Micromobility’s Macro Aspirations: A Spatial and Econometric Analysis of Destinations, Demographics, and Modal Interactions

David Whyman

April 24, 2020

Submitted in partial fulfillment of the requirements for the degree of
Bachelor of Arts in Public Policy *at* The University of Chicago

Preceptor: Allison Kolar

Reader: Dr. Kevin Credit

Abstract

Micromobility companies and some policymakers tout scooters as an emissions-reducing solution to the last-mile problem of public transportation and a boon to low-income mobility. Yet there is surprisingly little empirical understanding of whether scooters are living up to these aspirations. With a focus on Washington, DC and comparisons to Los Angeles and Louisville, this paper uses 2-stage least squares methods to model variations in supply and demand for scooter rides across locations within cities. Interpretations of this model generate insights about (1) destination patterns within Washington and other cities (2) the demographic profile of riders and capacity utilization in low-income areas, (3) whether scooter usage complements or substitutes for public transportation and ultimately reduces greenhouse emissions. The analysis concludes that three non-demographic landuse factors (metro stations, businesses with alcohol licenses, and proximity to the downtown) explain 60-80% of variations in scooter ridership within most American cities. Scooters are primarily used for travel to leisure destinations. Moreover, scooters in low-income areas are systematically underutilized due to low effective demand. This result casts doubt on whether the current municipal policy focus on expanding supply will be effective in boosting low income mobility. Trip pattern analysis suggests that scooter usage is deeply interconnected with the light-rail network in Washington, DC, and may offer a scalable solution to public transit's last-mile problem.

Table of Contents

Introduction

Scooter share services are a burgeoning phenomenon in the urban mobility scene, expanding from just 5 US cities in the beginning of 2018 to over 200 today ("Mapping" 2019). At 38.5 million scooter trips in their first year in operation, scooter usage already outstripped bikeshare trips (NACTO 2019). Scooter trips even approached the order of magnitude of bus trips in some places. In Austin, TX in September 2019, for example, approximately 20,000 scooters were ridden 535,000 times, nearly a third of the 1.7 million bus rides that month ("Ridership" 2019). This is especially impressive considering the number of scooters is strictly limited by municipal operating permits, while city buses are supported and subsidized. The scooter appears to be on its way to becoming a legitimate, quantitatively important mode of public transportation, like the city bus.

Amidst scooters' sudden ubiquity, there is surprisingly little empirical understanding of what they are used for. Companies claim that scooters are a lifeline to the poor in areas underserved by public transportation. Social media and popular news coverage claim that scooters are just toys for tourists and college students. Anecdotal evidence indicates that urban residents use scooters for essential trips such as errands. Perhaps some young white-collar professionals even use scooters as their principal commute mode, including a quarter of all scooter users in one survey (NACTO 2019). Amid this cacophony, this paper attempts to shed light on key empirical issues of (1) destination patterns, and (2) demographics of use. Regarding (1) destination patterns, (A) What drives where scooter rides are concentrated, and what can we infer is the primary purpose of scooter trips: commuting, leisure, or just joyriding? (B) Are these destination patterns consistent in cities across the country? Regarding (2) demographic patterns: (A) What demographic patterns characterize scooter ridership, and (B) will supplying more scooters to low-income neighborhoods generate more scooter use there, contributing to low-income mobility? This paper has the advantage of an unprecedentedly granular "thousandth-of-a-degree" block group-level analysis of scooter trip origins and destinations: Carefully using location as a proxy for demographics and destination, this paper models patterns in scooter usage using 2-Stage Least Squares (2SLS) methods to identify key drivers.

The notion that scooters could help low-income people might raise eyebrows. Yet, evidence about potential usage suggests that low-income commuters can access more jobs by scooter than by public transit in some places ("Job Access" 2018). Moreover, Washington, DC and many other cities already require companies to offer low-income users heavily discounted rides and the option to sign up without a smartphone or credit card. Further, Washington, DC requires scooter companies to place a minimum amount of their fleet in low-income areas. This minimum is set to increase from dozens to hundreds. Will municipal policies to increase the supply of scooters be effective, or is there a demand-side issue that needs to be addressed? Extending the 2SLS model, we can identify whether the existing number of scooters in low-income areas is underutilized; if so, this indicates that there is a lack of demand, and city policies to induce low-income usage through increased supply alone may fail.

This paper also addresses a third key empirical issue: (3) Public transit complementarity and carbon footprint. What exactly is the relationship between the scooter and other forms of transportation, such as the city bus and the subway? If people are using scooters to reach transit stops that were otherwise prohibitively out of walking distance, the presence of the scooter may enable people to complete trips by bus or light-rail that otherwise would have required a car. Is the scooter replacing the car for some short-distance trips? What if, on the other hand, people who would have taken public transit are instead using scooters to go directly to their final destination? At stake is whether the expansion of scooters –which pollute more than buses but less than cars per passenger mile travelled– will increase or decrease greenhouse gas emissions from transportation (Hollingsworth et al 2019). With an unprecedentedly granular trip pattern analysis of origin-destination scooter trip data, this paper explores whether scooter usage (3A) complements and substitutes for public transit ridership, and (3B) reduces or increases net greenhouse gas emissions, considering its substitution for autos and walking.

Background

Not everyone is happy with scooters. Amid high-profile media stories about scooters cluttering sidewalks, inviting vandalism, and causing crashes, criticism has been directed at local policymakers for insufficiently protecting citizens from these hazards (NACTO 2018). In Austin, TX, scooters have been the subject of hundreds of 311 complaints every month ("Austin" 2019). Across cities, scooters have spawned a variety of regulatory responses. Some major cities such as Washington, DC, Austin, TX, and Los Angeles, CA took a robust managerial stance, delineating tightly-regulated scooter 'pilot' frameworks: scooter companies apply for permits to operate under strict fleet size limitations, subject to a plethora of equity, safety, and data-sharing rules and significant fees (Herrman 2019). The legal basis for these regulations is that the scooters operate in the public "right-of-way" (sidewalks and streets), and therefore require discretionary permits. In these places, the apparent discord of scooters on the streets contrasts with orderly, top-down regulatory efforts. These three cities in particular have chosen to significantly expand their programs after an initial evaluation phase. In other cities, however, resources were not allocated towards robust processes for enforcing comprehensive regulatory frameworks (Herrman 2019). This is especially true for smaller cities with less available resources. Some cities large and small, some as big as New York, NY, and Chicago, IL, have maintained bans on scooters following brief pilot programs that appeared chaotic or politically unpopular. In these locations, the regulatory environment is rapidly evolving.

Identifying key segments of scooter users and destination activities is very relevant to current municipal policy dilemmas. One way to frame the municipality's scooter regulatory decision is a weighing of costs against benefits. By some measures, safety hazard appears to be the most salient cost of allowing scooters. Out of concern for safety, the governor of New York recently vetoed a bill to overturn a statewide scooter ban. But what exactly are the benefits? As a mode of transportation, scooters benefit those who use them by enabling access to certain destinations in order to perform certain activities (such as commuting to work, going to a restaurant, etc). This mobility is an important benefit of scooters; but mobility for whom, and to what end? Policymakers may weigh the mobility benefits of scooters differently based on whether the group of people receiving those benefits has historically unmet mobility needs. Likewise, policymakers may value this form of mobility more highly if they believe the destination activities are normatively important. For instance, if scooters have the potential to ease low-income people's access to jobs, policymakers may value the scooters enough to tolerate a certain amount of safety hazard. On the other hand, if scooter usage is primarily recreational[1], they may opt to restrict or ban scooters instead. Therefore, producing a quantitative understanding of the profile of users and destinations is important as policymakers weigh the mobility benefits of scooters against their safety costs.

---

[1] All scooter rides can be categorized as either 'destination-driven' or 'recreational'. 'Destination-driven' refers to all rides initiated in order to arrive at a destination (i.e. the scooter is an actual mode of transport), regardless of whether that destination is a workplace or a friend's house. 'Recreational' includes only those rides where the purpose of using the scooter is solely to enjoy the experience of the ride itself (i.e. a joyride).

Literature Review

Given the importance established above, surprisingly little research has been produced on basic questions surrounding scooters. This is especially the case regarding low-income usage. While a micro-simulation in Nashville showed that scooters could more than double the number of jobs accessible in 45 minutes from many low-income areas (in comparison to jobs accessible by public transit), no study of usage has attempted to empirically confirm whether poor people are actually using scooters in this way ("Dockless" 2018). The few studies that have commented on the demographics of scooter usage simply note very low usage in black and low-income neighborhoods in Washington, DC (McKenzie 2019a, McKenzie 2019b). However, no research exists attempting to explain *why* volume is low. Poor people could have a low propensity to use scooters, or scooter companies could be placing inadequate numbers of scooters in low-income areas. Neither the degree to which scooters have been supplied to low-income neighborhoods nor the scooter preferences of low-income people have been studied. Policy efforts are underway to induce scooter usage in low-income areas and ensure equitable geographic coverage in practically every city where scooters are present (Herrman 2019). To what degree have these policies been successful? City regulations mandating a minimum number of scooters be placed in low-income areas have not been evaluated. In addition, there is almost no research on the design, implementation, or uptake of scooter ride discount programs for low-income residents, even though these programs exist in nearly every city with scooters. This paper will shed light on these ignored but important issues by offering a more thorough understanding of scooter usage patterns in low-income areas and throughout cities.

A somewhat greater volume of research comments on the profile of usage. One theory is that scooter usage is primarily recreational. It requires a certain amount of physical fitness that could be especially discouraging for the elderly and perhaps even the middle-aged: exposure to the elements and the necessity of remaining standing and balanced on the moving scooter for the duration of the trip. Under this reasoning, most of the population would not want to rely on scooters to make a necessary trip or get to work on time. Some, though, might take pleasure in the sensation of moving quickly through the air on paved surfaces where foot and car traffic is low and when conditions are pleasant. Interestingly, most of the evidence supporting the purported unsuitability of scooters for destination-driven usage is derived from temporal rather than spatial evidence (Noland 2018, McKenzie 2019a). One study of scooter trips in Louisville, KY indeed found that usage was largely recreational, noting that weather has a statistically significant influence on trip volume (Noland 2018). However, that study did not attempt to actually examine origin-destination trip patterns. A study in Washington, DC found that scooter usage is recreational because volume is lower during weekday rush hours but rises in the afternoons and on weekends (McKenzie 2019a). However, this study does not account for the possibility of multiple discrete segments of usage; a large portion of usage could be leisure-driven, but a small segment could be commuting; if this were the case, rush-hour peaks would not be detectable looking at all of the data combined. Indeed, in a national survey, on the other hand, 25% of scooter riders nationally report commuting as their primary trip, while 30% report their purpose as recreational (NACTO 2019). This paper will deepen the understanding of scooter usage by examining spatial patterns rather than temporal patterns.

Research suggests that scooters have incredible potential to reshape the urban transportation scene and lower greenhouse gas emissions, but the literature lacks empirical evidence on how this is progressing. Based on an examination of all stages of production and usage in a scooter’s lifetime, researchers have estimated the level of per passenger-mile (PPM) greenhouse gas emissions of scooters in comparison to other modes: Scooters produce less than half the PPM emissions of cars, but more than twice the PPM emissions of high-ridership buses (Hollingsworth 2019). Needless to say, scooters produce far higher PPM emissions than walking or biking. It is worth noting that there is some disagreement among studies on the exact degree to which scooters reduce greenhouse gas emissions. This is because the majority of the emissions are not from the actual scooter rides, but from initial manufacturing and daily van routes that deploy the scooters. The Hollingsworth estimates are therefore quite sensitive to assumptions about scooter service lifespan and number of uses per day; the greater these are, the more trips needed to defray manufacturing and van emissions. Even taking for granted that the Hollingsworth assumptions of a six-month lifespan and several uses per day are roughly accurate, scooters have the potential to decrease greenhouse gas emissions from transportation only if they are substituting for car trips (Bordes Roca 2019). One simulation involving data on real scooter rides conducted in Munich, Germany found that scooters have the potential to become the main transit mode for residents of core cities and substitute for cars (Hardt & Bogenberger 2019). However, this study was a mini-pilot involving only six scooters given to individuals as their property rather than as shared devices; generalizations cannot be made to the networks of tens of thousands of shared scooters.

Perhaps the most plausible and most well-studied way that scooters could influence the urban transportation landscape is as a new solution to an old problem: the first/last-mile problem of public transportation. While a person can drive a car directly from origin to their final destination, one can only take public transit from the closest station to their origin to the closest station to their destination. Often, light-rail (and to a lesser extent the bus) is able to compete with or outperform car travel in terms of speed of the vehicle; however, the public transit vehicle cannot get all the way to the destination. Travelling the “last mile” between the destination transit station and the actual destination can involve the sizable inconvenience of having to transfer to a bus or walk. The first and last mile of a transit trip constitute an outsize share of door-to-door time; this can ultimately lead people to choose cars over public transportation (Wang & Amadeo 2016; Zellner 2016; Desheng 2016). Much empirical evidence shows people are typically unwilling to use public transit if there is not a station within 0.5 miles of their origin and destination (Kuby & Barranda 2004; FTA 2017; Guerra, Cervero & Tischler 2012). The key: Some hope that dockless scooters can change the equation by providing a way for a person to quickly get from wherever they are to a public transit station that may be a mile away (Bordes Roca 2019). While a mile-long walk still can take 20-30 minutes, a mile-long scooter ride can take only 6 minutes. One survey found that 25% of scooter users’ primary trip purpose is to connect to public transit (NACTO 2019). However, a lack of analysis of empirical data leaves the matter uncertain.

Key Research Questions (RQs)

RQ 1 – Destination Patterns & Geographic Comparison

This paper hypothesizes that there exist certain locational attributes that can powerfully predict the variation in scooter usage across place and time within any American city. If trip pattern analysis or an econometric model can identify which locational attributes are the key drivers of scooter supply and demand, then we can understand the latent forces that underly patterns in scooter activity across the various areas of any city. Because different destinations are associated with different activities, identifying the locational drivers of scooter usage can illuminate the activities that motivate scooter use. An econometric analysis would involve aggregating scooter rides by location of origin or destination and identifying characteristics that distinguish between high- and low- ridership locations. Trip pattern analysis would involve identifying characteristics of pairs of locations that are connected to each other by a high volume of scooter trips. (A) First, we can perform these analyses in Washington, DC. (B) Then, we can see if the same patterns hold in other cities throughout the country, specifically Los Angeles, CA and Louisville, KY.

RQ 2 – Demographic Patterns & Low-Income Mobility

(A) What are the major demographic patterns in scooter usage? Because certain locations are associated with different types of people, the pattern of destinations can give clues as to the demographic profile of scooter users. (B) Can scooters help low-income people who cannot afford cars access their jobs or other activities? When future Washington, DC regulations requiring a high number of scooters be deployed in low-income areas go into effect, econometric analysis could be used to identify whether ridership increases. However, that is a task for future research. First, this paper will attempt to characterize the current volume and patterns of scooter usage by low-income individuals. Trip pattern analysis and econometric modeling will both assist in answering this question.

RQ 3 – Public Transit & Carbon Footprint

Another question is how scooters interact with other modes of transportation, especially public transit. (A) Trip pattern analysis can be used to look at existing connections between scooters and public transit. If scooters are used to go between transit deserts and transit stations, scooters likely complement transit, helping solve transit's last-mile problem by expanding the effective catchment zone of transit stations. Meanwhile, if scooters are used to go between locations within walking distance of transit stations on the same line, they likely substitute for transit, cannibalizing its ridership. This is important because it impacts greenhouse gas emissions. Do scooters substitute for cars, complement transit, and decrease emissions? Or do scooters substitute for transit and add to emissions? What modes scooter riders would have chosen in the absence of scooters is a difficult question to answer; it is hard to know how individual people would have made decisions under unobservable, hypothetical conditions.

Geography Selection Rationale

Washington, DC is selected as the main city of study in this paper because it satisfies a number of desirable characteristics. Washington, DC is a mid-size American city with a large scooter program, making its results more generalizable to cities across the country considering scaling their scooter programs. A notable attribute of Washington, DC is that its public transit system is highly developed compared to other American cities of the same size: Washington, DC's light-rail subway system has nearly 100 stations and notches 600,000 trips per weekday (in a city of 700,000 people) ("Ridership" 2020). The presence of a robust bus and light-rail system makes DC ideal for observing interactions between public transit and scooters which are the focus of RQ 3. In addition, Washington, DC has mandated generous low-income discounts as well as minimum requirements for scooter supply in low-income areas, making it ideal for observing low-income usage as per RQ 2.

Louisville, KY and Los Angeles, CA were selected as comparison cities with DC to maximize the generalizability of common patterns. Los Angeles is the second-largest city in the country, while the others are medium-sized. Washington has a robust, well-utilized public transit network, which the others lack. Louisville is in the nation's hinterland, while Los Angeles and Washington are on opposite coasts. The year-round warmth of Los Angeles precludes any notion that the wintry study period could discourage certain demographics or types of scooter usage that would change the results. Given the intrinsic differences across these three cities, any common destination pattern found among them is unlikely to be specific to these three cities and more likely to be nationally generalizable. In addition, the unique granularity and historical span of Louisville's scooter trip data makes possible laser-focused trip pattern analyses on two spatially distinct "scooter ecosystems" in the city: The University of Louisville campus and the historic downtown.

Data

The number of scooter rides originating in a given census block group within a given city on a given day was the unit of observation for the final dataset after aggregation and cleaning. Each observation was paired with demographic and economic data from the American Community Survey (ACS) and landuse data from city data portals. The cleaning and aggregation of the data was a very intensive process, described below, and relies on the ability to make inferences about scooter's status based on patterns in the API. As is the case in Washington, DC, municipal governments typically require scooter companies to provide APIs to the public. Data was collected and cleaned in the manner described below for Washington, DC and (separately) Los Angeles, CA from November 2019 through January 2020. On the other hand, Louisville, KY made available pre-cleaned scooter data at the trip level showing origin and destination coordinates and timestamps. Louisville's already-clean data was used to validate the data cleaning process for Washington, DC and Los Angeles, CA. After aggregation, the scale and patterns of Louisville scooter trips largely cohere with those of the data from Washington, DC and Los Angeles, CA.

The data collection for Washington, DC and Los Angeles, CA consisted of pulling the real-time latitude and longitude coordinates of every available scooter from the publicly available API every 2 minutes. Here, an available scooter is one that is available to be ridden by a customer. If a customer begins a ride on scooter A at a particular time, scooter A will disappear from the API at that time (see table 1 below).

Time	The Data: Scooter A is present in API?	Our inference about what is happening to Scooter A
T=0	Yes, Location A	Scooter A is not being ridden by anyone, and is **available** to be ridden

T=1	Scooter A disappears from API	customer began a ride on scooter A (at location A)
T=2	No	Customer is currently riding on scooter, so scooter is **not available** to other customers
T=3	Scooter A reappears in API	customer ends ride (at location B)
T=4	Yes, Location B	Scooter A is not being ridden by anyone, but is **available** to be ridden (at location B)

Table 1: Example scooter status inference from API

Further, scooter data could be aggregated in order to discern the number of available scooters in each census block group in a city throughout the day at a 2-minute temporal resolution. This enables the detection of the number of scooter rides starting in a given census block group on a given day (after intensive data cleaning). For instance, if the number of scooters in a block group decreases by one over a time increment (a 2- minute period), this means one scooter ride began in that block group during the time increment (see table 2 below):

Time	Number of scooters present in API located within block group A	Inference
7:00am	10	10 scooters are present in block group A at 7:00
7:02	9	1 ride began in block group A between 7:00 and 7:02
7:04	9	0 rides began in block group A between 7:02 and 7:04
7:06	11	2 rides ended in block group A between 7:04 and 7:06
7:08	10	1 ride began in block group A between 7:06 and 7:08
Total Inference: 2 scooter rides began in block group A between 7:00 and 7:08		

Table 2: Example aggregate scooter ride inference from scooter status data

This inference pattern makes possible the construction of a dataset in which the unit of observation is the number of scooter rides originating in a block group in one day.

The assumption in block-group aggregation is that scooter rides will not both end and start in the same census block group in the same 2-minute time increment. If one scooter ride ended and another scooter ride started in the same block group in the same minute, the inference would be that zero rides occurred. The relatively low spatial-temporal density of scooter rides as reported by official sources and the small land area of a census block group validates the likelihood that this assumption is correct. Washington, DC DOT reports that approximately 10,000 rides per day occur in the city. This means ~26 rides starting and ending in an average 2-minute increment, and these rides are spread across 450 census blocks of (on average) .15 square miles each. Viewed another way, the average block group experiences roughly 21 rides starting and 21 rides ending per day, spread across 330 time increments (assuming rides occur during daylight and into early evening). Although there might be some instances of undercounting in high-traffic outlier census block groups, the impact on overall analysis is minimal. Experiments were conducted where the data collection frequency was increased to 1-minute time increments to see if more rides could be detected; increases in rides were negligible.

Another element complicating the data cleaning is that agents of the scooter companies will occasionally remove a scooter from a census block group in order to charge it or deploy fully-charged scooters to a census block group. Without data cleaning, it is impossible to tell whether the number of scooters in a block group decreasing by one would be due to a customer beginning a ride on a scooter or due to a company removing a scooter in order to charge it. Under this scenario, inferring change in number of scooters as equal to number of scooter rides would lead to inaccuracies. Fortunately, the scooter battery level percentage provided in the API allows us to distinguish between scooters taken offline for charging versus those taken offline for riding. If a block group's scooter count increases as a result of a full-battery scooter appearing, that scooter must have been deployed by a company agent after charging and cannot possible be the result of the end of a ride (which would have decreased the battery level). Similarly, the disappearance of a scooter whose battery level is extremely low is not likely to be the start of a ride. Therefore, the disappearance from a block group of a low-battery scooter was not counted towards the total of rides, nor was the appearance of a high-battery scooter.

Another complexity arising from the data is the daily ‘rebalancing’ cycle, in which scooter company agents collect scooters each evening and move them to another area by early morning the following day. DDOT requires rebalancing to be completed by 7:00am, and the data shows a large drop in the number of scooters available beginning at 8:00pm (this time is also mentioned by a number of journalistic accounts as the beginning of rebalancing). In order to avoid confusing an agent of the company rebalancing a scooter with a customer riding a scooter, data collected after 8:00pm and before 7:00am was excluded from the dataset. Therefore, the number of scooters in a given block group at 7:00am is taken as the output of the scooter company’s rebalancing efforts, and therefore the initial supply of scooters to that block group. Therefore, an initial supply number as well as a daily ridership number can be obtained for each block group.

For most scooter companies in most cities, usage cannot be analyzed with confidence on the level of individual scooter trips because the identification numbers of the scooters are intentionally stripped or scrambled by companies in order to make origin-destination linkage impossible for researchers (e.g., scooter A from table 1 might appear in the API with a different ID number at T=3 than at T=1). For this reason, block group aggregation as described above was the chosen data processing method. Fortunately, there are two exceptions: First, all time-stamped, origin-destination linked scooter trips in Louisville, KY are available for public download due to a decision of that city’s Chief Data Officer. Second, the identification numbers on Jump scooters in Washington, DC and Los Angeles, CA do not appear to have been scrambled, enabling the backing-out of timestamped, origin-destination linked scooter trips. Origin-destination data (data from the two exceptions above) are used for trip pattern analysis, while the aggregated data (data from APIs processed in census block groups as described extensively in this section), will be used for econometric modelling, described in the following section.

Methodology: Locational Characteristics and Supply & Demand Modeling

This paper hypothesizes that there exist certain locational attributes that can powerfully predict the variation in scooter usage across place and time within any American city. In order to test this hypothesis, various locational characteristics were paired with scooter ride data aggregated on the block group level. Thus, one observation consists of the total number of scooter rides originating in a particular location (one census block group) over a particular period of time (one day).

2SLS Model:

This paper proposes the following general econometric model for estimating supply (number of scooters) and demand (scooter rides) across locations (subscripted L) and times (subscripted T) within a city. The demand equation below summarizes all relevant exogenous variables as locational effects; the actual model, elaborated later, will decompose this grouping into individual covariates. The supply equation below also describes "deployment effects" (to be represented as "company fixed effects" later on). Deployment effects account for the characteristics of the network of organizations and employees that distribute scooters subject to municipal regulations. The inclusion below of scooter ridership as a predictor of scooter supply, and scooter supply as a predictor of scooter ridership, is a notable endogeneity. This setup posits that (1) the number of scooters supplied to an area creates the conditions of possibility for scooter rides, and (2) scooter companies collect and analyze scooter trip data to identify which locations have the highest ridership and optimize scooter supply choices for maximal revenue. This means that locational factors affect ridership directly *as well as indirectly through their effect on company scooter supply decisions which effect ridership.*

Demand:

$$\text{Scooter Rides}_{\mathrm{L,T}} = B_0 + B_1\text{Scooters Supplied}_{\mathrm{L,T}} + B_2\text{Location Effects}_{\mathrm{L}} + e_{L,T}$$

Supply:

$$\text{Scooters Supplied}_{\mathrm{L,T}} = B_0 + B_1\text{Scooter Rides}_{\mathrm{L,T}} + B_2\text{Deployment Effects}_{\mathrm{L}} + e_{L,T}$$

This endogeneity between supply and demand dictates use of 2SLS modeling. This technique separates out the *direct* effect of locational factors on ridership from the *indirect* effect of locational factors on ridership by way of ridership-anticipating company scooter supply decisions. This is critically important because if we observe that there is low ridership in low-income areas, 2SLS is the only way to determine whether this is primarily because people in low-income areas have low demand for scooter rides (direct effect) or because companies choose not to supply scooters to low-income areas (indirect effect). This is a central question of the paper. Given a demographic characteristic A such that the number of rides for locations with that characteristic tends to be lower than average: if characteristic A is significant and negative in the demand equation above (which controls for the effects of supply), then this means that people of that demographic group (e.g. low income people of color) have a lower propensity to ride scooters (direct effect of characteristic A on demand). However, if such a demographic characteristic is significant and negative in the supply equation, this would mean that the decreased ridership for that demographic is principally due to company supply decision.

The model requires only conservative assumptions based on simple facts about the scooter business. The assumption of endogeneity of supply and demand described above is highly typical for all goods and services in the economy (though for most goods, this endogeneity occurs through prices). For scooters, however, prices are constant over the short term relative to supply and demand due to municipal regulations. Throughout, supply refers to the number of scooters supplied to a particular area by the companies, while demand refers to the number of scooter rides initiated in that area (e.g. ridership). Regarding the effect of supply on demand, the number of scooters placed in an area strictly limits the number of scooter rides that can begin in that area (no rides can start in an area if there are no scooters there). Further, the more scooters supplied to an area, the lower the average walking distance between any local consumer and the closest scooter in the area, and therefore the easier for a potential consumer to locate a scooter and initiate a ride. Regarding the effect of demand on supply, the decision to supply a certain number of scooters to an area should theoretically be a business decision calibrated to maximize profit. Scooter companies employ data scientists to analyze GPS data on the entire scooter fleet, generating organizational knowledge of which areas have more scooter rides and which have more scooters that are left unridden. Given this fact, rational firms use demand data in order to distribute their fleets of scooters across a city in a manner that would maximize the likelihood that each scooter is ridden, deploying more scooters (supply) to areas with historically more scooter rides (demand).

Econometric analysis under 2SLS is able to separate out direct and indirect effects of supply and demand if the researcher can identify "instrumental variables" or "instruments"; exogenous variables that affect supply without affecting demand (here, deployment affects), and those that affect demand without affecting supply (here, location effects). The first stage of 2SLS consists of two regressions predicting supply and demand, respectively, using the instrumental variables for each. Note that *all* instrumental variables are included in *both* of the equations.

Stage 1D:

$$\text{Scooter Rides}_{\text{L,T}} = b_0 + b_1\text{Location Effects}_{\text{L}} + b_2\text{Deployment Effects}_{\text{L}} + e_{L,T}$$

Stage 1S:

$$\text{Scooters Supplied}_{\text{L,T}} = b_0 + b_1\text{Location Effects}_{\text{L}} + b_2\text{Deployment Effects}_{\text{L}} + e_{L,T}$$

The second stage of 2SLS consists of estimating supply and demand again, this time dividing the instruments between the two equations according to the dependent variable. Instead of using the raw data for demand in the second-stage supply equation and vice versa, the predicted values for supply and demand from the first-stage regressions are used as “stand-ins” for supply and demand when they are represented as explanatory variables in the second stage:

Stage 2D:

$$\text{Scooter Rides}_{\text{L,T}} = b_0 + b_1\text{Location Effects}_{\text{L}} + b_2\text{Scooters Supplied } \mathbf{predictions\ from\ stage\ 1S}_{\text{L,T}} + e_{L,T}$$

Stage 2S:

$$\text{Scooters Supplied}_{\text{L,T}} = b_0 + b_1\text{Scooter Rides } \mathbf{predictions\ from\ stage\ 1D}_{\text{L,T}} + b_2\text{Deployment Effects}_{\text{L}} + e_{L,T}$$

This set up ensures that the coefficients of the exogenous variables in the second stage reflect direct effects only; the second stage estimate of supply (2S, above) uses the predicted values of demand from stage 1D to ‘control for’ demand, and the second stage estimate of demand (2D, above) uses the predicted values of demand from stage 1S to ‘control for’ supply. Therefore, the effect size for proximity to public transit station, in stage 2D represents the direct effect of the presence of a transit station on scooter ridership, independent of company supply decisions. On the other hand, effect sizes in the first stage regressions include indirect effects (e.g., an attribute effecting demand through its effect on supply).

Exogenous Variables:

Block group demographic and socioeconomic characteristics are included in order to proxy for the characteristics of the population of people who *could have been* the riders for the scooter rides originating in that block group. In purely residential areas, it is unlikely that people who do not live in the area are walking around looking for scooters as a means of transportation; foot traffic in residential areas almost entirely consists of nearby residents. It is true that average characteristics such as median age or income are not homogenous within a block group. However, even if the individual riders of scooters in a block group on a given day do not reflect the demographic distribution of that block group, the demographic distribution of the block group still characterizes the 'market of potential buyers' for a ride on the scooters in that block group, in the sense that the potential buyers are any individuals who would plausibly find themselves within walking distance of that scooter over the course of their day. If young people are more likely to use a scooter compared to elderly and middle-aged people, census block groups with a lower median age (or a larger population of 18-29-year-olds) may have a higher amount of scooter rides on average than other block groups when controlling for other factors. Spillover between neighboring block groups could potentially be a concern, as urban block groups are typically around a third of a mile across. Lack of spatial dependence weighting or spatial interaction modeling is a limitation of the methods in this paper and an avenue for future research.

Many key locational characteristics added to the data (in order to conduct the econometric analysis above) describe physical attributes of a place rather than demographic/socioeconomic attributes about the people who live in the place. These "abiotic" attributes are powerful analytical tools because they are applicable in downtown and non-residential areas, where the majority of the scooter rides are located. One key attribute is the landuse and zoning designation: downtown and commercial zones have a much higher density of potential destinations and foot traffic than residential zones. Another important attribute is the distance from the block group centroid to the geographic center of the city, relevant to downtown spillover effects. A critical variable for destination-purpose inference is the quantity of particular types of destinations in a block group. In particular, the number of businesses with liquor licenses in each block group was paired with the dataset. This includes destinations such as restaurants, bars and nightclubs, hotels, and grocery stores. Liquor license and zoning data were found in city Open Data Portal datasets (“Existing” 2019, “Liquor” 2019).

Another important locational characteristic to add to the dataset are transportation characteristics. These include block group-level behavioral characteristics, especially relating to commute mode. ACS data about median commute length as well as percentage commuting to work by car, public transit, and walking were added as variables. A binary variable indicating the presence of a metro station within a block group was added. Regarding demographic characteristics added to the data from the ACS, note that “low-income” block groups throughout the paper are defined as block groups with median household income below $50,000, approximately 200% of the federal poverty line for a family of four (DHCD 2017). The final dataset looked like this (see table 3 below, some characteristics not included):

		unique to a block group on a particular day:		*unique to each block group (regardless of day)*			
Block Group	Day	Daily Scooter rides	Initial daily supply	Dominant land use:	Median income (census)	Median age (census)	Metro Station
Block Group #1	1/1/2020	N rides	[# scooters present at 7:00am, 1/1]	residential	X $$$	Y years	0

Block Group # 1	1/2/2020	M rides	[# scooters present at 7:00am, 1/2]	residential	X $$$	Y years	0

Table 3: Example block group level scooter dataframe paired with locational data

Specification of Instruments

The instrumental variable format for supply ("deployment effects" placeholder in the equations above) is company fixed effects. This specification of deployment effects meets the exogeneity condition of a valid instrumental variable because company supply decisions directly affect supply and do not directly affect demand (they only affect demand indirectly through the effect on supply). The specification of company fixed effects is the number of companies that have served a particular census block group with scooters in the past week. Because the goods offered by the companies are functionally identical (the only difference between scooters of different companies are minor aesthetics such as color scheme) and easily substitutable (switching costs are simply downloading a free app), differences in supply behavior between companies in the same location can only be due to company-specific factors, such as location of the company warehouse and other deployment logistics. While these company-specific factors directly affect company supply behavior and thus total supply of scooters in a location, they are utterly invisible to users. Therefore, the only effect these company-specific factors could have on consumers is indirect, via their end effect on total supply. Therefore, company fixed effects meets the exogeneity criteria of only affecting demand through supply. Company fixed effects also satisfy the relevance criteria, meeting the .001 significance threshold and having a univariate R^2 of 0.24 (see appendix).

The various landuse and demographic variables mentioned are valid instruments for demand ("location fixed effects" placeholder in the equations above). They directly affect demand and do not directly affect supply (they only affect supply indirectly through the effect on demand). Non-demographic locational variables relating to landuse might affect the volume of street traffic, the density of nearby destinations, and the types of people living in a place. All of these things could affect the quantity of scooter rides demanded in a location. However, they would not affect company decisions about scooter supply directly. It is true that the landuse characteristics are observable in some form by the scooter companies. However, given that profit-maximizing companies are optimizing deployment to maximize rides, and given that these companies have the ability to collect and analyze granular data on rides, companies are likely to make deployment decisions based on landuse features only insofar as they believe those landuse features affect ridership. In this sense, landuse characteristics affect supply only through their effect on demand as perceived by the various companies. Because companies have access to granular population data on their customers and historic scooter rides, it is reasonable to believe company perceptions of landuse feature’s effect on rides is likely to be close to the truth.

Trip Pattern Analysis Methodology

The objective of trip pattern analysis is to infer trip purpose as confidently as possible for as many scooter trips as possible within a given city over a given timeframe. The general approach to this inference will be to identify particular segments of trips whose origin-destination locations indicate a trip purpose. Just as ride counts can be aggregated by the geographical unit of census block group, they can be aggregated for any series of geographical subdivisions related to destination. For instance, one could measure the number of rides starting and ending in close proximity to retail establishments, restaurants, movie theaters, offices, or schools, in a given city – even transit stations. One limitation of destination-purpose inference is that many different destinations can be spatially crowded together in downtown areas, making the exact purpose of some scooter trips hard to infer from location alone. In some cities with low densities, on the other hand, different types of destinations are clustered in different areas, forming distinct, separable "ecosystems" of scooter use. The scale of these ecosystems can be analyzed to gage their relative importance within citywide scooter usage.

Another key application of trip pattern analysis is identifying how scooter ridership interacts with other modes of transportation. This goes to the question of whether scooters complement or substitute for public transport, walking, and buses, and the net impact of scooters on greenhouse gas emissions. Given the known origin and destination coordinates and timestamp of each Washington, DC, Jump scooter trip, Bing Maps API can calculate the counterfactual travel time for each scooter trip had that trip been taken by bus, rideshare, or walking (accounting for congestion, waiting for the bus, etc). This allows us to discern how much time each rider saved (or sacrificed) to take a scooter as opposed to other modes. This information can be used to discern which modes would be feasible substitutes in absence of scooters, and which would be least preferred. This assumes that consumers strive to minimize expended money and travel time when choosing between modes.

Results

RQ 1(A): Destination Patterns

Given all locational variables examined, the following four factors were found to be highly-significant and strongly predictive of scooter usage in the econometric model (in descending order of explanatory power): number of businesses with alcohol licenses, downtown zoning designation, (inverse) distance to city center, and the presence of a public transit station. A fifth factor, presence of a large university campus in a given location, was also important in cities with such campuses, specifically Louisville. The land area of each census block group was included in the regression to prevent very densely populated but small block groups and very sparsely populated, geographically large block groups from skewing results. These several factors alone explain over 70% (R-squared>0.7) of the variation in the number of scooter rides between places within Washington, DC (see table 4). For Louisville and Los Angeles, the model explained approximately 80% and 60% (respectively) of the variation in rides (see appendix). Various demographic data (race, age, income, car ownership, and commuting behaviors) as well as other landuse and zoning data (commercial zoning and housing density) were omitted from the model because adding them did not result in increased explanatory power. Further, these patterns hold when rides are aggregated at the thousandth-of-a-degree level. As expected, scooter supply is also found to be a highly significant predictor of scooter ridership, both alone and when added to all configurations of exogenous locational factors. The analysis in this section focuses on the results from data from Washington, DC scooter trips in December 2019. Table 4 below contains the full 2SLS results for Washington, DC.

Supply 2

$$\text{Scooters}_i = \text{b}_0 + \text{b}_1\text{Company Fixed Effects}_i + \text{b}_2\text{Land Area}_i + \text{b}_3\hat{Rides}_i + \text{e}_i$$

Demand 2

$$\text{Rides}_i = \text{b}_0 + \text{b}_1\text{Metro}_i + \text{b}_2\text{Alcohol Licenses}_i + \text{b}_3\text{Downtown Distance}_i + \text{b}_4\text{Downtown Distance Squared}_i + \text{b}_5\text{Downtown Zoning}_i + \text{b}_6\text{Land Area}_i + \text{b}_7\hat{Scooters}_i + \text{e}_i$$

	Dependent variable:			
	Rides (Demand)		Supply	
	Demand 1	Demand 2	Supply 1	Supply 2
	(1)	(2)	(3)	(4)
Supply 1		3.680^{***}		
		(1.277)		
Demand 1				0.103^{***}
				(0.006)
company fixed effects			1.756^{***}	1.407^{***}
			(0.368)	(0.337)
alcohol licenses	4.532^{***}	1.961^{**}	0.616^{***}	
	(0.363)	(0.962)	(0.062)	
is downtown	237.824^{***}	156.599^{***}	21.244^{***}	
	(19.464)	(34.159)	(3.176)	
downtown distance	-78.459^{***}	-54.651^{***}	-3.904^{***}	
	(6.805)	(10.667)	(1.232)	
downtown distance squared	6.739^{***}	4.928^{***}	0.340^{***}	
	(0.769)	(0.988)	(0.129)	
metro station	36.550^{***}	3.497	8.027^{***}	
	(12.792)	(17.102)	(2.094)	
land area	0.0001^{***}	0.00002	0.00001^{***}	0.00001^{***}
	(0.00001)	(0.00001)	(0.00000)	(0.00000)
constant	176.520^{***}	128.789^{***}	2.699	-5.065^{***}
	(13.921)	(21.561)	(3.128)	(1.110)
Observations	450	450	450	450
R^2	0.768	0.772	0.673	0.654
Adjusted R^2	0.764	0.768	0.667	0.651
Residual Std. Error	65.859 (df = 442)	65.321 (df = 441)	10.731 (df = 441)	10.983 (df = 445)
F Statistic	208.591^{***} (df = 7; 442)	186.573^{***} (df = 8; 441)	113.330^{***} (df = 8; 441)	210.397^{***} (df = 4; 445)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Final 2SLS model and Washington DC results.

Regarding the final 2SLS results for Washington (table 4 above), alcohol licenses and downtown-related factors are significant in both demand stages 1 and 2, while the presence of metro stations is significant only in stage 1. The positive significance in demand stage 1 means that metro stations have more rides relative to other places, but the lack of significance in demand stage 2 indicates that metro stations don’t have any more rides than would be expected given the amount of scooters supplied to them. This significance pattern may indicate that companies are aware that metro stations are high-demand areas, and therefore supply them with a correspondingly high amount of scooters. Therefore, the lack of significance of metro stations in demand stage 2 does not mean that metro stations aren’t good predictors of higher ridership, but that companies have adjusted their behavior to supply metro stations adequately relative to demand. Meanwhile, not only are there more scooter rides in downtown areas and areas with many businesses with alcohol licenses than other areas, but there are also more scooter rides than the number of scooters would suggest. This indicates that people are riding their scooters from other locations to downtown and commercial areas, and that these scooters are then being ridden again after arrival there. This validates the hypothesis that the center organizes scooter activity as a hub with decaying influence over distance.

	Dependent variable:					
	arides					
	(1)	(2)	(3)	(4)	(5)	(6)
alcohol licenses	8.918***				4.603***	4.525***
	(0.441)				(0.395)	(0.365)
is downtown		480.842***			264.835***	239.661***
		(24.693)			(20.943)	(19.594)
downtown distance			-128.793***		-68.120***	-75.169***
			(10.231)		(7.238)	(6.747)
downtown distance squared			11.525***		6.291***	6.836***
			(1.215)		(0.833)	(0.773)
metro station				208.234***	49.158***	35.426***
				(21.430)	(13.814)	(12.879)
land area						0.0001***
						(0.00001)
constant	16.607***	41.982***	345.654***	43.488***	171.178***	171.831***
	(5.103)	(4.799)	(19.666)	(6.061)	(15.039)	(13.916)
Observations	450	450	450	450	450	450
R^2	0.477	0.458	0.363	0.174	0.723	0.764
Adjusted R^2	0.476	0.457	0.360	0.172	0.720	0.760
Residual Std. Error	98.132 (df = 448)	99.869 (df = 448)	108.454 (df = 447)	123.330 (df = 448)	71.695 (df = 444)	66.340 (df = 443)
F Statistic	408.747*** (df = 1; 448)	379.197*** (df = 1; 448)	127.213*** (df = 2; 447)	94.418*** (df = 1; 448)	232.217*** (df = 5; 444)	238.610*** (df = 6; 443)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5: Demand instruments regressed on scooter rides alone and combined; Washington, DC results

Table 5 above displays the explanatory power (R^2) of all the instruments (column 5) used in stage 1 of the demand model as well as each instrument alone. The instruments are clearly valid, with very high levels of significance and a combined R^2 of greater than 0.75. Alcohol licenses appear to be the most significant alone of all the factors, explaining nearly half of the entire variation of scooter rides in DC ($R^2 = 0.47$, column 1). On average, there are ~4-5 more scooter rides for each additional business with an alcohol license after other variables in the model are controlled for. It is important to note that number of businesses with alcohol licenses is not simply a proxy for number of businesses in general. When percentage of the block group zoned for commercial development is controlled for, businesses with alcohol licenses remain highly significant and explanatory, while commercial zoning is much less significant. Therefore, businesses with alcohol licenses rather than commercial businesses as a whole drive scooter usage. Counterintuitively, the vast majority of businesses with alcohol licenses in the alcohol

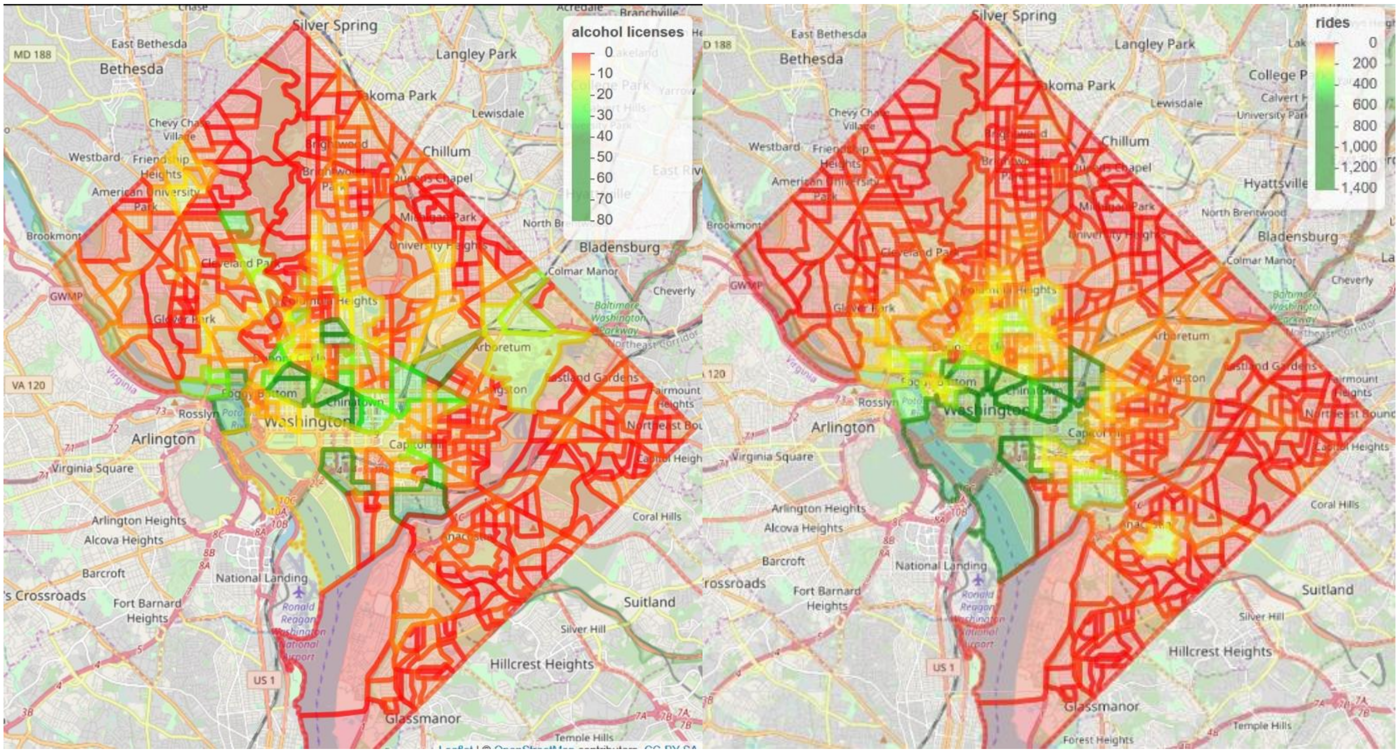

Figure 1: alcohol licenses (left) and scooter rides (right) by block group in DC

license dataset are not liquor stores, bars, or nightclubs, but are actually full-service restaurants. Also included in the dataset are supermarkets, general convenience stores, and hotels. Controlled regressions where each block group's count of businesses with alcohol licenses is disaggregated by the type of business show that almost the entire explanatory power of alcohol licenses on scooter rides comes from restaurants with alcohol licenses, while bars and liquor stores have no explanatory power. Hotels with alcohol licenses have some explanatory power as well.

The high explanatory power of the downtown, downtown distance, and downtown distance squared coefficients confirm the gravitational force exerted by the downtown area on scooter ride patterns. The binary variable for whether or not a census block group is in the downtown area predicts that even after controls, places in the downtown have an incredible 265 more scooter rides than places outside of the downtown on a given day! Further, table 5 column (3) indicates that as one moves away from the downtown area, the number of scooters diminishes (downtown distance coefficient is negative), though at a diminishing rate (downtown distance squared coefficient is positive). This complicates the narrative of a sharp break between the scooter-dense downtown and scooter-sparse non-downtown: areas nearby the downtown zone also see high “spillover” ridership. This means that in addition to many scooter rides between places within the downtown zone, there are a high number of scooter rides from near-downtown areas into the downtown. This could indicate commuting behavior, but it could also indicate leisure or sightseeing destinations. These patterns can be explored more deeply through trip pattern analysis.

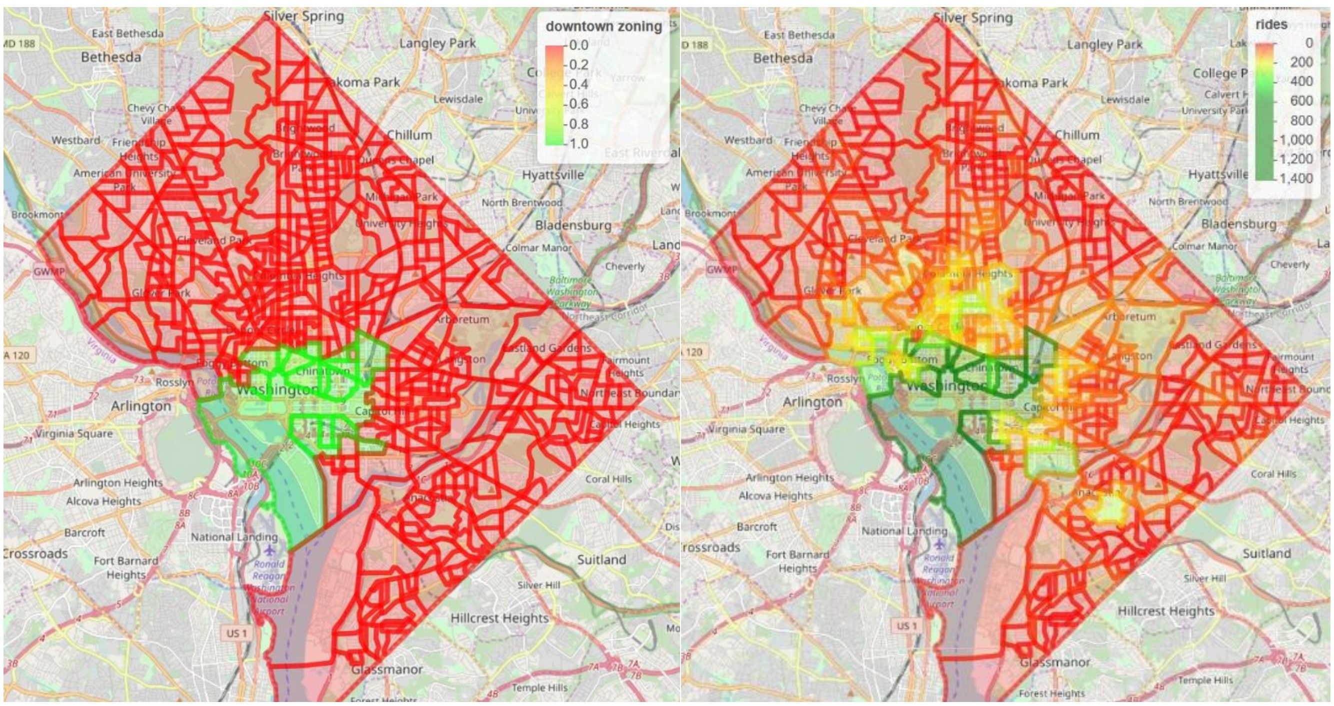

Figure 2: Downtown areas colored green (left) and scooter rides (right) by block group in DC

The final powerful predictor of scooter ridership, the presence of a metro station, could indicate high intermodal connectivity between scooter usage and transit. While the explanatory power is lower than for downtown-related measures or alcohol licenses, the effect size is still strong after these factors are controlled for: the average census block group with a metro station has 49 more scooters than the average census block group without one (table 5, column 5). This

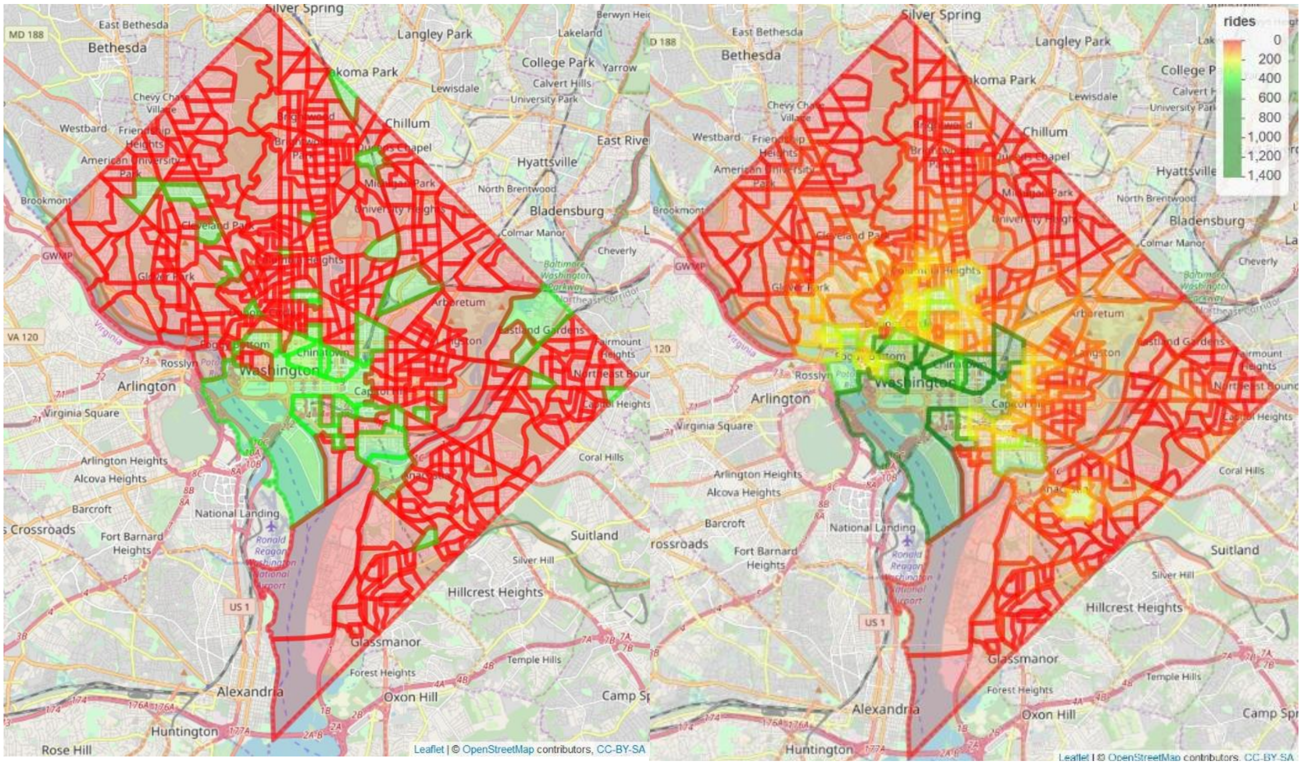

Figure 3: Areas with metro stations colored green (left) and scooter rides (right) by block group in DC

high effect size is especially impressive given the strong collinearity between metro stations and downtown zoning. Trip analysis further explores the strong implication that riders could be using scooters to go between metro stations and their final origins and/or destinations in light-rail scooter intermodal trips.

RQ 1(B) Geographic Comparison

When the econometric analysis trained on data from Washington, DC was applied to scooter rides from 2019 in Louisville, KY, similar results were produced. In stage 1D, alcohol licenses, factors relating to proximity to downtown, and the University of Louisville campus explained nearly 80% of the variation in the quantity of scooter rides (R^2 =0.798, see appendix). Campus was substituted for metro stations because unlike Washington, DC, Louisville lacks a light-rail system and its bus network is poorly utilized. Trip pattern analysis of Louisville, KY concludes that amusement destinations are the dominant usage pattern in downtown areas; this is the numerically largest form of usage, accounting for only somewhat less than half of all rides (concert venues, stadiums, museums, and major parks). The second largest component of usage is college students using scooters to get to class on time when they are running late, highly detectable on the University of Louisville campus. The third component of usage represents trips to restaurants and nightlife, which was also identifiable in Washington, DC. Due to destination crowding, most scooter trips could not be definitively pinned down in Washington, DC and Los Angeles. Connections to light-rail stations in DC is a fourth component of scooter usage identified. There is a concentration of ride endpoints near DC metro stations in low-income areas during the AM and PM rush hours that could suggest intermodal commuting behavior. However, these potential-commute rides were very small in number. Across the three cities studied, connections between downtown and residential areas were only a small proportion of trips.

More than 75% of Louisville scooter rides start or end in the downtown (56%) or on the University of Louisville campus (22%), yet rides connecting between the two are limited (<1%). This suggests that the two areas are separate scooter “ecosystems”, with different types of people using scooters for different purposes. The two zones also have starkly different temporal patterns. Trips in the downtown area always peak on weekends compared to weekdays, and always peak in early afternoons and are low during the morning rush hour, suggesting that the dominant pattern is not commuting, but leisure-related. Trips on campus, on the other hand, always peak on weekdays compared to weekends and always during the late morning, when many students have their first classes. In both downtown and campus areas, use is strictly concentrated at a small number of identifiable destinations. This discovery was made possible by aggregating the data at the 1000th of a degree level: In the maps below (figures 4 and 5), the size of a green circle is the number of scooter ride origins at that location, the size of a red circle represents the number of destinations, and yellow lines indicate flows between locations.

Downtown Louisville

As shown in figure 4 below, a very high proportion of downtown trips start or end at the following five attractions: slugger museum, tourism information center, concert hall, stadium, and a waterfront park (marked by blue stars). This implies that usage is associated with tourism. It is important to note that amusement destination ridership did not significantly increase during the Kentucky Derby; therefore, it is likely that a large portion of amusement destination users are locals engaging in leisure activities that tourists also frequent.

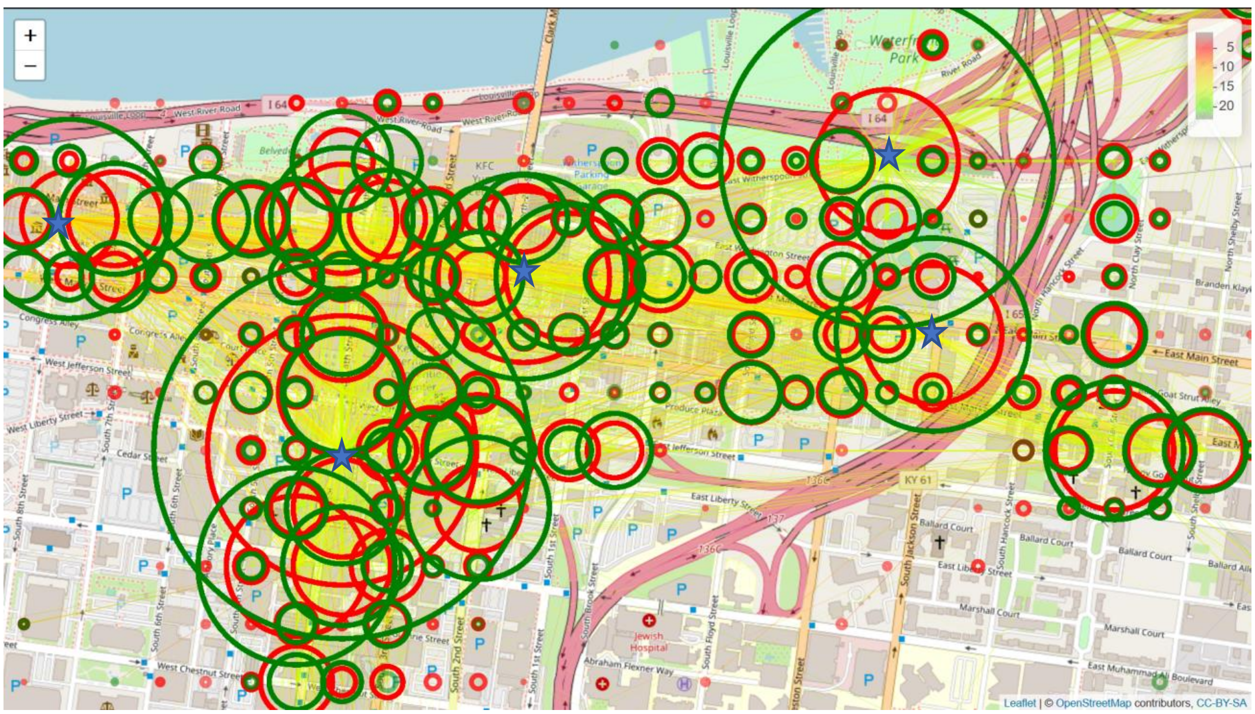

Figure 4: Concentrations of scooter ride origins (green circles) and destinations (red circles) within Downtown Louisville, KY (bigger circles = more rides). Yellow lines indicate flows of scooter rides (thicker lines = more rides). Blue stars mark tourist destinations.

University of Louisville

On the University of Louisville campus, a high proportion of morning origins are at a large dormitory building (big green circle at top left corner of Figure 5), while destinations are buildings throughout campus. This adds evidence to the hypothesis that primary usage here is students going to class.

Figure 5: Concentrations of scooter ride origins (green circles) and destinations (red circles) on the University of Louisville campus in Louisville, KY (bigger circles = more rides). Yellow lines indicate flows of scooter rides (thicker lines = more rides)

It is also instructive to divide morning and afternoon campus usage. It is clear that morning origins are much more concentrated at the dorm than are afternoon origins, and that morning origins are higher than are afternoon origins on weekdays (which have higher daily ridership than weekends). Given the lack of daily consistency in individual destination but high consistency in aggregate flows, it is likely that campus scooter usage represents students who are running late to their classes. Students would be less inclined to pay for a scooter to get back to the dorm after classes have ended in the afternoon because there is no longer the threat of being late to class.

RQ2(A): Demographic Patterns

	Dependent variable:				
	arides				
	(1)	(2)	(3)	(4)	(5)
income	0.0001				-0.0002
	(0.0001)				(0.0002)
(%) black		-119.790^{***}			-151.665^{***}
		(17.021)			(23.100)
non-car owning (%)			157.547^{***}		167.673^{***}
			(32.355)		(39.925)
age				-2.730^{***}	-0.835
				(0.826)	(0.848)
Constant	47.601^{***}	117.870^{***}	8.262	159.570^{***}	121.714^{***}
	(11.993)	(10.204)	(12.345)	(30.749)	(45.846)
Observations	450	450	450	450	450
R^2	0.003	0.100	0.050	0.024	0.183
Adjusted R^2	0.001	0.098	0.048	0.022	0.176
Residual Std. Error	135.475 (df = 448)	128.774 (df = 448)	132.251 (df = 448)	134.082 (df = 448)	123.059 (df = 445)
F Statistic	1.527 (df = 1; 448)	49.530^{***} (df = 1; 448)	23.710^{***} (df = 1; 448)	10.916^{***} (df = 1; 448)	24.953^{***} (df = 4; 445)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: Selected demographic characteristics regressed on scooter rides alone and combined; Washington, DC results (non-2SLS)

Refocusing on Washington, DC, it is instructive to observe the demographic patterns present in the data. In table 6 (above), demographic variables are simply regressed on rides aggregated at the census block level, without locational effects or 2SLS procedures. Among the demographic variables of race, income, age, and car ownership, some are highly statistically significant alone and when combined, but explain far less than the 2SLS model. Notably, income is not significant even when alone, while race is highly significant. Age loses significance after the other variables are controlled for. Notably, demographic characteristics such as income and age added no predictive power and are statistically insignificant when added to the model, yet collinearity with other model explainers is modest. The lack of significance for age is especially surprising given the commonly held view that scooter usage is highest among the young. One possible explanation for the divergence between residential demography and expected ridership patterns is that most riders are not initiating scooter rides near their residences. It is possible that scooters could be primarily used as a last-mile solution or a connection from traditional modes.

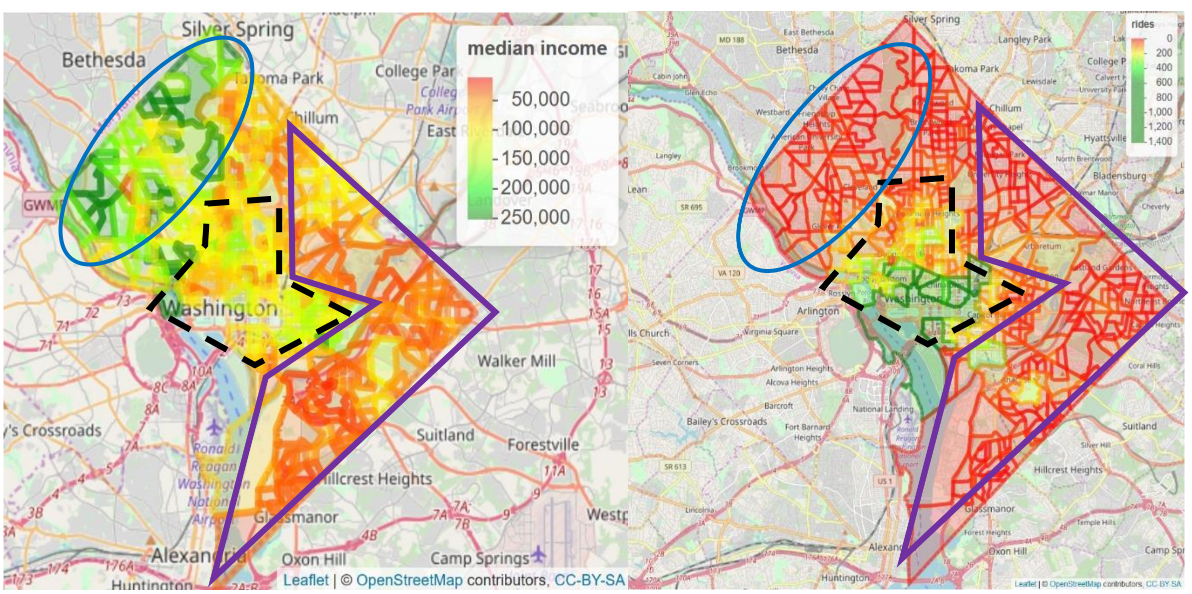

Figure 6: Median income (left) and scooter rides (right) by census block group in DC. Blue oval denotes areas of highest income, purple triangle denotes areas of lowest income, black dashed polygon denotes downtown areas.

The explanation for the significance of race but not income in predicting demand in Washington, DC (see table 6) is revealing: Both the highest-income and lowest-income areas consist of single-family housing located far (in opposite directions) from the city center and downtown area where scooters are concentrated. The scooter-dense downtown areas (black dashed polygon in figures 6), meanwhile, are higher in income than the lowest-income single family housing (purple triangular shape in figure 6), but not as high in income as the highest-income outlying single family housing (blue oval in figure 6).

But with regard to race, consider that both the highest income single-family housing areas and the downtown areas in Washington, DC are mostly white, while the lowest income single-family areas are overwhelmingly African American. Accounting for race appears to produce the correlation with rides one may have expected from income alone. The areas in DC that have high scooter ridership (green, figure 7 center) appear to be all the areas that are neither very high in income (green, figure 7 left) nor high in black resident percentage (green, figure 7 right).

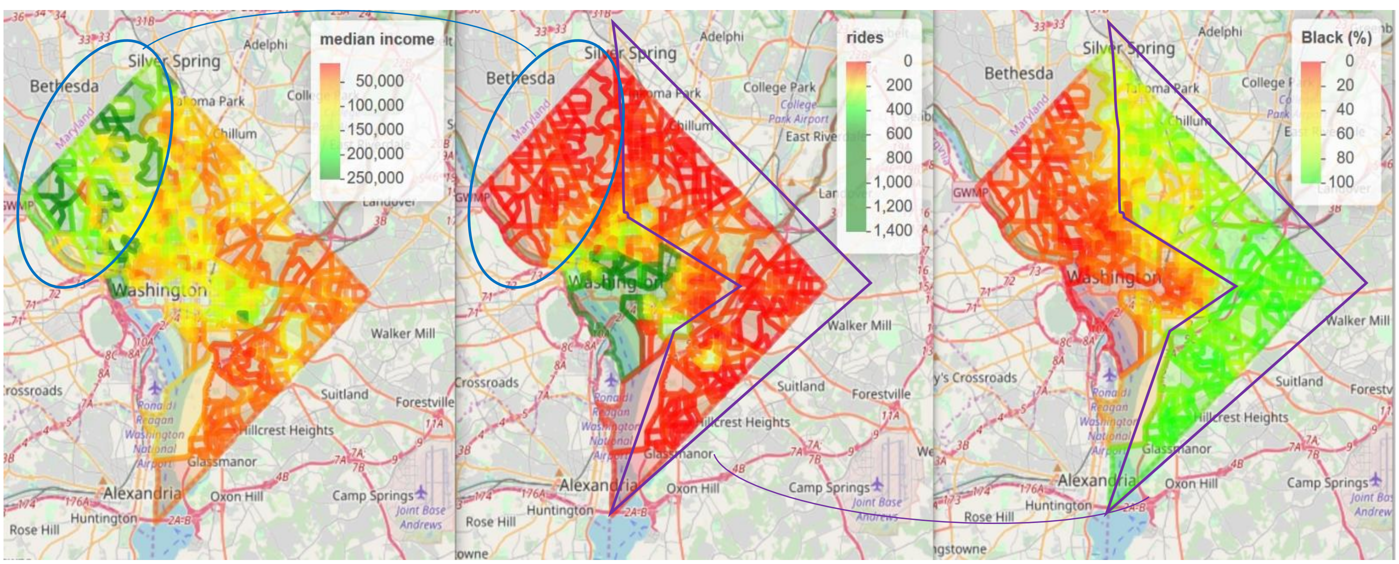

Figure 7: Median income (left), scooter rides (center), and percentage Black (right) by census block group in DC. Blue oval denotes areas of highest income, purple triangle denotes areas of lowest income, black dashed polygon denotes downtown areas.

At first glance, the figures 6 and 7 above suggest that these two demographic factors (race and income) would have high predictive power on the number of scooter rides. However, while a moderate correlation is present (correlation coefficient between rides and interaction of race and income is -0.37), the R-squared (a measure of what proportion of the variation in scooter rides is explained by those factors) is only .10 (albeit with extremely high statistical significance $p<.001$). In addition, the change in R-squared when a race-income composite is added to the 2SLS demand model is negligible. This high correlation and low R-squared combination indicates that while the race-income composite and scooter rides do rise and fall together, there are other factors that explain a far greater share of the variation in scooter rides than race and income. Additionally, other likely demographic factors such as age and car ownership are insignificant when added to the model. This suggests that spatial characteristics (such as the downtown designation and distance to city center included in the 2SLS model), not residential demographic characteristics, organize patterns of scooter usage.

If the variation in scooter use is driven by their relatively high usefulness near the destination-dense downtown, the observed demographic disparities in scooter usage could simply be reflections of disparities in which populations are near the downtown areas (black dashed line in figure 6). In this line of reasoning, low-income people exhibit low scooter use because they have access only to housing far from the city center (purple triangle in Figure 7), while the highest-income people also exhibit low scooter use because they choose to live in suburban neighborhoods far from the city center (blue oval in figure 7). Because the downtown is mostly mid- to high- income, income appears somewhat positively correlated with scooter-rides, but the low-scooter ride, wealthy suburbs throw off the explanatory power.

RQ 2(B) Low-Income Mobility

Even if the demographic factors are not important for explaining variation in scooter rides overall, they are important for presenting demographic disparities. One possible explanation for the demographic profile of usage is as follows: High income people in single-family suburban areas can easily afford cars or rideshare and perhaps as a result of this (or for whatever reason) have a low propensity for scooter usage, while low-income people with fewer alternatives have a *high* propensity to ride but qualify for reduced fares that are not very profitable for scooter companies. Therefore, it would make sense that scooter companies would place few scooters in either of these areas (except as required by city geographic coverage regulations). In this hypothesis, disadvantaged-area usage is low because of low supply relative to demand, and increasing supply would increase usage. However, it is also possible that the above hypothesis is false: low-income people do not see scooters as a desirable and affordable mode (regardless of if it be due to lack of awareness of the equity discount program, insufficient density of destinations, physical discomfort while riding, or any other reason). If our hypothesis is false, low-income ridership is low because of low demand among low income people rather than inadequate supply of scooters by companies. We can add a dummy variable for disadvantaged areas to the second stage demand equation to find an answer to this question. As per the analysis leading up to figure 7, disadvantaged areas refer to low-income, majority African American block groups. If the disadvantaged area coefficient is significant and positive when added to the 2SLS second stage supply equation, it would indicate that these areas have more scooters than anticipated given the level of demand. If it is significant and negative, this means

	Dependent variable:
	scooters supplied
demand	0.112***
	(0.007)
company fixed effects	0.873**
	(0.355)
land area	0.00001***
	(0.00000)
disadvantaged areas	5.085***
	(1.711)
Constant	-5.263***
	(1.283)
Observations	450
R^2	0.656
Adjusted R^2	0.653
Residual Std. Error	10.946 (df = 445)
F Statistic	212.551*** (df = 4; 445)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7: 2SLS Supply 2 on Washington, adding binary dummy for low-income and African American areas. "Demand" refers to predicted values from 2SLS Demand 1

that companies are inadequately supplying low income areas with scooters in proportion to their demand for scooter rides.

When disadvantaged areas are added to the second stage supply equation (table 7), the coefficient is positive and significant, indicating that disadvantaged areas are generally oversupplied with scooters relative to demand. As such, a lack of rides in low-income areas is unlikely to be due to inadequate aggregate supply. It is likely that ridership is low due to low demand of scooters in disadvantaged areas.

Furthermore, an analysis of fluctuations in the number of scooters supplied to metro stations in disadvantaged areas in the 7th and 8th wards show that increasing the number of scooters supplied does not increase the number of rides (table 8 below). Metro stations were selected because most scooters in low-income areas tend to be located at metro stations. For metro stations in non-disadvantaged areas, there is an induced demand effect, such that supplying more scooters will generate more rides. This indicates that increasing scooters supplied near light-rail stations outside of low-income areas would lead to increased last-mile scooter connections, but that increasing scooter supply in low-income areas will not increase use.

	Dependent variable:
	rides
scooters supplied to station (#)	0.535***
	(0.056)
station in wards 7 and 8	-1.385
	(2.376)
scooters supplied (#) X station in wards 7 and 8	-0.482***
	(0.102)
Constant	2.477***
	(0.907)
Observations	109
R^2	0.508
Adjusted R^2	0.494
Residual Std. Error	6.022 (df = 105)
F Statistic	36.209*** (df = 3; 105)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8: Non-2SLS relationship between scooters supplied and rides; results from DC metro stations, adding binary dummy for wards 7 and 8 in interaction with supply.

As shown in table 8, one additional scooter translates into .535 additional rides per block group (for every two more scooters supplied, roughly one more scooter is ridden), showing some induced demand propensity. The effect of adding an additional scooter to a station on the number of scooter rides *specifically in disadvantaged wards 7 and 8* can be found by summing the coefficients for the first explanatory variable (general effect of supplying another scooter on scooter rides) and the third one (interaction term showing additional affect for Wards 7 and 8 of supplying another scooter on scooter rides). Because the interaction term is negative, we see that an additional scooter in wards 7 and 8 translates into only .535 + -.482 = ~.05 additional rides on average (roughly 20 scooters would need to be added to generate an additional ride in wards 7 and 8). Therefore, existing capacity of scooters is underutilized in low-income areas especially relative to other areas: A metro station with four scooters outside of wards 7 or 8 would have two rides, while a metro station with four scooters in wards 7 or 8 would only have 0 rides on average (ignoring the constant). This demonstrates that low scooter usage in disadvantaged areas is largely to due to inadequate demand, not inadequate supply. This may be an indicator that the discount program is inadequately publicized, but it could also simply reflect modal preferences of the population. To the above claim, one could respond that perhaps there is high demand to ride scooters from disadvantaged areas far from metro stations, and companies are simply not "chasing" this demand by reconfiguring their supply. If this were true, then fluctuations in the number of scooters in disadvantaged block groups far from metro stations would be powerfully correlated with rides; however, the following table shows this is not the case (table 9 below).

	Dependent variable:	
	scooter rides	
	Wards 7 and 8	Wards 1-6
	(1)	(2)
scooters supplied	0.076***	0.426***
	(0.009)	(0.027)
intrinsic locational demand	0.013**	0.300***
	(0.006)	(0.030)
Constant	-0.028	-0.684***
	(0.040)	(0.226)
Observations	206	769
R^2	0.278	0.581
Adjusted R^2	0.270	0.579
Residual Std. Error	0.464 (df = 203)	4.783 (df = 766)
F Statistic	39.004*** (df = 2; 203)	530.096*** (df = 2; 766)

Table 9: Comparison of supply-induced demand across DC wards, excluding metro stations. "intrinsic locational demand" refers to predicted values from 2SLS demand 2

The side-by-side regressions above (table 9) show the effect of scooter supply fluctuations on rides in block groups without metro stations when intrinsic demand (as calculated by 2SLS model) is controlled for. The results show that scooter supply induces far more demand in wards 1-6 than wards 7 and 8 (when the population is restricted to areas far from stations). An additional scooter deployed in wards 7 and 8 far from a station translates into only 0.076 more rides (deploying 12 additional scooters generates only one new ride), while an additional scooter elsewhere translates into 0.426 rides (two rides for every five additional scooters deployed). While 12 scooters per ride in non-metro areas in wards 7-8 is indeed higher than the scooters-to-ride ratio near metro stations in wards 7-8, it is still quite low, and a far cry from the utilization in the rest of the city. The evidence is clear the scooters are underutilized in disadvantaged areas: this is a demand-side problem, not a supply-side one.

RQ 3(A) Public Transit Complementarity

Scooters are playing a last-mile role in light-rail transit trips in Washington, DC (figures 8 and 9: blue lines indicate trips starting or ending at metro stations). While it may be difficult to distinguish trips to metro stations in the downtown areas where stations are surrounded by other destinations, a large majority (61%) of the ridership outside of the downtown core clearly consists of trips that either start or end at metro stations (the estimate for downtown areas is 41%). This follows from the high explanatory power of metro stations in predicting ridership in the econometric model. Figures 8 and 9 clearly indicate that many scooter rides are serving as critical last-mile links in intermodal transit trips. Riders are using scooters to get from their origin to the metro station, or to get from the metro station to their final destination; meanwhile, the number of trips between stations on the same line appears to be low. This implies that scooters are complementing light-rail in Washington, DC rather than substituting for it. (In figures 8 and 9, blue lines represent trips starting or ending at metro stations, while orange lines are all other trips. Blue circles are the metro stations themselves).

Although it is clear many scooter trips link with public transit trips, it is difficult to know how many of those public transit trips would have happened anyway if the scooters had been absent. It is possible that many riders would have completed their transit trip by walking or taking the bus to or from the metro station if the scooters had been absent. In this case, the scooters would not be subtracting from greenhouse emissions. However, it is also possible that many riders would have used automobile rideshare to get to the metro station in the absence of

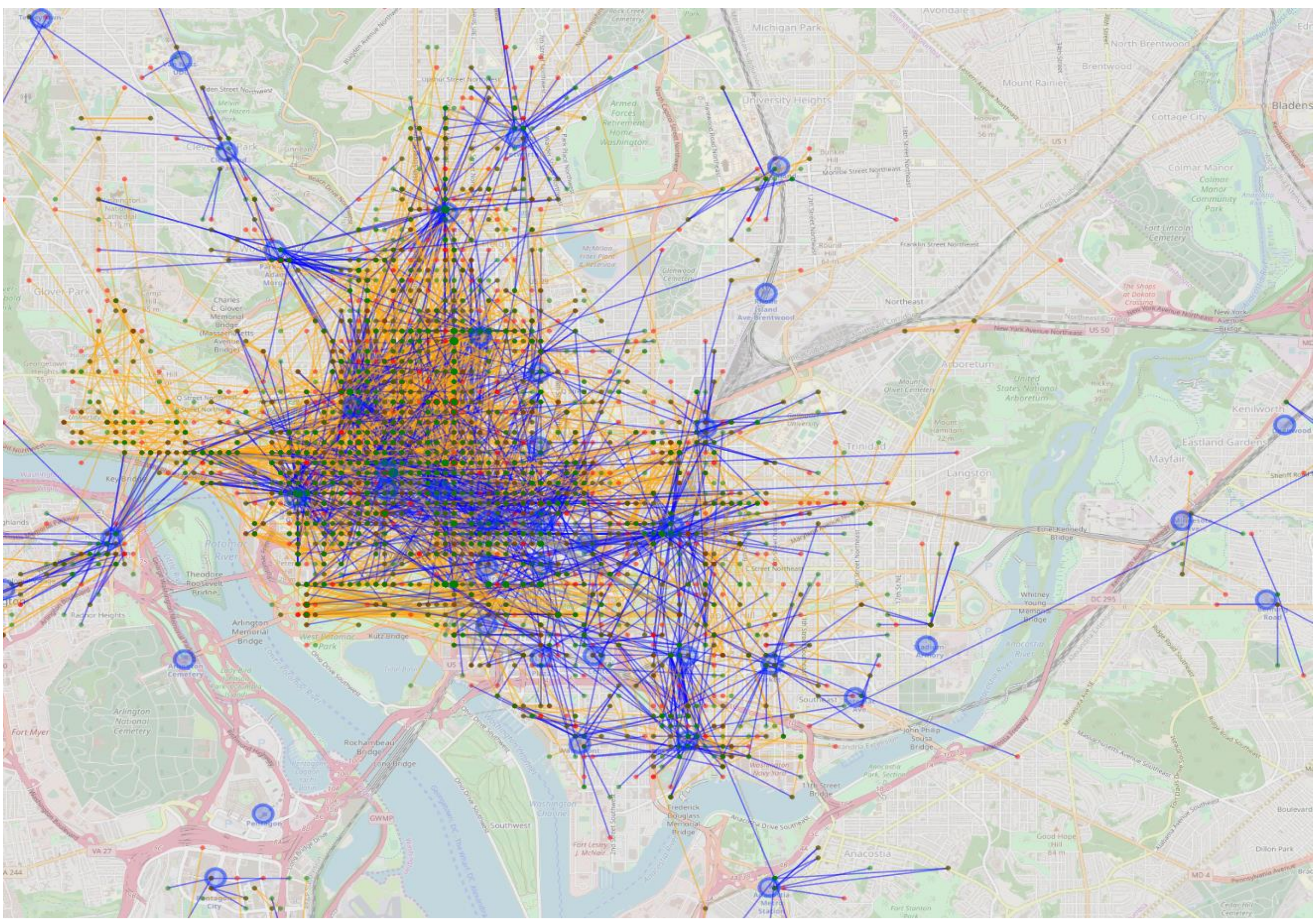

Figure 8 Scooter trips (blue lines) starting or ending at metro stations (blue circles) and other scooter trips (orange lines) in Washington, DC

scooters or cut out public transit entirely and drove or rideshared directly to their destination. In these cases, the presence of scooters is enabling public transit to substitute for car trips, creating net reductions in greenhouse emissions. It is impossible to know exactly what proportion of the scooter trips subtracted from greenhouse emissions. However, revealed preferences can be invoked to argue that the presence of the scooter reduces the disutility (perhaps in the form of total travel time) from a public transit trip: If people are choosing to use scooters to get to a metro station instead of walking or the bus, it is because their lives are improved by doing so (whether this be because of long wait times for buses, the enjoyment of riding a scooter, or any number of reasons). Therefore, in a strictly economic sense, the presence of the scooters lowers the "price" of using public transportation, thereby increasing the quantity of use (here price could mean the disutility of having to wait for the bus, for instance).

Figure 9: Scooter trips (blue lines) starting or ending at metro stations (blue circles) and other scooter trips (orange lines) in Washington, DC

Another interesting feature of the scooter and light-rail pattern is that scooter rides appear to some degree to be making up for geographical “gaps” in the light-rail system: There appear to be an especially high density of scooters trips between metro stations and “hip” neighborhoods with bustling commercial attractions that are inconveniently beyond walking distance from the closest metro station and where parking is scarce and expensive. DC residents have for many years complained about the difficulty of getting to the diverse cuisine and nightlife scene in the “hip” Adams Morgan and U-Street corridors and the upscale restaurant and retail scene of Georgetown. The lack of a metro station within walking distance of Georgetown University is a particularly long-maligned gap in the light-rail system. Before the advent of rideshare, travelling between these neighborhoods and the rest of the city without a car required walking for nearly a mile or waiting for a local bus to a rail station, creating long travel times. This was especially burdensome during the hours of peak nightlife and leisure activities in the late evening, when bus service is less frequent. The scooter data clearly show a high volume of trips between these areas and the closest metro stations. (U-Street and Adams Morgan in figure 10A and Georgetown in figure 10B below: scooter trips starting or ending near metro entrances are lines marked blue; metro stations are light blue circles). In these situations, the scooter is very clearly filling an unmet need for last-mile travel. Scooters are increasing the accessibility of these desirable areas and making public transit more competitive with rideshare by decreasing travel times for a linked transit trip.

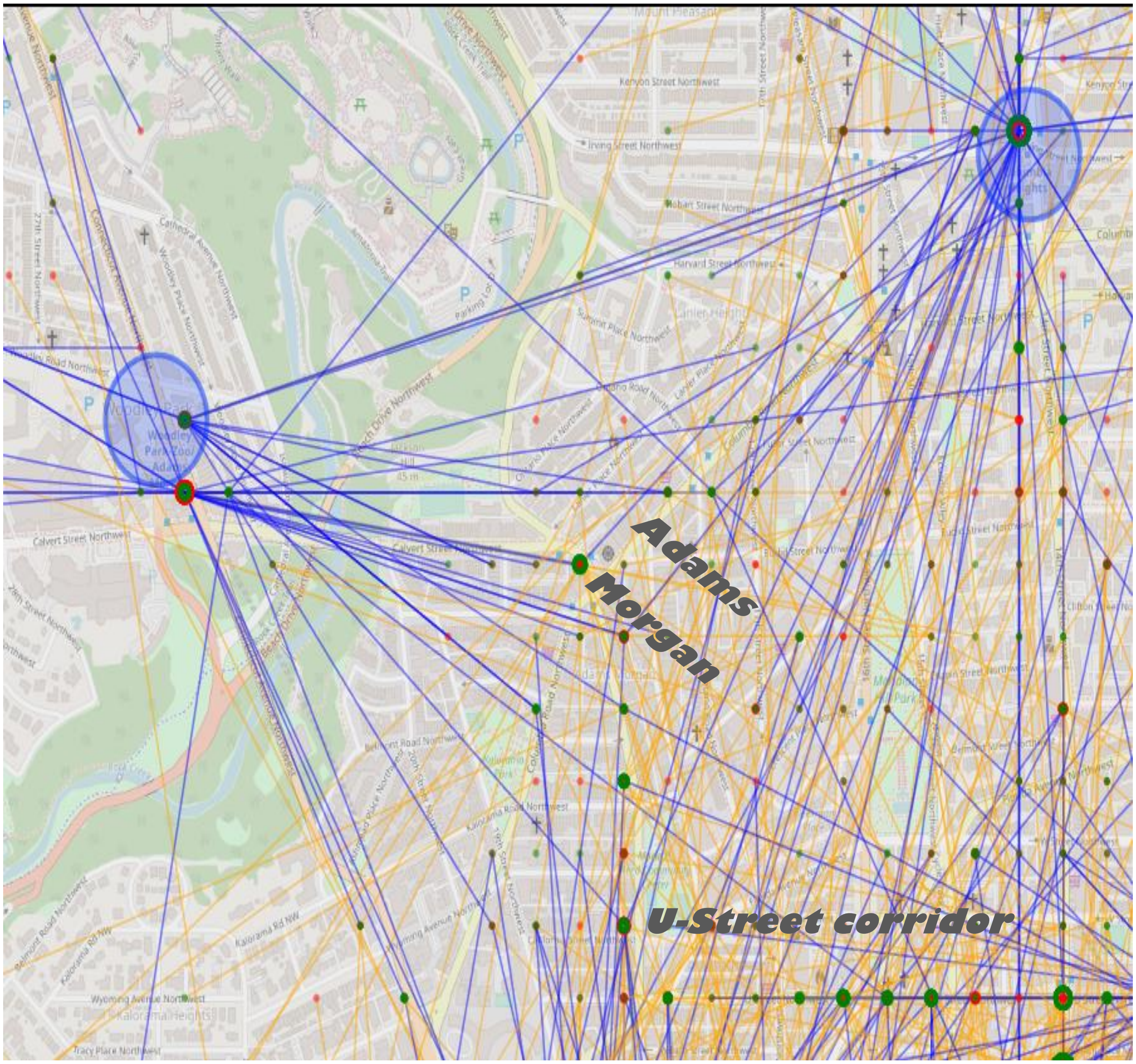

Figure 10A: Scooter rides (blue lines) between popular DC neighborhoods and metro stations (blue circles). Other scooter rides (orange lines)

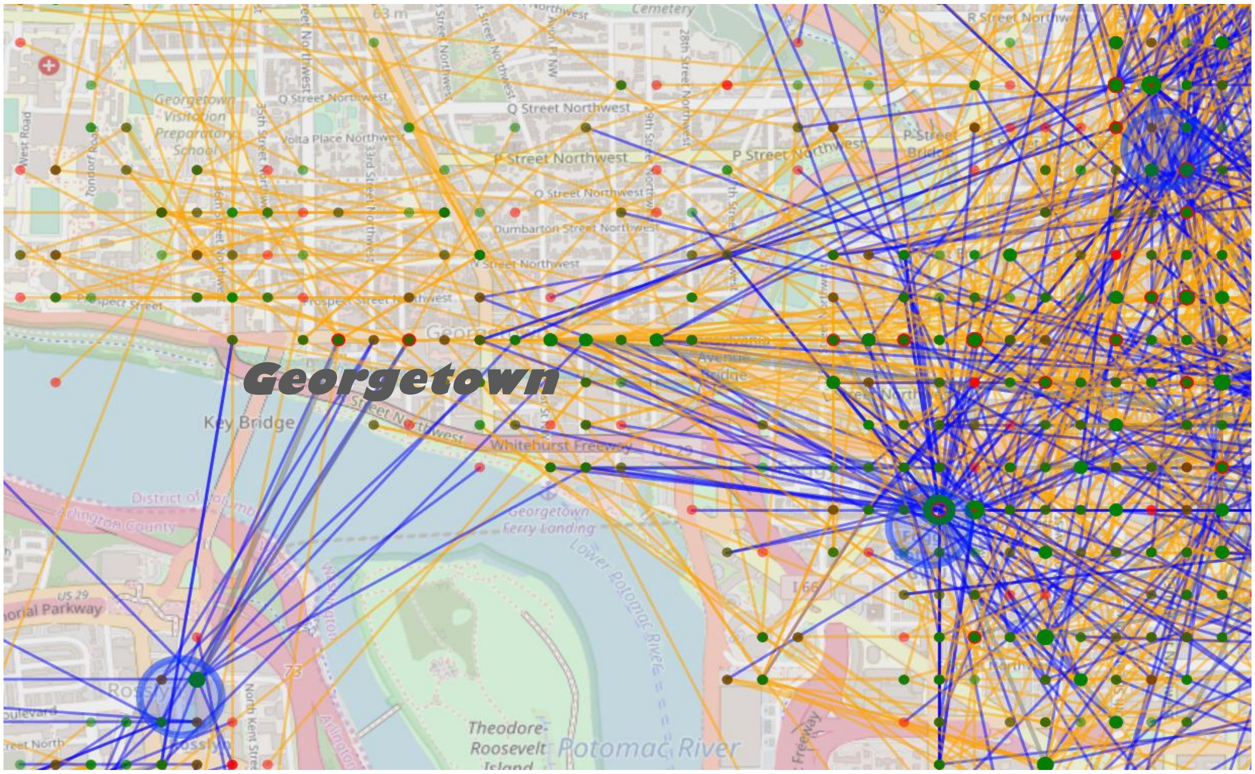

Figure 10B: Scooter rides (blue lines) from popular DC neighborhoods to or from metro stations (blue circles). Other scooter rides are orange lines.

Notably, scooter trips to and from light-rail stations are central to ridership patterns in both high- and low-income areas. However, the type of trip that light-rail to scooter connections are enabling is different for the metro stations in low-income areas. Unlike leisure destinations such as restaurants or nightlife in Adams Morgan, U-Street, and Georgetown described above, trips in low-income areas tend to connect with people's homes. Although there are far fewer trips in low-income areas, the pattern of association with metro stations is very clear: See trips from Union Station to low-income neighborhoods (figure 11 top), and trips to metro stations in low-density, disadvantaged 8th ward (figure 11 bottom). The metro-residential connecting trips could be an indicator of commuting pattern; in addition, trips to metro stations from low-income areas are more likely to occur during the AM and PM rush hour.

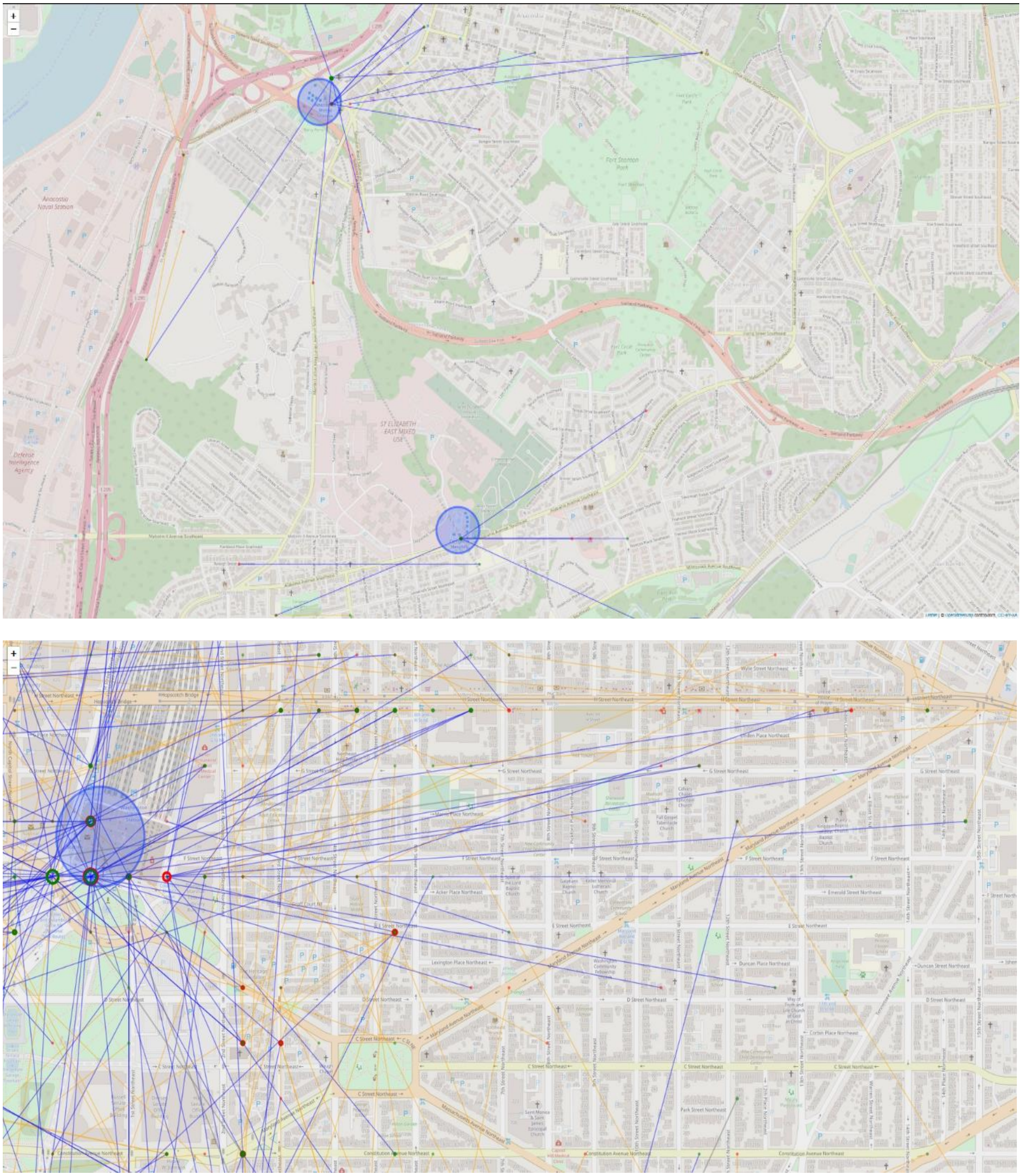

Figure 11: Scooter rides (blue lines) in low-income areas in Washington, DC nearly always start or end at metro stations (blue circles). Above: far Southeast DC, Anacostia and Congress Heights metro stations. Bottom: Noma neighborhood in DC, Union Station

RQ 3(B) Carbon Footprint

Distinct types of modal substitution likely associated with certain usage segments were identified. Short, on-campus scooter trips appear to substitute for walking, so this segment of usage will net increase greenhouse gas emissions. Intermodal scooter trips to light-rail stations would decrease net greenhouse gas emissions if the scooter-absent counterfactual would have been a car trip (but not if the alternative is to walk or ride the bus to the light-rail station). Trips in downtown areas could substitute for a mix of car (rideshare) and walking trips. Due to the greenhouse gas emissions estimates for scooters in Hollingsworth et al, they can only meaningfully reduce emissions if they are substituting for cars rather than buses and walking. Segmenting the usage produces an inconclusive picture of net carbon footprint.

Note that light-rail is not a plausible substitute for scooters. With the median scooter trip in all cities studied under 3/4^{ths} of a mile and 90% of trips under a mile, scooter trip distances appear too short for light-rail to be a plausible alternative. Light-rail stations are rarely less than 0.75 miles apart, and light-rail trips of only one stop are quite rare. Further, the trip pattern analysis in RQ 3(A) revealed that very few trips start near one metro station and end near another on the same line. This finding reinforces the important result that scooters largely complement light-rail rather than substitute for it.

Another approach to estimating net carbon footprint is exploring modal substitution on the basis of counterfactual travel time. By comparing the known travel times of scooter trips to the counterfactual travel times if riders had chosen the bus, ridesharing, or walking, it might be possible to guess whether more-polluting or less-polluting modes would have been chosen in absence of the scooters. First, the actual scooter trips (red) are scatter plotted by trip time and trip distance (figure 12). Next, those same actual trips (red) are plotted against hypothetical travel times for bus (black), walking (blue), and driving (yellow) trips between the same origin and destination (figure 13).

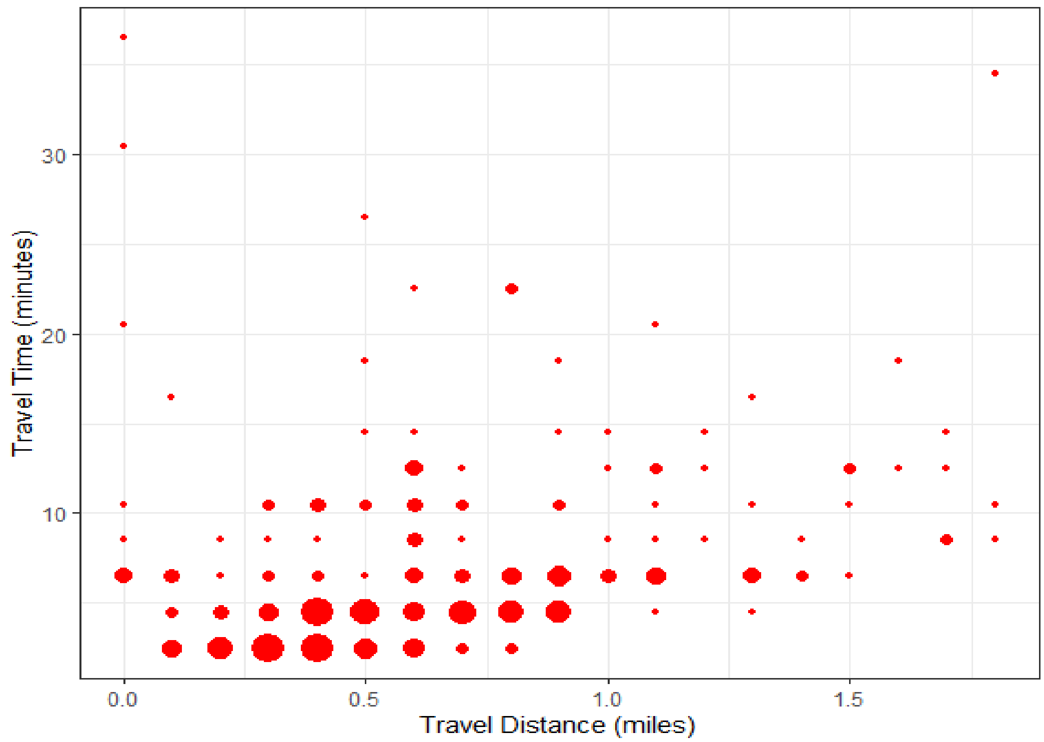

Figure 12: actual Washington scooter trips are plotted by trip time and distance

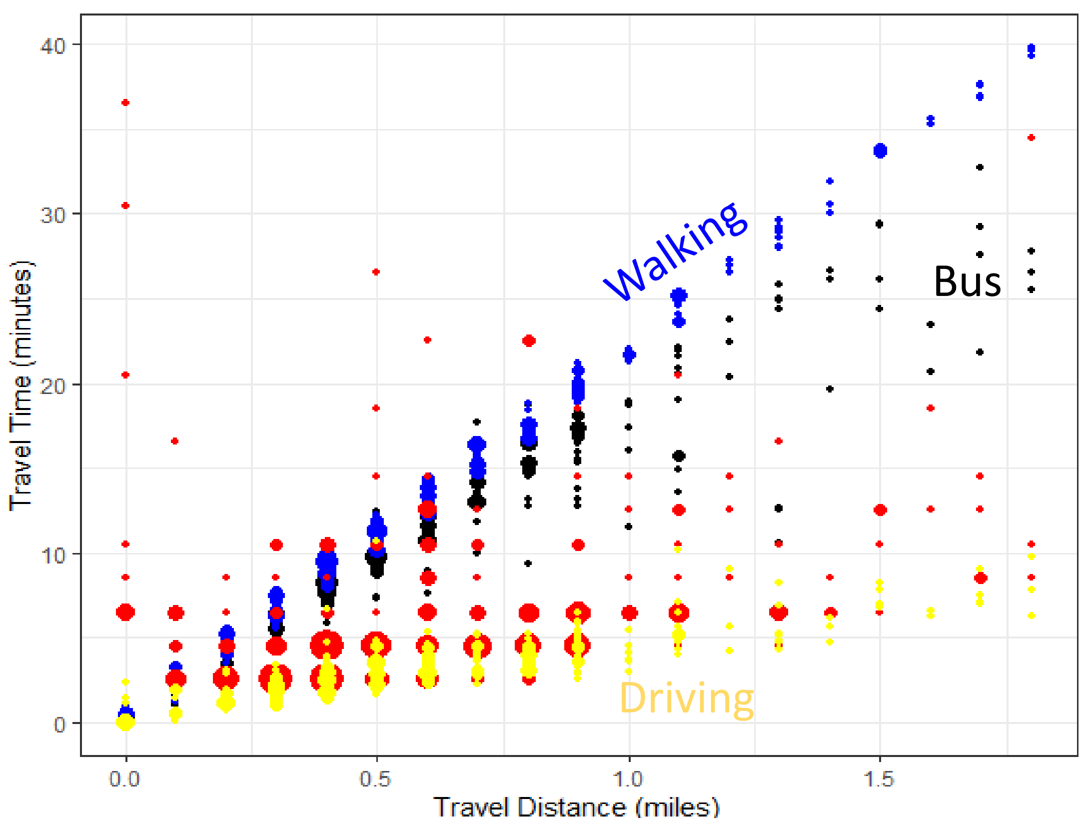

Figure 13: actual Washington scooter trips (red) are plotted against hypothetical travel times for bus (black), walking (blue), and driving (yellow) trips between the same origin and destination

If we assume that the rider cares about minimizing trip time and trip expense, we can see from figure 12 that in a world where the scooter is unavailable, the rider would have rarely chosen the bus. This is because in almost all cases, the bus would have taken practically as much time as walking and cost more money (walking is free). Scooter rides are typically for short distances which can be walked in little more than the time required to wait for the bus. Therefore, most consumers would have either chosen walking or automobiles in absence of the scooter. The important conclusion of this analysis is that it is very unlikely that scooters are cannibalizing bus ridership.

Whether scooters are substituting for more rideshare than walking –and therefore net subtracting from greenhouse gas emissions– is inconclusive based on the graph above. Those in a rush would choose rideshare, which guarantees similar travel times to scooters at twice the cost or more. Those opting to save money would walk, which would take substantially more time than scooters and rideshare but save money. While it is impossible to see inside the brains of scooter riders to know what they would have chosen, we can see their revealed preferences: All actual scooter trips represent people who had the option to walk for free yet chose scooters instead. The fact that the scooter riders chose *not* to walk even when the distances were so short (one third were less than 0.5 miles) indicates a high disutility from walking among scooter riders. This behavior suggests that those same scooter riders would be inclined to continue to avoid walking in absence of the scooters and many would choose to take rideshare. However, whether scooters net add or subtract from greenhouse gas emissions hinges on what proportion would have chosen rideshare and what proportion would have walked. On one hand, this indicates that greater research is necessary to pin down the modal substitution of scooters and quantify their carbon footprint. Regardless, it can be said that some indeterminate proportion of scooter rides do substitute for rideshare, meaning that some proportion of scooter rides do produce net reductions in greenhouse gas emissions.

Limitations and Future Research

Several general limitations were present in the results and interpretation of the 2SLS model. First, as in any study, the results are only as accurate as the data. Any inaccuracies or spatial or temporal lags in the APIs provided by scooter companies would bias the results. Because documentation for these APIs was never made available, logical inferences had to be used to interpret vehicle identification numbers. Any errors in these inferences or in the numeration of vehicles within the APIs would also greatly bias the results. Second, spatial weighting, spatial autocorrelation, and formal clustering analysis was not used in the 2SLS model. Therefore, any spatial spillover effects would not be captured by the results. A future study incorporating these advanced spatial techniques may be useful in confirming the general ideas laid out by the econometric analysis of this paper.

RQ 1(A)

The destination-inference method, while powerful, does have its limitations. It is unknowable whether scooter riders who rode to certain destinations actually entered them and performed activities there. Further, destination-inference is even more uncertain in downtown areas, when many different types of destination are clustered close together.

Attempts to detect commuting behavior were inconclusive. This was largely because many workplaces also serve commercial functions, are in mixed-use buildings, and/or are in downtown areas, complicating destination-inference techniques. Future research using novel techniques to isolate commuting trips would be very valuable.

RQ 1(B)

The three cities discussed in this paper (Louisville, Los Angeles, and Washington) were selected for maximum generalizability, and the general destination patterns hold across all three to a large extent. However, it is not impossible that other cities might have unique features and produce different results. Comparisons to more cities might be useful in confirming the generality of the destination pattern discovered in this paper.

RQ 2(A)

The most basic limitation with regard to demographic patterns is that demography could only be inferred from location of the ride, and the actual demographics of the riders themselves were unknowable in this analysis. It is not impossible that many of the users in predominantly low-income areas are simply high-income outliers, and that many of the users in downtown areas are low-income people. Another study that somehow gained access to granular rider demographic data would be extremely helpful in pinning down the demographic profile of scooter use.

While leisure destinations were widely found to be a key driver of scooter use in this paper, the split between tourists and local residents among leisure-driven users could not be definitively identified.

RQ 2(B)

This paper is able to make the fundamental conclusion that demand is low relative to supply in low-income areas; this creates an avenue for future research to answer the basic question of *why* demand is low. This paper offers two potential hypotheses that could generate confirmatory studies: (1) that Washington's low-income discount programs are inadequately publicized, and (2) that scooters are just fundamentally ill-suited to the travel preferences and needs of low-income people and/or not useful given the low density and distance from the city center of many low income areas. Very little is known about the actual travel preferences of low-income people and their knowledge of the Micromobility discount programs available to them. Even basic quantitative facts about the discount programs, such as sign ups and discounted rides are unknown, let alone more complex issues such as ease of use.

Little is known about the decision-making of scooter companies with regard to market entry and exit, as well as long term citywide supply changes. The threshold at which increased use of generous discounts could trigger company market exit is unknown. Research here could inform policy decisions about the optimal generosity of discount programs.

RQ 3(A)

This paper is able to find a high degree of complementarity between scooters and the metro. However, it is not possible to actually know for certain that all riders get on the metro (some might go to businesses near the metro) after disembarking the scooter.

RQ 3(B)

Attempts to quantify the degree to which scooters net contribute to greenhouse gas emissions were inconclusive. In order to conclusively estimate net carbon footprint, it would be necessary to estimate what modes scooter riders would have taken if the scooters had not been present. A study employing a discrete choice model to estimate modal split would be extremely useful. Further, this paper did not account for the role of biking and bikeshare; this mode could be experiencing cannibalization by scooter usage`q1, leading to net increased emissions.

Natural Experiment

Overall scooter volume is low in comparison to metro volume and other modes in Washington, so any scooter impact on carbon footprint and low-income mobility is currently limited. A planned policy change would quadruple the number of scooters and increase low-income area supply requirements; if this change occurs, scooters would become much more quantitatively important and create an exciting natural experiment.

Conclusion & Policy Recommendation

RQ 1 – Destination Patterns

The trip pattern analysis conclusions largely cohere with the econometric analysis, which finds that 60-80% of the variation in scooter ridership across locations within Washington, DC, Louisville, KY, and Los Angeles, CA can be explained by three key drivers: proximity to the downtown area, the number of businesses with alcohol licenses (mostly restaurants), and the presence of light-rail transit stations (or campuses in Louisville and Los Angeles). Interestingly, scooter companies appear to have increased supply to match the high demand at light-rail stations more so than for the high demand in downtown areas and alcohol license business areas. Surprisingly, the three factors above overpower demographic factors (age, race, car ownership, income, and commuting behavior): demographic factors did not increase explanatory power when added to the model in the cities studied. While moderate correlations with the final model covariates were present, the demographic model explained much less. This implies that the demographic disparities in scooter usage may be due to disparities in the spatial distribution of demographic characteristics with respect to downtown areas and transit access. Scooter rides are overwhelmingly clustered in downtown hubs, and to a lesser extent in large campuses, important commercial corridors near downtown areas, and light-rail stations. Destination inference concludes that a majority of usage is related to leisure destinations, especially restaurants though to a lesser extent nightlife as well as grocery errands.

RQ 2 – Demographics & Low-Income Usage

In Washington, ridership is clustered in middle-income, white, downtown areas; meanwhile, far from the city center, both high-income white areas and low-income African

American areas show low scooter usage. Similar patterns are replicated in both Los Angeles and Louisville. A key policy-relevant finding is that the status quo dynamics of scooter usage do not deliver mobility benefits to low-income people. The existing supply in low-income areas appears to be greatly underutilized, calling into question the wisdom of municipal regulatory stances that aim to increase low-income usage by expanding supply. Analysis of temporal fluctuations in the number of scooters supplied to low-income areas show that increases in supply do not induce increases in demand. The current oversupply implies that the binding constraint on low-income scooter usage is demand; demand, then, should be the focus of city policy efforts. One possible candidate for policy focus is the low-income discount program. It is very possible that this program is inadequately publicized, or perhaps other barriers to program uptake exist. Another possibility is that structural dynamics such as fundamental transportation preferences of low-income people, the low density of some low-income DC areas, or the distance from those areas to the city center result in conditions inhospitable to scooter use. If this is true, then no matter how accessible and well publicized the discount programs are, scooter use among the poor will not increase. This would follow from the observation that middle- and high-income areas at distances as far from the city center as DC’s low-income areas also have few scooter rides.

RQ 2 Policy Recommendation

The Washington, DC government ought to engage in the following actions:

(1) *Publicize Scooter Discount Programs* – A program that no one knows is available to them is little different in practice than a program that does not exist. Require scooter companies to expend resources advertising scooter discount programs in low income areas. This publicity push should also include billboards and posters on the sides of city buses and in metro stations, scooter company partnerships with local retailers, and information mailed directly to homes

informing residents of discount program eligibility. This could also include events: A registration fair or block party featuring a booth for low-income residents to sign up for discounts. Local civic associations and other neighborhood groups could also be used to disseminate this information. Especially if the binding constraint on scooter usage is effective demand, this action has the capacity to greatly increase usage of scooters by people who could benefit from them, while incurring minimal financial cost to municipal government. Without an effective, well-publicized discount program in place, efforts to increase low-income mobility by supplying more scooters may be futile.

(2) *Study Travel Preferences* – Conduct a fact-finding study to narrow down the binding constraint on low-income scooter use: Determine the knowledge and preferences of low-income people with regard to scooter use. At what price point would many low-income people consider scooters as a mode of transit? What factors could make scooter usage impractical for these groups? An understanding of these basic facts is necessary to inform any successful strategy to increase low-income mobility.

RQ 3 – Public Transit Complementarity & Carbon Footprint

The connection between a light-rail network and scooter usage discovered in DC is especially notable. Washington, DC's light-rail network organizes scooter ride patterns outside of downtown areas -- including in historically disadvantaged neighborhoods -- implying a high degree of transit-scooter intermodality. Fully 40% of downtown scooter rides and 61% of rides outside the downtown area either start or end at a metro station. Faster than walking or waiting for the bus, scooters are a convenient link between light-rail stations and final origins or destinations. As a last-mile solution in many places, scooters are effectively making areas that had before been transit deserts more convenient to reach without a car or ridesharing. The presence of scooters in effect reduces door-to-door travel time for light-rail trips, making them more competitive with rideshare and automobile travel. By expanding the reach of transit networks, scooters increase mobility for those who do not own cars and potentially reduce net greenhouse gas emissions. Notably, scooter trips may also substitute for walking; attempts to determine the net carbon footprint of scooters were inconclusive.

RQ 3 Policy Recommendation

Municipal governments in cities with light-rail networks should engage in the following action:

Promote Scooters as a Last-Mile Solution – Encourage scooter companies to maintain capacity in and around metro stations. Companies ought to be encouraged to place scooters at metro stations as well as in areas that are out of walking distance from public transit stations but within scootering distance: the radial zone greater than a half-mile but less than one mile from stations. This will maximize micromobility complementarity with the public transit system, potentially enabling residents to scooter to and from public transit instead of taking rideshare. If scaled up, these measures could enhance the environmental sustainability and emissions profile of urban transportation networks.

Bibliography

Austin Department of Public Health. Dockless Electric Scooter Related Injuries Study. April 2019. http://www.austintexas.gov/sites/default/files/files/Health/Web_Dockless_Electric_Scooter-Related_Injury_Study_final_version_EDSU_5.14.19.pdf

Finds injury rate of 20 per 100,000 scooter trips. Finds that head injuries are the most common form of injury.

Bordes Roca, Adrià. Impacts of implementation of electric scooters in daily transport: case study in Gävle. MS thesis. Universitat Politècnica de Catalunya, 2019. https://upcommons.upc.edu/handle/2117/173520

CDC. “Characterization of Dockless Electric Scooter Related Injury Incidents - Austin, Texas, September-November, 2019.” https://www.cdc.gov/eis/conference/dpk/Dockless_Electric_Scooter_Related_Injury.html

The CDC finds that almost half of e-scooter injuries involve head trauma. E-scooter injury rate was 14.3 per 100,000 trips.

DHCD. “DHCD Income Limits.” Washington, DC. 2017. https://dhcd.dc.gov/sites/default/files/dc/sites/dhcd/publication/attachments/2017%20CDBG%2C%20HOME%2C%20NSP%2C%20LIHTC%20and%20HPTF%20Program%20Limits.pdf

“Dockless Vehicle Sharing Demonstration: Phase 1 Evaluation.” Washington, DC Department of Transportation. 2018. https://ddot.dc.gov/sites/default/files/dc/sites/ddot/publication/attachments/Dockless%20Demonstration%20Evaluation%2012-17-18_FINAL.pdf

Analysis of DC scooter trip patterns. Finds concentration in downtown. Analyzes time of day pattern and detects concentration in weekends.

“Existing Land Use.” DC Open Data Portal. Washington, DC. 2019. https://opendata.dc.gov/datasets/245179183eee41e08852ff9d5dbd3bcb_4

Guerra, E., Cervero, R., & Tischler, D. (2012). Half-Mile Circle: Does It Best Represent Transit Station Catchments? Transportation Research Record, 2276(1), 101–109. https://doi.org/10.3141/2276-12

“Liquor Licenses” DC Open Data Portal. Washington, DC. 2019. https://opendata.dc.gov/datasets/cabe9dcef0b344518c7fae1a3def7de1_5

Hardt, Cornelius, and Klaus Bogenberger. "Usage of e-scooters in urban environments." *Transportation research procedia* 37 (2019): 155-162. https://www.researchgate.net/profile/Cornelius_Hardt/publication/328801770_Usage_of_e-Scooters_in_Urban_Environments/links/5c4afbf1458515a4c73eedf9/Usage-of-e-Scooters-in-Urban-Environments.pdf

Herrman, Mason. 2019. "A comprehensive guide to electric scooter regulation practices." *U of Kansas*. https://krex.k-state.edu/dspace/bitstream/handle/2097/39655/MasonHerrman2019.pdf?sequence=3&isAllowed=y

Hollingsworth, Joseph, Brenna Copeland, and Jeremiah X. Johnson. "Are e-scooters polluters? The environmental impacts of shared dockless electric scooters." *Environmental Research Letters* 14.8 (2019): 084031. https://iopscience.iop.org/article/10.1088/1748-9326/ab2da8?fbclid=IwAR2qJlgV1FxeBENrEyHzy-oygkt4e28olrjh4M3jxuibNxSW9AStYkG1rkc

"Manual on Pedestrian and Bicycle Connections to Transit." FTA. 2017. https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/researc-innovation/64496/ftareportno0111.pdf

"Mapping the impact of dockless vehicles." *Smart Cities Dive.* December 20 2019. https://www.smartcitiesdive.com/news/mapping-the-impact-of-dockless-vehicles/539263/

Shows number of cities with scooters

McKenzie, G (2019b). Urban mobility in the sharing economy: A spatiotemporal comparison of shared mobility services. *Computers, Environment and Urban Systems*. 79. 101418. Elsevier. [10.1016/j.compenvurbsys.2019.101418]

Compares scooter and rideshare travel patterns in DC using late-2018 data. Finds that in downtown areas during peak rush hour, scooters can actually be faster than cars. Finds that there is widespread similarity in spatial and temporal trip patterns across different scooter providers. Will use this to argue that scooters are highly commoditized, such that there are no differences across providers.

McKenzie, G (2019a). Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. *Journal of Transport Geography*. 78. 19-28. Elsevier. [10.1016/j.jtrangeo.2019.05.007]

Compares the time of day pattern of scooter and bikeshare trips in DC using late-2018, finding that bikeshare trips show a pronounced commute pattern while scooter trips peak at midday. Finds dense concentration of scooter usage in the downtown area, and that residential-commercial trips account for a small proportion (~15%) of total trips. Finds a disproportionate lack of scooter activity in DC's low-income and African American areas.

Michael Kuby, Anthony Barranda, Christopher Upchurch, Factors influencing light-rail station boardings in the United States. *Transportation Research Part A: Policy and Practice* (2004): 38(3), pp 223-247 https://www.sciencedirect.com/science/article/abs/pii/S0965856403001046

"Micromobility and Job Access in Nashville." The Micromobility Coalition. 2018. https://micromobilitycoalition.org/wp-content/uploads/2019/07/Micromobility-and-Job-Access-in-Nashville-Summary-Report.pdf

Simulation finds that the average number jobs reachable without a car in 45 minutes from neighborhoods in Nashville, TN doubles (from 46,000 to 97,000) when commuters use scooters instead of public transit. Increases due to scooters for many individual neighborhoods exceeded 150,000 additional reachable jobs. Finds that in 45 minutes, the bottom quartile of workers can access fewer than 1,500 jobs on average by public transit, but they can access 20,000 jobs with scooters.

Noland, Robert B. 2019. "Trip Patterns and Revenue of Shared E-Scooters in Louisville, Kentucky." *Transport Findings*, April. https://doi.org/10.32866/7747.

Concludes that scooters are used for recreation based on effect of precipitation and temperature on scooter rides and concentration on weekends.

"Shared Micromobility" Transportation Data and Performance Hub. *Austin, TX*. September 2019. https://data.mobility.austin.gov/micromobility-data/

"One Bird." *Bird*. Press Release. July 19, 2018. https://www.bird.co/press/bird-announces-one-bird/

"Ridership." Metro (2019). https://capmetro.org/ridership-stats/

Austin monthly bus ridership

"Ridership." WMATA (2020) https://www.wmata.com/initiatives/ridership-portal/

Washington DC daily light-rail ridership

Shared Micromobility in the US: 2018 Report. *NACTO*. https://nacto.org/shared-micromobility-2018/

At 38.5 million total trips, scooter use outpaced docked bikeshare use nationally in its first year in operation. As of the end of 2018, 85,000 scooters are currently deployed to over 100 US cities. Many bikeshare companies switched to scooters in 2018. Most importantly, aggregated survey data show that over 25% of riders use scooters for commuting purposes, over 25% use them to connect to public transportation, and only ~30% use them for recreation (~70% of trips are destination-driven). Crucial evidence that scooter usage is largely non recreational and quantitatively important.

Wang, Hai, and Amedeo Odoni. "Approximating the performance of a "last mile" transportation system." *Transportation Science* 50.2 (2016): 659-675.

Zellner, Moira, et al. "Overcoming the last-mile problem with transportation and land-use improvements: An agent-based approach." *International Transportation* 4.1 (2016): 1-26.

Zhang, Desheng, et al. "Last-mile transit service with urban infrastructure data." *ACM Transactions on Cyber-Physical Systems* 1.2 (2016): 1-26.

Appendix

Relevance of Company Fixed Effects as Supply Instrument

	Dependent variable:
	rides
company fixed effects	5.336***
	(0.447)
Constant	-4.670***
	(1.414)
Observations	450
R^2	0.242
Adjusted R^2	0.240
Residual Std. Error	20.582 (df = 448)
F Statistic	142.795*** (df = 1; 448)
Note:	*p<0.1; **p<0.05; ***p<0.01

Demand 1 Model on Louisville

Note: metro station is replaced with campus, because Louisville has a major campus hub but lacks a well-utilized public transit system. High numerical values for coefficients due to dataframe containing aggregated rides from the entire year 2019.

	Dependent variable:
	Demand 1
alcohol licenses	135.234***
	(4.953)
is downtown	3,725.241***
	(1,089.375)
downtown distance	-691.315**
	(305.345)
downtown distance squared	115.056*
	(67.556)
campus	5,349.345***
	(1,234.779)
Constant	-937.340***
	(200.974)
Observations	276
R^2	0.801
Adjusted R^2	0.798
Residual Std. Error	1,997.469 (df = 270)
F Statistic	217.877*** (df = 5; 270)

Demand 1 Model on Los Angeles

Note: campus is added because Los Angeles has a major campus hub

	Dependent variable:
	Demand 1
metro station	40.674***
	(6.425)
alcohol licenses	6.371***
	(0.350)
is downtown	172.576***
	(13.699)
downtown distance	-705.681***
	(126.724)
downtown distances squared	559.347***
	(91.551)
campus distance	-302.029***
	(113.527)
land area	-0.00000
	(0.00000)
constant	69.243***
	(22.381)
Observations	784
R^2	0.584
Adjusted R^2	0.581
Residual Std. Error	49.043 (df = 776)
F Statistic	155.870*** (df = 7; 776)