THE IMPACT OF SHARED MOBILITY OPTIONS ON TRAVEL DEMAND

FINAL PROJECT REPORT

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16. Abstract

Newly available shared mobility options are having a large impact on travel. Car- and bike-sharing and ride-hailing have become increasingly viable and attractive travel modes since they have been app-based and able to link riders and vehicles in real time and space. This project aimed to provide much needed information on how app-based shared mobility options are affecting travel behavior, and specifically how they are changing the parameters leading to mode choice and mode share. We used three available secondary data sets to explore whether shared mobility options substitute for or complement traditional modes.

The first set of data came from the 2017 Puget Sound regional Household Travel survey. We found that car-sharing and ride-hailing substituted for household vehicle trips. Yet they induced more travel, which could add to traffic congestion but could also improve access to activities. Substitution effects with transit and biking, and additional walking, differed by day of week and commute status, suggesting that future research focus on the temporal and purpose characteristics of trips by shared mobility.

The second set of data came from the Washington State Commute Trip Reduction (CTR) program. We found that in the immediate, CTR instruments used to collect data on commute trips could add questions about shared mobility options. In the long run, CTR employer and employee surveys could be redesigned to facilitate the evaluation of employers' TDM efforts. Also, deploying apps to support the commute trip could yield invaluable and timely information for transportation policy and research.

The third set of data addressed "shared micro-mobility," an increasingly popular form of shared mobility that includes bicycles and scooters. Companies that offer this service have dispersed hundreds or even thousands of bicycles and scooters across individual cities for customers to use. A few companies provide real-time location data for their bikes and scooters via the Internet. We created a computer program to continuously "scrape" and archive such data. A technical description of the online database system was provided. A pilot-study served to analyze one year of data and to create trip generation models.

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SI* (Modern Metric) Conversion Factors

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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List of Abbreviations

AADT: Average annual daily trips

ACS: American Communities Survey

AWS: Amazon Web Services

CTR: Commute Trip Reduction

EC2: Elastic Cloud Compute

GPFS: General Bikeshare Feed Specification

GPS: Global positioning system

ICT: Information and Communication Technology

NABSA: North American Bikeshare Association

PacTrans: Pacific Northwest Transportation Consortium

POI: Points of interest

PSRC: Puget Sound Regional Council

RDS: Relational Database Service

SOV: Single occupancy vehicle

TDM: Transportation Demand Management

TNC: Transportation Network Company

VMT: Vehicle miles traveled

WSDOT: Washington State Department of Transportation

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Executive Summary

Newly available shared mobility options are having a large impact on travel. Car- and bike-sharing and ride-hailing have become increasingly viable and attractive travel modes since they have been app-based and able to link riders and vehicles in real time and space. This project aimed to provide much needed information on how app-based shared mobility options are affecting travel behavior, and specifically how they are changing the parameters leading to mode choice and mode share. We used three available secondary data sets to improve the understanding of how the new app-based shared services are used and to explore whether shared mobility options substitute for or complement traditional modes.

The first set of data came from the 2017 Puget Sound regional Household Travel survey of 6,254 individuals in 3,100 households. We found that car-sharing and ride-hailing remained a small portion of mode share. However, they substituted for household vehicle trips, and they induced more travel, which could add to traffic congestion but could also improve access to activities. Substitution effects with transit and biking, and additional walking, differed by day of week and commute status, suggesting that future research should focus on the temporal and purpose characteristics of trips by shared mobility.

The second set of data came from the Washington State Commute Trip Reduction (CTR) program. The program has more than 1,000 employers statewide and in 2015-2016 collected information on some 1.5 million commuting trips of 224,590 individuals from 598 worksites. We found that in the immediate, CTR instruments used to collect data on commute trips could add questions about shared mobility options. In the long run, CTR employer and employee surveys could be redesigned to facilitate the evaluation of employers' TDM efforts. Also, deploying apps to support the commute trip could yield invaluable and timely information for transportation policy and research.

The third set of data addressed "shared micro-mobility," an increasingly popular form of shared mobility that includes bicycles and scooters. Companies that offer this service have dispersed hundreds or even thousands of bicycles and scooters across individual cities for customers to use. A few companies provide real-time location data for their bikes and scooters via the Internet. We created a computer program to continuously "scrape" and archive such data.

A technical description of the online database system was provided. A pilot study served to analyze one year of data and to create trip generation models.

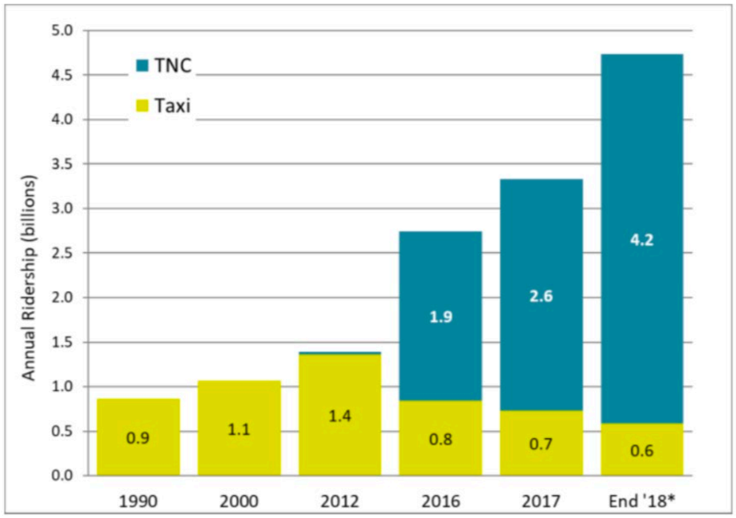
Shared mobility has been greatly enabled by mobile information and communication technologies. As app-based travel becomes ubiquitous, various forms of shared mobility will doubtless continue to permeate travel as convenient and practical options. This project showed that some data on app-based shared mobility are publicly available and useful for exploring trends; more research can and should be done using these data. Yet data from most travel surveys are insufficiently fine-grained to help shape policies and programs that can integrate shared mobility with traditional mobility options. Data from shared mobility providers would further benefit travel and transportation.

CHAPTER 1. Introduction

1.1. Emerging Shared Mobility Options

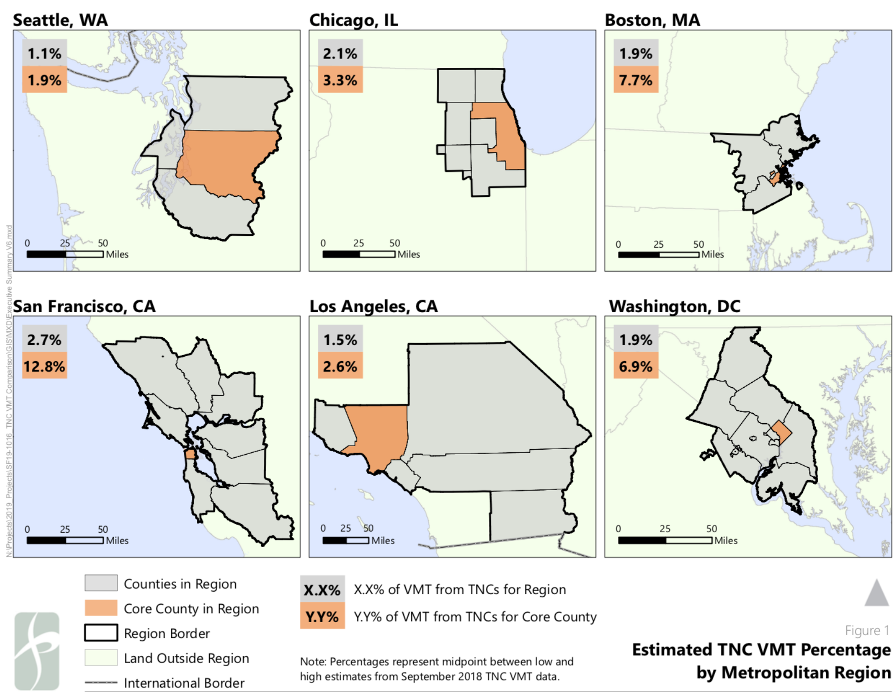
Mobility sharing has long existed in many forms, such as taxi riding, car renting, carpooling, and vanpooling; even public transit qualifies as mobility sharing. In recent years, mobile information and communication technologies (mobile-ICTs) have enabled many new forms of smartphone-based shared mobility options, such as car-sharing, bike-sharing, ride-hailing, and micro-transit (Clewlow and Mishra, 2017; Federal Highway Administration, 2018). Among the new shared mobility options, ride-hailing has drawn most attention from transportation scholars and practitioners because of its exponential growth. Ride-hailing services, which are offered by transportation network companies (TNCs, e.g., Uber and Lyft), refer to the transportation services that allow travelers to request a driver and a vehicle through a smartphone app to go to their location and then drive them to a given destination (Shaheen and Cohen 2019; Clewlow and Mishra 2017, 4). With the ubiquitous use of smartphones and the support from mobile-ICTs, GPS services, and routing algorithms, ride-hailing is popular. A recent study indicated that the annual ridership of TNCs reached 4.2 billion in 2018—less than 10 years after the launch of Uber (figure 1-1). If TNC use continues to grow at the current pace, for-hire ridership in TNCs and taxis will very soon surpass ridership in local buses in the United States (Schaller 2018, 7). Thus, in comparison to traditional mobility sharing options, ride-hailing has grown beyond being a niche market and has become one of the major players in the urban transportation sector.

TNCs have been used disproportionally in certain regions and by certain demographic groups. Geographically, the services have concentrated in large and densely populated metropolitan areas (Schaller 2018, 8), and within these metropolitan areas, they have disproportionally served central-city neighborhoods (Schaller 2018; Clewlow and Mishra 2017; Circella and Alemi 2018). As a result, a joint analysis by Uber, Lyft, and Fehr and Peers estimated that TNCs contribute a substantial share of vehicle miles traveled (VMT) in the urban core of many cities: 12.8 percent in San Francisco, 7.7 percent in Boston, and 6.9 percent in Washington DC (figure 1-2) (Balding et al. 2019). Demographically, young, well-educated, affluent, and independent millennials are the early adopters of ride-hailing services (Circella and Alemi 2018; Clewlow and Mishra 2017). However, pilots have been launched to encourage older travelers to use ride-hailing services (Gray 2016; Gottlieb 2019).



Source: Schaller, 2018 using Lyft estimates for TNC travel and authors' estimates for taxi travel
Note: According to Schaller, "ridership" means one person making one trip between two points, whereas "trips" refers to vehicle trips. Therefore, two people traveling together in a TNC or taxi count as two riders but one trip.

Figure 1-1 Growth of annual ridership (in billions) of TNCs and taxis in the U.S.



Source: Balding et al., 2019
Note: The report used data from Uber and Lyft for TNC VMT estimation and data from the Highway Performance Monitoring System (HPMS) for total regional VMT estimation. TNC VMT includes the miles travelled when the driver is cruising and picking up the riders, but not the miles travelled when the driver commutes to his/her market area if the app is not turned on.

Figure 1-2 Estimated percentage of VMT attributed to TNC travel, by metropolitan region

1.2. Gauging the Impacts of Ride-Hailing on Regional Mobility

Popular ride-hailing services have had a profound impact on individual travel behavior and regional mobility, yet two factors have prevented planners from fully understanding the scope of such impacts: confusion remains as to what the term “ride-hailing” entails and access to ride-hailing trip data has been restricted.

Ride-hailing services were first known as ride-sharing or “peer-to-peer mobility” services, indicating a potential for the efficient use of transportation resources (Clewlow and Mishra 2017). Such a definition can be misleading because the drivers in typical ride-hailing services function as professional service providers similar to those in the traditional taxi industry, not as travelers who share trips as is the case for carpooling. In fact, a recent study in Denver showed that, when the extra travel distance induced by ride-hailing (i.e., deadheading) is accounted for, the average distance-weighted vehicle occupancy falls below 1, which is lower than SOV travel (Henao and Marshall 2018). Therefore, not differentiating ride-hailing from other forms of shared mobility options may lead to overly optimistic estimation of regional mobility trends.

Furthermore, limited access to fine-grained trip data makes it difficult to assess whether TNCs are enhancing (complementing) or challenging (substituting) public transportation. Many recent studies have suggested that TNCs are likely taking a substantial number of riders away from public transit (Circella and Alemi 2018; Shaheen, Totte, and Stocker 2018; Clewlow and Mishra 2017; Henao and Marshall 2018; Schaller 2018). When asked what transportation mode would be chosen if shared mobility were not an available travel option, respondents in many regions of the U.S. have often ranked public transit at the top of the list of alternatives (Schaller 2018; Shaheen, Totte, and Stocker 2018).

1.3. Other New Shared Mobility Options

Aside from ride-hailing services, other shared mobility modes also play increasingly important roles in moving people around. Car-sharing (e.g., Zipcar, car2go, RelayRides) continues to provide access to individual vehicles for people who, by choice or by circumstance, do not own or do not have access to a car. Bike-share systems are also spreading in U.S. cities, especially since docking station bike-sharing has switched to dock-less systems, thereby offering greater flexibility and operational efficiency (Sun, Chen, and Jiao 2018). Shared e-bikes are also emerging as a new option. Moreover, many traditional mobility sharing modes, such as carpooling and vanpooling, have upgraded themselves into more interactive forms of travel with the help of mobile-ICTs (Shaheen et al. 2016; Créno 2016; Buliung et al. 2010). For example, employers in the Seattle region have partnered with app-based carpooling service providers (e.g., Scoop, Waze Carpool) to encourage the use of carpooling among workers at the same worksite. King County Metro, the major transit operator in the Puget Sound region, has also launched a carpool incentive fund to provide monetary incentives for workers who use app-based carpooling to commute (Shen, Wang and Gifford, 2019).

1.4. The Uses of Smart-Phone Apps in Travel Decision Making

The critical difference between traditional and new shared mobility options is that all new options are mobile-ICT-enabled and app-based. Such growing use of mobile-ICTs has profound impacts on the transportation service supply and, by extension, on travel demand and transportation demand management (TDM). On the supply side, mobile-ICTs enable shared mobility services to be shaped by algorithms that make optimal or quasi-optimal decisions for travelers (Moudon 2020). The algorithms pair up massive numbers of users in mobility sharing platforms and coordinate temporal sharing of transportation assets and services (Gössling 2018). On the demand side, *mobile ICTs empower travelers by providing accurate real-time door-to-door travel information*, thus allowing informed decision-making about seamless travel between origin and destination, travel time, trip route choice, and mode choice (Moudon 2020; Gössling 2018; Line, Jain, and Lyons 2011). For example, an increasing number of people now rely on Google Maps to compare different modes (e.g., auto, transit, TNC, walking, biking), and many make the trips following the instructions and navigations of the app. Some research has already been conducted to probe whether app-based travel might help improve not only mobility patterns but also TDM and the related need for travel behavior change (Sunio and Schmöcker 2017). On the other hand, however, the growing reliance on apps for traveling has imposed additional costs to users—for example, the cost of owning a smartphone and subscribing to mobile services—which has enlarged the digital divide in the mobility sector. Last, as individuals are increasingly relying on smartphones and apps to make their travel decisions, policy efforts to manage travel demand and enhance regional mobility will need to change accordingly. For example, traditional TDM programs, such as company-wide carpool matching programs, may be less effective than app-based carpooling systems that can reach a larger number of users. Yet TNCs and other mobility companies remain reluctant to provide trip information to public authorities. This lack of fine-grained information has impeded the understanding of the new mobility trends, which, in turn, has prevented public policy to adjust to the new options and to respond proactively. This lack of data on how the new options affect mode share and specifically the mode share of traditional modes including SOVs, transit, and human-powered travel has become a prominent issue in transportation planning.

In summary,

1. The use of ride-hailing and other shared mobility options is rapidly growing in U.S. cities.
2. Their impacts on travel and travel mode choice, particularly in cities, could be profound and could vary depending on the mode.
3. As the most popular new travel option, ride-hailing will likely have long-term impacts on travel mode choice and vehicle ownership.
4. Mobile-ICTs and smartphone apps have reshaped travel supply and demand, requiring the public sector to change its approach to TDM.

1.5. Structure of This Report

This project aimed to address the need for travel data related to the new shared mobility options. The focus was on using existing data and to extracting information specific to shared mobility. In Chapter 2, we describe the use of data from the Puget Sound Regional Council Travel Survey to assess the impacts of car-sharing and ride-hailing on the demand for other travel options. Chapter 3 reviews Washington State Commute Trip Reduction data for inclusion of shared mobility options in survey instruments used to capture employees' travel behavior and employers' accommodation of these options. Chapters 4 and 5 focus on bike share programs, with Chapter 4 reviewing how data on bike locations can be obtained from websites uploading the information in real time. Chapter 5 illustrates how temporally fined-grained data can be analyzed to estimate demand for micro-mobility.

Each data set is reviewed for its applicability and usefulness to better understand the impact of current shared mobility options on mode choice and mode share. Each chapter offers a conclusion of what is possible and what is needed to better integrate the new app-based shared mobility options into existing transportation policies and programs. Conclusions are provided at the end of each chapter, in line with the three different foci on car-sharing and ride-hailing; on Commute Trip Reduction; and on bike-sharing data.

CHAPTER 2. Impacts of Car-Sharing and Ride-Hailing on the Demand for Other Travel Options

2.1. Introduction

Shared mobility options have become popular in cities. Some studies have found a substitutional relationship between these new and existing travel modes, while others have suggested a complementary relationship. The mixed findings reported in the literature make it difficult to provide clear guidelines for the integration of new and traditional mobility options in traffic management and transportation infrastructure development. Possible reasons for the mixed findings include the heterogeneity found in trip attributes and differences between car-sharing and ride-hailing services. However, few studies have comprehensively examined these heterogeneous conditions and how the impacts of shared mobility on existing travel options vary accordingly. To bridge this gap, this study attempted to empirically examine the impacts of shared mobility on other travel options by utilizing recently published data from the 2017 Puget Sound Regional Travel Survey.

2.2. Literature Review

There is a growing body of literature on shared mobility. Yet, as noted by Le Vine and Polak (2015), consensus is lacking on definitions. We adopted the concept proposed in a report by the U.S. Department of Transportation in which shared mobility was defined as "the use of a motor vehicle, bicycle, or other low-speed mode in a way that enables users to obtain short-term access to transportation as needed, rather than requiring ownership (i.e., requiring users to own a vehicle" (McCoy et al., 2018, p. 3). By this definition, both the new emerging services, such as car-sharing (e.g., car2go, Zipcar) and ride-hailing (e.g., Lyft, Uber), and traditional services, such as taxis and car rentals, are considered to be shared mobility. While the new emerging services may not be entirely analogous to the traditional ones, the differences between them have become obscured by the increased adoption of new e-hailing apps by traditional shared mobility companies (He and Shen, 2015). From all the articles identified through the literature review process, we selected 32 articles that directly examined the impacts of two shared mobility services—car-sharing and ride-hailing—on other travel options. The following pages synthesize the selected publications and organize the findings by the impacts of shared mobility options on each traditional travel option.

2.2.1. Impacts on Public Transit

A number of studies have examined the relationship between shared mobility services and existing public transit. Muheim and Reinhardt (1999) studied car-sharing programs in Switzerland and found that users made more public transport trips and owned fewer cars. In contrast, Tyndall (2019), by using the event of unforeseen service disruption of the public transit rail system in Vancouver, Canada, as a natural experiment, found that car2go served as a substitute for public transit . Other studies yielded mixed findings. Studying an urban U.S. car-sharing operator over a 16-month period from 2006 to 2007, Stillwater et al. (2009) found that the availability of light rail and regional rail services was positively associated with car-sharing uses whereas public transit access did not have a significant effect. Martin and Shaheen (2016) found that car2go could either substitute for or complement public transit. Using booking data from Shanghai, China, Hu et al. (2018) estimated a non-linear but overall declining curve of car-sharing use as distance to transit stations increased.

In terms of the impacts of ride-hailing services, Rayle et al. (2016) employed 380 intercept surveys and reported that a third of the respondents said they would have otherwise used bus or rail if ride-hailing had been unavailable. Clewlow and Mishra (2017) found that ride-hailing use led to a 6 percent reduction in transit use among seven major U.S. cities, although the specific impact varied by the type of transit service. Gehrke et al. (2019) collected 944 in-vehicle intercept surveys from ride-hailing passengers and found that the most common reason that ride-hailing was used for a trip instead of public transit was that it was considered a quicker alternative.

In contrast, Mitra et al. (2019) investigated travel patterns among older ride-hailing users and found that they made more transit trips than their nonuser counterparts, which suggested a potential complementary relationship. Young and Farber (2019) investigated the socioeconomic and trip characteristics of ride-hailing users and suggested that transit ridership was not affected in terms of trip time, trip purpose, and traveler's age for the two different travel options.

A majority of the aforementioned studies were conducted at the individual traveler level. Other studies examined the impacts of shared mobility services at a macro-level. Hall et al. (2018) examined the impacts of Uber entry and exit on public transit ridership from 2004 to 2015, with transit agency as the unit of observation. They found that Uber complemented the average transit agency services by increasing ridership by 5 percent after two years. Nelson and

Sadowsky (2018) investigated the impacts of ride-hailing companies on the monthly public transit ridership of U.S. urbanized areas and showed that the initial entry event of the first ride-hailing company was likely to increase public transit use in the short term. However, as the number of ride-hailing companies increased, public transit use would decrease to the initial level or below it, which suggested a substitution effect in the long term.

2.2.2. Impacts on Driving

Studies have consistently identified a substitutional effect of shared mobility services on driving. Cervero et al. (2007) investigated the City CarShare in San Francisco, California, over four years and found that 29 percent of the members had gotten rid of one or more cars, and 4.8 percent of members' trips and 5.4 percent of their vehicle miles traveled were in CarShare vehicles. Martin and Shaheen (2016) found that a minority of the population used car2go as a substitution for personal automobiles. Nijland and Meerkerk (2017) surveyed 363 car-sharing users in the Netherlands and found over 30 percent lower car ownership and a 15 percent to 20 percent reduction in driving associated with the use of car-sharing. Similarly for ride-hailing, Rayle et al. (2016) reported that 6 percent of the respondents to a survey would drive their own car if ride-hailing had not been available.

Other studies have found indirect evidence of the relationship between shared mobility and car ownership. Mishra et al. (2015) and Clewlow (2016) both showed that car-sharing members owned significantly fewer vehicles than non-members according to the 2010-2012 California Household Travel Survey. However, Clewlow (2016) noted that lower levels of vehicle ownership were observed only among households in urban areas, suggesting a modifying effect of urban density. In a more recent report, Clewlow and Mishra (2017) surveyed seven major U.S. cities in 2014 and 2016 and found that only a minority of ride-hailing users (9 percent) had reduced the number of cars they owned and the associated total driving by substituting those trips with increased ride-hailing use. Becker et al. (2017; 2018) examined the impacts of a new car-sharing program on vehicle ownership in Basel, Switzerland, and found a 6 percent reduction in private vehicle ownership among the 1,218 surveyed customers.

2.2.3. Impacts on Biking and Walking

The impacts of shared mobility on biking and walking remain underexplored. Kopp et al. (2015) compared free-floating car-sharing users with nonusers in Munich and Berlin, Germany, and found that car-sharing users took a higher percentage of bike trips than nonusers. Dill et al.

(2019) interviewed the members of a car-sharing program and indicated that those who decreased driving were walking, biking, and taking transit more often. As for the impacts of ride-hailing, mixed findings were reported in the literature. Young and Farber (2019) suggested that ride-hailing services could motivate more active travel among young people, although the observed impact was minimal. In comparison, Gehrke et al. (2019) found that shorter distance ride-hailing trips were more likely to substitute for biking and walking trips.

2.2.4. Impacts on Total Trips

A number of studies have examined the net impacts of shared mobility on total number of trips. Schaller (2017) reported that ride-hailing contributed to significant growth of vehicle travel in New York City. Similarly, Clewlow and Mishra (2017) deployed a survey in seven major U.S. cities and estimated a net growth in VMT on the basis of data o mode substitution and ride-hailing use frequency. On the basis of an intercept survey in the Greater Boston area, Gehrke et al. (2019) found that 59 percent of ride-hailing trips added a new vehicle on the road. Martin and Shaheen (2016) estimated that most driving activities by car2go added to total trips because of the fact that car2go was generally used to satisfy incidental mobility needs. However, they found that a small group of car2go users tended to decrease their driving by selling their personal vehicle and postponing a vehicle purchase. As the group that replaced a self-owned vehicle with car2go had a relative larger impact, the study concluded that the net effect of car2go was to reduce total driving.

2.3. Social and Demographic Factors

The social and demographic features of shared mobility users have been another focus of previous studies. Users of shared mobility services were described as being younger, wealthier, better educated, and male (Alemi et al. 2018; Lempert et al., 2019; Bulteau et al., 2019; Prieto et al., 2017; Burkhardt and Millard-Ball, 2006; Young and Farber, 2019; Clewlow and Mishra, 2017; Rayle et al., 2016; Klintman, 1998).

The presence of children in the household has been found to have a negative impact on the use of ride-hailing services. Dias et al. (2017) examined the 2014-2015 Puget Sound Regional Travel Study and found that when children were present in the household, low income family were less likely to adopt ride-hailing and car-sharing services; middle income families ($50 K - $100 K) were also less like to use ride-hailing and car-sharing.

In terms of associations between mobility options and features of the built environment, Klintman (1998) concluded that residential areas with high density were perceived as the best locations for having car-sharing near homes. However, in a more recent study, Brown (2019) used detailed data from 6.3 million Lyft trips in Los Angeles and found that the service coverage was not limited to dense urban cores but extended to suburban and even rural neighborhoods.

2.4. Data and Methodology

2.4.1. Research Questions

The overall research objective was to examine the relationships between shared mobility services, particularly car-sharing and ride-hailing, and other travel options, including driving, public transit, biking, and walking. The research aimed to address two specific questions:

1. How do the relationships differ by trip attributes, including weekdays versus weekends and commuting versus non-commuting trips?
2. How do the relationships differ between car-sharing and ride-hailing services?

Answering these questions could help bridge some of the existing gaps in our understanding of the travel behavior patterns of shared mobility users and could provide useful guidelines for planners and policy makers as they try to integrate the new services into transportation planning.

2.4.2. Definitions of Shared Mobility and Shared Mobility Users

Data came from the 2017 Puget Sound Regional Travel Survey (PSRC survey), which collected detailed trip information and social economic characteristics from 6,254 individuals in 3,100 households in the central Puget Sound region. The data covered 0.21 percent of the population in the region. To reduce the sampling bias, the survey implemented a stratified sampling strategy to match the demographic distribution of the region (RSG, 2018).

We used the more inclusive definition of shared mobility, which includes traditional taxi and car rental services as a part of car-sharing or ride-hailing. There were two justifications for such choice. First, the boundaries between traditional and new shared mobility services have become blurred with the increased adoption of e-hailing apps by traditional shared mobility companies (He and Shen, 2015). Second, trips by each shared mobility service consisted of a small percentage of total trips. As a result, aggregation of traditional and new services helped address the zero-inflation problem created by low trip counts.

The PSRC survey is a general-purpose household travel survey, and most trips reported in the survey were not by shared mobility services. We separated the survey participants into "users" and "nonusers" of each shared mobility service and excluded the "nonusers" from the analysis. A "nonuser" of a shared mobility service was defined as a survey participant who had never used that shared mobility service before or during the survey. For example, a "nonuser" of car-sharing was a participant who responded to the question "times used car-sharing in past 30 days" with "I've never used car-sharing before" and reported taking zero car-sharing trips during the survey. After the aforementioned selection process, 1,672 participants, or 29 percent of all participants, were identified as car-sharing users, while 3,188 participants, or 51 percent of all participants, were identified as ride-hailing users. The higher number of ride-hailing users suggested that ride-hailing services had a relatively larger market, which corresponded to the same observation in a previous study (Clewlow and Mishra, 2017).

Table 2-1 compares the socioeconomic and demographic features of users and nonusers of car-sharing and ride-hailing services. The variables were selected on the basis of previous studies (Burkhardt and Millard-Ball, 2006; Dias et al., 2017; Young and Farber, 2019). A clear distinction between users and nonusers was found. Car-sharing and ride-hailing users had similar characteristics. When compared with nonusers, users were younger, wealthier, a higher percentage male, owned fewer vehicles, and lived in denser neighborhoods, all of which was consistent with the literature. Only differences in education and the presence of children in the household had not been found in previous studies (Dias et al., 2017).

Table 2-2 presents trip counts by users and nonusers for car-sharing and ride-hailing services. Users exhibited travel behaviors distinct from those of nonusers. In particular, both car-sharing and ride-hailing users took fewer trips by household vehicle and more trips by bike per person per day. Additionally, ride-hailing users on average took more transit trips and more walking trips than nonusers.

Table 2-1 Summary statistics: social and demographic characteristics by car sharing/ride hailing users vs nonusers

	Car-Sharing Users				**Car-Sharing Nonusers**				**T-test**	**Ride-Hailing Users**				**Ride-Hailing Nonusers**				**T-test**
	Mean	SD	Min	Max	Mean	SD	Min	Max	P	Mean	SD	Min	Max	Mean	SD	Min	Max	P
Age (1=under 18 years, 2=18 to 34 years, 3=45 years or older)	2.11	0.83	1	3	2.38	0.51	1	3	0.00 ***	1.83	0.75	1	3	2.27	0.49	1	3	0.00 ***
Female (=1)	0.46	0.5	0	1	0.51	0.5	0	1	0.00 ***	0.48	0.5	0	1	0.51	0.5	0	1	0.07 **
Race: white (=1)	0.4	0.49	0	1	0.69	0.46	0	1	0.00 ***	0.54	0.5	0	1	0.68	0.47	0	1	0.00 ***
College (=1)	0.55	0.5	0	1	0.91	0.28	0	1	0.00 ***	0.75	0.44	0	1	0.88	0.32	0	1	0.00 ***
HH income (1= Under \$50k, 2= \$50k-\$100k, 3 = Over \$100k)	2.43	0.75	1	3	2.29	0.8	1	3	0.00 ***	2.42	0.76	1	3	2.22	0.82	1	3	0.00 ***
Avg. # household owned vehicle per adult	0.75	0.49	0	4	0.83	0.46	0	4	0.00 ***	0.77	0.45	0	4	0.83	0.49	0	4	0.00 ***
Presence of children (=1)	0.51	0.5	0	1	0.22	0.42	0	1	0.00 ***	0.34	0.47	0	1	0.27	0.44	0	1	0.00 ***
Gross housing density (unit/acre)	12.8	15	0.1	139	12	14	0.03	139	0.00 ***	13.8	16	0.03	138.9	9.5	11.7	0.1	105.7	0.00 ***
N	**1,672**				**4,582**					**3,188**				**3,066**				

*Note: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Table 2-2 Summary statistics: trip counts per day by car sharing/ride hailing users vs nonusers

	Car-Sharing Users				**Car-Sharing Nonusers**				**T-test**	**Ride-Hailing Users**				**Ride-Hailing Nonusers**				**T-test**
	Mean	SD	Min	Max	Mean	SD	Min	Max	P	Mean	SD	Min	Max	Mean	SD	Min	Max	P
Avg. total trips	3.63	2.33	0	22.17	3.73	2.47	0	19.71	0.15	3.82	2.33	0	22.17	3.55	2.53	0	17	0.00 ***
Avg. car share trips	0.08	0.54	0	11	0	0	0	0	0.00 ***	0.03	0.32	0	11	0.02	0.27	0	8	0.03 **
Avg. ride hail trips	0.04	0.19	0	2.14	0.03	0.2	0	4	0.1	0.06	0.26	0	4	0	0	0	0	0.00 ***
Avg. HH vehicle trips	1.81	2.01	0	20.71	2.3	2.34	0	19.71	0.00 ***	2	2.13	0	20.71	2.36	2.39	0	16	0.00 ***
Avg. transit trips	0.39	0.8	0	6.86	0.36	0.81	0	8	0.28	0.42	0.82	0	6.86	0.31	0.79	0	8	0.00 ***
Avg. bike trips	0.12	0.54	0	7	0.08	0.47	0	7	0.00 ***	0.11	0.52	0	6.33	0.07	0.45	0	7	0.00 ***
Avg. walking trips	0.85	1.34	0	11	0.8	1.42	0	10	0.18	0.94	1.41	0	10	0.67	1.36	0	11	0.00 ***
N	**1,672**				**4,582**					**3,188**				**3,066**				

*Note: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

2.4.3. *Travel Demand Variables*

Person-level analyses were carried out by using two methods to measure travel demand: average trip count per day by mode and average accumulated trip duration per day by mode. The average duration measurement was used to consider heterogeneity between modes and its impacts on trip substitution identified in a previous study (Gehrke et al., 2019). Three separate sets of models were estimated for car-sharing and ride-hailing, with trip count and trip duration as the dependent variables. Four subsets of trips were first stratified from the full trip data table based on the day of week and the purpose of an individual trip. Monday to Friday were defined as weekdays and Saturday and Sunday were defined as weekends. Commuting trips included those destined for school, primary workplace, or a work-related place. Other trips were considered to be non-commuting trips. Trips returning home were excluded from the non-commuting trips for this analysis because the survey questions did not differentiate between trips from workplace to home and trips from other places to home. Given the fact that many survey participants reported more than one workplace address, it was difficult to identify trips returning home from the workplace without introducing additional assumptions.

For average trip count and duration, we first aggregated individual trips by travel mode by person and by day within each subset of trip data and then calculated the average value per day for each person. Table 2-3 presents the summary statistics for average trip count and duration per day at the person-level for car-sharing and ride-hailing trips. Because only users of the corresponding service were included in the final models, the Ns in the table show the number of users defined above during the given time period or for the indicated trip purpose.

Table 2-3 Individual-level average trip count/duration per day

	Car-Sharing									Ride-Hailing								
		Trip Count				Trip Duration					Trip Count				Trip Duration			
	N	Mean	SD	Min	Max	Mean	SD	Min	Max	N	Mean	SD	Min	Max	Mean	SD	Min	Max
Weekday	1,672	0.14	0.74	0	11	3.35	20.2	0	314	3,188	0.1	0.41	0	5	1.84	12.3	0	452
Weekend	497	0.21	0.96	0	8	2	7.9	0	58	815	0.17	0.58	0	5	2.63	9.73	0	85
Commute	1,243	0.04	0.3	0	5	1	8.72	0	207	2,415	0.03	0.2	0	2	0.86	12.4	0	562
Non-commute	1,283	0.12	0.59	0	7	2.86	16.3	0	233	2,442	0.07	0.3	0	3.5	0.99	4.93	0	60

Note: some trips have missing values for trip duration, which results in the small differences in Ns between trip count and trip duration

2.5. Results

All trip count and trip duration variables were transformed under natural logarithm to address the over-dispersion of the data. After the transformation, the variables were standardized so that coefficients could be compared directly with each other. Variance inflation factor tests were conducted and variables with collinearity were excluded from the final models.

Table 2-4 compares trip count with accumulated trip duration as two different measurements of travel demand. On the basis of adjusted R-squares and AIC scores, the duration models performed better than the count models. However, because travel behavior is affected by a number of factors, the overall R-squares remained relatively low. As seen in rows 5 and 10, the duration models also produced different estimated effects of walking than the count models. For both car-sharing and ride-hailing trips, the average *duration* of walking trips per day was positively associated with the average duration of corresponding shared mobility trips per day. However, the average *count* of walking trips per day was negatively associated with the average count of car-sharing trips and not significant in the ride-hailing count model.

For the remaining regression analysis, only duration models were estimated. Table 2-5 shows differences between weekdays and weekends. Row 2 shows that for both car-sharing and ride-hailing, the duration of trips by household-owned vehicle had a statistically significant and negative effect in both the weekday and weekend models. The magnitudes of the coefficients suggested that the substitutional relationships between trips in household-owned vehicles and shared mobility options were stronger over the weekend. Rows 4 and 5 show that for both car-sharing and ride-hailing, biking and walking trip durations were significant for weekdays but not significant during weekends. Row 6 shows that for both car-sharing and ride-hailing, total trip duration had a positive effect in each of the models. Because it was only an association, the direction of association is not known, and it could be that people who traveled more were more likely to use shared mobility options, or that shared mobility options increased total demand for travel.

Table 2-4 Models with weekday trips: average trip count vs average accumulated trip curation

	Avg. Trip Count by Car-Sharing			Avg. Trip Duration by Car-Sharing			Avg. Trip Count by Ride-Hailing			Avg. Trip Duration by Ride-Hailing		
	Est.	t	Sig	Est.	t	Sig	Est.	t	Sig	Est.	t	Sig
1. (Intercept)	0.11	0.74		0.00	-0.01		0.25	3.29	***	0.18	2.46	*
2. Avg. count by HH vehicle	-0.51	-7.81	***				-0.15	-4.20	***			
3. Avg. count by public transit	-0.13	-2.59	**				0.00	0.08				
4. Avg. count by biking	-0.14	-3.63	***				-0.07	-3.11	**			
5. Avg. count by walking	-0.21	-3.79	***				0.03	0.97				
6. Avg. total trip count	0.57	8.97	***				0.17	4.93	***			
7. Avg. duration by HH vehicle				-0.42	-7.29	***				-0.18	-5.94	***
8. Avg. duration by public transit				-0.12	-2.32	*				-0.01	-0.46	
9. Avg. duration by biking				-0.10	-2.73	**				-0.07	-3.32	***
10. Avg. duration by walking				0.13	2.98	**				0.14	5.99	***
11. Avg. total trip duration				0.52	9.89	***				0.27	9.89	***
12. Avg. number of household owned vehicle	0.12	1.15		0.16	1.56		-0.14	-2.44	*	-0.14	-2.45	*
13. HH income ($50,000-$99,999)	0.25	1.80	.	0.18	1.31		0.00	-0.03		-0.02	-0.28	
14. HH income (above $100,000)	0.35	2.73	**	0.28	2.26	*	0.03	0.47		0.04	0.57	
15. With children	-0.43	-4.38	***	-0.18	-1.86	.	-0.22	-4.25	***	-0.10	-2.02	*
16. Female	0.09	1.00		0.07	0.76		0.09	2.05	*	0.11	2.45	*
17. N	1,672			1,669			3,188			3,184		
18. Adj. R2	0.08			0.10			0.04			0.08		
19. AIC	6,496			6,432			10,515			10,336		

*Note: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Row 3 shows that in comparing car-sharing and ride-hailing, the duration of public transit trips was negatively associated with the duration of car-sharing trips in both the weekday and weekend models. However, the coefficient was not significant in either of the ride-hailing models. There may have been a substitutional relationship between public transit and car-sharing but not ride-hailing. In terms of control variables, rows 7 to row 11 show that the average number of household-owned vehicles was negatively associated with car-sharing and ride-hailing. In contrast, household income was positively associated with car-sharing trips but not with ride-hailing. The presence of children was negatively associated with both car-sharing and ride-hailing. Being female was more likely to correspond to a higher demand for ride-hailing services during weekdays.

Table 2-5 Models with average accumulated trip duration: weekday vs weekend

	Avg. Trip Duration by Car-Sharing Weekday			Avg. Trip Duration by Ca- Sharing Weekend			Avg. Trip Duration by Ride-Hailing Weekday			Avg. Trip Duration by Ride-Hailing Weekend		
	Est.	t	Sig	Est.	t	Sig	Est.	t	Sig	Est.	t	Sig
1. (Intercept)	0.00	-0.01		0.34	1.80	.	0.18	2.46	*	0.14	1.23	
2. Avg. duration by HH vehicle	-0.42	-7.29	***	-0.49	-6.56	***	-0.18	-5.94	***	-0.26	-5.40	***
3. Avg. duration by public transit	-0.12	-2.32	*	-0.23	-3.88	***	-0.01	-0.46		0.01	0.14	
4. Avg. duration by biking	-0.10	-2.73	**	-0.09	-1.51		-0.07	-3.32	***	-0.06	-1.48	
5. Avg. duration by walking	0.13	2.98	**	-0.07	-1.02		0.14	5.99	***	0.00	0.07	
6. Avg. total trip duration	0.52	9.89	***	0.41	5.72	***	0.27	9.89	***	0.16	3.48	***
7. Avg. number of household owned vehicle	0.16	1.56		-0.26	-1.82	.	-0.14	-2.45	*	-0.05	-0.53	
8. HH income ($50,000-$99,999)	0.18	1.31		-0.05	-0.26		-0.02	-0.28		-0.05	-0.44	
9. HH income (above $100,000)	0.28	2.26	*	0.29	1.63		0.04	0.57		0.04	0.37	
10. With children	-0.18	-1.86	.	-0.32	-2.31	*	-0.10	-2.02	*	-0.28	-3.10	**
11. Female	0.07	0.76		0.05	0.40		0.11	2.45	*	0.07	0.94	
12. N	1,669			497			3,184			815		
13. Adj. R2	0.10			0.19			0.08			0.09		
14. AIC	6,432			1,669			10,336			2,390		

*Note: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Table 2-6 Models with average accumulated trip duration: commute vs non-commute trips

	Avg. Trip Duration by Car-Sharing Commute			Avg. Trip Duration by Car-Sharing Non-commute			Avg. Trip Duration by Ride-Hailing Commute			Avg. Trip Duration by Ride-Hailing Non-commute		
	Est.	t	Sig	Est.	t	Sig	Est.	t	Sig	Est.	t	Sig
1. (Intercept)	0.12	0.75		0.07	0.48		0.13	1.53		0.16	2.04	*
2. Avg. duration by HH vehicle	-0.45	-6.72	***	-0.56	-8.10	***	-0.28	-7.64	***	-0.10	-2.79	**
3. Avg. duration by public transit	-0.37	-6.07	***	-0.11	-2.25	*	-0.18	-5.49	***	0.04	1.50	
4. Avg. duration by biking	-0.06	-1.34		0.01	0.20		-0.10	-3.90	***	0.00	0.05	
5. Avg. duration by walking	0.02	0.53		0.05	0.94		0.01	0.56		0.14	5.28	***
6. Avg. total trip duration	0.48	8.61	***	0.72	9.98	***	0.31	9.95	***	0.21	5.38	***
7. Avg. number of household owned vehicle	0.03	0.25		-0.03	-0.26		-0.11	-1.82	.	-0.11	-1.81	.
8. HH income ($50,000-$99,999)	0.14	0.88		0.10	0.70		-0.07	-0.88		-0.02	-0.22	
9. HH income (above $100,000)	0.11	0.80		0.39	2.84	**	0.01	0.08		0.00	0.05	
10. With children	-0.21	-1.84	.	-0.20	-1.88	.	-0.03	-0.42		-0.17	-2.96	**
11. Female	0.07	0.70		0.09	0.91		0.13	2.50	*	0.12	2.44	*
12. N	1,241			1,282			2,412			2,440		
13. Adj. R2	0.08			0.12			0.06			0.07		
14. AIC	4,744			4,889			7,799			7,880		

*Note: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

2.6. Discussion

This study produced results that were both similar to and different than results from previous studies. Consistent with most previous publications, the model results showed negative relationships between shared mobility services and driving by car, and positive relationships with total daily trips. As for differences, we found only negative relationships with public transit, whereas previous studies had shown mixed results (Shaheen et al., 2018).

The model results might help explain some of the previous mixed findings. The comparison between the trip count models and the duration models showed that for walking, a plausible explanation for the mixed findings from previous studies is that shared mobility services induce fewer but longer walking trips.

The model results for car-sharing and ride-hailing also suggested that the two mobility options had similarities and differences by types of travelers and by travel behavior. In terms of similarities, car-sharing and ride-hailing users took significantly more trips per day or travelled for a longer time per day (by all modes). The positive relationship between shared mobility options and total travel might be concerning from an environmental perspective. From a social perspective, it might indicate that the new services have improved the mobility of people who previously had only limited access (Brown, 2019). While their total travel was higher in trip count and duration, car-sharing and ride-hailing users took fewer trips or traveled less time in household vehicles. The net impact on VMT is unclear without knowing the numbers of travelers in each vehicle per trip. Having children was negatively associated with both trip count and duration of car-sharing and ride-hailing, which was consistent with previous findings (Dias et al., 2017).

In terms of differences, transit trip count or duration was negatively related to car-sharing but not significant in most of the ride-hailing models. The conditions under which the relationships with walking and biking were significant differed between the users of car-sharing and ride-hailing. Female travelers tended to use ride-hailing more but appeared to be indifferent to car-sharing. An improved understanding of these differences could inform policy makers to better target interventions without causing unintended consequences.

2.7. Conclusions

For the last decade cities have witnessed a dramatic growth in app-based shared mobility service options. While the services could increase accessibility and expand the choices in daily travel, they might also increase total vehicle miles traveled, and therefore aggravate traffic congestion and emissions. To understand the relationship between shared mobility and other travel options, this study used the regional data from the large 2017 PSRC travel survey. On the basis of the results of this study, the authors conclude that the mixed findings of previous studies might stem from three sources. First the findings might vary because of measurement bias. A number of studies have used trip count/frequency to measure travel behavior. Our model comparison showed that travel behavior was better captured by trip duration than by trip count. Second, the relationship might change by trip attributes. For example, transit and ride-hailing were only negatively associated for commuting trips but had no association for other trips. Not specifying these conditions might lead to unstable modeling results and thus to inconsistent findings. Third, although both are perceived as shared mobility, car-sharing and ride-hailing differed in terms of their overall relationship with other travel options and with the conditions under which they substituted for or complemented other options.

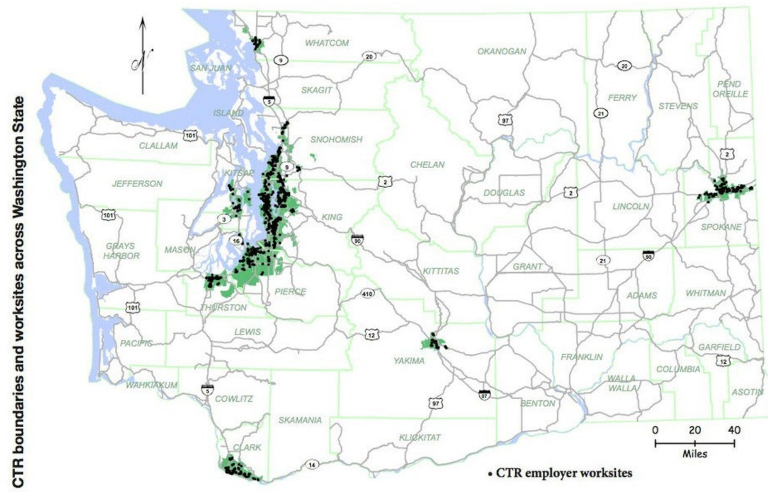
The study provides new insights into the relationships between shared mobility and other travel options, but more research is needed in at least two directions. First, the study used only one year of the PSRC survey, meaning that model estimates from the cross-sectional design could be interpreted only as associations but not as causation. It is unclear whether the associations were outcomes of shared mobility impacts on other travel options or were outcomes of self-selection, in that travelers with certain travel patterns were more likely to use shared mobility options. Using two or more years of the PSRC surveys could help to provide a more direct measurement of the underlying mechanism. Second, while the models helped to identify the relationships with various travel options and to specify them by trip attributes, the social implications of these findings remain unclear. Future models could be further stratified by users' social and demographic features to better illuminate the social impacts of shared mobility.

CHAPTER 3. Washington State Commute Trip Reduction Program

3.1. Introduction: CTR and Its Current Survey Strategies

The Washington State Commute Trip Reduction program is a statewide travel demand management program. It aims at addressing major transportation issues, such as traffic congestion, air pollution, and petroleum fuel consumption in Washington state. It was first launched in 1991 with the passage of the Commute Trip Reduction (CTR) law by the Washington State Legislature. In 2006, legislators passed the CTR Efficiency Act, requiring local governments in urban areas with traffic congestion to develop programs that reduce drive-alone trips and vehicle miles traveled per capita. According to the Washington State Commute Trip Reduction Board (2017), it is the only comprehensive statewide employer-based commute trip reduction program in United States.

CTR targets employers who have 100 or more full-time employees at a single worksite. It requires targeted employers to develop strategies to support and encourage more sustainable commuting modes that are alternatives to single-occupancy vehicle (SOV), which can include shared rides with others through carpooling and vanpooling; riding a bus, train or bicycle; walking; or reducing commutes through telework or compressed workweeks. In 2017, the CTR program had more than 1000 employers and 550,000 commuters statewide (figure 3-1), encompassing jurisdictions in six metropolitan planning organizations, over 12 transit agencies and 60 local governments (Washington State Commute Trip Reduction Board 2017, 1). The Washington State Department of Transportation (WSDOT) administers funding support for CTR jurisdictional representatives to oversee employers' efforts in reducing SOV use, provides technical support for the implementation of the program, analyzes the program’s data, and evaluates the program’s performance.



Source: Jaffe, 2015

Figure 3-1 CTR worksites in 2015

CTR has proved to be effective for reducing SOV use. The mode share of non-SOV modes among the CTR affected commuters increased from 34.3 percent in 2007 to 39.1 percent in 2016, which was 43 percent higher than the state average and 66 percent higher than the national average (Washington State Commute Trip Reduction Board 2017, 2). Mode shifts from SOV to other modes contribute to a reduction of regional congestion, tail-pipe emissions, and automobile dependency (Washington State Commute Trip Reduction Board 2017). Such great benefits come at a relatively low cost, as the CTR program requires only $6 million in funding for every two years (Jaffe 2015).

To periodically measure employees' commuting behaviors and evaluate the performance of the CTR program, WSDOT regularly conducts two biennial surveys: an employer survey and an employee survey. The employer survey seeks to collect basic information on the worksites and the implementation of CTR-related policies. The employee survey gathers information about each employee's work schedule, commuting mode choices, and factors affecting such mode choices. The employee survey is characterized by its large sample and comprehensiveness. For example, in the 2015-2016 survey period, it collected data on more than 1.5 million commuting trips of 224,590 individuals from 598 worksites. Therefore, the CTR survey not only serves as a tool to evaluate the outcome of the CTR program but also provides transportation researchers with invaluable information regarding how commuters in Washington state travel to their work locations. For example, Hallenbeck et al. (2017) and Aras (2017) used CTR data, together with fare transaction data from the One Regional Fare Card for All (ORCA), to evaluate the impacts of employers' transit subsidy programs and parking strategies on transit utilization rates. Wu and Shen (2019) conducted a comprehensive analysis of the effectiveness of the CTR program in affecting employees' commuting mode choice.

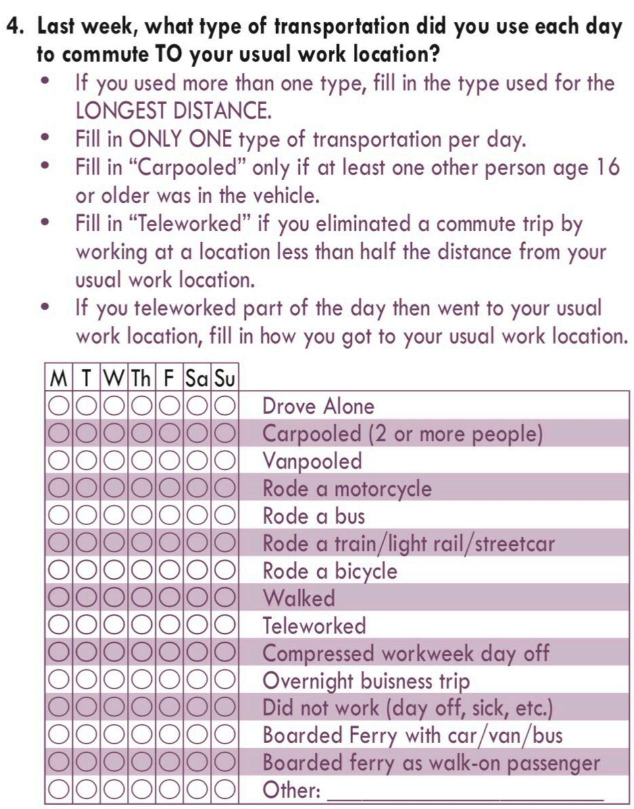
The design and content of the CTR survey has remained relatively stable over the past decade, even though there have been significant changes in the way people travel in Washington cities. One major change is the emergence of new shared mobility options. They have become increasingly common for all types of travel. While the CTR program is focused on employer-specific efforts to reduce commute trips to their worksites, using the CTR survey to collect information on new shared mobility modes usage could provide additional tools to employers while also serving as a way to better understand the impacts of new shared mobility options in the region. In this context, it is reasonable to ask the following questions:

- Are the current CTR surveys able to gather information on new shared mobility options?
- If not, what are the possible strategies for CTR to update its surveys to provide additional insights into the new shared mobility options?

This chapter is an attempt to answer these two questions and to provide recommendations for the CTR program to better incorporate emerging shared mobility options. It proceeds with an analysis of issues we identified in existing CTR surveys. We reviewed the survey instruments used by CTR employers and employees and found two areas where the instruments could be improved to collect data on the use of the new shared mobility options. One of the areas (named Gap #1) is to simply add questions that will help fill the current gap in the coverage of the new shared mobility options. A second area (named Gap #2) is to better integrate the data collected in the employers' and the employees' surveys so that any change in travel policies instigated by employers can be coupled with information on how employees may have reacted to the changes. This would facilitate any evaluation of the effectiveness of CTR policy and program changes. We then make specific recommendations based on our analysis to update the CTR survey.

3.2. Gap #1: Limited Coverage of the CTR Survey on the Emerging App-Based Shared Mobility

What are the trends in the commuting mode choices in our region? Are ride-hailing services being commonly used? This section reviews data from two local data sets. First data were analyzed from 2007-2018 CTR employee surveys to determine changes in commuters' mode choice. However, because the CTR employee survey does not directly ask any question about new shared mobility options (as shown in figure 3-2), another source was used, the 2014 and 2017 Puget Sound Regional Council (PSRC) Household Travel Surveys to obtain information regarding the use of new shared mobility options (survey data are available at: https://www.psrc.org/household-travel-survey-program). The PSRC survey is conducted in King, Pierce, Snohomish, and Kitsap counties, which constitute the most populated region in Washington state. The survey contains questions regarding households' travel behavior and regional mobility (Puget Sound Regional Council, n.d.). More importantly, it includes questions about the use of the two new shared mobility modes, car-sharing and ride-hailing.


4. Last week, what type of transportation did you use each day to commute TO your usual work location?

- If you used more than one type, fill in the type used for the LONGEST DISTANCE.
- Fill in ONLY ONE type of transportation per day.
- Fill in "Carpooled" only if at least one other person age 16 or older was in the vehicle.
- Fill in "Teleworked" if you eliminated a commute trip by working at a location less than half the distance from your usual work location.
- If you teleworked part of the day then went to your usual work location, fill in how you got to your usual work location.

M	T	W	Th	F	Sa	Su	
○	○	○	○	○	○	○	Drove Alone
○	○	○	○	○	○	○	Carpooled (2 or more people)
○	○	○	○	○	○	○	Vanpooled
○	○	○	○	○	○	○	Rode a motorcycle
○	○	○	○	○	○	○	Rode a bus
○	○	○	○	○	○	○	Rode a train/light rail/streetcar
○	○	○	○	○	○	○	Rode a bicycle
○	○	○	○	○	○	○	Walked
○	○	○	○	○	○	○	Teleworked
○	○	○	○	○	○	○	Compressed workweek day off
○	○	○	○	○	○	○	Overnight buisness trip
○	○	○	○	○	○	○	Did not work (day off, sick, etc.)
○	○	○	○	○	○	○	Boarded Ferry with car/van/bus
○	○	○	○	○	○	○	Boarded ferry as walk-on passenger
○	○	○	○	○	○	○	Other: ______________________

Figure 3-2 Question 4 in the CTR employee survey about commuting mode choice

To make the two sets of data comparable, we included only PSRC trips that were commute trips from home to the respondent's primary workplace. The CTR survey asks employees to report what mode was used for the longest portion of the commute. Therefore, for trips with multiple travel modes in the PSRC's data, we looked only at the primary mode. Also, we included only CTR worksites that were located within the PSRC's jurisdictions (King, Snohomish, Pierce and Kitsap counties), which account for approximately 80 percent of all statewide CTR trips. We excluded telework and compressed workweek/day off from the CTR data, as they were not included in the PSRC survey. And lastly, we grouped the individual modes into aggregated categories so that the trends could be easily compared.

Table 3-1 CTR commuting mode choice from 2007 to 2018

		2007/ 2008	**2009/ 2010**	**2011/ 2012**	**2013/ 2014**	**2015/ 2016**	**2017/ 2018**
	Total number of trips	**1,223,308**	**1,154,366**	**1,066,683**	**1,069,256**	**1,207,236**	**1,271,236**
Category	**Mode share**						
Drive alone	Drive alone	65.0%	60.8%	60.9%	61.0%	57.7%	55.7%
	Motorcycle	0.1%	1.2%	1.0%	1.0%	1.2%	0.9%
Carpool/ vanpool	Carpool	11.5%	11.4%	10.6%	9.7%	9.0%	8.6%
	Vanpool	2.5%	3.0%	2.9%	2.8%	2.4%	2.7%
Walk/ Bike	Walk	1.9%	2.2%	2.6%	3.1%	4.3%	5.2%
	Bike	1.6%	1.9%	2.1%	2.3%	2.4%	2.3%
Public transit	Bus	14.9%	16.0%	16.0%	16.1%	17.9%	18.4%
	Train	1.1%	1.4%	1.8%	1.9%	2.6%	3.3%
	Ferry walk-on	0.0%	0.8%	0.8%	0.7%	0.8%	1.1%
	Ferry drive-on	0.0%	0.3%	0.3%	0.3%	0.3%	0.4%
Other	Other	1.4%	1.0%	1.1%	0.9%	1.2%	1.6%
	Total	100%	100%	100%	100%	100%	100%

As shown in table 3-1, since the 2007-2008 survey of the Puget Sound four-county region population, the mode share of driving alone consistently decreased (from 65 percent in 2007-2008 to 55.7 percent in 2017-2018), suggesting that the CTR program has been a successful policy tool to reduce the use of SOVs. At the same time, the mode shares of sustainable travel options increased, such as walking (from 1.9 percent to 5.2 percent), biking (from 1.6 percent to 2.3 percent), bus (from 14.9 percent to 18.4 percent) and train (from 1.1 percent to 3.3 percent). However, as carpooling decreased in mode share (from 11.5 percent to 8.6 percent). However, aside from traditional mobility sharing modes such as carpooling and vanpooling, the CTR survey offers no information regarding the use of new shared mobility options such as ride-hailing, car-sharing, and bike-sharing. Therefore, we relied on the information provided by the PSRC survey data, which is shown in table 3-2 and compared to CTR data.

Table 3-2 Trends in commuting mode share: CTR vs PSRC survey data

	CTR			**PSRC**		
Category	**2015/2016**	**2017/2018**	**Change in %**	**2014**	**2017**	**Change in %**
	%	%		%	%	
Drive alone	58.9%	56.6%	**-2.3%**	68.14%	65.29%	**-2.85%**
Carpool/vanpool	11.4%	11.3%	**-0.1%**	9.10%	12.36%	**3.26%**
Walk/bike	6.7%	7.5%	**0.8%**	11.38%	8.95%	**-2.43%**
Public transit	21.6%	23.2%	**1.6%**	10.38%	12.34%	**1.96%**
Private shuttle	NA	NA	**NA**	0.44%	0.53%	**0.09%**
Car-sharing	NA	NA	**NA**	NA	0.02%	**NA**
Ride-hailing	NA	NA	**NA**	0.04%	0.14%	**0.10%**
Other	1.2%	1.6%	**0.4%**	0.52%	0.36%	**-0.16%**
Total # of trips	**1,207,236**	**1,271,236**		**6,623**	**6,604**	

The trends in commute mode choice were somewhat consistent. Use of driving alone as the commuting mode decreased, and the usage of public transit increased. Differences between the two data sources included a decrease in the mode shares of walking and biking in the PSRC data but a slight increase in the CTR data. Carpooling/vanpooling showed an increase in mode share in the PSRC data but a small decrease in the CTR data. These differences could be due to two reasons. First, the sample size for the PSRC data was smaller than that for the CTR data, which may produce a greater margin of error. Second, the CTR data only included employers and employees at worksites with 100 or more full-time employees. However, the overall consistency between the PSRC and CTR data is encouraging and provides a basis for discussing the potential impacts of the new shared mobility in the region.

Shared mobility options, especially ride-hailing, are increasingly popular. Within only three years (2014 to 2017), the commuting mode share of ride-hailing tripled. Figure 3-3 illustrates this growth. The mode share of ride-hailing in commuting trips grew from 0.04 percent to 0.14 percent. and ride-hailing’s mode share for all trips has increased from 0.08

percent to 0.29 percent. The absolute share of ride-hailing was still relatively small in 2017. However, if it continues to grow at the current pace, one can reasonably expect that future ride-hailing services will play a substantial role in determining travel in the region.

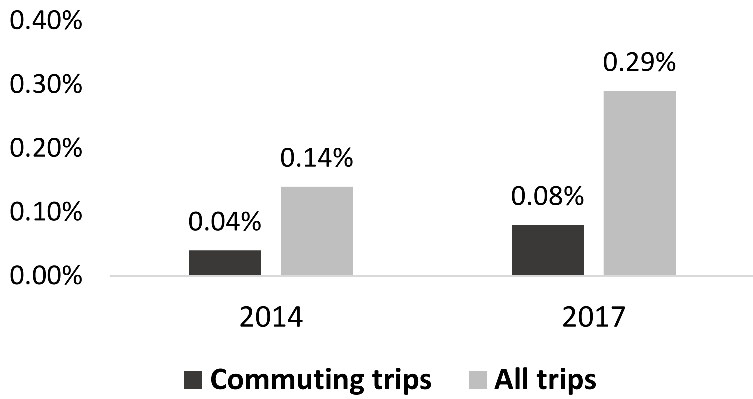


Figure 3-3 Growth in ride-hailing mode share in the Puget Sound region (Puget Sound Household Travel surveys 2014, 2017)

In summary, modes of shared mobility, especially ride-hailing services, are used with increased frequency in the Pacific Northwest. Yet the current design of the CTR survey includes only two traditional shared mobility options, carpooling and vanpooling, without any coverage of new app-based shared mobility options (table 3-3**)**.

Table 3-3 also presents examples of other travel surveys, although their purposes might be different from those of the CTR surveys. These surveys have already accounted for some new shared mobility options in their design. In addition to the PSRC survey, we also refer to the recent 2017 National Household Travel Survey (NHTS) administrated by Federal Highway Administration (FHWA) and the 2018 Commute Survey conducted by the San Diego Association of Governments (SANDAG), the transportation planning agency for San Diego County.

As mentioned, while the CTR employee survey's shared mobility options are limited to carpooling and vanpooling (figure 3-2), the 2015 PSRC survey incorporated taxi and ride-hailing services. It also differentiated between carpooling with members of the household and with non-household members. The 2017 PSRC survey further updated its questionnaire to include car-sharing as an option. The NHTS survey functions as the authoritative source of travel behavior data on the entire U.S. population, and the data provide information on both personal and household travel (Federal Highway Administration, n.d.). The NHTS 2017 survey incorporated ride-hailing and car-sharing as options, although it did not cover carpooling and vanpooling. The 2018 SANDAG survey (True North Research 2018) took a step further by separating individual use of ride-hailing services (Uber, Lyft, etc.) and pooled services that allow passengers to share rides (Uber Pool, Lyft Line, etc.) because the latter is likely to have a much higher vehicle occupancy rate. Overall, it is clear that travel surveys are being updated to include new shared mobility options into their questions.

Table 3-3 The inclusion of shared mobility modes as a commuting mode choice in the questions in various surveys

<table>
<tr><th></th><th>CTR Employee Survey</th><th>PSRC 2015</th><th>PSRC 2017</th><th>NHTS 2017</th><th>SANDAG (San Diego) 2018</th></tr>
<tr><td rowspan="4">Traditional shared mobility options</td><td>Carpool</td><td>Carpool with household members</td><td>Carpool with household members</td><td></td><td>Carpool</td></tr>
<tr><td></td><td>Carpool with people not in the household</td><td>Carpool with people not in the household</td><td></td><td></td></tr>
<tr><td>Vanpool</td><td>Vanpool</td><td>Vanpool</td><td></td><td>Vanpool</td></tr>
<tr><td></td><td>Taxi (e.g., Yellow Cab)</td><td>Taxi (e.g., Yellow Cab)</td><td rowspan="4">Taxi / Limo (including Uber / Lyft)

Rental car (including Zipcar / Car2Go)</td><td>Taxi</td></tr>
<tr><td rowspan="3">New shared mobility options</td><td></td><td>Other hired car service (e.g. Lyft, Uber)</td><td>Other hired car service (e.g. Lyft, Uber)</td><td>On-demand rideshare service like Uber, Lyft, or Waze Carpool</td></tr>
<tr><td></td><td></td><td></td><td>Pooled rideshare service (Uber Pool, Lyft Line)</td></tr>
<tr><td></td><td></td><td>Carshare vehicle (e.g., Zipcar, Car2Go, RelayRides, etc.)</td><td>Zipcar</td></tr>
</table>

To sum up, the CTR survey could benefit from adopting the following approaches to update Question 4 in the employee survey:

- Add a new option that is related to the use of ride-hailing services. It could either be designed as an option that combines both taxi and new ride-hailing services (Uber, Lyft, etc.) or preferably as separated options.
- To fully capture the nuances in the usage of ride-hailing services, it could further separate typical ride-hailing services (Uber, Lyft, etc.) from shared ride-hailing services (Uber Pool, Lyft Line, etc.).
- Depending on the policy interests and capacity of WSDOT, it is also recommended that the CTR survey include other new shared mobility options such as car-sharing and bike-sharing
- Differentiate between traditional carpooling and taxi services and app-based services.

3.3. Gap #2: The Lack of Correspondence between the CTR Program's Employee Survey and Employer Survey

The CTR employer survey asks questions about the employer's transportation policies, programs, and infrastructure available at the worksite, including many that are related to mobility sharing. Table 3-4 summarizes the shared mobility-related questions in the CTR program's employer survey.

Table 3-4 List of shared mobility-related questions in the CTR employer survey

Category	List of shared mobility-related questions in CTR's employer survey
Cash benefit	Is your organization aware that employers can receive a tax credit or grant for ridesharing subsidies?
	Has this employer received a tax credit or grant for ridesharing subsidies?
	Are you aware that employers may allow employees to set aside a portion of their pre-tax income for the purpose of purchasing a transit or vanpool pass?
	Does this employer allow employees to set aside a portion of their pre-tax income for transit or vanpool fare?
Vehicle/ infrastructure support	Does your organization offer employer provided vehicles for vanpooling?
	Does your organization offer employer provided vehicles for carpooling?

	Does your organization offer employer provided vehicles for work-related business trips?
	Does your organization offer employer provided vehicles for Non-work-related errands
	Is the employer-provided internal circulator system available at your worksite?
	Is the guaranteed/emergency ride home program available at your worksite?
	Are the employer-provided bicycles available at your worksite?
	Do you offer on-site loading/unloading zones or shelters for non-SOVs?
Subsidy/Discount	Do you offer to employees vanpool subsidy/incentive?
	Do you offer to employees vanshare subsidy/incentive?
	Do you offer to employees carpool subsidy/incentive?
Parking	How many on-site/off-site parking spaces does your organization own/lease for employee usage?
	How many of the parking spaces listed above are reserved for HOV parking?
	How much do you charge employees per month for drive-alone (SOV) parking?
	How much do you charge employees per month for carpool parking?
	How much do you charge employees per month for vanpool parking?
	How many SOV spaces were eliminated in the past 12 months?

Notes: Green color indicates that responses to the question can be directly compared with CTR's employee survey responses to evaluate the potential impacts of employer policies on employees' travel mode choice.

As shown in table 3-4, the CTR employer survey asks a relatively extensive list of questions that are related to shared mobility, covering many common TDM strategies, including cash benefits, vehicle/infrastructure support, ride-match program, monetary subsidy/discount, and parking strategies. It would be ideal if the outcomes of these policies could be directly evaluated through the CTR program's employee survey, so that every employer could tell which shared mobility policy was effective at reducing the use of SOVs.

However, fewer than half of employer policies can be directly evaluated by tallying answers to questions 11 and 12 in the CTR employee survey (see figure 3-4, where red rectangles mark the choice options related to shared mobility policies/programs), which asks about factors affecting the decision to commute by driving alone. The rest of the policies in table 3-4 can only be evaluated indirectly through statistical modeling and regression analysis of employees' mode choice, which requires much richer data at the individual level, as well as sophisticated data processing and analysis by the Employee Transportation Coordinator or anyone who conducts the analysis. In other words, if employers witness changes in their employees' commuting mode choices, it is difficult for them to figure out which policy or policies are working effectively. As mentioned in the introduction, some studies have sought to understand the impacts of employers' policies. For example, using ORCA smart card records to evaluate the performances of employers' transit subsidy program (Hallenbeck et al. 2017; Aras 2017) or operationalizing a series of additional variables and using a series of statistical models (Wu and Shen 2019). However, a more consistent design of the CTR employer and employee surveys would achieve better analytical outcomes with fewer burdens.

Besides increasing the correspondence between the employer and employee surveys, there are additional improvements that could potentially be made. As discussed in the previous section, mobile-ICTs and smartphone apps nowadays play increasingly important roles in shaping travel behavior, yet the survey addresses the use of smartphone apps and related commuting mode choices in only a limited way. In fact, many employers in our region have started to encourage the use of new app-based shared mobility options (e.g., ride-hailing, bike-sharing) by offering subsidies and discounts. Also, many employers have started collaborating with app-based carpooling service providers (e.g., Scoop, Waze Carpool) to match carpooling (King County Metro 2019; Shen et al., in 2019). If the CTR survey were to ask about these new policies that have been playing substantial roles in the era of the ubiquitous use of smartphone apps and the growing use of shared mobility, employers in the region would be able to learn about the impacts of these policies and make informed decisions.

11. When you do not drive alone to work, what are the three most important reasons?

- ○ Financial incentives for carpooling, bicycling or walking
- ○ Free or subsidized bus, train, vanpool pass or fare benefit
- ○ Personal health or well-being
- ○ Cost of parking or lack of parking
- ○ To save money
- ○ To save time using the HOV lane
- ○ I have the option of teleworking
- ○ Driving myself is not an option
- ○ Emergency ride home is provided
- ○ I receive a financial incentive for giving up my parking space
- ○ Preferred/reserved carpool/vanpool parking is provided
- ○ Environmental and community benefits
- ○ Other: ______________________________

12. When you drive alone to work, what are the three most important reasons?

- ○ Riding the bus or train is inconvenient or takes too long
- ○ I need more information on alternative modes
- ○ My job requires me to use my car for work
- ○ My commute distance is too short
- ○ Family care or similar obligations
- ○ I like the convenience of having my car
- ○ Bicycling or walking isn't safe
- ○ There isn't any secure or covered bicycle parking
- ○ Other: ______________________________

Note: Red rectangles mark the choice options related to shared mobility policies/programs.

Figure 3-4 Corresponding questions in the CTR employee survey

Admittedly, to be able to cross-reference questions in the CTR employee and employer surveys will require that some changes be made in the CTR survey design. To facilitate a smooth transition, we propose that WSDOT take the following short-term and long-term actions.

In the short run, the following updates can be applied with minor revisions to the survey content:

- Add questions in the employer survey to cover new app-based shared mobility related policies, e.g., ride-hailing subsidy/discounts, bike-sharing subsidy/discounts, partnerships with third-party app-based carpooling companies or other shared mobility service providers.

- Add questions regarding other major TDM policies that are commonly used. For example, questions regarding the availability and the number of employer buses.
- Given the ubiquitous use of the smartphone apps nowadays, add questions asking whether employers use an app to connect employees to various commuting options.

In the long run, WSDOT can re-design Question 11 and Question 12 in the employee survey (see the red rectangles in figure 3-4) to match the employers' policies in the employer survey. If the CTR survey will remain in paper form, this could be done by adding more shared mobility-related factors into Question 11 and Question 12. Or if WSDOT plans to discontinue the paper survey and make the survey solely electronic/online, Question 11 and Question 12 could be customized to accommodate variations in TDM policies among different worksites.

3.4. Conclusions

The Washington State CTR program has long been a successful statewide travel demand management program, generating impressive performance since its implementation. The emergence of new shared mobility options requires changes and additions to the surveys administered to CTR-affected employers and employees in order to evaluate the program performance. On the one hand, new shared mobility options have challenged the dominance of the SOV, thus contributing to CTR goals. On the other hand, some of the new mobility services, especially ride-hailing, may replace transit and bike trips, thereby negatively affecting existing sustainable mobility options. Those services are also likely to add trips. To help CTR programs continue to thrive in the era of shared mobility, the CTR survey should be updated to collect information regarding the use of new shared mobility options.

To summarize, this report emphasizes that in the short run, by adding only a few more options in the mode choice questions in the employee survey (Question 4, 11 and 12), WSDOT will gather richer information regarding the use of traditional and new shared mobility options. In the long run, CTR employer and employee surveys should be redesigned to better correspond to each other, so that employers' TDM efforts can be directly evaluated through employees' commuting mode choices. In all, if the CTR survey incorporates more questions regarding the use of new shared mobility options as well as the use of apps to support the commute trip, it can serve as an invaluable information source not only for WSDOT itself, but also for all transportation researchers and TDM policymakers who are interested in studying travel behavior and policy responses in the era of shared mobility.

CHAPTER 4. Technical Database Description for Shared Micro-Mobility

4.1. Introduction

In recent years another form of shared mobility has become popular called “shared micro-mobility.” This includes a variety of low speed vehicles (typically less than 25 mph) such as bicycles, ebikes, and electric scooters. Shared micro-mobility companies deploy large fleets of their vehicles throughout cities worldwide. Customers rent the bicycles or scooters through various payment schemes and methods, such as rental via a smart phone app for $2 dollars per 30 minutes. Most trips are short (<1.5 miles) and in one direction. The first generation of shared micro-mobility utilized docking stations from which customers were required to pick up and drop off bicycles. The next generation utilized GPS tracking and sophisticated self-locking systems to allow bicycles and scooters to be picked up and dropped off anywhere in the city. These are referred to as free-floating or dockless systems. Today many systems are a hybrid mix of station-based and dockless systems, and all include GPS location tracking.

The introduction of GPS tracking of bicycles and scooters provides an exciting opportunity to study and analyze travel demand for shared micro-mobility. This project aimed to study travel demand over a one-year period in order to create models for seasonal variation and trip generation (production and attraction). At the time of this project, no company was making one year’s worth of historical raw GPS data readily available, and although we pursued opportunities to purchase data, our negotiations with various companies stalled as they failed to establish data acquisition policies that would balance their concerns for customer privacy and the desire for external research. Nevertheless, a few companies provide real-time, live feeds of bike and scooter location data that are updated every minute on the Internet. These data are not automatically archived, so they do not provide the ability to conduct post-annum historical analysis. Consequently, we created a computer program to continuously “scrape” the live feeds and archive the data in an online database cloud.

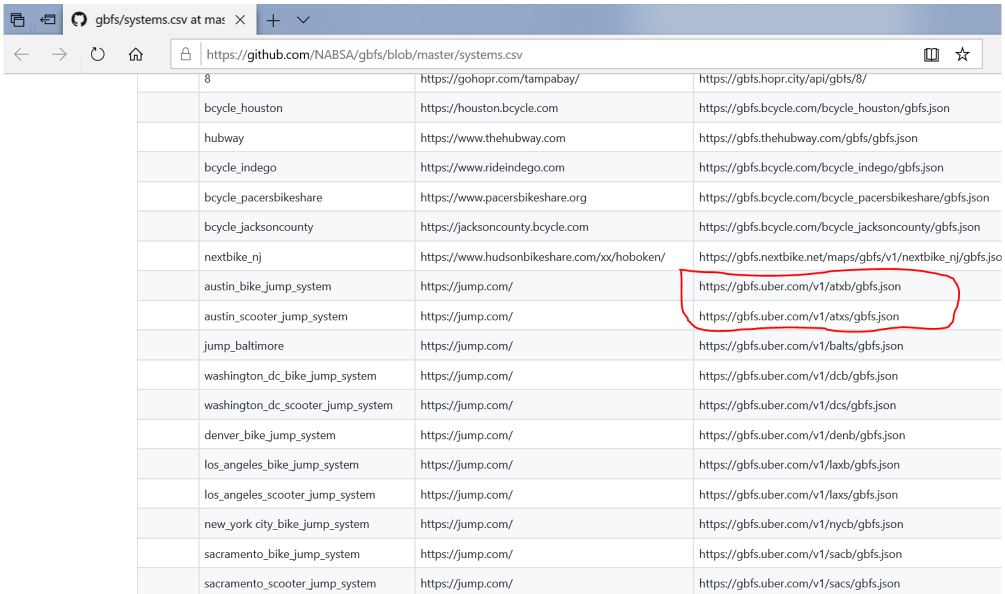
This chapter presents a technical description of the online database archive system. The chapter is written for people who are interested in how the system was created and to provide documentation for our research team for future modification. The system began archiving data in October 2019 with the intent to collect data from two companies in five cities for the entire year of 2020[1]. This would provide one complete of year of data, which is needed to model *annual* seasonal variation and *annual* trip generation. In the meantime, we performed a pilot study of annual data that were spatially modified and truncated for privacy concerns by the City of Portland. The pilot study analysis is presented in the next chapter.

4.2. Shared Micro-Mobility Data Feed

A nonprofit advocacy group called the North American Bikeshare Association (NABSA) devised a technical specification standard for data feeds from shared micro-mobility companies called the General Bikeshare Feed Specification (GBFS). As of this writing, 165 shared micro-mobility companies in 274 cities around the world provide GBFS data.

The GBFS website provides a list of the participating companies and cities on a page called systems.[2] Figure 4-1 shows a screenshot of the list with a read ring showing example data feed URLs. This column can be found by scrolling to the far-right of the table (the column can be easily missed because it lies off screen). You can paste the URL in a browser to see the specific URLs for that company and city, as shown in figure 4-2. Next, find the URL for "free_bike_status," which will be the desired data feed.

[1] Unfortunately, as this report goes to publication there is an ongoing global pandemic of coronavirus, and all shared micro-mobility companies in the United States have curtailed their services. Many of the live data feeds have been altered or discontinued. We hope to resume archiving data for 2021.
[2] The GBFS homepage: https://github.com/NABSA/gbfs



gbfs/systems.csv at mas
https://github.com/NABSA/gbfs/blob/master/systems.csv

	8	https://gohopr.com/tampabay/	https://gbfs.hopr.city/api/gbfs/8/
	bcycle_houston	https://houston.bcycle.com	https://gbfs.bcycle.com/bcycle_houston/gbfs.json
	hubway	https://www.thehubway.com	https://gbfs.thehubway.com/gbfs/gbfs.json
	bcycle_indego	https://www.rideindego.com	https://gbfs.bcycle.com/bcycle_indego/gbfs.json
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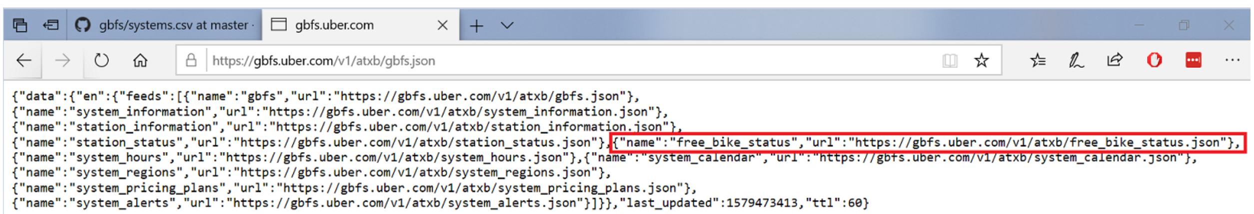
	austin_bike_jump_system	https://jump.com/	https://gbfs.uber.com/v1/atxb/gbfs.json
	austin_scooter_jump_system	https://jump.com/	https://gbfs.uber.com/v1/atxs/gbfs.json
	jump_baltimore	https://jump.com/	https://gbfs.uber.com/v1/balts/gbfs.json
	washington_dc_bike_jump_system	https://jump.com/	https://gbfs.uber.com/v1/dcb/gbfs.json
	washington_dc_scooter_jump_system	https://jump.com/	https://gbfs.uber.com/v1/dcs/gbfs.json
	denver_bike_jump_system	https://jump.com/	https://gbfs.uber.com/v1/denb/gbfs.json
	los_angeles_bike_jump_system	https://jump.com/	https://gbfs.uber.com/v1/laxb/gbfs.json
	los_angeles_scooter_jump_system	https://jump.com/	https://gbfs.uber.com/v1/laxs/gbfs.json
	new_york city_bike_jump_system	https://jump.com/	https://gbfs.uber.com/v1/nycb/gbfs.json
	sacramento_bike_jump_system	https://jump.com/	https://gbfs.uber.com/v1/sacb/gbfs.json
	sacramento_scooter_jump_system	https://jump.com/	https://gbfs.uber.com/v1/sacs/gbfs.json

Figure 4-1 GBFS data feed URLs

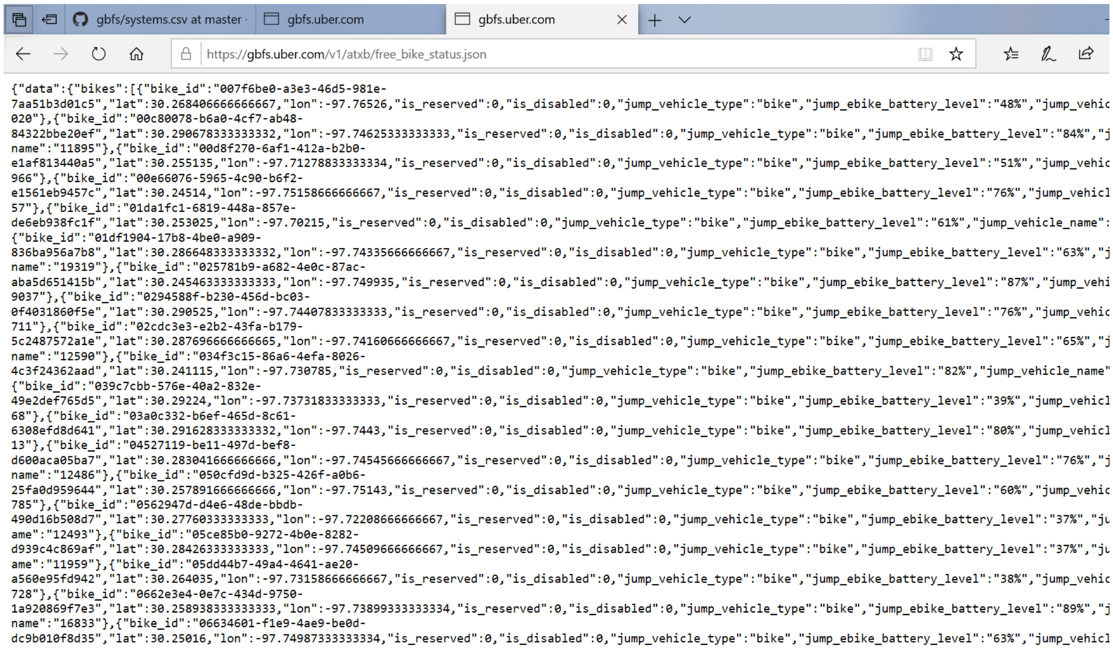


gbfs/systems.csv at master · gbfs.uber.com
https://gbfs.uber.com/v1/atxb/gbfs.json

{"data":{"en":{"feeds":[{"name":"gbfs","url":"https://gbfs.uber.com/v1/atxb/gbfs.json"},
{"name":"system_information","url":"https://gbfs.uber.com/v1/atxb/system_information.json"},
{"name":"station_information","url":"https://gbfs.uber.com/v1/atxb/station_information.json"},
{"name":"station_status","url":"https://gbfs.uber.com/v1/atxb/station_status.json"},{"name":"free_bike_status","url":"https://gbfs.uber.com/v1/atxb/free_bike_status.json"},
{"name":"system_hours","url":"https://gbfs.uber.com/v1/atxb/system_hours.json"},{"name":"system_calendar","url":"https://gbfs.uber.com/v1/atxb/system_calendar.json"},
{"name":"system_regions","url":"https://gbfs.uber.com/v1/atxb/system_regions.json"},
{"name":"system_pricing_plans","url":"https://gbfs.uber.com/v1/atxb/system_pricing_plans.json"},
{"name":"system_alerts","url":"https://gbfs.uber.com/v1/atxb/system_alerts.json"}]}},"last_updated":1579473413,"ttl":60}

Figure 4-2 URLs for a company and city.

Figure 4-3 shows a screenshot of real-time bicycle traffic data for a given city and company. These example data are for bicycles that belong to the company Jump in Austin, Texas. The data are real-time, and they are updated about every second. As shown below, the format used by the data feed consists of a list of records, such that each record belongs to an individual rental bike. Information such as the bike's current latitude/longitude coordinates, electric battery level, unique ID, etc., are included for each record, and the records are updated as the values of the parameters in the record change. For instance, over the course of 5 seconds, the latitude/longitude values reported for a given rental bicycle will change according to the movement of the bicycle, as the web page updates each second.



{"data":{"bikes":[{"bike_id":"007f6be0-a3e3-46d5-981e-
7aa51b3d01c5","lat":30.268406666666667,"lon":-97.76526,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"48%","jump_vehic
020"},{"bike_id":"00c80078-b6a0-4cf7-ab48-
84322bbe20ef","lat":30.290678333333332,"lon":-97.74625333333333,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"84%","j
name":"11895"},{"bike_id":"00d8f270-6af1-412a-b2b0-
e1af813440a5","lat":30.255135,"lon":-97.71278833333334,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"51%","jump_vehic
966"},{"bike_id":"00e66076-5965-4c90-b6f2-
e1561eb9457c","lat":30.24514,"lon":-97.75158666666667,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"76%","jump_vehicl
57"},{"bike_id":"01da1fc1-6819-448a-857e-
de6eb938fc1f","lat":30.253025,"lon":-97.70215,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"61%","jump_vehicle_name":
{"bike_id":"01df1904-17b8-4be0-a909-
836ba956a7b8","lat":30.286648333333332,"lon":-97.74335666666667,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"63%","j
name":"19319"},{"bike_id":"025781b9-a682-4e0c-87ac-
aba5d651415b","lat":30.245463333333333,"lon":-97.749935,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"87%","jump_vehi
9037"},{"bike_id":"0294588f-b230-456d-bc03-
0f4031860f5e","lat":30.290525,"lon":-97.74407833333333,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"76%","jump_vehic
711"},{"bike_id":"02cdc3e3-e2b2-43fa-b179-
5c2487572a1e","lat":30.287696666666665,"lon":-97.74160666666667,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"65%","j
name":"12590"},{"bike_id":"034f3c15-86a6-4efa-8026-
4c3f24362aad","lat":30.241115,"lon":-97.730785,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"82%","jump_vehicle_name"
{"bike_id":"039c7cbb-576e-40a2-832e-
49e2def765d5","lat":30.29224,"lon":-97.73731833333333,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"39%","jump_vehicl
68"},{"bike_id":"03a0c332-b6ef-465d-8c61-
6308efd8d641","lat":30.291628333333332,"lon":-97.7443,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"80%","jump_vehicl
13"},{"bike_id":"04527119-be11-497d-bef8-
d600aca05ba7","lat":30.283041666666666,"lon":-97.74545666666667,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"76%","j
name":"12486"},{"bike_id":"050cfd9d-b325-426f-a0b6-
25fa0d959644","lat":30.257891666666666,"lon":-97.75143,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"60%","jump_vehic
785"},{"bike_id":"0562947d-d4e6-48de-bbdb-
490d16b508d7","lat":30.277603333333333,"lon":-97.72208666666667,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"37%","ju
ame":"12493"},{"bike_id":"05ce85b0-9272-4b0e-8282-
d939c4c869af","lat":30.284263333333333,"lon":-97.74509666666667,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"37%","ju
ame":"11959"},{"bike_id":"05dd44b7-49a4-4641-ae20-
a560e95fd942","lat":30.264035,"lon":-97.73158666666667,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"38%","jump_vehic
728"},{"bike_id":"0662e3e4-0e7c-434d-9750-
1a920869f7e3","lat":30.258938333333333,"lon":-97.73899333333334,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"89%","j
name":"16833"},{"bike_id":"06634601-f1e9-4ae9-be0d-
dc9b010f8d35","lat":30.25016,"lon":-97.74987333333334,"is_reserved":0,"is_disabled":0,"jump_vehicle_type":"bike","jump_ebike_battery_level":"63%","jump_vehicl

Figure 4-3 GBFS free bike status data

The intent of GBFS is to provide real-time location data, not historical data. The creators imagined that the data might be used, for example, by a web developer who wanted to publish dynamic maps of bicycle availability. GBFS was not intended for historical analysis. Consequently, it was necessary to create a computer program to retrieve and archive the real-time data continuously for a desired timespan to conduct historical analysis. This process is called scraping. Our system was set up to scrape GBFS data once every minute for an entire year.

Various fields of data can be scraped. The most important are timestamp, vehicle_id, latitude, and longitude. An active community of GBFS users and contributors discusses different aspects of GBFS in online chat rooms, and there has been considerable discussion about security concerns. Some argue that it might be possible to reconstruct bicycle trips and exploit the data for nefarious purposes and perhaps even determine the personal identity of the bike share customer. When we started this project, all companies were providing vehicle_id, but over time a few companies discontinued providing that field in response to privacy concerns. This makes it extremely difficult, if not impossible, to reconstruct the movements of an individual bike throughout the day. As of this writing the company Jump was still providing vehicle_id. Consequently, this project focused on scraping Jump data.

4.3. Cloud Technologies

Not all the information from the data feed was needed for this project. Some fields were not relevant, but more importantly some records were essentially redundant because stationary bikes and scooters report the same GPS coordinates, or roughly the same coordinates, with each scrape. So once a day, the system goes back through the data collected from the previous day and removes the duplicate latitude/longitude records that are not needed. These tasks are accomplished by using a system of scripts, cloud databases, and scheduling technologies. Several different cloud computing platforms were initially considered, including Amazon Web Services (AWS), Microsoft Azure, and IBM Cloud. AWS was eventually chosen because it offered the widest array of cloud technologies for a minimal price. The following are descriptions of each technology used in the system.

4.3.1. AWS Elastic Cloud Compute

AWS Elastic Cloud Compute (EC2) is a cloud computing service provided by AWS. Using this service, users set up and log into remote cloud computers called instances to run large-scale computations, and they are only charged for the amount of compute resources that they use. The work of collecting, analyzing, and archiving data from GBFS is done by three EC2 cloud computers that were set up for this project, shown in figure 4-4. The cloud computer named *Test_Spinup* is used for development, and the computers called *Scraper* and *Consolidator* are used in production. *Scraper* runs continuously to scrape the GBFS data, and *Consolidator* analyzes and archives the data set collected each day, which is why it is more expensive to run. To lower the cost incurred by using this high-performance compute instance, a system was set up using AWS Cloudformation, described in a later section, to run the instance at only a particular time of the day. This was accomplished by setting up an automatic schedule called *ec2-times* in the AWS cloud environment that was linked to *Consolidator* by adding it as a tag value. Figure 4-4 is a screenshot of the three EC2 instances used in this project ,with *Consolidator* selected to show its tag value containing the schedule that controls when it runs throughout the day.

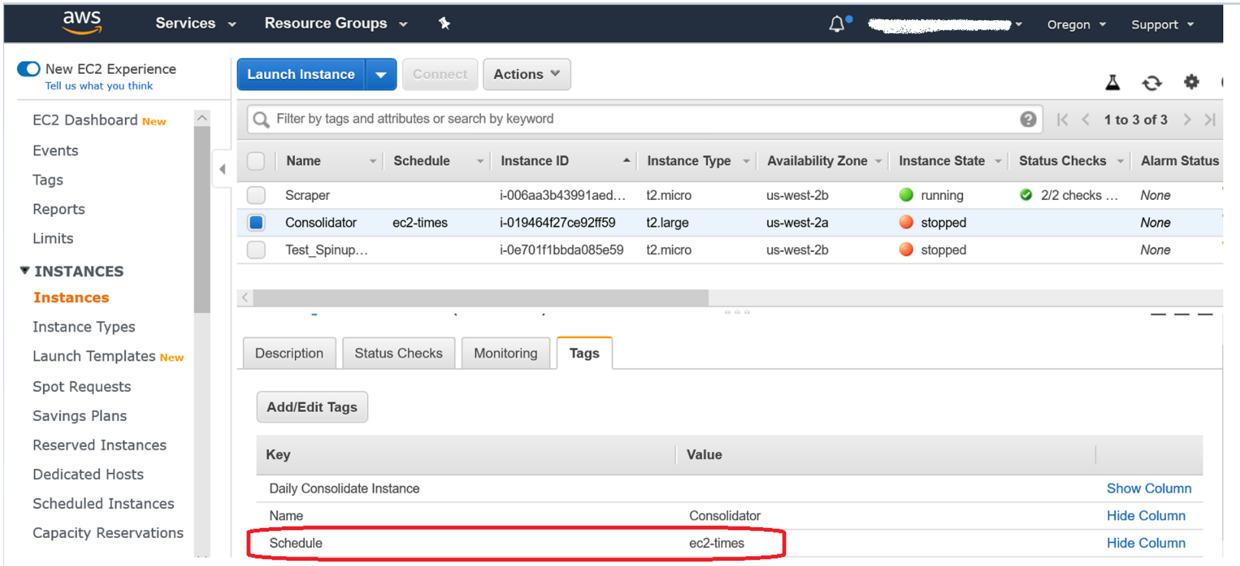


Figure 4-4 AWS EC2 instances

The AWS documentation provides a useful tutorial to set up an EC2 cloud computer.[3] The documentation also provides a helpful table showing the various types of cloud computers provided for EC2.[4] Each type of compute instance corresponds to a unique use case. For example, the c5 family of instances are compute-optimized, meaning that they use typical memory performance combined with optimized processing power. Also, the t2 family of instances is used for general computing, and the r5 family of instances are memory optimized, meaning that they are equipped with standard processing capabilities combined with optimized memory performance.

The cost of running these cloud computers depends on demand.[5] The authors recommend that after completing the EC2 setup tutorial users navigate to *Instances* in the left-hand column shown in figure 4-5. If no instances are displayed, users should check to ensure that they are in the correct geographic zone in the top-right corner of the screen.

[3] https://docs.aws.amazon.com/AWSEC2/latest/UserGuide/launching-instance.html
[4] https://aws.amazon.com/ec2/instance-types/
[5] https://aws.amazon.com/ec2/pricing/on-demand/

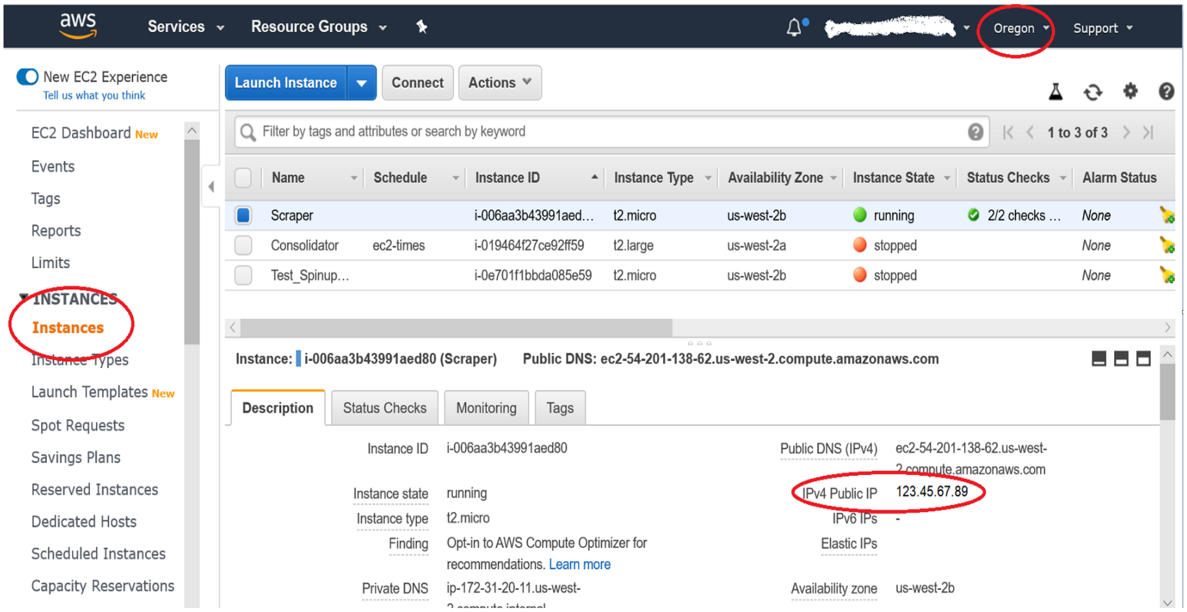


Figure 4-5 The public IP address of EC2

Log into an instance and select its checkbox to copy the public IP address, as indicated by the red circle. Next, for Windows users, start the application *Windows Powershell*, and for Mac users, start a terminal session. The following steps rely on the ssh utility, which performs the same regardless of the operating system being used. Then, in the command prompt, type the following line and hit enter:

ssh -i path/to/private_key/private_key.pem user_name@123.45.67.89

If the EC2 instance being logged into is an Ubuntu machine, then the username is ubuntu. If it is an Amazon Linux AMI, the username is ec2-user. Figure 4-6 shows the command required to log into the ubuntu EC2 instances. Figure 4-7 shows the authentication message, for which the response should be *yes*. Finally, users should see a screen similar to figure 4-8. This means that users are now located in the home directory of the cloud computer they have just set up. The cloud computer runs a Linux operating system.[6]

[6] https://tutorials.ubuntu.com/tutorial/command-line-for-beginners#0

```
Windows PowerShell
Windows PowerShell
Copyright (C) Microsoft Corporation. All rights reserved.

Try the new cross-platform PowerShell https://aka.ms/pscore6

PS C:\Users\Matthew> ssh -i C:\Users\Example\AWS\private_key.pem ubuntu@123.45.67.89
```

Figure 4-6 Logging into an EC2 instance

```
The authenticity of host '52.26.235.60 (52.26.235.60)' can't be established.
ECDSA key fingerprint is SHA256:10wllw3SwUYO10vmEUMfNNv8WxTDIh0otqXUtoKB+Y4.
Are you sure you want to continue connecting (yes/no)? yes
```

Figure 4-7 Authentication message

```
Welcome to Ubuntu 18.04.3 LTS (GNU/Linux 4.15.0-1057-aws x86_64)

 * Documentation:  https://help.ubuntu.com
 * Management:     https://landscape.canonical.com
 * Support:        https://ubuntu.com/advantage

  System information as of Mon Jan 20 22:52:19 UTC 2020

  System load:  0.18              Processes:           91
  Usage of /:   23.7% of 7.69GB   Users logged in:     0
  Memory usage: 15%               IP address for eth0: 172.31.26.56
  Swap usage:   0%

 * Overheard at KubeCon: "microk8s.status just blew my mind".

     https://microk8s.io/docs/commands#microk8s.status

 * Canonical Livepatch is available for installation.
   - Reduce system reboots and improve kernel security. Activate at:
     https://ubuntu.com/livepatch

2 packages can be updated.
0 updates are security updates.
```

Figure 4-8 The AWS EC2 home screen

4.3.2. AWS Relational Database Service and pgAdmin

The AWS Relational Database Service (RDS) is a cloud database service. It offers a variety of database tools, including PostgreSQL, MySQL, Aurora, etc. This project chose a PostgreSQL database because it is open source and has a well-established interface with Python. The Python library that was used to access the PostgreSQL database for this project hosted in RDS is called *psycopg2*. More information about *psycopg2* is given in the source code for this project.

A step by step tutorial is available to create an RDS database.[7] Modifications can be made by accessing the database.[8] Select *Databases* to see a screen like that in figure 4-10.

Figure 4-9 PostgreSQL and AWS RDS logos

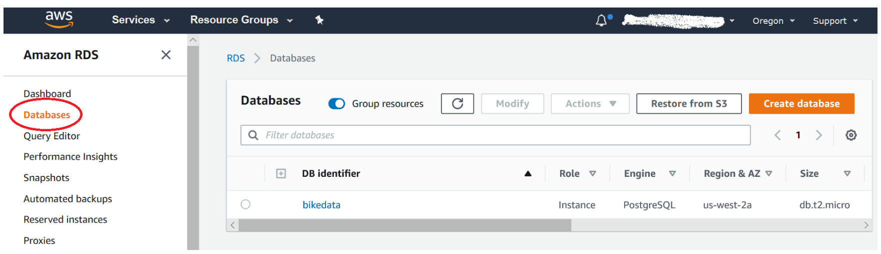


Figure 4-10 Home screen of the AWS RDS

After the database has been selected, text boxes will appear as shown in figure 4-11 that contain information about the database, such as its host name, port number, and networking settings. Take note of the *Endpoint* value and *Port* value because these will be needed to connect to the database.

It is also possible to access the database without using a Python interface. This project used a software tool called pgAdmin for this purpose.[9] This tool allows users to make a connection to a database and manually run queries and operations that can add, remove, and change the data stored in the database.

---

7 https://docs.aws.amazon.com/AmazonRDS/latest/UserGuide/CHAP_Tutorials.WebServerDB.CreateDBInstance

8 https://console.aws.amazon.com/rds

9 https://www.pgadmin.org/download/

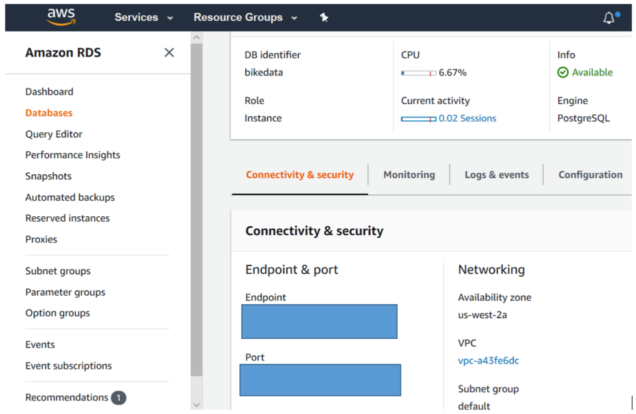


Figure 4-11 Database statistics and info

Once users have successfully installed pgAdmin, they can connect to the database in RDS by following a tutorial.[10] They will need the *Endpoint* and *Port* values discussed above. The *Host name/address* value in the following tutorial should be set to the value of *Endpoint* given for the database in the RDS console. The *Port* value in the tutorial should also be set to the value of *Port* given for the database in the RDS console. The username and password mentioned in the tutorial will be the same as the ones that were set when the database was created.

When users are successfully connected, they should see a screen similar that in figure 4-12. To run a query, select the name of the database and then select the lightning bolt button that is circled. This will cause a text editor to appear in which users can type SQL queries as shown in figure 4-13.

[10] https://www.pgadmin.org/docs/pgadmin4/development/server_dialog.html

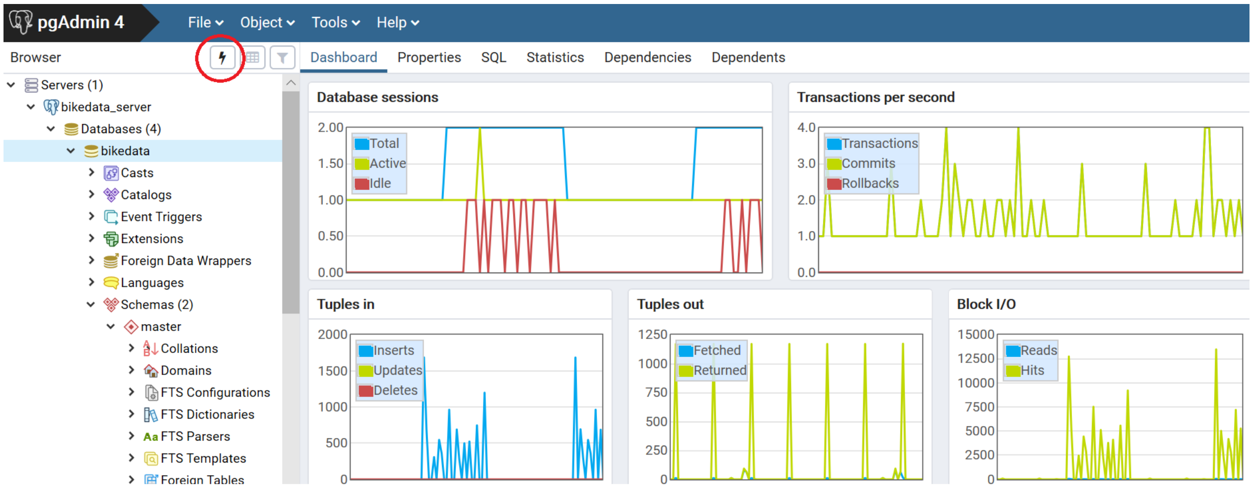


Figure 4-12 pgAdmin home screen

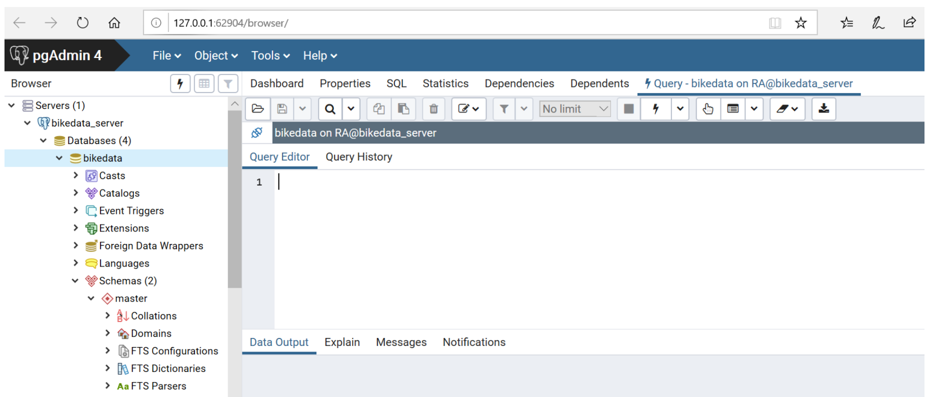


Figure 4-13 Query editor for a selected database

PostgreSQL database organization dictates that a server contains one or more databases, a database contains one or more schemas, a schema contains one or more tables, and a table contains one or columns. A schema is an organization layer of the database that consists of a set of formulas and constraints that define its member tables. A table is defined as a set of columns whose values take on a particular form. One way of conceptualizing schemas and tables is by understanding the following analogy: a database schema is to the tables contained within that schema as a Microsoft Excel file is to the worksheets contained within that Excel file. Just as an Excel worksheet contains columns of data, so a database table contains columns of data, and just as an Excel file can contain multiple worksheets, so a database schema can contain multiple tables.

The database created for this project was named *bikedata*, and one schema named *master* was created for the database. Within the schema *master*, 18 tables were created to serve different purposes. A screenshot of the list of tables within *bikedata* is shown in figure 4-14.

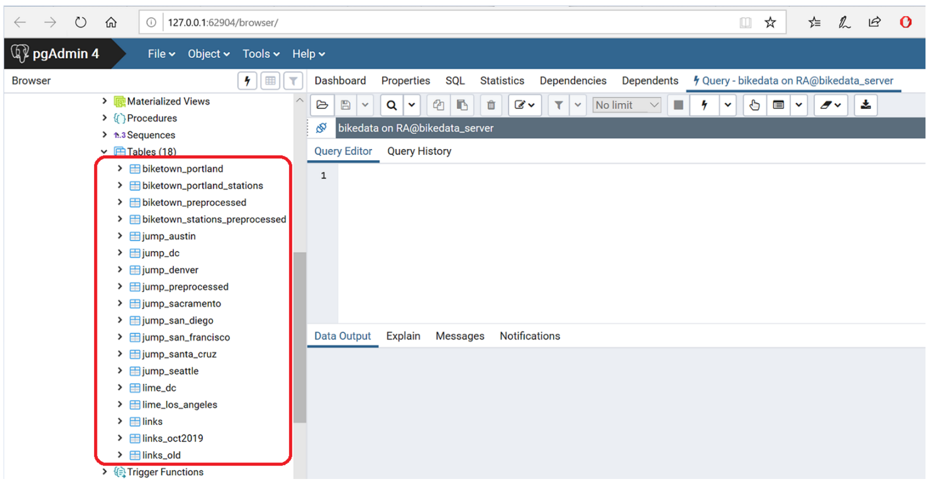


Figure 4-14 List of tables used for the micro-mobility project

Tables whose name end in *preprocessed* store the data collected from the scraping process. These tables are updated once a minute with new data. With the exception of *jump_preprocessed*, tables whose name start with the word *jump* contain the consolidated data for the city in the name of the table. Also, with the exception of *biketown_preprocessed* and *biketown_preprocessed_stations*, tables whose names contain the word *biketown* contain the consolidated data for the city of Portland. The table named *links* is used once a minute by the scraping processes, and it contains the city name, company name, and URL for each GBFS data feed being scraped. All other tables displayed above are obsolete and have been kept purely for archival purposes. More information about the tables created for this process will be given in a later section. To demonstrate how SQL was used during this project, consider the following query:

select * from master.biketown_portland where local_time like '20200103%'

This query will return all data records within the table called *biketown_portland* whose *local_time* column values begin with the number *20200103*. This means that all bicycle traffic records collected from January 3, 2020, in Portland will be returned. Figure 4-15 illustrates this process.

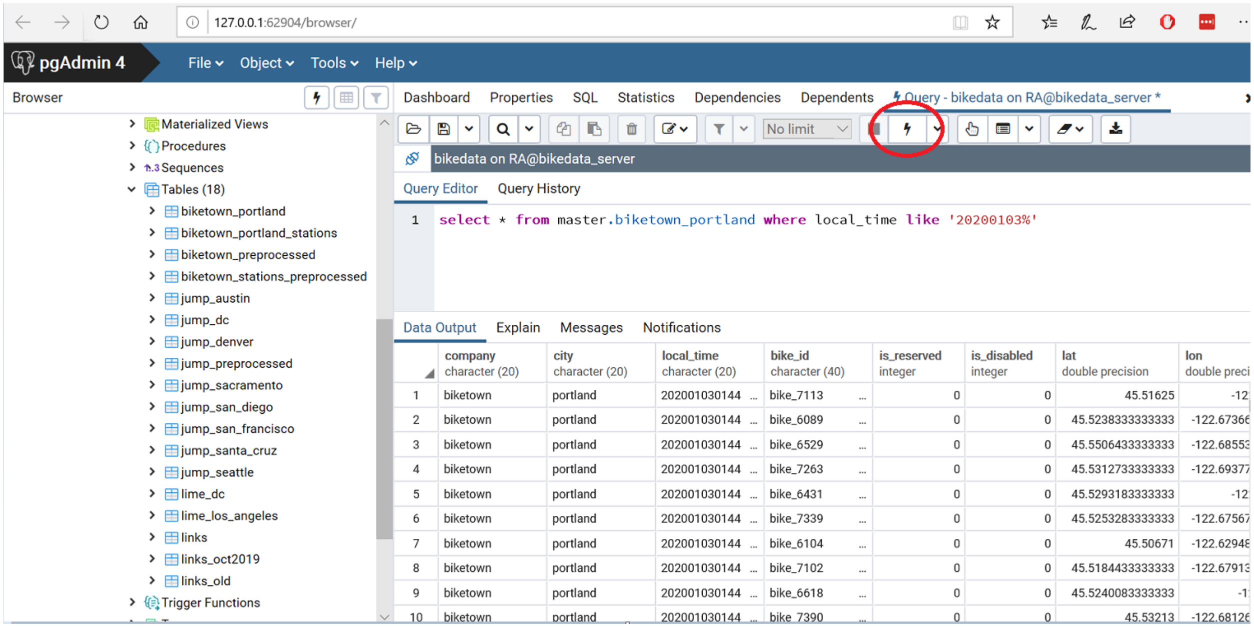


Figure 4-15 Query results

In order to run this query and get the above results, all users have to do is enter the query into the text editor and click the lightning bolt button circled in red. Other useful query tasks include inserting data from the database, deleting data from the database, and modifying data from the database. More information about SQL and the process used to verify the data collected will be discussed in a later section.

4.3.3. AWS Cloudformation

After an initial prototype for the data scraping and consolidating system had been developed, it became apparent that a significant cost was incurred by running the t2.large EC2 instance continuously, even when it was not performing any tasks. Therefore, research began into possible methods that would automatically turn the t2.large EC2 instance on at a specified time and turn it off at a specified time. Eventually, the method that was chosen to do this relied on AWS Instance Scheduler.[11]

The above method relies on creating a stack on the AWS Cloudformation platform. This was done successfully, and the t2.large EC2 instance now starts at 12:50 a.m. and shuts down at

[11] https://docs.aws.amazon.com/solutions/latest/instance-scheduler/welcome.html

3:10 a.m. The consolidation process requires only about 40 minutes to execute, but an additional hour and 40 minutes were included to ensure that the instance runs long enough to complete the process in the event that unexpected latency occurs. Note that this methodology will automatically create AWS lambda functions that run at given intervals to check the time. The lambda function generated for the stack created for this system checks the time once every 5 minutes, which is why 10 minutes of additional time were added before and after the target start and stop times, which were originally selected to be 1:00 a.m. and 3:00 a.m., respectively.

Access the AWS Cloudformation stack created from the above process.[12] If no stacks are displayed on the resulting webpage, click on the geographic region indicated in the top-right corner of the console, as shown in figure 4-16, to ensure that users are in the geographic region that belongs to the instance scheduler that was created. Then select the name of the stack that was created. In the window that appears, select the *Resources* tab, and then select the config table, as shown in figure 4-18. In the window that appears, select the *Items* tab to view the periods and schedules created on this stack.

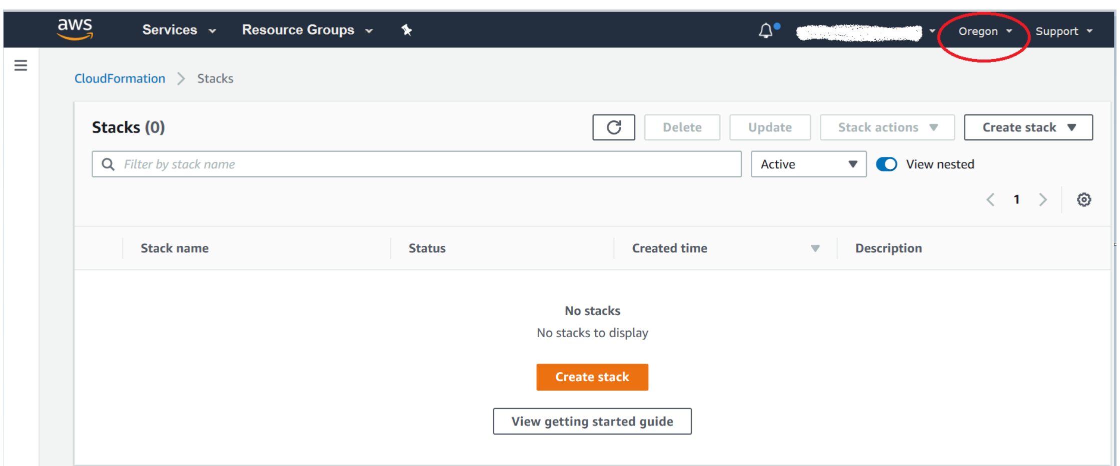


Figure 4-16 AWS Cloudformation home screen

[12] https://console.aws.amazon.com/cloudformation/

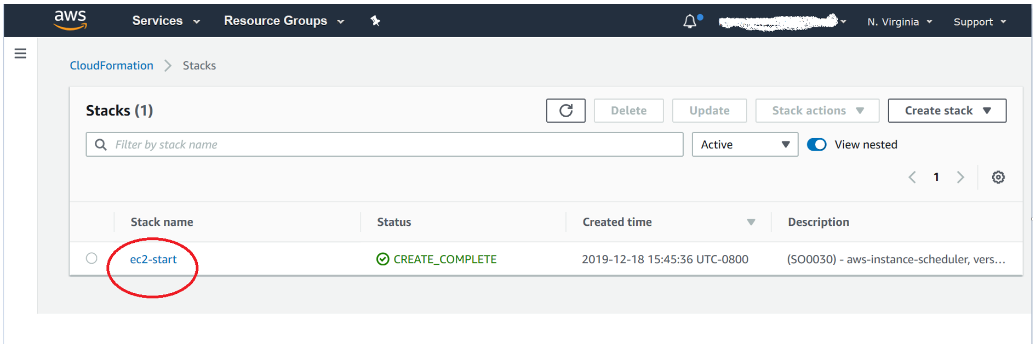


Figure 4-17 AWS Cloudformation stack

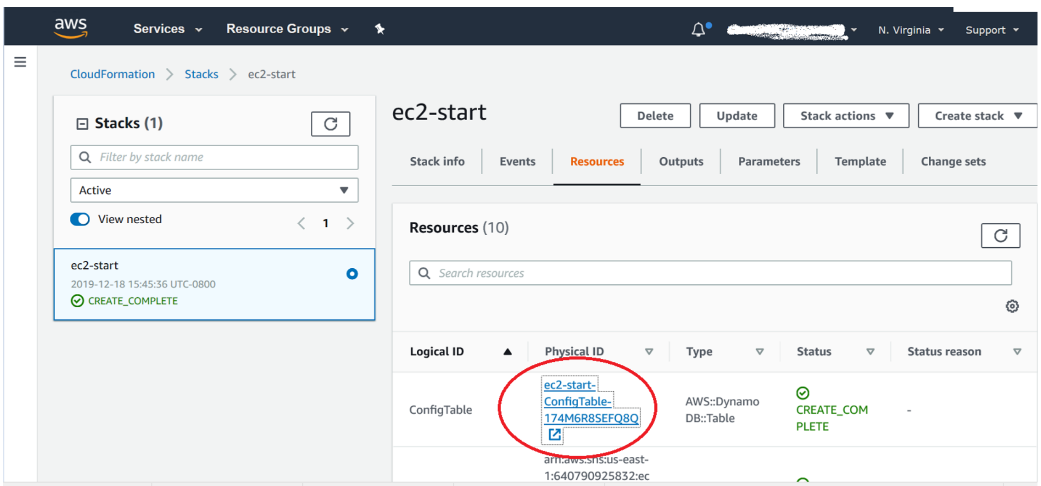


Figure 4-18 Stack configuration table

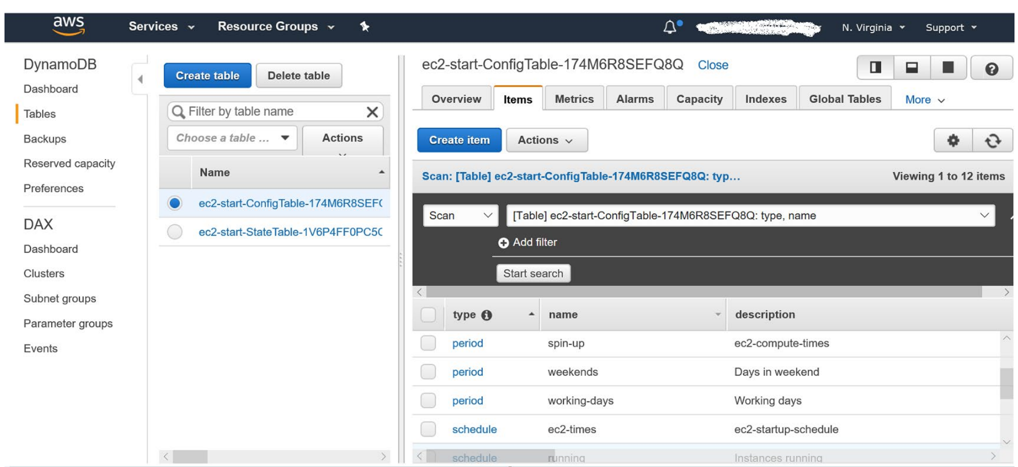


Figure 4-19 Stack configuration table items

Figure 4-20 shows the period called *spin-up,* which is a cloud object that describes the times in which an EC2 instance should start and stop. The window that appears when this object is clicked is shown below. Notice that the time values are in military time format, and that they apply to all days of the week, Sunday through Saturday.

This period is then included in the definition of a formal Schedule, which can be referenced by other cloud resources as shown in a previous section. Below is the window that appears when the schedule called *ec2-times* is clicked. Notice in figure 4-21 that this is the name of the Schedule that was given in the tags of the EC2 instance shown previously. Therefore, to start and stop the EC2 instance automatically, it was first necessary to use the Instance Scheduler method and AWS Cloudformation to create a stack with the desired period and schedule. A tag added to the EC2 instance—whose name was *Schedule* and value was the name given to the schedule created in Cloudformation (in this case *ec2-times)*—triggers the EC2 instance to start and stop automatically.

Also, as mentioned in the documentation for AWS Instance Scheduler, if users choose to edit the stack through the method shown above, they should not edit it through any other method, since that could create a conflict in the stack values that are backed up separately on different cloud services.

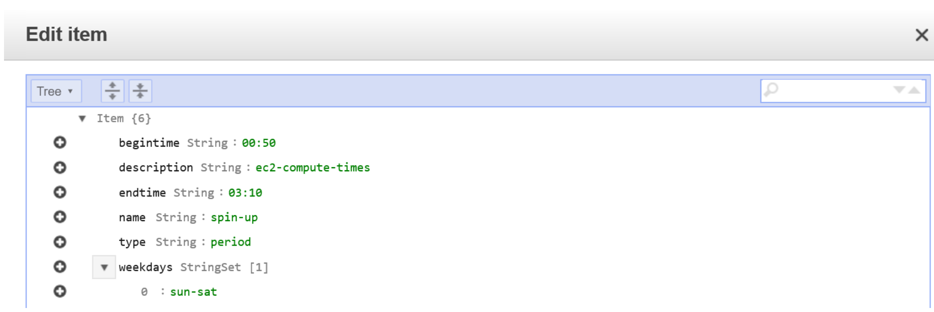


Figure 4-20 Example oeriod in the stack

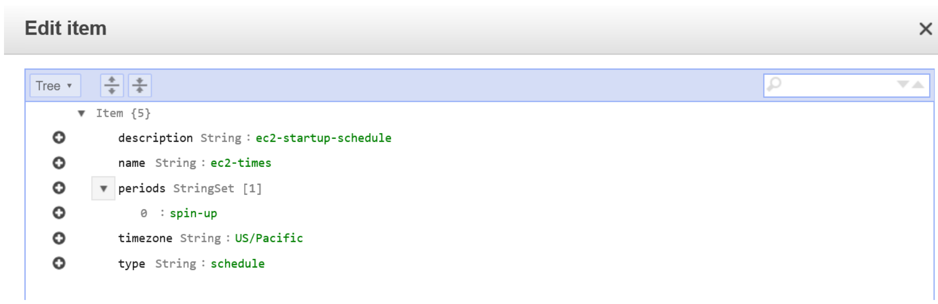


Figure 4-21 Example schedule in stack

4.4. Data Collection and Processing

Two main phases of work are accomplished by the data archival system. First, the system scrapes the GBFS data and stores them in a temporary database table. Second, the system retrieves those data from the temporary tables, performs data processing on them, and stores them in a permanent location in the database.

4.4.1. Scraping Phase

This section describes the *data scraping* phase. The task of scraping GBFS data and storing them in a temporary location in the database is handled by an AWS EC2 instance that was named *Scraper*. This instance is classified as t2.small on the AWS website, meaning that it is a general purpose computing instance. *Scraper* runs continuously, meaning that it is never turned off, and a Python interpreter is installed on this instance. By using a UNIX system utility called *crontab*,[13] the Ubuntu operating system on *Scraper* was configured to run a Python script called *start_scraper.py* once every minute. This script was designed for this research project, and its general process is described in detail below.

1. **Connect to the database:** A secure connection is established between the *bikedata* database and the *start_scraper.py* application process using the *psycopg2* Python library for PostgreSQL and private key encryption protocol.

2. **Get GBFS URLs for live data feeds:** An SQL query is run to the table called *links* in *bikedata* that returns each GBFS URL that is being scraped, as well as the city and company to which it belongs.

[13] https://linuxconfig.org/linux-crontab-reference-guide

3. **Scrape the data:** The GBFS URLs are scraped using the Python library *requests*, and the desired data are selected from the content of the data scraped from them. The Python library *datetime* is used to convert the epoch time reported in the scraped data into local time for each city, including the GMT offset. The local time is stored in the following form: YYYYmmddHHMM, i.e., a 12-digit integer, such that the first four digits are the year, the next two digits are the month, the next two digits are the day, the next two digits are the hour, and the last two digits are the minute value. A local time value in a given data record represents the time down to the minute in which the latitude/longitude values occurred for the bike ID in that record.

4. **Store the data in a temporary database table:** Once the desired data have been successfully retrieved from the GBFS URLs, the final step of the data scraping process involves inputting the data into a query operation that stores the data in the temporary location by using the SQL command *INSERT*. Data are collected for rental bicycles from designated cities, as well as station data for Biketown stations in Portland, Oregon. The data fields selected from the GBFS bicycle data that are inserted into the database are described below:

- Company: this is the name of the company providing the data feed from which the given record was scraped. In this project, data from only two companies are being studied: Jump and Biketown.
- City: this is the name of the city in the U.S. from which the traffic data are being collected. This process collects data from Jump bikes in the following cities: Austin, Texas, Sacramento, Calif., San Diego, Calif., San Francisco, Calif., Santa Cruz, Calif., Seattle, Wash., Denver, Colo., and Washington D.C. It also collects data from bikes belonging to the company Biketown in Portland, Oregon.
- local_time: this is the local time value that was explained above.
- bike_id: this is the unique identifier value reported in the GBFS feed that is given to each rental bike in the system and assigned by the rental company. It is a random string of 36 alpha-numeric characters.
- Is_reserved: this is a Boolean value indicating whether a client from the given company has reserved the bike to which the given record belongs.
- Is_disabled: this is a Boolean value indicating whether the bike in the given record is out of service.

- Lat: this is a float value indicating the given bike's current latitude coordinate at the time the record was uploaded to the GBFS data feed.
- Lon: this is a float value indicating the given bike's current longitude coordinate at the time the record was uploaded to the GBFS data feed.
- Vehicle_type: this is a string field with the value of either *bike* or *scooter*. Of the two companies whose data are being collected, only Jump reports both scooters and bikes. Biketown only reports bikes.
- Last_updated: this field reports the epoch time at which the given record for the given bike was uploaded into GBFS.
- Id: this is a unique identifier value that is generated and used exclusively by the backend database engine.

The following fields from the GBFS Biketown station data are inserted into the database:

- Company: same as above.
- City: same as above.
- Local_time: same as above.
- Station_id: analogous to *bike_id* described above.
- Num_bikes_available: this field is an integer value indicating the number of bikes available for rent in the given station.
- Num_bikes_disabled: this field is an integer value indicating the number of bikes in the station that are out of service.
- Num_docks_available: this field is an integer value indicating the number of spaces available to place a returning bike in the given station.
- Is_installed: this field is a Boolean value indicating whether the given station is operational.
- Is_renting: this field is a Boolean value indicating whether the given station has any available bikes to rent.
- Is_returning: this field is a Boolean value indicating whether the given station has any available spaces to return a rental bike.
- Last_updated: same as above.

Once the rental bike and station data have been successfully transferred from GBFS into the temporary database table, they stay there until the end of the day, when the consolidation process queries them out of the temporary table, analyzes them, stores the resulting data in a permanent table, and deletes all of the data from the temporary table.

4.4.2. Consolidation Phase

The next step in archiving the GBFS data involves transferring data from temporary locations into permanent locations. This is accomplished by a t2.large AWS EC2 instance named *Consolidator* that is turned on and off each day by an AWS Cloudformation stack schedule name *ec2-times*. The reason that a t2.large instance was chosen to do this job is because the queries involved in the process require an amount of memory larger than that provided in smaller instances, such as the t2.small that is used for scraping. However, because the t2.large instance provides much more memory, it is also much more expensive, and if it ran continuously for an entire year, the fees incurred would total over $700. Therefore, *ec2-times* was created to run *Consolidator* only for as long as needed—which is roughly two hours. This will reduce the cost of using the t2.large instance to about $80 for the entire year. The general process carried out by *Consolidator* each day is described below.

1. **Turn on the large compute instance:** Each day at 12:50 a.m., the AWS Cloudformation stack called *ec2-times* turns on the t2.large instance named *Consolidator.*
2. **Execute the consolidation script:** At 1:00 a.m., the crontab controls configured in *Consolidator*'s Ubuntu operating system call a Python program called *daily_consolidate.py.*
3. **Create a list of city/company pairs:** This program reads in a file containing information about all the cities and companies. For each city/company pair, the following process is accomplished:
    a. Query the data from the temporary data table and store them in a Pandas Dataframe.
    b. Using NumPy vectorization, loop through the data in the Dataframe and remove any records whose latitude and longitude values are identical to those of the records just prior and just after. This happens because the records that are

removed do not indicate movement of the bicycle, so they are unnecessary. The data that remain are stored in a dataframe.

c. Delete the data for the given company from the given city from the temporary database table.

d. Write the resulting dataframe to a csv file in the directory called *temp_csv_repo.*

e. Upload the newly created csv file into its corresponding database table and delete the csv file.

f. For the Biketown station records, scrape the latitude/longitude data for each Biketown station reported on GBFS and use the SQL UPDATE command to backfill those latitude/longitude values into the database table for Biketown station data. The consolidation process is now finished.

4. **Turn off the large compute instance:** At 3:10 a.m., the AWS Cloudformation stack *ec2-times* shuts down the EC2 instance *Consolidator.*

4.5. Summary

This chapter provides a technical description of the database system that was created to collect, process, and archive shared micro-mobility GPS data. The data is part of the General Bikeshare Feed Specification. Python scripts and AWS cloud computing services clean and archive the data. At the time of this document, the data are being scraped once a minute and stored in a database. The goal is to continue this process for the entire year of 2020. This will allow analysis of seasonal averages and annual trip generation rates. The next chapter describes pilot-study analysis.

CHAPTER 5. Shared Micro-Mobility Analysis

5.1. Introduction

This chapter presents an analysis of shared micro-mobility data. Shared micro-mobility primarily refers to shared bicycle and scooter use but also includes any system for sharing low speed vehicles that travel less than 25 mph. Companies that offer this service disperse hundreds or even thousands of vehicles across a city for customers to pick up and drop off for their traveling needs. This project aimed to study shared micro-mobility travel demand across a one-year period to create annual-based models for trip generation and seasonal variation. The previous chapter describes a computer program we created to archive GPS location data that various shared micro-mobility companies are providing through live data feeds over the Internet. We intend to collect one full year of data for future analysis. In the meantime, this chapter describes our pilot-study of annual data that were obtained from the City of Portland. The data were spatially modified and truncated for privacy concerns.

The next two sections describe the data and explain the method of analysis we used. This is followed by modeling results for trip generation and seasonal variation.

5.2. Data

Bike-share data were obtained for 2018 from the City of Portland, Oregon. Its bicycle-share system is called Biketown and serves a 20-square-mile area with roughly 1,000 bikes in service at a time. Figure 5-1 is a screenshot of the website that customers can use to find available bikes and determine the system boundary. In 2018, 399,775 trips occurred with an average trip duration of 24 minutes. The data were provided as a csv file, with each record representing a trip. For privacy, no identifying information about bicyclists was included other than whether the customer rented the bicycle as a subscribing member. Each record included a latitude, longitude, and timestamp for the trip origin and a latitude, longitude, and timestamp for the destination; however, these latitude and longitude points were snapped to the closest arterial to provide a layer of anonymity to the bicyclists. Figure 5-2 shows the nearly 800,000 points from the data set. Note that the points clearly coincide with roadway alignments. The limitations of these data will be discussed in the final section of this chapter.

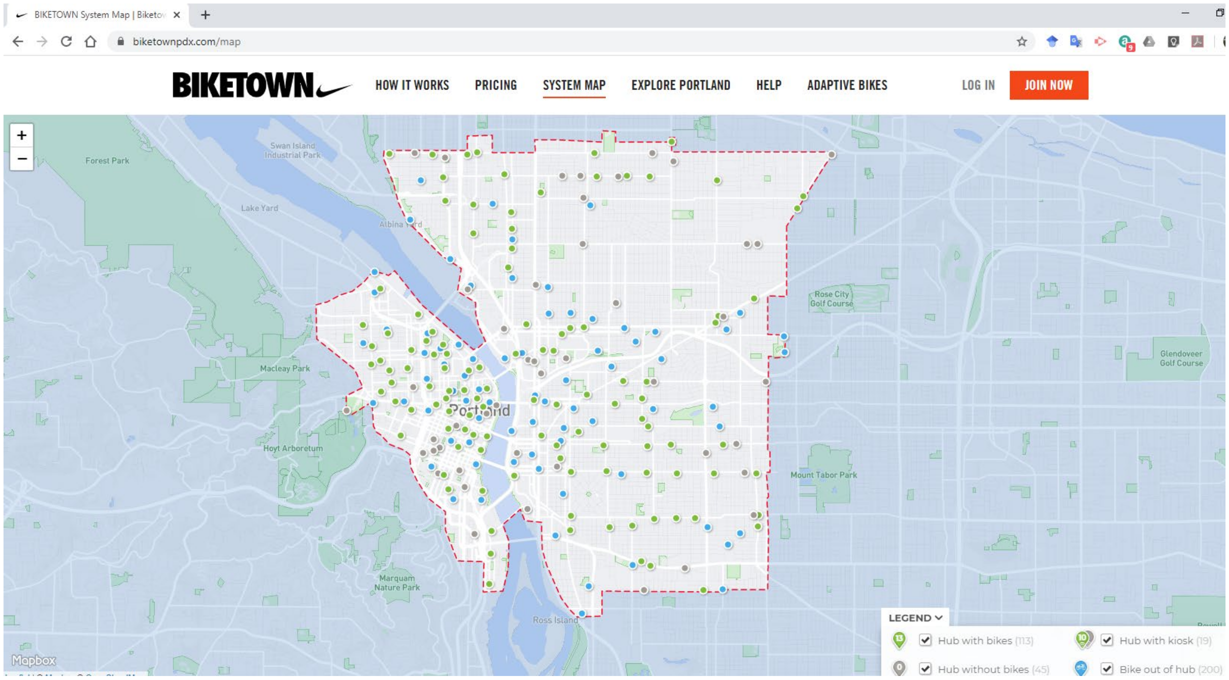


Figure 5-1 Portland's bike-share website.

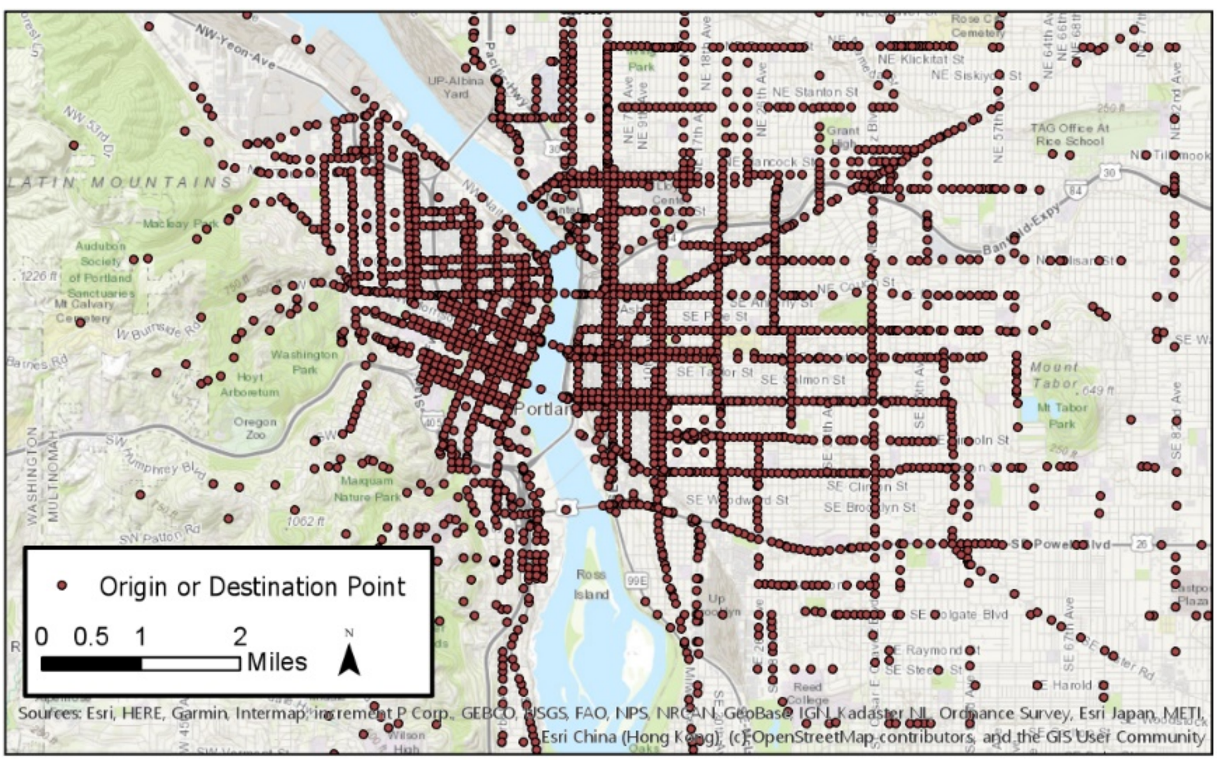


Figure 5-2 Origins and destinations snapped to the nearest arterial road.

5.3. Method

Travel demand forecasting, i.e., creating models to predict travel, can be done for different scales of space and time, depending on the intended purpose. Figure 5-3 is a quadrant schematic illustrating this concept. The horizontal axis represents time granularity and spans from predicting travel over short time intervals, such as one minute, to predicting travel over long time intervals, such as one year. The vertical axis shows space granularity and spans from predicting the travel of individuals bikes to predicting the travel of all bikes over a large geographic region. Travel demand forecasting for short time intervals and for individual bikes (lower-left quadrant) is useful for operation and management. Aggregate modeling over longer time intervals and larger geographic areas (upper-right quadrant) is useful for planning purposes. Aggregate models can be used, for example, to prioritize capital investments or to explore seasonal and year-to-year trends, perhaps for fund raising or post-policy evaluation. In some situations, aggregate models can be transferred to other cities or areas of a city where the service is currently not available to make scenario analysis predictions.

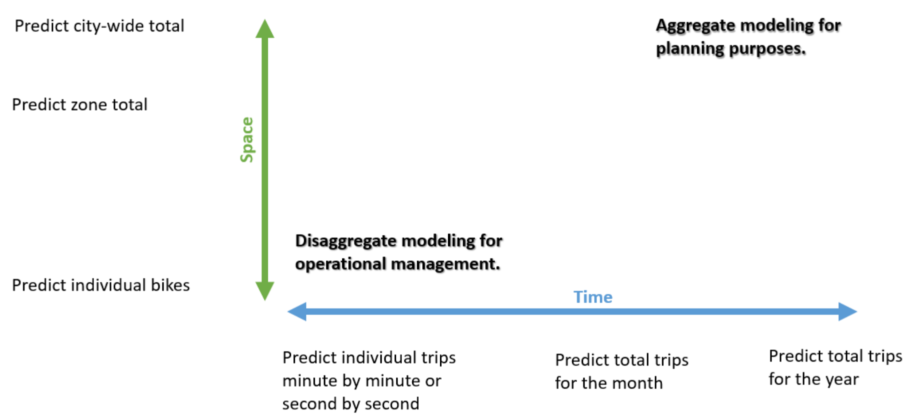
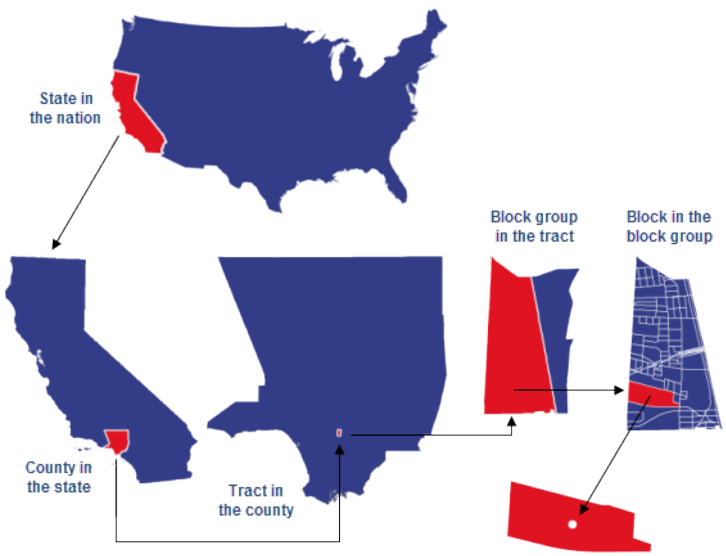


Figure 5-3 Scales of trip modeling across space and time.

This project focused on producing aggregate models at the zone level for planning purposes. Zones were defined by using Block Group boundaries because it was determined that data from the Census Bureau are uniform and readily available across the United States. The next phase of this project will examine data for various cities across the country to compare model results. A Block Group is a geographical unit between a Tract and Block, as shown in figure 5-4. The smaller Block might be more appropriate for planning purposes, but the Census Bureau does not provide enough data at that geographic level; Block Groups correspond with the "5-year estimates" of the American Communities Survey (ACS). The ACS is an ongoing survey administered annually to a random sample of 3.5 million homes. The responses are statistically extrapolated across Census geographies on a running average over 5 years, hence the name 5-year estimate. To preserve privacy, different questionnaire response data are made available for different geographies. Block Group data include population, race, age, employment, housing, and journey to work information (USCB, 2019). The Block Group boundaries for Portland, Oregon, are shown in figure 5-5. The bike-share system is covered by165 Block Groups. These were considered the analysis zones for this study.



Source: ESRI, 2019

Figure 5-4 Depiction of Census geographies. Block Groups were used for analysis.

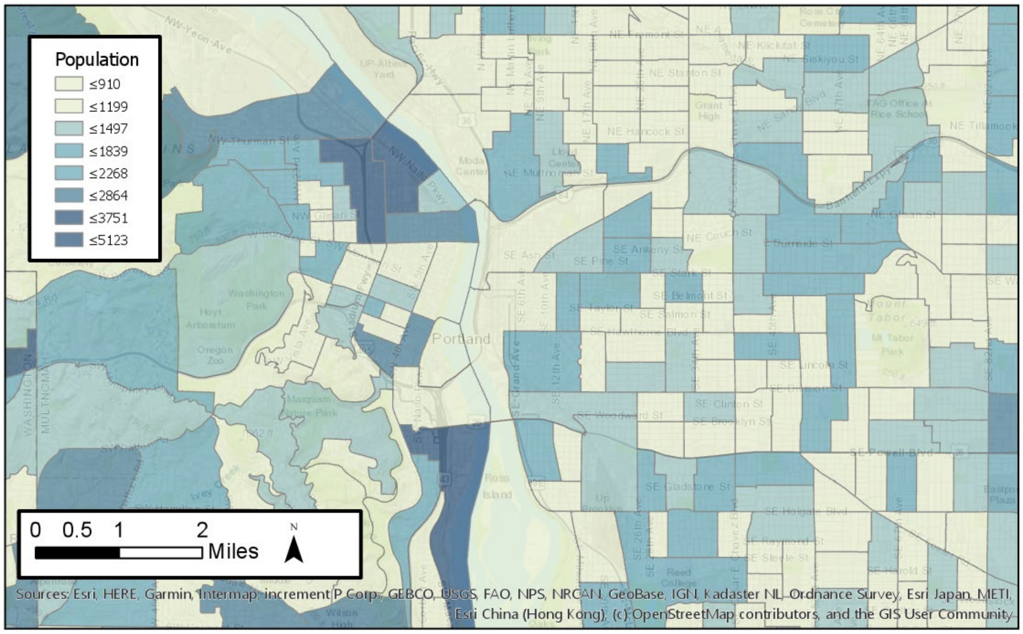


Figure 5-5 Portland's Census Block Group boundaries.

We also collected geographic information for points of interest (POI) throughout the study area. We wrote a computer program to download and map the relevant POIs that are available through the Google Places API. These are mapped in figure 5-6. A total POI count was calculated for every zone. Table 5-1 shows descriptive statistics for the POI count and demographic data obtained from the ACS. These variables were selected as candidate explanatory variables to estimate/predict zone trip rates.

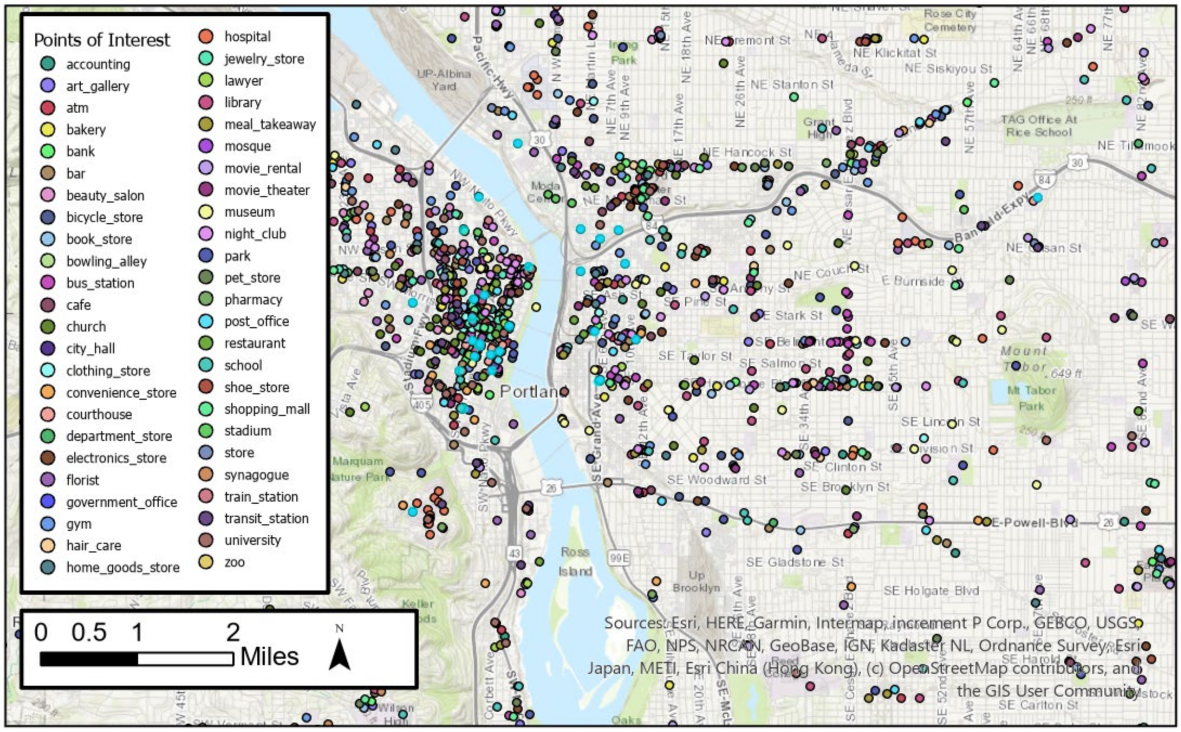


Figure 5-6 Points of interest obtained from Google Places.

Table 5-1 Descriptive statistics for zone variables

Zone Variable	Description	Min	Max	Mean	SD
points of interest	Count of POIs in the block group	0	123	8	16
population	Total block group population	563	4,655	1,291	581
bike%	Percent work-commute by bike	0%	32%	11%	6%
transit%	Percent work-commute by transit	0%	59%	15%	9%
walk%	Percent work-commute by walk	0%	49%	10%	11%
white%	Percent race is white	55%	100%	82%	9%
median age	Median age	21	65	38	6
median income	Median household income	$0	$209,821	$79,143	$35,401

The zones are defined by Census Block Groups. Points of interest were obtained from Google Places; all other data were from the American Communities Survey 5-year estimate for 2018.

5.4. Zone Trip Generation

The origins and destinations were spatially joined to the zones and summed for each zone. The total was divided by 365 to obtain annual average daily trips (AADT) with units of trips per day. Figure 5-7 shows the highest AADT occurred in the zones downtown. AADT is an average rate, and the actual day-volume for any given day can vary widely. For example, the busiest zone had an AADT of 231 trips per day, but over the year the daily volume for that zone ranged from 18 to 1,766 trips per day. The variation depended on season, climate, weather, and other factors. (The next section addresses this variation.)

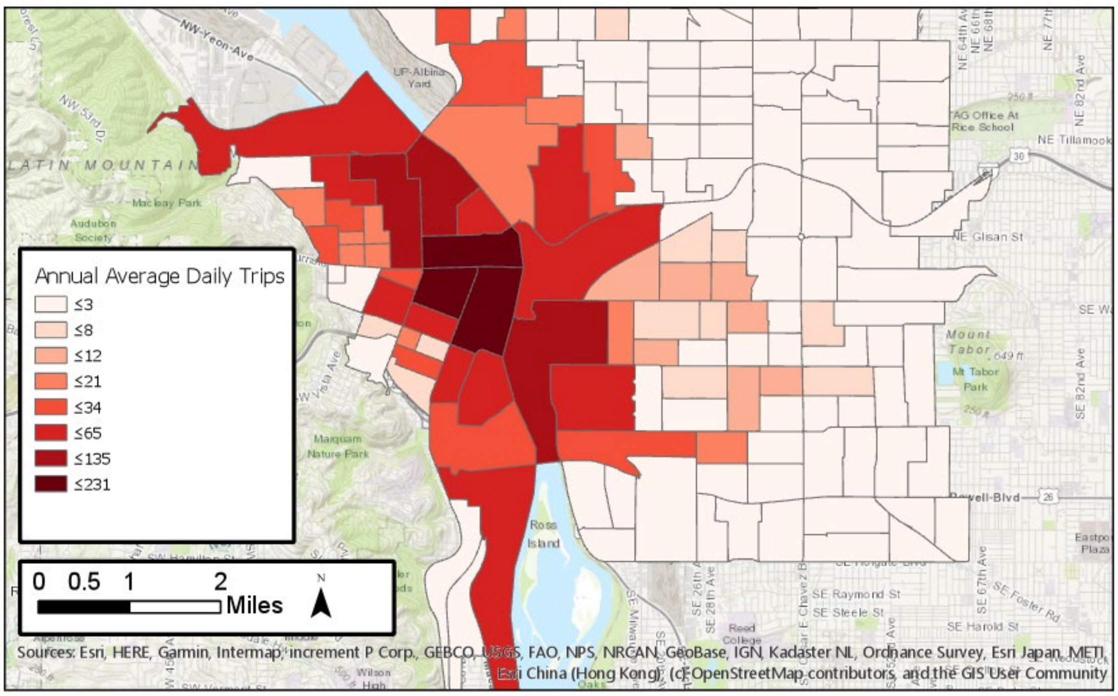


Figure 5-7 Annual average daily trips for Portland's bicycle-share program

We selected eight variables described in the previous section as candidate explanatory variables to estimate/predict AADT. The relationship between these variables is shown in figure 5-8. The trends matched expectations, such as walking and transit use declining with income, bicycling declining with age, and income increasing with age.

AADT can be considered count data, i.e. non-negative integers. Two common modeling techniques for count data are Poisson Regression and Negative Binomial Regression. Poisson Regression is a special case of the latter, wherein the mean and variance of the dependent variable can be considered equal. On the basis of a statistical test of the over-dispersion parameter, we concluded that Poisson Regression was appropriate for modeling. The data were fit by using a Python module called statsmodels. Table 5-2 shows the model results. All eight variables were statistically significant on the basis of a 99 percent confidence level. Positive coefficients suggested that an increase of the variable value correlated with an increase in AADT. The negative coefficients for white percentage, median age, and median income implied an inverse relationship.

Unlike Ordinarily Least Squares regression, the magnitude of the coefficients from Poisson Regression is not readily meaningful. An additional step is required to calculate elasticities (or marginal effects) for each variable. The elasticities are shown in the last column of table 5.2 and indicate the expected change in AADT for a change in the explanatory variable. For example, an increase in one POI corresponded to 0.4 more trips per day or 160 more trips per year. An increase in 1,000 people corresponded to 3,149 more trips per year. An increase of 1 percent for bike, transit, and walk commuting corresponded to an increase of 3,359, 1,570, and 2,555 more annual trips, respectively. Note that these are not evidence of causation but rather association, which might be because zones that were good for bicycling, transit, and walking were also conducive to more bicycle-share. Or perhaps, because in zones where there was a culture for those modes, there tended to be more bicycle-share.

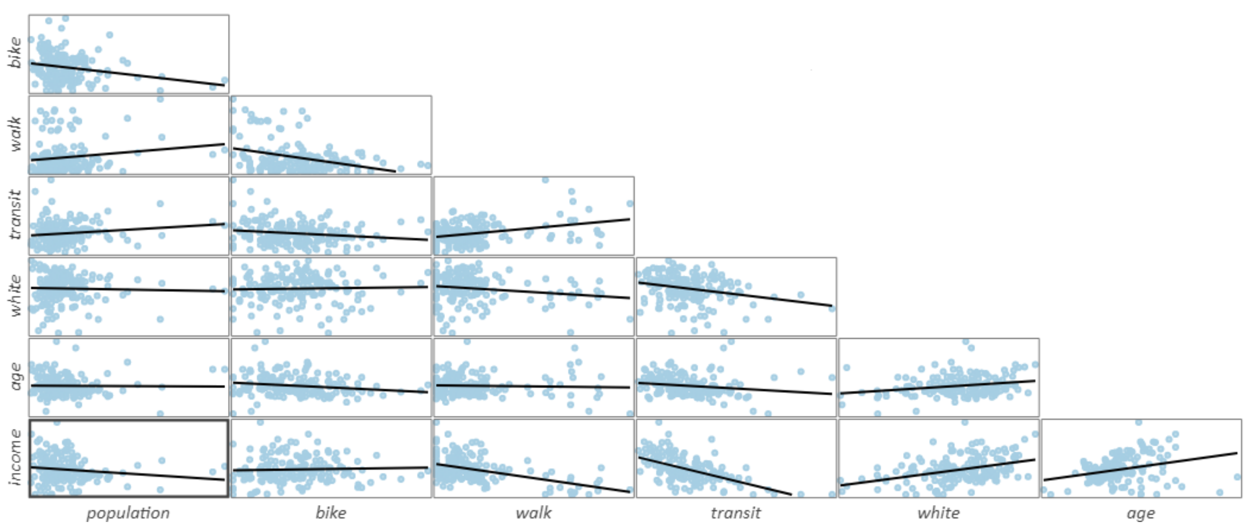


Figure 5-8 Relationship between explanatory variables.

Table 5-2 Poisson Regression for bicycle-share zone annual average daily trips

Zone Variable	Coefficient	p-value	Day Elasticity	Annual Elasticity
constant	9.260	0.000	-	-
points of interest count	0.034	0.000	0.4	160
population (thousands)	0.656	0.000	8.6	3149
bike%	0.702	0.002	9.2	3359
transit%	0.094	0.008	4.3	1570
walk%	0.327	0.000	7.0	2555
white%	-0.072	0.000	-0.4	-160
median age	-0.033	0.000	-0.9	-344
median income (thousands)	-0.015	0.000	-0.2	-72

See previous table for description of variables. Dependent variable is number of trips. n = 165 zones, Pseudo R-squared = 0.62, all variables are significant at α=0.01

5.5. Seasonal Variation Modeling

AADT is an average rate, and the actual day-volume for any given day can vary substantially for many different reasons, including weather, community events, or perhaps malfunctions in the bike-share system. This is true for all traffic modes and across all transportation facilities. The Traffic Monitoring Guide, published by the Federal Highway Administration, provides calculations and procedures to analyze variations (patterns) in seasonal, daily, and hourly traffic volumes (Federal Highway Administration, 2016). Essentially the calculations are a series of ratios and averages across different time periods to create "adjustment factors" that aim to capture the temporal variation. For example, Month Adjustment Factors are an average across the month divided by the average across the year. By taking averages, the analyst can "smooth" out the sharp, erratic fluctuations that occur day to day to create a less precise, but more consistent description of temporal trends. Consider for example the impact of climate versus the impact of weather on travel. Weather refers to short-term changes, whereas climate describes weather over long periods of time. We can expect less bicycling in the winter because of climate conditions. However, an anomalous sunny day might cause a sudden spike in bicycling. For long-term planning, these "noisy" fluctuations are not helpful. Seasonal variation modeling provides a means to make rough estimates for planning purposes.

Adjustment factors were calculated for every zone by using the full year of data. For example, table 5-3 shows the Month and Day-of-Week factors for one of the zones (this zone will be used for subsequent examples). These factors represent the inverse of "seasonal" variation. They provide a means to understand how trips vary across the year. For example, this particular zone had AADT of 95 trips per day, and so a rough estimate of trips on a particular month and day-of-week (DOW) can be calculated by dividing AADT by the factor. For example, midweek in the summer:

$$\#Trips_{(June,\ Thursday)} = \frac{95}{0.68} = 140\ trips$$

Here is another example, showing the number trips expected midweek in winter:

$$\#Trips_{(January,\ Thursday)} = \frac{95}{3.47} = 27\ trips$$

Table 5-4 shows Summer Hour and DOW factors for the same zone. These factors represent the proportion of daily trips. Because the number of trips expected on a Thursday in June was previously estimated to be 140 trips, then an expected hourly volume can be calculated like this:

$$\#Trips_{(June,Thursday,8am)} = 140 * 0.06 = 8\ trips$$

Here is another example, showing an estimate of the number trips during the evening peak period:

$$\#Trips_{(June,Thursday,4pm-7pm)} = 140 * (0.07 + 0.09 + 0.10) = 36\ trips$$

Table 5-3 Example Month and Day-of-Week adjustment factors for a specific zone

Month\DOW	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
January	2.40	2.64	2.26	3.47	2.28	2.46	2.11
February	2.31	2.41	2.57	2.43	2.13	1.89	2.57
March	1.68	1.82	2.06	2.04	1.91	1.38	1.29
April	1.40	1.19	1.22	1.26	1.43	1.30	2.06
May	0.47	0.57	0.51	0.64	0.52	0.44	0.41
June	0.76	0.72	0.73	0.74	0.68	0.63	0.91
July	0.68	0.63	0.50	0.60	0.52	0.43	0.53
August	0.70	0.67	0.69	0.76	0.65	0.73	0.70
September	0.84	1.01	0.97	0.85	0.82	0.87	0.85
October	1.20	0.99	1.08	1.07	1.28	1.21	1.43
November	1.51	1.27	1.53	1.25	1.63	1.72	1.74
December	2.09	1.79	1.75	1.56	1.67	2.00	2.88

Table 5-4 Example Hour and Day-of-Week adjustment factors for a specific zone

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
0	0.01	0.01	0.02	0.01	0.01	0.02	0.03
1	0.00	0.00	0.00	0.01	0.00	0.02	0.02
2	0.00	0.00	0.00	0.00	0.00	0.01	0.01
3	0.00	0.00	0.00	0.00	0.00	0.00	0.01
4	0.01	0.00	0.01	0.01	0.00	0.00	0.00
5	0.01	0.01	0.01	0.01	0.01	0.00	0.01
6	0.02	0.02	0.01	0.01	0.02	0.01	0.01
7	0.04	0.04	0.04	0.04	0.04	0.01	0.02
8	0.06	0.07	0.05	0.06	0.05	0.02	0.03
9	0.05	0.06	0.05	0.07	0.04	0.04	0.04
10	0.03	0.04	0.03	0.05	0.04	0.05	0.05
11	0.05	0.05	0.04	0.04	0.04	0.05	0.06
12	0.05	0.05	0.04	0.06	0.05	0.06	0.07
13	0.06	0.06	0.06	0.06	0.05	0.07	0.06
14	0.06	0.05	0.06	0.06	0.06	0.07	0.08
15	0.06	0.05	0.06	0.06	0.07	0.08	0.09
16	0.07	0.08	0.07	0.07	0.08	0.09	0.08
17	0.10	0.10	0.09	0.09	0.10	0.08	0.09
18	0.09	0.09	0.08	0.10	0.08	0.09	0.08
19	0.06	0.06	0.09	0.07	0.08	0.08	0.04
20	0.06	0.06	0.05	0.04	0.05	0.06	0.05
21	0.06	0.04	0.06	0.04	0.06	0.05	0.04
22	0.02	0.03	0.04	0.03	0.03	0.02	0.03
23	0.02	0.02	0.03	0.02	0.01	0.02	0.01

The adjustment factors for every zone were plotted and compiled into pdfs to allow visual inspection of seasonal variation patterns. Figure 5-9 shows the plots for the example zone. The plots were derived from the two previous tables. The top left plot highlights the monthly variation by averaging across days and plotting the inverse. The summer months exhibited considerably more trips than the winter months. The top right plot highlights the day of week variation by averaging across months and plotting the inverse. For this particular zone, there was insignificant day-of-week variation when averaged across the entire year (other zones produced markedly different plots, such as dramatic decline or increase on the weekend). The other four plots highlight the hourly variation for the four seasons. Two lines are plotted in each chart to emphasize the difference in weekday and weekend variation. The weekday lines for all seasons exhibited the typical bimodal peak pattern for the morning and evening commute peak periods.

Likewise, the weekend lines exhibited the typical pattern for recreation travel, i.e., a single peak in the afternoon.

The next step was to group the zones by their pattern of variation and then calculate average factors for the Factor Group. There are various ways to identify Factor Groups, including using cluster analysis or through manual grouping based on subjective visual inspection. Another approach that was developed specifically for bicycle adjustment factors by Miranda-Moreno et al. (2013) and modified by Nordback and Lowry (2017) is to group locations on the basis of ratios between peak and off-peak time periods. According to Nordback and Lowry the first ratio is called the Weekend Ratio and defined as

$$Weekend\ Ratio = \frac{Peak\ hour\ weekend\ traffic}{Peak\ hour\ weekday\ traffic}$$

where *Peak hour traffic* is the greatest hourly traffic volume for the location. The second is called the Morning Ratio and defined as

$$Morning\ Ratio = \frac{Average\ of\ weekday\ hourly\ traffic\ 7am - 9am}{Average\ of\ weekday\ hourly\ traffic\ 11am - 1pm}$$

The first ratio is intended to identify patterns of high weekend volume, which would indicate more recreational use than commute use. The second ratio is intended to identify bimodal or unimodal peak patterns for commute and recreational travel, respectively. Figure 5-10 shows the criteria to group a location into one of three groups: commute, mixed, and non-commute.

The 165 zones in the study were assigned to one of three groups on the basis of the seasonal pattern of the zone. Figure 5-11 shows the groups. The results were consistent with expectations. The Commute group consisted primarily of residential zones. The Mixed group consisted primarily of commercial and high density zones downtown. A closer inspection of the Recreation group revealed that these zones comprised points of interest such as the convention center, sports arena, public parks, the promenade along the river, and other greenspace. The zone factors were averaged across all members of a group to get Factor Group factors. This provided additional “smoothing” of noise in the data in order to provide less precise but more consistent AADT estimation and prediction. The factors could be used, for example, to make predictions about AADT in the future as the bike-share system expands to new zones.

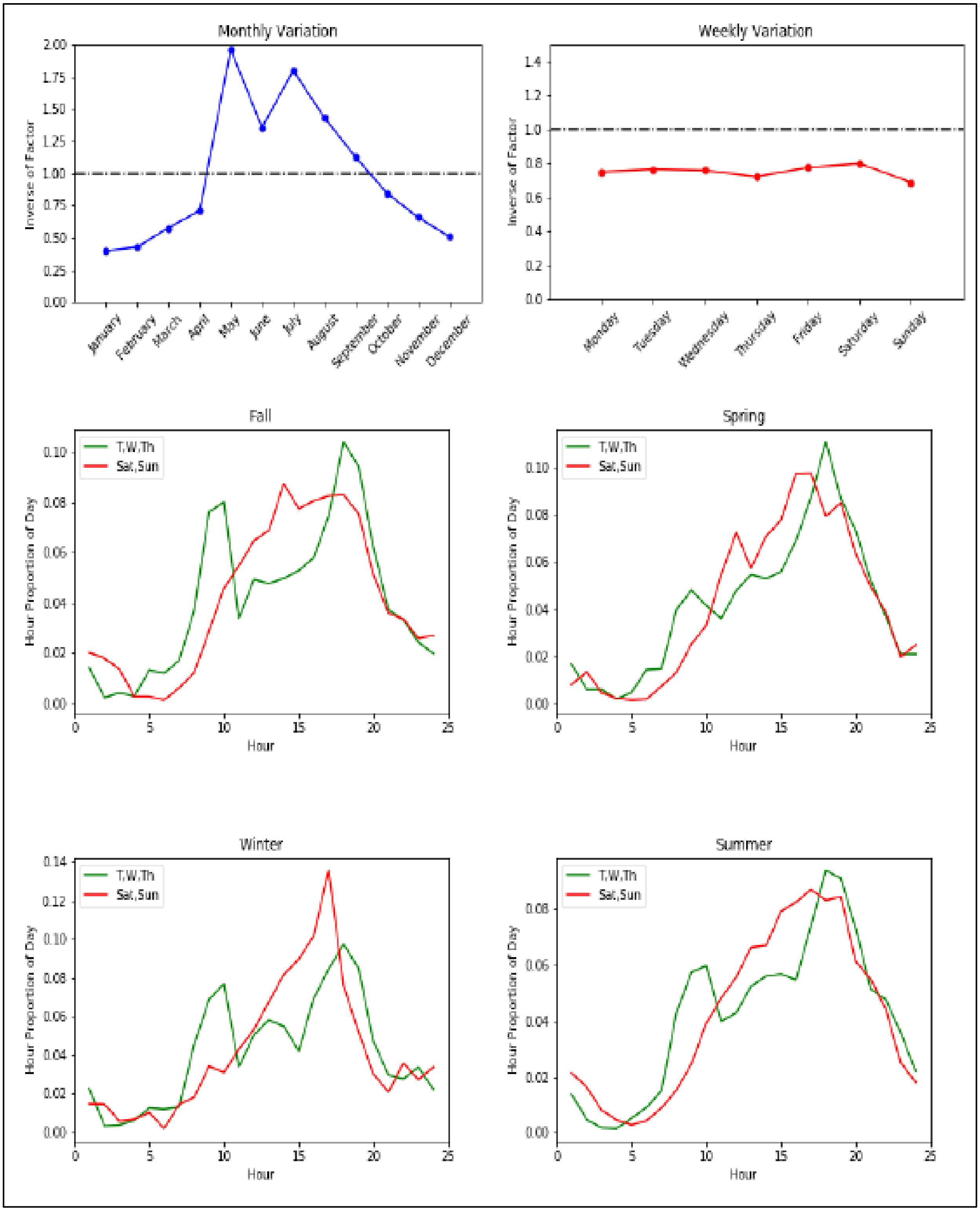


Figure 5-9 Example seasonal adjustment factor plots for a specific zone.

Travel Pattern		Weekend Ratio		Morning Ratio
Commute		less than 1.0	*and*	greater than 1.5
Mixed or Multipurpose		less than 1.0	*and*	less than 1.5
	-or-	1.0 - 1.8	*and*	greater than 1.5
Non-Commute or Noon Activity		1.0 - 1.8	*and*	less than 1.5
	-or-	greater than 1.8	*and*	any

Source: Nordback and Lowry (2017)

Figure 5-10 Classification ratio values

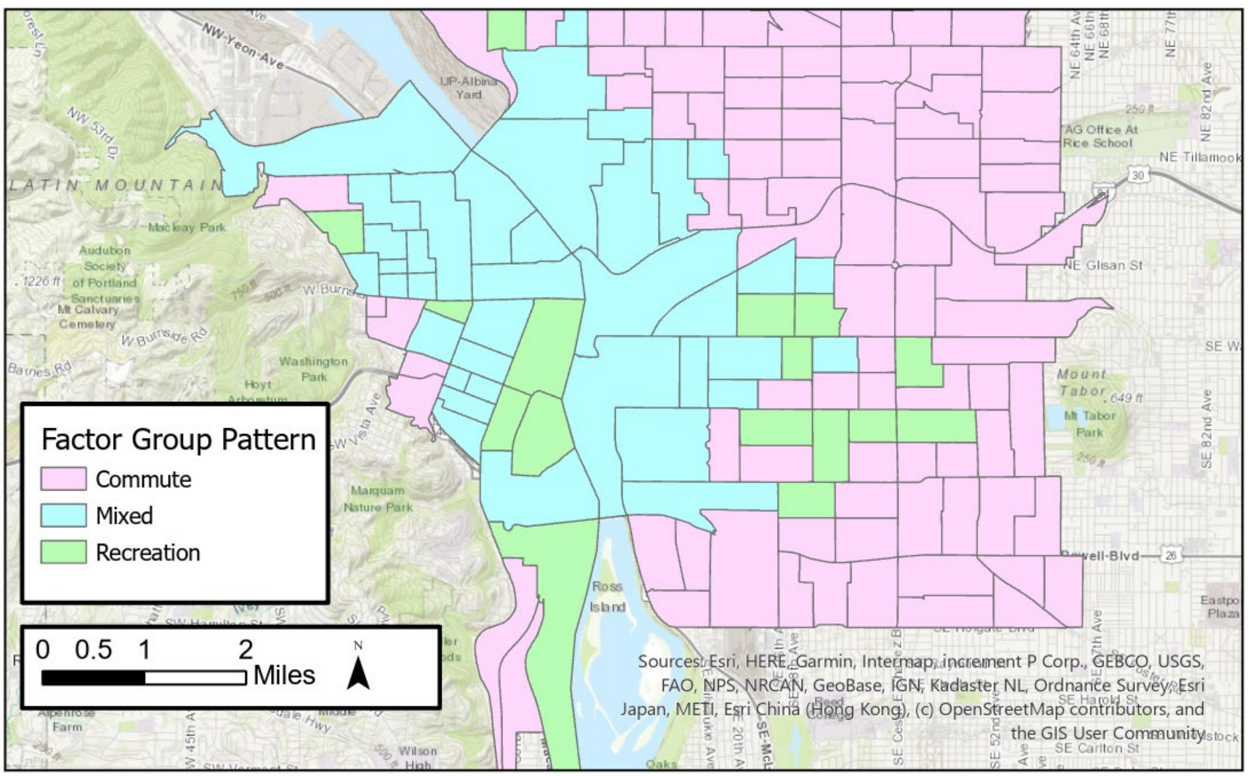


Figure 5-11 Factor groups

5.6. Summary, Limitations, and Next Steps

This chapter presents a pilot study of shared micro-mobility data. The analysis required one full year of GPS location data for bike-share trip origins and destinations. At the time of this project the only data available to the researchers were those provided by the City of Portland; however, they had been spatially modified for privacy concerns. The latitude/longitude coordinates of every GPS point were altered by snapping the point to the closest arterial road. This introduced potential limitations to the analysis because many of the zones had boundaries that corresponded to arterial roads. Consequently, it is likely that some bicycle trips were incorrectly associated with the wrong zone, perhaps impairing the models that were developed.

Nevertheless, despite the potential limitation, the findings were consistent with expectations and would certainly be useful for an engineer or planner. The trip generation model exhibited an acceptable goodness-of-fit (Pseudo R-squared = 0.62). All eight explanatory variables were found to be statistically significant and provided insightful information about the association of bike-share use and key demographics. Likewise, the seasonal variation models seemed logical and useful. Most importantly, this pilot study provided a successful proof of concept and opportunity to develop tools for future analysis.

Next steps will include completing the data collection for multiple cities, as described in the previous chapter, and conducting analysis that pools explanatory information across cities.

CHAPTER 6. References

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