Exploring the Impact of Shared Mobility: An In-depth Look at How Bike Share Services and Shared Automated Vehicles Will Impact our Transportation Systems

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Abstract

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This thesis looks at the effects of new mobility services on emissions, via travel behavior and vehicle design improvements. Using NHTS data we find that right sizing allowed by shared mobility services would significantly affect CAFE compliance because most fuel standards would be met by moving people into more fuel efficient vehicles and thus increasing the number of these sold by companies. We then found that right sizing has the ability to reduce fuel consumption by more than 40% depending on the car replacement scenario. These reductions can make additional improvements by incorporating bikeshare within the shared mobility service. To further understand the possible effects of bikeshare, we then focus our research in the Chicago area, where we find that bikeshare has a net positive impact on transit ridership, and that this effect increases as more time passes. We then looked at Portland's Biketown to understand the effect of transit on bikeshare, but results were inconclusive. Overall we find that mobility services will likely reduce fuel use, and increasing bikeshare use can be used to grow this reduction, while also increasing the use of transit.

Table of Contents

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1.0.0 Introduction

In Lester Brown's book World on the Edge, he outlines what he believes are the major causes of climate change and how to go about stabilizing CO_2. One of these major stressors is overpopulation, which he says increases the magnitude of the different negative feedback loops which increase greenhouse gases (Brown, 2011). These issues of overpopulation place many stresses on our natural and built environments, but perhaps one of the most inconveniencing on a daily basis is the increase of traffic in metropolitan areas. In the Seattle area, this is illustrated by almost a twenty-minute commute time increase on the 24 mile trip from Everett to Seattle from 2012 to 2016 (Lindblom,2018). These increased travel times can partially be attributed to an influx of over 700,000 people to the Seattle metropolitan area since 2000 (Trimbath, 2016).

As population continues to increase, so will these transportation problems. To alleviate these problems, it becomes important to provide alternative modes of transportation that are equally or more attractive than driving oneself to work in a 7 passenger SUV, this is not sustainable or efficient. Transit and more recently shared services are these alternatives. Unfortunately, these modes currently represent a small percentage of the total mode share. With this in mind, it becomes very important to find ways to make these modes more attractive so that more users will change their travel habits, and alleviate the stress on our roadways, parking, and environment.

In the past 5 years, shared services have increasingly gained traction in most major cities. These shared services include both carsharing and bikesharing services, and also encompasses ridesharing services like Lyft Line or Uber Pool. Essentially what each of these services are able to do, is maximize the utilization of a car by nature of it being shared and used more often than if its only used by one person. This becomes attractive because of the reduced prices these services are offered at. Take Car2go carsharing for example, which offers members shared vehicles that they can use for less than \$0.50 a minute. In this form, users are able to pay as they go, rather than pay a large initial cost, which is required when you own a car. With cars, typically the utilization rate is about 5%, meaning the vehicle is only being driven 5% of the day. This means that on average 95% of the time vehicles are not being used, meaning there is a surplus of vehicles. These shared services are able to take advantage of this surplus by increasing the demand and thus utilization for these vehicles while making a small profit per trip. On top of these monetary benefits, the services provide many different levels of convenience and peace of mind. Moreover, as the mode share increases and technologies such as automation are introduced, we will see even more benefits, and reduced costs due to greater service area and vehicle density. More specifically, one of the benefits of these services will be their ability to be right sized to each user's needs, and right sized to the demand of the service area.

This thesis will attempt to outline some of the effects that these shared services will have on transportation and how different modes and their placement can be used together in order to increase ridership and quality of service. Chapter 2 will specifically cover the benefits right sizing will have on CAFE compliance, emissions, and what these shared fleets might look like on a national as well as local scale. Chapter 2 will then look at how integrating bikeshare into a service like this would further reduce emissions. To gain a better understanding of how these bikeshare services can become more successful, we will then look at the relationship of bikeshare with transit services in Chapter 3. Understanding this relationship will give us an idea of how to increase efficiency, so more people will use them and thus further reduce emissions. Chapter 3 will look at how station based bikeshare services will affect the use of transit when these services are used in proximity to train stations. Finally, chapter 4 will look at how proximity to transit effects the use of bikeshare services as well as how free float and station based systems effect bikeshare ridership.

2.0.0 Fleet Right-sizing: The Corporate Average Fuel Economy Effect of a Transition to a Shared Autonomous Fleet

2.1.0 Introduction

For many, the combination of smart phones and mobility services has dramatically changed the way we travel. As of May 20th, 2017, Uber alone has served 5 billion trips worldwide (Etherington, 2017). Most mobility service companies can be broken up into two separate groups, ridesourcing and carsharing services. The latter further subdivides into one way and two-way services. For this chapter, ridesourcing will be defined as "a single, or recurring ridesourcing trip with no fixed schedule, organized on a one-time basis, with matching of participants occurring as little as a few minutes before departure or as far in advance as the evening before a trip is scheduled" (Amey, 2014). Peer to peer ridesourcing like Uber and Lyft have already disrupted the taxi industry. They have achieved substantial market share by utilizing mobile technologies to provide easy access to their services (Cohen, 2014; Rayle, 2014; Wirtz, 2016). Evidence of their success can be seen with each of their 2015 valuations, putting Uber at $51 billion and Lyft at $2.5 billion (Wirtz, 2016). For this chapter carsharing will be defined as a short-term car rental service that can be operated in both a one way and two-way model, that also has both free float and stationary drop off points. Carsharing companies like Zipcar and Car2go on the other hand provide one and two-way services that allow customers to pick up the vehicle on demand and return it within set boundaries (Cohen, 2014). These mobility services have already caused many disruptions to transportation services while using existing vehicle designs. However, as the mode share for these services increases, it will be more likely that we see vehicles and fleets tailor made to the needs of these mobility services. This introduction of specialized fleets and vehicles present an unknown effect on the future of regulatory compliance. This chapter seeks to understand how fleet right-sizing will affect regulatory compliance, such as Corporate Average Fuel Economy (CAFÉ), and how greenhouse gas (GHG) emissions might change. In attempting to gain this understanding, this chapter sets up a methodological framework for answering these questions. Beyond the initial answers today, it is valuable to establish this framework for when more accurate data is available, so that researchers and original equipment manufacturers (OEM's) have the tools needed to predict how automated fleet right-sizing will affect their regulatory compliance.

2.1.1 Effect of Mobility Services Today

These ridesource companies have been able to thrive due to the inefficient regulations placed upon their taxi counterparts (Cramer, 2016). In locations where regulations permit their existence, the reduced regulation, more efficient driver-passenger matching, and a closer match of supply and demand, has enabled ride sourcing companies to have higher capacity utilization than taxi services (Cramer, 2016). Carsharing companies have attempted to do the same with car ownership that ridesourcing has done with the taxi. Various research has shown that the introduction of carsharing services reduces the number of vehicles in a community because it influences users to sell private vehicles and forego the purchase of a vehicle at all (Martin, 2016). Namazu and Dowlatabadi found that among carshare survey respondents who reduced their vehicle ownership, 70% of them became zero vehicle households, suggesting that carsharing is a substitute for private vehicle ownership (Namazu, 2016). Lower car ownership rates are also present amongst ridesource users in San Francisco. However, the difference likely had little to do with the introduction of ridesourcing (Rayle, 2014). This literature points to the fact that people are willing to give up ownership of their vehicles when there is a service that provides a viable alternative. As these services progress and the network of vehicles increases, more people may begin to make the transition and replace their personal vehicle with the service. For example, Chen expects that an autonomous mobility fleet in a city the size Austin would likely represent 14%-39% of the mode share (Chen, 2016).

2.1.2 Benefits of Todays Mobility Services

Today's mobility services offer both economic and environmental benefits. One benefit of both types of services is that they have been found to reduce total vehicular travel within certain groups (Cervero, 2004; Rayle, 2014). However, reductions in emissions will be realized when these services can provide vehicles with higher efficiency in comparison to user's current vehicles. By doing this, these services will reduce the emissions of vehicles even if the vehicle miles traveled (VMT) of the users remains consistent. In most cases, you will see a per capita reduction in gas consumption and also greenhouse gas emissions (Cervero, 2004; Martin, 2016). Understanding who your users are and increasing the quality of service through technological advancements are important factors that play into this transition of demand that is necessary to reduce GHG.

In addition to the reduction of vehicular travel, research claims these companies claim to offer environmental benefits. One study that looked at a life cycle assessment of ridesourcing companies vs. cars claimed that when traveling within more efficient ridesourcing vehicles lifetime emissions of CO_2 will be reduced by 92.7% in comparison to the highest emitting CO_2 case, furthermore these reductions are increased when using hybrid vehicles (Carranza, 2016). Moreover, because car sharing vehicles are estimated to be between 17%-44% more efficient than the average vehicle, fuel consumption and therefore energy and GHG emission will decrease (Chen, 2016). Of this emission reduction 19%-20% of this reduction could be attributed to the newer vehicles in the carsharing service, on top of this, an additional 16%-19% came from vehicles optimization of size and power (Namazu, 2015). Furthermore, as carsharing becomes more popular, use of transit, as well as walking and biking could increase (Chen, 2016). Older studies have found similar results, Martin and Shaheen found that in their sample there was a significant reduction in public transit. However, biking, walking, and carpooling exhibited significant increases (Martin, 2011). This literature suggests that the potential of fuel saving and emission reductions exist in a large transition to mobility services over private vehicle ownership.

2.1.3 Utilization Rates of Mobility Services

Cars left in locations without demand hamper the benefits of mobility services. In the case of ridesourcing, drivers are forced to drive without a passenger (deadhead), to a location where they get another customer (Henao, 2017). The same issue of reshuffling for demand is true for carsharing companies because cars are picked up in high demand areas, and then left in areas with low demand and therefore are less likely to be used for trips, thus making the system unbalanced and inefficient (Pavone, 2016). Various utilization rates for the different services can be found in Table 1 below. Higher utilization rates for carsharing are probably inflated because some users will check out the car, drive it to a location, and then keep it checked out but not utilized while they do something. A study performed in Lisbon by the International Transportation Forum predicts that these utilization rates will increase with the introduction of shared autonomous vehicles (ITF, 2015). They predict that SAV's without ridesourcing will have an idle time of 39%, while a service with ridesourcing would have an idle time of 27%. Understanding how these services are utilized in different cities and at different times of day is vital to accurately predicting the demand necessary to meet the needs within a given region.

Table 1: Current and Predicted Utilization Rates of Mobility Services

Source	Service Type	Utilization Rate
Barter, 2013	Base: Current Fleet	5%
Cramer, 2016	UberX	44%-55%
Henao, 2016	Uber and Lyft	31%
Hampshire, 2014	Carsharing	40%

2.1.4 Temporal and Spatial Variation of Demand

One explanation for these utilization inefficiencies can be attributed to the demand for these services being both spatially and temporally dependent (Pavone, 2016). By looking at surge pricing of Uber rides, we can see that during "party" hours on Saturday night and early Sunday morning, surge pricing is the highest (Cohen, 2016). Conversely, during weekday work hours, surge pricing is the lowest. Due to surge values being a factor of supply and demand, it is possible these increases can be correlated with busy times for drivers. However, this still shows that demand varies across different times of day in order to both encourage more drivers and reduce demand for the service (Cohen, 2016). This variation of demand within a day can be seen when looking at aggregated demand data from 2009 NHTS report (NHTS,2009). In general by day vehicle trips will peak during commute hours and midday. When looking at individual trips it becomes clear that they are much different from the aggregated whole, it is only when you start to aggregate individuals that the trends start to look like the whole (Tamor, 2013).

Not only is demand dependent on the time of day, but it is also spatially dependent. Work done on Barcelona's bikeshare system by Froehlich et al. shows that bikeshare stations in different locations have peak levels of demand on different days and during different times (Froehlich, 2008). By having highly aggregated data, our assumptions and results will fit a much smaller proportion of the population, and thus it is important to leave data relatively disaggregated.

Moreover, it is important not to overgeneralize, but rather focus on individual areas and times, to gain a clear understanding of what demand really looks like.

2.1.5 Deadheading and Induced VMT

These logistical issues of unbalanced demand and increased operating cost are what drive up the price of using mobility services, thus making them less competitive and more expensive than owning your vehicle (Carranza, 2016). These issues are difficult to solve without generating large additional costs, however, introducing high levels of automation into these services will allow rebalancing to be done automatically, and the cost of deadheading will decrease because it will no longer include the cost of a driver's time. Automation will not completely solve deadheading because there will still be unbalanced demand. In addition, by comparing autonomous driving predictions with current driving, the use of automated vehicles could potentially increase deadheading and overall VMT by 8% - 44% (Fagnant, 2015; Fagnant, 2014; Chen, 2016; Martinez, 2016). This literature suggests that automation will not come without the potential for negative side effects which can place increased stress on congestion and fleet operators.

2.1.6 Integration of Automation Into Mobility Services

To understand the effect of an automated mobility service, it is first important to understand the different levels of automation. These levels range from 0 to 5, with 0 representing no automation and level 4 representing full automation restricted to specific modes and areas, and the 5th level representing full automation (SAE, 2014). For mobility services to safely and successfully integrate automation into their services, a fully or highly automated vehicle would be necessary (level 4 or 5), so that no human interaction would be needed. Although we have not reached this level of automation yet. It is believed that by 2040 full automation could represent 20% of all vehicles on the road (Begg, 2014). This estimate is close to current estimates that suggest that by 2045 25% of vehicles will have full automation assuming a 5% price drop and a consistent willingness to pay (WTP) (Bansal, 2017). Another survey that sampled experts in the field suggests that full automation would begin deployment by the year 2030 (Underwood 2014).

2.1.8 Environmental Benefits of Automation

Strategies made possible by automation will also provide environmental benefits. One area that has garnered attention with the prospects of automation is the reduced need for over engineered vehicles (Pavone, 2016). A move to mobility services would allow fleets to match people to a vehicle with the exact needs of their trip. In addition, there would be a reduced need for high-performance vehicles, due to passenger's reduced desire for high acceleration forces in shared transportation services (Hoberock, 1997; AF Wahlberg, 2006). With a reduction in demanded performance, automated vehicles would no longer need to have fast acceleration times. This reduced performance could mean large reduction in fuel consumption, because fuel consumption decreases by 0.44% with each 1% decrease in 0-97 km/h acceleration time (Mackenzie & Meywood, 2015). Moreover, the introduction of automation into vehicles will help increase vehicle utilization which currently stands at 5% (Pavone, 2016; Barter, 2013). Furthermore, techniques like platooning and crash avoidance technologies can be used to realize further reductions in fuel consumption (Wadud, 2016). With the increased safety of compact vehicles due to automation, a shift in demand to smaller more efficient vehicles could also yield an upper bound reduction of average per-kilometer fuel consumption by 18% (Wadud, 2016).

2.1.9 Vehicle Right-Sizing

Pairing this reduction of vehicle size with the integration of automation into TNC's would enable vehicles to be right-sized to the needs of the customer. Right sizing was found by Wadud and Mackenzie to have the greatest potential for energy consumption reduction with a range from 21% to 45% (Wadud, 2016). However, that paper did not look at the variation of demand of vehicle size by day and different times. Accounting for this would address the issue that different sized vehicles might have different peaks in demand and thus the fleet may have to be sized to meet these peaks. Additionally, Fagnant demonstrated how under a idealized city, dynamic ridesourcing with shared autonomous vehicles (SAV) would allow companies to optimize an entire fleets size and replace 8.7 conventional vehicles per every SAV (Fagnant, 2015). This optimization is specific to the Austin area and does not look at the variation by day and time or the variation in vehicle size needed by users. Their paper simply assumes that the vehicles will be mid-sized and thus there will be a large amount of underutilized passenger capacity in the vehicles because many trips will be done with just one passenger. A case study found that a fleet of these shared autonomous vehicles would have the potential to reduce the fleet by 90% in comparison to self-owned personal vehicles (Fagnant, 2014). In Lisbon, when assuming the rides are shared, autonomous vehicles would replace 10 vehicles, whereas if the vehicles were not shared then they would replace 6 vehicles for every automated vehicle (International Transport Forum, 2015). Lower estimates suggest that vehicle replacement could range from 3.7 to 6.8 vehicles for every shared autonomous vehicle (Chen, 2016). This upper range is consistent with the work of Burns et al. which found that 6.7 vehicles would be replaced by each autonomous vehicle (Burns et al., 2014) . Furthermore, estimates made by Spieser et al. suggest that this could be as low 3 vehicles replaced in the

Singapore area (Spieser et al., 2014). A synthesis of these literature findings can be found in Table 2 below.

Table 2: Induced VMT and Vehicle Replacement Rates.

Source	Induced VMT	Vehicle Replacement Rate
Fagnant, 2016	8% increase	1:10
Chen, 2016	7.1%-14% increase	1:3.7-6.8
Spieser et al., 2014	-	1:3
Burns et al., 2013	-	1:6.7
International Transport Forum, 2015	6% increase (with ridehsharing) 44% increase	1:10 (with ridesourcing) 1:6
Fagnant, 2014	10% increase	1:11
Fagnant, 2015	8% increase	1:9

2.2.0 Methodology

Unbiased national level travel survey data is key to gaining insights on the GHG and regulatory compliance of an automated fleet. National level survey data allows for the development of a robust methodological framework for estimating demand as it varies throughout the day. This will provide a sturdy foundation for the different right-sizing optimization methods, which will assess the proportion of vehicles that are necessary in each group. Each proportional fleet mix can then be used to calculate fuel efficiency scores for comparisons with regulatory targets and for emissions reduction calculations.

2.2.1 Data Cleaning and Data Collection

To create fuel efficiency values, we must first analyze disaggregated survey data to find peaks in the data and then use clearly defined optimizations to size the fleet based off the different rules of the optimization. This method requires a very large dataset that can be extrapolated to a larger population, while still having a high degree of resolution when focusing on specific metropolitan statistical areas (MSA's). For these reasons, this study uses data from the 2009 National Household Travel Survey (NHTS).

This NHTS data was cleaned by removing trips that occurred on public transportation, walking, or biking. Additionally, trips of a distance greater than 800 miles were excluded from the analysis because 800 mile trips were considered to be the upper limit to the distance people would be traveling in a day (Pearre, 2010). Additionally, when variables used in calculations were omitted in a trip, the entire trip was eliminated, to avoid the need to make assumptions of their responses. Removing these data points eliminated 18.7% of the trip data or 218,639 trips. This should not be viewed as a substantial loss of data because many of the trips removed are those that were on modes this study is not interested in. The data was pooled into different MSA's then the same methods were applied to each group. The MSA's we looked at are New York, Los Angeles, San Francisco, Dallas, Washington D.C., Houston, and Seattle. The complete pool of NHTS data or the national data was also analyzed.

2.2.2 Demand Calculation

Data was aggregated into each quarter hour of each day of the week so that temporal changes and peak levels of demand could be analyzed. Within these units of analysis, the total number of minutes for trips of different passenger sizes were calculated. This analysis is limited to the demand of size 7 and smaller because this represents 99% of the trip demand. The number of minutes was calculated by multiplying each trip by its daily weighting value and then adding them up with the other trips that fell within its same count of passengers and quarter hour of the week (NHTS, 2011). The count of passengers is the number of people accompanying the respondent on their trip.

2.2.3 Size-mix Calculation

The following steps will vary based on the optimization used. To size the fleet to minimize total vehicles, we must look at the peak level of minutes of demand of all vehicles larger than or equal to each size group. This allows us to account for the excess demand of smaller vehicles that can be met with larger vehicles when those larger vehicles are not being used. However, this means that sometimes the vehicles will be fully occupied. The equation below shows the calculation for peak demand for a travel size party of n where X is the minutes of demand.

$$Peak\ Demand\ of\ Travel\ Size\ Party\ n\ and\ larger = Max(\sum_{n}^{7} X_n)$$

(Equation 1)

$$Proportion\ of\ fleet\ represented\ by\ vehicles\ of\ size\ n$$
$$= \frac{Max(\sum_{n}^{7} X_n) - Max(\sum_{n+1}^{7} X_{n+1})}{\sum_{1=i}^{7} Max(\sum_{i}^{7} X_i) - Max(\sum_{i+1}^{7} X_{i+1})}$$

(Equation 2)

(Note: for the equation 2 if n+1 = 8 then $Max(\sum_{n+1}^{7} X_{n+1})$=0)

On the other hand, to optimize for having the minimum number of seats in each vehicle, we must size to the peak demand of each individual size and only that size. This will give us the max number of vehicles that are demanded for each class, which are then met by that class. To minimize the total number of vehicles means you will have reduced costs for the fleet. However, because of how the fleet is sized, you have a greater chance for an unbalanced system and thus a higher chance for larger vehicles driving a small number of passengers. If you want to remedy this problem, you can size the fleet to minimize the number of empty seats. This will minimize the emissions of the fleet. However, this means that you must produce more vehicles to do this and therefore spend more money. The equation for peak demand at party travel size n can be seen below where X is the minutes of demand.

$$Peak\ Demand\ of\ Travel\ Size\ Party\ n\ and\ larger = Max(X_n)$$

(Equation 4)

$$Proportion\ of\ fleet\ represented\ by\ vehicles\ of\ size\ n = \frac{Max(X_n)}{\sum_1^7 Max(X_n)}$$

(Equation 5)

2.2.4 NHTS Fleet Calculation

To determine the CAFE values for the NHTS fleet, we must first properly distinguish which vehicles fall into each of the size classifications. For this chapter, cars will be considered passenger cars. Within the data, each vehicle was matched with CAFE fuel efficiency lab values provided by Toyota and their corresponding fleet grouping based off the make, model, and year of each vehicle. For those vehicles that did not have a match with the available CAFE data, reported vehicle type from the NHTS data was used to attach a fleet classification. For those without a vehicle type, model number was then used to decide if it is a truck or a car. For those without both values, it was assumed to be a passenger car. When the individual vehicles in the NHTS data were paired with two or more vehicles, we calculated the harmonic average of the fuel economy using the sales for each model. Each observed vehicle was also weighted with their weighting factor.

Finally, for the vehicles without CAFE values, we created a linear regression of vehicles with both CAFE scores and EPA scores (which every vehicle has) to model the difference between the two fuel efficiency values. This gives us a more accurate representation of what the CAFE score would be if we had the data. The CAFE score for this fleet was calculated using the fleet groupings assigned and the fuel efficiency calculated and acquired for each of the vehicles.

2.2.5 Proposed Fleet and CAFE Calculation

When calculating the CAFE numbers for the proposed fleet, we used three different model years for fuel efficiency and reproduced these results for both internal combustion engine (ICE) vehicles and hybrids. The first fleet used the most efficient ICE's from 2010 models that were determined to be of adequate size for that level of demand. The second set of values used were best case scenario ICE's from 2016 fleet. The final set of numbers for our 2025 fleet took 2016 efficiency and assumed a 2% yearly increase in efficiency until 2025. We then created the same fleets as above, but instead of using ICE's we used the most efficient hybrids for each size. Understanding the effect of hybrids in these scenarios is important because they have separate emissions implications. For companies like Toyota, which has emissions goals for 2050, it is important to understand the additional benefit this company would be able to gain from using these types of vehicles.

Next, we classified cars of five seats and down as part of the passenger cars part fleet and those of 6 and up were placed in the light trucks fleet. Within each of the different vehicle size groupings, footprint and fuel efficiency were assumed to be constant. The grouping used were 1-

2, 3-4, 5, and 6-7 (Wadud, 2016). These groupings come from Wadud's fleet groupings except for the 3-5 grouping being separated by 3-4 and 5. This was done because smaller five passenger vehicles like the Yaris would be large enough for four people, however, as a service people would probably be more comfortable in a larger five passenger Camry. At these sizes the company will have a higher quality of service and will be able to occupy a larger market share. The 1-2 vehicle grouping for hybrids uses the Prius because it is the most efficient hybrid on the market. Realistically, a two-passenger version would probably be more efficient, however a two passenger hybrid does not exist in the US market.

Finally, the CAFE standard and score for each of the fleets was calculated using a harmonic average and accounting for vehicle footprint. These results were then compared to one another and the CAFE score of the 2009 NHTS fleet.

2.2.6 Fuel Savings Calculation

To calculate the total fuel savings of the fleet, the number of gallons used in each NHTS trip was calculated based off trip mile estimates and fuel economy. This number was compared to the projected gallons used when implementing the autonomous fleet vehicles from the ICE groups. To account for an increase in demand due to automation, we assumed a 10% increase in VMT for the autonomous fleet (Fagnant, 2014). Once we had an estimate for fuel used for each fleet, the weighted sum of the differences was taken to estimate the total number of gallons saved. Once fuel savings has been calculated, we will then measure the fuel savings effect of replacing various percentages of bikes for trips less than 2 miles, while accounting for a 10% increase in VMT. The number of gallons saved is based off a 2010 smart car with a MPG of 49.5.

2.3.0 Results

2.3.1 NHTS Descriptive Statistics

The total number of trips within the NHTS sample is 948,683 trips. This comes from 308,901 respondents who own 309,163 vehicles. Of these trips, the average weighted number of passengers per trip is 1.93 people. The average weighted travel time is 18.7 minutes long per trip. Figure 1 below shows the weighted frequency of trips for the different passenger sizes. The weighted total minutes of each trips separated by the number of passengers can be seen in figure 2 below.

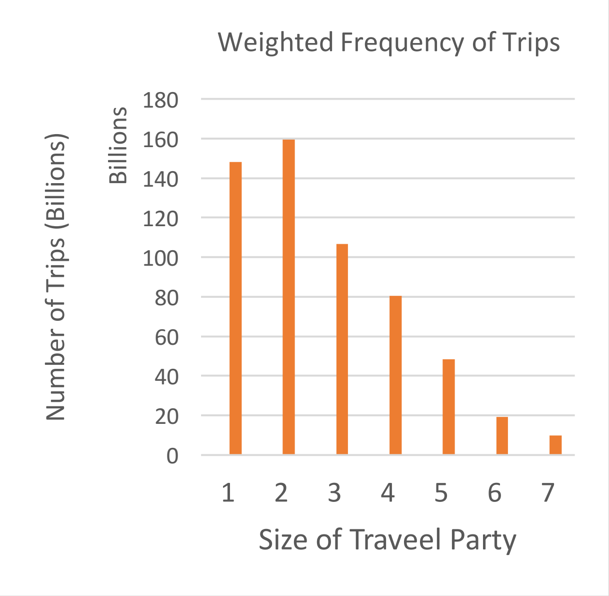


Figure 1: Weighted Frequency of trips.

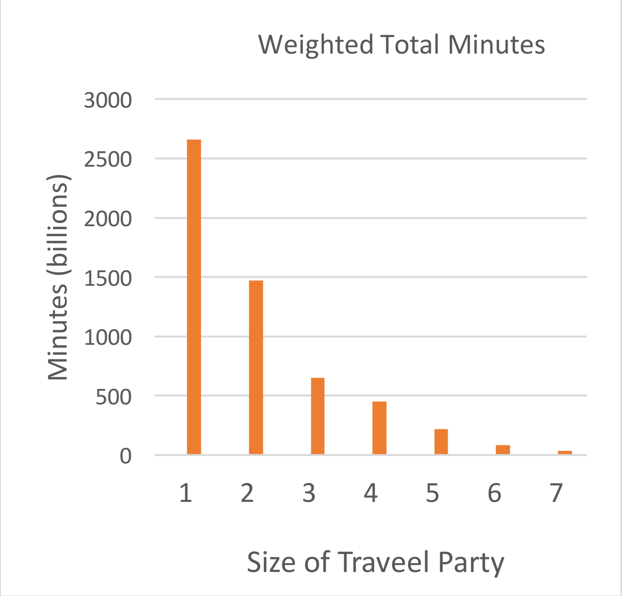


Figure 2: Weighted total minutes.

Surprisingly the two passenger group's trips accounts for the highest weighted frequency of trips. However, this doesn't tell the whole story. The variation between figures 1 and 2 illustrate the importance of looking at minutes per trip, to better understand demand. In this case, we can see that single passenger trips occupy the largest minutes demanded of the different groups.

2.3.2 Minutes of Demand

Separating the minutes of demand by the different levels of seats demanded nationwide reveals that all weekdays have very similar patterns of demand. There is a peak occurring during morning commute hours and a larger peak occurring during afternoon commute times. Weekends also exhibit similarities. Within each day, peak uses of each level of passenger demand appears to follow the spikes in demand exhibited by the whole. On weekdays, single passenger occupancy is clearly the greatest level of demand for all times. On weekends two passenger demand is greater than single passenger demand at certain times. These trends become clear when looking at figure 3.

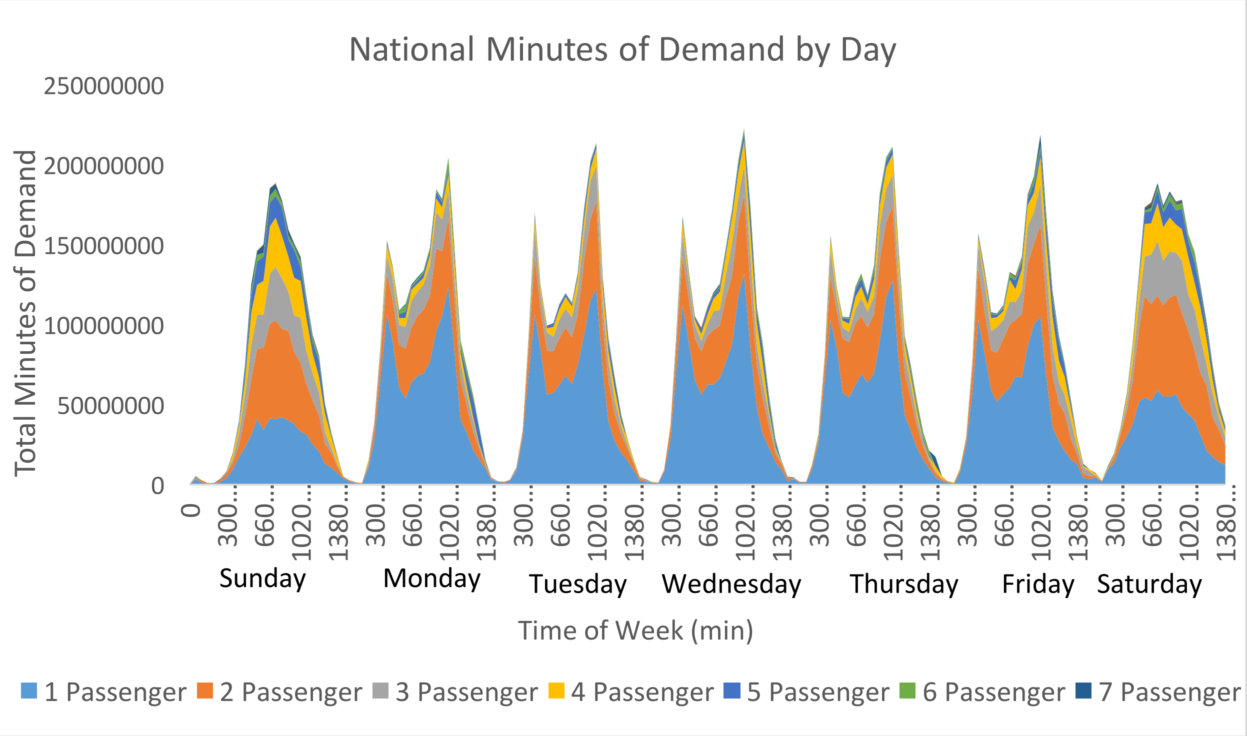


Figure 3: Minutes of demand by day binned into 15 minute groups.

The minute demand for larger vehicles is greater on weekends and represents a larger proportion of total demand during these times. During times of low levels of demand, it is possible that a larger level of demand can occupy a greater percent of demand due to the limited amount of data available during these times.

Results from individual MSA's typically follow the same trends as the national level. However, in cities with data like DC, the peak demand of four passenger vehicles represents the greatest proportion of peak demand. When there are less observations available for each of the different MSA's the results tend to vary more from the national results. Additionally, there are periods when the level of demand for these cities is zero. This is often during the middle of the night, and happens because there are no trips that occur during that time within the dataset. These periods are not important to us because they are during times that peak levels of demand are not occurring and thus are not necessary for the analysis. Seattle is a good example of a city that does not have enough data to make accurate conclusions. The Seattle MSA data contains less than 2,000 trips. Without unbiased data, researchers will not be able to make actionable decisions for those cities.

2.3.3 Proportion of Vehicles Needed

We assume the proportion of vehicles needed for each level of demand will remain consistent regardless of induced VMT or deadheading. If we assume that the demand mix for increased VMT is consistent with the demand mix found in the study, then VMT and deadheading will only affect the number of vehicles needed. The national proportion of demand by size group when optimizing for a minimum total number of vehicles can be seen in Table 3 below.

Table 3: Proportion of vehicles for each size grouping when optimizing for minimum vehicles.

MSA	1 Passenger	2 Passenger	3 Passenger	4 Passenger	5 Passenger	6 Passenger	7 Passenger
National	**39%**	26%	12%	11%	8%	1%	4%
Dallas	21%	22%	13%	15%	13%	12%	5%
DC	16%	20%	1%	**37%**	21%	2%	2%
Houston	**35%**	21%	13%	5%	10%	0%	16%
LA	17%	**28%**	**17%**	12%	12%	2%	13%
NY	28%	16%	13%	19%	0.1%	**23%**	1%
SF	17%	22%	7%	27%	4%	0%	24%
Seattle	6.3%	4%	3%	0%	**50%**	0%	**36%**

Levels of demand that show a proportion of 0% or 0 vehicles does not mean that there is zero demand at that passenger size. In these cases, the peak level of demand of that vehicle size can be fulfilled by the excess vehicles that are larger than it and thus there is no need to have vehicles of that size.

If we decide to optimize for a minimum number of vehicles, the fleets will have the proportional mix found in Table 4. This mix will have a larger amount of smaller vehicles and more vehicles total because each passenger size is being met with the exact number of seats needed. Zeros found in this table means there is no demand at that level.

Table 4: Proportion of vehicles for each size grouping when optimizing for minimum number of seats.

MSA	1 Passenger	2 Passenger	3 Passenger	4 Passenger	5 Passenger	6 Passenger	7 Passenger
National	45%	20%	12%	10%	7%	3%	3%
Dallas	36%	17%	14%	14%	9%	7%	3%
DC	24 %	23%	14%	26%	11%	2%	1%
Houston	33%	15%	11%	13%	14%	4%	9%
LA	37%	17%	11%	12%	10%	6%	7%

NY	27%	22%	14%	15%	11%	11%	0%
SF	27%	14%	14%	14%	8%	12%	12%
Seattle	16%	11%	13%	10%	31%	7%	1%

2.3.4 CAFE Fuel Efficiency Regression Model and Current Fleet CAFE Score

To complete our CAFE dataset for the different vehicles, a regression model was performed on vehicles with both NHTS fuel economy and CAFE fuel economy. This model allows us to estimate the CAFE fuel efficiency based off the NHTS values. Using this model gives us the estimated CAFE score of all the vehicles in the 2009 NHTS, which can be seen in Table 6. These values are not separated by footprint size or by domestic and international production.

Table 6: CAFE testcycle fuel economy for 2009 NHTS vehicles.

Fleet	**CAFE Fuel Economy(MPG)***
Passenger Cars	**28.65**
Light Truck	**21.64**
***If no CAFE value available, NHTS unadjusted value plugged into model for CAFE fuel economy.**	

2.3.5 Automated Fleet CAFE Scores

After determining the fleet mix for each optimization, each vehicle level was assigned the most efficient vehicle in that size class for both ICE's and hybrids. Tables 7, 8, and 9 below show the CAFE score for both optimizations when using only ICE vehicles. Table 7 uses only 2010 vehicles, Table 8 uses 2016 vehicles, and Table 9 uses 2025 vehicles. The values within the parentheses are the values for optimizing for minimum empty seats, while the first value is when optimizing for minimum number of vehicles.

Table 7: CAFE score using 2010 ICE vehicles only.

MSA	Cars (Optimized for min empty seats)	Trucks (Optimized for min empty seats)
National	46.09 (**46.19**)	29.2(29.2)
Dallas	44.11 (**45.13**)	29.2(29.2)
DC	42.52 (**44.39**)	29.2(29.2)
Houston	**45.50** (44.28)	29.2(29.2)
LA	44.38 (**45.24**)	29.2(29.2)
NY	**46.27** (44.63)	29.2(29.2)
SF	**45.23** (40.67)	29.2(29.2)
Seattle	36.47 (**44.74**)	29.2(29.2)

Table 8: CAFE score when using 2016 ICE and 2010 Smart Car with 2% yearly efficiency increase.

MSA	Combined Cars (Optimized for min empty seats)	Combined Trucks (Optimized for min empty seats)
National	48.47 (**48.54**)	30.00 (30.00)
Dallas	47.27 (**48.06**)	30.00 (30.00)
DC	46.20 (**47.97**)	30.00 (30.00)
Houston	**47.81** (47.15)	30.00 (30.00)
LA	47.54 (**47.84**)	30.00 (30.00)
NY	**49.77** (47.89)	30.00 (30.00)
SF	**48.93** (43.91)	30.00 (30.00)
Seattle	39.13 **(47.99)**	30.00 (30.00)

Table 9: CAFE score when using 2025 ICE calculated based off 2016 ICE and 2010 Smart Car with 2% yearly efficiency increase.

MSA	Cars (Optimized for min empty seats)	Trucks (Optimized for min empty seats)

National	60.99 (**61.16**)	33.80 (33.80)
Dallas	57.11 (**59.42**)	33.80 (33.80)
DC	55.11 (**58.31**)	33.80 (33.80)
Houston	**59.92** (57.93)	33.80 (33.80)
LA	58.17 (**59.54**)	33.80 (33.80)
NY	**61.62** (58.59)	33.80 (33.80)
SF	**59.82** (51.91)	33.80 (33.80)
Seattle	45.04 (**58.84**)	33.80 (33.80)

The CAFE scores in the tables above increase from 2010 to 2025 because of the efficiency increase of the vehicles. Light truck values remain the same regardless of the MSA and the optimization, because the vehicle being used is the same across the fleet. This is the same thing that happens when using hybrid vehicles in the fleet. These results are available below in Tables 10, 11, and 12. Table 10 uses only 2010 vehicles, table 11 uses 2016 vehicles, and Table 12 uses 2025 vehicles.

Table 10: CAFE score using 2010 hybrid vehicles only.

MSA	Cars (Optimized for min empty seats)	Trucks (Optimized for min empty seats)
National	**67.9** (58.6)	35.1 (35.1)
Dallas	65.4 (**68.1**)	35.1 (35.1)
DC	63.2(**67.0**)	35.1 (35.1)
Houston	66.5(**66.9**)	35.1 (35.1)
LA	**65.9** (65.1)	35.1 (35.1)
NY	**70.7** (66.6)	35.1 (35.1)
SF	**68.9** (66.2)	35.1 (35.1)
Seattle	**67.9** (66.9)	35.1 (35.1)

Table 11: CAFE score when using 2016 hybrids.

MSA	Cars (Optimized for min empty seats)	Trucks (Optimized for min empty seats)
National	**78.3** (69.9)	38.7 (38.7)
Dallas	76.1 (**78.4**)	38.7 (38.7)
DC	74.1 (**77.5**)	38.7 (38.7)
Houston	77.1 (**77.4**)	38.7 (38.7)
LA	**76.6** (75.8)	38.7 (38.7)
NY	**80.7** (77.1)	38.7 (38.7)
SF	**79.2** (76.8)	38.7 (38.7)
Seattle	61.3 (**77.4**)	38.7 (38.7)

Table 12: CAFE score when using 2025 hybrids calculated based off 2016 hybrids with 2% yearly efficiency increase.

MSA	Cars (Optimized for min empty seats)	Trucks (Optimized for min empty seats)
National	**93.6** (83.6)	46.3 (46.3)
Dallas	91.0(**93.8**)	46.3 (46.3)
DC	88.6 (**92.7**)	46.3 (46.3)
Houston	92.2 (**92.5**)	46.3 (46.3)
LA	**91.6** (90.7)	46.3 (46.3)
NY	**96.5** (92.2)	46.3 (46.3)
SF	**94.7** (91.9)	46.3 (46.3)
Seattle	73.4 (**92.6**)	46.3 (46.3)

2.3.6 NHTS 2009 Fleet Comparison

The best and worst case results for the NHTS fleet CAFE score compared to the proposed fleets are shown in Tables 13 and 14. In any scenario the fleet improves by a large margin and can even improve by 65 mpg in best case. The tables show the values of both optimizations. The values within the parentheses are the values for optimizing for minimum empty seats, while the other value is when optimizing for minimum number of vehicles.

Table 13: Best case difference between current NHTS fleet and proposed fleets (2025 Hybrids).

Fleet (Best Case)	**Automated (Optimized for min empty seats)**	**Current**	**Difference (Optimized for min empty seats)**
Passenger Car	**93.6** (83.6)	28.65	64.95 (54.95)
Light Truck	46.3 (46.3)	21.64	24.66 (24.66)

Table 14: Worst case difference between current NHTS fleet and proposed fleets (2010 ICE).

Fleet (Worst Case)	**Automated (Optimized for min empty seats)**	**Current**	**Difference (Optimized for min empty seats)**
Passenger Car	46.09 (**46.19**)	28.65	17.44 (17.54)
Light Truck	29.2 (29.2)	21.64	7.56 (7.56)

2.3.7 Fleet CAFE Score Compliance

Tables 24 and 25 in the appendix shows all footprint size groups disaggregated, to show the individual scores used when calculating the fleet score. The results for CAFE compliance can be seen in Tables 15 and 16 below. These tables contain all proposed fleets compared to the model year CAFE standard for the vehicles used. Both optimizations are listed in the same table in the same way as above.

Table 15: CAFE compliance for fleets with ICE's only.

Year	Fleet	Automated standard fuel score (Optimized for min empty seats)	CAFE Standard (Same for both)	Difference (Optimized for min empty seats)
2010	PC	46.09 (46.19)	27.5	**18.59 (18.69)**
	LT	29.20 (29.20)	23.5	**5.70 (5.70)**
2016	PC	48.47 (48.54)	40.5	**7.97 (8.04)**
	LT	30.0 (30.0)	27.8	**2.2 (2.2)**
2025	PC	60.99 (61.16)	59.3	**1.69 (1.86)**
	LT	35.9 (35.9)	36.2	**-0.3 (-0.3)**

In the above table, light trucks in the year 2025 are not compliant with CAFE standards. However, they make up a very small proportion of the fleet and don't use Hybrids. Table 16 shows how hybridization can affect CAFE compliance.

Table 16: CAFE Scores for hybrid only fleet.

Year	Fleet	Automated standard fuel score (Optimized for min empty seats)	CAFE Standard (Same for both)	Difference (Optimized for min empty seats)
2010	PC	67.9 (58.6)	27.5	**40.4 (31.10)**
	LT	35.1 (35.1)	23.5	**23.5 (23.5)**
2016	PC	78.3 (69.9)	40.5	**37.8 (29.4)**
	LT	38.7 (38.7)	27.8	**10.9 (10.9)**
2025	PC	93.6 (83.6)	59.3	**34.3 (34.3)**
	LT	46.3 (46.3)	36.2	**10.1 (10.1)**

As we see in the table above, hybridization creates an even greater margin between the fleet and compliance. Additionally, all classes are now compliant with CAFE. This illustrates the first benefit of using hybridization moving forward.

2.3.8 Fuel Savings Estimate

The results for fuel saving while accounting for a 10% increase in total VMT caused by automation are available in Table 17. These results assume a 100% market share. These results show that there is a huge potential for GHG mitigation by using right-sized fleets. Even without hybridized fleets, the reduction could be about 50%.

Table 17: Fuel savings when using ICE rightsized fleets with 100% market share and 10% induced VMT.

Fleet model year	Reduction (hybrid)	Billions of gallons of gas saved (hybrid)
2010	40% (59%)	45.7 (67.3)
2016	47% (64%)	53.5 (73.3)
2025	56% (70%)	63.4 (80.0)

2.3.9 Replacing Short Trips with Bikeshare

The results for the replacement of shorter trips of less than two miles with bikeshare can be found in Table 18 below. These calculations assume a 10% increase in VMT.

Table 18: ICE carshare trips replaced by bikeshare.

Percent of miles replaced	Number of miles replaced	Total Gallons Saved Compared to Today	Total Gallons Saved
0%	0	-123,998,099.7	0
10%	6,137,905,935	0	123,998,099.7
25%	15,344,764,838	185,997,149.6	309,995,249.3
50%	30,689,529,676	495,992,398.8	619,990,498.5

2.4.0 Discussion

The results for minutes of demand by day show that there is peak demand during commute times as we would expect. There are larger proportions of greater than one seat demands on the weekends. When looking at individual cities, especially those with less observations we see deviations from the national trends. In some cases, where ample data is available, we can make conclusions based off these results. For instance, DC shows that you have a higher demand of four passenger vehicles. Because this MSA has more data we can more accurately make conclusions. However, with cities like Seattle, where there are very few observations, we are unable to accurately predict the size mix of the fleet because we don’t have enough data to make our estimates reliable. In these instances, it becomes important for MSA’s to conduct similar surveys to the NHTS so that MSA’s can make actionable predictions in the future. Seattle is one example where they have already created their own household travel survey.

The proportion of each vehicle class estimate is what allowed us to predict whether the fleet will be CAFE compliant. These values are unaffected by the increase in VMT and deadheading. Separating these values by MSA shows that each MSA will vary from the national level. This makes it important to understand the demand mix of each MSA. By doing this you can more accurately satisfy the demand of that area. Within each MSA, there will be rebalancing issues with the vehicles, because demand is not spatially or temporally even. This is what will cause deadheading. For larger vehicles, this might be a bigger concern because they emit more and because there is a smaller amount of them in the fleet. To understand how these issues might play out, it is important to research how demand changes spatially and temporally within different MSA's. Having a better understanding of this will help properly size the fleet and reduce deadheading of vehicles.

Accurate data is necessary when trying to predict the number of vehicles that will be in the fleet, rather than just the proportion. To calculate the number of vehicles, you must adjust for the induced VMT caused by the availability of the service as well as the deadheading caused by reshuffling. The numbers used in this study are averages across times of the day and thus they are not the most accurate estimates because these adjustment values will vary spatially and temporally. With more precise VMT increase and deadheading data, one will be able to accurately estimate the number of vehicles within the fleet and enable OEM's to make accurate predictions for credits and penalties. However, this information is not necessary in answering the question of whether the fleet will be compliant with a standard.

Under our assumptions, all of our fleets will be compliant except for the 2025 ICE's of passenger size 3 and up. However, when you take the harmonic average of each fleet group, the passenger cars are compliant and the light truck fleet is not. However, because the light trucks represent about 5% of the total demand, it will be easy to make up for this with passenger car credits. Additionally, when switching to hybrid vehicles, all the fleets are compliant. These results demonstrate that right sizing has a huge potential to help meet future compliance. Moreover, when having a right sized fleet, it becomes clear that creating a compliant light truck is key to compliance in the fleet. This is because under our assumptions there is only one vehicle in the fleet grouping. However, because this group represents a much smaller proportion of all vehicles demanded, it may not be as important as it is today. This could lead to the potential combination of the passenger and light truck fleets in compliance if everything is right-sized. By making this change, OEM's will try to make the most cost effectively efficient vehicle for each size group, which probably means a reduced footprint. This would make it so that only the larger trucks have the larger footprints. Perhaps the best solution for this would be to have standards based off the number of passenger a vehicle can carry. This would eliminate the need for footprint measurements and prevent OEM's from making large inefficient vehicles for cars with less seats because the footprint allows them to do this. Another possible solution for non-compliant light trucks would be to utilize hybrids to satisfy just this group. This would keep costs down, and ensure the fleets are compliant. In comparison to the fuel consumption of 2009 NHTS respondents, a right-sized fleet has the potential to reduced emissions from 40%-70%. This represents a huge reduction in gasoline consumption, which means reduced sales and revenue for petroleum companies. The bikeshare integration results show that this reduction can be further realized when integrating bikeshare trips for trips 2 miles and less.

2.5.0 Conclusions and Future Work

This study has established a methodological framework for predicting the effects of rightsizing at the national and the MSA level. First, it establishes steps to bin survey data in a way that enables manipulation for different optimizations. It then predicts the peak levels of demand for different vehicle classes using 2009 NHTS data. These methods, provide the tools for estimating the fleet mix given levels of demand for different vehicles. It then establishes a procedure for manipulating minutes of demand to estimate the number of vehicles needed in each size group. Once researchers gain a better understanding of deadheading and utilization rates of automated vehicles, we will be able to estimate the credits and penalties proposed fleets might incur. Next, the study lays out steps to calculate CAFE scores for the fleet once the vehicles being used have been established. As technological trends become more defined, fuel efficiency of future vehicles will be more reliable and thus results will be more accurate. With reliable vehicle efficiency values for the fleets researchers will be able to produce accurate emissions reductions results. Future studies can build off this analysis by using these methods and the updated data highlighted above.

Until then, it is valuable to test the sensitivity of these methods by altering vehicles classification groupings, so that all vehicles might be passenger cars, or that five passenger vehicles might be grouped as light trucks. Additionally, assigning individual fuel efficiency values to each of the different levels of seats demanded would show even greater reductions in GHG. However, this would increase manufacturing costs because of the increased variation of vehicles. This could also increase wait times, because of the reduced flexibility of having vehicles of every size. Additional research that uses varied fuel efficiency improvements when predicting future fuel efficiency of vehicles could also be done to test the sensitivity of results for long term effects. Manipulating these values would give an idea of the yearly improvements needed to meet standards. Finally, it would be valuable to estimate the effects of this fleet at different levels of market share.

3.0.0 Unravelling the Relationship Between Bike Share and Rail Transit Use: A Chicago Case Study

3.1.0 INTRODUCTION

Increased public transportation use has the potential to reduce congestion and increase the sustainability of the transportation sector. Unlike driving, however, transit requires an access mode to get users to their local stop or station, and increasing the utility of a particular access mode can increase overall transit demand and use. One option for users to access transit is by cycling, either using a personal bicycle or a bicycle obtained through a bikesharing service. Cyclists see improved health due to everyday physical activity and also produce zero emissions while consuming less road space (Garrard, 2012). Furthermore, a study conducted in the Netherlands found that cycling is the preferred access mode for public transportation, and integrating cycling with public transport could increase the mode share for sustainable transport (Rietveld, 2000; Krizek,2014).

In recent years, bikesharing has provided an opportunity to expand transit access by facilitating a connection to transit for users that do not have ready access to a bicycle or prefer using a shared bike. An analysis of three U.S. bikeshare systems found that demographics, proximity to other bike stations, and availability of bike infrastructure influence utilization of a bikeshare system. In particular, non-white populations tend to use bikeshare systems less frequently, while more nearby bike stations and bike infrastructure increase use; bus route availability was not a significant predictor of bikeshare use (*Rixley, 2014*).

Although this study found no significant relationship between bus transit and bikeshare use, other studies find that bikeshare systems could be used as part of a last-mile connection to a rail transit stop (*Ma, 2015*). Bike share can be especially beneficial for connecting users with a bicycle at their destination since historically, cycling rates are lower at the activity end of the trip (*Reitveld, 2000*). However, the precise relationship between rail transit use and bikeshare use is still unclear; transit and bikeshare systems can either function in complementary or substitutional manners (*Ma, 2015*). Current literature suggests that a substitution relationship exists at short distances while a complementary relationship exists at longer distances, although the exact threshold depends on the trip purpose, weather, and the individual user (*Daddio,2012*). Empirical analysis generally finds that transit use and bikeshare are complementary although only a few studies currently exist (*Ma, 2014*).

One of the most studied bikeshare systems is the Washington D.C. Capital Bikes. Origin-destination (OD) matrices were estimated using trip information from Capital Bikes which shows that most trips are short (between 0.62 and 1.24 miles), seasonal effects influence ridership, and being in the proximity of a Metro stop increases utilization (*Ma, 2014*). Similar results were observed in New York City; bikeshare stations near heavily trafficked subway stations have higher utilization (*Noland, 2016*). The same study also estimated elasticities for bikesharing and found that a 10% increase in bikeshare ridership would lead to a 2.8% increase in Metro ridership (*Ma, 2014*). More recent work in the New York area suggests that the placement of docks along bus routes has a negative impact on the number of bus trips along each route (*Campbell, 2017*).

Additional work conducted on the Capital Bikes system demonstrated that a complementary relationship between transit and bikeshare exists predominantly on the urban fringe, while a substitutional relationship is observed in the city center (*Martin, 2014*). In particular, substitution is highest at the most congested Metro stops, indicating that bikeshare allows users to avoid an otherwise short rail trip (*Martin, 2014*). This confirms work conducted in Helsinki which found that the time savings associated with installing a bikeshare system in conjunction with the existing transit system are greater for more remote locations (Jäppinen, 2013).

Understanding how bikeshare and transit systems encourage users to adopt sustainable mode choices is vital as both planners and engineers work towards developing bikeshare systems which can serve each other and the needs of users. Work recently conducted in Chicago, IL, and Austin, TX, found that high volume bikeshare stations are not necessarily located immediately next to rail transit stations, indicating that either the relationship between bikeshare and transit has not been fully realized or the relationship between them is not as significant as previous work would suggest (*Griffin, 2016*). Despite this, in Chicago, 76% of bikeshare members used bikeshare to travel to transit sometimes or often according to a survey of members (*Griffin, 2016*). To best meet future transportation needs, it is imperative that the relationship between bikeshare and transit is better understood to ensure that the systems are built to facilitate a complementary relationship and encourage increased use of these transportation modes.

Current literature indicates that there is either a complementary or substitutional relationship between bikeshare and rail transit depending on the urban area under consideration; however, most of the research has focused on how bikeshare use is affected by proximity to transit. This study will address how rail transit passenger volume is influenced by the proximity of bikeshare trips in the city of Chicago through the following question:

> Does rail transit ridership increase in Chicago when bikeshare stations are provided near the station after controlling for other confounding factors?

By addressing this question, the relationship between rail transit use and bikeshare use can be identified and used by both planners and engineers to better place bikeshare locations to facilitate transit use.

3.2.0 DATA AND ANALYSIS

The subject population of this study is the L train system located in Chicago, Illinois. Daily ridership data for each L train station was acquired from the CTA from January 2001, until the end of October 2016, and the daily ridership data was combined into monthly totals for each individual train station. Ridership data for the L train is collected only when users enter a station. Because no data is collected when a user leaves the station, only station origin information is available; the destination or train line used are not available with this data set. In 2001 there were 146 stations, however, there are currently only 144 stations. These two stations were closed in 2001 and 2009, before the introduction of Chicago's bikeshare system, so they were excluded from this analysis.

The bikeshare system in Chicago, Divvy, started operations in June, 2013, and, as of 2016, has since expanded to cover more areas of Chicago, with 6000 bikes and over 580 stations (*International, 2017)*. The average Divvy member takes 83 trips per year with an average trip length of 2 miles (*Divvy, 2016).* Bikeshare data was acquired from Divvy's website and includes the time, origin station, and destination station, among other measures that were not included in this analysis, for rides between June 2013 and October 2016. The origin and destination of the bike trips are recorded when a bike is checked out and then returned. When this is completed, the date and time are also recorded. Each of these measures were included in the dataset to analyze their effect on L ridership.

Point shapefiles for both the L train and the Divvy stations were acquired from the CTA website and loaded into ArcGIS. A 400-meter (0.5 mile) buffer was then created around each of the L stations, to identify the Divvy stations that fall within the standard transit walking distance (*Daniels, 2013*). These Divvy stations were then assigned to each of the L station buffers that they fell within. Figure 4, below, shows a map of the Chicago L stations and Divvy bikeshare stations that fall within the buffer area.

The Divvy data set provides the origin and destination of each bikeshare trip. This information was separated to analyze the effect on L ridership from both bikeshare trips originating from an L station area and bikeshare trips terminating at an L station area. For this study, bikeshare trip counts starting within an L station buffer area will be referred to as origin trips while bikeshare trips ending within an L station buffer will be referred to as destination trips. Total monthly origin and destination rides were then computed for each Divvy station by month and year. These values were then totaled for each L station buffer, to give the total origin and destination rides within each buffer.

FIGURE 4 Divvy stations within 400 meters of an L station in Chicago

Because new bikeshare stations would be phased in over time, it was assumed that a bikeshare station would only begin to have an effect on L station ridership after at least one ride had been taken from that bikeshare station. When this threshold was reached, the Divvy station was then included in the analysis and in the count for total number of bikeshare stations within that buffer. Depending on the year of the first ride, the years of operation could be calculated to identify any lag effects in ridership after the introduction of bikeshare. To calculate the years of operation, 2016 was used as the final year of interest; since bikeshare was first installed in 2013, this variable ranged from zero to four. For example, if an L station was assigned a four for this variable in year 2016, bikeshare has been available in the station vicinity since 2013 whereas if the L station was assigned a zero in year 2016, bikeshare is still not available near the L station.

In addition to bikeshare ridership, L ridership likely varies based on transit service quality, the built environment, and neighborhood demographics. A previous study on subway ridership in the Washington D.C. area fit a linear regression model that included bikeshare as a predictor variable, in addition to factors like transit service quality, the built environment, and demographics for one year of data (*Ma, 2014*). Typically, bikeshare stations in areas with a greater proportion of minority residents tend to have lover levels of demand (*Buck, 2014*). Conversely, higher income areas and those with a greater proportion of the population ages 18 to 34 tend to have greater levels of demand (*Fishman 2015*). Areas with higher population levels also exhibit increased demand in bikeshare ridership (*Hampshire, 2012*). Due to the spatial and temporal variation of these sociodemographic factors a random effect must be included in the model to account for variation in utilization between bikeshare stations.

The final dataset used for analysis consists of repeated measures of monthly L station ridership over a 10 year period. Each L station record also contains the number of bikeshare origin and destination trips within that given month and year, in addition to recording the number of years of operation for the bikeshare system in that location and the number of bikeshare stations within the station's buffer. Sociodemographic data is assumed to vary across all measures although it was not explicitly considered in the model. To account for the repeated measures within the data, panel regression was used by developing a nested logit model with random effects to understand how changes in bikeshare ridership correspond to changes in L train ridership over time while still accounting for station level variations. This model nested month within station ID to capture how L ridership changes over different years across stations.

3.3.0 RESULTS

Before developing the model specification, descriptive statistics were used to evaluate how the data for both the bikeshare ridership and L station ridership vary across time. Results from these descriptive statistics and model results are summarized below.

3.3.1 Descriptive Statistics

Both L ridership and bikeshare ridership vary across time and space making pure descriptive statistics for the data challenging and complicated to interpret. Generally, L ridership has been increasing over the 15 years of passenger volumes provided by the CTA. Additionally, variation from month to month shows that there is a seasonal effect in L ridership with a decrease in ridership during winter months. Figure 5, below, shows how average bikeshare ridership has generally been increasing as bikeshare has been in effect longer; 2016 has higher ridership volumes for both the maximum and average monthly volumes compared to 2013. This figure also shows strong seasonality effects for bikeshare ridership, especially for the maximum number of rides. July 2016 did have a significant drop in bikeshare use and the reason for this is unknown, although it could indicate some issues with the collected data. Minimum bikeshare volumes are not shown on these figures because some L station areas are still lacking bikeshare facilities in their immediate vicinity, leading to zero total bike rides for this station. Although this figure just illustrates the number of bikeshare trips originating from a station area, similar patterns are observed for trips terminating in an L station area. The increase in bikeshare ridership volumes is also correlated with an increase in the number of bikeshare stations, particularly in the vicinity of L train stations, as seen below in figure 6. In this figure, the size of the circle around the L station area is correlated with the number of bikeshare stations within the buffer area; as there are more bikeshare stations in the vicinity of the L station, the buffer size grows, indicating that Divvy has been focused on expanding its operations throughout Chicago, particularly in the downtown core.

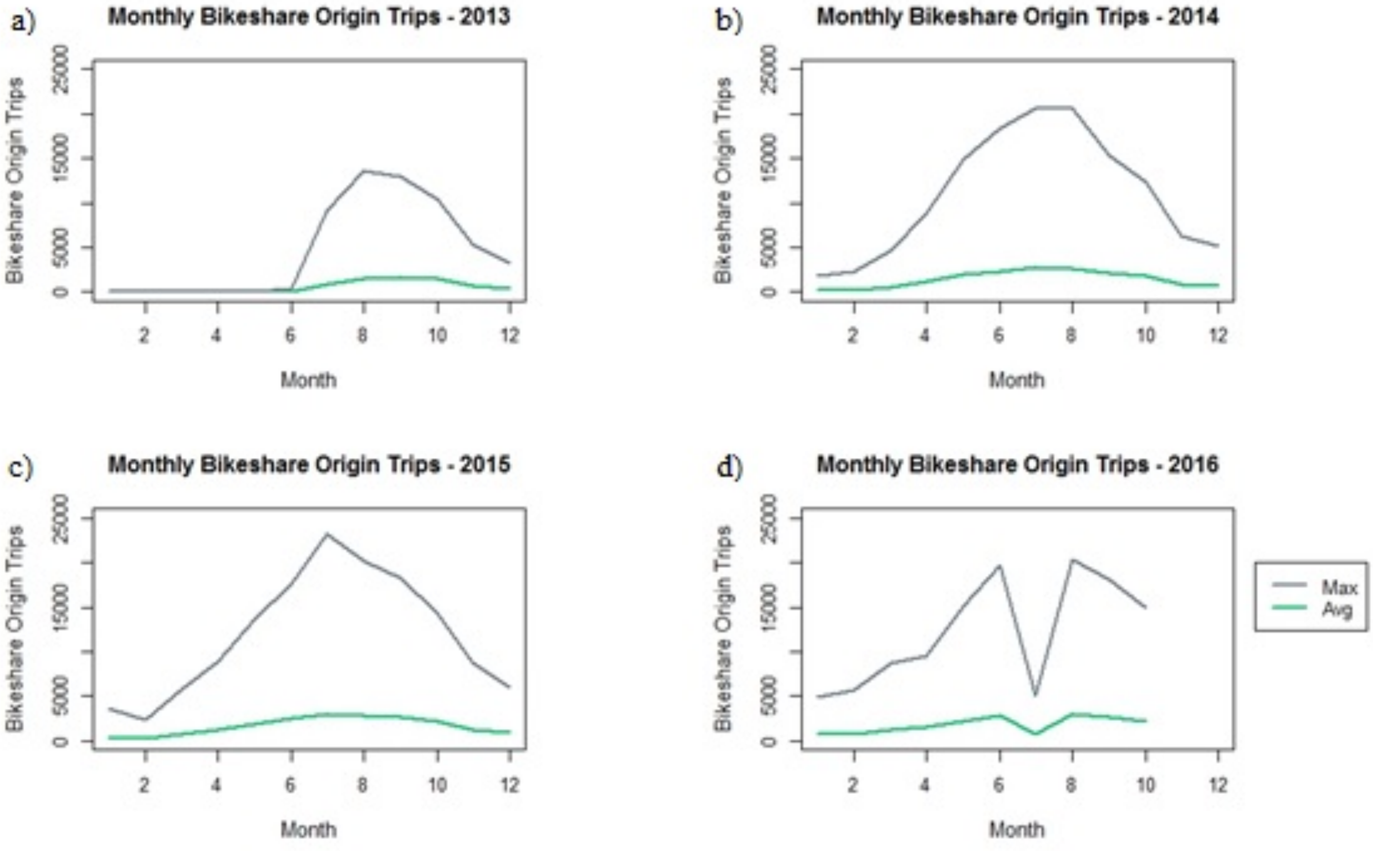


FIGURE 5: (a),(b),(c), AND (d) Monthly bikeshare origin trips in year 2013 (a), 2014 (b), 2015 (c), and 2016 (d)

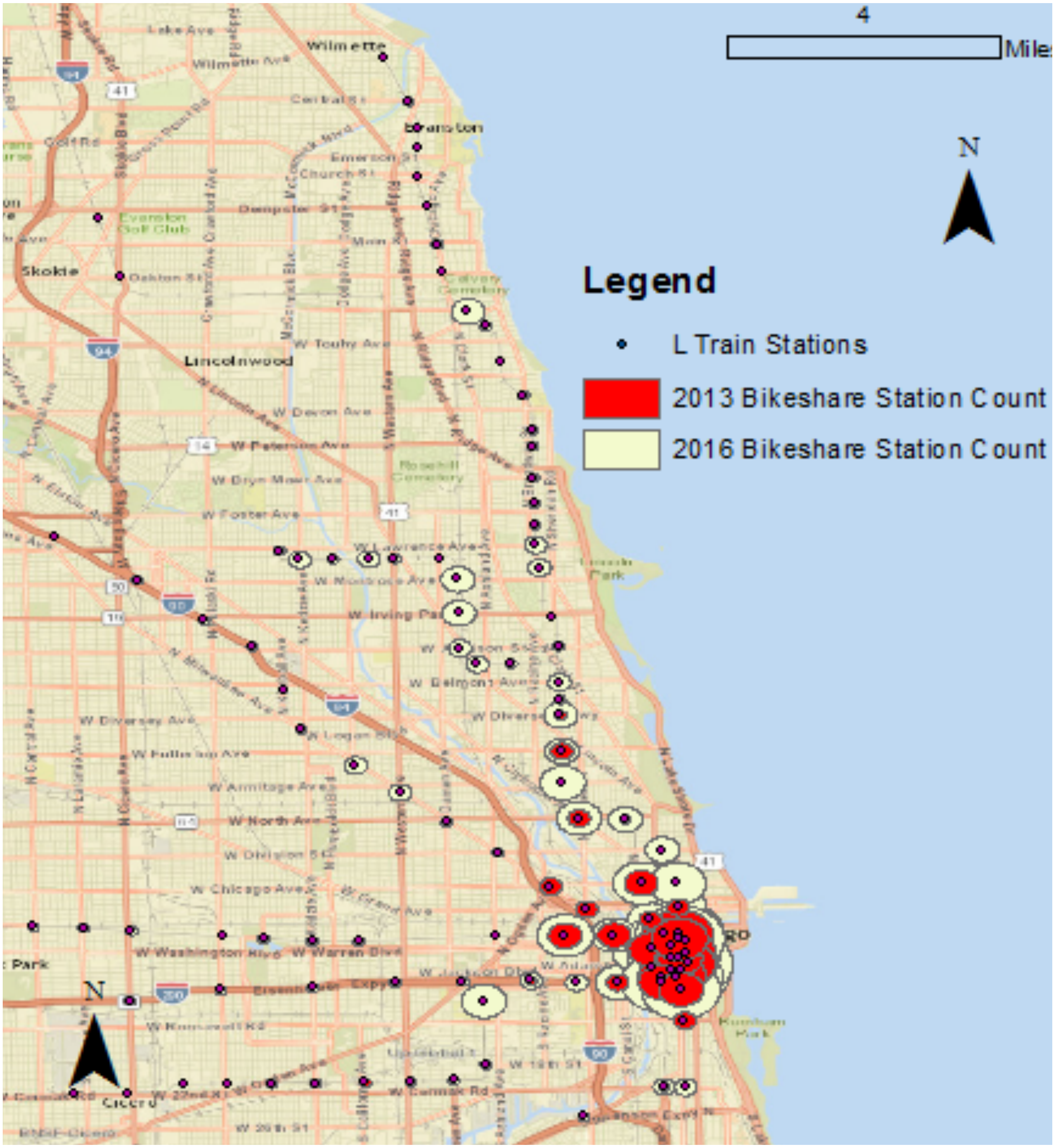


FIGURE 6: Change in number of bikeshare stations in L station buffer area from 2013 to 2016

3.3.2 Model Results

The results of the panel regression with random effects can be seen in Table 19 and 20, below. Table 19 shows the random effects for the nested portion of the model results while Table 20 shows the fixed effects for the model. Station level effects are not included in the following table. The model was specified using the following equation with the β parameters referring to the coefficient estimates seen in Table 19 or 20. In this equation, the index *i* indicates that the value varies across space while the index *t* indicates that the value varies across time.

$$\begin{gathered} \mathit{Num.\ of\ L\ Rides}_{i,t} = \beta_0 + \beta_1 * \mathit{Dest.\ Trips}_{i,t} + \beta_2 * \mathit{Origin\ Trips}_{i,t} + \beta_3 * \mathit{Bikeshare1}_{i,t} + \\ \beta_4 * \mathit{Bikeshare2}_{i,t} + \beta_5 * \mathit{Bikeshare3}_{i,t} + \beta_6 * \mathit{Bikeshare4}_{i,t} + \beta_7 * \mathit{Bikeshare\ Station} \\ \mathit{Count}_{i,t} + \sum_{t=1}^{12} \beta_{8t} * \mathit{Month}_{i,t} + \sum_{t=1}^{16} \beta_{9t} * \mathit{Year}_{i,t} + \sum_{t=1}^{144} \beta_{10t} * \mathit{Train\ Station}_{i,t} + \varepsilon_{i,t} \end{gathered}$$

The variables included in the model for analysis are all statistically significant and confirm the results of previous work. Trips that terminate in the vicinity of an L station, referred to as destination trips, lead to an increase in the total number of L rides while trips that originate in the vicinity of an L station, referred to as origin trips, tends to decrease the overall number of L rides observed. This indicates the complementary and substitutional relationship previously observed between bikeshare and transit, although overall, there appears to be a net complementary effect. This effect is also shown to grow as bikeshare has been in the vicinity of a given L station longer as evidenced by the larger intercept values associated with a longer period of bikeshare operation.

TABLE 19: Random Effects Panel Regression

Groups	Variance	Std. Dev
Month nested in Station	78501755	8860
Station	363508577	19066
Residual	375656958	19382

TABLE 20: Random Effects Panel Regression Model Fixed Effects

Variable	Estimate	Std. Error	T Value
Intercept	29525.3	19310.6	1.53
Destination Trips	12.4	1.4	8.61
Origin Trips	-10.5	1.4	-7.51
Bikeshare - 1 Year	6958.5	959.2	7.25
Bikeshare - 2 Years	8732.3	945.0	9.24
Bikeshare - 3 Years	12819.5	1201.3	10.67
Bikeshare - 4 Years	16467.5	1346.3	12.23
Bikeshare Station Count	1967.6	283.1	6.95
Baseline Month: January			
February	-2228.8	1196.2	-1.86
March	8277.5	1196.2	6.92
April	7070.0	1196.2	5.91
May	8761.9	1196.6	7.32
June	10170.9	1197.3	8.49

July	12647.4	1197.2	10.56
August	11661.2	1198.5	9.73
September	12918.7	1198.3	10.78
October	18535.1	1197.4	15.48
November	5375.0	1202.4	4.47
December	-1950.6	1202.2	-1.62
Baseline Year: 2001			
2002	368.9	666.9	0.55
2003	-903.5	666.9	-1.35
2004	-2285.8	666.9	-3.43
2005	1376.2	666.9	2.06
2006	6021.6	666.9	9.03
2007	4899.7	666.9	7.35
2008	9265.9	666.9	13.89
2009	10403.6	666.9	15.60
2010	14154.4	666.9	21.22
2011	20435.1	666.9	30.64
2012	23483.1	665.5	35.28
2013	18463.5	665.5	26.55
2014	16952.1	767.2	22.10
2015	14177.8	836.5	16.95
2016	9446.0	936.9	10.08

3.4.0 DISCUSSION

The results of the panel regression with random effects model suggest that the number of destination bike trips for a given station has a positive effect on the number of L rides and the number of origin bike trips has a negative effect on the number of L rides. This difference likely arises due to the way the L passenger volumes are collected; rides are only counted when the user enters the station and not when they exit. Therefore, a Divvy user could be riding to the train station and then boarding the train. The docking of their bike at a bikeshare station near a L station would count as a destination trip, and if they board the train at this station there would be a recorded L ride. However, if someone rides the train and then exits the station and undocks a bike as an origin trip, only the action of undocking of the bike is captured.

Another alternative explanation for this negative correlation is that people are using the bikeshare rather than the train to get around. If their trip origin falls within the buffer of a train station, it is also possible that their bikeshare trip functions as a substitute for the L train in that area. It is probable that in some areas it might be more efficient to use the bikeshare rather than walking to a station and waiting for the train, particularly if the trip is short. Due to this increased efficiency, some people may be choosing to use the bikes instead, thus creating a substitution effect for the L train station. Given the nature of the data available, it is unknown how much of the origin trips are truly substituting for transit use.

These effects demonstrate that there is likely both a complementary and substitutional relationship between bikeshare and transit use. In this analysis, the absolute value of the effect of destination trips is larger than the absolute value of the effect of origin trips, indicating that the effect is largely complementary. If both the origin and destination trips increase by the same amount within a given station area, there will be a net positive expected increase in the number of L rides from a given station, indicating that bikeshare is complementing transit use in Chicago. Furthermore, the results indicate that the increase in the number of bikeshare stations in a buffer also leads to increased L ridership. This outcome also points towards a complementary effect between bikeshare and transit.

While there is a net complementary effect between bikeshare and transit, this effect might not emerge immediately after the installation of a bikeshare system. The results also show that there is a lag in the effect that bikeshare stations have on the total number of L trips. When a given station has had bikeshare stations nearby for four years, there is a greater number of L rides from that station, as indicated by the larger coefficient values in the random effects model for the indicator variables. This shows that over time the positive effect of having bikeshare stations within the buffer zone around an L station increases. Over time, more people are using the bikeshare system and realizing the possibility to link these trips to transit, increasing the overall mode split in that area for transit and biking. The total amount of passenger trips in the area may have remained the same, but as people become more familiar with the bikeshare, they are more likely to use it, increasing the overall mode share for cycling and transit.

3.5.0 Limitations and Future Work

Although this study provided meaningful insights on the relationship between bikeshare ridership and transit use, it does have limitations that could not be addressed due to the nature of the data used in this analysis. Including demographic information or transit service quality information that varies over time could provide a better way to estimate how these station level characteristics influence L ridership in Chicago rather than relying on the model estimation for station level effects. This is especially notable considering previous research that indicates the importance of including these factors as they influence both bikeshare and transit use overall (*Ma, 2014; Buck, 2014; Frishman, 2015; Hampshire, 2012*).

This study could also be enhanced by considering a similar model for a city where both entry and exits from train stations are counted. Since the L system in Chicago does not record exits, confirming the precise nature of the relationship between origin bikeshare trips and the recorded number of L rides is challenging. The negative effect of origin trips on L ridership could indicate a substitutional effect, or it could arise purely due to the nature of the collected data. If both entry and exits from the transit system of interest were recorded, the true nature of the relationship between origin trips and transit ridership is more likely to appear. This limitation could also be overcome by studying a system that has an incorporated fare payment system between bikeshare and transit. This would allow a researcher to identify when a user is moving between bikeshare and transit as different links in their trip rather than merely assuming this linkage occurs when the trips happen within a given area.

Finally, future work for this model should identify and control for the total number of bikes available at different times around a train station. Controlling for this effect would help to accurately predict the effect of bikeshare on transit ridership. When there are no bikes around a station people cannot use the bikeshare system, even if there is demand for linking transit with bikeshare. In this study however, the demand is zero if no bikes are available for people to use, which could possibly underestimate the true demand for the system. Extending the current research in these future directions will address some of the limitations of the current study and help to further explain the relationship between bikeshare and transit use.

3.6.0 CONCLUSIONS

This analysis has shown that bikeshare has both a complementary and substitutional effect on transit ridership. An increase in the number of origin bike trips has a negative effect on the number of L rides, suggesting a substitution effect while an increase in the number of destination trips has a positive effect on the number of L rides, suggesting that there is a complementary effect. Overall, this model indicates a net complementary effect between bikeshare and transit as evidenced by the relative magnitude of these effects. This complementary effect is further evidenced by the increase in the total number of L rides as more bikeshare stations are located in the vicinity of an L station. This effect is not immediately realized, however. There is evidence of a lag effect on the total number of L rides for the presence of bikeshare in the vicinity of an L station; the longer bikeshare has been in operation near an L station, the greater impact on the total number of L rides. Understanding the complementary nature between bikesharing and heavy rail transit reinforces the idea of placing and expanding the total number of bikeshare stations near transit to increase train ridership.

4.0.0 An Exploratory Analysis on the Effect of Transit on Portland's Bikeshare Program

4.1.0 Introduction

As the world's population has grown and people have flocked to major cities, it has become increasingly important to find alternative modes of transportation that are both efficient and sustainable. Recently, traditional public transit systems have begun to be replaced by shared travel modes like carsharing and bikeshare. However, these modes do not offer the same level of comfort one experiences in a personal vehicle. This is compounded by a lack of access and long wait times to use these services. Krygsman et al found that these portions of transit trips are the weakest and most disadvantageous to riders. Moreover, they found that egress had a larger effect on trip time than access (Krygsman, 2007). Thanks to increased transit information and the societal permeation of smart phones, egress is becoming less of a factor, because people are able to arrive when buses do, rather than wait at a stop. As for accessibility, Krygsman says that bikes can be used in order to reduce accessibility barriers to riding transit (Krygsman, 2007).

One study in the Netherlands found that biking was a crucial access mode to transit, and by instead electing to drive, one might eliminate any emission reductions saved by riding public transit (Rietveld, 2000). Unfortunately, driving is a very common way for people to access transit. This suggests that there is demand for increased access to transit, and that riding a personal bike is not worth it for most people. One solution to this problem is to make biking more attractive. Bikesharing attempts to do this by eliminating the hassle of maintenance and fear of having your bike stolen. In addition to increasing access to other transit modes, bikeshare also helps to fill gaps in transit service as a relatively cheap alternative.

Bikeshare started in the Netherlands in 1965 as White Bikes, with the intention of increasing public mobility (DeMaio, 2009). Since 1965, bikeshare has gone through multiple iterations and has also made its way to the United States and other countries (DeMaio, 2009). Bikeshare systems are gaining traction as both an access mode to transit, and as substitutions for both shorter personal vehicle and transit trips. Not only do these bike trips reduce emissions relative to transit and car trips, they can also provide health benefits and quicker travel times than transit alone (Gerrad, 2012) (Jappinen, 2013).

In order to maximize the demand on a bikeshare systems, it is important to have a dense network that allows for easy connectivity, and close proximity to demographic and geographic features. It is also important to maximize the total amount of people being served by the system, which requires a larger coverage area. In the past, bikeshare systems started on a much smaller trial stage in a city center, before expanding relative to their success. Stations were supplied in popular destinations to ensure bike availability and reduce loss due to damage and theft. More recently, bikeshare has been implemented in free float systems. These systems reduce costs due to the absence of station infrastructure, and allow services to immediately fill a larger coverage area because the bikes are not limited to the positioning of stations. In Seattle, these system differences seem to have been just the cure for a city whose station based system failed in March of 2017. So much so that within the first two months of the city's three services, they were able to serve over one third of all previously taken station-based lifetime trips (SDOT, 2017). Unfortunately, these new free float systems are private, and the data for these systems are under lock and key. This makes it difficult to understand the true effectiveness of the service, and where they have had the most success.

Although the potential benefits of bikeshare are impressive, they can only realized when people are using the system. When creating a system, it is still not completely understood how to designate stations in a way that best maximizes demand. Studies suggest that placing stations relative to demographic factors including population, income, and race can have positive impacts on demand (Rixley, 2013) (Wang, 2015). For example, they found that non-white population size had a negative effect on ridership. In addition, geographic factors such as being within proximity to other bikeshare stations, bike lanes, and other features of the built environment within our cities, have positive impacts on demand (Rixley, 2013) (Wang, 2015)(Buck, 2012). Moreover, being within close proximity of metro stations in the New York area has positive effects on bikeshare demand (Noland, 2016). Shaheen in turn suggests that bikesharing has a positive effect on transit use (Shaheen, 2012). This supports the findings of chapter 3 of this thesis, which shows that bikeshare positively affects transit ridership during destination trips, rather than poaching rides. Clearly, transit has a positive impact on bikeshare, however, many of these cities have different transit options and the effect of all of them at once has not been considered. Many of these locational and demographic factors are used to help select locations for new systems, however, this does not always lead to expected results. In the DC area, one study attempted to predict ridership using these factors and found that often areas which were expected to have greater ridership did not (Daddio, 2012). Understandably, there is still uncertainty about what causes demand for bikeshare. To further understand these uncertainties, this chapter will explore how different types of transit and free float services affect bikeshare dwell time at the census block level in the portland area. In this study, dwell time is used as a estimate of demand, which measures the amount of time a bike sits without being used. Thus bikes with longer dwell times represent areas with lower demand, and those with shorter dwell times have greater demand.

4.2.0 Data and Analysis

The subject population for this study are the individual block groups where Portland's Biketown bikeshare system is used. Bikeshare trips from July 19th 2016 to August 6th 2017 were all included in the study. This time frame incorporates a little over 350,000 trips. Biketown is a hybrid system; this means it has stations, but also incorporates a GPS component in each bike. This allows operators and users to locate bikes, and thus enables riders to park anywhere in the service area, whether or not it is at a bike share station. The service launched in July 2016 with 1000 bikes and over 100 stations, it has since increased to 139 stations (Biketown, 2018).

To begin cleaning the data, bike dwell times were calculated across the entire study period for each bike using the difference between the current trip start time and previous trip end time. This was only done for trips where the start and previous end locations were the same. For those that were a partial free float trip, we assume that the bike has not been moved unless the location changes. For the very first trip of each bike, we are unable to predict a dwell time because we don't know when the bikes were dropped off. For this reason, these trips have been omitted from the data. When a bike has a different previous end location than the current start location, we assume that these bikes have been rebalanced. For these rebalanced bikes we are unable to predict how long bikes have been sitting in certain areas, and thus cannot determine the proper dwell time. These trips have been omitted from the study.

Next, we used GIS software to create a 100-meter buffer around all of Portland's transit stops to determine which bike trips start within these transit zones in order to help estimate the influence of these stations presence on bikeshare trips. Each transit stop was then attached to the different trips within its buffer. For example if a bike trip fell within two bus stop buffers and one link buffer, it would have a bus value of two and a link value of one. Next, we associated all bike trips to a block group and then aggregated by block to calculate the averages of transit, free float, and our dependent variable dwell time. Finally, an additional cleaning step was performed by removing blocks containing 4 or less trips, since we felt that these blocks lacked the sample size to give reliable statistics.

In order to understand the effect of these different block level averages, we built the OLS model seen below. Within this model, the blocks were weighted by the square root of the number of trips in each block.

$$
\begin{aligned}
&Avg.\_Bike\_Dwell\_Time_i = \beta_0 + \beta_1 * [Average\_\#\_Bus\_Stations]_i + \beta_2 * [Average\_\#\_Link\_Station]_i + \\
&\beta_3 * [Average\_\#\_Street\_Car\_Stations]_i + \beta_4 * [Average\_\#\_Tram\_Stations]_i + \\
&\beta_5 * [Percent\_of\_Trips\_Free\_Float]_i + \beta_6 * [Population]_i + \beta_7 * [Average\_Income]_i \\
&+ \beta_8 * [African\_American\_Population]_i + \varepsilon
\end{aligned}
$$

To further explore the data, we built a spatial error model. Within this model, the tracts were weighted by the square root of the number of trips in each block. A spatial error model is a modification to the Ordinary Least Squares model that attempts to account for similarities in error terms due to the proximity of measurements. If the groupings chosen (in this case census blocks) do not directly represent the dependent variables used in the model, spatial autocorrelation can occur in nearby groupings that are more likely to have similar properties. A spatial error model reconciles this oversight by estimating the covariance of blocks and separating it from the error term of the model(Ullah, 1998). The model is important because it allows us to account for spatial autocorrelation that may appear in the data. This autocorrelation is the result of using census blocks as a means to group turnover rates. Since the census blocks do not precisely group certain turnover rates from others, and are instead a proxy for measuring that phenomenon, there is a likelihood that the tracts will autocorrelate with one another (Ullah, 1998). In this case, we believe there is a spatial autocorrelation in the turnover times for bikeshare systems due to census blocks with certain levels of activity tending to be closer to other blocks with the same level of activity. A spatial error model then would not assume independency of the error terms, but instead account for their proximity by using a spatial weight matrix and corresponding coefficients for each block. The spatial error model assumes that the error term for each variable in our OLS incorporates a spatially weighted effect as described below (Ullah, 1998;Hughes & Mackenzie, 2016):

$\varepsilon = \lambda W \varepsilon + \zeta$
ε = *error term*
λ= *spatial coefficient*
W = *spatial weight*
ζ= *remaining uncorrelated error*

Finally, after estimating our various models, a Moran's I test was performed as an attempt to validate the suspicion of spatial autocorrelation in our data.

4.3.0 Results

4.3.1 Descriptive Statistics

Descriptive statistics for the bikeshare trip census block level averages of transit stops, as well as free float and dwell time measurements can be seen in the table below. Note that for link, streetcar, and tram the median is 0 and the mean is very close to 0, this is because many of the blocks do not have these types of transit stops.

Table 21: Descriptive statistics for each model variable, including the number of blocks (max 193 blocks)

Variable	Mean	Median	Min	Max	St. Dev.	IQR	# Blocks
Bus	1.06	0.85	0.00	7.42	1.09	1.62	173
Link	0.07	0.00	0.00	2.30	0.30	0.00	25
Streetcar	0.03	0.00	0.00	1.19	0.14	0.00	20
Tram	0.01	0.00	0.00	1.64	0.12	0.00	1
# of Trips	1397.2	67.0	5.0	32678.0	3766.5	962.0	193
Dwell Time (min)	767.2	667.9	6.7	3572.1	690.8	943.3	193
Freestart	0.60	0.94	0.02	1.00	0.42	0.87	193

4.3.2 Maps

Maps that show the block variation of this data can be seen below in figures 7-13. Figure 1 shows the average block dwell time. Initially, figure 1 is surprising given that the dwell time is shortest on the exterior of the city and further away from the downtown area. When you look at both figures 8 and 13 we see that this is a combination of two things. Most of these block groups have less than 105 trips and are all free float trips. In addition, these are areas where bikes are more likely to be rebalanced and thus these data points do not appear in our calculations. Bus stop averages in figure 9 are pretty consistent across the city except in a few tracts in the downtown area. Link stop averages in figure 10 are only available in 25 blocks. The greatest average is across the river from the downtown area, where bikeshare trips totals are lower than some of those observed in the downtown area. Streetcar averages in figure 11 show the highest use on the downtown side of the river. Tram average is only available in one block as seen in figure 12. Figure 13 shows free float percentage increases as you get further away from the city, which is due to less stations or no stations at all in these areas.

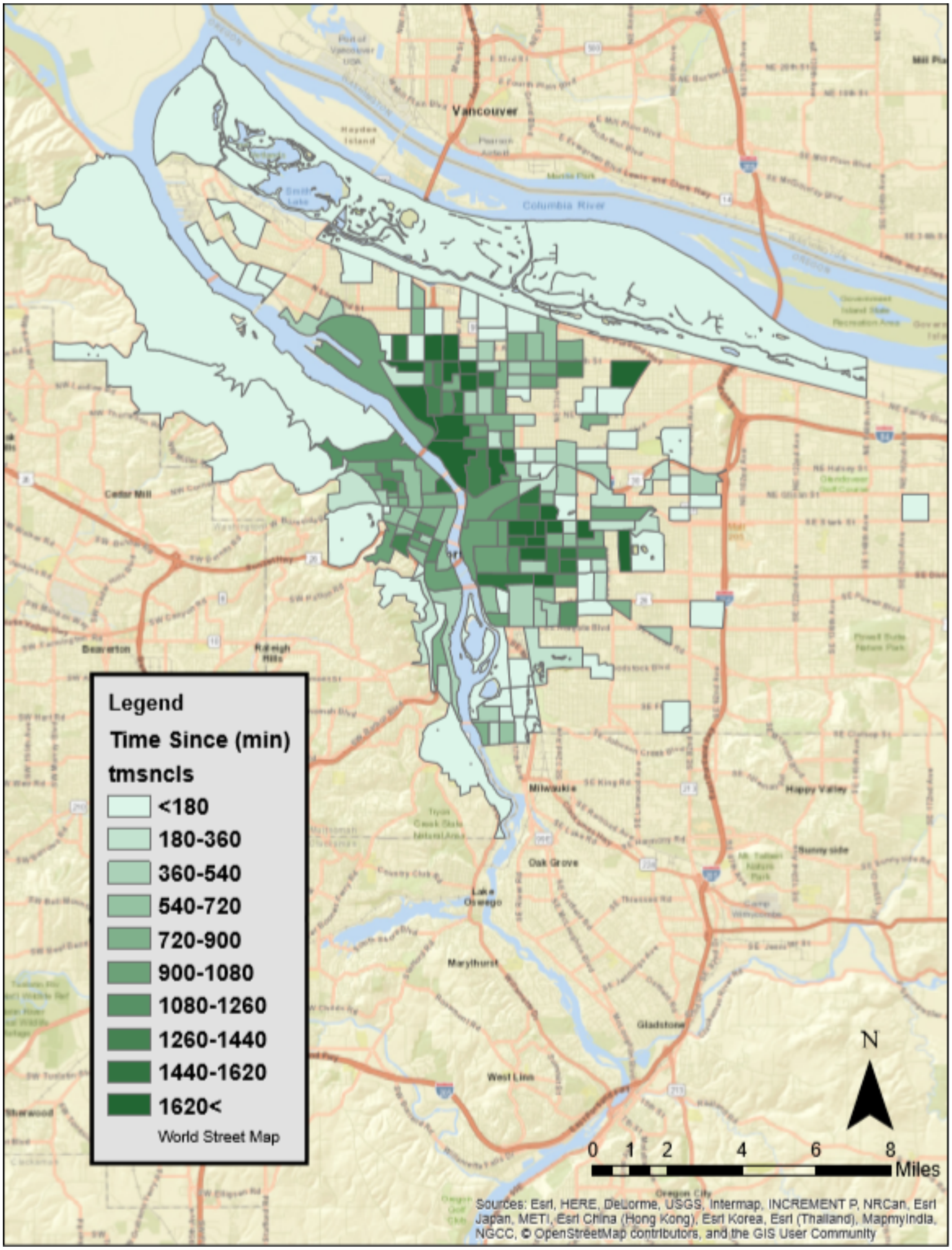
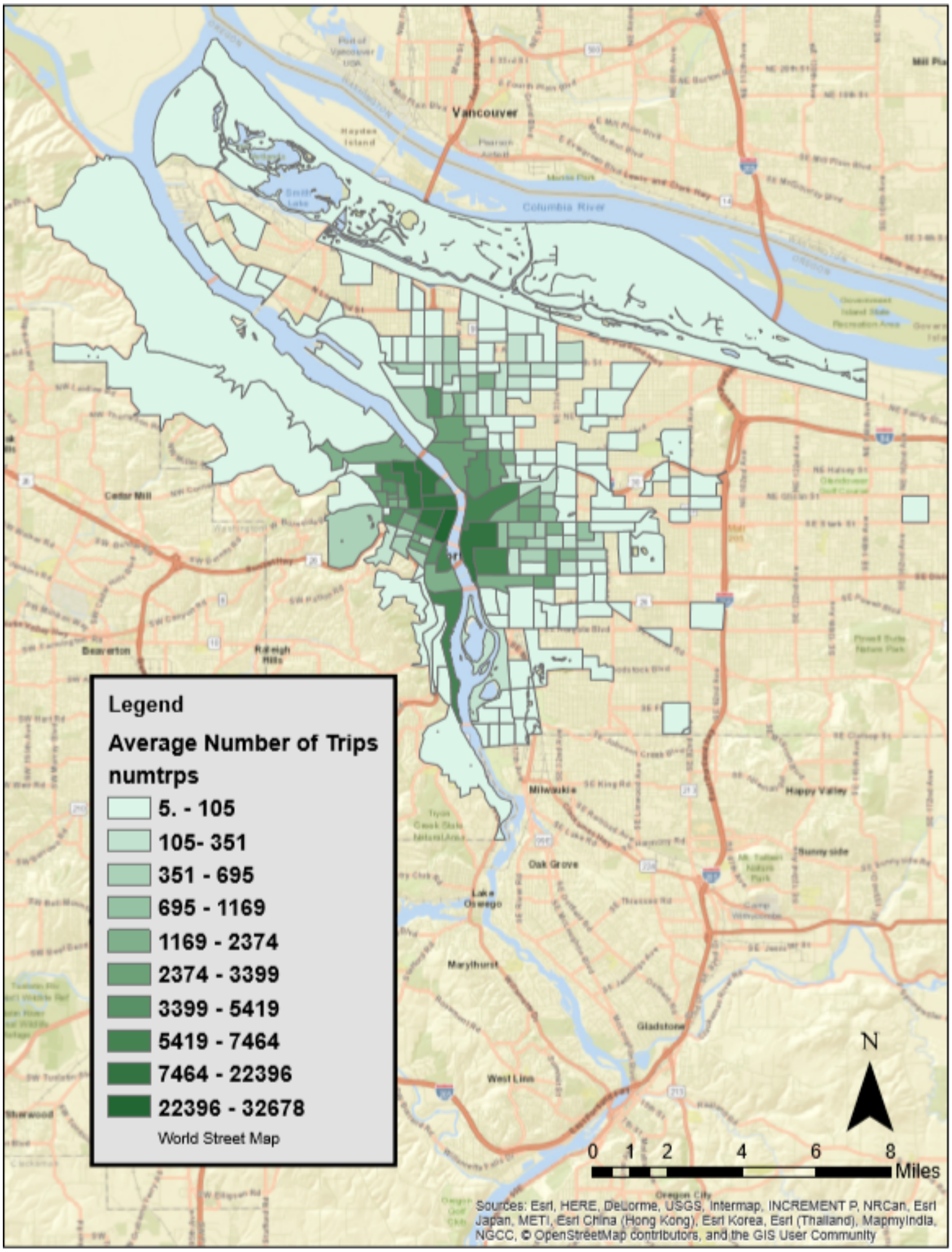
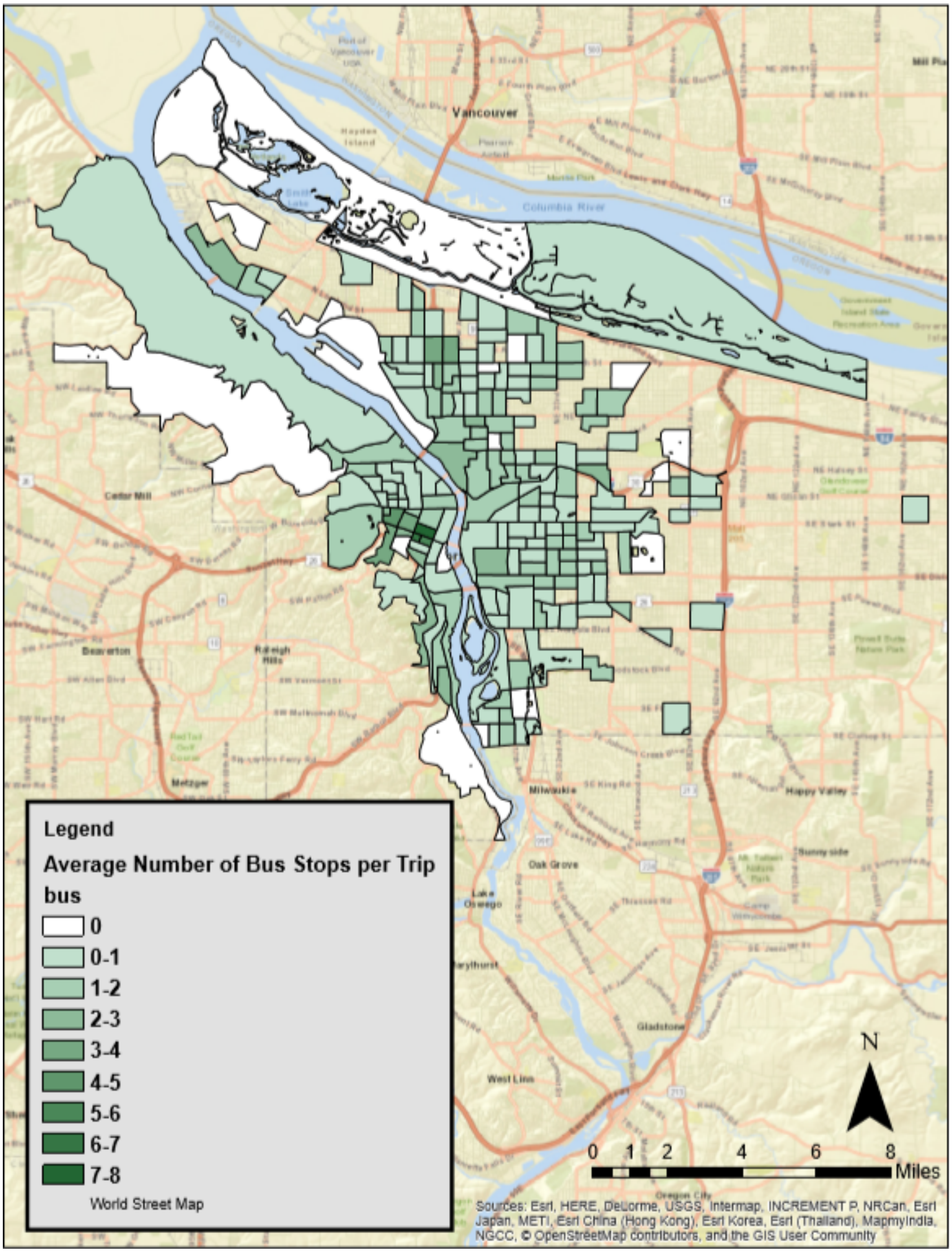


Figure 7: Average bike dwell time by block.



Sources: Esri, HERE, DeLorme, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), MapmyIndia, NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 8: Average number of trips by block.



Sources: Esri, HERE, DeLorme, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), MapmyIndia, NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 9: Average number of bus stops per trip across blocks. White shading indicates no bus stops associated with any bike share trips.

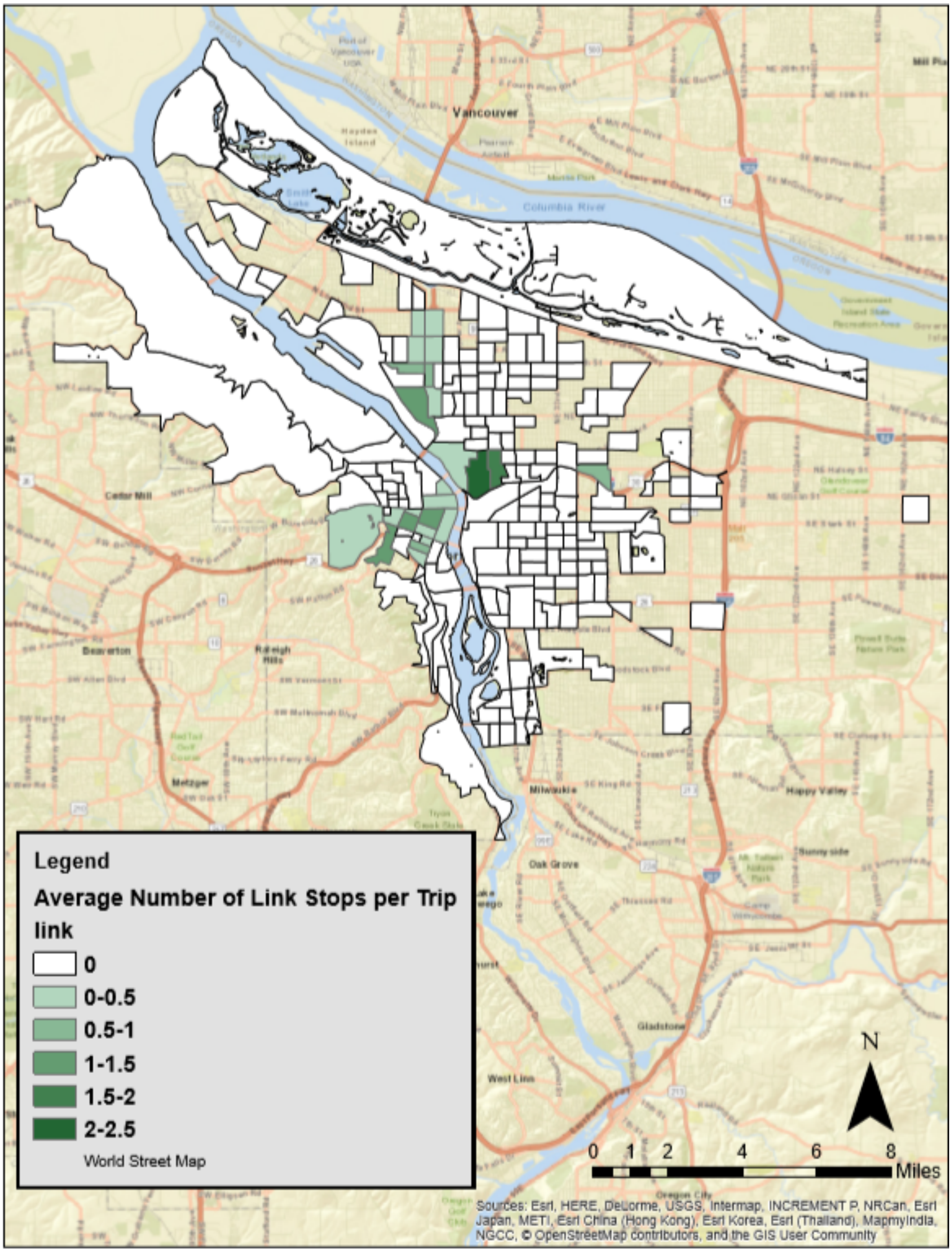


Figure 10: Average number of link stops per trip by block. White shading indicates no bus stops associated with any bike share trips.

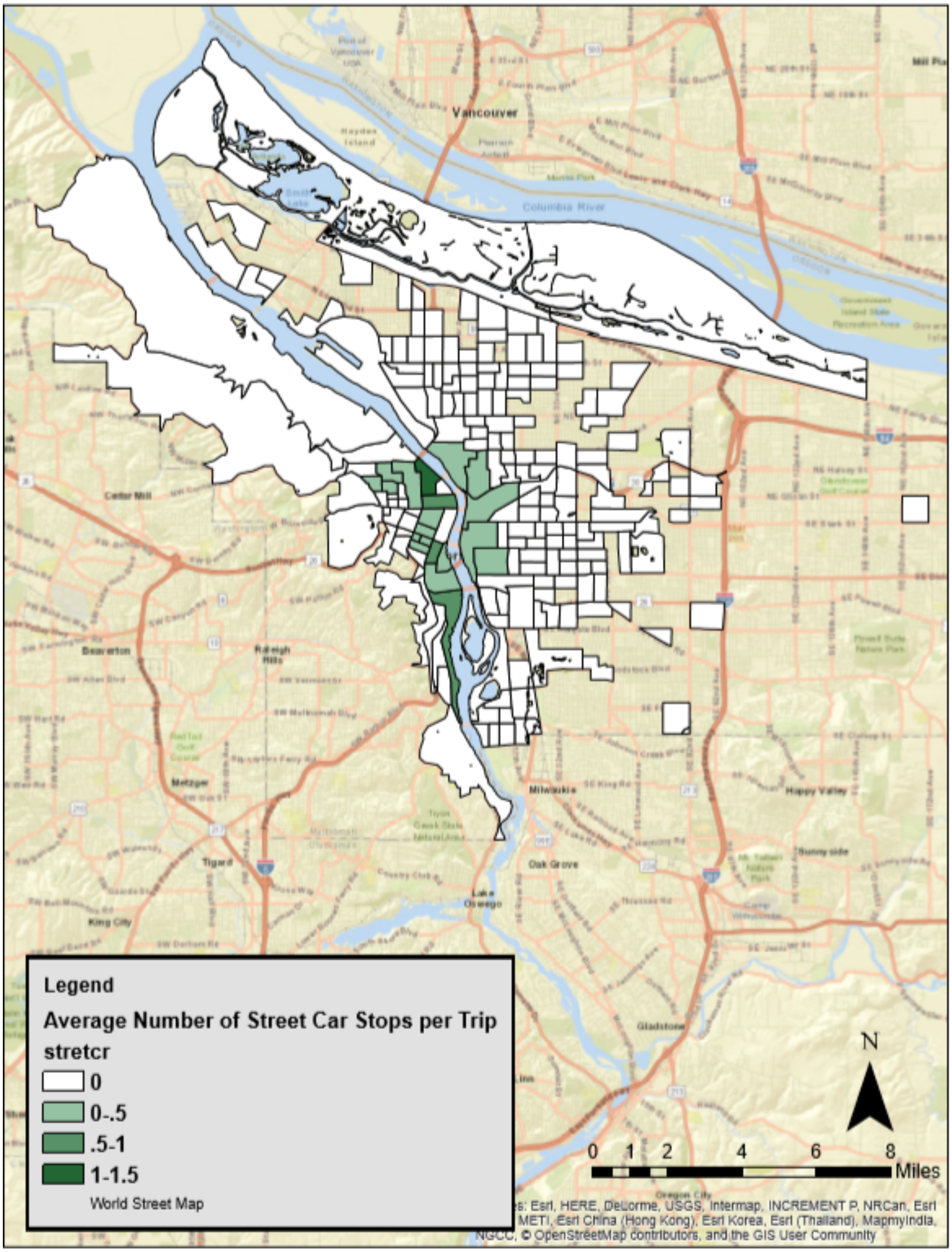
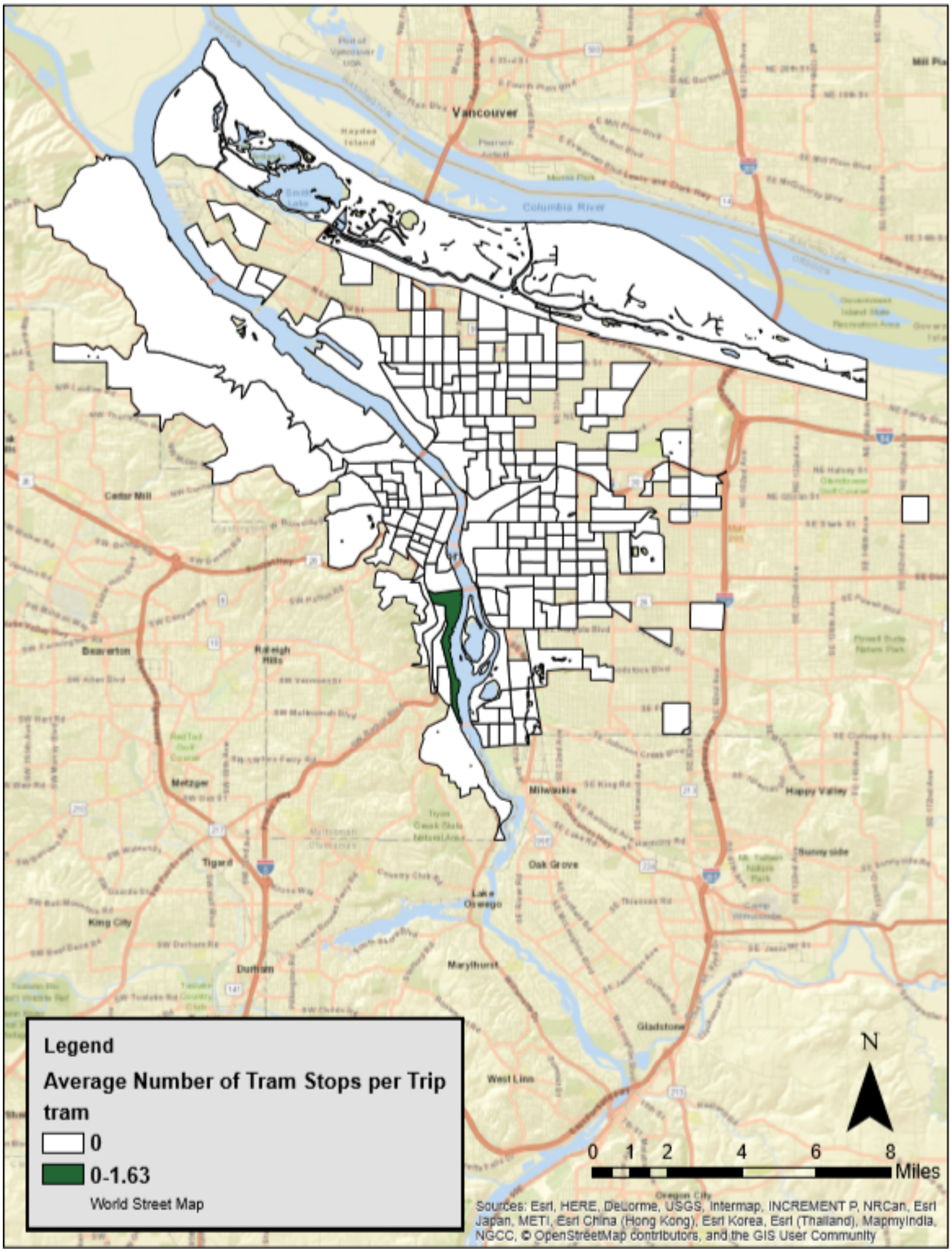


Figure 11: Average number of streetcar stops per trip by block. White shading indicates no bus stops associated with any bike share trips.



Sources: Esri, HERE, DeLorme, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), MapmyIndia, NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 12: Average number of tram tops per trip by block. White shading indicates no bus stops associated with any bike share trips.

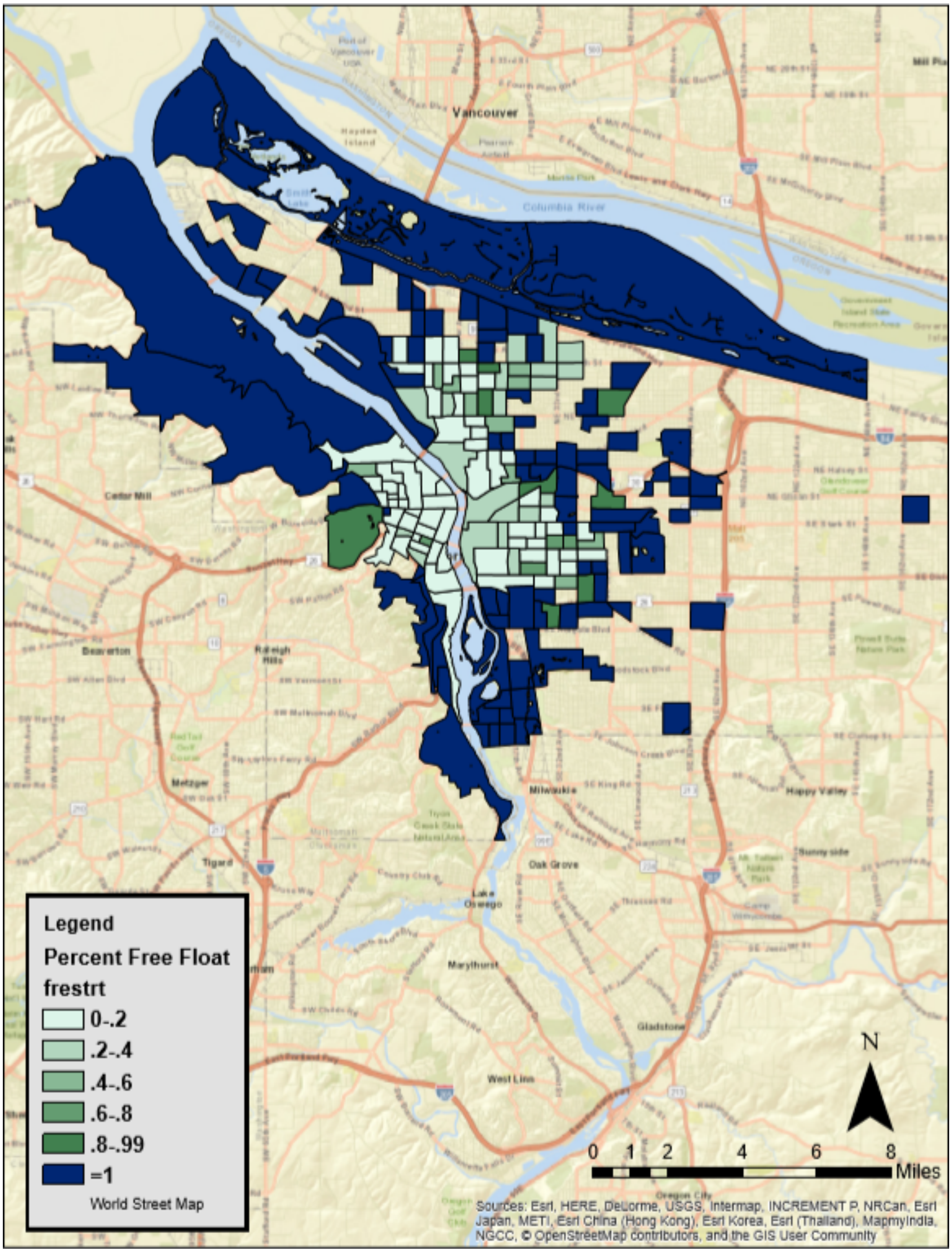


Figure 13: Average number of link stops per trip by block. Blue shading indicates a block where all trips in that block are free float trips.

4.3.3 OLS and Spatial Error Models

The results of both the OLS and spatial error models can be found in Table 22 below. The values in the table are the beta coefficients, and those in bold are the ones found to be significant at the 0.05 level. Models 1 and 2 are OLS models, and models 3 through 7 are Spatial Error Models.

Table 22: Model results for both OLS's and Spatial Error Models.

Predictor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	**1362.9**	**1346.2**	**1370.4**	**1320.6**	**1316.3**	**1335.9**	**1336.4**
Bus	2.1	12.7	1.2	4.3	1.9	15.0	15.4
Link	29.6	32.0	26.0	25.8	33.3	22.3	21.9
Street Car	**-492.2**	-386.4	**-577.1**	**-563.7**	**-637.2**	**-415.8**	-410.2
Tram	-198.4	-258.3	X	-181.7	X	-247.1	-251.9
Free Float Start	**-1069.9**	**-1051.1**	**-1067.4**	**-1073.8**	**-1073.4**	**-1107.6**	**-1108.2**
Population	X	0.16	X	0.043	0.051	0.175	0.18
Income	X	-0.27	X	X	X	-0.287	-0.30

African American Population	X	-0.002	X	X	X	X	-0.03
Lambda (SEM Component)	X	X	-0.088	-0.088	-0.097	-0.097	-0.098

The results show that the intercept, street car, and free float are the only variables that are significant. The directionality of each of these is as we would expect. For buses and link however, we find positive coefficients. Each of the spatial error models do not return a significant Lambda coefficient.

4.3.4 Moran's I Test

The results of the Moran's I test for spatial autocorrelation of our dependent variable, dwell time, are shown in Table 23 below.

Table 23: Results for Moran's I test.

Moran's I Test	
Moran I Statistic Standard Deviate	0.54
P-Value	0.295

This test does not confirm that there is spatial autocorrelation in our data.

4.4.0 Discussion

The results of the models suggest that there is likely more data that must be incorporated within the model in order to more accurately understand the effects of transit in the Portland area on bikeshare. All models do not confirm a negative or positive effect of link, bus, or tram stops on bikeshare dwell time. Previous research has suggested that these effects are most likely negative as is the case for most of our streetcar coefficients. In this case, it suggests that the presence of streetcar stops likely decreases the average dwell time in a block. For both the link and bus, it is possible that the various spatial difference for what part of the city the stops are in is causing bias in the data. This is because both modes have stops in the downtown area and in more residential locations. Perhaps in either of these areas there are different effects of transit on bikeshare that we are not capturing. In the case of the tram, it is difficult to make any strong conclusions on its effect, because it is only available in one tract. Both the OLS and spatial error models show that being a free float bike has a negative effect on dwell time, meaning if a bike is left undocked then it is going to be picked up faster than a bike that is not. These results cannot be applied to stationless systems because this system is a hybrid system. In addition, Biketown offers an incentive to those who pick up bikes that are free floated and bring them to a station. With this in mind, we are unable to tell if the dwell time is shorter because it is free float or because there is an incentive to ride these bikes.

Each of our spatial error models do not confirm that there is spatial autocorrelation of our average dwell time measurement. This is not to say that it is not possible that a spatial autocorrelation does not still exist, it simply means that we have not confirmed it. In addition, Moran's I test does not confirm that there is spatial autocorrelation. In further work, it is important to not dismiss the possibility of this effect once more data is incorporated in the model. Within this exploratory analysis, we are able to see that freefloat and streetcars likely decrease dwell time, while we are unable to make any conclusions on the effect of other modes and spatial autocorrelation. Using this information, we can better understand where to focus future research efforts.

One variable assumption that was not tested for sensitivity in this analysis was the buffer distance of 100 meters. This variable should be chosen such that it best represents the influence area of any given transit station, and further testing should be performed as to what that ideal area is. It was also assumed that bus, link, and streetcar stations all exert the same distance of influence. By using a larger area than necessary, we may overestimate the number of transit stops that have an effect on bike dwell times. By using a smaller area we run the risk of underestimating this effect. One possible solution to this is to measure the distance of each bike trip to the transit stops. However, this is a much more computationally intensive.

This work has brought to light some potential areas for future dwell-time analysis, one such being the transition from station based bikeshare to free float systems. Without stations to incentivize users to leave the bikes in popular locations, we may see higher dwell times as bikes are snapped up in high demand locations, and ridden to low demand destinations. One issue hindering research in this subject is the relatively unavailable trip data for these free float systems. Work needs to be done in opening companies up if they continue to gain popularity, so that we can better understand how bikeshare is used and push it to meet the user's needs. This data may come at a caveat, since consumer-grade gps is known to be inaccurate, particularly in obstruction ridden areas such as downtown cities. Nevertheless, as shown in this study even approximate destinations, when aggregated, can be revealing of system-wide usage behavior.

Furthermore, additional research should be performed on other possible dwell time correlations in station based bikeshare. This study does not consider the effects of weather, time of day, or season on the system dwell times. It is likely that trips ending later at night have a higher dwell time, since there is much lower demand for the system at that time. Weather, particularly rainfall, could have a strong impact on dwell times for bikes since users will once again be in short supply. A study considering both spatial and time based autocorrelation may find that certain stations have shorter dwell times during different parts of the day. For example, stations near residential areas might have shorter dwell times in the morning; as any bikes that are dropped off get immediately taken by commuters. Tourism may have a strong effect on usage across the whole system, with stations near recreational attractions seeing shorter dwell times during the summer months.

When modeling these additional effects, future research should consider using different methods that are more appropriate for this data. A locally weighted regression in this situation might allow the model to be flexible enough to capture more of the variation between the blocks, while also allowing us to model the temporal differences. Conversely, by grouping blocks into larger sub groups, we could use a geographically weighted regression which would allow us to understand how these effects vary across different regions of the city. This likely would be most important for understanding the effect of buses, because they are available across the whole service area. Lastly, it is important to incorporate up to date trip data in further analysis. This is important because it is likely there could be a lagged effect of users realizing that they can use bikes as a last mile solution to their transit trips. With this lag effect, we would expect to see increased use in these transit areas, and thus our relationships could be stronger. In this case, we only have the first year of data, thus users are still inexperienced as to how they can most effectively use the system.

Overall, the potential for benefit in either system is strong enough to validate further research. If we can better understand the exact temporal, and spatial transportation needs that bikeshare addresses, we can better develop our systems to encourage sustainable travel behaviors.

5.0.0 Conclusions

This thesis looks at the effects of new mobility services on emissions, via travel behavior and vehicle design improvements. It then explores how these effects can be increased with the incorporation of a bikeshare service, within the mobility service. It next explores how bikeshare services impact transit and how transit impacts bikeshare. Understanding each of these aspects of bikeshare allows us to gain insights on how bikeshare can best be implemented to effect emissions.

In chapter 2 of this thesis we explore the effect of a mobility service, which allows for fleet and vehicle right sizing. We then explored the effect this would have on CAFE compliance, as well as the effect this will have on gas consumption. These results showed that right sizing would significantly affect CAFE compliance because most requirements would be met simply with right sizing and minor technology advances, even with the use of only ICE's. We then found that right sizing had the ability to reduce fuel consumption by more than 40% depending on the scenario. Finally, we looked at how Bikeshare would be able to further reduce gas consumption. In these cases, we find that bikeshare allows for an additional 123 million gallons of gas saved a year across the US when it represents 10% of all single passenger trips less than 2 miles. This savings was further increased when we assumed a larger mode split for these trips. This increase in savings as mode share increases outlines the importance of increasing the use of bikeshare and incorporating it as a part of this shared service. In this case we see that as bikeshare adoption on short trips increases we greater reductions in emissions. Learning how bikeshare will affect other modes and how we can increase this mode share leads us into chapters 3 and 4 where we attempt to understand how bikeshare will interact with transit, so that we can understand how to increase mode share for transit and bikeshare, thus increasing our reductions in gas consumption.

In chapter 3 we explore how transit is effected by the use of bikeshare in proximity to L train stops in the Chicago area. These results show that as bikeshare trips increase in the region of L train trips, we will see an increase in the use of the L. We see the same result as we see an increase in the number of bikeshare stations that reside within buffer regions of L trips. Lastly, we find that there is a lagged effect of these findings. This means that as time increases, each of these relationships is going to grow. This is most likely because it takes people a little while to realize that they can use the systems together.

In chapter 4 we continue our exploration of the interaction of transit and bikeshare by analyzing the effect that different modes of transit have on bikeshare dwell time. In this case we found mostly inconclusive results, which prevents us from making strong conclusions on this research. The one consistent result from this study was that blocks with a larger free float bike percentage had a significantly lower dwell time than those that had a smaller percentage. This result cannot be generalized to all free float bikes though because these bikes have a monetary incentive associated to them, so it is difficult to tell if the reward or fact that this bike was free float is causing reduced turnover times.

In summary, we have explored how a carsharing mobility services might be able to influence policies and emissions. Next, we looked at how bikeshare and increase these emissions reduction. Through these insights we then looked at the effect bikeshare would have on transit ridership, in order to understand if there would be a negative effect. Finally, we attempted to understand how transit and free float effects bikeshare dwell time, so that we can learn how to increase bikeshare ridership and increase mobility service emission reducations. These results suggest that shared services will help reduce gas consumption and that it will be important to understand how to increase ridership of these services in order to maximize reductions in gas consumption.

6.0.0 References

Af Wåhlberg, A. E. "Short-term effects of training in economical driving: Passenger comfort and driver acceleration behavior." International Journal of Industrial Ergonomics 36.2 (2006): 151-163.

Amey, Andrew, John Attanucci, and Rabi Mishalani. "Real-time ridesourcing: opportunities and challenges in using mobile phone technology to improve ridesource services." Transportation Research Record: Journal of the Transportation Research Board 2217 (2011): 103-110.

Bansal, Prateek, and Kara M. Kockelman. "Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies." Transportation Research Part A: Policy and Practice 95 (2017): 49-63.

Barter, Paul. "'Cars Are Parked 95% of the Time'. Let's Check!" Reinventing Parking, Blogger, 29 June 2016, www.reinventingparking.org/2013/02/cars-are-parked-95-of-time-lets-check.html.

Begg, David. "A 2050 vision for London: what are the implications of driverless transport?." (2014).

BIKETOWN, Motivate International, Inc. "Portland's Bike Share System." 2018. *Biketown*.www.biketownpdx.com/.

Brown, Lester Russell. World on the Edge: How to Prevent Environmental and Economic Collapse. Earthscan, 2011.

Buck, D., & Buehler, R. "Bike lanes and other determinants of capital bikeshare trips." In *91st Transportation research board annual meeting*. 2012, January.

Buck, Darren, et al. Are bikeshare users different from regular cyclists? A first look at short-term users, annual members, and area cyclists in the Washington, DC, region. Transportation Research Record: Journal of the Transportation Research Board, No. 2387, 2013, No. 112-119.

Burns, Lawrence D., and Jordan, William C. "TRANSFORMING PERSONAL MOBILITY." (2012).

Campbell, Kayleigh B., and Candace Brakewood. Sharing riders: How bikesharing impacts bus ridership in New York City. Transportation Research Part A: Policy and Practice, No. 100, 2017, pp.264-282.

Caranza, V., et al. "Life Cycle Analysis: Uber vs Car Ownership." Environment 159 (2016): 1-19.

"Corporate Average Fuel Economy (CAFE) Standards." US Department of Transportation, United States Department of Transportation, 11 Aug. 2014, www.transportation.gov/mission/sustainability/corporate-average-fuel-economy-cafe-standards.

Cervero, Robert, and Yuhsin Tsai. "City CarShare in San Francisco, California: second-year travel demand and car ownership impacts." Transportation Research Record: Journal of the Transportation Research Board 1887 (2004): 117-127.

Chen, T. Donna, and Kara M. Kockelman. "Carsharing's life-cycle impacts on energy use and greenhouse gas emissions." Transportation Research Part D: Transport and Environment 47 (2016): 276-284.

Chen, T. Donna, and Kara M. Kockelman. "Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes." Transportation Research Record: Journal of the Transportation Research Board 2572 (2016): 37-46.

Chen, T. Donna, Kara M. Kockelman, and Josiah P. Hanna. "Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions." Transportation Research Part A: Policy and Practice 94 (2016): 243-254.

Cohen, Boyd, and Jan Kietzmann. "Ride on! Mobility business models for the sharing economy." Organization & Environment 27.3 (2014): 279-296.

Cohen, Peter, et al. Using big data to estimate consumer surplus: The case of uber. No. w22627. National Bureau of Economic Research, 2016.

Cramer, Judd, and Alan B. Krueger. "Disruptive change in the taxi business: The case of Uber." The American Economic Review 106.5 (2016): 177-182.

Daddio, D. W., & Mcdonald, N. "Maximizing bicycle sharing: an empirical analysis of capital bikeshare usage." *University of North Carolina at Chapel Hill*. 2012.

Daniels, Rhonda, and Corinne Mulley. Explaining walking distance to public transport: The dominance of public transport supply. Journal of Transport and Land Use, No.6.2, 2013, pp.5-20.

DeMaio, Paul. "Bike-sharing: History, impacts, models of provision, and future." *Journal of public transportation* 12.4 (2009): 3.

Divvy bikes. Divvy Data Reveals Our Most Popular Destinations of 2015. Divvy: Chicago's Newest Transit System. Divvy Bikes, 11 Feb. 2016. Accessed Web. 10 Mar. 2017.

Etherington, Darrell. "Uber Crosses the 5 Billion Trip Milestone amid Ongoing Issues."TechCrunch, TechCrunch, 29 June 2017, techcrunch.com/2017/06/29/uber-crosses-the-5-billion-trip-milestone-amid-ongoing-issues/.

Fagnant, Daniel J., and Kara M. Kockelman. "Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles." Transportation Research Board 94th Annual Meeting. No. 15-1962. 2015.

Fagnant, Daniel J., and Kara M. Kockelman. "The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios." Transportation Research Part C: Emerging Technologies 40 (2014): 1-13.

Fagnant, Daniel J., Kara M. Kockelman, and Prateek Bansal. "Operations of shared autonomous vehicle fleet for austin, texas, market." Transportation Research Record: Journal of the Transportation Research Board 2536 (2015): 98-106.

Fishman, Elliot, et al. Factors influencing bike share membership: an analysis of Melbourne and Brisbane. Transportation research part A: policy and practice, No. 71, 2015, pp.17-30.

Froehlich, Jon, Joachim Neumann, and Nuria Oliver. "Measuring the pulse of the city through shared bicycle programs." Proc. of UrbanSense08 (2008): 16-20.

Garrard, J., Rissel, C., & Bauman, A. “Health benefits of cycling.” *City cycling*, 2012, *31*.

Griffin, G.P. and I.N. Sener. Planning for bike share connectivity to rail transit. Journal of Public Transportation, Vol. 19, No. 2, 2016, pp. 1-22.

Hughes, R., & MacKenzie, D. “Transportation network company wait times in Greater Seattle, and relationship to socioeconomic indicators.” Journal of Transport Geography, 2016, 56, 36-44.

Hampshire, Robert, and Craig Gaites. "Peer-to-peer carsharing: Market analysis and potential growth." Transportation Research Record: Journal of the Transportation Research Board 2217 (2011): 119-126.

Hampshire, Robert C., and Lavanya Marla. An analysis of bike sharing usage: Explaining trip generation and attraction from observed demand. 91st Annual meeting of the transportation research board, Washington, DC. 2012.

Henao, Alejandro. Impacts of Ridesourcing-Lyft and Uber-on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior. Diss. University of Colorado at Denver, 2017.

Hoberock, Lawrence L. "A survey of longitudinal acceleration comfort studies in ground transportation vehicles." ASME, Transactions, Series G-Journal of Dynamic Systems, Measurement, and Control 99 (1977): 76-84.

International, Inc. Motivate. About Divvy: Company & History."Divvy Bikes. Divvy Bikes, n.d. Accessed Web. 10 Mar. 2017.

International Transportation Forum. “Urban Mobility System Upgrade.” Https://Www.itf-Oecd.org/Sites/Default/Files/Docs/15cpb_self-Drivingcars.pdf, International Transportation Forum, 2015, www.itf-oecd.org/sites/default/files/docs/15cpb_self-drivingcars.pdf.

Jäppinen, S., Toivonen, T., & Salonen, M. “Modelling the potential effect of shared bicycles on public transport travel times in Greater Helsinki: An open data approach." 2013. *Applied Geography*, *43*, 13-24.

Krizek, Kevin, and Eric Stonebraker. Bicycling and transit: A marriage unrealized. Transportation Research Record: Journal of the Transportation Research Board, No. 2144, 2010, pp. 161-167.

Krygsman, S., Arentze, T., & Timmermans, H. “Capturing tour mode and activity choice interdependencies: A co-evolutionary logit modelling approach.” *Transportation Research Part A: Policy and Practice*. 2007. *41*(10), 913-933.

Lindblom, M. “It's worse than you think: Everett leads the nation in traffic congestion, report says.” 2018, February 06. Retrieved from https://www.seattletimes.com/seattle-news/transportation/its-worse-than-you-think-everett-leads-the-nation-in-traffic-congestion-report-says/

Ma, Ting, Chao Liu, and S. Erdogan. Bicycle Sharing and Transit: Does Capital Bikeshare Affect Metrorail Ridership in Washington, DC., University of Maryland, College Park, 2014.

MacKenzie, Don, and John B. Heywood. "Quantifying efficiency technology improvements in US cars from 1975–2009." *Applied Energy* 157 (2015): 918-928.

Martin, Elliot, and Susan Shaheen. "The impact of carsharing on public transit and non-motorized travel: an exploration of North American carsharing survey data." Energies 4.11 (2011): 2094-2114.

Martin, Elliot W., and Susan A. Shaheen. Evaluating public transit modal shift dynamics in response to bikesharing: a tale of two US cities. Journal of Transport Geography, No. 41, 2014, pp.315-324.

Martin, Elliot, and Susan Shaheen. "Impacts of car2go on Vehicle Ownership, Modal Shift, Vehicle Miles Traveled, and Greenhouse Gas Emissions: An Analysis of Five North American Cities." Transportation Sustainability Research Center (TSRC), UC Berkeley. Accessed online, available at: http://innovativemobility. org/wp-content/uploads/2016/07/Impactsofcar2go_FiveCities_2016. pdf (2016).

Martinez, Luis, and P. Crist. "Urban Mobility System Upgrade–How shared self-driving cars could change city traffic." International Transport Forum, Paris. 2015.

Namazu, Michiko, and Hadi Dowlatabadi. "Characterizing the GHG emission impacts of carsharing: a case of Vancouver." Environmental Research Letters 10.12 (2015): 124017.

Namazu, Michiko, and Hadi Dowlatabadi. "Understanding when carsharing displaces vehicle ownership." Transportation Research Board 95th Annual Meeting. No. 16-2685. 2016.

National Research Council. Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles. National Academies Press, 2015.

NHTS 2009 Santos, Adella, et al. Summary of travel trends: 2009 national household travel survey. No. FHWA-PL-ll-022. 2011.

Noland, R. B., Smart, M. J., & Guo, Z. " Bikeshare trip generation in New York city." *Transportation Research Part A: Policy and Practice*. 2016. *94*, 164-181.

Pavone, Marco. "Autonomous mobility-on-demand systems for future urban mobility." Autonomous Driving. Springer Berlin Heidelberg, 2016. 387-404.

Pearre, Nathaniel S., et al. "Electric vehicles: How much range is required for a day's driving?." Transportation Research Part C: Emerging Technologies 19.6 (2011): 1171-1184.

Rayle, Lisa, et al. "Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco." Transport Policy 45 (2016): 168-178.

Rietveld, P. "The accessibility of railway stations: the role of the bicycle in The Netherlands." *Transportation Research Part D: Transport and Environment*. 2000. *5*(1), 71-75.

Rixey, R. "Station-level forecasting of bikesharing ridership: Station Network Effects in Three US Systems." *Transportation Research Record: Journal of the Transportation Research Board*. 2013. (2387), 46-55.

SAE, 2014 Smith, Bryant Walker. "SAE levels of driving automation." Center for Internet and Society. Stanford Law School. http://cyberlaw. stanford. edu/blog/2013/12/sae-levels-drivingautomation (2013).

SDOT. "SDOT Blog Department of Transportation." SDOT Blog, 19 Sept. 2017, sdotblog.seattle.gov/2017/09/19/rolling-with-the-homies-seattle-bike-share-pilot-is-a-model-for-other-cities/.

Shaheen, S. A. "Public Bikesharing in North America: Early Operator and User Understanding, MTI Report." 2012. 11-19.

Spieser, Kevin, et al. "Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore." Road vehicle automation. Springer, Cham, 2014. 229-245.

Tamor, Michael A., Chris Gearhart, and Ciro Soto. "A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation." Transportation Research Part C: Emerging Technologies 26 (2013): 125-134.

Trimbath, Tom. “The Region Has Grown Enough To Add Another Seattle.” Curbed Seattle, Curbed Seattle, 25 Mar. 2016, seattle.curbed.com/2016/3/25/11301860/seattle-grows-enough-to-add-another-seattle.

Ullah, A. (Ed.). “*Handbook of applied economic statistics*.” CRC Press. 1998.

Underwood, S. E. "Automated vehicles forecast vehicle symposium opinion survey." automated vehicles symposium. 2014.

United States, Congress, NHTS. “2009 NHTS User Guide.” 2009 NHTS User Guide, NHTS, 2011.

Wadud, Zia, Don MacKenzie, and Paul Leiby. "Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles." Transportation Research Part A: Policy and Practice 86 (2016): 1-18.

Wang, X., Lindsey, G., Schoner, J. E., & Harrison, A. “Modeling bike share station activity: Effects of nearby businesses and jobs on trips to and from stations.” *Journal of Urban Planning and Development*. 2015. *142*(1), 04015001.

Wirtz, Jochen, and Christopher Tang. "Uber: Competing as market leader in the us versus being a distant second in china." SERVICES MARKETING: People Technology Strategy. 2016. 626-632.

Appendix:

Table 24 Fuel economy and fleet classifications for proposed ICE fleets

Model Year	Vehicle grouping	Fuel economy values in mpg	Footprint (sq ft)
2010	(1-2)	49.5 (2010 Smart Car)	NA
	(3-4)	42.6 (2010 Yaris)	NA
	(5)	34.2 (2010 Camry)	NA
	(6-7)	29.2 (2010 Highlander)	NA
2016	(1-2)	55.8 (From 2010 Smart Car)	41>Smart Car
	(3-4)	49.8 (2016 Yaris)	41.2
	(5)	36.9 (2016 Camry)	47.2
	(6-7)	30.0 (2016 Highlander)	49.0

2025	(1-2)	66.6 (From ‘10 Smart Car)	41>Smart Car
	(3-4)	59.5 (From 2016 Yaris)	41.2
	(5)	44.1 (From 2016 Camry)	47.2
	(6-7)	35.9 (From ’16 Highlander)	49.0

Table 25 *Comparison between CAFE and Fleet scores for each given model year using ICE.*

Year	**Fleet**	**Automated (Optimized for min empty seats)**	**Footprint (sq ft)**	**CAFE Standard**	**Difference (Optimized for min empty seats)**
2010	PC	46.09 (46.19)	NA	27.5	**18.59 (18.69)**
	LT	29.20 (29.20)	NA	23.5	**5.70 (5.70)**
2016	PC	55.8 size 1-2	41>	41	**14.8**
		49.8 size 3-4	41.2	40.8	**9.0**
		36.9 size 5	47.2	35.9	**1.0**
	LT	30.0 size 6-7	49.0	27.8	**2.2**
2025	PC	66.6 size 1-2	41>	60	**6.6**
		59.5 size 3-4	41.2	59.7	**-0.2**
		44.1 size 5	47.2	52.9	**-8.8**
	LT	35.9 size 6-7	49.0	36.2	**-0.3**