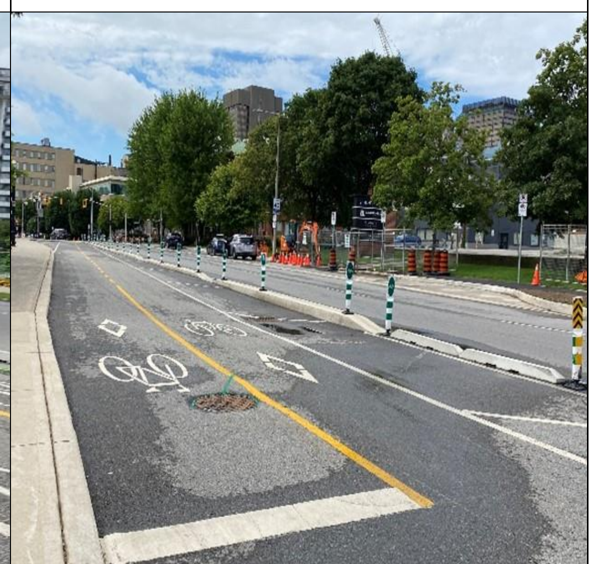
3. Locke Street, from Hunter to King
* Note: the barriers depicted were added after the study period. The yellow markings are the original buffer-separated intervention.

4. Victoria Avenue, from Cannon to Copeland

5. York Boulevard, from Dundurn to Hess (Westbound)

6. York Boulevard, from Dundurn to Hess (Eastbound)

6. Hunter Street, from Queen to Park



7. Hunter Street, from Park to Catherine

9. Hunter Street, from Catherine to Liberty	**10.** Hunter Street, from Liberty to the Keddy Access Trail

3. INVESTIGATING THE IMPACTS OF BIKE LANES ON BIKE SHARE RIDERSHIP: A HOLISTIC APPROACH AND DEMONSTRATION

3.1. Introduction

There has been growing recognition of the importance of active transportation, and specifically, cycling, as a sustainable, healthy, environmentally-friendly, and economically beneficial means of urban travel (Pucher and Buehler, 2017; Pucher and Buehler, 2012). Cities are using various methods as means of encouraging a modal shift towards cycling, including the development of more complete, connected, and well-planned cycling networks – making cycling safer and easier for individuals – as well as implementing bike share systems (BSSs), to make cycling more available and convenient (Buehler and Dill, 2016; Dill, 2009; Félix et al., 2020). BSSs offer a variety of benefits to their users and the urban environment in which they exist (Shaheen et al., 2010). Perhaps most important to transportation planners, widespread availability and ease-of-access to BSSs can increase both public and private cycling ridership, as well as potentially "normalizing" the mode (Goodman et al., 2014; Shaheen et al., 2013). Evidence suggests a synergy between BSSs and improvements to the cycling network to improve cycling levels, and the perception of safety when cycling – or lack thereof – can be a significant deterrent to choosing to cycle (Bateman et al., 2021; Félix et al., 2020). As such, the construction of cycling infrastructure and the consequent improvement of the cycling network are seen as effective ways to encourage cycling ridership (Braun et al., 2016).

Within the Canadian policy, planning, and funding framework, significant effort has been made to encourage the development of more complete, connected, and safer urban cycling networks. This includes the Government of Canada's Active Transportation Fund, which was established in 2022, and allocated nearly half a billion dollars over the next five years to active transportation projects, including infrastructure construction, across the country (Infrastructure Canada, 2022). Day-to-day travel is largely a provincial responsibility in Canada, and cycling is promoted and prioritized by provincial transportation policy statements and grants across the country (Assunçao-Denis and Tomalty, 2019; Wilson and Mitra, 2020).

The City of Hamilton, specifically, has made encouraging cycling a financial and policy priority in recent years. Its original cycling master plan, *Shifting Gears*, was published in 2009 and updated in 2018 as a component of the overarching Transportation Master Plan (City of Hamilton, 2018). The Master Plan is guided by the province of Ontario's Growth Plan for the Greater Golden Horseshoe, and its self-acknowledged goal is to "provide a comprehensive and attainable transportation blueprint for Hamilton as a whole that balances all modes of transportation to become a healthier city." It aims to do this by "Reduc[ing] dependence on single occupant vehicles; Promot[ing] accessibility; Improv[ing] options for walking, cycling and transit; and maintain[ing] and improv[ing] the efficiency of goods movement" (p. 2). Balancing these goals with cost-effectiveness is also a priority in the Plan, and the estimated expenditures in the coming decades within the Plan for cycling-related infrastructure total over Can$38 million (City of Hamilton, 2018). Likewise, Hamilton Bike Share (HBS) – established in 2015 – has become an important part of the transportation landscape within the City, and the Cycling Master Plan, as far back as 2018, recognizes the use of the bike share system as an important micromobility tool (City of Hamilton, 2018). One recent project completed as a component of the City's broader cycling plans is the Victoria Avenue cycle track, from Cannon Street (which also has its own cycle track) to Copeland Avenue.

While many works in the literature address components of cycling or bike share ridership change as a result of an infrastructure intervention such as the Victoria Avenue cycle track, the goal of this study is to examine the effects of the intervention on bike share ridership holistically – simultaneously targeting multiple aspects of the intervention's potential influences. It explores the spatial distribution of ridership using Victoria Avenue, before and after the intervention; classifies the potential nature of trips after the intervention using a novel theoretical categorization mechanism; and explores the intervention's impact on diverting HBS traffic from surrounding network links. This study combines established and novel methods to examine the efficacy of the Victoria Avenue intervention holistically, while also establishing a useful framework for future active transportation research by academics, planners, and policymakers.

The following sections outline the foundational literature which informed this work. Next, the specific methods, including the distance decay calculations, the development of a novel trip classification scheme, and the route diversion investigation, are outlined. Results of the analyses are presented next and are subsequently discussed and explained in the discussion section. Finally, the conclusion outlines the broader findings of this work, and discusses the study's limitations as well as future research pathways.

3.2. Background

3.2.1. Generated Traffic and 'Induced Demand' Defined

In transportation planning, the impacts of increasing the supply of road lanes have been the subject of interest for researchers and planners for decades, with Jorgensen (1947) first attempting to measure these effects on freeways, and Downs (1962) postulating a law of traffic equilibrium: "On urban commuter expressways, peak-hour traffic congestion rises to meet maximum capacity" (p. 393). Generated Traffic is often used as the generalized term for this effect, in which the increase in roadway supply results in an increase in traffic along the expanded segments (Litman, 2022). Generated Traffic has been thought to have a theoretical basis in the fundamental economic concepts of supply and demand; as more of a good is produced and therefore its scarcity is decreased, the costs to consumers decreases and thus demand for the good increases (Litman, 2022; Noland, 2001). By increasing the number of roadway lanes, for example, short-term travel times – a dominant cost to the traveler – may decrease, and the resulting demand for travel increases (Noland, 2001). This assumes the presence of 'latent demand' for the good, and the provision of an adequate supply of the good unlocks the latent demand for it (Lee, 1999).

Downs (1992) used the term 'triple convergence' to denote growth in traffic coming from three primary components: the diversion of routes, travel times, and modes, where the modal shift is the component in which demand is genuinely 'induced' (Cervero, 2002). This is the case predominantly in the short-term (Litman and Colman, 2001). Induced traffic was defined by Schmidt and Campbell (1956) and included in Cervero (2002)'s review of studies examining its impact, as: "the added component of traffic volume which did not previously exist in any form, but which results when new or improved transportation facilities are provided" (p. 4). It stems from a change in travel mode, the making of a trip previously not considered an option (latent demand), or the increase in trip frequency (Cervero, 2002; Hills, 1996; Litman, 2022; Litman and Colman, 2001). Existing trips, whose routes were altered due to the improvements, are diverted (Litman, 2022; Litman and Colman, 2001).

3.2.2. Separated Infrastructure and Bike Share Ridership Impacts

Safety, or perceived safety, continues to be a major barrier preventing individuals from choosing to cycle privately or through bike share (Bateman et al., 2021; Fishman, 2016; Fishman et al., 2012; Sanders and Judelman, 2018). Geller (2006) classified cyclists in Portland, Oregon, into 4 categories: "Strong and Fearless", "Enthused and Confident", "Interested but Concerned", and "No Way No How." The "Interested but Concerned" category was described as individuals not opposed to cycling, but too fearful to partake in it, and the category was estimated to make up 60% of Portland's population (Geller, 2006). This categorization was confirmed by Dill and McNeil (2013). Examining existing War Eagle Bike Share users specifically, Burmester and Lamondia (2022) created a typology of riders which found 84% of users being categorized into cohorts found to be less confident cyclists and more prone to using off-road cycling facilities. These works provide evidence of 'latent demand' for cycling, where one of the major hindrances is lack of real or perceived safety. Dedicated cycling infrastructure, and more specifically, separated cycling infrastructure, has been found to decrease this safety barrier to individuals hesitant to cycle

(Akar and Clifton, 2009; Branion-Calles et al., 2019; Coughenour et al., 2015; Monsere et al., 2012; Sanders and Judelman, 2018).

Cycling infrastructure's associated positive influence on cycling and, of particular interest to this study, bike share system ridership, has been found to be largely positive, through a variety of research methods (Buehler and Dill, 2016; Eren and Uz, 2020). As an aggregate approach, using 42 US cities, Dill and Carr (2003) found that each added mile of bike lane per square mile of land correlated with a 1% increase in cycling commuting. Many studies have taken a more localized approach. For example, Xu and Chow (2019), in employing a network-wide time series analysis of the impacts of total cycling infrastructure lane miles on average daily ridership, found that one additional mile of cycling lanes led to more than 700 additional average weekly Citi Bike trips in New York City. Karpinski (2021) determined the construction of a separated cycling lane on Commonwealth Avenue, in Boston, to have increased Boston Bike Share ridership by 80%. Other studies focusing on private cycling have shown similar positive intervention impacts (Goodno et al., 2013; Heesch et al., 2016; Hong et al., 2019, Parker et al., 2013). Damant-Sirois and El-Geneidy (2015), however, also suggest that separated cycling infrastructure could be perceived as the only safe places to cycle and therefore decrease modal share in a neighborhood.

Route diversion is an important aspect of changes in ridership levels. Bike share users prefer using lower stress routes (Prabhakar and Rixey, 2017; Ubhi, 2022). The presence of cycling infrastructure has been found to significantly impact bike share users' routes, with many users detouring to incorporate infrastructure in their routes (Broach et al., 2012; Lu et al., 2018; Scott et al., 2021). Wergin and Buehler (2017) found that Capital

Bike Share members used cycling infrastructure in approximately a third of all trips, despite the segments with this infrastructure being a small minority of all total network segments. In the Hamilton-specific context, Lu et al. (2018) found that the shortest routes were not the dominant routes, and that many Hamilton Bike Share users showed a strong preference for riding on cycling infrastructure. This effect can be even more pronounced with separated cycling infrastructure. Broach et al. (2012) found separated infrastructure equivalent to reducing at least 10% of the distance for either a leisure or commute trip via bicycle, and that cyclists would go well out of their way to use separated infrastructure.

Similarly, research shows significant locational impacts associated with both cycling infrastructure, bike share hubs, and their spatial relationships with each other (Eren & Uz, 2020). Close proximity between bike share hubs and cycling infrastructure has been found to increase non-member participation in bike share systems (Faghih-Imani and Eluru, 2016). Likewise, perceptions of cycling infrastructure nearby, whether true or not, may increase the likelihood of cycling more (Dill and Voros, 2007). As such, the impacts of the infrastructure intervention on both the distance from the trip's origin, as well as trip diversion from other routes are important factors for investigation. Buck and Buehler (2012) found the presence of an additional one kilometer of cycling infrastructure within a half mile of a Capital Bike Share Hub, was associated with 0.855 additional bike share checkouts per day at all hubs within a half mile of the additional infrastructure. In bike share hub location optimization, Banerjee et al. (2020), adjusted their final location recommendations to be closer to cycle tracks, as these were found to have the highest intensity of bike share usage.

To the best of our knowledge, no work in the literature has consolidated the three components of our investigation within one study: examining the spatial draw and distance-decay of a network segment pre- and post-intervention; more precisely classifying the nature of the growth in ridership along segments of the cycling network, to differentiate and parse apart the generated traffic as induced trips, diverted trips, or those trips not influenced by the interventions (the base traffic trips); and finally, examining route diversion impacts of the infrastructure pre- and post-intervention, within the surrounding network.

3.3. Methods

3.3.1. Study Area

Hamilton, Ontario is a mid-sized Canadian city of 569,355 people, as of the 2021 Canadian Census. Hamilton launched its public bike share program, Hamilton Bike Share (HBS), in 2015 (Hamilton Bike Share, 2020). With a service area of approximately 25 km^2 in the City's urban center, below the Niagara Escarpment, the HBS fleet is now comprised of over 800 GPS-equipped smart bicycles, which can be rented out and checked back into over 140 hubs (stations) within the service area (see Figure 3.1).

3.3.2. Victoria Avenue Cycle Track (Study Segment)

Victoria Avenue is an arterial, northbound one-way road within Hamilton Bike Share's Service Area. It originates on Hamilton's Claremont Access (which climbs the Niagara Escarpment) and runs through the eastern end of Hamilton's Central Business District, passing Hamilton General Hospital, and ending near Pier 11 of Hamilton's harbor. In 2021, the City undertook the design and construction of a two-way, curb-separated cycle track along Victoria Avenue North, between Cannon Street and Copeland Avenue (City of Hamilton, 2022). The track, completed in December 2021, is shown in Figure 3.1.

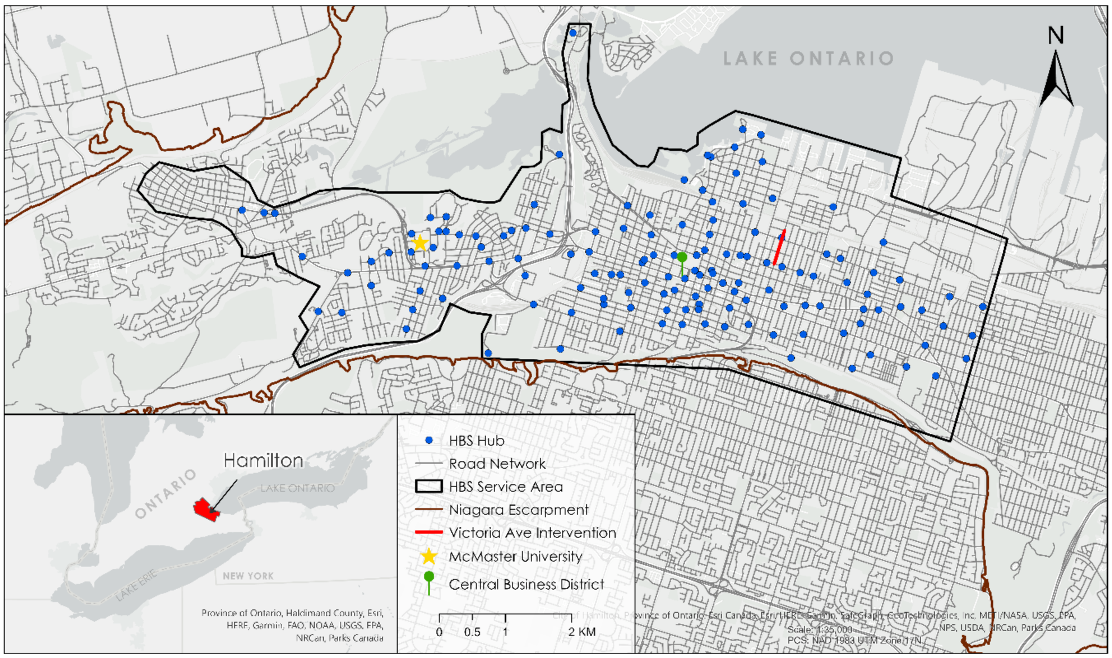


Figure 3.1. The location of the Victoria Avenue cycle track intervention, contextualized by surrounding HBS hubs and Service Area, as well as relevant locations in Hamilton.

3.3.3. HBS Trip Data

Trip and associated membership logs for each HBS trip from January 1st, 2019, to August 31st, 2022, were collected (*n* = 741,369). Trip records contained information on start and end locations, times, durations, and trip distances. Along with this, each trip had an associated User Identifier Number, which was anonymous, but consistently associated with an HBS member for any trip they took. Trip logs were joined with HBS membership data, which included information on the members' original sign-up dates, dating back to

HBS' inception. While some members had more than one sign-up date (indicating the individual's membership expired, but the individual signed up again), their first sign-up date was used, as it represented the first time the individual was inclined to join and use HBS.

3.3.4. HBS Route GPS Data

Each time an HBS bike is rented, it registers a GPS trajectory for the entirety of the user's trip. For this study, all trips with valid and existing HBS GPS trajectories from January 1st, 2019, to August 31st, 2022, were collected (n = 609,746). These GPS trajectories were map-matched to a complete cycling network dataset of Hamilton, using Dalumpines and Scott's (2011) python-based map-matching algorithm, as part of Dalumpines and Scott's (2018) *GIS-based Episode Reconstruction Toolkit*. The full map-matching process and information on the cycling network's creation can be found in Lu et al. (2018), and Brown et al. (2022), respectively. The final map-matched dataset contained 578,211 routes, which represented 94.8% of valid GPS trajectories and 78.0% of valid trips logged.[3,4]

3.3.5. Examining Spatial Ridership Trend Changes and Distance Decay

Intersections of HBS users' routes with the Victoria Avenue intervention were computed in ArcGIS® Pro. These intersections showed which trips used the cycle track, as well as the length of intersection between the trips and the track (in kilometers). The trips

[3] Valid trips in the trip logs were those between 1 and 480 minutes in duration, distances traveled were greater than 0.1 and less than 100 km, and the speed of travel was between 1 and 35 km/h.
[4] For more information on why 100% of all trajectories and trip logs were not map-matched, see Brown et al. (2022).

intersecting with the cycle track were separated as either 'pre-' or 'post-intervention', with December 1st, 2021, set as the intervention date. Trip origin latitude and longitude coordinates were isolated, and network distances (km) between trip origin coordinates and the centroid of the Victoria Avenue cycle track were calculated using the cycling network. To avoid the potential impacts of outlier routes, such as recreational cycling trips or trips with uncommonly circuitous routes, the shortest network distance in kilometers was calculated, which served as a standardized measure of the individual's proximity to the cycle track at their trip's origin. Pre- and post-intervention proximities to the Victoria Avenue cycle track were rounded to the nearest tenth of a kilometer and tabulated for the pre- and post-intervention periods. These distances, in intervals of 0.1 km (n = 62, pre- and n = 49 post-intervention), were used in the calculation of distance-decay functions.

Distance-decay functions are a key method used by transportation planners (Iacono et al., 2008) to describe the decreasing levels of interaction between phenomena because of increasing distance between them (Halás et al., 2014). We assumed a negative exponential distance decay function, with a dependent variable measured in cumulative percentages of frequency, where the dependent variable's value corresponds to the percentage of trips with distances greater than the distance value of interest (Gao et al., 2021). Using percentages, rather than discrete numbers of occurrences, normalizes trip quantities across different time periods (Iacono et al., 2008). As in Gao et al., (2021), a minimum threshold was used. We used a minimum threshold value of 0.1 km. The decay function, developed from Gao et al. (2021), is:

$$P(x) = \begin{cases} 100 & x \leq k \\ \alpha e^{\beta(x-k)} & x > k \end{cases} \quad \textbf{(1)}$$

where *P(x)* is the cumulative frequency or probability of occurrence of distance values greater than *x*, α is the intercept value for the distance decay function (the cumulative frequency of distances > *x* = 100%), *k* is the 0.1km threshold value, and β is the distance decay parameter – indicating the rate of decay as distance, *x*, increases. These were estimated as natural logarithm-transformed ordinary least squares in *R*.

3.3.6. Individual Trip Classification Process

All trips intersecting with Victoria Avenue were isolated (*n* = 10,578). A classification process, depicted in the workflow in Figure 3.2, was developed to categorize the nature of trips on Victoria Avenue after the intervention had taken place. Specifically, the categorization was used to define three classes of trips: ‘induced’, ‘diverted’, and ‘unchanged’. The precise classification labels developed are: New Member Induced Trips, Existing Member Induced Trips, Segment Induced/Diverted Trips, and Unaffected Trips. Each of these is defined and described in the following sections.

3.3.6.1 New Member Induced, and Existing Member Induced Trips

Induced trips were classified in two ways. Trips that used Victoria Avenue post-intervention, taken by members whose sign-up dates were after the cycle track installation, were considered ‘New Member Induced.’ While it is difficult to know the exact reasons behind an individual’s decision to sign-up for bike share and use the infrastructure, given the relatively short time period after the intervention included in the study, we assume the infrastructure intervention was at least a factor in the decision. Trips considered ‘induced’ using this measure, were tabulated and removed from the dataset so as not to affect the remaining classification calculations.

‘Existing Member Induced’ trips were calculated using trips from both before and after the intervention took place. Members who signed up prior to the intervention’s completion, had their monthly average of trips using the intervention calculated for the period before and after the intervention took place. Members whose monthly trip average rose after the intervention were classified as existing members with induced trips. A counterfactual of expected trips was calculated, using the members’ pre-intervention monthly average usage on the intervention, and the difference between the expected count of trips, and the actual count of trips was tabulated and labelled as Existing Member Induced. Precisely which trips within the dataset were Existing Member Induced, could not be determined; rather, only the quantity of Existing Member Induced trips could be determined using the previously defined method. These trips were not removed from the dataset but would not be classified as any other type (see Figure 3.2).

3.3.6.2 Segment Induced/Diverted Trips

Trips by members who had not used Victoria Avenue prior to the intervention, but began using it after the intervention, belong to a classification of trips that is difficult to parse apart without either complementary survey data or a complete origin-destination matrix for each participant, to determine if they began using a new route incorporating Victoria Avenue to complete a trip they regularly undertook prior to the intervention. These trips are titled: Segment Induced/Diverted Trips, meaning they are not necessarily system-wide induced trips, but rather, are trips which have been added to the intervention segment beyond what it had before. These can come either as purely induced trips (members began making a trip they had not done before), or diverted trips, where members began to 'funnel' toward the intervention, diverting away from previous routes used for the same trip. Figure 3.2 provides a visual representation of the classification framework proposed in this case study.

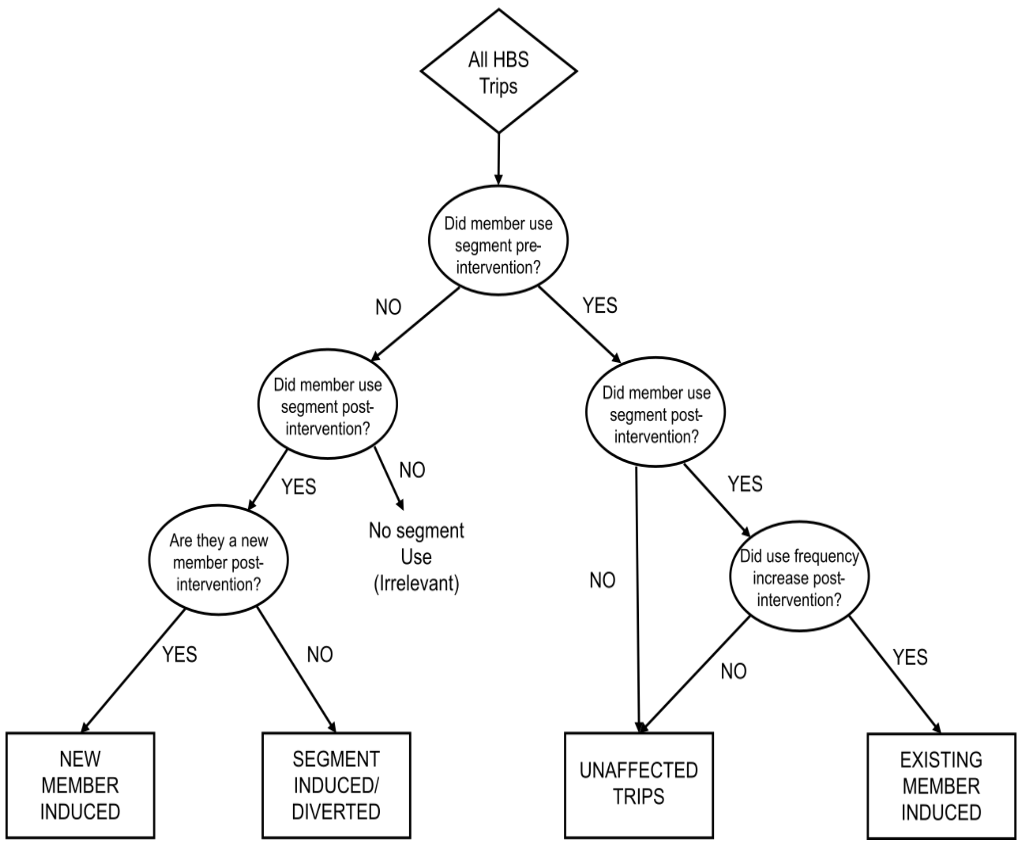


Figure 3.2. Process Diagram depicting the trip classification mechanism used to categorize and tabulate post-intervention trips by Hamilton Bike Share members.

3.3.7. Examining Trip Diversion Effects

All trips occurring during the study period were intersected with a feature class of cycling network links surrounding the intervention. Each of these neighboring street segments, even if adjacent and contiguous, were kept separate, and the proportion of all HBS trips which used each of these segments are displayed in the Results section (Figure 3.6), for the pre- and post-intervention time periods. This setup was used to determine potential route diversion resulting from the Victoria Avenue cycle track.

3.4. Results

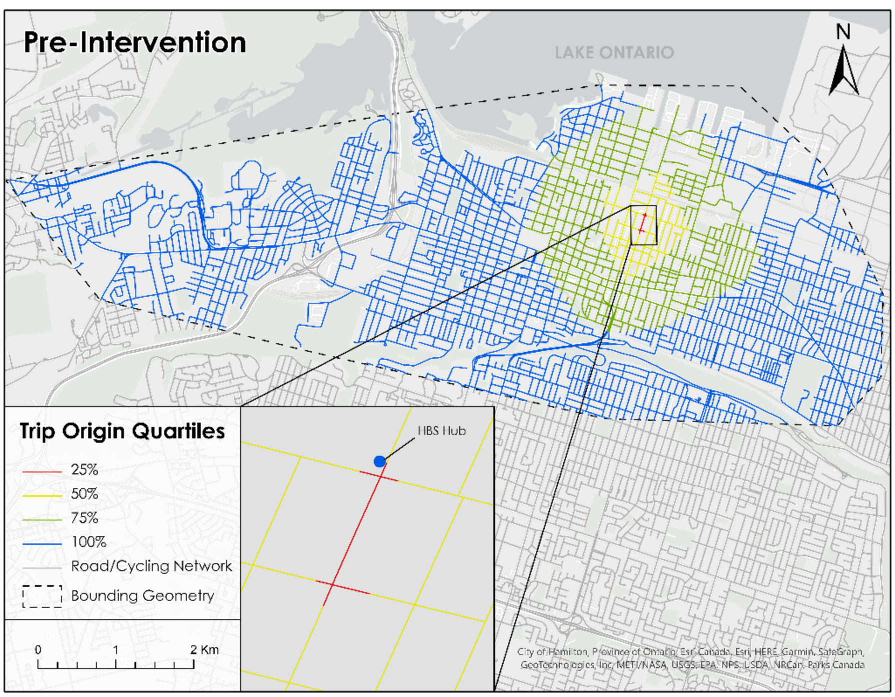
10,578 trips with intersections between the HBS users' routes and at least one section of the Victoria Avenue cycle track were found for the study period. Of those, 8,445 occurred prior to the intervention, over a period of 35 months. 2,133 intersections occurred post-intervention, over 9 months. These intersections' spatial characteristics were analyzed. Intersections were then deconstructed and classified using the developed categorization process. Diversion effects were mapped using intersections of HBS trips and neighborhood links, and changes in percentages of use for each link are presented in Section 4.3.

3.4.1. Spatial Ridership Changes and Distance Decay

Distances between latitude/longitude coordinate pairs for the origins of HBS users' trips which used the cycle track and the center of the cycle track itself were calculated. In both the pre- and post-intervention periods, 25% of trips came from within a network distance of 0.15 kilometers. The 100% quartiles, however, differ. 100% of pre-intervention trips came from within a network distance of 9.31 km; post-intervention this value was 6.40 km. The medians differ, with the distance traveled by 50% of post-intervention trips to

Victoria Avenue being longer than the pre-intervention trips (1.14 km and 0.78 km, respectively). Table 3.2 presents descriptive statistics of HBS trip origins pre- and post-intervention.

Minimum bounding geometry was calculated for each quartile's trip origin locations. The bounding area containing 100% of pre-intervention origins covers a cumulative road length of 408.67 km, while post-intervention covers 291.70 km of road length. The cumulative road lengths for the median boundary geometries differ greatly as well (14.08 km pre-intervention, and 27.22 km post-intervention). Figure 3.4 compares minimum bounding geometries for each quartile, before and after the intervention.



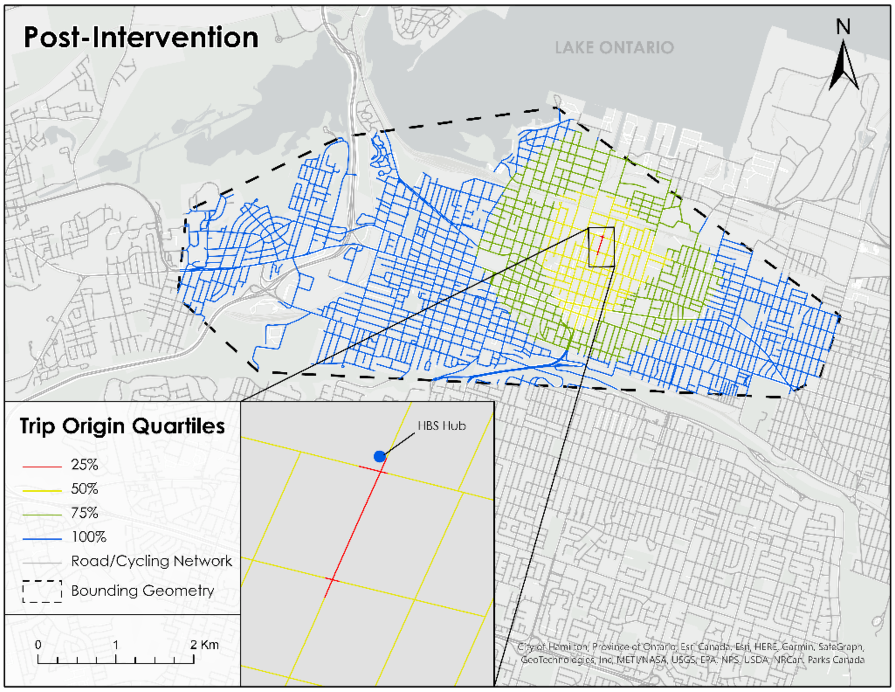


Figure 3.3. Road network areas for each quartile (25%, 50%, 75%, and 100%) of trip origins, for the periods before and after the Victoria Avenue intervention.

Figure 3.4 compares both the cumulative percentages of trips which originate from a range of distances (km), as well as the respective distance-decay functions for pre- and post-intervention periods. Prior to the intervention, a quick and significant drop in percentages of trips which originate from distances beyond 300m exists. After construction of the cycle track, however, the decay is less steep, with a more pronounced *'s'* shape. Subsequently, both distance-decay functions contained α and β parameters that were statistically significant ($p < 0.001$). The pre- and post-intervention distance decays both had similar intercepts, which were converted into percents (120.30 and 122.73 percent, respectively), but the post-intervention rate of decay, or impedance parameter, β, was less in magnitude (-0.96, as opposed to -1.01), suggesting a lower cost of distance to Victoria Avenue after the cycle track had been built. Both models have very high R^2 values, explaining 98% and 95% of the pre- and post-intervention variances, respectively.

Table 3.1. Pre- and post-intervention descriptive statistics of HBS trips involving the cycle track.

Victoria Avenue Period	Months Analyzed	#	Mean Distance (km) to Intervention from Trip Origin (SD)	25th Percentile Distance (km) from Origin to Intervention	50th Percentile Distance (km) from Origin to Intervention	75th Percentile Distance (km) from Origin to Intervention	100th Percentile Distance (km) from Origin to Intervention
Pre-Intervention	35	8445	1.12 (1.15)	0.15	0.78	1.81	9.31
Post-Intervention	9	2133	1.22 (1.18)	0.15	1.14	1.98	6.40

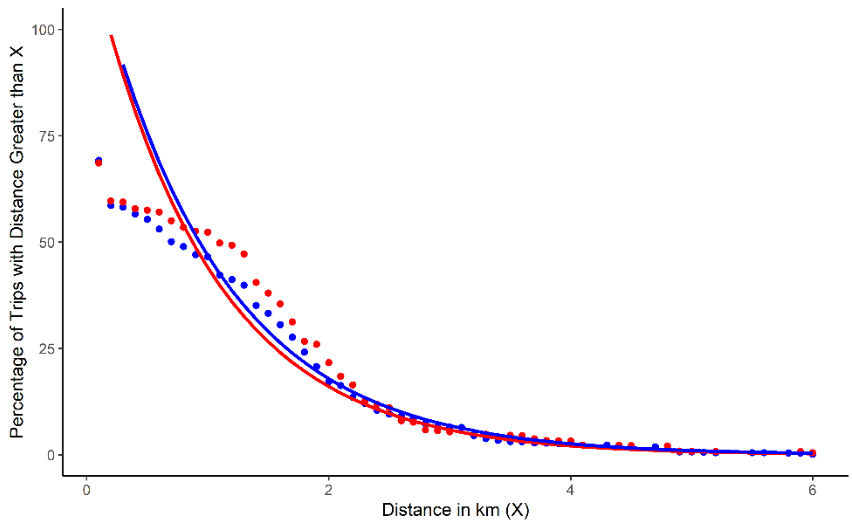


Figure 3.4. Percentage of trips where the distance from the trip origin to Victoria Avenue is greater than the distance demarcated on the *x*-axis, and the corresponding distance-decay functions for the pre-intervention (left) and post-intervention (right) periods.

Table 3.2. Distance decay models' parameter estimates, standard errors, and significances.

Model	Dependent Variable: Percentage of Trips with Distance > X			
	Parameter	Estimate	Std. Error	*t*-statistic
Pre-Intervention	α	120.30	0.07	72.53***
	β	-1.01	0.02	-60.55***
Post-Intervention	α	122.73	0.10	47.14***
	β	-0.96	0.03	-30.51***

DF: Pre = 60, Post = 45

R^2: Pre = 0.98, Post = 0.95

*** $p < 0.001$

3.4.2. Individual Trip Classification

Trips taken after the cycle track's construction were classified using the novel categorization scheme. Table 3.4 shows the results of the classification process. Approximately 27% of trips taken by individuals, who used Victoria Avenue after the intervention, were taken by members who had signed up after the intervention and were thus classified as 'New Member Induced.' Likewise, 19.7% of post-intervention trips were tabulated as trips taken by existing members, beyond their pre-intervention rates of Victoria Avenue use. A near-equivalent number of trips (418, or 19.6%) were classified as 'Segment Induced/Diverted,' and could not be distinguished. The remaining 33.5% of trips taken were classified as 'Unaffected.'[5]

Table 3.3. The four classification categories developed in Section 3.4, and numbers of trips classified in each category (total = 2133)

Trip Classification	**Count**	**Percent of Post-Intervention Trips**
New Member Induced	580	27.2
Existing Member Induced	420	19.7
Segment Induced/Diverted	418	19.6
Unaffected Trips	715	33.5

[5] To test potential seasonality effects and the robustness of the classification process, 4 months (September-December) were removed from the data, and a variety of year-on-year comparisons were made. These are presented in the Appendix. The results, using January-August of all 4 study years, remain largely consistent with the overall findings of the classification process.

3.4.3. Trip Diversion Investigation

All map-matched HBS trips during the study period (n = 578,211) were intersected with individual component links (blocks) of the Victoria Avenue cycle track, as well neighboring streets, and the total number of intersections between users' routes, and all neighborhood streets were tabulated. Figure 3.5 shows pre- and post-intervention comparisons of the Victoria Avenue cycle track's neighborhood, and the corresponding percentages of trips taken, which included the user cycling along each respective street as part of their trip. The cycle track sees a substantial increase in usage post-intervention (averaging 0.91% of all HBS trips before construction, and 1.49% of all HBS trips after it). Streets running parallel to the intervention are shown to have generally decreased in their percentage of occurrences. For example, Wellington Street North, which runs one-way southbound, decreased from an average of 0.37% of trips, to 0.18%. Likewise, East Avenue North, east of Victoria Avenue, decreased in its share of traffic from an average of 0.17% to 0.07% of trips. Cannon Street East, which runs perpendicular to Victoria Avenue, and has an established cycle track, experienced an increase in traffic across its individual component segments (averaging 4.2% before, to 5% of trips after the intervention). Barton Street East, which also runs perpendicular to the intervention, saw a decrease in use from an average of 1.23% to 0.81% of trips.

With general usage, the neighborhood surrounding Victoria Avenue saw a slight decrease in trips (9.29% to 8.98%), but trips along the intervention, as a percentage of all trips, increased (1.77% to 2.10%). Moreover, trips in the surrounding neighborhood that did not include any of the intervention decreased (7.53% to 6.87% of all trips). Table 5 presents neighborhood street network usage before and after the Victoria Avenue cycle track project's completion.

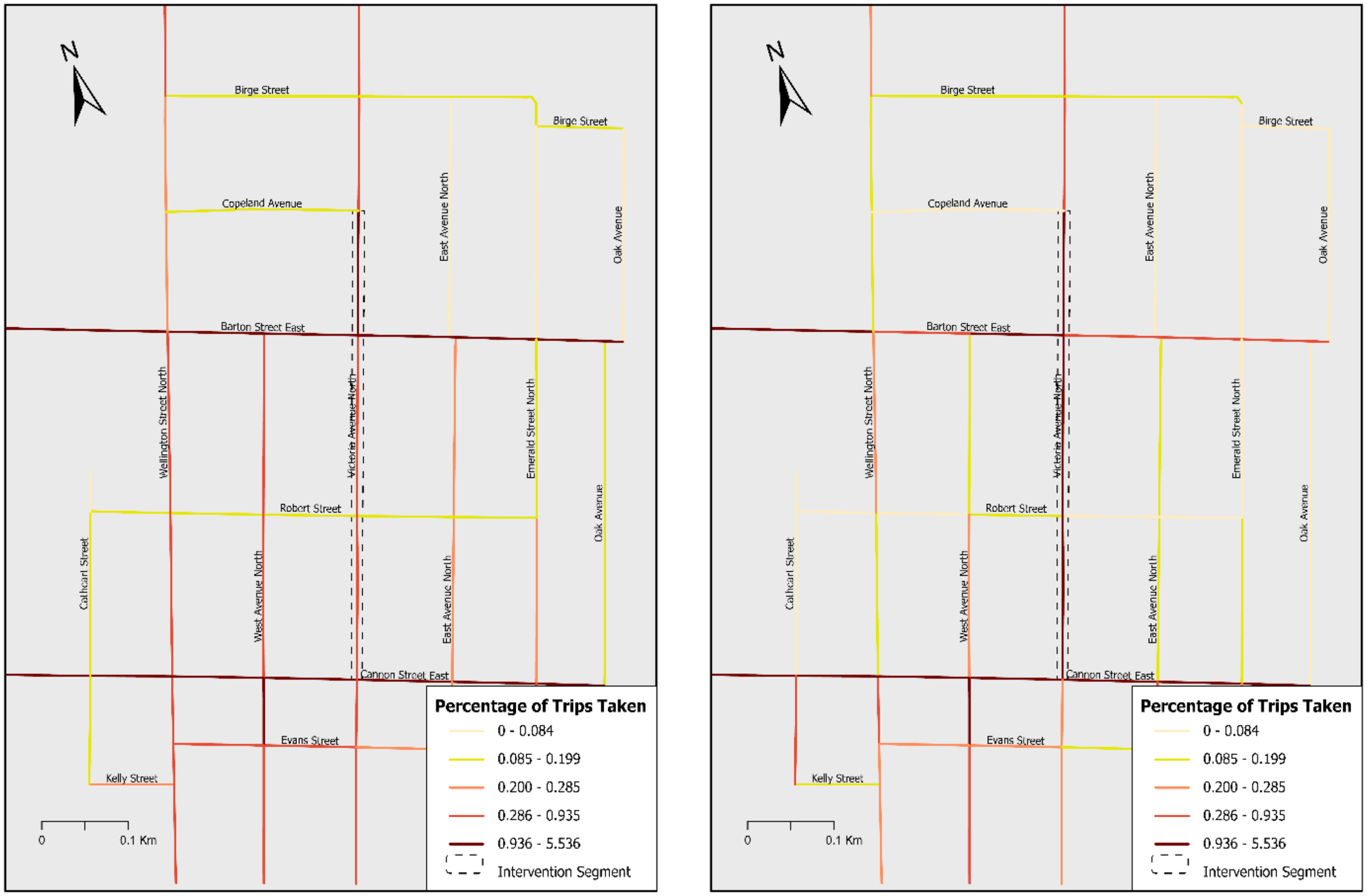


Figure 3.5. Comparison of pre- (left) and post-intervention (right) segment usage (percent of all HBS trips taken) of individual Victoria Ave. component segments and neighboring network links.

Table 3.4. Comparison of bicycle network usage on Victoria Avenue, and its neighboring segments (parallel and perpendicular), pre- and post-intervention.

Victoria Avenue Period	HBS Trips	Trips in Victoria Avenue Intervention Neighborhood (% of All Trips)	Trips using Components of Intervention Segment (% of All Trips)	Trips on Neighboring Segments but not Victoria Avenue (% of All Trips)
Pre-Intervention	477,032	44,346 (9.29%)	8445 (1.77%)	35,924 (7.53%)
Post-Intervention	101,179	9081 (8.98%)	2133 (2.10%)	6948 (6.87%)

3.5. Discussion

Investigating the effects of the Victoria Avenue intervention on the spatiality of HBS trips using the cycle track shows a flattening of the distance-decay function (a lesser decay parameter in magnitude) post-intervention. This indicates a lessening friction of distance effect felt by HBS users, regarding the Victoria Avenue cycle track. Trips originated farther away from the intervention more frequently, once the cycle track was installed, and members appear more willing to travel longer distances while cycling, to use the intervention. The cumulative percentages of network distances from trip origins to the cycle track show a much slower drop off, and mapping the quartiles confirms this: post-intervention, the second quartile of network distances (median) is larger, while the 100% quartile is smaller post-intervention. It should be noted that the average trip length, for all trips using at least a portion of the intervention before construction, was 2.29 km, whereas after the intervention took place, it was 2.48 km. As an additional comparison of means, a one-sided paired-sample Wilcoxson Test was used to compare medians of the average length of trips taken by members using Victoria Avenue pre-intervention, with the median of members' corresponding average lengths of trips using Victoria Avenue post-intervention. The test showed pre-intervention, the average trip length by users who also used Victoria Avenue after construction, was significantly shorter ($p = 0.01$). Lu et al. (2018) and Scott et al. (2021) found that for HBS users, the shortest routes were not necessarily the dominant routes used between origins and destinations, and often more circuitous routes were used to incorporate cycling infrastructure. Additionally, Khatri et al. (2016) found a significant distance trade-off with cyclists' trips; 1 mile of trip with cycling facilities was equivalent to 0.47 miles without facilities.

Of the 2133 trips intersecting the Victoria Avenue intervention, more than 27% were classified as 'New Member Induced,' meaning these trips were taken by users who signed up to HBS membership after the intervention and began using the cycle track as well. While it is difficult to know the exact reasoning behind an individual's decision to sign up for HBS without a complementary survey, there is evidence that the intervention on Victoria Avenue could, at very least, be a factor in the decision to begin using the system, as users began immediately using the cycle track after first signing up for the system, post-construction. The end of COVID-19 lockdowns in Ontario in March 2022 is another potential factor in these new sign-ups, as bike share offers a more private transportation mode than public transportation (which has seen a decrease in ridership post-COVID-19), for those still concerned about public health after restrictions had been lifted (Paul et al., 2022). 3841 members were added to the system post-intervention, and 285 (7.41%) of these new additions began using the intervention – emphasizing the likelihood of impact.

19.6% of trips were classified as 'Segment Induced/Diverted,' meaning they are additional to the intervention, but the exact classification cannot be determined without further analysis into the habitual travel routines and patterns of the individual members. This would determine whether these additional trips were the result of a diversion of a regular trip to use the intervention. The 'Unaffected Trips' classification had the most (33.5%) trips, and represent a portion of the base-level of usage, unaffected by the intervention.

Likewise, the intervention appears to have had an impact on the routing of trips within its surrounding neighborhood. Streets running parallel to the Victoria Avenue cycle track nearly all saw decreases in percentages of HBS trips using them – indicating diversion of trips to use more of the intervention, post-construction. This aligns with Broach et al. (2012) and Lu et al. (2018), who found cycling infrastructure to be preferred by cyclists and inspire longer routes that incorporate more bike facilities. Moreover, the cycle track component segments all became part of the highest-used group of streets analyzed (between 0.94 and >5% of all HBS trips). The proportion of all HBS trips taking place in the neighborhood that used Victoria Avenue increased, and the proportion of neighborhood trips which did not use Victoria Avenue decreased, thus indicating a funneling effect of trips to use the cycle track post-construction.

Finally, streets perpendicular to the cycle track saw a channeling effect of rides toward use of Cannon Street, which has its own pre-existing separated cycle track. Barton Street, which also intersects the intervention, saw a decrease in ridership. It, unlike Cannon Street, does not have any pre-existing cycling infrastructure. This also emphasizes the importance of a connected cycling network, and the preference of users (particularly those less comfortable with cycling) for dedicated infrastructure (Hunt, 2007); while many of the perpendicular streets are quiet, minor-level roads, cyclists began using the separated facilities along Cannon and Victoria more frequently, once the cycle tracks were connected to each other.

There are several limitations within this work to note. For one, the work is unable to ascertain causality regarding the spatial distribution changes in trip origins. It is entirely possible that longer trips are more prevalent because of easing COVID-19 restrictions, changes in surrounding land uses over time, or other environmental factors. Moreover, the classification process is unable to ascertain causality; new sign-ups to HBS may not necessarily be directly caused by the new infrastructure, but instead, a variety of other factors. The use of a complementary survey would greatly help determine more precise influences on new member sign-ups. Additionally, valid trips were occasionally missing

GPS trajectories, and map-matching resulted in a total data loss of ~6% of all GPS trajectories. In total, ~22% of valid logged trips could not be included in the analysis, as a result of one or both of these issues.

3.6. Conclusion

With growing financial and political investment in active transportation federally, provincially, and municipally, there is a strong need for data-driven, revealed-preference research into the various impacts of an infrastructure investment like the Victoria Avenue cycle track in Hamilton, Ontario. Infrastructure construction is an important strategy adopted by Canadian municipal governments, to encourage cycling for both recreation and utilitarian purposes (Pucher and Buehler, 2011). The goal of this study was to explore and present, empirically and longitudinally, the different ways the Victoria Avenue cycle track has generated traffic, altered pre-existing routes, and impacted the friction of distance felt by HBS users cycling along Victoria Avenue, having originated in various areas across the city. It sought to achieve this goal using more than half a million Hamilton Bike Share users' routes, map-matched to Hamilton's cycling network. Analysis in this work suggests that the Victoria Avenue project has helped lower the friction of distance on ridership on the affected segments, is associated with variously classified 'induced' HBS trips, and has resulted in various route diversions. The project can be seen as a success, for these reasons. Moreover, this paper presents a general foundation for researchers and municipal governments to further investigate the effects of their active transportation investments, like cycle tracks, which represent significant expenditures of tax revenue.

There are several potential avenues for further research, building off the methodology and findings of this work. For one, with advancements in revealed-preference data available for private cyclists (e.g., Strava), the use of GPS data from private cyclists in this methodology would provide important insights into the similarities and differences in the effects of the intervention, or other interventions, on cyclists not using the bike share system. Moreover, using the origin and destination data of individual trips, establishing 'regular' inter-hub trips made by bike share users to further parse apart induced and diverted trips would represent an important improvement in the precision of the project's determined effects.

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Appendix

Table 3a. Trip classification results for various period comparisons. In each, to control for potential seasonality effects, September through December are left out.

Time Period Comparison	# Pre	# Post	New Member Induced (%)	Existing Member Induced (%)	Segment Induced/Diverted (%)	Unaffected (%)
All Januarys to Augusts (2019-2022)	5341	1986	580 (29.2)	370 (18.6)	649 (32.7)	387 (19.4)
Jan-Aug 2019 & Jan-Aug 2022	2692	1986	580 (29.2)	151 (7.6)	1137 (57.3)	118 (5.9)

Jan-Aug 2020 & Jan-Aug 2022	1330	1986	580 (29.2)	239 (12.0)	1080 (54.4)	87 (4.4)
Jan-Aug 2021 & Jan-Aug 2022	1319	1986	580 (29.2)	495 (24.9)	729 (36.7)	182 (9.2)

4. CONCLUSION

The preceding chapters, through the use of econometric modeling techniques, descriptive statistics, cartographic visualization, and a novel trip classification approach, have worked to investigate and more directly and holistically quantify the impact of separated cycling infrastructure on bike share ridership in a mid-sized Canadian city. Five objectives were considered and addressed within this research:

I. Quantify the impacts of various separated cycling 'interventions' on Hamilton Bike Share ridership, controlling for confounding factors.

II. Using longitudinal, and empirical revealed preference data, develop a methodology that more reliably establishes a causal link between cycling infrastructure and increased ridership.

III. Evaluate the heterogeneity in intervention success in generating HBS ridership across the cycling network and examine potential factors behind any heterogeneity.

IV. Evaluate the impacts of separated cycling infrastructure projects on the spatial distribution of bike share rides, and the cost of distance associated with use of a street segment with or without separated cycling infrastructure.

V. Evaluate the nature of bike share rides, to further a causal link between infrastructure and ridership, by parsing apart 'induced' ridership from 'diverted' ridership.

How the research addressed each of these objectives, a summary of the results, areas for potential improvement, and avenues for future research are discussed in the proceeding sections of this conclusion chapter.

4.1. Research Contributions

A number of meaningful results which contribute to the literature were achieved within the research presented in this thesis. Additionally, many of these results are in agreement with, or enhance the robustness of, findings from the literature. Chapter 2 directly addresses Objectives I, II and III, and Chapter 3 focuses on Objectives I, IV, and V.

The results in both chapters found that the introduction of the separated cycling infrastructure interventions had positive results on Hamilton Bike Share ridership, in agreement with the literature, which has found a positive association and potential causal link between infrastructure and ridership (Eren & Uz, 2020; Félix et al., 2020; Karpinski, 2021; Xu and Chow, 2019), as well as a stated desire by cyclists for separated infrastructure (Desjardins et al., 2021a; 2021b). Of the ten projects examined in Chapter 2, five projects had statistically significant, positive, impacts on monthly Bicycle Kilometers Traveled (BKT) along their respective intervention segments, increasing traffic between 71.60% and 441.95%, and other segments had impacts that were nearly statistically significant at the 95% confidence level. While other studies have found similar results with regard to specific interventions, indicating generated traffic post-intervention, to the author's best knowledge, no other study has found these results in the context of bike share using empirical routes taken by users, while providing controls for confounding factors as recommended by Buehler and Dill (2016) (Research Objective II).

With regards to Objective III, there is strong heterogeneity of intervention efficacy across the city of Hamilton, with certain projects having extremely positive impacts on ridership, while others show very little impact. As discussed in Chapter 2, a variety of different infrastructure types were examined, ranging from painted buffer bike lanes to concrete-separated cycle tracks. As expected and suggested in the literature, 3 of the 5 positively-significant interventions were concrete-barrier cycle tracks (Sanders, 2016; Sanders and Judelman, 2013; Vasilev, 2022). Additionally, 3 of the 5 positively-significant interventions neighbored another intervention included within the study, and the fourth neighbored a pre-existing cycle track built prior to the study period – reaffirming the importance of cycling network connectivity to growing ridership levels. The features of more successful projects – concrete barriers, high levels of connectivity and accessibility to the system – are all in agreement with findings of Desjardins et al. (2021b), who interviewed cyclists in Hamilton, and found that there was a strong preference for dedicated infrastructure, and that cyclists would travel out of their way to use infrastructure. Moreover, Desjardins et al. (2021a) and (2021b) found gaps in the cycling network to be significant barriers to some cyclists, and the connectivity of the infrastructure was a component of their route decision-making. Chapter 2 of this thesis emphasizes the importance of these characteristics, as well as other characteristics discussed in the literature, such as slope, in the potential success – or lack thereof – of the various infrastructure interventions studied. While other revealed-preference studies have also found similar results, to the author's knowledge, this is the only study which examines in detail multiple interventions with bike share ridership simultaneously – providing a middle ground between single-case studies and an aggregate city-wide analysis where all infrastructure is counted equally.

Using a novel classification system and the Victoria Avenue cycle track as a case study, the specific natures of trips post-intervention that contributed to the generated traffic along an intervention segment, were determined (Research Objective IV). 46.9% of post-intervention trips taken along one intervention segment were determined to be induced trips, with potentially additional induced trips unable to be fully parsed apart. Only 33.5% of trips post-intervention were determined to be unaffected by the intervention and therefore would have occurred along the segment regardless of the cycle track's construction.

There is strong evidence of significant route diversion to use the new projects post-intervention (Objectives IV and V). Moreover, the associated cost of distance for using Victoria Avenue was lessened post-intervention (-1.01 to -0.96 post-intervention)[6] – indicating Hamilton Bike Share users were using the segment despite their trips originating further away from Victoria Avenue post-intervention than prior to the cycle track's construction (Objective IV). The notion of cyclists travelling longer distances in order to use dedicated infrastructure is well-established in the literature, including in the Hamilton-specific context (Broach et al., 2012; Desjardins et al., 2021b; Khatri et al., 2016; Lu et al., 2018; Scott et al., 2021). This research, to the author's knowledge, is the first instance of a neighborhood-level analysis of empirical data evidencing route diversion from parallel streets towards use of an intervention segment.

[6] These values refer to the distance decay parameters found in the models from Chapter 3.4.1 (Table 3.2). Lower distance decay parameter values (i.e., closer to 0) indicate a flattening of the distance decay curve, meaning there is a lesser cost of distance associated between trip origins and the Victoria Avenue intervention segment.

4.2. Areas for Potential Improvements

The research methods presented within the two papers included in this thesis can be improved upon in several ways. As discussed in both sections 2.6 and 3.6, data loss presents a limitation to the results. The map-matching process was unsuccessful in map-matching all of the GPS trajectories provided by Hamilton Bike Share, and there were fewer trajectories found than trips logged by the system. Within the two studies, there was an average of 20.5% of valid logged trips which were not map-matched, either due to missing GPS trajectories or the algorithm's inability to match the trajectories to a route along the cycling network. While this value appears relatively high, the map-matching algorithm successfully map-matched an average of 95% of all valid GPS trajectories tracked by Hamilton Bike Share. While the majority of the data loss occurred as a result of invalid GPS trajectories, or trips without trajectories (including trips where a bike is checked out but is checked back in shortly after to the same hub), the data collection could be improved through further advancements in GPS technology on the bikes themselves, or manual map-matching and validation of trips which could not be map-matched through the algorithm.

Secondly, while controls were used in the study to account for many time-variant and invariant factors affecting the impacts of the infrastructure on ridership, the study could be improved through the incorporation of a single street or multiple streets without infrastructure into the research papers to be designated as a distinct control group, thus more closely refining the study to be experimental in nature, would better adhere to Buehler and Dill's (2016) recommendations for causality determination. While the inclusion of these parallel segments could require an alteration to the model setup, and the study of the neighborhood surrounding Victoria Avenue in chapter 3 does represent a more quasi-experimental setup, without this control group (a group of streets for chapter 2 and a single parallel street for chapter 3), the results reported cannot fully ascertain causality. In addition to this, the precise proportions of diverted trips in the reported impacts of interventions on generating traffic could not be determined, and this potentially affects the accuracy of the reported impacts on 'inducing' trips. As such, the use of concurrent stated-preference data would complement the revealed preference data used here, to explain the motivations more precisely behind decisions made by Hamilton Bike Share users, such as why users signed up for the system and whether the infrastructure projects examined played a role in user decision-making.

Finally, there is strong evidence in the literature that bike share members and frequent users differ in terms of their socioeconomic statuses, demographic characteristics and cycling frequency or experience (Buck et al., 2013; Crossa et al., 2021; Martin et al., 2016). Moreover, there is evidence in the literature that the purpose of bike share trips may often differ from private cycling trips (Buck et al., 2013; Wergin and Buehler, 2017). This research only used bike share revealed-preference data, with no comparative analysis with data from private cyclists. Thus, the results determined in this research cannot necessarily be generalized to the greater cycling population, nor can they determine the impacts of infrastructure on generating private cycling trips or encouraging new potential cyclists to pick up a bike and begin riding. As indicated in greater detail within the proceeding section, these methods could be further enhanced by including a second analysis using private cycling data, to both provide a comparison between bike share members' and private cyclists' use of infrastructure, as well as to provide a more comprehensive investigation of the overall impacts of the infrastructure.

4.3. Directions for Future Research

There are a number of promising avenues for future research, based on the results, methodologies and identified areas for improvement presented by this research. To begin, the methods used and developed within this research can be used in a variety of capacities, including for future work with bike share or with similar revealed-preference GPS data for private cyclists. Future research should consider similar analyses with private cyclists, to investigate potential differences in effects of infrastructure. This could include the use of GPS data from apps like *Strava*, or a larger-scale travel study using revealed-preference data for a representative sample of the population. Several studies have been using *Strava* data to examine cyclist travel behavior, including with regards to infrastructure's influence on ridership (e.g., Hong et al., 2020a; Hong et al., 2020b; Livingston et al., 2020). Similar approaches in the Canadian context can be made, to examine and compare the impact differences of cycling infrastructure between these different segments of the cycling population.

Several methods used within this research can be expanded upon, to enhance the nonspuriousness of the experiments. For one, the modeling methods from chapter 2 can be further expanded with more control variables, including fuel prices or inflation-related variables to better account for additional exogenous factors on bike share ridership, as these have been found to impact ridership levels and may not be fully accounted by the current control variables (He et al., 2020). Another potential variable that could be expanded upon is the system-wide membership rates, which are time-variant, and could further control for ridership changes. While these are accounted for through the time-varying control variables, they could be underrepresented, and therefore explicit variables coupled with additional months of data could improve the accuracy of results. Likewise, the modeling system can also incorporate parallel streets to be used as a control group or counterfactual, to further explore whether ridership changes attributed to the infrastructure projects can be observed along other segments in the cycling network, which would indicate the potential presence of system-wide effects on ridership being felt.

In both research papers presented within this thesis, there was a limited number of post-intervention months analyzed (less than one year for both studies in Chapters 2 and 3). This is not long enough to determine some of the medium and long-term impacts of the infrastructure projects. Future research should work to investigate these projects' efficacies in generating bike share traffic in the short, medium, and long terms. Likewise, as Hamilton continues to grow its cycling network, additional projects should be added and accounted for within future research. These longer-term analyses will inform planners and policy makers on the possible multi-year impact, as well as the potential impacts of increased network connectivity, as more projects are added within the cycling network, to bike share ridership. Moreover, this research's methods and results allow planners and policy makers to prepare longer-term analyses, examining land uses and accessibility metrics, which could be explanatory factors in the heterogeneity of intervention efficacy.

Similarly, by using origin-destination matrices, there is the possibility of further classifying diverted trips that use infrastructure segments, if there are changes made in habitual routes between certain origin and destination hubs. Future research should work to further parse apart diverted trips from the general generated traffic, to better determine who is most benefitting from infrastructure investments – users who were pre-existing to the system, or individuals who represented 'latent demand' for cycling (i.e., new members).

Finally, the methods postulated in this research should be used in other scenarios, by other municipalities or regions with access to GPS data, to not only further validate and enhance the techniques, but to determine differences in impact across city sizes, local policy, and built-environment contexts. For example, a comparative analysis of infrastructure effects on cycling or bike share ridership, across cities of varying population sizes or densities, or in different countries, such as Canada and the United States, would address a gap in the literature and provide important evidence for local planners and policymakers to better plan their active transportation networks for their own specific city contexts.

This research has the potential to impact future policy. For one, the findings of this research indicate that the construction of separated cycling infrastructure has had positive impacts on the levels of Hamilton Bike Share ridership (including substantial rates of trips which were considered 'generated'), the use of the respective segments which have undergone the interventions, as well as the spatial distribution of trip origins using a cycle track. This confirms the positive associations between infrastructure and ridership, found by previous works in the literature, and adds further credence to the causal link postulated by previous works on private cycling, as well as bike share, and infrastructure interventions. From a policy perspective, further validation of the positive impacts of infrastructure on cycling ridership shown by this thesis can provide a data-driven mandate for planners locally in Hamilton, as well as in other mid-sized cities across North America, to continue and enhance their funding and master planning, with cycling network construction and connectivity being top-of-mind. This could encourage municipalities to expedite cycling infrastructure construction, making it a greater priority within their transportation planning. The results in this thesis also confirm previous works in the literature, including those with a Hamilton-specific focus, indicating cyclists show a preference for physically-separated infrastructure – particularly physical barriers such as concrete medians – as well as a connected cycling network, and this could encourage municipal policy documents, such as transportation master plans or active transportation master plans, to more frequently encourage the implementation of these preferred types of infrastructure in a manner that emphasizes connectivity and accessibility. This all serves to make cities in Canada and North America more bike share and cyclist-friendly going forward.

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