Complementarity of Dockless Mircomobility and Rail Transit

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Abstract

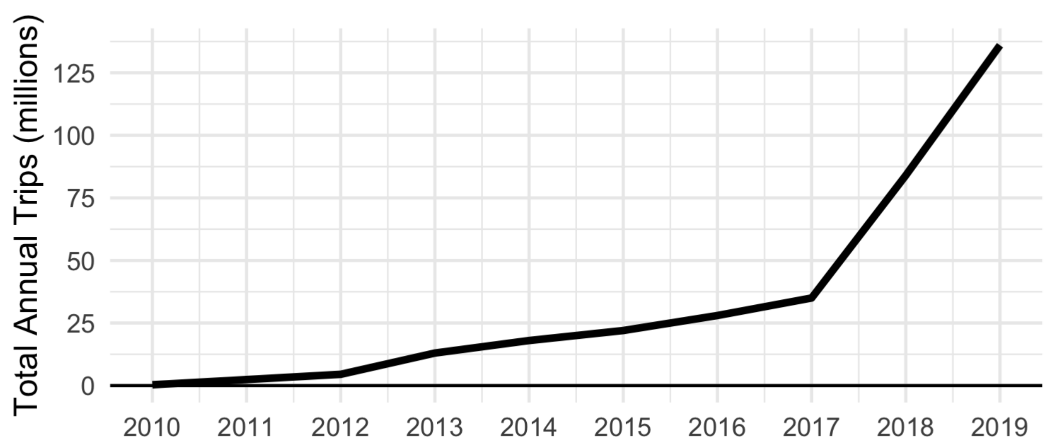
Shared micromobility services have undergone rapid growth in cities throughout the world, including expansions in bike sharing and e-scooter sharing services. Shared micromobility provides a potential complement to public transit by accommodating first and last-mile trips. I analyze detailed data on shared, dockless bikes and e-scooters from Seattle, Washington. I find micromobility vehicles cluster near Seattle's rail transit stations. During the study period, Seattle expanded its rail system into a new section of the city. I use the system expansion as a natural experiment to provide evidence of complementarity between shared micromobility and public transit. Using a difference-in-difference strategy I find that, after a new light rail station opened, the flow of new micromobility vehicles increased significantly within a five minute walking radius of the station. I provide causal evidence that local rail transit increases the use of dockless micromobility vehicles.

Cycling, E-scooters, Transit, Shared Micromobility, Sustainable Transportation

1 Introduction

Shared micromobility services have spread rapidly in US cities (Figure 1), representing a shock to urban transportation systems. Station based bikeshare systems have attained wide adoption across many cities, but the introduction of "dockless," free-floating systems of bicycles and e-scooters represent a new transportation technology. How dockless micromobility devices interact with public transit systems is largely unknown. Some past research has proposed that dockless micromobility vehicles could complement public transit systems by helping to overcome the "last-mile problem," wherein transit users face difficulties traveling from transit nodes to their final destination, or similarly remedy the "first-mile problem." I provide detailed analysis of a large, new data set of shared bicycles and e-scooters from Seattle, Washington. I use the recent expansion of Seattle's light rail transit (LRT) system as a natural experiment and test for local complementarity between micromobility vehicles and public transit. Using a difference-in-difference estimation method, where I compare areas directly adjacent to existing and new LRT stations, I find a large increase in the use of micromobility vehicles around new LRT stations, after station openings.

Figure 1: Annual Trips Completed on Micromobility Devices in the US



Trip totals include station-based bicycle share systems, dockless bicycle share systems and dockless e-scooter share systems. Source: National Association of City Transportation Officials, Shared Micromobility in the US, 2019.

Past literature has established that micromobility vehicles tend to cluster around transit stations. However, this spatial correlation could be because the built environment around transit nodes tends to be more dense, urbanized and potentially more suitable for micromobility vehicles. For example, some studies have looked at whether the presence of bike lanes increase use of micromobility vehicles. Mateo-Babiano et al. (2016) found greater bikeshare usage in neighborhoods with cycle lanes and Caspi et al. (2020) found higher shared e-scooter use in areas with cycle lanes. Huo et al. (2021) found greater e-scooter use in areas of higher density and mixed land use. By leveraging a sudden and substantial change in transit infrastructure, I provide the first causal evidence relating rail transit stations to local dockless shared micromobility activity. I also provide a contribution to the literature by making use of a data set that includes both e-scooters and bicycles operated by the same provider (Lime), and accessed through the same mobile application, allowing their use patterns to be directly contrasted.

While the adoption of dockless micromobility systems in cities is a relatively recent occurrence, there is a quickly growing body of literature attempting to better understand the use patterns of this new transportation mode. Station based bicycle share systems have been analyzed across a number of studies (Faghih-Imani et al., 2014; Mateo-Babiano et al., 2016; Noland et al., 2016). Studies of both docked and dockless bikesharing systems have consistently found that trips peak during morning and evening rush hours, suggesting that commuting trips are a common use. Analyzing station based systems, commuting by bikeshare was found to be common in Brisbane (Mateo-Babiano et al., 2016), Chicago (Faghih-Imani and Eluru, 2015), Montreal (Faghih-Imani et al., 2014), and New York City (Wang et al., 2018).

Use patterns of e-scooter systems have also been studied in a number of cities. Zou et al. (2020) analyzed detailed trip level data from the e-scooter share system in Washington, DC. The data showed that trips were generally less than two miles and trip generation was highest in the midday and evening, rather than during commute hours. Bai and Jiao (2020) looked at data on e-scooter locations from Minneapolis and Austin, examining usage patterns. The authors found usage most common in the downtown areas and on University campuses. Analysis of transit stops showed that e-scooter use was also more common in areas of better transit access, demonstrating a spatial correlation between transit and e-scooters. Some studies of e-scooters have found that the majority of trips are non-commuting (Caspi et al., 2020; McKenzie, 2019). Comparing e-scooter share studies to bikeshare studies, there is growing evidence that shared bicycles have a larger role in urban commuting than e-scooters. However, the literature is still developing, and past studies compared bicycle and e-scooter systems across different platforms, potentially introducing confounding variables. McKenzie (2019) examined e-scooters in Washington, DC and made some comparisons between e-scooter use and Washington's station based bikeshare system. Consistent with other research, the authors found bikeshare was more likely to be used for commuting than e-scooters. While apparently used less for commuting, e-scooters may still be providing valuable trips.

The central question of this study concerns the complementarity of dockless shared micromobility and rail transit. Shared bicycles and e-scooters may improve the accessibility of rail transit by providing trips that connect the rail station to the original or final destination. Martens (2004) generally explores the complementarity of rail transit and cycling through the examination of "bike-and-ride" practices in Europe, finding well established systems that integrate cycling with rail transit. The effect of dockless e-scooters on bus ridership was estimated in Ziedan et al. (2021), using Louisville, Kentucky as a case study. The authors did not find any evidence that the arrival of e-scooters impacted bus ridership. Existing research relating shared micromobility systems and transit is mainly limited to station based bike systems. Operators of station based systems may intentionally place vehicle docks near rail transit stations based on an assumption that the two modes are complements and will be used as parts of an integrated network (Wang and Chen, 2020). Nair et al. (2013) provided spatial analysis of Paris's bikeshare system, and found ridership levels benefit from collocation of transit stations and bikeshare docks. Noland et al. (2016) analyzed bikeshare trip behavior in New York City, finding that bikeshare stations near busy subway stations experienced greater use. The authors attribute this correlation to the bikeshare system complementing public transit by accommodating "last-mile" trips. However, docked systems force riders to complete their micromobility trip at a designated station, which may not precisely correspond to their desired destination and therefore station based systems provide an incomplete solution to the last-mile problem. In contrast, dockless systems allow users to leave the vehicle at their destination.

The interaction of transit and shared micromobility may differ across types of users. Past research has contrasted the behavior of users who are subscribed as members of the systems compared to casual users who pay for individual trips. Caspi and Noland (2019) provided clear evidence from Philadelphia that subscribed users use bikeshare largely for commuting while casual users do not. Buck et al. (2013) and McKenzie (2019) showed that subscribers of the bikeshare system in Washington DC were largely completing commuting trips. McKenzie (2019) also showed that subscribed users of e-scooter share were largely completing non-commuting trips. Buck et al. (2013) showed that subscribers replaced relatively more transit trips while casual users replaced more walking trips. In the below analysis I only observe aggregate system activity and therefore report average effects inclusive of all user types.

A growing literature has also examined equity concerns related to access to shared vehicle systems. The local supply of shared vehicles is partially determined by the likelihood that a user will end their trip in that area. If shared vehicles appeal to particular demographic groups more strongly, its possible that patterns of availability relative to local demographics could differ. Mooney et al. (2019) investigated equity in access to dockless bikes in Seattle, finding that bike availability was higher in areas with high rates of college-educated residents. Studying Philadelphia's bikeshare system, Caspi and Noland (2019) found lower trip generation in low-income areas. Meng and Brown (2021) compared station based and dockless shared micromobility programs across 32 US cities, finding station based systems strongly exclude areas of low socio-economic status, whereas dockless systems provide more equitable spatial coverage. Ogilvie and Goodman (2012) and Anaya-Boig et al. (2022) examined London's and Barcelona's bikeshare systems respectively, and both found station coverage was skewed towards more affluent areas. The findings of these papers mirror results from studies of free-floating car share programs which were also found to provide better availability in neighborhoods where the college-education rate was high (Hjorteset et al., 2021; Tyndall, 2017). Less study has been done to determine whether dockless e-scooters are more or less accessible to areas of lower affluence. Caspi et al. (2020) found that, in Austin, e-scooter usage is not strongly associated with local income levels, in contrast to the literature on bikeshare systems.

Local jurisdictions have needed to adapt regulations to cover the emergence of shared micromobility services. Button et al. (2020) and Riggs et al. (2021) both provided summaries of micromobility regulation in the US, finding a diversity of approaches taken by cities. As shared micromobility devices may generate both positive and negative externalities, the optimal slate of regulations requires careful consideration regarding the likely effect of rules that act as encouragements or discouragements to micromobility adoption. This study will provide new evidence for a potential positive externality of dockless micromobility: the ability of micromobility vehicles to support public transit system access.

This paper will proceed as follows. Section 2 describes the Seattle study area.

Section 3 lays out the data collection and processing methods. Section 4 provides the econometric approach to estimating the effect of a rail station on shared micromobility use. Section 5 provides regression results and Section 6 concludes.

2 Study Area

This study will be limited to the municipality of Seattle, Washington. Seattle has a population of 737,000 and is the center of a metropolitan area of 4.0 million.[1] A summary of demographic characteristics is provided in Table 1 as well as national statistics for comparison. Seattle has a highly educated population. The share of the local adult population with a college education (64%) is double the national rate (32%). Median household income in Seattle is also high, at $92,000. Seattle has an Asian population share roughly three times the national rate, and a relatively small Hispanic population share (6.7%).

Table 1: Demographic Characteristics of Study Area

	Seattle, WA	**USA**
Population	737,015	331,449,281
Median household income	92,263	62,843
College education rate† (%)	64.0	32.1
Median Age	35.3	38.1
White (%)	67.3	72.5
Black (%)	7.3	12.7
Asian (%)	15.4	5.5
Hispanic (%)	6.7	18.0
Commuter mode share:		
Drove alone (%)	46.5	76.3
Public transportation (%)	23.0	5.2
Cycling (%)	3.5	0.6
Walking (%)	11.3	2.7

Population estimates are from the 2020 US Census. Data for the remaining demographic variables are from the 2019 5-year American Community Survey.
† Bachelor's degree or above, among population 25 years and older.

The public transportation system in Seattle enjoys significant use. 23% of the workforce use public transportation for commuting, compared to the national rate of 5%. Cycling and walking are also much more common forms of commuting when compared to the US as a whole.

[1]Population estimates from 2020 US Census.

Local culture has been shown to be an important determinant of cycling uptake (Pucher et al., 1999; Smiley et al., 2016; Tyndall, 2022), and is likely also an important determinant of shared micromobility use. Seattle is home to numerous technology companies and a young, educated workforce that might be predisposed to engage with alternative modes of transportation. The main campus of the University of Washington is located in the study area, which might also contribute to uptake as college campuses have been found to experience high rates of micromobility use (Bai and Jiao, 2020).

Seattle is relatively monocentric, with a dense cluster of jobs in the downtown area. The rail system is centered on the downtown area, providing access to a large share of the city's employment opportunities. The topography of Seattle includes many hills, which could represent a barrier to cycling uptake (Heinen et al., 2010; Parkin et al., 2008; Rietveld and Daniel, 2004). However, some research has found hills to be unimportant to overall cycling uptake in the US context (Tyndall, 2022). Hills do not necessarily represent a barrier to e-scooter use because e-scooters do not require any additional physical exertion to overcome hills.

The specific climate of Seattle may effect micromobility use. Seattle has a temperate climate, experiencing significant annual rainfall with relatively dry summer months. Past studies have shown that daily fluctuations in weather affect daily bikeshare usage (Miranda-Moreno and Nosal, 2011; Winters et al., 2007), and e-scooter usage (Noland, 2021). However, across metropolitan areas, Tyndall (2022) finds that differences in climate do not play a significant role in cycling uptake. Seattle experienced snowfall events during the study period, I discuss the effect of snow events in the empirical section.

Seattle's unique socioeconomic characteristics, culture, and climate, combined with the existing popularity of alternative transportation modes, means that caution should be exercised when attempting to apply the findings of this paper to other locations.

The study period of this paper will span February 1, 2021 to January 31, 2022. Over this period, Lime was the largest provider of micromobility devices in Seattle. Lime provided access to both e-scooters as well as bicycles. Users could book either a bicycle or e-scooter through the same smartphone application. The cost of a ride included a \$1 unlocking fee plus a \$0.36 per-minute fee. Payment is processed automatically through a credit card linked to the user's account.

Prior to the study period, there were significant changes to the micromobility marketplace in Seattle. In 2017 three companies launched dockless bikeshare schemes in Seattle: Lime, Spin and Ofo. In 2018, Uber launched an additional dockless bikeshare scheme branded as Jump. All providers reported financial losses to various degrees. In 2018, both Spin and Ofo announced they were discontinuing service. In 2019, Lime announced plans to discontinue service of their dockless bicycles. In May of 2020, Uber and Lime announced an agreement in which Lime would take over operation of the Jump bike system in Seattle, combining the Jump fleet with Lime branded bicycles and allowing Lime service to continue. In September of 2020, enabled by new regulations from the Seattle Department of Transportation (SDOT), Lime added e-scooter service in addition to its bicycles, starting with a fleet of 500 e-scooters. Also in 2020, two other operators began offering e-scooters for rent: Link and Wheels. Spin was subsequently licensed to become the fourth provider of e-scooters in Seattle and had commenced a gradual roll-out of its services during the final months of 2021.

Although the history of micromobility in Seattle has been turbulent, this paper analyzes a relatively stable period. I look only at Lime's service (including Jump bikes), which operated continuously through the study period. Lime continued to expand the size of its fleet over the study period. In July of 2021, the midpoint of the study period, Lime reported operating 2,000 bikes and 2,000 e-scooters within Seattle.[2] Due to fleet maintenance and charging of e-scooters, the entire fleets were not available at all times.

The distribution of Lime's fleet across Seattle neighborhoods is largely determined by where users elect to leave vehicles at the conclusion of their trip. However, Lime makes efforts to "rebalance" their fleets of vehicles across the city. The company makes use of internal data on vehicle locations and trip generation, and employs algorithms to predict which areas of the city will experience high levels of demand. For the empirical analysis in this paper I assume that Lime is profit maximizing and is successfully directing vehicles to areas of high demand. I treat rebalancing efforts as an endogenous reaction of the firm to changes in demand. If an area experiences a positive shock in demand, vehicles may migrate to the area due to a higher probability of users ending trips in the area, or from Lime intervening to provide vehicles. SDOT introduced a requirement for micromobility providers in the city, which compelled them to ensure at least 10% of their vehicle fleet was available in a defined set of neighborhoods that were either low-income or had high non-white or immigrant populations. However, data provided from the initial months of e-scooter service showed that Lime failed to meet this requirement.[3]

[2] King 5 News. July 13, 2021. *Bike and scooter sharing is keeping Seattle on a roll.*

[3] Seattle Times. October 6, 2021. *Will rental scooters serve all Seattle neighborhoods? Vendor missed equity target with bikes last year.*

I examine the interactions between Lime vehicle use and Seattle's rail system. Seattle's public transportation system is centered on a LRT system referred to as Link. Prior to October, 2021, the system operated 13 stations within the city of Seattle and an additional three stations extending south of the city, connecting to the airport.[4] On October 2nd, 2021 Link opened three new stations in the north section of Seattle. Figure 2 maps the location of the Link stations, including the system expansion. Because I observe vehicle distributions both before and after the opening of the October 2nd expansion, I am able to test for changes in micromobility use that coincided with the station openings.

Figure 2: Location of LRT Stations

The Link LRT system expanded the number of stations operated within the city of Seattle from 13 to 16 on October 2nd, 2021.

[4]Link also operates a six station system in the city of Tacoma. However, the Tacoma stations are not connected to the Seattle system and are outside the study area.

The study period falls within the COVID-19 pandemic. Lime service was maintained through the study period. The Link LRT line also remained open despite reduced ridership levels. The frequency of trains was reduced in response to lower ridership during the pandemic. Link trains ran with with increased, 12 minute headways at peak hours during the first half of 2021.[5] Beginning June 12th, 2021 service was restored to the previous level, with eight minute headways.[6] The specific use patterns of both Lime services and LRT could be related to unique travel behaviors during the pandemic. Reduced use of public transit may suggest that the level of complementarity between micromobility and transit may be stronger in times when a pandemic is not discouraging a share of the population from public transit use.

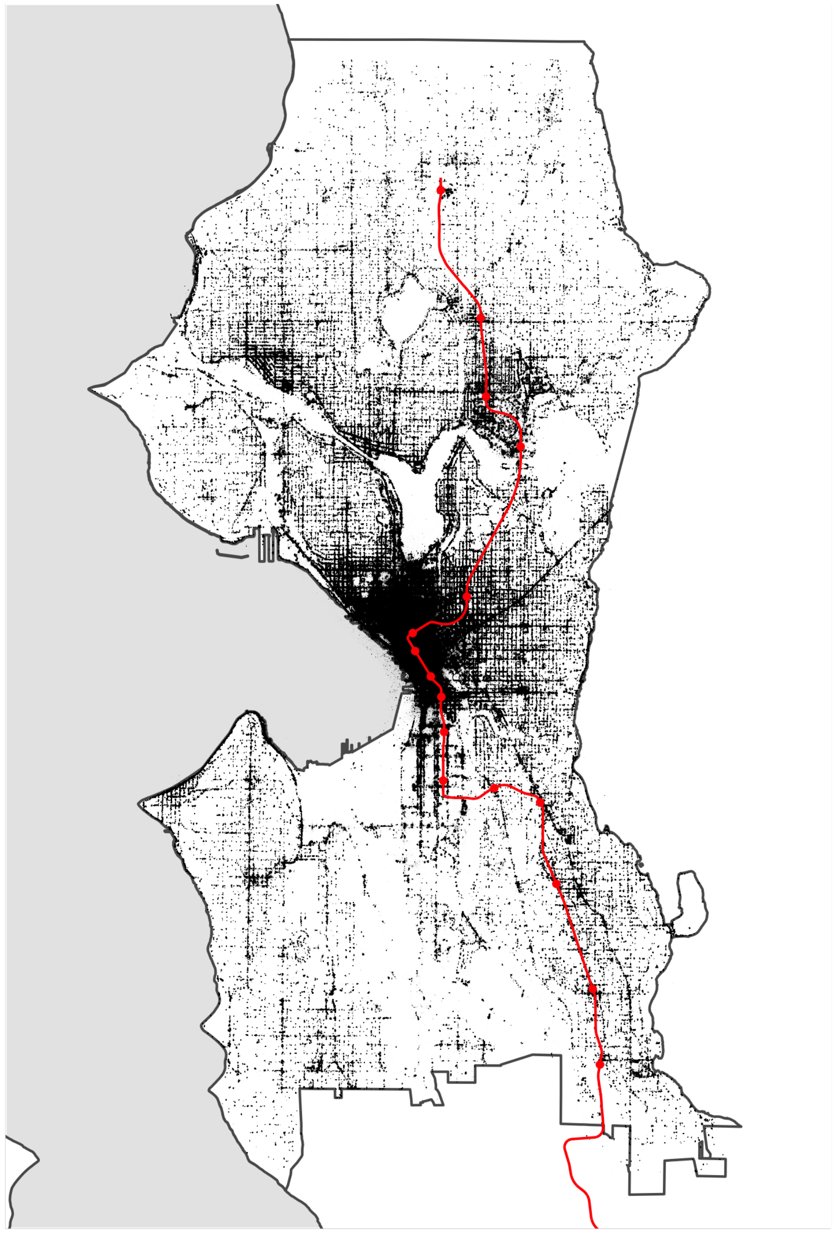
3 Data

I rely on an original, scraped data set of shared bicycle and e-scooter locations within Seattle from the micromobility provider Lime. A public API provides live data on the current location of every available bicycle and e-scooter in the system. I downloaded the location of all available bicycles and e-scooters at five minute intervals for a full year, from February 1st, 2021 to January 31st, 2022. I do not observe the location of vehicles while they are in use, only the locations of vehicles that are parked and available. The scraping process was able to maintain stable internet connectivity with few exceptions, successfully recording the data for 98.0% of scheduled queries. The final data set contains the results of 103,004 API queries, which cover 175,022,498 vehicle locations. The API queries are limited to only return vehicles that are geographically located within Seattle's municipal boundaries. Each observation includes the latitude and longitude of the vehicle, with precision up to the fourth decimal place. After spatially plotting data, I observe parked vehicles aligned precisely along the street grid, and rarely in the interior of blocks, providing some evidence that the location information is highly accurate. The API also returns whether the vehicle was a bicycle or e-scooter. Each query is precisely time stamped. Figure 3 provides a visualization showing the location of all 175 million observed vehicle positions, where one observation is represented by one dot. Vehicles are heavily concentrated in Seattle's downtown core, and relatively less common as distance increases from the city center.

[5]Sound Transit press release. December 4, 2020. *Sound Transit required to temporarily reduce peak hour service on Link light rail.*

[6]Sound Transit press release. June 4, 2020. *Link light rail to increase frequency starting June 12.*

Figure 3: Density of Shared Bicycles and E-scooters



Each black circle corresponds to an observed bicycle or e-scooter. Repeated observations are represented by a darker circle, with transparency proportional to the number of observations. Data is pooled across the study period, with the figure displaying all 175 million vehicle observations.

Given that the interval between observations is five minutes, the majority of observed vehicles from one API request to the next are repeated observations. The observations do not include unique vehicle identifiers. I identify observations in the data that were not present in the previous query as a way to estimate vehicle turnover. I look at the observation's latitude, longitude and type (bicycle or e-scooter) and consider an observation to be new if there is no corresponding observation in the prior query, based on these three characteristics. I account for instances where multiple observations have identical latitude, longitude and type during the same query by counting the number of duplicates from one query to the next and inferring how many vehicles were dropped-off or picked-up at this location. Possibly, if a vehicle was rented between queries, and an other vehicle of the same type was parked at the same location within that same five minute period between queries, I would not be able to observe this instance of turnover. Similarly, if a vehicle were dropped off and picked up between two sequential queries I would not observe this instance at all. As a test of the sensitivity of results to the five minute gap between queries, I attempted to collect data at one minute intervals. In observing the data I found that the Lime API itself refreshes approximately every six minutes. Therefore, scraping the data from the API at intervals of less than five minutes provides no advantage in terms of improved data collection. I provide a detailed exploration of the potential impact of this data limitation in the results section and in Appendix A.

By identifying new vehicle arrivals I use the flow of new vehicles as a proxy for the level of local micromobility use. In the long run, in a specific geographic area, the rate of drop-offs and pick-ups must be equal or else all vehicles would eventually end up in that area. The equating of drop-offs and pick-ups could occur naturally through user behavior, or it could be the result of intentional rebalancing efforts by the system operator. I explore unequal rates of drop-offs and pick-ups in the empirical analysis by studying the average number of vehicles that are available locally.

I do not observe whether a dropped off vehicle is from a user or from a rebalancing effort undertaken by the system operator. Lime operates cargo vans to facilitate vehicle rebalancings, dropping off vehicles in areas where demand exceeds supply. I can note instances in the data where multiple vehicles were dropped at the same location and first appeared in the same API query, where the same location means identical coordinates with precision to the fourth decimal place. Given location precision, observations with identical coordinates are within a common areal unit of roughly seven by eleven meters. I find that for 88.0% of observed vehicle drop-offs, the vehicle was the only new observation at that location and time. For 96.0% of observations no more than two new vehicles appeared simultaneously and for 98.2% of observations no more than three vehicles appeared simultaneously. These figures provide some rough evidence that mass vehicle drop-offs by the service provider represent at most a small fraction of overall vehicle activity. Furthermore, multiple vehicles with identical drop-off locations and times could be from users traveling together. Because I cannot confidently identify rebalancing drop-offs, I interpret my causal effects as the combined effect of any changes in user behavior and company drop-off behavior.

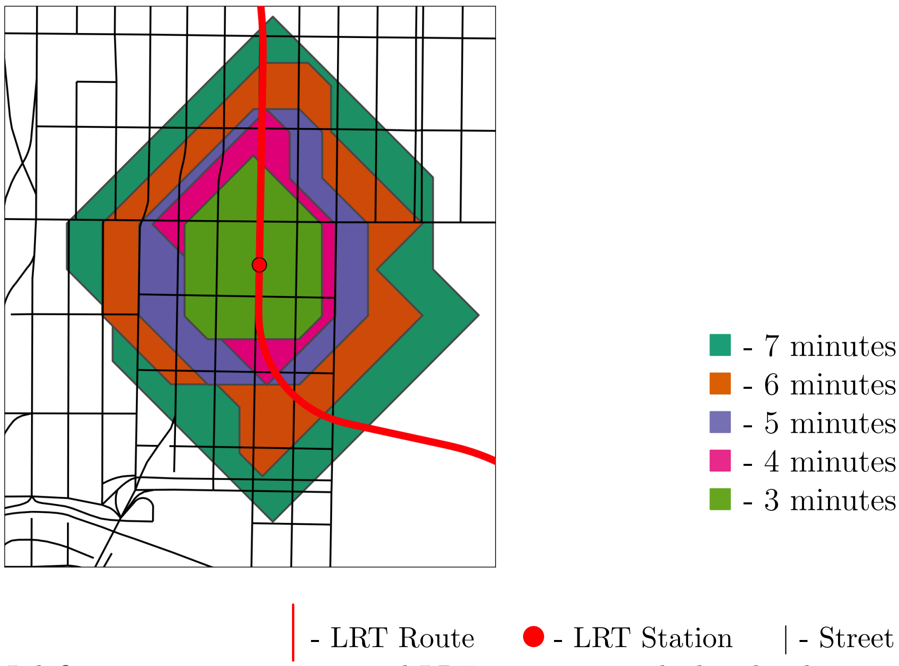
For LRT station locations, I use spatial data directly from Sound Transit, the public operator of Seattle's LRT system. The data provides latitude and longitude coordinates of all LRT stations. I calculate buffers around LRT stations to define treatment areas. I calculate walking isochrones for each of the 16 station locations. The edge of an isochrone is defined by the distance that could be traveled in a set amount of time. I construct polygons that are bound by the maximum travel distances. Using isochrones, which account for physical barriers in the built environment, will capture whether a micromobility vehicle location is "near" to a LRT station. I use the API provided by the transportation routing firm TravelTime to calculate walking isochrones of various lengths centered on the stations. I will use three minute and five minute isochrones in main specifications and provide results for isochrones of up to seven minutes. Isochrones below three minutes generated poorly defined polygons in some cases. An example of the polygons generated are provided in Figure 4.

After defining local areas around stations, I count the number of new vehicle arrivals observed within each treatment area and collapse the data to the month-station area level. I drop observations between the hours of midnight and 5 am as the LRT system does not operate during these hours. I normalize the measure by dividing by the number of hours of active API requests made over the month and by the land area of the treatment area in square kilometers. The normalization produces a measure of vehicle flow to the area defined in terms of new vehicles per hour per square kilometer. I also generate these metrics for bicycles and e-scooters separately.

My final data set is a balanced panel containing 192 observations spanning 16 LRT station sites with 12 monthly observations per site. Table 2 shows vehicle flow summary statistics. For the five minute isochrone defined treatment areas, the average station area saw 0.41 new vehicles arriving per hour per square kilometer. Of this flow, 0.21 were bicycles and 0.20 were e-scooters.

Table 2 shows higher rates of vehicle flow occurring closer to LRT stations, suggesting a general spatial correlation between LRT stations and dockless micromobility vehicle use. Figure 5 shows the average of bicycle and e-scooter flows near LRT stations,

Figure 4: Treatment Area Definition Example, U District Station



I define treatment areas around LRT stations to calculate local micromobility activity. The figure shows pedestrian isochrones of varying lengths. I show the U District Station as an example but perform similar calculations for the remaining 15 station locations.

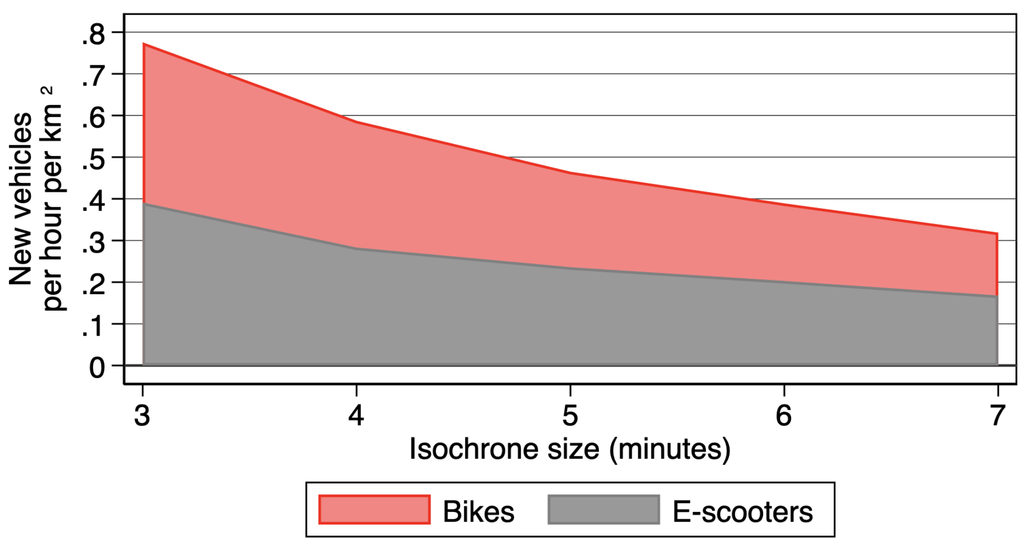
including only the 13 stations open through the entire study period. The treatment areas are defined according to isochrones and the size of the areas increase from left to right in the figure. Within three minutes of a station, an average of 0.78 vehicles are dropped off per square kilometer per hour. Using seven minute isochrones, the flow of vehicle arrivals is only 0.32. This correlation demonstrates that micromobility vehicle drop-offs cluster around LRT stations. However, LRT stations may also be located near to commercial centers, areas of high population density, or local bicycle infrastructure. Therefore, spatial correlation between LRT stations and micromobility vehicle use does not establish that the presence of a LRT station is specifically raising use of micromobility devices. The subsequent section will lay out a methodology to identify a causal effect.

Table 2: Flow of Micromobility Vehicles Around LRT Stations

Treatment area and vehicle type		Mean	Std. Dev.	Min.	Max.
3 minute isochrone:	All vehicles	0.672	0.766	0	4.167
	Bicycles	0.344	0.423	0	2.562
	Scooters	0.328	0.524	0	3.073
5 minute isochrone:	All vehicles	0.408	0.456	0.004	3.085
	Bicycles	0.209	0.240	0	1.571
	Scooters	0.199	0.270	0	1.581
N			192		

Vehicle flows are shown in units of newly arrived vehicles per hour per square kilometer. The unit of observation is a station area-month.

Figure 5: Vehicle Flow Clustering Around LRT Stations



The figure includes data from only the 13 stations operating throughout the entire study period. Vehicle flow is more than twice as large in the area within a three minute walk of a LRT station compared to the area within a seven minute walk of a LRT station. The relationship is estimated at one minute intervals and interpolated between these points.

4 Methodology

I provide quasi-experimental evidence of complementarity between shared micromobility and public transit. I make use of the Link LRT system expansion that took place on October 2nd, 2021. Through a difference in difference approach I test for a change in micromobility vehicles around LRT stations after station openings. I use local treatment areas as defined in the prior section.

Equation 1 provides the main regression equation. V_{it} captures the flow of micromobility vehicles around station i during month t. I also run specifications where V_{it} represents either bicycles or e-scooters separately, rather than the combined total. E_i is a dummy variable that takes a value of one if the station opened as part of the October 2nd, 2021 expansion, and takes a value of zero for stations that were not part of the expansion and existed throughout the study period. P_t is a dummy variable that takes a value of one for any month during or after October, 2021. I consider October, 2021 and beyond as months that were treated by the new stations.[7] Ψ_i is a station area fixed effect and Φ_t is a month fixed effect. One station that existed throughout the study period was located on the University of Washington campus. Micromobility activity around this station could be significantly correlated with whether classes are in session. I include a dummy variable (U_{it}) in all regressions that takes a value of one if the observation is from the University of Washington station, and is during a month where full classes are in session (October-May). Classes are also offered from June-September, but enrollment is lower.

$$V_{it} = \beta_0 + \beta_1(E_i \times P_t) + \beta_2 U_{it} + \Psi_i + \Phi_t + \varepsilon_{it} \tag{1}$$

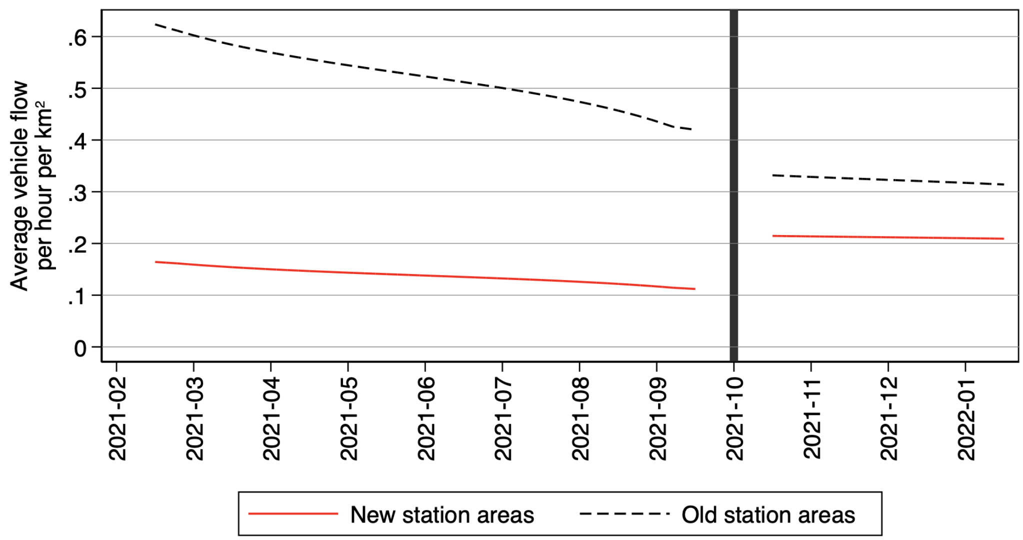
The station fixed effects control for idiosyncratic characteristics of station locations. In particular, the fact that some station areas may generally experience a larger flow of micromobility devices across the study period is controlled for. Month fixed effects will absorb any city wide changes in vehicle flow over time, including increases or decreases to the total vehicles supplied by Lime. Seasonal effects, such as changing weather, are also absorbed by the month fixed effects. The coefficient of interest is β_1, which will represent the partial effect of a new LRT station on local micromobility vehicle flow.

In order for the difference in difference methodology to be valid the period before the new stations opened must abide by the parallel trends assumption. If, for example, the areas receiving new LRT stations had experienced a rise in vehicle flow relative to the existing station areas, before the LRT stations opened, this would be evidence of a separate causal mechanism affecting vehicle flow, and could bias estimation. Figure 6 plots the trend of local vehicle flow within a five minute walk of the station locations, normalized to vehicles/hour/km^2, fitting a local polynomial line to the data. Prior to October, 2021 I find locations close to open LRT stations had dramatically higher rates

[7] I exclude observations from October 1st, 2021 because they were made while the new stations were still closed. October observations are therefore averaged across October 2nd to 31st.

of vehicle flow compared to the locations of future stations, consistent with a complementarity between transit and micromobility. Importantly, the two pre-expansion lines are roughly parallel, both exhibiting a slight downward slope. The downward slope suggests that the frequency of vehicles being dropped off near stations was declining over the study period. The trend may be due to seasonal effects that change micromobility flow around transit stations, the changing influence of the COVID-19 panedmic on travel, or changes in the total number of active vehicles, all of which will be controlled for in the regression methodology.

Figure 6: Evidence of Parallel Trends



The figure displays four separate local polynomial fitted lines, dividing the data by whether the local station was new or existing and whether the observation is made before or after new station openings. The vertical line indicates the date when new stations opened. The treatment areas are defined according to five minute isochrones.

The areas surrounding the three new LRT stations are likely to have built environment characteristics that are relatively similar to existing station locations. For example, all areas around LRT stations tend to be denser and contain more commercial areas than the average Seattle neighborhood. However, the areas surrounding the new stations happen to contain residents with relatively high income and high education levels. In census tracts that can be reached within a five minute walk of a new station, 75% of the adult population is college educated and median household income is $122,000. For tracts within a five minute walk of the previously existing stations, 41% of the population is college educated and median household income is $79,000. While location fixed effects can account for these level differences in the empirical model, it is important to note that the treatment and control neighborhoods have unique demographics. The response I observe in the treatment locations may be specific to areas of high education and income.

By only studying areas directly adjacent to LRT stations I aim to provide a clear comparison of treated areas to a valid control group. However, this methodology involves ignoring the statistical variation present in all other areas of Seattle, as I drop all vehicle observations that are not near to LRT stations. An alternative methodology would be to analyze census tracts or grid squares across a larger area (for example Caspi et al. (2020)) and test for changes in vehicle activity, comparing polygons with and without transit stations. This method would benefit from more statistical power provided by more observations. However, such a method would also rely on an assumption that areas far from transit are a valid control group for the treated areas. This is a stronger assumption than what I make, which is that neighborhoods with transit stations are experiencing the same unobserved forces that affect micromobility use over time.

5 Results

Table 3 provides main (Equation 1) regression results, and displays robust standard errors clustered at the station level.[8] Columns 1-3 adopt a three minute walking distance treatment area around stations. The outcome variable is the hourly flow of new micromobility vehicles per square kilometer. With this treatment definition I find that new stations caused an increase in the flow of new vehicles of 0.55 vehicles/hour/km^2. Before stations opened, the average flow of vehicles around new station sites was 0.13. I therefore estimate that a new LRT station increased the flow of micromobility vehicles by more than four times the initial level. Columns 2 and 3 show the effects on bicycles and e-scooters respectively. I find a statistically significant increase in both types of

[8]For regression results in this paper I report cluster-robust standard errors, clustered at the LRT station site level. The small number of clusters (16) could potentially result in biased standard errors. A commonly proposed solution in such cases is to estimate clustered standard errors through a bootstrap method (Cameron et al., 2008). However, the small number of observations within clusters (12) may reduce precision in clustered bootstrap estimation. As a robustness check, I reestimate my standard errors using a clustered bootstrap method and find results are highly robust. For example, for the Table 3, column 1 estimate, I report a cluster-robust standard error of 0.132, whereas the clustered bootstrap method generates an estimate or 0.135. Across other regressions, the estimate of the standard error generated by the two approaches is similarly robust.

vehicles. I estimate the new stations attract a larger flow of arriving bicycles (0.31 vehicles/hour/km^2) compared to e-scooters (0.25). However, before the LRT stations opened, the flow of e-scooters was relatively low (0.04) compared to bicycles (0.09). I find that, as a ratio of pre-station levels, LRT stations caused e-scooter flow to increase by more than bicycle flow.

Table 3: Effect of LRT Station on Local Flow of Micromobility Vehicles

	(1)	(2)	(3)	(4)	(5)	(6)
New station x	0.551**	0.305**	0.247**	0.288**	0.146*	0.142**
Post opening	(0.132)	(0.089)	(0.067)	(0.081)	(0.065)	(0.031)
UW station x	0.271*	0.326**	-0.055	0.042	0.071*	-0.029
Non-summer month	(0.110)	(0.060)	(0.080)	(0.047)	(0.030)	(0.031)
Day fixed effects	Y	Y	Y	Y	Y	Y
Station fixed effects	Y	Y	Y	Y	Y	Y
Vehicle type	All	Bikes	Scooters	All	Bikes	Scooters
Isochrone radius	3 min	3 min	3 min	5 min	5 min	5 min
R^2	0.237	0.248	0.209	0.304	0.337	0.253
Adjusted R^2	0.181	0.193	0.151	0.253	0.289	0.199
N	192	192	192	192	192	192

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis.

In columns 4-6 of Table 3 I repeat the analysis of columns 1-3, but expand the definition of treatment area from a three minute to a five minute isochrone. I again find a highly significant increase in vehicle flow. The effect is significantly smaller when using the larger radius. A reduced effect is consistent with a spatial decay in the effect of LRT stations in attracting micromobility devices, with the most intense effects directly adjacent to the stations. I also find diminished effects at greater distances when looking at either bicycles or e-scooters separately.

I imperfectly observe vehicle turnover due to the possibility that a vehicle is both dropped off and picked up between successive API queries. Missing observations suggest that the point estimates could be underestimating the causal effect of a station on vehicle flow. I assume these missed observations are rare given the short gap between API requests. In Appendix A I estimate the relationship between the rate of API query requests and the number of additional missed observations. By assigning a functional form to this relationship I estimate that roughly 13% of new vehicle drop-offs were missed during data collection. The significant effects I report can not be explained by missing observations as long as instances of missed observations are equally likely across locations and time.

While seasonality is controlled for by the month fixed effects, Seattle experienced two significant snow events during the study period, in February and December of 2021.[9] Snowfall may have significantly affected micromobility use. I rerun all models while dropping observations from the seven days that experienced positive amounts of snowfall and find that results are nearly identical, suggesting snowfall days are not significantly affecting results.

I make use of pedestrian isochrones to define treatment areas as described above. In Appendix B I provide alternative results where treatment areas are defined using circles of constant geodesic distance. I find results are robust to this alternative method.

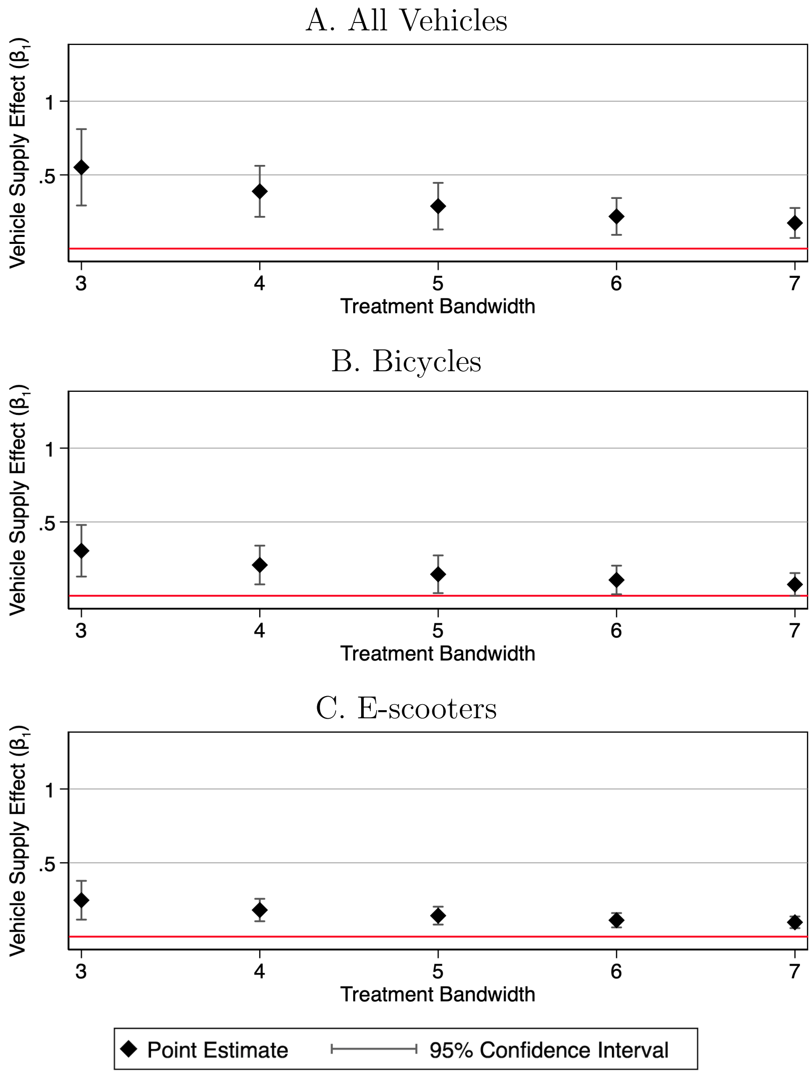
I adopt a linear regression model (Equation 1) for estimation of the main results of this paper. The distribution of vehicle flows across observations is not normally distributed but is skewed, with some stations having significantly higher vehicle flow across the study period. Considering the rightward skewed distribution of the dependent variable may imply the need to log transform the flow rates. However, transformation of the dependent variable complicates coefficient interpretation and introduces other potential issues. I re-estimate main results using a log transformed dependent variable as well as a specification where I transform the dependent variable according to an inverse hyperbolic sine function. I provide these results, interpretations and discussion in Appendix C. I find results are robust to these alternative specifications.

As treatment definition size increases I find decreasing effects, consistent with LRT stations having the strongest effect on micromobility use closest to the station. Figure 7 provides a more direct representation of this decay effect, extending the analysis to larger treatment areas. In each graph I provide the results of five regressions that are identical except for the treatment area definition. In the top panel I show the estimated causal effect on total vehicle flow, the center panel shows bicycle flow and the lower panel shows e-scooter flow. Across all three figures I find a consistent decline in point estimates moving towards larger treatment area definitions. I find significant results for 14 out of 15 regressions, with the exception being the seven minute treatment bandwidth for bicycle flow.

Figure 8 uses a similar framework to Figure 7 but rather than increasing the size of the treatment bandwidth, I divide the treatment area into "donuts" of increasing radii. For example, the leftmost point estimate in Figure 8A shows the partial effect of LRT treatment on vehicle flow for a three minute isochrone bandwidth, matching

[9] I use snowfall data from the National Oceanic and Atmospheric Administration (NOAA) recorded at SeaTac Airport.

Figure 7: Effect of Bandwidth Choice on Estimate

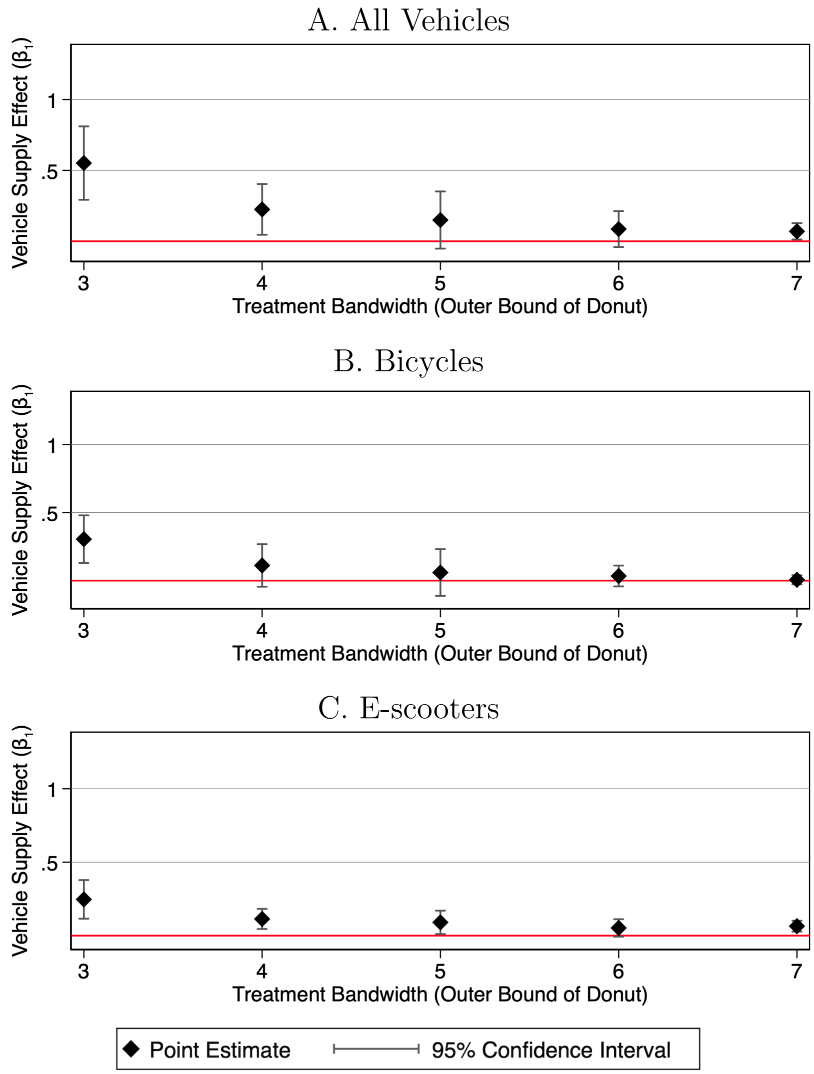


The point estimates decrease as the definition of the treatment area is expanded. The bandwidths are represented in minutes.

the estimate in Figure 7A. However, the subsequent point shows the effect of treatment on vehicle flow in the area within the four minute isochrone but outside of the three minute isochrone. The bandwidths reported in Figure 8 represent the outer edge of the treatment area, with the inner edge bound by the preceding estimate's bandwidth and the innermost estimate extending to the station.

I find a statistically significant effect for the innermost three minute ishochrone, and the donut bounded by the three and four minute isochrones. Moving to larger

Figure 8: Estimating Effect by Treatment Donuts



The positive effect of treatment is largest in areas very close to stations. The bandwidths are represented in minutes.

isochrones, point estimates consistently become smaller due to the effect of the station diminishing with distance. I also find a significant effect for the donut bound by the six and seven minute isochrones, suggesting the influence of the station extends a significant distance from the stations. However, the point estimate for this outer donut is comparably small. I estimate a 0.07 vehicles/hour/km^2 increase for this donut

The most dramatic increase in vehicle flow occurs directly beside stations. The finding strongly suggests that users are dropping vehicles off as close as they can to LRT stations, implying that they use dockless micromobility devices as a way to access rail transit stations. I find smaller, but highly statistically significant evidence of increased vehicle use in the surrounding neighborhood. A possible mechanism would be that users are getting off the LRT at a station, picking up a nearby shared bicycle or e-scooter and dropping it off at their final destination within that neighborhood, which increases the flow of new vehicles in the surrounding area. The main findings of this paper show that the presence of a LRT station increases the local use of shared micromobility devices. I do not analyze transit ridership and therefore do not show whether the presence of micromobility services are affecting transit ridership. I also do not directly observe whether micromobility trips are being linked with LRT trips. However, the pattern of vehicle drop-offs directly adjacent to LRT stations strongly suggests that the two modes are being used as part of an integrated system, with shared micromobility trips providing a means to access LRT stations.

In the above analysis I use the flow of newly dropped off micromobility vehicles as a proxy for local micromobility use. In Table 4 I provide results for how a new LRT station affected the average number of locally available vehicles. Rather than using new vehicles per hour per km^2 as the outcome variable I use total available vehicles in the area per km^2. On average, in a five minute isochrone, a station had 3.5 vehicles available per km^2. I find no significant change in the average number of available vehicles around new stations. The finding suggests that, although LRT stations caused a large number of new vehicle drop-offs, they caused an approximately equal number of vehicle pick-ups. This activity could be from users or from rebalancing efforts of Lime. Looking at results for bicycles specifically, I find that the average bicycle availability goes up due to a LRT station. For the five minute isochrone treatment areas, I estimate that a LRT station increased the number of locally available bicycles by 0.76 per km^2. New LRT station sites averaged 0.54 bicycles per km^2 before stations opened, suggesting the opening of a new station caused bicycle availability to more than double. I find a larger increase in bicycle availability when using a smaller treatment area, suggesting that bicycles are accumulating near LRT stations as more people choose to end their micromobility trip at a LRT station.

6 Conclusion

I present a new and extensive data set of dockless micromobility vehicles in Seattle. Using the expansion of the Seattle LRT system, I test for the complementarity of

Table 4: Effect of LRT Station on Local Vehicle Availability

	(1)	(2)	(3)	(4)	(5)	(6)
New station x	0.742	1.569**	-0.827	-0.005	0.757*	-0.762
Post opening	(1.174)	(0.531)	(0.906)	(0.569)	(0.317)	(0.550)
UW station x	0.628	1.294**	-0.665	-0.093	0.315	-0.408
Non-summer month	(0.669)	(0.295)	(0.428)	(0.371)	(0.195)	(0.207)
Day fixed effects	Y	Y	Y	Y	Y	Y
Station fixed effects	Y	Y	Y	Y	Y	Y
Vehicle type	All	Bikes	Scooters	All	Bikes	Scooters
Isochrone radius	3 min	3 min	3 min	5 min	5 min	5 min
R^2	0.184	0.232	0.262	0.238	0.294	0.309
Adjusted R^2	0.125	0.176	0.208	0.182	0.243	0.259
N	192	192	192	192	192	192

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis.

micromobility vehicles with public transit. I show that the local use of micromobility vehicles rose dramatically after new LRT stations opened. I contribute the first causal evidence to the literature linking transit use and shared micromobility use by leveraging a discrete change in a public transit system.

I calculate short term effects of transit stations on the use of shared bicycles and e-scooters. Micromobility devices and transit could be stronger complements over longer time horizons as users adjust behavior. For example, a local resident who is provided access to both quality transit and plentiful shared micromobility devices may find it less necessary to own a car, and might substitute away from private vehicle use entirely. Short of abandoning car use altogether, additional residents may substitute some car trips for linked micromobility-transit trips over longer time horizons as more residents become familiar with the newly introduced travel modes. Therefore, I may be understating the long term complementarity of transit and micromobility.

Shared micromobility devices may be uniquely suited to overcoming the first and last-mile problem of accessing public transit. Because trips can be booked instantly and routes are flexible, shared micromobility allows for complex, dynamic integration with existing modes. The results above suggest shared bikes and scooters are being used in tandem with rail transit. However, the option of micromobility might present an attractive substitute for short public transit trips. I am not able to determine the overall impact of shared micromobility on transit ridership. Similar to studies of ride-hailing's relationship to transit (Hall et al., 2018), future research can provide more details on how micromobility affects overall transit ridership.

As shared micromobility services have become more common in many cities, so have the availability of car sharing and ride hailing services. Some evidence exists that car sharing services are used to connect riders with transit nodes (Tyndall, 2019), while research also finds trip substitution from transit to car sharing (Rotaris et al., 2019). Studying Turin, Italy, Ceccato and Diana (2021) found that car sharing is a complement to both transit and bike sharing. Hall et al. (2018) provided evidence that Uber increased transit ridership in the US because it aided in connecting riders to transit nodes. The combined effect of these rapidly expanding transportation technologies may produce complex trip substitution patterns that will require further study.

The findings of this paper have important and direct implications for policy. Urban form in the US is often characterized by low-density, sprawling development. Rail transit systems may struggle to find significant ridership if a limited number of residents live or work within walking distance of transit stations. The provision of ubiquitous dockless micromobility vehicles to neighborhoods provides a valuable complement for transit, by allowing prospective riders to quickly travel between transit stations and their origin or destination. Ridership on rail systems could potentially be expanded by providing consistent dockless micromobility access in the areas surrounding transit system nodes.

As dockless micromobility services enter markets in additional cities, and these cities develop regulations regarding their use, it will be increasingly important to understand how these systems interact with existing transportation infrastructure. The current paper is able to provide precise estimates for a specific setting. The specific culture and demographics of Seattle may be a strong contributor to the rapid expansion of micromobility. Further research is needed to create generalizable results to inform future policy on the proper regulatory approach to shared micromobility services.

References

Anaya-Boig, E., Cebollada, À., and Bueno, M. C. (2022). Measuring spatial inequalities in the access to station-based bike-sharing in Barcelona using an Adapted Affordability Index. *Journal of Transport Geography*, 98:103267.

Bai, S. and Jiao, J. (2020). Dockless E-scooter usage patterns and urban built Environments: A comparison study of Austin, TX, and Minneapolis, MN. *Travel behaviour and society*, 20:264–272.

Buck, D., Buehler, R., Happ, P., Rawls, B., Chung, P., and Borecki, N. (2013). 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*, 2387(1):112–119.

Button, K., Frye, H., and Reaves, D. (2020). Economic regulation and E-scooter networks in the USA. *Research in transportation economics*.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The review of economics and statistics*, 90(3):414–427.

Caspi, O. and Noland, R. B. (2019). Bikesharing in Philadelphia: Do lower-income areas generate trips? *Travel behaviour and society*, 16:143–152.

Caspi, O., Smart, M. J., and Noland, R. B. (2020). Spatial associations of dockless shared e-scooter usage. *Transportation Research Part D: Transport and Environment*, 86:102396.

Ceccato, R. and Diana, M. (2021). Substitution and complementarity patterns between traditional transport means and car sharing: A person and trip level analysis. *Transportation*, 48(4):1523–1540.

Faghih-Imani, A. and Eluru, N. (2015). Analysing bicycle-sharing system user destination choice preferences: Chicago's Divvy system. *Journal of transport geography*, 44:53–64.

Faghih-Imani, A., Eluru, N., El-Geneidy, A. M., Rabbat, M., and Haq, U. (2014). How land-use and urban form impact bicycle flows: Evidence from the bicycle-sharing system (BIXI) in Montreal. *Journal of Transport Geography*, 41:306–314.

Hall, J. D., Palsson, C., and Price, J. (2018). Is Uber a substitute or complement for public transit? *Journal of urban economics*, 108:36–50.

Heinen, E., Van Wee, B., and Maat, K. (2010). Commuting by bicycle: an overview of the literature. *Transport reviews*, 30(1):59–96.

Hjorteset, M. A., Böcker, L., Røe, P. G., and Wessel, T. (2021). Intraurban geographies of car sharing supply and demand in Greater Oslo, Norway. *Transportation Research Part D: Transport and Environment*, 101:103089.

Huo, J., Yang, H., Li, C., Zheng, R., Yang, L., and Wen, Y. (2021). Influence of the built environment on e-scooter sharing ridership: A tale of five cities. *Journal of transport geography*, 93:103084.

Martens, K. (2004). The bicycle as a feedering mode: experiences from three European countries. *Transportation Research Part D: Transport and Environment*, 9(4):281–294.

Mateo-Babiano, I., Bean, R., Corcoran, J., and Pojani, D. (2016). How does our natural and built environment affect the use of bicycle sharing? *Transportation Research Part A: Policy and Practice*, 94:295–307.

McKenzie, G. (2019). Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, DC. *Journal of transport geography*, 78:19–28.

Meng, S. and Brown, A. (2021). Docked vs. dockless equity: Comparing three micromobility service geographies. *Journal of Transport Geography*, 96:103185.

Miranda-Moreno, L. F. and Nosal, T. (2011). Weather or not to cycle: Temporal trends and impact of weather on cycling in an urban environment. *Transportation research record*, 2247(1):42–52.

Mooney, S. J., Hosford, K., Howe, B., Yan, A., Winters, M., Bassok, A., and Hirsch, J. A. (2019). Freedom from the station: Spatial equity in access to dockless bike share. *Journal of transport geography*, 74:91–96.

Nair, R., Miller-Hooks, E., Hampshire, R. C., and Bušić, A. (2013). Large-scale vehicle sharing systems: analysis of Vélib'. *International Journal of Sustainable Transportation*, 7(1):85–106.

Noland, R. B. (2021). Scootin' in the rain: Does weather affect micromobility? *Transportation research part A: policy and practice*, 149:114–123.

Noland, R. B., Smart, M. J., and Guo, Z. (2016). Bikeshare trip generation in New York City. *Transportation Research Part A: Policy and Practice*, 94:164–181.

Ogilvie, F. and Goodman, A. (2012). Inequalities in usage of a public bicycle sharing scheme: socio-demographic predictors of uptake and usage of the London (UK) cycle hire scheme. *Preventive medicine*, 55(1):40–45.

Parkin, J., Wardman, M., and Page, M. (2008). Estimation of the determinants of bicycle mode share for the journey to work using census data. *Transportation*, 35(1):93–109.

Pucher, J., Komanoff, C., and Schimek, P. (1999). Bicycling renaissance in north america?: Recent trends and alternative policies to promote bicycling. *Transportation Research Part A: Policy and Practice*, 33(7-8):625–654.

Rietveld, P. and Daniel, V. (2004). Determinants of bicycle use: do municipal policies matter? *Transportation Research Part A: Policy and Practice*, 38(7):531–550.

Riggs, W., Kawashima, M., and Batstone, D. (2021). Exploring best practice for municipal e-scooter policy in the United States. *Transportation research part A: policy and practice*, 151:18–27.

Rotaris, L., Danielis, R., and Maltese, I. (2019). Carsharing use by college students: The case of milan and rome. *Transportation Research Part A: Policy and Practice*, 120:239–251.

Smiley, K. T., Rushing, W., and Scott, M. (2016). Behind a bicycling boom: Governance, cultural change and place character in Memphis, Tennessee. *Urban Studies*, 53(1):193–209.

Tyndall, J. (2017). Where no cars go: Free-floating carshare and inequality of access. *International journal of sustainable transportation*, 11(6):433–442.

Tyndall, J. (2019). Free-floating carsharing and extemporaneous public transit substitution. *Research in Transportation Economics*, 74:21–27.

Tyndall, J. (2022). Cycling mode choice amongst us commuters: The role of climate and topography. *Urban Studies*, 59(1):97–119.

Wang, K., Akar, G., and Chen, Y.-J. (2018). Bike sharing differences among millennials, Gen Xers, and baby boomers: Lessons learnt from New York City's bike share. *Transportation research part A: policy and practice*, 116:1–14.

Wang, K. and Chen, Y.-J. (2020). Joint analysis of the impacts of built environment on bikeshare station capacity and trip attractions. *Journal of Transport Geography*, 82:102603.

Winters, M., Friesen, M. C., Koehoorn, M., and Teschke, K. (2007). Utilitarian bicycling: a multilevel analysis of climate and personal influences. *American Journal of Preventive Medicine*, 32(1):52–58.

Ziedan, A., Darling, W., Brakewood, C., Erhardt, G., and Watkins, K. (2021). The impacts of shared e-scooters on bus ridership. *Transportation research part A: policy and practice*, 153:20–34.

Zou, Z., Younes, H., Erdoğan, S., and Wu, J. (2020). Exploratory analysis of real-time e-scooter trip data in Washington, DC. *Transportation research record*, 2674(8):285–299.

Appendix A: Estimating Missed Observations Due to API Query Latency

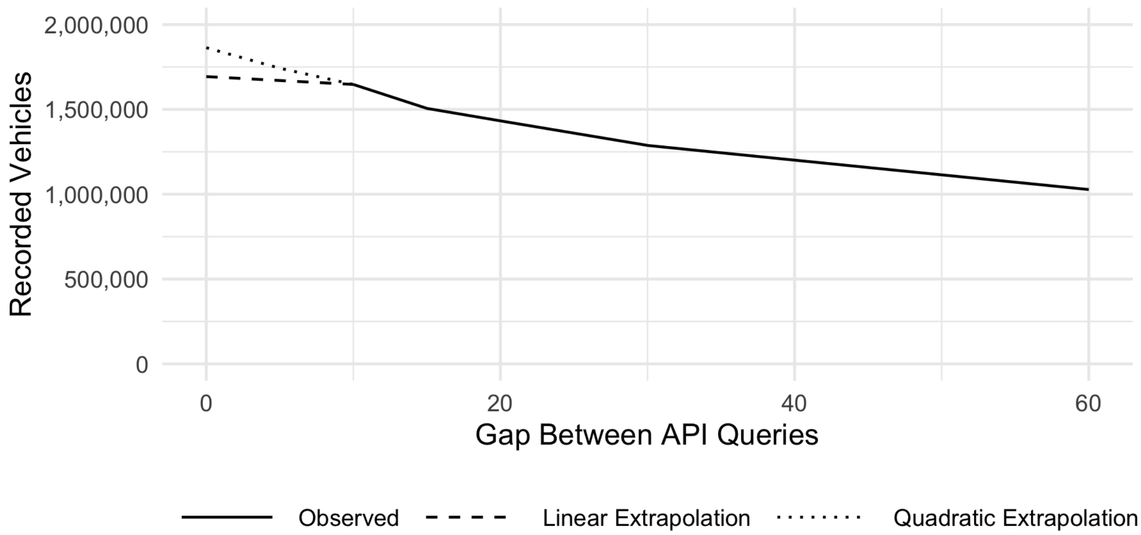
To record vehicle data from Lime I query their public API every five minutes. As discussed above, the delay between requests could cause the methodology to miss some instances of arriving new vehicles. Because the API itself is only refreshed at approximately six minute intervals, it is not possible to record higher frequency data. In this section I provide some evidence regarding the likely level of missed observations introduced by this data limitation.

While I am not able to record higher frequency data, I can estimate the rate at which observations are lost as the delay between queries is increased. Across the full year of data, using a five minute query interval, I record a total of 1,649,491 instances of a vehicle becoming available, meaning it appears in an API query but was not present in the previous query. I make observations every five minutes starting at the top of the hour. By using only the API queries that occurred at ten minute intervals, starting at the top of the hour, and repeating the methodology, I record only 1,647,187 instances of an arriving vehicle, at a 15 minute interval I record 1,506,020 vehicles, and at a one hour interval I record 1,027,604 vehicles. The difference between the figures is the result of additional missed observations. The missed observations occur when a vehicle is both dropped off and subsequently picked up between queries. In Figure A1 I plot the change in recorded observations, while extending the API query gap all the way to one hour. I do not include the five minute interval because the number of captured observations is very close to the ten minute method, but this is mainly an artifact of the limit imposed by the six minute API refresh rate.

By projecting a fitted line in Figure A1 back to the vertical intercept of the graph I can provide a rough estimate of the likely number of new vehicle observations I would have had if I was able to continuously observe vehicle locations. To achieve this, I must assume a functional form of a fitted line. In Figure A1 I show both a linear and quadratic extrapolation line. The linear approach suggests I would record 1,693,441 new vehicles if I was able to continuously observe vehicle locations. The quadratic approach suggests I would record 1,863,791 new vehicles.

Assuming the quadratic approach, the difference between the true number of vehicle drop-offs (1,863,791) and the actual number I use in analysis (1,649,491) is equal to 13.0%, meaning the final data set omits 13.0% of new vehicle observations. Overall, I determine this source of bias is fairly small. It is also unlikely that this type of bias

Figure A1: Estimating Missed Observations



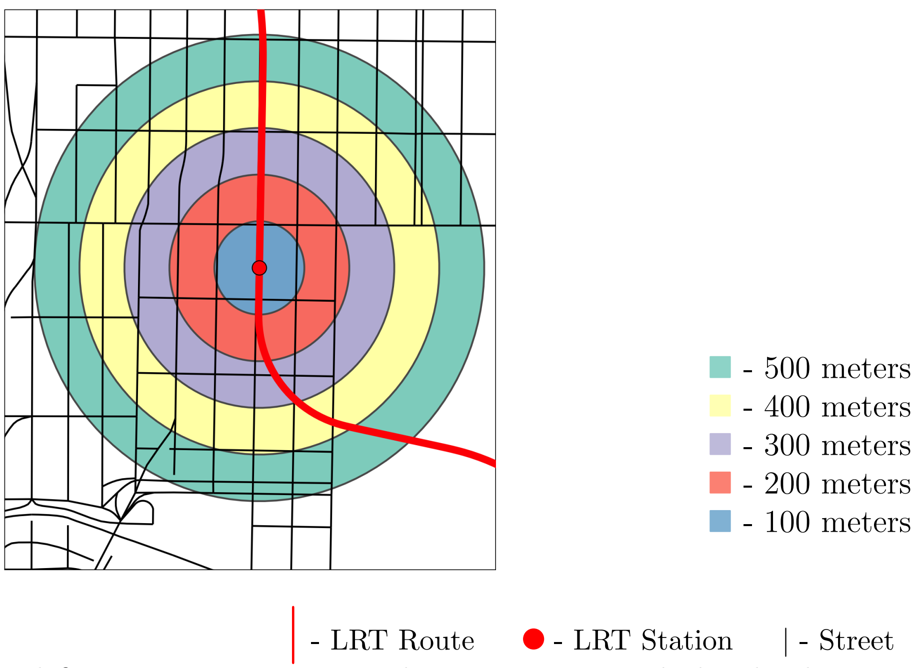
The solid line plots the number of new vehicle arrival observations made when using API data with sampling intervals of 10, 15, 20, 30 or 60 minutes. I use these data points to fit a line and extrapolate the data back to the vertical intercept to approximate the true rate of vehicle generation.

could explain the significant results of this paper. If missed observations are equally common across both treatment and control areas and through time then missed observations would not contribute to higher drop-off rates in treated areas specifically. I therefore ignore this source of bias when reporting main estimates.

Appendix B: Alternative Definition of Local Areas

In the main results of this paper I define local treatment areas by creating isochrone boundaries around LRT stations. In this appendix I test the robustness of results to an alternative method for drawing local treatment areas. Rather than isochrones, I draw circles of a set geodesic radius, centered on the station platform, and define these circles as the treatment area (Figure B1).

Figure B1: Circle Area Definition Example, U District Station



I define treatment areas around LRT stations to calculate local micromobility activity. The figure shows treatment areas defined by circles with a constant geodesic radius. I show the U District Station as an example but perform similar calculations for the remaining 15 station locations.

Table B1 provides main results for the circular treatment area method. In columns 1-3 I adopt a 100 meter treatment radius, while in columns 4-6 I adopt a 200 meter radius. I find results that are consistent with the isochrone method. I find overall vehicle arrivals rose by 0.77 vehicles/hour/km^2 within 100 meters of newly opened stations (column 1). The 100 meter treatment areas are smaller than any of the isochrone defined areas. The larger effect estimated closer to stations provides evidence of a dramatic rise in micromobility vehicle flow directly beside LRT stations, providing evidence that vehicles are being dropped off specifically at the stations. At a 200 meter treatment radius I estimate smaller, but more precisely estimated results. The smaller point estimates are consistent with a spatial decay of the stations' effect on micromobility flow. I find declining, but significant, results up to a 500 meter treatment radius.

Table B1: Effect of LRT Station on Local Flow of Micromobility Vehicles, Circle Method

	(1)	(2)	(3)	(4)	(5)	(6)
New station	0.767**	0.555**	0.213*	0.332**	0.196**	0.136**
x Post opening	(0.160)	(0.097)	(0.087)	(0.073)	(0.062)	(0.030)
UW station	0.386*	0.431**	-0.046	0.106	0.147**	-0.041
x Non-summer month	(0.136)	(0.078)	(0.089)	(0.053)	(0.029)	(0.041)
Day fixed effects	Y	Y	Y	Y	Y	Y
Station fixed effects	Y	Y	Y	Y	Y	Y
Vehicle type	All	Bikes	Scooters	All	Bikes	Scooters
Geodesic radius	100 m	100 m	100 m	200 m	200 m	200 m
R^2	0.164	0.239	0.122	0.304	0.306	0.247
Adjusted R^2	0.103	0.184	0.058	0.253	0.256	0.192
N	192	192	192	192	192	192

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis.

Appendix C: Effect of Dependent Variable Transformations

In the main regression specifications of this paper I follow Equation 1 and use a nontransformed dependent variable. Estimating a linear relationship allows for a simple interpretation of coefficient estimates, as β_1 corresponds to the increase in vehicle flow caused by treatment, represented in vehicles per hour per km^2. However, the flow of new vehicles is mechanically bound at zero and some stations have much higher rates as compared to the average, causing the dependent variable to be rightward skewed. In this appendix I test the robustness of results to transformation of the dependent variable.

In Table C1 I repeat the main analysis of this paper but use a log transformed dependent variable. In cases where the value of the dependent variable is zero I impute a value equal to a case where I observed one new vehicle in that month. Instances of zero are rare. For example, using five minute isochrone treatment areas I only have one instance of a zero out of 192 observations. In 5 out of 6 regressions in Tables C1 I find statistically significant, positive results, consistent with the paper's main results.

Table C1: Main Results with Log Transformed Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
New station x	2.352**	2.314*	1.698*	1.272*	1.131	1.793**
Post opening	(0.778)	(0.803)	(0.613)	(0.438)	(0.561)	(0.521)
UW station x	0.497**	0.395*	0.359	0.353*	0.146	0.088
Non-summer month	(0.158)	(0.149)	(0.260)	(0.124)	(0.153)	(0.224)
Day fixed effects	Y	Y	Y	Y	Y	Y
Station fixed effects	Y	Y	Y	Y	Y	Y
Vehicle type	All	Bikes	Scooters	All	Bikes	Scooters
Isochrone radius	3 min	3 min	3 min	5 min	5 min	5 min
R^2	0.361	0.273	0.371	0.426	0.356	0.419
Adjusted R^2	0.314	0.220	0.325	0.384	0.308	0.377
N	192	192	192	192	192	192

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis.

An alternative functional form that may be appropriate for this setting is an inverse hyperbolic sine (IHS) transformed dependent variable. The IHS transformation is a common way to approximate the shape of a log transformation in cases where there are observations with zero values. Table C2 shows main results using an IHS transformed dependent variable. In six out of six regressions I find statistically significant, positive results. Overall, the results of this paper are not changed qualitatively when applying log or IHS transformations to the dependent variable. Quantitatively, results are also similar, with log transformations implying slightly larger effects and IHS transformations implying slightly smaller effects compared to the main estimates of the paper.

Table C2: Main Results with Inverse Hyperbolic Sine Transformed Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
New station x	0.430**	0.276**	0.194**	0.234**	0.132*	0.128**
Post opening	(0.101)	(0.075)	(0.055)	(0.068)	(0.061)	(0.027)
UW station x	0.255**	0.259**	-0.040	0.072*	0.074*	-0.022
Non-summer month	(0.067)	(0.045)	(0.060)	(0.032)	(0.025)	(0.028)
Day fixed effects	Y	Y	Y	Y	Y	Y
Station fixed effects	Y	Y	Y	Y	Y	Y
Vehicle type	All	Bikes	Scooters	All	Bikes	Scooters
Isochrone radius	3 min	3 min	3 min	5 min	5 min	5 min
R^2	0.288	0.267	0.235	0.355	0.352	0.278
Adjusted R^2	0.237	0.213	0.179	0.308	0.305	0.225
N	192	192	192	192	192	192

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis.