Impact of One-way Carsharing on Car Ownership and Public Transit: an Empirical Analysis from Metro Vancouver

by

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the degree of	Master of Science	
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Abstract

While first conceived as cooperative station-based car ownership in the 1950s, smartphones have led to a rapid growth of free-floating carsharing in urban areas in the past 15 years. Their low-barrier to entry has had strong proponents and opponents. Proponents assert that it reduces car ownership and enhances the reach of public transit into less well-served neighbourhoods. Opponents worry that carsharing leads to more congestion and competes with public transit. Countless user surveys have explored the validity of these questions, indicating positive spillovers. In contrast to these studies, this thesis uses empirical data on vehicle booking and use from one-way carsharing providers in Vancouver to assess their impacts. This analysis reveals:

- Actual shared vehicles are used 5-6 times per day on average. Past surveys indicate that each free-floating carsharing vehicle leads to 2-13 fewer vehicles owned. This study estimates 4.3 and shows that the majority of the users who change their vehicle ownership plans use carsharing with low frequency (1-4 trips per month). This could suggest that the major benefit from car-shedding due to free-floating carsharing is in relieving parking pressure and less so of traffic congestion.

- Empirical data show that the most popular neighbourhoods for carsharing in which 75% of carsharing trips occur, host 59% of the population, retaining 37% of the carsharing service area and 63% of direct rapid transit routes. In other words, this group of neighbourhoods have 2.5 times higher population density than the rest of the neighbourhoods. The ratio of direct rapid transit routes available between these neighbourhoods to the rest of the direct rapid transit routes is 1.7, whereas the number of

carsharing trips inside this group of neighbourhoods is 3 times higher than the rest of carsharing trips recorded. Thus, carsharing is primarily competing with public transit in denser neighbourhoods rather than complementing it in less dense areas.

Finally, this study identified an understudied user misbehaviour. Roughly 30% of all vehicle reservations lapse; each time rendering these vehicles inaccessible to other users for 30 minutes. This leads to over-investment in the shared vehicle fleet and higher pressure on parking in popular neighbourhoods.

Lay Summary

Empowered by Mobility-as-a-Service programs, free-floating carsharing is a fairly new mode of transportation. Questions around the impacts of carsharing on urban mobility have been explored in the past, with survey reports being the primary source of reasoning. This study incorporates log data of the free-floating carsharing companies operating in Vancouver. The analyses show that carsharing can be beneficial for relieving parking pressure. On the other hand, daily usage patterns reveal that carsharing is used more during morning and afternoon peak hours, suggesting that one-way carsharing may be detrimental to the peak-hour traffic problem. Moreover, the study demonstrates that while carsharing can provide mobility to more neighbourhoods than rapid transit, it mainly competes with rapid transit in the neighbourhoods with access to both. Lastly, the users' reservation pattern shows that reservation cancellation varies spatiotemporally, making cars unavailable up to 70% of the time in some hours in different neighbourhoods.

Preface

This research topic was identified and designed by my research supervisor -- Hadi Dowlatabadi. Data scraping software was written by Dr Michiko Namazu as part of her PhD. Initial database manipulations were conducted by Mr Rainer Lempert as part of his MSc. Final database management, cleaning, verification and analysis activities were conducted by myself. This thesis has been authored by me with editorial suggestions by my supervisor, Hadi Dowlatabadi.

No part of this research has been published elsewhere. Three papers are planned for peer review publication with appropriate acknowledgement of co-authors (Namazu, Lempert and Dowlatabadi). This research was based on anonymized data collected about vehicle use available publicly on the internet. As such, the research did not require BREB approval.

Table of Contents

List of Tables

List of Figures

Acknowledgements

I am highly grateful to my supervisor, Hadi Dowlatabadi, who believed in me before starting my program and supported me during it. Your emphasis on having critical thinking about any system and event is a precious lesson I will always strive to follow. Your insights, continuous follow-ups on my research progress, and patience are invaluable to me and this thesis. I am also thankful to Alex Bigazzi, as the second reviewer of my thesis, for providing me with many insightful comments. I need to thank Michiko Namazu, who laid the foundation for this research by scraping the data set used here. Her efforts were followed by Rainer Lempert, who cleaned and did an initial analysis of the data set. I am very thankful to you, Rainer, especially for your insights which inspired many parts of my analysis section.

Many thanks to the IRES family. Your on-point research studies addressing different multi-dimensional problems inspired me to better my research and make it more meaningful and relevant to real-world problems. Thanks to St. John's College, which provided a safe and healthy living space during my stay as a student. I also acknowledge their financial support for my study. I'm also thankful to my friends nearby and far away for their moral support.

Last but not least, thank you to my parents and my sister for your unwavering support and encouragement throughout my life.

Dedication

To the victims of Ukraine Flight PS752.

Chapter 1: Introduction

1.1 Definition and history of carsharing

Innovation, Science and Economic Development Canada defines carsharing as "a car rental service that allows people to use vehicles for short periods of time, often by the hour." Following the definition suggests that carsharing can be an economical and eco-friendly option for people who only need occasional access to vehicle (ISED, 2020). While many published works provide their own description of the term, they all provide four main themes: 1) users need to pay a membership fee; 2) members gain access to a common fleet; 3) there is a fee paid per use; 4) the arduous procedure involved in traditional car rental is avoided (Millard-Ball, Murray, Schure, Fox, & Burkhardt, 2005).

Carsharing has been used around the world for more than 70 years. The driving forces behind the adoption of carsharing systems and the stakeholders involved have grown in number and magnitude. The first identified use of carsharing goes back to the 1940s in Switzerland. Individuals who were economically strained started to share a car instead of purchasing one in a cooperative manner. It was in the 1980s and 90s that carsharing became more popular in Europe. The service started to be recognised by the governments and be subsidized (S. Shaheen, Sperling, & Wagner, 1998). In the 90s carsharing started to show up in North America as well as Asia. Later, auto manufacturers were indulging in supporting of these systems, especially Honda and Toyota in Japan (Barth, Shaheen, Fukuda, & Fukuda, 2006). In the 21st century, the usage of carsharing services has seen booming. Advancements in Information Communication

Technologies (ICTs) with the rapid growth of cellular phones and smartphones lowered the operational and transactional costs (Namazu, 2017). They also helped the users with localization of the fleet cars which paved the way for the adoption of the more complex type of carsharing systems, free-floating carsharing. GPS technology is used by the service to track and locate each vehicle (Kortum, Schönduwe, Stolte, & Bock, 2016). The first free-floating carsharing system was started by Daimler through its subsidiary Car2Go in 2008. Before merging with another carsharing company in 2019, Car2Go had 3.6 million members worldwide.

The main two types of carsharing systems are one-way and two-way. Akin to typical car rentals, two-way carsharing requires the user to bring the car back to the starting location. In contrast to its elder brother, the car can be picked up and parked in different stations in a one-way system. As a subgroup of one-way carsharing, free-floating systems let the users start and end their trips anywhere in the service area.

The motivations for the adoption of carsharing services varies among different stakeholders. For individual users, the economics of not being able to own a car was the primary motivation in the early days. The presumed social and environmental advantages of carsharing inspired governments to support carsharing. They also encouraged people with higher environmental awareness to use the service. Bardhi and Eckhardt contend that a shift in the sociocultural politics of consumption is another catalysis for the consumers to embrace sharing as opposed to owning (2012). Automakers have had their own motivations to step into the carsharing service market. They intended to explore a new business model of providing mobility service alongside a new market for their products (Firnkorn & Müller, 2012). Moreover, carsharing systems have allowed them to promote their brand to new customer groups by allowing users to gain first-hand experience with their products. Finally, the provision of carsharing services enhances their corporate image among consumers who view carsharing as a more environmental-friendly alternative (Herodes & Skinner, 2005).

Carsharing has also been promoted based on its potential positive impacts on social and environmental goals in urban areas. More specifically, policy-makers have presumed that carsharing would:

1. Reduce car ownership by encouraging car owners to relinquish their private vehicle and the prospective buyers to forgo;
2. Promote alternative transportation modes by removing the bias to "drive" due to the availability of privately owned vehicles. Carsharing would, therefore, encourage users to decide between alternatives with more emphasis on the hierarchy of the travel mode choices in a trip by trip manner (Migliore, D'Orso, & Caminiti, 2020);
3. Ease the pressure on parking space developments as a result of having fewer cars parked in the city;
4. Improve access and use of public transit systems by providing first/ last leg trips;
5. Provide mobility equity, especially for people with lower income;
6. Reduce emission by incorporating cleaner cars and higher usage of alternative transportation modes (S. A. Shaheen, Schwartz, & Wipyewski, 2004);

7. Contribute to a sense of inclusion and belonging for the users as a result of participating in a practice dependent on the goodwill and collaboration of others in the neighbourhood (Kent, 2014).

Besides these potential benefits, some negative impacts have also been postulated. Carsharing might encourage more people to choose driving as their travel mode, increasing aggregate vehicle-kilometres travelled (VKT), especially after considering the necessity for fleet relocation by the operator (crucial in fleet management of one-way carsharing systems) (Vasconcelos, Martinez, Correia, Guimarães, & Farias, 2017). Moreover, reliance on local public transit could be undermined by carsharing services (Mattia, Guglielmetti Mugion, & Principato, 2019). Furthermore, a carsharing user can be more conscious about the financial cost of each trip. Coupled with moral hazard due to not owning the vehicle, this factor may lead to a more reckless driving while carsharing (Paundra, Rook, van Dalen, & Ketter, 2017). Additionally, the economics of a carsharing system is complex. Many service providers have failed to reach utilization rates that lead to a sustained business model. For example, ShareNow (formerly Car2Go), the biggest one-way carsharing company globally, decided to exit North America in 2020 due to competition from ride-hailing and other carsharing services in a fast-changing mobility landscape. The consequent reduction in mobility choices might nudge some members to buy a car. More importantly, for households who did not have mobility demand initially, carsharing could work as a motivator of vehicle ownership, especially if the service gets terminated (Namazu & Dowlatabadi, 2018).

As relayed above, there are a variety of motivations and potential social and environmental impacts, some contrasting each other, regarding the carsharing service. Academics and researchers have strived to assess some of the aforementioned presumptions and estimate their effects on the environment, quality of life, traffic congestion, etc. The common sources for these studies are qualitative and quantitative surveys (Ferrero, Perboli, Rosano, & Vesco, 2018). The collected data are mainly analyzed using logit models. Longitudinal data is the best type of data to infer causality; however, most of the data available for research is of cross-sectional type. Therefore, these analyses suffer from various biases such as selection, simultaneity, and recall biases. Mishra et al. found that only 20% of the difference in units of vehicle holding between members and non-members of a two-way carsharing service in San Francisco could be attributed to the effect of carsharing. The remaining difference is because of the differences in demographics and features of the built environment, reverse causality, and systematic differences in unobserved characteristics between members and non-members (2019).

1.2 Research goals and literature review

In this study, I employ empirical data collected from real-time carsharing usage in Metro Vancouver to assess some of the hypothesized impacts of carsharing on private vehicle. Three particular questions were addressed in this thesis, as described below.

1.2.1 Vehicle ownership

As a shared automobility option, carsharing operations are likely to profoundly impact personal mobility decisions, particularly decisions related to car ownership. From the early years of emergence, this impact has been studied in the literature. One study on the carsharing service in San Francisco in the 1990s reported that more than 75% of the members would sell/ avoid buying a private vehicle. Another convenient way to report the impact is to check the number of private vehicles that would be removed per each carsharing vehicle. A study on a carsharing service system in Philadelphia in 2003 concluded that 23 private vehicles were removed per carsharing vehicle. Martin et al. showed that based on continent-wide survey research in 2008, 23% of households reduced their cars, and each carsharing vehicle removes between 9 to 13 private vehicles in North America (Martin, Shaheen, & Lidicker, 2010). Given self-selection bias and a wide range of patterns of use among respondents to a survey about any service, Namazu and Dowlatabadi used uncertainty ranges informed by Metro Vancouver's trip diary entries to re-estimate survey data gathered from Car2Go users in Vancouver in 2013. They found that despite the reportedly high vehicle shedding rates among those who participated in the survey, the likely figure among all users would average 2.5 private vehicles are shed per free-floating carsharing vehicle (2018). The percentage of vehicle ownership reduction, according to the survey result, was 12%. In a quasi-experimental study using a two-wave survey and controlling for a set of underlying socio-demographic differences, it is calculated that between 2014 and 2015, 6% of free-floating carsharing users in Basel, Switzerland reduce their car ownership (Becker, Ciari, & Axhausen, 2018).

It is important to note that intuitively, carsharing would have higher adoption and impact on vehicle ownership in the cities with higher density and better public transport. Therefore, the studies in European and Asian cities may show more substantial impacts than the North American cities. Transitioning from early adopters to the common public can be assumed as a reason for the decrease in the estimates of the number of private cars removed per shared vehicle among the newer studies. It is also important to note that two-way carsharing users tend to reduce their car ownership before joining their service and reduce ownership further after becoming members more than one-way users (Giesel & Nobis, 2016; Namazu & Dowlatabadi, 2018). Finally, later studies have been able to collect more data and address some of the biases.

Regarding the characteristics of the users who shed a private vehicle, Namazu and Dowlatabadi assert that the infrequent users are more likely to reduce the car ownership based on their regression model (2018). Kim et al., on the other hand, in a repeated cross-sectional analysis, contends that the users in Seul, South Korea, who use carsharing for regular commute trips are more likely to shed a private vehicle (Kim, Park, & Ko, 2019).

In this study, using the carsharing fleet's empirical trip data, I add to the literature of carsharing impact on car ownership reduction from the standpoint of the number of usages each carsharing vehicle has on a daily basis. In other words, this study answers the following question: "What can the recorded usage per carsharing vehicle tell us about the potential impact on car ownership reduction?"

1.2.2 Interaction with public transit

Many studies have posited the potential for carsharing services to complement public transport by providing mobility to the user with limited access to public transit. The idea being that whereas public transit can very effectively serve high-density urban areas, carsharing can provide a bridge to less well-served (i.e., lower density neighbourhoods). Ideally, carsharing increases public transport ridership and discourage private car ownership. With this in mind, cities have facilitated carsharing stations' location close to major public transit stations (S. Shaheen & Chan, 2016). Furthermore, transit providers and carsharing companies have bundled their mobility services to increase the convenience of such multimode uses (Sharma, 2020).

In recent years, many studies have been conducted to assess the impact of transportation network companies (TNCs) on urban mobility. The literature is inconclusive. Some studies, mainly surveys, have confirmed the assertion that TNC essentially complements public transit (e.g., Feigon and Murphy 2018). While other studies have shown that TNC, although being used in cases that public transit is not available, is also largely used during peak hours when transit service is frequent (Erhardt et al., 2019). Other research on overall urban mobility trends asserts that the entrance of TNC has adversely affected the overall public transit ridership, meaning that TNC has acted as a substitute for public transit generally (Diao, Kong, & Zhao, 2021).

In the context of carsharing, the studies that touch upon the topic of impact on public transit are based on surveys or empirical data or both. Many surveys have revealed that the self-reported percentage of transit among mode shares is higher for carsharing members than non-members (Clewlow, 2016; Lempert, Zhao, & Dowlatabadi, 2019). Some other survey studies show that the impact varies among different demographics, some increasing their public transit use and some decreasing (Martin & Shaheen, 2016). Among the studies based on empirical data, one focusing on a station on the boundary of a free-floating carsharing service area in Montreal shows that 19.7% of the carsharing trips starts or ends near the subway station. It also depicts that more users start their carsharing trip rather than ending it near a subway station (Wielinski, Trépanier, & Morency, 2019). Another study looking at station-based carsharing in Shanghai finds a nonlinear relation between the number of carsharing trips and proximity to transit stations. The number of trips is high close to transit stations. Moving away from transit stations, the carsharing usage decreases and then increase after 1.2 kilometres of distance from transit. The paper explains that this nonlinearity might be due to the complementarity of carsharing as well as providing first/ last leg trips to connect the users to public transit (Hu, Chen, Lin, Xie, & Chen, 2018). To the best of our knowledge, no peer-reviewed literature has utilized actual trip data from bundled Maas platforms to analyze multimode-travel that incorporate carsharing. Typically, self-reported survey data has been used, with systemic omissions and biases, precluding accurate partitioning of multi-modal travel from carsharing used to access locations close to public transit stations.

This section of our study aims to answer the question of "how does carsharing interact with public transit? What percentage of the trips connect the users to public transit or substitute it?". By classifying the origins and destinations throughout the service area in Metro Vancouver, the distribution of trips in comparison to public transit is analyzed.

1.2.3 Booking behaviour impact on the system performance

The matter of reservation in carsharing systems is studied in the field of fleet management mostly through simulation; however, to the best of our knowledge, there has not been any research done on the reservation patterns of carsharing users. The reservations that get cancelled do not lead to a trip and prevent revenue for the company. This study provides a preliminary study of lapsed booking occurrence and attempts to answer the question of "how do lapsed bookings affect car availability in different Metro Vancouver neighbourhoods?"

Chapter 2: Data collection and preliminary analysis

2.1 Data collection

Data used in this study was collected from Car2Go and Evo's public open application programming interfaces (APIs) for the Metro Vancouver service areas. Data collection for Car2Go started on 13-02-2017 and ended on 31-01-2018 (352 days). Evo's data was collected from the same date until 03-09-2018 (567 days). In both cases, data collection terminated when open access to APIs was ended.

Data collection was programmed to occur every 5 minutes. At each time step, data were collected on all available vehicles for use in the respective fleets; the data collected were: hash (a fixed-length string of characters as a representative for each individual vehicle for security protection, used in the Evo data)/ license plate (used in the Car2Go data), and percentage of fuel of the cars, longitude and latitude of their location, and in the case of Evo, an address field. This data were saved to Amazon Web Services using a Python script. Due to various factors, such as server outages, API response delays, local cellphone service disruption, etc., the data have some variation on timing and gaps. For example, in some instances the time interval increases to 7-25 minutes. Moreover, throughout the data collection, a handful of times there is a gap in the data for more than an hour. By another glitch that was apparent in the Evo data recorded on 30th, January 2018, longitude and latitude of each vehicle was changing between two far locations between each time interval.

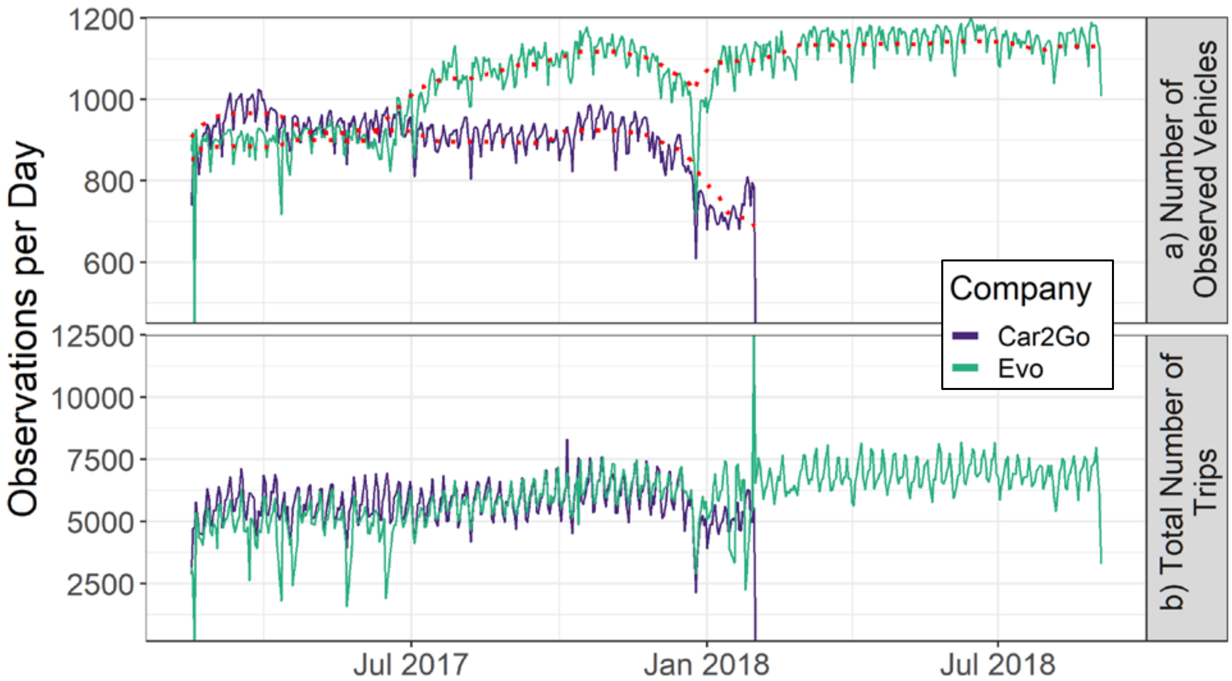

Figure 2-1 Number of a) available cars in each fleet; b) trips taken each day

In order to prepare the data for analysis data-collection glitches should be addressed. These addressed data glitches are:

1. Large time gaps in the data collection (> 60 mins), affecting a handful of days; these days are filtered out.

2. Geographic coordinate shifts, on 30th, January 2018; longitude and latitude of each vehicle was changing between two far locations between each time interval. This day is filtered out for the Evo fleet.

After addressing these data collection glitches displayed in Figure 2-1 "a" & "b", we have a database of vehicle availabilities, which can be used to gain insight into how Car2Go and Evo fleets are utilized.

Figure 2-1.a displays the number of vehicles in the available fleet. The moving average of vehicles available for each fleet over 30 days is plotted as a dotted red line. At the beginning of the data collection, Evo and Car2Go had 880 and 960 cars in their fleets, respectively. By the time data collection ended for each of the companies, Evo had 1135 vehicles in its fleet, while Car2Go's fleet shrunk to 725 vehicles. Figure 2-1.b displays the number of "trips" taken on each day. We explain our methodology for the identification of a trip in Sections 2.2.1 and 2.2.2 below. The trips taken by Evo rise above Car2Go as their fleet grows larger. However, the ratio of trips taken per available car favour Car2Go (see Section 2.2.4).

During the data collection, Evo expanded their service area. In May 2017, they added the New Westminster territory to their service area. Later in August 2017 Capilano University stations were added to the service area, as well.

It is important to note that a consistent method of trip identification is needed to filter out long vehicle absences from the data. Long absence is most probably due to the car being repaired. Therefore, in this study 36 hours (1.5 day) is considered as the maximum trip length and vehicle absences of longer duration are excluded from the analyses.

A summary of the data in Figure 2-1 "a" & "b" is presented in Table 2.1.

Table 2.1 Summary of data collected by Service provider

	Car2go	Evo
Average number of vehicles available	895	1050
Total number of trips	2,015,000	3,355,000
Days of data collection	352	567
Trips per day	5,725	6,045

The open API of both car services ensured their members' privacy by neither revealing information about the path taken by a car while in use nor any information about the user. The cars "blink" on when available for reservation/use and blink off when reserved/used. The API simply displays the geographic and temporal patterns of availability for each vehicle. In more than 96% of all entries, the location of the car stays unchanged. Therefore, it can be assumed that the vehicles do not take a new GPS reading each time they appear in the API, and while a car is at rest, its longitude and latitude do not change. Based on this assumption, if a car's location in two consecutive entries is geographically apart, we can surmise that it was used in a trip (or was being repositioned or serviced by the provider).

At the time of data collection, Car2Go was comprised of a fleet of Smart Fortwo, and 250 newly added Mercedes-Benz CLAs and GLAs (CBC News, 2017) and Evo's was comprised of only one type of vehicle, Toyota Prius C.

The focus of Chapter 3 is mostly on the Evo fleet data set as it has a longer period of record. Also, because Car2Go is not operating anymore in the region at the time of writing. For chapter two we continue to explore both data sets and learn about the state of free-floating carsharing in Vancouver.

2.2 Preliminary Data analysis

2.2.1 What constitutes a trip?

This data exploration focuses on the location(s) of a vehicle being unavailable and available again. When vehicles appear far from where they were last available, there is no question that it has been moved. However, what is the explanation for a vehicle reappearing in the exact same location as its last recorded location? Or close to it? The answers to these questions shed light on how bookings and potential roundtrips are reflected in the data collected from the open APIs.

The first exploration of the data involves a plot of duration of unavailability vs distance between availabilities. Based on Figure 2-2, more than 23% of all observations belong to vehicles reappearing exactly where they were last reported as being available. We need to establish whether these are lapsed bookings or roundtrip bookings.

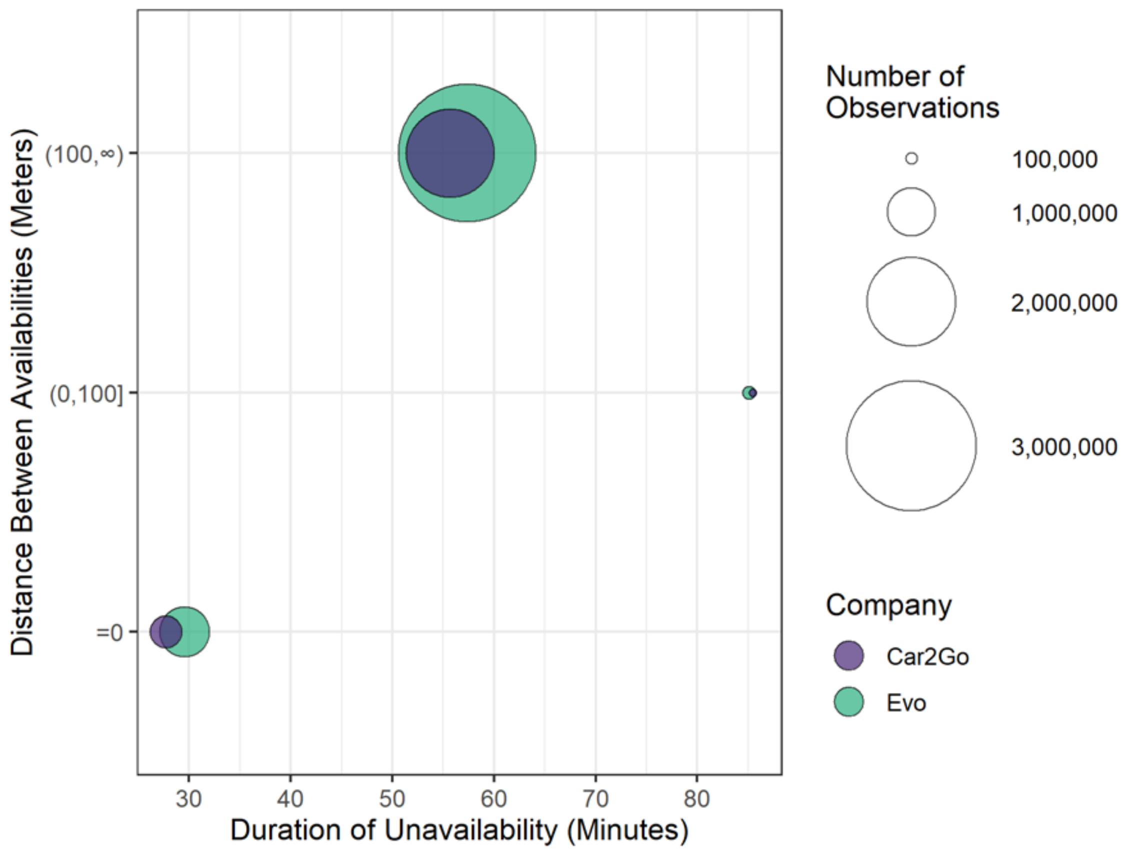

Figure 2-2 Count of observations at three distances between availabilities plotted against duration of unavailability

2.2.2 Lapsed bookings vs roundtrip bookings

Literature shows that ordinary mobile GPS locators have a typical accuracy of 15 meters, 95% of the time (Valbuena, Mauro, Rodriguez-Solano, & Manzanera, 2010). Therefore, the "trip distance" analysis is refined even further to explore why the average time of unavailability with zero distance travelled is close to 30 minutes.

Figure 2-3 depicts the distribution of vehicles that return to availability at exactly the same location, vs within 15 meters of the previous location. Two features of this graph allow distinction between lapsed bookings and roundtrips.

1. The ratio of availability at exactly the same location vs more than 0 but within 15m is a factor of 15. So, up to 6.3% of this category of observations could be roundtrips lasting up to 2 hours.[1]

2. There is a peak in the number of observations at the 35 minutes time interval for zero displacements for both companies.

Both car services have a grace period of 30 minutes for booked vehicles. Based on the observed peak, we hypothesize that vehicles that return to availability at exactly the same location as they became unavailable represent bookings that did not lead to a trip – we call these "lapsed bookings".

Due to the 5-minute time intervals for data collection, the number of cancelled bookings after 30 minutes could be counted in the data at 30 to 40 minutes time intervals, with the most observations showing up in 35 minutes time interval.

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[1] Please note, these slightly shifted positional readings could also be due to a stationary vehicle whose GPS is called upon to make a 2nd location reading due to various operational causes.

A secondary feature of Evo's chart shows a similar peak for displacements between 0 and 15 meters displacement. The number of observations under this peak is around 2% of the zero-displacement peak[2].

This section concludes that reappearance of a vehicle after an observed absence in the data with 0 displacement is a result of a lapsed booking. Moving forward, trips and lapsed bookings are separated. To view the complete steps of data preparation please see Appendix A.1.

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[2] We have no direct information about why this may be so. However, anecdotal evidence leads us to suspect this may be related to the vehicles being dropped from the network and needing to be "woken up" through access by the dispatch center (and as part of that process taking a new GPS reading).

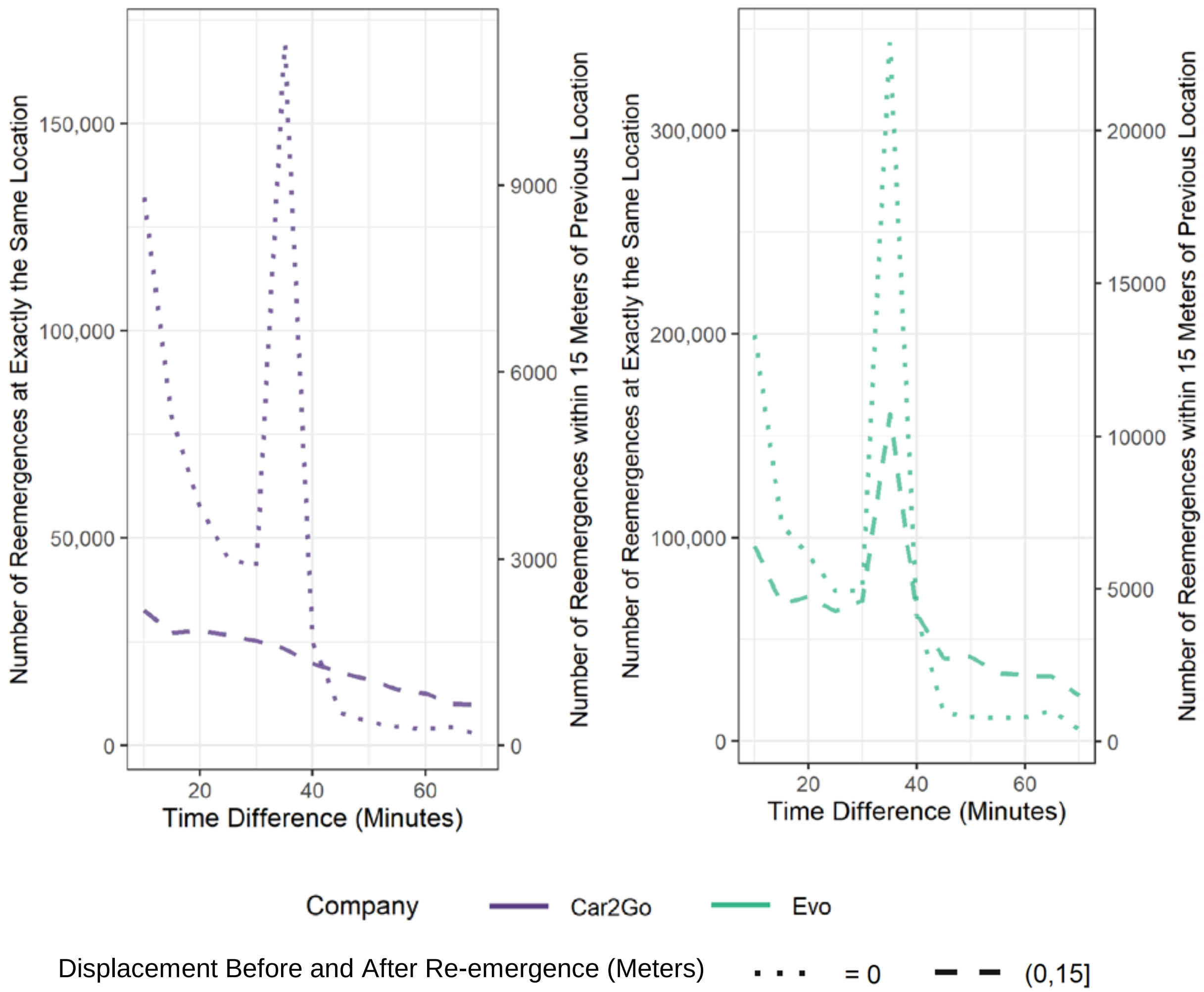

Figure 2-3 Count of re-emergence plotted against time (0 vs. (0,15] displacement)

2.2.3 Trip characteristics once lapsed bookings are removed

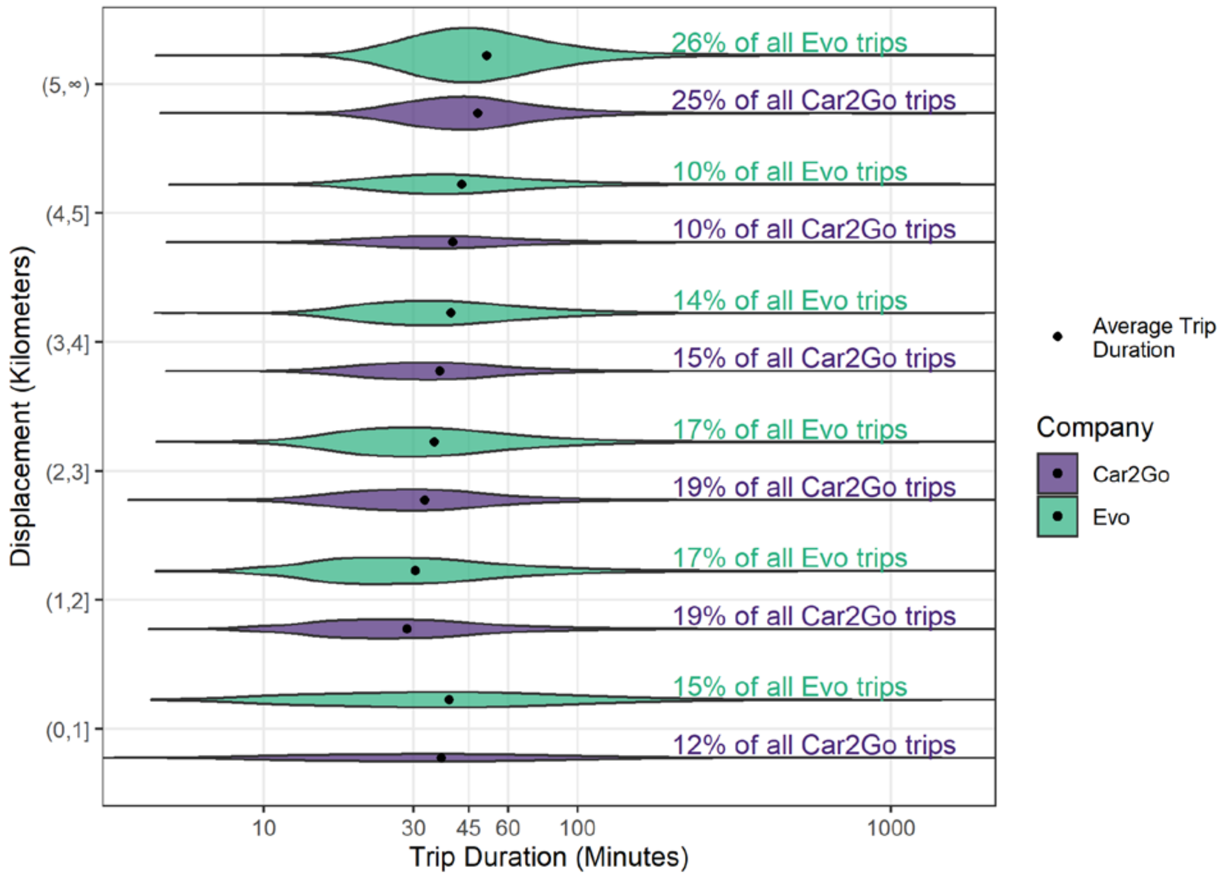

Figure 2-4 Trip duration vs displacement and their respective quota of all trips[3]

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[3] Please note, "trip duration" includes the period between booking and accessing the vehicle, while only time users spend with the vehicle is the trip itself and generates revenues for the service provider.

Figure 2-4 shows the general pattern of trips taken by members of Car2Go and Evo. The average trip duration increases as the displacement increases. This statement is valid for trips with displacement higher than 1 kilometre. The average duration of trips with less than 1 kilometre of displacement does not follow the same pattern, mainly due to the roundtrips included in this group (See Appendix A.2 for more related information.) Lack of access to vehicle odometers stymies attempts to identify roundtrips any further, especially where trip durations are less than two hours. For the rest of the study, geodesic displacement is used as a proxy for distance travelled in the analyses as a last resort.[4]

The average trip duration and distance are reflected in Table 2.2. It is important to note that roundtrips provide short geodesic distances and long trip durations in these statistics. In order to get a better sense of one-way trips, roundtrips can be filtered out. If we assume a maximum distance between the origin and destination of roundtrips to be 400 meters, by removing trips with less than 400m of displacement, for Car2Go and Evo, the average distance travelled would be 3.8 and 4.1 km. In contrast, the average duration would be 54 and 55.5 minutes, respectively.

[4] Fuel level data is also explored, however the data was too inconsistent and proved to be too unreliable for analysis. The fuel level for the idle vehicles have fluctuations in 5 minute intervals. Also, since the cars sometimes are refueled in-between idle states, it becomes more complicated to derive meaningful data from before and after reappearance of the car.

Table 2.2 Summary of trip characteristics by the service provider

	Car2go	Evo
Average duration of booking + trip (minutes)	56	59
Average geodesic distance travelled (kilometres)	3.6	3.8

2.2.4 Vehicle usage per day

Figure 2-5 shows the histogram of the average number of daily trips for each car for weekdays and holidays. For this effort, the recorded days are separated as workdays and non-workdays that encompasses weekend and public holidays in BC. There were 50 weekends and 7 holidays on Monday in the shorter time span (352 days). For the longer time span (567 days), 81 weekends and 12 holidays on Monday are counted. Three holidays that were not on Monday were not included in the analysis. In this study, all the weekends and holidays are categorized as "holidays" and studied along with the workdays.

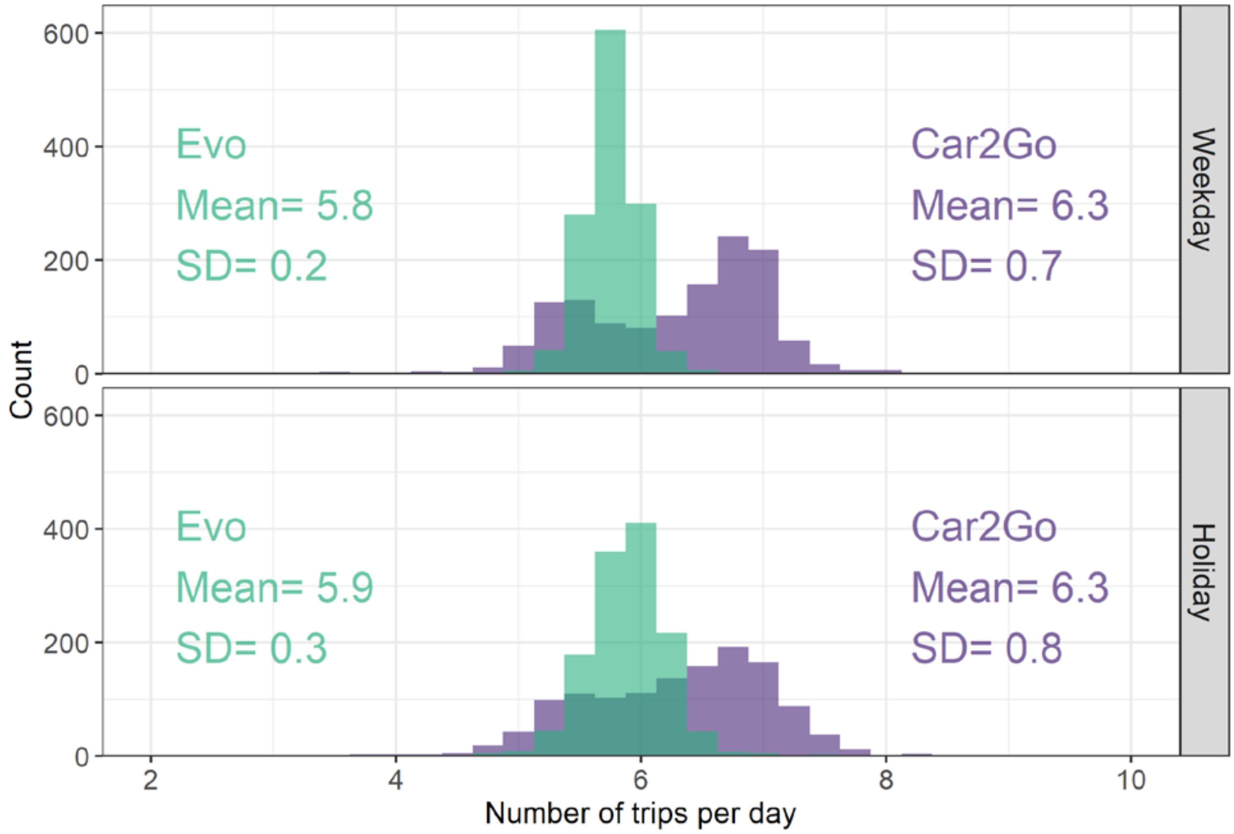


Figure 2-5 Average daily usage of a carsharing vehicle

The results show no significant difference in the average daily number of trips per vehicle between workdays and holidays for both fleets. Moreover, the average daily number of trips per vehicle for the Car2Go fleet (6.3) is higher than that for the Evo fleet (5.8) by half a unit. An apparent difference in the figure above is in the shape of the charts for the two companies. In contrast to Evo's unimodal distribution, Car2Go follows a bimodal distribution (Hartigan's dip statistics p-value (Hartigan & Hartigan, 2007; Maechler, 2021) for Car2Go is $< e^{-15}$). We believe that the difference stems from two factors. First, Car2Go's fleet at the time of data collection had three types of vehicle in comparison to Evo which had only one model in its fleet. Moreover, different types of vehicle in Car2Go's fleet had different pricing schemes. Therefore they could provide different mobility utility to the members. Another factor could be attributed to the way each company had been managing their fleet. Evo expanded their fleet in response to the expansion of their service area and increasing demand while gaining more share of the market. Car2Go, on the other hand, as shown in Figure 2-1, reduced its fleet size on aggregate, especially closer to the end of the data collection period. Shown in Figure 2-6, as time proceeds, the daily usage frequency of Car2Go vehicles rises at a higher rate than that of Evo vehicles. The values in this figure are calculated for each week. The Evo fleet of Toyota Prius C vehicles increased in number for the 2nd half of 2017 and remained unchanged to the end of data collection. Meanwhile, Car2Go introduced Mercedes 4-door models to its fleet of vehicles while reducing the number of cars in the fleet towards the end of our data collection period. Both the capability of the new vehicles and reduction of the overall fleet size led to a rising vehicle usage through the data collection period. For more information see Appendix A.3.

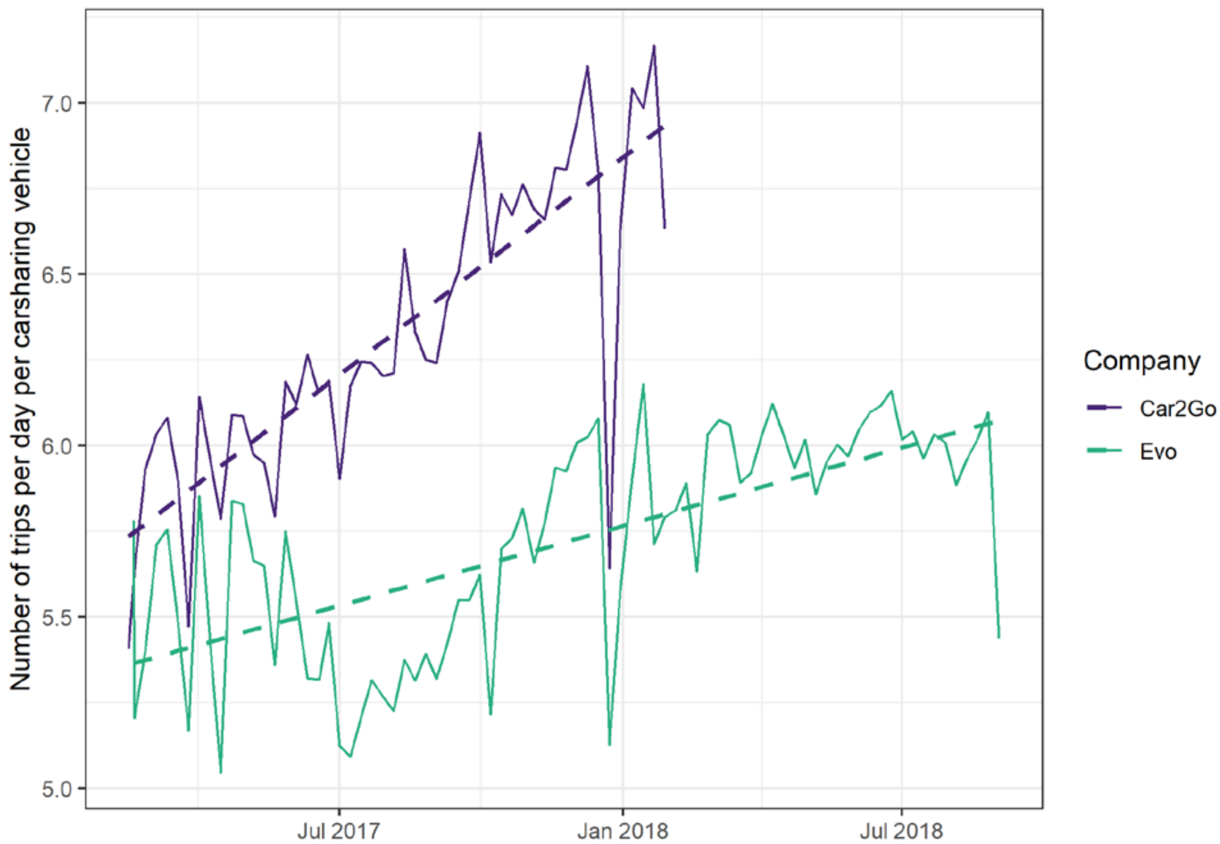


Figure 2-6 Average daily use per available vehicle in Car2Go and Evo fleets. During the study period, Car2Go was decreasing its fleet size while Evo was increasing their fleet size.

Figure 2-7 shows that 75% of times a carsharing vehicle would be used equal or less than eight times per day. For a more detailed plot regarding the daily number of trips per carsharing vehicle, see Appendix A.4.

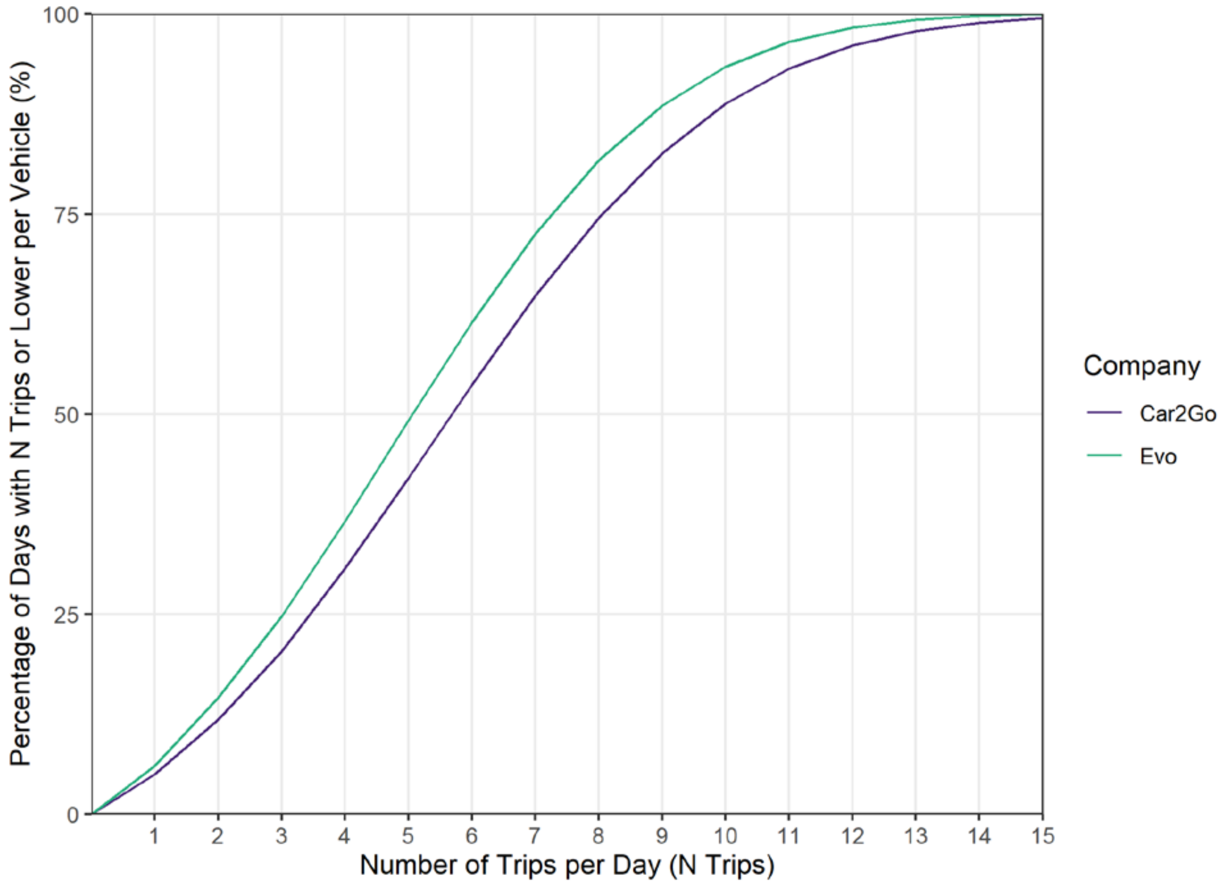


Figure 2-7 Cumulative distribution function of the number of trips per day

Average hourly usage of a carsharing vehicle is presented in Figure 2-8. The starting time of trip is used for the calculation of hourly usage in this figure. The figure shows that the usage of carsharing vehicle throughout the day is different for weekdays and holidays. During weekdays, the commuting hours have higher numbers of trip starts in which 4 PM with less than 0.5 trips is the hour with the highest number of trip starts. It is important to note that regarding the differences between the service providers, the variances of hourly usage among Car2Go is higher than that of Evo. This could be related to the higher rate of change of number of usage per day, as shown in Figure 2-6, or the different usage behaviour for different car models in Car2Go fleet.

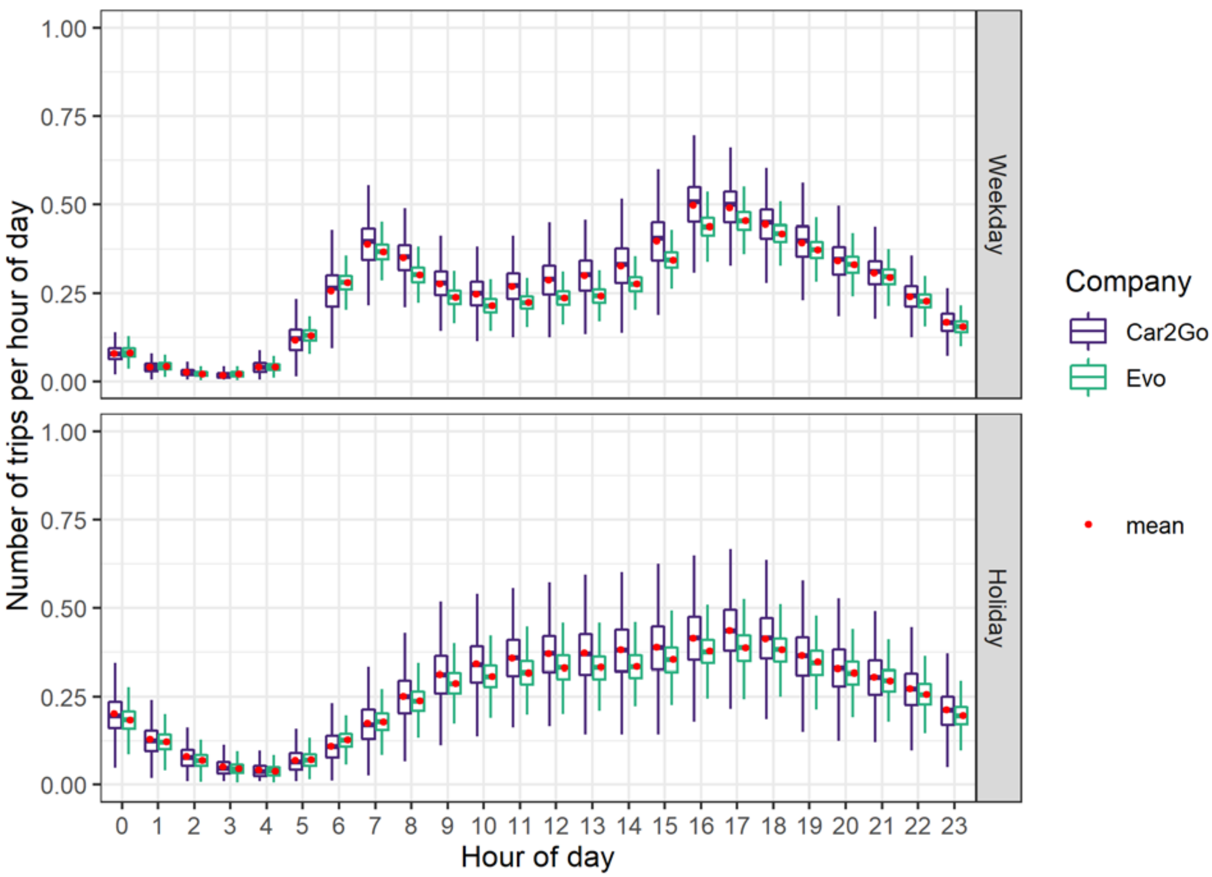


Figure 2-8 Average hourly number of trip starts per available carsharing vehicle

Furthermore, on average less than one trip is made per day per carsharing vehicle during morning or afternoon commute hours. Table 2.3 illustrates the timing of trips in more detail.

Table 2.3 Average number of trips per car per day during commute hours

	Car2Go	Evo
Morning Commute Hours (7:00-9:30 AM)	0.77	0.69
Afternoon Commute Hours (4:00-6:30 PM)	0.9	0.76

According to Metro Vancouver Regional Trip Diary Survey (TransLink, 2013), in 2011, a daily average of 2.77 trips per person is recorded in Metro Vancouver, for which 57% is accounted for by the auto-driver mode. Therefore, on a daily basis, 1.58 trips per person were made by driving in 2011. TransLink executive summary of the 2017 survey (2017) indicates an 11% and 9% increase in the number of vehicle trips and population from 2011, respectively. Considering the combined effect of population and trip rate growths on total daily trips, these values translate to 1.8% growth in the region's daily vehicle trip rate. Putting all the findings together, in 2017 a daily average of 1.61 trips per person is done by driving.

With a simple assumption that a carsharing vehicle can be used as a substitute for the trips done with a private vehicle, an Evo vehicle (with 5.8 daily trips on average) can satisfy the needs of 3.6 regular residents in Metro Vancouver (3.9 for a Car2Go vehicle). Furthermore, the average daily trips per carsharing vehicle during commute hours (Table 2.3) indicate that each car can hardly substitute the need of one private vehicle owner who adopts the driving mode for the daily commute.

The next question relates to patterns of trips completed at different times of day, different days of the week at different locations.

2.2.5 Trip characteristics by time of day and location

The distribution of the number of trips starting within every hour of the day is shown in Figure 2-9. Based on this figure, it is evident that carsharing vehicles are used throughout the day, with higher usage around morning and evening commute hours. The aggregate trip pattern is different among the days of the week. Moreover, different groups of trips with similar starting and ending locations have different patterns throughout the day. In order to incorporate these two parameters in the analysis, hourly idle time over the weekdays is studied, which provides hourly information about the fleet in between the trips. A car during an idle period is located in one place, which connects the end of the previous trip to the start of the next one. Therefore, focusing on idle time reduces the number of spatial parameters and makes the study simpler.

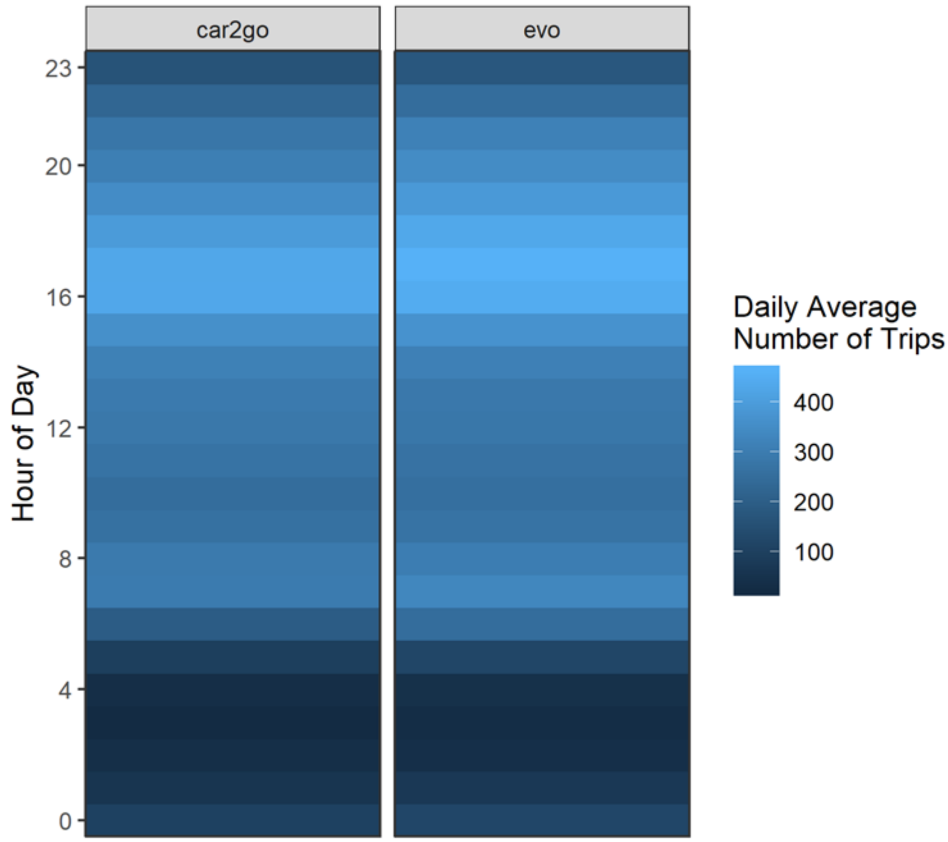


Figure 2-9 Number of trips for each service provider by the time of day

As a pre-requisite of hourly idle time study, the idle cars' locations are mapped to one of the 75 neighbourhoods in the region where the carsharing companies operate (see Figure 2-10) The neighbourhood boundaries are drawn based on the 2016 Census Boundary Files (Statistics Canada, 2016).

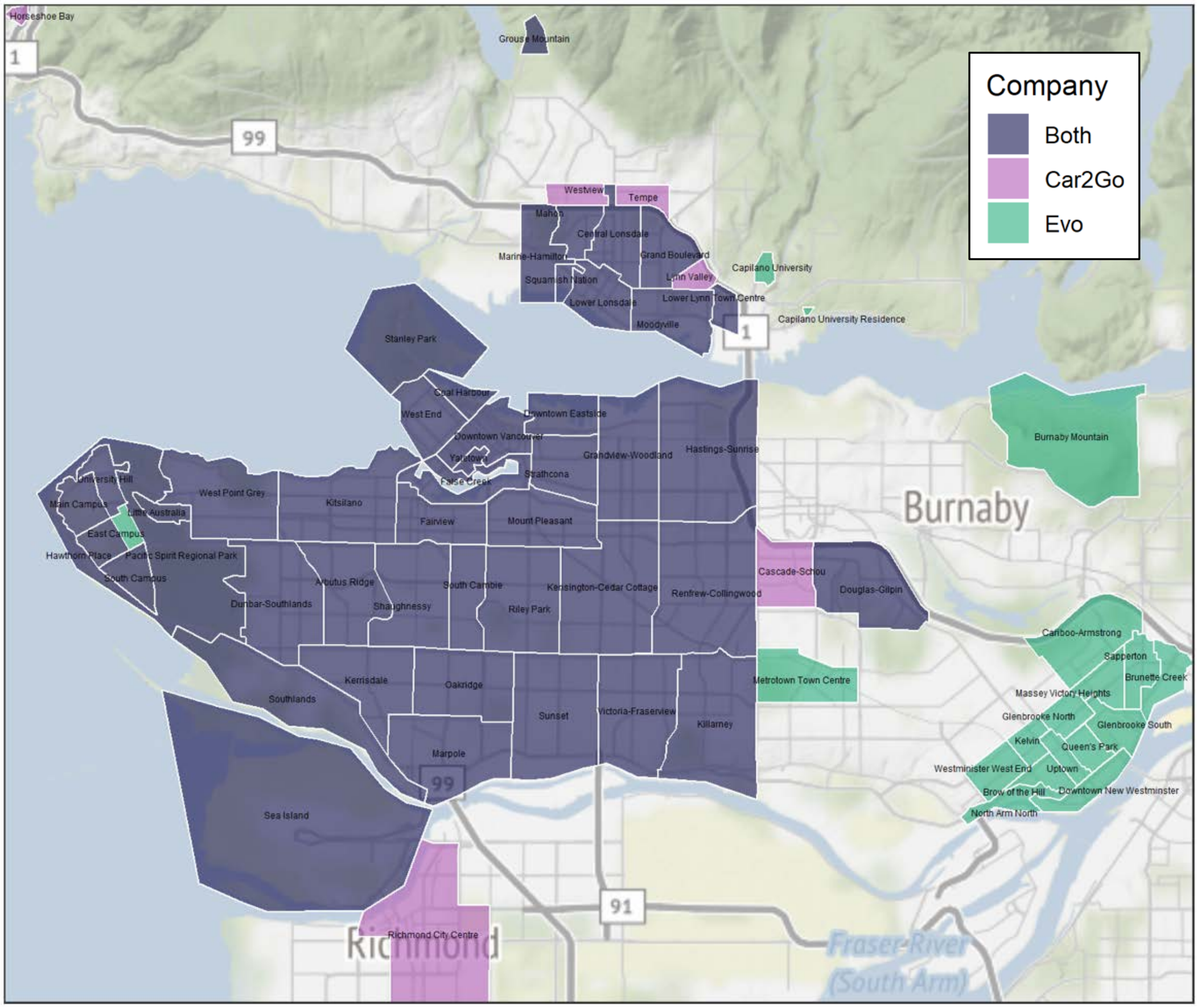


Figure 2-10 Metro Vancouver neighbourhoods coloured by the companies operating in them

After preparing the data, hourly idle time can be studied for each neighbourhood. As examples, we display the distribution of hourly aggregate fleet idle time for the neighbourhoods of UBC Main Campus and Dunbar-Southlands (see Figure 2-11) in Figure 2-12 "a" & "b".

Hourly aggregate fleet idle time distribution figures are designed to convey variation in aggregate vehicle use/availability by the day of the week and by the time of day. Each block in the figure represents an hour of a day of the week. For each block, the fraction of the hour that every vehicle is idle in the neighbourhood is calculated for the duration in which the car is in the neighbourhood. The fractions are then summed and averaged to give the aggregate fleet idle time for that specific hour of the day of the week. Afterwards, the distribution of aggregate hourly fleet idle time for each day of the week is normalized, and the respective Z-scores values are displayed in the figures. This standardization allows direct comparison of the statistical distributions of vehicle idle time across days and between neighbourhoods with vehicles populations that could be very different from one another. In the figures, the daily mean of aggregate hourly idle time and its standard deviation (SD) are shown on top of each day for completeness.[5]

Figure 2-12 "a" & "b" show a complementarity of UBC Main Campus and Dunbar-Southlands patterns during the work week. For example, on Tuesday at 7 am, the average fleet idle time at UBC Main Campus has a negative Z-score close to zero, which translates to 13 hours of fleet idle time. This value rises to 32 hours in midday (Z-score = 1.64), stays approximately the same until 6 pm, then decreases to 5.7 hours at 11 pm (Z-score = -0.93). On the same day, Dunbar-Southlands has an average fleet idle time of 30 hours with a positive Z-score near zero at 7 am, which decreases to 12.3 in midday with a Z-score of -1.35 not changing until 6 pm. Afterwards,

[5] In order to calculate actual aggregate fleet idle time for any given hour of a day of week please multiply the Z-score value by the SD and add to the mean.

Dunbar-Southlands fleet idle time increases to 43 hours at the end of the day (Z-score = 1.14). This explanation is an example of the stark differences in the trip patterns observed in various neighbourhoods.

Moreover, one can observe the difference in the distributions on working days and holidays. In the UBC Main Campus figure, the hour with the highest fleet idle time on Sunday occurs between 1–2 pm, while on a regular working day, the aggregate fleet idle time pattern is more uniform during the midday maxing at 11 am. Please note that the high number of holiday Mondays in the calendar necessitated that we separate them out as a separate category of days for our analyses. The aggregate fleet idle time distribution figures are used in Section 3.2 to characterize various neighbourhoods through the statistical clustering of their vehicle use patterns.

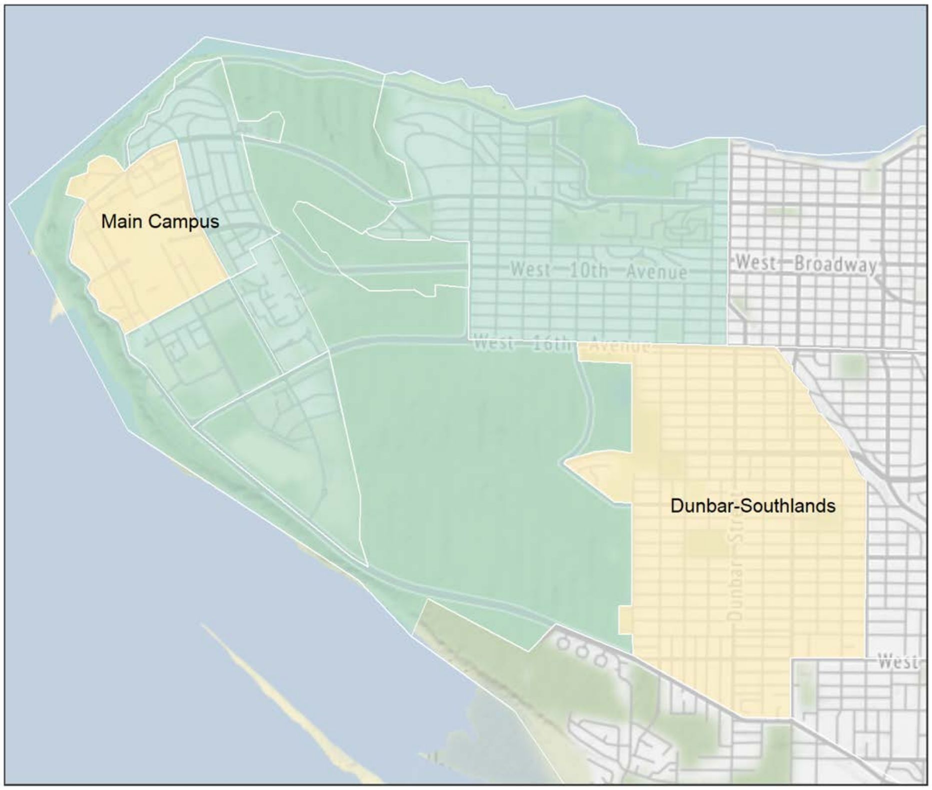


Figure 2-11 UBC Main Campus and Dunbar Southlands neighbourhood boundaries

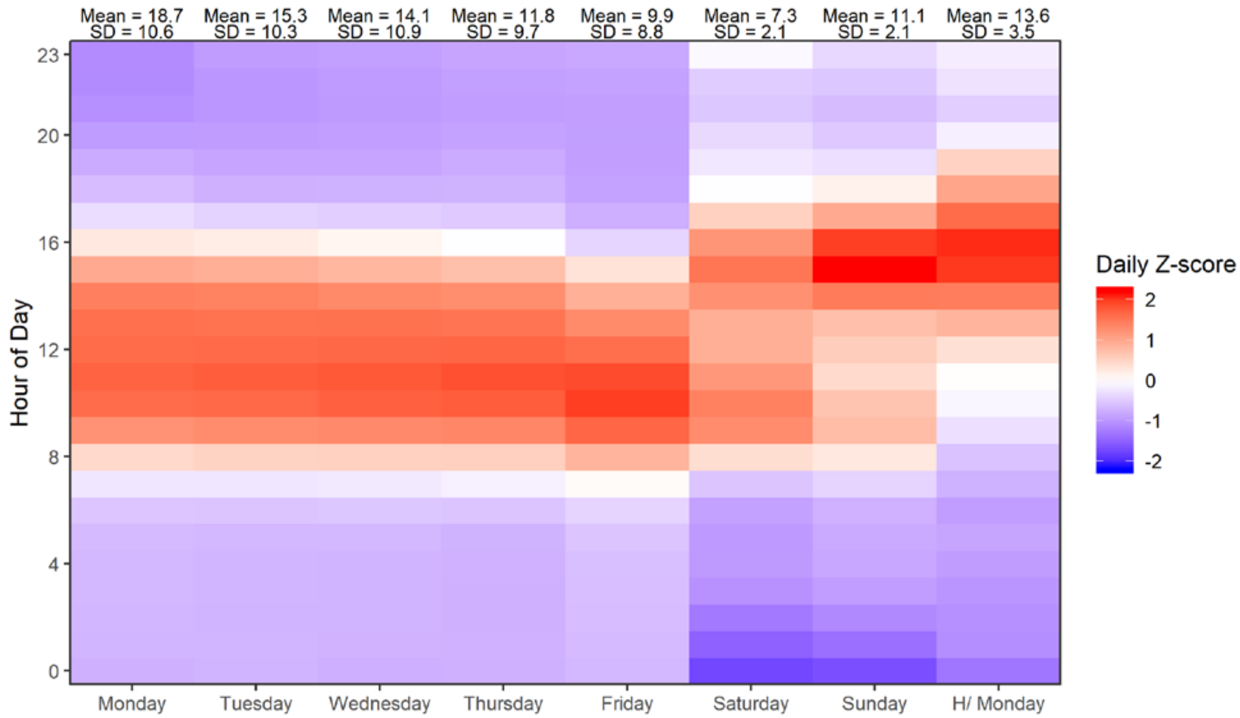


Figure 2-12 Distribution of hourly aggregate fleet idle time in a neighbourhood for Evo fleet

a) UBC Main Campus

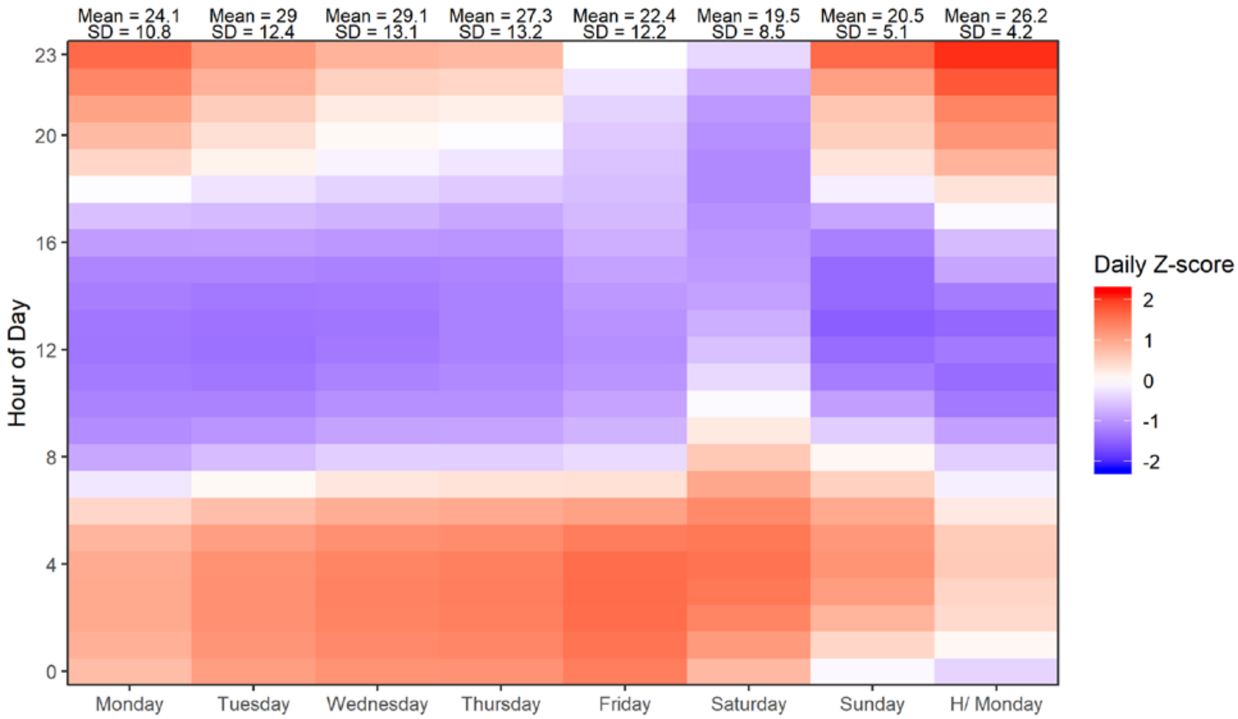


Figure 2.12 Distribution of hourly aggregate fleet idle time in a neighbourhood for Evo fleet

b) Dunbar-Southlands

Chapter 3: Analysis

3.1 Private vehicle substitution

In Section 2.2.4, the daily average number of times a carsharing vehicle is used was examined. An average of 5.8 trips per day is recorded per Evo vehicle on weekdays. This finding by itself is discussed in the Data Section, showing that each carsharing vehicle provides mobility to a limited number of users. Here I explore the possibilities of connecting the average daily trips per carsharing vehicle to private vehicle ownership reduction while differentiating between users with different usage frequencies.

Two of the most common indices that survey studies report regarding the impact on private vehicle ownership on aggregate are: 1) the number of private vehicles removed from the road per carsharing vehicle, and/ or 2) percentage of members that sold a private vehicle or forgone purchasing one. Table 3.1 provides an overview of the reported numbers in literature. The selected studies pertain to free-floating carsharing systems only.

The differences in the results can be attributed to various factors such as the location under study, the operator, and the methods used for data collection and analysis. The studies in London show bigger impacts on private vehicle ownership. London is a special case among the cities presented in Table 3.1 for its rigorous transportation policies that discourage private vehicles perhaps contributing to the higher impacts reported. More specifically, the city has a long-standing road pricing scheme in place especially for the center of the city since 2003.

Table 3.1 Literature review of reported values regarding the impact of free-floating carsharing on vehicle ownership

Paper	Operator	Location	Data collection and analysis method	# of private vehicles removed per carsharing vehicle	% of members that reduced vehicle ownership	% of members that forgone increasing vehicle ownership
Firnkorn & Müller, 2012	Car2Go	Ulm, Germany	Hypothetical, intercept survey	-	4%	10%
Martin & Shaheen, 2016	Car2Go	Canada and USA	Cross-section, online survey	7-11	2-5%	7-10%
Giesel & Nobis, 2016	DriveNow	Berlin and Munich, Germany	Cross-section, online survey	-	7%	-
Becker *et al.*, 2018	-	Basel, Switzerland	Panel, online survey, tracking	-	6%	-
Namazu & Dowlatabadi, 2018	Car2Go	Vancouver, Canada	Cross-section, online survey	2.5 (6 for early adopters)	12%	-[6]
Gleave, 2018	DriveNow	London, UK	Online survey, Operator data collection	13	4.75%	27%
Le Vine & Polak, 2019	DriveNow	London, UK	Cross-section, online survey	-	4%	30%
Liao, *et al.*, 2020	-	Netherlands	Stated choice experiment	-	20%	

[6] 30% of members with no change in vehicle ownership report they would increase vehicle ownership if carsharing services ceased. This suggests that carsharing allow these households to forgo the purchase of vehicles. However, it does not differentiate between users who intended to increase vehicle ownership prior to joining the carsharing service and those who were motivated to gain vehicle ownership after experiencing the convenience of access to a personal vehicle through carsharing.

In this study, I use Monte Carlo simulation to model a population of carsharing users with different usage frequency with different tendencies to reduce their vehicle ownership.

3.1.1 Monte Carlo simulation

The first step is to find a proper distribution of frequency for members' use of carsharing vehicles. Table 3.2 provides a summary of the studies that have the distribution of usage frequency published for their case study.

Table 3.2 List of studies reporting the distribution of carsharing members' usage frequency for their case study

Paper number	Study	Carsharing type	Operator	Location
1	Costain, Ardron, & Habib, 2012	Two-way	AutoShare	Toronto
2	Nehrke, 2019	Free-floating	Car2Go	Stuttgart, Frankfurt, Cologne
3	Bi, Zhi, Xie, Zhao, & Zhang, 2020	Station-based one-way	-	Gansu, China
4	Zhang, Schmöcker, & Trépanier, 2021	Free-floating	Communauto	Montreal
5	Ye, Wang, Li, Axhausen, & Jin, 2021	Station-based one-way	Evcard	Shanghai

Among the papers represented in Table 3.2, Paper 2-5 study one-way carsharing, among which paper 2 and 4 belong to free-floating carsharing services. Six different nonlinear equations are used to find the best fit to the usage frequency distributions: 1- exponential (ab^x), 2- exponential with a constant ($ab^x + c$), 3- power curve (ax^b), 4- logarithmic ($a + b\log x$), 5- Weibull ($\frac{b}{a}(\frac{x}{a})^{b-1}e^{-(\frac{x}{a})^b}$), and 6- Gamma ($\frac{x^{b-1}e^{-\frac{x}{a}}}{a^b\Gamma(b)}$). For each data set, the data points are converted to ranges of usage frequency and treated as CDF. Therefore, the integral of the nonlinear equations are used for regression. Figure 3-1 show the regression lines for each paper with one-way carshring data. All the nonlinear equations except logarithmic, visually have good regression to the data sets. In order to choose the best model and its respective parameters, paper 4 is selected for further analysis. The paper studies a free-floating service in Montreal, Canada which among the case studies have the closest social, cultural, and economic equivalency to this study. Paper 2, the other free-floating data set, is another good candidate; however, it is discarded for its low granularity. Table 3.3 show the result of the regression analysis.

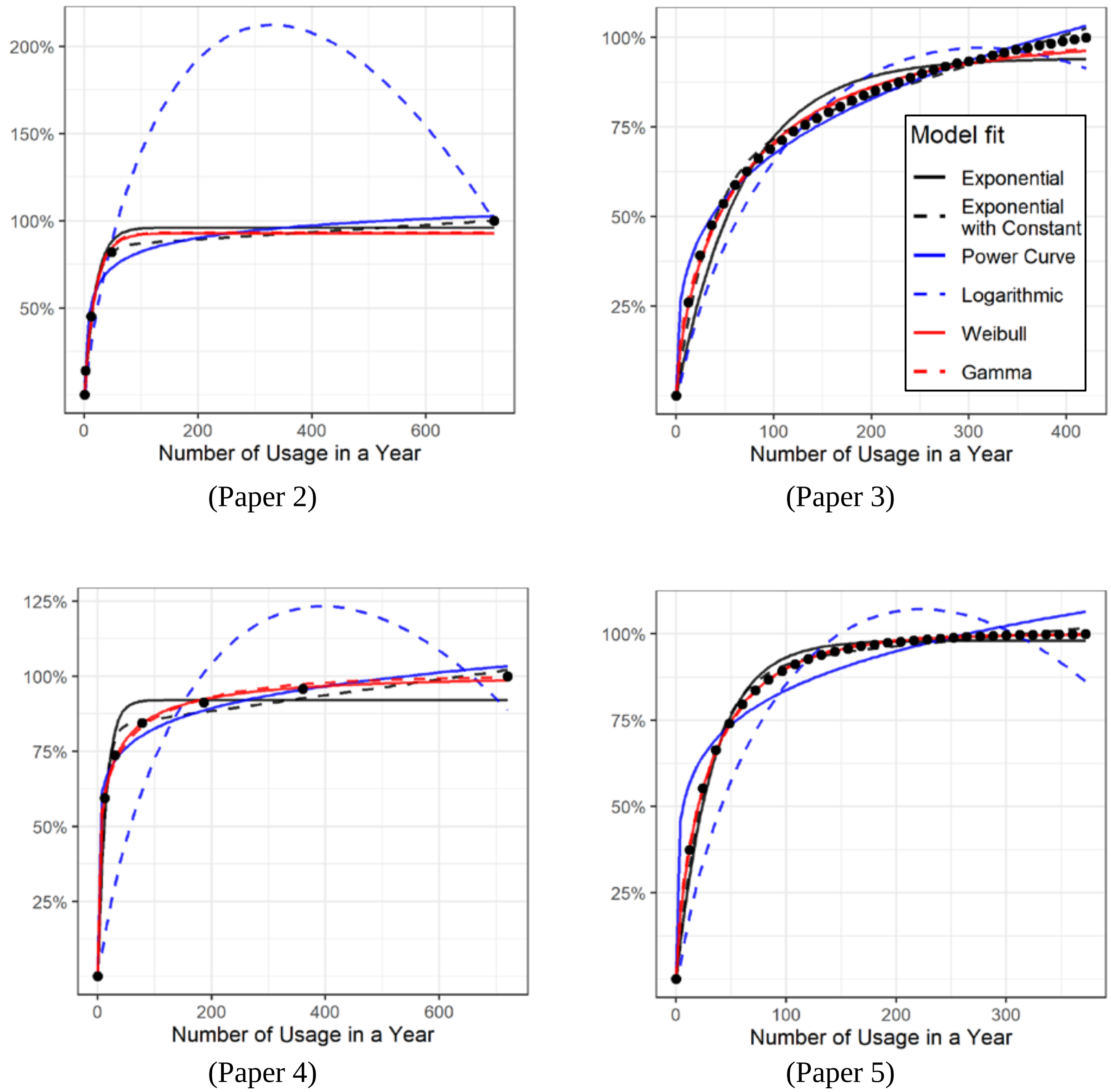


Figure 3-1 Usage Frequency probability distribution and their respective regression lines for papers 2-5.

Table 3.3 Comparison of the usage frequency regression models for papers 4

Nonlinear equation	Formula	Paper 4	
		Residual Standard Deviation	AIC
Exponential	ab^x	0.07	-14.23
Exponential with a constant	$ab^x + c$	0.04	-21.54
Power curve	ax^b	0.04	-22.73
Logarithmic	$a + b \log x$	0.33	7.96
Weibull	$\boldsymbol{\frac{b}{a}(\frac{x}{a})^{b-1}e^{-(\frac{x}{a})^b}}$	**0.01**	**-40.76**
Gamma	$\frac{x^{b-1}e^{-\frac{x}{a}}}{a^b\Gamma(b)}$	0.02	-34.14

Visual observation of the regression figures and the lower values of Residual Standard Deviation and AIC suggest Weibull equation to be used for the members' usage frequency distribution. It is necessary to choose an appropriate value for the scale (a) and shape (b) parameters of Weibull distribution. Table 3.4 shows the values of a and b of the regression model for paper 4.

Table 3.4 Parameters a and b of the Weibull regression model for paper 4

Parameter	Estimate	Standard Error	P-value
a	14.98	0.84	1e-05
b	0.37	0.02	2e-06

Equation 3-1 shows the use of Weibull distribution for modelling the usage frequency distribution per each carsharing vehicle. In this representation, u is the usage frequency, or the number of carsharing usage per year and $nu(u)$ is the number of users. c is a coefficient for calculating counts from Weibull distribution. Equation 3-2 calculates $nt(u)$, the number of trips per carsharing vehicle for different usage frequencies. Its integral gives the total number of trips per carsharing vehicle, which should be equal to 6 trips per day ($\sim 6 \times 30 \times 12$ trips per year) (Equation 3-3). This value is adopted from Section 2.2.4 and rounded up. Coefficient c can be calculated from the latter equation. For each iteration, parameter a and b are randomly chosen from normal distributions with the means and standard deviations equal to the estimates and standard errors acquired from regression analysis (Table 3.4). In Weibull distribution, the parameters need to be greater than zero. Therefore, the model checks a and b to be greater than zero in each iteration. It also checks b to be less than 1. That is because the shape of the distribution depends on the value of b and Weibull distribution with b values greater than 1 would not follow the pattern seen in literature (Figure 3-1). The limits of integration are considered to be 1 usage per year and 60 usage per month ($\sim 60 \times 12$ trips per year).

$$nu(u) = c \times Weibull(u, b, a) \qquad \text{Equation 3-1}$$

$$nt(u) = u \times nu(u) \qquad \text{Equation 3-2}$$

$$total\ number\ of\ trips =$$

$$\int nt(u) = \int_{1}^{60\times 12} u \times c \times Weibull(u, b, a) \times du = 6 \times 30 \times 12 \qquad \text{Equation 3-3}$$

Next, a function for the percentage of the users who would reduce their vehicle ownership or forgo a planned increase in their vehicle ownership needs to be defined. Literature has asserted that users with different trip usage patterns have different tendencies to reduce their car ownership. In a cross-sectional study in Seoul, South Korea, commuting users are more willing to decrease their vehicle ownership than users with non-commuting trips (Kim et al., 2019). A study of European cities has shown that households with higher frequencies of carsharing usage are more willing to sell a private vehicle (Jochem, Frankenhauser, Ewald, Ensslen, & Fromm, 2020). Namazu and Dowlatabadi estimated that households who use carsharing once per month were twice as likely to shed vehicle ownership than those who used vehicles four or more times per month (2018).

Here, a simple linear relation between usage frequency and the tendency to reduce/ forgo increasing vehicle ownership ($nu(u)$) is considered (Equation 3-5). It is assumed that for a user to be impacted by carsharing and reduce/ forgo increasing their vehicle ownership, they need to be an active user. An active user is considered to be a user with at least one trip per month. Here, for each iteration of the simulation coefficients d and e are randomly and uniformly chosen in a way that the percentages assigned for the least active (1 trip per month) and the most active (considered to be 60 trips per month) users would be between 0-100%. This way the model considers both cases in which the more frequent the users, the more or less susceptible to reduce/ forgo increasing vehicle ownership. Shown in Equation 3-5, the $t(u)$, the tendency function, multiplied by the $nu(u)$ function gives the number of users with different usage frequency that reduce/ forgo increasing vehicle ownership, and its integral gives N, the total number of private vehicles removed per carsharing vehicle (Equation 3-6). It is important to note that N includes both the number of vehicles reduced and forgone to be purchased.

$$\boldsymbol{t(u) = \begin{cases} d + e \times u & if\ 1 \times 12 \leq u \leq 60 \times 12 \\ 0 & otherwise \end{cases}}$$

$$\boldsymbol{0 \leq t(u) \leq 1}$$

Equation 3-4

$$\boldsymbol{n(u) = t(u) \times nu(u)}$$

Equation 3-5

$$\boldsymbol{N = \int n(u) = \int_{1\times12}^{60\times12} (d + e \times u) \times c \times Weibull(u, b, a) \times du}$$

Equation 3-6

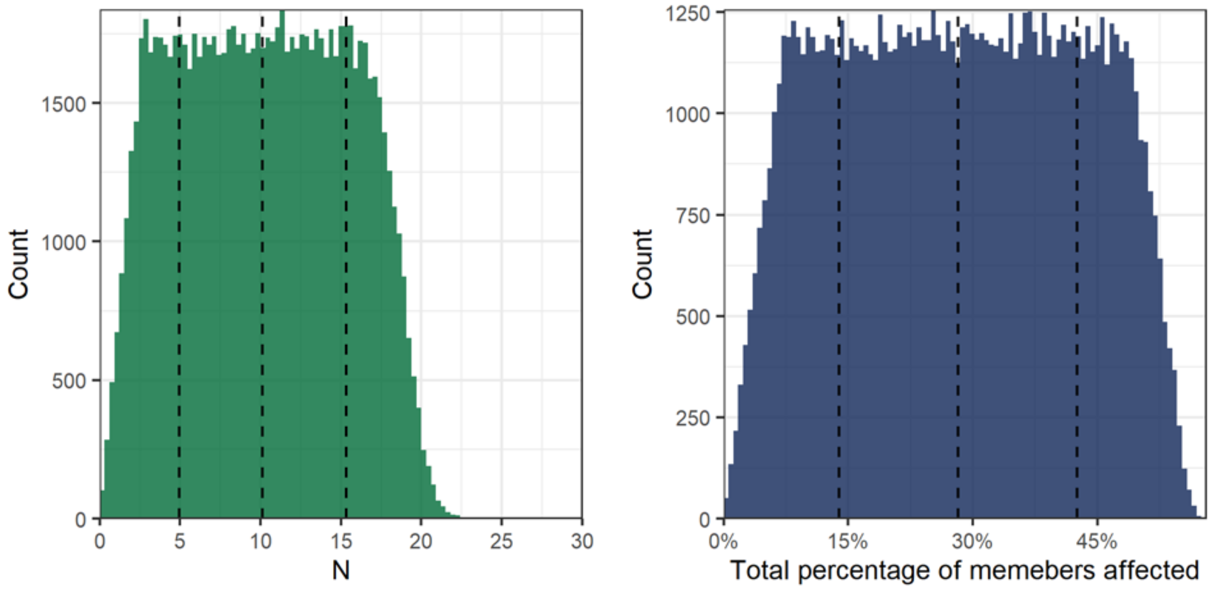
The total percentage of members that reduce/ forgo increasing vehicle ownership equals N over total number of users as shown by Equation 3-7.

$$\boldsymbol{Total\ percentage\ of\ memebers\ that\ reduce\ or\ forgo\ increasing\ vehicle\ ownership = \frac{N}{\int number\ of\ users} = \frac{\int_{1\times12}^{60\times12} (d + e \times u) \times c \times Weibull(u, b, a) \times du}{\int_{1}^{60\times12} c \times Weibull(u, b, a) \times du}}$$

Equation 3-7

The Monte Carlo simulation is ran for 100,000 iterations. This model is named as model 1. The results are shown in Figure 3-2 and Figure 3-3. The vertical lines on each distribution represents mean, and one standard deviation away from the mean. For a better representation of the differences among users, they are classified into 6 classes by usage frequency:

- Infrequent users use carsharing less than once per month (between 1 and 12 trips per year).
- Low-frequency users use carsharing between 1-4 times per month (between 12-48 trips per year)
- Low-medium-frequency users use carsharing between 1-2 times per week (between 48-96 trips per year)
- Medium-frequency users use carsharing between 2-4 times per week (between 96-192 trips per year)
- Medium-high-frequency users use carsharing between 4 times per week and once per day (between 192-360 trips per year)
- High-frequency users use carsharing more than 30 times per month (between 360-720 trips per year)



(a) (b)

Figure 3-2 Distribution of Model 1 results: (a) N, total number of removed private vehicle per carsharing vehicle (b) Total percentage of members that reduce or forgo increasing vehicle ownership

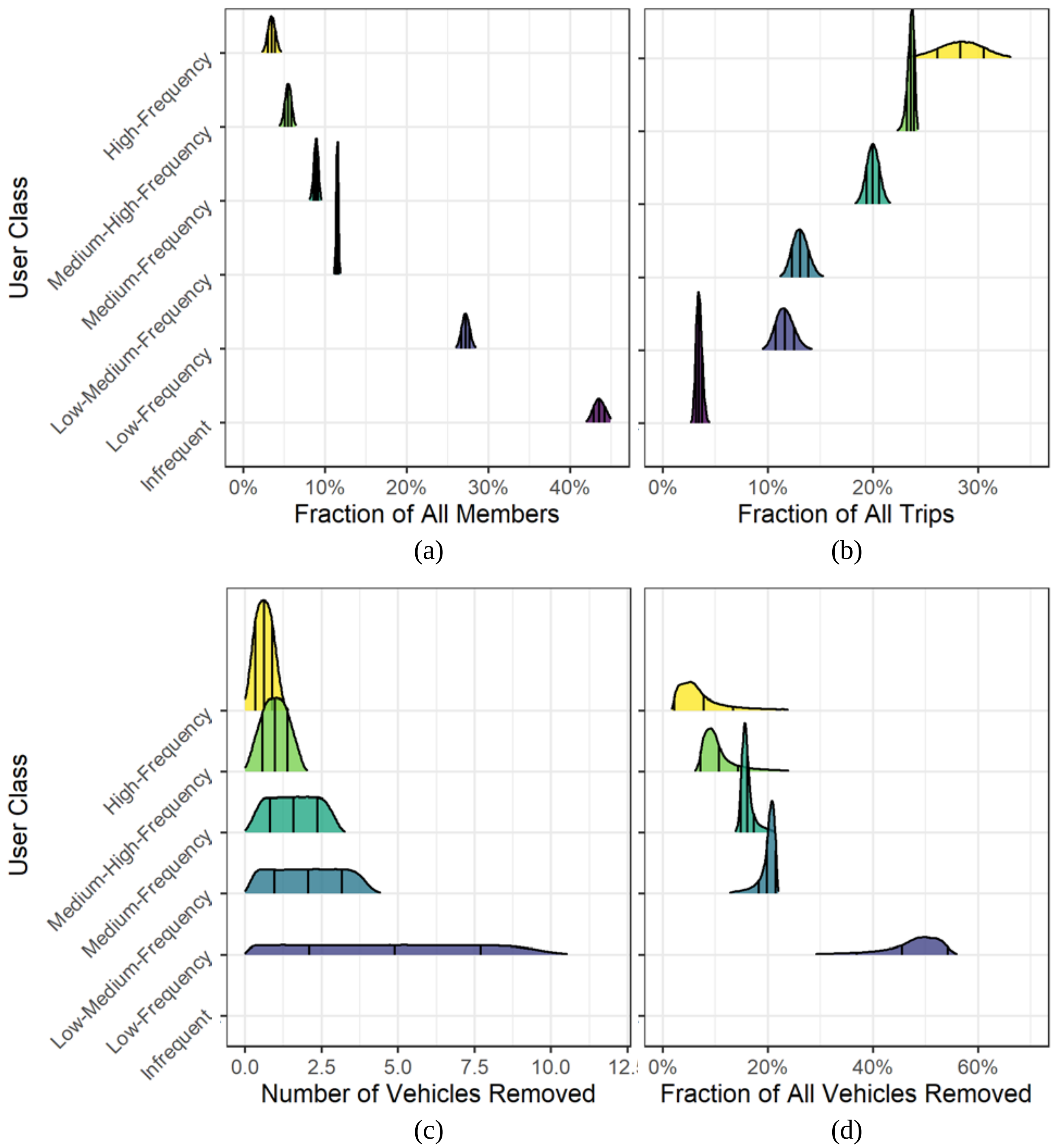


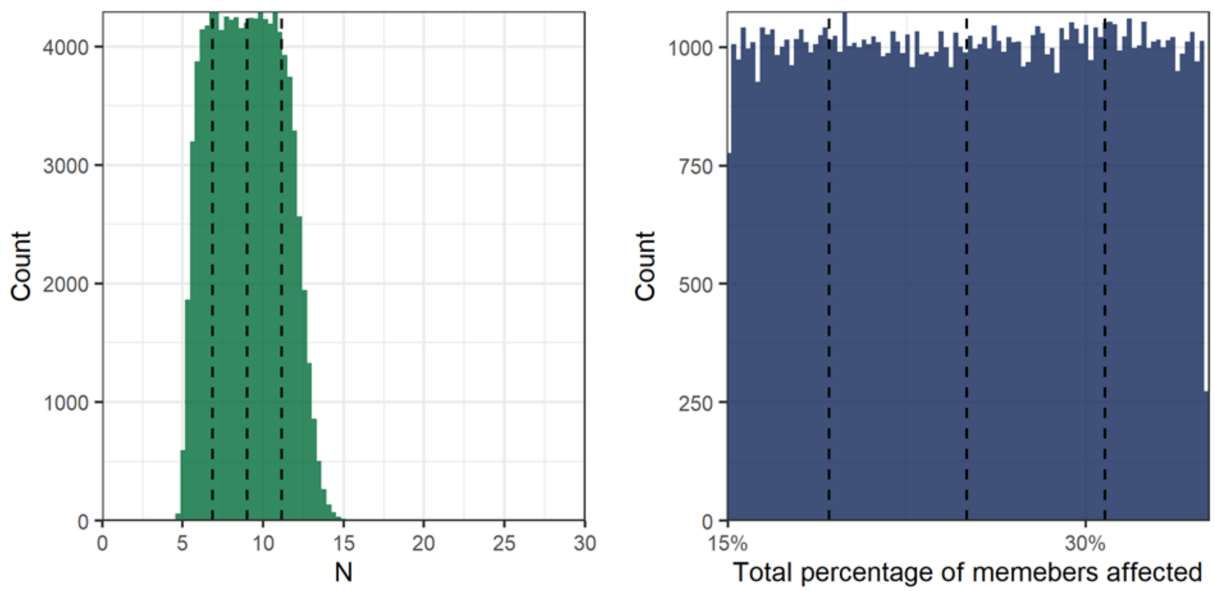
Figure 3-3 Distribution of Model 1 results for different user classes: (a) fraction of total number of users, (b) fraction of total number of trips per carsharing vehicle, (c) Number of vehicles removed from the road per carsharing vehicle, (d) fraction of all the vehicles removed from the road per carsharing vehicle

The model predicted an average of 10.1 vehicles to be removed per carsharing vehicle and 28% of the users to be affected by carsharing in their vehicle ownership plan. Out of the 10.1 vehicles, on average 66% of the vehicles belong to the low and low-medium-frequency classes of users. Another 16% of the cars come from the medium-frequency class of users. Among iterations, As N increases, the share of removed vehicles for the lower frequency users rises and for the higher frequency ones falls. Moreover, 43% of the users belong to infrequent class. Another 27% and 11% of the users are from low and low-medium-frequency classes.

The distribution of N and percentage of users who reduce/ forgo increasing vehicle ownership in Figure 3-2 show that close to the mean the model's result follows the estimates found in literature. However far from the mean, the results are incongruous with the literature. Therefore, new models are simulated in which conditions are implemented to limit these two values.

3.1.2 Monte Carlo simulation with conditions model

Two different models are simulated. One with a more optimistic condition than the other. In Model 2, in each iteration the percentage of users who reduce/ forgo increasing vehicle ownership is checked to be in the range of 15-35%. In Model 3, this range is considered to be between 9-15%. These ranges are chosen based on the literature (Table 3.2). Model 2 includes the ranges that are reported in London, which, as discussed before, can be a special case for its sterner transportation policies. If an iteration does not comply with the conditions, it is repeated again. This would make changes in the marginal distributions of the parameters of the model (such as b). For more information about these changes see Appendix B.1. The results of the simulation are shown in Figure 3-4 and Figure 3-5 for model 2. It is visible that the distributions among different user classes remains similar to Model 1 except with smaller variances. Average N for model 2 is 9.0, while the average of total percentage of members that reduce or forgo increasing vehicle ownership is 25%.



(a) (b)

Figure 3-4 Distribution of Model 2 results: (a) N, total number of removed private vehicle per carsharing vehicle (b) Total percentage of members that reduce or forgo increasing vehicle ownership

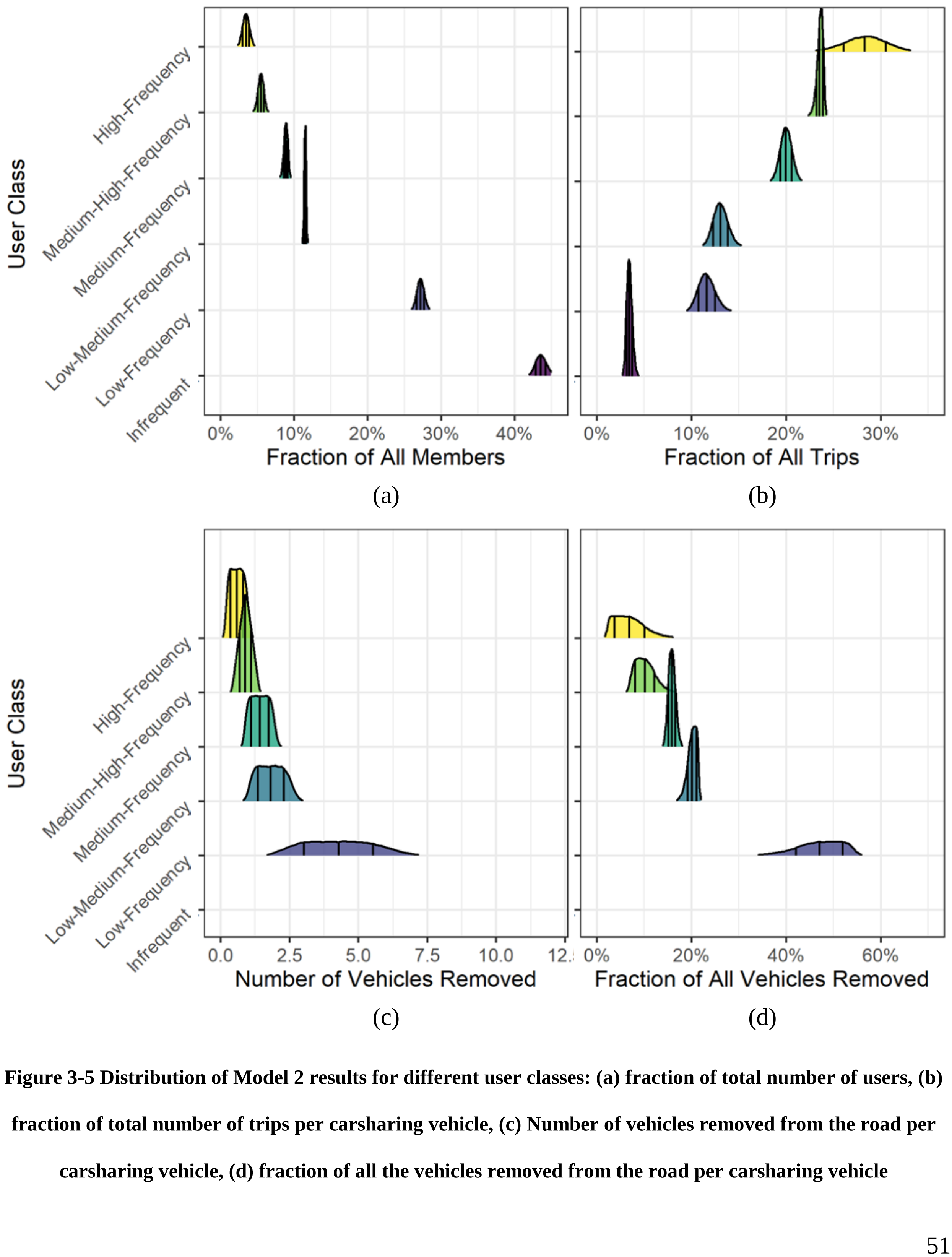


Figure 3-5 Distribution of Model 2 results for different user classes: (a) fraction of total number of users, (b) fraction of total number of trips per carsharing vehicle, (c) Number of vehicles removed from the road per carsharing vehicle, (d) fraction of all the vehicles removed from the road per carsharing vehicle

The results for Model 3 are presented in Figure 3-6 and Figure 3-7. N on average in Model 3 is 4.3, while the average of total percentage of members that reduce or forgo increasing vehicle ownership is 12%. The distribution of N among different classes of users have changed in comparison to Models 1 and 2. Out of the 4.3 vehicles, on average 58% of the vehicles belong to the low and low-medium-frequency classes of users. 25% of the vehicles reduced or forgone to be purchased belong to the medium-high and high-frequency classes of users which is 7% higher than that for Models 1 and 2.

An important result of the simulation models is about the distribution of tendency of reducing/ forgoing increasing vehicle ownership among different classes of users. In Model 1, the coefficients of tendency function are randomly and uniformly chosen. Hence, the tendency for every class of user on average is 50% (except for the infrequent class which is assumed to be 0.) In Models 2 and 3, the conditions that are applied changes the marginal distribution of tendency among users. In Model 2, tendency on average is 44% for the low-frequency users and increases up to 48% for the high-frequency users. The changes are more drastic for Model 3, with 18% of tendency for low-frequency class of users that would increase to 40% for the high-frequency class of users. A summary of these modelling results is presented in Table 3.5.

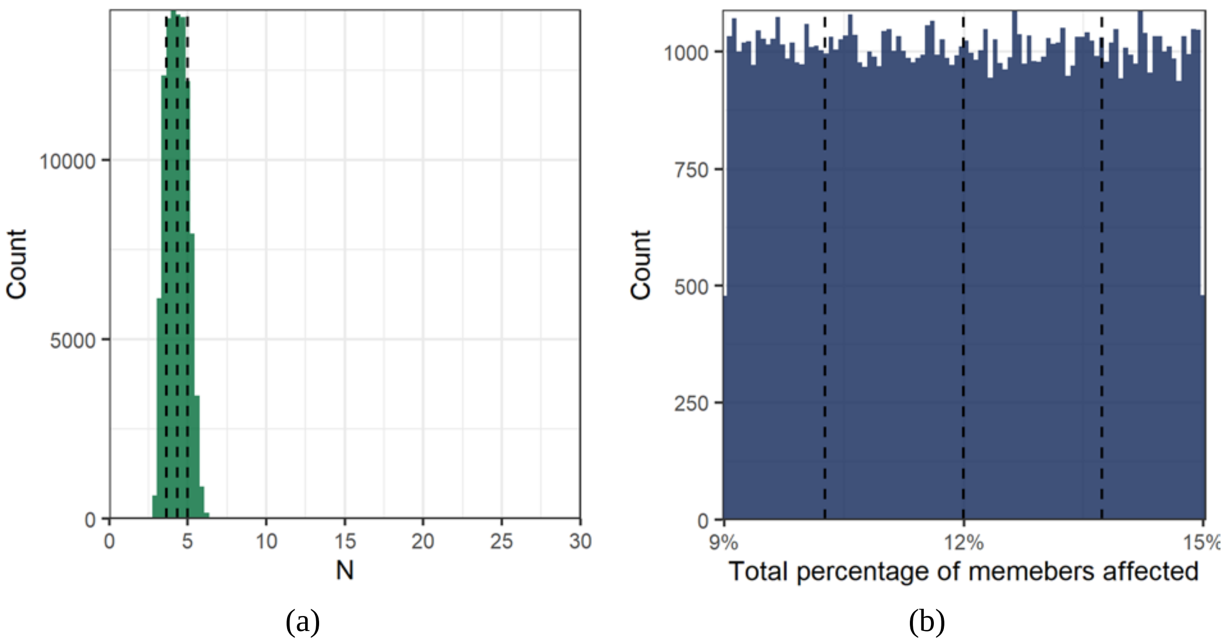


Figure 3-6 Distribution of Model 3 results: (a) N, total number of removed private vehicle per carsharing vehicle (b) Total percentage of members that reduce or forgo increasing vehicle ownership

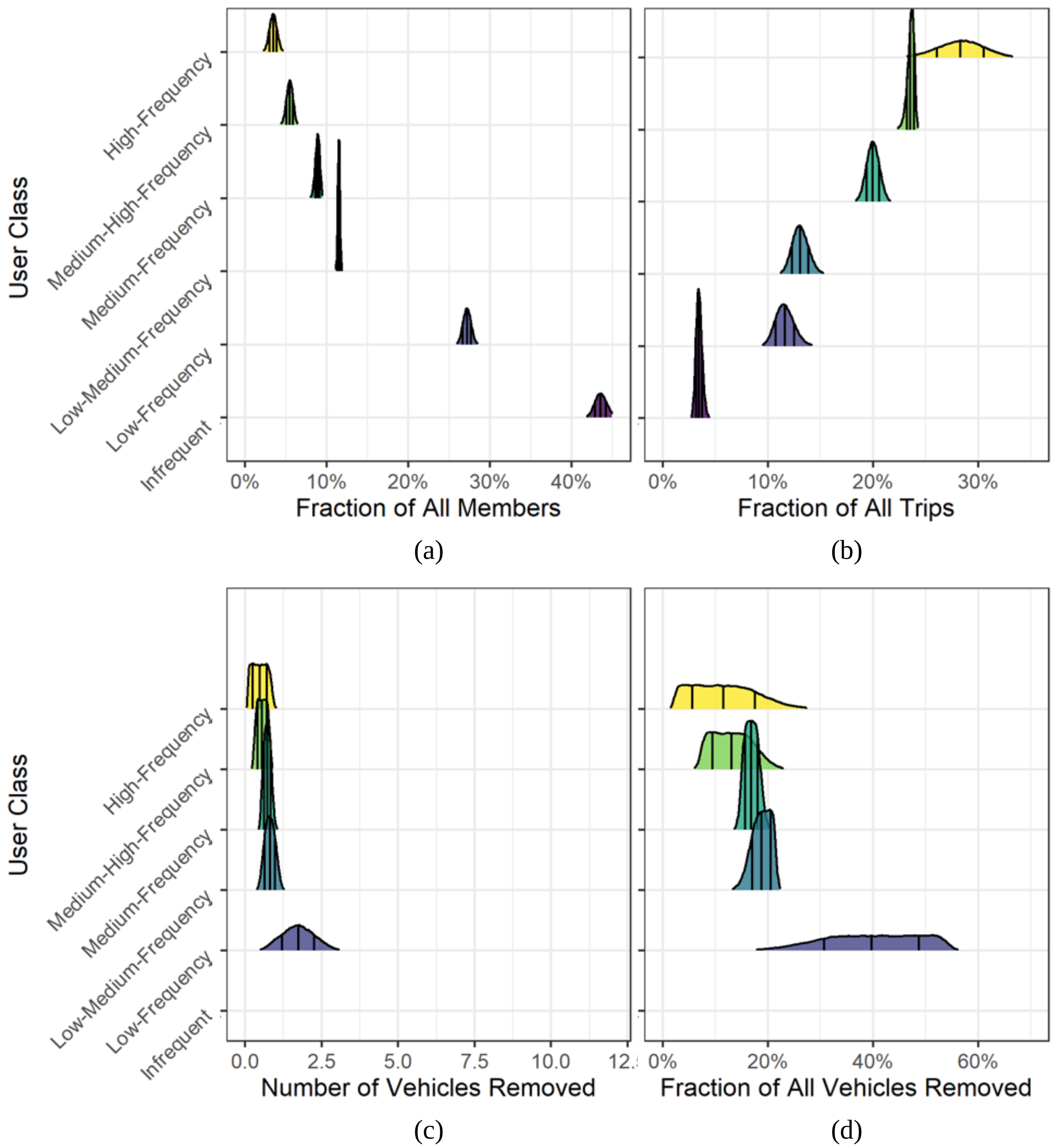


Figure 3-7 Distribution of Model 3 results for different user classes: (a) fraction of total number of users, (b) fraction of total number of trips per carsharing vehicle, (c) Number of vehicles removed from the road per carsharing vehicle, (d) fraction of all the vehicles removed from the road per carsharing vehicle

Table 3.5 Summary of results for Monte Carlo simulation models 1-3.

Result on average		**Model**		
		1	**2**	**3**
N		10.1	9	4.3
Total percentage of members that reduce/ forgo increasing vehicle ownership (%)		28	25	12
Percentage of members (%)	Infrequent	44	44	44
	LF	27	27	27
	LMF	11	11	11
	MF	9	9	9
	MHF	5	5	5
	HF	3	3	3
Percentage of vehicles reduced/forgone to be purchased (%)	Infrequent	0	0	0
	LF	46	47	38
	LMF	20	20	19
	MF	16	16	17
	MHF	11	10	13
	HF	8	7	12
Tendency (percentage of users who reduce/forgo increasing vehicle ownership) (%)	Infrequent	51	0	0
	LF	51	44	18
	LMF	50	44	20
	MF	50	45	23
	MHF	50	46	27
	HF	50	48	40

3.2 Typology of neighbourhoods by carsharing use

In Section 2.2.5, the normalized hourly aggregate fleet idle time distribution is introduced as a metric to study the carsharing usage patterns in various neighbourhoods. Here, we identify neighbourhoods with similar patterns of vehicle idle time using k-mean clustering. The hourly aggregate fleet idle time distributions, used as the input data, are normalized for each day of the week (as described in Section 2.2.5) and consist of 192 variables for 24 hours of 7+1 (Holiday Monday) days of the week for each of the neighbourhoods. As a requirement for k-Mean, the neighbourhoods that lack data in any of the 192 variables are filtered out, resulting in 58 neighbourhoods with complete data.

In k-mean clustering, k represents the number of clusters to which the data are assigned. There is no robust method for identifying an appropriate k value. However, a parametric search of k-space allows identifying k values that have the lowest hard to assign data points. After this parametric search for a k-value with the highest discriminatory power, we arrived at k=4 (for further details, please seeB.2). Moreover, k-mean clustering has a random initialization step which can lead to different clustering in each run. Here, expert judgment based on the region's urban form is used to choose the clustering result. The sum-of-squared-error (SSE) of the chosen result is the lowest among the clustering trials with k=4, confirming the prior judgement.

Figure 3-8 displays the neighbourhoods using x and y axes representing the first two variables in a Principal Components Analysis of their distributions. These two principal components explain 66.6% of the variance among the idle time patterns of the neighbourhoods. Figure 3-8 illustrates that the first explanatory axis completely differentiates between purely residential neighbourhoods and more mixed-use neighbourhoods. The second axis provides clear differentiation between "Office & Entertainment" and "Mixed Usage." The third axis, not shown, provides separation between "Office & Entertainment" and "Day Destination" (see Appendix B.3.)

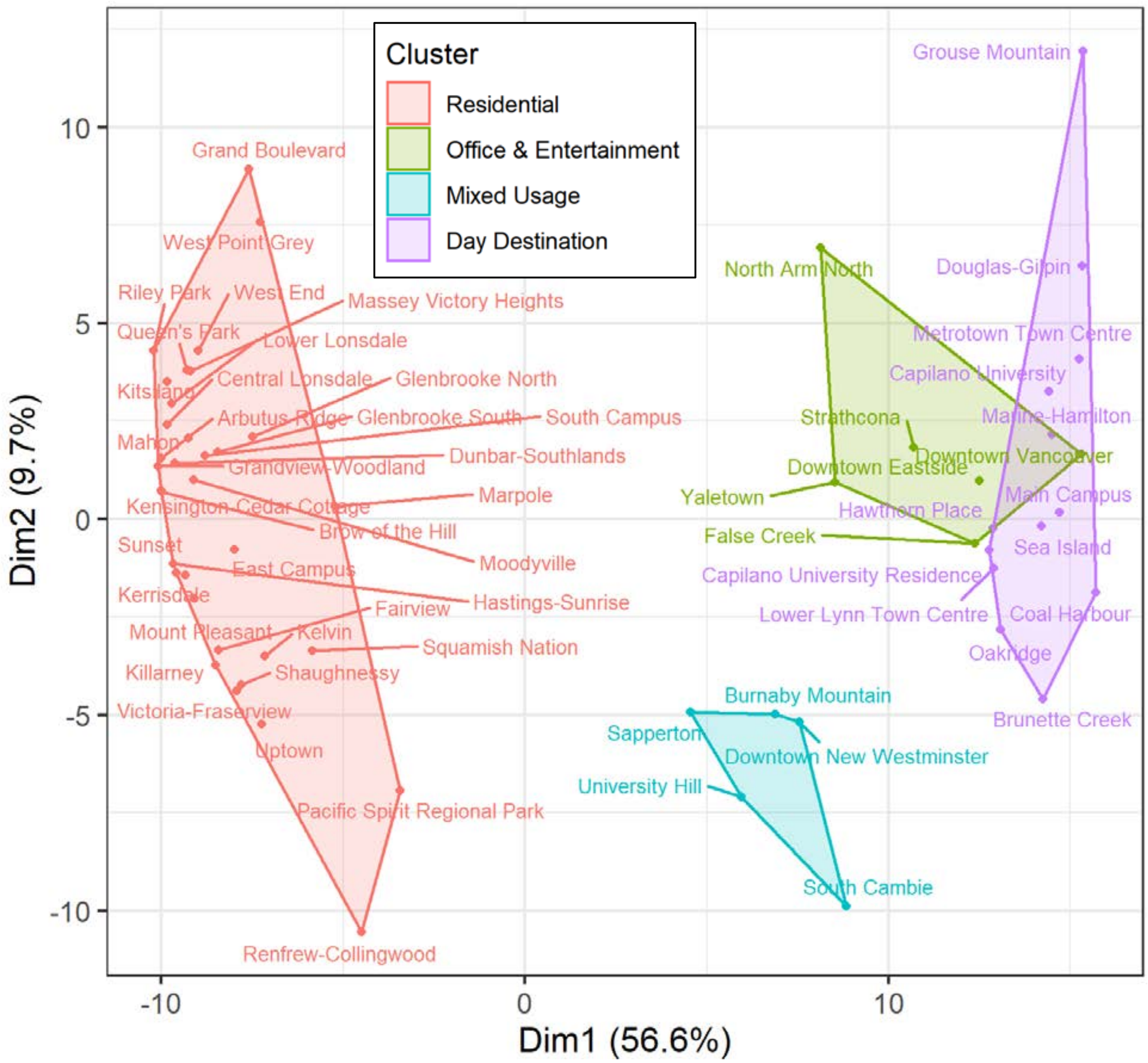


Figure 3-8 Clustering results of the neighbourhoods' hourly aggregate fleet idle time on PCA plot

The neighbourhoods are mapped in Figure 3-9, coloured according to their cluster classification. The average hourly pattern of the aggregate fleet idle time of the neighbourhoods in each cluster is represented in Figure 3-10 "a"-"d". The red cluster that contains 34 neighbourhoods can be described as predominantly residential, including neighbourhoods such as Shaughnessy, Arbutus-Ridge and West End. The pattern in Figure 3-10.a shows a lower number of idle cars during midday throughout the week. On Friday and Saturday nights, this paucity extends into the evening as vehicles are used in trips to other neighbourhoods for entertainment.

It can be observed that during workdays, the clusters depicted in Figure 3-10 "b"-"d" are destinations during commuting hours. The hourly aggregate fleet idle time is high in midday and decreases around 4 pm, only rising again the next morning at around 8 am. This distinction between the first cluster and the rest explains the separation in Figure 3-8 on the first axis as well. The three non-residential clusters, however, have different idle patterns on weekends/holidays.

The second cluster depicted in green comprises six neighbourhoods such as Downtown Vancouver, Yaletown, and False Creek. Based on Figure 3-10.b, it can be understood that they are destinations for evening entertainment on weekend/ holidays. Hence, this cluster is named Office and Entertainment.

The blue cluster has a pattern similar to the first cluster on holidays (Figure 3-10.c). Having a working pattern during weekdays and a residential pattern during holidays, this cluster with five neighbourhoods is labelled Mixed Usage. An example from this cluster is Burnaby Mountain, where Simon Fraser University's main campus is located. While the neighbourhood is a working destination during workdays, during weekend/holidays, there is not much of an attraction in midday, and carsharing appears only to serve the university residences similar to Residential neighbourhoods.

The last cluster and the biggest one among the working clusters with 13 neighbourhoods is the Day Destination cluster garnering its name for an idle pattern during midday that shows it to be daytime destinations every day of the week. UBC Main Campus, Grouse Mountain, and Sea Island are some members of this cluster. Grouse Mountain is a midday destination all week long, as are Oakridge, Metrotown, and Sea Island with the McArthur Glen Designer shopping mall (established in July 2015) and Vancouver International Airport.

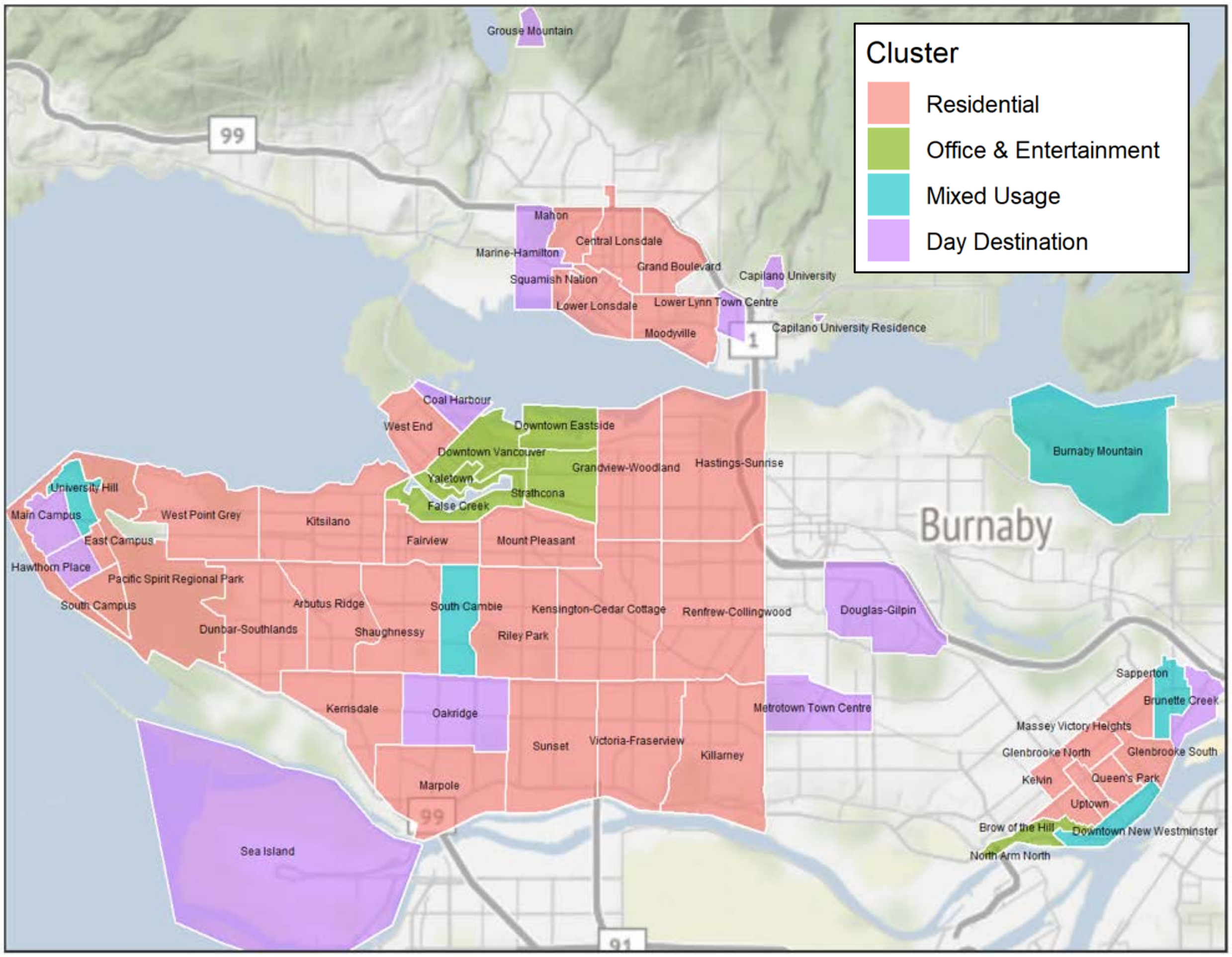


Figure 3-9 Neighbourhoods coloured by their respective clusters

An interesting implication of these vehicle idle time patterns is that a much smaller fleet of autonomous shared vehicles would be able to service these trips by virtue of not being stationary at key destinations for long periods.

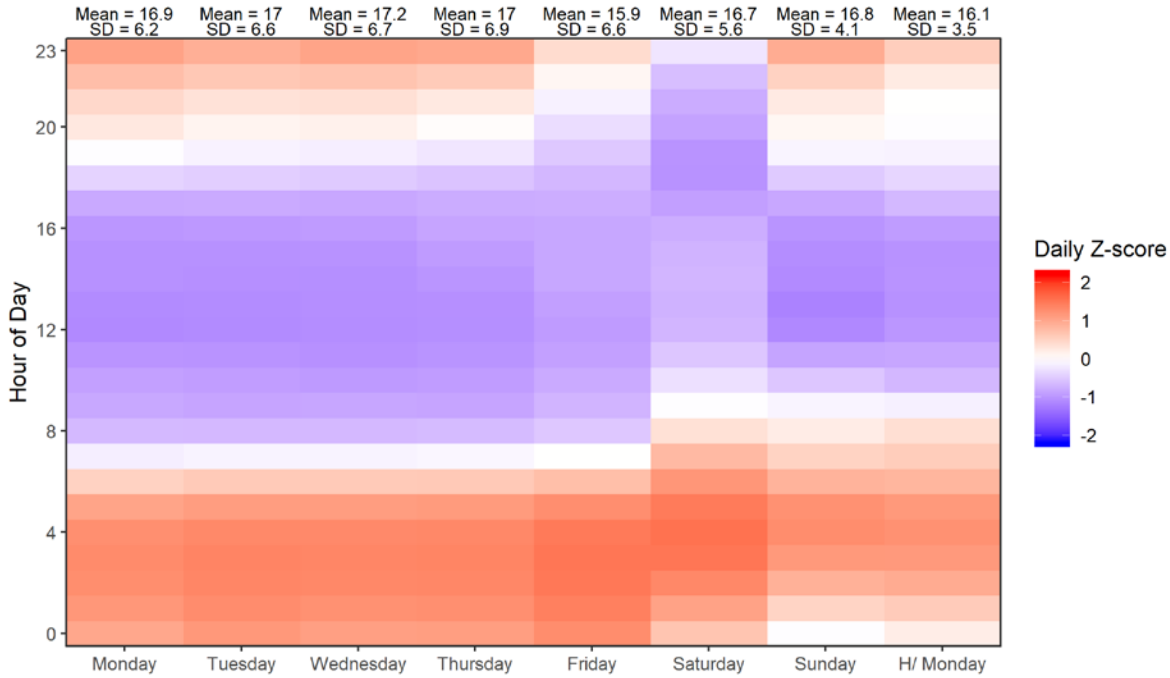


Figure 3-10.a Distribution of average hourly aggregate fleet idle time for the neighbourhoods in cluster Residential

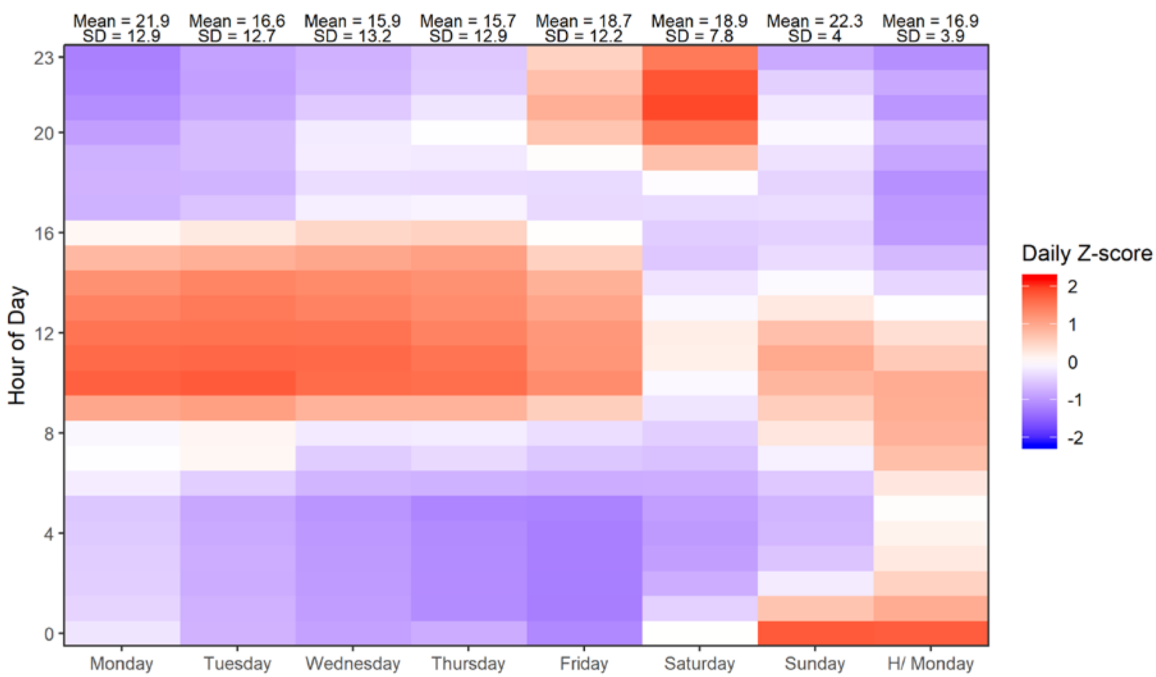


Figure 3.10.b Distribution of average hourly aggregate fleet idle time for the neighbourhoods in cluster Office & Entertainment

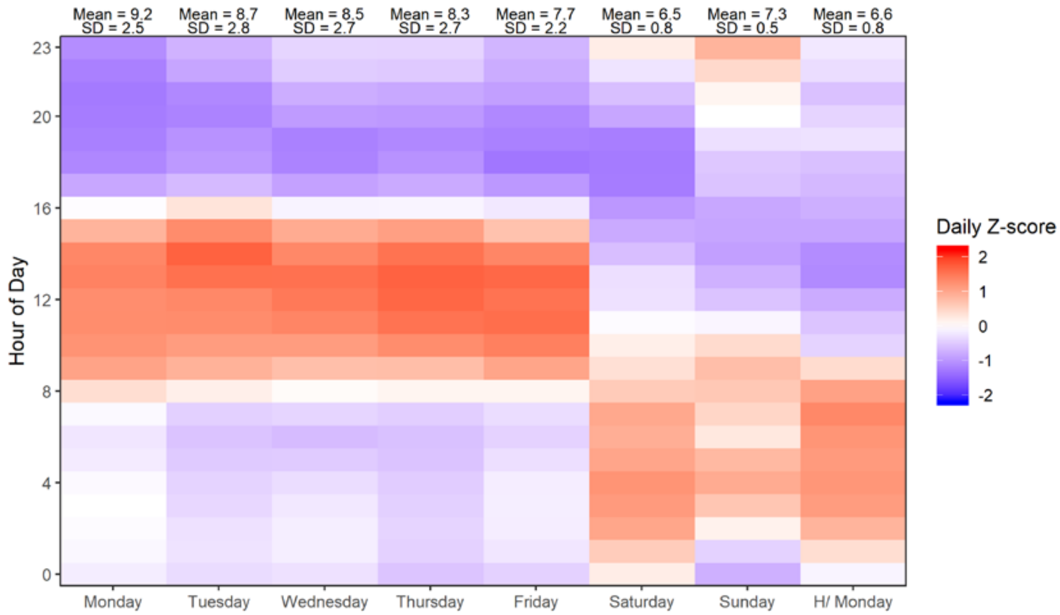


Figure 3.10.c Distribution of average hourly aggregate fleet idle time for the neighbourhoods in cluster Mixed Usage

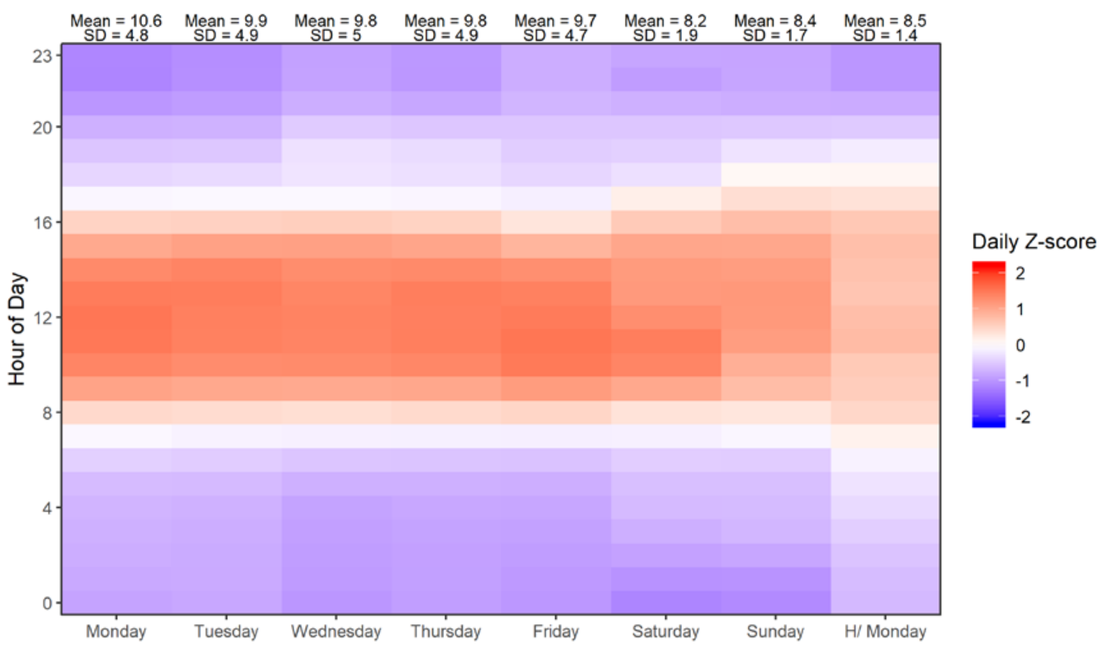


Figure 3.10.d Distribution of average hourly aggregate fleet idle time for the neighbourhoods in cluster Day Destination

3.3 Is one-way carsharing a substitute for or complement to public transit?

Active transit (walking, biking, etc.) and public transit are the preferred modes of travel by city planners for their higher sustainability rates. High-frequency rapid transit is particularly favoured as substitutes for private vehicles for longer trips/commutes. However, such a service requires high ridership to be economically sustainable. Hence, it is rarely available outside high-density neighbourhoods.

One-way carsharing has been touted as a solution that can bridge the gap between lower density neighbourhoods and hubs of rapid transit. When carsharing is used as a first/last leg in multi-modal trips, it is complementary to public transportation. However, should one-way carsharing be used in trips that parallel public transit routes, it is a substitute mode that reduces public transit ridership and adds to congestion and parking pressure at popular destinations. In this section, we use the origin and destination of carsharing trips in relation to public transit hubs to gain insight into the question of carsharing impact on public transit.

We have to acknowledge a major limitation of our methodology. Since we have no direct information about carsharing users and their travel plan, we can only characterize trips by their proximity to rapid transit stops. We cannot discern trips that were completed to a destination close to a transit station from those that are first or last legs using carsharing to bridge the gap between rapid transit stations and less well-served neighbourhoods. Nonetheless, if one-way carsharing is used to take trips to and from locations close to well-served public transit stations, these can be assumed to be substituting for public transit. The service areas are served by Canada, Expo, and Millennium Skytrain lines and the B99 express bus service (see Figure 3-11).

Therefore, we are likely to overestimate the proportion of carsharing trips categorised as first or last leg. Trips that follow public transit routes are, however, less-ambiguously substitutes for transit.

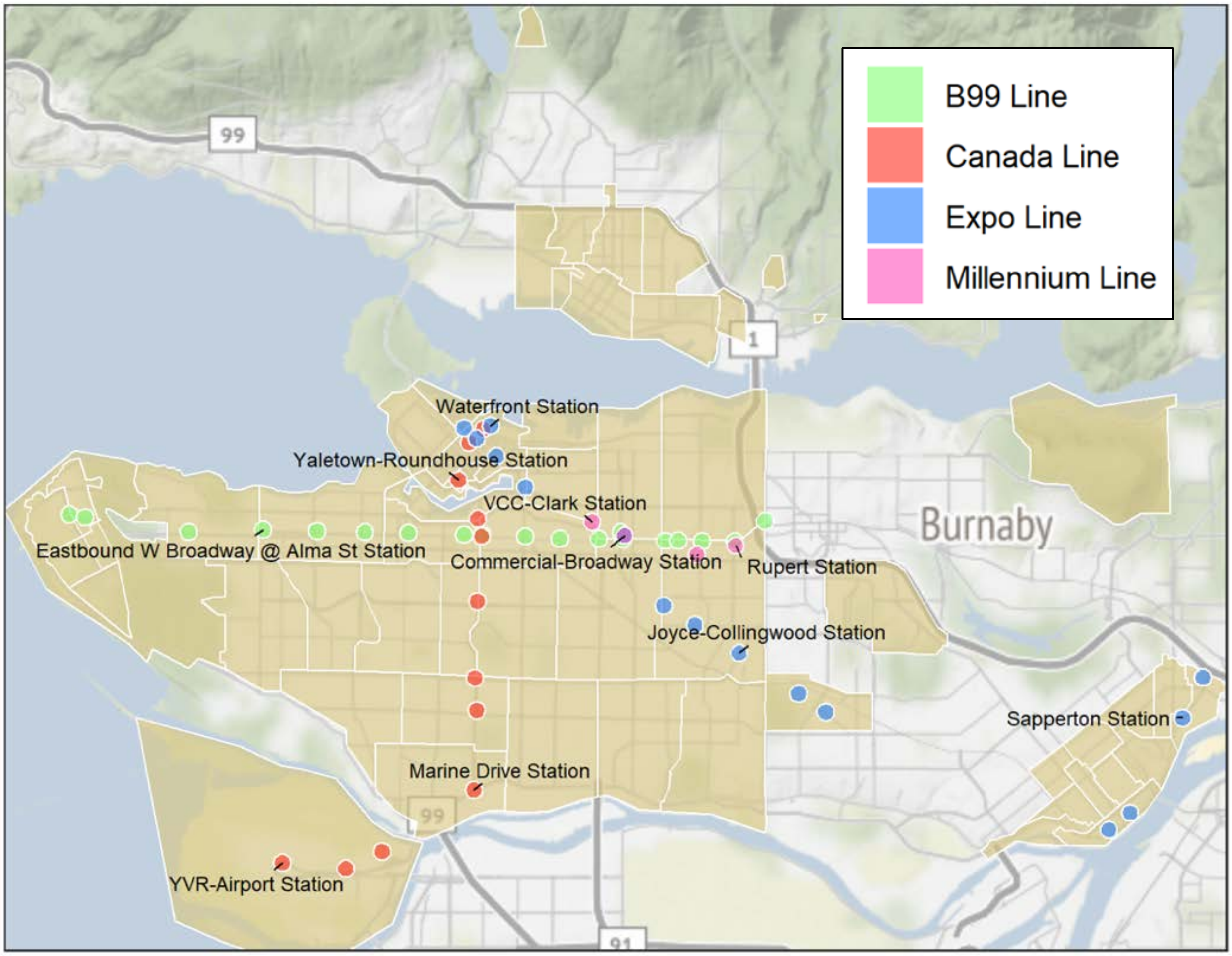


Figure 3-11 Rapid transit stations map

3.3.1 Macro-exploration of carsharing usage and rapid transit

As the first step, we create a 58x58 matrix of neighbourhoods with (and without) rapid transit access. We then use a heat map to plot the number of trips per day among the 3364 origination-destination pairs (see Figure 3-12).

In this figure, origin and destination neighbourhoods directly connected via a rapid transit line are marked as red boxes. Moreover, for better visualization, the neighbourhoods on both axes are sorted by descending number of trips. Thus, origin-destination parings in the top left corner have the highest number of trips. Not surprisingly, these are high-density locations and are also the neighbourhoods most likely to be served by rapid transit. We will explore the specific use of carsharing in these cells in further detail below.

The higher frequency of trips along the leading diagonal represent roundtrips and short hops within neighbourhoods. We could further segregate these trip types by their duration. However, that is beyond the focus of this study.

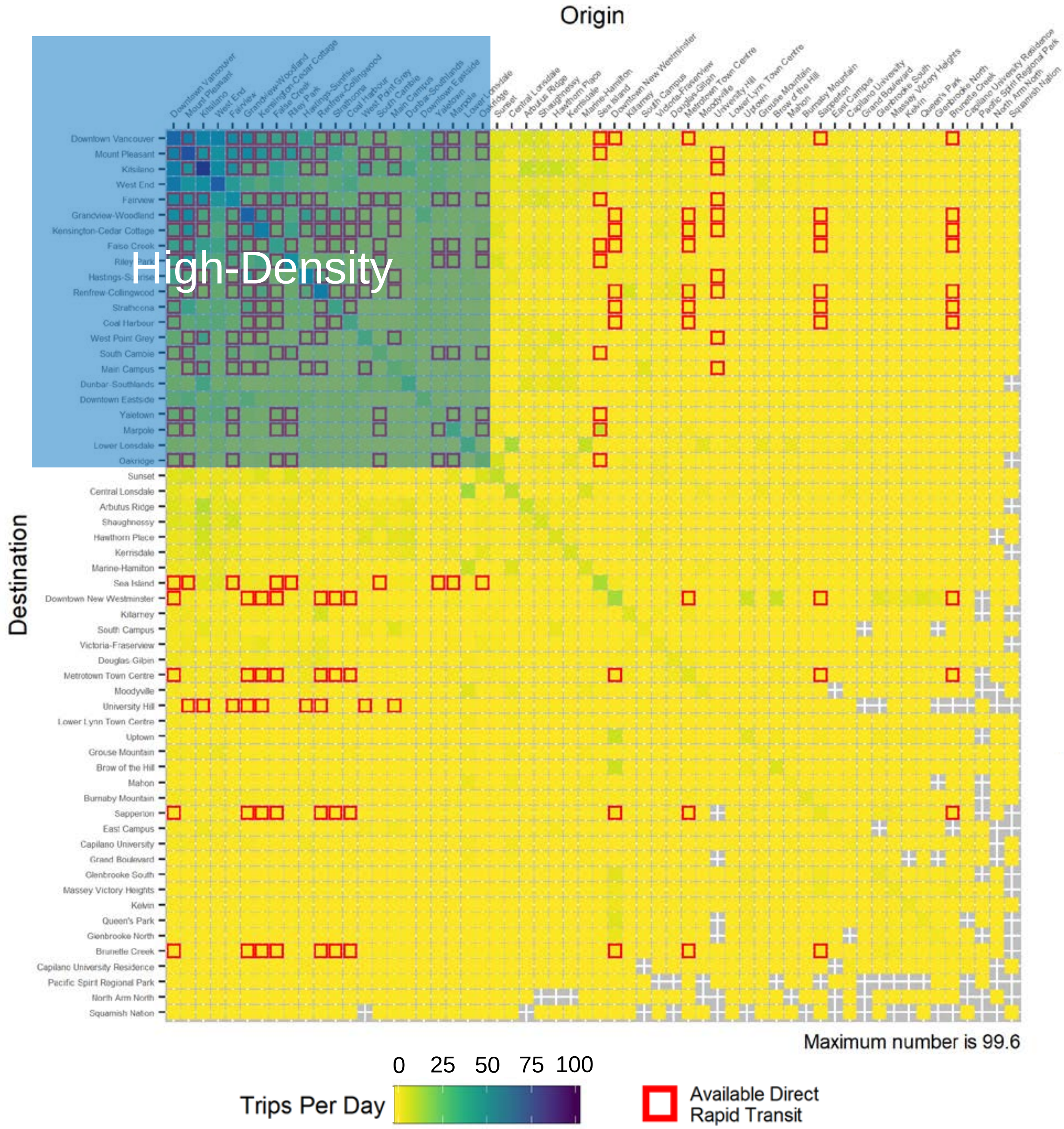


Figure 3-12 Distribution of trips among origin and destination neighbourhoods

Table 3.6 Descriptive statistics of Figure 3.5 according to a gross characterization of the neighbourhoods with the highest number of trips (top left hand corner) vs the lowest number of trips

	Higher density	Lower Density[7]
Population (capita/km2)	6260	2540
Percentage of total population (%)	59	41
Percentage of total area (%)	37	63
Percentage of rapid transit routes[8] (%)	63	37
Percentage of carsharing trips (%)	75	25

A summary of the macro-exploration results is provided in Table 3.6. It is evident from the results that the population is split between the high-density and low-density neighbourhoods by a

[7] The neighborhoods that are not in the higher density group as shown in Figure 3-12 are in the lower density group. Any origin-destination pairings not included in the higher density group in Figure 3-12 are considered as a lower density pairing.

[8] Each two stations of a rapid transit line that are located in the region of study equals to one rapid transit route.

1.4 to 1 ratio. Similarly, the ratio for the number of rapid transit routes is 1.7 to 1. However, the percentage of carsharing trips in the high-density group is 3 times higher than that in the low-density group. This simple analysis shows that the notion that carsharing serves to extend public transit networks is not evident at this scale of analysis. Therefore, we explore the problem at the scale of each neighbourhood in the section that follows.

3.3.2 Catchment area for First/ last leg trips

Catchment distance is a handy tool in the industry for studying and designing transit stations. The acceptable walkable distance to public transportation varies between 400-800 meters depending on the type of public transit and the station. In this study, to catch first/ last leg trips, an appropriate walkable distance between the car and transit station should be established.

Figure 3-13 shows the density of available cars based on their distance from B-99 and Canada stations. For B-99, the available vehicle density peaks at 150 meters from stations. The peak for Canada Line is at 100 meters. The density falls from these peaks for both lines, with distance from the station, which indicates that these stations are hotspots for parked carsharing vehicles. We suspect that with increasing distance from the stations, the likelihood that a vehicle is being used to arrive at or leave the station as part of a multi-modal trip falls while the likelihood that the trip is being made for amenities near the station rises. Therefore, for the purpose of this analysis, excluding trips that started/ ended near other public transit hubs, we use a distance of 200 meters from stations as the limit for a carsharing trip being labelled as first/ last-leg. Vehicles picked up or parked further away are likely being used for trips related to amenities near the stations.

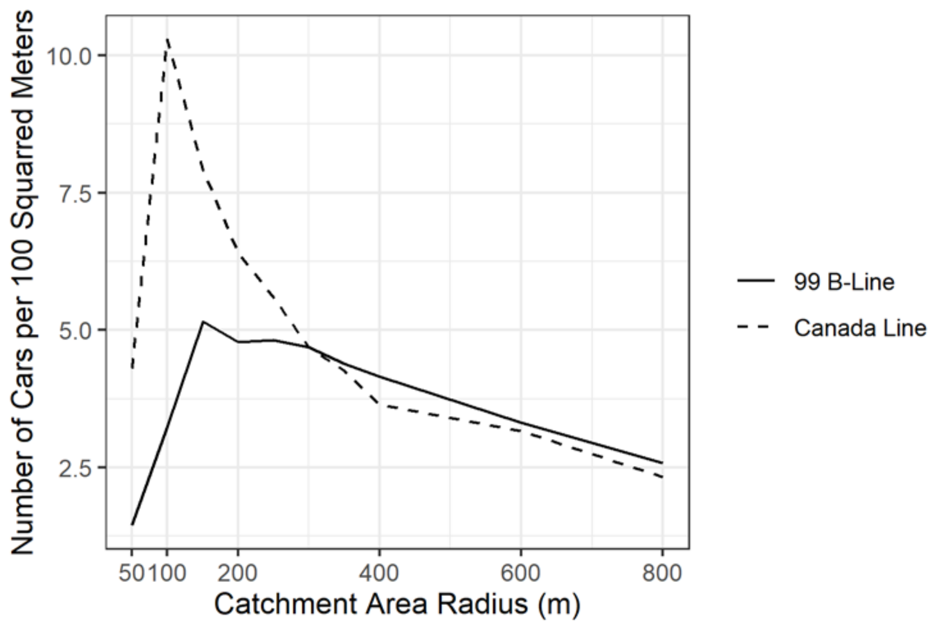


Figure 3-13 Density of cars by the radius of the circles around stations

3.3.3 First/ last leg trips during rush hours

During rush hours, the origin and destination of the carsharing trips can be predicted. In the morning, most trips originate in residential neighbourhoods and end in working neighbourhoods. First leg users might take the car from home to a convenient public transit station and continue their commute on public transportation. Another group might use public transportation as the first leg of their commute and switch to carsharing for the remaining part of their journey to work. The pattern is reversed for afternoon commute hours.

For each neighbourhood, the stations on a line that would serve the users for first/ last-leg differs. For example, for someone living in Kensington-Cedar Cottage who works at UBC and takes 99

B-Line for part of her commute, Granville St. Station would not be a preferable choice for the first-leg. She would choose a station closer to her home, such as Clark Dr or Commercial Dr.

Therefore, in this analysis, for each neighbourhood, the 3 closest stations to the centre of the neighbourhood on each line are chosen as the stations that can be considered for a first/ last-leg trip. The stations located in Downtown Vancouver and Yaletown are excluded from consideration except for the neighbourhoods situated in the downtown peninsula, including West End, Coal Harbour, Downtown Vancouver, and Yaletown. That is because those stations are in areas with high traffic congestion and would be highly unlikely to be chosen for a first/ last leg trip to/from a neighbourhood such as Kitsilano. Lastly, the number of trips that originate and end in the vicinity of the same line's rapid transit stations are grouped separately as trips that substitute rapid transit.

The suggested walking distance to access limited-stop rapid transit is 800m (Translink, 2012). For the B99 express line, this value is suggested to be 600m. In this analysis, a trip that starts and ends within 600 meters of the same line's rapid transit stations is considered a substituting trip.

Some of the trips start or end at locations inside the catchment areas of multiple stations. This is because of the high station density in Downtown Vancouver and Commercial-Broadway. We used the total boardings for various transit options to assign first and last leg trips in shared catchments – see Table 3.7.

Table 3.7 Annual Boarding on the rapid transit lines in 2017 (TransLink, 2018a, 2018b)

	Rapid Transit Line		
	B-99	Canada	Expo/Millennium
Annual Boarding (millions)	17.2	46.2	105.1

Figure 3-14 and Figure 3-15 depict the commuting trips in the morning and afternoon commuting hours, respectively. In both figures, the last four rows represent first-leg trips from the origins to each rapid transit line. Similarly, the last four columns display last-leg trips. The diagonal blocks in the 4x4 matrix in the bottom-right display commuting trips that substitute for rapid transit lines.

The results demonstrate that most of the first/ last leg trips connect users' homes to transit stations and vice versa. They also show that regular trip rates are higher for some origins and destinations than their corresponding first/ last leg trip rates. Moreover, a proportional number of trips are carried out along rapid transit corridors. To have a better picture of carsharing usage and rapid transit, the trips during midday are depicted in Figure 3-16 as well. In this figure, without any differentiation between commuting and other types, all the trips between neighbourhoods have been represented.

Comparing the pattern in Figure 3-16 with the commuting trips pattern suggests that multi-modal trips containing carsharing services are less popular outside commuting hours. Furthermore, substitution trips are also more prevalent at these times. Table 3.8 provides an aggregate result of the analysis. First/ last leg trips stands for less than 18 % of commuting trips, while 4.4 % of commuting trips substitute rapid transit. At midday, the rate of first/ last leg trips is less than half of that among commuting trips, whereas the substituting trip rate during midday is triple the rate among commuting trips.

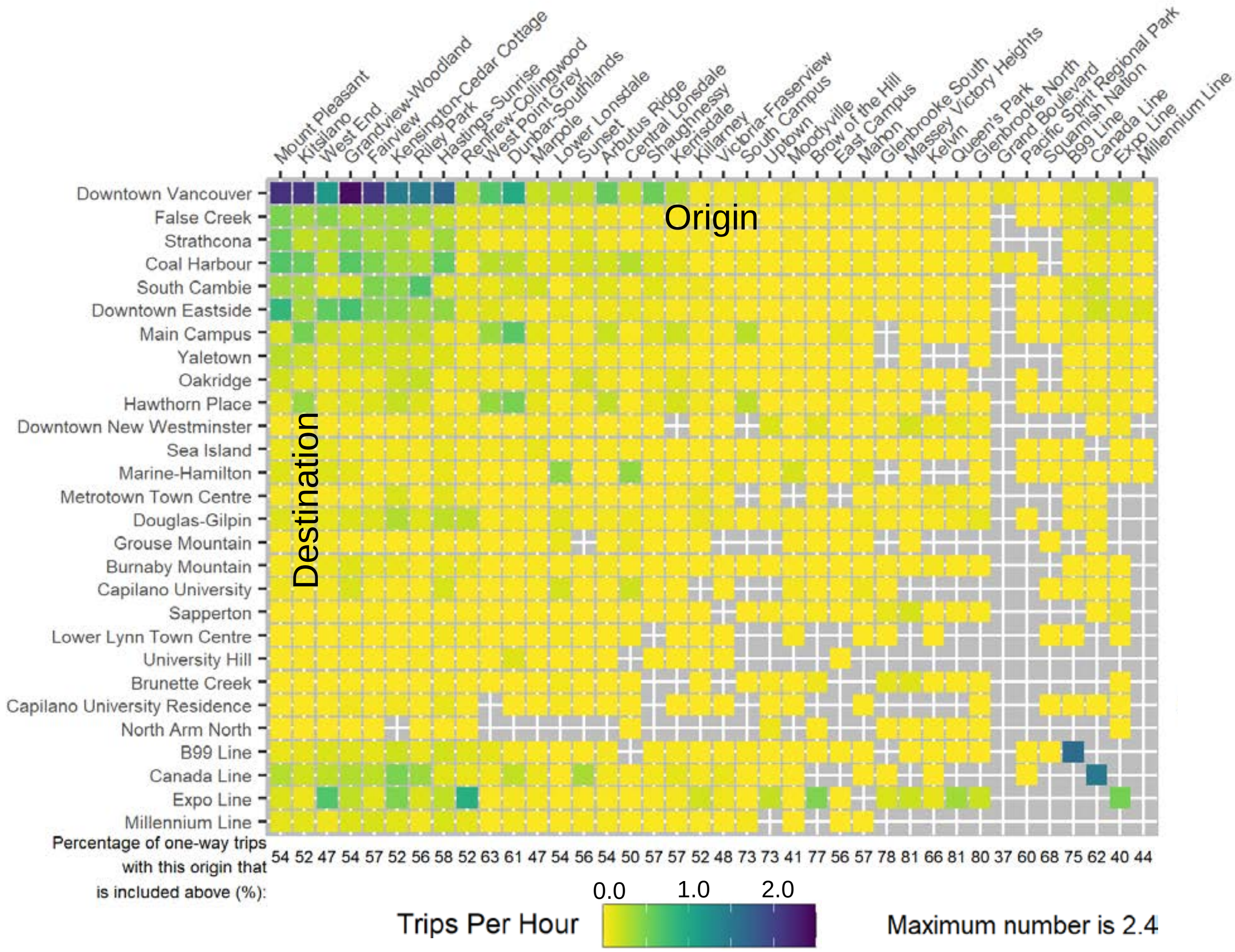


Figure 3-14 Number of trips per hour from residential neighbourhoods to working neighbourhoods as regular, first/ last leg, or substitute trips between 7:00 -9:30 AM.

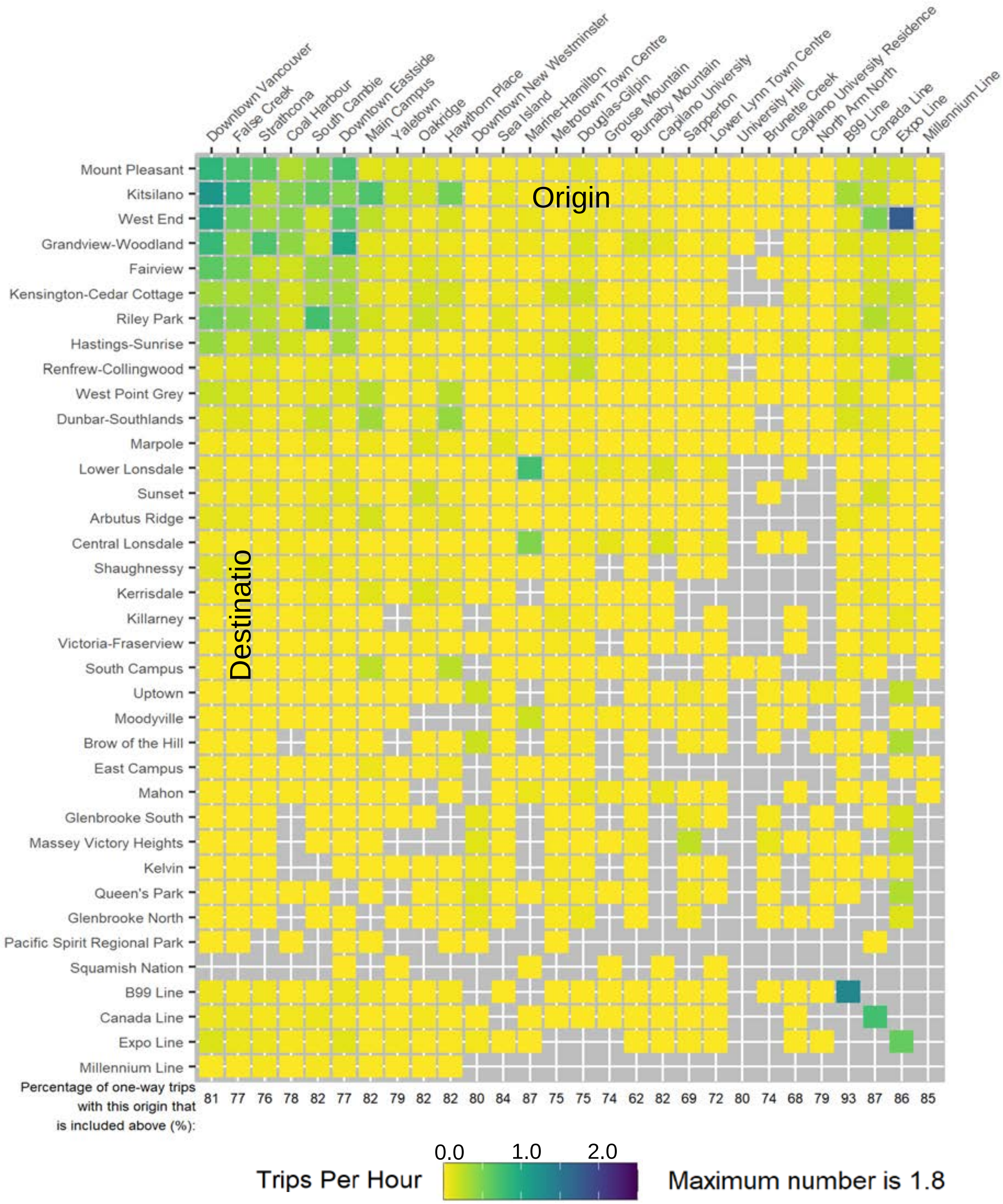


Figure 3-15 Number of trips per hour from working neighbourhoods to residential neighbourhoods as regular, first/ last leg, or substitute trips between 4:00 - 6:30 PM.

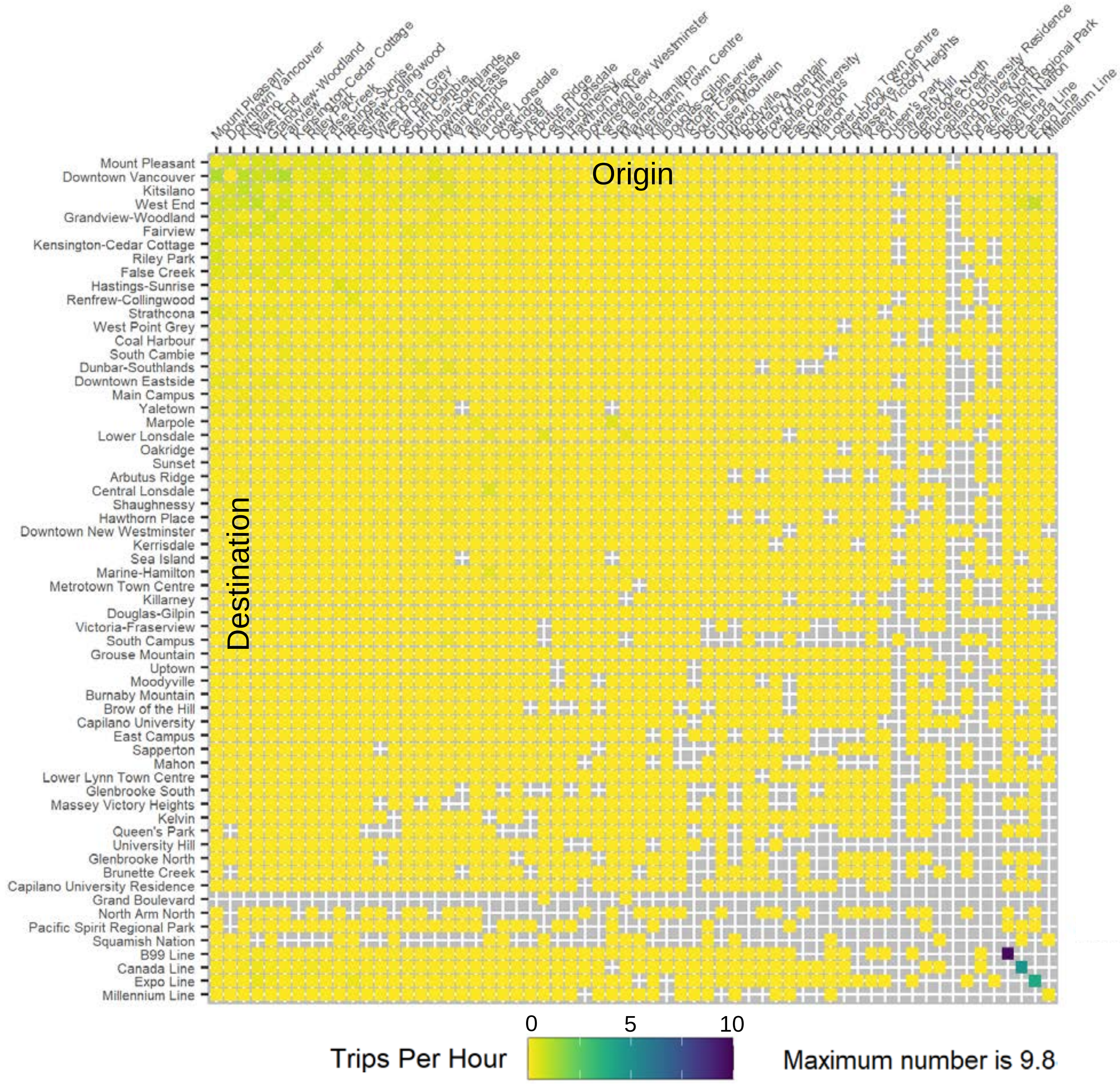


Figure 3-16 Number of trips per hour among neighbourhoods as regular, first/ last leg, or substitute trips between 9:30 AM - 6:30 PM.

Table 3.8 Commuting trips vs midday trips

Type	B99 Line	Canada Line	Expo Line	Millennium Line	Total
Morning First leg (%)	1.7	**4.3**	**6.2**	1.5	**17.0**
Morning Last leg (%)	0.7	1.2	1.1	0.4	
Morning Substitution (%)	1.7	2.0	0.7	NA	**4.4**
Midday First leg (%)	0.7	1.2	1.4	0.2	**8.1**
Midday Last leg (%)	0.8	1.5	2.0	0.4	
Midday Substitution (%)	**7.4**	**3.9**	**3.1**	0.1	**14.5**
Afternoon First leg (%)	0.6	0.7	1.0	0.2	**17.8**
Afternoon Last leg (%)	2.7	**4.0**	**7.8**	0.9	
Afternoon Substitution (%)	1.9	1.4	1.1	NA	**4.4**

3.4 User Booking Behaviour

In Section 2.2.2, we differentiated lapsed bookings from roundtrips. In this section, we explore the impact of lapsed bookings on the under-utilization of available vehicles. Our data gathering interval allows noting vehicle position and availability every 5 minutes. The grace period for bookings is 30 minutes – leading to most lapsed bookings being recorded in the 35th and 40th-minute data bins. Sometimes a user may extend a booking at 30 minutes during the interregnum of our 5-minute data collection sweeps. These sequential bookings last longer than 40 minutes – see Figure 2-3. Table 3.9 shows a summary of lapsed booking data. Here, the lapsed booking durations longer than 40 minutes are separated into 30 minutes intervals and a remainder.

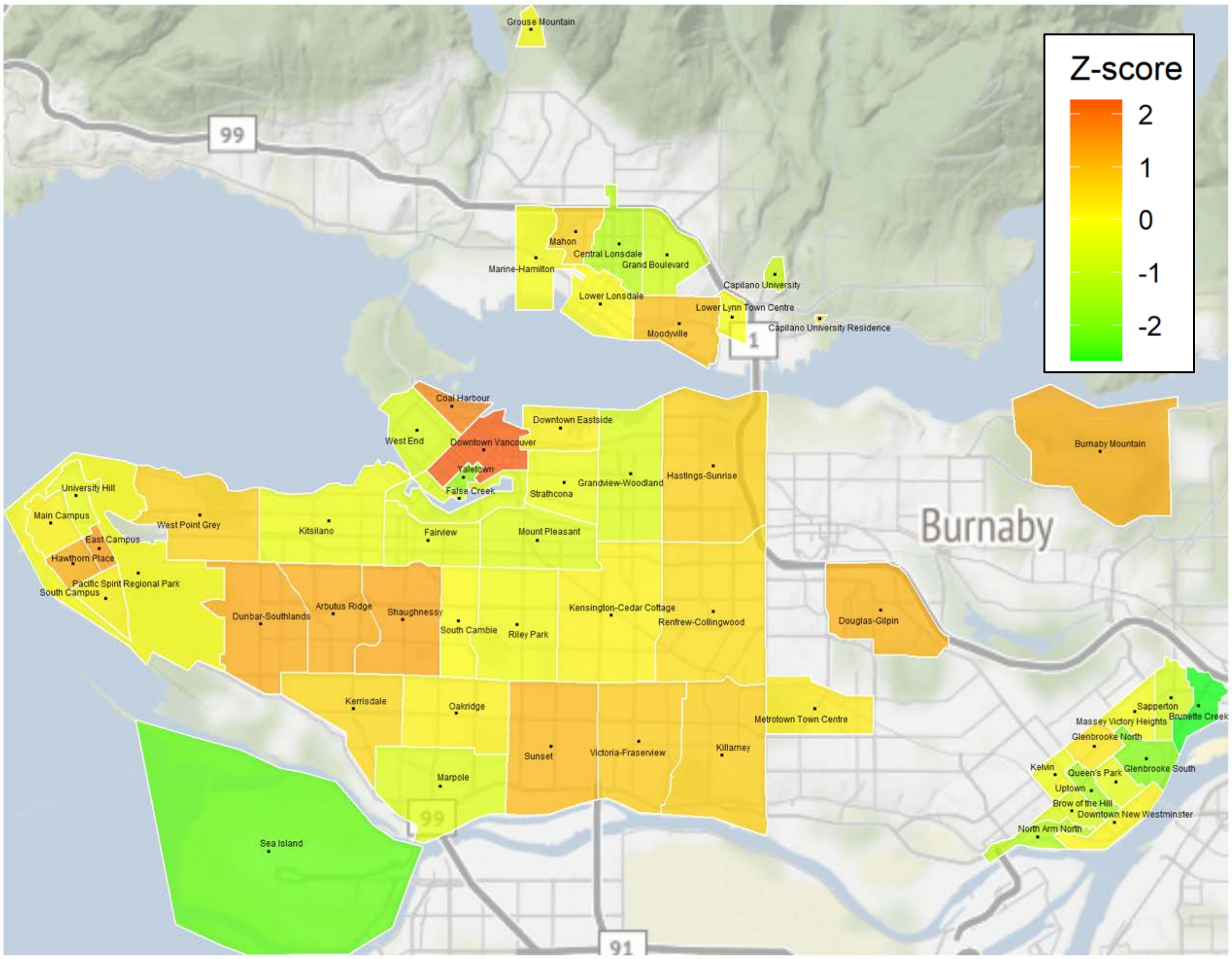
Table 3.9 Summary of lapsed booking data

	Car2go	Evo
Average duration of lapsed bookings per car (minutes)	24.2	25.6
Daily average number of trips per car	5.9	5.8
Daily average number of lapsed booking per car	3	2.7

The majority of lapsed bookings are from users who reserve a car expecting to use it within the 30-minute window. A small fraction are actively cancelled before the 30 minute limit. These cancellations fall into two categories: a) alleviation of demand b) finding an available vehicle closer than the one booked initially.

3.4.1 Geography of lapsed bookings

The rate of lapsed bookings varies across the service area (Figure 3-17). Downtown Vancouver has the highest rate of lapsed bookings (31%) for the Evo fleet, whereas in Brunette Creek, a neighbourhood in New Westminster, only 20% of all bookings lapse (lowest rate). We suspect the balance of supply and demand are key drivers of lapsed bookings. For example, at the airport, arriving passengers face either a surfeit of vehicles (early during the weekends) or no available vehicles (late weekend). Most lapsed bookings may reflect user miscalculation of how long it takes to disembark from planes and be ferried to the carpark.



Mean = 26%, SD = 2%

Figure 3-17 Fraction of bookings that laps for Evo fleet

3.4.2 Rate of car unavailability due to lapsed booking

Figure 3-18 displays the geography of vehicle unavailability by neighbourhood. To acquire these percentage values, the sum of all lapsed booking durations in each neighbourhood is divided by the sum of all idle durations for the cars in the neighbourhood. Yaletown, in particular, has a significant rate of unavailability due to lapsed bookings (28%) – calculated as a 24-hour average and much higher during peak demand periods.

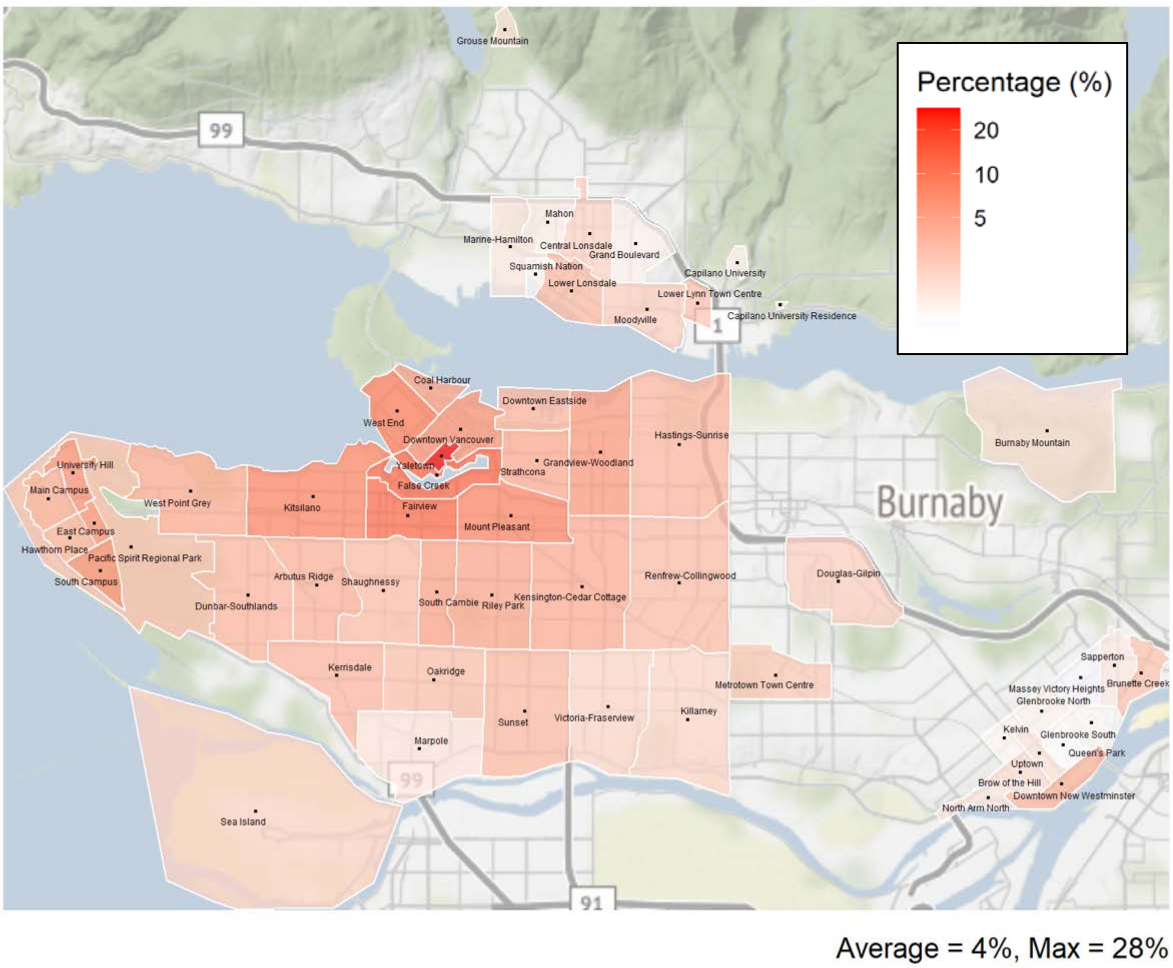


Figure 3-18 Average Fraction of idle time a vehicle is unavailable due to bookings that will lapse for Evo fleet

Booking in Yaletown as a special case is studied further. There is a similarity of patterns between the hourly unavailability of a car due to lapsed bookings (Figure 3-19, right) and the hourly aggregate fleet idle time (Figure 3-19, left) in this neighbourhood. The similarity delineates that when the number of cars parked in the neighbourhood is lower, there is a tendency for the users to abuse the booking policy in order to save the car for later. This misbehaviour degrades the availability of cars for other users. In the case of Yaletown, the average unavailability rate, due to spurious bookings, between 5 and 6 PM is more than 55 %. Implementing policies that discourage such booking behaviour will increase the utilization rate of each vehicle, helping to lower demand for owned vehicles and the economics of offering carsharing services in Vancouver.

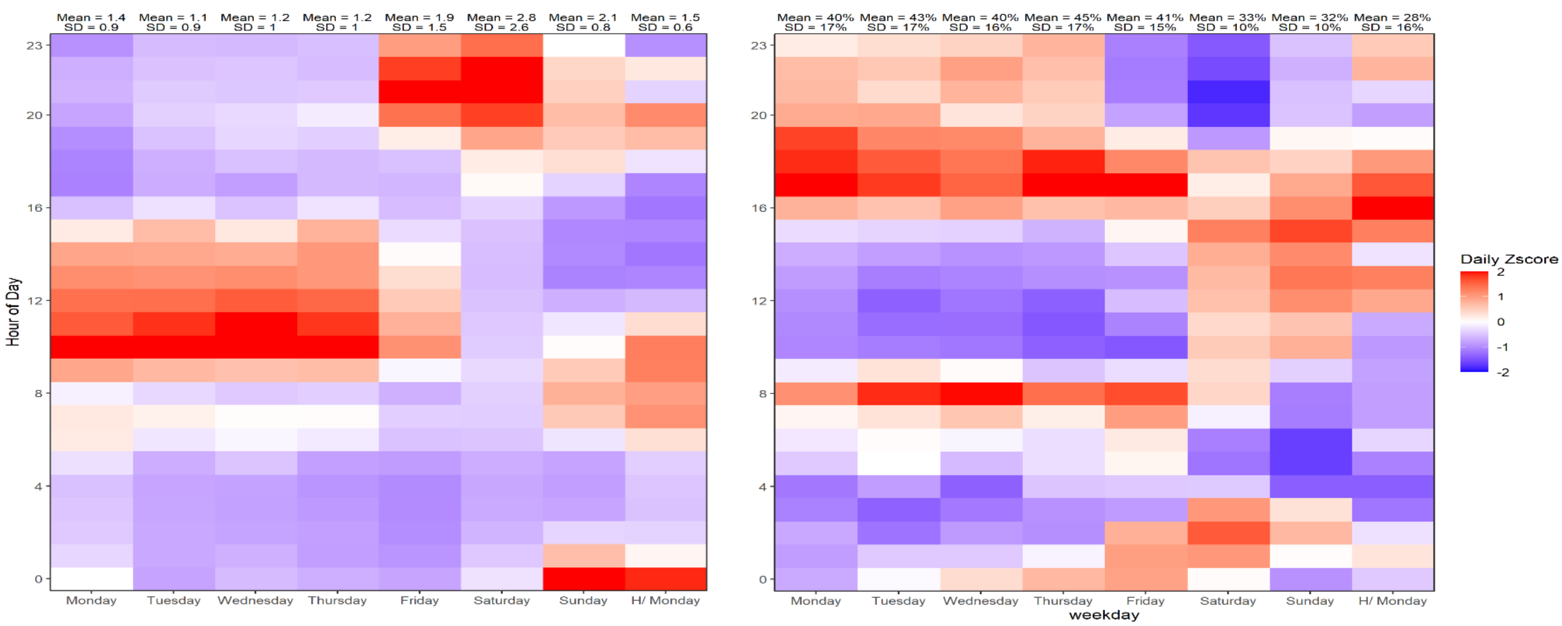


Figure 3-19 Yaletown: Hourly aggregate fleet idle time (left) vs unavailability of a car due to bookings get lapsed (right)

Chapter 4: Conclusion

4.1 Summary of contributions

The basis of this study is a data set comprising of one-way carsharing vehicle locations for an approximate period of one year or more. Striving to extract meaningful findings from the data set, this study provides some answers and insights to the questions around the performance of carsharing systems and their effect on people's transportation behaviour.

The data show that each carsharing vehicle, on average, is used approximately six times per day, with one-fourth of which occurring during commuting peak hours. Therefore, the number of users that would use carsharing on a daily basis is limited. This study connects the number of usages per day per carsharing vehicle to the potential number of private vehicles reduced per carsharing vehicle using Monte Carlo simulation. The result of the models shows that 58% of the removed private vehicles per carsharing vehicle comes from a user class with 1-4 trips per month and 25% belongs to users with more than 16 trips per month. Therefore, most of the cars that would be shed are the ones with low-frequency usage, which implies that carsharing would be helpful in alleviating street parking pressure.

This study also investigates the relationship between carsharing and public transportation. In low-density regions where public transit is too expensive to operate, it is presumed that carsharing can complement public transit. In the service area of Evo, 59% of the population reside in neighbourhoods with 2.5 times higher density than the other neighbourhoods. These high-density neighbourhoods accommodate 63% of rapid transit routes while 75% of carsharing trips occur. In other words, the low-density neighbourhoods have two times the area and 0.6 times the number of rapid transit routes available in the high-density neighbourhoods whereas the number of carsharing trips in low-density neighbourhoods is 0.3 the one in high-density neighbourhoods. The finding contradicts the presumption mentioned earlier.

Next, neighbourhoods with similar carsharing usage throughout the days of the week are identified and classified into four different groups. The main differentiating factors are being residential/business hubs during weekdays and serving different utilities during weekends. After labelling the trips between residential and business neighbourhoods during morning/ afternoon peak hours as commuting trips, the study shows that less than 20% of the commuting trips connect the users to rapid transit and more than 4% substitute rapid transit. Moreover, it is found that the percentage of substitution is triple during midday (considered as non-commuting hours).

Lastly, the reservation behaviour of users is explored. The study shows that each Evo vehicle gets 2.7 bookings daily that would not be followed by rent (lapsed booking) per day. The rate of bookings that get lapsed varies among different neighbourhoods. Moreover, in some neighbourhoods, the total hours the vehicles are unavailable because of bookings that get lapsed are significant. For example, on average, about 20% of the time that a carsharing vehicle is idle in Yaletown, the car is unavailable because of lapsed bookings. The unavailability rate due to bookings that get lapsed even reaches 70% at 8 AM on Wednesdays. Lapsed bookings are not profitable for carsharing companies. Therefore, these findings call carsharing companies to improve their booking policy.

4.2 Caveats

While relying on actual data provides a better understanding of the carsharing system, the study's caveats have to be acknowledged. In analysing the relationship with private vehicle ownership, it is assumed that the users' driving usage behaviour is the same for using private vehicle and carsharing. However, it has been reported that vehicle-kilometres-travelled (VKT) can vary for a user that switches to carsharing due to several reasons such as transportation mode change and trip aggregation (Liao et al., 2020; Namazu & Dowlatabadi, 2015). Moreover, in the analysis, it is assumed that there is a linear relationship between the usage frequency of a user and their tendency to reduce or forgo increasing vehicle ownership. These simplistic assumptions make the analysis possible. More information is required about VKT changes and the users to improve these assumptions. The literature has used the private vehicle ownership reduction impact as a proxy to understand carsharing's socio-ecological impacts. Here, by differentiating between different types of active users, it is concluded that the impact of carsharing systems is less apparent on traffic volume and GHG emission, and more on the on-street parking pressure.

The relationship with public transportation is based on the geographic proximity of vehicles to public transit stations. The estimates calculated in the analysis are undoubtedly an upper bound because rapid transit hubs are located near commuting destinations, and we have no capacity to distinguish between trips starting/ ending at a hub because they are the origin/ destination or those that are a part of a multi-modal trip accompanying another mode of transit. Furthermore, the scale of analyses is neighbourhood. Therefore, the neighbourhoods are classified based on their most prominent type of use and lose the details for different uses. For example, Downtown

Vancouver is labelled as a business neighbourhood while it provides residential uses more than many of the neighbourhoods labelled as residential in the model.

At the core of this thesis study, it has been assumed that a trip has happened when a car disappears from the data at a timestamp and re-emerges later in a different location. However, operational activities can also result in the disappearance and reappearance of the cars as well. The operation team of a one-way carsharing system needs to relocate the vehicles frequently to meet the demand in a different location. They also need to take the cars out of the radar for short services (i.e. maintenance, refuelling and cleaning) and long services (i.e. repairing). Except for the long services, which are avoided by putting a cap on trip duration (1.5 day), these factors inflate the trip counts in our study.

Furthermore, a car disappears from data when it gets booked by the user. Before the trip starts, the user might have taken between 0 to 30 minutes to get on the wheels. Therefore, the length of trips in the analyses is inflated. This latest mentioned inflation does not have a direct impact on the results of the analyses.

The study explores the reservation behaviour of Evo users as well. The reasoning behind the method based on which lapsed bookings are derived from the data is explained in Sections 2.2.1 and 2.2.2. In Figure 2-3, it is shown that for the Evo data set, there is a peak of re-emergence with less than 15 meters of non-zero displacement around 30 minutes; hence, there can be some bookings that are misidentified as trips.

4.3 Policy recommendations

Our study clearly demonstrates the importance of empirical data as a resource for studying the usage behaviour and impacts of carsharing systems. Therefore this study supports a better framework for data sharing as discussed in the literature (Hassanpour, Bigazzi, & Mackenzie, 2020; Lempert, 2018; Wolff, 2019). The results of our study show that a carsharing vehicle in Vancouver on average is used less than 6 times per day, which is equivalent to city-wide average usage of less than 4 private vehicles per day. Moreover, the usage frequency model shows that less than 5 private vehicles are removed from the road per carsharing in a realistic scenario. Therefore, the effect of carsharing system services on vehicle ownership is limited and less than most of the numbers reported in the literature. The estimated composition of the active users shows that carsharing systems are potentially effective on reducing on-street parking pressure. The limited usage of carsharing for first/ last leg trips implies that more efforts other than the provision of parking stations around transit hubs is needed to encourage the usage of public transportation and multi-modal trips. Mobility-as-a-Service programs can provide the opportunity to not only garner better and more accurate data regarding the first/ last leg problem, but also implement pricing schemes as incentives. Furthermore, the study shows that each carsharing car is unavailable for approximately 70 minutes on daily average due to reservations that get canceled with spatiotemporal variation throughout the city. This duration which is equal to more than 20% of the revenue time, does not generate revenue for the carsharing companies. We recommend the service providers to find solutions using incentives and disincentives in a way to lower the unavailability rate without weakening the trust of the users in the system and the level of access they have to it.

4.4 Future work

A richer data set that includes information regarding the users and their actual trips can vastly improve all the analyses in this thesis. Moreover, more research, preferably longitudinal studies, are required to estimate the impact on private vehicle reduction quantitatively. Incorporating data regarding booking behavior (booking that lead to trip) can reduces inaccuracies regarding the trip duration. The exact duration of driving can be used to calculate velocity (displacement over time) which would help in distinguishing between single-leg and multi-trips. This can improve the commute travel study by focusing solely on single-leg trips and their comparison with the transit mode. A neighbourhood-level analysis of local bus line routes and carsharing trips can provide insightful information regarding their interaction. Moreover, the first/ last leg usage study can benefit from a station-by-station analysis of transit lines. Lastly, the study on the users' reservation behaviour is a preliminary take on the subject matter and can be explored further. For example, the reservation patterns can be identified, and correlation analysis with the neighbourhoods' characteristics would provide more information about the phenomena.

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Appendices

Appendix A - Additional figures for section 2

A.1

The steps taken to find trips and lapsed bookings from raw data:

1. Extracting the time stamps of recorded data for each fleet (RECORDED-TIME-STAMPS)
2. For each row of the data log of a vehicle the following variables are defined:
   - The current time stamp (T_1) and location (L_1)
   - The time stamp (T_2) and location (L_2) of the next appearance of the vehicle in the data
   - The next time stamp after T_1 in RECORDED-TIME-STAMPS list (T_2^*)
3. If L_1 != L_2, a trip is considered to be carried out during that period of time. If L_1 == l2 & T_2 == T_2^*, the vehicle is assumed to be idle for that period of time. Otherwise (L_1 == L_2 & T_2 != T_2^*), a lapsed booking is considered to have occurred.
4. Reappearance of a vehicle (T_2-T_1) after an absence longer than 1.5 days (2160 minutes) is removed from the trip data.
5. Two main glitches are addressed before passing the data for analysis:

- Large time gaps in the data collection (> 60 mins), affecting a handful of days; the days are filtered out.

- Geographic coordinate shifts, on 30th, January 2018; longitude and latitude of each vehicle was changing between two far locations between each time interval. The day is filtered out for the Evo fleet.

A.2

The figure below, depicts the distribution of displacement of trips that have a duration of approximately a day. The graph shows that majority of 1-day car rentals are used for roundtrips.

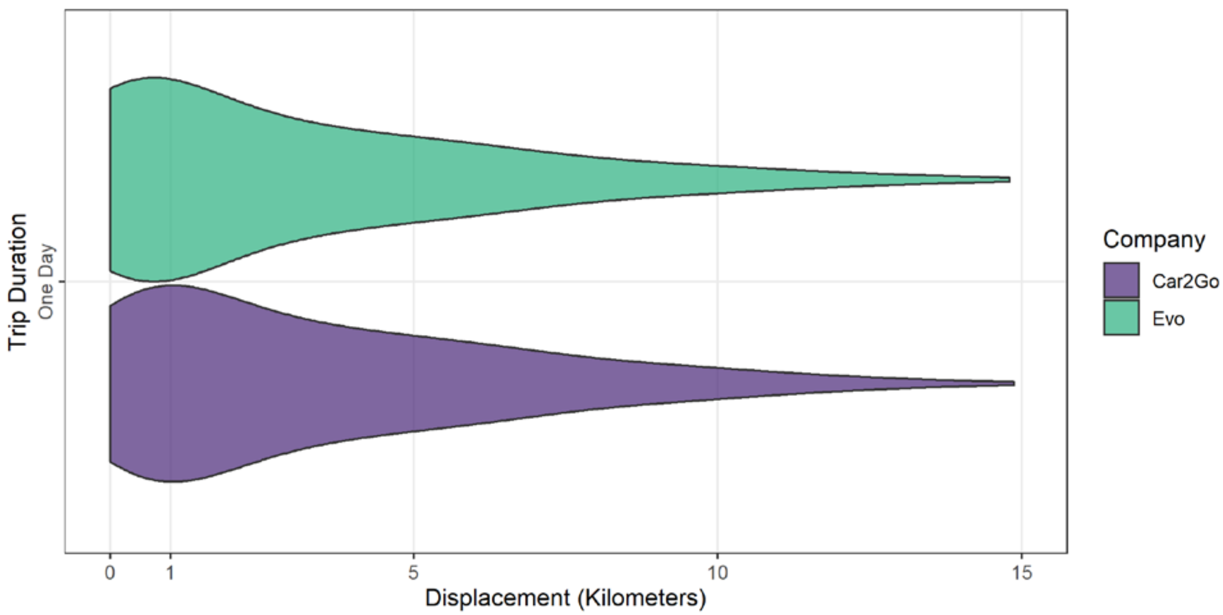

Figure 0-1 Displacement distribution for long trips (one-day)

A.3

This section portrays the in/out-flow of vehicles in Car2Go and Evo fleets. Figure 0-2 shows the expansion of Evo fleet in July 2017 after the introduction of the new service areas. Most of the vehicles stayed in the fleet up until the end of data collection. Figure 0-3 depicts the Car2Go fleet vehicles. Car2Go cars which were in the fleet from the beginning of data collection had been frequently being replaced with new ones, while the fleet size in total for the most part of the data collection period was shrinking. Most of the cars that stayed in the fleet around the end of the

Car2Go data collection period had higher daily number of trips.

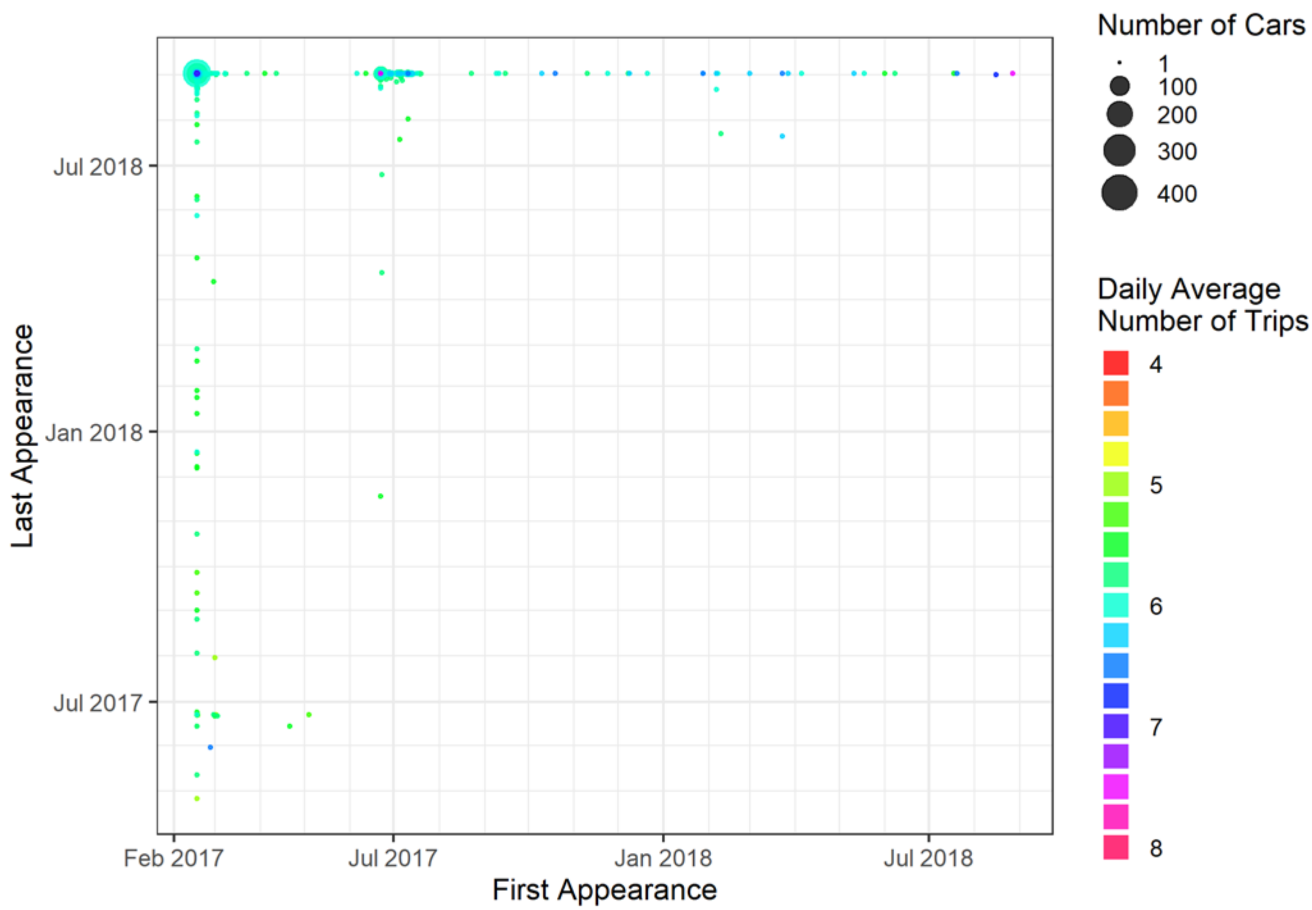

Figure 0-2 First and last appearance of each vehicle with its respective daily average number of trips in Evo fleet during its data collection.

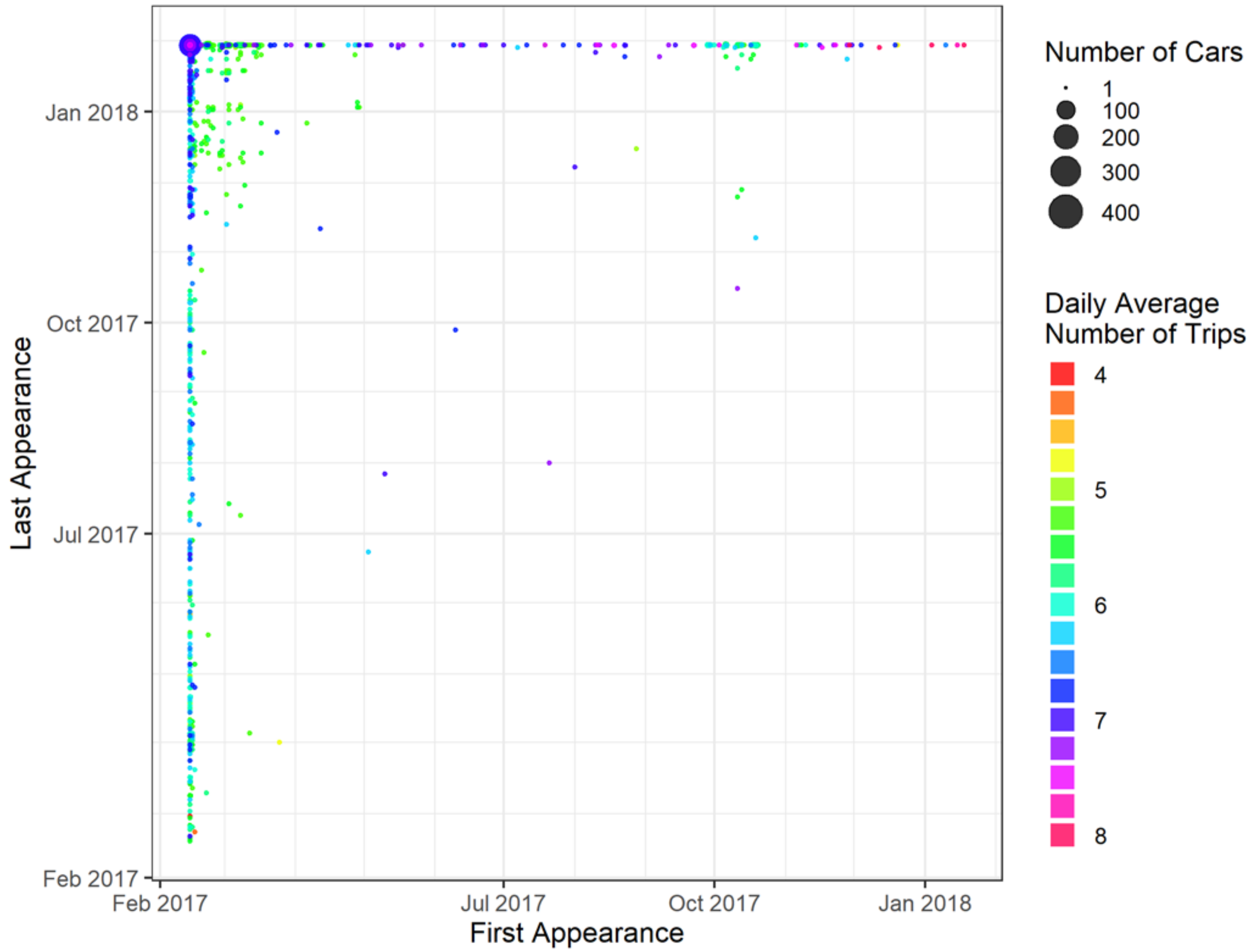

Figure 0-3 First and last appearance of each vehicle with its respective daily average number of trips in Car2Go fleet during its data collection.

A.4

The figure below shows the average start time of each trip for vehicles with different number of trips per day. The maximum number of usages per day shown in the graph is limited to 15. The percentage of all times a vehicle has n usage per day is written above each line.

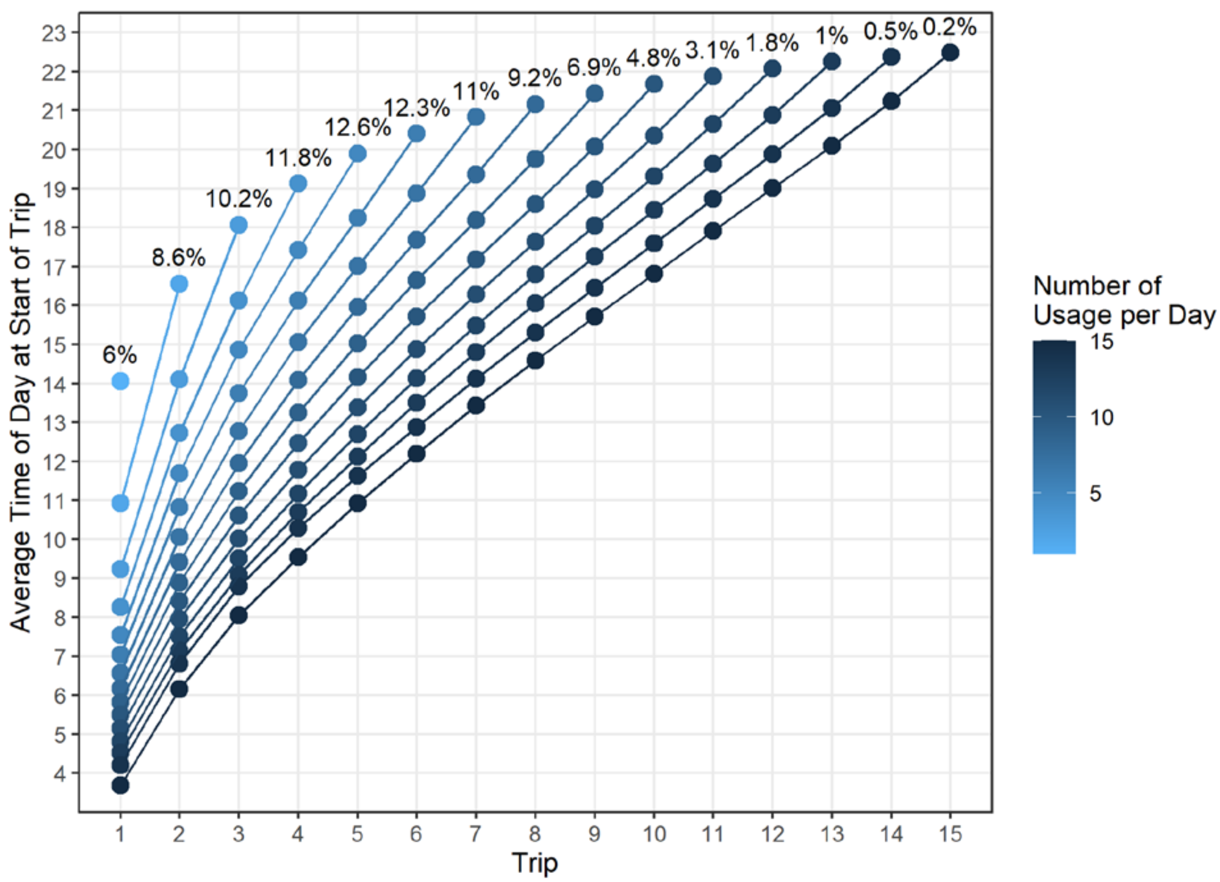

Figure 0-4 average start time of each trip for vehicles with different number of trips per day

Appendix B - Additional figures for section 3

B.1

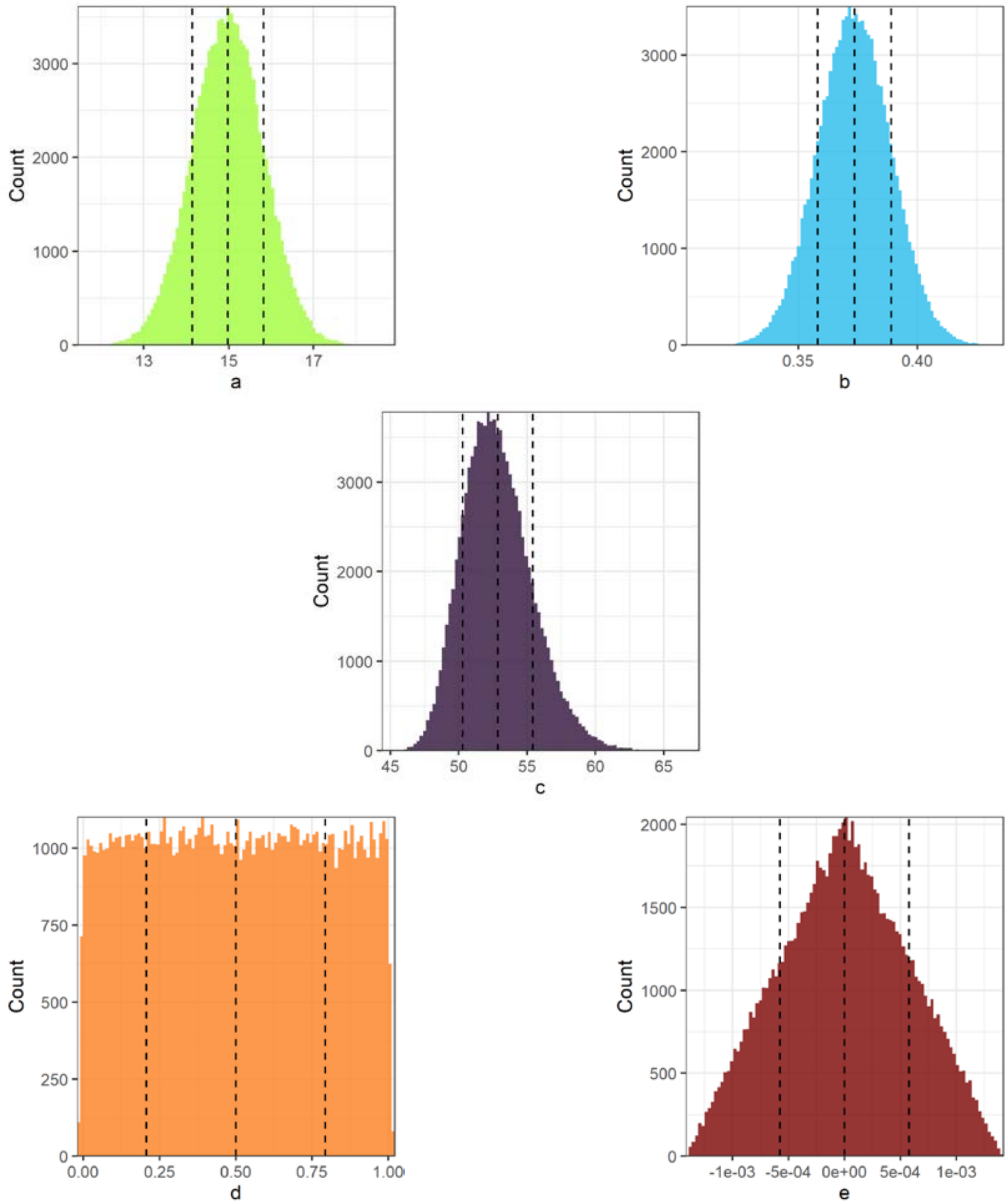

Figure 0-5 Monte Carlo Simulation model 1 coefficients' marginal distributions

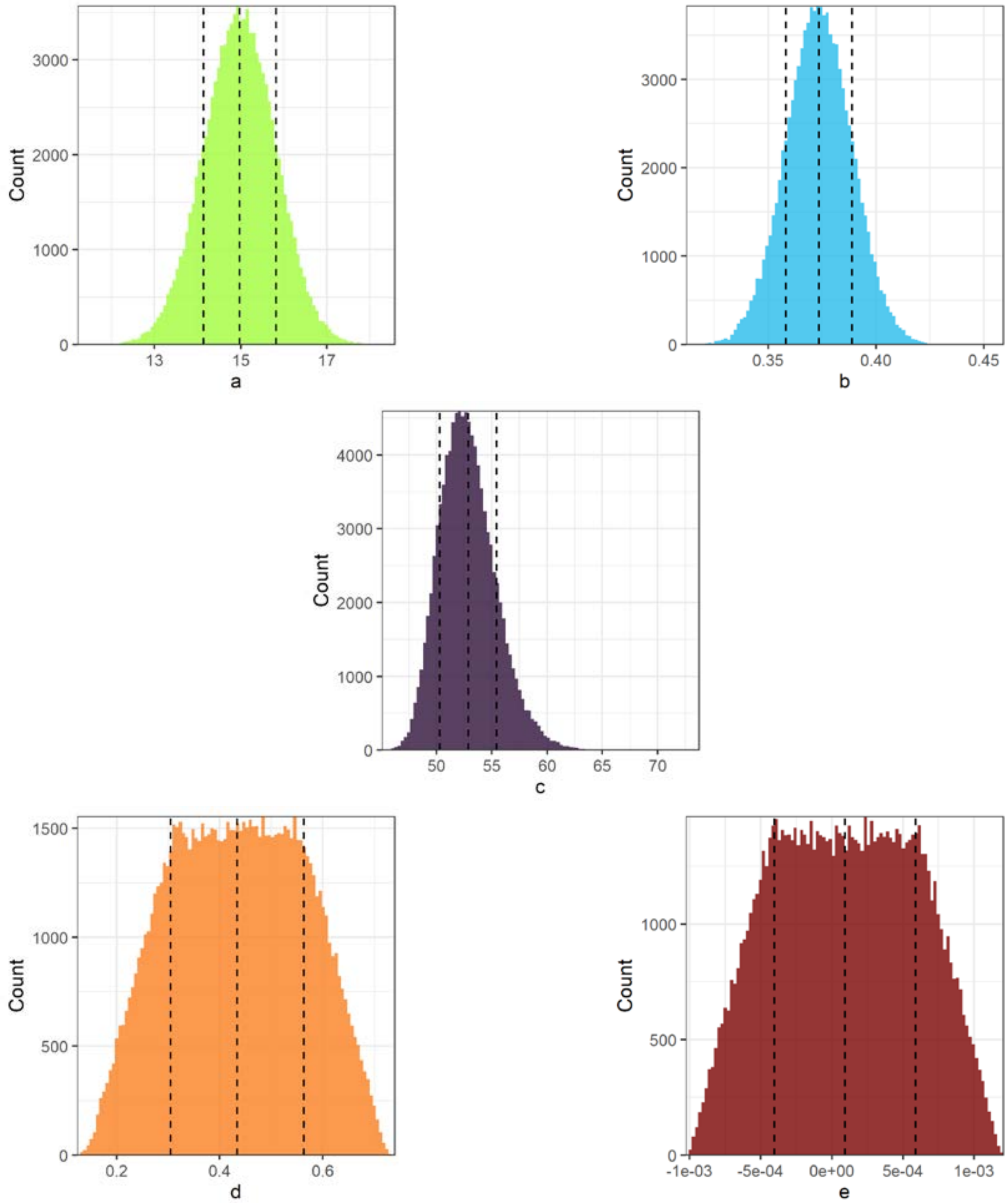

Figure 0-6 Monte Carlo Simulation model 2 coefficients' marginal distributions

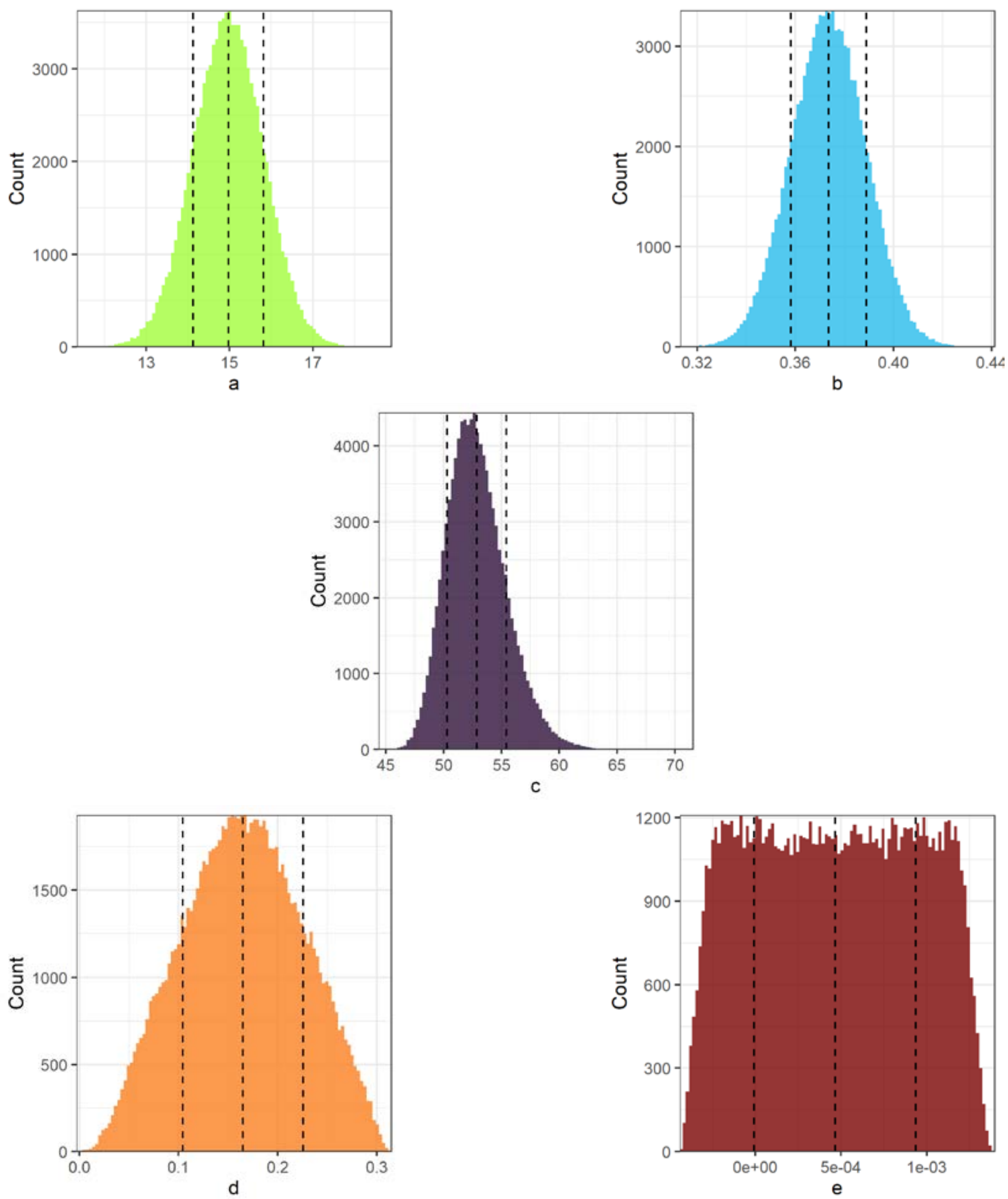

Figure 0-7 Monte Carlo Simulation model 3 coefficients' marginal distributions

B.2

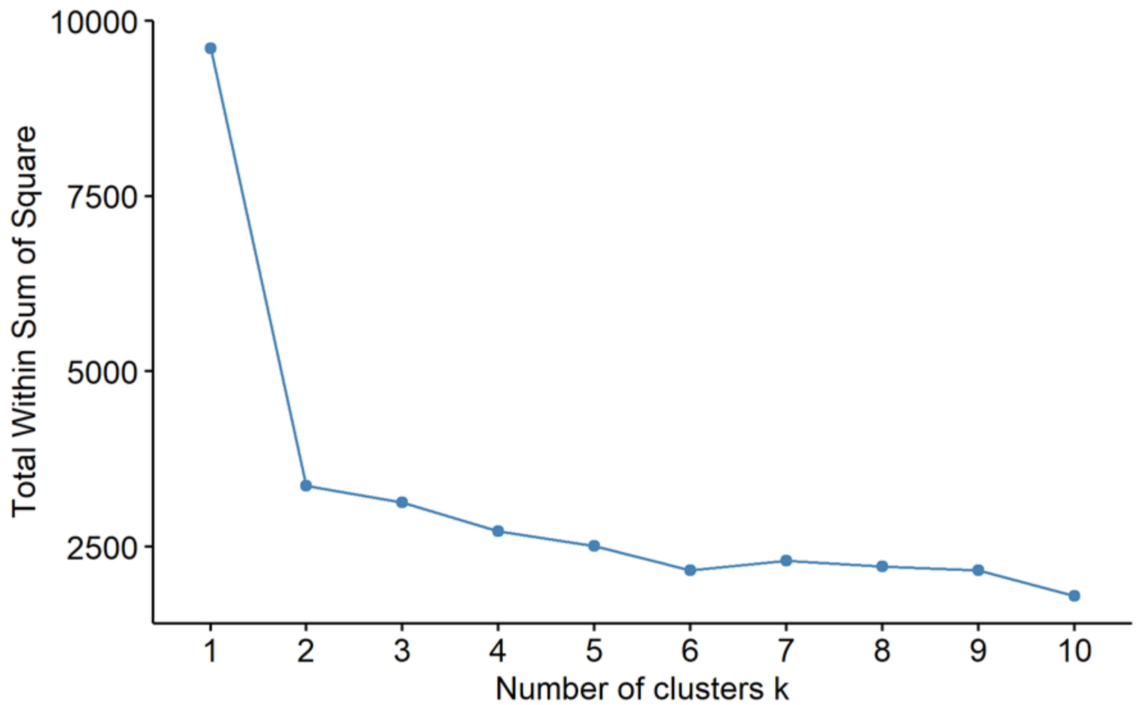

Figure 0-8 Within-group sum of squares by the number of clusters extracted

B.3

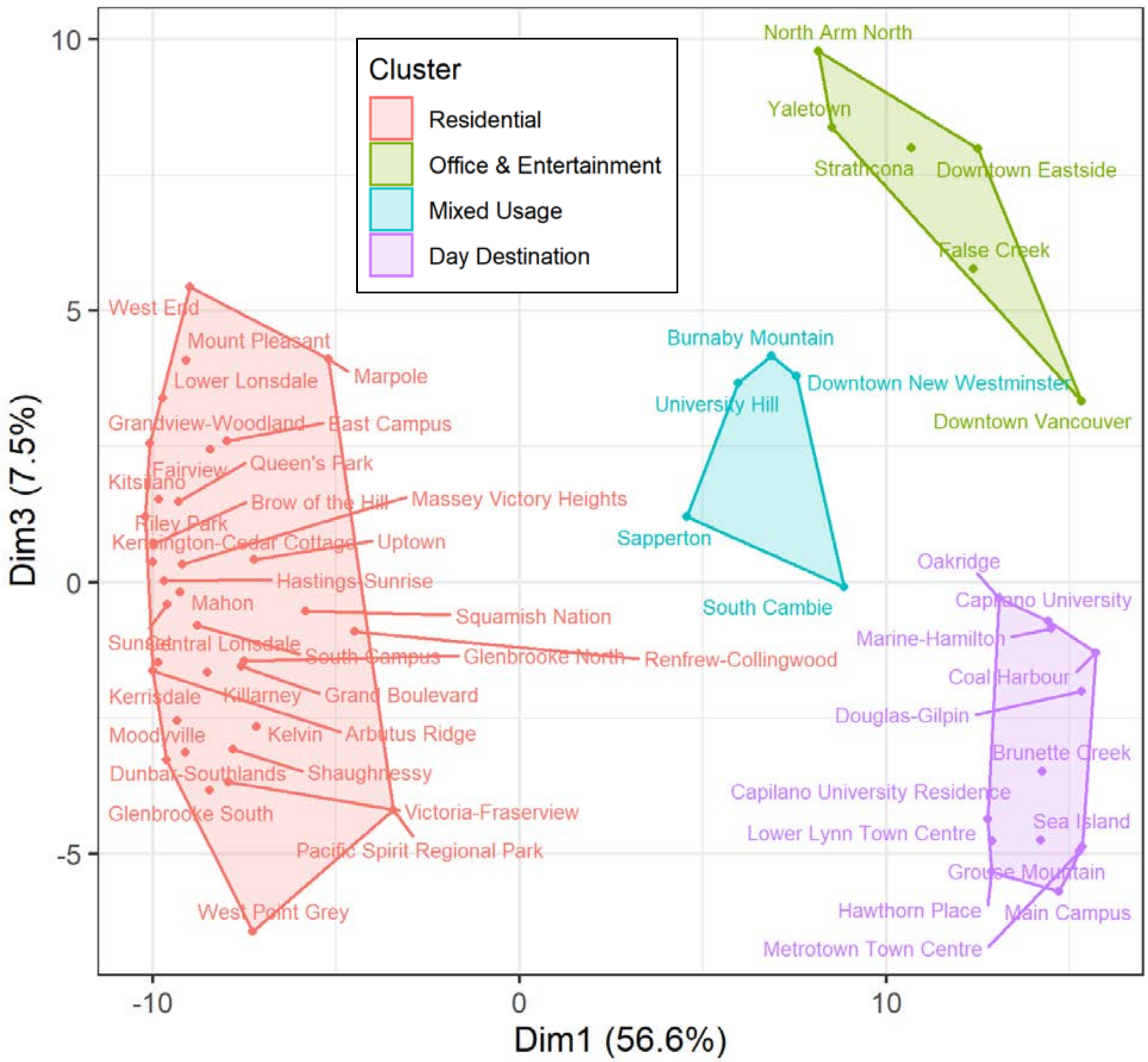

Figure 0-9 Clustering results of the neighbourhoods' hourly aggregate fleet idle time on PCA plot (1st and 3rd dimensions)