

## ABSTRACT

Title of Dissertation: PLANNING TOWARDS AN EQUITABLE  
SHARING ECONOMY: ON HOUSING, ON  
TRANSPORTATION, ON POLICYMAKING

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The sharing economy has experienced phenomenal growth in the past decade. Its two most popular sectors, short-term rental (STR) and shared mobility, have significantly transformed people's travel behavior and disrupted the urban housing/transportation markets. On the other hand, planning and policy efforts lag behind the growth of the sharing economy due to its novelty and its market-based business model. In this dissertation, I use three empirical studies to demonstrate one of those planning and policymaking challenges from the equity perspective. In the first study, I investigate the impact of STR on single-family housing prices in Washington DC using a data-driven, hedonic analytical framework. Not only do I find a significant price inflation as a result of increasing STR activities, but I also identify the spatially uneven impacts that can adversely affect housing affordability in some minority-populated neighborhoods in the city. In the second study, I focus on the built and social environment factors to explain the spatial distribution of e-scooter sharing trips on

Washington DC's streets. Using real-time, trip trajectory level data, I am able to examine not only the built environment factors for a trip's origin and destination neighborhoods, but also the street design factors for a trip's traversing paths. Moreover, I apply a machine-learning based clustering analysis to segment trips by their temporal patterns, built environment, and social environment attributes. With both data-intensive analyses, I identify potential equity issues and opportunities associated with the emerging e-scooter sharing in DC. In the third study, I expand my analysis on STR and shared micromobility in a cross-city, cross-section exploration. I find similar tourist-oriented spatial patterns for three types of activities, including STR, station-based bike-sharing, and dockless bike/e-scooter sharing. Additionally, I find a significant lag in their uses in socially disadvantaged neighborhoods in eight cities, as well as identifying a potential connection between active STR business and gentrification in communities of high social vulnerability. The policy heterogeneities within the eight cities provide different angles to understand the feasible and effective planning practices and policy approaches to address the equity concerns on the rising sharing economy.

PLANNING TOWARDS AN EQUITABLE SHARING ECONOMY: ON  
HOUSING, ON TRANSPORTATION, ON POLICYMAKING

by

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## Dedication

To this world:

Wonderfully weird.

Weirdly wonderful.

## Acknowledgements

I would like to express my gratitude to my committee members. They are part of the journey for this dissertation. In particular, Dr. Gerrit-Jan Knaap provides me a supportive, flexible, and creative space in the National Center for Smart Growth that fosters my personal growth throughout the PhD program.

I would like to thank my parents in China who always support me unconditionally. I feel indebted to their sacrifice for me to accomplish the PhD degree. I would also like to thank my host family in Oregon, who show their love and support to me when I need words of kindness and perspective to carry on my dissertation research.

Lastly, I would like to dedicate this dissertation to friends, colleagues, and many people who helped me one way or another. It is not a monumental achievement to finish a PhD dissertation, but I am glad you cast a ray of light along the way!

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## Chapter 1: Overview

During the course of my PhD life, I stay in a number of Airbnb properties for leisure trips and conferences. I ride with Uber/Lyft once or twice a month. I never use bike-sharing or e-scooter sharing because, ironically, I do not know how to bike. These “shared” economic activities play an integral role in the urban life. Shared mobility like Uber/Lyft and short-term rental like Airbnb are umbrellaed under the global concept of “the sharing economy”. Having personal experience with the study objects of this dissertation helps me form the intuitive expectations on the research outcomes. Yet, I am genuinely amazed at times when research uncovers the hidden perspectives that I cannot easily observe from the personal experience otherwise. This is my over-arching goal in academic research: To empirically confirm my instincts, to pick up where my intuitions fall short of, and to generate new knowledge about the emerging technology’s broad impact on urban economy and urban policy. This dissertation serves the purpose to generate new knowledge about the sharing economy, particularly from a social equity perspective. Before I dive into the dense research materials, I will introduce the sharing economy concept and outline the equity debates on its two most popular applications (Short-term rental (STR) and shared mobility) in this chapter.

### *1.1 The rising sharing economy*

The sharing economy is not a well-defined concept. The term “sharing” is somewhat deceptive as a communal experience or a sense of reciprocity is implied. In reality, participants in the sharing economy do not “share” cost or benefit, at least

directly. While I am not trying to define the concept, I characterize the sharing economy into three themes based on the existing literature:

*Reliance of online platform:* Information and telecommunication technologies (ICTs), such as cloud-based computing, enable transformative services from the traditional business-to-consumer market (e.g., shopping in a physical store or an online store) to a platform-based ecosystem consisting of content creators and subscribers (Kenney & Zsyman, 2016; Belk, 2014).

*Access without ownership:* People can fulfill their temporary needs of access goods and services via subscription while other people can provide idling resources simultaneously in the sharing economy. The crowdsourcing nature of the sharing economy means that the physical ownership (such as a bike, a car, or a vacation home) becomes unnecessary (Sundararajan, p.30; Kenney & Zsyman, 2016; Schor, 2017).

*A decentralized matching marketplace:* Thanks to the significant advancements in search algorithms, digital infrastructure, as well as a high share of ownership for smart devices (personal computer, smartphone, tablet, etc.), a peer-to-peer marketplace is able to match heterogeneous demands and supplies in real time and make seamless transactions in the sharing economy possible (Einav, Farronato, & Levin, 2016).

Owing to its economic efficiency, the sharing economy business model has been successfully diffused into many private and public sectors: In housing/lodging, STRs, supported by tech platforms like Airbnb and HomeAway, have significantly disrupted the real estate market. In transportation, transportation network companies (TNCs) like Uber and Lyft have gained a substantial share of the mobility market.

Public bike-sharing systems and private e-scooter sharing companies have jointly contributed to the rising popularity of micromobility in large and medium-sized cities in the U.S. and across the globe. It is projected that the global sharing economy will reach \$335 billion by 2025 (Martin, 2016).

Besides the obvious economic benefit, the sharing economy can contribute to the sustainable urban development with its broader social benefits: The sharing economy spurs localized economic activities associated with tourism (Sheppard & Udell, 2016). The sharing economy could potentially be eco-friendly. For instance, cities invest into shared micromobility (bike-sharing and e-scooter sharing) to encourage emission-less active travel to replace high-emission auto travel (He et al., 2020). An increase in active travel from bike-/e-scooter-sharing could generate health benefit, as well (Xu, 2019). Last but not the least, the concept of “sharing” implies reciprocity and trust, which leads to scholarly reflection on digital trust and human connection within the sharing economy (Sundararajan, 2019). The sharing economy gradually becomes an integral part of the smart city vision that could reshape urban economy, transforms urban governance, delivers urban mobility, and improves urban quality of life.

### *1.2 The neoliberal sharing economy on equity*

Technology advancement is always accompanied by controversies. From a social equity perspective, the techno-economic concept of sharing economy is blamed for reinforcing a neoliberal economic agenda (Martin, 2016). A neoliberal economy is characterized by strong property rights, a free and decentralized market, and a minimalist state (Harvey, 2007, p.2; Brand, 2015). The sharing economy’s emphasis

on the reliance of private platforms and a decentralized marketplace certainly flirts with the neoliberal ideal. In a capitalist society like the United States, one can argue that an emphasis of a free market is not intrinsically problematic. Yet, as planning scholars point out, market imperfections (such as monopolistic power, information asymmetry, and externalities) and the inherent limitations of democracy (e.g., the existence of power and hierarchy) determine that an allocation of resources based on the market mechanism can never reach the Pareto optimum – where the society’s maximum utility level is achieved without sacrificing any individual’s welfare (Banerjee, 1993; Fainstein, 2010, p.36). Therefore, it is worthy examining the distributional consequences of the sharing economy, in its multiple applications, among different subpopulations and communities. Only when the notion of distributional equity is reached such that each person is treated appropriately that we can achieve social justice in the sharing economy.

In a more substantive way to describe the equity issues about the sharing economy, my dissertation research focuses on the following aspects: (1) the spatial distribution of shared micromobility trips among different socioeconomic groups. The vertical equity with respect to socially disadvantaged groups would require that the disadvantaged groups (e.g., racial minority, senior population, and low-income households) be not underserved by the new mobility (Litman, 2019); and (2) the housing market consequences of STR (price effect and spatial distribution) on housing affordability. These issues are manifested from data-driven, quantitative research. Nevertheless, I acknowledge the qualitative aspect of understanding the heterogenous needs from different subpopulations and communities, which is beyond the scope of



the dissertation research but requires my attention and future research endeavor. To understand what drives the decisions regarding new mobility preference/usage, surveying users/non-users is more straightforward than correlating passive trip data with the underlying population characteristics to infer user profiles and preferences.

### *1.3 Structure of the dissertation*

The dissertation adopts a three-paper format with each of the following chapters leads an independent study: Chapter 2 focuses on the impact of STR on single-family housing prices and the equity implications in Washington DC. Chapter 3 provides data-intensive analyses on the spatial distribution of e-scooter sharing trips in the District of Columbia and discusses the equity challenges and opportunities associated with e-scooter sharing. Chapter 4 explores the spatial patterns of three types of sharing economy activities (STR, station-based bike-sharing, and dockless e-scooter sharing) in eight U.S. cities. The heterogenous social, built environment, and policy contexts from different cities offer unique insights on the commonalities and differences in the equity issues on STR and shared micromobility markets. Lastly, Chapter 5 summarizes highlights and limitations from the three empirical studies and provides forward-looking thoughts on future research.

Without further ado, let us dive into the empirical work of the dissertation!

# Chapter 2: Examining the Impact of Short-Term Rentals on Housing Price in Washington, D.C.: Implications on Housing Policy and Equity<sup>1</sup>

## *2.1 From niche to mainstream: the global and local rise of STRs*

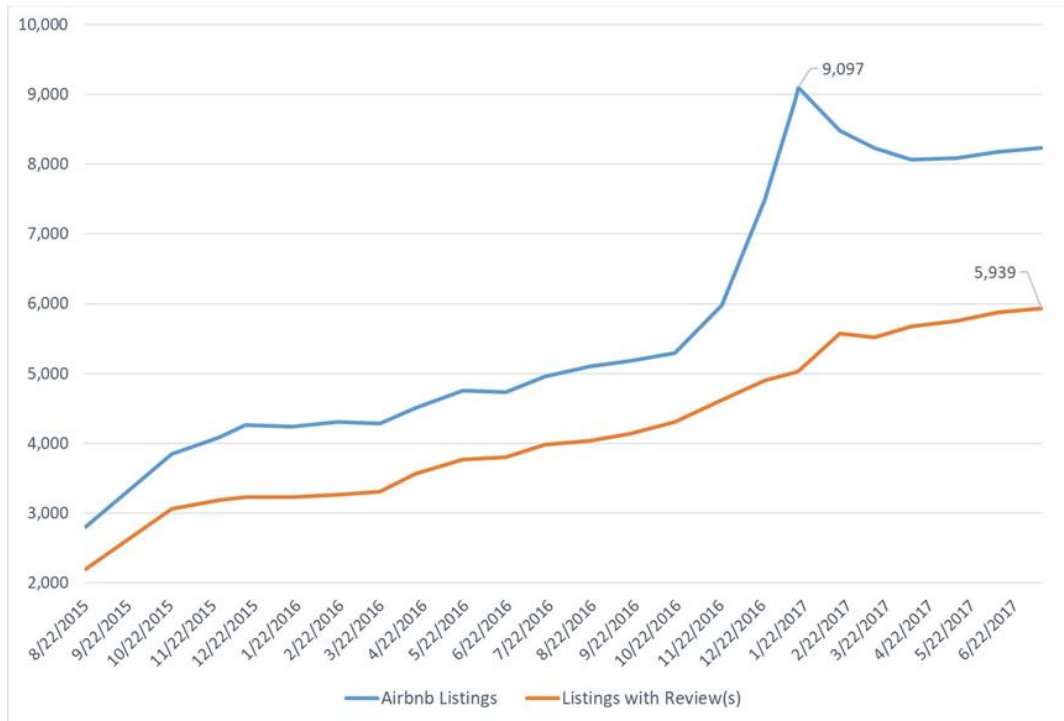
Charles Dickens would probably reckon, had he lived in the 21st century, that “It is the best of times; It is the worst of times – for sharing”: We hail a ride with strangers in an Uber; we sit in a cubicle next to an entrepreneur at WeWork; we, certainly, dare an adventure to stay with other travelers in an Airbnb rental. The ideology behind “sharing” is collaborative consumption – a concept built upon a set of principles, such as a critical mass of idling capacities, belief in the commons, and trust in strangers (Sundararajan, 2016). The sharing economy is a utopia painted by some as a solution to the underutilized resources in our society and a dystopia suspected by many as a road to digital elitism (Kenny and Zysman, 2016).

The global success of on-demand short-term rental (STR) platforms like Airbnb highlights the phenomenal sharing economy. Thanks to the advancements of information and communication technologies (ICTs) and the advent of an integrated (matching, booking, payment, etc.) peer-to-peer marketplace, searching cost for STRs has notably decreased for both the demand and the supply side (Einav et al., 2016). Contrary to a centralized economy, where transactional cost is lowered through

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<sup>1</sup> This paper is published by Housing Policy Debate (<https://doi.org/10.1080/10511482.2019.1681016>). Minor modifications have been made since the publication came out in December 2019.

economies of scale, the sharing economy creates a decentralized market that facilitates heterogeneous product choices (Einav et al., 2016). In addition, crowd-based networks and access without ownership remove the hurdle for ordinary people to participate in the sharing economy, blurring the boundary between a personal property and a professional establishment (Sundararajan, 2016).



**Figure 2-1. Number of Airbnb listings in DC, January 2015 – July 2017.**

In the global context, the soaring sharing economy translates into a rapid STR market expansion: Since its first booking in 2008, Airbnb has accumulated more than five million listings in 191 countries around the world and accommodated more than 300 million guests in the past decade (Airbnb, 2018). In the local context – the study area of this paper, Airbnb entered Washington D.C. in 2009 and other platforms like HomeAway and VRBO followed suit. A typical STR host accommodates guests 32 days out of a calendar year and makes an average income of \$3,400, according to a

survey conducted by Airbnb in 2016 (Airbnb, 2016). As of August 2017, the number of Airbnb listings in Washington D.C. exceeded 8,000 based on web-scraped Airbnb data<sup>2</sup>. The number of listings peaked around the inauguration of the Trump Administration and the following Women’s March in the middle of January 2017, when hundred-thousands of visitors gathered in the nation’s capital to witness those historical moments (New York Times, 2017). When filtered by whether a listing has a review, an indicator of STR business activities (Barron et al., 2017), active Airbnb listings grew steadily in number. **Figure 2-1** shows time trends for the total number of listings accessible through Airbnb.com and the number of listings with at least one review from August 2015 to July 2017. According to an Airbnb’s report (2017), 88% of the hosts in Washington D.C. share space in their permanent home. In 2016, 7,100 entire home listings hosted at least one stay. In another report (Airbnb, 2016), the platform claimed that 76% of its hosts rent out their primary dwelling for STR activities. Cross-referencing different data sources, I come up with the following first impressions of STRs in D.C.: (1) Washington D.C. is an emerging STR market, owing to its unique status as the nation’s capital and its numerous tourist attractions; (2) The majority of Airbnb’s thousands of listings were “registered” under a primary residential dwelling, though Airbnb (or other STR platforms) never revealed the number of additional listings registered by a single host or whether all hosts complied with local zoning codes, which may strictly prohibit STRs at certain locations; And (3) there is a sizeable

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<sup>2</sup> The main data source for this paper is from the Inside Airbnb website supported by Tom Slee (<http://insideairbnb.com/about.html>). I appreciate his data collection efforts, both in terms of frequency and quality. However, the data collection process stopped by the mid of 2017. According to another source, Airdna, current number of Airbnb listings in Washington D.C. fluctuates around 7,000. This could be a result of market saturation, policy uncertainty, or a combination of both.

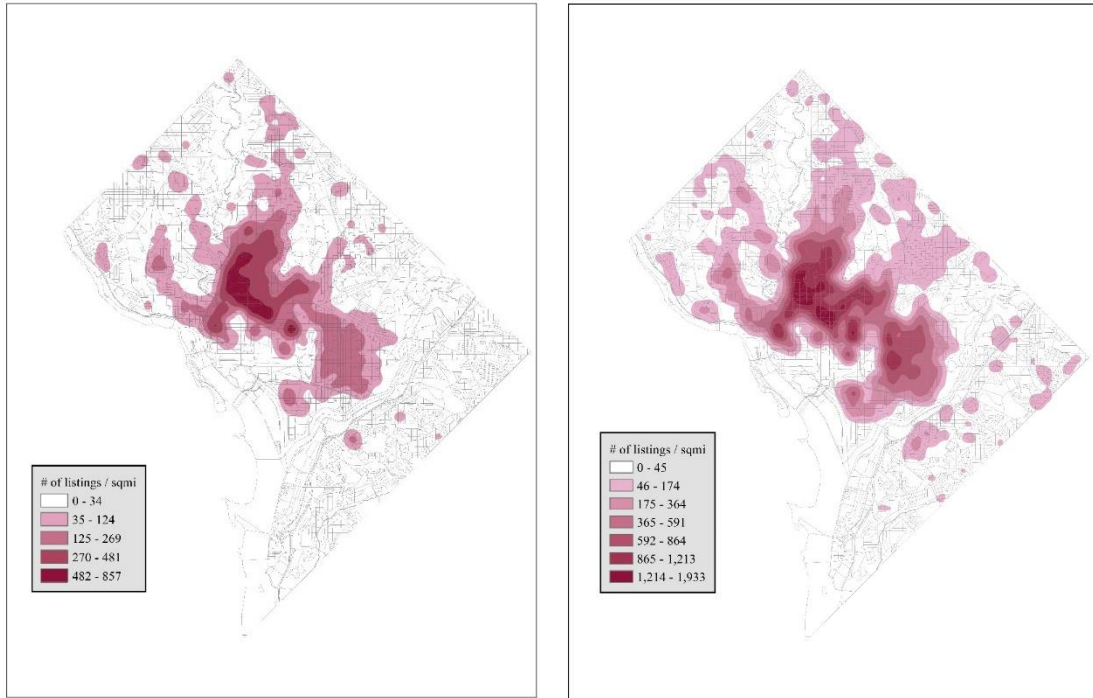
commercial STR market, in which the primary function of a property is STR business instead of long-term rental or residency.

Spatially, STR listings tend to cluster at tourist hot spots and mixed-use residential areas. I plotted two kernel density maps of Airbnb listings at two points in time (February 2015 and February 2017) based on web-scraped, geocoded Airbnb listing data<sup>3</sup> (See **Figure 2-2a** and **Figure 2-2b**). In addition to clusters in the densely populated historical and commercial neighborhoods, STRs also expanded to residential neighborhoods in the Northwest, the Northeast, and across the Anacostia River (Southeast) within a two-year span. Such a market expansion can be intriguing as the east side of D.C. is traditionally a less heated housing market with a noticeable growth in recent years (the Washington Post, 2018a).

Innovations in business and technology oftentimes outpace legislation that confines the boundaries of their practice. Once a niche market product, STRs are no exception. While triumphed by many who profited in the sharing economy, STR platforms increasingly clash with cities as issues, such as illegal listings and unmannerly guest behavior, start to make headlines. The central research question in this paper asks whether the thriving STR business in Washington D.C. is a significant factor that drives up single-family property prices in the owner housing market. In addition, it is vital to understand which neighborhoods are most impacted by STRs, especially the neighborhoods with high shares of racial minorities.

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<sup>3</sup> According to the disclaimers on Inside Airbnb, the locational information of an Airbnb listing that is publicly available on airbnb.com is typically within a 450-foot distance from its actual address to protect anonymity of a host's information. This is not a problem for the purpose of this study because Airbnb listing is characterized as a "density" attribute within a certain buffer distance.



**Figure 2-2a (left). Airbnb listing density, February 2015**  
**Figure 2-2b (right). Airbnb listing density, February 2017**

Many issues and discussions about STRs are described in literature. In the following section, I thoroughly review broader literature on this novel yet controversial topic with a focus on the welfare impacts STRs have imposed on different communities.

## 2.2 STR literature review

### 2.2.1 Virtues and vices of STRs

STRs only became a popular research subject recently because of its novelty. Early research focused on descriptive analyses of successes and setbacks of the STR business model: By adopting a trust and reputation system, STR platforms managed to minimize the potential risks of sharing with strangers (Frenken & Schor, 2017; Abrahao et al., 2017). On the other hand, a rating system could introduce unintended statistical and social biases due to information asymmetry. For instance, Zervas et al. (2015)

found that ratings on Airbnb were overwhelmingly positive, disguising variations in service quality. In addition, STR platforms introduced a two-sided feedback system for guests and hosts, where ratings were usually inflated out of fear of retaliation (Tadelis, 2016). Fradkins et al. (2017) conducted two field experiments to improve the effectiveness of the rating system for Airbnb. They found that both financial rewards and simultaneous reviews could readily eliminate strategic reciprocity in the STR rating process.

While addressing the importance of designing a robust rating system for STR platforms, researchers also found worrisome evidence where social biases were held against STR participants of color. Edelman et al. (2017) implemented an audit experiment on Airbnb and found a significantly higher number of booking request rejections against African American guests as compared to Caucasian guests. In addition, black hosts were found to earn significantly less rent from STRs than their white counterparts after controlling for housing conditions and location factors (Edelman and Luca, 2014). STR platforms claimed that they were not liable for such social biases as a result of their ambiguous policies on user profile photos and listing descriptions (Edelman & Luca, 2014). As allegations against discriminatory cases accumulate, public appeals for regulatory measures to hold STR platforms accountable for nondiscriminatory business conducts also increase.

Having observed the global success of STRs, researchers in tourism and hospitality tried to assess how this emerging market would impact the traditional lodging industry. Zervas et al. (2017) suggested that Airbnb could be responsible for 8% - 10% revenue loss for traditional hotel chains in Austin, TX. The new competition

from STR platforms, however, can substantially benefit consumers as lodging cost is brought down (Guttentag, 2015). It is no surprise that the incumbent hotels and lodging establishments will defend their business interests by pursuing legislation/regulation against the disruptive STRs. A major argument against the platforms is that they essentially created a deregulated market without enforcing regulation, such as business registration, on their participating hosts (Guttentag, 2015). Unlicensed accommodation providers could impose safety and public health risks on guests (Gurran, 2018). Furthermore, unlicensed STR listings could escape tax liabilities, providing an unfair advantage against traditional lodging establishments that obey tax rules (Gurran, 2018; Guttentag, 2015). This tax issue is typically resolved through tax agreements between a city government and STR platforms, allowing a city to collect hotel-like taxes on each booking (Bibler et al., 2018). Yet, it is not commonly practiced at all levels of city governments in the U.S., especially in small cities (DiNatale et al., 2018).

### 2.2.2 STRs' externalities

In addition to affecting subscribers and the hospitality industry, STRs also impact the welfare level of the broader community through externalities. Externalities exist naturally as the market is imperfect. While subscribers (hosts and guests) and STR platforms are tied to a legally binding contract, non-subscribers cannot hold platforms accountable for their behavior. Neither can non-subscribers invoke market incentives, such as withholding their patronage, to change platforms' behavior (Edelman & Geradin, 2016).

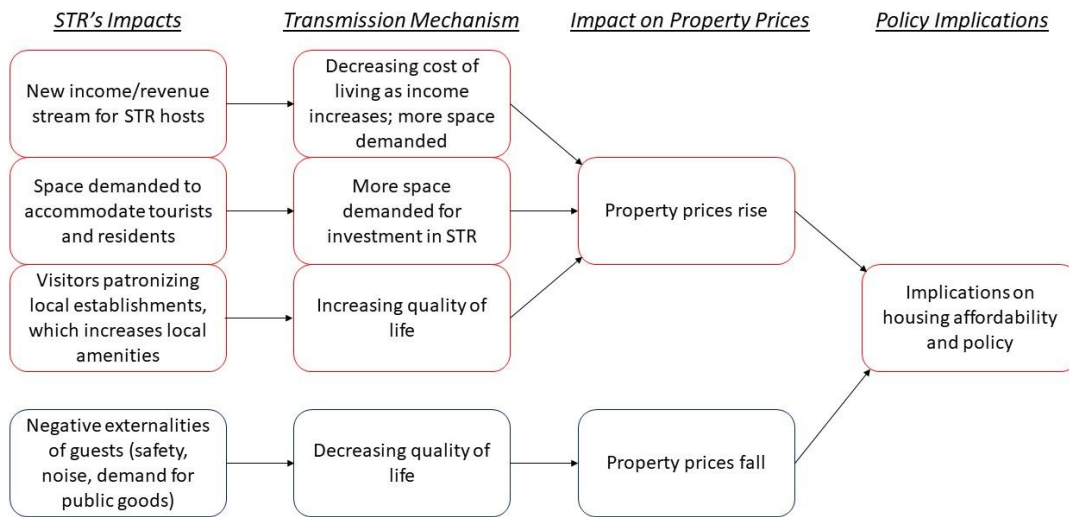
In the context of STR, the most obvious externality comes from changes to quality of life. Neighborhood quality, unbounded by ownership, could fall victim to a



“tragedy of the commons”, such as constant interruptions to the neighbors from STR guests, over-consumption of rivalrous public goods (e.g., parking space), and reckless guest behavior (e.g., hosting loud parties) (Edelman & Geradin, 2016). Filippas & Horton (2017) theoretically articulate that negative home-sharing externalities cannot be entirely internalized in a “tenant decide” regime. The externalities associated with STRs are complicated in that they are both “technological” (i.e., spillovers) and “pecuniary” (Scitovsky, 1954). Technological externalities of STRs refer to the social cost incurred by STR guests and borne by the public, such as littering, noise, excessive demand for parking and public goods. Pecuniary externalities of STRs, on the other hand, refer to the overall housing price and value changes as a result of the advent of STRs in a city (Filippas & Horton, 2017). Empirically, quantifying externalities is a difficult task due to its non-market nature. Hedonic pricing is a popular empirical approach for non-market goods valuation, which implicitly embeds non-market locational characteristics into determinants of property prices/values (Rosen, 1974).

While policymaking towards eliminating technological externalities is straightforward, such as restrictions against the use of STRs for events and zoning compliance (e.g., Office of Short-Term Rentals San Francisco, 2018), policymaking towards remedying pecuniary externalities involves a complicated planning issue. Specifically, STR platforms are condemned for exploiting the affordable rental housing stock that could have been rented by long-term renters and for inflating rent and property value (Gurran, 2018; Gurran & Phibbs, 2017; Edelman & Geradin, 2016). Pecuniary externalities are a product of interdependence among members of the economy. They cannot be resolved by simply applying policy tools to move the

economic equilibrium from the private optimum to the social optimum (Scitovsky, 1954). A change in policy to address pecuniary externalities, such as restricting the number of listings per host, is likely to change the dynamics of the entire STR market. A summary of STR externalities is provided in **Figure 2-3** (modified from Sheppard & Udell, 2016).



**Figure 2-3. Short term rentals (STRs') welfare impact and mechanism. Modified from Sheppard and Udell (2016, p.9).**

Unlike green space or air pollution, which can be unambiguously categorized as an amenity or a dis-amenity to quality of life, having STRs in a neighborhood can be considered both an amenity and a dis-amenity. What is revealed through differences in property prices/values is the net effect of STR externalities. Recent empirical results suggest that STRs seem to boost property values or rent (Wachsmuth & Weisler, 2018; Horn & Merante, 2017; Wachsmuth et al., 2017; Sheppard & Udell, 2016), indicating that the positive externalities associated with STRs dominate the negative ones.

Previous literature theorizes potential mechanisms of STRs' positive impact on property prices. STRs offers an extra income that can help property owners hold onto the ownership for longer as the cost of ownership is reduced (Sheppard & Udell, 2016). This extra income stream is capitalized into property prices (Barron et al., 2017). This is a plausible mechanism in particular for those who would have been evicted from their property due to financial struggles. In addition, STRs could generate new interests in real estate investment: Urban space becomes more valuable as tourists and residents take advantage of STRs (Sheppard & Udell, 2016). With limited urban land supply for new development, investors will seek to convert the existing housing stock into STRs, bidding up property prices and making life more difficult for first-time homebuyers and long-term renters. This is exactly what Wachsmuth & Weisler (2018) described as "gentrification without redevelopment": A rent (price) gap emerged as a result of a strong tourist demand for STRs. A strong economic incentive followed for real estate investors to evict existing long-term tenants or to cash out existing homeowners. They then converted properties into STRs without building anything new.

### 2.2.3 STRs' housing market implications

Empirically, existing research reached an early consensus that the advent of STR platforms, such as Airbnb, resulted in net increases in either property prices or rent (Barron et al., 2017; Horn & Merante, 2017; Sheppard & Udell, 2016; Wachsmuth et al., 2017). As new evidence emerged, the debate intensified over whether STRs exacerbated the housing affordability crisis in major U.S. and international cities. Nevertheless, a lack of robust rental housing transaction data made it difficult for housing policy researchers to produce fruitful results to stir up a conversation. Previous

analyses on rental data are aggregated either at the census tract level (e.g., Horn & Merante, 2017) or the metropolitan area level (e.g., Barron et al., 2017). No property/parcel level rental housing analysis exists at this point to my knowledge.

Many STR proponents found the argument of a direct substitution between STRs and long-term rentals unconvincing. A report on the impact of Airbnb on the Portland housing market suggested that “somewhere between 83 and 377 units (or 0.03% of the total housing stock in Portland) would be considered full-time Airbnb rentals (ECONorthwest, 2016).” It is unclear whether restraining the number of full-time STR listings in a city could significantly shrink the rental housing shortage. Opponents of unregulated STRs focused on the issue in regard to commercial STR hosts, who rented multiple listings for an extended number of days in a year (from three months to all year round). According to a local nonprofit organization, more than 1/3 of all listings in D.C. could be categorized as “commercial listings” (D.C. Working Families, 2017). In Canada, researchers found that 13,700 “entire homes” out of 81,000 Airbnb listings were rented more than 60 days a year in Montreal, Toronto, and Vancouver (Wachsmuth et al., 2017), which are unlikely to be rented to long-term renters. The definition of “an entire home” is tricky, since it does not necessarily mean that the property owner lives elsewhere. In the ECONorthwest’s report (2016), a fair observation was made that the definition of “entire home” from Airbnb also includes (a) accessory dwellings attached to a property, (b) parts of a property with a separate entrance and private rooms, or (c) a basement unit without a separate entrance. In addition, a property owner can list multiple bedrooms as multiple listings on the platform, contrary to the D.C. report’s argument that a commercial host must have rented out more than one property. As

Wachsmuth et al. (2017) point out, current observations about Airbnb are based on third-party information and data sources (e.g., web-scraped data). Any statement with a high level of confidence would require data from STR platforms directly with accurate details.

The rest of the paper is organized as follow: In Section 2.3, I highlight controversies around STRs in Washington D.C. and ongoing efforts towards regulating the STR market. In Section 2.4, I summarize Airbnb and property data used in the analysis. Empirical frameworks and results are presented in Section 2.5. Robustness checks are provided in Section 2.6. Lastly, I discuss the policy implications and conclude the paper in Section 2.7.

### *2.3 STR Controversies and regulations in the District of Columbia*

#### 2.3.1 Growing STR business amid controversies

There are no doubts that STR platforms like Airbnb provide economic benefit to D.C. residents. However, the relationship between STR platforms and the city is not always cheerful. A major concern about STRs is that commercial hosts occupy precious housing resources that could have housed long-term renters in the city. In a defense from Airbnb (2017), the platform argued that only 0.22% of the “entire home” listings were booked for more than half a year in 2016. In addition, the average monthly income for an STR host (\$680) is only a fraction of the average monthly rental income in D.C. (\$2,299)<sup>4</sup>. Therefore, from an economic perspective, part-time STRs rented for 90 days

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<sup>4</sup>According to Insider Airbnb, the estimated full-time STR monthly income is about \$986 (<http://insideairbnb.com/washington-dc/>), still much lower than the average rental price (even for a studio).

or fewer in a calendar year, which consist of 60% of all entire home units, can hardly substitute long-term rentals.

Another concern regarding STRs' housing market impact has to do with its spatial concentration around tourist hot spots. Areas like downtown and Capitol Hill are real estate heavens and attract heavy tourist traffic. It is, to state the least, worrisome that STRs may significantly change the housing market dynamics in these areas. If a property price premium is transmitted to the rental housing market in such areas, then long-term renters will have to endure inflating rent as a spillover from increasing housing prices.

Other stories unfolded that STR platforms barely regulated their hosts on business registrations or compliance with local zoning ordinances, such as the strict condominium rules that prohibit short-term sublets (the Washington Post, 2017a). In one case, several apartment buildings were converted illegally into full-time STRs as opposed to being leased to long-term renters (Greater Greater Washington, 2017). STR platforms were not well-received by all. Therefore, the city government decided to step up and intervene in the unregulated STR market.

### 2.3.2 D.C.'s STR regulatory framework

In January 2017, Kenyan McDuffie, city councilmember representing Ward 5, first introduced the Home/Short-term Rental Regulation and Affordable Housing Protection Act of 2017 (B22-92), heralding the first official attempt to legalize and regulate STRs. Both proponents and opponents fiercely exchanged their stands during the first public hearing in April 2017 over the current state and practice of STRs in D.C.

and to what extent the STR business should be regulated. (Council of the District of Columbia, 2018).

The initial proposal was not well-received as STR platforms and subscribers described the bill as “goes too far and is too restrictive” by capping the number of days in a year for STR operation to 15 days (the Washington Post, 2017b). After inaction for more than a year, the city council moved forward the legislation in October 2018 with significant amendments to the original bill: An STR listing is capped to have 90 business days per calendar year; The monetary penalty on violations is reduced; Any STR listing located outside of a host’s primary residence requires a license for operation (Council of the District of Columbia, 2018). The city council passed the bill unanimously in November 2018, marking the end of an era of unregulated STRs in Washington D.C.

**Table 2-1** highlights the legislative contexts of B22-92. It also describes approved STR bills and ordinances from the neighboring counties, including Arlington County, VA, Prince George’s County, MD, and Montgomery County, MD. Through parallel comparisons, we can observe many similarities amongst these legislations: A STR is defined as the transient occupancy of a residential dwelling (owned or rented); A business license is acquired conditional upon inspections from the regulatory body; Only the primary residence is allowed for STRs, where physical presence of the residents is required for at least 180 days in a calendar year; The maximum number of STR days in a calendar year and the maximum number of guests are specified. On the other hand, these bills and ordinances also differ from each other: While both two counties in Maryland and the D.C. government passed jurisdictional bills, Arlington

County (VA) only revised its zoning ordinances. Having the zoning commission enforcing the ordinances with the power to suspend or revoke a permit may yield better enforcement outcomes, but it could also cause an administrative burden. D.C.'s STR bill remains the most restrictive in terms of the 90-day cap for STR (as opposed to 120 days or 180 days) with special exemptions. In addition, B22-92 is the only bill that specifies the penalty on each violation. In response to the legislative approval, STR platforms quickly denounced the council's action and warned to bring the case directly to a 2020 ballot initiative (the Washington Post, 2018b).

If passing a legislation on STRs requires year-long efforts, then enforcing STR regulations entails administrative readiness and coordination. Underprepared implementation of STR regulations results in unintended consequences. One such consequence is a cumbersome registration process. As one of the first cities to pass an STR legislation in 2016, San Francisco only registered 2,168 Airbnb hosts as of early 2018, leaving the majority of its 8,000 STR listings with no legal status (San Francisco Chronicle, 2018). Similarly, eight months after the legislation took effect, Arlington County government only issued 101 transient rental permits on an estimated 1,600 STR owners base (INSIDENOVA, 2017). If the low registration rate is a mixed outcome of uncooperative STR owners and inefficient administrative procedures, then the existence of unregistered/commercial listings heightens a lack of regulatory enforcement. Airdna's (2018) data suggest that 5,778 Airbnb listings in San Francisco remain active, despite the fact that the municipal STR bill has been in effect for two years. Should the platforms be fined for listing unregistered STRs? Should the city go after each unregistered STR owner? These are commonly asked policy questions.



**Table 2-1 Comparison among different STR legislative frameworks in the D.C. Metropolitan Area**

Jurisdiction	Washington D.C.	Arlington County, VA	Montgomery County, MD	Prince George's County, MD
Legislative Framework	B 22-92 (Proposed bill & amendments)	Zoning Code 12.9.11 & 12.9.12	Zoning Text Amendment 17-03 & Senate Bill 2-16	CB-10-2018 & CB-11-2018
Definition	A STR means paid lodging for transient guests with the host presence unless it is a vacation rental. A STR is not a hotel, inn, motel, boarding house, or b&b.	An accessory homestay is a special type of home occupation that allows the occupant of a residential dwelling unit to host short-term overnight guests.	A STR means the residential occupancy of a dwelling unit for a fee for less than 30 consecutive days. A STR is not a Bed and Breakfast.	A STR means a residential dwelling unit occupied by a STR guest, other than a permanent occupant, for fewer than 31 consecutive days and no more than 90 days per calendar year.
Business license	A license issued by the Department of Consumer and Regulatory Affairs. Valid for a period of 2 years.	Accessory homestay permit from the Zoning Administrator. Renew annually.	A license issued by the director of the Department of Health and Human Services is required. Renew annually.	Annual issuance of a license by the Department of Permitting, Inspections, and Enforcement.
Zoning ordinance	D.C. Zoning Commission will revise zoning codes to permit STRs.	Arlington County Zoning Code 12.9.11 and 12.9.12	Montgomery County Zoning Text Amendment 17-03	CB-10-2018 (Sec.27-464.09 "Tourist Home as an 'accessory use'.")
Days of STRs in a calendar year	90 days (unless the host has received an exemption.)	180 days	120 days (no cap for rental days with physical presence of the owner.)	90 days if not occupied by the owner or 180 days if occupied by the owner.
Primary dwelling requirement	Primary residence only, which means the property is eligible for the homestead deduction pursuant.	Primary residence only. The dwelling unit must be occupied for at least 185 days per year.	Primary residence only (farm tenant dwelling or on-site accessory dwelling prohibited.)	Primary residence to get the license. However, no stated restriction on rental dwellings once license is obtained.
Maximum number of dwellings per host	1	1 (single family. Multi-family is subject to the same rule as condo/apartment.)	1 (owner's property or owner-authorized resident's primary residence.)	Multiple, but the combined allowable time frames shall not exceed the permissible calendar days.

Maximum number of rooms per dwelling	No cap, as long as all rooms/suites within the property.	No cap. All rented bedrooms must be in the main building. Accessory dwelling allowed with a permit.	No cap. Only habitable rooms can be used by guests.	No cap. Only habitable rooms can be used by guests.
Maximum number of guests per dwelling	8 (or 2 per bedroom, whichever is greater.)	6 (or 2 per bedroom, whichever is greater.)	6 (only counting guests 18 years or older and maximum 2 per bedroom.)	8 (and no more than 3 guests per bedroom.)
Requirement on safety codes	Smoke detectors and carbon monoxide detectors.	Fire extinguishers, smoke detectors, and carbon monoxide detectors.	Smoke detectors and carbon monoxide detectors. Sanitation facilities.	Smoke detectors and carbon monoxide detectors. Fire extinguishers. A posting of emergency contact and a floor plan.
Other requirements	Insurance of liability required. No visitor parking permit for STR guests.	Forbidden for commercial meetings, or other gathering for direct or indirect compensation.	HOA, Condo, and co-op associations will be notified when an application is filed. An application is not prohibited by HOA, condominium document, or a rental lease.	Insurance of liability required. Compliance with the requirements of HOA, condo association, etc. One parking space for every three guests.
Tax	14.50%	7.25%	7%	7%
Penalty	Any host who violates regulations is subject to a civil penalty of \$500, \$2,000, and \$6,000 for the first, second, and third violation, respectively. Suspension and revocation of the license.	The permit may be revoked with no new permit for one year in the event of three or more violations, failure to comply with the zoning ordinance, or refusal to cooperate in a complaint investigation.	The license is suspended for an applicant receiving at least three complaints that are verified as violations within a 12-month period. No new issuance within 3 years after a license is revoked.	A STR license may be suspended or revoked at any time due to non-compliance with the requirements, citation, violations of the building, electrical, plumbing or zoning code. In addition, subject to a civil fine up to \$1,000.
Legislative outcome	Adopted on Nov. 13, 2018, and effective in Oct. 2019.	Adopted in Nov. 2017 and effective since Jan. 2018.	Senate Bill 2-16 and ZTA 17-03 became effective on July 1, 2018.	Adopted on Oct. 23, 2018, and effective Oct. 1, 2019.

In the housing policy debate over STRs' impact on D.C.'s housing market, a missing piece of the puzzle is how STRs could impact property owners and homebuyers. In the following sections, I will empirically investigate this issue using unique open-source data.

## 2.4 *Empirical Data*

### 2.4.1 Data sources

*Airbnb data:* While data from STR platforms are almost impossible to acquire, third-party web-scraped data have become popular for research purposes (e.g., Wegmann & Jiao, 2017). Web-scraped STR data are subject to some limitations, such as the use of location proxies. Yet, such data provide a comprehensive set of information about an available listing, including listing amenities and reviews. Through real-time data scraping, researchers can describe STR activities subject to a degree of discretion. Researchers either design their own scraper (e.g., Barron et al., 2017) or rely on third-party scrapers, such as Inside Airbnb (e.g., Gurran & Phibbs, 2017; Horn & Merante, 2017) and Airdna (e.g., Wachsmuth & Weisler, 2018). In this study, I used data collected by Tom Slee from September 2014 to July 2017<sup>5</sup>.

Six web-scraped Airbnb datasets at half-year intervals were combined to represent Airbnb listings in D.C. from early 2015 to mid-2017. The half-year intervals deliberately take into account seasonal fluctuations in tourism (March – August are typically the popular months for D.C.). While the data do not cover the initial entry of

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<sup>5</sup> The scraper operator, Tom Slee, stopped Airbnb data collection after the summer 2017 due to an overwhelming number of requests. He directed requestors to other open data sources like Inside Airbnb.

Airbnb into the D.C. market, they cover the period when the STR business took off in D.C. (recall **Figure 2-1**).

*Housing data:* Housing information came from the Open D.C. data portal with periodically updated property sales records and city-wide housing appraisal records. The appraisal data provide underlying housing attributes, such as number of rooms, bathrooms, stories, square-footage, and the estimated building year. Property sales records from the Integrated Tax System Public Extract (ITSPE) and appraisal data from the Computer Assisted Mass Appraisal (CAMA) database were extracted and combined using a unique identifier, Square Suffix Lot (SSL). After trimming the dataset by matching criteria, completeness of attributes, and exclusions of extreme values, I derived the final dataset of property sales records during September 2014 – July 2017.

*Neighborhood data:* Aside from housing attributes, neighborhood characteristics are also deterministic in hedonic prices. I included the most important attributes in the final dataset, such as access to Metrorail stations, public schools, and historical landmarks. In addition, underlying population attributes at the census tract level were extracted from the American Community Survey database and were incorporated into the final dataset.

#### 2.4.2 Data processing

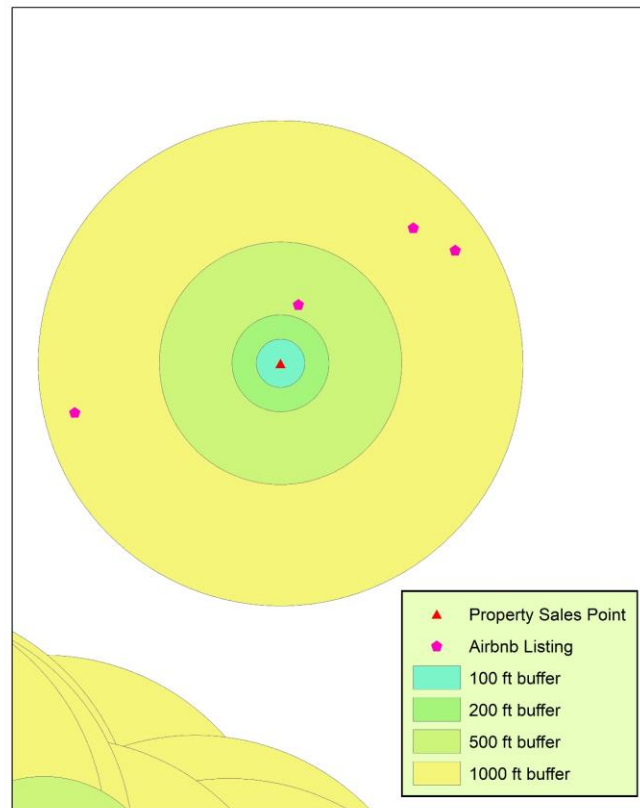
Due to the size of the housing datasets, neither sales records nor appraisal data were geocoded. I applied the Master Address Repository (MAR) geocoder to geolocate each SSL within the ITSPE database by a 92 percent matching criterion. Only 7,334 out of the 110,883 records were dropped due to low matching rates. The ITSPE data

were then merged with the CAMA residential data based on a unique identifier, Square Suffix Lot (SSL). 52,577 single-family property sales records were successfully matched<sup>6</sup>. 12,680 records between September 2014 and July 2017 were kept in the final single-family housing dataset.

I measured “Airbnb density” by counting the number of listings within a certain buffer distance of a property sales point at a given period of time. Four buffer sizes were included in the analyses: 100 feet, 200 feet, 500 feet, and 1,000 feet. The choice of buffer size is a state of art: While a smaller buffer captures a STR’s most direct impact on a property’s price, a larger buffer allows for more variations in “Airbnb density” and captures the broader economic impact of Airbnb activities on the neighborhood. As a comparison, Sheppard & Udell (2016) tested different buffer sizes from 200 meters (656 feet) to 2,000 meters (6,560 feet). Some studies also calculated “Airbnb density” at the aggregated level, such as census tracts (Horn & Merante, 2017). I did not include a buffer size smaller than 100 feet or a buffer size larger than 1,000 feet because (a) the variation in Airbnb density was insignificant for a smaller buffer and (b) the neighborhood impact of a single listing was too weak for a much larger buffer. With an increasing buffer size, more listings will be included, but the listings farther away from the centroid will have a smaller impact on property prices. **Figure 2-4** illustrates the “Airbnb density” at different buffers in the ArcGIS environment.

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<sup>6</sup> Another 39,886 records were matched for condominium and multifamily sales records. Condominium data were excluded from this study due to unobserved attributes (such as condominium management quality) that could be crucial in determining their prices.



**Figure 2-4. Example of Airbnb density buffers around a property sales point.**

### 2.4.3 Summary statistics

Summary statistics of the final dataset are presented in **Table 2-2**. The average number of Airbnb listings within 100 feet of a single-family property sales point is 0.21. The variation is small for this search radius that it may affect the precision of the point estimate in the hedonic regression model. The “Airbnb density” increases to 0.85, 5.06, and 18.63 for the 200 feet, 500 feet, and 1,000 feet search radiuses from a property sales point, respectively. In theory, the marginal effect of each Airbnb listing on a property’s price will decay as the buffer size increases. Therefore, I anticipate a declining magnitude in hedonic point estimates for the Airbnb density variable for a

larger buffer.

The sample average single-family property price is \$762,000 and the median price is \$630,000, higher than the median home value in D.C. of \$544,000 in 2017<sup>7</sup>. The sample average property land area is 3,000 square feet (sqft) and the average structure area is about 1,700 sqft, with 7.5 rooms, 2.2 bathrooms, 0.6 half-bathrooms, and 1.2 kitchens. In addition, basic amenities are usually equipped, such as a fireplace, an air-conditioner, and a heating system.

As for neighborhood attributes, a typical property resides in a populated urban area with heavy traffic (as indicated by the number of crash incidents within a half-mile buffer) and some crime incidents. A property usually has a good access to public schools within walking distance (0.5 miles). A property also has an easy access to a Metrorail station and commercial areas. In Washington D.C., it is especially common to have historical landmarks in the neighborhood. Such amenities can have significant impacts on property prices.

In terms of neighborhood demographics, a typical D.C. property is located in a neighborhood of an employed, educated, middle-class population. However, the population demographics differ significantly by zip code. I carefully controlled for such “zip codes” fixed effects and STR clustering effects in the models specified in the next section.

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<sup>7</sup> The median value for condominium is \$440k, but the condominium sample was excluded due to lack of detailed condominium attributes from the appraisal database.

**Table 2-2. Summary statistics**

Variable (name)	Mean	S.d.	Variable	Mean	S.d.
<i>Airbnb attributes</i>			<i>Neighborhood attributes</i>		
Airbnb listings in 100 ft (Airbnb100ft)	0.21	0.56	Annual N of traffic incidents in .5 mile (numCrash)	152.3	114.7
Airbnb listings in 200 ft (Airbnb200ft)	0.85	1.52	Annual N of crime incidents in .5 mile (numCrime)	326.0	265.3
Airbnb listings in 500 ft (Airbnb500ft)	5.06	7.35	Number of public schools in .5 mile (pubschool)	2.38	1.82
Airbnb listings in 1,000 ft (Airbnb1000ft)	18.63	26.12	Number of charter schools in .5 mile (chaschool)	2.60	2.59
<i>Housing attributes</i>			Number of Metrorail stations in .5 mile (metro)	0.43	0.66
Property Prices in \$ (last_sale_price)	762,842	754,505	Number of historical sites in .5 mile (landmark)	9.53	15.12
Land area in 1,000 sqft (landarea)	3.087	2.835	<i>Demographic attributes (Census tract level)</i>		
Estimated year built (eyb)	1970	17.44	Total population in a tract (totalpop)	3,904	1,458
Number of rooms (rooms)	7.44	2.51	Population density per acre (popden)	15.20	9.69
Number of bathrooms (bathrm)	2.24	1.06	Percentage adult (pct_adult)	0.18	0.06
Number of half-bathrooms (hf_bathrm)	0.65	0.60	Percentage Hispanic/Latino (pct_hisp)	0.09	0.08
Number of kitchens (kitchens)	1.24	0.63	Percentage highly educated – post-bachelor (pct_educated)	0.29	0.19
Number of fireplaces (fireplaces)	0.60	0.89	Percentage high income – >\$20,000 (pct_highinc)	0.15	0.14
Square footage (sqft)	1,693	818.6	Unemployment (pct_unemp)	0.11	0.07
Air-conditioning – dummy variable, 1 is yes (ac)	0.73	0.45	Poverty rate (pct_poverty)	0.15	0.10
Number of stories (stories)	2.19	0.80	Number of observations	12,680	
Grade – 1 is low, 12 is exceptional (grade)	4.25	1.38	Other housing attributes: exterior wall type (extwall), roof type (roof), interior wall type (intwall), heating type (heat), building structure (structure), land use code (usecode)		
Condition – 1 is poor, 6 is excellent (condition)	3.81	0.80			



I conducted a Pearson's correlation test<sup>8</sup> to examine the preliminary bivariate relationship between "Airbnb density" and property prices and to detect the unusual signs of different housing and neighborhood attributes in explaining property prices. All "Airbnb density" variables were positively correlated with property prices, suggesting a net positive externality from STRs. Most signs of the correlation statistics made sense. No perfect collinearity was found except for income and education at the Census tract level.

## *2.5 Hedonic analyses of Airbnb on property prices*

Empirically, the hedonic pricing model is one of the most widely adopted approaches to study consumers' willingness to pay a non-market goods. In this study, Airbnb density, defined by the number of Airbnb listings within a distance from a property sales point, runs into the regression analyses as a hedonic attribute. I constructed three models to fully investigate Airbnb's impact on property prices: a pooled cross-sectional model, a fixed effects model at the census block level, and a first-difference model.

### 2.5.1 Model specifications

The full-sample cross-sectional model considers the most comprehensive set of explanatory variables, including housing attributes, neighborhood factors, sociodemographic attributes at the census tract level, and series of time and location fixed effects. The model is specified as follows:

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<sup>8</sup> Due to the size of the Pearson's correlation matrix, I decided not to include it in the final paper.

$$lgprice_{in} = \alpha + Airbnb_{in}\beta + X_{in}\delta + N_n\varphi + \varepsilon_{in}$$

Housing price takes a logarithm form to account for the right-skewedness in distribution;  $X_{in}$  represent housing and neighborhood attributes;  $N_n$  represent demographic attributes that are common to each property  $i$  in census tract  $n$ .

The census block level fixed effects model controls for unobserved time-invariant characteristics that may jointly affect housing prices and Airbnb activities, such as commercial activities, infrastructure, and public facilities. In addition, a time trend is added in the model to control for common housing market fluctuations over different periods. The model is specified as follows:

$$lgprice_{bt} = \alpha + Airbnb_{bt}\beta + X_{bt}\delta + N_{bt}\varphi + \omega_b + \theta_t + \varepsilon_{bt}$$

The unit of observation is a representative property at the census block  $b$  during period  $t$ . Both block level fixed effects  $\omega_b$  and common time trends  $\theta_t$  are included.

The nation's capital experienced a historical influx of visitors in January 2017. Both supporters and protesters congested the city during the Trump administration's inauguration and the Women's March a day after – the latter attracted much heavier traffic. Having sensed the unprecedented demand for lodging, the local STR community expanded dramatically between November 2016 and January 2017, from 5,975 listings to 9,097 listings according to the web-scraped data. This exogenous demand shock created a unique opportunity for me to conduct a “before/after” type of analysis on how new Airbnb listings/activities affected property prices.

I selected block-level data between March 2016 and November 2016 for the “before” period and data between February 2017 and July 2017 for the “after” period.

The final dataset consists of 2,047 observations for 1,027 blocks. I then applied a first-difference model to understand how changes in Airbnb density fluctuated property prices:

$$\Delta \ln price_b = \alpha + \Delta Airbnb_b \beta + \Delta X_b \delta + \Delta N_b \varphi + \Delta \varepsilon_b$$

### 2.5.2 Empirical results

The main estimation results are presented in **Table 2-3**. Panel A reports the regression coefficients and standard errors for the most important variables in the pooled cross-sectional model. It is evident that (a) having Airbnb listings in the neighborhood mildly raises a single-family property's price and (b) the average effect of a listing decays as the search buffer broadens. Other significant variables also help explain property prices, such as good property appraisal grades and conditions, having public schools and historical landmarks within walking distance, as well as dwelling in a wealthy community. The model's goodness of fit is high with  $R^2 > 0.80$ .

Panel B shows regression coefficients and standard errors of the Airbnb listing density variables for the fixed effects model. The coefficients on the Airbnb densities at the 200-foot, 500-foot, and 1000-foot buffers hold their statistical significance and they are slightly larger in magnitude than those in Panel A. While the fixed effects model controls for unobserved time-invariant characteristics at the census tract level, the model's goodness of fit drops due to aggregation. Nevertheless, the results from both models suggest a price premium on properties due to the presence of Airbnb listings in the neighborhood.

Panel C shows hedonic regression results for the first difference model. Again,

the coefficients on Airbnb densities at the 200-foot, 500-foot, and 1000-foot buffers remain statistically significant. The magnitudes are much larger due to the dramatic increase in Airbnb density between November 2016 and January 2017. One possible explanation is that the transition to a new administration led to a temporary spike in housing demand to accommodate new residents. Airbnb (and STRs in general) fulfilled the transitional housing need.

**Table 2-3. Empirical results of three models**

Panel A: Pooled Cross-Sectional Model (Dependent variable: logarithm of property price)								
	100 ft buffer		200 ft buffer		500 ft buffer		1000 ft buffer	
Variable Name	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
<b>Airbnb density</b>	<b>0.0065</b>	<b>(0.006)</b>	<b>0.0051*</b>	<b>(0.003)</b>	<b>0.0026**</b>	<b>(0.001)</b>	<b>0.0011**</b>	<b>(0.000)</b>
Landarea	0.0107***	(0.002)	0.0107***	(0.002)	0.0108***	(0.002)	0.0109***	(0.002)
Eyb	0.0002	(0.000)	0.0002	(0.000)	0.0002	(0.000)	0.0002	(0.000)
Ac	0.0723***	(0.017)	0.0725***	(0.017)	0.0724***	(0.017)	0.0723***	(0.017)
Fireplaces	0.0227***	(0.006)	0.0228***	(0.006)	0.0226***	(0.006)	0.0224***	(0.006)
Rooms	0.0051*	(0.003)	0.0051*	(0.003)	0.0051*	(0.003)	0.0051*	(0.003)
bathroom	0.0648***	(0.004)	0.0648***	(0.004)	0.0649***	(0.004)	0.0652***	(0.004)
hf_bthroom	0.0278***	(0.005)	0.0278***	(0.005)	0.0278***	(0.005)	0.0278***	(0.005)
Sqft	0.0002***	(0.000)	0.0002***	(0.000)	0.0002***	(0.000)	0.0002***	(0.000)
Stories	0.0002***	(0.000)	0.0002***	(0.000)	0.0002***	(0.000)	0.0002***	(0.000)
Grade	0.0397***	(0.010)	0.0397***	(0.010)	0.0397***	(0.010)	0.0397***	(0.010)
Condition	0.1233***	(0.007)	0.1233***	(0.007)	0.1231***	(0.007)	0.1232***	(0.007)
Kitchens	-0.0291	(0.018)	-0.0288	(0.018)	-0.0282	(0.018)	-0.0281	(0.018)
Pubschool	0.0072**	(0.003)	0.0071**	(0.003)	0.0068**	(0.003)	0.0064**	(0.003)
Metro	0.0229	(0.013)	0.0227	(0.013)	0.0220	(0.013)	0.0222	(0.013)
Landmark	0.0029***	(0.001)	0.0029***	(0.001)	0.0028***	(0.001)	0.0028***	(0.001)
pct_adult	0.3242**	(0.131)	0.3214**	(0.131)	0.3144**	(0.130)	0.3078**	(0.129)
pct_educated	0.5133***	(0.113)	0.5046***	(0.114)	0.4819***	(0.114)	0.4650***	(0.116)
pct_unemp	-0.4268***	(0.136)	-0.4306***	(0.136)	-0.4365***	(0.135)	-0.4387***	(0.137)
Constant	11.4146***	(0.882)	11.4154***	(0.879)	11.4058***	(0.862)	11.4174***	(0.846)
Other controlled variables	heat type, land use type, structure type, interior & exterior wall type, roof type, # of traffic & crime incidences, # of charter school, population density, % Hispanic population, % high income household, poverty rate							

Zip-code dummies	✓		✓		✓		✓	
Period dummies	✓		✓		✓		✓	
Cluster s.e.	✓		✓		✓		✓	
N	12,680		12,680		12,680		12,680	
R <sup>2</sup>	0.8095		0.8095		0.8097		0.8099	
Robust s.e. in parentheses, *** p<.01, ** p<.05, * p<.1								
Panel B: Fixed Effects Model at Census Tract Level (Dependent variable: average logarithm of property price)								
	100 ft buffer		200 ft buffer		500 ft buffer		1000 ft buffer	
Variable Name	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
<b>Airbnb density</b>	<b>0.0060</b>	<b>(0.008)</b>	<b>0.0078*</b>	<b>(0.003)</b>	<b>0.0037**</b>	<b>(0.001)</b>	<b>0.0012***</b>	<b>(0.000)</b>
Other controlled variables	land area, estimated year built, air-conditioning, fireplaces, rooms, bedrooms, bathrooms, half-bathrooms, sqft., stories, grade, condition, heat type, land use type, structure type, interior & exterior wall type, roof type, # of traffic & crime incidences, constant							
Period dummies	✓		✓		✓		✓	
N	7,624		7,624		7,624		7,624	
N blocks	2,378		2,378		2,378		2,378	
R <sup>2</sup>	0.3905		0.3910		0.3923		0.3925	
Robust s.e. in parentheses, *** p<.01, ** p<.05, * p<.1								
Panel C: First Difference Model at Census Tract Level (Dependent variable: average logarithm of property price)								
	100 ft buffer		200 ft buffer		500 ft buffer		1000 ft buffer	
Variable Name	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
<b>Airbnb density</b>	<b>0.0212</b>	<b>(0.016)</b>	<b>0.0136*</b>	<b>(0.008)</b>	<b>0.0103***</b>	<b>(0.002)</b>	<b>0.0031***</b>	<b>(0.001)</b>
Other controlled variables	land area, estimated year built, air-conditioning, fireplaces, rooms, bedrooms, bathrooms, half-bathrooms, sqft., stories, grade, condition, heat type, land use type, structure type, interior & exterior wall type, roof type, # of traffic & crime incidences, constant							
After	0.0283	(0.017)	0.0275	(0.017)	0.0249	(0.017)	0.0240	(0.017)
N	2,047		2,047		2,047		2,047	
N blocks	1,027		1,027		1,027		1,027	
R <sup>2</sup>	0.3704		0.3712		0.3804		0.3792	
Robust s.e. in parentheses, *** p<.01, ** p<.05, * p<.1								

### 2.5.3 STRs' inequitable impact on property prices

To quantify the impact of Airbnb listings on property prices, I calculated the aggregate impact by multiplying the point estimates from the fixed effects model and

the average density of Airbnb listings for each buffer size. The impacts were then summarized by zip code to account for the unbalanced spatial distribution of Airbnb listings. The results are presented in **Table 2-4**. In particular, the underlying demographic composition varies significantly across zip codes in D.C. due to historical redlining (Lloyd, 2016). Certain zip code areas have a much higher concentration of Hispanic/Latino and/or African American population. Historically, displacement of the black population was prominent in D.C. (Jackson, 2014). It is vital to understand whether STRs have significantly impacted people of color in the city.

For the entire city, Airbnb alone could account for an increase in single-family property price by 0.66% to 2.24%. The impact was mild yet non-trivial. Alarmingly, Airbnb was accountable for a significant leap (> 5%) in property prices at tourist hot spots, such as downtown (zip code: 20005), Shaw (20001), Adams Morgan (20009), Dupont Circle (20036), and Foggy Bottom – George Washington University (20037). These neighborhoods were already overheated in housing demand due to their advantageous locations. STR-related housing investment will only aggravate the housing affordability issue.

What is more unsettling is the fact that Shaw (20001), NOMA – Trinidad (20002), Capitol Hill (20003), and Columbia Heights (20010) also experienced a noticeable price inflation (>3%) because of STRs. These zip code areas are populated with Hispanic and African Americans as shown in the columns for racial compositions in **Table 2-4**.

**Table 2-4. Aggregate impact of Airbnb on property price by zip code**

<b>Zip code</b>	<b>200-ft den.</b>	<b>200-ft impact</b>	<b>500-ft den.</b>	<b>500-ft impact</b>	<b>1000-ft den.</b>	<b>1000-ft impact</b>	<b>% Hispanic</b>	<b>% Black</b>	<b>% Owned</b>
20001	2.61	2.04%	15.33	5.67%	55.49	6.66%	9.22%	50.75%	37.1%
20002	1.51	1.18%	8.78	3.25%	32.45	3.89%	4.39%	61.33%	37.7%
20003	1.45	1.13%	8.64	3.20%	31.37	3.76%	5.12%	36.41%	45.4%
20005	2.68	2.09%	24.23	8.97%	102.09	12.25%	16.77%	15.17%	23.6%
20007	0.79	0.62%	4.92	1.82%	17.72	2.13%	7.12%	3.12%	55.4%
20008	0.41	0.32%	2.53	0.94%	9.74	1.17%	7.67%	5.10%	38.5%
20009	3.43	2.68%	20.63	7.63%	79.21	9.51%	15.13%	20.69%	36.3%
20010	1.89	1.47%	11.41	4.22%	43.68	5.24%	30.11%	31.07%	35.9%
20011	0.44	0.34%	2.7	1.00%	10.11	1.21%	21.18%	65.31%	52.2%
20012	0.21	0.16%	1.4	0.52%	4.71	0.57%	11.22%	64.29%	59.7%
20015	0.17	0.13%	1.09	0.40%	3.54	0.42%	6.52%	9.00%	71.4%
20016	0.15	0.12%	0.98	0.36%	3.55	0.43%	7.30%	4.25%	70.3%
20017	0.35	0.27%	2.15	0.80%	7.54	0.90%	6.49%	71.42%	58.5%
20018	0.16	0.12%	1.05	0.39%	4.21	0.51%	5.87%	85.08%	59.2%
20019	0.15	0.12%	0.7	0.26%	2.16	0.26%	2.41%	94.98%	35.8%
20020	0.21	0.16%	1.32	0.49%	4.44	0.53%	1.41%	95.00%	32.2%
20024	0.7	0.55%	5.62	2.08%	18.11	2.17%	5.16%	54.50%	36.7%
20032	0.07	0.05%	0.38	0.14%	1.12	0.13%	2.33%	90.00%	19.2%
20036	4.36	3.40%	29.64	10.97%	86.79	10.41%	7.62%	7.78%	34.6%
20037	3.2	2.50%	19.97	7.39%	65.79	7.89%	5.77%	6.32%	38.6%
<b>D.C.</b>	<b>0.85</b>	<b>0.66%</b>	<b>5.06</b>	<b>1.87%</b>	<b>18.63</b>	<b>2.24%</b>	<b>9.10%</b>	<b>50.03%</b>	<b>41.67%</b>

While the increasing price is good news to current homeowners, it puts a potential hurdle to new homebuyers to move into these neighborhoods. The last column of **Table 2-4** reveals the housing tenure composition for each zip code. It appears that the neighborhoods highly affected by Airbnb activities tend to have a relatively low percentage of owned housing units (below the city’s average level), suggesting that the housing price effect could get magnified due to a limited owner-housing stock. Moreover, it is reasonable to worry that the price premium will be eventually borne by long-term renters, jeopardizing low-income minority renters who could be displaced

from the city. This is the missing piece previously ignored in the debates over STRs' housing market consequences in Washington D.C.: Not only could STR platforms occupy valuable housing stock, but their business could significantly inflate housing cost in neighborhoods with a concentrated minority population.

## *2.6 Robustness check*

### 2.6.1 Robustness check on active Airbnb listings

As mentioned in Section 2.3, housing advocacy groups and other STR opponents were most concerned about the “entire home” STR listings that might have consumed the existing housing stock. To inquire into this issue, I further subset the Airbnb listing data by two additional criteria: (a) A listing was categorized as “entire home”; and (b) A listing had at least one review to signal its active status. About 70% of the observations were preserved after the additional screening.

After rerunning all three models, I present robustness check results in **Table 2-5**. Surprisingly, while the statistical significance of the regression coefficients and the goodness of fit resemble the results from those in **Table 2-3**, the magnitudes of coefficients are larger for the 100-foot and 200-foot buffers and smaller for the 500-foot and 1000-foot buffers as compared to the results in **Table 2-3**. Such interesting results can be explained by a perfectly reasonable rationale: Active STR listings have a stronger localized impact on property prices as their activeness indicates business success and attractiveness to new investors. On the other hand, the broader economic benefit usually requires a cluster of listings in a larger buffer area. With fewer listings in a large buffer, the magnitude of the “Airbnb density” impact declines.



**Table 2-5. Robustness check with entire-unit Airbnb listings with reviews**

Panel A: Pooled Cross-Sectional Model (Dependent variable: average logarithm of property price)								
	100 ft buffer		200 ft buffer		500 ft buffer		1000 ft buffer	
Variable Name	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
<b>Airbnb density</b>	<b>0.0140</b>	<b>(0.008)</b>	<b>0.0071*</b>	<b>(0.003)</b>	<b>0.0028**</b>	<b>(0.001)</b>	<b>0.0011***</b>	<b>(0.000)</b>
N	12,680		12,680		12,680		12,680	
R <sup>2</sup>	0.8091		0.8091		0.8092		0.8092	
Robust s.e. in parentheses, *** p<.01, ** p<.05, * p<.1								
Panel B: Fixed Effects Model at Census Tract Level (Dependent variable: average logarithm of property price)								
	100 ft buffer		200 ft buffer		500 ft buffer		1000 ft buffer	
Variable Name	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
<b>Airbnb density</b>	<b>0.0096</b>	<b>(0.011)</b>	<b>0.0086*</b>	<b>(0.005)</b>	<b>0.0033**</b>	<b>(0.001)</b>	<b>0.0008***</b>	<b>(0.000)</b>
N	7,624		7,624		7,624		7,624	
N blocks	2,378		2,378		2,378		2,378	
R <sup>2</sup>	0.3906		0.3909		0.3913		0.3910	
Robust s.e. in parentheses, *** p<.01, ** p<.05, * p<.1								
Panel C: First Difference Model at Census Tract Level (Dependent variable: average logarithm of property price)								
	100 ft buffer		200 ft buffer		500 ft buffer		1000 ft buffer	
Variable Name	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
<b>Airbnb density</b>	<b>0.0258</b>	<b>(0.022)</b>	<b>0.0050</b>	<b>(0.011)</b>	<b>0.0057*</b>	<b>(0.003)</b>	<b>0.0017*</b>	<b>(0.001)</b>
N	2,047		2,047		2,047		2,047	
N blocks	1,027		1,027		1,027		1,027	
R <sup>2</sup>	0.3705		0.3698		0.3718		0.3715	
Robust s.e. in parentheses, *** p<.01, ** p<.05, * p<.1								

### 2.6.2 A robustness check on the rental housing market

While the focus of this paper is the single-family owner housing market, it will enrich the discussion by looking into STRs' impacts on the rental housing market. I

could not access disaggregated rental transaction data, so the robustness check was done at the aggregate zip-code level. I used Zillow Rent Index (ZRI), a smoothed measure of the median estimated market rate rent, across zip codes in Washington D.C. over time for this exercise<sup>9</sup>. When applied to the same empirical models, the rental data yielded statistically insignificant results (See **Table 2-6**).

**Table 2-6. Empirical results for median rent price at the zip code level**

Fixed Effects Model at the Zip Code Level (Dependent variable: logarithm of median rent price)								
	100 ft buffer		200 ft buffer		500 ft buffer		1000 ft buffer	
Variable Name	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
<b>Airbnb density</b>	<b>-0.0002</b>	<b>(0.016)</b>	<b>0.0065</b>	<b>(0.005)</b>	<b>0.0011</b>	<b>(0.001)</b>	<b>0.0004</b>	<b>(0.000)</b>
Other Controls	land area, estimated year built, air-conditioning, fireplaces, rooms, bedrooms, bathrooms, half-bathrooms, sqft., stories, grade, condition, # of traffic & crime incidences, constant							
N	119		119		119		119	
N Zip Codes	20		20		20		20	
R <sup>2</sup>	0.4202		0.4310		0.4283		0.4373	
Robust s.e. in parentheses, *** p<.01, ** p<.05, * p<.1								

The most plausible estimate is the coefficient on the Airbnb density at the 200-foot buffer. The estimate is positive yet statistically insignificant. In addition, Washington D.C. adopted a strict Rent Control Act, in which any rent hike falls under rent control except for a few exemptions (such as rental units built after 1975 and Federally/District-subsidized rental units)<sup>10</sup>. From the housing dataset, 74% of the single-family units and 60% of the multifamily/condominium units were built prior to 1975, suggesting that the majority of the older housing units in D.C. fall under the rent

<sup>9</sup> See the methodology to calculate the Zillow Rent Index here: <https://www.zillow.com/research/zillow-rent-index-methodology-2393/>

<sup>10</sup> See the Rent Control Fact Sheet here: [https://dhcd.dc.gov/sites/default/files/dc/sites/dhcd/service\\_content/attachments/Rent%20Control%20act%20Sheet%202018.pdf](https://dhcd.dc.gov/sites/default/files/dc/sites/dhcd/service_content/attachments/Rent%20Control%20act%20Sheet%202018.pdf)

control umbrella. This is somewhat reassuring to the most vulnerable renters in the city. Nevertheless, I acknowledge that thorough and robust research using high-quality disaggregated rental housing data must be conducted to solve the rental housing puzzle of STRs' housing market consequences.

## *2.7 Discussion*

### 2.7.1 Policy implications

This paper provides empirical evidence on STRs' impacts on property prices. The topic has pivotal welfare implications that should not be neglected. Previous attempts to understand STRs' housing market impacts in D.C. were descriptive and lacked in rigor. In this paper, I took advantage of innovative web-scraped Airbnb data and demonstrated the indirect impact (externalities) of Airbnb listings on single-family property prices through hedonic analyses. The results suggest that unregulated growth in STR business created an inequitable property price premium that could distress first-time homebuyers who try to seek for affordable single-family housing in D.C., especially in some gentrifying, historically minority-populated neighborhoods. Furthermore, STR could negatively affect long-term renters if it results in higher rent.

This study comes out in a particularly meaningful time in the wake of new STR regulations in the District of Columbia. The lengthy legislative process took almost two years to finish, with yet another 11 months of transition period before the regulations come into effect. While stories about how STR business helped struggling families afford their homes in one of the nation's most expensive cities (the Washington Post, 2018a) should not be neglected, cities ought to realize that anxious STR investors can

make life much harder for people who are still seeking a home.

STR regulation should by no means deprive a resident's right to earn an extra income through home-sharing. The unanimous criticisms of the stiff cap on STR days in the original bill proposal is a living proof. Strict as it still is, the final version allows for a primary dwelling to be rented 90 days a year. While it is yet to be tested how effectively the regulation will be enforced, the bill can hopefully cool down STR-related housing investment by prohibiting commercial listings outside of a host's primary dwelling. It remains challenging as the city must get STR platforms on board to make considerable efforts to remove illegal listings. Any attempt to resolve the conflict between pro-STR and anti-STR communities without a collaborative approach has no chance to succeed.

From a planner's perspective, functional zoning ordinances and an effective zoning board play critical roles in regulating STRs. **Table 2-1** shows that all passed STR legislations revise zoning ordinances to unambiguously confine a residential property's STR usage. In the case of Arlington County, VA, the zoning commission is also the issuer of STR licenses, empowering the county's planning body to oversee STR operation and law compliance.

In addition to revising zoning codes, planning and housing authorities should also keep a keen eye on the affordable housing stock and ensure that the valuable rental housing resources for voucher holders and other affordable housing program participants are not jeopardized by illegal or irrational STR investments. On the other hand, there is a silver lining to foster collaboration between the housing authority and STR platform in home sharing programs (e.g., HUD, 2016). Rather than treating STRs

as a threat to affordable housing, cities could potentially benefit from the crowd-sourcing technology supported by STR platforms to match voucher holders and rental housing owners. Cities should embark on the smart city concept by thinking and acting innovatively to address the existing conundrums. A new type of home sharing program through STRs can be a great experiment to produce a social good through the private-public partnership between a city and STR platforms.

### 2.7.2 Limitations and beyond the study

I acknowledge that this study cannot directly answer the question: How do STRs gentrify a city? Gentrification is a complicated issue that goes beyond the scope of partial equilibrium analyses presented in this paper. We will have to reflect on the money-chasing real estate development that is by no means affordable to low-income households and racial minorities.

Instead, this study confirms a hypothesis that STRs do make it more expensive to own a property in a tourist paradise like Washington D.C. Moreover, and perhaps more alarmingly, they have made the historically minority-concentrated neighborhoods more expensive. Due to the short observation time, the data did not support a parcel level repeated sales model, which would have been a more robust empirical approach. Nevertheless, all three hedonic models confirmed that STRs indeed inflated single-family property prices. To put this paper into perspective, I compared the empirical results to the findings from previous studies: In this paper, I find a 0.78% increase in property prices with respect to one additional Airbnb listing within the 200-foot buffer; Barron et al. (2017) find a 0.64% increase in property prices with respect to a 10% increase in Airbnb listings; And Sheppard & Udell (2016) find a 6% - 9% increase in

property prices when the number of Airbnb listings doubles within the 300-meter buffer, which translates into a 1.30% - 1.96% increase in property prices with respect to one additional listing in New York City. Different as methodologies, data, and studies areas are, we come to a similar conclusion.

Although I included a robustness check on Airbnb's price effect on aggregated median rent at the zip code level, the results are rather inconclusive. Unsurprisingly, the level of geographic aggregation and the length of the time series both limited the interpretability of the results. Referring to Barron et al. (2017) and Horn & Merante (2017), I believe that the story for Washington D.C. is probably not so different: i.e., STRs also increase rent. Recent studies using web-scraped Craigslist data (e.g., Boeing & Waddell, 2017) inspire new research on STRs' rental housing market impact.

Last but not least, hedonic models were only able to allow me to derive the net impact of "Airbnb density" on property prices. It is unclear what the driving factor is in determining the positive net externality. Judging from the literature (Wachsmuth & Weisler, 2018), investors bidding up prices due to the extra income from STR is the more plausible mechanism than the other two mechanisms.

As a new wave of jurisdictions start to legalize and regulate STRs, it will be interesting to compare the STR market before and after regulations take effect. One of the greatest debates of all time is whether innovation and technology improve quality of life. In the case of STR, it is a housing policy debate centering on an innovation in technology that redefines how we live and how we travel.

## Chapter 3: With A Little Help from the Built Environment: Boosting E-scooter Sharing in the Socially Disadvantaged Neighborhoods in Washington D.C.

### *3.1 Introduction*

2018 and 2019 are years of e-scooter sharing in the United States: 84 million shared micromobility trips were made in 2018, a 140% increase from the previous year; Another 52 million trips were added in 2019 (NACTO, 2020). Station-based bike-sharing (SBBS) and dockless bike-sharing had mild increases in both years. It was e-scooter sharing that stimulates the significant growth. Washington D.C. (DC for short), an exemplar of shared micromobility, runs both a successful public SBBS program (Capital Bikeshare, or “CaBi”) and an emerging dockless program. The District Department of Transportation (DDOT, 2021) currently partners with eight operators (Bird, Lime, Lyft, Razor, Skip, Spin, Helbiz, and JUMP) and oversees about 14,000 dockless vehicles (70% of which are e-scooters). DC has always seen shared micromobility as a viable solution to address transportation sustainability. The city lays out an ambitious plan to grow e-scooter (and bike) operations to a maximum of 20,000 vehicles by October 1, 2023, despite the financial losses of the operators during the COVID-19 pandemic (Lazo, 2020).

On the other hand, the city has become more rational towards e-scooter sharing operation. The ambitious expansion plan comes with tougher measures that confine e-scooter vendors’ operation, such as requiring the devices have lock-to capacity by October 1, 2021 (Lazo, 2020). A major complaint from the local residents on dockless

vehicles is the unregulated parking fleets on sidewalks and on the street. The lock-to capacity requirement aims to address the safety concerns. In addition, DDOT has installed many off-sidewalk parking corrals at some targeted intersections and street curbsides to regulate e-scooter parking behavior (DDOT, n.d., a.). Overall, e-scooter sharing is widely accepted by cities as an eco-friendly mobility option that encourages a modal shift away from private vehicles. Cities like New York City and San Francisco have re-invited e-scooter sharing into the city coupled with some targeted regulatory measures.

The equity perspective is sometimes treated as an after-thought when new mobility options are first introduced into a city, as is for e-scooter sharing. In DC, e-scooter sharing was initially well-received by the transportation authority and users during the pilot phase (WBUR, 2018). Safety issues and travel patterns were top priorities. The city later recognized the potential equity concerns on an overwhelming concentration of trips in downtown against few trips generated in East and Southeast DC, where low-income residents of racial minorities live. DDOT implements a dockless equity program targeting at low-income adults and households (DDOT, n.d., b). In addition, DDOT designates dockless equity emphasis areas and requires vendors to place an adequate number of vehicles within these areas during morning hours (Open Data DC, n.d.). Equity is a difficult metric to observe and evaluate: In the context of e-scooter sharing, it can mean an equal distribution of dockless fleets in different neighborhoods. It can mean lowering the out-of-pocket cost for the socially disadvantaged individuals. It can also mean a favorable allocation of vehicles and biking infrastructure in the disadvantaged communities to over-compensate their



mobility gaps, providing that an adequate financial assistance is also included. There is also an underlying policy debate over the idea of “if you build it, they will come” in a sense that a favorable allocation of e-scooters may not generate a proportional, if not an additional, number of trips taken by those who have mobility needs.

In this study, I aim to examine the built environment and street-level urban design factors that can explain the uneven spatial distribution of e-scooter sharing trips in DC. While previous studies try to connect social and built environment factors with e-scooter trips one way or another, this study has two major innovations that contribute to current literature: (1) The high-resolution, real time trip trajectories are used to not only describe the built environment of where a e-scooter trip starts and ends, but also the paths it traverses. The street configuration (design) factors can explain why e-scooter trips are concentrated along certain corridors in DC. (2) I apply a machine-learning based approach that clusters a large number of trip origin-destination (O-D) pairs and identifies different types of e-scooter trips in hope that some cluster(s) reveal opportunities for residents in socially disadvantaged neighborhoods to ride e-scooters.

The rest of the chapter is organized as follows: I review emerging literature on e-scooter sharing, with a focus on the equity perspective, in Section 3.2. I describe this study’s empirical framework in Section 3.3. I provide detailed information on the data used for two separate analyses in Section 3.4. The empirical results are then presented in Section 3.5. I discuss the empirical contributions and the policy implications in Section 3.6. Lastly, I offer my thoughts on the limitations of this research and work beyond this study in Section 3.7.

### 3.2 *Literature review*

While e-scooter sharing is an emerging mode of transportation that came out four years ago in the U.S., researchers in transportation, urban planning, and geography have taken advantage of public data and self-collected data to understand the transportation, social, health, and environmental impacts of this newcomer.

#### 3.2.1 E-scooter sharing

I collaborated on two research papers that describe e-scooter sharing in DC previously (Younes et al., 2020; Zou et al., 2020), which build the foundational work for this study. In Younes et al. (2020), we study the temporal dynamics of e-scooter sharing trips and identify the significant temporal trip determinants, such as weather, time of day, special events (e.g., the Cherry Blossom Festival), and fluctuations in gasoline prices. In addition, we compare the temporal determinants between e-scooter sharing and CaBi and find that e-scooter rides are less sensitive (measured in elasticity) to adverse weather conditions. We also empirically identify a possible competition between casual CaBi trips and e-scooter trips, which coincides with the insights from DDOT on a decline of casual CaBi trips due to the popularity of e-scooter sharing (Smith, 2020). In Zou et al. (2020), we explore the spatial dynamics of e-scooter trips on DC's streets. We find that the average trip trajectory distance is significantly longer than the O-D (Euclidean) distance. A significant number of trips are taken on busy arterial roads with high auto traffic volume. A significant number of trips also fall inside the National Park Service (NPS) areas. In addition, we suggest a potentially positive impact of bikeway design on e-scooter trips. Last but not least, we identify street segments of safety priority and suggest policy tools to manage e-scooter growth

in DC. It is worth mentioning that several informative conversations between the research team and DDOT throughout the two projects have mutually benefited the refinement of research and the city's dockless program management.

Other studies have also focused on e-scooter sharing in DC: McKenzie (2019) compares the spatial and temporal patterns between SBBS trips and LIME e-scooter trips, where he finds largely similarities between the two modes. He also compares the temporal and spatial differences between different vendors, providing more nuanced spatiotemporal distributions of e-scooter trips (McKenzie, 2020). Hawa et al. (2021) investigate e-scooter appearances by considering socio-demographic characteristics, land use, transportation infrastructure (bus stops, Metrorail stations, CaBi stations, etc.), and temporal factors (time of day, weather, etc.). They find significantly higher average number of trips during mid-day hours, on weekdays, in areas of high population density and low-medium income level, near many points of interest and bus/Metrorail/CaBi infrastructure. Surprisingly, they find no significant correlation between the existence of bike lanes and e-scooter trips volume, although bike lanes significantly increase the odds of the presence of a e-scooter trip. Merlin et al. (2021) conduct a street-segment-level analysis on e-scooter trip origins and destinations. They associate built environment and social environment factors with e-scooter trip O-Ds. They find that e-scooter trips tend to start and end where college-educated, younger residents live. In addition, tourist attractions, transit stops, and commercial areas are likely to generate higher e-scooter trip demand. Yan et al. (2021) use self-collected e-scooter trip O-D data to build a travel-time-based analysis classifying the e-scooter trips that potentially compete or complement public transit and bike-sharing trips. They find a trade-off

between out-of-pocket cost and time cost between e-scooter (fare higher, time cost lower) and public transit (fare lower, time cost higher). In addition, they find potential complementary effect of e-scooter trips on public transit/ bike-sharing trips in underserved neighborhoods in DC, hinting at an equity improvement associated with e-scooter sharing.

Out of the study area, DC, a growing volume of e-scooter literature covers numerous topics. The most common topic is the spatial and temporal dynamics and determinants of e-scooter trip distributions. On the temporal determinants side, Mathew et al. (2019) describe e-scooter trip patterns in Indianapolis, IN, where mid-day weekday trips persist into evening hours. Noland (2019) describes the temporal trip patterns using a small e-scooter trip dataset from Louisville, KY, and shows negative correlations between adverse weather conditions (wind gusts and precipitation) and daily e-scooter trip volume/ average trip distance. Noland (2021) refines the empirical model by controlling for temporal serial correlations in daily e-scooter/SBBS trip volume using data from Austin, TX and finds similar results as Younes et al. (2020). Sanders, Branion-Calles, & Nelson (2020) survey university staff in Tempe, AZ and find that e-scooter users are not particularly fond of scooting in hot Arizona weather. On the spatial patterns and determinants side, Bai & Jiao (2020) compare the spatial patterns of e-scooter daily ridership between Austin, TX and Minneapolis, MN. They compare the sociodemographic (based on census data) and built environment covariates on ridership and find significant heterogeneity: For instance, a younger demographic in Minneapolis can positively explain e-scooter ridership, but not in Austin; On the other hand, Austin sees a positive correlation between open space/ parks

and e-scooter ridership, but the correlation is statistically insignificant for Minneapolis. Caspi, Smart, & Noland (2020) focus on the Austin case and identify significant spatial heterogeneity in the relationship between e-scooter trips and the underlying neighborhood income levels in a geographically weighted regression (GWR) analysis. The relatively high usage of e-scooter in relatively low-income areas can be explained by a large proportion of college students. Lazarus et al. (2020) investigate into the potential complementary and competitive relationship between SBBS and e-scooter sharing in San Francisco. They conclude that the two modes are more likely to complement each other in a sense that SBBS trips are shorter, taken more heavily in high population density areas, and connecting to/from transit stations, whereas e-scooter trips are longer and taken in relatively low-density, residential neighborhoods. Gehrke et al. (2021) study trip generation and trip duration of dockless e-bikes/e-scooters in the Greater Boston Suburbs by accounting for the socioeconomic context, built environment, and trip characteristics (temporal factors and trip route characteristics). In addition to the commonly found correlations, a significant impact of low-stress street links on longer trip durations is identified, providing a refreshing take on the importance of bike-friendly infrastructure to dockless e-bike/e-scooter usage. In two separate studies, Hosseinzadeh et al. (2021a, 2021b) analyze e-scooter trips in Louisville, KY. They find strong, locally correlation between a younger demographic (based on census data) and e-scooter trips. They also find locally heterogeneous, positive association between commercial/open/public space and e-scooter trips, reinforcing what is found in other studies (2021a). They also find neighborhood walk-/bike-ability positively influences e-scooter usage (2021b). Huo et

al. (2021) compare the influence of built environment on e-scooter usage in five U.S. cities (Austin, Minneapolis, Kansas City, Louisville, and Portland). The results are somewhat similar to previous empirical results.

In the policy and planning context, a few papers try to address some outstanding issues with e-scooter sharing in America. Gössling (2020) conducts a content analysis on local media reports about e-scooters in ten U.S. and international cities. The author identifies irresponsible riding behavior, cluttering of vehicles, safety, and vandalism as issues surrounding e-scooter sharing operations in Dallas and Los Angeles. The author concludes that many cities were not adequately prepared when e-scooters were first introduced to their city. Button, Frye, & Reaves (2020) review academic and gray literature on the viability of the economic model for e-scooter sharing business within the regulatory environment in the U.S. They find that the transportation authorities struggled to develop regulatory structures on e-scooter operations even before the COVID-19 intervention. On the other hand, e-scooter sharing vendors struggled to prove financial viability to sustain their business in the long haul. Not to mention some cities create regulatory barriers for vendors, such as the arbitrary capacity limit on the number of fleets each vendor is permitted. It is unclear how such regulatory decisions should be made to effectively match supply with demand. Fedorowicz et al. (2020) interview representatives from ten local and regional planning organizations, as well as three new mobility companies on protocols of data sharing, distribution of responsibility, and strategies for including the equity perspective into planning. They conclude that cities should outline equity goals and identify potential equity gaps (thereby making targeted policy) prior to the entry of new mobility companies, which

can be tough to realize as the future is always difficult to predict. For medium-sized cities, the authors suggest that learning lessons from other larger jurisdictions can help them develop equity strategies. Nonetheless, cities should be aware of the differences between locales.

Last but not least, e-scooter sharing has become a global phenomenon that inspires research in an international context: Degele et al. (2018) segment e-scooter customers using a clustering analysis. They identify a significant cluster of millennial casual users in a German city. Moran, Laa, & Emberger (2020) study the spatial patterns of e-scooter geo-fencing zones from six operators in Vienna, Austria. They find that e-scooter no-parking zones are commonly drawn near parks, pedestrian corridors, and cultural institutions. Their results can shed some lights on e-scooter management for the public sector. Tuncer et al. (2020) use video footage of e-scooter riders in Paris to capture the rule-abidance/-breaking behavior of e-scooter riders and unexpected interactions between pedestrians and e-scooter riders. By and large, e-scooter riders coordinate with what occurs on the street. Riders also rely heavily on signals, marks, and bike infrastructure to self-regulate their riding behavior. Christoforou et al. (2021) survey e-scooter users in Paris to understand the user demographics and their motivations to ride e-scooters. They find that e-scooter users rarely own a bike, are mostly men, aged between 18 and 29, and well-educated. Time savings is the most significant motivation to use e-scooters for Parisians. Aguilera-García, Gomez, & Sobrino (2020) also find age and education level are two significant socioeconomic drivers for the adoption of e-scooter sharing in Spain. In the Asian context, Cao et al. (2021) analyze e-scooter trip O-D data and public transit trip data.

They find e-scooters can potentially replace short-distance transit trips in Singapore, as the latter are negatively affected by transfers and access-egress walking distances. Lee et al. (2021) identify the factors causing heterogeneity in willingness to use e-scooter sharing in Seoul, Korea in a stated preference survey study. They find that younger, higher-income e-scooter users who are unsatisfied with the current public transit system are more likely to ride e-scooters for commutes than for first-/last-mile trips connecting public transit.

While the existing literature touch upon different angles to understand trip characteristic, user characteristics, and regulatory frameworks about e-scooter sharing. I believe my research fills at least two gaps in academic research: (1) there is no rigorous analysis on e-scooter trip trajectories and the impact of built/social environment on the paths that e-scooters traverse; (2) There lack studies that both identify equity gaps and acknowledging equity potentials of e-scooter sharing in terms of its usage in socially disadvantaged communities characterized by census data.

### *3.3 Empirical framework*

There are two outstanding research questions to be addressed in the empirical work: (1) What factors influence the e-scooter trip distribution on DC streets? (2) What is the ideal built environment that can attract the use of e-scooter sharing, especially in neighborhoods populated with socially disadvantaged households? To be able to answer these questions, I apply a data-intensive empirical framework that combines conventional regression approaches with a data-driven machine learning approach. In the data section, I will detail the data sources and descriptive statistics. In this section, I will provide the high-level analytical framework of the empirical work.



### 3.3.1 Street segment level analysis

The first part of the empirical analysis aims to identify multitudes of factors that can explain where e-scooter trips are taken on DC's streets. As aforementioned, previous studies either only explain where trips start (origin) and end (destination) or only describe trip trajectories. Few studies are able to rigorously explain trip trajectories using statistical models. Taking advantage of the real-time LIME trip trajectory data and various types of high-resolution geospatial data, I establish regression-based models to explore the relationship between the following factors and the daily average e-scooter trip density at the street segment level:

- (1) *Street configuration (SC)*: Street functional class indicates both traffic volume and proximity to various points of interest. Arterial roads are expected to attract more e-scooter trips, even though such streets may not be the safest to traverse. Bikeway design, including bike lanes and bike trails, should attract e-scooter trips. Cameras (speed camera, stop camera, etc.) and signals (traffic, pedestrian crossing, etc.) are safety features for e-scooter rides. Lastly, urban tree canopy provides amenities to cyclists, such as shades and views during a trip.
- (2) *Population sociodemographic characteristics (SD)*: E-scooter sharing is used disproportionately by different sociodemographic groups. Therefore, I control for the sociodemographic factors that underscore the inherent individual preferences over this emerging mobility option at the census block group level, including senior population (%), African American population (%), non-white Hispanic population (%), disabled population

(%), and population with limited ability to speak English (%). These factors also represent the socially disadvantaged populations of interest to this study. The low-income population variable and the household vehicle variable are omitted from the regression due to high collinearity with other sociodemographic factors.

(3) *Built environment (BE)*: Besides street design, I also control for the more macro level density and walkability factors at the block group level, including population density, employment density, and a walkability index. These factors determine in which neighborhoods e-scooter trips are most likely to be taken. Employment diversity and intersection connectivity variables are considered, but they are dropped in the regression due to collinearity.

(4) *Points of interest (POIs)*: Besides the macro-built environment on density/walkability and the micro-built environment on street design, I also include the meso-built environment factors on various points of interest that attract e-scooter sharing trips, including shopping (grocery stores, pharmacies, clothing stores, home goods, electronic supplies, office supplies, shopping malls, and convenience stores), education (schools, universities, and libraries), public services (hospitals, the city hall, court houses, police stations, and post offices), parks (parks, museums, indoor sports facilities, and arenas), and transportation (commuter rail, subway, and train stations). Food & drink and local business are also considered in

the regression, but they are dropped due to collinearity with other POIs and relatively low explanatory power in the regression.

I first run an ordinary least squared (OLS) model that build the multivariate correlation between the daily average LIME trip density (miles/street mile) at the street segment ( $i$ ) level and the four types of factors, specified in **Equation (1)**:

$$\ln TripDensity_{in} = \alpha + SC_{in}\beta + SD_n\delta + BE_n\rho + POI_n\varphi + \varepsilon_{in} \quad (1)$$

In addition to the OLS regression, I also consider the *spatial nonstationarity* exhibited in the estimated parameters across the specified geography. The OLS estimation assumes that the relationship being measured are *stationary* over space, meaning that the global parameter estimates can be applied equally over the region (Fotheringham, 1998). However, the residuals of the OLS estimation may reveal unevenly distributed spatial patterns. In this case, I apply the geographically weighted regression (GWR) technique to allow coefficients to vary across space. The coefficients are estimated locally as specified in **Equation (2)**:

$$\beta_i = (X^T W_i X)^{-1} X^T W_i Y \quad (2)$$

In this equation,  $W_i$  is a matrix of spatial weights for street segment  $i$  such that observations closer to  $i$  are given greater weight than observations from distance. A spatial distribution of coefficients can be mapped in the post-regression analysis. Both the OLS and GWR models are run in R. The GWR regression is run using the *spgwr* package, where the kernel bandwidth for a GWR is estimated (Páez, Farber, & Wheeler, 2011) and the range of coefficients are presented in quartiles.

### 3.3.2 Machine learning e-scooter trip origins and destinations (O-D)

The second part of the empirical framework is a machine-learning based clustering analysis that segments e-scooter trips by: (1) a trip's temporal characteristics, such as time of day, weekday/weekend, whether the trip is taken during the Cherry Blossom Festival; (2) POIs at a trip's starting/ending block group, including food & drink, shopping, education, business, public services, parks, and transportation; (3) sociodemographic characteristics at a trip's starting/ending census block group, including age group (Generation Z, Millennial, Generation X, and Baby Boomer), race (Hispanic and African American), disability, low-income jobs, poverty, limited English-speaking, and no-car population; (4) the density of schools and transit/bike-sharing stations at a trip's starting/ending block group; (5) built environment at a trip's starting/ending block group, including population density, employment density, and walkability index; and (6) whether a trip's starting/ending block group is within DC's dockless mobility equity emphasis zone. A total of 68 features (34 for trip origins and 34 for trip destinations) are run into the clustering analysis on 690,221 trips O-D combinations after data cleaning.

A K-means clustering technique is used for this analysis. K-means clustering is an unsupervised machine learning technique. By *unsupervised*, it means that the algorithm does not rely on the *a priori* to recognize which data point belongs to which cluster. This data-driven machine learning approach has been adopted in transit and bike-sharing research to study questions such as the relationship between transit ridership and user experience/satisfaction (Grisé & El-Geneidy, 2017) and the spatiotemporal patterns of bike-sharing trips (Zhou, 2015). The only criterion to

determine clusters is the “proximity” between data points, i.e., how similar one data point is compared to other data points. This “proximity” becomes analytically abstract and complex as more features are introduced in the clustering process to determine the similarity between points. The end goal of the clustering algorithm is to minimize an objective function, the squared error function, which can be mathematically expressed in **Equation (3)**:

$$W(S, C) = \sum_{k=1}^K \sum_{i \in S_k} \|y_i - c_k\|^2 \quad (3)$$

“Where  $\mathbf{S}$  is a  $K$ -cluster partition of the entity set represented by vectors  $y_i (i \in I)$  in the  $M$ -dimensional feature space, consisting of non-empty, non-overlapping clusters  $S_k$  each with a centroid  $c_k (k = 1, 2, \dots, K)$ .” (Kodinariya & Makwana, 2013)

To determine the optimal number of clusters for this analysis, I apply an Elbow method – a method looking at the percentage of variance explained as a function of clusters ( $K$ ). The percentage of variance explained by the clusters is plotted against the number of clusters. As  $K$  increases, the sum of squared errors drops until a “plateau” is reached where the marginal return of increasing the number of clusters flattens – hence, “the elbow criterion” (Bholowlia & Kumar, 2014). I present the elbow method’s plot in **Figure 3-3**.

### 3.4 Data

In this section, I list the data sources for this study. Then, I summarize variables used in the street segment analysis and in the trip O-D analysis, respectively.

### 3.4.1 Data sources

The multitudes of data come from different sources:

*The data of e-scooter trip origins, destinations, and trajectories* are collected by web-scraping the general bikeshare feed specification (GBFS) information in real time for LIME bikeshare over the course of the year 2019 with only few disruptions. GBFS is an open data standard for a bike-sharing system's fleet availability (NABA, n.d.). Prior to September 2019, LIME's GBFS was updated for individual e-scooter fleet, reserved or not, at the 30-second frequency. Thereby, it allows me to draw high-resolution trip trajectories that depict not only an e-scooter trip's O-D, but also the paths of the trip. Ever since September 2019, however, LIME has randomized fleet ID to prevent third-party tracking by mining GBFS data, part of their efforts to protect user privacy. The detailed data collection and sample selection criteria are documented in my previous research (Zou et al., 2020). In this study, I process more than 16 million unique GPS records on LIME e-scooter trips taken between January 1 and August 31, 2019. After filtering excessively short/long/fast trips and connecting the GPS points from the origin to the destination within a trip, I assemble an e-scooter trajectory dataset that consists of more than 690,000 unique trips.

*The POI data* come from the 2019 Here Map data (Here, n.d.). Here is a world leading company in navigation, mapping, and location experiences. I group the most relevant POI classes to this study into seven categories: food & drink, shopping, education, business, public services, parks, and transportation. The detailed class information is listed in previous section.

*The sociodemographic data* come from the American Community Survey (ACS) 5-year Estimates for 2014 – 2018. The block-group level data are used as it is the finest-grained resolution with a relatively robust estimation.

*The built environment data* come from EPA’s Smart Location Database (EPA, n.d.). Population and employment density variables are constructed based on Census LEHD 2010 data. The Walkability Index characterizes every Census 2019 block group in the U.S. based on its relative walkability. Although the Smart Location Database is slightly dated considering the age of other datasets, it is the most available and widely adopted public database that describes built environment. Besides, long-range population and employment densities are arguably stable over the years.

*The street configuration data* come from Open DC data portal. The centerline shapefile contains information about the street functional class. In addition, I spatially join shapefiles of bike lanes, bike trails, camera points, signal points, and tree canopy points together onto the centerline file. They are joined within a 25-foot buffer of the centerline to capture features on streetways and the sidewalks.

*Other DC data* used in the clustering analysis also come from Open DC data portal, such as Metrorail station points, CaBi station points, schools (public and charter), university campus, and dockless mobility Equity Emphasis Areas.

### 3.4.2 Summary statistics

I provide summary statistics for the street segment analysis and the clustering analysis in **Table 3-1** and **Table 3-2**, respectively. These statistics offers some initial

insights about the high level sociodemographic, street design, and built environment characteristics of the study area.

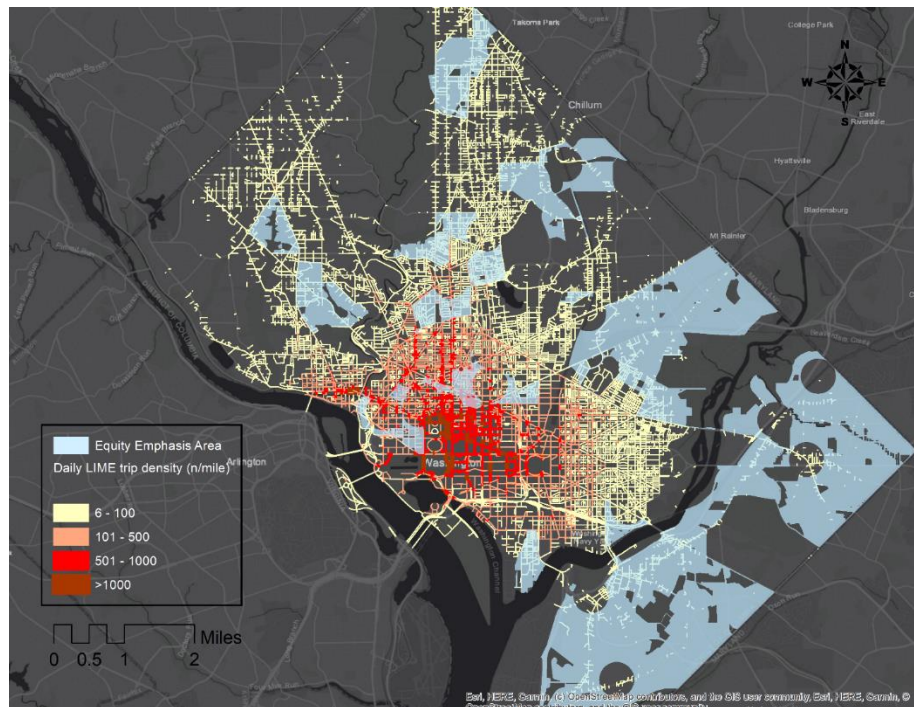
**Table 3-1. Summary statistics for the street segment analysis**

<b>Variable Name</b>	<b>Variable Description</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>s.d.</b>
Ln_LIME_den	Logarithm of average daily LIME trip density	0	8.72	2.28	1.81
Functionality	Street functional class, 1-6: local roads – interstates	1	6	2.08	1.15
Bikelane	An indicator of bike lane existence, 1 for “yes”.	0	1	0.06	0.24
Biketrail	An indicator of bike trail existence, 1 for “yes”.	0	1	0.01	0.10
Camera	An indicator of traffic camera existence, 1 for “yes”.	0	1	0.03	0.19
Signals	The number of traffic signals/signages along the segment	0	48	2.03	5.23
Tree_den	Tree canopy density (trees per street mile/1,000) <sup>11</sup>	0	2.22	0.19	0.16
Walkability	The walkability index 1-20: least – most walkable	7.67	19.50	14.76	2.29
Pop_den	Population density (per square mile/1,000)	0.03	114.81	15.01	12.19
Emp_den	Employment density (per square mile/1,000)	0	346.05	12.59	40.57
Pct_black	Percentage African American population	0	1	0.49	0.35
Pct_senior	Percentage senior (64+) population	0	0.49	0.14	0.09
Pct_hispanic	Percentage non-white Hispanic/Latino population	0	0.44	0.05	0.08
Pct_disabled	Percentage population with some disability	0	0.99	0.22	0.14
Pct_limeng	Percentage population with limited English-speaking skill	0	0.14	0.01	0.02
Poi_shop	Density of POI – shopping (per square mile/1,000)	0	0.75	0.04	0.07
Poi_edu	Density of POI – education (per square mile)	0	144.08	8.28	11.58
Poi_ser	Density of POI – services (per square mile)	0	118.19	1.74	5.82
Poi_park	Density of POI – parks (per square mile)	0	141.41	4.83	12.04
Poi_tran	Density of POI – transportation (per square mile)	0	32.03	1.27	4.32
Sample size = 33,652					

<sup>11</sup> Some variables are divided by 1,000 because the magnitude of the variable is large, so is the variance.



On average, the daily LIME e-scooter trip density is about 2.3 trips per street mile. This density is constructed by overlaying trip trajectories within the 25-foot buffer of street centerlines to include as many trip segment on the street as possible. There is a measurement error for the GPS locations provided by GBFS, so a tolerance buffer is needed to capture trip trajectories. I plot the spatial patterns of the street-segment level daily average trip density in **Figure 3-1**. The high-density street segments are spatially clustered in downtown, the National Mall, Georgetown, and downtown adjacent neighborhoods. The residential neighborhoods in the northwest, east, and southeast have low e-scooter trip density. In particular, East and Southeast DC are considered the dockless equity emphasis areas by DDOT. It is critical to understand the factors that cause the low usage of e-scooter sharing in such neighborhoods.



**Figure 3-1. Daily LIME trip density at the street segment level**

Noticeably, most DC street segments do not include a bike lane (protected, lane separated, or shared use) or a bike trail. The city has an ambitious plan to build 20 miles of new protected bike lanes in the course of three years, but the existing facilities only consist of 16.6 miles of protected bike lanes as of the end of 2020 (DDOT, n.d., c). Most of DC’s traffic cameras are placed at busy arterial roads and intersections. The signal/signage coverage and tree canopy coverage are very dense on the street. These are bike-friendly factors. DC is one of the most walkable major U.S. cities, as suggested by the relatively high average walkability index. Population density and employment density are also high, suggesting the city’s compact urban form. In terms of the socio-demographic environment, the city has a diverse racial composition of 49% African Americans and 5% non-white Hispanic/Latino population. In addition, there are about 14% senior population, 22% of the population with some disability, and 1% of the population with limited English-speaking ability. The large variance of the POI density variables suggests that POIs are unevenly distributed in the city, most likely at/near downtown.

**Table 3-2. Summary statistics for the clustering analysis at the O-D level**

<b>Variable Name</b>	<b>Variable Description</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>s.d.</b>
<i>LIME trip temporal characteristics</i>					
AMP	An indicator of a trip starting at AM peak hours	0	1	0.07	0.26
MD	An indicator of a trip starting at midday hours	0	1	0.46	0.50
PMP	An indicator of a trip starting at PM peak hours	0	1	0.31	0.46
NT	An indicator of a trip starting at nighttime hours	0	1	0.13	0.33
MN	An indicator of a trip starting at midnight hours	0	1	0.04	0.19
Wknd	An indicator of a trip taken during weekends	0	1	0.31	0.46

Wkdy	An indicator of a trip taken during weekdays	0	1	0.69	0.46
Cherry	An indicator of a trip taken during the Cherry Blossom Festival (March 20 – April 14, 2019)	0	1	0.15	0.36
<i>Trip origin's block group characteristics</i>					
O_Pop_den	Population density (per square mile/1,000)	0.03	114.81	13.69	15.61
O_Emp_den	Employment density (per square mile/1,000)	0.01	346.05	73.68	91.60
O_Pct_noveh	Percentage population owning no auto vehicles	0	0.56	0.21	0.11
O_Pct_black	Percentage African American population	0	1	0.15	0.19
O_Pct_lowinc	Percentage population with low-income jobs	0	1	0.12	0.09
O_Pct_senior	Percentage senior (64+) population	0	0.49	0.07	0.07
O_Pct_hispanic	Percentage non-white Hispanic/Latino population	0	0.44	0.03	0.05
O_Pct_disabled	Percentage population with some disability	0	0.99	0.14	0.19
O_Pct_limeng	Percentage population with limited English-speaking skill	0	0.14	0.01	0.02
O_Pct_poverty	Percentage population below the poverty line	0	1	0.20	0.20
O_Pct_genz	Percentage population of Generation Z	0	0.98	0.20	0.21
O_Pct_millen	Percentage Millennial population	0	0.78	0.47	0.19
O_Pct_genx	Percentage population of Generation X	0	0.39	0.13	0.11
O_Pct_boomer	Percentage Baby Boomer population	0	0.52	0.11	0.09
O_Poi_food	Density of POI – food & drink (per square mile/1,000)	0	1.12	0.24	0.29
O_Poi_shop	Density of POI – shopping (per square mile/1,000)	0	0.75	0.10	0.12
O_Poi_edu	Density of POI – education (per square mile)	0	144.08	11.36	15.07
O_Poi_bus	Density of POI – business (per square mile/1,000)	0	0.29	0.05	0.07
O_Poi_ser	Density of POI – services (per square mile)	0	118.19	1.74	5.82
O_Poi_park	Density of POI – parks (per square mile)	0	141.41	20.53	23.73
O_Poi_tran	Density of POI – transportation (per square mile)	0	32.03	4.20	6.41
O_Walkability	The walkability index 1-20: least – most walkable	7.67	19.50	16.36	1.42
O_Nps	An indicator of a trip starting in the NPS area	0	1	0.13	0.34
O_Themall	An indicator of a trip starting on the National Mall	0	1	0.24	0.43
O_Metro	An indicator of a trip starting within 0.5 mile of a Metrorail station	0	1	0.15	0.36
O_Cabi	An indicator of a trip starting within 0.1 mile of a CaBi station	0	1	0.02	0.15

O_Pubschool	An indicator of a trip starting within 0.5 mile of a public school	0	1	0.01	0.11
O_Charter	An indicator of a trip starting within 0.5 mile of a charter school	0	1	0.01	0.12
O_Uni	An indicator of a trip starting within 0.5 mile of a university's campus area	0	1	0.05	0.22
O_Equity	An indicator of a trip starting within the dockless equity emphasis areas	0	1	0.10	0.30
<i>Trip destination's block group characteristics</i>					
D_Pop_den	Population density (per square mile/1,000)	0.03	114.81	13.58	15.70
D_Emp_den	Employment density (per square mile/1,000)	0.01	346.05	70.39	91.28
D_Pct_noveh	Percentage population owning no auto vehicles	0	0.56	0.21	0.11
D_Pct_black	Percentage African American population	0	1	0.15	0.19
D_Pct_lowinc	Percentage population with low-income jobs	0	1	0.12	0.10
D_Pct_senior	Percentage senior (64+) population	0	0.49	0.07	0.07
D_Pct_hispanic	Percentage non-white Hispanic/Latino population	0	0.44	0.03	0.05
D_Pct_disabled	Percentage population with some disability	0	0.99	0.13	0.18
D_Pct_limeng	Percentage population with limited English-speaking skill	0	0.14	0.01	0.02
D_Pct_poverty	Percentage population below the poverty line	0	1	0.20	0.20
D_Pct_genz	Percentage population of Generation Z	0	0.98	0.20	0.20
D_Pct_millen	Percentage Millennial population	0	0.78	0.48	0.20
D_Pct_genx	Percentage population of Generation X	0	0.39	0.12	0.11
D_Pct_boomer	Percentage Baby Boomer population	0	0.52	0.11	0.09
D_Poi_food	Density of POI – food & drink (per square mile/1,000)	0	1.12	0.23	0.28
D_Poi_shop	Density of POI – shopping (per square mile/1,000)	0	0.75	0.09	0.12
D_Poi_edu	Density of POI – education (per square mile)	0	144.08	11.14	15.09
D_Poi_bus	Density of POI – business (per square mile/1,000)	0	0.29	0.05	0.07
D_Poi_ser	Density of POI – services (per square mile)	0	118.19	4.87	10.58
D_Poi_park	Density of POI – parks (per square mile)	0	141.41	19.81	22.79
D_Poi_tran	Density of POI – transportation (per square mile)	0	32.03	3.86	6.17
D_Walkability	The walkability index 1-20: least – most walkable	7.67	19.50	16.32	1.44
D_Nps	An indicator of a trip starting in the NPS area	0	1	0.15	0.36
D_Themall	An indicator of a trip starting on the National Mall	0	1	0.26	0.44

D_Metro	An indicator of a trip starting within 0.5 mile of a Metrorail station	0	1	0.12	0.32
D_Cabi	An indicator of a trip starting within 0.1 mile of a CaBi station	0	1	0.02	0.13
D_Pubschool	An indicator of a trip starting within 0.5 mile of a public school	0	1	0.01	0.12
D_Charter	An indicator of a trip starting within 0.5 mile of a charter school	0	1	0.01	0.12
D_Uni	An indicator of a trip starting within 0.5 mile of a university's campus area	0	1	0.05	0.21
D_Equity	An indicator of a trip starting within the dockless equity emphasis areas	0	1	0.10	0.30
Sample size: 690,221					

For the trip O-D data, a majority of trips were taken during the midday hours (10 AM – 3 PM), followed by PM peak hours (3 PM – 7 PM), nighttime hours (7 PM – 11PM), AM peak hours (6 AM – 10 AM), and midnight hours (11 PM – 6 AM). About 70% of the trips were taken during weekdays. About 15% of the eight-month trips were taken during DC’s Cherry Blossom Festival between mid-March and mid-April.

There are minimal distinctions between the social and built environment for the aggregate trip origins and destinations. LIME trips mostly start and end in high population and employment density block groups. The average employment density for such block groups is much higher than the city’s average density (See **Table 3-1**). Such neighborhoods usually have lower-than-average percentage of African American and Hispanic/Latino populations, as well as senior or disabled populations. When breaking down by generations, trips were taken with a high share of millennials (aged between 25 – 39 in our data). They are the young, tech-savvy, working professionals in DC. On average, 21% of the individuals own no vehicles at home in the trip origin and destination block groups. However, only about 12% of the individuals have a low-income (<\$1,300/month) job. About 20% of the individuals live below the poverty line.

The average block group for trip O-Ds have various POIs. It is also quite walkable. About 26% of the trips fall inside the National Mall area – DC’s single largest tourist attraction. In addition, another 15% trips fall inside a National Park Services (NPS) area. About 12% of the trips fall inside the Metrorail catchment area (within 0.5 mile of a station). A small percentage of trips fall inside a Capital Bikeshare’s catchment area (within 0.1 mile of a bike-sharing station). A small percentage of trips fall inside a school/university campus’ catchment area. Last but not least, about 10% of the LIME trips were taken within DC’s designated dockless equity emphasis areas (Open Data DC, 2020), which cover much of the geographic areas in East and Southeast DC.

The summary statistics provide straightforward, overarching, and preliminary insights about DC’s dockless mobility trip characteristics. The quick sketch reveals that: (1) e-scooter trips are primarily taken during mid-day hours (likely for non-commuting purposes); (2) e-scooter trips are taken in high-density, walkable neighborhoods with various POIs; (3) many trips are taken on the National Mall (for leisure purposes, most likely) and Metrorail’s catchment area; and (4) the average trip O-D block group is populated with white and young individuals who are less likely to be socially disadvantaged.

### *3.5 Results*

Following the two-part empirical framework, I will present the empirical results in two subsections, including the results for the regression-based, street-segment analysis on the factors associated with the e-scooter sharing trip distribution, and the machine-learning based, trip O-D clustering analysis.

### 3.5.1 Street segment analysis

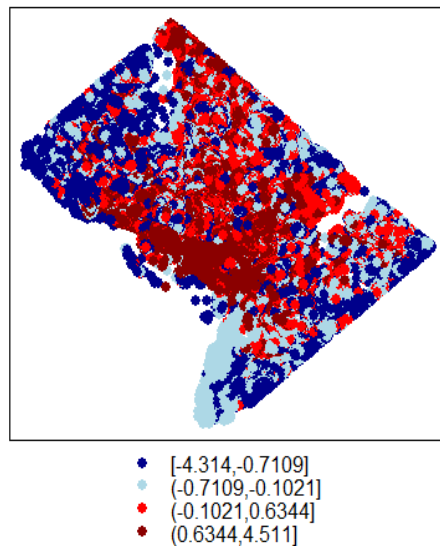
The regression results are presented in **Table 3-3**. The regression coefficients and t-statistics for the OLS regression and the GWR coefficients at the 25<sup>th</sup> percentile, the 50<sup>th</sup> percentile, the 75<sup>th</sup> percentile, and the global level (the same as the OLS coefficients) are included.

**Table 3-3. Street segment level regressions**

Variable	dependent variable: Ln_LIME_den					
	OLS regression		GWR regression			
	Coeff.	t-stat	25 pctl.	50 pctl.	75 pctl.	Global
Functionality	0.203***	33.80	0.094	0.165	0.224	0.203
Bikelane	0.343***	13.56	-0.016	0.170	0.351	0.343
Biketrail	0.846***	14.91	-0.667	-0.084	0.386	0.846
Camera	0.161***	5.21	-0.124	0.068	0.275	0.161
Signals	0.047***	35.84	0.023	0.036	0.053	0.047
Tree_den	0.663***	17.77	0.605	0.966	1.351	0.663
Walkability	0.117***	39.01	-0.053	0.040	0.156	0.117
Pop_den	0.033***	60.12	-0.001	0.007	0.029	0.033
Emp_den	0.006***	30.87	-0.025	0.004	0.005	0.006
Pct_black	-1.317***	-72.46	-1.688	-0.271	1.622	-1.317
Pct_senior	-3.434***	-44.94	-2.895	-0.563	1.769	-3.434
Pct_hispanic	-0.799***	-8.84	-4.360	-0.641	3.039	-0.799
Pct_disabled	-1.976***	-43.31	-1.835	-0.269	1.301	-1.976
Pct_limeng	-2.282***	-6.19	-8.288	2.187	15.590	-2.282
Poi_shop	1.898***	16.85	-4.928	0.507	5.481	1.898
Poi_edu	0.011***	19.37	-0.010	0.003	0.020	0.011
Poi_ser	0.018***	18.02	-0.032	0.005	0.040	0.018
Poi_park	0.017***	32.53	-0.022	0.002	0.025	0.017
Poi_tran	0.016***	11.31	-0.035	0.013	0.082	0.016
Intercept	0.607***	11.27	-1.394	0.945	3.174	0.607
$R^2$ (quasi-global for GWR)	0.6634		0.8802			
Adjusted $R^2$	0.6632		-			
GWR kernel distance	-		0.00231 mile			
n	33,652					
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05.						

The OLS model has a high goodness of fit ( $R^2 = 0.66$ ). It is evident that the factors of street configuration are significantly associated with e-scooter trip density. As expected, streets of higher functional class (e.g., arterial roads) tend to attract more e-scooter trips. The bike-friendly features, including bike lanes, bike trails, cameras, signals, and tree canopy, are significantly positively correlated with e-scooter trip density on the street. A high-density, walkable built environment also explains high e-scooter sharing usage. Different types of points of interest attract e-scooter rides. A neighborhood's sociodemographic characteristics also significantly relate to e-scooter sharing usage. A block group with more minority, senior, disabled, or limited English-speaking populations tends to attract fewer e-scooter trips, all else equal.

I then plot the OLS regression residuals spatially (see **Figure 3-2**). It is clear that the residuals are spatially autocorrelated, with street segments of a higher e-scooter trip density clustered at the downtown neighborhoods. Therefore, it is appropriate to consider spatial models.



**Figure 3-2. The spatial plot of regression residuals for the street segment model**



I then calculate the bandwidth using a kernel density function to weight data as a function of distance from each point. The kernel optimization is calibrated using the *gwr.sel* function in the *spgwr* package. For a large dataset containing more than 30,000 points, the calibration takes more than half a day due to the large number of spatial relationships to be established. The bandwidth converges at 0.00231 miles.

I then run the GWR model that allows spatially varying coefficients for all 33,652 street segments. Considering the size of the spatial weight matrix, this estimation process takes about two weeks (on a workstation with 64GB build-in memory) due to the high computational cost. A summary of the 25<sup>th</sup> percentile, 50<sup>th</sup> percentile, 75<sup>th</sup> percentile, and global coefficients are provided in **Table 3-3**. For street configuration factors, the majorities of spatially varying coefficients on street functional class, signal, tree canopy are positive. A small number of local coefficients are negative on bike lane and traffic camera. The coefficients on bike trail are negative more than 50 percent of times, albeit the significantly positive global coefficient, indicating some locally relationship between e-scooter trip density and the existence of bike trail is negative. As Zou et al. (2020) point out, bike trails have weaker correlation with e-scooter trip density than bike lanes, especially during nighttime. It is possible that, for some areas, the daily average trip density of a bike trail is lower than its neighboring arterial/local roads with no bike trails as those trails do not attract e-scooter traffic during peak hours (for commutes) and nighttime (due to the lack of streetlights/distance from POIs). On the other hand, popular bike trails at the National Mall, Georgetown, and the Rock Creek Park still attract heavy e-scooter traffic, explaining the globally positive coefficient. The similar logic can be applied to the

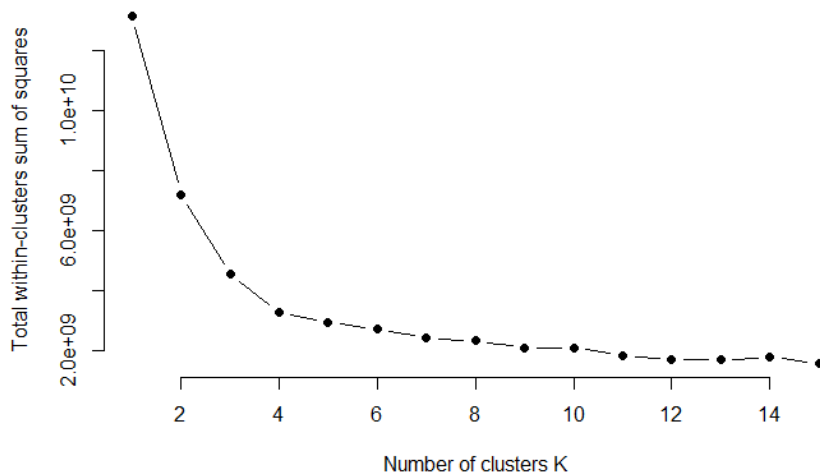
interpretations for the spatially varying coefficients on built environment and POI variables: The majority of local coefficients are positive, indicating their contribution to more e-scooter sharing usage. A quarter of street segments find the reverse relationships (for each variable, the street segments vary), which require a closer examination of the unspecified confounding factors that may affect the relationships between POIs/ built environment and e-scooter trip density. For the sociodemographic characteristics, the majority of spatially varying coefficients are negative on the disadvantaged population indicators. Yet, in about a quarter of the neighborhoods with more racial minority, senior, and disabled populations, there is a tendency to observe more e-scooter sharing trips on the street. These are possibly downtown adjacent, mixed-used neighborhoods with local activity centers. While there are many racially and socially disadvantaged residents in such neighborhoods, I cannot confirm that they actually ride e-scooters for daily activities. The quasi-global goodness of fit for the GWR model is 0.88 – a significant improvement from the OLS model, suggesting that spatial autocorrelations significantly vary regression coefficients locally. There may be interesting spatial patterns for further reviews.

By and large, the OLS and GWR estimates confirm my early speculations: E-scooter sharing trips are most likely to be taken on the streets with bike-friendly features in high-density neighborhoods of various points of interest and a high share of white, young, high-income individuals. The street segment level analysis reveals three major takeaways: (1) E-scooter sharing trips are concentrated in activities centers and major arterial roads with various POIs. (2) E-scooter sharing may not significantly benefit communities with many socially disadvantaged individuals, such as racial

minorities and the elderly/ physically frail individuals. (3) E-scooter sharing benefits from a bike-friendly built environment, including bike-friendly street features and an overall compact, walkable urban form. These takeaways further infer the important policy implications in boosting the eco-friendly shared micromobility in an equitable fashion.

### 3.5.2 Trip O-D clustering analysis

While the street segment analysis provides insightful information on the social and built environment factors that could influence e-scooter trip on the street, it focuses on the aggregate impacts across the city. The trip O-D clustering analysis relaxes the assumptions about a factor's average impact on e-scooter sharing trips, instead, it relies solely on the similarities between different data points (with its associated features) to group trips and summarize the common traits among data points within the same cluster.



**Figure 3-3. Elbow method plot**

I first use the elbow method to determine the optimal number of clusters for all 690,221 trip points with 68 features. **Figure 3-3** shows the graphical representation of

the variances as a function of the number of clusters. The intra-cluster variation (total within-cluster sum of square) reached the plateau at seven clusters. I therefore specify seven clusters in the K-means clustering analysis.

The K-means clustering analysis is run in R using the default algorithm in Hartigan and Wong (1979). The clustering results are presented in **Table 3-4**, including the group mean for each variable in all seven clusters and the sample mean for each variable. The smallest cluster is Cluster 4 (n = 19,079) and the largest cluster is Cluster 6 (n = 275,389). In addition, I plot trip origins and destinations for seven clusters. I will describe the characteristics of each cluster and then make inferences about what it means to management e-scooter sharing in DC.

**Table 3-4. K-means clustering summary results**

Variable Name	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Mean
AMP	0.051	0.086	0.085	<b>0.159</b>	0.069	0.061	0.099	0.072
MD	<b>0.500</b>	0.494	0.465	0.464	<u>0.315</u>	<b>0.519</b>	0.487	0.458
PMP	0.322	0.289	0.303	<u>0.257</u>	<b>0.342</b>	0.292	0.285	0.306
NT	0.097	0.098	0.100	0.087	<b>0.212</b>	0.099	0.099	0.126
MN	0.030	0.032	0.047	0.033	0.062	0.029	0.030	0.039
Wknd	0.289	<u>0.243</u>	0.282	<u>0.213</u>	0.309	0.341	0.298	0.309
Wkdy	0.711	<b>0.757</b>	0.718	<b>0.787</b>	0.691	0.659	0.702	0.691
Cherry	0.138	0.139	0.140	0.147	0.138	0.166	0.147	0.150
O_Pop_den	<u>8.966</u>	<u>9.424</u>	17.042	<b>21.412</b>	<b>25.609</b>	<u>6.995</u>	15.217	13.689
O_Emp_den	<b>255.716</b>	<b>241.550</b>	<b>144.579</b>	63.417	<u>15.273</u>	<u>30.460</u>	<u>34.221</u>	73.685
O_Pct_noveh	<b>0.356</b>	<b>0.358</b>	0.233	0.224	<u>0.171</u>	0.177	0.201	0.214
O_Pct_black	<u>0.067</u>	<u>0.080</u>	0.190	0.118	<b>0.270</b>	0.110	0.137	0.150
O_Pct_lowinc	0.099	0.098	0.069	0.110	<b>0.207</b>	0.086	0.093	0.118
O_Pct_senior	0.095	0.100	<b>0.116</b>	0.066	0.098	0.047	0.053	0.074

O_Pct_hispanic	0.041	0.036	<u>0.012</u>	0.029	<b>0.054</b>	0.016	0.029	0.031
O_Pct_disabled	<u>0.081</u>	0.096	<b>0.366</b>	<b>0.214</b>	0.173	0.097	0.117	0.136
O_Pct_limeng	<b>0.020</b>	0.018	0.014	0.010	0.013	<u>0.004</u>	0.007	0.010
O_Pct_poverty	0.155	0.177	<b>0.476</b>	<b>0.275</b>	<b>0.273</b>	<u>0.139</u>	0.166	0.204
O_Pct_genz	<u>0.151</u>	0.163	<b>0.380</b>	0.281	<u>0.119</u>	0.233	0.220	0.201
O_Pct_millen	<u>0.368</u>	<u>0.379</u>	<u>0.293</u>	0.442	0.417	<b>0.562</b>	<b>0.541</b>	0.471
O_Pct_genx	<b>0.243</b>	<b>0.227</b>	0.112	0.108	0.159	<u>0.071</u>	0.088	0.126
O_Pct_boomer	<b>0.173</b>	<b>0.156</b>	0.106	0.091	0.148	0.078	0.085	0.113
O_Poi_food	<b>0.756</b>	<b>0.719</b>	<b>0.356</b>	0.219	<u>0.149</u>	<u>0.096</u>	<u>0.115</u>	0.243
O_Poi_shop	<b>0.247</b>	<b>0.232</b>	0.095	0.086	0.081	<u>0.056</u>	<u>0.050</u>	0.097
O_Poi_edu	13.659	<b>17.520</b>	<b>30.204</b>	15.753	13.167	<u>5.583</u>	8.985	11.365
O_Poi_bus	<b>0.188</b>	<b>0.178</b>	0.097	0.045	<u>0.015</u>	<u>0.019</u>	<u>0.023</u>	0.053
O_Poi_ser	4.550	6.911	<b>9.259</b>	8.830	<u>2.833</u>	5.445	6.183	5.274
O_Poi_park	<b>49.954</b>	<b>41.256</b>	22.107	18.594	<u>6.889</u>	18.451	17.330	20.532
O_Poi_tran	<b>9.199</b>	<b>8.166</b>	4.744	3.190	2.639	3.336	3.432	4.200
O_Walkability	17.703	17.569	15.802	16.050	15.967	16.202	16.133	16.361
O_Nps	<u>0.018</u>	<u>0.019</u>	<u>0.022</u>	0.113	<u>0.026</u>	<b>0.264</b>	0.149	0.133
O_Themall	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	0.215	<u>0.031</u>	<b>0.490</b>	<b>0.381</b>	0.244
O_Metro	<b>0.276</b>	<b>0.264</b>	<b>0.205</b>	0.131	0.120	0.127	0.119	0.155
O_Cabi	0.017	0.019	0.022	0.028	0.021	0.028	0.025	0.024
O_Pubschool	<u>0.006</u>	0.012	0.013	0.014	<b>0.029</b>	<u>0.006</u>	0.009	0.013
O_Charter	<b>0.041</b>	<b>0.031</b>	0.018	0.009	0.018	0.003	0.007	0.014
O_Uni	<u>0.017</u>	0.031	<b>0.190</b>	<b>0.120</b>	0.048	0.038	0.044	0.050
O_Equity	<u>0.047</u>	0.112	<b>0.311</b>	<b>0.182</b>	<b>0.165</b>	<u>0.023</u>	0.109	0.098
D_Pop_den	15.748	9.925	17.450	<u>5.250</u>	<b>25.852</b>	<u>6.722</u>	12.329	13.577
D_Emp_den	<u>33.324</u>	<b>233.986</b>	<u>41.827</u>	<b>340.594</b>	<u>13.041</u>	<u>32.215</u>	<b>199.934</b>	70.392
D_Pct_noveh	0.196	<b>0.354</b>	0.190	<b>0.412</b>	0.166	0.174	<b>0.312</b>	0.210
D_Pct_black	0.127	<u>0.083</u>	0.125	<u>0.063</u>	<b>0.282</b>	0.105	0.121	0.149
D_Pct_lowinc	0.104	0.098	0.103	0.098	<b>0.213</b>	0.083	0.094	0.120
D_Pct_senior	0.053	0.101	0.063	0.086	0.100	<u>0.046</u>	<b>0.116</b>	0.073
D_Pct_	0.030	0.033	0.030	<b>0.081</b>	0.056	<u>0.016</u>	0.018	0.031

hispanic								
D_Pct_disabled	0.123	0.102	<b>0.188</b>	0.118	<b>0.176</b>	0.109	0.117	0.132
D_Pct_limeng	0.008	0.018	0.009	<u>0.002</u>	0.014	<u>0.004</u>	<b>0.023</b>	0.010
D_Pct_poverty	0.173	0.184	0.248	0.204	<b>0.279</b>	<u>0.151</u>	0.211	0.200
D_Pct_genz	0.223	0.161	<b>0.272</b>	<b>0.428</b>	<u>0.118</u>	<b>0.247</b>	<u>0.103</u>	0.199
D_Pct_millen	<b>0.536</b>	<u>0.382</u>	0.475	<u>0.309</u>	<u>0.409</u>	<b>0.555</b>	<u>0.389</u>	0.475
D_Pct_genx	0.086	<b>0.230</b>	0.086	0.078	0.161	<u>0.067</u>	<b>0.249</b>	0.124
D_Pct_boomer	0.086	0.150	0.093	0.156	0.150	<u>0.075</u>	<b>0.160</b>	0.112
D_Poi_food	<u>0.122</u>	<b>0.703</b>	<u>0.140</u>	<b>0.734</b>	<u>0.137</u>	<u>0.095</u>	<b>0.653</b>	0.234
D_Poi_shop	<u>0.055</u>	<b>0.226</b>	<u>0.062</u>	<b>0.291</b>	0.074	<u>0.055</u>	<b>0.192</b>	0.095
D_Poi_edu	9.842	<b>18.195</b>	12.293	<b>25.185</b>	13.035	<u>6.163</u>	<b>16.964</b>	11.137
D_Poi_bus	<u>0.023</u>	<b>0.170</b>	<u>0.031</u>	<b>0.276</b>	<u>0.013</u>	<u>0.021</u>	<b>0.133</b>	0.051
D_Poi_ser	5.352	<b>7.573</b>	5.416	6.217	<u>2.441</u>	5.114	6.291	4.866
D_Poi_park	17.356	<b>39.392</b>	18.106	15.543	<u>6.345</u>	18.695	<b>45.859</b>	19.809
D_Poi_tran	2.883	<b>7.950</b>	2.746	6.217	2.101	3.079	<b>8.835</b>	3.856
D_Walkability	16.113	17.520	15.887	17.617	15.862	16.129	17.309	16.322
D_Nps	0.178	<u>0.019</u>	0.174	<u>0.016</u>	<u>0.029</u>	<b>0.290</b>	<u>0.020</u>	0.153
D_Themall	<b>0.383</b>	<u>0.000</u>	<b>0.312</b>	<u>0.000</u>	<u>0.030</u>	<b>0.498</b>	<u>0.000</u>	0.259
D_Metro	0.082	<b>0.230</b>	0.080	<b>0.248</b>	0.075	0.095	<b>0.229</b>	0.117
D_Cabi	0.017	0.019	0.019	0.021	0.015	0.018	0.018	0.017
D_Pubschool	0.011	0.011	0.016	<b>0.027</b>	<b>0.032</b>	<u>0.007</u>	<u>0.006</u>	0.015
D_Charter	0.010	<b>0.029</b>	0.011	<u>0.000</u>	0.022	0.004	<b>0.033</b>	0.014
D_Uni	0.037	0.037	<b>0.089</b>	0.054	0.051	0.036	0.056	0.046
D_Equity	0.111	0.100	<b>0.145</b>	<b>0.159</b>	<b>0.181</b>	<u>0.042</u>	0.064	0.099
<b>n</b>	<b>58,115</b>	<b>62,913</b>	<b>44,277</b>	<b>19,079</b>	<b>167,481</b>	<b>275,389</b>	<b>62,567</b>	<b>690,221</b>
The group mean statistics are <b>bolded</b> if they are significantly larger than the sample mean and <u>underlined</u> if they are significantly smaller than the sample mean.								

*Cluster 1: Mid-day downtown – adjacent neighborhood trips.* The first cluster has a higher share of mid-day trips than the sample average. Trip origins are clustered in downtown DC (**Figure 3-4a**). Population density is low, but the employment density

is much higher than the sample average. The residents tend to own fewer auto vehicles, predominantly white, middle aged – senior (Generation Xers and Boomers), and live close to an array of POIs (food and drink, shopping, business, parks, and transit stations). A much higher-than-average share of trips start within the Metrorail’s catchment areas. On average, trips are less likely to start near a public school or the university campus, but slightly more likely to be near a charter school. Few trips start within the dockless equity emphasis areas. These trips end in downtown adjacent neighborhoods (**Figure 3-4b**), where the population density is average and the employment density is much lower than the city’s average. The trip destination block groups also have fewer POIs of various types than average (food & drink, shopping, and business). A good number of trips end on the National Mall. Cluster 1’s O-D characteristics suggest that these trips are either mid-day utility trips from activity centers to residential neighborhoods or leisure trips between downtown and the National Mall area. Trips in Cluster 1 are unlikely to benefit DC residents of lower socioeconomic statuses.

*Cluster 2: Weekday downtown trips.* Cluster 2 trips start and end in downtown DC (**Figure 3-4c** and **Figure 3-4d**). Specifically, Chinatown, City Center, McPherson Square, Golden Triangle, and Dupont Circle areas. This cluster of LIME trips are concentrated within the commercial district with many POIs of all types. People who can afford to live in these neighborhoods are likely to be middle-aged (Generation Xers), white residents. They are less likely to be socially disadvantaged. Their neighborhoods are highly walkable and well-covered by the Metrorail network.

*Cluster 3: University neighborhood trips.* While not all trips in Cluster 3 start in the two largest university campuses in DC (Georgetown University and George Washington University) (**Figure 3-4e**), a big share of them do (19% versus 5% for the entire city). This becomes a distinct trait to characterize this cluster. In addition to the underlying student population for trip origin block groups, a significant share of senior population, disabled population, and people who live below the poverty line (likely to be students) reside in the trip origin block groups (east of the National Mall and in south DC near Buzzard Point). A significant share of trip origins are located within the dockless equity emphasis area. These “outbound” trips travel across downtown adjacent neighborhoods, much like the trip destination block groups in Cluster 1. A good number of trips end on the National Mall (31.2%) and some on university campuses (8.9%) (**Figure 3-4f**). It is reasonable to assume that university students are the riders for these trips. The trip destinations are mostly residential, with fewer POIs (food & drink, shopping, and business) than the average.

*Cluster 4: Weekday AM peak commuting trips.* This is the smallest cluster of all seven clusters in size ( $n = 19,079$ ). A much higher-than-average number of trips are taken during the AM peak hours on weekdays. The trips start in downtown adjacent residential neighborhoods (**Figure 3-4g**), where the population density is higher than average and employment density is about the average. The socio-demographic characteristics are at the city’s average level with a slightly higher share of disabled population and people who live below the poverty line (likely to be students). A good number of trips start on university campus and within the downtown equity emphasis areas. Cluster 4’s trip destinations are concentrated in downtown activity and



employment centers (**Figure 3-4h**). These block groups have low population density but high employment density. People who live in these block groups lean towards younger, white residents who do not own a car. Interestingly, a higher-than-average share of non-white Hispanic population is found in these areas. There are various POIs in these destination block groups, especially education POIs (e.g., schools and libraries). Indeed, a higher-than average percentage (2.7% versus 1.5% for the sample average) of trips are taken within half a mile of a public school. It indicates that some of the e-scooter commuting trips may be taken by high school students between 16 and 18. Many trips are taken within the downtown equity emphasis areas. The trip destination block groups are also residential, instead of commercial. This is expected as e-scooter sharing is primarily used for short trips under one or two miles. The neighborhoods on the peripheries of the city are largely residential with scattered POIs.

*Cluster 5: PM peak hours and nighttime trips.* Cluster 5 is one of the larger cluster (n = 167,481). Geographically, trip O-Ds spread across the city (**Figure 3-4i** and **Figure 3-4j**). Comparing to other clusters, Cluster 5 have a significant higher share of trips taken during PM peak hours and nighttime. The trip origins are likely to be residential areas with a higher population density and a lower employment density than the sample means. The trip origin block groups accommodate significantly more racial minorities, low-income individuals, people living below the poverty line, and car-dependent individuals. The trip origin block groups also have less accessibility to various POIs and are slightly less walkable. These block groups are not well-integrated into the Metrorail system, either. Nonetheless, a fair share of trips start within a public school's catchment areas. A good number of block groups are marked as dockless

equity emphasis areas (in East and Southeast DC), which indicates an opportunity for the disadvantaged populations to utilize e-scooter sharing during PM peak/nighttime hours. In particular, public transit services are significantly reduced for off-peak, evening hours in those neighborhoods. The destination block groups, again, have a much higher share of the socially disadvantaged populations (racial minorities, low-income individuals, and disabled individuals). A small number of trips end within half a mile of a public school. A fair share of trips end in the dockless equity emphasis areas. Cluster 5 indicates an opportunity for DDOT to collaborate with e-scooter vendors to deploy more fleets into the equity priority areas during PM peak and nighttime hours to entice their usage among the socially disadvantaged populations.

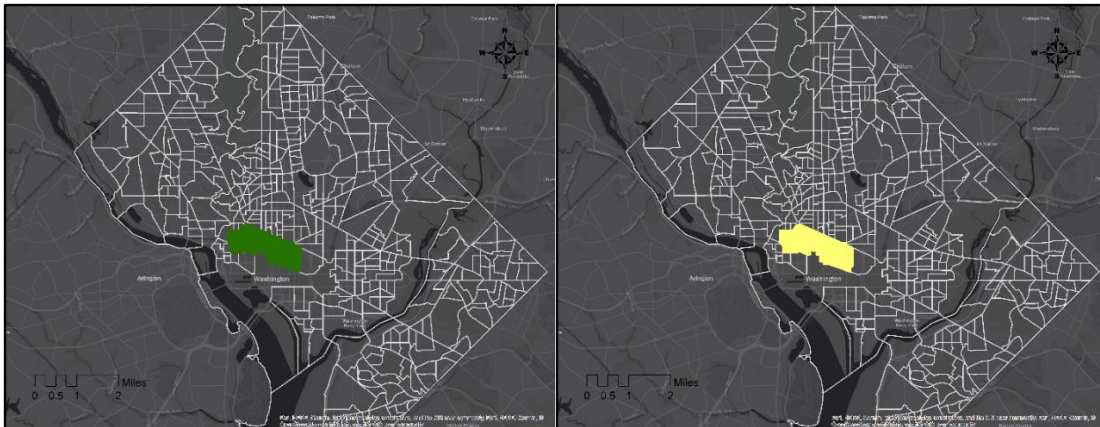
*Cluster 6: Mid-day leisure trips.* Cluster 6 is the largest cluster (n = 275,389). More than half of the trips are taken during mid-day hours (10 AM – 3 PM). A slightly higher share of trips are taken during weekends, especially during the Cherry Blossom Festival, than the average. About half of the trips start/end on the National Mall. The spatial patterns suggest the same result (**Figure 3-4k** and **Figure 3-4l**). The National Mall areas have mostly federal buildings, museums, green space, and historical sites with fewer businesses, restaurants, coffee shops, stores, or schools. It enhances the results shown in Zou et al. (2020) that the NPS areas and the National Mall are the largest attractions for e-scooter sharing trips. The results also coincide with the temporal dynamics suggested in Younes et al. (2020). E-scooter sharing in DC primarily caters leisure users for mid-day sightseeing/leisure trips.

*Cluster 7: Downtown adjacent – downtown trips.* Cluster 7 almost mirrors Cluster 1 as trips start in the residential areas adjacent to downtown and end in the

downtown area (**Figure 3-4m** and **Figure 3-4n**). The trip origin block groups are more residential than commercial, with a high share of millennial residents. A higher-than-average share of trips start on the National Mall, as well. The trips end in downtown block groups of high employment density and various POIs. These block groups also house many Generation Xers and Baby Boomers, as well as car-less individuals. The Metrorail coverage is excellent in these neighborhoods, too.



**Figure 3-4a, 3-4b: Trip origins (left) and destinations (right) in Cluster (1)**



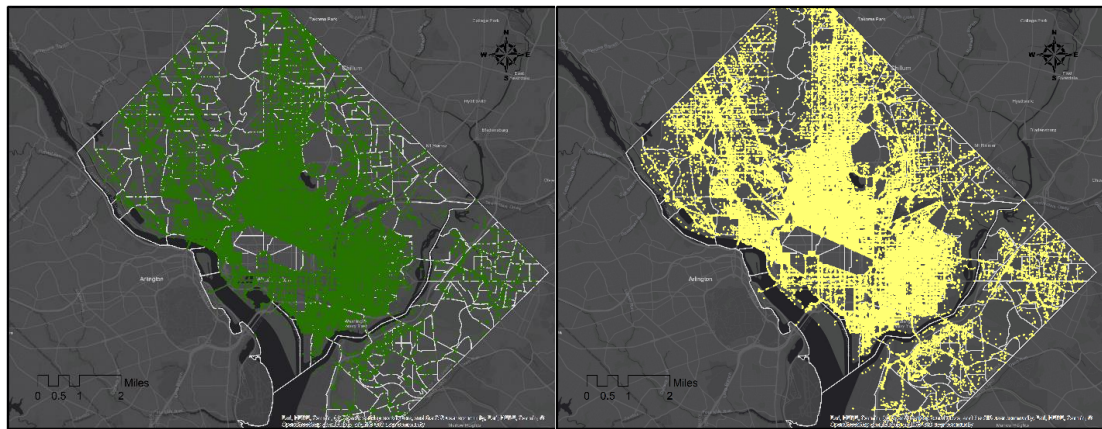
**Figure 3-4c, 3-4d: Trip origins (left) and destinations (right) in Cluster (2)**



**Figure 3-4e, 3-4f: Trip origins (left) and destinations (right) in Cluster (3)**

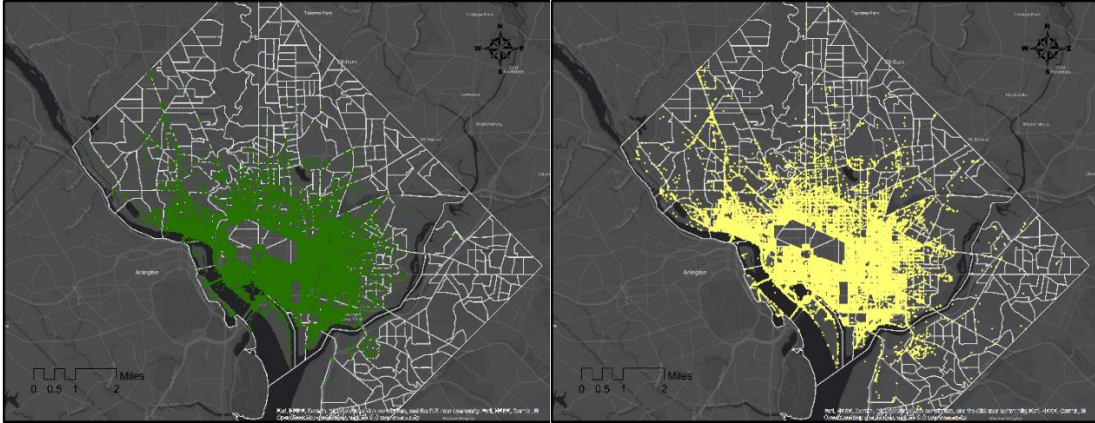


**Figure 3-4g, 3-4h: Trip origins (left) and destinations (right) in Cluster (4)**



**Figure 3-4i, 3-4j: Trip origins (left) and destinations (right) in Cluster (5)**





**Figure 3-4k, 3-4l: Trip origins (left) and destinations (right) in Cluster (6)**



**Figure 3-4m, 3-4n: Trip origins (left) and destinations (right) in Cluster (7)**

### 3.6 *Discussions*

Dockless e-bike/e-scooter sharing becomes a popular shared micromobility option in less than three years before taking a hit by the COVID-19 pandemic (See Bureau of Transportation Statistics, 2021). Chances are that shared micromobility (station-based bike-sharing, dockless bike-sharing, and e-scooter sharing) ridership will quickly recover and continue to grow in the post-pandemic era (NABSA, 2020). The empirical data used in this study dated back to 2019. The insights generated from this study are very much relevant for transportation agencies and transportation planners/policymakers in managing the dockless shared micromobility program and evaluating the effectiveness of the private-public partnership between the city and e-

scooter vendors. In particular, overlaying e-scooter sharing trip O-Ds and paths over the underlying spatial patterns of social and built environments, I reveal where trips were less likely to be taken – including a significant part of the equity emphasis areas in east and southeast DC.

Using real-time e-scooter trip trajectory data, I am able to examine the spatial patterns of e-scooter trips at a refined resolution. The trajectory data allow me to not only consider the built/social environments at the e-scooter trip origins and destinations, but also the desirable and undesirable street design factors that may affect e-scooter sharing usage on the street. The street segment level analysis reveals the multivariate relationship between trip density and street design, built environment, social environment, and points of interest. The main takeaways are: (1) A pedestrian/ bike favorable built environment and bike-friendly street design are significantly positively associated with more e-scooter sharing trips on the street. Not surprisingly, e-scooter riders prefer to ride on streets with bikeways (lanes and trails), trees, and cameras/signals that could slow down traffic. In addition, the more walkable and high-density neighborhoods with various points of interest attract the most e-scooter traffic; (2) When the locally spatial autocorrelations are specified using the GWR approach, I find significant spatial variance in the effect of built environment, street design, and sociodemographic factors on e-scooter sharing usage, which means a localized review is needed when analyzing e-scooter sharing trips in specific neighborhoods.

Using a data-intensive, machine-learning based clustering analysis, I specify seven e-scooter trip origin-destination clusters for a total of 690,221 trips from January to August in 2019. Five clusters are either concentrated in downtown or downtown

adjacent areas (either residential neighborhoods or tourist hot spots). Trips in these clusters are most likely to be mid-day activity/ leisure trips, except for one cluster (Cluster 4) that has a relatively high share of AM peak-hour trips that may serve the commute needs for residents and students who live in the downtown adjacent areas. The largest cluster (Cluster 6) have a high share of trips starting and ending on the National Mall during mid-day hours, indicating that dockless e-scooter sharing primarily satisfies the travel demand for a large volume of visitors and local residents for leisure and sightseeing. There is an opportunity to promote e-scooter sharing in the more socially disadvantaged areas outside of the central city during PM peak hours and nighttime, as revealed by Cluster 5. The public transit service is typically reduced during the nighttime hours, so dockless e-scooter sharing can serve as an alternative mode to meet local residents' travel needs. Combining with the insights from the street segment analysis, I argue that it should be a policy priority to improve bike-friendly street design and plan for a more compact, mixed-used built environment in such disadvantaged neighborhoods so that more residents are convinced that their neighborhoods are safe and favorable for biking and scooting. I further argue that more financial assistance should be provided by dockless vendors to the low-income individuals to make sure that not only e-scooter sharing is a safe option, but also an affordable option to meet their daily travel needs.

### *3.7 Conclusions*

When e-scooter sharing disrupted the U.S. shared micromobility market in 2017 – 2018, cities held different opinions on e-scooter sharing's potential impacts on the urban transportation system. DC takes a rather optimistic outlook on the economic

(more money spent on business and leisure activities, see Buehler & Hamre, 2014), social (improving people's mobility), health (more outdoor, non-motorized activities), and environmental (modal shift from auto to e-scooter) benefits it can harness. Along e-scooter sharing's rapid expansion in the District of Columbia, policymakers begin to address safety and parking issues associated with this emerging mobility. The equity component of the policy package is underwhelming in a sense that only two sets of equity strategies are considered to encourage the socially disadvantaged groups to use e-scooter sharing: (1) The "Making Dockless Vehicles Accessible to all Washingtonians" program requires all dockless partners to provide unlimited 30-minute rides for low-income residents/households in the DC. I look into similar programs at the neighboring counties, including Montgomery County (MD), Prince George's County (MD), and Arlington County (VA). There does not exist an explicit countywide program in each county that emphasizes e-scooter equity like the one in DC, although there exists information about each vendor's equity program. I advocate that cities and counties within the Capital Metropolitan Regions to work together on a uniform equity program for any low-income resident within the metropolitan area to participate. (2) A map of equity emphasis areas is drawn by DDOT, within which a minimum number of fleets are required for morning hours. This approach is a reactive, rather than proactive, equity strategy as the areas are updated infrequently (very little change between the version in 2019 and 2020), unlikely to reflect changes in e-scooter demand from those socially disadvantaged communities. For vendors, they only need to meet the minimum requirement and ignore the additional mobility needs from the low-income, racially diverse populations. Realistically, e-scooter sharing is not a



profitable business as for now (Schellong et al., 2019), so vendors have no incentive to serve the disadvantaged communities as they could have allocated vehicles to high-demand areas that offer a high profit margin.

This study reveals a third possibility that could explain the low e-scooter ridership in DC's most disadvantaged neighborhoods in the east and across the Anacostia River: the unfavorable built environment for cycling and walking. By underpinning e-scooter trips at the trajectory level, I am able to describe the impact of not only the built environment at an e-scooter trip's origin and destination, but also the street configuration and the built environment en route. A street that has a bike lane, lots of trees, a traffic camera and signals/signages, in a highly walkable, compact, and mixed-use neighborhood tends to attract higher e-scooter traffic. Density and points of interest are closely related to e-scooter trip generation, while bike-/pedestrian-friendly street design matters for the perceived safety and level of comfort to ride an e-scooter. Both matter to the success of an uptake of e-scooter sharing; both are the weakness in the equity priority areas. However, the story does not end here: The e-scooter trip clustering analysis reveals a potential demand for e-scooter sharing in east/southeast DC. It is the PM hours and evening hours, when transit services start to slow down, that a number of e-scooter trips are made in those neighborhoods. This cluster of trips indicate that people do use e-scooters in the disadvantaged neighborhoods. For DDOT and policymakers, this means that DDOT needs to work with vendors to address the growing or unmet demand for e-scooter during those hours in such neighborhoods. More importantly, DDOT needs to address biking and pedestrian facilities in those

neighborhoods, making sure that people feel safe, comfortable, and happy to embrace walking/biking/e-scooter around their neighborhoods.

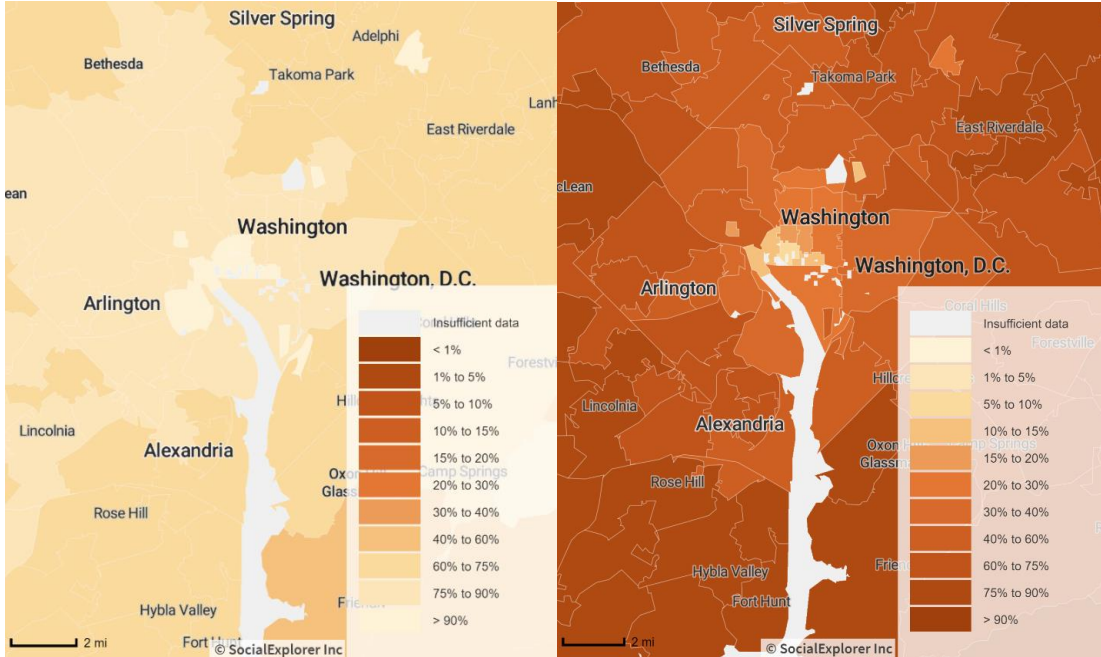
I also acknowledge the shortcomings of this study, both in empirical work and in its equity implications. To begin with, the GWR model reveals significant local heterogeneity in the estimated coefficients. The local-specific nuances between e-scooter trip density and the built/ social environment covariates need a more careful examination as they may produce localized insights that differ from the global insights generated from the full model. In addition, I could run the spatial analysis in a more computationally efficient way by sampling the large street-segment level dataset. The significant computational cost of creating a spatial matrix for all 33,652 street segments hinders the flexibility to improve the empirical work by trial and error. In retrospect, I would use different sampling techniques to derive a smaller set of representative segment-level observations (e.g.,  $n = 1,000$ ). I would also try multi-level regression models that differentiate the impacts of street-segment level factors from those of neighborhood level factors.

For the equity implications, a few questions remain unanswered from this study: (1) Is there an unmet demand for e-scooter sharing in the socially disadvantaged neighborhoods? I would argue there is one because the American Community Survey (ACS) data (5-year estimates, 2014 – 2019) show that more than a quarter of non-home workers in the Anacostia areas take a commuting trip that lasts longer than 45 minutes (**Figure 3-5a**). In addition, car dependency is a more prominent issue in the north, east, and southeast DC, where many racial minority communities are located (**Figure 3-5b**). E-scooter sharing trips can substitute short car trips and complement long transit trips.

Boosting e-scooter sharing usage in the socially disadvantaged neighborhoods can be a cost-effective strategy for a modal shift away from cars. (2) What are unobserved factors that may adversely affect the preference for e-scooter sharing? Due to the lack of user information, I cannot tell whether low-income residents systematically ride fewer trips than other more economically robust residents, even in popular locations outside of the disadvantaged communities. If so, it is likely that affordability may be an issue for the uptake of e-scooter sharing among the low-income, unbanked populations. In order to derive such insights on affordability, more qualitative approaches (surveys, interviews, case studies) must be combined with the data-driven quantitative analysis. (3) Do local residents actually welcome e-scooter sharing? Not all residents are going to immediately love riding e-scooters. Senior and disabled populations may find an increasing number of e-scooters on the street and at the curbside a nuisance rather than convenience. The conflicting views on e-scooter sharing heightens the importance of the proactive regulatory approaches to manage e-scooter vendors' conducts and e-scooter riders' behavior. To build a mobility for all, there needs to be public policy that listen the feedback from all communities and reflect their feedback in infrastructure building and rulemaking processes.

This study is not the end of the equity conversation vis-à-vis e-scooter sharing. Rather, it opens up more conversations on both equity concerns and equity opportunities surrounding the new mobility. I aim to build a comprehensive and mixed-approach research agenda on the equity perspectives of shared micromobility in an intra-city, even cross-country, context. Ultimately, cities can benefit from less driving

and more cycling, walking, or scooting, but it needs to be addressed in an equitable way.



**Figure 3-5a (left): The percentage non-home working adult population whose average commute trip time >45min (ACS 2014 – 2019, zip code level, map generated by Social Explorer)**

**Figure 3-5b (right): The percentage of working population whose primary commute mode is auto (ACS 2014 – 2019, zip code level, map generated by Social Explorer)**

## Chapter 4: The Spatial Patterns in Sharing Economy and Its Implications on Urban Policy: Explorations of Eight U.S. Cities

### *4.1 Background: Proliferation of the sharing economy in U.S. cities*

The sharing economy, broadly defined as the platform economy that relies on online platforms and a peer-to-peer marketplace to allow subscribers to temporary access services without actual ownership (Sundararajan, 2016, p.30; Frenken & Schor, 2017), has been closely related to tourism and the hospitality industry at heart since the concept emerged in the mid-2010s. The motivation for starting Airbnb is to provide a platform for people to afford a stay in a bed-and-breakfast style rental in a host's guest bedroom. Similarly, ridesourcing platforms like Uber or Lyft are seen as Airbnb in transportation in a sense that subscribers can afford a ride (alone or with another party) in a Uber/Lyft driver's vehicle (Sundararajan, 2016, p.6-8). Bike-sharing has also been thought to benefit tourism (Shaheen, Cohen, & Martin, 2013). Nevertheless, it raises the question about whether the sharing economy serves the interest of people who live in a city, rather than those who visit a city. This paper aims to reveal the spatial patterns of different sharing economy activities, namely short-term rental like Airbnb and shared micromobility like bike and e-scooter sharing, and to overlay the socioeconomic factors on top of such spatial patterns to make policy inferences about the equity perspectives on the sharing economy.

#### 4.1.1 The tourist-oriented sharing economy

The sharing economy has been studied extensively in transportation and housing research due to the popularity of shared mobility (bike-sharing, e-scooter

sharing, ridesourcing, car-sharing, etc.) and short-term rental (STR). The sharing economy plays an important role in boosting tourism, but the rapid, unregulated growth of the sharing economy oftentimes clashes against the interest of traditional tourism and hospitality business, like taxis (Cramer & Krueger, 2016) and hotels (Zervas, Prosperio, & Byers, 2017). The industry incumbents argue that the disruptive sharing economy platforms takes advantage of regulatory loopholes (e.g., the informal employment of Uber/Lyft drivers and the loosely taxed STR business) and gain an unfair advantage in market competitions. Cities also express two major concerns over the sharing economy: (1) Platforms avoid making their business binding with the city's regulatory framework; (2) It is debatable whether the sharing economy truly provides an equitable and sustainable pathway to the urban economy: For instance, it could casualize the labor force and reinforce exclusivity of those who own an asset to share (Cheng, 2016). In particular, critics of the sharing economy show signs of worry that it would reinforce the neoliberal economy by heavily relying on the decentralized market mechanism. Meanwhile, platforms may neglect the inherent disparities of the neoliberal economy in market participation and welfare distributions (Martin, 2016).

These are legitimate concerns as an increasing volume of academic literature, especially empirical work using statistical analysis, reveals that the sharing economy, while undoubtedly benefits short-term visitors with more affordable mobility/lodging options, tends to be associated with inequitable welfare outcomes. Empirical studies on STR reveal that racial minority hosts earn significantly less than white hosts (Kakar et al., 2018; Marchenko, 2019; Laouenan & Rathelot, 2020). African American guests are also more likely to be rejected for booking a rental according to an audit study

(Edelman, Luca, & Svirsky, 2017). In addition, the STR activity level in affluent, white neighborhoods are significantly higher than non-white, socially disadvantaged neighborhoods in DC (Zou, 2020), Boston, and Chicago (Wegmann & Jiao, 2017). Studies demonstrate an implicit racial bias against Uber riders (Ge et al., 2020; Brown, 2019). In addition, a number of studies suggest that bike-sharing stations and trips are spatially concentrated in affluent, white-populated neighborhoods in multiple U.S. cities (Qian & Niemeier, 2019; Caspi & Noland, 2019). For the emerging mode of e-scooter sharing, preliminary studies suggest mixed results: some researchers find relatively high ridership in low-income areas in Austin, TX (Bai & Jiao, 2020), while some observe a slightly higher ridership in high-income areas in Seattle, WA (Mooney et al., 2019). More evidence-based research is needed before we can generalize the broader equity impacts of e-scooter sharing.

The bottom line is the sharing economy, credits to all the economic benefits it injects into a city, is not a business model designed to focus on the potential welfare consequences it sheds on different socio-demographic groups and communities in a city. In fact, the market-based, platform-based sharing economy often causes unintended adverse welfare consequences, such as the transactional gentrification resulted from STR activities (Sigler & Wachsmuth, 2020). It is not the platforms' intention for STRs to crowd out long-term renters in the city, but they defend themselves fiercely when cities try to regulate their growth and confine their level of activeness. Similarly, cities have to step in and require private e-scooter vendors to offer discounted membership/fare to low-income residents and distribute a fair share of their vehicles in the equity priority areas because an inequitable access to their

services (either due to the high monetary cost or the low spatial coverage) would only enlarge the existing mobility gaps.

This study serves the purpose of examining the spatial patterns of STR and shared micro-mobility in eight different cities and understanding whether these patterns may reveal the inequity/ equity perspectives regarding their potential welfare impacts on the more socially vulnerable populations. In addition, the rich nuances in the policy contexts can hopefully shed light on the direction of policymaking towards addressing the equity concerns on the tourist-oriented sharing economy.

The rest of the chapter is organized as follows: In Section 4.2, I concisely describe the eight cities in this study, with a summary of each city's STR regulatory framework and the policy efforts on bike-sharing/ e-scooter sharing equity. I then outline the methodological framework of the empirical work in Section 4.3. I summarize data source, provide summary statistics, and discuss the spatial patterns of the three sharing economy activities in Section 4.4. I then provide more refined and targeted analytical results in Section 4.5. In Section 4.6, I discuss important findings from the empirical work. Lastly, I offer my final remarks and recognize both limitations and future work on the topic in Section 4.7.

#### *4.2 Eight U.S. cities*

In this study, I intentionally choose eight U.S. cities for the comparative analyses on spatial patterns of three types of sharing economy activities, including short-term rental (STR), station-based bike-sharing (SBBS), and dockless bike (e-scooter) sharing (DBS). The eight cities are: Washington DC, Boston (MA), Chicago



(IL), Louisville (KY), Minneapolis (MN), Austin (TX), Los Angeles (CA), and Portland (OR). Not only are the cities located in different geographic regions (two coasts, Midwest, and the south) and differ in population sizes, but these cities also approach differently towards regulating and managing the emerging sharing economy. One common characteristic of the eight cities, arguably, is the endeavor to make data available for researchers to study STR and shared micromobility. The policy targets for STR and shared micro-mobility in each of the eight cities, albeit agreeing with each other in the general directions, distinct from each other and could determine where and how widespread the sharing economy markets are able to expand in these cities. I aim to connect the policy heterogeneities, together with the locational factors (in social and built environments), to the spatial heterogeneities for the three sharing economy activities that are observed in statistical and mapping analyses. I will concisely summarize the policy contexts for each city in the following paragraphs.

*Washington DC:* The nation's capital passed its citywide legislation (B22-92) on STR on November 13, 2018, marking the end of a two-year regulatory battle between the pro-STR camp (platforms and STR interest groups) and the pro-regulation camp (city council and housing interest groups). The bill became effective a year later, with restrictions on business capacity per host (only on a primary dwelling with a cap of 90 days of STR in a calendar year) and the licensing requirement to de-incentivize commercial listings that could overtake the precious rental housing stock or bid up housing prices. The STR listing data I used in the analysis dated back to September 2019, so it should reflect the signaling effect of the regulation. On the shared micromobility side, DC is the pioneer in public bike-sharing in the U.S. with the Capital

Bikeshare (CaBi) program launched in 2010. The city was also an early adopter of dockless e-bike/e-scooter sharing in September 2017. The city fully embarks on shared micromobility as a strategy to promote sustainable transportation. In addition, DDOT pays attention to equity issues in both SBBS and DBS programs. It emphasizes equity by (1) offering financial assistance to the low-income individuals and households (Capital Bikeshare, n.d.; DDOT, n.d., b), and (2) designating dockless equity emphasis areas that requires the morning staging of e-scooters/e-bikes.

*Boston:* Boston implemented STR regulations in 2019. Boston allows a host to rent (a) part of a unit, (b) a full unit as the primary residence, or (c) a full unit on a multi-unit property as the primary residence. The listing must be registered and a host must obtain a business certificate to operate the STR business. The city prepares a property database that clarifies whether a property is eligible to conduct the STR business (Keycafe Team, 2019). The end goal of the regulation is also to limit unregulated growth of STR that may adversely affect housing affordability of the city. For shared micromobility, the city's public bike-sharing system, Bluebikes, has been successfully covered the majority of the city. However, the city never legalized dockless e-scooter sharing, even though its neighboring jurisdictions partnered with popular dockless vendors like Bird and Lime to provide DBS services (Vaccaro, 2020). The regulatory ban makes Boston a unique case as dockless trips were made into the city's territory, but mostly in neighborhoods bordering Brookline, Cambridge, Somerville, Chelsea, and Winthrop. While the city offers financial assistance to the low-income individuals to subscribe their own bike-sharing program, it does not offer incentives to use e-scooters.

*Chicago:* Chicago enacted the original Shared Housing Ordinance in June 2016. An amended version was passed in September 2020 that enhance the licensing process and regulatory enforcement. The data I use in this study dated back in 2019, which means the tightened regulations are not considered. For shared micromobility, Chicago's Divvy bike-sharing system was launched in 2013 and has been expanding in stations and fleets. However, the DBS program was still in the pilot phase in 2019, with only a limited number of neighborhoods west of "the Loop" in the pilot program. This makes Chicago another interesting case to study the spatial patterns of DBS trips within a policy boundary. In addition, while financial assistance on Divvy rides is offered to low-income residents, no equity priority was specified during the DBS pilot program.

*Louisville:* The Derby City has a set of standard short-term rental rules just like other major U.S. cities. It only allows for one registration per host. Any unregistered listings that are advertised on STR platforms will result in a fine (Louisville-Jefferson County Metro Government, n.d.). There is not a clearly stated goal of the STR rules, in terms of the potential housing market consequences STR could cause. For shared micromobility, Louisville operates a small, citywide SBBS program, LouVelo, of which stations are mostly concentrated in downtown, the University of Louisville, and across the Ohio River in Jeffersonville, IN. The DBS program was piloted in 2018 and the city invited four vendors (Bird, Lime, Bolt, and Spin) with a total number of 1,200 fleets per day on the street. Like other cities, Louisville also offers discounted fare for its own SBBS program and direct the low-income residents to sign up for the

discounted ride plans offered by each DBS vendor. There is no equity evaluation per se from the city.

*Minneapolis:* Prior to November 2020, there are minimal regulations towards the STR market in the city. A host only needed to comply with the licensing procedure. In November 2020, the city council passed STR ordinance that limits the number of listings and the hosting capacity within each listing for all types of dwellings in the city. This means the data I use in this study does not reflect any regulation on the STR business. For shared micromobility, the city's public SBBS system (Nice Ride) is among the earliest bike-sharing programs in the country. In 2018, the city permitted three dockless vendors in their Phase I pilot. The city significantly increased the number of scooters available to the public in 2019 (the Phase II pilot). Minneapolis emphasizes bike equity for their SBBS system in terms of station deployment and discounted rides for eligible residents (Nice Ride, 2020) and the city provides information about the dockless vendors' low-cost mobility programs. Nonetheless, the city does not require equitable deployment of DBS fleets.

*Austin:* Austin passed the city ordinance on STRs in 2016, which included a clause banning type 2 STRs (non-homestead). The ban was overruled by a state appeals court as "unconstitutional" in November 2019, which means STR hosts in Austin (and Texas) can rent out properties other than their primary residence (Largey & Weber, 2019). The data I use does not reflect the ruling that potential relaxes multiple restrictions on STR business in Austin. For shared micromobility, the city operates a small SBBS program (Metro Bike) with almost all stations built near downtown, the waterfront, and the University of Texas at Austin. The geographic concentration of the

SBBS stations means that a majority of the socially disadvantaged communities outside of the downtown areas are not served by SBBS. The city introduced many DBS vendors for operations in the city. Almost 10,000 e-scooters are deployed by Bird and Lime alone on Austin's streets. However, the city has minimum equity requirements on their operations.

*Los Angeles:* Los Angeles is the country's largest STR market in terms of the total number of listings. The city's home-sharing ordinance came into effective on November 1, 2019. There is a clear policy agenda behind the ordinance to control the unregulated growth of STR that may have affected the city's precious housing supply. The regulatory restrictions on hosts and listings are strict, with multiple capacity limits. The STR data I use in the study should reflect the signaling effect of the regulations. For shared micromobility, Los Angeles operates a citywide SBBS program (Metro Bike Share). The stations are largely concentrated in downtown and Venice Beach, leaving much of the city's residential areas underserved by SBBS. The city began the dockless pilot program in 2019 and it became an immediate triumph in terms of the large volume of trips taken (more than 10 million in its first year of operation). LADOT also has a comprehensive equity evaluation of the pilot program (LADOT, 2020).

*Portland:* Portland's accessory STR permit allow a host to rent either no more than 2 bedrooms up to 5 overnight guests (Type A) or between 3 and 5 bedrooms to overnight guests (Type B) in a property. The intention of the regulation was to limit commercial STR activities that could cause a shortage in rental housing stock, although a report from ECONorthwest claimed that the impact of STR on housing affordability in Portland was minimal (ECONorthwest, 2016). For shared micromobility, Portland's

own SBBS program – Biketown – is a successful private-public partnership between Portland Bureau of Transportation (PBOT), Nike, and Lyft. Discounted memberships are offered to students and eligible low-income residents. However, there is no specific policy on an equity priority in neighborhoods of low social mobility. As for DBS, PBOT launched its pilot DBS program as early as 2018 and six vendors (Bolt, Lime, Razor, Shared, Spin, and Bird) were permitted for operation by August 2019 (PBOT, 2020). Equity is a major policy priority for the dockless program, including an equitable deployment of fleets in East Portland and an evaluation of the low-income pricing plans offered by each vendor (PBOT, 2020).

I summarize the STR regulation time frame and the basic information on the shared micromobility programs (SBBS and DBS) in **Table 4-1**. The heterogeneities in STR regulations, SBBS deployment, and DBS equity priority can hopefully explain variations in the spatial patterns of the three types of sharing economy activities revealed in the analytical sections.

**Table 4-1. City level regulation on STR and adoption of shared micromobility**

City	STR Regulation Effective Year	SBBS Launch Year	SBBS Public/ Partner	SBBS Equity	DBS Launch Year	DBS Vendors	DBS Equity
Washington DC	October 2019	2010	Public	Yes	Piloted in 2017; Full launch in 2019	9	Yes
Boston MA	January 2019	2011	Public	Some	No ride zone; Left in 2020	2	No
Chicago IL	June 2016 (Amended in September 2020)	2013	Partnered with Lyft	Some	Piloted in 2019; Full launch in 2020	3	No

Louisville KY	December 2015 (Amended in May 2019)	2013	Public	Some	Piloted in 2018	4	Some
Minneapolis MN	November 2020	2010	Public	Yes	Pilot I in 2018, Pilot II since 2019	3	Some
Austin TX	February 2016 (Partly overruled in November 2019)	2013	Partnered (Bike Share of Austin)	Some	Piloted in 2018, regulated in 2019	10	No
Los Angeles CA	November 2019	2016	Public	Some	Piloted in 2019	8	Yes
Portland OR	July 2014 (Agreement with Airbnb in September 2019)	2016	Partnered with Lyft	Some	Piloted in 2018, updated in 2019-2020	5	Yes

#### *4.3 Methodology*

In this section, I discuss research strategies to unveil the spatial patterns of STR listings, SBBS trips, and DBS trips in eight cities. In addition, I outline the analytical framework that establish the relationship between the spatial patterns of the sharing economy activities and a neighborhood’s underlying social vulnerability, which leads to a policy discussion manifested from the analytical results.

##### 4.3.1 Examining spatial patterns

To describe and compare different spatial patterns for the three types of sharing economy activities, I adopt three strategies: (1) normalizing the activity (STR listings, SBBS trips, and DBS trips) distributions by households/population at the census tract level, (2) mapping the spatial distributions for eyeballing spatial patterns (clusters, dispersion, and absence), and (3) statistically evaluating spatial similarities/differences.

STR listing density is normalized by the number of households while SBBS/DBS trip densities are normalized by population in a census tract. In map visualizations, the same set of five levels of density (including a null level) are applied to all eight cities for cross-city comparisons. The summary statistics of the density variables overview the level of activeness or diffusion of STR, SBBS, and DBS in a city. Map observations further display where STR, SBBS, and DBS are most popular in eight cities. Combining the knowledge about neighborhood points of interest and land use, I can make initial inferences on the likely users and their purposes of use for all three types of sharing economy activities.

To evaluate the spatial similarities/differences in a quantitative, rigorous fashion, I apply Lee's  $L$  statistics (Lee, 2001) to quantify the bivariate spatial association between STR, SBBS, and DBS densities. Lee's  $L$  statistic is an elegant way that integrates Pearson's  $r$  statistic, which is conventionally used to evaluate the bivariate association of two distributions, and Moran's  $I$  statistic, which is used as a univariate indicator of spatial clusters and dispersions (Lee, 2001; Kim et al., 2018). Lee (2001) describes it as "*univariate spatial associations of two variables and their point-to-point association in a certain form.*" It is a class of local indicators of spatial association (LISA) globally defined by Anselin (1995).

Lee's  $L$  statistic is formally defined in **Equation (1)** (Lee, 2001):

$$\begin{aligned}
 L_{X,Y} &= \sqrt{\frac{\sum_i (\tilde{x}_i - \bar{x})^2}{\sum_i (x_i - \bar{x})^2}} \cdot r_{\tilde{x},\tilde{y}} \\
 &= \sqrt{\frac{\sum_i (\tilde{x}_i - \bar{x})^2}{\sum_i (x_i - \bar{x})^2}} \cdot \sqrt{\frac{\sum_i (\tilde{y}_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2}} \cdot \frac{\sum_i (\tilde{x}_i - \bar{x})(\tilde{y}_i - \bar{y})}{\sqrt{\sum_i (\tilde{x}_i - \bar{x})^2} \cdot \sqrt{\sum_i (\tilde{y}_i - \bar{y})^2}} \quad (1)
 \end{aligned}$$



where  $\tilde{x}_i = \sum_j \omega_{ij}x_j$  and  $\tilde{y}_i = \sum_j \omega_{ij}y_j$  are the weighted averages of neighbors defined by the row-standardized spatial weights matrix  $\mathbf{W}$  with weight elements of  $\omega_{ij}$  between the two observations  $i$  and  $j$ .  $\bar{\tilde{x}}$  and  $\bar{\tilde{y}}$  are the spatially lagged (SL) vectors of  $\mathbf{X}$  and  $\mathbf{Y}$ , the underlying variables of interest. A spatial smoothing scalar (SSS) is defined as the ratio of two sums of squares. It measures the degree of smoothing of a geographic pattern with its observations represented by the corresponding elements in a SL vector.

It is revealing that Lee's  $L$  is a more robust quantitative measure than Pearson's  $r$  when evaluating the correlation between two geographically associated variables (distributions) in that the spatial relationship (geographical weights) is nested in Lee's  $L$  to allow for spatially varying variances or local instability in variance (Lee, 2001).

When establishing the spatial relationship (weights) using the census tract shapefiles for eight cities, I adopt the row standardized neighbors consistent with the spatial weight matrix ( $\mathbf{W}$ ) specified in Lee's  $L$  statistics. Row-standardization takes the given weight  $\omega_{ij}$  and divides them by the row sum such that each row sum of all weights equals 1 and the sum of all weights for all rows equals  $n$ , the total number of observations (census tracts). Formally, row standardization is expressed in **Equation (2)**:

$$\omega_{ij}(s) = \frac{\omega_{ij}}{\sum_j \omega_{ij}} \quad (2)$$

Last but not least, the queen contiguity is assumed when defining neighbors, which means any census tract that shares a common edge or a common vertex is considered the “neighbor” for a given census tract.

#### 4.3.2 The sharing economy activities and neighborhood social vulnerability

While examining the spatial patterns of different sharing economy activities is meaningful in itself, I take another step by interacting the spatial patterns with the social vulnerability of an underlying neighborhood (census tract). By doing so, I aim to understand whether the sudden rise of the sharing economy may benefit the socially vulnerable population in these major cities, or it has minor/potentially negative effects on their neighborhoods.

I introduce the social vulnerability index (SVI) created by the Centers for Disease Control and Prevention (CDC) as an objective metric that evaluates a community's social vulnerability against hazardous events or economic hardship. Without pettifogging the details about the methodology behind SVI (documented in CDC (2020)), I briefly describe SVI as a percentile index (between 0 and 1, higher value means higher social vulnerability) that ranks census tracts on 15 social factors<sup>12</sup> that can be grouped into four themes: socioeconomic status, household composition and disability, minority status and language, and housing type and transportation. SVI ranks census tract within each state and the District of Columbia, which means it measures relative social vulnerability within each state. The composite index is primarily used in my analysis when interacting with the distribution of the sharing economy activities at the census tract level.

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<sup>12</sup> The list of factors include below poverty, unemployed, income, no high school diploma, aged 65 or older, aged 17 or younger, civilian with disability, single-parent households, minority, speaking English "less than well", multi-unit structure, mobile homes, crowding, no vehicle, and group quarters.

I first calculate Lee's  $L$  statistics between STR/SBBS/DBS density variables and SVI at the census tract level to derive a city-level spatial correlation between the activeness of the sharing economy activities and the level of social vulnerability. If Lee's  $L$  statistics are significantly negative, then I can make the case that the sharing economy activities are not popular in the more disadvantaged communities in a city, which can say a great deal about whether the emerging economy can potentially generate localized benefit to the socially vulnerable population.

I then highlight census tracts with (1) relatively low social vulnerability ( $SVI < 0.25$ ) and relatively high level of activeness in STR, SBBS, and DBS; (2) relatively high social vulnerability ( $SVI > 0.75$ ) and relatively high level of activeness in STR, SBBS, and DBS; and (3) relatively high social vulnerability ( $SVI > 0.75$ ) and relatively low level of activeness in STR, SBBS, and DBS. I will explain how the levels of activeness are drawn in the result section. Through the simple bivariate tabulation and visualization, I can confirm (1) whether some socially advantageous neighborhoods coincide with high intensity of the sharing economy activities; (2) whether some socially vulnerable neighborhoods get exposed to highly active sharing economy activities and what it means to such neighborhoods; and (3) that the three types of sharing economy products are not frequently utilized in the majority of the socially vulnerable neighborhoods.

Finally, I single out neighborhoods with relatively high STR density and relatively high social vulnerability in each of the eight cities and use previous empirical findings on neighborhood gentrification to assess whether STR could potentially accelerate or aggravate the ongoing gentrification trend in those neighborhoods and

jeopardize the socially vulnerable population by increasing their housing burdens. A growing volume of literature (Barron, Kung, & Proserpio, 2021; Horn & Merante, 2017; Zou, 2020) suggests that the rapid growth of STR market is making housing less affordable in major U.S. cities. Therefore, identifying gentrifying neighborhoods that house socially vulnerable population with a burgeoning STR market is of policy interest towards housing justice.

#### *4.4 Data*

In this section, I explain the data source for three types of activities in eight cities. They largely from publicly available sources through third-party web-scraping or a city's open data portal. I then summarize the density variables and visualize spatial patterns in map representations. I will discuss potential implications on three types of activities based on summary statistics and map patterns.

##### 4.4.1 Data sources

Data availability is the golden standard for quantitative research on emerging urban technologies as high-quality data are rarely available publicly. Democratization of data has long been recognized in the planning community as a key component of community-based planning process (Sawicki & Craig, 1996), especially in the age of smart cities where data from information and telecommunication technologies (ICTs) are ubiquitously generated, processed, and analyzed to facilitate decision-making (Goodspeed, 2021). While data does not always reveal the ground truth of mobility and activity patterns, it can potentially capture the city's pulse (people and vehicle's

movement, ongoing business transactions, etc.) in real time, at a fine-grained geography.

The data used in this chapter come from multiple sources: (1) Individual Airbnb listing data come from Inside Airbnb (n.d.) – an independent, non-commercial website that provides monthly updated, web-scraped Airbnb data. Inside Airbnb data provide detailed information about an Airbnb’s listing (including the proxy location), its host (anonymized), and its booking activities. One exception is Louisville, where the STR registration data is publicly available on their open data portal. (2) SBBS trip data are fetched from each city’s bike-sharing data portal. While the information contained in the data may differ slightly, the most useful information for this study is the station location for a SBBS trip’s origin. (3) The main reason that the eight cities are selected in this study is the availability of DBS data. Except for Washington DC, where I am able to collect DBS trip data through web-scraping, the other cities provide aggregated DBS trip data either at the street segment level (Boston and Minneapolis), the census block group level (Los Angeles and Portland) or the census tract level (Chicago, Louisville, and Austin). For analytical consistency, I further aggregate the more disaggregated data at the census tract level for all three types of sharing economy activities. The data sources are summarized in **Table 4-2**.

Notice that September is used as a representative month for all three types of activities for most cities due to (1) data availability and (2) the seasonal activeness of the sharing economy activities. If I choose another month in the winter, the level of activeness and geographical spread of STR listings and shared micromobility trips

could be significantly underestimated. It is not accurate to average monthly statistics, either, especially for the spatial data.

**Table 4-2. Data sources for eight cities**

City	Airbnb Data	STR Listing	SBBS Data	SBBS Station	SBBS Trips	DBS Data	DBS Trips
Washington DC	Inside Airbnb, September 2019	9,201	Capital Bikeshare trip data, August 2019	563	360,044	LIME trip data (GPS location), August 2019	127,071 <sup>13</sup>
Boston MA	Inside Airbnb, September 2019	5,711	Bluebikes trip data, September 2019	325	363,186	LIME trip data (by street segment), average month in Q3 2019	34,080 <sup>14</sup>
Chicago IL	Inside Airbnb, September 2019	8,852	Divvy bikes trip data, September 2019	608	493,219	Chicago e-scooter trip data (by census tract), September 2019	160,558
Louisville KY	Jefferson County Data, February 2020	1,105	LouVelo trip data, July 2018	28	4,762	Louisville dockless open data (by census tract), September 2019	62,087
Minneapolis MN	Inside Airbnb, September 2019	6,675	Nice Ride trip data, September 2019	200	52,800	Minneapolis scooter trip (by street segment), September 2019	218,110
Austin TX	Inside Airbnb, September 2019	11,339	MetroBike trip data, September 2019	96	8,611	Shared micromobility trip data (by census tract), September 2019	584,688
Los Angeles CA	Inside Airbnb, September 2019	44,986	Metro Bike Share trip data, September 2019	243	30,781	Dockless trip open data (by census block group),	1,103,000

<sup>13</sup> LIME is one of the six vendors active at the time when data were collected. According to Younes et al. (2020), approximate ¼ of the trips in the District of Columbia were made by LIME bikes/e-scooters. Therefore, for a popular month like September, the overall number of trips should be around half a million for all dockless vendors.

<sup>14</sup> It is expressed in total DBS mileage on all street segments rather than DBS trip count from the raw data in Boston. The average DBS trip distance is between 0.6 miles (Younes et al., 2020) and 0.7 miles (Zou et al., 2020). Therefore, I can assume that the trip volume for Boston is probably between 50,000 – 60,000 in one month.

						September 2019	
Portland OR	Inside Airbnb, September 2019	4,495	Biketown trip data, September 2019	133	35,308	E-scooter trip open data (by census block group), September 2019	119,553

Based on **Table 4-2**, Los Angeles, Austin, and Washington DC all have a sizable Airbnb market, especially Washington DC considering the size of the city itself. These three cities also accommodate a large volume of DBS trips, suggesting the quick diffusion of the sharing economy technologies from the private sector in these cities. On the other hand, Louisville has a relatively small market for Airbnb and DBS. Because SBBS programs are owned by the city, the deployment of SBBS fleets depends on a city’s investment into shared micromobility. In this case, Washington DC, Boston, and Chicago operate a sizable SBBS program compared to other cities in the study (and perhaps other U.S. cities). Los Angeles has a surprisingly small SBBS trip volume given the geographical extent and the population size of the city. Similarly, Austin has a rather small SBBS program for the size of the city. Louisville, again, has the smallest SBBS program among the eight cities in the study.

#### 4.4.2 Summary statistics of STR, SBBS, and DBS densities

I first normalize STR listings by households and SBBS/DBS trips by population at the census tract level for all eight cities. This allows me to cross-compare density between different neighborhoods in a city and between different cities. The aggregate city-level densities (and the standard deviations) for STR, SBBS, and DBS are listed in **Table 4-3**.

At the aggregate, Washington DC has the highest density in Airbnb listings (32.6 listings per 1,000 households) among eight cities while Louisville has the lowest (3.6 listings per 1,000 households). It is no surprise that the major tourist destinations like DC, Boston, Austin, and Los Angeles are popular for STR businesses. The standard deviation of STR density is also high for these cities, suggesting that STR listings are not even distributed amongst neighborhoods (census tracts).

**Table 4-3. STR, SBBS, and DBS densities by census tract in eight cities**

City	STR density (listings/ 1,000 households)	s.d.	SBBS density (trips/ person in a month)	s.d.	DBS density (trips/ person in a month)	s.d.	N tracts
Washington, DC	32.614	38.816	0.458	45.461	0.182	35.404	179
Boston, MA	17.294	17.241	0.248	0.628	0.041 <sup>15</sup>	0.740	212
Chicago, IL	7.560	10.462	0.161	0.425	0.047	0.324	864
Louisville, KY	3.561	10.075	0.006	0.060	0.081	0.501	191
Minneapolis, MN	13.139	9.729	0.102	0.194	0.388	0.822	144
Austin, TX	22.363	39.207	0.007	0.029	0.478	2.639	222
Los Angeles, CA	18.240	29.070	0.006	0.066	0.238	0.962	1153
Portland, OR	12.851	14.264	0.044	0.195	0.221	0.889	173

Citywide public bike-sharing is more popular in Washington DC, Boston, and Chicago, especially in the nation’s capital where CaBi is heavily invested and promoted as a citywide mobility strategy for mode shifts from auto to the sustainable non-motorized travel. On the other hand, not as many SBBS trips are taken in Louisville, Austin, Los Angeles, and Portland. It is evident that Louisville, Austin, and Portland have not had massive a deployment of SBBS fleets or built as many stations as other cities, even though population wise they are comparable to Minneapolis, Boston, and

<sup>15</sup> The unit of analysis is trip miles/person in a month for Boston as the raw data are DBS mileages rather than trip counts.



Washington DC (between 0.4 – 1 million within the city boundary). Los Angeles' Metro Bike Share struggled to attract riders due to stiff competitions from other dockless operators at the time (Nelson, 2018).

The DBS trip density is relatively high in Austin, Los Angeles, and Portland, but quite low in Louisville. For Boston and Chicago, the regulatory restrictions/pilot curbed e-scooter sharing's diffusion. Washington DC is probably still the single largest DBS market among the eight cities as the data I collected only reflects DBS trips taken by one of the six vendors at the time. The standard deviations for SBBS and DBS trip densities in DC are visibly high for their means due to the extremely high trip densities at the National Mall where an overwhelming number of trips were taken in a business/sightseeing neighborhood with few residents.

Overall, SBBS and DBS usages are low in all eight cities, with less than one trip per person in a month. On average an American takes four trips per day (120 trips per month)<sup>16</sup>, which means that shared micromobility takes less than one percent of the mode share even in a city like Washington DC. Louisville is not popular for any of the three types of sharing economy activities, possibly due to the fact that the city is not a popular tourist destination. The summary statistics imply that the tourist-oriented sharing economy thrive in cities with a high volume of visitors.

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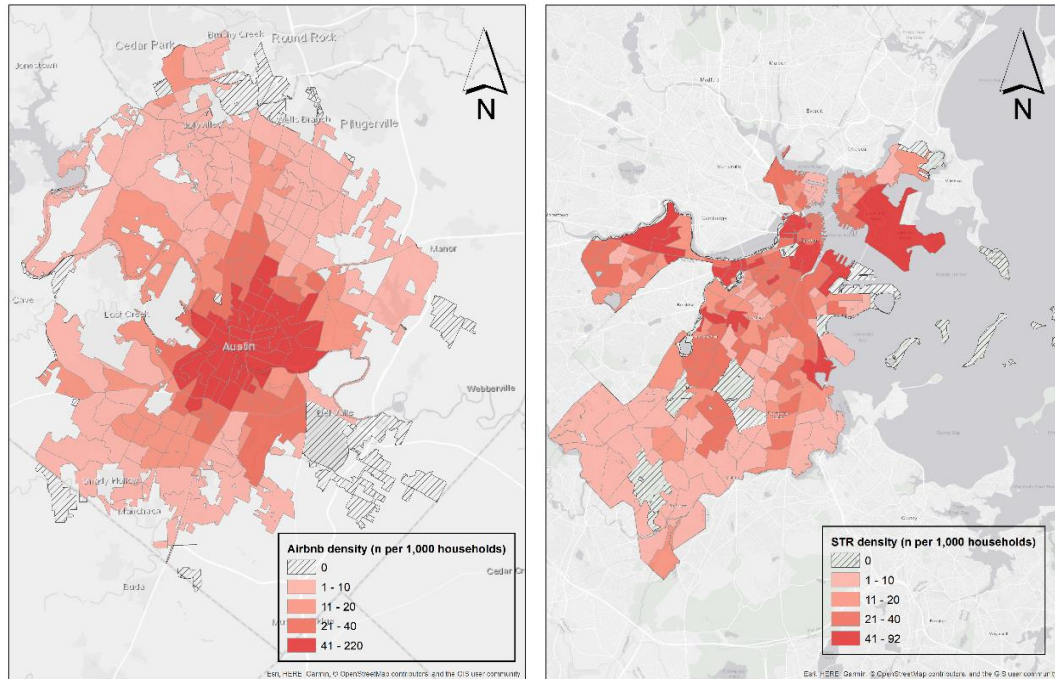
<sup>16</sup> Bureau of Transportation Statistics (n.d.): based on data from the 2017 National Household Travel Survey.

#### 4.4.3 Mapping the Spatial Patterns of STR, SBBS, and DBS

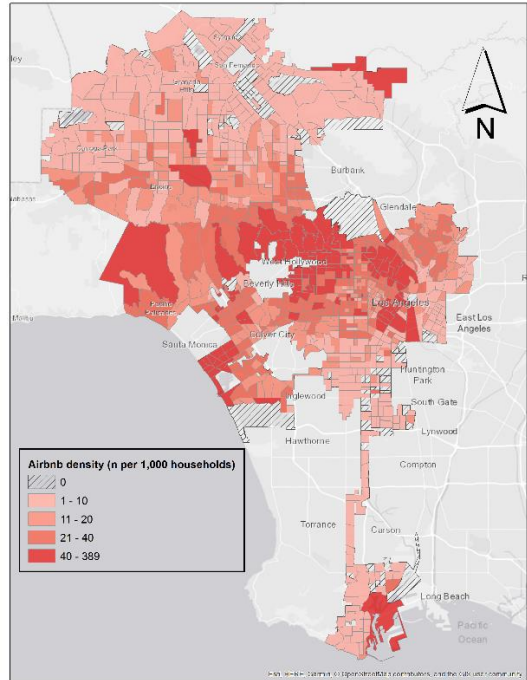
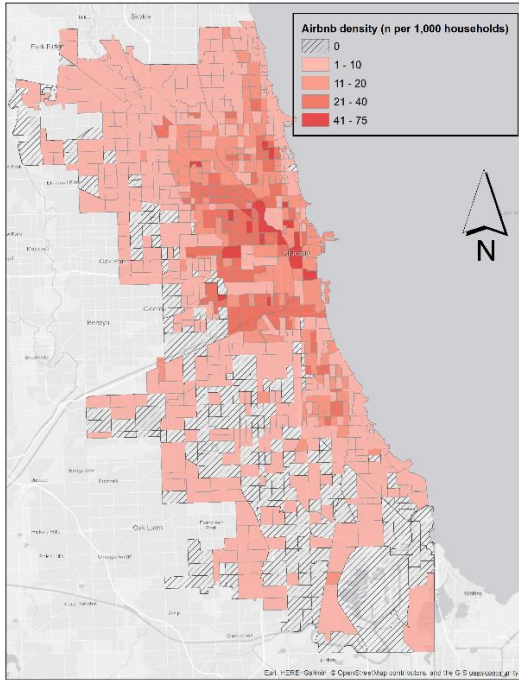
I then map the spatial distributions of STR, SBBS, and DBS densities at the census tract level to (a) visually examine where the sharing economy activities are clustered in eight cities, (b) compare the activity density (of STR, SBBS, DBS, respectively) across eight cities by applying the same density cutoff values for different cities, and (c) visually identify the similarities and differences between different activity densities (STR, SBBS, and DBS) within the same city.

The maps of STR listing density are visualized in **Figure 4-1a – Figure 4-1h**. I use three cutoff values for mapping purposes (10, 20, 40 listings per 1,000 households) across all eight cities to allow observations of the spatial patterns within a city, as well as direct comparison across eight cities. These three cutoff values reasonably divide census tracts into four density categories (besides the category with null value for STR density). From the direct map observation, I identify three types of STR clusters: (1) city center where business and tourist attractions are located; (2) touristy areas, such as neighborhoods along Charles River in Boston, seaside neighborhoods in Venice and Long Beach in Los Angeles, and west side of Washington DC; and (3) neighborhoods adjacent to the airport in Boston (BOS), Los Angeles (LAX), and Portland (PDX). The further away from the central city, the residential areas are less popular for STR activities. I am interested in examining the relationship between a neighborhood's social vulnerability and its activeness in STR business. I hypothesize that STR listings are concentrated in socially advantageous areas in a city. In addition, STR may also cluster in gentrifying neighborhoods home to minority/low-income populations. In the next section, I will establish the aggregate correlation between social vulnerability and

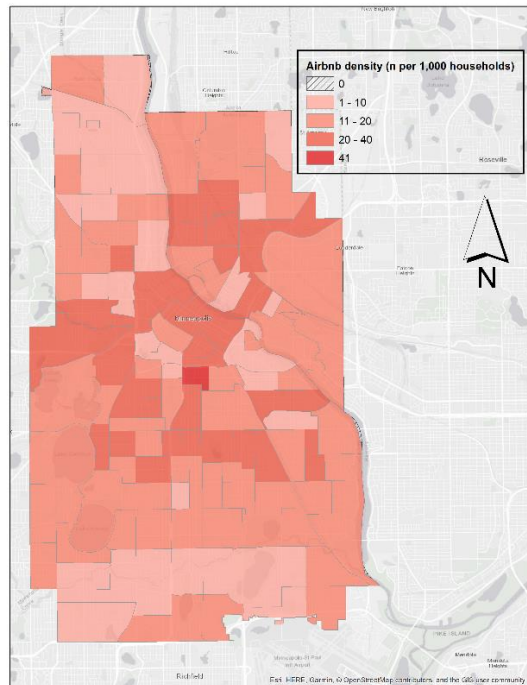
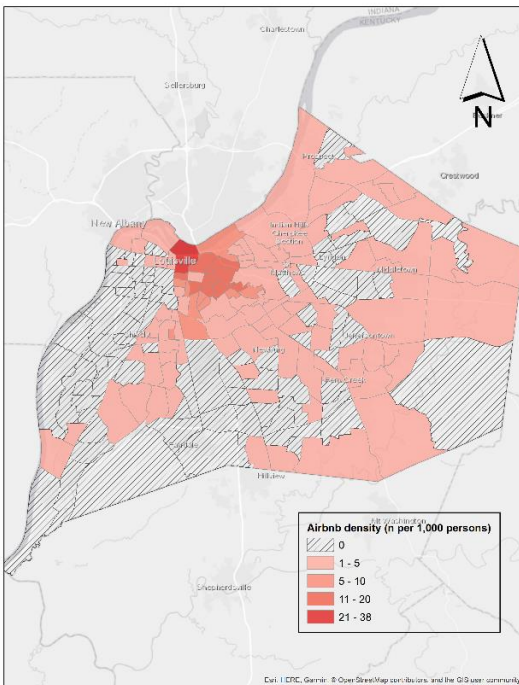
STR density by census tract in eight cities. In addition, I will single out census tracts of a relatively high STR density and high social vulnerability and cross-reference empirical work on gentrification to identify potential acceleration or aggravation of neighborhood gentrification from the growing STR business.



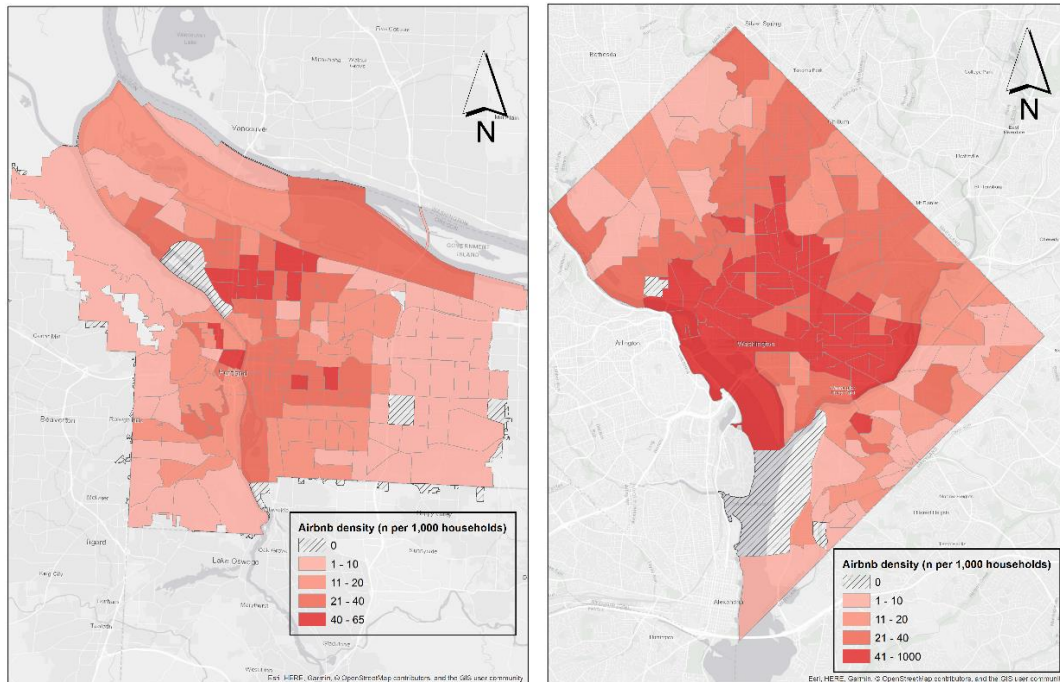
**Figure 4-1a (left): STR density – Austin; 4-1b (right): STR density – Boston**



**Figure 4-1c (left): STR density – Chicago; 4-1d (right): STR density – L.A.**



**Figure 4-1e (left): STR density – Louisville; 4-1f (right): STR density – Minneapolis**

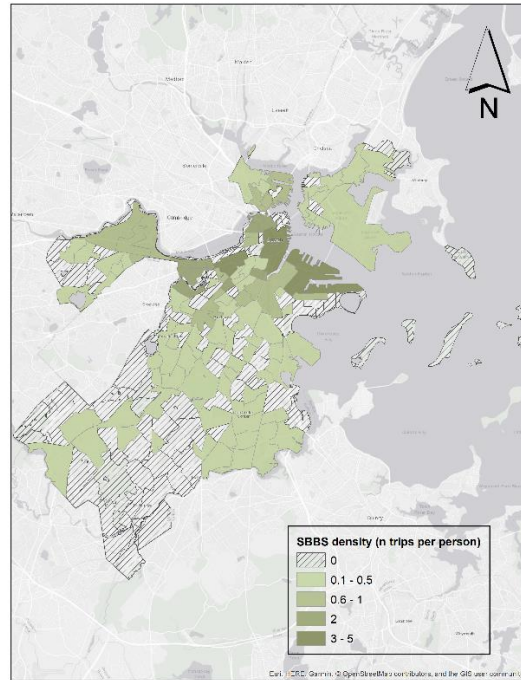
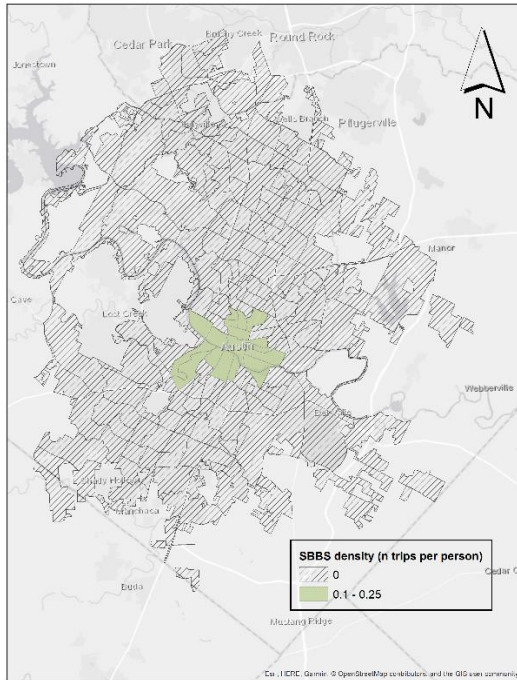


**Figure 4-1g (left): STR density – Portland; 4-1h (right): STR density – DC**

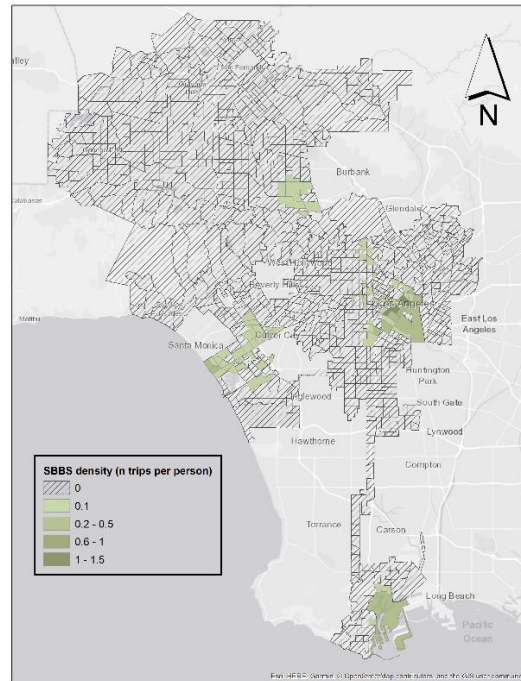
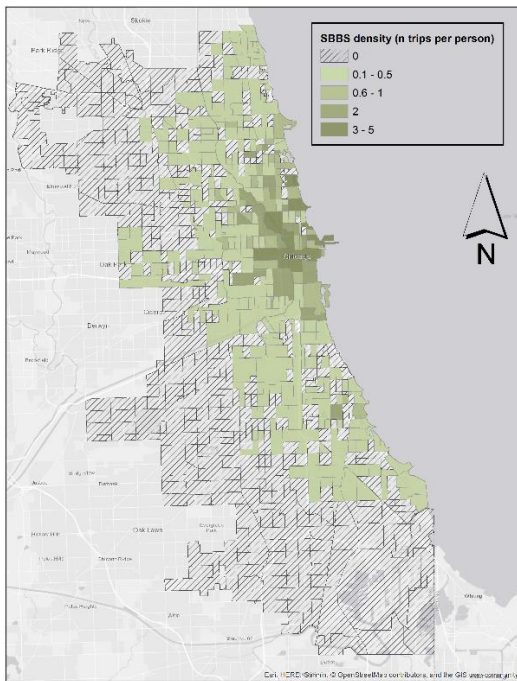
The maps of SBBS density are presented in **Figure 4-2a – Figure 4-2h**. I use three cutoff values: 0.5/1/2 trips per person in a month. These cutoff values are chosen for an underlying consideration of SBBS trip frequency. In addition, a trip is located where its starting station is (inside of a census tract), which means there is a good chance that some intermediate trips taken outside of the station areas are omitted from the dataset. However, I argue that the use of SBBS is closely related to the location of a docking station, which means a station’s trip start count is a fairly good indicator of SBBS trip density. When examining the spatial patterns of SBBS trip density, I find that Boston, Chicago, Minneapolis, Portland, and Washington DC have more widespread spatial coverage across the city. Boston, Chicago, and Washington DC have relatively abundant SBBS trips taken in central city and its adjacent

neighborhoods, suggesting substantial public investment into their public bike-sharing programs in three cities. Indeed, these three cities are among the top six cities of SBBS ridership in the U.S. (NACTO, 2020), as evident in their number of stations and monthly ridership provided in **Table 4-2**. While the overall ridership is not as high in Minneapolis and Portland as it is in the other three aforementioned cities, the even coverage suggests the adequacy of infrastructure (stations) across their city boundary. On the other hand, for a geographically extended, heavily populated metropolis like Los Angeles, the SBBS trips are limited to a few activity centers/ tourist attractions (downtown, Venice, Burbank, and Long Beach). Previous bike-sharing study (Crowther et al., 2019) and news coverage (Clark, 2016) on the Metro Bike Share system attribute the low ridership to its less ambitious plan to cover the large metropolitan area, the lack of integration with the mass transit network, and its relatively high fare (later reduced to a reasonable level). As for Austin and Louisville, two mid-sized (around 1 million population) metropolises, have limited public bike-sharing services that are constrained in the city center.

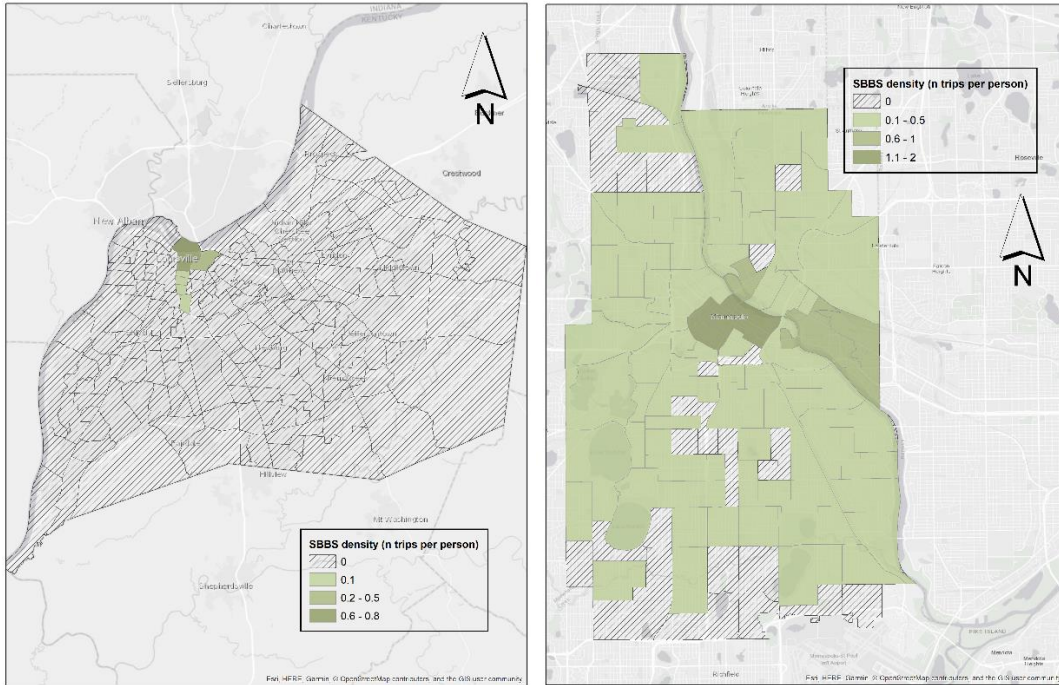




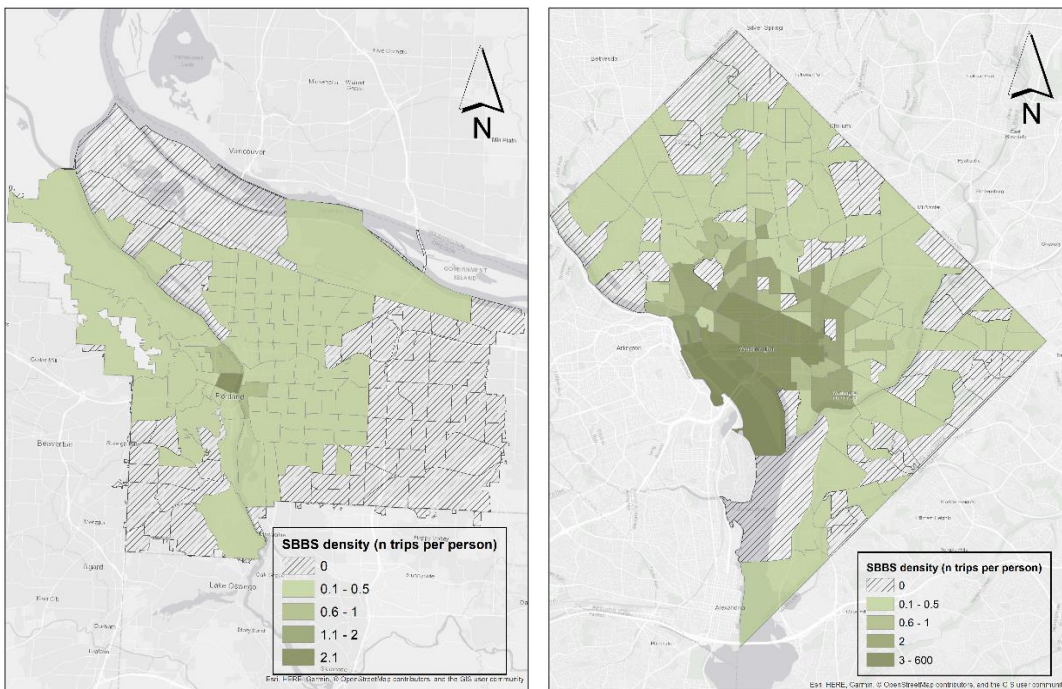
**Figure 4-2a (left): SBBS density – Austin; 4-2b (right): SBBS density – Boston**



**Figure 4-2c (left): SBBS density – Chicago; 4-2d (right): SBBS density – L.A.**



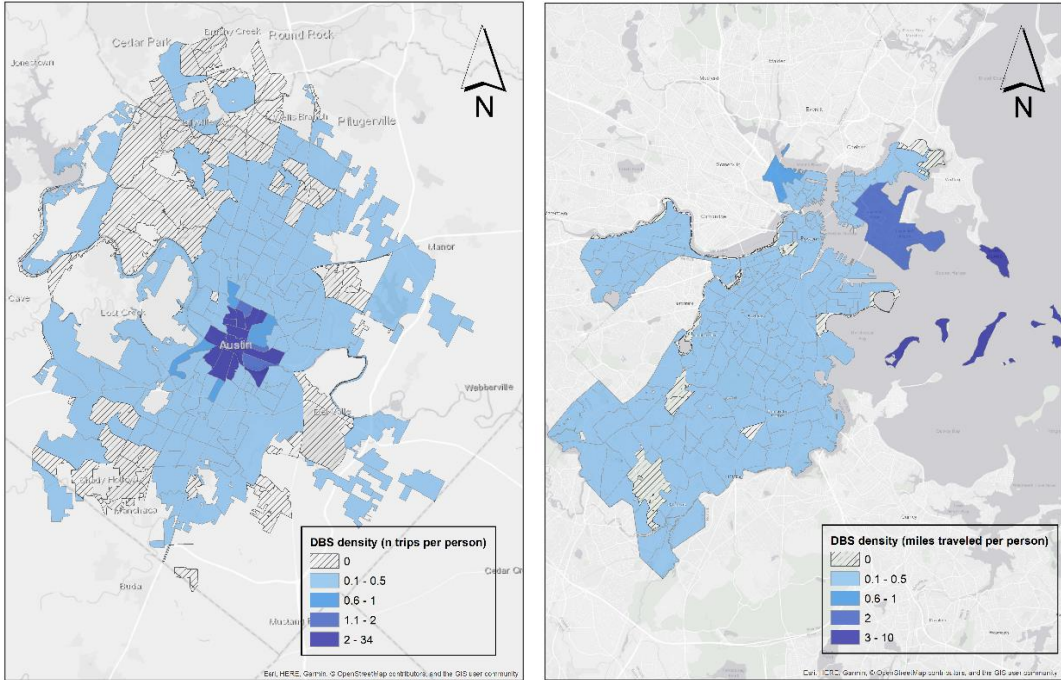
**Figure 4-2e (left): SBBS density – Louisville; 4-2f (right): SBBS density – Minneapolis**



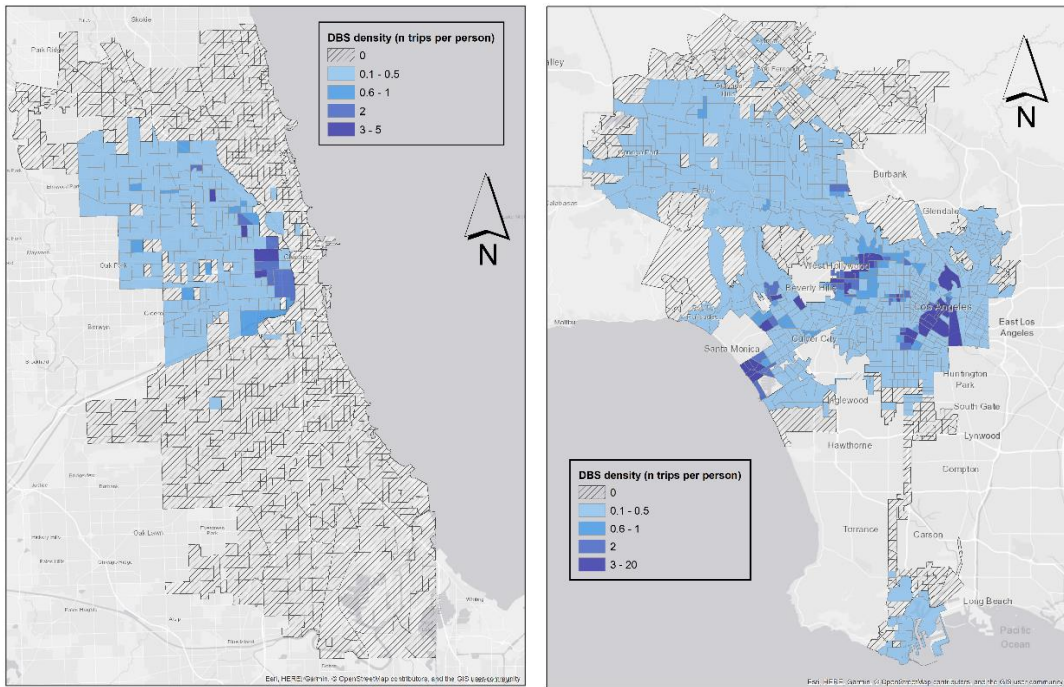
**Figure 4-2g (left): SBBS density – Portland; 4-2h (right): SBBS density – DC**



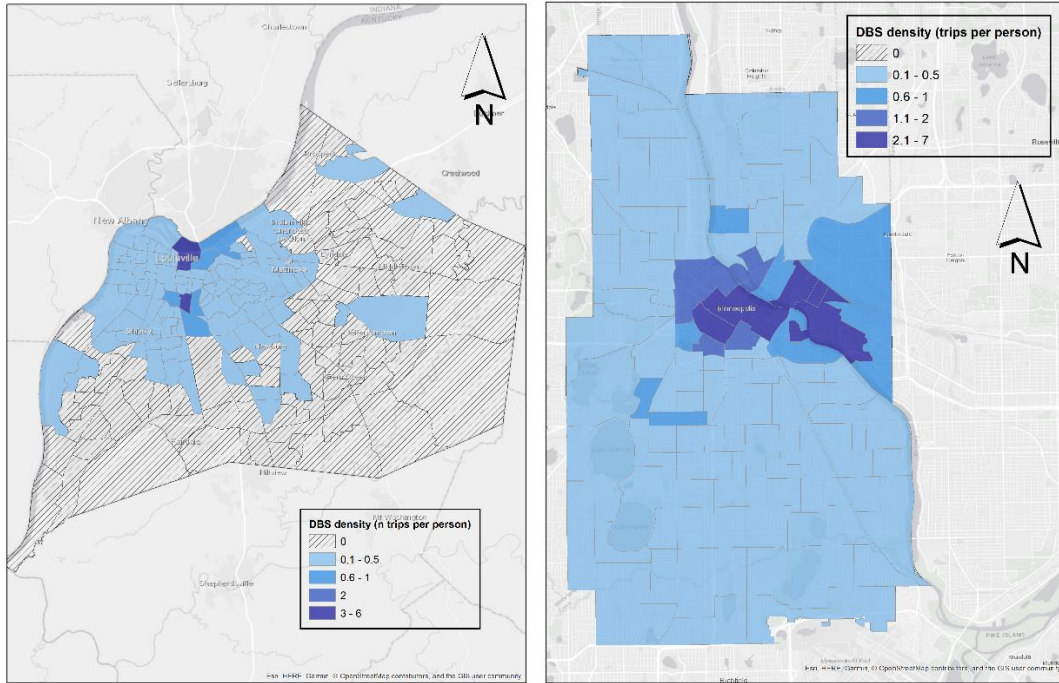
The maps of DBS density are presented in **Figure 4-3a – Figure 4-3h**. I apply the same threshold values as those for SBBS density maps. It is noticeable that DBS trips are more widespread than SBBS trips across the city boundary for Austin, Los Angeles, and Louisville. From **Table 4-2**, the total number of DBS trips are 68 times, 36 times, and 13 times of the number of SBBS trips for these cities, respectively. Because dockless e-bikes and e-scooters are not confined by the location of a docking station, they provide more flexible mobility than SBBS bikes. Hence, we also observe a more widespread coverage of DBS trips in Minneapolis, Washington DC, and eastern Portland. Unlike SBBS, DBS trips are infrequently taken in western Portland (evident in PBOT, 2020). As explained previously, Chicago's and Boston's regulatory restrictions make their DBS market unique cases to study. Spatially, DBS trips well cover the entire pilot area in Chicago, with a cluster of trips to the west of the Chicago Loop. For Boston, since e-scooters are prohibited for parking inside the city, the trips are not frequently taken on the street except in neighborhoods adjacent to Cambridge, Somerville, Chelsea, and Winthrop, where DBS vendors were permitted for operation. Especially on Deer Island south of Winthrop (the dark blue tip on the seashore), many DBS trips were taken perhaps for recreational purposes.



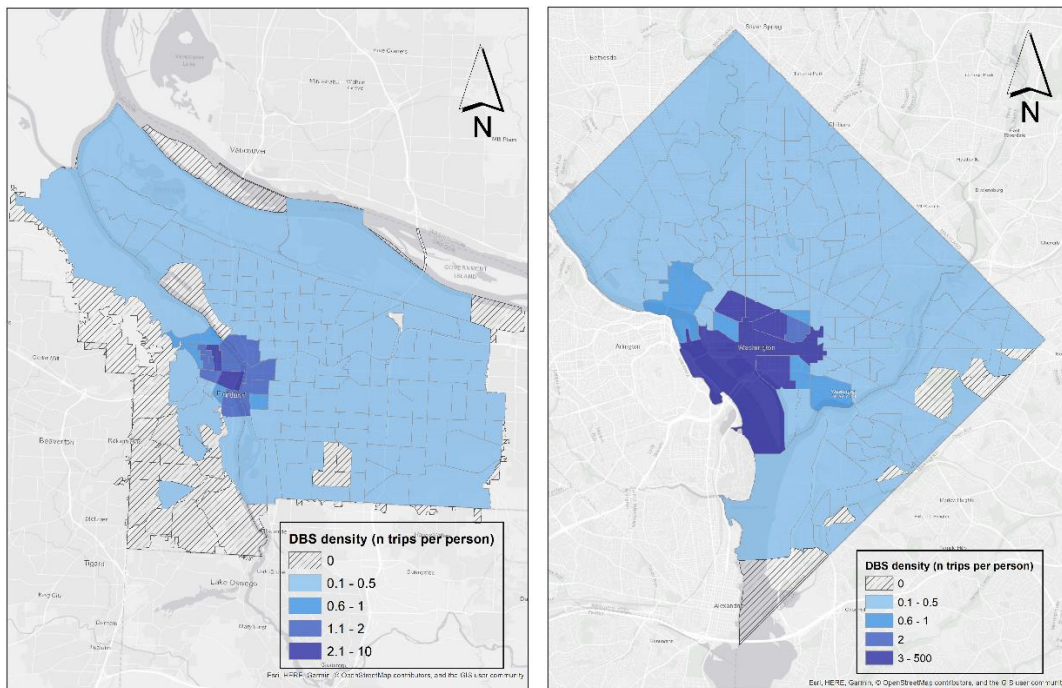
**Figure 4-3a (left): DBS density – Austin; 4-3b (right): DBS density – Boston**



**Figure 4-3c (left): DBS density – Chicago; 4-3d (right): DBS density – L.A.**



**Figure 4-3e (left): DBS density – Louisville; 4-3f (right): DBS density – Minneapolis**



**Figure 4-3g (left): DBS density – Portland; 4-3h (right): DBS density – DC**

One may argue that DBS seems to provide more accessible services than SBBS based on the initial map comparison between the two types of shared micromobility. While the perception may be true for most cities, DBS trips seem to be more concentrated in neighborhoods of the central city than SBBS trips in Washington DC. Younes et al. (2020) find that DBS are more likely to be used for mid-day and weekend leisure trips than SBBS, which could explain the deeper geographic concentration of DBS trips taken on the National Mall and its surrounding commercial/historical neighborhoods.

Overall, STR listings, SBBS trips, and DBS trips all tend to cluster in central city, where commercial, social, and leisure activities are most vigorous and out-of-towners would spend time visiting. For STR, there is also a tendency of clustering at residential neighborhoods near a metropolitan's Airport, which makes sense as STR can function as a transient lodging for overnight travelers to/from an Airport. These findings support the tourist-oriented sharing economy in terms of where the lodging/transportation demand and resources are for catering visitors. From the city's perspective, this means a more critical evaluation should be made to each type of the sharing economy activity (STR, SBBS, and DBS). More importantly, attentions must be focused on neighborhoods overwhelmed with/ lacking the activities. In the next section, I will present correlational analytical results on spatial similarities/differences between the three types of activities, between their densities and the underlying social vulnerability of a neighborhood, and whether STR business may accelerate/aggravate gentrification in some socially vulnerable neighborhoods in the eight cities of this study.

#### 4.5 Results

In this section, I first present the Lee's  $L$  statistics that identify the bivariate spatial similarities/differences between the STR, SBBS, DBS, and SVI variables for eight cities. Then, I summarize the interactions between SVI and the density variables to reveal census tracts of high social vulnerability and low/high STR/SBBS/DBS densities. Lastly, I list the neighborhoods of high STR density and high social vulnerabilities (in different themes) and combine previous empirical evidence on gentrification to reveal the potential impact of STR activities on the gentrification trend in some highly vulnerable neighborhoods.

##### 4.5.1 The spatial similarities and differences between STR, SBBS, and DBS

The Lee's  $L$  statistics of spatial correlation (**Table 4-4**) exhibit bivariate similarities in spatial distributions between STR listing density, SBBS trip density, and DBS trip density. The three types of sharing economy activities are distributed similarly (Lee's  $L \geq 0.25$ ) in Washington DC, Austin, and Los Angeles. These cities, regardless of their size, have strong activity centers with various tourist attractions and points of interest. For Minneapolis, public bike-sharing and private e-scooter sharing trips are densely distributed in the downtown area, explaining the relatively high Lee's  $L$  statistics. However, Airbnb listings are more even distributed in downtown adjacent neighborhoods than SBBS and DBS. Public bike-sharing and Airbnb activities are distributed in Similarly for Portland, SBBS and DBS trips are concentrated in downtown areas while STR listings also cluster in residential neighborhoods across the Willamette River. Boston and Chicago are two cities with different levels of restriction on e-scooter sharing: The former strictly prohibits e-scooter sharing on the street

(however, it does not specify how to enforce such restriction, thereby a number of trips were taken in the city); The latter permits DBS operations in a demonstrative zone outside of the city center, which introduces a policy intervention that would disagree with the business-as-usual target market for e-scooter sharing (for downtown commuting and leisure trips). Reflected in Lee's *L* statistics, SBBS trips and STR listings are distributed somewhat similarly ( $>0.25$ ) in both cities while DBS trips are distributed differently. Unless cities significantly interfere with the entry or expansion of the sharing economy, the spatial patterns of STR, SBBS, and DBS generally agree with where activities are concentrated.

**Table 4-4. Lee's *L* Statistics between STR, SBBS, DBS densities, and SVI**

City	STR – SBBS	STR – DBS	SBBS – DBS	STR – SVI	SBBS – SVI	DBS – SVI
	(1)	(2)	(3)	(4)	(5)	(6)
Washington DC	0.463	0.459	0.667	-0.376	-0.227	-0.224
Boston, MA	0.264	-0.047	-0.032	-0.057	-0.150	-0.117
Chicago, IL	0.392	0.220	0.199	-0.354	-0.360	-0.111
Louisville, KY	0.201	0.240	0.170	0.002	0.083	0.095
Minneapolis, MN	0.167	0.159	0.381	0.106	0.042	0.089
Austin, TX	0.417	0.451	0.429	0.043	-0.039	-0.010
Los Angeles, CA	0.256	0.355	0.413	-0.232	0.033	-0.063
Portland, OR	0.181	0.105	0.378	-0.274	-0.070	-0.021

I then test the bivariate spatial correlation between STR listing density/ SBBS trip density/ DBS trip density and the level of social vulnerability of a neighborhood. In Washington DC, Airbnb listings are clustered in neighborhoods of moderate/low social vulnerability, as suggested in the negative correlation (-0.376). There is also a tendency of fewer SBBS/DBS trips taken in neighborhoods of high social vulnerability



in DC, but the spatial correlations are not as obvious as the one for STR listings. The negative correlation between Airbnb listing density/ SBBS trip density and a neighborhood's level of social vulnerability is strong ( $<-0.25$ ) in Chicago. The majority of Chicago's West Side and South Side are considered socially vulnerable, yet these areas are not desirable for STR or the usage of public bike-sharing. West Side and South Side are less prosperous areas with high crime rates, which is deemed undesirable for short stays for a tourist or cycling for leisure. In Los Angeles, STR listings are usually found in touristy neighborhoods near Santa Monica and Long Beach, the wealthy, mountainous neighborhoods in Laurel Canyon and Hollywood Hills, and the gentrifying neighborhoods in Korean Town, Chinatown, and downtown Los Angeles. Hence, I observe a negative correlation ( $-0.232$ ) between Airbnb listing density and the social vulnerability index. A similar pattern is found in Portland, where Airbnb listings are clustered in less socially vulnerable neighborhoods in central/northeastern Portland.

#### 4.5.2 Are sharing economy activities reaching socially vulnerable neighborhoods?

If the STR density is  $<10$  listings per 1,000 households in a census tract, I denote it as low density; if the STR density is  $>40$  listings per 1,000 households in a census tract, I denote it as high density. For shared micromobility (SBBS and DBS), if the density is  $<0.5$  trips per person (in one month) in a census tract, I denote it as low density; if the density is  $>2$  trips per person (in one month) in a census tract, I denote it as high density. There is no uniform standards in determining what is low density versus high density. My rationale is primarily based on the underlying density

distribution for the three types of sharing economy activities (See **Table 4-3**). For SBBS and DBS, the low-density cutoff is larger than the average city-level density to reflect the fact that shared micromobility is a niche product in the transportation system, not as widely adopted as one hopes to achieve a significant influence on mode share.

I then interact these densities with the underlying SVI level of a census tract. The number of census tracts of high SVI (>0.75) as a percentage of all census tracts within a city, and the cross-tabulation of high-SVI tracts by high/low density of STR/SBBS/DBS are listed in **Table 4-5**.

**Table 4-5. Summary of census tracts on STR/SBBS/DBS densities & SVI**

City	High-SVI tracts/ All tracts (Percentage)	STR		SBBS		DBS	
		High density	Low density	High density	Low density	High density	Low density
Washington DC	60/179 (34%)	3	25	0	57	0	60
Boston, MA	61/212 (29%)	2	30	1	57	0	61
Chicago, IL	357/864 (41%)	1	311	0	357	0	352
Louisville, KY	54/191 (28%)	1	47	0	53	1	51
Minneapolis, MN	51/144 (35%)	1	10	0	25	0	24
Austin, TX	35/222 (16%)	6	18	0	35	2	33
Los Angeles, CA	530/1153 (46%)	23	345	1	529	16	503
Portland, OR	34/173 (20%)	1	31	1	33	1	33

The city that has the highest percentage of highly socially vulnerable neighborhoods is Los Angeles (46%) while the lowest is Austin (16%). All eight cities have at least one census tract of high SVI and high STR density. Austin and Los Angeles arguably have more such tracts. It is worth examining the gentrification trend on these census tracts. If they are gentrified or gentrifying, then active STR businesses



could further aggravate/accelerate gentrification and displace the disadvantaged households by flipping long-term rental space for short-term rental purposes (to accommodate transient visitors, in lieu of housing local residents) or bidding up rents/housing prices.

Furthermore, almost all of the highly socially vulnerable neighborhoods in eight cities have low usage of shared micromobility. By mapping highly socially vulnerable census tracts with high/low SBBS/DBS densities, I argue that the current level of shared micromobility usage in minority-populated, low social-opportunity neighborhoods is marginal to impact local residents' travel behavior. The interactions maps are attached in **Appendix A**.

In summary, in neighborhoods where socially vulnerable populations are concentrated, there are not as many sharing economy activities as some less socially vulnerable activities centers. On the one hand, it signifies the inherent disadvantages of such neighborhoods (lack of points of interest, lack of tourists, lack of well-off, tech-savvy residents), which could explain their low demand for shared micromobility or tourist accommodation. On the other hand, it imposes the equity concerns over the uneven distribution of STR/SBBS/DBS activities. For SBBS and DBS, a city's transportation authority, policymakers, and community leaders need to look into the low ridership in the socially vulnerable neighborhoods: what are the potential causes? Could it be low availability of fleets or stations? Could it be that the price is out of the reach for low-income households? Could it be the unfavorable built environment that makes residents feel less safe to bike? Such information can only be obtained through survey or qualitative research. For STR, the implications are two-folded: (1) Just like

SBBS and DBS, there are inherent reasons to explain the unpopularity of STR in much of the high vulnerability neighborhoods. Improving neighborhood quality of life can not only attract tourist visits/lodging, but also provide economic opportunities for local residents. (2) the housing authority and policymakers should pay close attention to the gentrifying neighborhoods that are also active in STR activities, making sure that commercial STR activities are prohibited and STR regulations are enforced to prevent an overheated STR market that may worsen the gentrification trends.

#### 4.5.3 Socially vulnerable neighborhoods of active STR: On the verge of gentrification?

In the previous subsection, I identify the number of census tracts of high social vulnerability and high STR activity level in each city. In this subsection, I will further examine each of such census tract in terms of the dimensions of their social vulnerability (as reflected in the themes of SVI) and their gentrification status based on existing empirical evidence. The results are presented in **Table 4-6**.

**Table 4-6. The list of census tracts of high STR density and high SVI**

City	District	Census Tract	SVI: (1)	SVI: (2)	SVI: (3)	SVI: (4)	Gentrifying/ Gentrified?
Washington DC	Capitol Hill	11001006804	<b>H</b>	M	M	L	Gentrified <sup>1</sup>
Washington DC	Capitol Hill	11001007100	M	M	M	<b>H</b>	Gentrified <sup>1</sup>
Washington DC	Anacostia	11001007503	<b>H</b>	<b>H</b>	M	<b>H</b>	Gentrified <sup>1</sup>
Boston MA	South End	25025070200	<b>H</b>	L	<b>H</b>	<b>H</b>	Not gentrified <sup>1,2</sup>
Boston MA	Mission Hill	25025081100	M	M	<b>H</b>	<b>H</b>	Gentrified <sup>1,2</sup>
Chicago IL	Near West Side	17031837800	<b>H</b>	M	M	<b>H</b>	Not gentrified <sup>1,3,4</sup>
Louisville KY	Downtown	21111004900	<b>H</b>	L	M	<b>H</b>	Not gentrified <sup>1</sup>

Minneapolis MN	Ventura Village	27053005902	<b>H</b>	<b>H</b>	<b>H</b>	<b>H</b>	Not gentrified <sup>1,5</sup>
Austin TX	East Austin	48453000902	M	L	<b>H</b>	<b>H</b>	Gentrifying <sup>1,3,6</sup>
Austin TX	East Austin	48453001000	M	M	<b>H</b>	<b>H</b>	Gentrifying <sup>1,3,6</sup>
Austin TX	East Austin	48453000802	M	M	M	<b>H</b>	Gentrifying <sup>1,3,6</sup>
Austin TX	East Austin	48453000801	<b>H</b>	M	<b>H</b>	<b>H</b>	Gentrifying <sup>1,3,6</sup>
Austin TX	East Austin	48453002111	<b>H</b>	M	<b>H</b>	M	Gentrifying <sup>1,3,6</sup>
Austin TX	East Austin	48453002110	<b>H</b>	M	<b>H</b>	M	Gentrifying <sup>1,3,6</sup>
Los Angeles CA	UCLA	06037701100	<b>H</b>	<b>H</b>	<b>H</b>	M	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037190201	<b>H</b>	L	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037190802	<b>H</b>	L	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037190801	<b>H</b>	M	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037190902	<b>H</b>	L	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	East Hollywood	06037191110	M	L	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037191710	<b>H</b>	L	<b>H</b>	M	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037191720	<b>H</b>	M	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037191610	<b>H</b>	M	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Hollywood	06037192510	<b>H</b>	M	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Wilshire Park	06037212701	<b>H</b>	M	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Koreatown	06037212203	<b>H</b>	M	<b>H</b>	<b>H</b>	Gentrified <sup>1,3</sup>
Los Angeles CA	Koreatown	06037212420	<b>H</b>	L	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Pico-Union	06037212220	<b>H</b>	L	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Pico-Union	06037221120	<b>H</b>	M	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Echo Park	06037195600	M	L	<b>H</b>	<b>H</b>	Gentrified <sup>1,3</sup>
Los Angeles CA	Elysian Park	06037980010	<b>H</b>	<b>H</b>	<b>H</b>	<b>H</b>	Not gentrified <sup>1,3</sup>
Los Angeles CA	Chinatown	06037207101	<b>H</b>	L	<b>H</b>	M	Gentrified <sup>1,3</sup>
Los Angeles CA	Downtown	06037207400	M	L	<b>H</b>	<b>H</b>	Gentrified <sup>1,3</sup>
Los Angeles	Downtown	06037209300	<b>H</b>	M	<b>H</b>	<b>H</b>	Gentrified <sup>1,3</sup>

CA							
Los Angeles CA	Downtown	06037224020	<b>H</b>	M	<b>H</b>	<b>H</b>	Gentrified <sup>1,3</sup>
Los Angeles CA	Downtown	06037224010	<b>H</b>	M	<b>H</b>	<b>H</b>	Gentrified <sup>1,3</sup>
Los Angeles CA	Downtown	06037226002	<b>H</b>	L	<b>H</b>	<b>H</b>	Gentrified <sup>1,3</sup>
Portland OR	Downtown	41051010600	<b>H</b>	M	M	<b>H</b>	Not gentrified <sup>1,3,7</sup>
“H”: High; “M”: Moderate; “L”: Low SVI (1) for socioeconomic statuses; SVI (2) for household composition; SVI (3) for minority statuses; SVI (4) for housing and transportation burdens							
Reference	<sup>1</sup> NCRC. (n.d.). Gentrification and Opportunity Zones <sup>2</sup> Preis, et al. (2020). Mapping gentrification and displacement pressure: An exploration of four distinct methodologies <sup>3</sup> Urban Displacement Project. (2020). <sup>4</sup> Institute for Housing Studies at DePaul University. (2020). Mapping Displacement Pressure in Chicago, 2020. <sup>5</sup> Goetz, et al. (2019). The diversity of gentrification: Multiple forms of gentrification in Minneapolis and St. Paul. <sup>6</sup> Way, H., Mueller, E., & Wegmann, J. (2019). Uprooted: Residential displacement in Austin’s gentrifying neighborhoods and what can be done about it. <sup>7</sup> Bates, L. (2013). Gentrification and Displacement Study: implementing an equitable inclusive development strategy in the context of gentrification.						

The target census tracts of high SVI and high STR density in Louisville, Chicago, Minneapolis, and Portland are not experiencing gentrification yet, it is thereby important to monitor the activeness of STR in those neighborhoods and make sure long-term rental housing stock is not replaced for STR purposes. In Washington DC, the target census tracts in Capitol Hill and Anacostia have already experienced significant gentrification (NCRC, n.d.). Active STR business could further inflate housing prices (Zou, 2020) in those neighborhoods and jeopardize housing affordability. In Boston, the South End neighborhoods has not experienced significant gentrification, but the active STR business could become a gentifier considering the neighborhood’s close proximity to downtown and commercial areas, which makes it attractive for real estate investment into STR. The Mission Hill area is gentrifying, housing a large Asian population and a low-income population (Boston Planning & Development Agency, 2017), and dense in transit network. The high STR density could accelerate

gentrification and adversely affect low-income residents, including Boston's and Cambridge's college students (Sullivan, 2018). In Austin, the "high SVI, high STR density" tracts are clustered in East Austin adjacent to the downtown area. In a study conducted by researchers at the University of Texas, Austin (Way, Mueller, & Wegmann, 2019), the revitalized neighborhoods surrounding Austin's affluent urban core are socially vulnerable, changing in demography, high in housing burden, and dynamic in the gentrification process. The SVI themes confirm the high degree of vulnerability in terms of minority population and housing affordability in East Austin as well. There is a strong incentive in real estate development to entice young, working professionals to move in these gentrifying neighborhoods, but the incentive also runs the risk of displacing the low-income, community of color who historically call these neighborhoods home (Formby, 2018). For Los Angeles, the City of Angels is one of the hottest tourist destination in the country, which explains the popularity of STR – an affordable lodging option and a way of experiencing the local lifestyle. A number of "high SVI, high STR density" tracts are located in (East) Hollywood, a tourist hot spot. The housing market is yet to be gentrified, but a cautious evaluation is needed to understand the potential impact of active STR business on housing stock/housing cost there. On the other hand, several neighborhoods in Koreatown, Echo Park, Chinatown, and downtown Los Angeles are already gentrified. Yet, the rising popularity of STR could further deteriorate the gentrification trends in these low-income, Asian, and Latino enclaves (Lee, 2016).

By investigating into the individual census tract, I identify numerous cases where STR business take off in gentrifying, highly socially vulnerable neighborhoods.

Local housing authority and policymakers need to pay close attention to the affordable rental housing stock and rent/ housing price fluctuations in such neighborhoods. Prioritizing housing affordability for long-term, socially disadvantaged renters and enforcing STR regulations to prevent the STR market from overheating are closely related policy tools for these neighborhoods. In addition, monitoring housing stock and housing cost in gentrifiable neighborhoods (indicated by a high level of STR activities) should also become a housing policy priority vis-à-vis STR regulations.

#### *4.6 Discussions*

The data-driven statistical and spatial explorations of the three types of sharing economy activities (STR, SBBS, and DBS) in eight U.S. cities reveal insights about their unevenly distributed, tourist-oriented business conducts. This study aims to identify common trends and issues associated with these activities across cities, as well as city-specific issues and policy contexts when it comes to the welfare implications of the three types of activities at the socially vulnerable neighborhoods. I come up with the following empirical observations:

*The major tourist destinations have high activity density for STR, SBBS, and DBS. STR density is high in Washington DC, Boston, Austin, and Los Angeles. DBS density is relatively high in Washington DC, Austin, Minneapolis, Los Angeles, and Portland. Policy restrictions on dockless shared mobility explain the low level of DBS usage in Chicago and Boston. On the other hand, a less popular tourist destination like Louisville attracts less STR business and SBBS/DBS usage. For public bike-sharing, due to infrastructure constraints (stations) and competitions from other micromobility choices, trip density is low in many cities.*

*The sharing economy activities are clustered in central city.* The spatial patterns of STR listings, SBBS trips, and DBS trips suggest that downtown activity centers with various points of interest attract the most sharing economy activities. In addition, STR listings cluster at residential areas adjacent to the airport to accommodate overnight air travelers. The spatial patterns further reinforce the impression that STR, SBBS, and DBS are primarily used for leisure purposes to cater for travelers. The spatial similarity statistics further suggest that the overall spatial distribution of STR, SBBS, and DBS tend to agree with each other, except when regulatory interventions (e.g., DBS in Boston) are factored in.

*Most neighborhoods of high social vulnerability have low bike-sharing activity density.* The majority of highly vulnerable census tracts (SVI>0.75) have low SBBS and DBS trip density. There are different interpretations of the lackluster activities: One interpretation is no infrastructure (e.g., SBBS stations) is built in those neighborhoods. In that case, the socially vulnerable communities are inequitably treated in the sharing economy. While all eight cities implement a bike-sharing equity program, not all of them address the equitable spatial distribution of SBBS stations (and bikes) and DBS fleets (e-bikes and e-scooters). Cities like Washington DC, Los Angeles, and Portland require DBS vendors to distribute a minimum number of bikes/scooters in the disadvantaged communities and evaluate trip distribution periodically. Other cities should follow suit and guarantee SBBS and DBS fleet availability in the socially vulnerable neighborhoods. Another interpretation is that SBBS and DBS trips are too expensive/inconvenient for the socially vulnerable population. For instance, Los Angeles' SBBS program was initially criticized for being

too expensive for the services they provided, which partly explain the low ridership before a reduced fare was implemented (Clark, 2016). In that case, cities need to find a balance between financial viability to support a bike-sharing program and providing affordable services to the low-income individuals. A third possibility is the underlying undesirability for cycling in many of the socially vulnerable neighborhoods. Such undesirability could be associated with incomplete/deteriorated bike facility, auto-centric street design, homogenous land use, and poor connectivity to public transportation. A pedestrian/bike-friendly built environment is crucial to boost non-motorized travel, so it is important that a city's transportation authority and policymakers dedicate more resources and approve capital investment plans to improve the built environment in the socially vulnerable neighborhoods. The long-range land use plan should also consider land use diversity and street connectivity to transit, which can also boost bike-sharing usage. This study is unable to tell the exact cause of low bike-sharing ridership. I would argue that while the low ridership issue is common, we need to look into individual city/program and search for user/individual-based evidence to reveal the causes.

*Gentrifying, socially vulnerable neighborhoods with active STR business require our attention.* Like bike-sharing, STR listings also cluster in neighborhoods of relatively moderate/low social vulnerability. It underlines the geographical disadvantages (e.g., distance from activity centers, tourist hot spots, or transit centers) and social disadvantages (e.g., neighborhood safety) of such areas. However, unlike bike-sharing, there are a good number of socially vulnerable census tracts of high STR density in all eight cities. For those neighborhoods, active STR business is a double-



edge sword: On the one hand, some low-income households may enjoy the financial profit from operating an Airbnb. On the other hand, I identify tracts that are gentrifying or gentrified, which means there exists a risk of rental housing stock shortage or inflation of housing cost caused by active STR business in such neighborhoods that is likely to displace their low-income, socially disadvantaged, long-term renters. They live in Capitol Hill/Anacostia in Washington DC, Mission Hill in Boston, East Austin, and Koreatown/Chinatown in Los Angeles. City governments and housing interest groups should examine the potential impacts of short-term rental business on the housing market in those neighborhoods. Furthermore, enforcing STR regulations and cooling the fervor in commercial real estate investment in STR business are necessary to protect the interest of long-term residents who are feeling the burden of the increasing housing cost.

#### *4.7 Final Remarks*

The sharing economy has experienced a phenomenal growth in recent years. While its various applications bring convenience to users and economic opportunities to service providers (Airbnb hosts, for instance), it is criticized for disrupting the quality of life for local communities (from dockless bikes and scooters cluttering sidewalks to noisy parties on Airbnb properties). In this study, I explore the similarities and differences in the activity level and spatial patterns of three types of sharing economy activities – STR, SBBS, and DBS – in eight U.S. cities. Combining map observations, statistical analysis, and existing empirical evidence, I find that STR and shared micromobility are spatially distributed in a way to serve tourists. In particular, shared micromobility is not frequently used in socially vulnerable neighborhoods, where a

lack of affordable mobility choice could be a major transportation issue. Short-term rentals could become a new gentrifier that exacerbate gentrification in areas largely consisting of socially disadvantaged populations, who are faced with an increasing cost of living in the core urban area. While the adoption of STR, SBBS, and DBS greatly depends on each city's regulatory approach, the aforementioned issues are manifested across cities of different population sizes, sociodemographic compositions, and built environment, suggesting that the rise of sharing economy follows a somewhat similar logic despite the specific city profile. In addition, one city's lessons in managing the growth of STR/SBBS/DBS can be learned by another city.

The limitation of this study lies in its lack of in-depth investigation and explanation of the causes for the uneven spatial patterns in STR listings and SBBS/DBS trips in each city. The anecdotal news coverage and previous empirical research hint at the possible reasons that can explain why STR listings, public bike-sharing stations, and dockless e-scooters are concentrated at certain part of a city. Nevertheless, to fully uncover the equity issues surrounding these sharing economy activities, the passive data on STR listings and shared micromobility trips must be analyzed with other types of descriptive data, such as stated preference survey data and user profile data, to arrive at the nuanced insights.

The other limitation of the study is the level of geographic resolution in the analysis. While census tract is an appropriate analytical level for this study, the degree of aggregation means losses of more nuanced information. I can describe the general built environment and points of interest in a census tract and make inferences on their relationship with the underlying activity level for STR and shared micromobility.

However, the usage of bike-/e-scooter-sharing is sensitive to the block level locations and street designs. STR business is also sensitive to the distance from neighborhood activity centers and amenities. Disaggregated analyses using big data on shared micromobility trips and STR listings/host profiles enable researchers to overcome measurement errors in analyses at the more aggregated level.

Hospitality to tourists should not come at the cost of hostility to local residents. Introducing short-term rental business to the city should not make housing less affordable for low-income households. Building public bike-sharing stations should consider areas of insufficient transit coverage to satisfy people's daily mobility needs. Dockless e-scooter vendors should offer affordable options for low-income, unbanked individuals to access their services. It is only when the sharing economy improves the quality of life for local residents that we can truly find a sustainable pathway for it to be integrated into the urban economy.

## Chapter 5: Conclusions and Future Research

The three empirical studies, each with a focal point on the sharing economy's broader social impact, explore and explain the equity issues and opportunities that need to be addressed in policymaking and planning practices. In addition, I apply multiple innovative techniques in GIS, economics, spatial analysis, and data sciences to take advantage of the disaggregated big data in STR and shared micromobility. Together, the research topics and the empirical analyses contribute to academic literature of interdisciplinary research on emerging urban technologies. Furthermore, the results from the empirical work are relevant to the local government's planning practices and their policy agenda.

### *5.1 Conclusions and contributions*

The short-term rental market, supported by platforms like Airbnb, Vrbo, and HomeAway, imposes significant regulatory challenges to many U.S. cities. My research on the housing market impact of STR on housing prices provides critical insights about the equity and policy implications of this controversial sector:

- (1) *The quick STR market expansion significantly inflates the average single-family housing prices in Washington DC:* The unregulated market growth prior to the city's STR bill coming into effect in 2019 provides a nontrivial incentive for real estate investment that bids up housing prices in an already expensive city like Washington DC.
- (2) *The price effect of STR unevenly affects different neighborhoods in Washington DC:* Because of the uneven spatial distribution of STR listings,

the price inflation is more prominent in STR hot spots, such as downtown, Adams Morgan, Shaw, Dupont Circle, and Foggy Bottom. Airbnb accounts for more than 10% increase of single-family housing prices in downtown DC between 2015 and 2017.

- (3) *The spatially uneven price effect could adversely affect racial-minority new homebuyers in certain neighborhoods:* Some historically racially diverse areas are significantly experiencing redevelopment in recent years, such as Shaw, Capitol Hill, NOMA-Trinidad, and Columbia Heights. Gentrification has already significantly impacted housing affordability in these areas. Yet, highly concentrated STR listings further bid up housing prices in such areas, making it more difficult for minority homebuyers to afford to live there.

Methodologically, my research combine innovative data sources on Airbnb listings, housing data from DC, and other disaggregated data sets in three hedonic analyses. The study is published by Housing Policy Debate and receive multiple media coverages that draw a broad discussion on the necessity of STR regulations in DC.

The emerging e-scooter sharing operations disrupt the mobility market in the District of Columbia and many other U.S. cities in the past three years. While riders enjoy the convenient, eco-friendly mobility, issues start to emerge around e-scooter regulations and management. The second study of the dissertation deals with the equity implications of e-scooter sharing:

- (1) *E-scooter sharing trips are significantly associated with street design, built environment, social environment, and neighborhood points of interest:*

Using real-time e-scooter trip trajectory data, I examine factors that could

explain where e-scooter trips are taken down to an unprecedented street segment level. Not only the trip origin-and-destination built environment matters to e-scooter usage, but the bike-/pedestrian-friendly infrastructure can significantly boost e-scooter rides on the street. At the same time, neighborhoods of a higher share of the socially disadvantaged population tends to attract fewer e-scooter trips, all else equal. It raises the equity concern about whether e-scooter vehicles are adequately allocated to such neighborhoods and whether the unfavorable built environment may affect their usage in such neighborhoods.

(2) *E-scooter sharing provides equity opportunities in the equity emphasis areas in Washington DC*: While the average treatment effect from the street segment analysis suggests that the use of e-scooter sharing is significantly lagged in the disadvantaged communities. The clustering analysis reveals that a higher-than-average number of PM and night-time trips are taken in such areas as an alternative mobility option for residents to get around. This provides the transportation authority a refreshing angle to address e-scooter equity issues in the equity emphasis areas.

I apply the traditional regression technique, the spatial econometric technique, and the machine-learning based clustering technique to a data- and computational-intensive analytical framework in this study. Together with the real-time, trip trajectory big data, the empirical work significantly improves the analytical granularity of the emerging e-scooter sharing from current literature.

Washington DC is an exemplar of the sharing economy. Its unique status in the urban policy world both gives it a comparative advantage to study various urban issues and limits the broader policy implications on other cities.

The third paper serves the purpose to compare DC to other seven U.S. cities of various population sizes, social and built environments, and policies on three types of sharing economy activities. The heterogeneity in these contexts allow me to identify common patterns of where these activities are clustered, the common attributes that may explain such patterns, the differences in spatial patterns, the city-specific policy or social/built environment context that can explain the differences. The cross-city exploration generates the following insights:

- (1) *Sharing economy activities (STR, SBBS, and DBS) are tourist oriented.* STR listings and shared micromobility trips oftentimes cluster in downtown areas with many tourist attractions and various points of interest. In addition, STR listings also cluster near an airport to accommodate overnight flyers.
- (2) *The socially vulnerable neighborhoods tend to have low level of sharing economy activities:* The neighborhoods of high social vulnerability, characterized by a high share of racial minority, a high share of low-income households, a high share of the elderly/disabled population, and/or high housing and transportation costs, are not as attractive as the affluent areas to open a STR and to ride a bike-/e-scooter-sharing trip.
- (3) *Many gentrifying neighborhoods of high social vulnerability have active STR business:* Active STR business offers real estate investment incentives that can be translated into a price/rent premium reflected in the housing

market. For a gentrifying neighborhood that is populated with socially vulnerable residents, such a price/rent premium could become the last straw that displaces the long-term residents. For this concern, I identify census tracts that needs further examinations.

(4) *The policy contexts can definitely explain the spatial patterns and activity levels of STR and shared micromobility:* By cross-referencing the existing regulations and equity policies on STR and shared micromobility in each city, I understand why the sharing economy activities exhibit the patterns they have. In a city that advocates micromobility, like DC or Chicago, the public bike-sharing are more widely used. In a city with little regulations on the sharing economy like Austin, STR and DBS activity levels are high, but also unevenly clustered in downtown commercial areas. In a city that has explicit restrictions on DBS like Boston and Chicago, the spatial patterns of DBS trips significantly differ from other cities. Such nuances are difficult to quantify, but my analysis provides a semi-quantitative, semi-qualitative approach to address them.

The third study also tries to address multiple sectors in a cross-city comparison – something that has never been tried in empirical literature on the sharing economy before. I acknowledge both the potentials and the drawbacks of this research approach and will try to improve it in future research.



## *5.2 Limitations and future research*

There are areas of limitations for the dissertation research, where I hope to revisit and refine in future research. To begin with, the equity perspectives are implied in each empirical work, rather than directly measured. The difficulty of equity research is the dichotomy between what a researcher believe is “inequitable” versus what the disadvantaged populations and communities of interest perceive as “inequitable”. For instance, while I argue the unregulated STR market could overheat the housing market in an expensive city like Washington DC, to many STR hosts of high social vulnerability (e.g., low-income, renters) a prosperous STR market could mean the necessary extra income to make their livelihood in the city. Similarly, the belief of “if you build it, they will come” for a more favorable allocation of e-scooters and bikes in neighborhoods of high social vulnerability may not coincide with what the local communities prioritize. They may as well find that the truly useful solution to fill the mobility gap is to expand public transit’s coverage. The dichotomy speaks to the heart of quantitative research’s limitations: inability to accurately capture individual or group preferences. Equity, on the other hand, emphasize nothing but the appropriate allocation of resources based on individual preferences.

In addition, I intersect STR listings and micromobility trips with the census data on socially vulnerable population within a neighborhood (either at the census block, the block group, or the tract level) to approximate the adoption/usage of STR and shared micromobility among such subpopulations. While it is a common research approach to use census demographic characteristics as a proxy for user demography, the caveat of this approach is obvious: Fewer trips/listings appearing in neighborhoods

of many socially disadvantaged individuals do not equal to fewer such individuals renting out STRs or taking micromobility trips. They may simply do so in the popular neighborhoods like others. While this caveat can hardly be fixed empirically with limited information on user profiles (by all mean, protecting data privacy is the bottom line for data-driven analytics), what I can do is to combine qualitative evidence (such as news coverage, nonacademic reports, or qualitative studies) that may support my equity arguments deduced from the empirical results.

These shortcomings of analyses on passive data (data gathered without the involvement of the data provider, meaning that no user information can be traced) can be addressed with more qualitative research approaches that targets at users/non-users, such as survey, interview, field study, audit study, and content analysis (analyzing text, documents, and other communication artifacts). I am fully willing to adopt these research approaches in future research on the equity topics related to the sharing economy.

In addition to the general limitations in defining equity issues and measuring equity with passive data, I acknowledge other drawbacks specific to subtopics within each empirical chapter. The empirical work in Chapter 2 examined the period of rapid STR market expansion in D.C. (2015 – 2017). Now that the city’s STR bill has taken effect for almost two years and we just witnessed an unprecedented global pandemic that smashed global tourism. It is highly relevant to revisit the study and examine new housing market outcomes as a result of these policy/external shocks. In the second study (and the third study), I focus on shared micromobility due to data availability (at a fine-grained resolution or available for multiple cities). Another important player in

shared mobility, ridesourcing (operated by transportation network companies like Uber and Lyft), is largely neglected from the conversation. As someone who has published work on ridesourcing, I would love to include ridesourcing in future research on the broader equity implications of shared mobility. I firmly believe that these shared mobility options ought to serve all people, especially for those who live in transit underserved areas without a private vehicle. In the third study, while I am able to pin down census tracts of high social vulnerability and high STR density that undergo the gentrification process, I cannot differentiate gentrification caused by STR and gentrification caused by other reasons, such as urban revitalization/ economic development. In reality, disentangling the sources of gentrification and understanding the relationship between gentrification and displacement are tricky tasks for housing researchers. As I stated, the empirical work in Chapter 4 is more exploratory than explanatory at this point. I will need to establish multivariate analyses to truly control for confounding factors besides STR activities that may explain gentrification and displacement in the study areas.

In addition, I could further polish the empirical analyses in each of the three empirical studies: I could extend the study period of the first study to capture the regulatory signaling and regulatory effectiveness of the city's STR bill on the level of STR activeness. Perhaps, a dramatically different picture may occur as the price bidding behavior could have stopped due to stricter restrictions on STR. I could adopt a multi-level analysis and try more elegant ways to sample the large dataset in the second study to diminish the non-negligible computational costs. I could build multivariate analyses (regression based or machine-learning based) for the third study

to formally quantify the impact of policy variations and social/built environment variations by different cities on the spatial densities of STR, SBBS, and DBS activities. I could also find a less arbitrary way to set the density cutoffs for the three types of sharing economy activities.

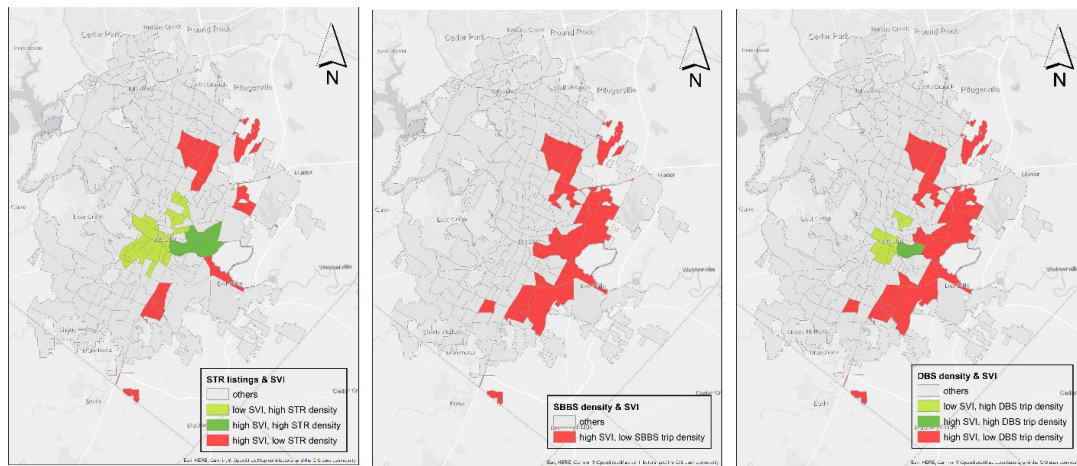
Last but not least, I did not spend a significant number of words addressing the existing policy tools/ planning practices (taxation, pricing scheme, mapping of the equity priority area, etc.) and their effectiveness in controlling the unregulated STR market growth, correcting the non-random distribution of shared micromobility vehicles/trips, and supporting the overarching equity goals in overseeing the sharing economy. While I acknowledge the importance of bridging research with planning practices, I admit that a comprehensive review is needed to make sure that I do not overlook any useful resources of planning and policymaking vis-à-vis the equity perspectives of the sharing economy (or even the broader smart cities vision).

The theory of everything does not exist, yet. I shall continue improving my research skills, widening my eyes to the rapidly evolving academic world, and keeping my head up for the outlook of an academic career beyond PhD studies. As for now, I conclude this chapter of my PhD life with this dissertation.

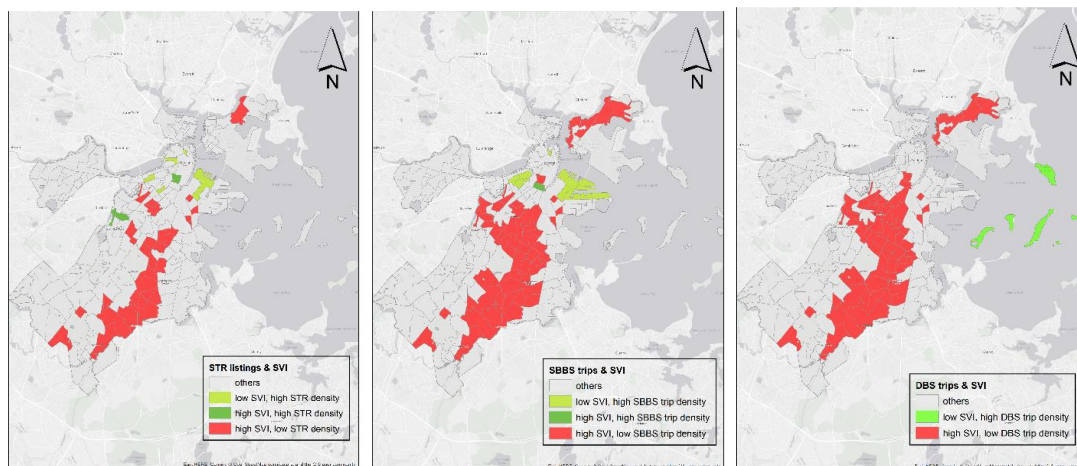
# Appendices

## Appendix A: STR/SBBS/DBS densities in highly socially vulnerable census tracts for Eight Cities

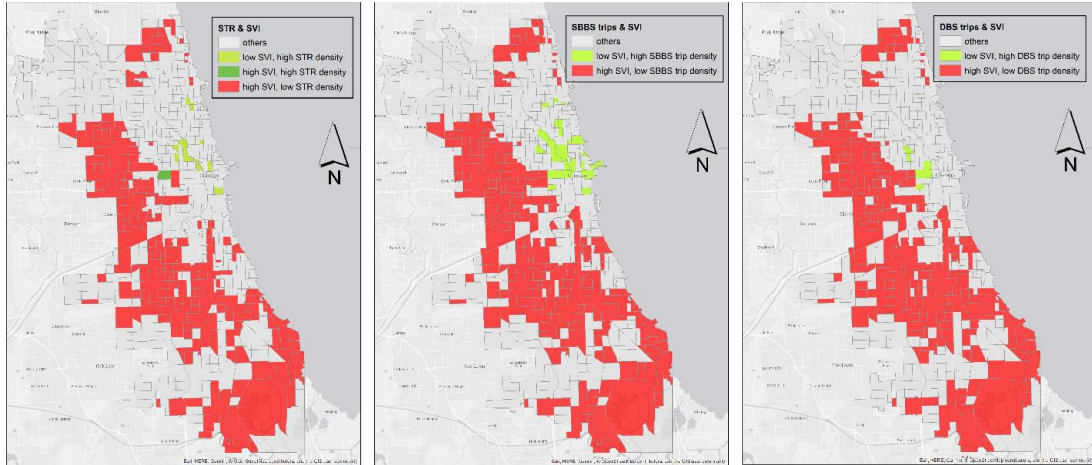
The maps are presented in the sequence of STR – SVI, SBBS – SVI, and DBS – SVI interactions for each city. The red tracts identify areas with high SVI and low activity level; the light green tracts identify areas with low SVI and high activity level; and the dark green tracts identify areas with high SVI and high activity level.



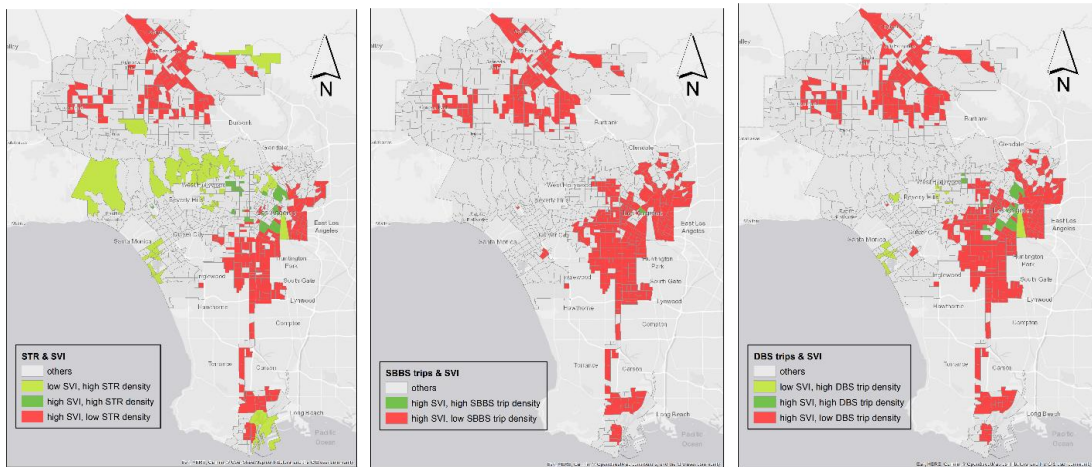
**Figure A-1a – A-1c: STR, SBBS, DBS & SVI interaction in Austin**



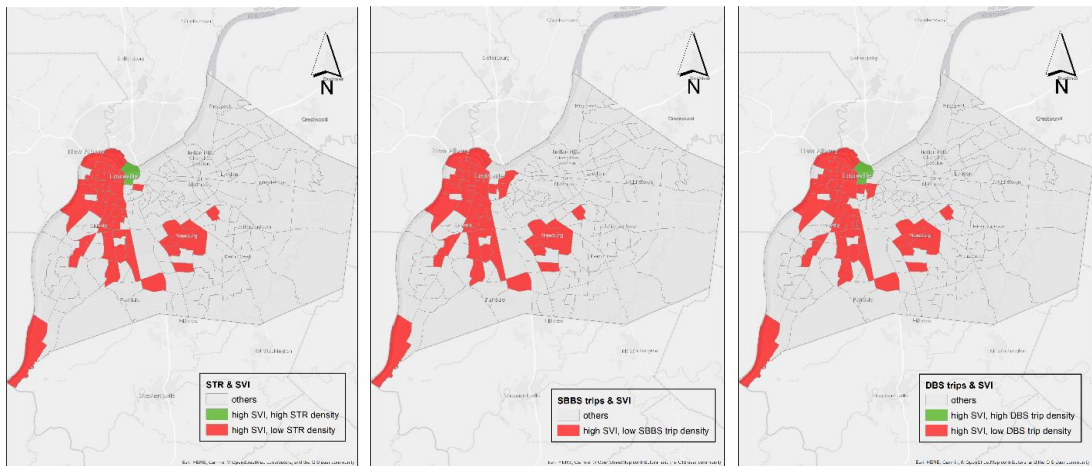
**Figure A-2a – A-2c: STR, SBBS, DBS & SVI interaction in Boston**



**Figure A-3a – A-3c: STR, SBBS, DBS & SVI interaction in Chicago**

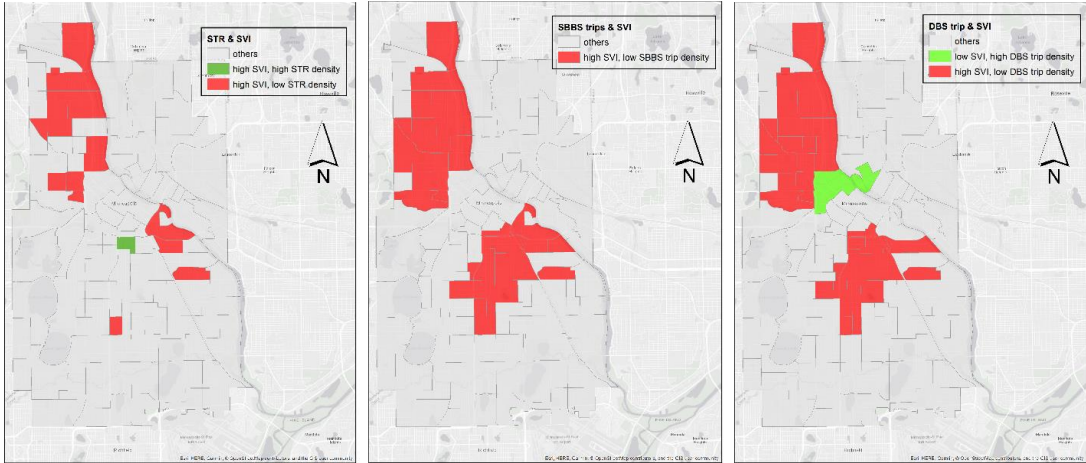


**Figure A-4a – A-4c: STR, SBBS, DBS & SVI interaction in Los Angeles**

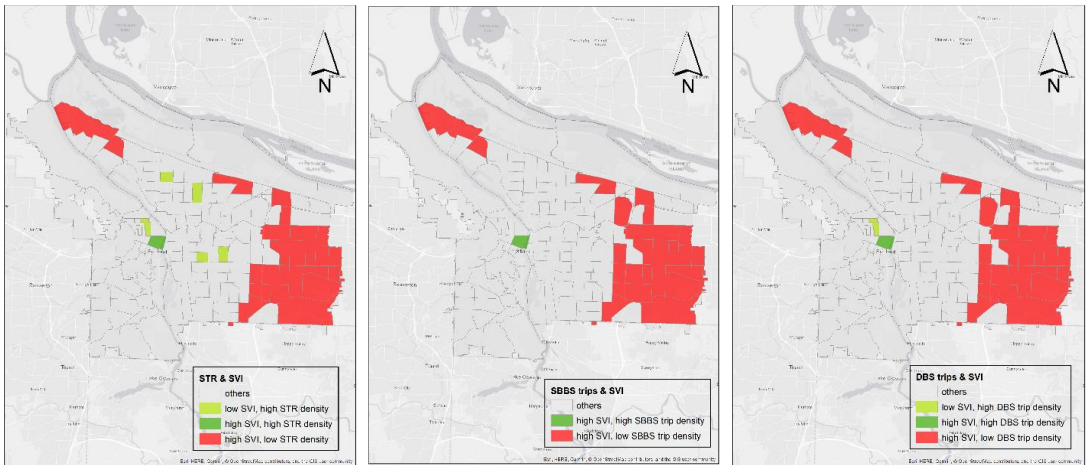


**Figure A-5a – A-5c: STR, SBBS, DBS & SVI interaction in Louisville**

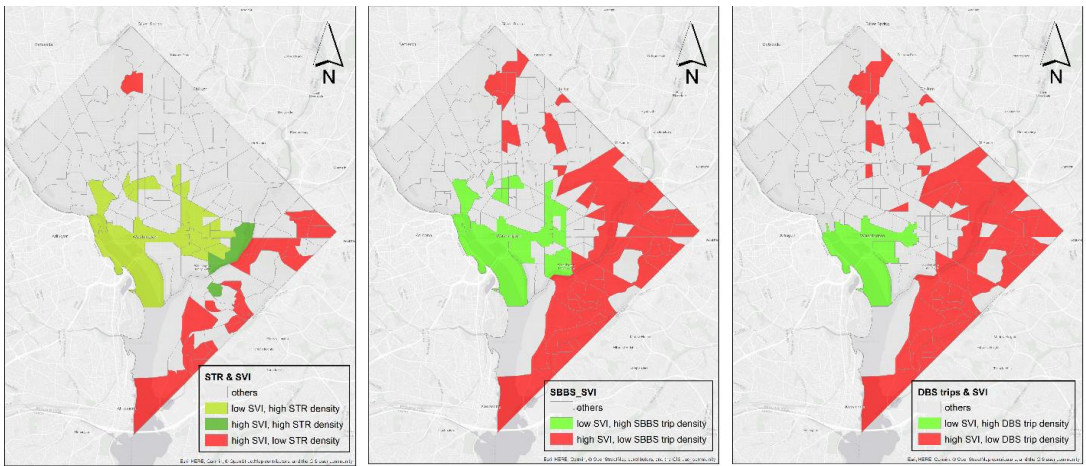




**Figure A-6a – A-6c: STR, SBBS, DBS & SVI interaction in Minneapolis**



**Figure A-7a – A-7c: STR, SBBS, DBS & SVI interaction in Portland**



**Figure A-8a – A-8c: STR, SBBS, DBS & SVI interaction in Washington DC**

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