Splitting rides in transit deserts: Ride-splitting dynamics in Chicago before, during and after the pandemic

by

Paris Charitatos

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Authored by: Paris Charitatos
MIT Department of Urban Studies and Planning
May 12, 2023

Certified by: Fábio Duarte
Lecturer of Technology and Urban Planning
Thesis Supervisor

Certified by: Siqi Zheng
STL Champion Professor of Urban and Real Estate Sustainability
Thesis Supervisor

Accepted by: Jinhua Zhao
Associate Professor of City and Transportation Planning Chair, Transportation Education Committee

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ABSTRACT

Transportation Network Companies (TNCs) might constitute a solution for transit dependent population who live in areas with limited or even non-existent public transit service, also known as "transit deserts". Ride-splitting was introduced by TNCs as an affordable on-demand mobility option which offers door-to-door service while sharing a trip with another passenger. Due to its affordability, ride-splitting can increase even more the accessibility of low-income and disadvantaged population. Few studies have focused explicitly on the role of ride-splitting in underserved communities. We studied if ride-splitting services compensate for the lack of transit in transit deserts. We leveraged the suspension of ride-splitting services during the COVID-19 pandemic to examine how ride-splitting user behavior changed throughout three time periods: (1) pre pandemic, (2) during the pandemic and (3) post pandemic. By doing so, we study if ride-splitting users switched to single mode during COVID-19 and if ride-splitting levels have recovered in the post-pandemic era. For our analysis we used TNC trip records, provided by the city of Chicago, transit data from four different transit authorities, as well as demographic and job density data. We identified transit deserts by calculating a transit supply score for every census tract during five time periods: (1) weekday daytime hours; (2) weekday overnight hours; (3) weekday peak hours; (4) weekend daytime hours and (5) weekend overnight hours. We developed cluster and bivariate maps along with spatial regression models to determine the correlation between ride-splitting pickups/drop-offs, transit supply and neighborhood characteristics along these five temporal periods. Results revealed that in Chicago low transit supply is not significantly correlated with disadvantaged communities, suggesting that transit deserts can occur regardless of the racial and income composition, and spatial sorting of the area. Pooled pickups/drop-offs were negatively correlated with transit route density, transit stop density and proximity to rail station, which means that ride-splitting supplements the role of transit in transit deserts. We found that communities of color and transit-dependent population had a moderate positive influence on ride-splitting. There is little evidence that ride-splitting users switched to single mode during COVID-19, but overall single trips were relatively higher compared to pre pandemic.

Thesis supervisor: Fábio Duarte

Title: Lecturer of Technology and Urban Planning

Thesis supervisor: Siqi Zheng

Title: STL Champion Professor of Urban and Real Estate Sustainability

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Chapter 1

Introduction

On July 5, 2010, the first Uber-trip was requested in San Francisco (Uber Newsroom, n.d.). In the following years Lyft and Via also introduced similar ride-sourcing services. Transportation Network Companies (TNCs) offer point-to-point on-demand mobility, often costing less than taxis, which can be accessed via smart-phone apps. In 2014 TNCs launched a new service mode (e.g., UberPool, Lyft Line) which enables passengers headed in the same direction to share a ride with a reduced fare. This idea could make the trip more affordable, reduce the aggregated number of trips and thus alleviate congestion and pollution in metropolitan areas (Shaheen, 2018; Shaheen and Cohen 2019). To prevent confusion, we refer to TNC trips in general as ride-sourcing which can be divided into single trips and pooled/shared trips – henceforth referred to as ride-splitting. The adoption of ride-splitting varies widely, from 6% to 40% of the total trips (Shaheen and Cohen, 2019; Schaller, 2018; Li et al., 2019; Roy et al., 2020; Hou et al., 2020).

Considering the lower cost, when compared to single trips, ride-splitting services might help to serve transit-dependent population who live in so-called "transit deserts". With the term transit-dependent population we refer to individuals of low-income, elderly, of young age or in general people without access to a private vehicle or who are unable to drive. Transit deserts are defined as areas of high demand for public transportation, but with a very limited or even non-existent supply (Al Mamun and Lownes, 2011; Currie, 2004; Jiao and Dillivan, 2013). Especially in the U.S., transit deserts have become an issue due to insufficient funding for transit agencies and crumbling infrastructure.

Sharing a ride with another passenger can lower the cost of the trip, which makes ride-splitting an attractive option for transit-dependent population living in transit deserts. However, even though ride-splitting seems to serve more diverse communities, there is still no substantial evidence that it compensates for the lack of transit (Soria and Stathopoulos, 2021). There could be several reasons why ride-splitting is underutilized in such areas. According to literature, barriers exist which prevent access to those services such as financial difficulties, mobility problems and lack of familiarity with technology. Most TNC services require a credit card which a large percentage of low-income population may not have access to. Since those services are offered through a smartphone application, users are expected to have access to smartphones and data plans which is not true for disadvantaged communities. Also, lack of Wheelchair Accessible Vehicles (WAVs) combined with inadequate driver training for assisting passengers makes it difficult for people with disabilities to use ride-splitting services.

The disruption of COVID-19 had severe impacts on most transportation systems and their consequences are still prevalent today. Since teleworking was in motion, transit ridership declined sharply along with transit revenue. Most transit agencies cut down service and more specifically in areas that were poorly served in the first place. In March 2020, TNCs suspended ride-splitting operations in an effort to contain the COVID-19 cases. Thus, only single trips were offered until November 2021, when ride-splitting options were resumed for some of the companies. The side effects of all the aforementioned disruptions were mostly felt by low-income and disadvantaged communities who did not have the option of teleworking or driving. Construction workers, healthcare personnel and grocery store employees were still commuting during the pandemic having to endure unreliable service while getting heavily exposed to COVID-19. In the post COVID-19 era, transit ridership has still not recovered, and most U.S. transit agencies are facing a financial cliff. Moreover, transit users who shifted towards a private vehicle during the pandemic, are still reluctant to come back to the system.

Since TNCs were introduced to the mobility stage, several studies have suggested that ride-sourcing activity is a major cause of traffic congestion, transit ridership decline and air pollution. Ride-sourcing can be used to serve a variety of demographics such as transit-dependent populations. Consequently, the popularity of such services has increased the number of cars on the streets and the Vehicle Miles Traveled (VMT) due to deadheading. Drivers tend to drive around without any passengers trying to find the next ride. Ride-sourcing companies are for profit companies; thus, drivers are looking to take on higher cost rides in order to get a larger commission. To address the issue of congestion and increased CO_2 emissions local authorities decided to impose taxes on TNC services and nudge people to opt for ride-splitting instead. Chicago was one of the first cities to implement such a congestion tax policy in 2020 after a steep rise of TNC rides. The tax was imposed for trips starting or ending in the downtown area of Chicago and several tourist attractions. The goal is to shift users towards ride-splitting and act as a revenue source for local authorities and transit agencies. However, imposing a tax on an already high fare means that low-income and disadvantaged communities living in transit deserts need to pay even more for their mobility. As a result, the mobility expenses of transit-dependent households rise, thus people may choose to not travel at all.

Although TNCs have been accused to undermine public transit, ride-sourcing services and in particular ride-splitting, can contribute to more efficient, sustainable, and equitable mobility. The U.S. Government has developed the Mobility On-Demand Sandbox Program which was created to incentivize potential partnerships between TNCs and transit authorities. Such partnerships can have various forms and can offer many types of services including first mile/last mile trips, low-density service, service during off-peak hours, and paratransit service. Many transit authorities have experimented with such initiatives including Massachusetts Bay Transportation Authority (MBTA), Pinellas Suncoast Transit Authority (PSTA), and Livermore Amador Valley Transit Authority (LAVTA). In most cases, users responded positively, thus service was expanded, and transit agencies managed to decrease their operational cost. However, these partnerships do not come without challenges. Depending on the partnership, transit agencies may not have access to ride-sourcing data and therefore it's difficult to assess the success of the program. In addition, lack of WAVs, long response times and failure to comply with Title VI and American Disability Act (ADA) protocols might hinder the wide adoption of such services and can ultimately result in their termination.

Until today, most studies related to ride-sourcing discuss the impact of TNCs on traffic congestion (Schaller, 2017, 2018; San Francisco County Transportation Authority, 2017) or whether they complement or substitute public transportation (Tirachini, 2020; Tirachini and del Rio, 2019; Babar and Burtch, 2020; Kong et al., 2020). Few studies (Barajas et al., 2021; Jiao and Wang, 2021) have analyzed how TNCs serve transit-dependent population in transit deserts but do not focus explicitly on ride-splitting trips. When COVID-19 hit in March 2020, TNCs suspended ride-splitting operations in an effort to contain the COVID-19 cases. Thus, only single ride trips were offered until November 2021, when some companies resumed ride-splitting services. The disruption in ride-splitting provided us with a good opportunity to better quantify its effect on transit-dependent population living in transit deserts. To the best of our knowledge, this is the first study to investigate how the suspension of shared rides changed the mobility of ride-splitting users. This study utilizes the disruption in ride-splitting services to tease out its effects, and to discuss the following questions, focusing on Chicago

1. In comparison to single trips, could ride-splitting services effectively fill the mobility gap for those living in transit deserts?
2. How did the suspension of ride-splitting, due to the pandemic, influence mobility choices, particularly of those living in transit deserts?

Our hypothesis is that focusing only on ride-splitting services, after standardizing with the total number of trips we anticipate high shares of pooled rides in transit deserts and specifically in low-income and disadvantaged communities.

In Chapter 2 we analyze the literature related on TNCs, transit deserts, COVID-19 impacts, and regulatory policies. In Chapter 3 we present in detail the data and methodology that we are using and in Chapter 4 we report our results. Finally, in Section 5 we discuss our results in more detail and we conclude.

Chapter 2

Literature Review

2.1. Transit Deserts

The term “transit deserts” has emerged from the similar term of “food deserts”, meaning urban areas where there is a high concentration of people without access to fresh food (Clarke et al. 2002; Whelan et al. 2002; Wrigley 1993; Wrigley et al. 2002; Jiao et al. 2012). According to Jiao et al. (2013, p. 24), transit deserts are defined as “areas that lack adequate public transit service given areas containing populations that are deemed transit-dependent”. We use the term “transit-dependent” population to refer to those who are too young, too old, of low-income or people with disabilities who are unable to drive (Grengs, 2001). In 2018, 4.5 million people lived in transit deserts across 52 U.S. cities (e.g., Chicago, Cincinnati, San Antonio) (U.S. News, 2018).

Historically, it’s true that in the U.S. the automobile was prioritized over transit which impacted negatively transit ridership (Allen, 2017). Car-culture combined with urban-sprawling have exacerbated transit deserts in the U.S. There are no definitive metrics that measures transit demand and transit supply. According to previous studies, transit demand is defined as the number of persons who do not own a car (Jiao and Dilivan, 2013; Jiao, 2017) while transit supply is determined by factors such as the number of stops, weekday bus arrivals, number of routes, total length of sidewalks, bike routes and density of intersections (Jiao and Dilivan, 2013; Jiao, 2017). However, transit-dependency is not related only to car-ownership but also other social factors such as low-income, age and disability problems (Jomephour et al., 2020). Assessing transit supply using only weekdays or daytime hours is not representative of transit service considering that many people perform shopping trips during weekends or work the late-night shift (Jomephour et al., 2020). In our study we follow the approach of (Barajas et al., 2021) which incorporates all aspects of transit-dependency and the temporal characteristics of transit supply.

2.2. TNCs and Transit Deserts

High density areas tend to have an adequate level of transit service whereas low-density areas are served by a lower number of rail and bus routes with much lower stop frequencies. TNCs can fill in the transit gaps in the form of first mile/last mile trips or by substituting transit entirely. We define as transit gap the difference between the levels of transit service (supply) and the needs of a specific population (demand) (Jiao and Dilivan, 2013). Jiao and Wang (2021) found that in New York City TNCs are more prevalent among people who do not own a private vehicle or have physical difficulties which hinder their mobility. Additionally, ride-sourcing is more common in wealthier areas of the city which have a much better public transit service. The same pattern was observed by (Soria and Stathopoulos, 2021; Barajas et al., 2021) who reported that ride-sourcing activity in Chicago is concentrated in neighborhoods with higher median household income, higher levels of transit stop density, overnight service, and proximity to rail station. With respect to demographic characteristics, ride-sourcing trips in Chicago are mainly generated in mixed racial neighborhoods and not in isolated communities of color (Barajas et al., 2021). The fact that TNCs are not utilized as much in disadvantaged neighborhoods can be attributed to lack of information and skills to use TNCs (Jiao and Wang, 2021). However, it's important to clarify that most of the studies related to TNCs do not distinguish between single and pooled trips. Therefore, the above results are heavily influenced by the greater numbers of single trips.

In 2014 TNCs launched ride-splitting, which enables passengers headed to the same direction to share a ride with a reduced fare (e.g., UberPool, Lyft Line). By sharing a ride, the trip becomes more affordable, congestion is reduced due to the lower demand for vehicles and thus CO_2 levels drop in urban areas (Shaheen, 2018; Shaheen and Cohen 2019). Apart from the aforementioned positive effects, ride-splitting services might constitute an alternative mobility option for transit-dependent groups, in particular those living in transit deserts. Soria and Stathopoulos (2021) found that ride-splitting has a complementary role for lower income households and for people with limited access to a private vehicle (Tirachini and del Rio, 2019).

One of the major challenges of ride-splitting is successfully matching riders with drivers. More specifically, there seems to be a low percentage of truly pooled trips in peripheral areas in metropolitan regions. Part of this can be attributed to the dispersion of pooled trips destinations which are detected in areas with relatively lower total ride-sourcing demand (Soria and Stathopoulos, 2021). Drivers tend to concentrate where there is increased demand thus making it difficult for the algorithm to match ride-splitting users with the same driver. Dean and Kockelman (2021) found that census tracts with more household members tend to share rides with strangers more frequently possibly because they are more familiar with the idea of sharing due to intrahousehold interaction. Also, areas characterized by high pedestrian infrastructure were less correlated with ride-splitting due to higher use of active modes.

2.3. Disruptions due to COVID-19

The COVID-19 pandemic brought major disruptions to transportation systems. Most transit agencies cut services due to insufficient funding while at the same time ride-splitting services were suspended to prevent high-risk exposure. The Metropolitan Transportation Authority (MTA), which operates New York transit and is the largest transit agency in the U.S., still faces a $1.5 billion operating deficiency through 2024, despite the COVID-19 economic relief package offered by the U.S. Government (Goldbaum & Verna, 2021). In addition, teleworking became the new normal, thus people did not have to commute to work. As a chain effect, transit ridership and transit revenue plummeted. During the pandemic, transit and ride-splitting services were considered risky options in terms of exposure, therefore users shifted to alternative modes of transport such as driving, biking, or walking (Shamshiripour et al., 2020). According to a survey by Phelan (2020), 46% of respondents would not use public transportation in the future while 34% would consider purchasing a private vehicle to limit their exposure. As expected, single and pooled trips experienced a decrease during the pandemic, especially after March 2020 when TNCs suspended pooled rides. Ride-splitting trips in particular were lower by 71% in early March 2020 and dropped to zero on March 17th, 2020 (Du and Rakha, 2020).

2.4. Regulating TNCs

Over the years, TNCs have been accused of having some unintended consequences in the transportation ecosystem. Research has shown that ride-sourcing has contributed to transit ridership decline (Grahn et al., 2021; Schwieterman and Smith, 2018) and increased VMT due to deadheading (Henao and Marshall, 2019; Schaller, 2018; Ward et al., 2021; Wu and MacKenzie, 2021). A study by Balding et al., (2019) highlights that 2-13% of total traffic in the core county of six U.S. metropolitan areas is due to TNCs. To mitigate such negative effects, policymakers have come up with creative measures to regulate TNCs, such as imposing fees and taxes. These measures aim to promote ride-splitting and act as a revenue source for transit agencies.

Chicago was one of the first cities to implement TNC fees which later were consolidated in a ground transportation tax. The city experienced a 271% increase in TNC rides after 2015 (City of Chicago, 2019). Even though an initial set of fees had been implemented in 2014, the Ground Transportation Tax was modified on January 6, 2020, for both single and pooled trips. More specifically, tax for single trips starting or ending within the CBD increased approximately four times (i.e., \$0.72/trip to \$3.00/trip), whereas in shared trips it increased by 74% (i.e., \$0.72/trip to \$1.25/trip). The goal of this policy was to incentivize people to opt for ride-splitting instead of a single trip. A study by Abkarian et al. (2023), revealed a 3.87% increase in the share of shared trips, a 27% increase in the count of shared trips, and a 12% decrease in the count of single rides. Therefore, this policy moderately increased ride-splitting levels but still more incentives are needed for shared rides to gain traction (Abkarian et al., 2023). Safety issues, long waiting times and difficulty in matching riders with drivers are a few of the reasons why ride-splitting is not taking off (Abkarian et al., 2023).

On another note, imposing a tax uniformly across all populations of Chicago, might not contribute towards equitable mobility. More specifically, even though the above policy aims to nudge people towards ride-splitting, at the same time it increases the mobility expenses of low-income population living in transit deserts who would otherwise use this service. In fact, a study reports that disadvantaged communities living in the South and West of Chicago use ride-sourcing services to substitute for the lack of transit when searching for job opportunities (Coren and Lowe, 2021).

2.5. Public-Private Partnerships between MOD and Transit

Although TNCs have been accused of undermining public transit, ride-sourcing services can also improve efficiency and quality of public transportation service under certain circumstances. In 2016, the U.S. Federal Transit Administration (FTA) developed the Mobility On-Demand (MOD) Sandbox Program which provided $8 million in funding for public authorities to collaborate with MOD services such as TNCs and micro-transit (FTA, 2023). These synergies are created in the form of Public Private Partnerships (PPPs) and according to (Lucken et al., 2019) can be divided along three key dimensions: asset contribution, service provision and vehicle type. With regard to asset contribution, there is Agency-Operated MOD and Agency-Subsidized MOD. In the former one, the transit agency is using the routing software created by the private partner while in the latter the private partner is also responsible for contracting the vehicles/drivers. Depending on which model is implemented, transit agencies may or may not have full data access and control over the operations. As a result, assessing the success of the program can be challenging. In terms of service, there are four types: (1) First-Mile/Last-Mile (FMLM) service in which only trips starting or ending at a public transit stop are subsidized, (2) Low-Density service which offers point-to-point trips but only within specific geographic areas of low-density in which it is difficult to support frequent fixed-route bus or rail service, (3) Point-to-point or first/last mile trips provided only during off-peak hours and 4.) Paratransit service which offers subsidized trips for individuals with disabilities or elderly population. The travel mode choices in such partnerships are vans, taxis, and personal vehicles owned by TNCs.

In February 2016, Pinellas Suncoast Transit Authority (PSTA) created “Direct Connect” to offer first/last mile service in collaboration with Uber, United Taxi and Care Ride (National Academies of Sciences et al., 2019). At the beginning, the pilot program was deployed in a so called “transit desert”, but it was expanded throughout the county in January 2017. Each ride was subsidized at 50% of the cost, up to a total of $3.00 which later increased to $5.00. In this particular case, the subsidy did not differ between single ride and ride-splitting. Considering the advantages of ride-splitting, it would be more beneficial to increase the corresponding subsidy. Customers had the option to pay both in credit card and cash, which resolved issues regarding credit card possession. Following the success of the program, PSTA offered an off-peak service named “TD Late Shift” which provided low-income residents free Uber rides between 9pm and 6am. Residents who qualified, (i.e., live in Pinellas County, do not have access to a personal car, have a documented income at or below 150%

of federal poverty guidelines, and have a job that begins or ends between 10am and 6am) received 25 free Uber or Lyft rides each month when they purchased a monthly bus pass (National Academies of Sciences et al., 2019). Both programs were successful, attracting a lot of participants in Pinellas County and "Direct Connect" in particular saved $40,000 per year in operating costs compared to the fixed-route circulator that it replaced.

In January 2017, Livermore Amador Valley Transit Authority (LAVTA) partnered with Uber, Lyft, and Desoto Cab to enhance its pilot on-demand program GoDublin! (National Academies of Sciences et al., 2019). The program subsidized 50% of the cost, up to $5, for any ride-splitting trip (through Uber Pool, Lyft Line, or Desoto Share) which started or ended within Dublin city limits. This promotion was eligible for only ride-splitting trips. This initiative also featured cash payment and paratransit service through Desoto. Although ridership increased, it was challenging for LAVTA to assess the program's success due to lack of data availability.

One of the most notable cases of paratransit service was the partnership between MBTA, Uber and Lyft which started in September 2016 (National Academies of Sciences et al., 2019). The goal was to provide an alternative to "The Ride", the traditional ADA paratransit service in Boston. The Ride uses shuttles to provide door-to-door service to people with a temporary or permanent disability (MBTA, 2023). The service covers 58 cities and towns in the greater Boston metropolitan area with similar operating hours as the MBTA. Customers need to book their trips on The Ride one to five days in advance (MBTA, 2023). In the first phase, 400 Ride customers signed up for the pilot and could take an unlimited number of Uber or Lyft trips per month. Customers paid a $2 copay for each trip, the MBTA subsidized the next $13, and the customer paid for any costs above $15. In the second phase, MBTA put an upper limit of 20 rides/month which later on was modified and was based on the user's ride history. They also introduced shared trips via UberPool which cost $1 and could be subsidized up to $40. As a result of this partnership, service expanded by 28% while the cost was reduced by 6%. Overall, this initiative provided paratransit customers with same-day service, decreased response time, and did not add extra operational cost to MBTA.

Ride-sourcing, whether it is single rides or ride-splitting, can provide efficient and equitable service to disadvantaged communities living in transit deserts, and act as a feeder to transit. However, ride-splitting offer more advantages for the system which should be taken under consideration when determining each subsidy. Pooled rides can increase vehicle utilization which means less congestion and reduced air pollution. In contrast, single rides can potentially increase VMT due to deadheading and CO2 emissions which is not a desired result. To address these negative externalities, cities have imposed fees on single rides and incentivized people to shift towards ride-splitting. Most partnerships showcase such policies as they offer a larger subsidy for ride-splitting trips.

Although such partnerships can improve transit equity and efficiency, they do not come without challenges. Transit agencies and TNCs must comply with certain policies and regulations as outlined by the FTA, Title VI, and ADA. Adhering to those standards will make ride-sourcing services more equitable towards low-income and minority populations. Currently, unbanked, and underbanked populations are excluded by those services since they do not have access to a bank account or a credit card (Westervelt, et al., 2017). According to the Federal Deposit Insurance Corporation, in 2021 4.5% of U.S. households were unbanked and 14.1% were underbanked (FDIC, 2021). To address this problem TNCs and transit agencies should develop new payment systems that would allow customers to pay in cash, via invoice, or through a smart fare card which can be charged with cash. Another obstacle in using ride-sourcing services is access to smartphones and data plans. A survey done by Los Angeles County Metropolitan Transportation Authority (LA Metro) in 2015 revealed that only 47% of rail customers and 38% of bus customers have access to such technologies (LA Metro, 2015). Transit agencies should collaborate with transportation companies which provide the alternative of a dispatcher or phone scheduling. Moreover, to successfully provide paratransit services, transit and TNCs should secure enough WAVs and make sure that all drivers have received adequate training to assist passengers get in and out of the vehicle (Westerwelt et al., 2017; National Academies of Sciences et al., 2019; Monahan et al., 2022).

Another issue that usually emerges in such partnerships is data sharing. Depending on the asset contribution model, transit agencies may have limited access to ridership data. In more detail, in the case of Agency-Subsidized MOD, TNCs may not be willing to share all data with the transit agency partner which makes it difficult to evaluate the program's performance and provide improvements if necessary. Common reasons as of why TNCs may be hesitant to share data are mostly about privacy, public records requests, and competition (Westerwelt et al., 2017). The data most usually requested are origin-destination trips, VMT, fare data, temporal characteristics of trips and trips made by WAVs. Acquiring these data sets from TNCs means that transit agencies can determine TNCs' impact on traffic congestion and whether it is competing with fixed-route transit networks. Data-sharing terms are often one of the key challenges when implementing a collaboration between a public transit agency and TNCs.

To the best of our knowledge few studies exist that focus on the role of ride-sourcing services in transit deserts, but they do not distinguish between single and pooled rides. Thus, we contribute to the existing literature by filling that gap and examine if ride-splitting suggests an alternative mobility option for underserved communities. In addition, we leverage the disruption of COVID-19 to study how ride-splitting users changed their mobility choices since ride-splitting services were suspended during the pandemic. Therefore, we will investigate how important these services are and how people reacted to their absence. Answering those questions will enable us to contribute to the literature related to TNCs, public transit, and transportation equity.

Chapter 3

Data and Methods

3.1. Chicago Context

Chicago is the third largest city in the United States with a population of nearly 3 million people, spread across 77 community areas, divided in 100 neighborhoods (City of Chicago, 2023). According to the U.S. Census Bureau (2021) people of color account for 58% of the population. Chicago is also known as one of the most segregated cities in the U.S. Most high-income neighborhoods are in the North part of city whereas neighborhoods in the South are primarily low-income and populated by Black/African Americans and Latinx. The median household income (in 2021 dollars) is $65,781, and 17.1% of the population lives in poverty. The main transit authority is Chicago Transit Authority (CTA) with more than 455 million annual unlinked trips in 2019 and an average of 1.5 million trips during weekdays. CTA operates 1,164 rail cars and 1,566 buses (Federal Transit Administration, 2019). Apart from CTA, other transit authorities operate mostly in the suburbs of Chicago such as Metra, Pace bus and South Shore Line (SSL). Uber was first introduced in Chicago in 2011 (Rao, 2011) and Lyft arrived in 2013.

3.2. Data and Variables

For this study we used Barajas et al. (2021) as a benchmark. Barajas et al. (2021) measured transit supply in Chicago and examined if ride-sourcing services substitute or complement transit. Findings suggest that ride-sourcing was mostly associated with high-income neighborhoods rather than transit deserts. However, when controlling for sociodemographic, they report lower ride-sourcing activity in areas served adequately by bus but higher ride-splitting activity in close proximity to rail stations. We used the same data and followed a similar methodology. We differentiate by focusing on ride-splitting instead of ride-sourcing in general, and we leverage COVID-19 as a natural experiment which gives us the opportunity to isolate and study exclusively ride-splitting services during and post pandemic.

We used a combination of datasets related to TNC trips, transit, and job data. From November 2018, TNCs are required to report to local authorities all trips that are made within the metropolitan area of Chicago. This process was initiated as an effort to regulate ride-sourcing in Chicago and study the interaction between TNCs and transit. We used trip-level data provided by Chicago Transportation Network Providers trip database (Chicago Data Portal, 2018) for three time periods; pre COVID-19 (Nov 1st, 2018 - Dec 31st, 2019), during COVID-19 when ride-splitting services were suspended (Apr 1st, 2020 - July 18th, 2021), and post COVID-19 (July 19th, 2021 - Sep 23rd, 2022) (Figure 1). Since COVID-19 is still prevalent, we define as post pandemic era the time-period between the day ride-splitting services were relaunched until the last day for which we have available data. It's worth mentioning that between the two major ride-sourcing companies, Lyft and Uber, the latter relaunched ride-splitting services one year later. The reported data include information about origin, destination, travel time, travel cost and authorization for ride-splitting. Data are aggregated to a census tract level to protect the user privacy and account only for trips that are made within the metropolitan area of Chicago. Ride-sourcing users in Chicago performed over 120 million trips pre pandemic, 19 million trips during COVID-19, and 36 million post pandemic. We used trips with a known origin and destination, and we removed outliers and trips that were identified as wrong records in the database — for instance, cases where ride-splitting authorization was "FALSE" but pooled trips were greater than 1. We used the processed datasets for both descriptive and spatial analysis. Due to the volume of data, we used clouding services (Reuther et al., 2018) to run our models.

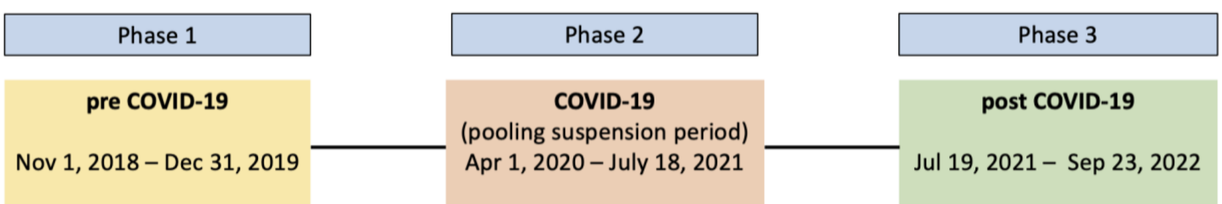


Figure 1: Research timeline throughout COVID-19

To define transit deserts, we used data from four transportation authorities which operate in the greater area of Chicago: (1) Chicago Transit Authority (CTA), Metropolitan rail (Metra), Pace bus and South Shore Line (SSL). CTA, which is the largest one, operates the rail system, also known as "The L", and the extensive bus network of Chicago. Metra is a commuter rail service while Pace operates multiple suburban bus lines. SSL is a single railway line connecting Millennium Station (Chicago CBD, IL) and South Bend International Airport (South Bend, IN). To identify transit gaps, we constructed a transit supply score based on the methodology of Barajas et al. (2021). In more detail, a tract's overall transit supply consists of four variables: transit stop density (number of stops per km^2), route density (route lengths in kilometers per km^2), median daily transit service headway (min), and the number of overnight (11 p.m. - 5 a.m.) stops. We standardized each variable into a Z-score and calculated the mean of all four variables to determine the overall transit supply score for each census tract.

Transit variables information was obtained from General Transit Feed Specification (GTFS) data of each transit authority. In case data were unavailable for a specific transit authority, we used the solely input from CTA. Most of the transit schedules were in effect from May 31, 2019, which is the midpoint of the pre COVID-19 period. We used the same transit supply score for all three time periods of the study even though in reality there might be some discrepancies due to scheduling changes. We estimate that the results would not differ substantially considering that transit was operating normally during COVID-19 as many workers continued to commute. For the descriptive and bivariate analysis, we used the overall transit score, but we decomposed it into the several transit variables when developing the spatial regression models. Moreover, considering that rail plays an important role in the generation of first/last mile trips, we identified census tracts that intersected with 400m buffers around rail stations. Although larger buffers are usually considered to measure the willingness to walk to rail stations, we choose a smaller buffer to understand the attraction near train station themselves (Barajas et al., 2021).

After establishing in which neighborhoods both transit and TNC operate, we obtained census tract-level demographic data from the 2014-2018 5-Year-American-Community-Survey (ACS) (U.S. Census Bureau, 2021). We included variables such as percentage of population by race, percentage of foreign-born population (i.e., not U.S. citizen at birth, including U.S. citizens through naturalization) and population density. Furthermore, we used variables related to transit dependency, including the percentage of households without a vehicle, percentage of young population (i.e., age 10-17), percentage of elderly population (i.e., over 64), percentage of unemployed and median household income. Using the 2017 Longitudinal Employer-Household Dynamics (LEHD) (U.S. Census Bureau, 2017) we complemented the demographic data with job density data and job density by income category (low wage, mid wage, high wage). Low wage jobs are considered jobs with a salary (in 2017 dollars) of $1,250 per month or less, mid-wage jobs at $1,252-$3,333 per month, and high-wage jobs at more than $3,333 per month.

3.3. Methods

3.3.1. Descriptive Analysis

Following the methodology of Barajas et al. (2021) used for all TNC trips, we studied ride-splitting pickups and drop-offs in Chicago in total and across five temporal periods throughout the day that correspond approximately to the CTA transit schedules: (1) weekday daytime hours (5 a.m.–11 p.m.); (2) weekday overnight hours (11 p.m.–5 a.m.); (3) weekday peaks (6 a.m.–9 a.m., 4 p.m.–7 p.m.); (4) weekend daytime hours (5a.m.–11 p.m.); and (5) weekend overnight hours (11 p.m.–5 a.m.). We implemented the local Moran's I, which is used as an indicator of autocorrelation, to identify hotspot and coldspot clusters of ride-splitting trip ends (Anselin, 1995). The local Moran's I statistic for an observation is given by equation (1):

$$I_i = cz_i \sum_j w_{ij} z_j \quad (1)$$

where z is the relevant variable's deviation from the mean with i and j denoting different locations (i.e., census tracts), w_{ij} is the spatial weight between census tracts i and j, and c is a scaling factor, ignorable for interpretation. We also used queen contiguity to define spatial weights for each neighbor. When using queen contiguity, neighbors are considered only census tracts which share any length of their sides or corner. Neighboring tracts receive a weight of 1 while non-neighbors receive a weight of 0. The spatial algorithm can identify hotspot and coldspot clusters. Hotspot clusters are characterized by a value with large positive deviation from the mean surrounded by other high values while coldspot clusters are characterized by a value with large negative deviation from the mean surrounded by other low values. In addition, the algorithm can detect outliers of high values surrounded by low (high-low clusters) and vice versa (low-high clusters). A cluster is considered significant when the observed I values are significantly different from I values generated by random permutations.

Bivariate analysis was implemented to examine the spatial correlation between pooled pickups/drop-offs, socio-demographic variables, and transit supply. Similarly, as above, we used the bivariate version of local Moran's I (I_B), whose interpretation is the same as the univariate version, to identify significant clusters and outliers. The formula is similar and is given by equation (2):

$$I_{B,i} = cx_i \sum_j w_{ij} y_j \quad (2)$$

and it captures the relationship between the value for one variable at location i, x_i, and the average of the neighboring values for another variable at location j, y_j. The x and y variables are standardized with a mean of zero and variance of one. We conducted separate analyses for ride-splitting pickups and drop-offs, though results were generally consistent for both trip ends.

3.3.2. Spatial Regression Models

The next step is to develop multivariate spatial regression models to determine the correlation between transit supply and ride-splitting pickups/drop-offs for each census tract. If our initial hypothesis stands, which means ride-splitting services fill the transit gap, we expect to see negative correlation between transit supply and ride-splitting trip ends. Similarly, if segregated communities are transit-dependent but live in areas without transit supply, then we should observe a positive association between specific demographics (e.g., the share of Black/African Americans, the share of households without a vehicle) and ride-splitting trips. Considering the above, our independent variables for all models remain the same. We include variables for race, foreign born status, population density, transit-dependence variables, employment density by wage classification, and the individual transit metrics that we estimated for the total transit score. In addition, we include the variable which denotes if a census tract intersects with a 400m-buffer around a rail station. The reason we divide the total transit score into its components is because we want to examine if there is a hidden relationship between a specific transit service variable and ride-splitting trips. We created models for the total pooled pickups/drop-offs for the entire dataset but also separately for each time-period of the day: (1) weekday daytime, (2) weekday peak, (3) weekday overnight, (4) weekend daytime, (5) weekend overnight.

The regression models included all census tracts within city limits which had ride-splitting activity apart from certain census tracts without population such as the two international airports and several open spaces. We used the same methodology as in Elhorst (2010) to determine the most suitable model. We started testing an ordinary least squares (OLS) regression using pool pickups/drop-offs as the dependent variable. To avoid multicollinearity between the independent variables we performed the variable inflation factor (VIF). However, none of the independent variables had a high VIF apart from some demographic characteristics (e.g., race) but we decided not to remove them because Chicago is highly segregated, thus we expected a moderate correlation.

We observed that the OLS model had a significant degree of spatial autocorrelation (Moran's I = 0.34, $p < 0.001$). Using Lagrange Multiplier tests and null hypothesis tests we rejected the OLS model in favor of spatial error and spatial lag models, and null hypothesis tests rejected both in favor of a Spatial Durbin Model (SDM). An SDM model offers insight about both endogenous and exogenous relationships with neighboring census tracts (Yang et al., 2015; LeSage at al., 2009). This means that the number of pool pickups or drop-offs in a census tract is impacted by the number of equivalent trips in neighboring tracts. Furthermore, demographic characteristics within but also outside the census tract also play a key role in the number of pool trips that are generated or received. The SDM is given by equation (3):

$$Y = \varrho WY + \alpha I_N + X\beta + WX\Theta + \varepsilon \quad (3)$$

where Y is the number of ride-splitting pickups or drop-offs divided by the total ride-sourcing trips; W is the spatial weights matrix indicating influence of neighbors; X is the matrix of explanatory variables, including socioeconomic characteristics, employment type and density, and transit service levels with parameters β to be estimated; ι_N is an $n \times 1$ vector of 1s with intercept α to be estimated; ϱ is the spatial autoregressive term; and Θ is a vector of spatial effects of WX. The error term ε is normally distributed with mean of 0 and variance of $\sigma^2 I_n$ where In is an identity matrix.

To determine the weights between neighbors we used a queen contiguous spatial weights matrix. We started by fitting the model with the normalized pooled pickups/drop-offs as the dependent variable and all independent variables as described earlier. However, after testing the model we observed that spatial autocorrelation was still prevalent and that's why in the end we used k-nearest neighbors weights matrix where $k = 10$.

In the remainder of this paper, we interpret the results focusing both on direct and indirect effects, meaning the contribution of the variables of the in-question census tract as well as the influence of the neighboring census tracts according to the spatial weights matrix. We performed cluster analysis using GeoDa (Anselin et al., 2009) while regression models were estimated using the spdep package (Bivand et al., 2008) in R (Team, 2013). The coefficients for each model are presented in the Appendices (Table 4, Table 5, Table 6).

Chapter 4

Results

4.1. Transit Supply in Chicago

As we observe in Figure 2, census tracts with high transit supply appear to be clustered around the Loop and the Near North Side neighborhoods. In addition, Chicago has higher transit supply along the subway corridors and as the distance from the transit line increases, transit supply is found scattered in various neighborhoods without exhibiting a specific pattern. As it was expected, areas serviced by rail experience better transit supply than areas serviced only by bus.

By running an OLS regression model, we cannot establish a strong correlation between transit supply and sociodemographic characteristics such as race or income and this is also confirmed by Barajas et al., (2021). This observation might be specific to Chicago since literature suggests that most transit deserts appear to be in low-income areas where people of color reside. When regressing transit score with the percentage of Black/African Americans we did not establish any significant correlation between them (Figure 3). The same observation was also made regarding transit supply and median household income (Figure 4). Moreover, high income households do not necessarily experience higher levels of transit supply and vice versa. Finally, transit supply was mostly correlated with employment density.

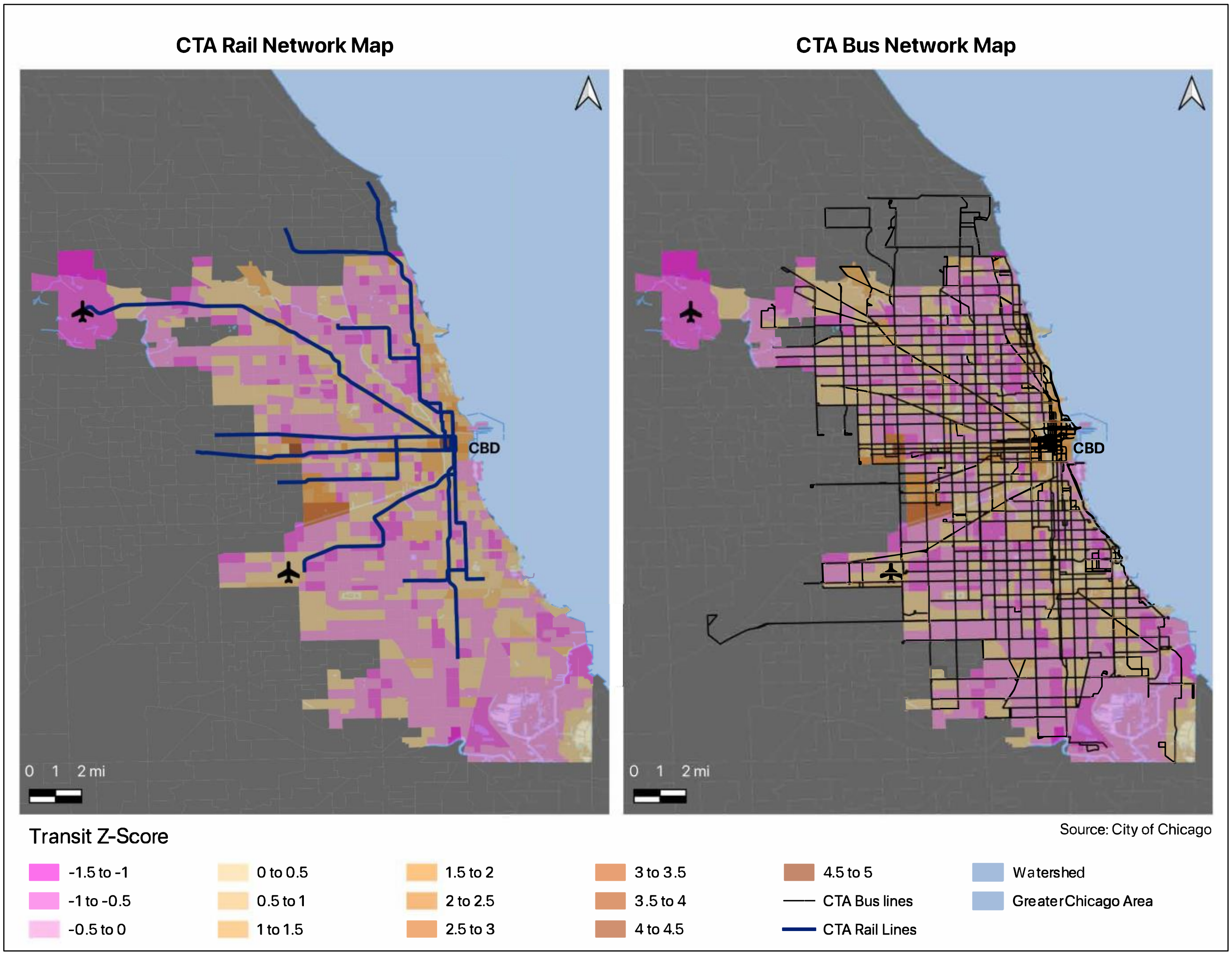


Figure 2: Distribution of transit service in Chicago (CTA: Chicago Transit Authority)

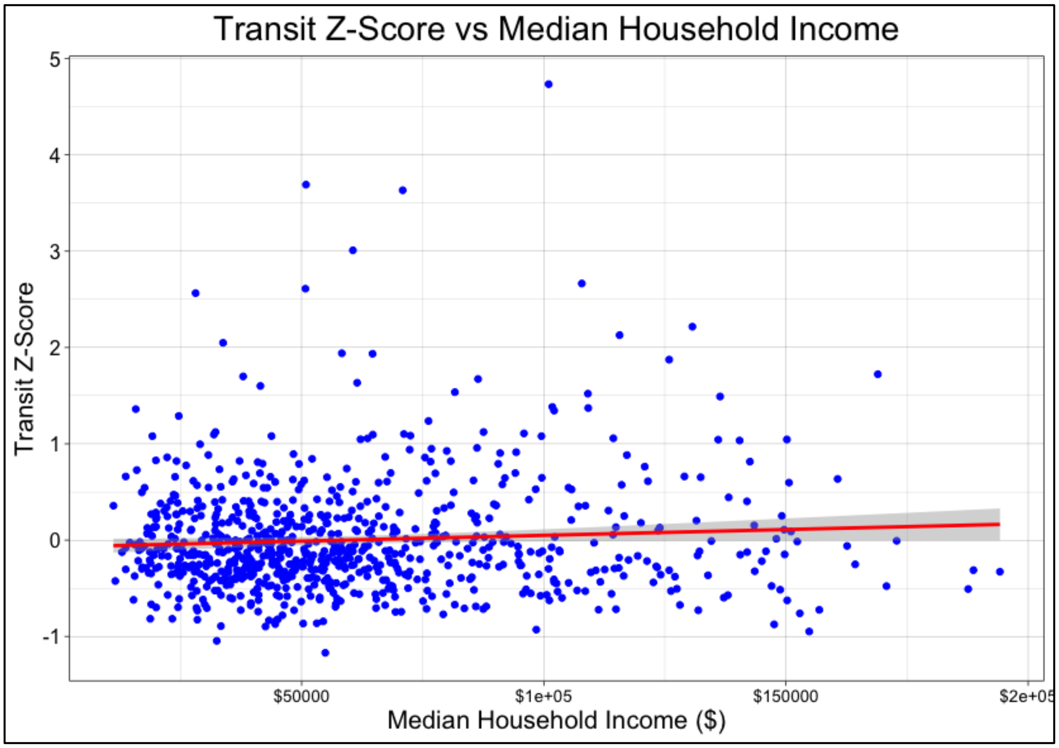


Figure 3: Correlation between transit score and % of Black/African Americans

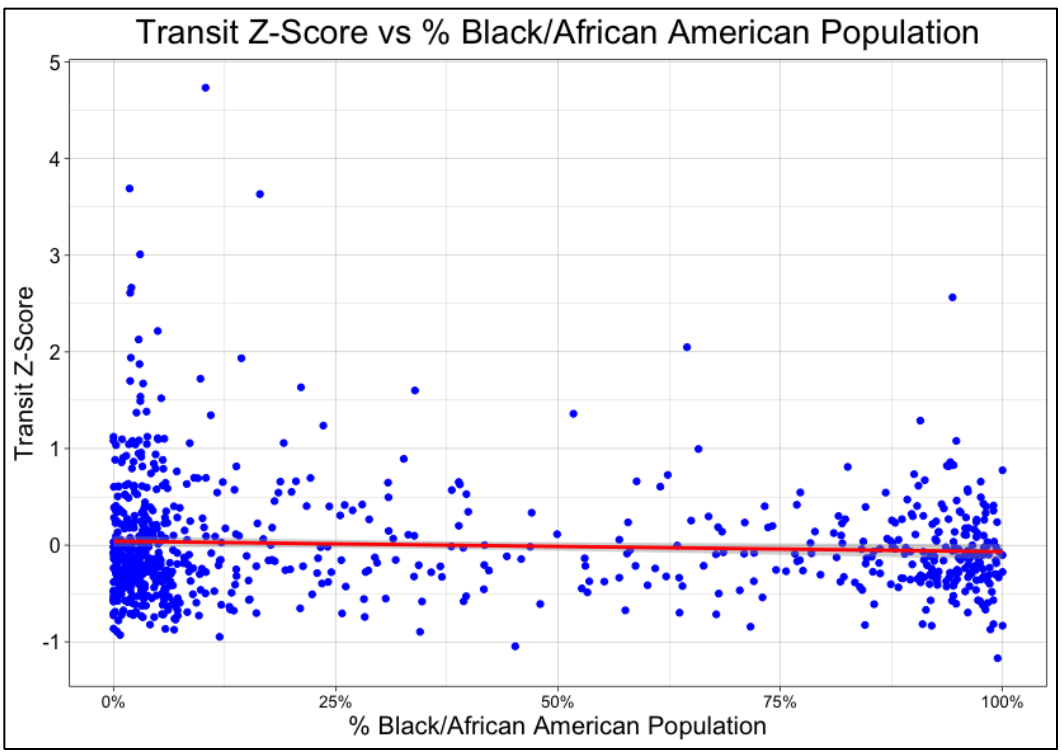


Figure 4: Correlation between transit score and median household income ($)

4.2. Ride-sourcing Travel in Chicago pre COVID-19

The pre COVID-19 phase is the time-period between November 1, 2018, and December 31, 2019. During that period, more than 128 million ride-sourcing trips were performed in the City of Chicago. After cleaning the dataset, we end up with 85,025,324 trips (Table 1). 176,997 trips were performed on an average weekday and 255,886 trips were performed on average during weekends. Also, we should mention that the percentage of pooled trips is approximately 17%, which is within the ranges we find in literature.

Table 1: Chicago ride-sourcing statistics pre COVID-19

Chicago Ride-sourcing Statistics

November 1, 2018 to December 31, 2019

Variable	Mean (SD) or %
Trip distance (mi)	4.41 (4.22)
Trip time (min)	15.74 (10.08)
Total fare ($)	13.06 (8.34)
Trips in peak period[1]	32%
Shared trip authorized	17%
Trips per weekday	176,997 (35,799)
Trips per weekend day	255,886 (34,841)
N	85,025,324

Note 1: peak = weekdays, 6 a.m.-9 a.m., 4 p.m.-7 p.m.

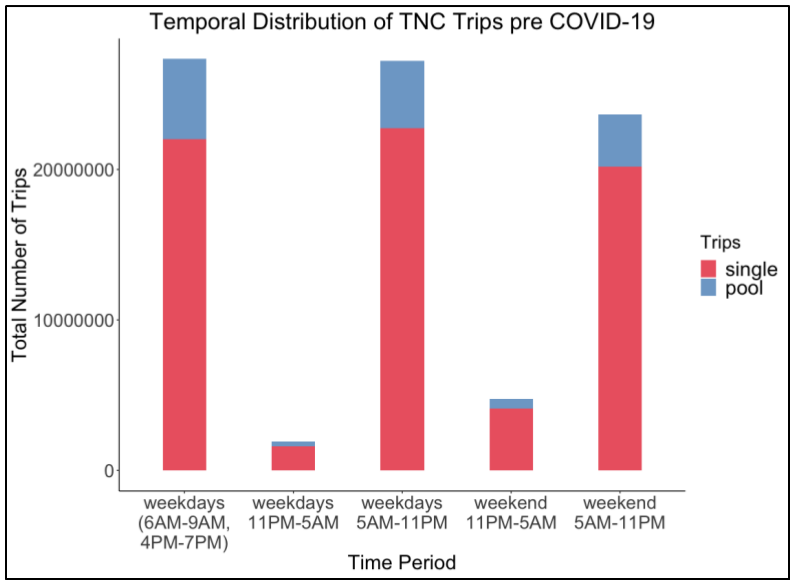


Figure 5: Temporal distribution of TNC trips pre COVID-19

As expected, most trips take place on weekday mornings and afternoons (i.e., commuting trips) or on weekend nights (i.e., leisure trips) (Figure 5). We observe similar trip patterns for both pool pickups and drop-offs share with slightly higher percentages for drop-offs (Figure 6). More specifically, higher percentages of ride-splitting pickups are mostly found in the West and South part of Chicago in the community areas of Fuller Park (48.4%), West Garfield Park (47.6%), Riverdale (47.3%), West Englewood (46.8%) and Washington Park (46.6%). Similar distribution is observed with respect to drop-offs, but more community areas pass the 40% threshold of shared rides. All the areas mentioned above are populated predominately by Latinx and Black/African American populations. In contrast, community areas around and within CBD appear to have less than 10% of shared trips. According to our analysis ride-splitting is mostly utilized by disadvantaged and low-income communities.

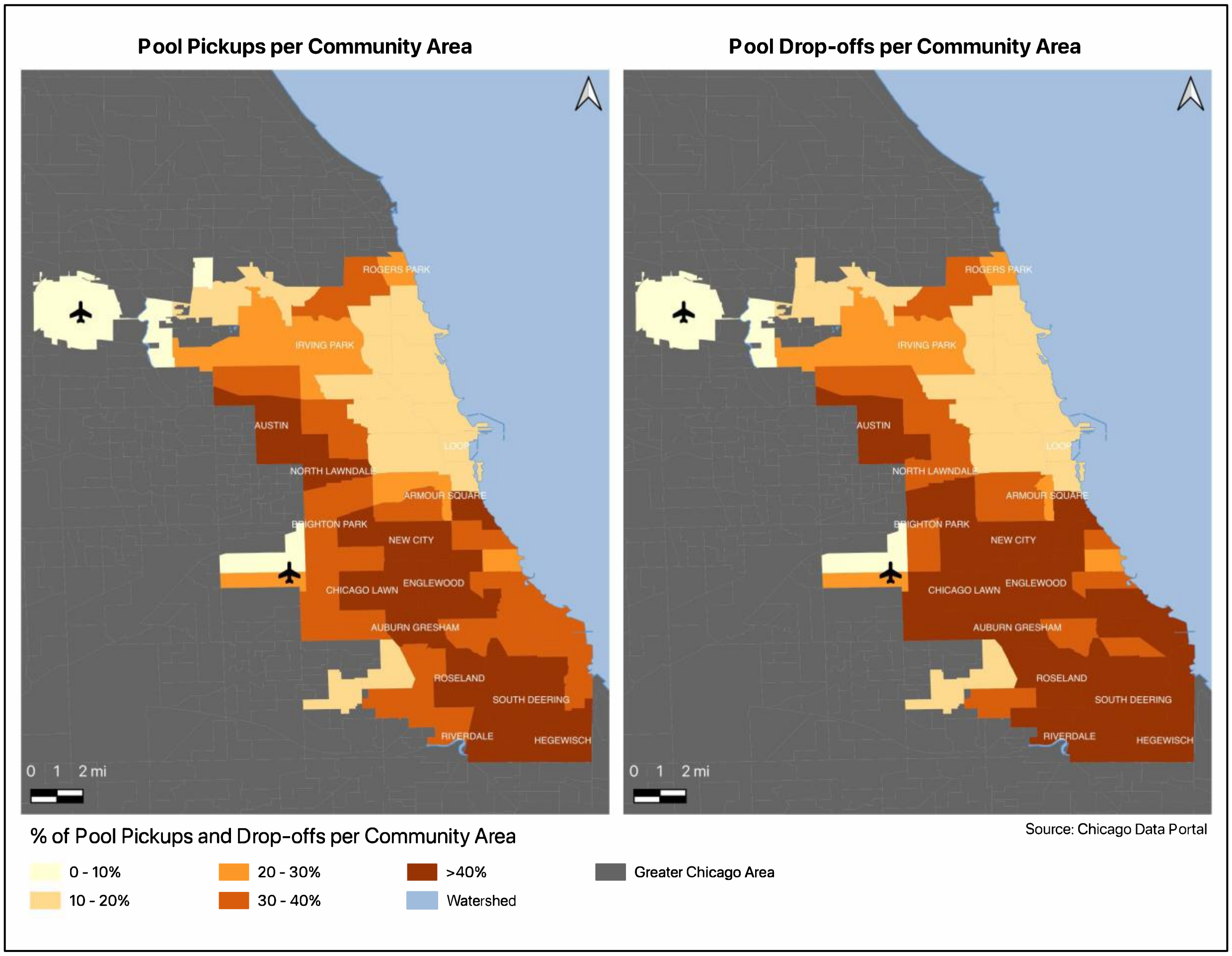


Figure 6: Pool pickups (%) and drop-offs (%) pre COVID-19 per community area

We also performed cluster analysis to determine hotspot and coldspot clusters of ride-splitting shares in the City of Chicago. We observe once again that cluster patterns are similar between pooled pickups and drop-offs (Figure 7). Most pooled pickup/drop-off hotspots are observed in the West and South part of Chicago. In contrast, pooled pickup/drop-off coldspots are located in CBD and in the North part of Chicago. As before, it becomes clear that ride-splitting is primarily used by Black/African American and Latinx neighborhoods of low-income.

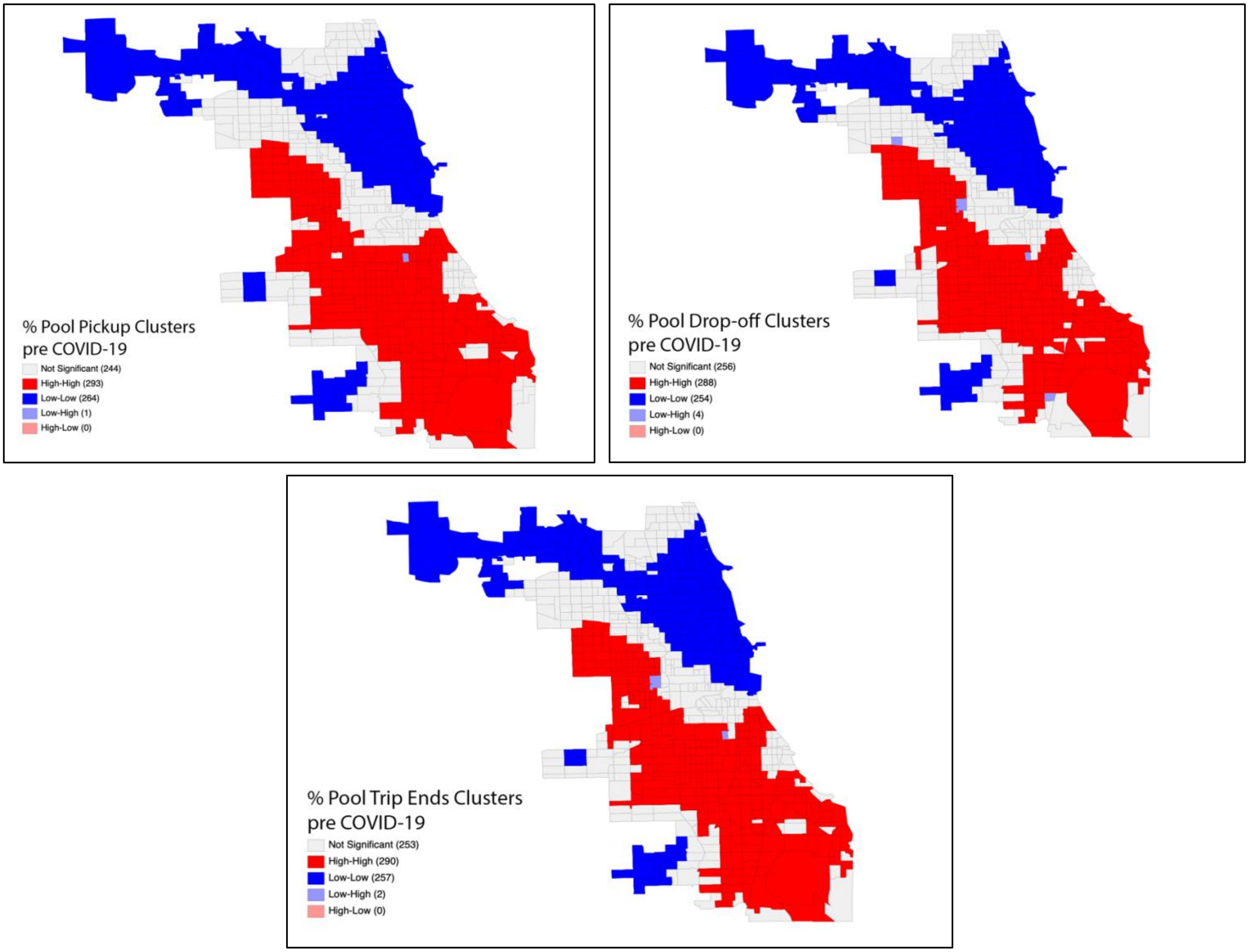


Figure 7: Pool pickup, drop-off, and trip ends clusters pre COVID-19

By plotting the variables and fitting a regression line, we found that ride-splitting pickups and drop-offs are significantly correlated with specific racial and ethnic characteristics. In more detail, Figure 8 reveals that a high percentage of Black/African American and Latinx population results in higher ride-splitting activity. In contrast, areas that are primarily populated by White residents exhibit low percentages of ride-splitting trips which seems to confirm our hypothesis that ride-splitting is utilized mostly by disadvantaged and low-income communities.

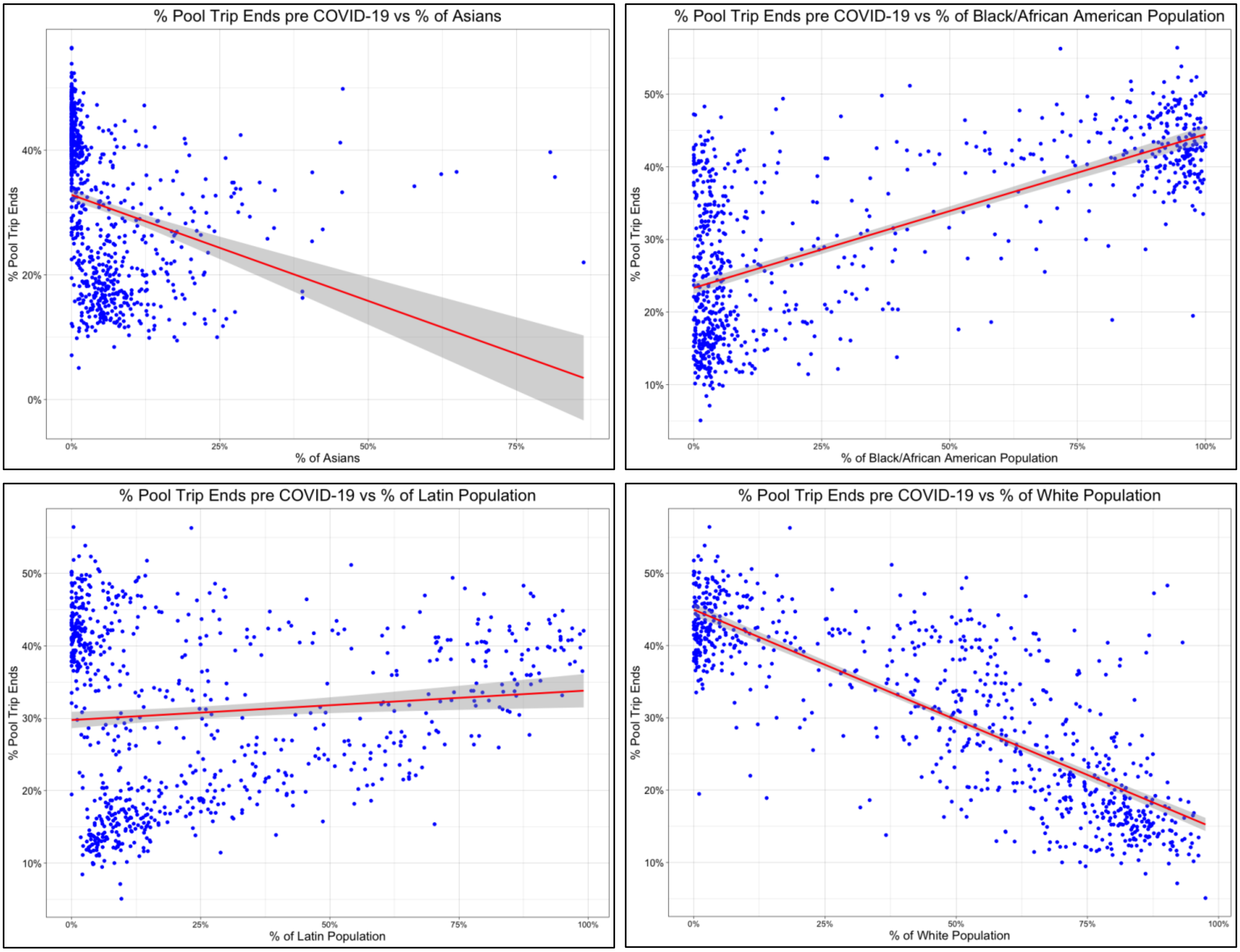


Figure 8: Correlations between pool trip ends and racial characteristics

4.3. In comparison to single trips, could ride-splitting services effectively fill the mobility gap for those living in transit deserts?

According to the bivariate maps, there is not a strong negative correlation between ride-splitting trips and transit deserts. As shown in Figure 9, 35 census tracts are classified in the category of high ride-splitting percentage vs low transit score and are mostly found in the South part of Chicago. Interestingly, we observe more census tracts in the high-low category with respect to pooled trips compared to single rides which means that indeed ride-splitting is a stronger preference for people located in transit deserts compared to single service. Also, it's worth mentioning that single trips seem to act as a substitute for the lack of transit in wealthier neighborhoods located in the North part of Chicago. Therefore, ride-splitting is moderately utilized by disadvantaged and low-income communities to fill transit gaps while single mode is used as an alternative to transit in more affluent neighborhoods. Furthermore, during weekday night, when transit supply is lower, we observe that 11 more census tracts are utilizing ride-splitting in transit deserts (Figure 10). Although there is a lack of significant correlation (Figure 11), we do observe that ride-splitting activity is decreasing as transit supply increases.

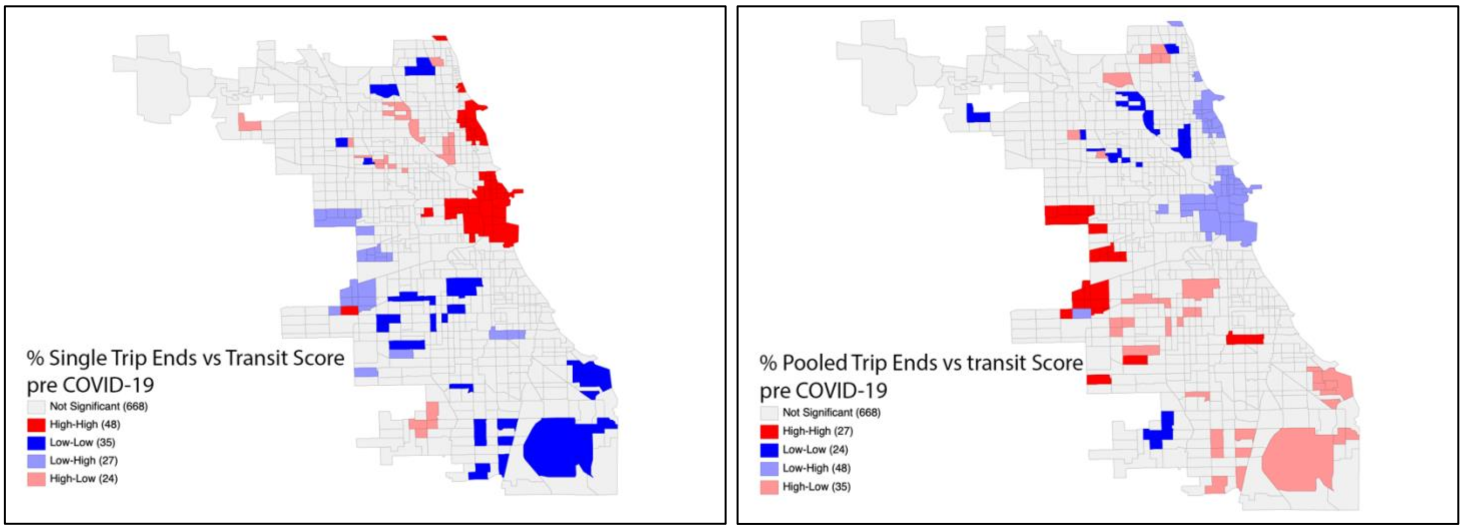


Figure 9: Bivariate maps of single and pool trip ends with respect to transit score pre COVID-19

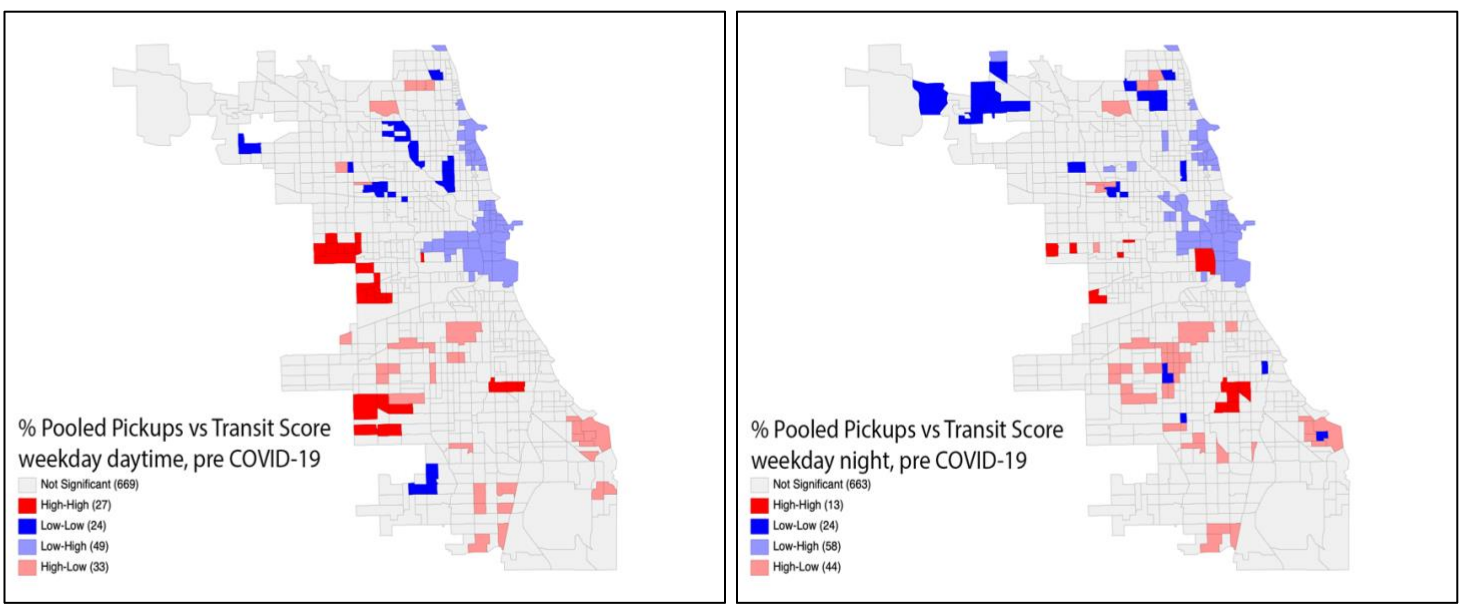


Figure 10: Bivariate maps of pooled pickups during weekday daytime and night

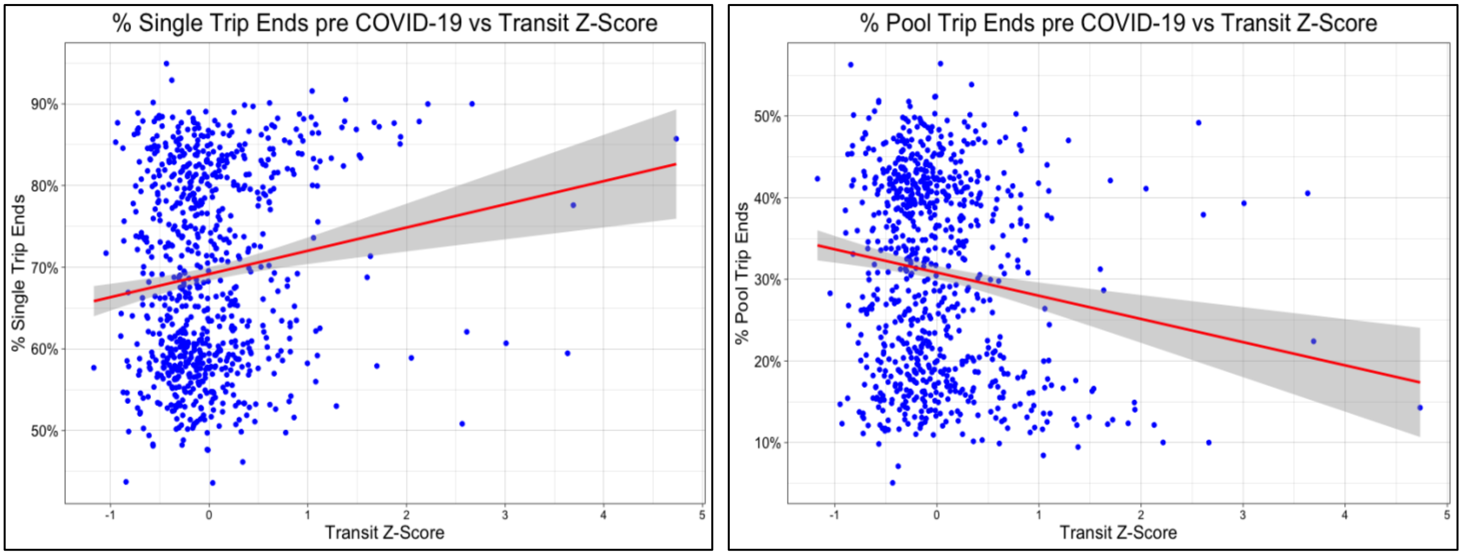


Figure 11: Correlation between trip ends and transit score regarding single and ride-splitting services

Although bivariate analysis revealed modest correlation between ride-splitting and transit supply, using spatial regression models we found that transit route density had a significant overall negative effect on ride-splitting trip shares. Lower transit route density resulted in a higher percentage of ride-splitting pickups and drop-offs, when we examined the total trips. The direct and indirect effect of transit route density also exhibit a negative correlation with ride-splitting trips. Apart from transit route density some other direct and indirect effects were found statistically significant in some models, such as transit stop density and proximity to rail station. Both variables were negatively correlated with the percentage of ride-splitting trip ends. Total overnight stops and median daily transit headway had very little influence in ride-splitting activity in most of the models, thus we do not report them in the analytical results.

When we examined the detailed coefficients, we found that for every 10% decrease in transit route density there is a 2.6% increase in the share of pooled pickups and a 1.4% increase in the share of pooled drop-offs. Regarding the direct effect of proximity to rail station, tracts which are not located within a walking distance of rail stations (400m) had 0.9 % and 1.6% increase in the share of ride-splitting pickups and drop-offs respectively. The effect of a nearby rail station seems to be consistent throughout all models. During overnight weekday service, we found that a 10% decrease in a tracts' transit stop density resulted in a 0.3% increase in the share of ride-splitting pickups within the tract while the indirect effect was almost seven times larger. Moreover, during overnight weekend service, a 10% decrease in transit route density led to 1.1% increase in ride-splitting pickup shares for neighboring tracts. Overall, we observe that lower levels of transit supply result in higher levels of ride-splitting activity which means that communities residing in transit deserts utilize ride-splitting, to some extent, to make up for the lack of public transit. At this point, we should state that the effects are not large in magnitude but still indicate that ride-splitting is used to fill transit gaps.

As far as sociodemographic characteristics are concerned, throughout all models there is a statistically significant direct effect between people of color and ride-splitting trip ends. In more detail, a 10 % increase in Black/African Americans and Latinx increased the percentage of ride-splitting pickups by 0.2% and 0.13% respectively. Similar were the effects on pooled drop-offs. Moreover, we found statistically significant positive correlation between transit-dependent population and ride-splitting activity: a 10% increase in households without a vehicle resulted in 1.3% and 0.7% increase in the ride-splitting pickup and drop-off shares respectively. The direct effect of young population was also found statistically significant and a 10% increase in young population resulted in 0.13% increase in the percentage of ride-splitting trip ends. In addition, income had a negative direct effect on ride-splitting and more specifically a 10% increase in income led in approximately 0.2% decrease in the percentage of ride-splitting pickups and drop-offs. During peak hours, a 10% increase in density led to 0.19% increase in the share of ride-splitting pickups and drop-offs regarding the direct effect. Similar were the effects of income and density during overnight weekday time. Interestingly, during overnight weekday and weekend hours, tracts with a higher percentage of young population saw less ride-splitting activity compared to daytime hours but a 10% increase in elderly population resulted in 1.9% and 2.1% increase in the percentage of ride-splitting pickups and drop-offs respectively.

Table 2: Total pool pickups and drop-offs model effects

Ride-splitting Model Effects						
	Pickups (all)			Drop-offs(all)		
	Direct	Indirect	Total	Direct	Indirect	Total
Black/African American population (%)	0.002	0.001	*0.003*	0.002	0.000	0.002
Latinx population (%)	0.001	0.008	0.009	0.002	0.004	0.006
Asian population (%)	0.001	0.001	0.003	0.002	0.000	0.001
Foreign-born population (%)	0.000	−0.009	−0.009	0.000	−0.005	−0.005
No household vehicles (%)	0.000	0.014	0.014	*0.000*	0.008	0.008
Population age 10-17 (%)	0.001	*−0.023*	*−0.022*	0.001	−0.009	−0.008
Population age 65+ (%)	0.000	0.016	0.016	0.000	0.017	0.017
Unemployed (%)	0.000	−0.004	−0.004	0.000	−0.002	−0.002
Median household income (log $)	−0.018	0.066	0.048	−0.020	−0.033	−0.052
Population density (log)	−0.006	0.040	0.034	0.012	0.026	0.038
Low-wage employment density (log)	0.000	−0.067	−0.067	−0.003	−0.050	*−0.053*
High-wage employment density (log)	0.000	0.038	0.038	−0.002	0.058	*0.056*
Transit stop density (log)	0.001	0.161	0.163	−0.002	0.058	0.056
Transit route density (log)	−0.005	−0.252	−0.257	−0.006	−0.133	−0.138
Number overnight stops	0.000	0.003	0.003	0.001	−0.004	−0.003
Median transit headway (min)	0.000	*−0.001*	*−0.001*	0.000	0.000	0.000
Rail station within 400 m	−0.009	−0.140	−0.149	−0.016	*−0.099*	−0.115

Note: Bold indicates $p < 0.05$, italics $p < 0.10$

4.4. How did the suspension of ride-splitting, due to the pandemic, influence mobility choices, particularly of those living in transit deserts?

TNC services suspended ride-splitting in March 2020 to prevent the pandemic from spreading. One of the objectives of this research is to examine how did the suspension of ride-splitting impact users and if ride-splitting has bounced back in the post pandemic era. To do that, we have gathered trip data before, during and after the pandemic. As mentioned before, the post pandemic era began the day ride-splitting was relaunched until the last day for which we have available data. We should also consider the fact that Uber reintroduced UberPool one year after Lyft re-introduced Lyft Line. To account for any discrepancies related to COVID-19 and telework we have standardized the number of single and pooled trips for every time-period. We subtracted the mean from every value and divided by the standard deviation. We created choropleth maps showing the new standardized trips for every census tract. One hypothesis that we would like to test is if people who were using ride-splitting switched to single mode during the pandemic or not. If they made the switch, then we expect to observe an increase in the number of single trips during COVID-19 compared to the pre COVID-19 period. In addition, we performed bivariate analysis as before to study how single trip patterns changed during COVID-19 related to transit deserts and if ride-splitting patterns have re-emerged in the post COVID-19 period.

From Figure 12 we observe differences in single standardized trips before and during COVID-19. Starting from the downtown areas and the surrounding suburbs we observe that single trips in CBD were reduced in total from 13.5 to 10.6 pickups. This means that during COVID-19, for this specific census tract, single trips were reduced by 2.9 standard deviations compared to pre COVID-19. However, in the census tract South of the Loop we observe that there was a surge of single trips from 4.9 to 6.1 standard deviations above the mean. The rest of the census tracts around CBD experienced subtle changes which are not worth reporting here. Also, in neighborhoods nearby West Town we do see some increase in single trips suggesting that people might be using TNC services more in the suburbs during COVID-19. An important observation is that in mid-pandemic several census tracts in the South of the city appear to have an increase in single trips, which means that in some few cases people switched from ride-splitting or transit to single TNC service.

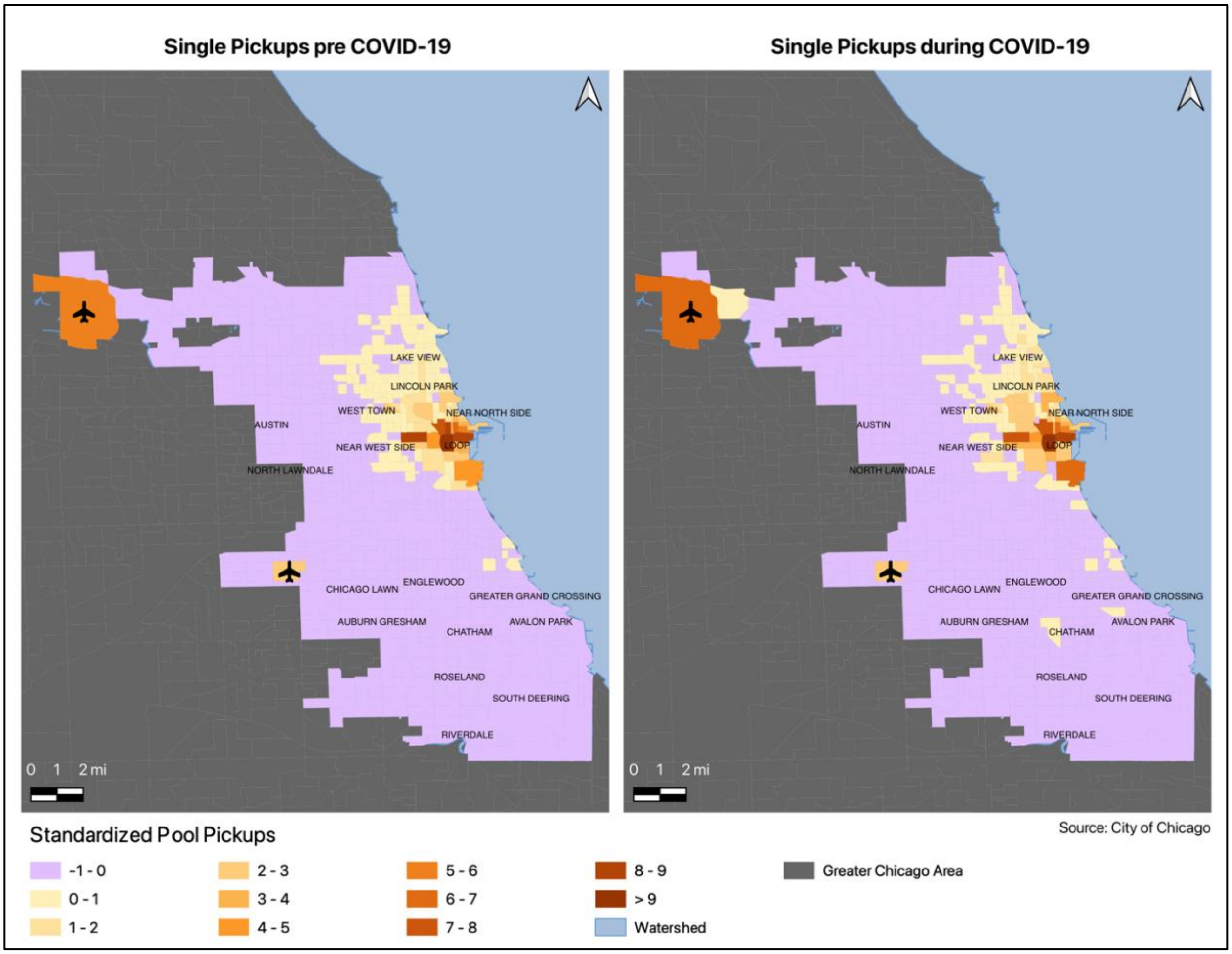


Figure 12: Standardized single pickups before and during COVID-19

With respect to ride-splitting, we can see that post pandemic pickups are lower in most census tracts (Figure 13). Census tracts that were utilizing ride-splitting in the South part of Chicago before COVID-19 have not recovered in the post COVID-19 era. It's too soon to confidently infer that ride-splitting has not recovered since most of the ride-splitting activity was observed by Uber which re-introduced its services one year later than Lyft and still, we don't have enough available data.

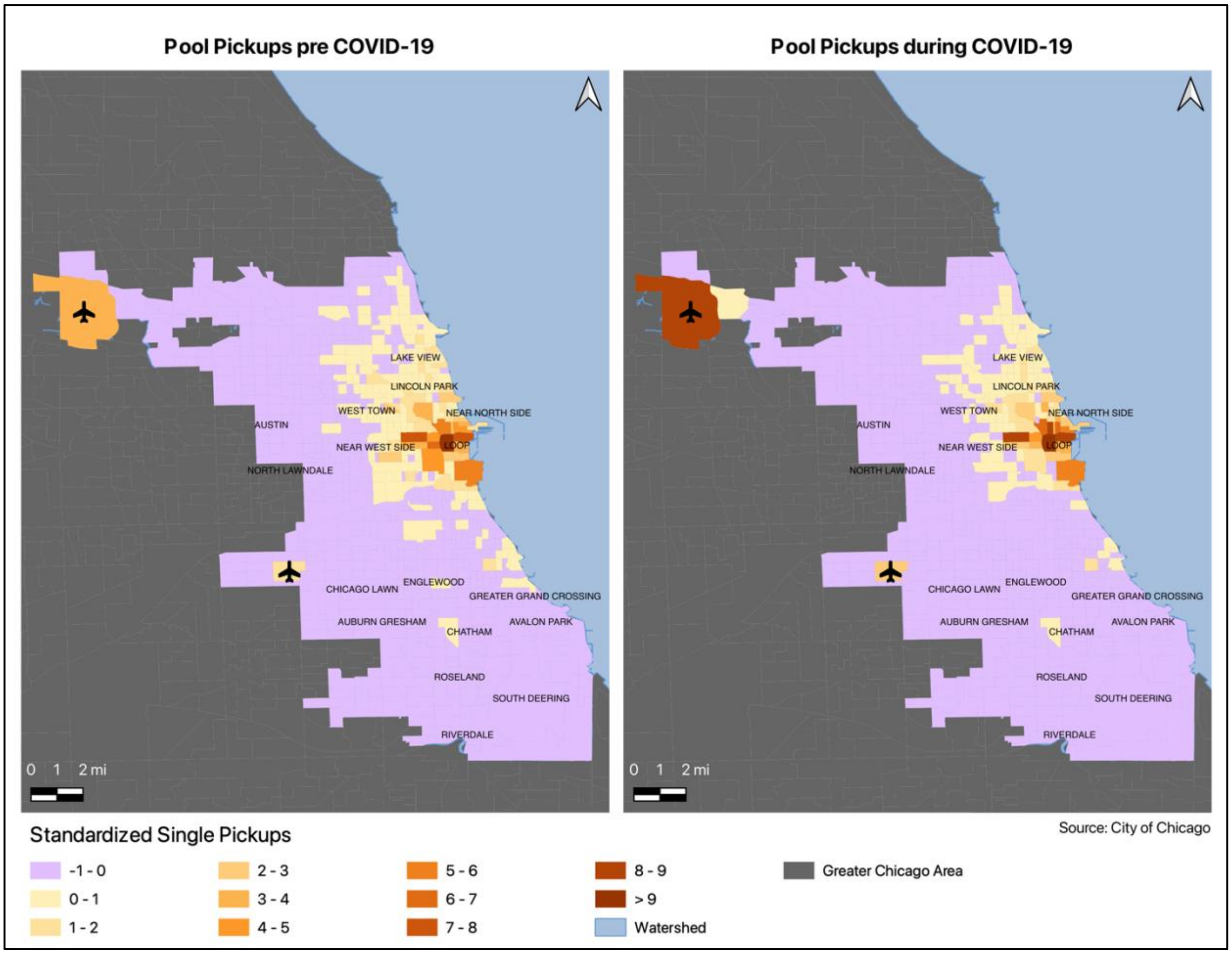
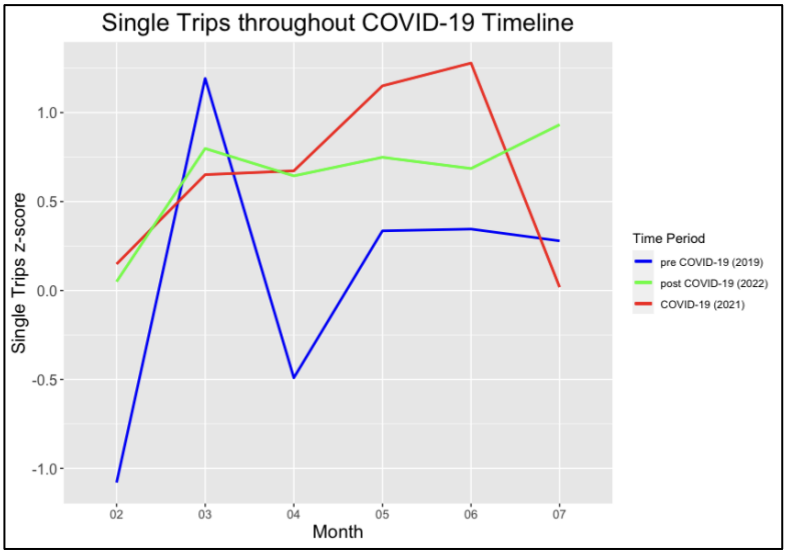


Figure 13: Standardized pool pickups before and after COVID-19

In Figure 14 we present how the z-score of single and pooled trips changed during six consecutive months for all three time periods of the study. We observe that single trips during COVID-19 were relatively higher for the months of April – July compared to the pre COVID-19 period which is a sign of substitution between single and ride-splitting services. Moreover, after COVID-19, single trips seem to be lower compared to mid-pandemic which strengthens our hypothesis that some people switched to single during COVID-19 because they did not have an alternative travel mode. It's worth mentioning that single trips during and after the pandemic remain higher compared to pre-pandemic levels. Lower transit ridership during and post COVID-19 is also another indication that people are still using other services to fulfill their mobility needs. According to CTA's September 2022 Ridership Report transit use is still 43% lower compared to September 2019 (Chicago Transit Authority, 2022).



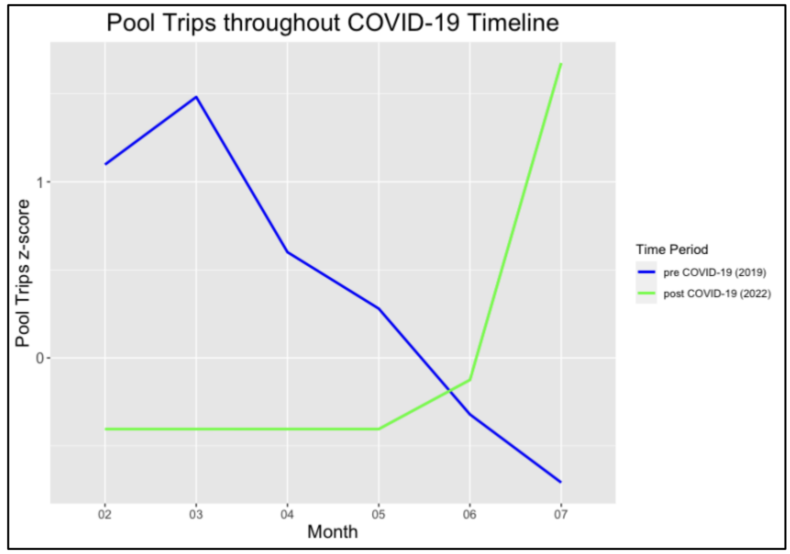
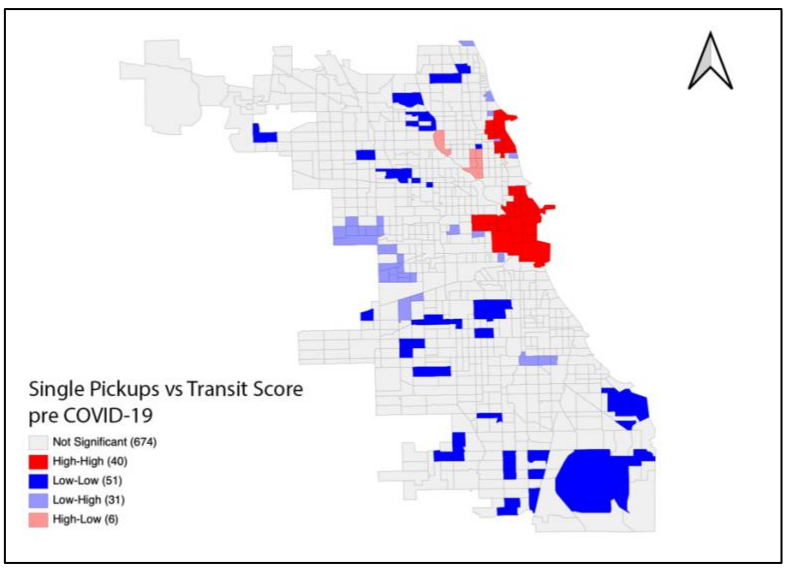


Figure 14: Monthly standardized single and pool trips throughout COVID-19 timeline



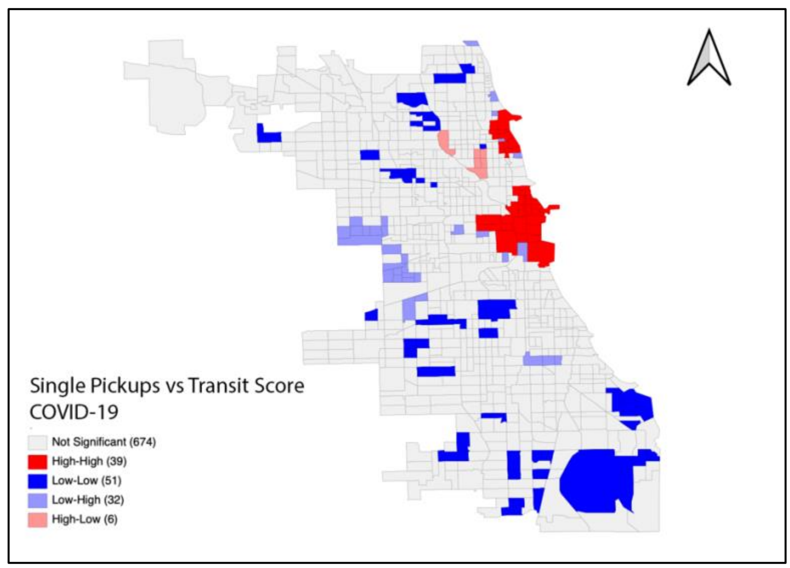


Figure 15: Bivariate analysis of single pickups vs transit score before and during COVID-19

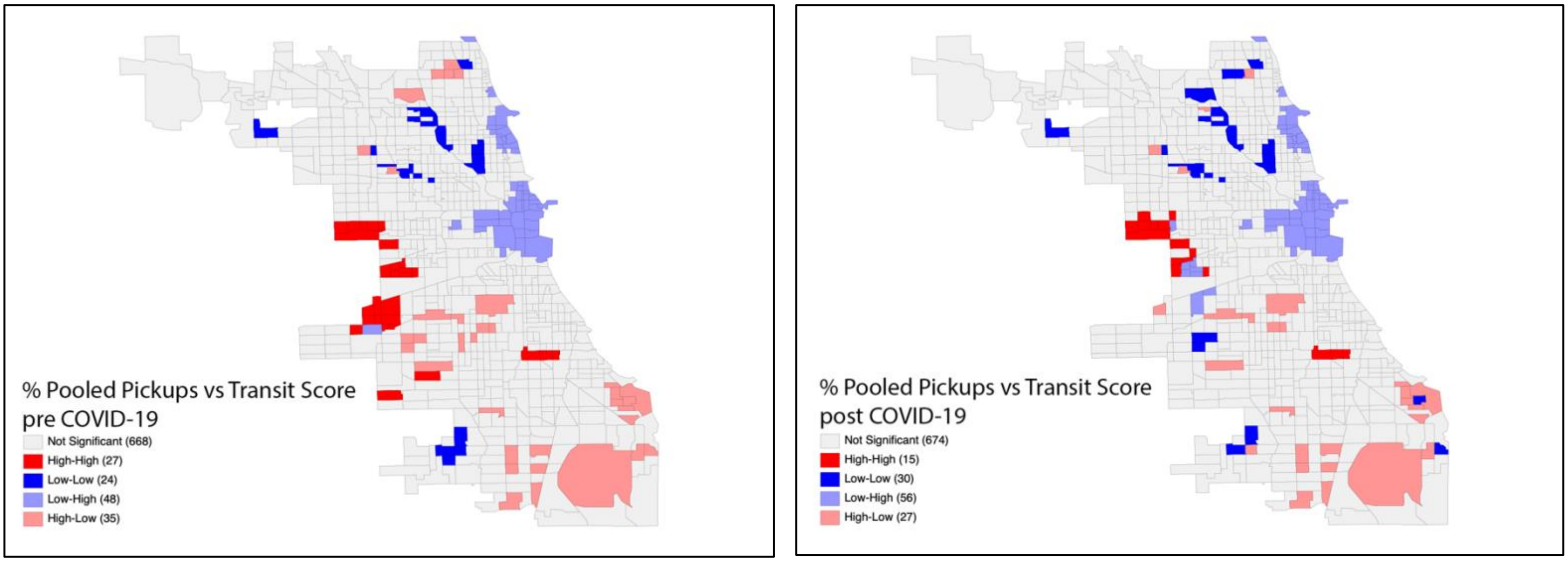


Figure 16: Bivariate analysis of pool pickups vs transit score before and after COVID-19

As far as the bivariate analysis is concerned (Figure 15), we observe that the outliers of high single pickups vs low transit score did not change during COVID-19, meaning that we cannot infer that people who used ride-splitting in transit deserts switched to single mode due to the pandemic. If the latter was true, then we would expect to see more outliers in single pickups during COVID-19. What is more, the census tracts classified in the high pool-low transit score category pre COVID-19 seem to have mostly recovered in the post COVID-19 era but still not completely (Figure 16).

4.5. Policy Analysis

Over the years it has been reported that TNC services have had some unintended consequences to metropolitan areas such as increased VMT due to deadheading, transit ridership decline and increased traffic congestion. To address these issues local authorities across the U.S. have tried to regulate ride-sourcing companies, including imposing fees or taxes. Such policies aim to reduce single rides by shifting users to ride-splitting and at the same time act as a revenue source for transit agencies. Chicago was one of the early adopters of such policies. The first set of fees was implemented in 2014 and then was increased incrementally over the next years without differentiation among single and pooled rides or whether the trip started or ended within the CBD (Lowe et al., 2021). However, a study undertaken by the City of Chicago (2019) showed a 271% increase in TNC rides after 2015, thus local authorities decided to change the initial fees to a congested-oriented tax starting from January 6, 2020. General per ride fees increased from $0.72 to $1.25, but more significantly adding a downtown surcharge of $1.75 on weekdays and retaining the special venue surcharge for trips to and from airports and two major visit destinations (Navy Pier and McCormick Place). Thus, TNC single trips starting or ending in the downtown zone are charged a $3.00 fee and if the trip includes a special venue, then it rises to $8.00. The structure of the new tax is described in more detail in the Appendix (Table 7).

To promote ride-splitting, pooled rides were exempted from the Downtown Zone Area fee and the general fee was reduced by $0.07 (BACP, 2019). The Downtown Zone Area is depicted in Figure 17. Imposing a tax uniformly across the population might not be the ideal measure to address congestion since low-income and disadvantaged communities are utilizing ride-splitting services to substitute for the lack of transit. Even a small tax can increase the mobility expenses of low-income households which would otherwise use this service. We used data before and after Jan. 6, 2020, to study the impact of the congestion tax on the average cost of a ride-splitting trip. We used trips that begin or end within the Downtown Zone Area and examined only the base fare including taxes but excluding extra charges and tips. The average cost change for TNC and transit services are depicted in Table 3.

Figure 17: Downtown zone area

Table 3: Cost comparison for trips starting or ending within the Downtown Zone Area

Cost Comparison for trips starting or ending in Downtown Zone	Nov 1, 2018 - Jan 6, 2020				Jan 6, 2020 - Feb 9, 2023 (excluding COVID-19 period)			
Variables	Average Cost	Tax	Total Average Cost	Change (%)	Average Cost	Tax	Total Average Cost	Change (%)
Single Ride	$10.78	$0.72	$11.50	6.67%	$15.41	$3.00	$18.41	19.47%
Pooled Ride	$7.05	$0.72	$7.77	10.21%	$12.87	$1.25	$14.12	9.17%
Transit	$2.50	$0.00	$2.50	0.00%	$2.50	$0.00	$2.50	0.00%

Before January 6, 2020, the total average cost for a single and pooled ride was $11.50 and $7.77 respectively (the subway fare did not change throughout the study period and remained at $2.50). After January 6, 2020, the total average cost for a single ride, was $18.41, which means that the new tax has increased the base fare by approximately 20% compared to 6.67% before the tax was reformed. As far as ride-splitting is concerned, the new total average cost was $14.12 lowering the percentage of change from 10.21% to 9.17%. The average single trip could cost approximately 30-50% more than a pooled trip which could result in substantial extra cost for a household. This is also confirmed by Schwieterman (2019) who found that by using ride-splitting services the cost can go down up to 50%. Indeed, the new ground transportation tax is lower for ride-splitting trips compared to the previous one, but the difference is negligible. Since transit-dependent population use ride-splitting to substitute for the lack of transit, we observe that ride-splitting costs almost 6 times more than taking transit (Figure 18). Therefore, the cost of ride-splitting still remains an expensive option for low-income and disadvantaged communities. Adding a tax to an already high fare does not contribute to equitable mobility.

We argue that if the tax is eliminated for ride-splitting trips and instead local authorities offer a 50% subsidy, up to $5.00, for every pooled trip, then the ride-splitting cost seems more competitive with respect to single mode and transit. According to Vance (2020) the ground transportation tax raised $190.5 million in 2020 of which only 10% was dedicated to improving transit. By allocating more funds towards such policies, the average cost of a ride-splitting trip can decrease approximately 42% from $14.12 to $8.20 (Figure 19).

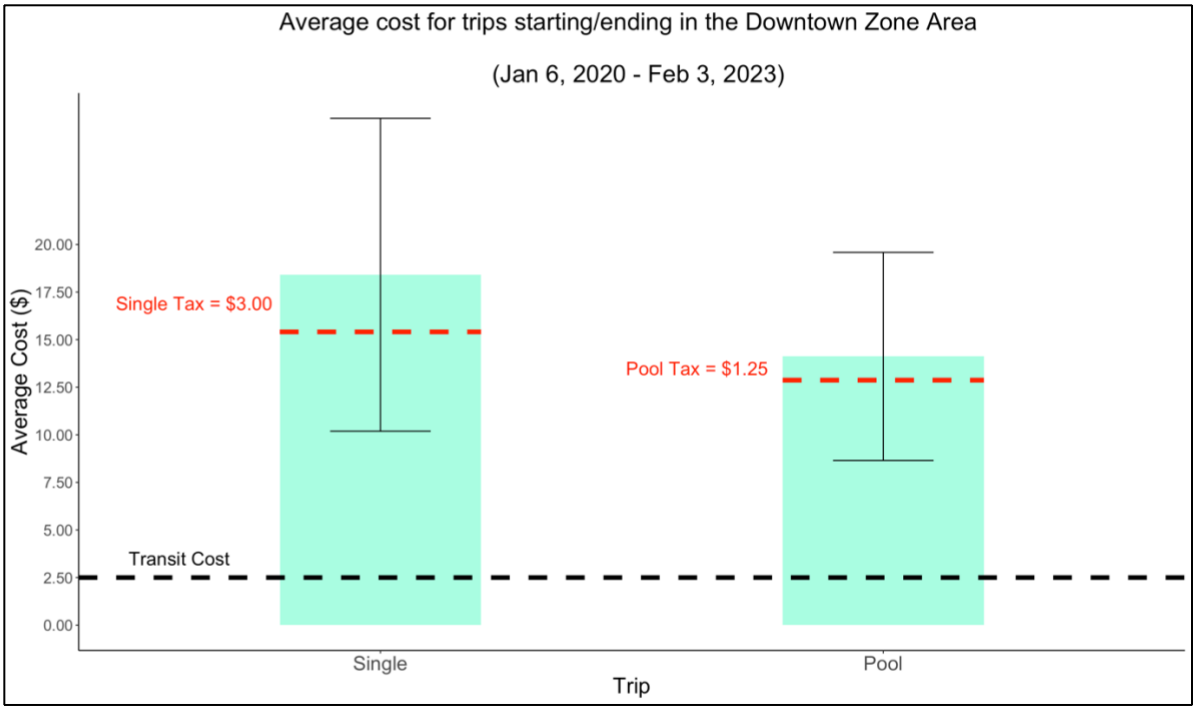


Figure 18: Cost comparison between single, pool and transit trips

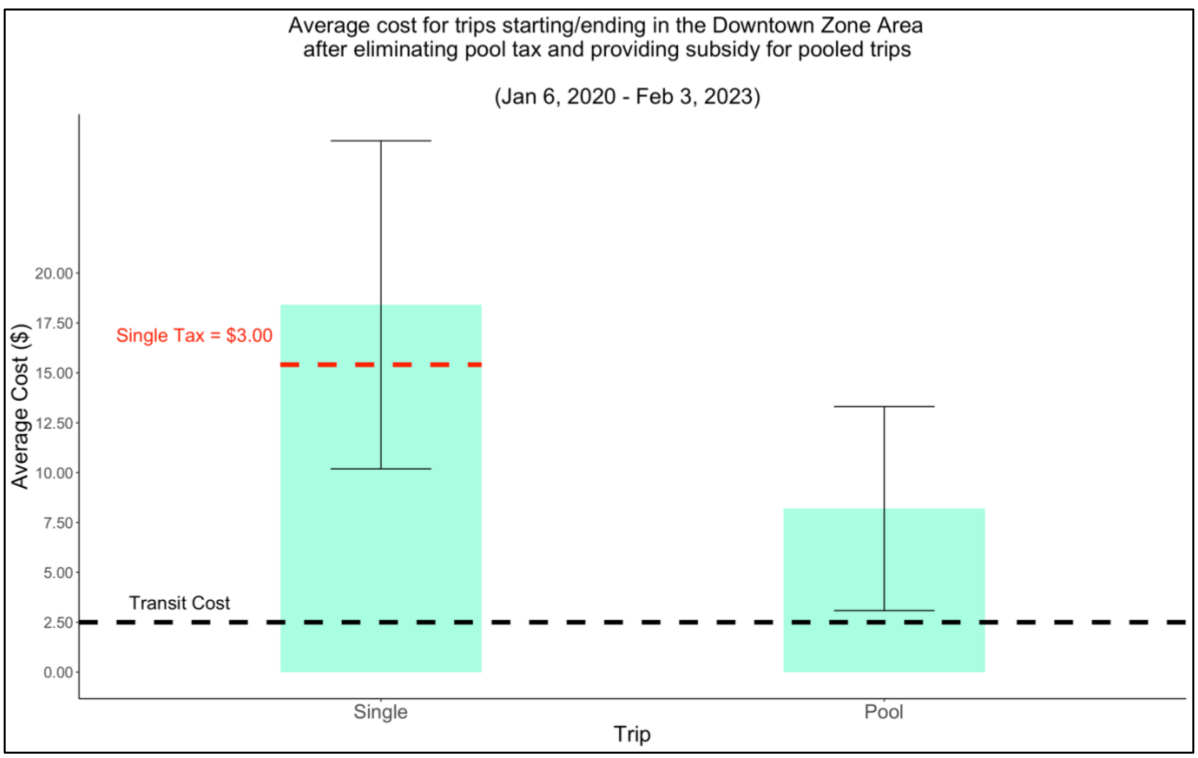


Figure 19: Cost comparison between single, pool and transit trips after eliminating tax and offering subsidy for ride-splitting

Chapter 5

Discussion and Conclusions

It is expected that in most metropolitan areas transit cannot reach every single neighborhood and offer adequate service. However, TNCs offer a potential alternative travel option. Considering the cost of a single TNC trip, communities which are transit-dependent but cannot afford a single ride can utilize ride-splitting as an alternative mode to either travel to their destination or connect to the nearest rail station. The purpose of this research is to examine if ride-splitting services fill the gap in transit deserts and how were ride-splitting users impacted by the disruption of COVID-19. For that reason, we used publicly available TNC trip level data in Chicago combined with transit and demographic data.

Results suggest that ride-splitting is being used to some extent as an alternative to transit in areas where transit supply is low. Transit deserts appear to be correlated with specific racial characteristics but still we cannot make a strong case that areas with low transit supply appear to be only in low-income and disadvantaged communities. As we mentioned in our analysis, areas with high-income in the North part of Chicago also experience low levels of transit supply. Moreover, we observe that census tracts with high transit supply can be scattered throughout transit deserts and vice versa. High shares of ride-splitting were mostly clustered in areas of low-income with inadequate transit supply. Black/African Americans, Latinx and transit-dependent population were positively correlated with high shares of pool pickups/drop-offs. In bivariate analysis we found that indeed ride-splitting is being utilized in some census tracts to fill the transit gaps; and ride-splitting is more widely used as an alternative service rather than single trips. Our spatial regression models revealed that transit route density is negatively correlated with ride-splitting rides. In addition, transit stop density and proximity to rail station were also found to be negatively associated with ride-splitting trips when considering the direct effect.

We should state that the effects are not large in magnitude, but they still reflect a possible substitution between public transit and ride-splitting services. Possible explanations of why ride-splitting is not heavily used in transit deserts is the fact that people who live in lower-income areas may not be very familiar with ride-sourcing in general (Jiao and Wang, 2021) or are hesitant to use ride-splitting because they must share the vehicle with a stranger. But the main reason is still cost, as ride-splitting is still expensive for certain demographics and even if transit supply is low, they decide to not make the trip (Barajas et al., 2021). However, in our analysis we found that a lower median household income generates more pooled trips compared to wealthy neighborhoods. Our cluster analysis revealed that ride-splitting hotspot clusters appear to be in the South part of Chicago where most low-income and disadvantaged communities are located. The latter is also found in Brown (2019). Furthermore, we found that there is a significant correlation between people of color and a higher share of ride-splitting trips but it's not quite large in magnitude to infer that ride-splitting is heavily utilized by segregated communities. It's worth mentioning that according to Ge et al. (2016) some ride-sourcing drivers seem to discriminate against people of color using their name as an indication for their race.

From a policy perspective, the tax that has been imposed by the local authorities in Chicago does not seem to incentivize ride-splitting to a larger extent. In more detail, even though the new tax is lower for ride-splitting, data suggests that a ride-splitting trip starting or ending within the Downtown Zone Area still costs almost six times more compared to transit. Therefore, communities who don't have access to public transit still need to pay a disproportionally higher fare to travel. Apart from alleviating congestion, tax measures are also a significant source of revenue for transit agencies. The changes that were proposed in 2019 were expected to generate an additional $43.9 million annually, adding to a total of $190.5 million in ground transportation tax revenue for 2020 (Vance, 2020). According to Kim (2019), the new legislation dedicated $16 million annually to support CTA's capital programs from which $2 million will be used for improving bus service on the South and West side of the city where most communities of color reside. However, this represents less than 10% of the total tax revenue.

Considering that ride-splitting services are primarily utilized by low-income communities in the West and South of the City, it doesn't seem equitable to impose a tax on ride-splitting. We suggest that Chicago authorities use part of the revenue created by the ground transportation tax to eliminate the tax for ride-splitting users and offer a subsidy which would act as a financial incentive for people to shift towards ride-splitting. We found that by providing a 50% subsidy, up to $5.00, for ride-splitting trips, the associated cost drops by 42% and it's competitive with transit cost considering that it offers door-to-door service. This subsidy can be provided exclusively by the Chicago authorities or in the context of a public-private partnership between TNCs and CTA. This partnership could offer first mile/last mile trips or trips within a low-density geographic area populated by low-income and disadvantaged communities. As previous experience has shown, by implementing such collaborations CTA can save capital while simultaneously offer adequate transit service. However, to implement such a plan and reach an agreement that benefits all stakeholders, both CTA and TNCs need to work on many different goals in terms of efficient and equitable operations, mutual data sharing and revenue generation.

It's difficult to assume that people switched from ride-splitting to single as the changes are not very stark in the level of census tracts. However, when we examined the normalized monthly single trips, we found that single trips were relatively higher during COVID-19 compared to the pre-pandemic period, thus there are indications of switching to single service. Since our data are up to September 2022 it is still too early for ride-splitting to show signs of full recovery. Finally, bivariate analysis revealed that during COVID-19 the outliers of (high single trips – low transit score) did not increase suggesting that people did not switch to single mode. Notably, most of the census tracts that were using ride-splitting pre COVID-19 located in transit deserts, have recovered in the post COVID-19 era.

Overall, it's important for local authorities, transit agencies and mobility providers to understand the socio-spatial context of Chicago in order to address transit equity issues more effectively. We hope that this research can inform all stakeholders on how to improve mobility for those communities that need it the most.

Appendices

Table 4: Ride-splitting model coefficients and additional effects

	Ride-splitting Model Coefficients											
	Pickups (all)		Dropoffs (all)		Pickups (weekday night)		Dropoffs (weekday night)		Pickups (weekend night)		Dropoffs (weekend night)	
	Estimate	Lagged estimate	Estimate	Lagged estimate	Estimate	Lagged estimate	Estimate	Lagged estimate	Estimate	Lagged estimate	Estimate	Lagged estimate
Intercept	−0.149 (1.32)		0.757 (1.43)		0.015 (6.08)		−9.757 (5.00)		−13.665 (7.69)		−20.473 **(7.19)	
Black/African American population (%)	0.002*** (0.00)	0.000 (0.00)	0.002*** (0.00)	0.000 (0.00)	0.002*** (0.00)	0.007 (0.00)	0.003*** (0.00)	0.012* (0.00)	0.002*** (0.00)	0.009 (0.00)	0.002*** (0.00)	0.021** (0.00)
Latinx population (%)	0.001*** (0.00)	0.004*** (0.00)	0.002*** (0.00)	0.004*** (0.00)	0.001*** (0.00)	0.007 (0.00)	0.002*** (0.00)	0.014*** (0.00)	0.001*** (0.00)	0.002 (0.00)	0.002*** (0.00)	0.012* (0.00)
Asian population (%)	0.001*** (0.00)	0.000 (0.00)	0.002*** (0.00)	0.000 (0.00)	0.001 (0.00)	−0.008 (0.01)	0.002*** (0.00)	0.007 (0.00)	0.001* (0.00)	−0.017 (0.01)	0.001** (0.00)	−0.026 (0.01)
Foreign-born population (%)	0.000 (0.00)	−0.005 (0.00)	0.000 (0.00)	−0.005 (0.00)	0.000 (0.00)	0.046* (0.02)	0.000 (0.00)	0.039** (0.01)	0.000 (0.00)	0.058 (0.03	0.000 (0.00)	0.114*** (0.03)
No household vehicles (%)	0.000 (0.00)	0.009*** (0.00)	0.000* (0.00)	0.008** (0.00)	0.000 (0.00)	0.026* (0.01)	0.000 (0.00)	0.035*** (0.00)	0.000 (0.00)	0.002 (0.01)	−0.001 (0.00)	0.014 (0.01)
Population age 10-17 (%)	0.001** (0.00)	−0.015* (0.00)	0.001** (0.00)	−0.008 (0.00)	0.002 (0.00)	−0.010 (0.03)	0.000 (0.00)	−0.014 (0.02)	0.001 (0.00)	0.045 (0.05)	0.001 (0.00)	0.014 (0.05)
Population age 65+ (%)	0.000 (0.00)	0.010 (0.00)	0.000 (0.00)	0.015** (0.00)	−0.001* (0.00)	−0.045* (0.02)	0.000 (0.00)	−0.054** (0.02)	0.000 (0.00)	−0.067* (0.03)	−0.001 (0.00)	−0.092*** (0.03)
Unemployed (%)	0.000 (0.00)	−0.003 (0.00)	0.000 (0.00)	−0.002 (0.00)	0.001* (0.00)	0.016 (0.02)	−0.001 (0.00)	0.023 (0.02)	0.000 (0.00)	0.053* (0.03)	0.000 (0.00)	0.037 (0.02)
Median household income (log$)	−0.018* (0.00)	0.048 (0.09)	−0.020* (0.00)	−0.028 (0.10)	−0.039 (0.02)	−0.109 (0.50)	−0.052*** (0.01)	0.715 (0.41)	−0.040** (0.01)	0.883 (0.62)	−0.042** (0.01)	1.251* (0.58)
Population density (log)	−0.006 (0.00)	0.027 (0.04)	0.012** (0.00)	0.022 (0.04)	−0.016 (0.00)	−0.440** (0.02)	0.011 (0.00)	−0.620*** (0.14)	−0.005 (0.00)	−0.450 (0.23)	−0.007 (0.00)	−0.881*** (0.22)
Low-wage employment density (log)	0.000 (0.00)	−0.042 (0.03)	−0.003 (0.00)	−0.045 (0.03)	0.012* (0.00)	0.141 (0.01)	0.000 (0.00)	0.097 (0.12)	0.004 (0.00)	0.197 (0.19)	0.003 (0.00)	0.368* (0.18)
High-wage employment density (log)	0.000 (0.00)	0.023 (0.02)	−0.002 (0.00)	0.053* (0.02)	−0.007 (0.00)	−0.078 (0.10)	−0.002 (0.00)	−0.091 (0.08)	−0.003 (0.00)	−0.301* (0.13)	−0.002 (0.00)	−0.557*** (0.19)
Transit stop density (log)	0.001 (0.00)	0.100 (0.05)	−0.002 (0.00)	0.053 (0.06)	0.027** (0.01)	−0.507 (0.29)	−0.011 (0.00)	−0.395 (0.24)	0.011 (0.00)	0.309 (0.35)	0.004 (0.00)	0.279 (0.33)
Transit route density (log)	−0.004 (0.00)	−0.154*** (0.03)	−0.006* (0.00)	−0.120** (0.04)	0.000 (0.00)	−0.253 (0.20)	0.001 (0.00)	−0.509** (0.16)	0.004 (0.00)	0.282 (0.24)	0.004 (0.00)	0.499* (0.23)
Median transit headway (min)	0.000 (0.00)	0.001** (0.00)	0.001 (0.00)	−0.004* (0.00)	0.000 (0.00)	−0.019 (0.00)	0.000 (0.00)	−0.020 (0.00)	−0.001* (0.00)	−0.025 (0.00)	−0.001 (0.00)	−0.022 (0.00)
Number overnight stops	0.000 (0.00)	0.000 (0.00)	0.000* (0.00)	0.000 (0.00)	0.000 (0.00)	−0.001 (0.02)	0.000 (0.00)	−0.002 (0.01)	0.000 (0.00)	−0.002 (0.02)	0.000* (0.00)	−0.002 −(0.00)
Rail station within 400 m	−0.009** (0.00)	−0.083 (0.05)	−0.016 (0.00)	−0.088*** (0.05)	−0.001 (0.00)	0.360 (0.20	0.002 (0.00)	0.281 (0.18)	0.010 (0.00)	0.393 (0.25)	−0.005 (0.00)	0.641** (0.24)
rho	0.38*		0.09		-3.13***		-2.50***		-1.51		-2.29***	
Num. obs.	752		752		583		583		477		477	
Parameters	37		37		37		37		37		37	
Log Likelihood	1383.73		1331.88		642.29		756.39		672.76		703.19	
AIC (Linear model)	-2691.60		-2591.60		-1192.40		-1421.80		-1270.60		-1327.60	
AIC (Spatial model)	-2693.50		-2589.80		-1210.60		-1438.80		-1271.50		-1332.40	
LR test:statistic	3.88*		0.19		20.21***		18.99***		2.91		6.79***	
Nagelkerke R^2	0.89		0.89		0.69		0.79		0.80		0.83	
Lagrange Multiplier test	1.85		0.07		2.14		1.12		3.82*		2.57	

***p < 0.001; **p < 0.01; *p < 0.05

Table 5: Ride-splitting model effects for weekday night

Ride-splitting Model Effects

	Pickups (weekday night)			Drop-offs (weekday night)		
	Direct	Indirect	Total	Direct	Indirect	Total
Black/African American population (%)	0.002	−0.004	−0.001	0.003	*−0.006*	−0.003
Latinx population (%)	0.001	0.000	0.002	0.002	0.000	0.002
Asian population (%)	*0.001*	−0.008	−0.007	0.002	0.006	−0.004
Foreign-born population (%)	−0.001	−0.004	−0.005	−0.001	−0.011	−0.011
No household vehicles (%)	0.000	0.003	0.003	0.000	0.005	0.004
Population age 10-17 (%)	0.002	−0.033	−0.032	0.001	*−0.022*	−0.020
Population age 65+ (%)	0.000	−0.001	0.000	0.000	0.005	0.006
Unemployed (%)	0.001	0.006	0.007	0.000	−0.002	−0.002
Median household income (log $)	−0.026	*−0.215*	*−0.240*	−0.037	0.260	*0.296*
Population density (log)	−0.013	0.030	−0.043	*0.013*	*−0.094*	-0.082
Low-wage employment density (log)	0.012	−0.005	0.007	−0.002	−0.007	−0.009
High-wage employment density (log)	−0.006	−0.009	−0.015	−0.000	0.001	0.001
Transit stop density (log)	0.030	−0.219	−0.188	−0.009	0.076	−0.084
Transit route density (log)	0.001	−0.036	−0.035	0.004	*−0.118*	*−0.115*
Number overnight stops	0.000	0.003	0.003	0.000	0.010	0.010
Median transit headway (min)	0.000	0.000	0.000	0.000	0.000	0.000
Rail station within 400 m	−0.007	0.000	−0.006	−0.002	−0.028	−0.030

Note: Bold indicates p < 0.05, italics p < 0.10

Table 6: Ride-splitting model effects for weekend night

Ride-splitting Model Effects

	Pickups (weekend night)			Drop-offs (weekend night)		
	Direct	Indirect	Total	Direct	Indirect	Total
Black/African American population (%)	0.002	0.001	0.003	0.002	*0.001*	0.003
Latinx population (%)	0.001	0.006	0.007	0.002	0.005	0.007
Asian population (%)	0.002	−0.001	0.001	0.002	−0.003	−0.001
Foreign-born population (%)	−0.003	0.000	−0.003	*−0.002*	−0.002	−0.003
No household vehicles (%)	0.000	0.005	0.006	0.000	0.003	0.003
Population age 10-17 (%)	0.000	−0.030	−0.029	0.000	−0.037	−0.037
Population age 65+ (%)	0.000	0.018	0.019	0.000	0.021	0.022
Unemployed (%)	0.000	−0.012	−0.012	0.000	−0.015	−0.015
Median household income (log $)	−0.017	−0.156	−0.174	−0.031	−0.290	−0.321
Population density (log)	−0.003	0.034	−0.038	-0.005	0.054	0.049
Low-wage employment density (log)	0.003	−0.014	−0.012	−0.002	−0.033	−0.035
High-wage employment density (log)	0.000	−0.001	0.001	0.004	0.012	0.017
Transit stop density (log)	0.007	0.001	−0.008	−0.001	−0.051	−0.052
Transit route density (log)	0.006	−0.117	*−0.111*	0.003	−0.081	−0.078
Number overnight stops	0.000	0.002	0.001	−0.001	0.004	0.002
Median transit headway (min)	0.000	0.000	0.000	0.000	0.000	0.000
Rail station within 400 m	0.005	−0.002	0.002	−0.009	0.037	0.028

Note: Bold indicates p < 0.05, italics p < 0.10

Table 7: TNC trip taxes and fees effective January 6, 2020

Transportation Network Company Trip Taxes & Fees Effective January 6, 2020			
TNC Trips	Current	NEW: Trip without Downtown Zone Surcharge	NEW: Trip with Downtown Zone Surcharge
Single Trip	$0.72	$1.25	$3.00
Single Trip starts or ends in Special Zone (Airports, Navy Pier, McCormick Place)	$5.72	$6.25	$8.00
WAV Trip (the $0.10/TNC Trip Accessibility Fund Fee does not apply)	$0.62	$0.55	$0.55
Shared Trips	$0.72	$0.65	$1.25
Shared Trip Trip starts or ends in Special Zone (Airports, Navy Pier, McCormick Place)	$5.72	$5.65	$6.25
WAV Trip (the $0.10/TNC Trip Accessibility Fund Fee does not apply)	$0.62	$0.55	$0.55

*The Downtown Zone Surcharge applies to any trip that starts or ends within the designated Downtown Zone Area during peak times, weekdays (M-F) between 6AM and 10PM

Source: City of Chicago (2019)

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