UNDERSTANDING BIKE SHARE USAGE: AN INVESTIGATION OF SOBI (SOCIAL BICYCLES) HAMILTON

UNDERSTANDING BIKE SHARE USAGE: AN INVESTIGATION OF SOBI (SOCIAL BICYCLES) HAMILTON

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ABSTRACT

This thesis examines factors that influence the daily number of trip departures and arrivals at over 100 hubs comprising Hamilton, Ontario's (Canada) bike share program – SoBi (Social Bicycles) Hamilton. SoBi operates all year, and during its first year of operation (April 1, 2015 to March 31, 2016), over 200,000 trips were generated on SoBi bikes. The study utilizes data from SoBi Hamilton, the 2011 Canadian Census, the 2011 Transportation Tomorrow Survey, Environment Canada, and Hamilton's Open Source Data initiative. From these master files, daily trips, meteorological data, temporal variables, socio-demographic and built environment attributes were obtained to generate a comprehensive suite of explanatory variables to explain the daily trips at each hub. A multilevel regression approach was used to understand the associations between bike share usage at each hub and each suite of explanatory variables at two temporal scales: total daily trips at hubs and total daily trips across four time periods of the day. Findings demonstrate that weather and temporal attributes play a significant role in trip departures and arrivals. In addition, hub attributes vary in significance throughout different times of the day for trip departures and arrivals. Overall, the methodology and findings allow us to identify factors that increase SoBi usage, which can also benefit city planners and engineers who are implementing a bike share system with the goal of maximizing bike share activity in urban centers.

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PREFACE

This thesis is organized as a compilation of related articles. It is comprised of the following two chapters:

Chapter 2: WHAT FACTORS INFLUENCE BIKE SHARE USAGE? AN INVESTIGATION OF SOBI HAMILTON'S HUBS

Chapter 3: WHAT FACTORS INFLUENCE BIKE SHARE USAGE AT DIFFERENT TIMES OF THE DAY? AN INVESTIGATION OF SOBI HAMILTON'S HUBS

Both journal articles have been co-authored with Professor Darren Scott (Master's supervisor). The content of each thesis chapter was the responsibility of myself. Research objectives, reviewing of literature, data analysis, specifying and estimating models, and interpreting results were designed by myself. Professor Darren Scott designed the technical apparatus of creating the hub attributes and land use variables used for analysis. His other contributions include suggestion of the research topic and methods, discussion of the empirical results and critical editorial advice prior to journal submission.

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CHAPTER ONE: Introduction

1.1 THE EVOLUTION OF BIKE SHARE SYSTEMS

The first bike sharing system was introduced in the 1960s in the Netherlands (DeMaio, 2009). Since then, there has been a drastic increase of bike sharing systems globally, with more than 1 million bicycles in service for public use (Meddin, 2017). As of 2017, there are 1,301 cities operating bike share systems worldwide and almost 400 more cities are planning or constructing one (Meddin, 2017). The concept of public bike share programs is relatively new as the first system was implemented just over 50 years ago (Bachand-Marleau et al., 2012). To date, there have been four generations of bike sharing systems. The first generation also known as “free bikes” were typically painted one colour, left unlocked, and placed randomly throughout an area for free use. Due to increased instances of theft, this process was abolished (Shaheen et al. 2013). As a result, the second generation emerged and was composed of a coin-deposit system where bicycles had designated docking stations. Unfortunately, this did not solve the problem of theft (Shaheen et al. 2013). It was not until the mid-1990s that an IT-based system (third generation) was implemented, which allowed the operator to identify the user while also tracking the bicycle (Shaheen et al. 2013). With the ability to track each bicycle through the use of an individual user’s credit or debit cards, theft of bicycles decreased. Following the success of the third generation system, the fourth generation built upon this technology by enhancing various features.

Today, the fourth generation systems, also known as demand-responsive multimodal systems includes features such as flexible docking stations or “dockless” bicycles, demand responsive innovations to facilitate system rebalancing, multimodal access with other transport modes, and global positioning system tracking (Shaheen et al., 2013). Hamilton Ontario’s bike share system, SoBi Hamilton, belongs to the fourth generation of systems. SoBi is flexible and convenient for each type of user, specifically the hourly, monthly, annual and power user. All of the users can ride the bike anywhere throughout Hamilton, and lock a bike at any of the hub locations free of charge or anywhere within the service area for only a small convenience fee.

1.2 RESEARCH MOTIVATION

Population growth and urbanization have brought great changes to cities in the past decade (Hao et al., 2010). As a result, urban travel patterns have become more complex, involving both individual and household decisions with respect to trip scheduling and chaining, mode and route choices, and car sharing (Hatzopoulo et al., 2007). Due to increasing automobile ownership and travel, cities experience urban sprawl, which also results in growing traffic congestion, poor air quality, as well as health problems (Handy et al., 2005). In Canada, the transportation sector emits more greenhouse gas (GHG) emissions than any other end-use sector, which coincides with the 2.0 percent per year growth of vehicles between the years 2000 to 2009 (Natural Resources Canada, 2009). Consequently, bike share systems have drawn considerable attention for their multiple benefits to the environment and both cyclists and society. For instance, bike share systems offer a low-cost, low-polluting, health-improving way to travel (Handy et al., 2014).

Traffic congestion costs the Greater Toronto Hamilton area $2.7 billion annually in lost opportunities for economic expansion (Transport Canada, 2011). In Canada, the average one-way commute is 31 minutes (Transport Canada, 2011). In an urban or suburban environment that would equate to a 25 km commute for cars, 8 km for cyclists, and 2.5 km for pedestrians (Transport Canada, 2011). Researchers have found that the travel decisions people make seem to be significantly associated with built environment factors such as density, location, mix of land uses and urban design (Philip & Taylor, 2017). Due to urban sprawl and a global trend toward increasing car use, a major goal of urban transportation is to encourage car users to leave the comfort and convenience of their automobiles and take alternative modes of transport. In a multi-city analysis of bike share's impacts on car use, Fishman et al. (2014) calculated bike share's overall impact on total vehicle kilometers travelled. The results showed that bike shares in Melbourne, Brisbane, Washington D.C., and Minneapolis/St. Paul all reduced car use. In Canada in 2010, 82% of workers travelled to work by car, 12% took public transit and 6% walked or bicycled (Turcotte, 2011). Drawn from these observations, it is evident that transportation policies and land development must be modified to deter population decentralization and alleviate traffic congestion. Furthermore, understanding commuters' preferences is of vital importance to increase bicycle use.

Increased reliance on motorized vehicles for everyday transport has contributed to a reduction in Canadians' physical activity levels, which has resulted in corresponding health impacts (Transport Canada, 2011). Consequently, the risk of obesity goes up 6% for every hour spent in a car each day, while the risk of obesity goes down by almost 5% for every kilometer walked a day (Transport Canada, 2011). An increase in obesity due to low physical activity also increases the risks to heart disease, stroke and other chronic conditions, including cardiovascular disease, type 2 diabetes, and various cancers which result in an estimated $5.3 billion per year in direct and indirect health care costs (Transport Canada, 2011). Previously mentioned, in a multi-city analysis of the impacts of bike shares, Fishman et al. (2014) estimated changes in physical activity due to bike share in Melbourne, Brisbane, Washington D.C., London and Minneapolis/ St. Paul. The results found that an average of 60% of bike share trips that replaced sedentary modes of travel had a positive impact on physical activity leading to an additional 74 million minutes of physical activity in London, through to 1.4 million minutes in Minneapolis/ St. Paul. Overall, introducing a bike share system has multiple individual health benefits, but could also confer substantial benefits for the entire community – for example, through reduced air and noise pollution, and economic benefits from reduced health care costs and fewer sick days (Handy et al., 2014; Garrard et al., 2012).

As previously mentioned, the transportation sector emits more greenhouse gas (GHG) emissions than any other end-use sector (Natural Resources Canada, 2009). By now, most scientists agree on the occurrence of climate change and the fact that human activities account for many of these changes (Böcker et al., 2013; National Research Council, 2010). Although there is uncertainty in the degree of climate change, the changing weather patterns on the transport sector will be impacted (Böcker et al., 2013; Koetse & Rietveld, 2009). In urban dense areas that are relatively congested, a bicycle can often offer a convenient sustainable mode of transport; however, weather conditions can often deter one to choose to cycle. It has been found in previous studies that weather affects bike share usage, not only on a seasonal basis, but at a daily level as well (El-Assi et al., 2017; Faghih-Imani & Eluru, 2016; Corcoran et al., 2014; Nosal & Miranda-Moreno, 2014). Although there have been several recent studies published on weather and cycling, there are still shortcomings in the literature as most studies have used survey data, brief manual counts or daily (aggregate) data, which cannot capture the effects of hourly (disaggregate weather) conditions (Nosal & Miranda-Moreno, 2014).

Yet, regardless of longer commute times, obesity and climate change, the determinants that influence individuals to cycle are not well understood in the Canadian bike share system context. In 2011, a bicycle as a mode of transportation for commuter purposes in Hamilton was only 0.7% (Statistics Canada, 2011). In addition, 22.2% of people reported making less than five short trips (<5 km) a week in Hamilton (Topalovic et al., 2013). Like all bike shares, SoBi promotes a convenient, healthy and sustainable mode of transportation while also eliminating worries of theft. For this research project, the scope of work investigates the effects of socio-demographics, built environment, and hub attributes on bicycle usage at hubs comprising the SoBi system. In addition, temporal characteristics and weather effects are evaluated. This knowledge is vital for rebalancing the hubs and the successful development and implementation of sustainable community and transportation planning.

1.3 RESEARCH OBJECTIVES

The goal of this research project is to quantify the influence of various factors on trip departures and arrivals at SoBi hubs using a general statistical modelling technique that other regions can adopt. The specific objectives of this research are as follows:

I. Evaluate the impact of socio-demographics, weather, temporal characteristics (day of week, seasonality, day of year), and hub attributes such as the built environment, and land use on daily trip-making behaviour at the SoBi hub-level.

II. Evaluate trip-making behaviour throughout the day at the hub-level exploring socio-demographics, weather, temporal characteristics (day of week, seasonality, day of year), and hub attributes such as the built environment and land use around SoBi hubs to assist in rebalancing the system.

In any bike share system, one of the keys to success is the location of hubs and their relation to trip demand (Lin & Yang, 2011). However, one of the main issues with bike shares is that bicycles are not uniformly distributed between the hubs, which causes some hubs to be full or empty over time. Therefore, modelling bicycle usage at hubs through various factors previously mentioned can help explain the underlying factors influencing trip departures and arrivals. A previous study, found that location determines the characteristics of each hub, either as a trip generator or attractor, depending on whether its potential demand comes from residential areas or areas of economic activity (Garcia-Palomares et al., 2012). Therefore, modeling land use in relation to other temporal and spatial characteristics at the hub level throughout the day can serve as an input to maximize efficiency throughout an entire system.

Meeting these objectives will contribute to the existing body of literature surrounding bike share usage by determining the effect of weather data, temporal characteristics, and hub attributes on SoBi trip departures and arrivals at the hub level using real time data. The objective of our research is similar to previous studies; however, some fail to capture the impact of variables that change in the short term (variations in weather and time of day effects) due to the level of aggregation chosen. Moreover, examining bike share usage at a daily level and throughout different time periods of the day will allow policy makers to better understand important contributors to trip departures and arrivals. The estimated multilevel models throughout the day allow us to predict changes in the system, which can assist in relocating and installing new SoBi hubs in Hamilton, or for city officials planning new bike share systems in other cities.

1.4 THESIS OUTLINE

Including this introduction, this thesis consists of four chapters. Chapters 2 and 3 consist of two stand-alone research papers, and Chapter 4 briefly summarizes the findings and conclusions.

Chapter 2 examines the factors that influence the daily number of trip departures and arrivals at over 100 hubs comprising SoBi Hamilton. The findings from the multilevel regression models indicate that temporal and weather characteristics influence usage, in addition to the built environment hub attributes. Findings demonstrate that larger populations around a hub does not necessarily promote more ridership, rather there are other contributing factors that need to be considered.

Chapter 3 goes one step further and examines the impact of SoBi daily trip departures and arrivals aggregated by time periods throughout the day. This study allows for a better representation of weather's influence on SoBi usage and how spatial attributes vary in significance at different times of the day. Separate multilevel regression models for each time period and trip departures and arrivals indicate that there is a significant difference between the hubs throughout the day. Furthermore, the time periods capture the effects of weather conditions in the morning versus mid-afternoon, and demonstrate that population and employment opportunities, the built environment and land use vary throughout the day.

In Chapter 4, the overall research findings and contributions are reviewed. This is followed by a discussion of the limitations of this research. This thesis concludes with suggestions for future research.

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CHAPTER TWO: What factors influence bike share usage? An investigation of SoBi Hamilton's Hubs

2.1 INTRODUCTION

In recent years, bike share systems have gained popularity as they have come to serve as an increasingly convenient source of transport (Fishman, 2016; Shaheen et al., 2013). From just a handful of bike share systems in the late 1990s, there is now over 800 systems providing bikes that can be picked up and dropped off at self-serving docking hubs (Fishman, 2016). Bike shares provide an alternative sustainable mode of transportation contributing to the creation of healthy cities. There are multiple benefits of bike share systems including, but not limited to, flexible mobility, reduced emissions, health benefits, reduced congestion and fuel use, individual financial savings, and support for multimodal transport connections (Shaheen et al., 2013). With respect to the latter benefit, bike shares enhance access to and from public transit, thus improving upon the issue of last-mile connectivity (Jäppinen et al., 2013). While bike shares can mitigate factors influencing climate change such as reducing fuel usage, and enhance multiple health benefits, they also normalize the image of cycling as an everyday travel mode, thus broadening the cycling demographic (Goodman et al., 2014). Moreover, installing bike shares encourages individuals to become more environmentally conscious and promotes active transportation that can enhance physical activity levels to obtain better health outcomes (Faghih-Imani & Eluru, 2015).

Many North American cities are actively investing in bicycle infrastructure (e.g., bicycle lanes, bicycle parking) and implementing new policies and bike share programs in an effort to reduce car use. However, little is known about users' preferences in using a bike share (Nosal & Miranda-Moreno, 2014; Fishman et al., 2013). With the implementation of various transport policies and strategies, many studies have found positive associations between active travel and infrastructure interventions such as walking and cycling paths (El-Assi et al., 2017; Pucher et al., 2011; Yang et al., 2010; Ogilvie et al., 2007). However, a review done by Song et al. (2017), found that the effectiveness of infrastructure interventions in promoting walking and cycling for transport was not a sufficient condition for modal shift, and infrastructure alone may not be enough to promote active travel. Therefore, prior to the implementation of new transportation and bicycle infrastructure throughout a city, understanding users' travel behaviour is a fundamental component in order to maximize the cost-benefit effectiveness of a bike sharing system.

The SoBi Hamilton bike share system was officially launched on March 22, 2015. At inception, the bike share system comprised over 110 hubs and a fleet of 750 bikes. Like all bike shares, SoBi promotes a convenient, healthy and sustainable mode of transportation while also eliminating worries of theft. Within its first year of operation, SoBi generated over 200,000 trips. In this paper, we investigate the effects of weather, temporal characteristics, socio-demographics, and built environment attributes on bike share usage between April 2015 and March 2016. Specifically, we explore daily trip departures and arrivals at each hub using real-time bicycle ridership data provided by SoBi Hamilton. For a new bike share system or existing system to succeed, demand modeling plays an important role in determining the required capacity of the system (Faghih-Imani et al., 2014). Therefore, in this study, we investigate the determinants that influence users' hub choice preferences for trip departures and arrivals.

This study contributes to the growing bike share literature. The results provide useful information for understanding cyclist's behaviour, which other cities can use to improve planning or plan bike share systems. Using year-round trip data provides meaningful insights on the temporal characteristics and different measures of weather that impact SoBi usage in relation to static hub attributes. A multilevel modelling technique is employed to examine these factors affecting SoBi usage throughout the year. This model takes into consideration the effect of repeated trip departures and arrivals at hubs throughout the year while accounting for day-to-day trip variations.

The next section of the paper reviews recent literature on existing bike share modeling. The review summarizes factors that are found to have significant influences on ridership and methods employed to examine these influences. The data and methods section presents a visual representation of SoBi hubs, and describes the study area, variables and modelling approach used for analysis. The results section presents the model specification and results. Finally, the conclusion summarizes the key findings and recommendations for future research on public bike shares.

2.2 BACKGROUND

Over the past few years, several studies have examined spatial and temporal factors that influence usage patterns of bike share systems. A few studies have used data from customer satisfaction surveys, while others have relied on real-time ridership data from systems in operation to predict trips made at hubs. When bike shares were introduced in the 1960s in the Netherlands, it was difficult to keep track of where bicycles were at all times (Shaheen et. al., 2010; DeMaio, 2009). Since then, there have been four generations of these systems: the first generation was "white bicycles" or free bicycles, followed by the second generation, a coin-deposit system, then the third generation, which added transaction kiosks to docking stations to solve the problem of theft from the previous generations. These were followed by the fourth and current generation (Shaheen et al., 2010; DeMaio 2009). SoBi Hamilton belongs to this latest generation of bike sharing systems also known as demand-responsive multimodal systems equipped with global position system (GPS) technology. Predicting bike share demand can be complicated. However, GPS-equipped bikes makes it easier to track their locations, on route and at hubs, which facilitates the prediction of trip demand at hubs.

The bike share experiences of other cities, as discussed in scientific studies and planning reports, often inform the development of new systems (García-Palomares et al., 2012). There have been numerous attempts to understand and define factors that affect bicycle use. A review by Heinen et al. (2010) identified the major contributing factors as the built environment (urban form, infrastructure, etc.), natural environment (topography, seasons, and weather), socio-economic and psychological factors (attributes and social norms, habits, etc.) and other factors related to utility theory (cost, travel time, effort, and safety). Previously, before the fourth generation of bike share systems was introduced, studies would collect cyclist ridership data through automatic counting stations measured by pneumatic tubes or human observation to observe cyclist trends (Nosal & Miranda-Moreno, 2014; Thomas et al., 2013; Miranda-Moreno & Nosal, 2011). More recently, a few studies have used real-time bicycle ridership data to examine spatio-temporal factors that affect bike share usage such as peak ridership times, and the impact of weather variations throughout the entire day.

Transportation research on the built environment has provided compelling evidence that the built form influences mode of travel (Cervero & Kockelman, 1997). Therefore, characteristics of the built environment allow a better understanding of geography's impact on cycling and subsequently, its influence on bike share systems. Various scholars have employed real-time bicycle ridership data to identify determinants that influence bike share hub demand (El-Assi et al., 2017; Faghih-Imani & Eluru, 2016; Wang et al., 2016; Faghih-Imani & Eluru, 2015; Faghih-Imani et al., 2014; Rixey, 2013). In these studies, bike share hub activity is defined as the sum or average of trips departing or arriving at hubs. To examine factors that influence hub demand, these studies explore the influence of bicycle infrastructure, transportation network infrastructure, land use, and urban points of interest, in relation to the influence of weather and temporal characteristics such as time periods and day of the week.

In Montreal, the BIXI system was analyzed to quantify the influence of various factors on arrival and departure flows at the hub level using a multilevel linear mixed modeling approach (Faghih-Imani et al., 2014). The results indicated that bicycle flow and usage increases when there are more bicycle facilities near a BIXI hub, while the length of minor roads within a specified buffer around a hub is associated with a positive impact, and the length of major roads has a negative effect on trip departures and arrivals (Faghih-Imani et al., 2014). Faghih-Imani and Eluru (2015) also found that metro hubs, restaurants and universities each increase the usage of a bike share hub, but restaurants only had a positive influence on both arrival and departure rates in the PM period and hubs near universities are more likely to experience higher volume arriving in the AM. Similarly, a study by El-Assi et al. (2017) for Toronto, using multilevel regression analysis to predict trip departures, trip arrivals, and hub-to-hub trips, showed that hubs located near university campuses, the downtown core area, and transit stations experienced higher trip activities. In addition, an increase in bicycle infrastructure such as paths and a decrease in the number of intersections with major roads have a positive impact on ridership demand. Although Wang et al. (2016) used a different modelling approach (ordinary least-square regression) on the Nice Ride Minnesota system, the study found similar results in that hubs closer to water bodies, the central business district (CBD), and parks have higher levels of activity. Also, the presence of trails have a positive influence, while close proximity to other stations has a negative impact on hub demand. Overall, land use and urban form, such as higher job density, population density, and points of interest such as restaurants, shopping and schools all have a positive influence on station activity (Wang et al., 2016; Zhou, 2015; Faghih-Imani et al., 2014; Rixey, 2013).

Previous studies have determined that weather conditions have a significant impact on bike trips, as inclement weather reduces them, as opposed to warm and dry weather conditions, which encourages them (El-Assi et al., 2017; Godavarthy & Taleqani, 2017; Corcoran et al. 2014; Gebhart & Noland, 2014; Sears et al., 2012;). Gebhart and Noland (2014) investigated the influence of weather on bike share usage for the Capital Bike Share in Washington D.C. Reduced ridership was correlated with cold temperatures, rain, and high humidity levels. El-Assi et al. (2017) also analyzed the effects of weather on Bike

Share Toronto demand at the hub level. Hourly weather data, including temperature, wind chill, humidity index (humidex), snow on ground, wind speed, precipitation and relative humidity were collected for the study. The results were similar to those of previous studies – a positive correlation between bike share activity and high temperature, and correlated negative correlation with precipitation, snow on ground, and humidity, as these are unfavorable weather conditions for outdoor physical activity (El-Assi et al., 2017; Corcoran et al., 2014; Faghih-Imani et al., 2014). Not all bike share systems operate yearly and it is no secret seasonality alters ridership; however, it is essential to analyze yearly trends because operating bike share systems throughout the year can yield a better benefit-cost ratio for the system (Godavarthy & Taleqani, 2017).

Some studies also focused on the user perspective and users' sociodemographic and ridership characteristics in addition to other attributes. A study done by Faghih-Imani & Eluru (2015) used a random utility maximization approach in the form of a multinomial framework to estimate destination hub choice probability between annual members and short-term customers from Chicago's Divvy System. The results found that both short-term and annual members are attracted to hubs with a higher number of restaurants in their vicinities and choose hubs that bring them closer to the CBD. However, the effects of number and capacity of neighboring hubs are opposite for members versus daily customers, as members are likely to favour the higher density of hubs with smaller capacities, while daily customers have a preference for fewer hubs with a large number of docks (Faghih-Imani & Eluru, 2015). In addition, Faghih-Imani & Eluru found that daily customers use the Divvy system for longer trips compared to annual members, demonstrating a difference between recreational and commuter purposes. Furthermore, examining Montreal's bike share system using survey data, it was found that convenience of a bike share system and having a hub closer to home encourages individuals to use the system (Bachand-Marleau et al., 2012; Fuller et al., 2011). Convenience was also found to be a predominant motivation for bike share use by Australian bike share systems, CityCycle and Melbourne Bike Share, along with Capital Bikeshare in Washington, D.C (Fishman, 2016). Few studies found that the demographics of bike share users play a significant role in ridership activity (Godavarthy & Taleqani, 2017; Fishman, 2016; Wang et al., 2016; Faghih-Imani & Eluru, 2015; Rixey, 2013). More or less, Fishman's (2016) review of recent literature synthesized that much of this research has revealed common trends – users tend to be of higher average income and education status and engaged in full-time or part-time work.

In summary, points of interest around a hub such as schools, parks, commercial shopping, restaurants, and businesses across all categories within a specified buffer around a hub could impact users' trip departures and arrival preferences. Within a bike share system, one would expect proximity to play a vital role in decision making concerning destination choice. However, there is the potential that individuals would ride farther in the presence of bicycle infrastructure and access to opportunities such as restaurants and employment (Faghih-Imani & Eluru, 2015). The level of aggregation for the analysis of ridership usage at each hub is also critical. Hub ridership data were aggregated differently between studies (i.e., daily totals, hourly totals, weekly/monthly). However, in this paper, we analyze total trips at hubs aggregated by day to capture the impacts of weather and temporal characteristics such as day of the week and day of the year. Analyzing user characteristics is also important to quantify hub usage; however, in this paper, SoBi user information is not available, and therefore Census data are used to measure sociodemographics.

2.3 DATA

2.3.1 Data and Study Area

For this study, daily trip departures and arrivals are modeled using SoBi bicycle data for all hubs in service (114) from April 2015 to March 2016. Figure 2.1 shows the distribution of SoBi hubs in Hamilton. To investigate factors affecting bike share usage at each hub several independent variables were generated.

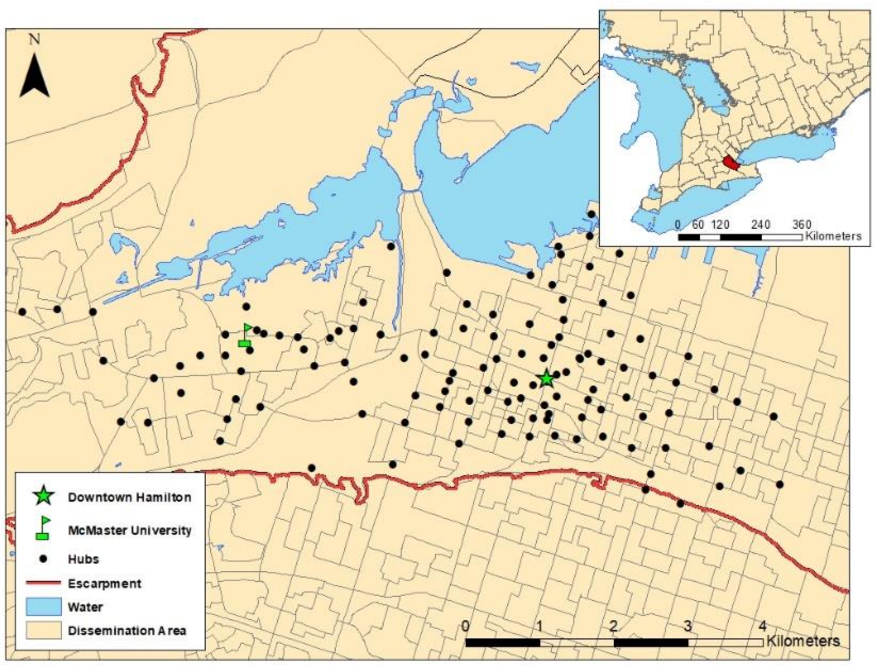

Figure 2.1: Study area.

The SoBi ridership data included trip start time and date, trip end time and date, trip duration, start hub, end hub, and bicycle ID. The data were analyzed at the hub level and trips were aggregated by day to account for temporal changes throughout the year and variability in weather effects. This study focuses on the daily trip departures and arrivals at each hub, over a leap year (366 days), which leaves a final sample of 41,724 observations. The total number of trips completed during SoBi's first year of operation was 203,427 after removing invalid trip records (e.g., trip duration less than 30 s). For the purpose of this study, bike share usage at each hub is measured by (1) the number of trip departures and (2) the number of trip arrivals at hubs. Four categories of independent variables are developed: weather variables, temporal trip characteristics, sociodemographic characteristics, and hub attributes, which include the built environment and land use.

2.3.2 Dependent Variable

The dependent variable in this analysis is the natural logarithm of the number of trips per hub per day (i.e., hub-day). The average number of trips generated per hub-day was 5 ranging from 0 trips to 75 trips. Likewise, the average number of trip arrivals per hub-day was 4 with a minimum of 0 and a maximum of 85. Daily trip counts for each hub were used to account for weather and temporal changes throughout the year of operation. The natural logarithm was selected to normalize the dependent variable as distributions of the two dependent variables were skewed by the higher hub values.

2.3.3 Independent Variables

Table 2.1 summarizes the independent variables developed for this study. To derive the spatial variables (socio-demographics and hub attributes), a 200 m buffer around each hub was found to be an appropriate walking distance considering the distances between SoBi hubs (300 to 600 m apart). A 200 m buffer was also chosen to minimize the number of proximate hubs within a buffer. Similarly, Faghih-Imani et al. (2014) used a 250 m buffer around each hub in Montreal's BIXI system to examine the spatial determinants influencing bicycle usage at each hub. The sociodemographic variables in this study were derived from Dissemination Area (DA) data allocated to appropriate land-use polygons to create a more refined dataset for each hub. The average DA size in the study area is 0.0264 km^2.

Weather Variables

Weather data, collected at the John C. Munro Hamilton International Airport weather station, was obtained from Environment Canada (2016). The variables included in the analysis are the average temperature (^oC) and a binary measure of precipitation indicating whether it rained or snowed (1) or not (0).

Table 2.1: Independent variables.

Variable	Definition	Mean or Proportion	SD
Weather Variables			
Mean temperature	^{o}C	9.384	±9.337
Precipitation	1 if rained or snowed, else 0	0.404	±0.491
Temporal Variables			
Spring	1 if between March 20 and June 20, else 0	0.254	
Summer	1 if between June 21 and September 21, else 0	0.256	
Fall	1 if between September 22 and December 20, else 0	0.245	
Winter (*ref.)*	1 if between December 21 and March 19, else 0	0.243	
Holiday	1 if holiday, else 0	0.035	
Weekday	1 if weekday, else 0	0.715	
Day of year	1 = April 1, 2015 to 366 = March 30, 2016	-	-
Socio-demographic Variables			
Population 16+	Number of people living in residential areas in 200 m buffer	0.557	±0.505
Employment	Number of people working in employment areas in 200 m buffer	0.561	±0.756
Hub Attributes			
Built Environment			
Major intersections	Number of major intersections in 200 m buffer	0.464	±0.864
Length of major roads	Length (km) of major roads in 200 m buffer	0.414	±0.348
Length of minor roads	Length (km) of minor roads in 200 m buffer	1.236	±0.577
Length of bike lanes	Length (km) of bike lanes in 200 m buffer	0.501	±0.339
Length of trails	Length (km) of trails in 200 m buffer	0.232	±0.371
HSR bus stops	Number of HSR bus stops in 200 m buffer	4.096	±4.206
SoBi hubs	Number of hubs in 200 m buffer	1.245	±0.573
Distance to McMaster	Distance (km) to McMaster University	3.465	±1.864
Distance to CBD	Distance (km) to Central Business District	2.164	±1.608
Land Use Variables			
Residential	Residential area ($km^2 \times 10^{-6}$) in 200 m buffer	0.0401	±0.0259
Institutional	Institutional area ($km^2 \times 10^{-6}$) in 200 m buffer	0.0152	±0.0232
Office	Office area ($km^2 \times 10^{-6}$) in 200 m buffer	0.0037	±0.0063
Commercial	Commercial area ($km^2 \times 10^{-6}$) in 200 m buffer	0.0108	±0.0017
Open Space/Parks	Open Space/Parks area ($km^2 \times 10^{-6}$) in 200 m buffer	0.0085	±0.0175
Industrial	Industrial area ($km^2 \times 10^{-6}$) in 200 m buffer	0.0032	±0.0087
Other	Other area ($km^2 \times 10^{-6}$) in 200 m buffer	0.0048	±0.0084

Note: SD = standard deviation, ref = reference variable.

Temporal Characteristics

The impact of seasons, day of the week, holidays, and day of the year on daily trips are investigated. As seen in Figure 2.2, the majority of trips occurred during the summer (36%), then fall (28%), spring (22%) and lastly winter (14%). The day of year is included to account for incremental growth in system usage over time that may be due to increased awareness as time progresses (fixed effect).

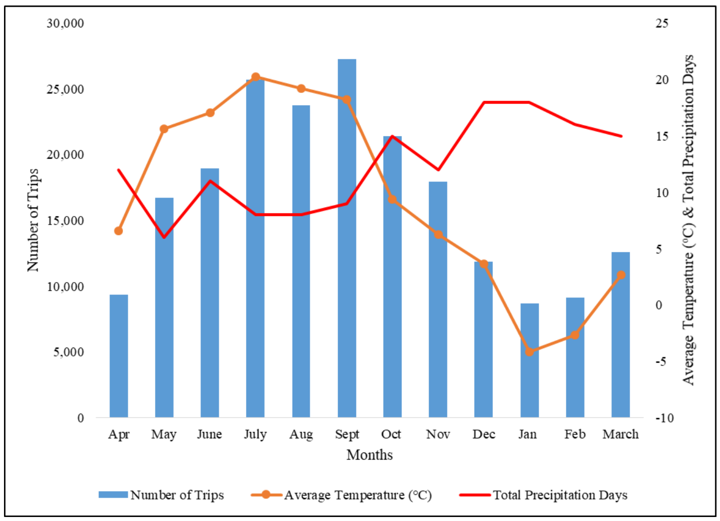

Figure 2.2: Number of trips, average monthly temperature (°C), and number of precipitation days.

Sociodemographic Variables

Two sociodemographic variables are constructed for a 200 m buffer around each hub using 2011 Canadian Census data and 2011 Transportation Tomorrow Survey data (Table 2.1). Population aged 16 and over from the 2011 Canadian Census is included to account for the total residents living within the buffer area. The variable only included persons 16 years of age and older as SoBi is only available to those such persons. Rather than assuming that people are distributed evenly throughout an entire DA, people are allocated to residential areas only. The second variable is total employment within 200 m buffers, retrieved from the 2011 Transportation Tomorrow Survey (TTS). Similarly, rather than assuming employment is distributed evenly throughout an entire Traffic Analysis Zone (TAZ), only employment parcels corresponding to institutional, office, commercial and industrial land uses are selected.

Hub Attributes

To account for the built environment and transport infrastructure around hubs additional variables were created. These variables were extracted from City of Hamilton planning data, some of which is available as "open" data through the City's website. Hub attributes created for the 200 m buffers are number of major intersections; lengths of major roads, minor roads, bike lanes and trails; number of HSR bus stops; and number of SoBi hubs. Also, the distance to McMaster and the CBD is based on the shortest path distance from each hub through the road network.

Land use is also considered in our analysis. As seen in Table 2.1 and Figure 2.3, these classes include: residential, institutional, office, commercial, open space/parks, industrial, and other (e.g., vacant, agricultural/farm, utilities, warehousing). If multiple land uses (e.g., residential and commercial) were found within a parcel, a second land use field was created to be used to reclassify parcels accordingly to their secondary land use.

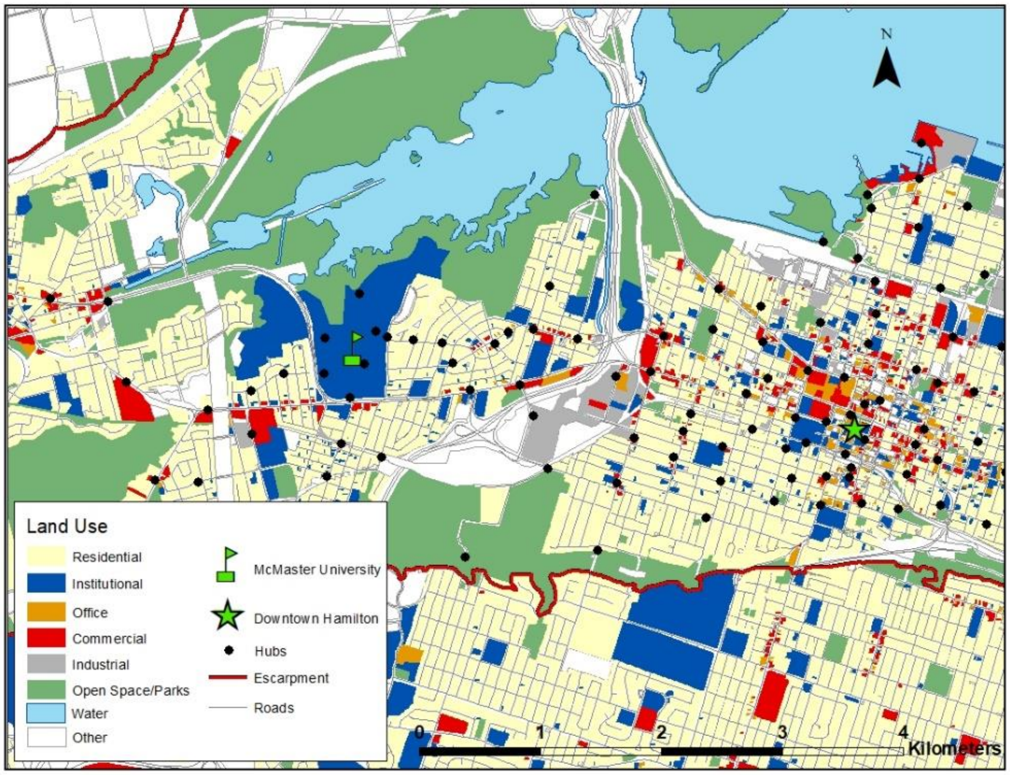

Figure 2.3: Spatial distribution of land use types.

2.4 METHOD

Repeated observations such as daily counts of trip departures and arrivals to bike share hubs violates the independence assumption of traditional linear regression, which is the most common modeling method applied to continuous dependent variables. For this reason, our study uses a multilevel model to investigate the determinants affecting SoBi usage at each hub. Figure 2.4 displays the average number of daily trips originating and terminating at SoBi hubs.

Two-level, multilevel models are estimated with SAS® using the PROC MIXED procedure. Levels 1 and 2 pertain, respectively, to the daily counts of trips grouped within hubs. An unstructured covariance matrix is selected to allow every term to be different and have the variances constrained to be nonnegative, and the covariance's unconstrained (SAS, 2017). For this study, multiple fixed effects are modeled and hubs are modeled as a random effect to account for differences in usage amongst hubs throughout the study period. Four models each are estimated in this study for, respectively, trip departures and trip arrivals. Models 2 through 4 are developed by adding an additional suite of independent variables to the preceding models. Model 1 is the null model, containing no independent variables. For this study, a random intercept multilevel model is used, which takes the following form:

$$y_{ij} = \beta_0 + \beta x_{ij} + u_j + \varepsilon_{ij}, \qquad i = 1, \dots, I, \qquad j = 1, \dots, J$$

where y_{ij} is a $n \times 1$ vector of observed values (in this case, the number of departures or arrivals on each day i for hub j), x_{ij} is a $n \times k$ matrix of observed independent variables for each hub-day, β_0 is the intercept, and β is a $k \times 1$ vector of coefficients. u_j and ε_{ij} are random error terms assumed to follow normal distributions with means 0 and variances σ^2. Maximum likelihood is used to estimate the models. Akaike's Information Criterion (AIC) is examined for improvement in model fit when the nested models differ in fixed effects (Bell et al., 2013). For AIC, smaller values represent better fitting models (Bell et al., 2013). Another commonly used measure of model fit is the likelihood ratio test when examining differences in the -2 log likelihood (-2LL) values of nested models; however, for this study, AIC measures are utilized as they are more versatile (Bell et al., 2013). Lastly, with PROC MIXED syntax, a Covariance Parameter Estimates table is generated, in which the Intraclass Correlation Coefficient (ICC) can be computed to indicate how much of the total variation in hub usage is accounted for by the effects measured in this study. The remainder of this paper focuses on Model 4, as the AIC value is the smallest indicating an overall improvement in model fit (Table 2.2).

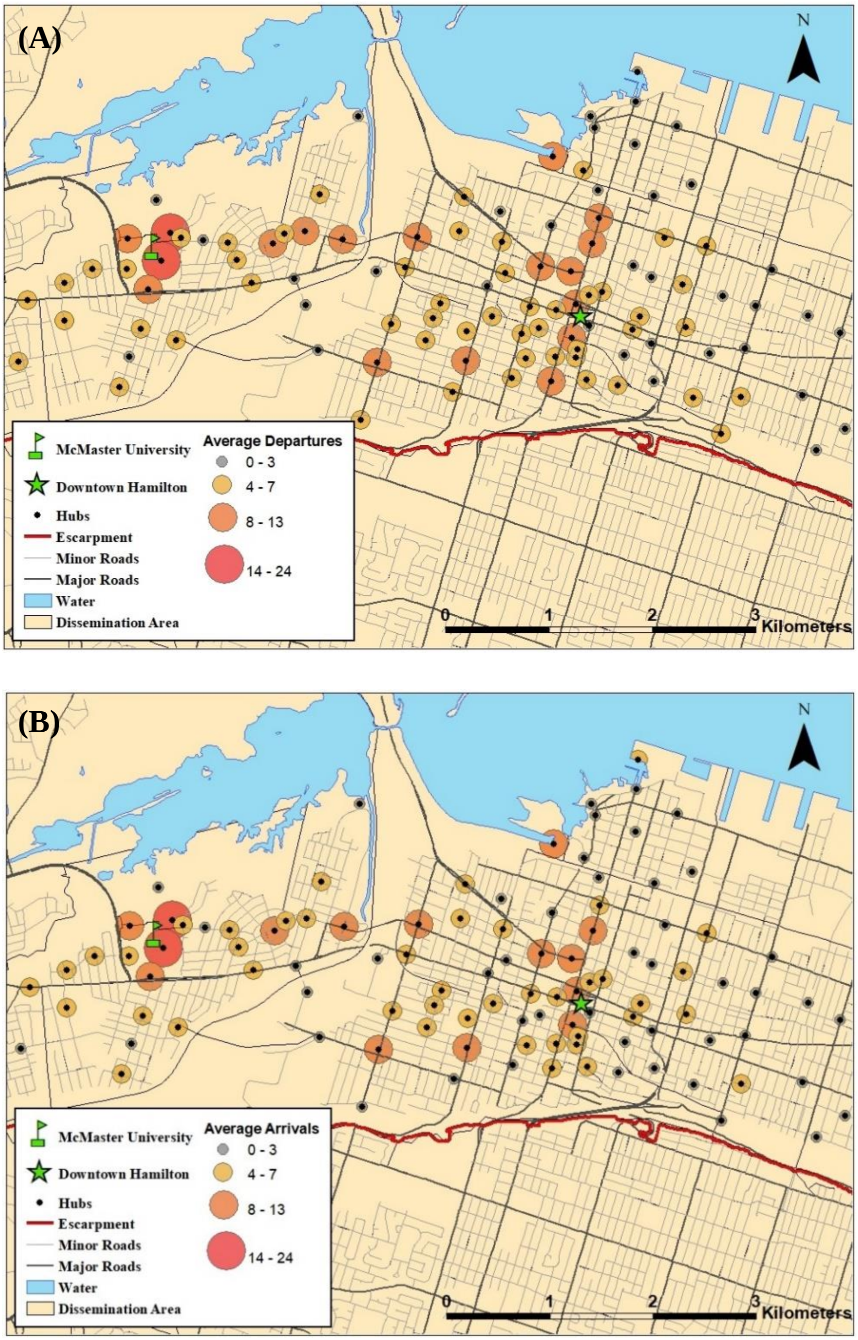

Figure 2.4: Average daily trip departures (A) and arrivals (B).

Table 2.2: Model estimation results.

Variables	**Trip Departures**		**Trip Arrivals**	
	Coefficient	***t*-value**	**Coefficient**	***t*-value**
Intercept	-3.671	-1.95*	-4.732	-2.45**
Weather Variables				
Mean temperature	0.094	30.67***	0.095	29.39***
Precipitation	-0.543	-16.75***	-0.573	-16.80***
Temporal Variables				
Spring	0.419	5.45***	0.481	5.95***
Summer	0.946	11.98***	1.092	13.13***
Fall	1.118	20.72***	1.219	21.46***
Holiday	-1.257	-15.05***	-1.302	-14.81***
Weekday	0.810	23.67***	0.931	25.86***
Day of year	0.003	5.85***	0.002	4.44***
Ln Day of year	0.373	7.99***	0.445	9.05***
Socio-demographic Variables				
Population 16+	-0.218	-0.61	-0.361	-0.98
Employment	0.031	0.08	-0.134	-0.33
Hub Attributes				
Built Environment				
Major intersections	-0.541	-2.09*	-0.436	-1.64
Length of major roads	0.861	1.30	0.875	1.28
Length of minor roads	0.482	1.06	0.513	1.09
Length of bike lanes	0.403	0.80	0.378	0.73
Length of trails	0.030	0.06	0.254	0.50
HSR bus stops	0.090	1.81	0.079	1.54
SoBi Hubs	-0.583	-1.94*	-0.539	-1.74
Distance to McMaster	-0.786	-6.04***	-0.707	-7.17***
Distance to CBD	-0.766	-8.20***	-0.631	-4.83***
Land Use Variables				
Residential	37.481	2.24**	33.699	1.96*
Institutional	38.989	2.35**	40.663	2.38**
Office	45.527	1.05	63.576	1.43
Commercial	50.709	2.25**	52.006	2.25**
Open Space/Parks	29.921	1.77	20.305	1.17
Industrial	-18.491	-0.76	-12.377	-0.50
Other	29.461	1.24	30.247	1.24
Random Effect				
Hubs	1.905	7.45***	2.034	7.44***

Summary Statistics				
-2 Log-likelihood	213481.7	-	217730.1	-
AIC	213541.7	-	217790.1	-
ICC (%)	16.48	-	15.74	-

Notes: *n* = 41,724. Significance levels: *** = 0.0001, ** = 0.001. * = 0.05.

2.5 RESULTS

2.5.1 Weather and Temporal Characteristics

As expected, as temperature increases, so does bicycle usage. Precipitation, on the other hand, dampens this effect. As shown, seasonality influences bike share activity. Compared to winter, usage increases with each passing season, peaking in fall. This finding is most likely due to the fact McMaster University's students are taking advantage of the system. The results also show that people tend to bike more on weekdays than on weekends, suggesting that SoBi is being used for utilitarian trips, such as commuting. Holidays are found to have an even greater dampening effect than precipitation. Lastly, as indicated by the day-of-the-year effect, SoBi usage has continued to grow over time since its launch. This is likely due to increased awareness of the bike share system over time. Figure 2.5 summarizes this effect for departures and arrivals, with all other variables set to their means.

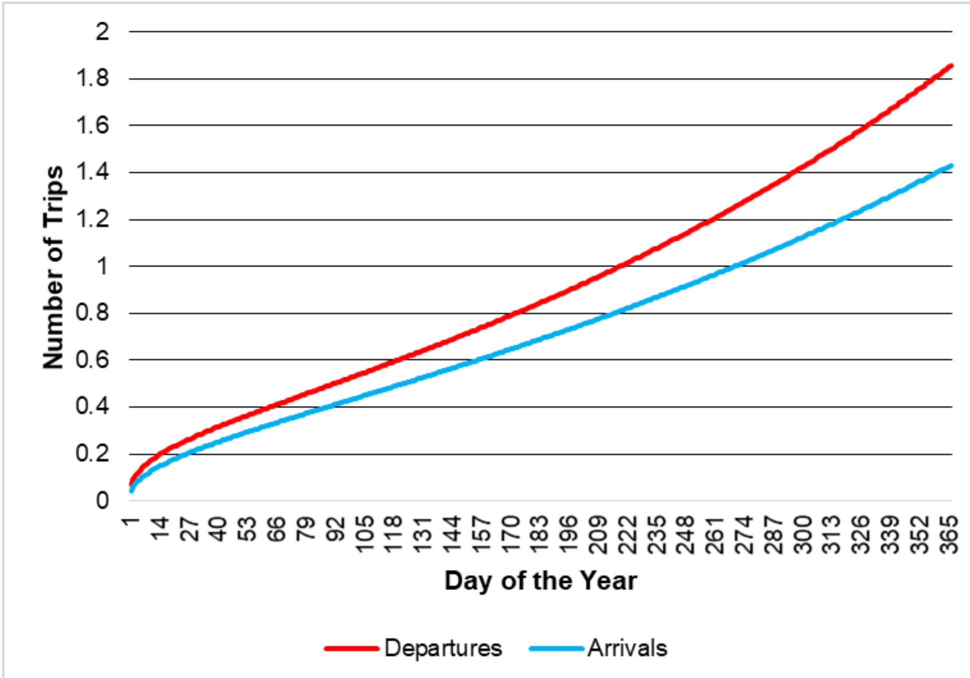

Figure 2.5: Incremental growth of trip departures and arrivals throughout the year.

2.5.2 Socio-demographic Characteristics

Population density was an important consideration for determining initial SoBi hub locations. Thus, population aged 16 years and older and people employed were accounted for in the models. When modeled in the absence of other variables, each one was found to increase usage. However, in the presence of other variables, neither attribute influences SoBi usage. This finding differs from that of other studies, where a positive relationship was found between population and bike demand at hubs (El-Assi et al., 2017; Faghih - Imani et al., 2014; Rixey 2013). Possible reasons for this include the student population around McMaster University is not captured through the 2011 Canadian Census or the fact that SoBi riders can pick up and drop off bikes at any hub, not necessarily those closest to their places of residence and work.

2.5.3 Hub Attributes

Of the hub attributes included in the trip departures model, number of major intersections, number of hubs within the buffer, and distances to McMaster University and the CBD are found to impact bike usage at hubs. Except for industrial, land use types, as measured by their areas within the 200 m buffers around hubs, are positive. For both the trip departures and arrivals models, only residential, institutional and commercial land uses are significant.

Transport infrastructure such as major intersections, lengths of major and minor roads, bike lanes and trails did not influence trips. In this study, only major intersections reduce trip departures. Similarly, El-Assi et al. (2017) found that as the number of major intersections increase within a buffer around a hub in Toronto, users are less likely to select that hub. Other hub attributes explored such as number of hubs and number of bus stops within the buffer, and distance to McMaster University and the CBD show similar impacts between trip departures and arrivals. Although the number of bus stops did not have an impact in either model, the positive coefficients offer some evidence suggesting that SoBi is perhaps used in conjunction with the Hamilton Street Railway bus system. The number of neighboring hubs within a specified buffer area had a negative impact on trip departures. This is in contrast to other studies where the effect has been positive (e.g., Faghih-Imani & Eluru, 2015). Interestingly, the coefficient suggests that as the number of hubs increases, the user has more options to choose amongst hubs, which, in turn, has a negative impact on the hub being analyzed. As expected, proximity to McMaster University and the CBD has a strong impact on hub usage, for both departures and arrivals. Specifically, as distance increases, usage decreases.

Including land use captures the potential activities that take place around each hub. As previously stated population density was a major criterion for hub locations and although was not found significant in the model, residential land use is found to have a positive relationship. Commercial land use also has a large impact on usage as businesses such as restaurants, or shops positively influence usage, which was also found in studies by Faghih-Imani et al., (2014) and Wang et al., (2016). Institutional captures McMaster University, which is expected to increase SoBi use because as previously shown when the distance to hubs increases usage decreases – this is supported from the positive institutional coefficient. Although other studies (e.g., Faghih-Imani & Eluru, 2016; Faghih-Imani & Eluru, 2015) have found job density to influence ridership, office land use is not found to impact daily usage. Lastly, open space/park land use is insignificant. This is expected as SoBi is primarily used for commuter purposes rather than leisure trips with few hubs by parks and along Hamilton's waterfront.

2.5.4 Random Effects

Hubs are added as random-effects, which are additional unknown random variables assumed to affect the variability of the data (SAS, 2009). In our study, the random effects account for common unobserved factors specific to each hub that affects usage. It must be noted that several models were generated with day of year also included as a random effect; however, this effect only accounted for minimal influence in usage and therefore was not included in the final model specification. Using the covariance parameter estimates, the

Intraclass Correlation Coefficient (ICC), indicates how much of the total variation of usage is accounted for by the hub. As seen, the ICC indicates that 16.48% of the variability between hubs per day is accounted for in trip departures and 15.74% in trip arrivals, leaving more than 85% of the variability in usage to be accounted by the variables modelled.

2.6 CONCLUSION

This study utilized a rich daily bicycle count dataset retrieved from SoBi Hamilton to investigate determinants that influence bike share usage. The findings contribute to the growing literature on bike sharing systems and allows policy makers to better understand what attributes increase the likelihood of bike ridership at the hub level. The multilevel modeling approach revealed significant relationships between various characteristics and number of arrivals and departures at each hub.

The multilevel models revealed that average temperature has a positive impact while precipitation and snow have a negative impact on SoBi bike ridership. Seasonal trips are positively correlated as seasons become warmer compared to winter, with fall having the largest impact reflecting student use during the academic year. In the development phase of SoBi, population and employment density were one of the main guidelines used for the placement of hubs. However, the findings from this study suggest that these densities are not the major contributing attributes that influence trips at the hub level.

After controlling for socio-demographics and hub attributes while accounting for weather and temporal characteristics, only a select few variables were found to impact ridership at hubs. These variables include: number of major intersections, total number of

SoBi hubs, and proximity to McMaster and the CBD. Hub usage is reduced when they are located around major intersections, greater number of neighboring hubs and increasing distances from McMaster and the CBD. The negative coefficient for total number of hubs within the buffer area provides an interesting insight in that proximity between hubs will not necessarily increase usage. This negative relationship can be due to the type of person using the system. A study conducted by Faghih-Imani and Eluru (2015) on Chicago's Divvy system found a significant difference between the type of bike share user and their decisions on hub selection. For members, the number of hubs in the buffer has a positive impact; however, the impact is opposite for daily customers. A negative impact for daily customers could be since these members are not familiar with the system and the presence of multiple hubs (Faghih-Imani & Eluru, 2015). Moreover, it is essential to understand the influences of self-selection and social influence. Therefore, future work on SoBi members needs to be addressed. Aside from the above, land use can also be used to examine possible locations of new hubs to maximize bicycle ridership. In this study, commercial, institutional, and residential land use area all influence hub departures and arrivals.

Overall, the final model including day of year as a fixed effect explains the most variability in Hamilton's bike share system. As individuals observe others using SoBi, awareness of the system grows demonstrating an incremental growth over time. Moreover, the findings of this study suggest that temporal characteristics, weather, proximity to universities and the CBD, and commercial land use play a prominent role in increasing the overall bike share usage. The multilevel modelling approach used in this study can be used in other cities to predict the trip departures or arrivals at hub locations. In addition, this approach with other cities bike share and hub characteristic data can help implement new/existing bike shares to maximize the system efficiently, while also assessing the impact of existing land use at hub locations.

Despite these findings, there are still numerous issues surrounding temporal characteristics and SoBi usage. Future research should focus on future years of operation in an effort to validate the finding of incremental growth over time. Although, user demographics is a limitation for our study, a more comprehensive analysis on users should be considered in future research. Finally, this study can be extended using the same methodology, except utilizing the rich hourly SoBi data set to consider changes in usage through the day.

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CHAPTER THREE: What factors influence bike share usage at different times of the day? An investigation of SoBi Hamilton's Hubs

3.1 INTRODUCTION

The number of cities offering bike share programs around the world has grown considerably since 1965 – the year when the first bike share made its debut on the world stage. As of 2017, about 1,300 cities operate bike shares and almost 400 more are planning or constructing a system (Meddin, 2017). The benefits of bike shares include, among others, access to low cost public transportation, increased physical activity, flexible mobility, support for multimodal connections, and reductions in fuel usage, traffic congestion and pollutant emissions (Shaheen et al. 2013). In addition, findings from past studies suggest that starting a bike share in a city improves driver awareness towards cyclists, thus increasing cyclist safety (Faghih-Imani & Eluru, 2016; Murphy & Usher, 2015). Consequently, bike shares have had a positive influence in broadening and expanding the cycling demographic group by improving the public's perception of cycling as an alternative mode for every day travel (Faghih-Imani & Eluru, 2016; Goodman & Woodcock, 2014).

In 2015, SoBi was launched in Hamilton, Ontario. At that time, the bike share comprised over 100 hubs and 750 GPS-equipped bicycles. While the majority of bike shares allow users to check out and drop off a bicycle at self-service docking hubs, a distinguishing feature of SoBi Hamilton is that it allows users to leave a bicycle anywhere within its service area for a small fee. Due to such flexible mobility, a common complaint of bike share users is the presence of empty or full hubs (Raviv et al., 2013). Bike share operators aim to minimize such occurrences by redistributing bicycles between hubs. However, the rebalancing process is a theoretically complex optimal routing problem (Médard de Chardon et al., 2016). There are three distinct types of rebalancing discussed in the literature: static, dynamic, and demand (Médard de Chardon et al., 2016). Static rebalancing aims at the optimal redistribution of bicycles in an effort to reduce hub outages when system use is at a minimum, for instance during the night. Dynamic rebalancing is similar, but focuses on redistribution while the system is in use during the day. This process involves rebalancing the system 24 hours a day with trucks to redistribute bikes (Médard de Chardon et al., 2016). Lastly, the third rebalancing technique is also dynamic, but aims to reach a bicycle distribution matching a demand forecast (Médard de Chardon et al., 2016). Forecasting demand is complicated because many factors influence bicycle usage across a city and throughout the year. Furthermore, such usage varies across times of day. While many past studies of bike shares have investigated factors influencing hub demand at the daily level (Wang et al., 2016; Rixey, 2013; Garcia-Palomares et al., 2012; Pucher et al., 2010), few studies have investigated such factors for finer periods of time throughout the day (Faghih-Imani et al., 2017; El-Assi et al., 2017; Faghih-Imani & Eluru, 2015).

This paper is motivated by the need for a more nuanced understanding of factors that impact bike share usage at different times of the day in an effort to improve forecasts aimed at rebalancing bike share systems. Usage can vary throughout the day for a variety of reasons. For example, weather conditions can vary during the day, which has different impacts on ridership levels. Recently, studies have begun investigating the impact of weather conditions using hourly trip data, if available. Various studies show that fewer trips are made in the rain, high humidity, high wind speeds and low temperature, yet they increase with higher temperatures (El-Assi et al., 2017; Faghih-Imani & Eluru, 2016; Gebhart & Noland, 2014; Nosal & Miranda-Moreno, 2014). In addition, the built environment and land use around hubs also influence the arrival and departure rates throughout different periods of the day. For instance, in Montreal, the presence of restaurants has a negative impact on BIXI trip departures in the morning period, but intuitively has a positive influence in both arrival and departures rates in the afternoon period (Faghih-Imani et al., 2014). In Chicago, members chose hubs that brought them closer to the CBD; however, the CBD was associated with a negative coefficient in the AM period, which became positive during the PM period, indicating the use of the Divvy system for the daily commute to/from work in the downtown area (Faghih-Imani & Eluru, 2015). Lastly, previous studies have found a difference between daily bike share customers and members (Faghih-Imani & Eluru, 2016; Faghih-Imani & Eluru, 2015). For example, in New York, the arrival and departure rates of daily CitiBike customers are less sensitive to population and job density variables than the arrival and departure rates of members (Faghih-Imani & Eluru, 2016). For members, the interaction of population density in the AM and PM are both positive for trip departures, but have the opposite impact on trip arrivals. The impact is also opposite for arrivals by daily customers as highlighted by a negative coefficient of population density in the AM and a positive coefficient in the PM (Faghih-Imani & Eluru, 2016). To this end, it is essential to explore how weather, built environment and socio-demographic characteristics around hubs vary throughout the day for rebalancing a system.

This study contributes to the growing bike share literature and is a continuation from a previous paper exploring daily factors that influence bike share usage. This paper analyzes trip departure and arrival rates with finer intervals of time to determine how weather and spatial hub attributes such as socio-demographics and land use might affect bike share usage. Exploring the differences of spatio-temporal determinants that influence usage throughout the day will assist operational staff in the redistribution of bikes when they are in demand most. A multilevel modeling approach is employed for each time period to explore how usage varies between hubs throughout the day. Although generating relocation plans for bikes is not the sole focus of this study, the results can provide hub usage measures that elucidate efficiency of current hubs before implementing new hub locations. Overall, this study provides a planning tool that can be used by transportation engineers and policy makers to predict hub usage to ensure a balanced bike share system.

The remainder of this paper is organized as follows. The next section reviews briefly the bike share literature focusing on factors that may influence usage. The study area and data are presented in Section 3 followed by the method and model specification in Section 4. Results are found in Section 5, and the paper concludes with a discussion of key findings and recommendations for future research.

3.2 BACKGROUND

As previously mentioned, several studies have investigated factors that influence bike share demand, yet few have focused on how variables such as weather and the built environment affect the frequency of rebalancing hubs throughout the day. With respect to weather, El-Assi et al.'s (2017) study of Bike Share Toronto found a positive relationship between bike share activity and temperature and negative associations with precipitation, snow on the ground, and humidity. Similar findings concerning relationships between weather and bike share usage have been reported in other studies (e.g., Corcoran et al., 2014; Faghih-Imani et al., 2014; Gebhart and Noland, 2014). Researchers have also investigated features of the built environment around hubs and have found positive relationships with population density, job density, and popular points of interest such as restaurants, retail stores, and schools (Faghih-Imani & Eluru, 2016; Wang et al., 2016; Faghih-Imani et al., 2014; Rixey, 2013). Both cycling and hub infrastructure (e.g., bicycle lanes, number of hubs, hub capacity) in the immediate proximity of bike share hubs have positive impacts on bike usage (Wang et al., 2016; Faghih-Imani et al., 2014). The relationship between public transit systems and bike shares has also been investigated. In some cities, it has been observed that people prefer using bike shares over other modes of transport, which also increased the number of people using other public transit options, creating a modal shift (Godavarthy & Taleqani, 2017; Nair et al., 2013; Shaheen et al., 2013).

Recently, a few studies have used real time ridership data to examine factors that affect usage throughout the day. Understanding such temporal fluctuations in bike share activity is essential given the need to rebalance the system, ensuring that bicycles are available for customers departing hubs and that docks are available for customers arriving at hubs (Nair et al., 2013). Comparing the bike share system in Barcelona to that of Seville, Faghih-Imani et al. (2017) found slightly different patterns with respect to the timing of trip arrivals and departures. In Barcelona, the total arrival rate had three peaks, corresponding to the morning, lunch and evening periods with the largest peak in the evening, around 7 PM. In addition, the lunch and evening time periods had the highest arrival and departure rates increasing rebalancing during these times, specifically located around businesses and restaurants. Meanwhile, in Seville, the total arrival rate peaked in the morning, lunch and evening, similar to that in Barcelona, but the activity in the evening period was less prominent compared to the morning and lunch periods, as compared to Barcelona (Faghih-Imani et al., 2017).

Across many bike share studies, researchers have found that weekday usage peaks during the morning and evening rush hours, while weekend usage is greatest during the middle of the day (Ahillen et al. 2016; Fishman 2016). Oliveira et al. (2016) studied the spatial and temporal characteristics of New York's Citi Bike, showing changes in the system across days and months. Results showed a clear difference between weekdays and weekends – weekdays had two peaks, one at 9 AM when commuters go to work and another at 6 PM when they return home. In addition, usage during the day is higher than in early morning or late at night. For weekends, there is only a single wider, lower and smoother peak that begins later than weekdays at 10 AM and ends later at 9 PM.

The location of hubs within a bike share system and features of the built environment surrounding hubs also influence hub usage – both departures and arrivals. For instance, studies have found that trip rates vary throughout the day around points of interest such as commercial businesses, restaurants and distances to the CBD or universities (Faghih-Imani et al., 2017; Faghih-Imani & Eluru, 2016; Faghih-Imani & Eluru, 2015; Corcoran et al., 2014; Faghih-Imani et al., 2014). Corcoran et al.'s (2014) study of Brisbane's bike share system found that early morning trip arrivals and departures are more spatially dispersed compared to those later in the morning. Early afternoon trips tend to be concentrated around the CBD and immediate surrounding suburbs. In the evening, they tend to be more dispersed into the suburbs. Conversely, in New York, Faghih-Imani and Eluru (2016) found that hubs located in areas with higher job density are more likely to have higher arrivals in the AM and higher departures in the PM. Overall, the New York CitiBike system along with Montreal's BIXI system demonstrate the use for daily commutes to work in the morning and back to home in the evening for regular member users by exploring population and job density variables and their interaction with the AM and PM periods (Faghih-Imani & Eluru, 2016; Faghih-Imani et al., 2014). In addition, Faghih-Imani et al. (2014) found that the number of restaurants around a BIXI hub increases the overall usage, but has a negative impact on departure rates in the AM period and a positive influence in both arrival and departure rates in the PM period. Meanwhile, the number of all other commercial enterprises around each hub during the PM and evening time periods is associated with a negative impact (Faghih-Imani et al., 2014).

In summary, weather, land use and points of interest around a hub such as schools, restaurants and commercial enterprises all influence trip departure and arrival rates sporadically throughout different times of the day. Studies have also found differences between the types of user and when and where they travel. As is evident, there are still several variables that remain unexplored in the bicycle sharing system literature. The objective of this paper is to develop models quantifying the impact of various attributes on departure and arrival rates at hubs during different periods of the day. This paper therefore seeks to provide better insights into where users are starting and terminating their trips during the day to gain an understanding of rebalancing the bikes throughout the city.

3.3 STUDY AREA AND DATA

To explore trip patterns throughout the day, hourly weather characteristics, temporal characteristics, socio-demographic characteristics and hub attributes were generated. Trip departures and arrivals are modeled using SoBi bicycle data for all hubs in service (114) from April 2015 to March 2016 (first year of operation).

3.3.1 Study Area

Hamilton, Ontario is a city located in the heart of the Greater Golden Horseshoe with a population of 536,930 people (see Figure 3.1). To accommodate future growth for 2031 and beyond in Hamilton, there is a high emphasis on significantly improving transit services, while also providing options for cycling and walking. A main goal is to reduce single occupancy vehicle use by 20% of projected mode split in 2031 (Topalovic et al., 2013).

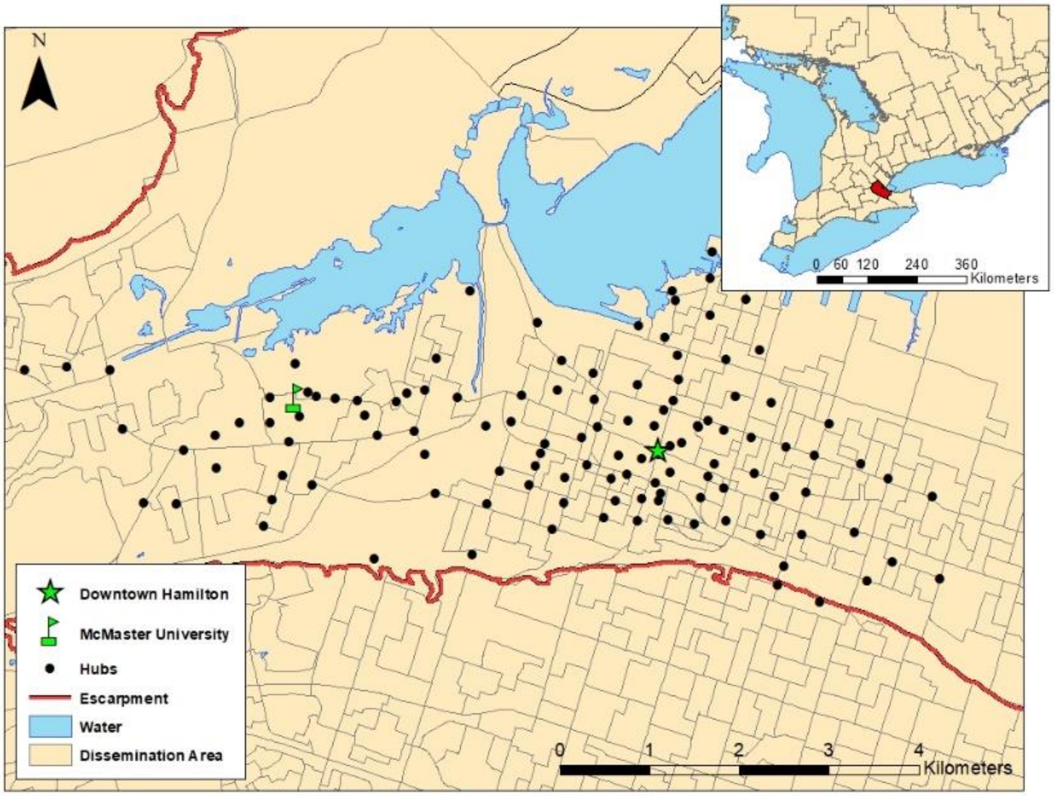

Figure 3.1: Study Area.

3.3.2 Dependent Variable

The dependent variable in this analysis is the natural logarithm of the number of trips per hub per day (i.e., hub-day) for the following time periods: morning (6 AM- 8:59 AM), day (9 AM-3:59 PM), evening (4 PM -6:59 PM) and night (7 PM-5:59 AM) to capture the effects of commuter peak travel times. The majority of trip departures are found during the evening (37.8%), followed by the morning (26.1%), night (24.4%) and day (11.7%). Similarly, the majority of trip arrivals are found during the day (37.0%), followed by the night (27.5%), evening (24.4%) and morning (11.1%). Absolute numbers are summarized in Table 3.1. Figure 3.2 shows the spatial distribution of trips for the morning period. Distributions for other periods of the day are found in the Appendix. The total number of trips completed during the first year of operation was 203,427 after removing invalid trip records (e.g., trip duration less than 30 s or trips without a hub record).

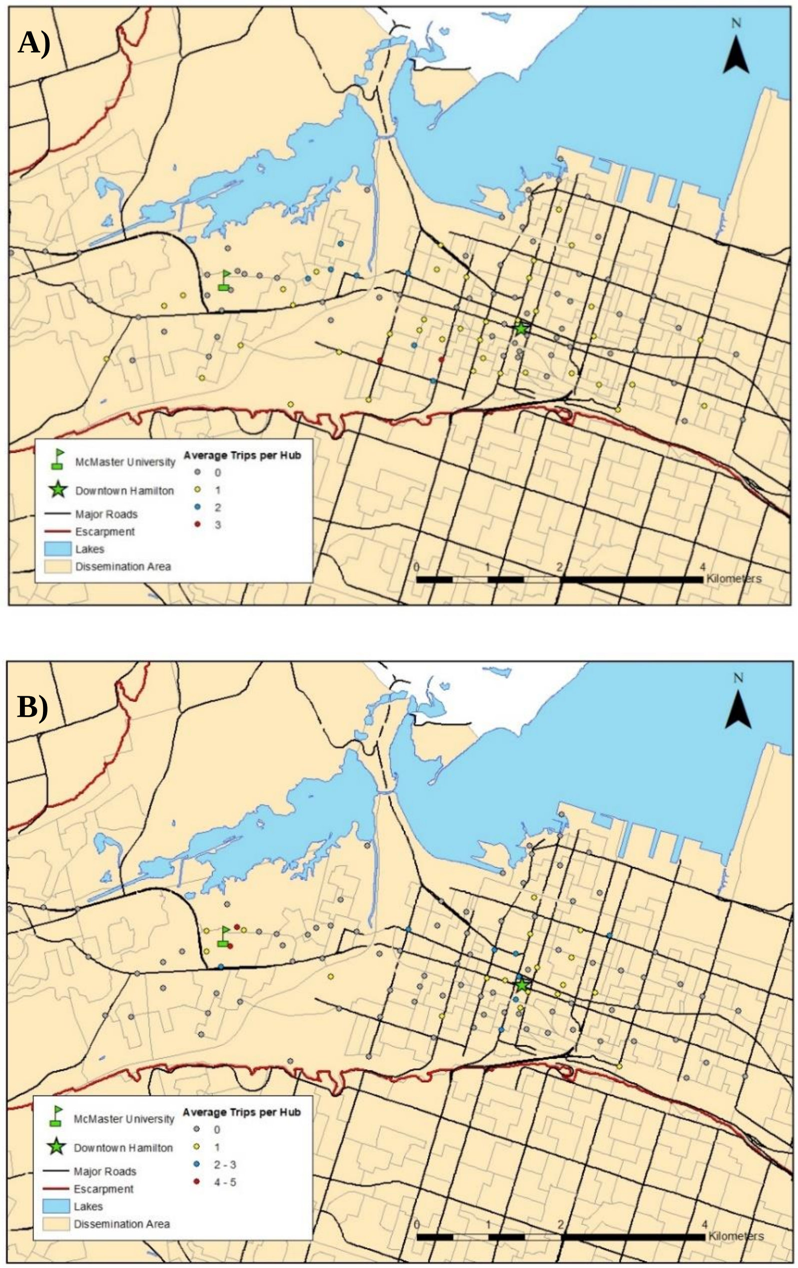

Figure 3.2: Average total trip departures (A) and arrivals (B) during the morning period.

Table 3.1: Total trip departures and arrivals for each time period.

Usage	Morning	Day	Evening	Night	Total
Departures	53,069	24,007	76,760	49,521	203,357
Arrivals	20,623	68,873	45,412	51,092	186,000
Total	73,692	92,880	122,172	100,613	389,357

3.3.3 Independent Variables

Several independent variables were generated to examine their impact on bicycle usage at each hub throughout the day (Tables 3.2 and 3.3). To derive the spatial variables (socio-demographic and hub attributes), a 200 m buffer around each hub was found to be an appropriate walking distance considering the distances between SoBi hubs (300 m to 500 m apart). A 200 m buffer was also chosen to minimize the number of proximate hubs within a buffer. The socio-demographic variables in this study were derived from Dissemination Area (DA) data allocated to appropriate land use polygons to create a more refined dataset for each hub. The average DA size in the study area is 0.0264 km^2.

Table 3.2: Descriptive statistics of weather variables for each time period.

Weather Variables	Unit/Notes	Mean/Proportion	S.D
Morning			
Temperature	Perceived average temperature (ºC)	7.283	±13.016
Very Cold	1 if below 0ºC, else 0	0.30601	±0.46084
Cold	1 if between 0 and 10ºC, else 0	0.25683	±0.43689
Cool	1 if between 10 and 20 ºC, else 0	0.24590	±0.43063
Warm	1 if between 20 to 30 ºC, else 0	0.18033	±0.38446
Hot (*ref.*)	1 if 30ºC or more, else 0	0.01093	±0.10397
Humidity	Relative humidity	0.84022	±11.266
Wind	Wind speed (km/h)	14.942	±8.286
Precipitation	1 if rained, else 0	0.05464	±0.22729
Snow	1 if snowed, else 0	0.03279	±0.17808
Day			
Temperature	Perceived average temperature (ºC)	12.083	±14.086
Very Cold	1 if below 0ºC, else 0	0.20765	±0.40563
Cold	1 if between 0 and 10ºC, else 0	0.24317	±0.429
Cool	1 if between 10 and 20 ºC, else 0	0.19945	±0.39959
Warm	1 if between 20 to 30 ºC, else 0	0.24044	±0.42735
Hot (ref)	1 if 30ºC or more, else 0	0.10929	±0.31201
Humidity	Relative humidity	0.67602	±14.828
Wind	Wind speed (km/h)	19.630	±9.236
Precipitation	1 if rained, else 0	0.02186	±0.14622
Snow	1 if snowed, else 0	0.02186	±0.14622
Evening			
Temperature	Perceived average temperature (ºC)	12.038	±14.117
Very Cold	1 if below 0ºC, else 0	0.21858	±0.41329
Cold	1 if between 0 and 10ºC, else 0	0.22951	±0.42052
Cool	1 if between 10 and 20 ºC, else 0	0.21038	±0.40759
Warm	1 if between 20 to 30 ºC, else 0	0.23224	±0.42227
Hot	1 if 30ºC or more, else 0	0.10929	±0.31201
Humidity	Relative humidity	0.66706	±15.972
Wind	Wind speed (km/h)	19.183	±8.857
Precipitation	1 if rained, else 0	0.04918	±0.21625
Snow	1 if snowed, else 0	0.04918	±0.21625
Night			
Temperature	Perceived average temperature (ºC)	7.736	±12.083
Very Cold	1 if below 0ºC, else 0	0.29235	±0.45485
Cold	1 if between 0 and 10ºC, else 0	0.2623	±0.43989
Cool	1 if between 10 and 20 ºC, else 0	0.27322	±0.44562
Warm	1 if between 20 to 30 ºC, else 0	0.16393	±0.37022
Hot	1 if 30ºC or more, else 0	0.0082	±0.09017
Humidity	Relative humidity	0.81384	±9.753

Wind	Wind speed (km/h)	14.662	±6.866
Precipitation	1 if rained, else 0	0.00546	±0.07372
Snow	1 if snowed, else 0	0.01366	±0.11608

Table 3.3: Descriptive statistics of static independent variables amongst hubs.

Variable	**Unit/Notes**	**Mean**	**S.D**
Temporal Variables			
Spring	1 if between March 20 and June 20, else 0	-	-
Summer	1 if between June 21 and September 21, else 0	-	-
Fall	1 if between September 22 and December 20, else 0	-	-
Winter (*ref.*)	1 if between December 21 and March 19, else 0	-	-
Holiday	1 if holiday, else 0	-	-
Weekday	1 if weekday, else 0	-	-
Day of year	1 = April 1, 2015 to 366 = March 30, 2016	-	-
Ln day of year	Natural logarithm day of year		
Time period	Variable categorized into four ranges see section (3.2)	-	-
Socio-demographic Variables			
Population 16+	Number of people living in residential areas in 200 m buffer	0.557	±0.506
Employment	Number of people working in employment areas in 200 m buffer	0.561	±0.756
Hub Attributes			
Built Environment			
Major intersections	Number of major intersections in 200 m buffer	0.46	±0.86
Length of major roads	Length (km) of major roads in 200 m buffer	0.415	±0.348
Length of minor roads	Length (km) of minor roads in 200 m buffer	1.237	±0.578
Length of bike lanes	Length (km) of bike lanes in 200 m buffer	0.502	±0.34
Length of trails	Length (km) of trails in 200 m buffer	0.233	±0.372
HSR bus stops	Number of HSR bus stops in 200 m buffer	4.097	±4.207
SoBi hubs	Number of hubs in 200 m buffer	1.246	±0.573
Distance to McMaster	Distance (km) to McMaster University	3.465	±1.864
Distance to CBD	Distance (km) to Central Business District	2.165	±1.609
Land Use Variables			
Residential	Total area ($km^2 \times 10^{-6}$) in 200 m buffer	0.040	±0.026
Institutional	Total area ($km^2 \times 10^{-6}$) in 200 m buffer	0.015	±0.023
Office	Total area ($km^2 \times 10^{-6}$) in 200 m buffer	0.004	±0.006
Commercial	Total area ($km^2 \times 10^{-6}$) in 200 m buffer	0.011	±0.002
Open Space/ Parks	Total area ($km^2 \times 10^{-6}$) in 200 m buffer	0.009	±0.018
Industrial	Total area ($km^2 \times 10^{-6}$) in 200 m buffer	0.003	±0.009
Other	Total area ($km^2 \times 10^{-6}$) in 200 m buffer	0.005	±0.008

Weather Variables

Weather data, collected at the John C. Munro Hamilton International Airport weather station, was obtained from Environment Canada (2016). The variables included in the analysis are the average temperature (ºC), average humidity (%), wind speed (km/h), precipitation, and snow on ground. The perceived temperature was estimated in this analysis as it is a better indicator of the overall feel of the bike user (El-Assi et al., 2017). The perceived temperature was estimated using formulas for wind chill and humidex from Environment Canada (2017). The temperature variables were categorized into five ranges for each time period similarly used in the El-Assi et al. (2017) study: Very cold (below 0ºC), Cold (between 0 and 10ºC), Cool (between 10 and 20 ºC), Warm (between 20 to 30 ºC) and Hot (30ºC or more).

Temporal Trip Characteristics

The impact of, seasons, day of the week, holidays, and day of the year on bike usage are investigated. The majority of trips occurred during the summer (36%), then fall (28%), spring (22%) and lastly winter (14%). The influence of weekend vs. weekday, holidays and day of year was also taken into account. Day of year is included to analyze incremental growth over time throughout the system given increased public awareness.

Socio-demographic Variables

Two socio-demographic variables are employed in this study: population and total employment. The variables are constructed for a 200-meter buffer around each hub using 2011 Canadian Census data for population and 2011 Transportation Tomorrow Survey (TTS) data for employment. Total population only includes 16 years of age and older as

SoBi is only available to those who are 16 years of age and older. Rather than assuming people are distributed evenly throughout an entire DA, people are allocated to residential areas only. The TTS was used for employment location, and similarly rather than assuming employment is distributed evenly throughout an entire Traffic Analysis Zone (TAZ), only employment parcels corresponding to institutional, office, commercial and industrial land uses are selected.

Hub Attributes

To account for the built environment and land use around hubs variables were extracted from City of Hamilton planning data, some of which is available as "open" data through the City's website. Hub attributes created for the 200 m buffers include: total major intersections, length of major roads, minor roads, bike lanes and trails, number of HSR bus stops and number of SoBi hubs. In addition, distance to McMaster and CBD is based on the straight-line distance between each hub. Land use was also considered in our analysis. If multiple land uses (e.g., residential and commercial) were found within a parcel in ArcGIS, a second land use field was created to reclassify parcels accordingly to their secondary land use.

3.4 METHOD

For the purpose of this study, bike share usage at each hub is measured as: (1) the number of trip departures and (2) the number of trip arrivals. Accordingly, eight datasets were created at the hub level to account for each time period analyzed.

A multilevel model is used in our analysis to investigate the determinants affecting usage at SoBi hubs throughout the day. In this study, two-level, multilevel models are estimated with SAS® using the PROC MIXED procedure. Levels 1 and 2 pertain, respectively, to the daily time period counts of trips grouped within hubs. An unstructured covariance matrix is selected to allow every term to be different and have the variances constrained to be nonnegative, and the covariance's unconstrained (SAS, 2017). For this study, multiple fixed effects are modeled and hubs are modeled as a random effect to account for differences amongst hubs throughout the study period. Four models are estimated for each trip departures and trip arrivals, respectively, one for each time period. Models 2 through 4 are developed by adding an additional suite of independent variables to the preceding models. Model 1 is the null model, containing no independent variables. For this study, a random intercept multilevel model is used, which takes the following form:

$$y_{ij} = \beta_0 + \beta x_{ij} + u_j + \varepsilon_{ij}, \qquad i = 1, \dots, I, \qquad j = 1, \dots, J$$

where y_{ij} is a $n \times 1$ vector of observed values (in this case, the number of departures or arrivals on each day i for hub j), x_{ij} is a $n \times k$ matrix of observed independent variables for each hub-day, β_0 is the intercept, and β is a $k \times 1$ vector of coefficients. u_j and ε_{ij} are random error terms assumed to follow normal distributions with means 0 and variances σ^2.

To estimate these models, maximum likelihood is used therefore, Akaike's Information Criterion (AIC) is examined for improvement in model fit when the nested models differ in fixed effects (Bell et al., 2013). For AIC, smaller values represent better fitting models (Bell et al., 2013). Another commonly used measure of model fit is the likelihood ratio test when examining differences in the -2 log likelihood (-2LL) values of nest models; however, for this study AIC measures are utilized as they are more versatile (Bell et al., 2013). Lastly, with PROC MIXED syntax, a Covariance Parameter Estimates table is generated, in which the Intraclass Correlation Coefficient (ICC) can be computed to indicate the variation of hub usage accounted for by the several effects measured in this study. The remainder of this paper focuses on Model 4 for each time period, as the AIC value is the smallest indicating an overall improvement in model fit. Tables 3.4 and 3.5 show, respectively, the model estimates for trip departures and trip arrivals.

Table 3.4: Model results for trip departure time periods.

Variables	**Morning**		**Day**		**Evening**		**Night**	
	Coef.	**t-value**	**Coef.**	**t-value**	**Coef.**	**t-value**	**Coef.**	**t-value**
Intercept	-8.876	-4.76***	-3.263	-1.62	-5.223	-2.98**	-6.819	-3.87***
Weather Variables								
Temperature (*ref. Hot*)								
Very cold	-0.647	-3.20**	-2.051	-18.06***	-2.022	-17.16***	-2.039	-8.13***
Cold	-0.077	-0.39	-0.963	-9.57***	-1.42	-13.35***	-1.254	-5.12***
Cool	0.335	1.78	-0.467	-5.17***	-0.491	-5.22***	-0.534	-2.27*
Warm	0.227	1.22	0.087	1.19	0.064	0.84	-0.211	-0.90
Average humidity	-0.004	-1.83	-0.027	-17.41***	-0.021	-13.02***	-0.019	-8.20***
Average wind speed	-0.011	-4.82***	-0.005	-2.28*	-0.010	-4.25***	-0.031	-9.07***
Precipitation	-1.124	-12.04***	-1.97	-13.47***	-0.983	-8.92***	-2.071	-7.17***
Snow	-0.186	-1.64	-0.747	-5.22***	-0.638	-5.88***	-0.641	-3.50***
Temporal Variables								
Holiday	-2.273	-21.80***	-0.977	-8.90***	-1.308	-11.42***	-0.738	-6.47***
Weekday (*ref. weekend)*	2.487	59.03***	0.538	12.19***	1.311	28.15***	0.298	6.42***
Seasons (*ref. Winter*)								
Spring	0.756	8.22***	0.356	3.58***	0.681	6.58***	1.039	10.11***
Summer	1.390	14.63***	1.126	11.11***	1.142	10.71***	1.962	18.37***
Fall	1.189	17.39***	1.286	17.51***	1.283	16.53***	1.285	17.31***
Day of year	-0.002	-2.81**	0.002	3.63***	0.002	2.31*	-0.002	-3.16**
Ln day of year	0.446	7.45***	0.346	5.58***	0.338	5.18***	0.785	12.04***
Socio-demographics								
Population 16+	-0.117	-0.34	-0.346	-0.91	-0.521	-1.58	-0.167	-0.51
Employment	-0.399	-1.04	-0.177	-0.42	0.056	0.15	-0.552	-1.54

Hub Attributes								
Built Environment								
Major intersections	-0.198	-0.79	-0.391	-1.41	-0.561	-2.35*	-0.373	-1.58
Length major roads	1.296	2.00*	0.349	0.49	0.215	0.35	0.544	0.90
Length minor roads	0.829	1.86	0.365	0.75	-0.133	-0.32	-0.069	-0.17
Length bike lanes	-0.097	-0.20	1.149	2.12*	0.955	2.04*	1.241	2.68**
Length trails	-0.423	-0.87	0.291	0.55	0.296	0.65	0.237	0.52
HSR bus stops	0.062	1.26	0.061	1.15	0.109	2.36*	0.150	3.29**
SoBi Hubs	-0.901	-3.07**	-0.940	-2.93**	-0.352	-1.27	0.054	0.20
Distance to McMaster	-0.431	-4.60***	-0.714	-6.98***	-0.653	-7.38***	-0.677	-7.73***
Distance to CBD	-0.552	-4.45***	-0.667	-4.92***	-0.702	-5.99***	-0.679	-5.86***
Land Use Variables								
Residential	31.514	1.93*	49.478	2.77**	36.185	2.34**	45.002	2.95**
Institutional	10.591	0.65	52.839	2.98***	53.260	3.47***	61.024	4.02***
Office	-13.192	-0.31	110.56	2.39**	111.24	2.78***	74.572	1.88
Commercial	13.092	0.60	62.489	2.60**	54.116	2.61**	69.881	3.40***
Open Space / Parks	26.395	1.60	24.329	1.35	16.27	1.04	12.377	0.80
Industrial	-14.398	-0.61	-23.312	-0.90	-2.657	-0.12	-12.448	-0.56
Other	-7.413	-0.32	31.784	1.25	39.936	1.82	46.279	2.13*
Random Effect								
Hubs	1.805	7.39***	2.157	7.40***	1.597	7.33***	1.562	7.32***
Fit Statistics								
-2 Log-likelihood	231043.9		234957.2		238422.8		238828.0	
AIC	231099.9		235013.2		238478.8		238884.0	
ICC (%)	0.109		0.118		0.083		0.081	

Notes: n = 41,724. Significance levels: *** = 0.0001, ** = 0.001. * = 0.05. Random effect only includes coefficients and intra class correlation (ICC).

Table 3.5: Model results for trip arrival time periods.

Variables	Morning		Day		Evening		Night	
	Coef.	**t-value**	**Coef.**	**t-value**	**Coef.**	**t-value**	**Coef.**	**t-value**
Intercept	-9.009	-4.70***	-4.493	-2.22*	-6.655	-3.34**	-6.357	-3.25**
Weather Variables								
Temperature (*ref. Hot*)								
Very cold	-0.377	-2.14*	-2.069	-17.65***	-1.879	-15.81***	-2.075	-8.31***
Cold	-0.006	-0.03	-1.089	-10.48***	-1.353	-12.60***	-1.359	-5.54***
Cool	0.322	1.95*	-0.59	-6.34***	-0.534	-5.62***	-0.458	-1.94*
Warm	0.279	1.71	0.033	0.43	0.059	0.77	-0.095	-0.41
Average humidity	0.000	0.19	-0.026	-16.53***	-0.021	-13.46***	-0.018	-7.67***
Average wind speed	-0.009	-4.62***	-0.004	-1.76	-0.012	-4.99***	-0.031	-9.35***
Precipitation	-0.850	-10.42***	-1.654	-10.96***	-0.993	-8.93***	-2.386	-8.25***
Snow	-0.094	-0.95	-0.552	-3.74***	-0.819	-7.48***	-0.294	-1.60
Temporal Variables								
Holiday	-1.615	-17.72***	-0.912	-8.05***	-1.585	-13.71***	-0.666	-5.82***
Weekday (*ref. weekend)*	1.714	46.54***	0.514	11.26***	1.801	38.31***	0.416	8.92***
Seasons (*ref. Winter*)								
Spring	0.445	5.54***	0.439	4.27***	0.563	5.40***	1.243	12.07***
Summer	0.890	10.72***	1.307	12.48***	1.095	10.18***	2.037	19.06***
Fall	0.856	14.33***	1.380	18.20***	1.287	16.44***	1.517	20.41***
Day of year	-0.001	-2.43*	0.002	3.09**	0.002	2.75**	-0.001	-1.92*
Ln day of year	0.318	6.07***	0.370	5.77***	0.326	4.95***	0.741	11.35***
Socio-demographics								
Population 16+	-0.802	-2.22*	-0.587	-1.53	-0.455	-1.21	-0.096	-0.26
Employment	0.234	0.59	-0.402	-0.96	-1.073	-2.60**	-1.085	-2.71**

Hub Attributes								
Built Environment								
Major intersections	-0.182	-0.69	-0.407	-1.47	-0.193	-0.71	-0.277	-1.05
Length major roads	0.044	0.07	0.501	0.70	0.495	0.71	0.819	1.21
Length minor roads	-0.525	-1.14	0.124	0.25	0.075	0.16	0.661	1.42
Length bike lanes	0.396	0.77	1.186	2.18*	0.822	1.54	0.791	1.53
Length trails	-0.043	-0.09	0.549	1.03	0.362	0.69	0.174	0.34
HSR bus stops	0.042	0.84	0.102	1.90	0.119	2.26*	0.127	2.51*
SoBi Hubs	-0.062	-0.20	-0.431	-1.34	-0.638	-2.02*	-0.529	-1.73
Distance to McMaster	-0.141	-1.46	-0.649	-6.31***	-0.612	-6.07***	-0.638	-6.53***
Distance to CBD	-0.394	-3.07**	-0.563	-4.14***	-0.587	-4.04***	-0.606	-4.68***
Land Use Variables								
Residential	4.566	0.27	35.307	1.97*	59.262	3.37**	41.392	2.43**
Institutional	45.339	2.70**	59.618	3.35***	54.677	3.13**	46.838	2.76**
Office	113.31	2.59**	125.42	2.70**	105.25	2.31*	62.268	1.41
Commercial	10.999	0.48	70.541	2.93**	82.967	3.51***	50.372	2.20*
Open Space / Parks	-5.945	-0.35	10.187	0.56	30.410	1.71	11.165	0.65
Industrial	-3.233	-0.13	-0.238	-0.01	-4.369	-0.17	-33.655	-1.36
Other	4.560	0.19	30.056	1.18	40.409	1.61	46.815	1.93*
Random Effect								
Hubs	1.937	7.43***	2.171	7.39***	2.088	7.38***	1.960	7.37***
Fit Statistics								
-2 Log-likelihood	219869.0		237600.1		239203.7		238976.5	
AIC	219925.0		237656.1		239259.7		239032.5	
ICC (%)	0.147		0.112		0.105		0.099	

Notes: n = 41,724. Significance levels: *** = 0.0001, ** = 0.001. * = 0.05. Random effect only includes coefficients and intra class correlation (ICC).

3.5 RESULTS

3.5.1 Trip Departures

As expected, there is significant difference between the explanatory variables studied amongst each time period. First, weather has a significant impact on usage throughout almost each time period of the day. As seen in Table 3.4, there is clear evidence that as perceived temperature increases so does the total number of trips. Users are more inclined to cycle during warm temperatures as verified by the positive coefficient; however, warm weather is not significant compared to other perceived temperatures amongst each time period. Average humidity is not significant during morning trips, but as the day progresses, humidity typically increases thus decreasing the likelihood of trip departures. In addition, as average wind speed increases there is a negative impact throughout the entire day. Lastly, as expected, there is a negative relationship between rain and snow throughout the day; however, snow only influences trip departures during the morning period.

Seasonality also influences total trip departures amongst each time period. Compared to winter, users are more inclined to cycle during the spring, summer and fall with summer and fall having the strongest relationship with bike share activity. Similarly, Oliveira et al. (2016) observed that fall had the most intense ridership with a strong decrease during the winter. This finding can be due to the fact McMaster University is in progress and students benefit from the system resulting in greater ridership levels. This finding coincides with the positive coefficients of the weekday variables for each time period indicating people tend to ride more on weekdays versus weekends and holidays. In addition, weekday usage is predominantly used during the morning and evening periods. The natural logarithm of day-of-the-year from the launch of SoBi until the end of the study period was included to show incremental growth, while all other variables were set to their means. As shown in Figure 3.3, trip departures has a positive relationship throughout each time period, especially during the day, but a relatively stable relationship for the remaining periods.

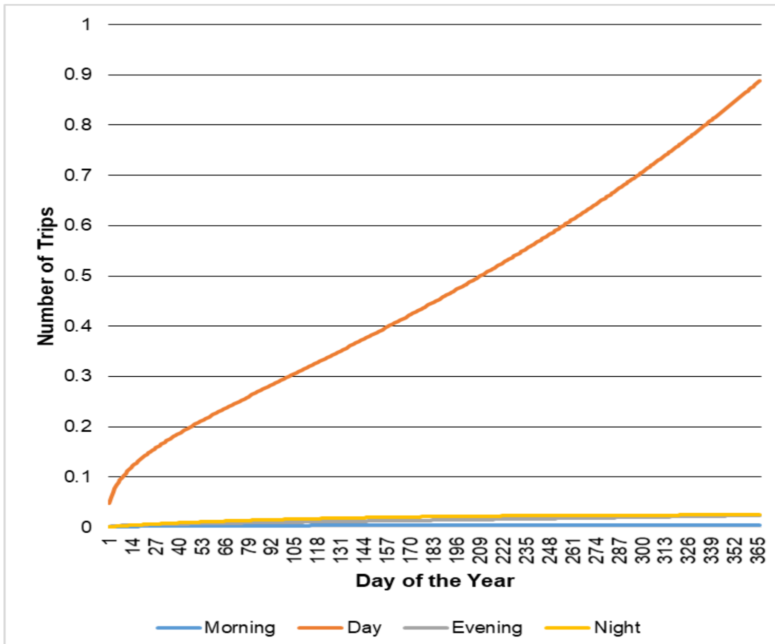

Figure 3.3: Day of year plotted as fixed effect for trip departures.

For each time period, the coefficients for population and employment are negative. It is apparent that total population and employment opportunities do not have a significant impact compared to other attributes. Employment was not found to be significant for each time period and has a negative effect for each except the evening indicating people leaving work. Population is also not significant throughout the day and has a negative relationship for each period.

Only a few built environment attributes are found to be significant for each time period. These include total number of major intersections, length of major roads and bike lanes, total number of HSR bus stops and SoBi hubs, and lastly distances to McMaster University and the CBD. Major intersections is found to have a negative impact on usage across all time periods, but is most significant during the evening. This finding is similar in Toronto's bike share – as the total number of major intersections increase within a buffer around a station a user is less likely to select that hub (El-Assi et al., 2017). Length of major roads has a positive relationship on usage throughout the entire day, but is only significant during the morning period. This indicates user's willingness to ride along major roads; however, at the same time, most bike lanes are on major streets with moderate to high vehicular traffic volumes. This finding coincides with the positive relationship for length of bike lanes with the exception during the morning period. Although it is expected bicycle infrastructure increases cycling, the total length of bike lanes is only found significant during the day and night periods.

The total number of HSR stops has a positive relationship throughout the entire day, but is only significant during the evening and night. Although not found significant throughout the entire day, the positive relationship coincides with most bike share motivations –to integrate seamlessly with transit to eliminate barriers of using transit such as the first and last mile of the commute (Topalovic et al., 2013). On the other hand, total number of hubs does not have a positive relationship with usage except during the night and is only found significant during the morning and day. The negative relationship might seem unintuitive; however, as also found in the Montreal BIXI system, as hubs increase so does the capacity of bicycles within the buffer which generates more options to choose amongst multiple hubs (Faghih-Imani et al., 2014). It is expected that departure rates decrease when a SoBi hub is located farther from McMaster University and the CBD. As observed by the negative coefficients, this is valid, and each time period is significant. It is interesting to note that McMaster during the morning period has the smallest impact for trip departures. This is plausible since students and instructors tend to have flexible schedules.

Through analyzing land use, we assumed more trip departures would occur in the morning with areas of high residential land use. As seen by the positive coefficients, residential land use is statistically significant throughout the entire day, with the largest impact during the day. Institutional also captures McMaster University and is significant during each time period except the morning, which coincides with the hub distances to McMaster having the smallest impact during the morning period. The majority of trip departures occur in the evening, which captures individuals leaving campus at the end of the day. Office land use also has a positive relationship and significant impact except during the morning. In addition, as commercial businesses such as restaurants or shops increase, there is a positive relationship for each time period that is significant for all but the morning. Lastly, land use classified as other includes areas such as vacant, agricultural/farm, utilities and warehousing, and is only significant at night.

3.5.2 Trip Arrivals

Similar to trip departures, the impact of explanatory variables for trip arrivals varied by time period as shown in Table 3.5. The impact of weather had similar effects on trip arrivals as it did for trip departures. As expected, there is a positive relationship between temperature and arrival rates for each time period of the day. On the other hand, humidity has a negative impact on arrival rates except during the morning. The negative impact of wind speed also varies throughout the day. Rain also has a negative effect for each time period whereas snow does not appear to impact morning trips.

As stated previously, seasonality influences the bike share usage. Findings similar to trip departures were also found for trip arrivals. Compared to winter, each season has a positive relationship with trip arrivals, which also varies throughout the day. Interestingly, the strongest effect is shown for summer evenings, which suggests that increased daylight might be responsible for increased usage. In addition, individuals are more likely to use SoBi during the weekdays compared to weekends and holidays, as seen by the positive and significant relationship for the weekday variable for each time period and the negative and significant relationship for holidays. Similarly, the natural logarithm of day-of-the-year for trip arrivals also has a positive relationship throughout each time period with the largest impact during the day and relatively stable relationship for the remaining periods (see Figure 3.4).

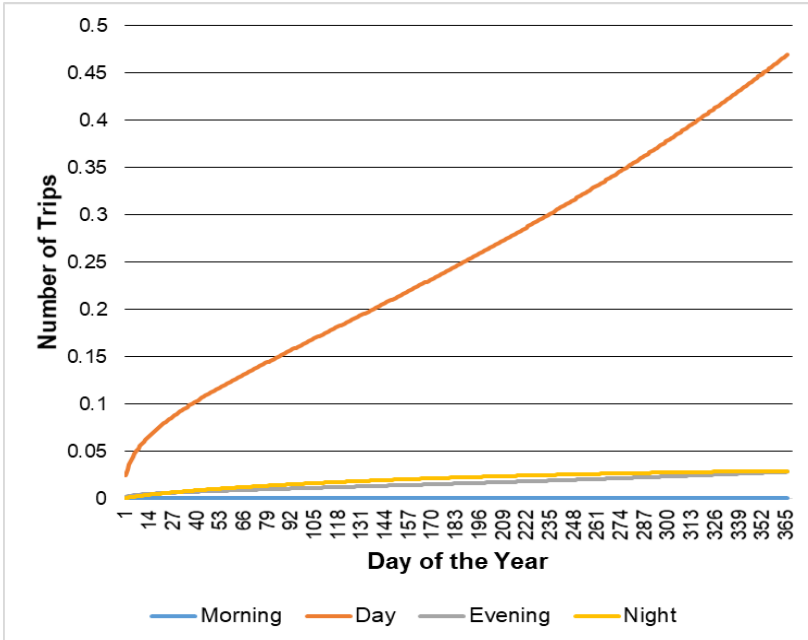

Figure 3.4: Day of year plotted as fixed effect for trip arrivals.

Population has a negative impact on arrivals in the morning, suggesting that morning users are leaving residential areas and heading to other locations in the City. Likewise, employment has a negative impact during the evening and night periods, which suggests that users have left such areas and are destined to other locations.

Hub attributes that are significant for trip arrivals include, length of bike lanes, total HSR stops and SoBi hubs, and distances to McMaster University and the CBD. Length of bike lanes was found to have a positive relationship for each time period, but is only significant during the day. HSR stops also has a positive impact for each time period, but is only significant during the evening and night similar to trip departures. In addition, SoBi hubs have a negative impact during the evening. This negative relationship for trip arrivals might be explained by the ability to dock the bicycles anywhere not only at designated hubs. Lastly, distances to McMaster University and the CBD have significant negative relationships for each time period except distance to McMaster during the morning.

Analyzing land use allows us to determine the type of places individuals are most attracted too. While residential land use is positively related to trip arrivals for all four time periods, it is significant for all but the morning, which is rather intuitive, as we would expect individuals to be traveling elsewhere in the City at that time of the day. Institutional is also positive and significant for each time period, with the largest impact of arrivals during the day and evening. Although office land use was shown to have an insignificant negative impact on trip departures, for trip arrivals, the opposite is true indicating individuals arriving to work in the morning. Furthermore, office land use also has a positive influence on trip arrivals during the day and evening. The majority of such land is found within Hamilton's CBD, which may suggest that "office" land use is a surrogate for the general attractiveness of the CBD as a destination for SoBi trips. Commercial land use is also positively associated with trip arrivals for all but the morning period. Interestingly, the evening period is associated with the greatest impact, which can be explained by restaurant customers or shopping trips at the end of the day.

3.5.3 Random Effects

Hubs are added as random-effects, which are additional unknown random variables assumed to affect the variability of the data (SAS, 2009). The random effects account for common unobserved factors specific to each hub that affects usage. Using the covariance parameter estimates, the Intraclass Correlation Coefficient (ICC), indicates how much of the total variation of usage is accounted for by the hub. As seen in Tables 3.4 and 3.5, it is evident that usage varies amongst hubs. During the morning period, 10.9% of the differences between hubs is accounted for in trip departures and 14.7% in trip arrivals. The day period accounts for 11.8% in trip departures, and 11.2% in trip arrivals. Meanwhile the evening accounts for 8.3% in trip departures and 10.5% in trip arrivals. Lastly, the night period accounts for 8.1% in trip departures and 9.9% in trip arrivals. These results indicate that the variables modeled in our study account for the majority of the variability between hubs in terms of usage throughout each time period of the day.

3.6 CONCLUSION

Despite the rise of bike shares, there has been limited research that considers how spatial and temporal factors affect bike share usage throughout the day. This study contributes to the literature by exploring the effects of weather, temporal characteristics, socio-demographics and hub attributes for four time periods using a multilevel approach. Through hourly data collection, this study better documents a more meaningful explanation of how usage varies across the day as a means to better redistribute bikes to maintain a balanced bike share system.

The multilevel model estimation approach reveals intuitive results for each time period of the day. Using this approach, it is observed that weather plays a significant role in trip departure and arrival rates, and people are more likely to ride SoBi under good weather conditions: warmer temperatures, less humidity, no rain/snow and on a less windy day. These results were consistent with other studies and are fairly applicable to other systems with similar climates to Hamilton, Ontario (El-Assi et al., 2017; Faghih-Imani et al. 2014;

Nosal & Miranda-Moreno, 2014; Gebhart & Noland, 2013). Seasonality also has a positive influence on bike share usage. It was demonstrated that as seasons change and we transition into the warmer months, ridership increases. In addition, during the weekends and holidays SoBi usage decreases, which was also found in a study conducted in Montreal (Faghih-Imani et al., 2014).

After controlling for weather, population and employment do not have a major impact affecting bike share usage at each hub. Employment was only found to be significant at the end of the day indicating individuals leaving work. Moreover, our results clearly demonstrate that population around a hub is not necessarily the main driving factor for a system's success, suggesting the importance of exploring the impact of other hub attributes.

In this study, as distance to the CBD or McMaster University increased, trips decreased for all but one period of the day. The significant built environment variables that were consistent between trip departures and arrivals were length of bike lanes, number of HSR bus stops and number of SoBi hubs. Aside from the above, land use also has a significant effect. Although population was not found to be significant, areas with greater residential land use had greater trip departures and arrivals during most time periods. Areas composed primarily of institutional, office and/or commercial space are important destinations given that there are more points of interest such as restaurants and shops. Moreover, focusing on points of interest during different time periods of the day can assist SoBi operators in ensuring which hubs should always be stocked, thereby assisting in rebalancing the system

Although this study has generated model estimates in which better elucidate the magnitude of effects of variables on the use of bike share systems, it can be further refined to fully understand the driving factors to forecast bike share usage at each hub. The model developed can be employed directly to study rebalancing operations based on time of day and usage at hubs through examining the impact of variables such as land use, built environment and bicycle infrastructure on user destination preferences. This study considered arrivals and departures separately; however, it is possible that these hubs share common characteristics that are unobserved. To capture the unobserved shared characteristics additional work is required. In addition, although a survey was not conducted on user preferences, it has been found that motivations and preferences for using a bike share can differ between types of user but convenience is the major perceived benefit identified (Fishman et al., 2013). Therefore, a more comprehensive analysis it is essential to understand users' preferences throughout different periods of the day to ensure hubs are balanced system wide.

3.7 APPENDIX

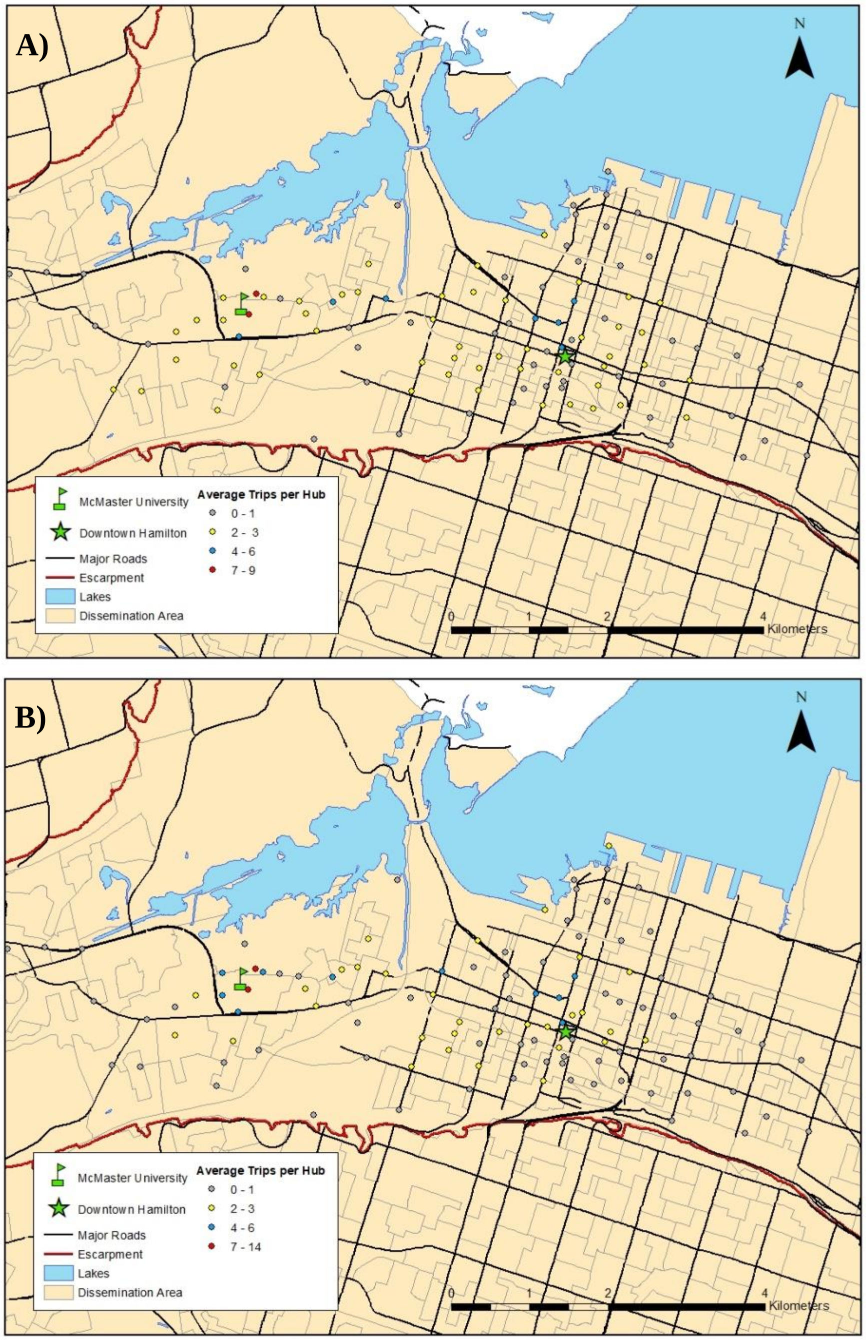

Figure 3.5: Average total of trip departures (A) and arrivals (B) during the day period.

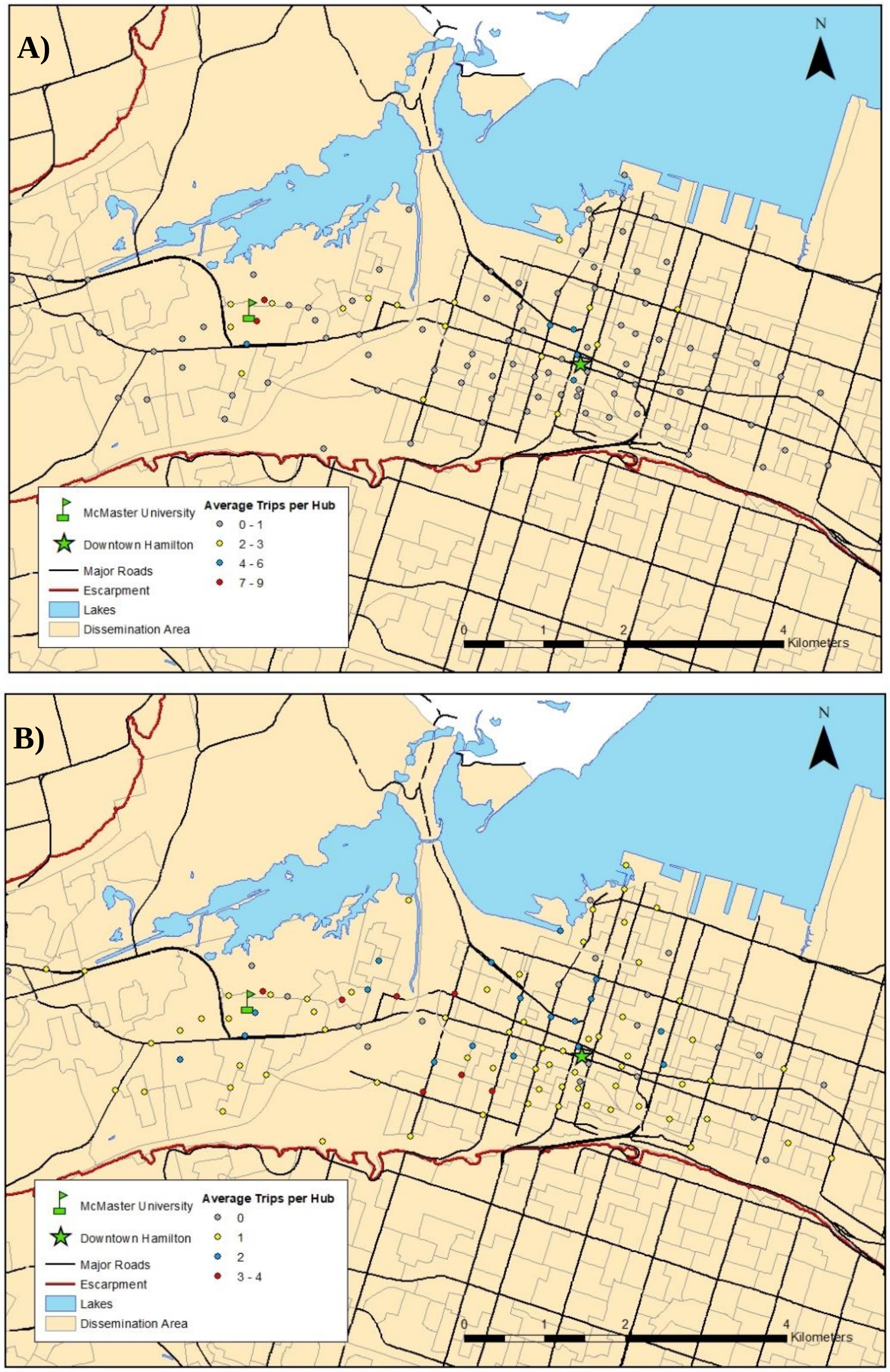

Figure 3.6: Average total of trip departures (A) and arrivals (B) during the evening period.

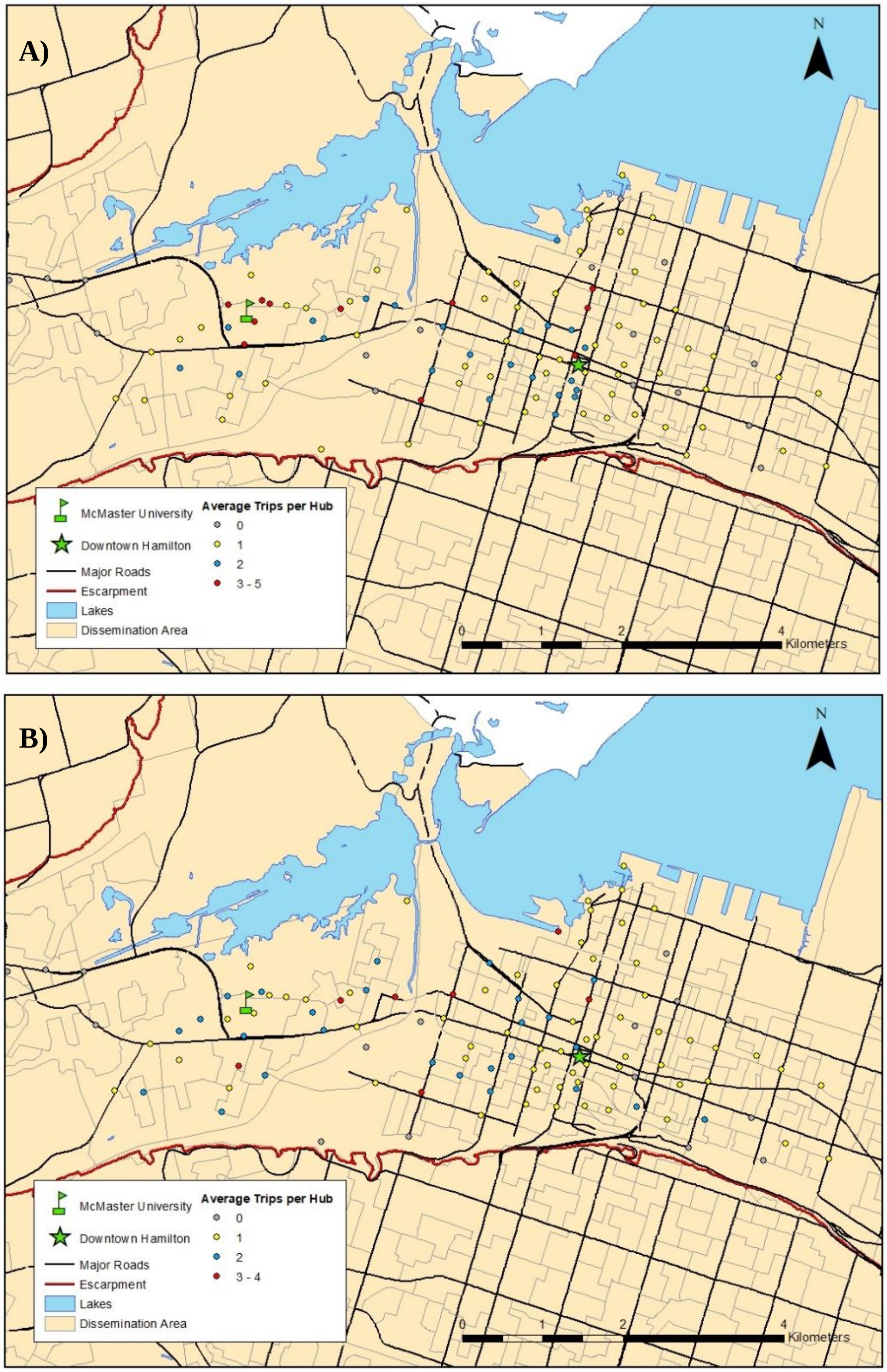

Figure 3.7: Average total of trip departures (A) and arrivals (B) during the night period.

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CHAPTER FOUR: Conclusions

4.1 INTRODUCTION

This thesis employed descriptive statistics and multilevel regression models in order to provide intuitive findings for SoBi Hamilton hub usage. Two objectives have been addressed by this research.

I. Evaluate the impact of socio-demographics, weather, temporal characteristics (day of week, seasonality, day of year), and hub attributes such as the built environment, and land use on daily trip-making behaviour at the SoBi hub-level.

II. Evaluate trip-making behaviour throughout the day at the hub-level exploring the socio-demographics, weather, temporal characteristics (day of week, seasonality, day of year), and hub attributes such as the built environment and land use around SoBi hubs to assist in rebalancing the system.

This Chapter summarizes the findings and research contributions of this thesis with respect to the above objectives, followed by the limitations of this research, and overall conclusions and recommendations for future research.

4.2 SUMMARY OF FINDINGS AND RESEARCH CONTRIBUTIONS

This thesis has examined the factors influencing hub usage of a bike sharing system in Hamilton, Canada. Both Chapters 2 and 3 report similar findings regarding the determinants that influence the bike usage at hubs. The findings are also similar to previous studies on public bike share systems in the transportation literature. This study builds on the current understanding of determinants that drive bike share ridership.

Results from both Chapters 2 and 3 contribute to findings found throughout the bike sharing system literature in relation to system effectiveness. First, weather impacts daily bike sharing trips (Chapter 2). However, Chapter 3 indicates that exploring weather for periods of the day is more meaningful as weather conditions vary throughout the day. The weather of Hamilton, Ontario contains almost all variations in weather – it rains and snows, has very cold and hot days and can be particularly humid and windy throughout the day. The results of this thesis show that fewer trips are made in the rain, cold temperatures, high humidity and high wind speeds. Meanwhile trips increase with higher temperatures. These findings correlate with other studies exploring the influence of weather on bike shares such as the Washington D.C bike share system (Gebhart & Noland, 2013) and Bike Share Toronto (El-Assi et al., 2017).

In the development phase of SoBi, population and employment density was one of the main guidelines used for the placement of hubs (Topalovic et al., 2013). However, the findings from this research suggest that these densities are not the major contributing attributes that influence hub usage. However, in Chapter 3 when analyzing time periods during the day, residential land use has the greatest impact on trip departures during the morning peak time. Looking more specifically at sociodemographic characteristics in Chapter 3, results indicate that population around hubs still does not have a positive impact throughout the day and is only significant during the morning period for trip arrivals. Meanwhile, total employment opportunities is only found to have a positive influence during the morning period attracting trips, otherwise the remainder of the day has a negative impact influencing usage at hubs. Furthermore, people who live around hubs do not necessarily use SoBi more than others and people are riding SoBi to travel to work however, other hub attributes need to be explored.

Although SoBi member demographic data is a limitation in this thesis, we are able to study the travel behaviour of users with the time and location specific data retrieved from SoBi. To understand the differences in hub usage we explore the temporal characteristics such as time of day, day of week and seasons, built environment attributes and land use around each hub. Chapters 2 and 3 show that seasonality has an influence on bike share usage with majority of trips during the summer with warmer temperatures, followed by fall, spring, and then winter. Taking into consideration day of week, findings showed that weekday ridership is greater than weekends and people are less likely to ride SoBi during a Canadian holiday, which can indicate users utilizing SoBi to commute to work/school. In addition, summer and fall have similar impacts for trip departures and arrivals, this could be due to the fact that McMaster University is back in session in the fall and students are using SoBi to travel to and from school.

Looking more specifically at institutional land use, which captures McMaster, and the distance from hubs to McMaster University, it is evident that both attributes play a significant role in hub usage. In Chapters 2 and 3, it was shown that as hub distance increases from McMaster, people are less likely to select that hub. In addition, Chapter 3 explores different time periods and it was revealed that users are less likely to travel to McMaster during the morning period, meanwhile the majority of trips depart from McMaster during the evening. Although employment was not found to influence usage, looking specifically at office land use suggests otherwise. The majority of office land use is located within the CBD that showed that as distance increases from the CBD, hub usage decreases. In Chapter 2, office land use had the greatest effect on usage for trip departures and arrivals. Looking more specifically at the time of day in Chapter 3 also indicates that hubs located around offices have the greatest impact for most trips attracted during the morning period and most trip departures in the evening. Overall, these findings suggest that people are using SoBi for work/school purposes. Lastly, commercial land use also increases the likelihood of SoBi ridership, as with more access to several points of interests such as shops and restaurants people are more inclined to travel to these areas.

As discussed in Chapters 2 and 3, transportation infrastructure and bikes lanes do not play a significant role in influencing trip departure and arrival rates. Though, when analyzing transportation infrastructure, total major intersections around a hub have a negative impact on usage as an individual is less likely to choose that hub. This is statistically significant during the evening rush hour in Chapter 3. However, length of major roads does not negatively impact hub usage compared to other studies in the past (Faghih-Imani & Eluru, 2015; Faghih-Imani et al., 2014). Majority of bike lanes are found along major roads, therefore this can explain the positive impact along major roads. Although in Chapter 2, bike lanes do not necessarily impact a user's willingness to use SoBi, Chapter 3 demonstrated a positive influence on hub usage except during morning trip departures. Lastly, it is expected as people become more aware of SoBi they will become more willing to take out a bike. This is confirmed in both Chapters through the day-of-the-year variables, which captures the incremental growth of the system – as each day passes greater awareness of the system also increases SoBi ridership.

4.3 RESEARCH LIMITATIONS

Both studies within this thesis faced minor data limitations. First, one of the most significant constraints in this thesis is the lack of demographic data on SoBi members. With access to member information, findings could be more comprehensive in understanding trip behaviours and purposes influencing bike share usage at hubs by analyzing information such as age, gender, income, education, and cycle experience. Additionally, with more detailed information on residential locations available, determining if population around hubs generates more trip activity could have been better estimated. Secondly, in Chapter 3 an ideal indicator of how the thermal environment affects human wellbeing is the Physiologically Equivalent Temperature (PET); however, the calculation of PET requires variables such as vapor pressure, mean radiant temperature and the physical work output of the bike share user (El-Assi et al., 2017). Due to weather data limitations from Environment Canada, the perceived temperature was instead calculated to analyze the influence of weather on bike share usage. In our multilevel model development, we considered trip departures and arrivals separately. However, according to Faghih-Imani and Eluru (2016), it is possible that these trips share common observed and unobserved attributes that affect each other, which would require additional work.

4.4 CONCLUSIONS AND FUTURE RESEARCH

Based on the models generated within this thesis, it is readily apparent that several factors need to be considered when attempting to fully understand daily bike share usage. This thesis sought to unravel the effects of weather, temporal characteristics, socio-demographic characteristics, and built environment attributes on hub usage. As this thesis previously states, bicycle usage varies under different weather conditions, measured at both the number of trips per day and trips per time period. In addition, institutional, office, commercial and residential land use all promote SoBi ridership, but some more than others. As a result, rather focusing on population densities for hub locations, other contributing factors such as restaurants, shops, employment opportunities, and schools should be evaluated when choosing hub locations. Therefore, without the insights offered by the collection of bike share system data, the successful development and implementation of hubs throughout a city will not perform to their full potential.

As outlined above, this thesis made several contributions to the bike share literature. From a planning and policy perspective, the most important contribution is that population densities around hubs do not drive bike share usage, and implementing new bike infrastructure or relocating hubs on bike lanes will not necessarily increase ridership. Although it is rather intuitive that weather impacts an individual’s decision whether or not use SoBi, it is important to explore these impacts as weather variables show a strong association with bike share usage. In addition, the statement “no one bikes in the rain” is simply not true as the impact was less pronounced than many would assume. Of course, one should be cautious in generalizations, as different types of SoBi users may respond differently to various weather conditions. Although, the research gap surrounding demographic information about users was limited, the period of the day SoBi data did provide substantial insight into factors that influence bike share usage.

Additionally, this thesis focused only on one year of operation, more specifically the first year SoBi was launched in Hamilton, Ontario. Although the use of longitudinal data provided greater detail in understanding seasonal and weather effects on SoBi usage, exploring the following year daily hub counts would confirm the incremental growth of the system found in Chapters 2 and 3. Models similar to the ones produced in this thesis need to be produced for the following years in order to allow for a better overall understanding of bike share usage in the city. Although this thesis showed that population is not a significant factor in bike share usage, we caution planners and policy makers that additional analysis on bike share users willingness to use the system will be needed in order to solidify this claim. Consequently, retrieving demographic information on bike share users in addition to temporal and spatial characteristics of hubs should be an area of focus for researchers in the future.

Overall, the developed models in this thesis can be used to predict trip rates at potential hub locations in Hamilton. Understanding the effects of bike share usage can assist city planners and bike share system operators in making better decisions on hub locations that maximizes bicycle ridership. Bike sharing programs play an important role in increasing sustainable transport in cities. Therefore, an understanding of their multiple user types, and potential use and impact is essential.

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