Exogenous drivers of public transit and ride-hailing ridership: a study of policy intervention, COVID-19, and the relationship between ride-hailing and public transit in Chicago

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Abstract

Public transit is a crucial component of the urban mobility system for many cities, but several recent shocks have threatened its continued function. Additionally, Transportation Network Companies (TNCs) have grown rapidly in recent years, expanding travel choices for some but posing a challenge to public transportation, prompting the City of Chicago to price and regulate TNC services. The backdrop of the COVID-19 pandemic has posed further shocks to both travel modes and their riders. In response to these changes, this thesis asks the question of "How have public transit and TNC riders responded to various external factors, including a direct policy intervention, a public health emergency, and emerging mobility services, and what lessons can be extracted for policymakers and transit system operators?"

Through Chicago-based case studies of the questions above, this thesis examines the impacts of these shocks to urban mobility and extracts relevant takeaways for policymakers and transit agencies. The studies find that policy interventions may not cause anticipated changes to travel behavior, and that the policy impacts may differ substantially across space. These case studies provide examples that policymakers can use to evaluate program impacts to inform future policy adjustments. Regression analysis and survey findings highlight the importance of public transit to move essential workers during the COVID-19 pandemic and identify core ridership among bus riders and minority populations. This thesis also demonstrates the role of TNC services as acting significantly in competition with public transit, but found that the relationship became less competitive during COVID-19.

Chicago's mobility landscape has undergone transformative change in recent years, and the future of the urban transportation system is uncertain as we recover from COVID-19. In the establishment of a post-pandemic normal, transit agencies and policymakers will need to continually evaluate the intended and unintended consequences of policy interventions, understand the behaviors and intentions of their riders, and assess their relationship with other modes of transportation. This thesis identifies analysis processes and provides practical examples for performing all these functions.

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Chapter 1

Introduction

Public transit serves a key role in the effective function of major cities worldwide, but it currently faces an unprecedented set of challenges to its success. Mass transit features an unparalleled ability to move people efficiently through a city, creating immense benefits for sustainability and agglomeration effects by leveraging the dense nature of urban downtowns. Transit provides an affordable mobility option for countless individuals who do not own a private automobile, enabling access to employment opportunities across a wide range of social and economic statuses. However, current long-term and short-term external challenges in urban mobility have shifted the trend of transit demand, creating interconnected challenges in system performance and ridership. This thesis aims to further explore three of these challenges through representative case studies of a targeted policy intervention, a public health crisis, and an emerging mobility mode.

By any account, the course of the research work informing this thesis has taken place in a shocking, uncertain, and unprecedented time in the recent history of transportation. The recent rise of Transportation Network Company (TNC) services has pulled many riders away from public transit, while contributing to worsening congestion which hinders transit performance [City of Chicago, 2019].This has prompted new forms of regulation by transit agencies and local governments, including an uptake in congestion pricing policies in several major cities. The COVID-19 pandemic has turned everyday life on its head, creating a shock to transit ridership and illuminating some of the many inequalities in mobility choice across economic and racial lines. While acknowledging the horrific impact of these various challenges on human health, this project recognizes that these circumstances create a set of 'natural experiments' which may be studied to help inform government policy and transit agency action to mitigate the detriment to our urban transportation systems.

Therefore, this project seeks to study the impact of three exogenous factors on public transit ridership, in pursuit of the following research question:

"How have public transit and TNC riders responded to various external factors, including a direct policy intervention, a public health emergency, and emerging mobility services, and what lessons can be extracted for policymakers and transit system operators?"

This question is investigated through three case studies in Chicago, corresponding to each of the various types of external factors:

- **Targeted policy intervention**: An investigation of the impact of Chicago's 2020 "Ground Transportation Tax" initiative, which was intended to reduce the impact of TNCs on congestion in the downtown and various other targeted areas.
- **Public health crisis:** A study of the impacts of the COVID-19 pandemic through a six-month panel survey of CTA riders and analysis of ridership trends for both transit and TNCs.
- **Emerging mobility mode:** A study of the substitutive, complementary, and independent nature of the relationship between TNC services and public transit in Chicago, assessing patterns under ordinary conditions, factors which influence the relationship, and its evolution through COVID-19.

1.1 Research Questions and Initial Hypotheses

In pursuit of the broader research goal described above, a detailed set of research questions and hypotheses is defined in this section. Specifically, research focuses on the three areas identified by the thesis case studies, with each elaborated upon in its respective subsection below.

1.1.1 Ground Transportation Tax

First, an investigation of Chicago's Ground Transportation Tax (GTT) program, implemented on January 6th, 2020, seeks to understand how the policy impacted TNC travel in Chicago's downtown. The guiding question behind this study is, "How did Chicago's Ground Transportation Tax (GTT) impact TNC and transit in the downtown area?" The tax has a stated goal of reducing TNC trip volumes and thereby alleviating congestion in Chicago's downtown area, and the case study seeks to determine whether reduced trip volumes were the immediate outcome of the policy. I hypothesize that while the policy may deter some trips from the downtown area, results may be limited because the tax primarily targets low-elasticity areas of travel which may not be responsive to price changes. To investigate this phenomenon, a difference-in-differences approach is employed to compare ridership changes before and after the policy, across treatment and control areas of the city.

This research area is further investigated through the following sub-questions:

- Did the GTT cause a significant change in TNC ridership in impacted areas following its initial implementation?
- How did TNC fares change following GTT implementation?
- How do the impacts of the GTT policy differ across space?

1.1.2 COVID-19

Secondly, the impacts of the COVID-19 pandemic are considered through multiple lenses, including changes to ridership and connections to various factors, as well as first-hand rider opinions regarding travel during and after the pandemic. Broadly, this chapter investigates the question of "How has COVID-19 impacted transit and

TNC ridership?" Through this case study, I seek to answer the following secondary questions surrounding travel and COVID-19:

- How did transit and TNC ridership change during the COVID-19 pandemic?
- What correlations (and trends in those correlations) exist between demographic, transportation network, and built environment factors and changes in ridership through COVID-19?
- How do individual stated (surveyed) attitudes and behaviors align with and offer greater insight to observed aggregate trends in COVID-19?
- What are individuals' attitudes toward transit and predicted behaviors for a post-COVID world?

I hypothesize that the inequitable nature of the pandemic will reveal itself through a study of correlations between various factors, highlighting the many transit-dependent low-income essential workers who were unable to establish alternative means of travel (or alternatives to travel, such as remote work) through the pandemic. Secondly, it seems likely that individuals may develop negative opinions of transit system cleanliness and safety through the pandemic, which to some extent may be elastic and thus recover following the pandemic, but for some riders may spark long-term changes in mobility preference which persist following recovery from COVID-19.

1.1.3 Relationship between TNC services and Public Transit

The emergence of TNC services as a new mode of urban mobility gives rise to many questions around their interaction with other components of the urban transportation system, particularly public transportation and private automobiles. Primarily, this chapter broadly asks, "How do TNC (ride-hailing) services interact with transit?". Transit agencies in recent years perceive this relationship as primarily competitive, expressing concerns that TNC services have attracted discretionary transit riders away from public transit and towards an inherently less sustainable, less equitable alternative. I approach the issue with the hypothesis that TNC services have likely taken riders from transit, however with an acknowledgement that the transit system may not be well-equipped to serve some TNC trips occurring in times or locations that are not effectively serviced by the transit system. Spatial and temporal patterns in this relationship are thus analyzed, with the hope of gaining a better understanding of which trips provide redundant service with public transit yet contribute to traffic congestion and slower transit travel times, and which trips complement the urban mobility system by serving purposes which are not covered by transit. To investigate this further, the following secondary questions are posed:

- What spatial and temporal patterns exist in the complementary, competitive, and independent relationship between TNCs and public transit?
- What demographic, transportation network, and built environment factors are associated with changes in the TNC-PT relationship?
- How has the TNC-PT relationship evolved over COVID-19?

Note that several sections related to the TNC-PT relationship analysis are adopted from a co-authored paper, currently under review. Specifically, Sections 2.5, 3.5, 4.4, 4.7, and Chapter 7 are adapted from the paper.

1.2 Policy Relevance

This thesis reveals various findings which are relevant in helping public transit agencies act directly in response to some changes in rider behavior, and to act within their power to encourage broader policy change by the City of Chicago or the state department of transportation. Given the lessons learned from the case studies in this thesis, transit agencies may apply this expanded knowledge of their riders' attitudes, behaviors, and preferences to inform policy decisions and guide aspects of public transit management. This may help to first retain and attract discretionary transit riders through the COVID-19 recovery, and secondly guide transit network design and lobby regulatory bodies to create policy, which will help transit to successfully coexist with TNC services in a broader mobility landscape.

Specifically, the findings of the individual case studies may directly inform policymaking. The results of the GTT impact analysis can be used to reassess the effectiveness of the policy around both changing ridership patters and generating revenue for sustainable mobility, knowledge which may be employed to adapt the policy going forward. Insights from the COVID-19 analysis can help to obtain a first-hand perspective on rider reactions to pandemic-related policies and services, gain an approximate estimate of when riders will return to transit, and prioritize health and safety policies which are most relevant to CTA riders. The TNC-PT relationship analysis may also be used to inform transit service planning, potentially to identify candidate areas for a partnership project or mobility-on-demand pilot, as well as to identify areas which may be appropriately targeted by future congestion pricing initiatives.

The findings of this thesis may be applied directly in response to the case study policies such as regulation of TNC providers, public transit management response to TNC services, and transit management priorities in the COVID-19 recovery process, but also carry broader implications. The case studies represent individual cases of broader trends, which may provide opportunities to learn from these events in preparation for future shocks in transit demand.

1.3 Thesis Overview

The remainder of this thesis is organized as follows. Chapter 2 describes the specific institutional context of Chicago in which the project case studies operate, highlighting public transit, TNC services, relevant policies, and COVID-19 as these factors all shape Chicago's broader mobility landscape. Chapter 3 then provides a comprehensive review of relevant literature in the areas of study for this thesis, including pricing of TNC services, regression and survey-based approaches to examining the impacts of COVID-19 on travel, and analysis of the relationship between TNC services and public transit. Chapter 4 describes the methods and data sources used to conduct research in the relevant case study areas. Chapters 5, 6, and 7 respectively discuss the results of each case study. Finally, Chapter 8 synthesizes the most salient findings of the research, highlighting limitations, policy implications, and directions for future research.

Chapter 2

Context: Study Area and Policy Background

This chapter provides contextual information about Chicago's mobility landscape. While the CTA is the focus of this thesis project, it is important to consider both the institutional actors with which the CTA interacts directly, as well as the broader set of alternative mobility providers (such as TNC companies) which influence the citywide operating conditions for mobility services. Furthermore, the COVID-19 pandemic has drastically changed mobility over the course of this study, and thus its role must be examined as well. This chapter introduces the City of Chicago and the CTA (Section 2.1), the broader public transit institutional landscape of Chicago (Section 2.2), the recent rise of TNC services (Section 2.3), the Ground Transportation Tax policy (Section 2.4), and the impacts of COVID-19 on transportation (Section 2.5).

2.1 Chicago and the CTA

Located on the western shore of Lake Michigan in the U.S. state of Illinois, Chicago is home to 2.7 million residents in the city and 9.5 million in the metropolitan area [City of Chicago, 2021a].The city may be broadly classified into nine regions, identified by the Social Science Research Committee at the University of Chicago [City of Chicago, 2021b]. These large-scale regions are further subdivided (in descending order of size) into 77 Community Areas, 801 Census Tracts, and 46,357 Census Blocks. Each geographic scale is referenced and used for different analyses throughout the thesis. Figure 2-1 shows Chicago's regions and census tracts.

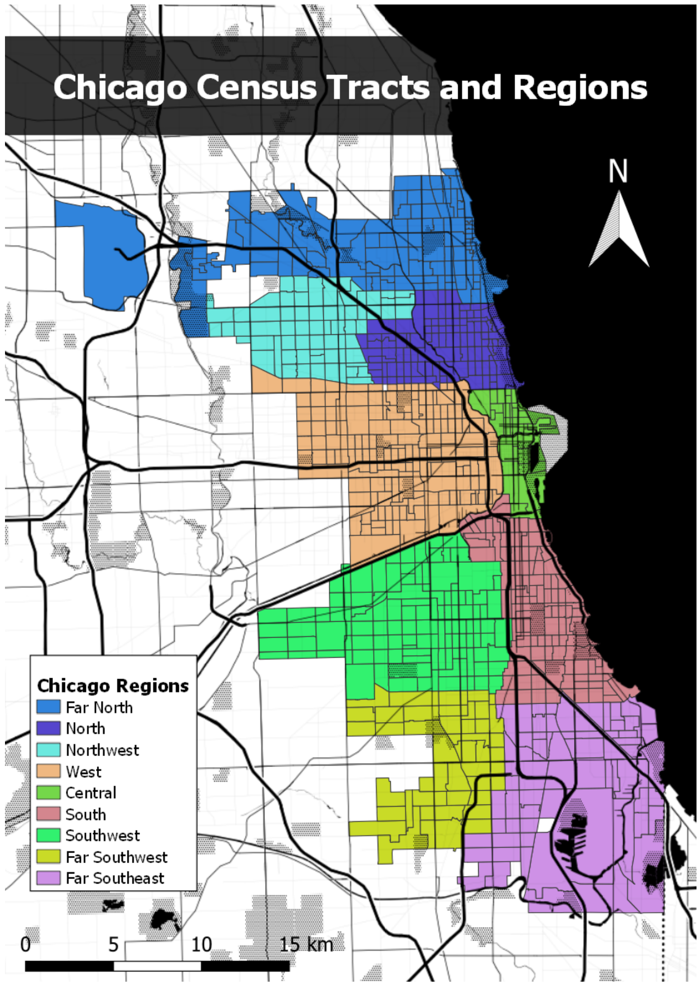


Figure 2-1: City of Chicago's 801 Census Tracts and 9 Regions (data: [Chicago Data Portal, 2010b])

2.1.1 Socioeconomic Divisions in Chicago

In understanding the context of Chicago, it is important to identify socioeconomic divisions that have persisted through the city's history, and largely define its regions today. Figure 2-2(left) shows the logarithm of median household income, while Figure 2-2(right) shows the percentage of African-American population by census tract within the city. A number of patterns are clearly apparent from these maps. First, racial divides are distinct. There is a bimodal distribution of African-American population, with the vast majority of areas having populations below 20% or above 80%. Second, divides in household income are clear across the city, with lower-income census tracts in neighborhoods to the city's far west and far southeast sides.

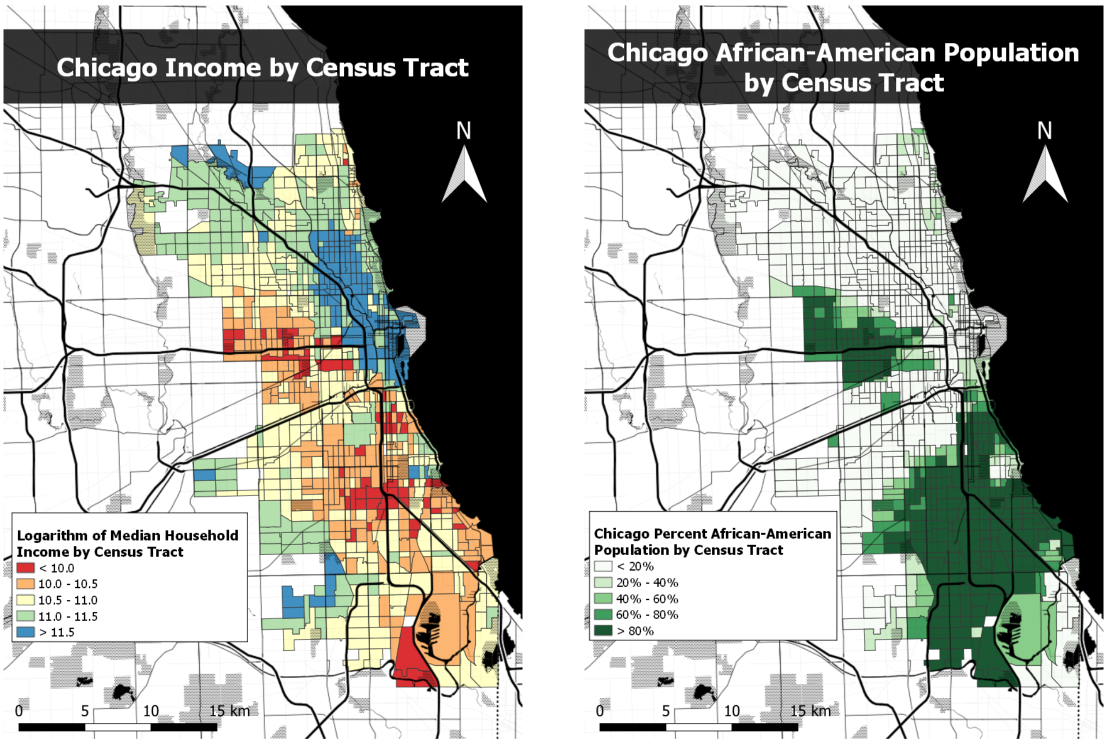


Figure 2-2: Maps of logarithm of median household income (left) and percent of African-American population (right) by census tract for the city of Chicago (data: [US Census Bureau, 2019])

These current spatial inequalities in race and income are a product of centuries of discriminatory policies. Like many other metropolitan areas in the U.S., Chicago experienced significant changes throughout the twentieth century: the Great Migration saw an influx of African-American people from southern states, along with a movement of white residents to Chicago's suburbs [Greer, 2014]. While the suburbs experienced immense housing construction, population growth, and economic prosperity, the central city saw the opposite. African-Americans were "barred from the suburban housing market by the realty industry, zoning and building code laws of localities, the active resistance of developers, as well as the underwriting standards of the federal government" [Greer, 2014]. In particular, the mortgage underwriting standards refer to the practice of 'redlining', which systematically prevented homes from areas with significant minority populations from obtaining financing through federally-insured mortgages. As a result of these actions, housing choices available to African-Americans, as well as the ability to obtain financing for home ownership (and the resultant growth of property equity) were severely restricted. Moving forward to present day, Xu [2021] identifies the legacies of these redlining policies in Chicago. As discussed, "These results highlight a process through which historical housing discrimination can leave a legacy of sociospatial stratification, as one of the factors contributing to the present-day racial wealth gap" [Xu, 2021]. Beyond the wealth gap, important racial disparities in homicide rates and life expectancy persist to the present day, which may be significantly predicted by measures of economic inequality [Wilson and Daly, 1997].

The concept of aldermanic prerogative is a unique feature of Chicago's local politics which has also significantly influenced the city's development. Through this unwritten precedent, representatives of each of Chicago's 50 'wards' are given the power to veto government actions which concern the ward that they represent [Chicago Historical Society, 2005]. The clause was most notably used in zoning changes and variances, before zoning variation was centralized in 1955 by Mayor Richard J. Daley [Chicago Historical Society, 2005]. The practice has also been cited as causing corruption in project approval, and enabling aldermen to unilaterally deny developments which may be perceived as unappealing or unpleasant [The Global Grid, 2018]. Among several other examples, alderman Berny Stone used the prerogative to veto a fully-funded bike bridge over the North Shore Channel in 2005 [Greenfield, 2019b]. As Zhang [2011] discusses in a comparison of two case studies of historic preservation initiatives, the aldermanic prerogative can lead to different outcomes of projects for different areas of the city, denying benefits to some residents. One project in Pilsen, which was contained in one ward, was supported by its alderman because of local economic benefits, but another in Bronzeville, which was spread across four wards, was "ignored by the aldermen because it may empower [community-based organizations] and weaken their local autonomy" [Zhang, 2011]. In recent years, Mayor Lori Lightfoot has acted to remove aldermanic prerogative in Chicago [Lightfoot, 2019].

2.1.2 The Chicago Transit Authority

The Chicago Transit Authority (CTA) began operating in 1947. The CTA currently operates public transit services within the City of Chicago and 35 surrounding suburbs. In total, the system serves a population of 3.5 million people. The CTA has an average weekday ridership of 1.6 million and a total annual ridership of around 500 million, making it the second largest transit system in the United States. The CTA operates both bus and rail services, with a fleet of 1,864 buses and 1,492 rail cars. Over its 224 miles of track, 8 lines, and 145 stations (system map shown in Figure 2-3), the rail system operates primarily above ground, earning its nickname of the "L", in reference to its famous network of elevated track [Chicago Transit Authority, 2017].

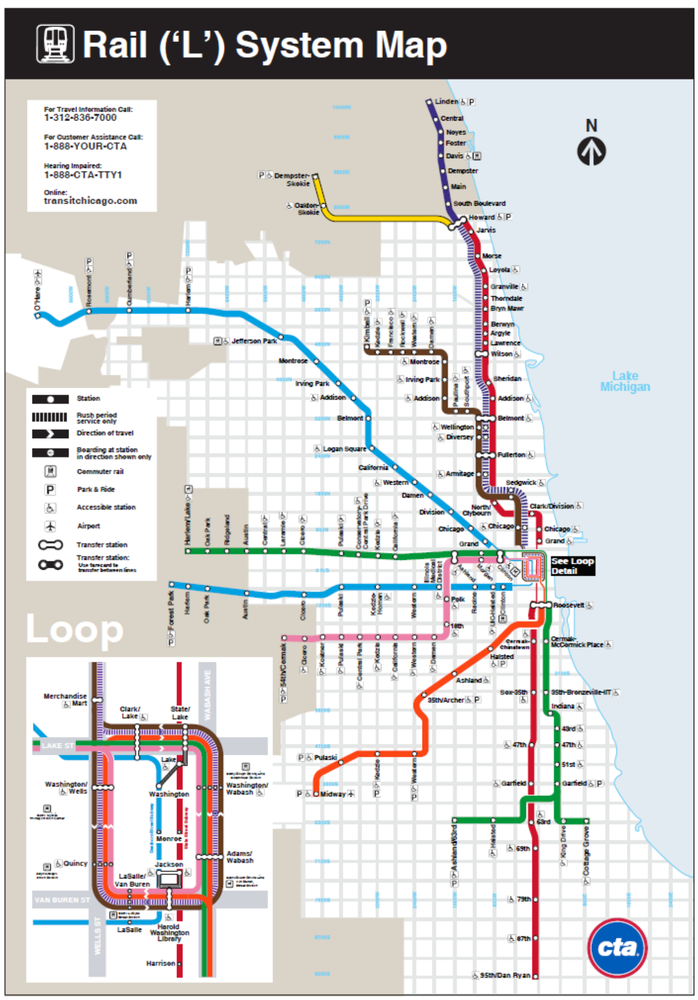


Figure 2-3: CTA Rail System Map [Chicago Transit Authority, 2019]

The CTA is an independent governmental agency, which is governed by seven members of the Chicago Transit Board. Four of these members are appointed by the City of Chicago Mayor, and three are appointed by the Governor of Illinois. The agency receives operating funds allocated by the Regional Transportation Authority (RTA), under a requirement that the farebox recovery ratio remain over 50%. As of 2019, the CTA maintained a farebox recovery of 56.3% [Chicago Transit Authority, 2020b].

In the past decade, the CTA has faced declining ridership system-wide, particularly on bus services. Table 2.1 provides a summary of total ridership and year-over-year change since 2010. As shown, bus ridership has declined over 22% in the past 10 years, while rail ridership has increased 3.7%, leading to a shift in overall mode share from 40.8% rail in 2010 to 47.9% rail in 2019. Since 2016, ridership declines have accelerated and persisted, with total boardings falling across both rail and bus. Notably, all annual ridership reports since 2016 have also attributed some amount of ridership losses to the continued growth of TNC services [Chicago Transit Authority, 2020e]. This relationship is explored in-depth through this thesis.

Table 2.1: Total CTA boardings by mode, 2010 - 2019 (Data from CTA Annual Ridership Reports) [Chicago Transit Authority, 2020e]

Year	**System Ridership**		**Rail Ridership**		**Bus Ridership**	
	Boardings (millions)	**% Change**	**Boardings (millions)**	**% Change**	**Boardings (millions)**	**% Change**
2010	517	-0.9%	211	+4.0%	306	-4.0%
2011	532	+3.0%	222	+5.2%	310	+1.4%
2012	545	+2.4%	231	+4.2%	314	+1.1%
2013	530	-2.8%	229	-0.7%	300	-4.4%
2014	515	-2.8%	238	+3.9%	276	-8.0%
2015	517	+0.4%	242	+1.6%	275	-0.6%
2016	497	-3.8%	238	-1.5%	259	-5.8%
2017	480	-3.3%	231	-3.2%	250	-3.5%
2018	468	-2.5%	226	-2.0%	242	-3.0%
2019	456	-2.6%	219	-3.3%	238	-2.0%
10-yr	**-60.7**	**-11.7%**	**+7.8**	**3.7%**	**-68.5**	**-22.4%**

2.2 Public Transit Institutional Landscape

Aside from the CTA, several other institutional actors play a major role in the overall public transit mobility landscape for Chicago. These include additional public transit providers serving suburban trips, city government, and regional financial oversight.

In addition to the CTA, two other transit agencies provide service in the Chicago Area. Pace Suburban Bus provides transit service in 284 municipalities surrounding the City of Chicago, and was created as a consolidation of various suburban bus agencies in the 1983 RTA Act. Pace covers a large service area of 3,677 square miles, operating a fleet of 810 buses and serving around 127,000 daily riders [Pace Suburban Bus, 2021]. Metra commuter rail was also created in 1983 as a service board of the RTA, with the goal of unifying services across several rail lines owned by various operators [Metra, 2021b]. As of 2019, Metra operates 11 radial lines serving 242 stations, with an average weekday ridership of 281,100. The agency posts a farebox recovery of 53.1% [Metra, 2021a]. Despite operating as separate agencies, the three Chicago-area transit providers share the Ventra farecard payment system. Additionally, all three agencies commonly receive funding from the RTA. The three agencies serve predominantly different markets within Chicago, as evidenced by their respective route service areas highlighted in Figure 2-5. Additionally, ridership trends for the three agencies are highlighted in Figure 2-4 from September 2014 to November 2020. While CTA ridership declined gradually, trip volumes for suburban services (e.g. Metra and Pace) remained relatively constant through the period examined.

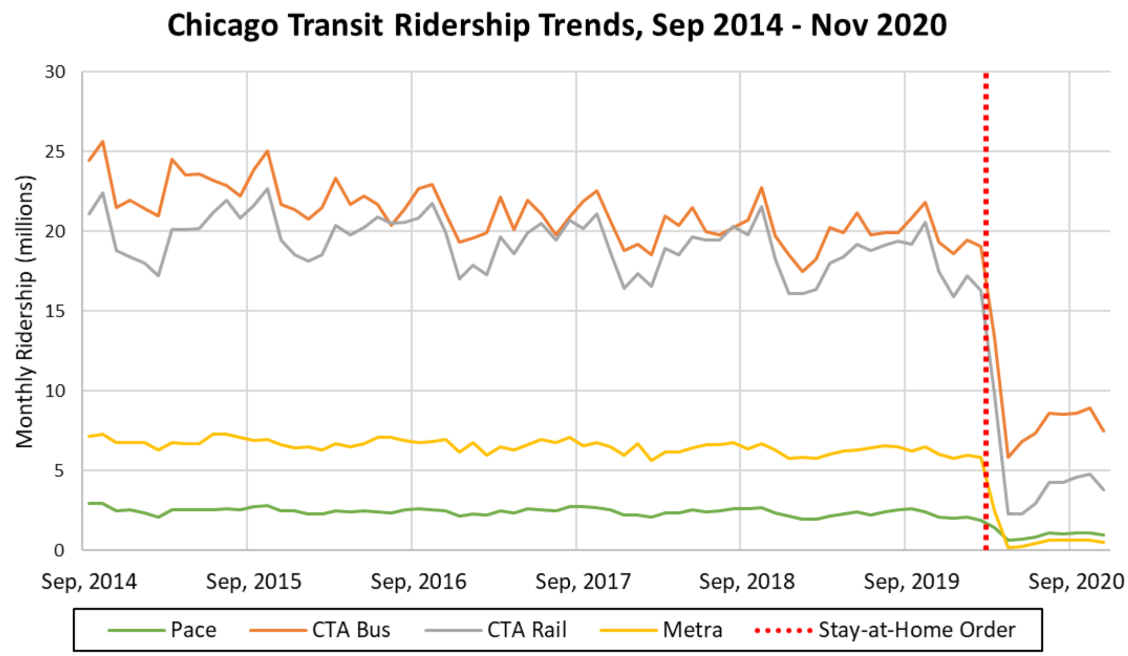


Figure 2-4: Chicago area transit ridership trends, September 2014 – November 2020 (Data sources: [Chicago Transit Authority, 2020e; RTAMS, 2021], compiled by author)

By limiting analysis to CTA services in the case studies for this thesis (rather than including Metra and Pace users), riders commuting from distant suburban and exurban areas are excluded (highlighted in the respective agency service areas shown in Figure 2-5). It is unlikely that many TNC trips would be omitted by this analysis, considering the high TNC fares for long-distance trips and the greater share of private vehicle ownership in suburban neighborhoods. However, for transit ridership, this may pose some limitations to enabling a region-wide analysis of transit in COVID-19. In particular, primarily work-based commuter trips on Metra services declined to a greater extent than CTA transit trips during the pandemic [RTAMS, 2021], and there may be some differential reaction between suburban and urban commuters during the pandemic. While these areas are out-of-scope for this thesis, they could be examined in future research efforts.

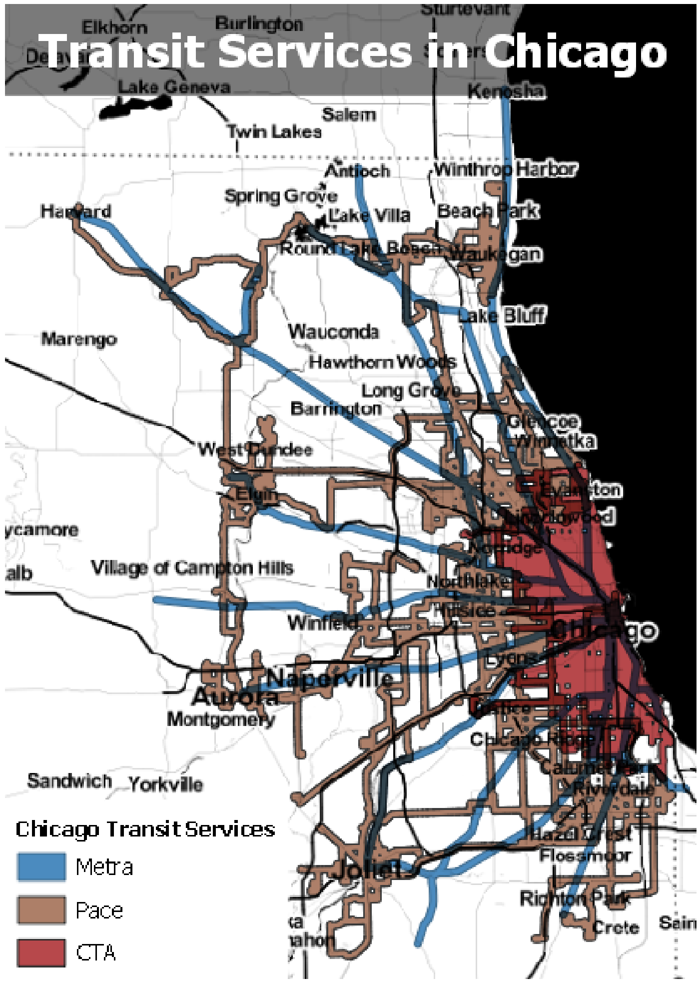


Figure 2-5: Spatial distribution of Chicago transit service by operating agency

Chicago's Regional Transportation Authority (RTA) is responsible for "financial oversight, funding, and regional transit planning for the region's transit operators" [RTA, 2021a]. The RTA obtains funding through a variety of different means, including service board (transit agency) revenue, state funding, sales tax, and real estate transfer tax. The RTA is allowed to impose a sales tax in six counties in Northeastern Illinois, which is currently set at 1.25% in Cook County and 0.50% in several surrounding areas. In total, the sales tax generates over $1 billion per year [RTA, 2021b]. The RTA also gains funding through the "CTA Portion" of the City of Chicago Real Estate Transfer Tax, which allocates a tax of $1.50 per $500 of transfer price for each property sold in the City, amounting to around $69 million in recent years [RTA, 2021c]. Annually, the CTA provides budget recommendations which are then used for the RTA to determine funding allocation.

The City of Chicago Transportation Department (CDOT) plays a major role in Chicago's mobility landscape. CDOT is responsible for "Chicago's roadways and bridges, sidewalks and bike lanes, the citywide bike share system, traffic signals and signage, streetlights, the permitting of activities in the public right-of-way, and policies focused on complete streets, climate adaptation, and new mobility" [CDOT, 2021a]. CDOT may have a significant impact on CTA's operations, particularly through changes to its operating environment. Through CDOT policies, changes may be made to the traffic right-of-way (e.g. transit signal priority or dedicated bus lanes) and regulatory policies governing the set of travel modes on Chicago streets (such as TNC congestion pricing). Additionally, CDOT owns over 50 CTA rail stations, along with more than 50 miles of track on which CTA operates trains [CDOT, 2021b].

2.3 Transportation Network Companies (TNCs)

Major Transportation Network Company (TNC) services have been operating in Chicago since September 2011, when Uber launched its initial luxury black-car service in the city [Rao, 2011]. A second major TNC company, Lyft, entered Chicago in 2013 [Rodriguez, 2013].

Since 2016, TNC services operating in Chicago have experienced massive growth. TNC service use over this period has more than doubled, and the City government sees the growing popularity of the service as a significant contributor to traffic congestion in the city. In particular, the dominance of single-occupant trips (as opposed to shared rides) and the prevalence of downtown-based TNC trips are cited as concerns that TNC services are worsening congestion [City of Chicago, 2020a]. As shown in Figure 2-6, TNC services have steadily grown in monthly ridership, though this value appeared to reach some plateau in the months preceding the COVID-19 pandemic. During this time, CTA rail and bus service ridership declined gradually. Note that '*' on the x-axis of Figure 2-6 indicates change of TNC data source from [City of

Chicago, 2019] to [Chicago Data Portal, 2020b] in November 2018.

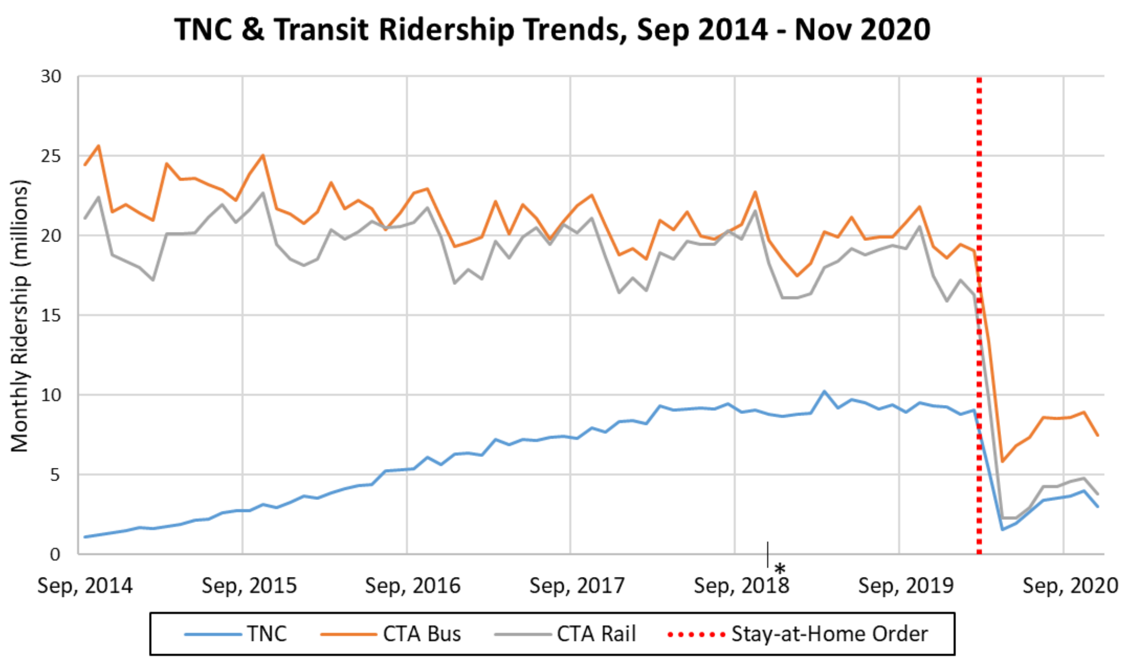


Figure 2-6: TNC & transit ridership trends in Chicago, September 2014 – November 2020 (Data sources: [Chicago Transit Authority, 2020e; Chicago Data Portal, 2020b; City of Chicago, 2019], compiled by author)

Chicago has responded to the entry of TNC services with considerable regulatory action, more rigorous than that seen in most U.S. cities. The City requires that TNC drivers obtain a vehicle registration emblem, among various other provisions, listed in the TNC Ordinance of the Municipal Code of Chicago which took effect in September 2014 [City of Chicago, 2020b]. Furthermore, the city requires TNC providers to report data on all vehicle trips taken [City of Chicago, 2017], which is provided in aggregate form to the general public [Chicago Data Portal, 2020b]. In January 2020, the City of Chicago imposed the Ground Transportation Tax on all TNC trips in the city, with the aim of reducing the negative impacts of TNC services on Chicago's traffic congestion [City of Chicago, 2020a].

2.4 Ground Transportation Tax Program

In response to perceived contributions to traffic congestion by TNC providers, the city of Chicago imposed the Ground Transportation Tax (GTT) starting from January 6, 2020. The GTT initiative replaces a previous flat TNC trip fee of $0.72, which was applied to all trips regardless of origin or destination. The City of Chicago estimates that the new GTT initiative will raise $40 million per year in additional revenue, $2 million of which will go to improving CTA bus services through dedicated bus lanes [Freund, 2020].

The rationale behind this tax expresses concern about rapid growth of TNC services and their role in the city's congestion levels, stating that the policy will "combat the plague of congestion, promote sustainable forms of transportation and support our essential public transit system, while making shared rides cheaper in the neighborhoods" [City of Chicago, 2020a]. The GTT levies a greater surcharge for trips which begin or end in a special area, including airports, Navy Pier, and McCormick Place, and applies an additional Downtown Zone Surcharge for trips which begin or end in the Downtown Zone Area (shown in Figure 2-7) between 6:00am and 10:00pm, Monday to Friday. Single-occupant TNC trips are also priced at a higher rate than shared trips (those which are conducted through UberPool or Lyft Shared services). For example, a single-occupant trip from O'Hare Airport to the Willis Tower on a weekday would incur a surcharge of $8.00, while a shared ride between the University of Illinois Chicago and Guaranteed Rate Field would incur a surcharge of $0.65. The full pricing scheme is provided in Table 2.2. The aim of this approach is to disincentivize these downtown and single-occupant trips relative to other TNC travel options and other modes of travel.

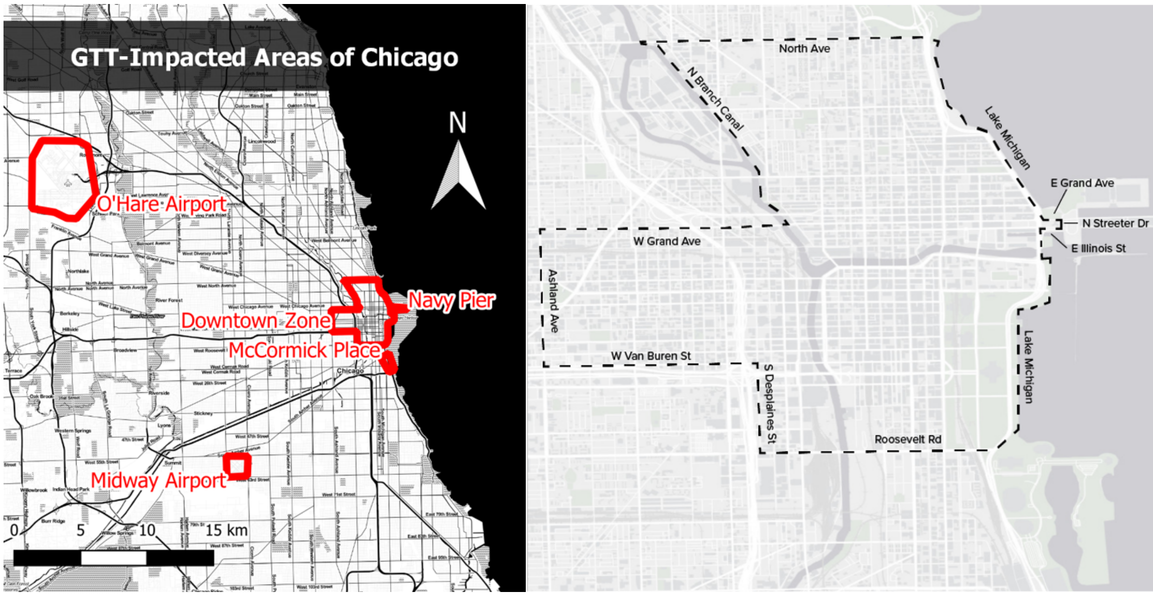


Figure 2-7: All areas charged higher fees under the GTT (left), and boundaries of the "Downtown Zone Area" (right) [City of Chicago, 2020a]

Table 2.2: GTT pricing policy [City of Chicago, 2020a]

	Trip Type	**Without Downtown Zone Surcharge**	**With Downtown Zone Surcharge**
Single-Occupant Trip	O/D outside Special Zones	\$1.25	\$3.00
	O/D in Special Zone	\$6.25	\$8.00
Shared Trip	O/D outside Special Zones	\$0.65	\$1.25
	O/D in Special Zone	\$5.65	\$6.25
Other	Wheelchair Accessible Vehicle Trip	\$0.55	\$0.55

As may be expected, the response to this new fee was mixed. Uber and Lyft (the region's main TNC operators) launched major public relations campaigns to combat the new pricing scheme, primarily arguing that the tax would disproportionately burden communities of color. In this effort, Uber engaged (and reportedly paid) 35 Black ministers to support their argument [Greenfield, 2019a]. This approach emphasizes the importance of local representatives in Chicago politics, highlighted by the role of aldermanic prerogative discussed in Section 2.1.1. However, these claims were generally proven false, considering that African American residents are disproportionately less likely to take single-occupant or downtown-based trips. Analysis from the Center for Neighborhood Technology (CNT) examined the City of Chicago TNC trip records with a focus on trip origin and destination locations, shared-ride use rates, and proportions of trips originating and terminating in GTT-impacted areas. Through this process, the CNT calculated the total cost of the fee borne by census tract (assuming constant usage patters) [Irvin, 2019]. As shown in Figure 2-8, residents of the lower-income South Side would bear a minority of the new tax, while those in the affluent downtown and North Side areas would pay the most [Greenfield, 2019a]. At the time of the tax's implementation, some downtown residents voiced frustration with the new pricing scheme, calling it a 'revenue grab' by the city which would have little impact on travel choices [NBC Chicago, 2020]. However, sustainable transportation advocates generally applauded the initiative, stating that it would encourage riders to switch to more sustainable options such as shared TNC trips and transit services [Greenfield, 2019a]. The long-term impacts of the tax are yet to be seen, as the COVID-19 pandemic began shortly after it went into effect, significantly disrupting regular travel activity.

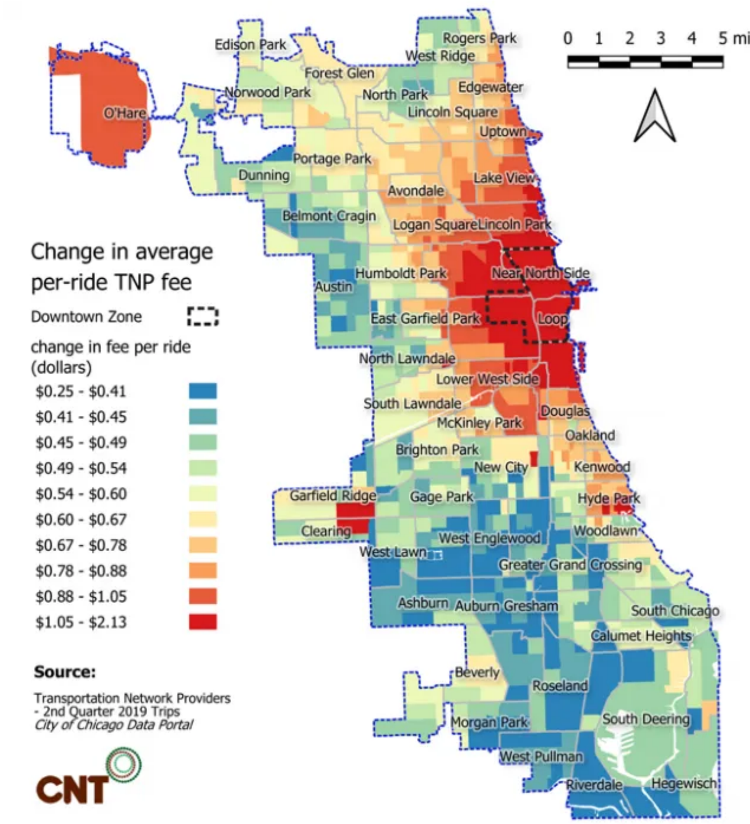


Figure 2-8: Spatial distribution of projected GTT cost burden [Irvin, 2019]

2.5 COVID-19 and Its Impact on Transportation

The COVID-19 pandemic is an ongoing global spread of coronavirus disease since 2019, which was declared a pandemic by the WHO in March 2020. In addition to its immeasurable impacts on all facets of life in cities, the COVID-19 pandemic has dramatically changed travel behavior in North America. Mass transit typically makes up a significant modal share for major cities such as Chicago (28.3%), New York (55.9%), and Boston (32.2%) as identified by the American Community Survey 1-year estimate [Data USA, 2018]. However, ridership for major transit agencies has plummeted following the onset of COVID-19, in attempts to enable social distancing and reduce the spread of the disease. Following Illinois' stay-at-home order on March 21st, ridership for the Chicago Transit Authority (CTA) declined by 84% for rail and 72% for bus from pre-COVID levels by the end of March [Chicago Transit Authority, 2020c]. This decline in ridership has largely persisted through the following year: As of November 2020, rail ridership has decreased 78% and bus ridership has decreased 61%, compared with 2019 levels [Chicago Transit Authority, 2020d]

In a study of New York City and Seattle, Gao et al. [2020] also found a dramatic reduction in both transit and traffic demand. Lessened congestion has resulted in higher traffic speeds and higher crash fatality rates, posing new dangers to all road users. Additionally, discrepancies in mode use recovery rates between transit and private vehicles lead the authors to conclude that a lasting shift from transit to private vehicles has occurred. Based on analysis of Chinese cities which are several months further in their recovery, Gao et al. predict that transit system recovery will be slow [2020].

Transportation Network Companies (TNCs) represent another mode of travel which has also been impacted by COVID-19. Prior to the pandemic, the number of daily TNC trips in Chicago had rested steadily above 400,000 per day. However, this has dropped substantially since the onset of the pandemic, as illustrated by public trip records from the City of Chicago [Chicago Data Portal, 2020b]. Trip levels dropped rapidly following the March 21st stay-at-home order, to 86,586 on March 24th and appear to stabilize below 50,000 for the remainder of March. However, these trip levels have increased considerably over the course of pandemic recovery, to above 100,000 daily trips by November 2020 [Chicago Data Portal, 2020b].

Although both TNCs and public transit are closely scrutinized under the impact of the COVID-19 pandemic, the study of how the relationship between the two modes has evolved during this period is lacking in academic literature. The changing mobility landscape means that the two modes may interact in different ways, potentially serving different types of travel. It is essential to determine how the two modes interact, and how this interaction will evolve as pandemic-related shutdowns are lifted. This study examines the change of TNC-PT relationship in the early stages of COVID-19, to understand the ever-changing landscape of urban mobility during the pandemic, and provides implications for regulations and management in response to the challenges it presents.

Chapter 3

Literature Review

This chapter provides a review of literature, conducted to establish research gaps and identify existing approaches which the methods identified in Chapter 4 seek to build upon. Existing studies are examined in five areas, beginning with an overview of traditional models of travel demand (Section 3.1) and then exploring the topics investigated in the case study applications. These include studies on regulation and pricing of TNC services (Section 3.2), approaches used to examine the impacts of COVID-19 through quantitative regression-based analysis (Section 3.3) and survey methods (Section 3.4), and the relationship between TNC services and public transit (Section 3.5).

3.1 Traditional Models of Travel Demand

Understanding transit ridership and the factors which influence it is a longstanding challenge in the study of travel behavior, particularly in the context of travel demand modeling. As Meyer and Miller state, "Estimating the demand for transportation facilities and services is one of the most important analysis tasks in urban transportation planning" [2001, p.1]. Estimations of demand for transportation services, as well as the likelihood with which a given unit of transport demand (e.g. a desired trip) will be taken by public transit are widely used by transportation planners and researchers. This section provides a brief overview of some theory behind this process, and ways in which the decision to ride transit is typically modeled.

The theory behind transportation demand analysis is largely derived from economic frameworks. Consumer travel behavior typically assumes that a given person will select a certain bundle of goods among a set of alternatives if it yields the greatest utility (or satisfaction for the user), a function of the benefits gained by the good [Meyer and Miller, 2001, p.11]. In the context of transportation, the price of these goods considers both monetary costs and some generalized cost of travel time. Secondly, the concept of derived demand generates the purpose for trips. It is generally assumed that individuals travel so that they may participate in activities at a spatially disparate set of destinations, such as workplaces, schools, and recreational facilities. Finally, the microeconomic supply curve indicates that under a static supply curve, the performance of transportation systems (e.g. the public transit system) worsen (reflected as an increase in 'price') as the quantity of demanded trips increase [Meyer and Miller, 2001, p.13]. In the case of transit, this may be reflected by greater crowding levels, longer runtimes, and increased delays with increasing passenger volumes. Using these assumptions and theories, various systems of travel demand estimation, such as four-step models and activity-based models, are developed.

3.1.1 Discrete Choice Models

Discrete choice models are a fundamental tool in the typical process of estimating modal share, and hence modeling individual decisions of whether to take transit. These models typically rest upon the notion that trip-makers are attempting to maximize their utility among a discrete set of alternatives. One common approach to this choice is the Multinomial Logit Model, which is formulated as [Meyer and Miller, 2001, p.24]:

$$P_{it} = \frac{e^{V_{it}}}{\sum_j e^{V_{jt}}} \tag{3.1}$$

For an alternative travel mode i among a set of j alternatives. In this case, P_{it} is the probability of individual t using mode i, and V_{it} is the observable utility of that mode. In this process, however, the challenge lies in defining the utility function and the choice of variables to consider. In the modal choice stage of a typical four-step travel demand model, this takes the form of predicting the proportion of travel flow which uses each mode among a set of possibilities. In common trip-interchange mode split models, the choice is evaluated based on the service characteristics (travel time, cost, etc.) of the modes available. Individual socioeconomic characteristics may also be considered, though they must be either used as alternative-specific variables or in some combination with a mode-specific variable [Meyer and Miller, 2001, p.50]. A sample discrete mode choice model structure is shown in Figure 3-1.

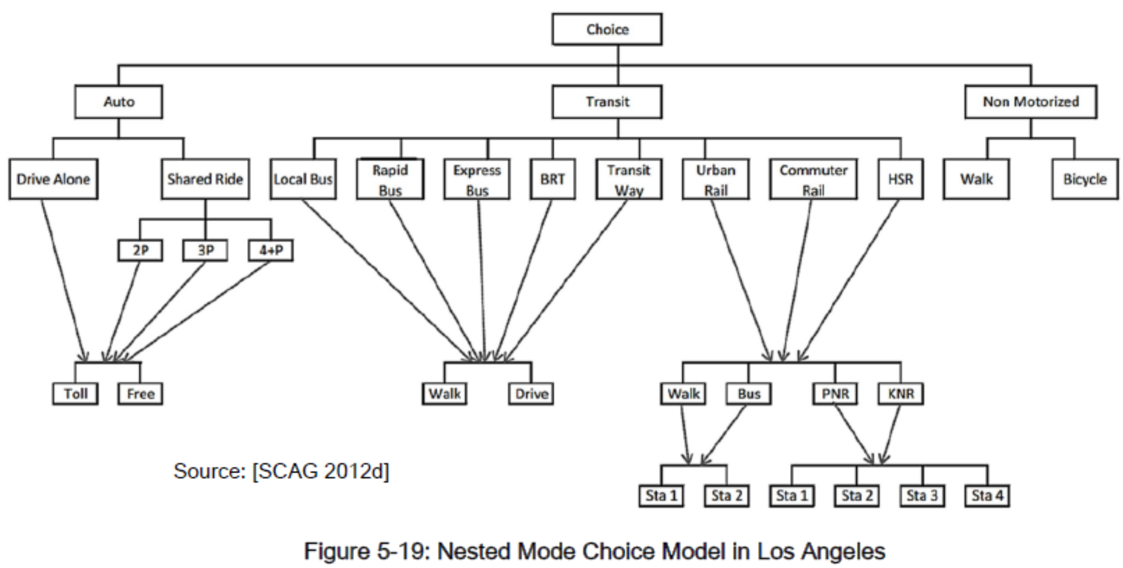


Figure 3-1: Sample mode choice model structure [Meyer and Miller, 2001, p.48]

3.1.2 Elasticity-Based Models

In a simpler framework, economic elasticities may also be used as a means of estimating transportation demand. These approaches are typically formulated using a direct elasticity of demand with respect to an explanatory variable of interest [Meyer and Miller, 2001, p.19]:

$$\varepsilon_{Dx} = \frac{\partial D/\partial x}{D_0/x_0} = \frac{\partial D/D_0}{\partial x/x_0} \tag{3.2}$$

Where D is the demand function, D_0 is the current level of demand, x is the variable of interest, and x_0 is the current level of the variable of interest. By estimating this elasticity, the change in an explanatory variable related to the travel mode (such as the fare or travel time) may be used to estimate the change in demand for that mode. Additionally, cross-elasticities which relate the demand for one mode to a variable attribute of another mode (e.g. transit ridership to the price of TNC trips), may also be used. However, these approaches require some knowledge of the key variables in the demand function for a given travel mode, as well as the sensitivity of demand to changes in these variables. Methods for estimating these models may use quasi-experimental approaches where the transportation system is altered (e.g. through some policy intervention), time-series analysis of demand levels, and derivation from cross-sectional demand models [Meyer and Miller, 2001, p.20].

3.1.3 Direct Demand Models

Direct demand modeling is a growing ridership estimation technique, which typically uses regression modeling to estimate travel demand as a dependent variable. By attributing travel demand to explanatory factors such as the built environment, station contexts, and individual characteristics, direct demand models may estimate ridership for both existing and hypothetical transit systems. These models are stated to provide a low-cost, efficient alternative to traditional four-step demand modeling [Kepaptsoglou, Stathopoulos, and Karlaftis, 2017].

Several studies predict transit system demand across a variety of contexts using a direct demand approach, including [Chen, 2013; Kepaptsoglou, Stathopoulos, and Karlaftis, 2017; Zhao, Deng, et al., 2014]. Chen [2013] and Zhao et al. [2014] use multivariate regression approaches to estimate transit station demand in Boston and Nanjing. Through this process, previous studies have found that the built environment, transportation network, and socio-demographic characteristics all play a key role in demand for public transit. In particular, Chen finds that the predictive power of these variables changed across various time periods, and that built environment factors surrounding the station area are important. Of note, greater area walkability was determined to increase transit ridership. Alternatively, Kepaptsoglou et al. [2017] apply direct demand modeling to predict hypothetical demand for a proposed LRT system in Cyprus, adopting a cost-efficient method which requires limited data obtained through roadside stated preference surveys.

This thesis aims to build upon traditional approaches to transit demand by accounting for more granular factors than are often considered in models of travel demand and modal choice. Through case studies, I will assess the change in travel demand (both qualitative and quantitative) arising from major interventions such as the growth of a potentially competitive mobility service provider, a direct policy intervention, and a public health crisis. Through this research, I hope to identify factors which may contribute to individual demand for travel, and thereby could be considered more intentionally by planners and policy-makers.

3.2 Regulation and Pricing of TNC Services

Existing literature on TNC regulation has predominantly focused on municipal responses to their sudden emergence and rapid growth, discussing issues of whether to allow operations and how to appropriately license TNC services to incorporate them into cities' formal mobility networks. Some papers have highlighted operating fee structures which have been implemented in North America, primarily including flat rate and fixed-percentage pricing schemes. While some literature exists on how to best design and implement TNC pricing structures to ensure equitable outcomes across user groups, Chicago's spatially heterogenous pricing model is a novel approach which has not been the topic of significant research to date.

Much of the existing literature has focused on the preliminary policy questions surrounding TNC services, particularly whether companies should be allowed to operate at all in cities and how they may be regulated and monitored as a new entrant to the mobility system. Beer et al. [2017] identify and compare various regulatory mechanisms used for TNC services in U.S. cities and states. The authors evaluate driver related policies such as background checks, driver's licenses, vehicle registrations, business licenses, and external vehicle displays, as well as company related policies including the number of vehicles operating in the metro area, a list of current drivers being provided to the city, and data on trips completed in the city. The authors find that regulation varies considerably by context, and no standard approach has yet been developed in the U.S. In Brazil, de Souza Silva et al. [2018] identify that the decision of whether to legalize and regulate or ban TNC services has dominated local dialogue, which is an important first step before cities will be equipped to appropriately regulate or tax the service providers. Brail [2018] conducts a case study which documents the process of legislation and regulation of TNC companies in Toronto, Canada. The study reviews the history of legislation, noting its similarity to other major North American cities, which progresses through an aggressive market entry by TNC companies, followed by a disputed right to operations by municipal government, and eventual legal push to establish a set of regulations which differentiate TNCs from other ground transportation providers such as taxis. Brail notes that the impacts of TNC services are borne not only by direct competitors (such as taxi companies) but by the broader city mobility network, and thus states that cities must consider whether regulatory policies are effectively designed to enable inclusive growth and avoid worsening inequity in cities.

Several studies and technical reports have sought to identify current TNC pricing policies in U.S. cities, and to set priorities for how these policies might be designed in the future. Multiple studies identify that current pricing structures levy flat rate or fixed percentage fees, and that the revenue generated is often used for general funds or to fill budget gaps, rather than to invest in improved mobility options [Welle, Petzhold, and Pasqual, 2018; Kim and Puentes, 2018; Zhao, Fonseca, and Zeerak, 2020]. These studies identify a need for fees to promote equitable outcomes and to further differentiate trips according to characteristics such as shared or single-occupant rides, as well as to examine impacts holistically in consideration of urban congestion. Furthermore, Kim and Puentes [2018] raise specific policy questions to consider in the development of TNC fee structures, regarding the impact of fees on congestion, use of revenue to fund infrastructure and transit, and promotion of fair competition between TNC services and taxis. The authors suggest that congestion improvements are unlikely to result from TNC fees, due to the much larger role of single-occupant private vehicle trips in creating traffic congestion.

Furthermore, Henao et al. [2018] and Slowik et al. [2019] investigate the role of TNC pricing in specific applications. By examining ground transportation revenue for airports in four major U.S. cities, Henao et al. identify a significant shift toward TNC travel for airport access, along with changing trends in revenue streams. While parking has been an important past revenue source, its volume has fallen in recent years. However, revenue gained from TNC-specific fees has grown significantly in cities that adopt such fees [Henao et al., 2018]. Slowik et al. [2019] identify an opportunity for differential TNC pricing to promote electrification of vehicle fleets in the U.S. and Europe, stating that per-trip fees within a reasonable range adopted by many cities would be sufficient to make electric vehicles an economically preferable option, and that a small portion of fee revenue (around 5-8% of fees collected) could be used to develop vehicle charging infrastructure.

In the Chicago context, one previous study by Brown [2020] has assessed the equity implications of various TNC fee structures. The study compares the hypothetical outcomes of four alternative pricing structures, including a flat fee, percentage of fare, varied rate for pooled trips, and per-mile fees, by assessing the potential fee volumes using TNC trip records. Examining these results in conjunction with neighborhood income groups (representing census tracts in the bottom 25%, middle 50%, and top 25% of household income), Brown finds that flat fees are less equitable when compared with percentage-based fees. This is because travellers in lower-income areas tend to make shorter-distance trips and use ride-pooling options to a greater extent. Brown asserts that in development of a TNC pricing structure, cities should set equity-based goals for fee programs, and require data from service providers which will enable a thorough assessment of whether these goals are met by the pricing scheme.

In sum, literature on TNC regulation and fees has lagged behind the rapidly changing environment of TNC operations in major U.S. cities. Much of the current body of research focuses on initial questions regarding legalization and basic regulation of

TNC services, but the state of practice has rapidly moved beyond this point. Some research papers and technical reports identify opportunities and priorities which should be considered in TNC fee structures, however these sources primarily concentrate on spatially and temporally fixed pricing structures. The case study in this thesis evaluates the ridership, revenue, and equity impacts of Chicago's spatially and temporally varied TNC pricing program, addressing a gap in the current state of research which may help other municipalities to assess the suitability of such a regulatory program in other contexts.

3.3 Regression Approaches and Studies of Transit Demand During COVID-19

In the context of COVID-19, several studies have sought to examine trends between changes in transit demand and various explanatory factors, particularly focusing on race, income, and other socioeconomic indicators. The majority of studies reviewed found increased likelihood for low-income, non-white and generally socioeconomically-disadvantaged communities to retain higher levels of public transit use in the early stages of the COVID-19 pandemic in the United States [Brough, Freedman, and Phillips, 2021; Wilbur et al., 2020; Sy et al., 2020; Hu and Chen, 2021]. Analysis in these studies was primarily conducted in the early stages of the pandemic, with focus on March and April of 2020.

These prior studies examined a variety of contexts: Wilbur et al. [2020] used agency ridership records (from farebox and APC systems) in Nashville and Chattanooga, Tennessee, which were then aggregated to the census tract level; Brough, et al. [2021] used APC and AFC system data to examine neighborhood-level and individual-level ridership changes for King County Metro in Washington state; Sy et al. [2020] used publicly available ridership data in New York City at the ZIP Code Tabulation Area scale; and Hu & Chen [2021] examined Chicago's rail system using stop-level public ridership estimates (though did not consider the bus system, which disproportionately serves low-income and minority groups in Chicago).

Analysis methods in prior literature typically focus on some sort of regression or investigation of correlation. Multivariate (OLS, partial least squares) regression approaches were used by Hu & Chen [2021], Liu et al. [2020], Brough et al. [2021], and Sy et al. [2020], while Wilbur et al. [2020] used Pearson Coefficients to estimate bivariate correlation between explanatory factors and transit ridership. Of particular note, Sy et al. [2020] further investigated the relationship between socioeconomic indicators and tendency to work in essential services, finding that the over-representation of minority groups in essential work accounted for increased transit dependence.

Each of the previously reviewed papers used ordinary regression methods, which did not explicitly separate and consider the effects of spatial interaction between analysis units. Spatial regression methods, including spatial lag and spatial error models, have proven benefits over standard Ordinary-Least Squares (OLS) approaches. Generally, these models account for spatial autocorrelation in a response variable which is neglected by non-spatial approaches. By examining the spatial dependence among OLS residuals, one may determine whether a spatial approach is required [Chi and Zhu, 2019]. In the area of transit system demand, Gan et al. [2019] apply various regression approaches to ridership in Nanjing, China. They find that spatial error and spatial lag approaches yield a greater fit of the data than standard OLS regression approaches, and emphasize the value of considering spatial patterns when analyzing station-level transit ridership [Gan et al., 2019].

One previous study adopted spatial regression techniques to investigate ridership trends for the full CTA system during the early stages of COVID-19. In this work, Fissinger [2020] estimated average weekly ridership for three periods: (1) a baseline period spanning 8 weeks (January 13 to March 8, 2020) before the COVID-19 pandemic; (2) an early-COVID period spanning two weeks (March 23 to April 5, 2020) in the early stages of the pandemic; and (3) an early-recovery period spanning four weeks (June 22 to July 19, 2020). The study adopted a spatial regression approach by comparing OLS, OLS with regional indicator variables, spatial lag, and spatial error models at the census tract scale of analysis. Using both demographic features and characteristics of transit ridership as explanatory variables, Fissinger identified a correlation between higher rates of transfers, bus use, racial and ethnic minorities, and low levels of peak ridership with higher levels of ridership during COVID-19 [2020, p.110].

Generally, previous studies investigating links between socioeconomic variables and transit dependence during COVID-19 have found a strong link between disadvantaged groups and transit dependence, but have been limited in some regards. In particular, the explanatory variable set used in previous studies is primarily limited solely to American Community Survey (ACS) or census data, and dependent variables focus on public transit rather than other components of the mobility landscape. Most studies do not account for spatial effects, and the body of research thus-far has concentrated on initial lockdowns in early 2020. This research seeks to address these gaps in current literature by (1) incorporating a broader set of explanatory variables including socio-demographic factors, the built environment, transit network characteristics, and TNC network characteristics; (2) considering correlated factors for both PT and TNC ridership in conjunction, to understand differences attributable to different modes (versus to travel in general); (3) adopting spatial regression techniques in regression analysis; and (4) examining a longer time period than previous studies which includes the first wave of the pandemic, subsequent re-openings, the second wave of the pandemic in Fall 2020, and early stages of the vaccination program in 2021.

3.4 Survey Methods and Travel Surveys During COVID-19

Survey-based approaches are important for transit agencies to assess the attitudes and behaviors of their riders, both in ordinary times and to an even greater extent during major disruptions such as the COVID-19 pandemic. Surveys provide a means of qualitative outreach to those who use the transit system, and give an opportunity to link outcomes such as travel behavior with individual-level characteristics such as geographic location, income, and socio-demographic factors. Various survey approaches are reviewed in this section, which provide both a methodological framework for the design of a COVID-19 recovery survey in this study, and baseline results across various contexts which may be used to evaluate and compare the outcomes of this study's survey.

In a methodological sense, studies by Chow [2014] and Luo et al. [2020] provide an initial framework which this survey builds upon. Chow demonstrated one approach to implementing and evaluating an online panel-based survey, identifying its suitability for widespread application through a case study with Boston's Massachusetts Bay Transportation Authority (MBTA). Chow [2014] also used AFC records to validate survey responses, as well as to prompt users with trips that they likely took. Luo et al. [2020] and Shamshiripour et al. [2020] both conducted panel-based surveys, demonstrating the value of repeated sampling of the same individuals, particularly to assess their response to an external phenomenon (in these cases, the COVID-19 pandemic).

Several existing surveys have studied transit riders' responses to COVID-19. Luo et al. [2020] conducted a two-wave study of 236 individuals in Singapore before and after COVID-19 lockdowns, with a focus on five themes of: (1) perceptions of the pandemic and preventative actions taken, (2) current travel behavior and attitudes toward transit, (3) self-reported travel activity, (4) ability to work from home, and (5) socio-demographics. Salon et al. [2020] are conducting a large, three-wave survey with 8,723 current respondents across the U.S., which examines experiences in the pandemic across many facets of life, including employment, work and study, shopping and dining, daily transportation, attitudes, demographics, and social network. In the Chicago context, two previous approaches have been found. Shamshiripour et al. [2020] conducted a stated preference-revealed preference survey in Chicago which examined longitudinal behavior changes from April 25 to June 2, 2020. Additionally, the Chicago RTA used a scenario-planning approach to evaluate potential transit recovery paths for the pandemic, ranging from a stalled economy to a strong, sustained recovery. Each scenario was evaluated based on economy (and implications for transit funding), commuting (considering changes in remote work and transit ridership) and transit mode share (for the workforce which continues commuting), using a survey of 58 participants and various qualitative workshops [RTA, 2020].

These various surveys have been consistent in many of their findings for the COVID-19 pandemic in the U.S. Most clearly, the inequity of the pandemic has emerged as a major theme across several studies. Salon et al. [2020] found that disadvantaged populations, including women and low-income persons, were less able to work from home, relied on public transit more, and lost employment at a higher rate than the general population. These findings were corroborated by Shamshiripour et al. [2020], who similarly found high rates of transit dependence and greater likelihood of losing employment for low-income persons in the pandemic. Luo et al. [2020] also found a correlation between the ability to take preventative action (such as social distancing) and socioeconomic status, potentially due to the disproportionate share of essential workers among disadvantaged groups. Transit dependent riders generally seem unable to shift to lower-occupancy modes during the pandemic, likely due to a lack of feasible alternatives (e.g. access to a personal vehicle).

Secondly, surveys have identified patterns in modal shift during the pandemic, independent of overall declines in travel activity. Salon et al. found significant discrepancies between private vehicle users and transit riders, notably that private vehicle users generally either continued driving or stopped travelling, while many transit riders (likely pre-pandemic discretionary riders) shifted to a personal vehicle when possible. Salon et al. [2020] state that 20% of respondents expect to drive more post-pandemic, while both rare and frequent transit riders expect to use transit less. Additionally, Shamshiripour et al. [2020] identified an averseness to shared mobility such as transit, but frame this as a potential benefit to emerging micro-mobility options such as active transportation.

In summary, current survey approaches to COVID-19 have provided a wealth of insight into the pandemic. However, there is a role for a CTA-focused survey through this project, which expands upon previous research by (1) directly considering the Chicago context, (2) spanning a greater time period which considers late 2020 and early 2021, potentially reflecting longer-term attitudinal changes, and (3) diving deeper into individual attitudes toward public transit specifically.

3.5 TNC-PT Relationship

Previous studies have used surveys, statistical models, and simulations to study the relationship between TNCs and public transit, and indicate the complexity of this relationship. It seems clear from existing research that the relationship may take many different forms depending on context, and is both highly sensitive to the city's existing infrastructure and to regulatory action taken by local governments. The concept of substitution, complementary, and independent relationships between goods in a classical economic sense is examined, in addition to other works which study this relationship specifically in the context of TNC services and public transit.

In a classical sense, the concept of substitution, complementarity, and independence is well-studied in microeconomics using cross elasticity of demand ($E_{P_A,\ Q_B}$), calculated as:

$$E_{A,B} = \frac{\partial Q_B}{\partial P_A} \times \frac{P_A}{Q_B} \tag{3.3}$$

Where P_A is the price of good A, and Q_B is the quantity demanded for good B. In this framework, substitution is defined as $E_{A,B} > 0$, complementarity is defined by products for which $E_{A,B} < 0$, and independence is the case where $E_{A,B} = 0$. Although effective for distinguishing products at an aggregate scale, the case of TNC and public transit services vary across space and time. Factors such as the quality of the service provided vary according to built infrastructure and operations, as well as the level of supply available when the trip is taken. Therefore, a consumer's relative preference between the two modes may also vary along these dimensions. A geospatial-based framework can identify the relationship between every TNC trip in its individual context with public transit. This paper adopts and develops a methodology for investigating this TNC-PT relationship with spatial and temporal granularity.

Several survey-based studies have previously examined the TNC-PT relationship, typically asking riders questions such as "If ridesourcing is not available, what other transportation modes would you use?" [Murphy, 2016; Rayle et al., 2016; Henao, 2017; Gehrke, Felix, and Reardon, 2018]. Findings often vary by context: Rayle et al. [2016] concluded that 33% of TNC trips replace public transit via their surveys in San Francisco on 380 TNC riders; research by Gehrke et al. [2018] on 1000 riders in Metro Boston showed that 42% of riders would have used transit if TNC was not available; Henao [2017] estimated this value as 22.2% based on a survey of 311 TNC riders in Denver. Similarly, the complementary relationship between TNC and PT is often examined by estimating the percentage of TNC trips taken by riders for transit connection. For example, one study conducted in California by King et al. [2020] was based on National Household Travel Survey data and suggested that approximately 11% of for-hire vehicle tours include first mile/last mile transit access; Gehrke et al. [2018] estimated this value as 9% for home-origin trips and 4% for home-destination trips (when including airports as transit); Henao [2017] found that only 5.5% of surveyed TNC trips connected to another mode and only 1% of trips used a TNC trip to access transit in place of driving from origin to destination. These survey-based findings are successful in examining individual decision making, but are very time- and labor-consuming, and may often be limited due to biased sampling and questions or small sample sizes.

Other research has employed big data analytics and statistical models: Hoffmann et al. [2016] examined the change of TNC usage when there is a subway disruption, and found the TNC trips increases over 30% when this special case occurs; Hall et al. [2018] found that transit ridership increased by 5% within two years after Uber enters the market via statistical models; while a study by Graehler et al. [2019] estimated a 1.3% decrease in heavy rail ridership and a 1.7% decrease in bus ridership for each year after TNC services enter the market. Erhardt et al. [2021] use aggregated TNC records and APC-inferred transit ridership to form a fixed effects panel data regression model, which estimated that TNC services caused a 10.8% decline in bus ridership in San Francisco in 2015, but no significant impact on light rail ridership. Grahn et al. [2020] also use APC-inferred transit boardings, in conjunction with surge pricing-based data indicating events of high TNC demand, applying a linear regression model to find that four of ten observed locations saw a significant change in bus boardings during periods of high TNC use. Such research is effective in capturing the overall effect of the TNC relationship by studying a large sample, but only captures the aggregate TNC-PT relationship across the whole study area without distinguishing granular spatial or temporal patterns. Specifically in Chicago, Barajas & Brown [2021] studied TNC pickup and dropoff locations to investigate the potential for the services to provide access to "transit deserts" (areas not adequately served by public transit). However, the study finds that TNC services to not provide significantly greater service in transit deserts, but are rather more associated with areas of higher transit coverage and household income.

Simulations of virtual situations have also been used to study the TNC-PT relationship [Basu et al., 2018; Stiglic et al., 2018]. For example, Basu et al. [2018]'s simulation of the TNC and PT system revealed that public transit is irreplaceable, and Stiglic et al. [2018] proved the potential benefits of an integrated system of TNC and public transit as well as the ride-matching technology required to support this system. Such studies reach conclusions based on virtual or assumed behavior, rather than empirical facts, and thus may confront some limitations when being applied to real-world planning.

Young et al. [2020] use a sample of 1,578 TNC trip records obtained through the 2016 Transportation Tomorrow Survey in Toronto, to investigate the relationship between TNC services and transit. The study compares travel times with hypothetical transit alternatives and investigates correlations with various factors using OLS and logistic regression models. The paper finds that 31% of TNC trips have a competitive transit alternative, and that these competitive trips are correlated with peak-period and downtown travel. This study builds upon these results by investigating a larger dataset (40,000 trips per day over 13 days of analysis) and differentiating TNC trips which may provide a first-mile or last-mile connection to transit services. Methodologically, both this thesis and Young et al. conduct travel time comparisons between real-world TNC trips and a hypothetical transit alternative using OpenTripPlanner and GTFS transit schedules, however the travel time method of comparison differs. While Young et al. [2020] use both proportional and absolute differences between TNC and transit travel times and apply the two separately, this study uses a combined approach based on the travel time of the TNC trip, as described in Section 4.7.3. Additionally, this study performs geographic (buffer) analysis and first mile/ last mile analysis to differentiate TNC trips which may connect with a transit station.

To better facilitate TNC regulations, transit route planning, or transit management, it is necessary to develop an analytical framework that examines the TNC-PT relationship at a more nuanced spatial and temporal scale. Two previous studies have attempted to understand the substitution effects of each TNC trip on public transit on a detailed geospatial and temporal scale, but both were limited due to a lack of data availability. Kong et al. [2020] used DiDi Chuxing trip data in Chengdu, China to recognize the DiDi trips that have the potential to substitute for public transit. However, public transit data in Chengdu was limited to only stop and route information (without schedule data), so it was only possible to draw partial conclusions on the nature of the TNC-PT relationship. Jin et al. [2019] applied buffer analysis and spatial cross-correlation to compare the Uber pickup data and public transit stops in New York City, to examine how Uber substitutes for public transit over time and across space. However, only pickup location information was available for TNC trips, again resulting in incomplete conclusions [Jin, Kong, and Sui, 2019].

In this thesis study, TNC trip data is available at a spatially granular level, along with comprehensive transit data through General Transit Feed Specification (GTFS). This enables us to examine the TNC-PT relationship thoroughly and to draw confident conclusions which may be operationalized by the transit agency (i.e. CTA) and urban planners. The analysis framework developed in this study aims to determine the relationship between each TNC trip and the public transit system (substitution, complementary, or independent) at a disaggregated level, and could be applied generally to other study areas.

3.6 Summary of Literature Review

Through this review of literature, I have identified the current state of research in several key areas related to assessment of transit system demand and factors which may impact this demand. In this thesis, I build upon this state of understanding by addressing several gaps in current research. In the area of regression analysis and transit demand in COVID-19, I expand the time period for consideration to include later stages of virus recovery, incorporate a wide array of explanatory factors and spatial analysis techniques, and consider transit demand in conjunction with demand for TNC services, an alternative mobility service. In my study of the relationship between TNC services and public transit, I leverage a wealth of data to develop a framework which differentiates independent trips from complimentary ones, and study spatial and temporal patterns in the relationship through the COVID-19 pandemic. Using survey methods, I also conduct a panel-based survey for the Chicago area which focuses specifically on the attitudes and behaviors of public transit riders during the pandemic, over the course of a six-month time period.

Chapter 4

Methods & Data

This section summarizes the methodological tools used in the thesis research. An overview of the natural experiments that enabled these investigations is provided in Section 4.1, which highlights the nature and experimental priorities for each of the three exogenous ridership drivers investigated. Section 4.2 provides an overview of the data sources which enabled the various techniques in this thesis, and Sections 4.3 through 4.7 outline several methodological approaches which were leveraged in the various studies.

4.1 Research Design

The three case study investigations conducted in this thesis emerge from 'natural experiments' which took place over the course of the study period, including deliberate policy interventions, emergence of a new mobility service providers, and the onset of COVID-19. Given the different nature of each of these shocks to mobility systems, each is analyzed differently. In particular, the varying temporal scales of these shifts necessitate the use of varied modeling techniques, although spatial patterns across Chicago remain a topic of interest for each.

First, the introduction of the Ground Transportation Tax is well-suited for a before-and-after study of the area impacted by the charge. Given the spatially constrained implementation of the fee, a difference-in-differences approach (described in

Section 4.5) is useful in this case to separate 'treatment' and 'control' geographic areas and isolate the impacts of the policy. This is performed using 'before' and 'after' TNC ridership snapshots at the census tract geographic level. However, the time windows available for analysis following the policy implementation are highly limited due to the onset of the COVID-19 pandemic approximately two months after it.

Second, the COVID-19 pandemic has reflected a longer-term evolution in the mobility landscape, with changing impacts throughout its course. What began in March 2020 as a sudden shock in transportation behavior evolved into a period of "pandemic-normal" over several months, though ever-changing case counts, regulations, and public health guidance caused shifts in attitudes and behaviors over the duration of the pandemic. For this reason, it is necessary to study COVID-19 through a longer-term lens. This study therefore investigates ridership over several key phases of the pandemic spanning almost 11 months (described in Section 4.4), and conducts a six-month panel survey (described in Section 4.6) to provide insight into individual behaviors and perceptions over a longer term.

Finally, the emergence of TNCs reflects a permanent shift in the competitive landscape for mobility service providers. Although the growth of TNC services was explosive and transient for the past decade, during the course of our study their emergence had reached an apparent 'normal' consistent state, though still growing generally over time. This enabled an analysis of how TNC services are interacting with public transit in our current 'normal' mobility landscape. However, in conjunction with the COVID-19 pandemic, this interaction was once again launched into a transient state, which is also investigated through longer-term periodic analysis. The framework used to evaluate this relationship is described in Section 4.7.

4.2 Key Data Sources

The following data sources were acquired and used in various ways through the course of this study. Each major source is discussed in its respective subsection, and metadata for some data sources is available in Appendix A. Where the data source is publicly available, a link its downloadable source is provided in its citation. Private data sources are provided through the CTA-Transit Lab partnership.

4.2.1 TNC Trip Data

The data contain both pickup and dropoff time and location for trips made by major ride-hailing companies, along with trip fares and surcharges, shared ride characteristics, and trip durations. This is reported per the City of Chicago's data sharing agreement with ride-hailing providers [City of Chicago, 2017]. Trips are reported to a temporal resolution of 15 minutes, with locations recorded as a census zonal geography centroid. Trips within the same 15-minute pickup time bin, which share both origin and destination census geography, are combined and averaged in the reported data.

A public version of the dataset is made available by the city of Chicago, with trip records aggregated to a census tract level of spatial resolution [Chicago Data Portal, 2020b].

4.2.2 GTFS Transit Schedule Data

Transit schedule data in the GTFS format is used to identify stop locations and scheduled vehicle arrival times for transit services. These are used both for geographic classification of transit services, and for transit travel time estimation. The schedule data is available publicly [OpenMobilityData, 2020].

4.2.3 Transit Ridership Data

Spatially granular transit ridership is estimated using the CTA automated fare collection system (Ventra) payment records. This provides an approximate daily ridership by boarding stop location. The data is not available publicly, but is accessed through the MIT Transit Lab – CTA partnership. SQL queries used to obtain and aggregate transit ridership data were developed by Fissinger [2020].

4.2.4 Panel Survey Data

Panel survey data used for analysis in the COVID-19 case study was obtained through a six-month panel survey of CTA riders, conducted by the authors as part of the research work supporting this thesis. The high-level survey approach is described in Section 4.6, while details of the survey implementation are provided in Section 6.2.1.

4.2.5 Socio-Demographic Data

The American Community Survey (ACS) data is used to produce socio-demographic data by census tract for regression analyses [US Census Bureau, 2019]. The 2019 ACS 5-year estimates are used generally, and for comparison in difference-in-differences approaches, ACS 5-year estimates from 2018 and 2019 are used. Tables used include B01003 (total population), B08201 (household size by vehicles available), B01001 (sex by age), B02001 (race), B15003 (educational attainment), B19013 (median household income), B19001 (household income), B06007 (place of birth), B16008 (citizenship status), and B08301 (means of transportation to work). These public data are extracted using the 'tidycensus' R package with a census API key.

4.2.6 City of Chicago Spatial Data

Various publicly available spatial datasets which are curated by the City of Chicago and published on the Chicago Data Portal are used in the case studies, which reflect the spatial distributions of several features and provide a geographic baseline for analysis.

Geographic boundaries for 2010 census geographies are used frequently for spatial analysis in these studies, both in conjunction with other spatial data sources (e.g. demographic and point of interest data), and as a fundamental analysis unit for spatial clustering and regression. The boundaries are available for census tracts [Chicago Data Portal, 2010b], and for census blocks [Chicago Data Portal, 2010a].

Crime records across Chicago are used to estimate the spatial distribution of crime rates for regression analyses. The 2019 crime data provided by the City of Chicago is used [Chicago Data Portal, 2020a].

The CTA openly provides parking lot information, including geographic location and lot capacity. These parking lots were used as a proxy to estimate the likelihood of first-mile or last-mile automobile trips using the adjacent station for TNC-PT relationship analysis, and the data is provided here [Chicago Data Portal, 2013].

4.2.7 Open Spatial Data

OpenStreetMap Point of Interest (POI) data (snapshot obtained September 15, 2019) is used to classify the level of activity in a given area, by estimating the potential attraction of people to an area according to commercial, public, and other services. A summarized version of the table used to classify points of interest by category label is provided in Appendix B.2.

Additionally, the street network used for travel time estimation in the TNC-PT relationship analysis process is provided by OpenStreetMap. Tile set data used for backgrounds in map visualizations throughout the thesis is provided by OpenStreetMap, Stamen, and Leaflet.

4.3 Spatial Analysis Techniques

A baseline toolkit of spatial analysis techniques is used to identify and measure spatial patterns in observed data. In particular, global spatial autocorrelation and local statistical clusters of an observed variable are used. This preliminary spatial analysis toolkit is used to identify the potential for spatial patterns, investigate residuals of regression models, and highlight spatial concentrations. This is useful for both quantifying spatial patterns which are observed visually, and performing exploratory analysis to substantiate the use of further spatial techniques.

The Moran's I statistic is used as a measure of global spatial autocorrelation. Spatial autocorrelation refers to the tendency for observations of a variable which are spatially near to one another to be more similar than observations which are distant. A measurement of spatial autocorrelation provides a means of accepting or rejecting a null hypothesis that a dataset is randomly distributed in space [O'Sullivan and Unwin, 2010a]. To measure global spatial autocorrelation across a dataset, the Moran's I statistic is used. This is calculated as follows [O'Sullivan and Unwin, 2010a]:

$$I = \left[\frac{n}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \right] \times \left[\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \right] \tag{4.1}$$

Where the elements y_i represent values of the observed variable, $\bar{y}$ represents the mean value of the observed variable, n represents the number of observation units, and w_{ij} represents elements of the of the spatial weights matrix ($\mathbf{W}$) which reflects the spatial links between analysis units. Therefore, the first term in the equation represents division by the overall data set variance, and the second term reflects a weighted covariance term between each analysis unit and the other units which it is spatially connected to [O'Sullivan and Unwin, 2010a]. A Moran's I value greater than 0.3 or less than -0.3 is generally considered to reflect strong autocorrelation in a dataset, though confidence intervals may be calculated to demonstrate statistical significance.

The Local Getis Ord (G_i^*) statistic is used as a measure of local spatial autocorrelation, to identify 'hot-spots' and 'cold-spots' of an observed spatially distributed value. This may be interpreted as finding clusters of like values: the G_i^* statistic will be high in an area with a cluster of high values, and the G_i^* statistic will be low in an area with a cluster of low values. The statistic for a location i is calculated as follows [O'Sullivan and Unwin, 2010b]:

$$G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_{j=1}^{n} x_j} \tag{4.2}$$

Where w_{ij} represent values of the spatial weights matrix, and x_j represents the values of the observed variable at location j. The statistic simply calculates the proportion of the overall value of the observed variable which is found in a local concentration [O'Sullivan and Unwin, 2010b]. By calculating the expected value of the G_i^* statistic (according to Equation 4.2), the variances and calculated G_i^* values may be used to find a Z score, which is used to establish deviation from the expected mean value, and thus the presence of a local concentration of high or low values. For this process, the expected value of G_i^* is calculated as follows [Getis and Ord, 1992]:

$$E[G_i^*] = \frac{\sum_j w_{ij}}{n} \tag{4.3}$$

4.4 Spatial Regression Techniques

Four different spatial regression modeling approaches are used in different sections of this study, to appropriately capture both a multivariate regression analyses and account for the impacts of spatially lagged dependent variables. These approaches may be used across various analysis units, including census tract, and community area. The selected models include: (1) an Ordinary Least Squares (OLS) regression model; (2) an OLS model with regional 'dummy' variables reflecting Chicago's nine regions; (3) a spatial lag model; and (4) a spatial error model. These models are considered both in the coefficients which they estimate and in the degree to which they account for spatial autocorrelation in the dependent variable, measured using a Moran's I test.

The OLS model is constructed as follows:

$$Y = X\beta + \varepsilon \tag{4.4}$$

Where Y represents the set of response variables (i.e. the TNC-PT substitution rate) for each census tract, X represents the set of explanatory variables, β represents the regression coefficients, and ε represents a set of normally and independently distributed error terms [Chi and Zhu, 2019]. Following a standard process, this model is estimated such that the value of the squared difference between the predicted and observed values of the response variables, $(Y - X\beta)^T(Y - X\beta)$, is minimized [Chi and Zhu, 2019]. This model does not account for spatial autocorrelation in the response variable aside from that which is implicit in the explanatory variables used.

The OLS with regional dummies model is constructed in the same manner as the regular OLS model, however it includes an additional nine binary variables which represent nine regions in Chicago classified by the Social Science Research Committee at the University of Chicago [City of Chicago, 2021b], shown in Figure 2-1 in Section 2.1. Each census tract maps to exactly one region. These dummy variables use a one-hot encoding to classify which region a given census tract belongs within. Aside from the addition of these variables (which modify the explanatory variable matrix X), the model is constructed and estimated identically to the OLS model.

The spatial lag model is constructed as follows:

$$Y = X\beta + \rho \, WY + \varepsilon \tag{4.5}$$

Where ρ is a spatial lag parameter, and W is a spatial weight matrix for each census tract relative to each other [Chi and Zhu, 2019]. This model considers the values of the observed variable (Y) in adjacent spatial areas when predicting coefficients for a given area. ρ provides a measurement of the strength of spatial dependence, and this model may generally be used to account for spatial autocorrelation in the observed data which may be left unaccounted for by a simple OLS model.

The spatial error model is constructed as follows:

$$Y = X\beta + u; u = \rho W u + \varepsilon \tag{4.6}$$

Where u is a set of error terms, ρ is a spatial error parameter, and W is a spatial weight matrix for each census tract [Chi and Zhu, 2019]. The purpose of the spatial error model is similar to that of the spatial lag model, however the approach differs in that a spatial error model produces an error term which considers both spatially lagged errors and normally distributed errors. Put simply, this model acknowledges that there are unexplained factors in the model which are spatially lagged.

In the application of these models to the thesis case studies, spatial regression is used to expand beyond the ordinary application of direct-demand models. While the end goal is different, as this thesis primarily seeks to identify the significance of specific explanatory variables rather than accurately predicting the dependent variable, the model specification is largely similar to examples provided in Section 3.1.3. These case studies build upon previous model specifications by using spatial regression to account for spatial autocorrelation, and by including both common demographic and built environment explanatory variables, as well as measures of the TNC and transit networks. The detailed programming application of this process to transit and TNC ridership through COVID-19 is provided in Appendix B.3.

4.5 Difference-In-Differences Models

To capture the impacts of a targeted policy, a difference-in-differences approach is used. The method functions by comparing an outcome variable of interest before and after a policy was implemented, across a treatment group and a control group. The intention of this comparison is to isolate the impacts of the policy from treatment group-specific factors that do not change over time, which is achieved by comparing the same group pre-treatment and post-treatment. Time-varying factors within the treatment group must also be considered, which are captured by examining time-varying factors for the control group, if the control group was exposed to a similar set of environmental conditions [Gertler et al., 2016]. It is thus necessary to select a control group which, in the absence of treatment, would have experienced a similar trend in the measured outcome. The impact of the policy is estimated by calculating the difference between the change in the treatment group before and after the policy, and the control group before and after the policy. This estimation is illustrated in Figure 4-1. For this study, a difference-in-differences approach is selected over a fixed effects model because the variable of interest (TNC ridership) is measured at an aggregate basis rather than at the individual level [Angrist and Pischke, 2008].

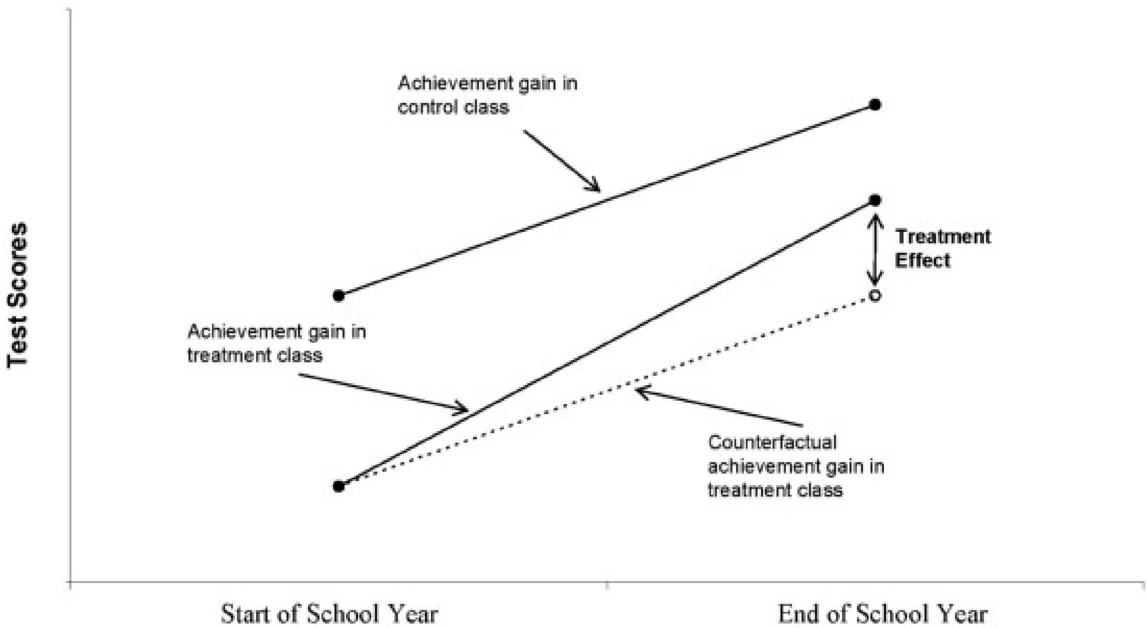


Figure 4-1: Difference-in-differences model [Schwerdt and Woessmann, 2020]

This approach rests upon the assumption that the outcome of interest is a function of the sum of a time-invariant 'group effect' (γ_{tr}), as well as a group-invariant 'time effect' (λ_{post}), along with a random error (ε) and the presence of the policy of interest (indicated by dummy variable $D_{tr,post}$) multiplied by some coefficient β [Angrist and Pischke, 2008]. Following this definition, the outcome of interest may be calculated according to Equation 4.7 [Angrist and Pischke, 2008]. Note that the random error is assumed to have expected value of zero.

$$y = \gamma_{tr} + \lambda_{post} + \beta D_{tr,post} + \varepsilon \tag{4.7}$$

To estimate a difference-in-differences effect of the policy on an overall level, a simple aggregate approach can be used. Specifically, the value of β may be obtained using the definition in Equation 4.7, subtracting across two time periods and between the treatment and non-treatment group, following the process in Equation 4.8 [Angrist and Pischke, 2008].

$$\begin{aligned} \beta = {} & [E[y|tr = 1, post = 1] - E[y|tr = 1, post = 0]] \\ & - [E[y|tr = 0, post = 1] - E[y|tr = 0, post = 0]] \end{aligned} \tag{4.8}$$

To obtain an estimate of the policy effects using a more granular process over several treatment areas, a regression approach is used. This also allows for control variables to be considered which may vary over space and time, potentially influencing the outcome of interest independently from the policy. For this estimation, two dummy variables are constructed: D_{post} reflects whether an observation takes place post-intervention, and D_{tr} indicates whether an observation is in the treatment or control group. The regression formulation shown in Equation 4.9 is used to estimate value and statistical significance of the difference-in-differences estimate (the 'treatment effect' in Figure 4-1).

$$y = \beta_0 + \beta_1 D_{post} + \beta_2 D_{tr} + \beta_3 (D_{post} D_{tr}) + \boldsymbol{\beta}\mathbf{X} + \varepsilon \tag{4.9}$$

Where y is the observed variable (in this case TNC ridership by community area), $\mathbf{X}$ is a set of control variables, and ε is the random error. The estimate of β_3 (the coefficient of the interaction term $D_{post}D_{tr}$) represents the effect of the policy intervention. Similar approaches to regression-based estimation of difference in differences models are shown in [Angrist and Pischke, 2008; Zheng et al., 2016].

This method assumes that there are not differences in trends between the treatment and control group over the analysis period that are unrelated to the program. Spatially concentrated growth of TNC services (particularly in the downtown) may violate this assumption over a long-term analysis period, potentially necessitating the use of samples taken closely before and after the intervention.

4.6 Panel Survey Methods

Various methods were undertaken to coordinate, distribute, compile, and analyze individual-level customer attitudes and behaviors through a six-month panel survey of approximately 1,000 CTA riders. The survey was conducted in six stages, seeking to address a guiding question of "How have CTA riders responded to COVID-19?" Survey questions assess individual travel behaviors before and during the pandemic, attitudes toward CTA pandemic response, perception of COVID-19, and planned returns to work and travel. The full set of survey questions is provided in Appendix B.1. Specific details of the survey implementation, including response rates, scaling, and results are discussed in 6.2.1.

4.7 TNC-PT Relationship Analysis Framework

This section introduces a more specialized approach than the general mathematical frameworks outlined in the preceding sections. For the purposes of analyzing the relationship between TNC trips and the transit network, a novel framework was adopted based on both prior research approaches and economic theory. This is a relatively new field, and it was thus necessary to define various components of the analysis process. This process is informed by prior work from Kong et al. [2020], as well as in direct consultation with planners at the CTA.

Due to better data availability and collaboration with the public transit agency (i.e. CTA), this paper improves existing disaggregate methods for analyzing the TNC-PT relationship from three perspectives. Firstly, previous studies [Kong, Zhang, and Zhao, 2020] are only able to recognize substitutive TNC-PT relationship, but this paper improves the method to recognize all three types of relationship (i.e. substitutive, complementary, independent). Specifically, we differentiate the non-substitutive TNC trips into complementary and independent trips, which could provide more significant policy implications. Second, data limitations also restricted previous studies in terms of spatial granularity and comprehensive knowledge of the transit system, which are overcome in this study thanks to a wealth of data access. The COVID-19 pandemic case study also provides an opportunity to examine a dramatic change in travel behavior, and how this change is reflected in the TNC-PT relationship. Third, this research was developed with ongoing consultation with planning experts at the CTA, which allowed us to develop criteria that reflect significant factors in transportation policy and transit operation.

The overall intention of the method developed is to create a process of analysis which categorizes a set of real-world TNC trips according to their relationship with public transit: substitution, complementarity, or independence. These three concepts are defined as follows:

- **Substitution**: TNC trips substituting public transit can be defined as those taking place when public transit provides a desirable alternative mode of travel (within a comfortable walking distance to transit and at comparable travel time and reasonable number of transfers).

- **Complementarity**: TNC trips which may be bringing passengers to or carrying passengers from the PT network (also known as first or last mile connections).

- **Independence**: TNC trips which operate between OD pairs where there is no transit service available. For example, this could be late at night or between neighborhoods where a transit journey would require many transfers or long travel time. Some researchers describe this situation as complementarity since TNCs fill in the 'transit desert', but in this study we define it as 'independence' to differentiate it from case when TNC serves a first-/last-mile connection to transit.

The process developed to perform this categorization follows three levels of analysis regarding each TNC trip and a hypothetical alternative public transit trip taken from the same origin to the same destination, at the same time. The overall analysis framework used to classify the TNC trips is shown in Figure 4-2. Three main types of analysis are used: buffer analysis (to determine whether a trip is geographically within the transit service area, represented by the variables A, B, and C described in Section 4.7.1), first mile/last mile analysis (to assess whether a trip is providing access to transit connections, described in Section 4.7.2), and service quality analysis (to estimate whether a hypothetical alternative transit trip would provide an acceptable quality of service, described in Section 4.7.3). The analysis is implemented in a series of several steps spanning data extraction to spatial analysis, according to the process highlighted in Appendix B.4.

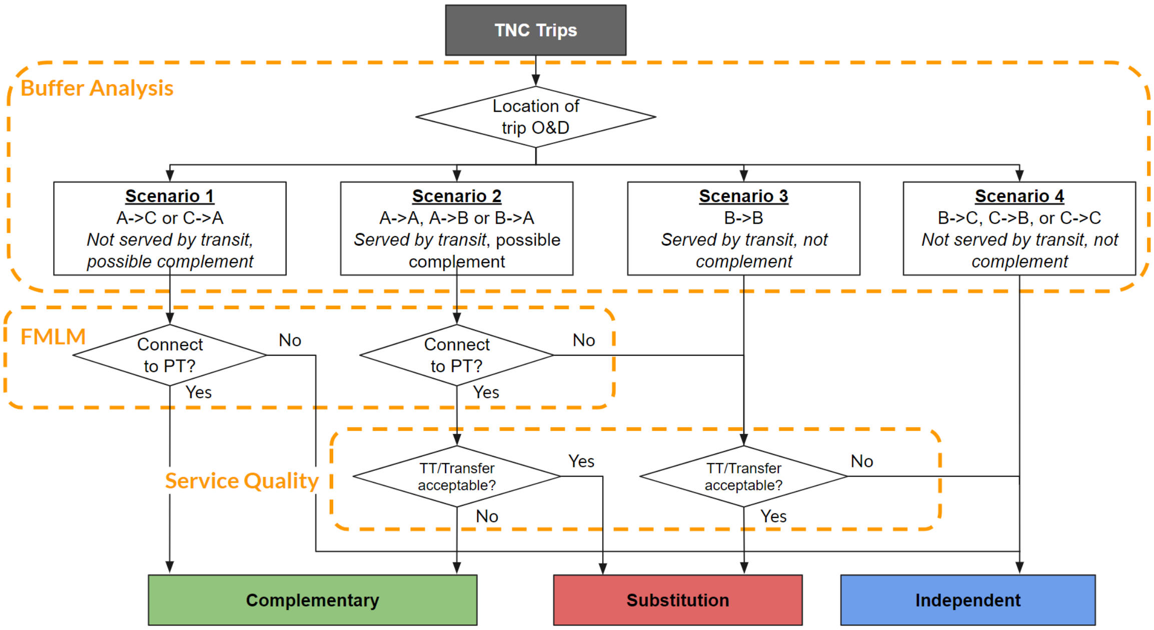


Figure 4-2: Overall analysis framework for determining the TNC-PT relationship (Note: 'A', 'B', and 'C' refer to buffer analysis zones, FMLM refers to First Mile/Last Mile Analysis, 'TT' refers to travel time)

4.7.1 Buffer (Coverage) Analysis

Firstly, buffer analysis is used to compare the TNC trip origin and destination with public transit network coverage. As illustrated in Figure 4-3, three types of transit coverage areas are identified: (1) 100m circular buffer zones are identified as areas wherein trips could possibly provide access to or from the transit stops and thus serve as the first or last mile (denoted as zone A), since the origin/destination of the TNC trip is close enough to the transit stop [Williams, 2017; Jin, Kong, and Sui, 2019]; (2) a buffer distance between 100m to 400m (denoted as Zone B) is used to identify the TNC trips that possibly substitute transit, since this distance is a comfortable walking distance to transit based on existing literature [Demetsky and Bin-Mau Lin, 1982; Murray et al., 1998; Wu and Murray, 2005; Hawas, Hassan, and Abulibdeh, 2016] while not close enough to transit stops to provide the first/last mile connection; areas outside of the 400m buffer are denoted as zone C, and TNC trips whose origin or destination is in this area are considered not covered by transit. TNC trips are categorized into potential substitution/complementary/independence according to the location of their origins and destinations in zone A, B and C (represented in Figure 4-3), according to four scenarios:

- **Scenario 1**: $A \to C$, or $C \to A$. The origin of the TNC trip is close enough to a transit stop (zone A) that the trip is potentially complementary while the destination is outside of transit service, or vice versa. Part of the trip is thus not served by transit, so FMLM analysis is used to test for complementarity. If this is not the case, the trip is independent since either its origin or destination is not covered by transit.

- **Scenario 2**: $A \to A$, $A \to B$, or $B \to A$: Origin/destination is close enough to transit service (zone A) that the trip is potentially complementary, and the trip is served by transit. FMLM analysis is used to test for complementarity. Travel time and transfer analysis is used to test for substitution (since both origin and destination are within transit coverage), and if not considered substitution then the result of the FMLM analysis is used.

- **Scenario 3**: $B \to B$: Origin and destination are served by transit but not close enough to be considered complementary, so travel time and transfer analysis is used to test for substitution.

- **Scenario 4**: $B \to C$, $C \to B$, or $C \to C$: Origin/destination outside of transit service and not potentially complementary (within an zone A), so the trip is classified as independent.

The buffer analysis is conducted for every 10 minutes, considering the real-time public transit service schedule. A transit stop is considered 'active' only when there is at least one bus or train passing through that stop within 10 minutes before and after the starting/ending time of the TNC trip, since 8 to 10 minutes is a typical waiting time of transit riders [Watkins et al., 2011].

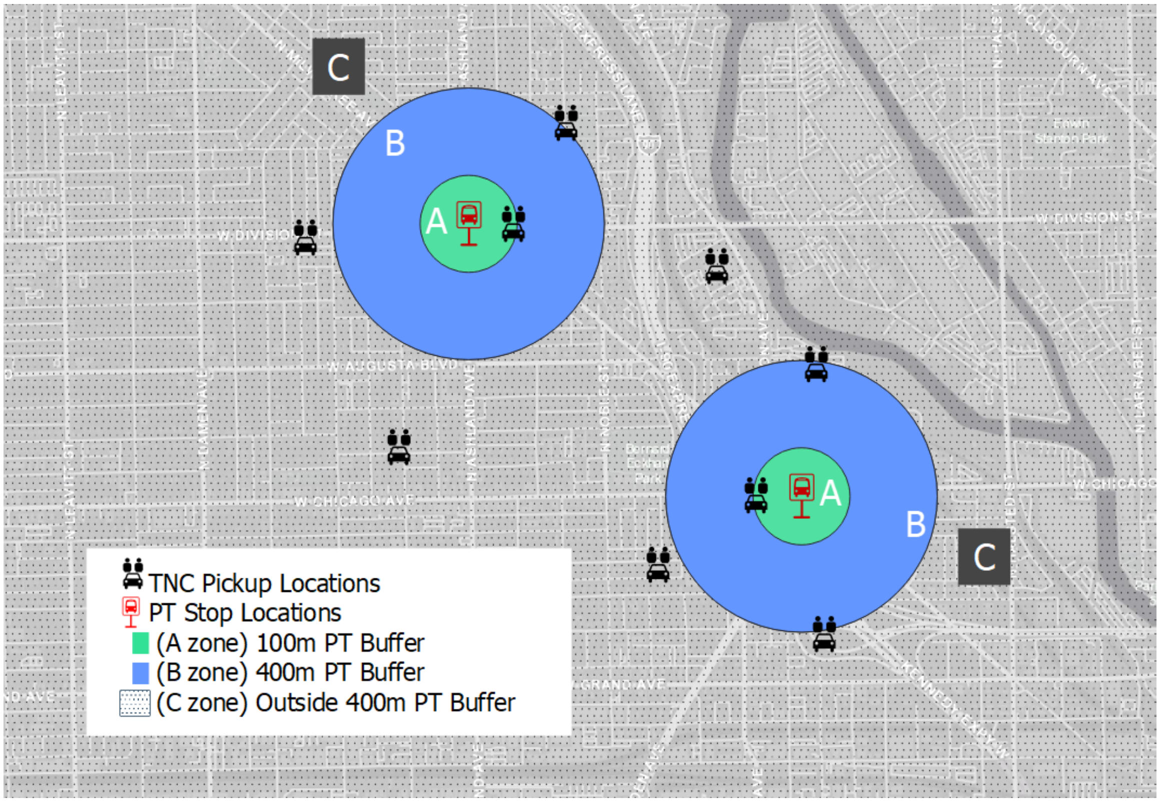


Figure 4-3: Sample schematic diagram of buffer analysis zone classifications

4.7.2 First Mile/ Last Mile (FMLM) Analysis

The TNC trips categorized in Scenario 1 and Scenario 2 in Buffer Analysis are potentially complementary to public transit, in other words, these trips may serve as the first/last mile connection to the transit system. However, it is also possible that these TNC trips access other facilities near the transit stops instead of the transit system. Therefore, first mile/last mile (FMLM) analysis is employed to determine an approximate likelihood that a given TNC trip which originated or terminated near a public transit station is a complementary trip. Recognizing that the decision to conduct a multi-leg transit and TNC trip is dependent on several individual factors which cannot be fully captured at this level of analysis, a likelihood is assigned rather than an arbitrary categorization. Therefore, in the process of estimating this step, a fraction of a single trip is considered complementary, while the remainder is considered as either independent or substitutive.

To estimate the likelihood that a TNC trip is used to connect riders to transit systems instead of accessing non-transit activities near transit stops, we predict the level of non-transit activity immediately around each station. Open Street Map (OSM) POI data is used for this process. The 'attraction power' (or number of potential attendees) and likely operating hours are assigned to each POI (Appendix B.2). The 'attraction power' and the likely operating hours are developed using professional judgement and in consultation with planners, though admittedly it is a subjective and approximate approach. For each TNC trip, the total attraction power ($\alpha(POI)$) of all points of interest which are operating at the time of the trip is summed across a 100m buffer around the station ($\Sigma_{100m}\alpha(POI)$). Using this, the likelihood of complementarity ($\%_{comp}$) is assigned between 0 and 1 on a linear scale, according to the fraction of this attraction power compared with a selected 'maximum' attraction power from a downtown station ($a_{downtown}$), at which activity level it would be unlikely for TNC trips to access the transit system:

$$\%_{comp} = \max\left(1 - \frac{\Sigma_{100m}\alpha(POI)}{a_{downtown}}, 0\right) \tag{4.10}$$

There are two exception cases to this general formulation, determined for particular situations in consultation with CTA planners. The first is to filter downtown origins and destinations. TNC trips which are in the 'loop' downtown area of Chicago, as well as approximately one station outside of it on each line, are considered not to be complementary. This decision was made because rail services are so pervasive in the downtown area and so many alternative destinations are available near each stop that for any given TNC trip it is extremely unlikely that a rider would be accessing transit services. Second, TNC trips that originate from or terminate at stations with one of the 17 CTA parking lots are considered more likely to be complementary, due to the frequent use of these stations for first or last mile transit connections. Based on the parking capacity, surrounding built environment, and potential alternative destinations near the station, each station with parking was assigned a percentage that represents the likelihood of TNC trips to it being complementary to PT.

In cases where the likelihood of complementarity is a fractional value, fractional classification of trips is allowed. For instance, a trip with $\%_{comp} = 0.6$ would be treated as 0.6 trips which passed the analysis, and 0.4 trips which did not. This is used to obtain the most accurate possible estimate on the aggregated spatial scale which is analyzed.

Due to the subjectivity involved in the FMLM analysis method, the results were further investigated by cross-referencing external sources (i.e., CTA survey data), to ensure that they fell in sensible ranges and did not constitute an extreme overestimation or underestimation. Additionally, an upper bound on the complementary trips percentage is calculated (provided in Section 7.2). To compute this estimate, all assumptions of the FMLM analysis process are removed. Trips classified in Scenario 1 or Scenario 2 of buffer analysis are assumed to connect to PT. Thus Scenario 1 trips are directly labelled as complementary, and Scenario 2 trips are passed directly to service quality analysis. This provides an approximate ceiling on the estimated number of complementary trips.

4.7.3 Quality of Service Analysis

The final stage to recognize the TNC-PT relationship is quality of service analysis, which aims to determine whether a hypothetical transit trip (which could be conducted in place of the TNC trip that was taken) provides an acceptable level of service to be considered a viable alternative. This level of service is determined based on two factors: transit travel time, and number of required transfers. Additional factors such as crowding levels may also be included into analysis, but this study did not consider these factors due to data limitations.

Travel time and number of transfers were determined using a local instance of OpenTripPlanner, based on GTFS transit operating schedules for each day. This approach was chosen among various alternatives, including real-time vehicle arrivals from Automated Vehicle Location data, and inferred passenger trip records from Origin-Destination Inference data. A comparative analysis of these various approaches and the variations in their results was conducted in support of this project by Li et al. [2021]. The study highlighted the feasibility and computational requirements of various methods, and identified variations in estimated travel time magnitude and spatial distribution. Ultimately, schedule-based travel times were selected for this study due to their ease of interpretation and scalability to the large set of trips required.

Travel time comparison was conducted using two different methods: proportional difference and absolute difference. Proportional difference measures the ratio of the transit travel time (t_{PT}) to the TNC travel time (t_{TNC}) according to $\Delta t_p = t_{PT}/t_{TNC}$, whereas absolute difference measures the difference between the two, as $\Delta t_a = t_{PT} - t_{TNC}$.

Some threshold for Δt is selected, above which an alternative transit trip is not considered a viable replacement for the TNC trip. This rests upon the assumption that TNC trips are only considered to substitute public transit if the travel time difference between the two modes is below some threshold, indicating that a TNC rider will likely not choose transit if the trip is overly time-consuming. Recognizing the importance of setting this threshold, sensitivity analysis was also performed on the percentage of trips being categorized as each relationship type when varying the time comparison threshold (samples shown in Figure 4-4). Results were highly sensitive to the selected threshold, particularly when using absolute differences. Upon examination of the results, and in consultation with CTA planners, an appropriate hybrid approach to the threshold was selected: for TNC trips with duration less than 15 minutes, an absolute difference of 15 minutes was used (to avoid skewing of results when absolute differences are very low – e.g. a 6-minute transit trip or a 3-minute TNC trip), and for TNC trips lasting more than 15 minutes, a proportional difference of double was used. For the number of transfers, an acceptable limit was set at two transfers, with transit trips requiring more than two transfers not being considered a competitive alternative.

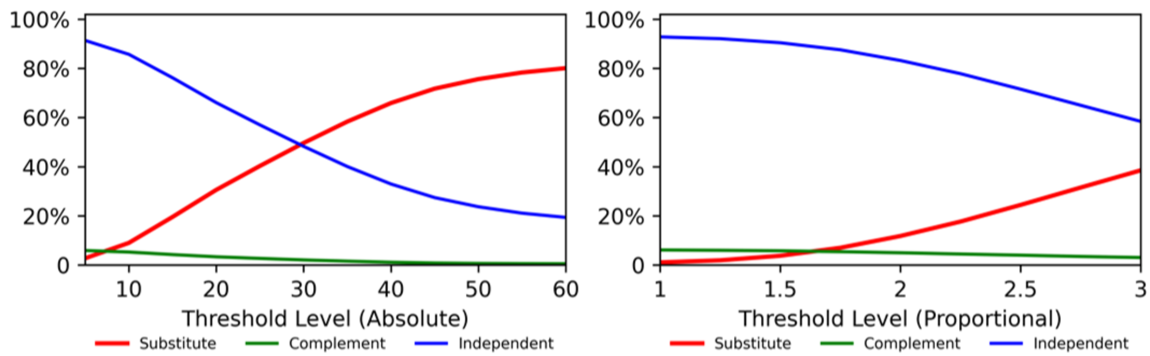


Figure 4-4: Sample travel time sensitivity analysis for substitution rates using absolute (left) and proportional (right) comparison

4.8 Summary of Methods

In summary, a variety of quantitative methods which integrate a wide array of data sources are used in this thesis to investigate three case studies. The case study contexts vary considerably in their temporal scales, from a single point-in-time policy implementation, to a multiple-year pandemic, to a permanent shift in the set of mobility service providers. These varying scales mean that different methods are best suited to each application, and are adopted accordingly as described. However, a common set of data sources and analysis methods (particularly methods to investigate spatial relationships) are used to extract meaningful insights and to perform exploratory analysis across the variety of studies.

Chapter 5

Results: TNC Congestion Pricing Policy

This chapter examines the impacts of a targeted congestion pricing policy, Chicago's "Ground Transportation Tax" initiative, on TNC ridership. Changes in ridership and surcharge revenue generation are considered, using a difference-in-differences (DID) modeling approach. In this section, the case study application is first described in Section 5.1, followed by initial exploratory analysis in Section 5.2. A detailed spatial investigation is conducted in Section 5.3, to identify the impacts of the policy on an area of interest. Results of the difference-in-differences modeling are provided in Section 5.4, and the general case study findings are discussed in Section 5.5.

5.1 GTT Case Study

This case study is undertaken in Chicago, before and after the TNC congestion pricing program (GTT) went into effect on January 6, 2020. The program itself is discussed in greater detail in Section 2.4.

Analysis dates are selected before and after the program implementation. Year-over-year comparisons are performed (to attempt to mitigate the impacts of seasonality), as well as comparisons immediately before and after the program implementation (to avoid influence from longer-term trends). Observations are not taken in the week immediately following the program implementation, to allow time for users to adjust behaviors. However, the time window available for analysis of the policy is strictly limited by the onset of the COVID-19 pandemic in March 2020. Two-week time periods are examined in aggregate, to filter out the potential impacts of daily fluctuations. Trip records are filtered so that only trips which took place while the downtown zone surcharge was in effect (or would have been in effect, in the case of pre-intervention samples) are considered, specifically on weekdays from 6:00am to 10:00pm. The periods studied are also checked for major weather anomalies using National Weather Service records [National Weather Service, 2021] to identify if weather might have influenced ridership significantly. The following dates observed are identified in Table 5.1, where D_{post} indicates whether the observed date occurred before (value of 0) or after (value of 1) the policy intervention took effect. Total trips are the sum of trips on weekdays from 6:00am to 10:00pm in the given analysis periods, and approximate surcharge revenue is calculated as the sum-product of these trip volumes with their average surcharge.

Table 5.1: Summary of GTT analysis periods

Month	**Start Date**	**End Date**	$\mathbf{D_{post}}$	**All Trips (millions)**	**Possible GTT Trips (millions)**	**Approx. Surcharge Revenue (millions)**
January 2019	2020-01-14	2019-01-28	0	4.23	1.73	$4.56
February 2019	2019-02-04	2019-02-18	0	4.38	1.80	$4.74
December 2019	2019-11-25	2019-12-09	0	4.12	1.54	$4.51
January 2020	2020-01-13	2020-01-27	1	4.18	1.62	$6.93
February 2020	2020-02-03	2020-02-17	1	4.38	1.70	$7.17

The treatment group defined for the case study includes trips which either originate or terminate in an area impacted by the GTT pricing. This includes the downtown, downtown (North), O'Hare airport, and Midway airport areas as identified in Figure 5-1. McCormick Place and Navy Pier are also impacted by the policy, but are geographically too small to be sufficiently differentiated by census tract (or resultant mappings to larger community areas) and are thus not considered in the difference-in-differences analysis. These two areas account for a very small fraction of all GTT-impacted ridership, approximately 3.5%. A summary map of adjusted

Chicago community areas mapped to GTT-impacted areas is provided in Figure 5-1.

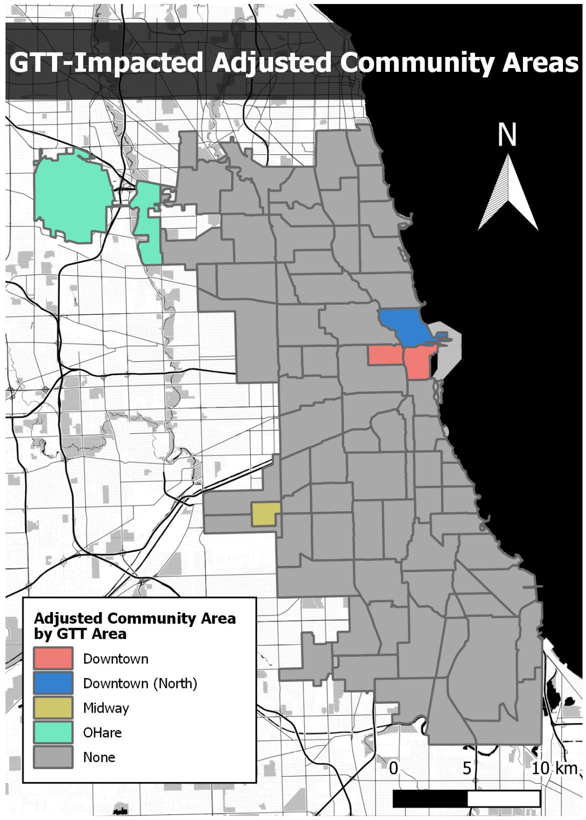


Figure 5-1: Map of adjusted Chicago community areas highlighting areas impacted by the GTT (note that the McCormick Place and Navy Pier are too small to be reliably mapped to community areas)

To perform analysis according to linked origin-destination pairs (as is done in Section 5.4), the Chicago community areas (which divide the city into 77 geographic subdivisions) are used. Two additional areas are added for this study by adjusting the mapping of census tracts to community areas, to differentiate Midway Airport and the West Loop areas, which are both impacted by the GTT policy. This results in 6,241 total linked origin-destination pairs, which allows for a less sparsely populated dataset than using linked origin-destination tract pairs (which would result in 641,601 pair combinations, a majority of which record only zero or one TNC trips over the two-week analysis periods). These areas map to aggregations of census tracts, and thus ACS demographic data is obtained at the tract level and aggregated to the community area scale, then summed across origin and destination for each O-D pair (similarly to Martin et al. [2018]). ACS 5-year estimates are used for demographic data, which does limit the variability of estimates by year. While ACS 1-year estimates would be preferable, these are not available for census geographies with a population under 65,000 [US Census Bureau, 2020], as was used for analysis in this study.

5.2 Initial Exploratory Analysis

To explore the impacts of the GTT program from a high-level perspective, initial exploratory analysis is performed with aggregate trip volumes for each GTT-impacted region of Chicago. Figure 5-2 shows aggregate TNC ridership (percent change from January 2019 levels) for the downtown GTT area, northern portion of the downtown GTT area, and the city overall. This indicates that ridership fluctuated significantly during the months analyzed, and that the general trend in trip volumes was similar for the downtown area and city overall.

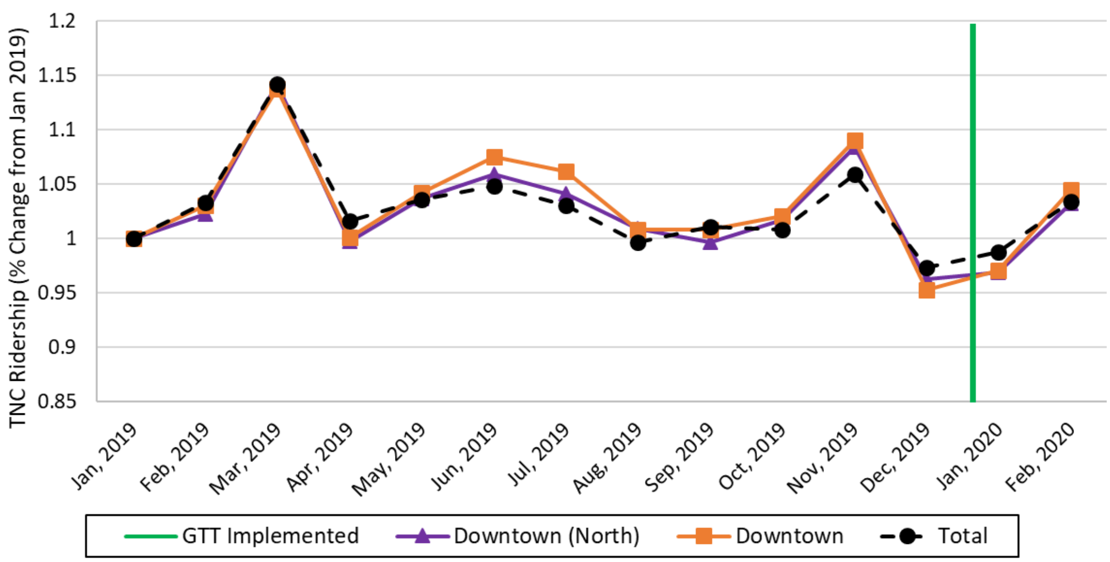


Figure 5-2: TNC ridership change (relative to January 2019) for overall trips and GTT-impacted areas from January 2019 to February 2020 (2-week samples taken for each month)

Changes in aggregate trip volumes before and after the policy intervention are examined using a four-stage process:

- Calculate ridership for pre- and post- intervention time periods, both aggregate and within GTT-impacted areas.

- Calculate the growth rate in total TNC ridership from the pre-intervention period to the post-intervention period, by dividing the total trips in the later period by total trips in the earlier period.

- Use the calculated growth rate to extrapolate a projected post-intervention ridership for GTT-impacted areas in absence of the policy.

- Compute the difference between the observed ridership in GTT-impacted areas and the projected ridership, expecting this value to be negative if the GTT successfully disincentivized TNC travel in the targeted areas.

The results of this process are provided in Table 5.2, comparing both pickups and dropoffs for from January 2019 to January 2020. Additional results are available for other comparison periods in Appendix C.1. As shown, ridership increased considerably year-over-year relative to the projection for both airports, potentially indicating a longer-term growth in TNC travel to airport destinations as a convenient option which may be inelastic to price changes. However, ridership to and from the downtown areas, which experience the most trips, decreased slightly relative to projections. This may be due to the 'Downtown Surcharge Zone' implemented in the GTT policy, which made trips to or from downtown significantly more expensive than other origins and destinations.

Table 5.2: Exploratory analysis of trip volumes in GTT-affected areas from January 2019 to January 2020 (aggregate growth rate = 0.9873)

Type	**Area**	**Trip Volume (2019-02) (thousands)**	**Projected Trips (2020-02) (thousands)**	**Trip Volume (2020-02) (thousands)**	**% Difference from Projection**
Pickup	McCormick	54.6	53.9	62.0	+ 15.0%
	Navy Pier	20.4	20.2	20.1	- 0.5%
	O'Hare	124.8	123.2	152.2	+ 23.5%
	Midway	29.4	29.0	32.1	+ 10.6%
	Downtown (North)	670.4	661.9	649.5	- 1.9%
	Downtown	1,316.2	1,299.5	1,277.1	- 1.7%
Dropoff	McCormick	51.8	51.2	61.8	+ 20.7%
	Navy Pier	16.9	16.7	16.8	+ 0.8%
	O'Hare	151.4	149.5	183.1	+ 22.5%
	Midway	32.2	31.8	34.9	+ 9.6%
	Downtown (North)	645.0	636.8	626.3	- 1.7%
	Downtown	1,332.6	1,315.7	1,291.3	- 1.9%

Generally, these results provide a mixed view of the potential impacts of the program. While some areas see a decrease in trip volumes (compared with the city-wide trend), this is not consistently the case. These observations vary significantly according to the period and area examined.

Various important limitations of this initial aggregate approach inform the analysis in the remainder of this chapter. In particular, the separated view of pickups and dropoffs (as opposed to linked origin-destination pairs) means that neither is capturing all GTT-affected trips entirely, and thus the neither "pickup" nor "dropoff" observations are an exhaustive set of trips impacted by the policy. The 'total' set of trips thus also contains some GTT-affected trips, and as a result does not reflect a pure control sample to project overall growth without the GTT program. Finally, the initial approach does not account for other control variables which differ across Chicago, such as demographics.

These mixed initial results warrant further investigation through a difference-in-differences approach, which is presented in Section 5.4. The modeling approach builds upon this analysis, addressing all of the limitations discussed for this process to gain a more thorough view of the policy intervention's impacts.

5.3 Spatial Investigation: Chicago's South Side

To better understand the spatial heterogeneity of the GTT policy's impacts, a focused spatial investigation is conducted for a region of interest. Figure 5-3 shows the percentage change in overall TNC ridership and average surcharge by pickup community area from January 2019 to January 2020, while comparisons for additional periods are provided in Appendix C.2. These figures indicate that from 2019 to 2020, the downtown area and surrounding neighborhoods to the north, west, and south experienced a modest decrease in TNC ridership. However, the far south side and both major airports experienced significant ridership increases, possibly due to decreased surcharges for shared trips and trips between regions of the city not targeted by the policy, as well as inelasticity of airport-access travel and a general shift toward

TNC use to access airports [Henao et al., 2018]. As shown in Table 2.2 in Section 2.4, the magnitude of the surcharge varies from \$0.55 to \$8.00. The greatest increase in fees is consistently observed in the downtown area (as would be expected by the downtown-focused GTT policy), while slight fee increases are persistent citywide with the exception of some areas to the city's south and west.

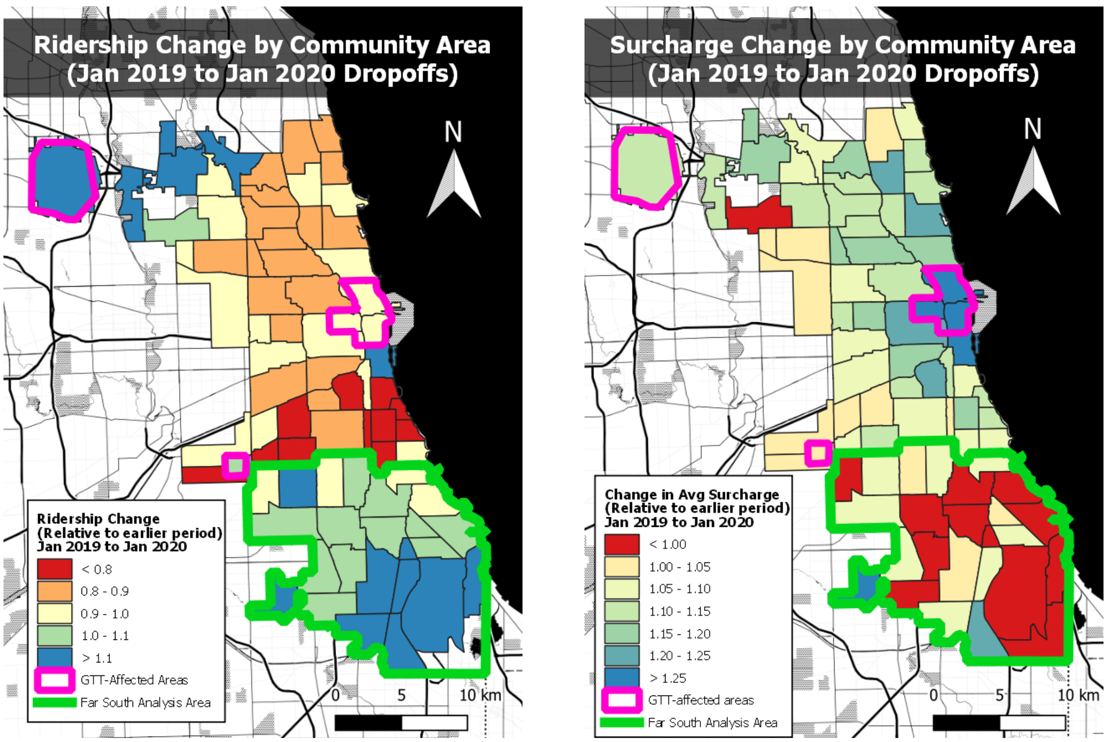


Figure 5-3: Percentage change in ridership (left) and average surcharge (right) by dropoff adjusted community area from January 2019 to January 2020

To further investigate the combination of higher ridership and lower average surcharge trips in the Far Southeast and Far Southwest regions of Chicago, a more detailed spatial exploration is performed. As shown in Figure 5-3, there is an apparent correlation between the policy and both increased ridership and decreased surcharge cost for trips in this area. Therefore, the Far South analysis area is defined for further inspection (shown in Figure 5-3 as a green boundary). This may indicate that the GTT policy made TNC travel a more desirable option for travellers in this lower-income region of Chicago.

Trips which originated in this area are then extracted from the full set of trips, and their respective changes in ridership by destination adjusted community area are observed. Figure 5-4 (left) shows the spatial distribution of ridership change by dropoff area for trips originating in the Far South, while Figure 5-5 (left) shows a histogram of the total ridership impact. This analysis is similarly performed for origin locations of trips which ended in the Far South analysis area, with results shown in Figure 5-4 (right) and Figure 5-5 (right). Additional results for other analysis time periods are provided in Appendix C.3.

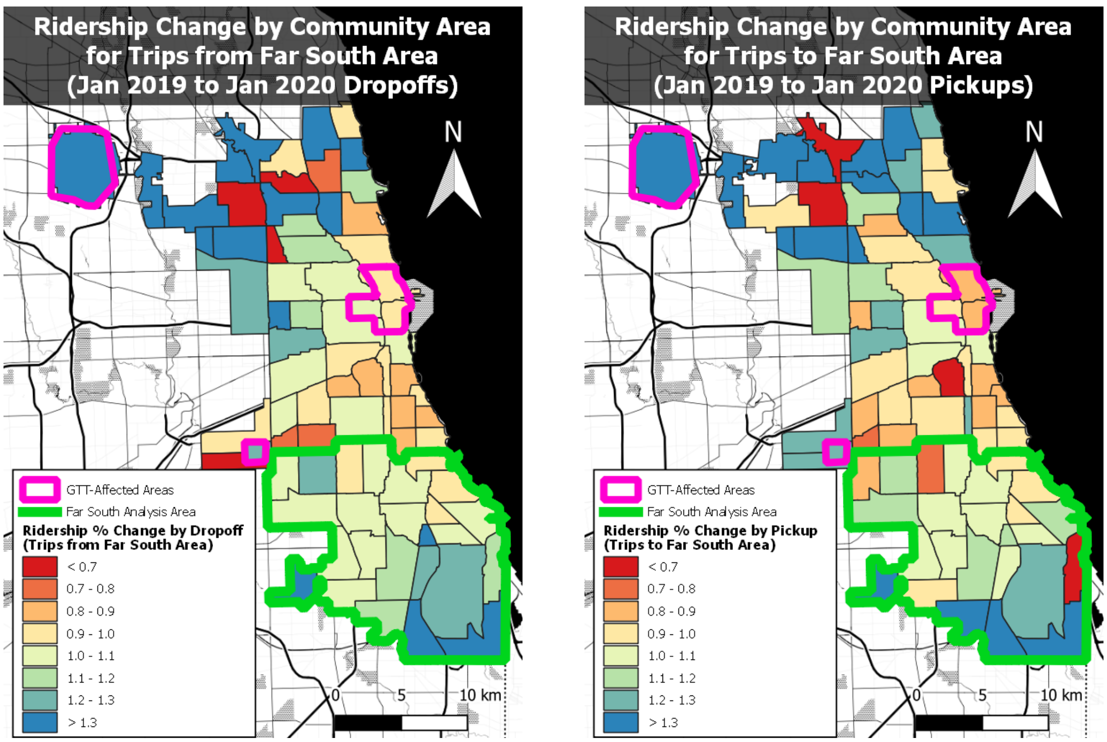


Figure 5-4: Spatial distribution of ridership change for trips originating (left) and terminating (right) in the Far South analysis area (from January 2019 to January 2020)

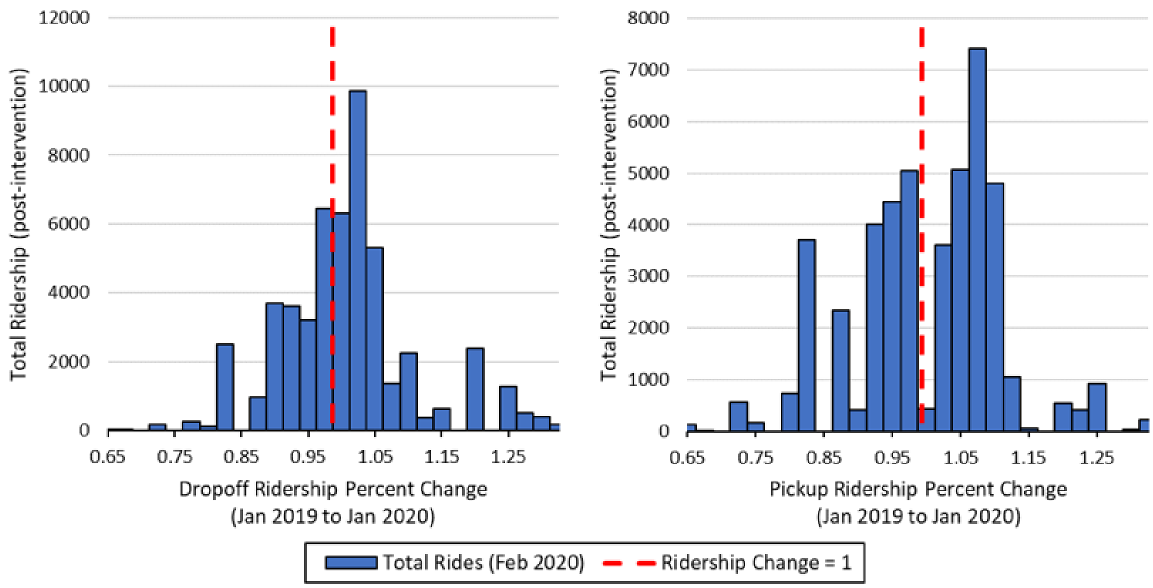


Figure 5-5: Distribution of ridership change for trips originating (left) and terminating (right) in the Far South analysis area (from January 2019 to January 2020)

These results indicate that while overall ridership increased for trips originating or terminating in the Far South analysis area, the balance of selected origins and destinations did not remain constant. Spatial patterns in these changes show an overall increase in travel within the analysis area, as well as in trips made to and from the Far North region of Chicago. Trips to the downtown remained fairly consistent over time, with some marginal decreases depending on the analysis period considered. This indicates a potential localized spatial impact of the GTT policy, which made trips more desirable in the identified area and might have caused an influx of ridership between certain origins and destinations which were not subject to high fees in the GTT policy.

5.4 Difference-in-Differences Model Results

To quantitatively estimate the difference-in-differences effect of the GTT policy, a regression estimation approach is used through the process described in Sectioin 4.5. The estimation model variables are described in Table 5.3, and an OLS regression method is applied. The analysis unit is linked (origin-destination) adjusted community area pairs, with aggregated trip observations during each 2-week study period.

A smaller subset of the demographic control variables used in other case studies is selected, as the purpose of this analysis is not predictive in nature, but rather control variables are used to account for possible changing trends between the treatment and non-treatment areas in the study.

Table 5.3: Variables used in difference-in-differences estimation model

Variable	**Definition**
Dependent Variables	
Rides	Total rides observed in the given period
Avg Surcharge	Average surcharge incurred on trips observed
DID Model Estimation Variables	
D_{tr}	Binary indicator if observation is in a GTT-affected area.
D_post	Binary indicator if observation is post-intervention.
$D_{tr}D_{post}$	Interaction term between treatment and post-intervention indicators.
Control Variables	
Total Population	Total population
Pct White	Percent of population that is white (%)
Pct <25k	Percent of households with income under $25,000 (%)
Pct Transit Commute	Percent of population commuting by transit (%)

The results of the model run for the total ridership by linked community area are provided in Table 5.4. Results are provided for year-over year comparisons (January 2019 – January 2020 and February 2019 – February 2020), before-and-after comparisons (December 2019 – January 2020), and a combined model with all analysis periods.

The consistently significant, positive, and very high-magnitude D_{tr} variable coefficient indicates a much greater prevalence of TNC travel in areas impacted by the GTT (likely a factor which contributed to their inclusion in the policy), regardless of the time period considered. This phenomenon is consistent with results of earlier studies on TNC ridership patterns [Young and Farber, 2019; Barajas and Brown, 2021; Marquet, 2020].

However, the D_{post} coefficient fluctuates between positive and negative, potentially indicating impacts of seasonality and small fluctuations, rather than a significant change in ridership due to the program. Its coefficient is negative for the December

2019 – January 2020 comparison, but positive for all other analysis periods. This change in sign might indicate a confounding impact of seasonality or general changes in travel behavior before and after winter holidays, which has been shown to impact TNC travel behavior [Rayle et al., 2016]. Its lack of statistical significance indicates that TNC ridership did not change significantly after the GTT program was implemented.

The $D_{tr}D_{post}$ interaction term is not significantly different from zero, indicating that the policy intervention is not shown to have a statistically significant effect on ridership. This result is persistent across all time periods compared. For year-over-year comparison models, the coefficient for this term is negative, indicating that the results tend to demonstrate a decrease in ridership due to the program, however not at a statistically significant level. Results which include December 2019 may introduce impacts of seasonality, which may have caused the change in coefficient sign between analysis periods. However, the magnitude of the coefficient is also quite low, and given the lack of statistical significance, random fluctuations could have caused the change in coefficient sign.

Control variables used in the estimation add further insight to the nature of TNC ridership in Chicago. Population is significantly and positively correlated with TNC ridership, indicating the prevalence of TNC use in dense areas such as the downtown, a pattern more clearly shown by the results in Section 7.2.2 and consistent with previous literature on TNC ridership [Young and Farber, 2019; Barajas and Brown, 2021; Marquet, 2020]. The percent of residents commuting by transit is significantly and positively correlated with TNC use, potentially highlighting the shared population of TNC and transit riders, in contrast to private vehicle owners who would be less likely to use either mode, as consistent with [Young, Allen, and Farber, 2020; Hall, Palsson, and Price, 2018]. The percent of low-income population is consistently negatively correlated with TNC ridership, but only statistically significant for the combined model. The negative correlation may substantiate TNC services as a 'luxury good' when compared with lower-cost modes such as transit, walking, or cycling, and is consistent with results from Marquet [2020]. The percent of white residents does not exhibit significant correlation, which differs from previous studies such as [Barajas and Brown, 2021] and [Marquet, 2020], which found percentages of minority populations to have significant and negative correlations with TNC ridership. While race did not constitute a significant variable in this estimation, perhaps due to confounding effects from other factors used to estimate the difference in differences model, the relationship may be examined using a more direct model to estimate TNC ridership using demographic factors.

Table 5.4: Difference in differences model estimation results for ridership by linked community area

Variable	**Dec 2019 - Jan 2020**	**Jan 2019 – Jan 2020**	**Feb 2019 – Feb 2020**	**Combined**
(intercept)	-918 (***)	-979 (***)	-971 (***)	-968 (***)
Model Estimation				
D_{tr}	1357 (***)	1478 (***)	1506 (***)	1449 (***)
D_{post}	11	-13	-10	-2
$D_{tr}D_{post}$	70	-46	-23	8
Control Variables				
Total Population (100,000s)	1140 (***)	1240 (***)	1280 (***)	1240 (***)
Percent White	-28	-43	-99	-65
Percent <25k	-764	-866	-940	-851 (*)
Percent Transit Commute	1483 (***)	1657 (***)	1692 (***)	1614 (***)
Summary of Statistics				
Number of observations	9,792	9,636	9,842	24,414
R^2	0.072	0.070	0.070	0.071

Significance: ***=0.001, **=0.01, *=0.05, .=0.10

The estimation models are similarly run with average surcharge per trip as the dependent variable, and results are provided in Table 5.5. Unsurprisingly, the interaction terms are significant in this estimation, indicating that the GTT policy did have a statistically significant impact on the per-trip surcharge collected for TNC services. Furthermore, the total surcharge collected during the analysis period increased by over 50% from before the policy was implemented (approximately $2.5 million over two-week observation periods), which reflects a major source of added revenue for the city to invest in mitigating the negative congestion impacts of TNC operations.

All of the variables used for model estimation for average surcharge are statistically significant and positively correlated. This indicates that (1) areas impacted by the GTT generally have higher surcharges, (2) the average surcharge increased following the GTT program, and (3) the presence of the program corresponds to a statistically significant increase in average surcharge. This result persists across all time periods considered, and all estimates are significant at the 0.1% confidence level. This result is intuitively expected, as the GTT directly increased surcharges in areas that it was implemented, relative to the city-wide flat surcharge which preceded it.

The control variables used in the estimation also provide interesting and significant results, although literature examining demographic correlations with TNC pricing is limited to provide a point of comparison. Total population is consistently negatively correlated with average surcharge, indicating that areas with a greater population paid a lower surcharge. This might identify a greater tendency toward the use of shared rides (which incur a lower surcharge than single-occupant rides under the GTT program), for residents of densely populated neighborhoods. Secondly, the percent of white residents is positively correlated with average surcharge, possibly identifying a lower willingness of white residents to use shared trips, or a greater propensity to travel to more costly areas such as the downtown or airports. This outcome is in line with results from Irvin [2019], which predicted that the costs of the GTT policy would be borne primarily by whiter, more affluent areas such as the North Side, Near West, or downtown. The percent of residents commuting by transit was significant in all periods except for the December 2019 – January 2020 comparison, and was consistently negative. This might identify that those who are willing to use transit services will forego higher-priced TNC trips, possibly indicating comfort in changing between travel modes or sensitivity to price.

Areas with a greater percentage of low-income residents also correlate with greater average surcharges, identifying a possible inequitable implementation of TNC pricing. However, upon examining auxiliary models which separate observations from before and after the GTT implementation, the magnitude of this coefficient decreases following the GTT. This indicates that the GTT reduces this potential inequity. Additionally, this aggregate census statistic does not differentiate whether lower-income residents are conducting the higher-priced TNC trips. For instance, areas such as the southern portion of downtown might contain higher-income workplaces and lower-income households, for which TNC usage patterns may differ considerably. To fully understand the impacts of TNC pricing on low-income individuals, it would be necessary to consider individualized data, which is not available for this study.

Table 5.5: Difference in differences model estimation results for average surcharge by linked community area

Variable	**Dec 2019 - Jan 2020**	**Jan 2019 – Jan 2020**	**Feb 2019 – Feb 2020**	**Combined**
(intercept)	1.088 (***)	1.191 (***)	1.420 (***)	1.236 (***)
Model Estimation				
D_{tr}	1.906 (***)	1.988 (***)	1.926 (***)	1.943 (***)
D_{post}	0.215 (***)	0.115 (***)	0.216 (***)	0.200 (***)
$D_{tr}D_{post}$	1.063 (***)	0.989 (***)	0.918 (***)	0.972 (***)
Control Variables				
Total Population (100,000s)	-0.735 (***)	-0.728 (***)	-0.772 (***)	-0.762 (***)
Percent White	1.969 (***)	1.953 (***)	1.917 (***)	1.946 (***)
Percent <25k	3.274 (***)	3.427 (***)	3.014 (***)	3.312 (***)
Percent Transit Commute	-0.178	-0.341 (*)	-0.538 (***)	-0.394 (***)
Summary of Statistics				
Number of observations	9,792	9,636	9,842	24,414
R^2	0.441	0.438	0.433	0.418

Significance: ***=0.001, **=0.01, *=0.05, .=0.10

5.5 Discussion of Findings

Through this analysis, three salient findings are extracted as results of the GTT policy. These findings include the identified lack of impact on TNC ridership, the demonstrated changes to surcharge revenue, and the spatial distributions of these changes.

First, this analysis shows that the GTT policy did not likely have a significant impact on TNC ridership in affected areas. Initial aggregate analysis highlighted mixed results in ridership changes, which was further substantiated by a lack of statistical significance in a difference-in-differences model analysis across several time periods. However, it is important to place this finding within the broader context of TNC ridership in Chicago, which has grown explosively in recent years. While it is possible that ridership naturally reached a point of saturation by January 2020, it may also be that the GTT policy served to slow or stop a continued period of ridership growth.

Second, the revenue impact of the GTT policy is clear. Through both difference-in-differences and aggregate calculations, it is apparent that the policy has generated significant revenue for the City of Chicago: over 50% more on aggregate for periods examined in January and February 2020 than 2019. This likely indicates that TNC ridership is inelastic, particularly in higher-income origins and destinations targeted by the GTT policy, and thus a tax increase is unlikely to change behavior significantly (as observed), but will generate considerable revenue. Furthermore, spatial examination of this impact corroborates findings from the Center for Neighborhood Technology [Irvin, 2019], as surcharges were increased predominantly in the downtown and higher-income residential areas, while lower-income communities saw very modest increases or even reductions in average surcharges. These results contrast stated concerns from TNC providers before the policy went into effect [Greenfield, 2019a]. While opponents of congestion pricing may argue that this surcharge decrease could be due to a deterrence of trips to the downtown core (and thus a potential loss of opportunities for low-income riders), the spatial investigation performed in Section 5.3 identifies a relatively consistent rate of trip-making to the downtown, as well as an influx of trips to lower-surcharge areas of the city. This important, progressive new revenue source may provide funds to help stimulate longer term change in behavior and incentivize travel alternatives such as transit and active transportation.

Finally, the spatial profile of the results obtained in this chapter is important to consider. Ridership growth for TNC services appears to be largely concentrated in Chicago's airports and other locations outside of the downtown core, while the downtown experienced only marginal to no growth, depending on the analysis period considered. As identified in the spatial investigation of Chicago's Far South region, localized impacts of the GTT policy may include an influx of trip demand between areas not impacted by the policy, accompanied by fairly consistent (or marginal decrease in) demand between impacted areas such as the downtown. This spatial disparity may limit the effectiveness of TNC congestion pricing in its current form, as increased ridership in other portions of the city may also cause adverse effects on traffic congestion, transit operations, and greenhouse gas emissions. This spatial profile of ridership should be monitored over the coming years, and surcharges on TNC services may be adjusted accordingly.

The findings in this chapter are limited by some characteristics of the modeling approach taken, particularly considering the selection of analysis time periods and limitations imposed by broader events. Fundamentally, the selection of analysis periods before and after the pricing policy involves important trade-offs. Choosing dates immediately before and after the policy (e.g. December 2019 and January 2020) reduces the influence of external long-term trends, but results in vulnerability to seasonal fluctuations. To some extent, trends in seasonality were controlled for by including temperature and precipitation as control variables, however further cultural factors could have impacts outside of the scope of analysis performed. Year-over-year comparisons (e.g. February 2019 to February 2020) should account for seasonality, but leave a longer period between observations during which external factors may play a role in the results. Additionally, the onset of the COVID-19 pandemic (and resultant dramatic changes in TNC usage) shortly after the GTT policy took effect meant that it was necessary to analyze ridership very shortly after the policy was introduced, which might reflect a transient state of response to the policy, rather than a steady-state 'new normal' under the GTT policy. This limited analysis time period took place over two winter months, creating further limitations for the study. A change in ridership may be observed during other periods of analysis, particularly in summer months when a greater number of discretionary trips are taken that could be more sensitive to changes in price.

Chapter 6

Results: COVID-19 Impacts on Transit and TNC Travel

This section presents two different approaches to measuring the impacts of the COVID-19 pandemic on public transit and TNC travel in Chicago. In Section 6.1, spatial regression is used to measure correlations between various explanatory variables and transit and TNC ridership levels through several periods during the pandemic. In Section 6.2, individualized behaviors and attitudes toward public transit and mobility during the pandemic are presented, gathered from a six-month panel survey of CTA riders. The two varying approaches are used to provide both an aggregate quantitative analysis of ridership, and a detailed investigation of individual behaviors, attitudes, and intentions over the course of the pandemic. Section 6.3 provides takeaways and common results.

6.1 Spatial Regression Approach to Transit and TNC Ridership

This section examines aggregate ridership patterns for TNC and transit services through the COVID-19 pandemic, using census tract-level rider counts and spatial regression. The details of the case study are provided in Section 6.1.1, while quantitative findings of the analysis are shown in Section 6.1.2. Common patterns and correlations for each travel mode, and comparisons between them, are provided in Section 6.1.3.

6.1.1 Case Study Details

The case study is designed to examine regular, aggregate counts of ridership to both track progress through different phases of the pandemic and to avoid volatility of results due to daily ridership fluctuations. Analysis is conducted through the COVID-19 pandemic, using periodic sampling over a single eight-week baseline period and several shorter periods. The following analysis periods are defined:

- Baseline (Period 1): January 13, 2020 - March 8, 2020 (8 weeks)
- Period 2: March 23, 2020 - April 5, 2020 (2 weeks)
- Period 3: June 22, 2020 - July 19, 2020 (4 weeks)
- Period 4: September 14, 2020 - September 27, 2020 (2 weeks)
- Period 5: January 25, 2021 - February 7, 2021 (2 weeks)

These periods are chosen as an expansion upon previous work by Fissinger [2020], who examined ridership changes during early COVID-19 for public transit in correlation with various demographic factors. Sample periods between April 9, 2020 and June 21, 2020 were avoided because the CTA rear-door boarding policy hindered reliable ridership data collection. A longer, 8-week baseline period is selected as a basis for comparison. Through these time periods, both aggregate ridership and COVID-19 case counts changed dramatically, as shown in Figure 6-1.

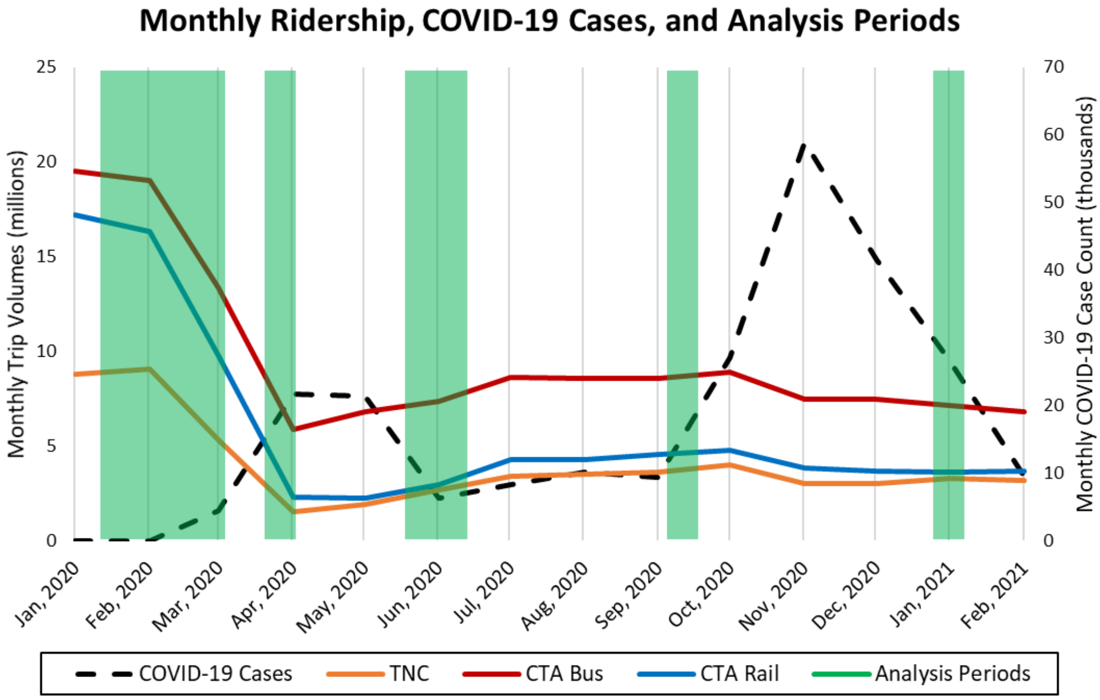


Figure 6-1: COVID-19 case counts, CTA ridership, TNC ridership, and selected analysis periods

The set of variables defined in Table 6.1 is selected for analysis. These explanatory variables are selected to capture relationships in multiple areas, including demographics, the built environment, the transit network, and TNC services. This builds upon previous ridership estimation models, which often capture explanatory variables related to demographic factors [Chen, 2013; Wilbur et al., 2020; Liu, Miller, and Scheff, 2020; Hu and Chen, 2021; Barajas and Brown, 2021; Marquet, 2020], the transit network [Chen, 2013; Hu and Chen, 2021; Gan et al., 2019; Barajas and Brown, 2021], and the built environment [Zhao, Deng, et al., 2014; Chen, 2013; Hu and Chen, 2021; Marquet, 2020]. The dependent variables selected are average weekly ridership percentage change relative to the pre-pandemic baseline for TNC services and public transit, and analysis is performed at the census tract unit of measurement. The sources used to obtain this data are described in Section 4.2.

Table 6.1: Descriptive statistics for variables used in COVID-19 ridership regression analysis for Period 2 (data sources described in Section 4.2)

Variable	Source	Mean	Std. dev.	Min.	Max.
Dependent variable					
Change in PT trips from baseline (%)	Ventra	-0.713	0.124	-0.981	-0.276
Change in TNC trips from baseline (%)	TNC	-0.897	0.155	-1.000	-0.147
Socio-demographics					
Percent African-American (%)	ACS 5-yr	0.383	0.403	0.000	1.000
Percent Spanish-speaking	ACS 5-yr	0.216	0.258	0.000	0.958
Percent aged 25-34 (%)	ACS 5-yr	0.197	0.097	0.037	0.562
Percent aged 35-64 (%)	ACS 5-yr	0.362	0.062	0.064	0.522
Percent aged over 65 (%)	ACS 5-yr	0.121	0.064	0.000	0.513
Percent college grad (%)	ACS 5-yr	0.355	0.263	0.005	0.950
Percent without vehicle (%)	ACS 5-yr	0.277	0.149	0.011	0.778
Percent foreign born (%)	ACS 5-yr	0.189	0.158	0.000	0.726
Logarithm of Median household income	ACS 5-yr	10.783	0.547	9.189	12.078
TNC network					
TNC trips per km^2 (10,000s)	TNC	0.006	0.014	0.000	0.143
TNC avg travel time	TNC	1065	141	732	1461
TNC avg fare	TNC	14.53	1.36	11.83	22.14
TNC percent peak trips (%)	TNC	0.406	0.077	0.209	0.705
PT network					
PT percent peak (%)	Ventra	0.482	0.080	0.261	0.897
PT percent weekend (%)	Ventra	0.155	0.037	0.006	0.273
PT percent bus (%)	Ventra	0.897	0.277	0.006	1.000
Percent commuting by transit (%)	ACS 5-yr	0.297	0.127	0.000	0.741
PT stops per km^2	GTFS	29.8	26.1	1.1	361.8
PT rail stop presence (0/1)	GTFS	0.128	0.335	0.000	1.000
Built Environment					
Population per km^2	ACS 5-yr	7386	10867	147	271569
Crimes per km^2	Other	664	631	26	6857
Walkability index (scale 0-20)	Other	13.76	1.88	8.67	19.33
POI count	OSM	10.01	21.52	0.00	323.00

To investigate potential correlations between the independent variables of interest, a correlation matrix is calculated, shown in Figure 6-2. Explanatory variables generally exhibit fairly weak correlations, sufficient to enable analysis to progress using the set of variables defined.

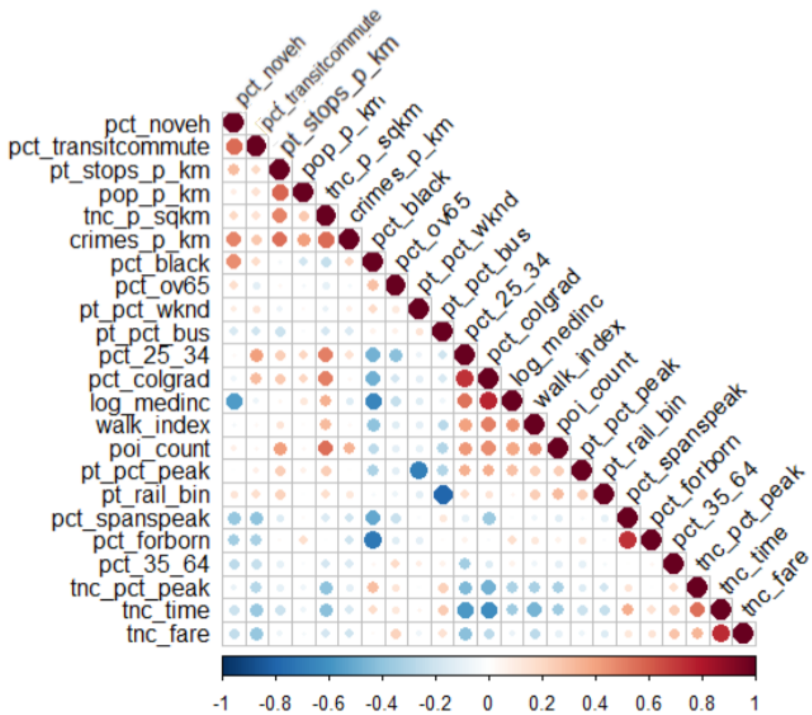


Figure 6-2: Correlation matrix of variables used in ridership regression analysis (size of icon indicates magnitude of correlation coefficient)

6.1.2 Regression Analysis Findings

Examining the dependent variables, histograms and spatial plots are first used to provide a first-glance profile of their distributions. Samples of these figures are shown in Figure 6-3 for Period 2, and are provided in Appendix D.1 for all periods. These plots indicate that a much greater proportion of census tracts experienced a very high loss of TNC trips (over 80% reduction from baseline) compared with transit trips. Many tracts continued to use transit to some extent, with the most common ridership reduction between 70% and 80% of pre-pandemic levels.

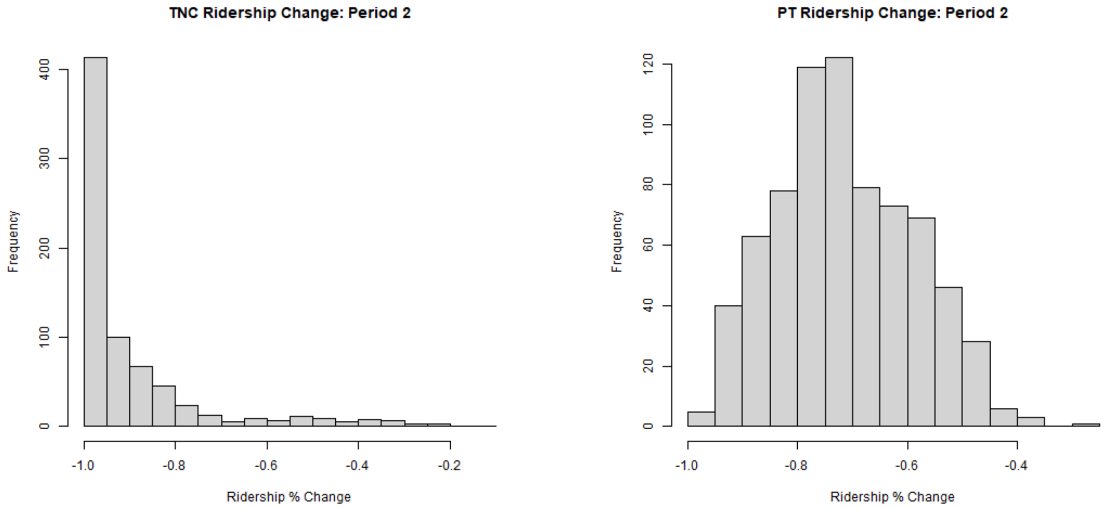


Figure 6-3: Distribution of TNC (left) and public transit (right) ridership change by census tract for period 2

Secondly, the ridership change by census tract is examined spatially in Figure 6-4 for Period 2, and in Appendix D.1 for all periods. Upon observation, it appears that these values are not randomly distributed in space. In fact, there seems to be a concentration of lower change in ridership for transit on Chicago's south side, along with a much greater drop in trip volumes in the downtown and near north side. For TNC trips, there similarly appears to be a lesser decrease on the south side, although this difference is less pronounced. To quantify these observations, a Moran's I test is first performed (results shown in Appendix D.1). The values of the test are statistically significant for all periods considered, indicating a clear spatial correlation in the observed data and a need to consider spatial patterns in subsequent analysis.

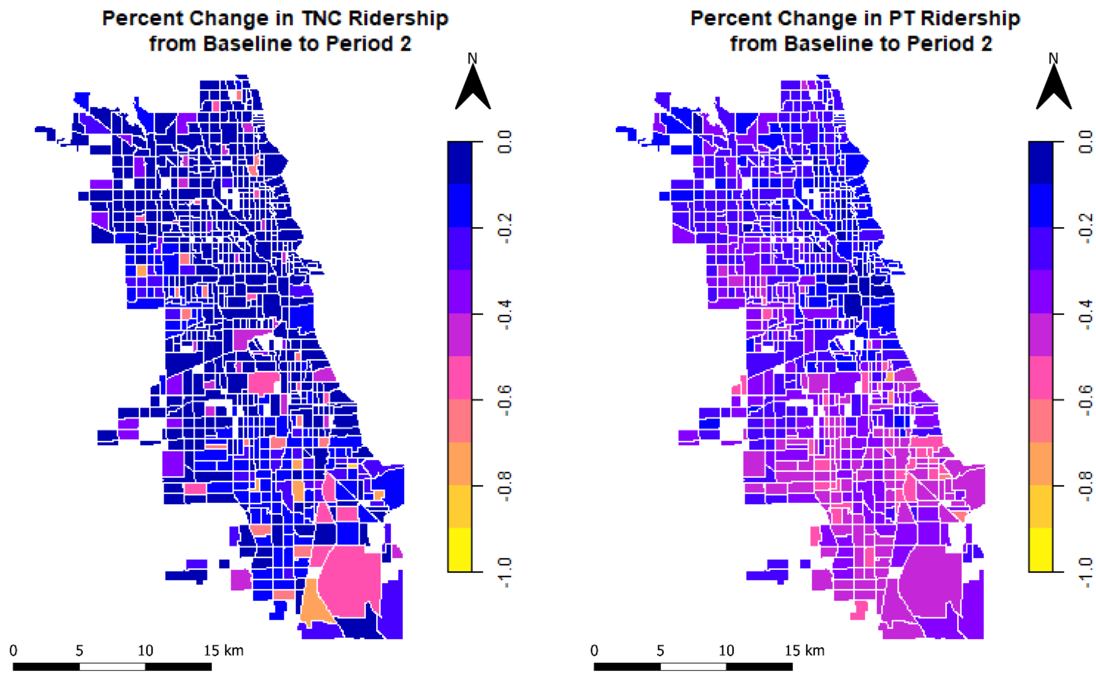


Figure 6-4: Spatial distribution of TNC (left) and transit (right) ridership change for period 2

The apparent spatial patterns are also assessed at a preliminary level using a Local Getis Ord (G_i^*) statistic, with sample results shown in Figure 6-5 and results for all periods shown in Appendix D.1. This analysis indicates spatial clusters of low ridership change for both TNCs and public transit on Chicago's south side, and clusters of higher decrease in ridership in the loop and near north side.

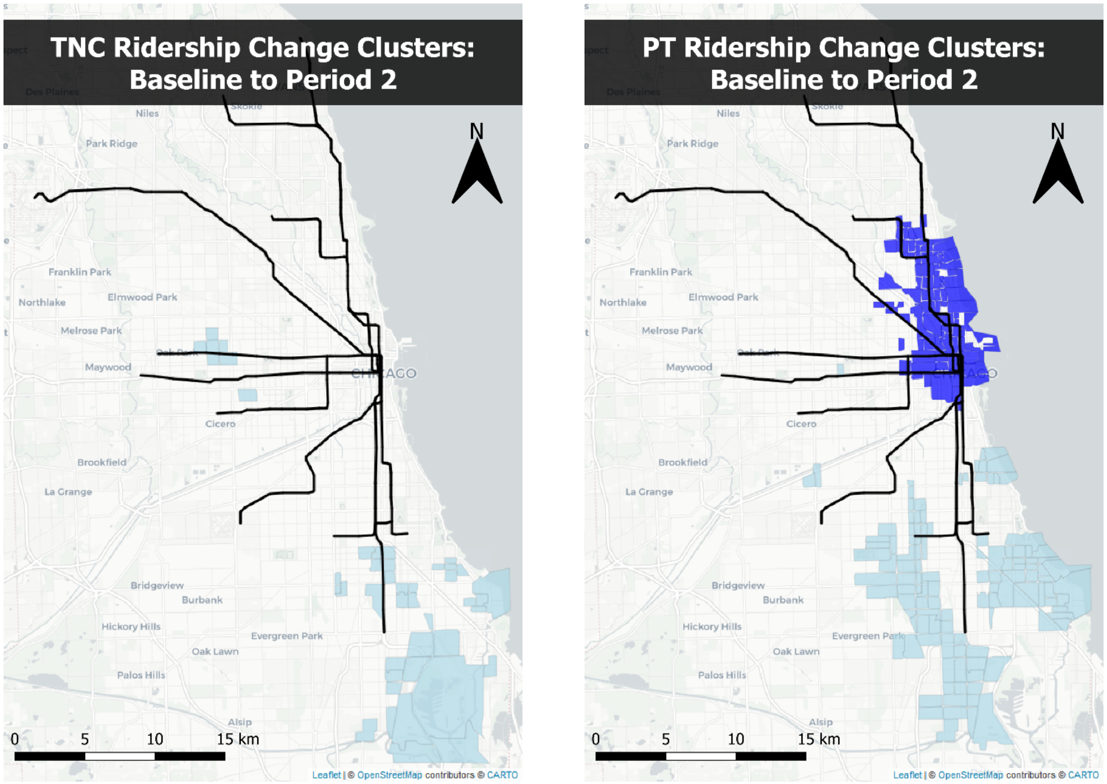


Figure 6-5: Spatial clusters of ridership change for TNC and transit (light color indicates little ridership change; dark color indicates large decrease)

To fully assess patterns connected to transit and TNC ridership, spatial regression analysis is performed using ordinary least-squares (OLS), OLS with spatial dummy variables, spatial lag, and spatial error models through the process described in Section 4.4. Spatial regression techniques are used to account for spatial dependence in the observed results, evaluated using a Moran's I test on each model's residuals. Generally, the spatial lag and spatial error models are found to appropriately account for spatial autocorrelation, and the resultant coefficient estimates and significance levels are provided in Table 6.2 for TNC ridership and Table 6.3 for transit ridership. Spatial lag model results are provided, as the model was determined to best fit the data using Akaike Information Criterion (AIC), log-likelihood, and Lagrange Multiplier tests. Results are discussed and compared with reference literature regarding correlations with TNC ridership before COVID-19, however limited sources are available that discuss the change in ridership over the pandemic.

As shown in Table 6.2, several socio-demographic variables correlate strongly with the change in TNC ridership from before COVID-19. The percent of African-American residents exhibits a very strong positive correlation throughout all time periods examined, which is consistent in magnitude and significance, identifying that areas with a greater proportion of African-American residents continued to use TNC services through the pandemic. On the other hand, the percent of population aged 25-34 shows a negative correlation of consistent magnitude and significance, which identifies that younger professionals, who are traditionally frequent users of ride-hailing services [Rayle et al., 2016; Young and Farber, 2019], stopped using the services to a greater extent – likely due to a greater tendency to work in jobs which may be conducted remotely during the pandemic. Other indicators of age were largely insignificant, although the percent of residents over age 65 exhibits a negative correlation with ridership change, significant at the 10% level in period 2 and period 5. Although older adults were not dominant users of TNC services before the pandemic [Young and Farber, 2019], concerns about public health and the disproportionate risks of COVID-19 for older populations may have driven this greater decrease in ridership. The percentage of residents who graduated college is significant and negatively correlated with ridership change throughout all analysis periods, possibly indicating the option to decrease ridership for those who could conduct work remotely. Interestingly, vehicle ownership only exhibited a significant correlation in period 2 (immediately following the pandemic), indicating that areas with a greater rate of vehicle ownership disproportionately stopped riding TNCs in the early pandemic, though as time progressed individuals in other areas (particularly higher-income areas) tended to purchase vehicles [Furcher et al., 2020] or possibly found alternative, non-shared mobility options. Immigration status and household income were not significantly correlated with TNC ridership change.

Several explanatory variables related to the TNC service network are significantly correlated with TNC ridership change. The density of TNC trips shows a significant, consistent positive correlation with ridership change, indicating that areas which rode TNCs to a greater extent before the pandemic did continue to use the service, perhaps identifying discrepancies in the service availability or desirability across the city, or comfort for those who were already familiar with TNC services. Baseline TNC travel time and fare are largely insignificant in this analysis, though travel time does show a strong, negative correlation in period 2. This may indicate that in the early stages of the pandemic, areas which would require a significant travel time to their destination may have foregone TNC trips to a greater extent, possibly due to concerns about extended exposure to COVID-19. Finally, the baseline percent of peak TNC trips is consistently significant and strongly negatively correlated with TNC ridership change, indicating that areas with high pre-pandemic peak TNC use stopped riding. This could identify a disproportionate decrease in the use of TNCs for work-based purposes in the pandemic, as corroborated by the results of Chapter 7.

Explanatory variables related to the public transit network are largely insignificant in their correlation to TNC ridership change. None of the baseline percent peak, percent weekend, percent bus, percent commuting by transit, or rail stop presence corresponded significantly with greater or lower change in TNC ridership during the pandemic. Although some of these variables may indicate socioeconomic divisions (such as percent bus or percent peak), these factors may be confounded by other characteristics of the transit network, and are more clearly captured by the sociodemographic variables. However, the transit stop density did exhibit a significant negative correlation of weak magnitude in periods 3 and 4, possibly indicating a greater loss of TNC ridership in more densely served areas (such as Chicago's central business district), a possible product of reduced TNC ridership for commuting trips. Other variables also capture this relationship, however (such as population density or POI count), and thus the relationship is not clearly defined.

Finally, factors of the built environment vary in their correlation with TNC ridership change. Crime rate is significant and negatively correlated with TNC ridership change through all periods examined, identifying that areas with more crime stopped riding to a greater extent. This pattern may be indicative of decreased ridership in Chicago's downtown, which has a high crime rate, high proportion of work-based TNC trips, and disproportionately greater reduction in trip volumes following the pandemic. It may also indicate that areas with higher crime rates which may have used TNC services due to concerns about personal safety before the pandemic, might have sought out less-costly travel alternatives as the pandemic brought about uncertainty in employment and finances for many. Neighborhood walkability is also significantly and negatively correlated with TNC ridership change, though with a lesser magnitude than other factors. Residents of more walkable, desirable neighborhoods may disproportionately have been able to work remotely or use active transportation during the pandemic, reducing the need for TNC travel. Finally, the number of points of interest and population density do not show significant correlations with TNC ridership change.

Table 6.2: Spatial Lag model results for TNC ridership change

Variable	Period 2	Period 3	Period 4	Period 5
(intercept)	0.194	-0.265	-0.080	0.297
Socio-demographics				
Percent African-American (%)	0.165 (***)	0.202 (***)	0.154 (***)	0.179 (***)
Percent Spanish-speaking	0.037	-0.032	-0.013	-0.050
Percent aged 25-34 (%)	-0.442 (***)	-0.372 (***)	-0.394 (***)	-0.506 (***)
Percent aged 35-64 (%)	-0.058	-0.082	-0.089	-0.170
Percent aged over 65 (%)	-0.143 (.)	-0.087	-0.070	-0.222 (.)
Percent college grad (%)	-0.182 (***)	-0.331 (***)	-0.210 (**)	-0.258 (***)
Percent without vehicle (%)	-0.169 (**)	-0.057	-0.060	-0.101
Percent foreign born (%)	-0.009	-0.048	-0.006	0.003
Log of Median household income	-0.022	0.033	0.019	0.007
TNC network				
TNC trips per km^2 (10,000s)	5.978 (***)	6.448 (***)	6.307 (***)	6.960 (***)
TNC avg travel time (10s min)	-0.003 (***)	-0.001	-0.001	-0.002 (.)
TNC avg fare ($10s)	0.105 (.)	0.037	0.015	-0.047
TNC percent peak trips (%)	-0.823 (***)	-0.931 (***)	-0.915 (***)	-0.969 (***)
PT network				
PT percent peak (%)	-0.068	0.101	0.080	0.072
PT percent weekend (%)	0.064	0.202	0.259	0.217
PT percent bus (%)	-0.015	0.021	0.013	0.030
Percent commuting by transit (%)	0.033	0.110	0.081	0.079
PT stops per km^2 (100s)	-0.040	-0.071 (*)	-0.072 (*)	-0.057
PT rail stop presence (0/1)	-0.006	-0.001	0.009	-0.001
Built Environment				
Population per km^2 (100,000s)	0.128 (*)	0.118	0.111	0.111
Crimes per km^2 (10,000s)	-0.662 (***)	-0.481 (**)	-0.481 (**)	-0.594 (***)
Walkability index (scale 0-20)	-0.015 (***)	-0.014 (***)	-0.016 (***)	-0.018 (***)
POI count (100s)	-0.024	-0.030	-0.033	-0.037
Summary of Statistics				
Number of observations	730	730	730	730
Rho	-0.083	0.095	0.050	0.069
Residual Moran's I	0.062	0.046	0.055	0.059
AIC	-1083	-667	-615	-593

Significance: ***=0.001, **=0.01, *=0.05, .=0.10

Table 6.3 provides results of the regression modeling for changes in public transit ridership. The results are interpreted according to the significance and magnitude of explanatory variables in each category.

Demographic explanatory variables highlight the disproportionate impact of COVID-19 on travel patterns for areas with minority communities. The percent of African-American residents and percent of Spanish-speaking residents are consistently positively correlated with PT ridership change, indicating a tendency for these populations to continue using transit during the pandemic. This result is consistent with estimates from other studies [Liu, Miller, and Scheff, 2020; Wilbur et al., 2020; Hu and Chen, 2021]. This may indicate a disproportionate tendency for minority populations to work in essential jobs which could not be conducted remotely [TransitCenter, 2020; Bolton, 2020; Rudick, 2020]. The percent of foreign-born population shows a similar correlation, though to a lesser degree of significance and magnitude – potentially highlighting the wide range of demographic groups encapsulated in this category. Factors related to age are mostly insignificant in the analysis, though it is worth noting that the sign of the coefficient for percent of population aged 25 to 34 changes from negative in period 3 to positive in period 4. This may indicate a greater (though not statistically significant) willingness of younger populations to return to public transit as pandemic recovery progressed. Conversely, the percent of population aged over 65 is negatively correlated with PT ridership change (though only significantly so in period 3), which might indicate a greater reduction in transit use for older adults, who face a greater risk of mortality from COVID-19. Other studies vary in their definitions of age-related variables; however Hu & Chen [2021] also estimate that young adults stopped riding to a greater extent in the early pandemic. Surprisingly, vehicle ownership did not correlate significantly with transit ridership reduction, possibly highlighting a relatively small proportion of discretionary riders on the CTA, or identifying that travel behavior in the pandemic depended to a greater extent on whether individuals could work remotely. This result is consistent with Liu et al. [2020], who did not find a significant correlation between vehicle ownership and change in transit ridership during COVID-19. Finally, household income is very weakly negatively correlated with ridership change. This result is consistent with other findings [Hu and Chen, 2021; Wilbur et al., 2020], and may indicate a greater likelihood for higher-income workers to work remotely during the pandemic.

Explanatory variables related to TNC services are also significant in predicting the change in transit ridership. The average TNC travel time shows a consistent weak negative correlation, similarly to that for TNC ridership. This may reflect an aversion to longer-distance rides, and thereby potential increased exposure to COVID-19. On the other hand, average baseline TNC trip fare was positively correlated with PT ridership change, identifying a possible price-inelasticity in trips that did not have a viable alternative. The baseline percent of peak TNC trips shows a consistent strong positive correlation with transit ridership change, an opposite pattern than for TNC ridership. This may indicate that some areas which used TNC services to commute might also include populations who rely on transit services, or might have sought a lower-cost option to conduct essential trips. TNC trip density was not a significant predictor of transit ridership change. These factors are not explored in reference literature, but may be further assessed using a similar modeling approach with expanded factors of the TNC network.

Factors related to the public transit network also show important correlations in this analysis. The percent of peak-period transit travel is consistently negatively correlated with PT ridership change, substantiating the observation of decreased travel for individuals working office-based jobs, which would require travel during peak periods. As seen in Section 6.2.2.3, baseline peak-period travellers are disproportionately more likely to work remotely during the pandemic, a result which is also corroborated by [Fissinger, 2020]. Additionally, areas with a greater percentage of bus riders consistently correlated with continued use of transit services. This finding is also supported by survey findings in Section 6.2.2.1, and regression analysis by Fissinger [2020]. The baseline percent of transit commuters, presence of a rail stop, transit stop density, and baseline percent of weekend ridership did not show consistent significant correlation with transit ridership change, and are not examined in reference literature.

Finally, factors related to the built environment were mostly not significant predictors of transit ridership change. Population density, walkability, and number of points of interest did not exhibit significant correlations. Similarly, Hu & Chen [2021] found no significant correlation between population density and change in transit ridership in COVID-19. However, the crime rate was significantly and positively correlated with continued transit use, which may highlight a continued need for travel to employment in some areas, along with a need to continue essential trips, while residents of high-crime areas might have disproportionately foregone discretionary trips in the baseline (as well as post-pandemic) periods.

Table 6.3: Spatial Lag model results for public transit ridership change

Variable	Period 2	Period 3	Period 4	Period 5
(intercept)	-0.422 (**)	0.368	-0.186	-0.130
Socio-demographics				
Percent African-American (%)	0.099 (***)	0.117 (*)	0.077 (*)	0.056 (.)
Percent Spanish-speaking	0.058 (**)	0.085	0.105 (**)	0.115 (***)
Percent aged 25-34 (%)	-0.037	-0.029	0.022	0.072
Percent aged 35-64 (%)	0.058	0.116	0.130 (.)	0.041
Percent aged over 65 (%)	-0.010	-0.405 (**)	-0.086	-0.025
Percent college grad (%)	-0.017	0.071	0.030	0.088 (*)
Percent without vehicle (%)	0.024	0.048	0.034	0.027
Percent foreign born (%)	-0.026	0.140 (.)	0.107 (*)	0.072
Log of Median household income	-0.012	-0.074 (*)	-0.029	-0.038 (.)
TNC network				
TNC trips per km^2 (10,000s)	-0.036	-0.471	0.062	-0.371
TNC avg travel time (10s min)	-0.001 (**)	-0.002 (*)	-0.001 (.)	-0.001 (*)
TNC avg fare ($10s)	0.121 (***)	0.124	0.093	0.101 (*)
TNC percent peak trips (%)	0.110 (**)	0.301 (**)	0.145 (*)	0.205 (**)
PT network				
PT percent peak (%)	-0.380 (***)	-0.629 (***)	-0.473 (***)	-0.476 (***)
PT percent weekend (%)	0.252 (**)	0.359	0.217	-0.011
PT percent bus (%)	0.077 (***)	0.164 (***)	0.144 (***)	0.149 (***)
Percent commuting by transit (%)	-0.046	-0.021	-0.001	0.023
PT stops per km^2 (100s)	0.005	-0.063	-0.051 (*)	-0.050 (*)
PT rail stop presence (0/1)	0.016	-0.015	0.002	0.009
Built Environment				
Population per km^2 (100,000s)	-0.014	0.052	0.081	0.033
Crimes per km^2 (10,000s)	0.061	0.498 (**)	0.205 (.)	0.311 (**)
Walkability index (scale 0-20)	0.000	-0.002	0.000	0.001
POI count (100s)	-0.017	-0.012	-0.017	-0.017
Summary of Statistics				
Number of observations	730	730	730	730
Rho	0.310	0.264	0.307	0.323
Residual Moran's I	-0.012	-0.005	0.008	0.001
AIC	-1959	-436	-1056	-1212

Significance: ***=0.001, **=0.01, *=0.05, .=0.10

6.1.3 Discussion of Regression Analysis

Across the periods examined, several explanatory factors remain consistent for both the TNC and public transit ridership regression results. Specifically, Table 6.4 shows variables which held a strong significance through all periods of analysis. The sign of the coefficient is indicated in parentheses, where a negative sign indicates correlation with larger negative changes in ridership, and a positive sign indicates smaller ridership declines.

Table 6.4: Consistently significant factors across all periods of regression analysis

TNC Ridership Change	**PT Ridership Change**
(+) Percent of African American residents (%)	(+) Percent of African American residents (%)
(-) Percent of residents aged 25-34 (%)	(+) Percent of residents speaking Spanish (%)
(-) Percent who graduated college (%)	(-) Avg Baseline TNC travel time (10s min)
(+) Baseline TNC trips per km^2 (10,000s)	(+) Baseline TNC trips during peak periods (%)
(-) Baseline TNC trips during peak periods (%)	(-) Baseline PT trips during peak periods (%)
(-) Crimes per km^2 (10,000s)	(+) Baseline PT trips taken by bus (%)
(-) EPA walkability index (scale 0-20)	

These results largely corroborate previous studies of public transit ridership during COVID-19 [Brough, Freedman, and Phillips, 2021; Wilbur et al., 2020; Sy et al., 2020; Hu and Chen, 2021]. The regression analysis found that areas with a high proportion of African American and Spanish-speaking residents reduced transit travel during the pandemic less, as did areas with a larger share of bus riders and off-peak transit users. Interestingly, baseline peak-period TNC riders (indicating those who likely used TNC services to commute to work pre-pandemic), and short-trip TNC use areas also tended to decrease transit use less. Generally, these results support the finding that many minority populations, who often comprise a disproportionate share of essential and in-person workers during the pandemic, continued to rely on transit services during COVID-19 [TransitCenter, 2020; Bolton, 2020; Rudick, 2020].

Upon examining the results for TNC ridership, a different message is clear. Areas with a higher share of young, college-educated people, and those with a high walkability metric, generally saw the greatest decreases in TNC use. This likely reflects a reduction in trips for those who used TNCs to access social events or employment, and moved to virtual work following the stay-at-home order. However, areas with a higher African American population decreased TNC use to a lesser extent, potentially indicating a reliance on TNCs for some trips, such as commuting to employment which could not be conducted remotely. Furthermore, areas with a high share of pre-pandemic peak period TNC trips (presumably work-based trips) saw a disproportionate decrease in ridership, perhaps indicating that those who conducted these trips were able to shift to remote work at a greater rate than others.

Generally, this ridership analysis has served to identify spatial and demographic factors that correlate with greater transit dependence through COVID-19. Findings remained consistent across the periods examined. Generally, areas with a greater share of minority populations, those located in Chicago's South Side, and those who use bus and off-peak transit services continued relatively stable use of public transit during the pandemic. Additionally, many neighborhoods which were pre-pandemic users of TNC services, particularly those which are walkable and contain a greater share of young, college-educated people, were able to reduce ridership to the greatest extent.

6.2 Surveyed Individual Attitudes and Travel Behaviors

This section discusses individual-level attitudes and travel behaviors for transit riders during the COVID-19 pandemic, obtained using a six-month panel survey. The survey methodology is discussed in greater detail in Section 6.2.1, including the process of survey distribution, assessment of representativeness, and weighting of results. Results are analyzed along three key dimensions in Section 6.2.2, including individual travel behavior changes, attitudes toward safety on the CTA, and intentions for remote work and COVID-19 recovery.

6.2.1 Survey Distribution and Representativeness

The panel survey (introduced in Section 4.6) was conducted through a six-stage process, implemented using Qualtrics and delivered to participants by email. A "Solicitation Survey" was first distributed to more than 60,000 CTA Ventra accountholders, to identify individuals who were interested in participating. A long-form initial survey was then distributed to respondents, which included a broad set of questions on pre-pandemic behavior, behavior in response to the pandemic and current travel behavior. From December 2020 to March 2021, each respondent was also asked to complete a monthly update survey, which posed a similar set of questions to update current behaviors and attitudes. A summary of the timeline and response rates for each survey is provided in Table 6.5, where response rate is calculated as the percentage of complete responses.

Table 6.5: Summary of component surveys and response rates

Survey Name	**Date Distributed**	**Recipients**	**Partial Responses**	**Complete Responses**	**Response Rate**
Solicitation Survey	2020-10-06	61,922	2,959	1,810	2.9%
Initial Survey	2020-10-27	1,810	1,046	840	46.4%
December Monthly Survey	2020-12-17	1,810	698	565	31.2%
January Monthly Survey	2021-01-17	1,810	761	621	34.3%
February Monthly Survey	2021-02-17	1,810	625	576	31.8%
March Monthly Survey	2021-03-17	1,810	618	562	31.0%

The demographic representativeness of the survey respondents is also assessed according to data available from the solicitation survey. Household size and age, employment, vehicle ownership, and income are considered, along with geographic location. Table 6.6 provides an overview of the demographic representativeness of the six surveys conducted, while Figure 6-6 describes the geographic representativeness of the initial survey by region of Chicago.

Table 6.6: Demographic representativeness by survey

	CTA OD Survey (weighted)	**Solicitation**	**Initial**	**Monthly (Dec)**	**Monthly (Jan)**	**Monthly (Feb)**	**Monthly (Mar)**
Total	1,001,704	2,089	971	645	744	685	674
Mean HH Size	2.49	2.42	2.30	2.28	2.28	2.17	2.25
Mean HH Employed Adults	1.70	1.58	1.55	1.54	1.52	1.46	1.51
Mean HH Children	0.46	0.41	0.32	0.30	0.30	0.25	0.28
Mean HH Vehicles	1.09	1.02	0.98	0.96	0.92	0.90	0.93
Household Income (%)							
Less than $15,000	12.8%	7.8%	6.2%	5.3%	6.0%	6.3%	5.0%
$15,000 to $24,999	9.0%	8.3%	7.2%	7.4%	6.5%	7.0%	6.2%
$25,000 to $39,999	14.2%	11.7%	10.3%	10.8%	9.4%	9.2%	9.3%
$40,000 to $59,999	16.6%	13.7%	12.0%	11.5%	10.5%	10.2%	9.8%
$60,000 to $74,999	11.8%	11.4%	10.6%	11.0%	9.7%	10.7%	10.2%
$75,000 to $99,999	12.0%	12.8%	13.3%	13.5%	10.6%	10.8%	11.1%
$100,000 to $149,999	12.7%	16.1%	18.3%	17.2%	16.8%	16.8%	18.2%
$150,000 or more	11.0%	18.1%	22.2%	23.2%	19.6%	17.8%	17.7%
Employment (%)							
Employed / Student	78.6%	79.2%	80.2%	80.2%	76.9%	76.5%	77.3%
Unemployed	8.0%	9.7%	9.3%	9.0%	10.2%	10.1%	9.1%
Retired	3.9%	5.9%	5.8%	6.2%	7.1%	7.4%	7.1%
Other	9.6%	5.2%	4.7%	4.7%	5.8%	6.0%	6.5%

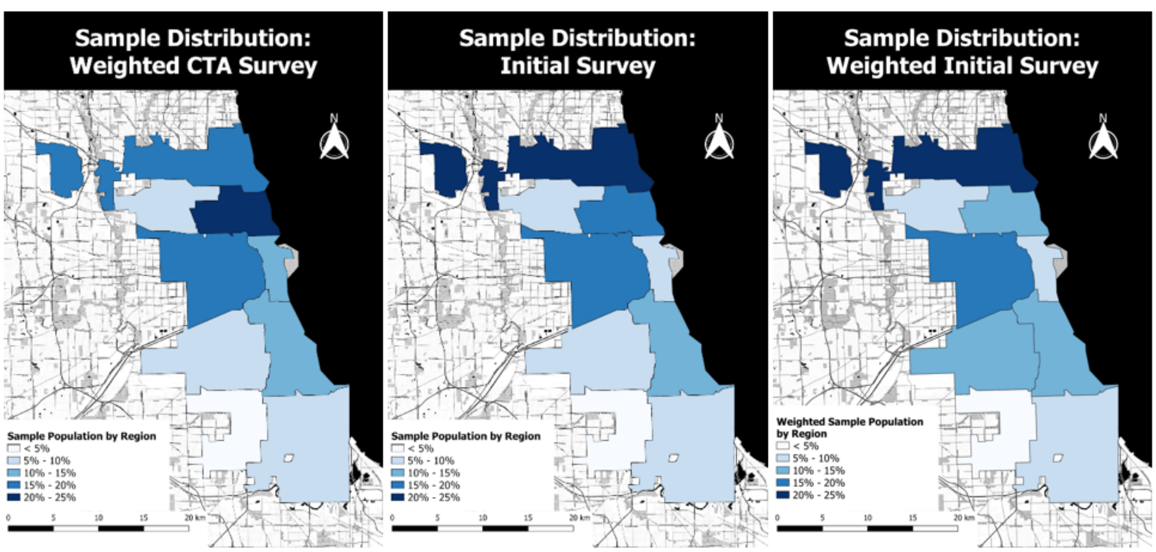


Figure 6-6: Geographic representativeness of weighted CTA survey, initial survey, and weighted initial survey

From these assessments, it is apparent that the obtained survey sample overrepresents higher-income riders and underrepresents lower-income riders, a pattern which becomes more apparent over the course of the six surveys as attrition rates appear higher for lower-income respondents. Additionally, the survey underrepresents larger households, households with children, and households with multiple vehicles. By home location, the results are similarly representative to the CTA O-D weighted survey.

Based on the demographic representativeness of the initial survey, an iterative proportional fitting approach is adopted to weight the survey results, using characteristics of household income and household vehicle ownership. Based on this approach, the demographic distribution of the weighted surveys shown in Table 6.7. This largely corrects for issues of sample representativeness which were highlighted, and adjusts the survey sample to more appropriately reflect the broader CTA rider population. Results also remain geographically representative of the CTA rider population (shown in Figure 6-6). These weighted responses are used in all subsequent findings presented in Section 6.2.2, though it is worth noting that the high-level findings of the survey questions do not change significantly between weighted and unweighted results. Appendix D.2 provides a comparison of results for the questions most significantly impacted by weighting, demonstrating the overall negligible impact on the survey conclusions.

Table 6.7: Post-weighting demographic representativeness by survey

	CTA OD Survey (weighted)	**Initial (Weighted)**	**Monthly (Dec) (Weighted)**	**Monthly (Jan) (Weighted)**	**Monthly (Feb) (Weighted)**	**Monthly (Mar) (Weighted)**
Total	1,001,704	966.7	669.5	724.5	665.1	657.4
Mean HH Size	2.49	2.41	2.39	2.35	2.23	2.33
Mean HH Employed Adults	1.70	1.54	1.56	1.49	1.43	1.49
Mean HH Children	0.46	0.35	0.31	0.30	0.25	0.30
Mean HH Vehicles	1.09	1.11	1.12	1.02	0.98	1.07
Household Income (%)						
Less than $15,000	12.8%	12.6%	10.5%	13.8%	14.3%	11.6%
$15,000 to $24,999	9.0%	8.9%	8.9%	8.7%	9.2%	8.3%
$25,000 to $39,999	14.2%	14.3%	16.2%	14.7%	14.1%	16.3%
$40,000 to $59,999	16.6%	16.3%	17.3%	16.5%	15.1%	15.2%
$60,000 to $74,999	11.8%	11.7%	12.9%	12.0%	13.5%	13.2%
$75,000 to $99,999	12.0%	12.1%	12.0%	10.8%	10.9%	11.5%
$100,000 to $149,999	12.7%	12.8%	11.3%	12.6%	12.8%	14.1%
$150,000 or more	11.0%	11.2%	10.8%	10.9%	10.1%	9.8%
Employment (%)						
Employed / Student	78.6%	78.1%	77.7%	73.4%	73.3%	74.0%
Unemployed	8.0%	12.2%	11.9%	14.5%	13.7%	12.0%
Retired	3.9%	5.2%	5.4%	6.3%	6.8%	7.1%
Other	9.6%	4.4%	5.0%	5.8%	6.3%	7.0%

6.2.2 Survey Results Analysis

The survey results are analyzed along a number of important dimensions which relate to the COVID-19 pandemic. Primarily, responses are considered over the course of the survey period to evaluate trends in how responses change over time, or assess the consistency of results which remain similar. Additionally, the following distinguishing features are assessed to compare across important rider groups:

- Current and lapsed riders
- Remote and in-person workers
- Pre-pandemic rider clusters (by mode, frequency, and peak use)

With these priorities in mind, the survey results are presented in three key areas in the following subsections: individual changes in travel behavior (Section 6.2.2.1), attitudes toward safety on the CTA (Section 6.2.2.2), and intentions for remote work and COVID-19 recovery (Section 6.2.2.3).

6.2.2.1 Individual Travel Behavior Changes

First, individual changes in travel behavior are examined both relative to pre-pandemic travel and over the course of the survey period. These results are intended to validate and complement analyses presented in 6.1, by supporting aggregate observations with individual-level reported ridership changes.

First, changes in overall CTA use from pre-pandemic to late 2020 (October and December) are shown in Figure 6-7 for the whole system, frequent rail riders, and frequent bus riders (identified as those who used the given mode at least 6 times per week pre-pandemic). This shows that over half of respondents stopped riding completely, while 85% are riding less than before COVID-19. However, this result is markedly different for pre-pandemic bus riders, for whom only 42% stopped riding completely and nearly 25% ride at or above pre-pandemic levels.

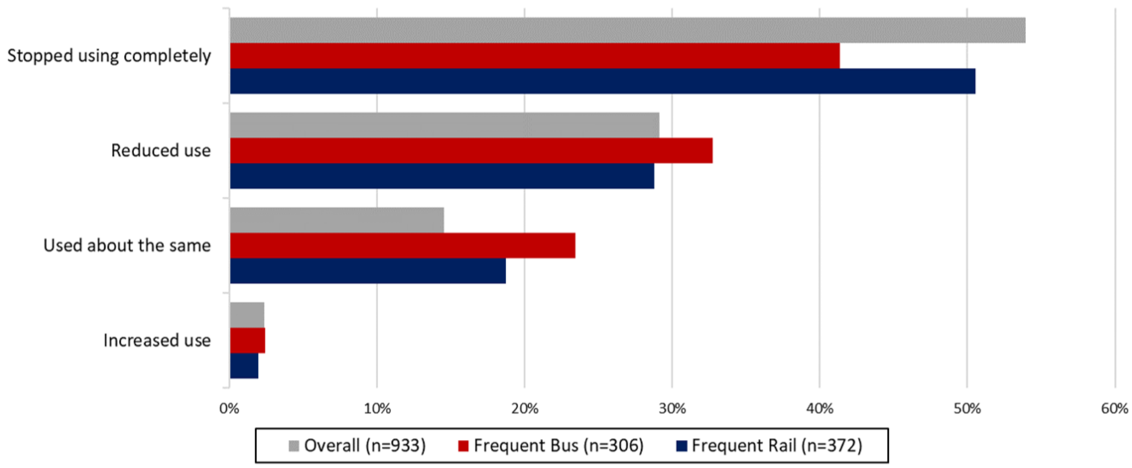


Figure 6-7: Change in weighted respondent CTA use (from pre-pandemic to 2020 Q4) for overall system, frequent rail riders, and frequent bus riders.

Individual stated reasons for this reduction in transit use are presented in Figure 6-8. The dominant factor is a lack of need for commuting trips, and a general reduction in recreational trips. This being said, many respondents report using a non-transit mode to complete the trips they did take. A reduction in work-based trips is much more persistent through the survey period, although approximately 10% of respondents no longer reported a lack of commuting need following December 2020. Additionally, recreational trips were foregone to a greater extent earlier in the panel, but recovered over the course of the survey period. The need for shopping-based trips remains fairly consistent through the survey. However, as recreational and commuting trips recover there does seem to be some increase in modal shift, as the number of participants reporting the use of an alternative mode for these purposes increases steadily over the survey duration.

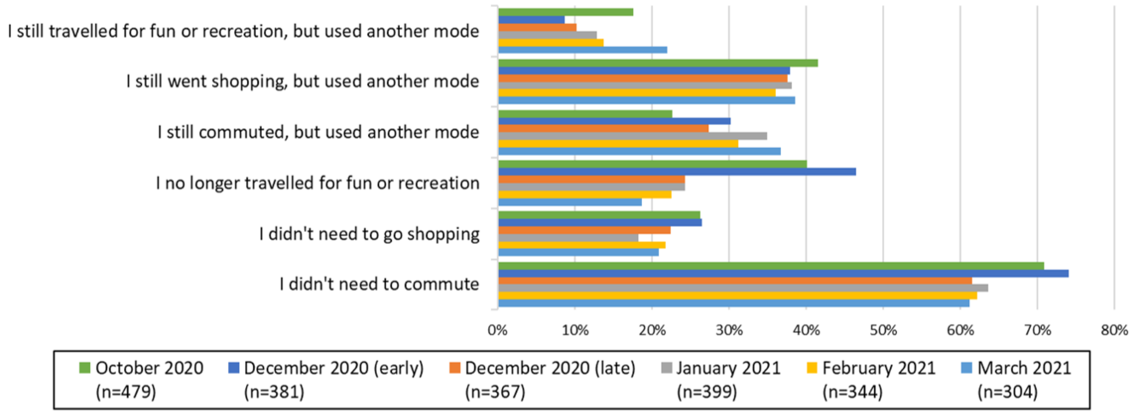


Figure 6-8: Reported answers to " Why did you reduce the use of or stop using CTA trains and/or buses in the last week? (select all that apply)"

Respondents' stated criteria to increase CTA use are examined in Figure 6-9. Generally, "when the pandemic is over", "when there are fewer COVID-19 cases", and "once I need to travel" are the dominant drivers of return to transit. However, over the course of the survey this does not persist. Pandemic-related drivers of return to transit decline significantly over time, while travel need-based drivers become more dominant. This may be because riders began to recognize that employers and other trip-generating activities did not immediately respond to declining cases and the progressing vaccination rollout, so overall travel demand remained fairly low.

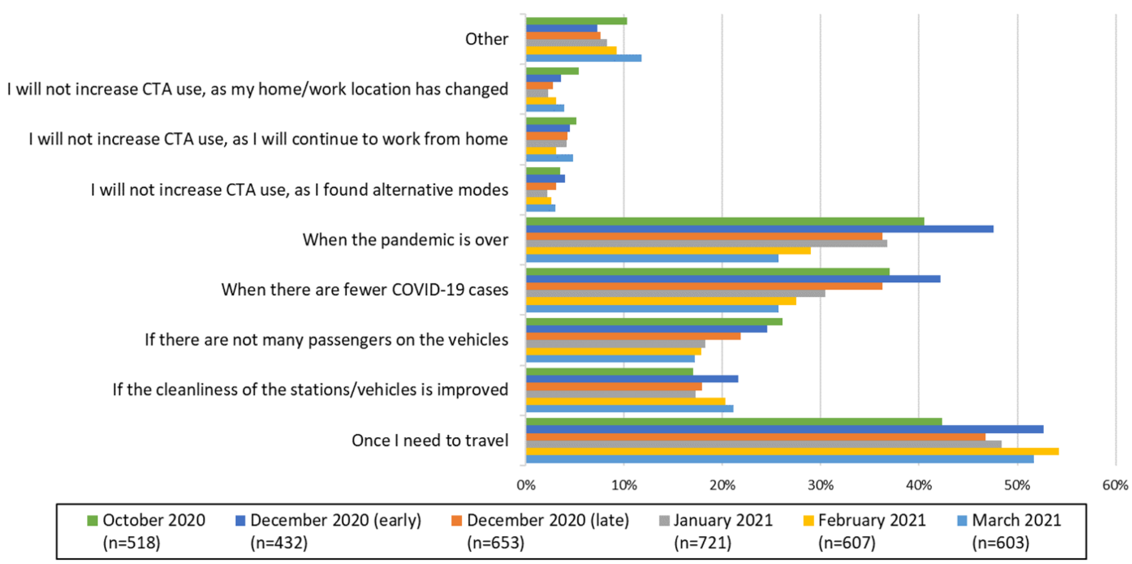


Figure 6-9: Reported answers to "Under what situation will you increase your use of CTA trains and/or buses? (select all that apply)"

6.2.2.2 Attitudes Toward Safety on the CTA

Individual attitudes toward safety on the CTA are also examined. Over the course of the survey period, surveyed feelings of overall individual safety on the CTA steadily increased from 41% of respondents in December 2020 to 49% of respondents in March 2021, as shown in Figure 6-10.

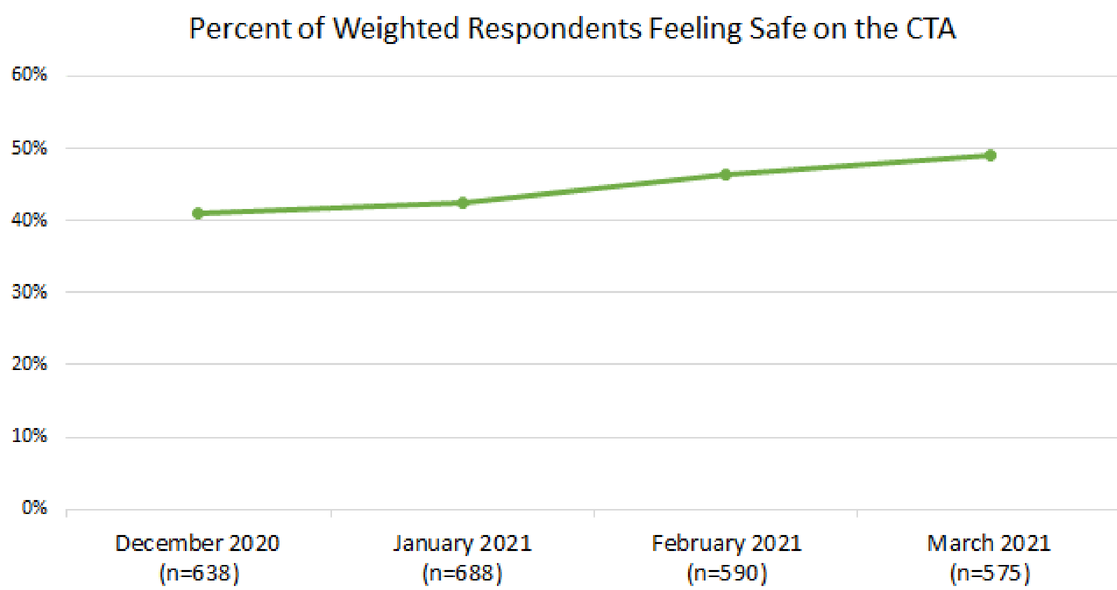


Figure 6-10: Reported answers to "Do you think that it is safe to ride the CTA this week?"

Examining this trend further, individual reasons for feeling unsafe on the CTA are also examined. As shown in Figure 6-11, respondents generally report a lack of compliance with mask-wearing requirements, a large number of other passengers on vehicles, and other general factors related to the risk of contacting COVID-19 as their primary safety concerns. Factors outside of the COVID-19 pandemic were not a major contributor to feeling unsafe on the CTA. This trend remained fairly stable over the course of the survey.

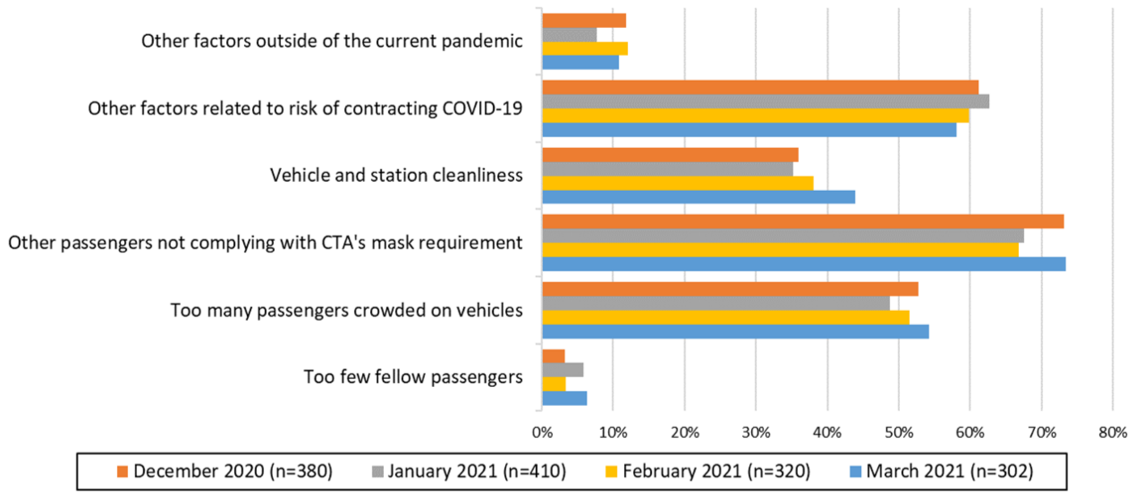


Figure 6-11: Reported answers to "What factors make you feel that it is unsafe to ride the CTA this week? (select all that apply)"

Examining contributors to feeling unsafe further, responses for those currently riding the CTA were separated from those of lapsed riders, as shown in Figure 6-12 for March 2021. Current riders reported a much greater overall feeling of safety on the CTA, and also reported much less concern for generalized COVID-19 factors. However, compliance with mask-wearing policies and vehicle crowding remained significant issues for both current riders and lapsed riders.

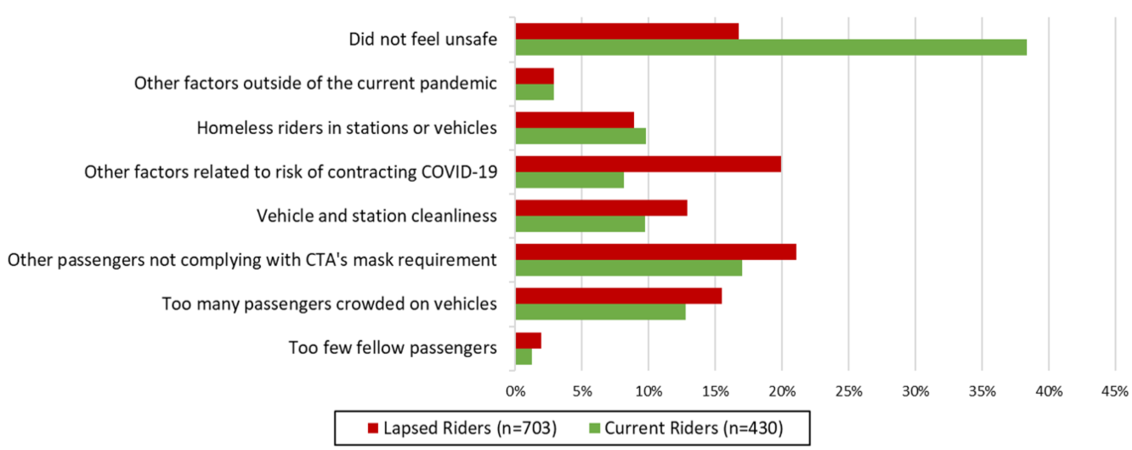


Figure 6-12: Reported answers to "What factors make you feel that it is unsafe to ride the CTA this week? (select all that apply)", separated between current and lapsed riders, for March 2021

To identify means by which the CTA could improve health and safety conditions in the current pandemic, respondents were asked to prioritize various health and safety improvement policies through a ranked order (results shown in Figure 6-13). Policies are ordered by descending total priority, calculated as the sum-product of rankings, with 4 points for 1st rank, 3 for 2nd rank, etc. These results show that mask-wearing is a very high priority for riders, far exceeding the other options. Better ventilation is also perceived as critical. Notably, these are both quite visible policies to riders, as compared with other initiatives such as increased service frequency, which would be more difficult for riders to perceive. Thus, attempts to improve the policies of interest could be very publicized and effectively marketed to riders.

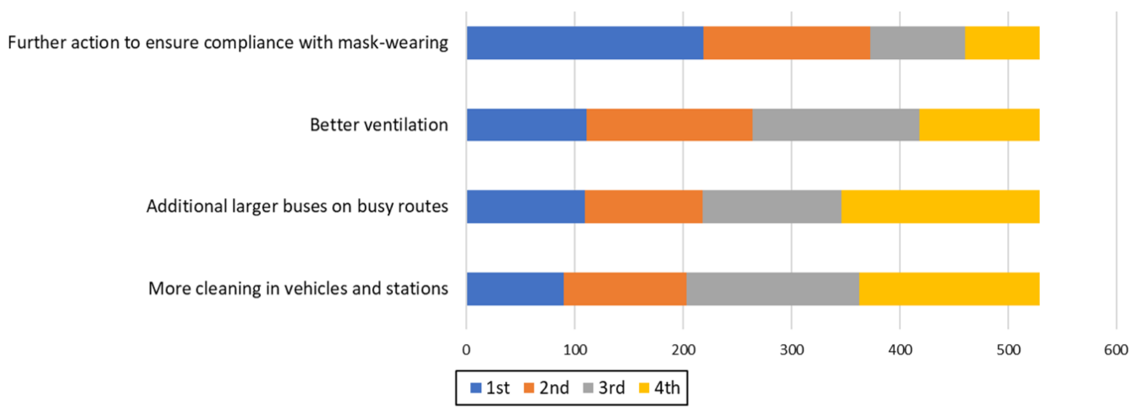


Figure 6-13: Reported answers to "What health and safety improvements could the CTA make to encourage you to ride transit more often in the future? (ranked options)", for March 2021 (n=499)

In sum, there are important signs of recovery in passenger attitudes from a safety point of view. Through the course of the survey, the number of respondents who feel safe on the CTA increased, a trend which will likely continue as COVID-19 case counts drop and the vaccine rollout progresses. Furthermore, many of the primary factors impacting passenger safety are promised to improve soon as risks of COVID-19 transmission decrease. However, it is important to note major discrepancies in perceived safety between lapsed and current riders, a gap which will need to be addressed through directed marketing campaigns to bring CTA ridership closer to pre-pandemic levels.

6.2.2.3 Intentions for Remote Work and COVID-19 Recovery

Surveyed intentions for remote work and CTA use through the COVID-19 recovery process are discussed in this section, with special attention paid to segmentation of these results by various rider groups. The objective of the following analysis is to provide a more comprehensive picture of rider perspectives going forward, and to highlight likely scenarios and make projections for possible outcomes of CTA ridership post-pandemic. Remote work, intended return to in-person occupations, and comfort on the CTA through the course of the vaccine rollout are discussed. First, a high-level breakdown of aggregate respondent remote work through the survey period is provided in Figure 6-14. The majority of respondents are working remotely, while around 25% are working in person and a considerable number are not currently employed. Through the course of the survey period, these values do not fluctuate to a great extent, likely reflecting a lack of employer shift toward in-person work between December 2020 and March 2021.

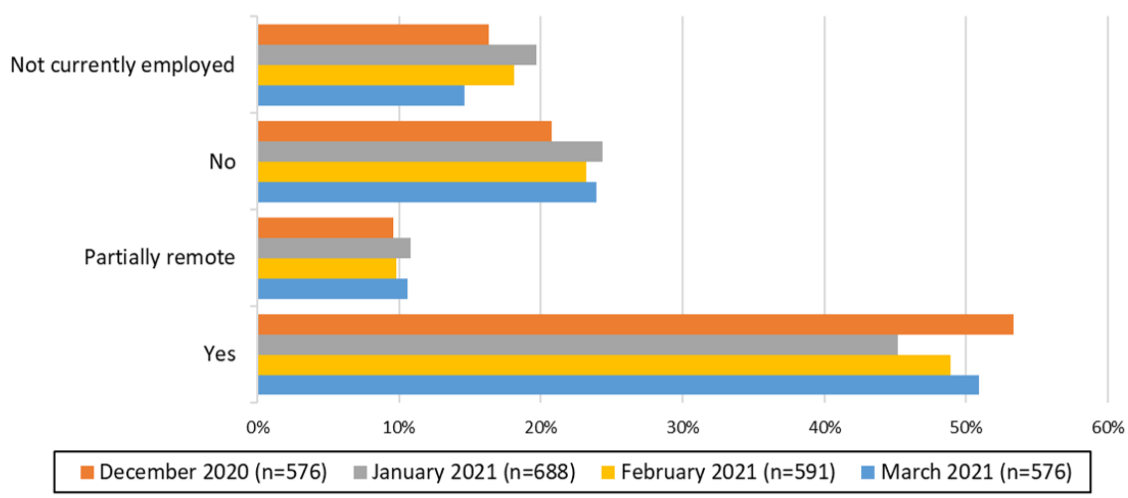


Figure 6-14: Reported answers to "Is your primary occupation (e.g. work or school) currently remote?"

To investigate remote working habits further, the previous question is cross-tabulated with pre-pandemic rider clusters for respondents (shown in Figure 6-15), highlighting major discrepancies by mode, frequency, and peak usage. The cluster representation for trips and riders is provided through previous work by Fissinger

[2020]. This analysis finds that frequent riders, rail riders, and peak riders were significantly more likely than others to be working remotely, making up a disproportionately greater share of trips. This finding largely corroborates agency observations of greater ridership loss in peak periods and on rail modes. To illustrate the scale of this difference, rail riders were more than twice as likely to report working remotely relative to bus riders.

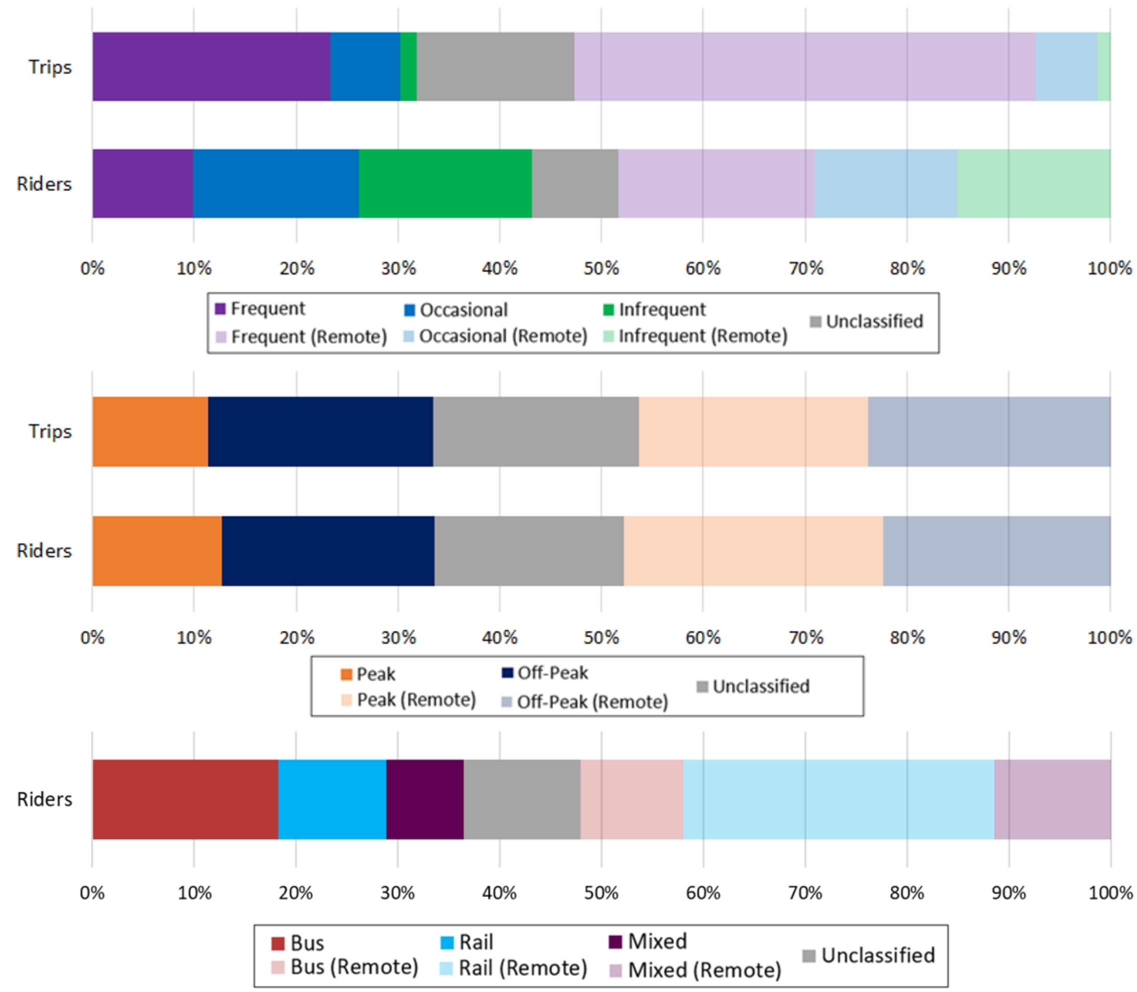


Figure 6-15: Weighted respondents reporting current remote work, separated by pre-pandemic rider cluster, for March 2021 (n=175 [top]; n=157[middle] ; n=175 [bottom])

Following the establishment of a dominant phenomenon of remote work (and a clear discrepancy in its distribution among the survey population), anticipated rider returns to work are examined. Figure 6-16 shows the distribution of anticipated post-pandemic in-person working frequency through the survey period. Interestingly, a minority of the overall population expects to return to a five-day workweek in the long term. Additionally, this proportion decreases over the course of the survey period, while those expecting three or four days of in-person work increases steadily. This likely reflects a remarkable change in attitudes from before COVID-19 if actualized, particularly when considering the implications of current remote work patterns. Specifically, if peak-period, frequent rail riders are the most likely to retain (at least partial) remote working patterns, the temporal and modal profiles of the CTA's ridership may change dramatically following the pandemic, facilitating reductions in peak capacity requirements and thereby potentially overall fleet requirements.

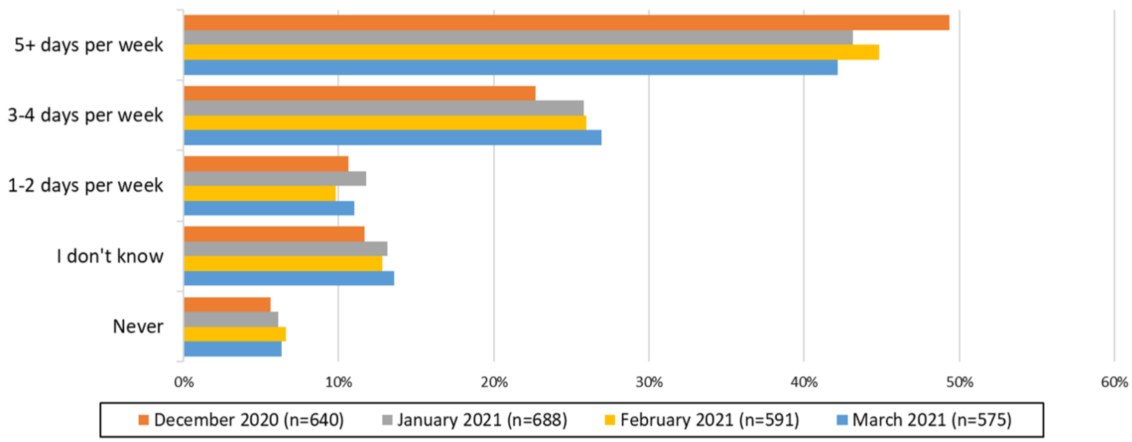


Figure 6-16: Reported answers to "In a post-pandemic world, how frequently do you expect to travel to your primary occupation (e.g. work or school) in person?"

This trend is further highlighted when examining anticipated return to work, divided between current remote and in-person workers (shown in Figure 6-17. The difference between the two is remarkable, as half the proportion of current remote workers (compared with in-person workers) report an expected five-day in-person workweek following the pandemic. Additionally, nearly as many remote workers expect a three to four day in-person workweek as those who expect a five-day workweek. This discrepancy is persistent across various pre-pandemic rider clusters (shown in Figure 6-15), specifically with rail riders more likely to anticipate a shortened in-person workweek than bus riders.

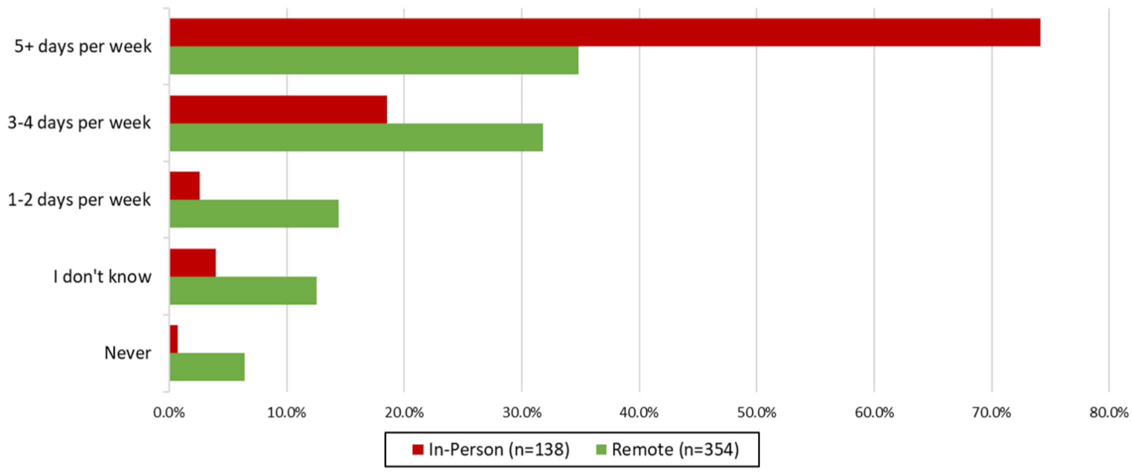


Figure 6-17: Reported answers to "In a post-pandemic world, how frequently do you expect to travel to your primary occupation (e.g. work or school) in person?", separated between remote and in-person workers, for March 2021

With this understanding of anticipated remote work, results next turn to focus on when these changes might be realized, particularly in consideration of the current COVID-19 vaccine rollout. Broadly, respondents are asked at which point over the course of the rollout they would feel comfortable riding transit (results shown in Figure 6-18). A majority of respondents either currently feel comfortable riding or would feel comfortable riding once vaccinated, however around 15% state that they will not feel comfortable riding regardless of the vaccine rollout.

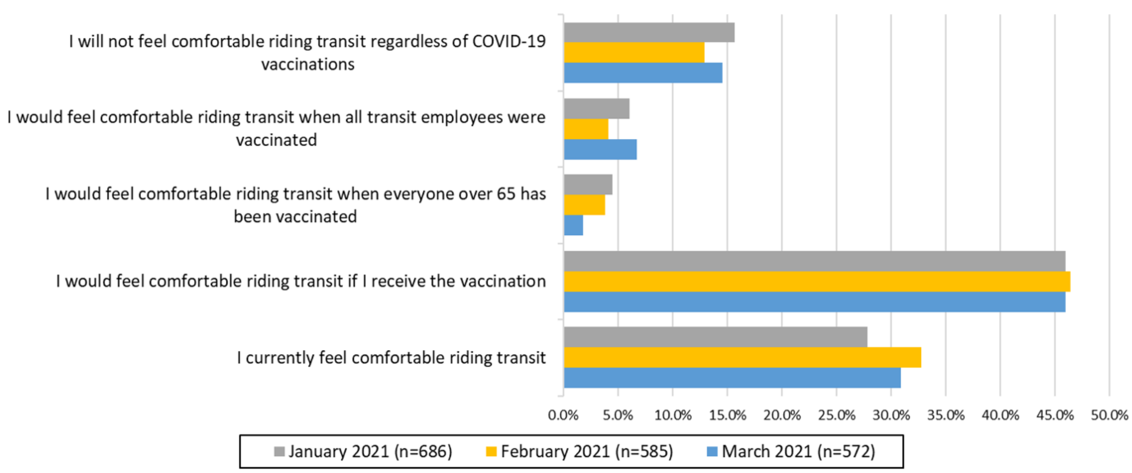


Figure 6-18: Reported answers to "Over the course of the current COVID-19 vaccine rollout, when would you feel comfortable riding transit?"

Reported comfort over the vaccine rollout is also examined by pre-pandemic rider cluster, as shown in Figure 6-19. Significant discrepancies are found here – in particular, frequent pre-pandemic riders are more likely to feel comfortable on transit than occasional or infrequent riders, while off-peak riders are slightly more likely to feel comfortable than peak period riders. However, these frequent riders (who feel comfortable on transit to a greater extent) are disproportionately working remotely (as discussed in Figure 6-15). Thus, efforts to regain ridership may focus on marketing the convenience of transit for non-work purposes.

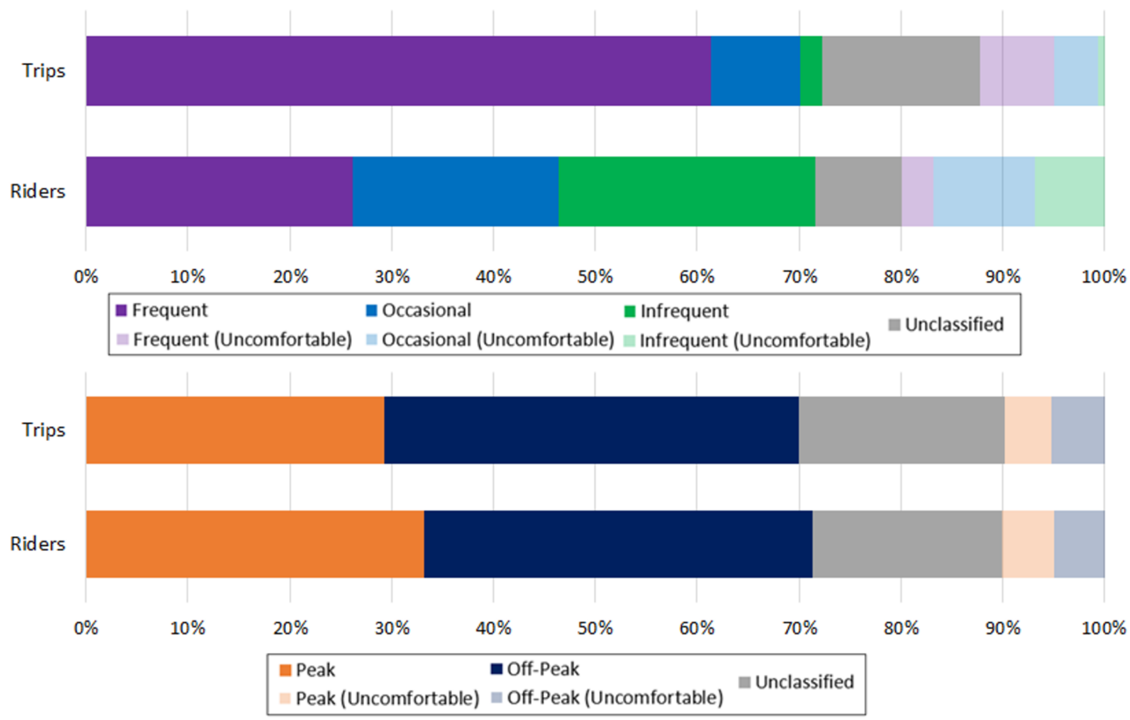


Figure 6-19: Proportion of weighted respondents who report that they will feel comfortable riding transit at some point during the COVID-19 vaccine rollout, separated by pre-pandemic rider cluster, for March 2021 (n=175 [top]; n=157[bottom])

These observations of anticipated comfort over the vaccine rollout are extrapolated to produce anticipated long-term ridership loss following the pandemic. Under the assumption that the vaccine rollout is a primary factor in willingness to return to transit, and that surveyed frequent, occasional, peak and off-peak riders match their corresponding pre-pandemic cluster groups, the anticipated loss of total ridership is shown by Figure 6-19. Overall, this forecasts a long-term ridership drop of approximately 12% for the system, with particularly significant losses from frequent riders. However, this is quite a cursory, scenario-based estimate which should be corroborated by more focussed studies of ridership trends.

6.3 Discussion and Takeaways

Through both the aggregate investigation of ridership and survey-based observations of individual attitudes and behaviors through the pandemic, four key findings are drawn regarding the spatial profile of ridership changes, correlations between demographic factors and transit dependence, perceptions of safety on the CTA, and rider intensions for remote work and COVID-19 recovery. Each is discussed below in greater detail.

First, the spatial analysis provided in 6.1.2 demonstrates a sudden, clear shock to the geographic profile of CTA ridership. This meant that flexibility in service management was important, particularly reallocating bus services to safely provide service, with reduced vehicle capacities, to areas of higher demand. For this purpose, system resilience may be enabled by a bus network which allows rapid changes to service patterns and frequencies. This could be further achieved on rail services, though to a lesser extent. Additionally, in the event of a future crisis which produces a similarly sudden shift in demand patterns, this thesis work may inform predictions of the spatial profile of these ridership changes, based on demographic factors. This could help adjustments in transit service be more proactive and thereby reduce the lag between demand observation and resource reallocation.

Secondly, regression and survey analyses identified spatial and demographic factors that correlate with greater transit dependence through COVID-19. These findings are consistent over the time through the pandemic, spanning both initial reactions and the establishment of a 'pandemic normal' through Fall 2020. It was generally found that areas with many African-American and Spanish-speaking residents retained relatively consistent levels of transit ridership, as did bus riders (also corroborated by individual surveyed responses). Young, college-educated, and walkable areas saw the greatest decreases in TNC ridership, possibly reflecting a demographic which was able to shift to remote work to a greater extent. These findings largely corroborate industry-wide observations that transit has served essential workers [TransitCenter, 2020; Bolton, 2020; Rudick, 2020], as well as racial and income groups who disproportionately serve as essential workers, through COVID-19.

From a safety point of view, there are important signs of recovery in passenger attitudes. Through the survey period, the number of respondents who feel safe on the CTA increased steadily, though this figure did vary significantly between current and lapsed riders. The majority of factors which respondents attribute to feeling unsafe on the CTA are promised to improve in the near future, particularly as COVID-19 case numbers reduce and the vaccination rollout progresses.

Finally, riders' intentions for returning to transit vary considerably. There is a clear current discrepancy in remote work by rider cluster, with frequent, rail, and peak-period riders considerably more likely to work remotely. A majority of respondents do expect to return to in-person work for at least three days per week, however as many current remote workers expect a shortened workweek as those who expect a five-day week. Furthermore, around 15% of respondents state that they will not feel comfortable riding transit regardless of COVID-19 vaccinations, which may be extrapolated to roughly project a long-term system ridership loss of 12%, concentrated in frequent riders. It is important to track these intentions through Fall 2021 to determine whether they translate into travel behavior as Chicago reopens. Additionally, campaigns to regain transit ridership may focus on the convenience of CTA services for non-work trips as commuting patterns undergo what may be a permanent shift.

Chapter 7

Results: TNC-Public Transit Relationship

This section describes results from a case study of the relationship between TNC services and public transit in Chicago. Using the analytical framework described in Section 4.7, TNC trips are classified into three categories according to their relationship with transit: complementary, substitutive, or independent. This section provides details on the case study implementation (Section 7.1), an overview of the TNC-PT relationship and the spatial and temporal patterns of this relationship under regular operating conditions (Section 7.2), an application of regression modeling to investigate factors that are associated with this relationship (Section 7.3), and an application of the framework to examine changes in this relationship during the COVID-19 pandemic (Section 7.4). The most significant findings of these analyses are summarized in Section 7.5.

7.1 TNC-PT Relationship Case Study

The case study was conducted in the City of Chicago to evaluate the change in the TNC-PT relationship under ordinary conditions, and over the course of the COVID-19 pandemic. The following five sample dates are used to analyze the baseline TNC-PT relationship under ordinary conditions:

- Tuesday, October 8, 2019
- Tuesday, November 19, 2020
- Tuesday, December 10, 2020
- Tuesday, January 21, 2020
- Tuesday, January 28, 2020

The dates were chosen across fall and spring to mitigate the influence of seasonality. Several analysis dates following the onset of the pandemic are used to examine the relationship in the early stages of COVID-19 and through its progression to Fall 2020. These dates include the following (visualized along with the progression of COVID-19 Trips and TNC ridership in Figure 7-1):

- Tuesday, March 24, 2020
- Tuesday, March 31, 2020
- Tuesday, May 12, 2020
- Tuesday, June 2, 2020
- Tuesday, June 30, 2020
- Tuesday, July 28, 2020
- Tuesday, August 25, 2020
- Tuesday, September 29, 2020

In selection of these analysis dates, various factors were considered. First, comparison was kept consistent across day of the week, to avoid influence from any cyclic fluctuations in daily travel behavior. Second, days with moderate weather (no precipitation or extreme temperatures) were chosen to minimize any external influence. Additionally, CTA planners confirmed that the dates did not reflect anomalies in terms of system operation or ridership.

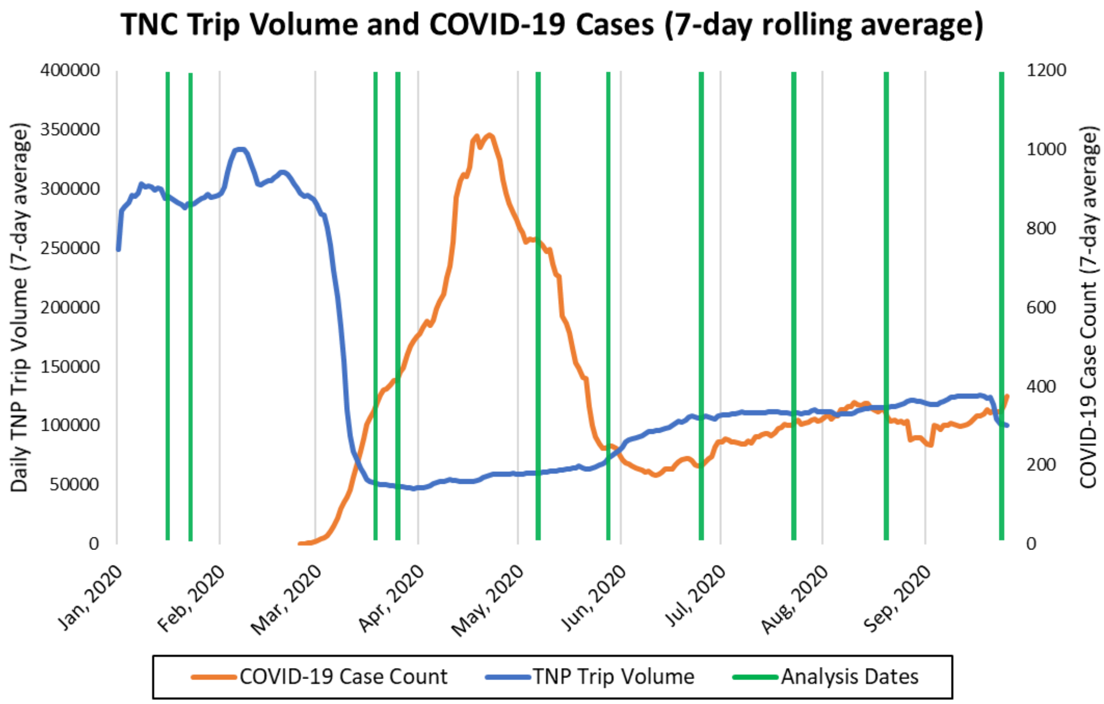


Figure 7-1: Progression of COVID-19 cases, TNC ridership, and selected analysis dates from January 2020 to October 2020

TNC trip data (described in Section 4.2) is used to conduct the analysis in this study. A 40,000-trip subset was randomly sampled for each of the thirteen selected study dates, which typically represents an approximate 10% sample for pre-COVID sample dates, and a 50% to 100% sample for post-COVID analysis dates. The distributions of the selected samples were compared with their respective populations regarding trip start times, trip durations, trip costs, and geographic distributions (shown in Appendix E.1). All were checked for similarity to show that results would not be skewed significantly due to the sampling process.

In the following sections, the TNC-PT analysis method is applied to various scenarios to understand the nature of this relationship through differing contexts. In Section 7.2 operations under ordinary conditions (before COVID-19 shutdowns) are analyzed and spatial and temporal patterns are examined. Section 7.3 applies regression modeling techniques to investigate demographic, built environment, and transportation network characteristics that are correlated with the substitution rate by census tract. Finally, Section 7.4 applies the analysis framework to operations through COVID-19, identifying evolving patterns in the aggregate relationship and spatial-temporal profiles.

7.2 TNC-PT Relationship Under Regular Conditions

The overall relationship between TNC and public transit services is estimated by conducting the analysis process described in Section 4.7. The findings under ordinary operating conditions (before COVID-19 shutdowns) are that potential substitution trips represent approximately 45% to 51% of the total, and potential independence trips make up from 47% to 53%.

These results also assert that complementarity plays a minor role in the overall relationship, ranging from 1.9% to 2.2% in ordinary conditions, an estimate which is lower than findings of various earlier papers for other contexts such as King et al. [2020]. While the author acknowledges the inherent subjectivity of decisions in the First-Mile/Last-Mile analysis process, a reasonable upper bound was calculated with all POI and activity assumptions removed (according to the process described in Section 4.7.2), which estimated the complementary trip percentage to be a maximum of 4.2%.

Table 7.1: Estimated aggregate TNC-PT relationship for baseline analysis dates

Analysis Date	Total Trips	Avg Length (min)	Avg Fare ($)	Complement (%)	Substitution (%)	Independent (%)
2019-10-08	429,119	17.4	$14.09	2.02	46.59	51.39
2019-11-19	484,938	17.5	$14.04	1.89	50.19	47.93
2019-12-10	532,375	16.8	$13.68	1.86	51.09	47.05
2020-01-21	459,862	16.4	$14.55	2.09	47.26	50.65
2020-01-28	440,328	15.9	$14.42	2.19	44.88	52.93

To further investigate the process through which this result was obtained, a breakdown of the analysis steps with trip volumes in each stage is provided in Figure 7-2. Geographically, it is clear that the majority of trips fall within the transit catchment area (Scenario 3 or Scenario 2), with reference to buffer areas A or B (where A is within 100m of a transit stop, B is within 400m, and C is outside 400m). However, many of these trips are not serviced in a desirable travel time or number of transfers by transit, and are thus categorized as independent.

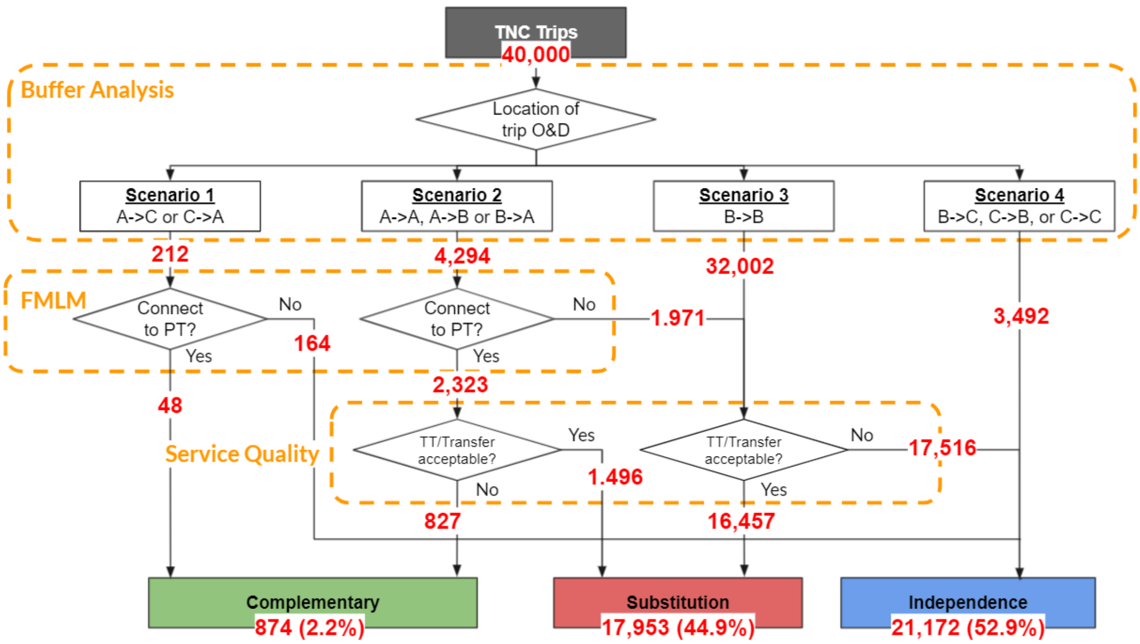


Figure 7-2: Detailed breakdown of TNC trip volumes calculated through each stage of analysis for January 28, 2020

7.2.1 Temporal Trend of TNC-PT Relationship in Regular Conditions

Looking in more detail, the trends of the TNC-PT relationship over the course of each analysis day may also be examined. Figure 7-3 shows the spread of overall trips, complementary trips, substitutive trips, and independent trips over the course of January 28th (results for all time periods are provided in Appendix E.2.1). This chart clearly demonstrates morning and evening peak travel periods, as well as spikes in substitution rates during these times. This indicates that a disproportionately large share of substitution trips may serve as work-based trips.

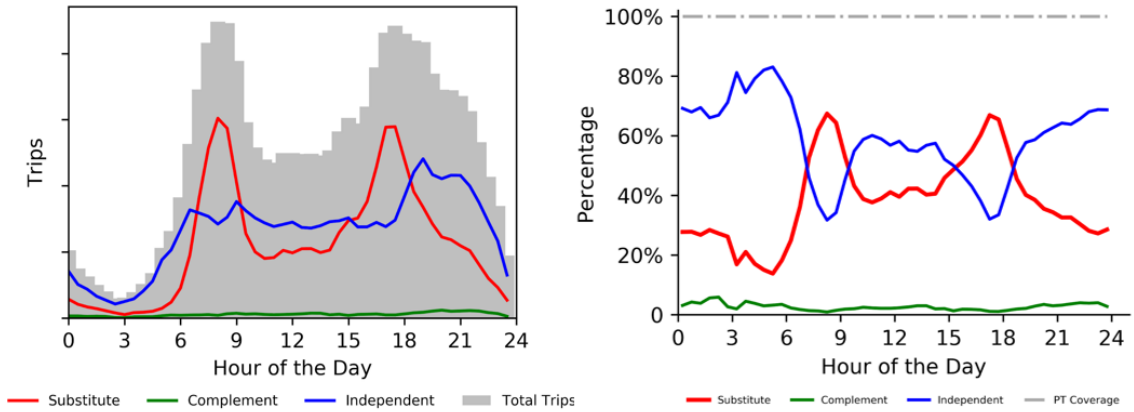


Figure 7-3: Temporal trends of volumes (left) and percentage (right) for TNC trips in each category on January 28, 2020

7.2.2 Spatial Distribution of TNC-PT Relationship in Regular Conditions

Based on the categorization of three types of TNC trips, spatial analysis is adopted to identify geospatial patterns in the TNC-PT relationship. This analysis is applied on the census tract level, though more granular analysis is possible with the current data and could be more effective if a smaller area was examined.

First, spatial distributions of complementarity, independence, and substitution rates by origin census tract are examined, by calculating the proportion of each trip category relative to the total number of TNC trips taken within that census tract, for a baseline case before COVID-19 (Figure 7-4). Independent trips are especially prevalent in areas further away from major rail transit lines, while substitution trips are most concentrated in the downtown core and along various rail lines. Complementary trips are generally uncommon, and seen primarily around the downtown area, as well as neighborhoods to the north and northwest of downtown which are served effectively by rail transit.

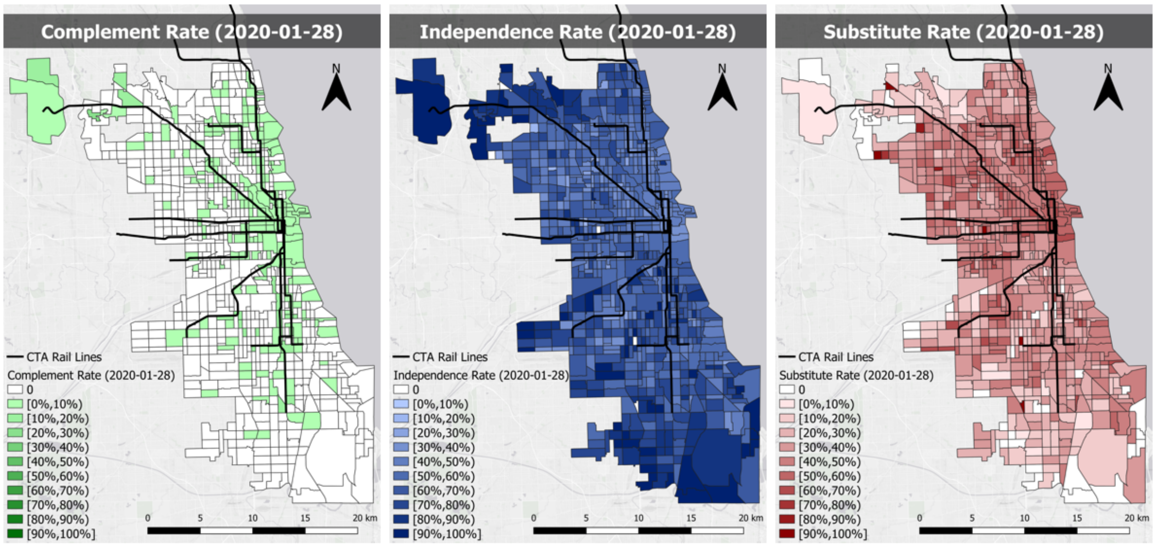


Figure 7-4: Spatial distribution of complementarity, independence, and substitution rates for ordinary operation on January 28, 2020

These patterns are also evaluated quantitatively to determine the statistical significance of spatial patterns in substitution rates. The substitution rate is highly spatially autocorrelated, indicated by a Moran's I statistic value of 0.313 (with variance of 0.00055). Additionally, clusters of high and low rate for each type of relationship are found using a local Getis Ord (G_i^*) statistic. Tracts found to be part of a hot-spot (dark color) or cold-spot (light color) at 90% confidence are illustrated in Figure 7-5 for each type of relationship on January 28, 2020 (results for all time periods are provided in Appendix E.2.3). This shows that the downtown area and some other regions along rail lines experience higher rates of substitution. Additionally, areas which are not well served by rapid transit (particularly on the south side of Chicago) experience consistently low substitution rates, indicating a lack of viable transit alternatives to TNC trips which are taken. The significant tracts identified for independence are almost identical, indicating that a hot-spot for substitution is almost exclusively accompanied by a related decrease in independence, and vice versa. This is likely due to the generally low percentage of complementary trips. Finally, complementarity hotspots are located almost entirely around a few major rail stations, potentially indicating areas which are popular first/last mile destinations for linked TNC-PT trips.

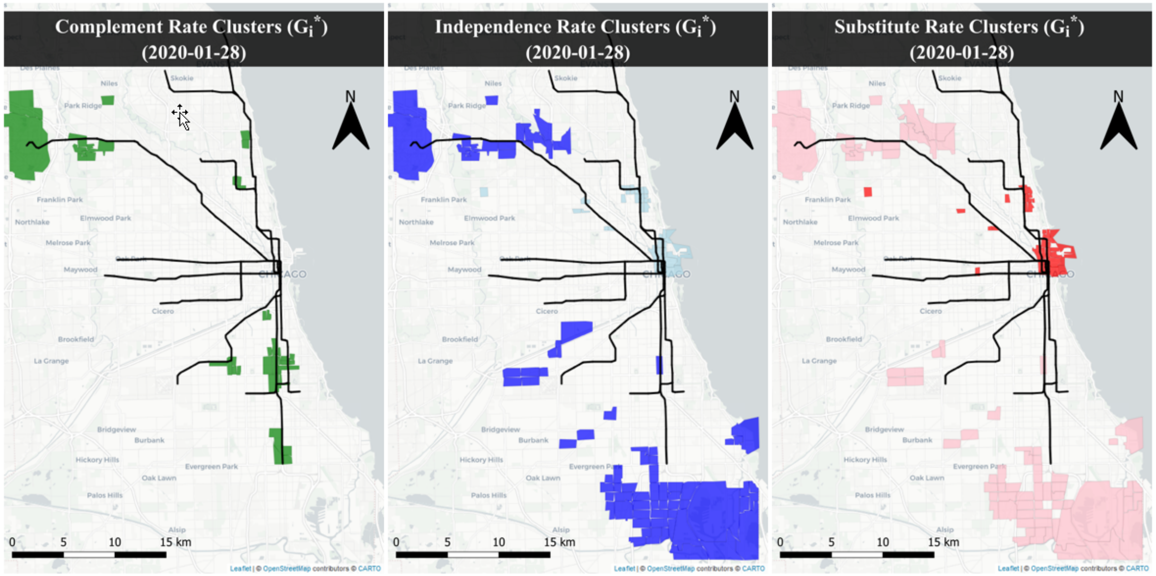


Figure 7-5: Identified clusters of high (dark color) or low (light color) rates using local Getis Ord (G_i^*) statistic for complementary, independent, and substitution trips

7.3 Factors Influencing the TNC-PT Relationship

To further evaluate the factors that are associated with the TNC-PT relationship, a spatial regression modeling approach is applied as described in Section 4.4, at the census tract unit of analysis. This process attempts to quantify the factors which correlate with the rate of substitution by census tract. The Moran's I statistic is used to evaluate spatial autocorrelation in both the original data and the residuals produced by various models. The analysis is performed for the baseline sample date of January 28, 2020. The explanatory variables used in the regression analysis are detailed in Table 7.2, falling into four main categories: socio-demographics, TNC network, PT network, and built environment. The dependent variable is the substitution share of TNC trips, meaning the percentage of TNC trips within the analysis unit which are classified as substitution by the TNC-PT analysis.

Table 7.2: Set of independent variables investigated in regression modeling (descriptive statistics provided are for the January 28, 2020 sample date)

Variable	Mean	Std. dev.	Min.	Max.
Dependent variable				
Substitution percent of TNC trips (%)	0.379	0.169	0.000	1.000
Socio-demographics				
Percent white (%)	0.456	0.326	0.000	0.967
Percent aged over 65 (%)	0.123	0.064	0.000	0.513
Percent aged 25-34 (%)	0.195	0.096	0.037	0.562
Percent college grad (%)	0.356	0.262	0.005	0.950
Percent without vehicle (%)	0.266	0.150	0.007	0.778
Percent foreign born (%)	0.192	0.160	0.000	0.726
Median household income ($100,000s)	0.573	0.323	0.098	1.788
TNC network				
TNC trips per km^2 (10,000s)	0.122	0.286	0.001	3.184
TNC avg travel time (10s min)	1.596	0.195	1.100	2.600
TNC avg fare ($10s)	1.315	0.143	1.000	2.300
TNC percent peak trips (%)	0.488	0.059	0.250	0.735
PT network				
Percent commuting by transit (%)	0.289	0.129	0.000	0.741
PT stops per km^2 (100s stops)	0.289	0.255	0.000	3.618
PT rail stop presence	0.120	0.326	0.000	1.000
Built Environment				
Population per km^2 (100,000s)	0.072	0.105	0.001	2.716
Crimes per km^2 (10,000s)	0.063	0.062	0.000	0.686
Walkability index (scale 0-20)	13.761	1.870	8.667	19.333
POI count (100s)	0.096	0.207	0.000	3.230

The explanatory variables are examined for potential collinearity, and median household income was found to strongly correlate with several other factors (including percent white, percent aged 25 to 34, percent college graduate, and percent without a vehicle). It is thus removed from the subsequent regression analysis.

The initial level of spatial autocorrelation of the dependent variable (substitution rate by trip origin census tract) is tested, yielding a Moran's I statistic of 0.313 (with variance of 0.00055). This indicates that the initial results are highly autocorrelated, which will need to be accounted for in subsequent regression models.

As a baseline first attempt, an Ordinary Least Squares (OLS) regression model is developed. The results of this model are shown in Table 7.3. The Moran's I statistic for the residuals of this OLS model is 0.066 (variance of 0.00055), which demonstrates that the OLS model is insufficient to fully capture the spatial autocorrelation of the dependent variable. However, this model may be adjusted slightly by incorporating dummy variables which indicate the region of the city which the tract is located in, according to the nine regions in Chicago classified by the Social Science Research Committee at the University of Chicago [City of Chicago, 2021b]. This is referred to as the "OLS w/ Regional" model in Table 7.3. Using this model, the Moran's I value of the residuals is 0.054 (variance of 0.00055), which still demonstrates positive autocorrelation. It is thus appropriate to explore other spatial regression modeling techniques.

To improve upon these baseline models, both spatial lag and spatial error models were developed and compared. Both results appropriately accounted for spatial autocorrelation, resulting in residual Moran's I values which were not statistically different from zero. The results of the two models were compared using Akaike Information Criterion (AIC), log-likelihood, and Lagrange Multiplier tests, to select the model which would better capture the intended effects. Ultimately, the spatial lag model produced the minimum AIC, maximum log-likelihood, and greater Lagrange Multiplier value. Thus, the spatial lag model is selected.

The results of this chosen spatial lag model are provided in Table 7.3. The spatial lag model predicts the same signs of coefficients for each variable, and identifies the same significant factors as the baseline OLS model, the OLS model with regional dummy variables, and the spatial error model. Additionally, an analysis of the model residuals yields a Moran's I statistic of -0.039 (variance 0.00055), which adequately accounts for spatial autocorrelation in our results.

Demographic variables provide important insight into factors that may influence the TNC-PT substitution rate. As shown in Table 7.3, the percentage of residents aged over 65 has significant and negative correlation with the TNC-PT substitution rate, indicating that in the census tracts with more elderly population, a lower percentage of TNC trips tend to substitute PT. Areas with a greater percentage of white residents, on the other hand, correlate with a greater likelihood to substitute transit with TNC trips. These results are all supported by previous studies of TNC riders, such as those by Rayle et al. [2016] and Young & Farber [2019]. These factors expand upon the spatial analysis by providing insight into demographic features, thus helping to better understand the individual decision to take, or not to take, a TNC trip in place of a transit trip. Other demographic factors, including age, immigration status, college education, and vehicle ownership did not show significant correlation with the TNC-PT substitution rate. Similarly, Young et al. [2020], did not find significant correlation between many individual demographic characteristics and more competitive TNC trip use.

Several characteristics of the TNC network are correlate with the substitution percentage. Areas with a greater TNC fare are less likely to substitute TNCs for transit, perhaps indicating a sensitivity of riders to the price difference between services (as transit prices remain constant across the CTA network). Tracts with a greater TNC average travel time correlate with increased rates of substitution, which might reflect the use of TNC services to access distant locations such as Chicago's airports, which are well-served by transit. Areas with a greater share of peak-period TNC trips are also correlated with greater substitution rates, further indicating that work-based TNC trips may disproportionately substitute for public transit. TNC trip density did not correlate significantly with the substitution rate.

Additionally, the level of PT network availability also correlated with increased substitution percentage. Both the density of transit stops and the presence of a rail stop correlate with increased substitution, likely because areas which are well-served by transit are more likely to have a competitive transit alternative to TNC trips. The percent of population commuting by transit did not significantly correlate with substitution rate.

Areas with high crime rates also substitute transit for TNC trips at increased rates. This indicates safety as a relevant factor for transit system operators, whether that be neighborhood safety or perceived safety on transit. This result was highly significant across all models, and corroborates findings by the Chicago Metropolitan Agency for Planning [2019] and San Francisco County Transportation Authority [2017]. These findings build upon previous research by Henao [2017], which identified that lower-income, potentially higher-crime areas have low TNC ridership relative to other portions of cities. This project similarly finds overall ridership to be low, but the findings which correlate crime rate with TNC substitution rate provide further insight into the ridership which does exist. Specifically, the results may reflect a subset of safety-concerned individuals who choose TNC travel (despite having a public transit option) due to concerns around personal safety. This influence of neighborhood crime rates on TNC substitution rates does indicate a potential for transit operators to regain TNC riders if they are successfully able to improve real or perceived safety levels on the transit system. Other factors of the built environment, including population density, walkability, and number of points of interest, did not correlate significantly with the TNC-PT substitution rate.

Table 7.3: Results of regression modeling (dependent variable is the percent of substitution trips for January 28, 2020)

Variable	OLS	OLS w/ Regional	Spatial Lag	Spatial Error
(intercept)	0.193 (*)	0.162	0.111	0.189 (.)
Socio-demographics				
Percent white	0.113 (***)	0.049 (**)	0.094 (**)	0.105 (**)
Percent aged over 65	-0.212 (*)	-0.191 (*)	-0.177 (.)	-0.202 (*)
Percent aged 25-34	0.109	0.074	0.081	0.114
Percent college grad	0.049	0.059	0.028	0.047
Percent without vehicle	0.062	0.051	0.041	0.064
Percent foreign born	-0.027	-0.005	-0.034	-0.033
TNC network				
TNC trips per km^2	-0.032	-0.048	-0.037	-0.034
TNC avg travel time	0.235 (***)	0.159 (**)	0.182 (***)	0.202 (***)
TNC avg fare	-0.456 (***)	-0.307 (***)	-0.356 (***)	-0.403 (***)
TNC percent peak trips	0.392 (***)	0.325 (***)	0.381 (***)	0.395 (***)
PT network				
Percent commuting by transit	0.060	0.072	0.045	0.050
PT stops per km^2	0.110 (***)	0.107 (***)	0.102 (***)	0.102 (**)
PT rail stop presence	0.036 (*)	0.035 (*)	0.035 (*)	0.037 (*)
Built Environment				
Population per km^2	-0.093	-0.066	-0.082	-0.086
Crimes per km^2	0.398 (*)	0.334 (*)	0.355 (*)	0.382 (*)
Walkability index	0.006	0.004	0.005	0.005
POI count	0.005	-0.010	0.004	0.005
Summary of Statistics				
Number of observations	791	791	791	791
Residual Moran's I	0.066	0.054	-0.039	-0.003
AIC	-805.0	-820.0	-826.0	-811.6

Significance: ***=0.001, **=0.01, *=0.05, .=0.10

7.4 COVID-19 Impact on the TNC-PT Relationship

The TNC-PT relationship on an aggregate level is shown for selected analysis dates in Table 7.4 and Figure 7-6. Over the course of the pandemic from March 2020 to September 2020, several key findings may be extracted which are discussed below.

Table 7.4: Estimated aggregate TNC-PT relationship for selected dates during the COVID-19 pandemic

Analysis Date	Total Trips	Avg Length (min)	Avg Fare ($)	Complement (%)	Substitution (%)	Independent (%)
2020-01-21	459,862	16.4	$14.55	2.09	47.26	50.65
2020-01-28	440,328	15.9	$14.42	2.19	44.88	52.93
2020-03-24	86,586	13.1	$13.82	2.89	12.67	84.44
2020-03-31	37,852	12.8	$13.54	2.93	13.51	83.56
2020-05-12	97,197	14.0	$14.06	2.82	12.10	85.09
2020-06-02	109,006	16.2	$15.32	3.19	14.51	82.30
2020-06-30	74,147	15.0	$14.84	3.04	13.59	83.37
2020-07-28	92,677	13.5	$13.79	3.29	15.15	81.56
2020-08-25	98,078	13.4	$14.26	3.57	14.74	81.70
2020-09-29	109,896	14.1	$14.92	3.35	15.06	81.59

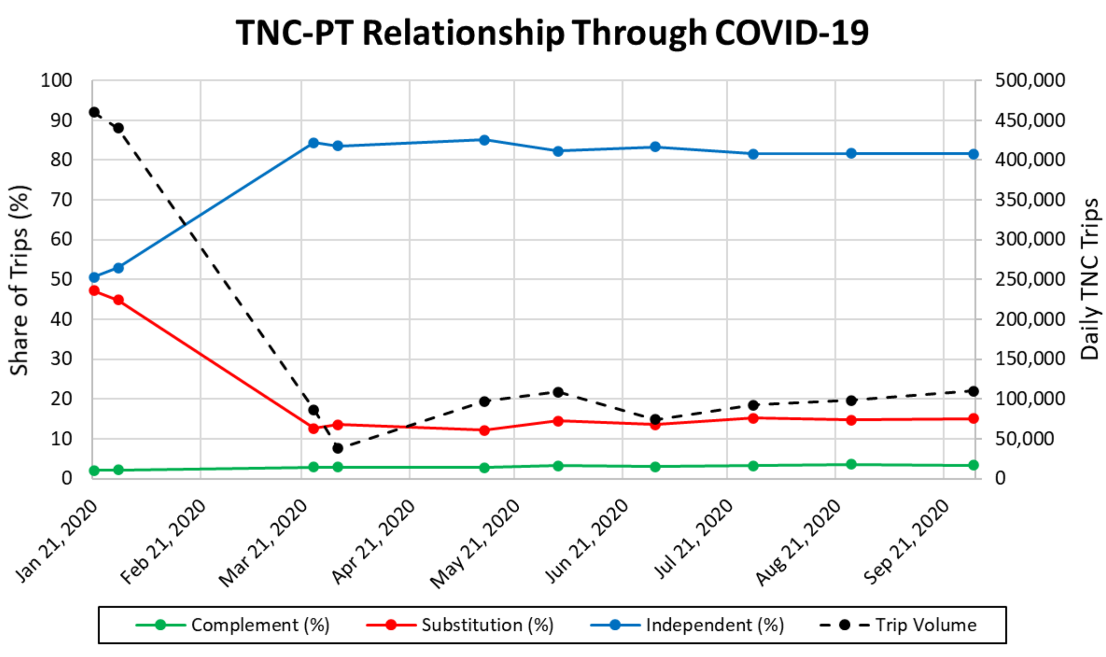


Figure 7-6: Rates of substitution, independent, and complementary TNC trips from January 2020 to September 2020

The characteristics of the TNC trips taken before and after COVID-19 are markedly different. Unsurprisingly, the overall volume of trips reduces dramatically from pre-COVID levels, down as much as 92% as of March 31st. The average length of trips which were taken also decreases notably (by 20% from January 28 to March 31). This length decrease was not, however, accompanied by a proportional decrease in trip fares. Customers were therefore paying a greater per-minute price for TNC trips, potentially due to a decrease in supply of drivers willing to complete trips.

Changes in the rates for each type of TNC-PT relationship are also clear. The share of substitution trips (those which could have viably been completed by public transit) decreases dramatically, by nearly 70% as COVID-19 shutdowns begin. This loss of substitution trips is absorbed entirely by independent trips, indicating that a greater share of trips took place in areas not sufficiently served by transit, or that TNC travel times may have been impacted by shutdowns and reduced traffic volumes (further discussed in Section 7.4.3). This decrease in substitution trips persists through the course of the analysis, although a gradual increase in the substitution share from 12.5% to 15% from March to September is apparent.

Patterns in the temporal distribution of TNC trips through COVID-19 are shown in Figure 7-7 (temporal distributions for all analysis periods are provided in Appendix E.2.1). Most clearly visible is a 'flattening' of the morning and evening peak periods, which are traditionally associated with work-based commuting travel. Before COVID-19 shutdowns, these periods generally corresponded to increased substitution activity, likely because trips are in-part serving high density employment centers that are commonly served by rapid transit. During the pandemic, the proportion of substitution trips is fairly consistent throughout the day. This decreased fluctuation of substitution rates could potentially indicate an increased uniformity of trip purpose throughout the day (e.g. grocery shopping and other essential non-commute trips), rather than peaks attributable to common commuting patterns.

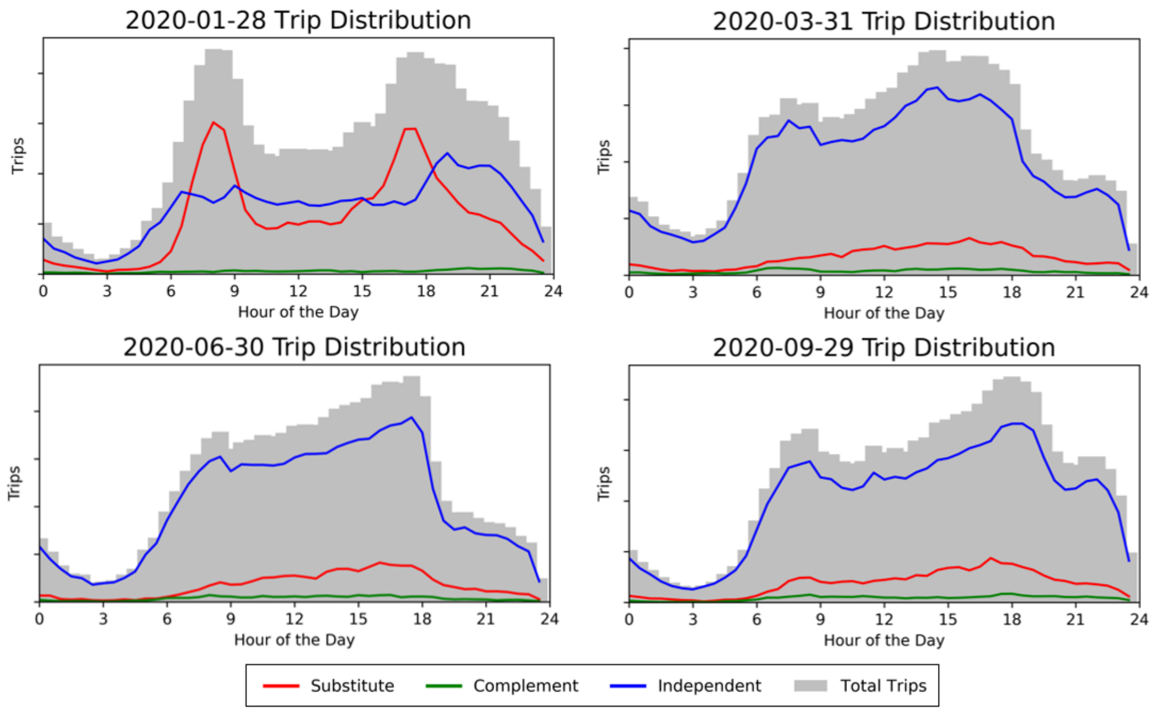


Figure 7-7: Temporal trip volumes and substitution shares for TNC trips for January 28, 2020; March 31, 2020; June 30, 2020; and September 29, 2020

7.4.1 Spatial Distribution of TNC Trips

The simple spatial distributions of TNC trips for snapshots before and after COVID-19 provide a high-level indication of changes in TNC usage patterns. Figure 7-8 shows the distribution of trip start locations on January 28 (before COVID-19 shutdowns), March 31, June 30, and September 29, 2020. Additional trip volumes for all analysis periods are provided in Appendix E.2.2. Scales are standardized across each plot.

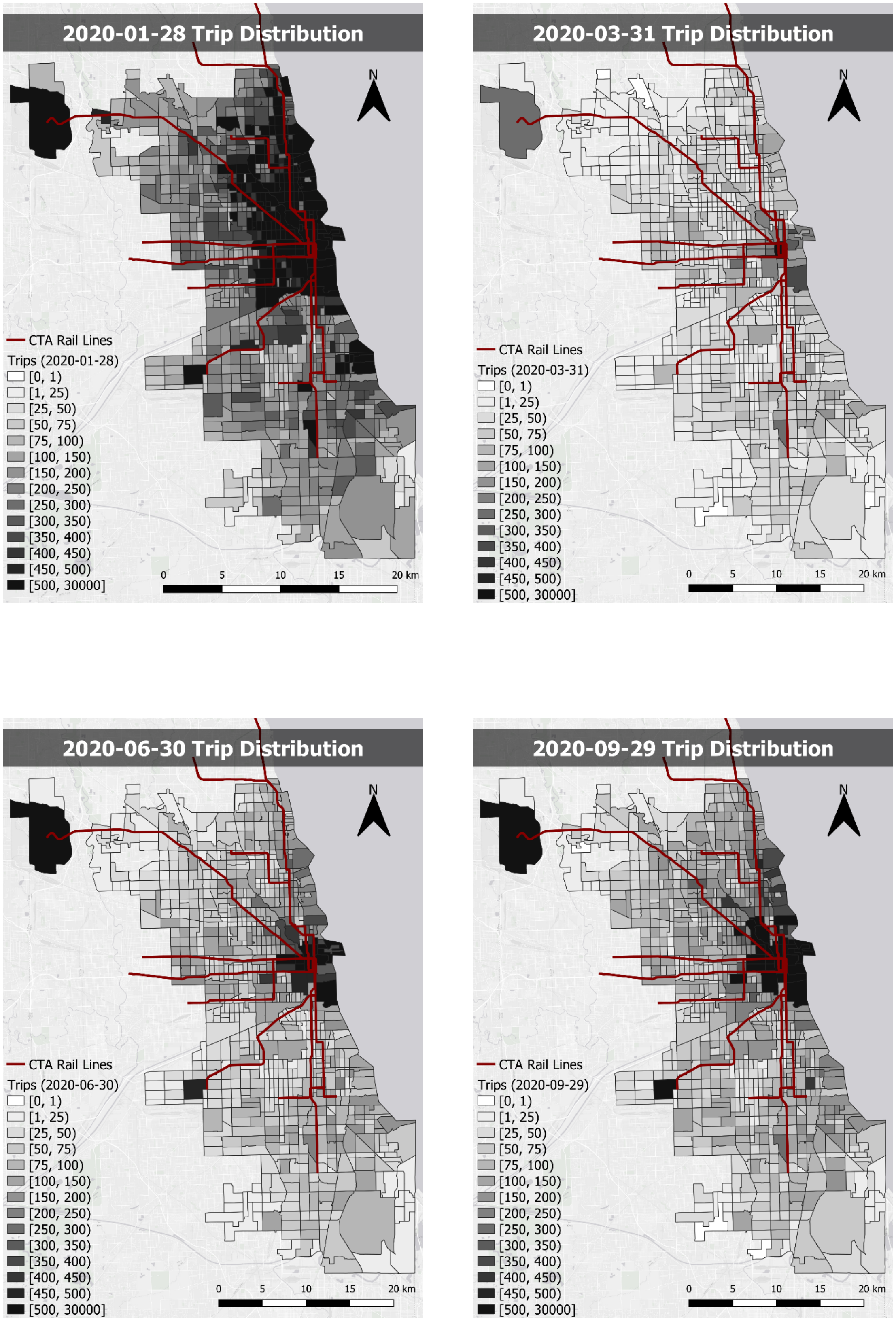


Figure 7-8: Spatial distribution of TNC trips on: January 28, 2020; March 31, 2020; June 30, 2020; and September 29, 2020

This image shows various key trends. First and foremost, there is a clear drop in overall ridership. As highlighted in Table 7.4, the total number of trips dropped from 440,328 on January 28, to 86,586 on March 24, to 37,852 on March 31. More interestingly, this loss of ridership seems to be primarily concentrated around Chicago's central business district (the 'loop'), as well as generally affluent neighborhoods immediately north and northwest of downtown [Dwyer, McGregor, and Gasulla, 2017]. This pattern is demonstrated by Figure 7-9, which visualizes the spatial profile of the ridership drop. As shutdowns and work-from-home orders due to COVID-19 set in, the TNC trip distribution appears relatively uniform for the following months, with a concentration of trip volumes persisting in the downtown area. This pattern could likely arise from a drop in work-related trips, particularly those travelling between higher-income residential areas (such as the regions north and northwest). These office-based jobs are among those most likely to be conducted remotely during COVID-19 [Brynjolfsson et al., 2020].

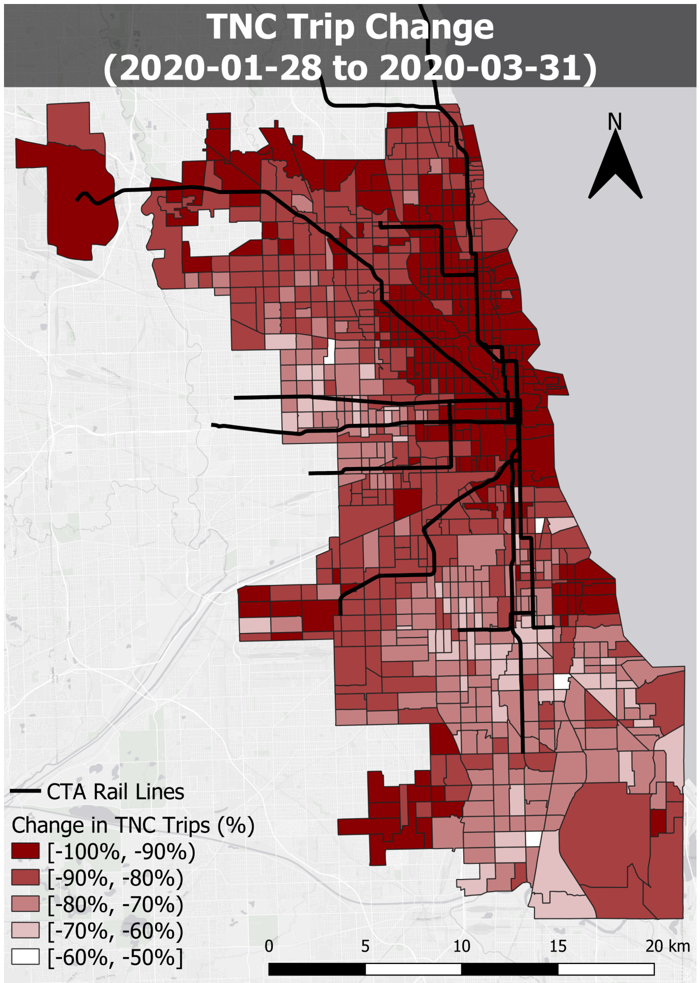


Figure 7-9: Spatial distribution of TNC trip volume percentage decrease from January 28, 2020 to March 31, 2020

7.4.2 Changes in the Spatial Profile of TNC-PT Substitution Rate during COVID-19

The change in substitution rates by census tract resulting from the COVID-19 pandemic is also studied for spatial significance. First, the absolute difference in substitution rate is calculated for each census tract, as the rate on January 28th minus the rate on March 31st. This is shown in Figure 7-10 (left). A test for spatial autocorrelation of these values yields a Moran's I value of 0.197 (variance 0.00038), which indicates significant spatial autocorrelation. Hotspots are once again located using a local Getis Ord (G_i^*) statistic, and statistically significant tracts at a 90% confidence level are shown in Figure 7-10 (right). This identifies a significant cluster of high substitution rate drop in the downtown area and near north side, as well as a cluster of low substitution rate drop on the south side – particularly in areas which previously had low substitution rates (likely due to a lack of rapid transit access), and thus were unlikely to drop much further.

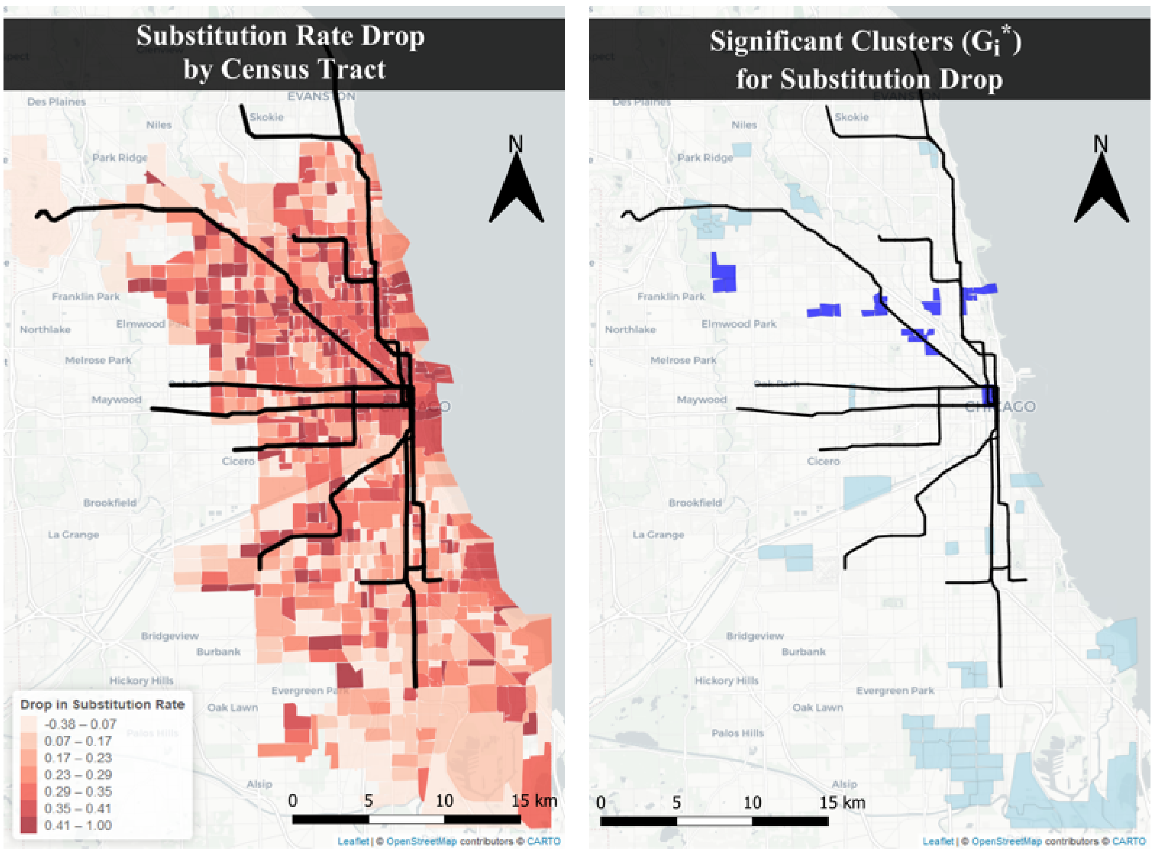


Figure 7-10: Drop in substitution rate by census tract (left), and clusters found with G_i^* statistic (right) from January 28, 2020 to March 31, 2020

Furthermore, changes to the spatial profile of complementary, substitutive, and independent trips are also observed. The full set of spatial cluster charts is provided in Appendix E.2.3, though the primary takeaway is that while these clusters were clearly defined in space and by neighborhood in ordinary operating conditions (shown in Figure 7-5), they are less clearly distinguished over the course of the pandemic. However, pockets of substitution in the downtown and near-north side remain, as do clusters of independence on the south and west sides, as shown in Figure 7-11 for March 31, 2020.

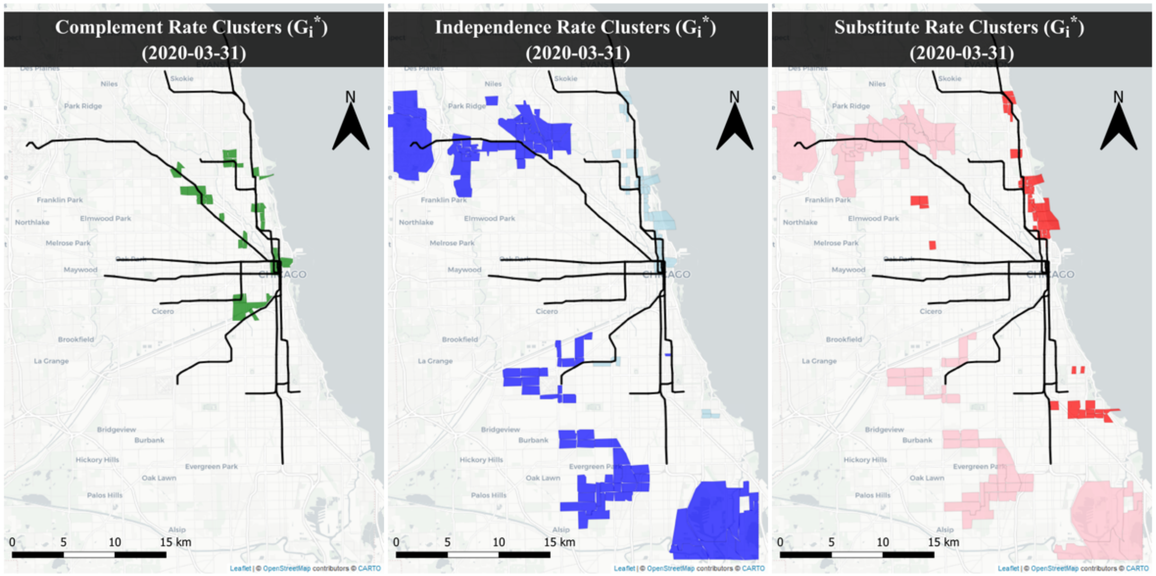


Figure 7-11: Spatial clusters of complimentary, independence, and substitution trip rates for March 31, 2020

7.4.3 Travel Time Analysis During COVID-19

With the knowledge that the TNC substitution rate dropped (and was accompanied by a proportional increase in the share of independent trips) following the pandemic, the cause of this trend may be further examined. Specifically, changes in the profile of TNC and PT travel times following COVID-19 are visualized to identify whether travel times between particular origin-destination pairs decreased significantly enough relative to transit travel times, that a trip which was categorized as substitution before COVID-19 may be considered independent after the pandemic. This process was completed by calculating average travel times for census tract-to-tract linked origin and destination pairs before and after the pandemic, using two sample dates of January 28, 2020 and September 29, 2020.

The resultant change in travel time classification is shown in Figure 7-12. Each data point represents an O-D pair that contained an observed TNC trip for both sample dates, which is plotted according to its travel time on TNC (Y axis) as well as on transit (X axis). The travel time threshold selected for quality of service analysis is shown in black – thus trips which were categorized as substitution (having a competitive travel time on public transit) are those which lie above the black line, while trips categorized as independent (not having a competitive travel time on transit) are those below the line.

Across the two sample dates, a change in the share of trips above the line is clear. A considerable portion of the trips experience a sufficient drop in their TNC travel time that they are now classified as independent, despite being substitutive before the pandemic. This may reflect savings in TNC travel times due to decreased congestion during the pandemic. These changes were most distinct during the AM peak travel period, but were present throughout all times of day. It is important to note that these trips, now classified as "independent," are served by transit and may be classified as substitution under different travel time thresholds (demonstrated by the sensitivity analysis performed in Section 4.7.3). This ultimately serves to identify the somewhat arbitrary nature of discrete classifications, as the complementary/substitution/independent relationship operates along a continuum. Another major limitation in this analysis is the potential increase in waiting time for TNC trips following the onset of the pandemic, due to a lesser overall trip volume and decreased availability of drivers. To fully capture this trend, waiting times for TNC services would need to be added to the analysis.

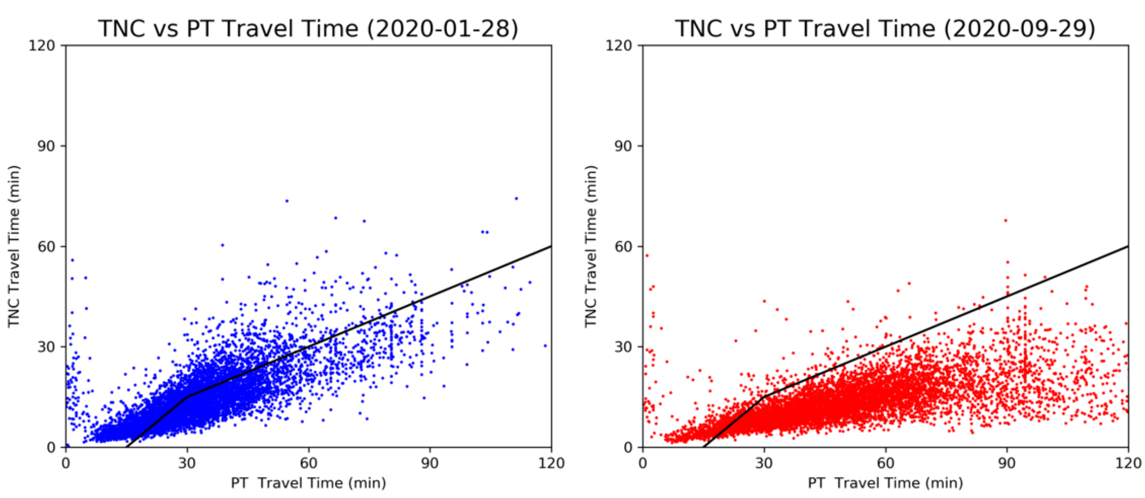


Figure 7-12: TNC and transit travel times for linked O-D pairs for January 28, 2020 and September 29, 2020, with line of acceptable transit time threshold represented by the region above the black line

7.5 Discussion

From the results presented above, several key takeaways regarding the relationship between TNC services and public transit in Chicago may be extracted. Specifically, findings include the role of complementarity in this relationship, the nature of the relationship under ordinary conditions, spatial and temporal patterns in the TNC-PT relationship, the impacts of the COVID-19 pandemic, and the factors associated with substitution rate.

First, complementary trips, or TNC trips which are used as a first- or last- mile connection with transit services, do not make up a significant number of TNC trips. Estimates from this analysis indicate that these trips comprise approximately 2% of all TNC trips, with a reasonable upper bound of around 4.2% of all trips. This result is lower than findings of various earlier papers for other contexts, such as work by King et al. [2020], however they are corroborated by various survey results for the Chicago area, as well as by previous estimates from the CTA.

Before the COVID-19 pandemic, around 45% of TNC trips could potentially substitute for PT, and around 53% of TNC trips were potentially independent from PT. This result is comparable with previous findings from Young et al. [2020], which estimated the proportion of TNC trips with a competitive transit alternative to be approximately 31% in Toronto. The results differ somewhat, likely due to the varying methodological approaches (discussed in Section 3.5) and case study contexts. Although the methods of travel time estimation are similar, the two studies apply different means of comparison. While Young et al. assess the absolute and proportional differences between TNC and hypothetical transit travel times separately, this study applies a hybrid travel time comparison (discussed in Section 4.7.3). Similarly to Young et al., thus study finds that a greater percentage of TNC trips compete with transit during peak travel periods, and in areas near the downtown.

Temporal and spatial patterns in the TNC-PT relationship under normal conditions are also clear. The rate of substitution is interestingly variable in both time and space. Trips completed during peak periods were found to generally correlate with a higher substitution rate, indicating that many work-based TNC trips have a viable transit alternative which individuals choose not to take – potentially due to decision-making factors such as crowding on transit lines, aversion to possible delays, or a greater sensitivity to travel time. Furthermore, higher substitution rates were spatially concentrated in areas served by high-speed rail services, particularly the downtown core.

As expected, independent trips (those with no desirable transit alternative) were concentrated in areas without access to high-speed rapid transit. This differs from conclusions reached by Barajas & Brown [2021], who claimed that TNC services do not correlate with use in these areas. This different conclusion may come from the stricter criteria utilized in this study, which identify TNC trips as independent from transit if the transit alternatives require long access walking times or experience very long travel times. Complementarity hotspots are located almost entirely around a few major rail stations, potentially indicating areas which are popular first/last mile destinations for linked TNC-PT trips.

The COVID-19 pandemic dramatically altered the landscape of Chicago's TNC-PT relationship. TNC trip rates plummeted, as did transit ridership. Transit capacity also reduced dramatically due to social distancing measures, which placed limits on buses and train cars of 15 and 22 riders, respectively [Chicago Transit Authority, 2020a]. More specifically, however, rates of substitution decreased substantially, as did the concentration of trips in areas north and northwest of downtown. Upon analyzing the changes in substitution rate, it was found that areas around downtown experienced the greatest drop, while various low-substitution areas outside of rapid transit coverage experienced little change. Temporally, the morning and evening peak periods flattened, and substitution rates appeared relatively consistent throughout the day. These findings also lead to the broader indication that many conventional work-based TNC trips in high-income areas were no longer being conducted, and that these trips are typically a substitution for transit services. Higher-income areas appear to forego desirable public transit trips in favor of TNC services at a rate significantly greater than the general population.

The regression modeling conducted provides further insight into factors which may contribute to greater rates of substitution for public transit with TNC services. Using regression, the study finds that locations with high crime levels, a greater rate of peak-period TNC use, a higher percentage of white population, and greater transit network availability all significantly correlated with greater TNC substitution rate for public transit, while areas with a greater percentage of older residents and a lower TNC fare price correlated with lower TNC substitution for public transit. These factors expand upon the spatial analysis by providing insight into demographic features, thus helping to better understand the individual decision to take, or not to take, a TNC trip in place of a transit trip. The significant correlation between neighborhood crime rates and TNC substitution rates indicates a potential for transit operators to regain TNC riders if they are successfully able to improve real or perceived safety levels on the transit system.

Chapter 8

Conclusion

In sum, this thesis has examined the impacts of several exogenous drivers of public transit and TNC ridership in Chicago. Through three case studies using various analysis methods, the study has provided insight into the impacts of (1) a targeted policy intervention, (2) a public health crisis, and (3) a potential competing mobility service provider. This chapter describes the most salient findings from each case study, with a particular emphasis on their policy relevance for transit authorities and local governments. These implications are generally applicable to policymakers beyond the project's scope of Chicago, as many large cities in the United States commonly face challenges in regulating new on-demand mobility providers, assessing the relationship between relatively new modes and public transit, and evaluating and recovering from the COVID-19 pandemic. Each case study is discussed in its respective subsection, including findings, limitations, and policy takeaways. The chapter concludes by suggesting future work which could build upon the efforts undertaken in this thesis.

8.1 Targeted Policy Intervention (GTT Case Study)

Through difference-in-differences modeling, aggregate exploratory analysis, and spatial investigation, the case study did not identify any statistically significant impacts of the GTT pricing policy on TNC ridership in targeted areas of Chicago. Ridership appears to have remained fairly steady overall through the analysis period. While this does contrast explosive ridership growth which had been observed in TNC services over the preceding years, it might also be that TNC ridership had reached somewhat of a saturation point before the period of analysis considered. However, spatial investigation of the policy's impact on trips originating from or terminating in Chicago's Far South region highlighted important results. As per-trip surcharges decreased or remained constant for shared trips to non-impacted areas of the city, an influx of new ridership emerged to certain areas of the city which were not targeted by the policy, while trip volumes to GTT-impacted areas remained consistent or declined slightly.

However, the policy's impact on surcharge revenue is abundantly clear. Gross surcharge volumes increased over 50% from pre-GTT periods, providing approximately $2.5 million in added revenue during the two-week periods of weekday trips that were examined (extrapolating, this could amount to approximately $65 million of additional income per year). This additional surcharge revenue is primarily collected from higher-income areas of Chicago, with downtown and affluent residential areas bearing the greatest fee increases, while lower-income areas typically saw either a slight increase or decrease in average surcharges from the previous flat rate fee. This demonstrates that the GTT has successfully created new city revenue without disproportionately burdening lower-income areas, extracting a cashflow which may be partially spent on reducing the negative externalities of TNC services by investing in sustainable alternative transportation modes.

As discussed in Section 5.5, the study is subject to several limitations of analysis dates. While changes in trip surcharges were immediately apparent and identifiable, ridership was likely influenced by several exogenous factors which could not be fully accounted for in the analysis. In particular, the COVID-19 pandemic (which began one-to-two months after the GTT policy was implemented) had a dramatic impact on TNC ridership, and thus neither the longer-term steady state ridership nor ridership fluctuations over multiple seasons following the GTT could be examined. It is possible that early stages of COVID-19 may have influenced travel behavior (while new of the virus was circulating, but government stay-at-home policies had not yet been enacted). Additionally, this limited analysis period took place in winter months, during which fewer discretionary trips are taken. Analysis of summer periods may uncover different results, as these discretionary trips might be more sensitive to changes in price. Factors of seasonality could also influence the short-term comparisons performed, while long-term changes in the TNC landscape may influence year-over-year comparisons.

As a means of informing policymaking, this case study demonstrated an effective tool for policy analysis, particularly in an important area that many cities are currently grappling with. As cities identify negative externalities from relatively new TNC services (such as low vehicle occupancy, mode shift away from sustainable alternatives, use of valuable downtown curb space, and contribution to increased traffic congestion and thereby worsened bus speed and reliability), they will need to react to mitigate these downsides while realizing the potential benefits of expanded mobility options. Chicago's GTT pricing initiative provides a leading North American example of a responsive policy which was both spatially targeted and progressively implemented, while the analysis in this thesis outlines a process which may be used to assess the impacts of such a policy and to provide feedback which might be incorporated into future adjustments to the policy. Specifically, the revenue increases and sources of those increases were identified, while the program was shown to have limited impact on ridership, identifying that further policy action (such as increased congestion pricing initiatives, transit or HOV roadway priority, or investment in public transportation and active transport services) may be necessary if the city hopes to spark a significant shift in travel mode choice.

8.2 Public Health Crisis (COVID-19 Case Study)

Through both a spatial regression analysis of ridership and a panel survey of individual attitudes and behaviors, this case study provided detailed insights into the COVID-19 pandemic and its relationship with travel behavior, both retrospectively by identifying patterns in ridership, and as a tool for anticipating behaviors as Chicago recovers from COVID-19. This study builds upon previous research on transportation in COVID-19 by considering both transit and TNC ridership in conjunction to compare impacts across different modes, examining an extended time period beyond the early stages of the pandemic, and incorporating a broad set of explanatory variables which includes demographics, the built environment, and attributes of the TNC and public transit networks.

Findings were concentrated in four key results, concerning spatial patterns in ridership drops, factors correlated with sustained transit use, trends in safety, and projections for post-COVID ridership. First, spatial patterns in both transit and TNC ridership changes are clear. Core ridership remained in areas with greater populations of African-American and Spanish-speaking residents, who make up a disproportionate share of essential workers whose employment could not be conducted remotely. This caused a sudden and dramatic shift in the spatial profile of ridership for both transit and TNCs. Interestingly, while this spatial change was most clear for transit ridership, it was also apparent for TNC services. Despite being commonly perceived as a luxury good, it may be the case that TNC services were used for essential trips during the pandemic, possibly due to individual fears of using public transit, or gaps in the network which transit was able to serve effectively. Regression analysis further substantiated these initial findings, identifying that areas with greater percentages of minority populations and bus riders remained reliant on transit, that areas with high pre-pandemic peak ridership disproportionately stopped riding both TNCs and transit, and that higher-income, college-educated, walkable neighborhoods (typically seen as frequent TNC users) experienced the greatest percent decrease in TNC ridership.

Panel survey results identified that overall attitudes toward safety on public transit are improving steadily, but that these attitudes vary considerably across different rider populations. Lapsed riders reported feeling unsafe on transit at over twice the rate of those who rode transit during the pandemic, and reported greater feelings of concern for all COVID-19-related safety hazards. While self-selection bias is acknowledged (those who feel safe riding transit will more likely do so), these findings indicate that the perception of safety on transit may be worse than its reality, and that lapsed riders may need additional incentives to return to transit in the longer term. For instance, the CTA has announced a fare discount for Summer 2021, which reduces the cost of short-term passes (one, three, and seven days) with the intention of bringing riders back to public transit [Chicago Transit Authority, 2021].

In conjunction with smartcard record-based rider clustering analysis, panel survey results were also used to understand riders' intentions for returning to both transit and in-person employment. While it was found that fears around safety on public transit decreased (removing, to some extent, the 'push' factor away from transit), a lack of required travel, particularly for commuting purposes meant that there were limited 'pull' factors which brought riders back to transit in the later stages of the survey. Patterns of remote work highlighted that riders assigned to the frequent cluster based on pre-pandemic use patterns are working remotely to a much greater extent than previously infrequent or occasional riders, and that this is contributing to a disproportionate share of trips that are no longer conducted. Additionally, peak period riders are working remotely to a greater extent than off-peak riders. Considering respondents' stated long-term concerns about riding transit, the analysis suggests that approximately 10% of transit trips may be lost in the long term. Furthermore, over half of current remote workers expect to return in-person work less than five days per week, likely indicating a decrease in frequency from riders who do return.

The most significant limitation in these results is the timeline of the survey. The survey was conducted over a six-month period and gained valuable time-series insights, but ended in mid-March of 2021. Following this, the United States COVID-19 vaccination program accelerated dramatically, and on June 11, 2021 Chicago entered 'Phase 5' of its reopening plan [Pritzker, 2021], during which a majority of restrictions on public life and gatherings were lifted, in addition to the removal of a mask mandate for fully vaccinated individuals in the majority of public spaces (with public transit being a notable exception). Given the rapid changes, it would expand the relevance of the results considerably to conduct additional surveys with the intent of understanding how individual attitudes and intentions evolved through these later phases of the pandemic. Secondly, inconsistencies in Ventra card records meant that a limited sample of riders was used for clustering analysis, approximately 30% to 40% of the overall survey samples.

In terms of policy implications, there are several major takeaways from this case study which are relevant for transit operations and service forecasting. Ridership analysis showed that flexible infrastructure is important to maintain service quality with a sudden and dramatic shift in the spatial ridership profile, along with reduced vehicle capacity to facilitate social distancing. This demonstrates the importance of robustness for fleet procurement and planning. Secondly, the ridership analysis identifies the importance of transit to move essential workers during the pandemic, which may be used in support of agencies seeking government support for continued operations in the future. Although CARES and CRRSA funds have already been disbursed to agencies, results such as these highlight the value which desirable transit services provide to cities and demonstrate the need for continued investment.

The case study also highlights important findings for COVID-19 recovery planning and policy. Findings regarding safety and evolving perceptions of safety, in conjunction with an understanding of factors which are preventing riders from returning, highlights the importance of policies such as fare discounts to incentivize return to transit in the short term, hopefully continuing to build rider comfort in the longer-term post-pandemic. Secondly, the ridership analysis projects changes in the CTA's long-term ridership profile, identifying a likely reduction in peak period demand, increase in flexible work schedules, and greater share of occasional and infrequent riders. This may help to plan longer-term service delivery, and to design flexible fare options to better suit future riders.

8.3 Emerging Mobility Mode (TNC-PT Relationship Case Study)

The case study of the TNC-PT relationship uncovered results regarding the nature of the relationship under ordinary conditions, various explanatory factors which are correlated with the tendency to use TNC services in place of transit, and the evolution of this relationship through COVID-19. In ordinary conditions, the study found that a very small proportion of the total (less than 4% of all TNC trips) were likely serving a first- or last-mile connection to public transit. Approximately 53% of TNC rides taken were found to serve trips that do not have a viable transit alterative, while around 45% of trips directly substituted for transit. These relationships were clustered in space, with higher rates of substitution observed in the downtown and near north sides, and greater concentrations of independence in Chicago's South Side, outside of rapid rail transit coverage. Additionally, greater rates of substitution were observed during peak periods of travel, indicating a possible tendency for work-based trips to disproportionately substitute for transit. Analysis of the factors which correlate with greater rates of substitution provide additional insight into these results, including greater substitution rates in locations with high crime levels, a greater rate of peak-period TNC use, a higher percentage of white population, and greater transit network availability.

By applying the analysis framework to various stages through the COVID-19 pandemic, a significant change in the TNC-PT relationship was observed. In particular, rates of substitution decreased substantially (to around 14% of the total), while independent trips rose to around 82%. Peak periods of travel flattened, serving to indicate that ridership was likely disproportionately lost from commuting trips during the peak period, which tended to be substitution pre-pandemic and may likely have served jobs which were conducted remotely during COVID-19.

It is also important to acknowledge the limitations of this study, particularly regarding judgement-based decisions made for analysis thresholds. For example, the categorization of complementary TNC trips was made primarily by estimating the likelihood of a rider taking the TNC trip to access the transit stops, rather than by the complete information of a rider's entire trip chain or travel purpose. Other decisions, such as selected thresholds for buffer analysis or travel time comparison, were made considering reference literature and sensitivity analysis. To mitigate these effects to some extent, analysis of the upper bound of complementary trips was calculated to be 4.2% of all trips. Additionally, TNC wait time data was not available, which necessitated aggregate estimations. However, as the TNC driver supply decreased through the pandemic (and wait times thereby increased), this aggregate assumption may have limited the ability to accurately capture the full TNC journey travel time.

This study provides a number of key findings which may be of use to policymakers. First, the project identified a surge in TNC trips taken for work during peak periods under ordinary conditions, which could feasibly be completed by transit. Policymakers may wish to structure regulation and incentives around encouraging shifts away from TNC services during these periods, as this could help to alleviate traffic congestion during the most constrained periods of ordinary travel. Furthermore, an identified tendency to replace transit with TNC services in high-crime areas underscores the need for enhanced public transit safety measures in these areas, to ensure that potential riders are not deterred from the PT system.

8.4 Summary of Implications for Public Transit and the Overall Transportation Landscape

Overall, this thesis has demonstrated the significant impacts of various exogenous factors on both public transit and TNC riders in the City of Chicago. Through case studies of a targeted policy intervention, a public health crisis, and a new potentially competitive mobility mode, several methods have been applied to assess impacts along different temporal scales ranging from a single point in time to changing conditions over multiple years. These analyses have yielded further insight into the patterns associated with the identified shocks to the mobility system, and produce valuable takeaways to inform transit agencies and policymakers.

Key takeaways from each case study are apparent through the research work. As identified, direct policy interventions may not achieve their intended outcome immediately, but may yield other benefits and are often not borne by all users equally. This demonstrates the need for continued monitoring, evaluation, and adjustment of policies such as the GTT to achieve stated goals. In the longer term, TNC services and increased availability of on-demand travel modes has created a permanent shift in the transportation landscape, which interacts with public transit differently over space and time. The COVID-19 pandemic has identified core transit ridership among minority and lower-income populations, and highlighted the importance of transit to move essential workers in a time of crisis.

As identified throughout the thesis, TNC services and other emerging transportation modes bring about disruptions to traditional transportation modes and the overall transportation system. This thesis has demonstrated the role of TNC services as acting significantly in competition with public transit. However, the nature of this relationship changed considerably in the COVID-19 pandemic, as peak-period commute trips (which disproportionately substitute for transit) decreased dramatically in volume, contributing to in a 70% drop in the rate of substitution between TNC services and transit . As long-term commute patterns may experience a permanent shift following the pandemic, the nature of the TNC-public transit relationship will continue to evolve. Given this, it is essential for transit operators to adjust to changing needs under the post-pandemic normal and to re-evaluate their relationships with competitors, to most effectively serve a potentially permanent shift in travel demand patterns.

It is clear that Chicago's mobility landscape has undergone transformative change in recent years, and the future of the urban transportation landscape is uncertain moving forward. As we recover from COVID-19 and establish a post-pandemic normal, it will be important for both policymakers and transit agencies to continually evaluate policy implications, assess interactions with other mobility service providers, and understand the experiences and future intentions of their riders. This thesis has provided methods and examples to approach all of these actions.

8.5 Future Work

Future research could be conducted to expand and enhance the findings presented in this thesis. Specifically, possible extensions of the three case studies described are outlined, recognizing the current overarching context of COVID-19 recovery in the United States.

First, some limitations of the TNC congestion pricing analysis may be overcome through additional research. Once TNC ridership reaches a post-pandemic normal, analysis could be conducted to examine the steady-state of TNC ridership in Chicago under the GTT. To fully evaluate the impacts of TNC ridership on congestion and transit operations, trip data may be better leveraged to consider trip duration and origin/destination location, in conjunction with transit operating statistics, to perform corridor-level analysis of TNC operations and their changes through targeted policy interventions. However, simulation or modeling would need to be conducted to obtain specific corridor volumes, as trip paths are not available. Additional spatial analysis such as that presented in Section 5.3 may be performed to understand the policy's impact on areas of particular interest, to further understand equity implications of the policy. Analysis of additional post-pandemic time periods may also be performed, to overcome limitations of the narrow time window between the GTT policy implementation and the COVID-19 pandemic.

Second, the relationship between TNC services and public transit will remain an important conversation in the urban mobility landscape. Methodologically, the analysis framework described in this thesis may be enhanced by further refining the first mile/last mile analysis process, incorporating additional metrics of service quality, and developing travel time estimation methods to both incorporate experienced individual travel times and attain computational efficiency required to scale up to sets of approximately 400,000 daily trips. The methods developed in this thesis may also be applied to additional scenarios, to understand the nature of the TNC-PT relationship following COVID-19 recovery. A continued evaluation of this relationship, as well as the ability to analyze granular spatial and temporal patterns in the relationship will help transit operators and city governments appropriately regulate TNC services, and may be used as an input to planning any pilot partnerships to serve first or last mile transit trips.

8.5.1 Future Survey Results Analysis

Finally, additional COVID-19 survey analysis will help to refine and assess forecasts made through this work, particularly reaching further into Chicago's pandemic recovery. While Section 6.2 has provided a glimpse at the possible analyses which can be conducted using this panel survey, it is far from an exhaustive use of the survey results. The survey provides a wealth of data which could be used by researchers beyond the scope of this thesis, some opportunities for which are identified here.

First, the majority of survey respondents are connected with Ventra account identifiers, which may be used for several expansions of this initial analysis. Ventra activity provides a very accurate estimate of individual ridership, which may be used both to corroborate reported ridership, and to gain a more specific profile of ridership than that provided by the survey responses. Ventra ridership may also be used to track individual return to transit in the future (e.g. Fall 2021), and to link this behavior to stated attitudes and intentions in the panel survey. For instance, many riders anticipated a 3-4 day in-person workweek following the pandemic, and the realization of this could be examined using Ventra travel records for those respondents.

Additionally, many survey respondents (a total of 501) consented to participate in future CTA-MIT survey efforts, and provided contact information. This provides a resource which would make follow-up surveys a very realistic goal without undergoing the arduous process of solicitation and panel formation. This resource could be used to track customer attitudes and behaviors further along the course of pandemic recovery, particularly following an anticipated return to in-person work, school, and travel in Fall 2021.

Appendix A

Data Descriptions

This section provides detailed descriptions of some publicly accessible data sources used in the project case studies, as referenced in Section 4.2.

A.1 Public TNC Trip Data

Table A.1: Data description for public TNC trips dataset Chicago Data Portal, 2020b. Available:
`https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips/m6dm-c72p`

Column Name	Type	Description
Trip ID	Plain Text	A unique identifier for the trip.
Trip Start Timestamp	Date & Time	When the trip started, rounded to the nearest 15 minutes.
Trip End Timestamp	Date & Time	When the trip ended, rounded to the nearest 15 minutes.
Trip Seconds	Number	Time of the trip in seconds.
Trip Miles	Number	Distance of the trip in miles.
Pickup Census Tract	Plain Text	The Census Tract where the trip began.This column often will be blank for locations outside Chicago.
Dropoff Census Tract	Plain Text	The Census Tract where the trip ended. This column often will be blank for locations outside Chicago.
Pickup Community Area	Number	The Community Area where the trip began. This column will be blank for locations outside Chicago.
Dropoff Community Area	Number	The Community Area where the trip ended. This column will be blank for locations outside Chicago.
Fare	Number	The fare for the trip, rounded to the nearest $2.50.
Tip	Number	The tip for the trip, rounded to the nearest $1.00. Cash tips will not be recorded.
Additional Charges	Number	The taxes, fees, and any other charges for the trip.
Trip Total	Number	Total cost of the trip. This is calculated as the total of the previous columns, including rounding.
Shared Trip Authorized	Checkbox	Whether the customer agreed to a shared trip with another customer, regardless of whether the customer was actually matched for a shared trip.
Trips Pooled	Number	If customers were matched for a shared trip, how many trips, including this one, were pooled. All customer trips from the time the vehicle was empty until it was empty again contribute to this count, even if some customers were never present in the vehicle at the same time. Each trip making up the overall shared trip will have a separate record in this dataset, with the same value in this column.
Pickup Centroid Latitude	Number	The latitude of the center of the pickup census tract or the community area if the census tract has been hidden for privacy. This column often will be blank for locations outside Chicago.
Pickup Centroid Longitude	Number	The longitude of the center of the pickup census tract or the community area if the census tract has been hidden for privacy. This column often will be blank for locations outside Chicago.
Pickup Centroid Location	Point	The location of the center of the pickup census tract or the community area if the census tract has been hidden for privacy. This column often will be blank for locations outside Chicago.
Dropoff Centroid Latitude	Number	The latitude of the center of the dropoff census tract or the community area if the census tract has been hidden for privacy. This column often will be blank for locations outside Chicago.
Dropoff Centroid Longitude	Number	The longitude of the center of the dropoff census tract or the community area if the census tract has been hidden for privacy. This column often will be blank for locations outside Chicago.
Dropoff Centroid Location	Point	The location of the center of the dropoff census tract or the community area if the census tract has been hidden for privacy. This column often will be blank for locations outside Chicago.

A.2 City of Chicago Spatial Data

Census Tract Boundaries

Table A.2: Data description for Chicago census tract boundaries dataset Chicago Data Portal, 2010b. Available:
`https://data.cityofchicago.org/Facilities-Geographic-Boundaries/Boundaries-Census-Tracts-2010/5jrd-6zik`

Name	Type	Description
the_geom	MULTIPOLYGON	Geometry definition
STATEFP10	2-digit int	State identifier
COUNTYFP10	2-digit int	County identifier
TRACTCE10	6-digit int	Tract identifier
GEOID10	15-digit int	15-digit GEOID
NAME10	Float	Tract identifier
NAMELSAD10	String	Tract identifier
COMMAREA	2-digit int	Community Area mapping
COMMAREA_N	2-digit int	Community Area mapping
NOTES	String	Comments

Census Block Boundaries

Table A.3: Data description for Chicago census block boundaries dataset Chicago Data Portal, 2010a. Available:
`https://data.cityofchicago.org/Facilities-Geographic-Boundaries/Boundaries-Census-Blocks-2010/mfzt-js4n`

Name	Type	Description
the_geom	MULTIPOLYGON	Geometry definition
STATEFP10	2-digit int	State identifier
COUNTYFP10	2-digit int	County identifier
TRACTCE10	6-digit int	Tract identifier
BLOCKCE10	4-digit int	Block identifier
GEOID10	15-digit int	15-digit GEOID
NAME10	String	Block name
TRACT_BLOC	10-digit int	Block identifier

Crime Records

Table A.4: Data description for Chicago 2019 crime records dataset Chicago Data Portal, 2020a. Available:
`https://data.cityofchicago.org/Public-Safety/Crimes-2019/w98m-zvie`

Column Name	Type	Description
ID	Number	Unique identifier for the record.
Case Number	Plain Text	The Chicago Police Department Records Division Number, which is unique to the incident.
Date	Date	Time & Date when the incident occurred.
Block	Plain Text	The partially redacted address where the incident occurred, placing it on the same block as the actual address.
IUCR	Plain Text	The Illinois Unifrom Crime Reporting code. This is directly linked to the Primary Type and Description. See the list of IUCR codes at https://data.cityofchicago.org/d/c7ck-438e.
Primary Type	Plain Text	The primary description of the IUCR code.
Description	Plain Text	The secondary description of the IUCR code, a subcategory of the primary description.
Location Description	Plain Text	Description of the location where the incident occurred.
Arrest	Checkbox	Indicates whether an arrest was made.
Domestic	Checkbox	Indicates whether the incident was domestic-related as defined by the Illinois Domestic Violence Act.
Beat	Plain Text	Indicates the beat (smallest police geographic area) where the incident occurred.
District	Plain Text	Indicates the police district where the incident occurred.
Ward	Number	The ward (City Council district) where the incident occurred.
Community Area	Plain Text	Indicates the Chicago community area where the incident occurred.
FBI Code	Plain Text	Indicates the crime classification as outlined in the FBI's National Incident-Based Reporting System (NIBRS).
X Coordinate	Number	The x coordinate of the location where the incident occurred in State Plane Illinois East NAD 1983 projection. Shifted within the same block for partial redaction.
Y Coordinate	Number	The y coordinate of the location where the incident occurred in State Plane Illinois East NAD 1983 projection. Shifted within the same block for partial redaction.
Year	Number	Year the incident occurred.
Updated On	Date	Time & Date and time the record was last updated.
Latitude	Number	The latitude of the location where the incident occurred. Shifted within the same block for partial redaction.
Longitude	Number	The longitude of the location where the incident occurred. Shifted within the same block for partial redaction.
Location	Location	The location where the incident occurred in a format that allows for creation of maps and other geographic operations on this data portal. Shifted within the same block for partial redaction.

Parking lot information

Table A.5: Data description for CTA parking lot location dataset Chicago Data Portal, 2013. Available:
https://data.cityofchicago.org/Transportation/CTA-Park-and-Ride-kml/2cys-9ux7

Name	**Type**	**Description**
geometry	MULTIPOLYGON	Geometry definition
Name	String	Parking lot name
description	String	Provides details of parking lot address, linked CTA station details, parking cost, number of spaces, and the total area of the parking lot.

Appendix B

Additional Details for Case Study Methods

This appendix provides further details on the case study methods and implementation processes, as referenced in Chapter 4.

B.1 Survey Questions

A complete set of survey questions for the Solicitation Survey (B.1.1), Initial Survey (B.1.2), and March Monthly Survey (B.1.3) are provided in this appendix. Questions used for the December, January, and February monthly surveys are contained within the set of March survey questions.

B.1.1 Solicitation Survey Questions

Thank you for your interest in participating in this survey! This project is being conducted by Chicago Transit Authority (CTA) in partnership with Massachusetts Institute of Technology (MIT).

If you are willing to participate in the surveys, please take about 3 minutes to complete the following questions.

Note: all data obtained from participants will be kept strictly confidential and will only be reported in an aggregate format (as combined results), never as individual responses. Any information provided in response to this survey will not be used to identify your personal information.

Q1 Please enter your email address to participate in future CTA studies:

Q2 Please confirm your email address:

Q3 How many people are there in your household (including yourself)? (Note: for the purposes of this survey, a household includes all the people who occupy a housing unit (such as a house or apartment) as their regular place of residence. A household includes all relatives as well as all unrelated individuals who share the housing unit, including but not limited to family members, roommates, friends, foster children, wards, coworkers, etc. A person living alone in a housing unit, or a group of unrelated people sharing a housing unit as partners or roommates, also counts as a household.)

- 1 (I live alone)
- 2
- 3
- 4
- 5 or more

Q4 How many employed adults live in your household?

- 0
- 1
- 2
- 3
- 4
- 5 or more

Q5 How many adults living in your household currently commute to/from work/school?

- 0
- 1
- 2
- 3

- 4
- 5 or more

Q6 How many children (age 16 and younger) live in your household?

- 0
- 1
- 2
- 3
- 4
- 5 or more

Q7 How many individuals over the age of 60 live in your household?

- 0
- 1
- 2
- 3
- 4
- 5 or more

Q8 What is your household yearly income in US dollars?

- Less than $15,000
- $15,000 to $24,999
- $25,000 to $39,999
- $40,000 to $59,999
- $60,000 to $74,999
- $75,000 to $99,999
- $100,000 to $149,999
- $150,000 to $199,999
- $200,000 or more
- Prefer not to answer

Q9 How many personal vehicles do you have in your household?

- 0
- 1
- 2
- 3 or more
- Prefer not to answer

Q10 What is the highest level of education you have completed/attained?

- Less than high school diploma
- High school diploma or equivalent (GED)
- Some college, no degree
- Associate's Degree
- Bachelor's Degree
- Master's degree
- Doctoral or Professional degree (PhD, M.D., J.D., etc.)

Q11 Which best describes your current employment status?

- Employed: working outside the home
- Employed: working remotely at home
- Unemployed
- Retired
- Student
- Other, please specify

Q12 What is your home ZIP code (5 digit)? This information will only be used for analysis and will not be used to identify any individual riders.

Q13 Do you have a Ventra Card?

- Yes
- No

Q14 If you've got your Ventra Card on hand, please provide the Ventra card number (It is a 16 or 19 digit ID that is located on the front or back of your Ventra Card, as is shown in the red box in the following images). If you don't have your Ventra Card handy, you can skip this question.

Q15 Please put in your Ventra card number again as a confirmation.

Q16 Note: this information will only be used for analysis and will not be used to identify any individual riders.

B.1.2 Initial Survey Questions

Introduction: CTA/MIT Survey: CTA ridership in response to COVID-19

Thank you for your interest in participating in our survey! This survey is being conducted by Chicago Transit Authority (CTA) in partnership with Massachusetts Institute of Technology (MIT), to study how your travel behavior changed in response to the novel coronavirus (COVID-19) pandemic.

Today, we are asking you to complete a simple, 10-15 minutes survey on your previous and current travel patterns. Following this initial survey, we intend to reach out to you again with shorter, follow-up surveys in the months to come. Your responses over time will help inform the Agency on how its service can best meet the changing needs of customers.

We appreciate your participation in our research, and are offering a chance to win one of five $50 VISA gift cards, drawn at the end of the survey period, to those who complete the initial survey and each of the four brief monthly surveys distributed from now until March 2021.

Note: all data obtained from participants will be kept strictly confidential and will only be reported in an aggregate format (as combined results), never as individual responses. Any information provided in response to this survey will not be used to identify your personal information.

Part 1. Travel before the outbreak and Stay-At-Home Order (March 21, 2020)

First, we would like to ask you a set of questions about your travel behavior before the outbreak of the COVID-19 and the start of the State of Illinois' Stay-At-Home

Order on March 21, 2020. Please recall your travel before the start of the Stay-At-Home Order, and answer the following questions.

Q1 Before the COVID-19 Stay-At-Home Order which began on March 21, 2020, on average how many trips did you take per week by each of the following travel modes? (A trip can include any travel to or from home, work, school, shopping, food, recreation, to caring for friend/family, social activity, healthcare, other social services/facilities, etc.)

	Never	**1-2 trips per week**	**3-5 trips per week**	**6-10 trips per week**	**11-15 trips per week**	**More than 15 trips per week**
CTA Train	o	o	o	o	o	o
CTA Bus	o	o	o	o	o	o
Driving alone	o	o	o	o	o	o
Walk (all the way to my destination)	o	o	o	o	o	o
Bike, Scooter or Divvy bike-share	o	o	o	o	o	o
Taxi	o	o	o	o	o	o
Uber, Lyft, or similar ride-sharing services	o	o	o	o	o	o
Ride or carpool with friend/family	o	o	o	o	o	o
Metra	o	o	o	o	o	o
Pace	o	o	o	o	o	o

Q2 Before the start of the Stay-At-Home order, for what travel purpose(s) did you use CTA train and/or bus? Please select all that apply.

- Commute between home and work
- Commute between home and school
- Work related business
- Medical/dental appointment
- Travel to care for friends/family
- Shopping for food and essential items
- Shopping for non-essential items

- Recreation/social
- Travel to or from airport
- Other, please specify:

Q3 Before the start of the Stay-At-Home order, how many trips did you take by CTA train and/or bus during the peak weekday hours (Monday through Friday, 6AM - 10AM, 4PM - 8PM)?

- More than 15 trips per week
- 11-15 trips per week
- 6-10 trips per week
- 3-5 trips per week
- 1-2 trips per week
- I never traveled during the peak hours before the outbreak

Q4 Before the outbreak and the start of the Stay-At-Home order, what percentage of your CTA trips involve the following types of transfer?

- bus-to-bus transfer
- bus-to-rail/rail-to-bus transfer
- rail-to-rail transfer
- no transfer

Q5 Before the outbreak and the start of the Stay-At-Home order, what type of pass did you use for the CTA services?

- I didn't utilize CTA services
- 1-day pass
- 3-day pass
- 7-day pass
- 30-day pass
- Pay as you go / transit value
- Cash payment on buses

Q6 Recall one month before the outbreak and the start of the Stay-At-Home order (e.g. February 2020), how many weeks in this month did you use the CTA train and/or bus one or more times?

- I never used CTA before the outbreak
- 1 week
- 2 weeks
- 3 weeks
- 4 weeks
- 5 weeks

Part 2. Travel during the Stay-At-Home Order (Mar 21, 2020 - Jun 3, 2020) Now we would like to ask you a set of questions about your travel behavior during the Stay-At-Home order. Please recall your travel patterns from March 21 through June 3, 2020 and answer the following questions.

Q7 During the Stay-At-Home order, how many trips were taken on average each week by each of the following travel modes? (A trip can include any travel to or from home, work, school, shopping, food, recreation, to caring for friend/family, social activity, healthcare, other social services/facilities, etc.)

	Never	**1-2 trips per week**	**3-5 trips per week**	**6-10 trips per week**	**11-15 trips per week**	**More than 15 trips per week**
CTA Train	o	o	o	o	o	o
CTA Bus	o	o	o	o	o	o
Driving alone	o	o	o	o	o	o
Walk (all the way to my destination)	o	o	o	o	o	o
Bike, Scooter or Divvy bike-share	o	o	o	o	o	o
Taxi	o	o	o	o	o	o
Uber, Lyft, or similar ride-sharing services	o	o	o	o	o	o
Ride or carpool with friend/family	o	o	o	o	o	o
Metra	o	o	o	o	o	o
Pace	o	o	o	o	o	o

Q8 During the Stay-At-Home order, for what purpose did you use the CTA train and/or bus? Please select all that apply.

- Commute between home and work
- Commute between home and school
- Work related business
- Medical/dental appointment
- Travel to care for friends/family
- Shopping for food and essential items
- Shopping for non-essential items
- Recreation/social
- Travel to or from airport
- Other, please specify:

Q9 Compared to your travel before the outbreak and the Stay-At-Home order, how much more or less did you use CTA trains and/or buses during the Stay-At-Home order?

- Stopped using completely

- Reduced use
- Used about the same
- Increased use

Q10 Why did you reduce the use of or stop using CTA trains and/or buses during the Stay-At-Home Order? Please select all that apply.

- I didn't need to commute, because I was unemployed or furloughed
- I didn't need to commute, because I was working from home
- I still commuted, but chose to drive my private car instead of taking transit
- I still commuted, but chose to travel by a mobility service (e.g. taxi, ride-hailing) instead of transit
- I still commuted, but chose to walk and/or bike instead of transit
- I didn't need to go shopping, because I was using online delivery
- I didn't need to go shopping, because I have reduced my consumption
- I still went shopping, but chose to drive my private car instead of taking transit
- I still went shopping, but chose to travel by another mode instead of transit
- I no longer travelled for fun or recreation
- I still travelled for fun or recreation, but was using another mode besides transit
- Others, please specify

Q11 Why did you increase the use of CTA trains and/or buses or use it about the same during the Stay-At-Home order? Please select all that apply.

- I had to use public transit, because I don't own a car
- I had to use public transit, because I cannot afford a taxi or ride-hailing service
- I continued to use public transit, because CTA has taken appropriate actions to respond to the pandemic
- I continued to use public transit, because I don't think public transit increases the risk of COVID-19 infection
- I continued to use public transit, because I don't think the COVID-19 outbreak is that severe
- Others, please specify

Part 3. Anticipated travel during the 'Gradually Reopening' (after Jun 3, 2020) Beginning in June 2020, the City of Chicago began its phased reopening. Now we would like to ask you a set of questions about your CURRENT travel behavior since Chicago began its social and economic reopening.

Q12 In the last week, how many trips were taken by each of the following travel modes? (A trip can include any travel to or from home, work, school, shopping, food, recreation, to caring for friend/family, social activity, healthcare, other social services/facilities, etc.)

	Never	**1-2 trips per week**	**3-5 trips per week**	**6-10 trips per week**	**11-15 trips per week**	**More than 15 trips per week**
CTA Train	o	o	o	o	o	o
CTA Bus	o	o	o	o	o	o
Driving alone	o	o	o	o	o	o
Walk (all the way to my destination)	o	o	o	o	o	o
Bike, Scooter or Divvy bike-share	o	o	o	o	o	o
Taxi	o	o	o	o	o	o
Uber, Lyft, or similar ride-sharing services	o	o	o	o	o	o
Ride or carpool with friend/family	o	o	o	o	o	o
Metra	o	o	o	o	o	o
Pace	o	o	o	o	o	o

Q13 In the last week, for what purpose did you use the CTA train and/or bus? Please select all that apply.

- Commute between home and work
- Commute between home and school
- Work related business
- Medical/dental appointment
- Travel to care for friends/family
- Shopping for food and essential items
- Shopping for non-essential items

- Recreation/social
- Travel to or from airport
- Other, please specify:

Q14 Compared to your travel before the COVID-19 pandemic, how much more or less did you use CTA trains and/or buses in the last week?

- Stopped using completely
- Reduced use
- Used about the same
- Increased use

Q15 Why did you reduce the use of or stop using CTA trains and/or buses in the last week? Please select all that apply.

- I didn't need to commute, because I was unemployed or furloughed
- I didn't need to commute, because I was working from home
- I still commuted, but chose to drive my private car instead of taking transit
- I still commuted, but chose to travel by a mobility service (e.g. taxi, ride-hailing) instead of transit
- I still commuted, but chose to walk and/or bike instead of transit
- I didn't need to go shopping, because I was using online delivery
- I didn't need to go shopping, because I have reduced my consumption
- I still went shopping, but chose to drive my private car instead of taking transit
- I still went shopping, but chose to travel by another mode instead of transit
- I no longer travelled for fun or recreation
- I still travelled for fun or recreation, but was using another mode besides transit
- Others, please specify

Q16 Why did you increase the use of CTA trains and/or buses or use it about the same in the last week? Please select all that apply.

- I had to use public transit, because I don't own a car
- I had to use public transit, because I cannot afford a taxi or ride-hailing service

- I continued to use public transit, because CTA has taken appropriate actions to respond to the pandemic
- I continued to use public transit, because I don't think public transit increases the risk of COVID-19 infection
- I continued to use public transit, because I don't think the COVID-19 outbreak is that severe
- Others, please specify

Q17 Under what situation will you increase your use of CTA trains and/or buses? For the statements below, please select all that apply.

- I will increase my use of CTA trains and/or buses, once I need to travel (e.g. commuting for work, shopping trips, recreation, etc.)
- I will increase my use of CTA trains and/or buses, if the cleanliness of the stations/vehicles is improved
- I will increase my use of CTA trains and/or buses, if there are not many passengers on the vehicles
- I will not increase my use of CTA trains and/or buses until there are fewer COVID-19 cases
- I will not increase my use of CTA trains and/or buses until the pandemic is over
- I will not increase my use of CTA trains and/or buses even if the pandemic is over, as I found alternate travel modes
- I will not increase my use of CTA trains and/or buses even if the pandemic is over, as I decide to continue working from home
- I will not increase my use of CTA trains and/or buses even if the pandemic is over, as my work/home locations were changed
- Others, please specify

Q18 Even if the pandemic is over, I will not increase my use of CTA trains and/or buses, because I plan to use the following mode(s) instead (please select all that apply):

- Driving alone
- Walk (all the way to my destination)
- Bike, Scooter or Divvy bike-share
- Taxi
- Uber, Lyft, or similar ride-sharing services
- Ride or carpool with friend/family
- Metra
- Pace

Q19 In the last week, which type of pass did you use for the CTA services?

- I didn't utilize CTA services
- 1-day pass
- 3-day pass
- 7-day pass
- 30-day pass
- Pay as you go / transit value
- Cash payment on buses

Part 4. Perceptions about the CTA actions CTA has taken multiple actions to respond to the COVID-19 pandemic. Now we would like to ask you a set of questions about your opinions towards these actions and general perception of CTA.

Q20 Responding to the COVID-19 outbreak, CTA increased its cleaning regimen for vehicles and stations. Please indicate your level of agreement with the following statements about this action.

	Strongly disagree	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**	**N/A (not applicable)**
The action to increase cleaning of CTA vehicles and stations was the right thing to do for public health.	o	o	o	o	o	o
CTA did a good job in improving the system cleanliness.	o	o	o	o	o	o
I am confident that CTA trains and buses are carefully sanitized to reduce public health risks.	o	o	o	o	o	o
CTA's cleaning makes me more likely to continue riding CTA service in the future.	o	o	o	o	o	o
Even after the coronavirus outbreak is over, I still hope CTA will continue its current cleaning regimen.	o	o	o	o	o	o

Q21 Please indicate your level of agreement with the following statements about CTA trains and/or buses since the start of the COVID-19 pandemic.

	Strongly disagree	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**	**N/A (not applicable)**
Maintaining public transit services is important for ensuring access to jobs, healthcare, and other services.	o	o	o	o	o	o
I am personally concerned about being exposed to the virus while taking public transit.	o	o	o	o	o	o
CTA's customer communications around social distancing and wearing face coverings is effective.	o	o	o	o	o	o
I regularly see other riders correctly wearing face masks.	o	o	o	o	o	o
CTA should do more to communicate about social distancing and wearing face masks.	o	o	o	o	o	o
CTA service is regularly crowded (more than 20 people per bus or train car).	o	o	o	o	o	o
Even after the coronavirus outbreak is over, I will be less likely to use public transit due to concerns about infectious diseases.	o	o	o	o	o	o

Part 5. Ventra card information Q22 Do you have a Ventra card?

- Yes
- No

Q23 If you've got your Ventra Card on hand, please provide the Ventra card number (It is a 16 or 19 digit ID that locates on the front or back of your Ventra Card, as is shown in the red box of the following images). If you don't have your Ventra Card handy, you can skip this question.

Q24 Note: this information will only be used for analysis and will not be used to identify any individual riders.

B.1.3 March Monthly Survey Questions

Thank you for your interest in participating in our survey! This survey is being conducted by Chicago Transit Authority (CTA) in partnership with Massachusetts Institute of Technology (MIT), to study how your travel behavior changed in response to the novel coronavirus (COVID-19) pandemic.

We appreciate your participation in our research, and are offering a chance to win one of five $50 VISA gift cards, drawn at the close of this survey, to those who complete the initial survey and each of the four brief monthly surveys distributed from December 2020 to March 2021. Prize winners will be contacted by email.

Today, we are asking you to complete a simple, 3-5 minute survey on your current travel patterns.

Note: all data obtained from participants will be kept strictly confidential and will only be reported in an aggregate format (as combined results), never as individual responses. Any information provided in response to this survey will not be used to identify your personal information.

Part 1. Current Travel Behavior (after Jun 3, 2020) Beginning in June 2020, the City of Chicago began its phased reopening. Now we would like to ask you a set of questions about your CURRENT travel behavior since Chicago began its social and economic reopening.

Q1 In the last week, how many trips were taken by each of the following travel modes? (A trip can include any travel to or from home, work, school, shopping, food, recreation, to caring for friend/family, social activity, healthcare, other social services/facilities, etc.)

	Never	**1-2 trips per week**	**3-5 trips per week**	**6-10 trips per week**	**11-15 trips per week**	**More than 15 trips per week**
CTA Train	o	o	o	o	o	o
CTA Bus	o	o	o	o	o	o
Driving alone	o	o	o	o	o	o
Walk (all the way to my destination)	o	o	o	o	o	o
Bike, Scooter or Divvy bike-share	o	o	o	o	o	o
Taxi	o	o	o	o	o	o
Uber, Lyft, or similar ride-sharing services	o	o	o	o	o	o
Ride or carpool with friend/family	o	o	o	o	o	o
Metra	o	o	o	o	o	o
Pace	o	o	o	o	o	o

Q2 In the last week, for what purpose did you use the CTA train and/or bus? Please select all that apply.

- Commute between home and work
- Commute between home and school
- Work related business
- Medical/dental appointment
- Travel to care for friends/family
- Shopping for food and essential items
- Shopping for non-essential items
- Recreation/social
- Travel to or from airport
- Other, please specify:

Q3 In the last week, how much more or less did you use CTA trains and/or buses compared to your travel a month ago?

- Stopped using completely
- Reduced use

- Used about the same
- Increased use

Q4 Why did you reduce the use of or stop using CTA trains and/or buses in the last week? Please select all that apply.

- I didn't need to commute, because I was unemployed or furloughed
- I didn't need to commute, because I was working from home
- I still commuted, but chose to drive my private car instead of taking transit
- I still commuted, but chose to travel by a mobility service (e.g. taxi, ride-hailing) instead of transit
- I still commuted, but chose to walk and/or bike instead of transit
- I didn't need to go shopping, because I was using online delivery
- I didn't need to go shopping, because I have reduced my consumption
- I still went shopping, but chose to drive my private car instead of taking transit
- I still went shopping, but chose to travel by another mode instead of transit
- I no longer travelled for fun or recreation
- I still travelled for fun or recreation, but was using another mode besides transit
- Others, please specify

Q5 Why did you increase the use of CTA trains and/or buses or use it about the same in the last week? Please select all that apply.

- I had to use public transit, because I don't own a car
- I had to use public transit, because I cannot afford a taxi or ride-hailing service
- I continued to use public transit, because CTA has taken appropriate actions to respond to the pandemic
- I continued to use public transit, because I don't think public transit increases the risk of COVID-19 infection
- I continued to use public transit, because I don't think the COVID-19 outbreak is that severe
- Others, please specify

Q6 Under what situation will you increase your use of CTA trains and/or buses? For the statements below, please select all that apply.

- I will increase my use of CTA trains and/or buses, once I need to travel (e.g. commuting for work, shopping trips, recreation, etc.)
- I will increase my use of CTA trains and/or buses, if the cleanliness of the stations/vehicles is improved
- I will increase my use of CTA trains and/or buses, if there are not many passengers on the vehicles
- I will not increase my use of CTA trains and/or buses until there are fewer COVID-19 cases
- I will not increase my use of CTA trains and/or buses until the pandemic is over
- I will not increase my use of CTA trains and/or buses even if the pandemic is over, as I found alternate travel modes
- I will not increase my use of CTA trains and/or buses even if the pandemic is over, as I decide to continue working from home
- I will not increase my use of CTA trains and/or buses even if the pandemic is over, as my work/home locations were changed
- Others, please specify

Q7 Even if the pandemic is over, I will not increase my use of CTA trains and/or buses, because I plan to use the following mode(s) instead (please select all that apply):

- Driving alone
- Walk (all the way to my destination)
- Bike, Scooter or Divvy bike-share
- Taxi
- Uber, Lyft, or similar ride-sharing services
- Ride or carpool with friend/family
- Metra

- Pace

Q8 In the last week, which type of pass did you use for the CTA services?

- I didn't utilize CTA services
- 1-day pass
- 3-day pass
- 7-day pass
- 30-day pass
- Pay as you go / transit value
- Cash payment on buses

Part 2. Current perceptions of COVID-19 and the CTA Now we would like to ask you a set of questions about your CURRENT perceptions of the COVID-19 pandemic and the CTA, since Chicago began its social and economic reopening.
Q9 Do you currently believe that COVID-19 poses a risk to your health, or the health of members of your household?

- Yes
- No

Q10 Do you think that it is safe to ride the CTA this week?

- Yes
- No

Q11 What factors make you feel that it is unsafe to ride the CTA this week? (select all that apply)

- Too few fellow passengers
- Too many passengers crowded on vehicles
- Other passengers not complying with CTA's mask requirement
- Vehicle and station cleanliness
- Other factors related to risk of contracting COVID-19
- Homeless riders in stations or vehicles

- Other factors outside of the current pandemic

Q12 What health and safety improvements could the CTA make to encourage you to ride transit more often in the future? Please rank the following options (by clicking and dragging) in order of importance to you, where 1 is most important and 4 is least important.

- Additional larger buses on busy routes
- Further action to ensure compliance with mask-wearing
- More cleaning in vehicles and stations
- Better ventilation

Q13 What transit service improvements could the CTA make to encourage you to ride transit more often in the future? Please rank the following options (by clicking and dragging) in order of importance to you, where 1 is most important and 5 is least important.

- Reduced fare price
- More flexible fare pass options
- Increased bus or rail service generally
- Increased bus or rail service during off-peak hours
- Improvements to bus speed and reliability (e.g., bus-only lanes)

Q14 Are there any other improvements which are important to you that were not listed? Please specify

Q15 How would you rate the reliability of CTA services this week?

- More reliable than usual
- About the same
- Less reliable than usual
- Not applicable

Q16 Why do you feel that CTA services are less reliable this week? (select all that apply)

- Buses running less frequently
- Trains running less frequently
- Other (please specify)

Q17 Is your primary occupation (e.g. work or school) currently remote?

- Yes
- No
- Partially remote
- Not currently employed

Q18 In a post-pandemic world, how frequently do you expect to travel to your primary occupation (e.g. work or school) in person?

- 5+ days per week
- 3-4 days per week
- 1-2 days per week
- Never
- I don't know

Q19 Over the course of the current COVID-19 vaccine rollout, when would you feel comfortable riding transit?

- I currently feel comfortable riding transit
- I would feel comfortable riding transit if I receive the vaccination
- I would feel comfortable riding transit when everyone over 65 has been vaccinated
- I would feel comfortable riding transit when all transit employees were vaccinated
- I will not feel comfortable riding transit regardless of COVID-19 vaccinations

Q20 Can the CTA/MIT survey team contact you about participating in other surveys in the future?

- Yes

- No

Q21 What would be the best email address to contact you at?

- The address which I used for this survey
- Other, please specify:

B.2 POI Attraction Power Table

Table B.1 specifies the attraction powers by general POI category, as used in the point of interest (POI) estimation process in the first mile/last mile analysis for the TNC-PT relationship case study.

Table B.1: Attraction power by general POI category

ID	General Category	Attraction Power	Active Period Start	Active Period End
1	bar	100 - 300	17:00	27:00
2	entertainment	10 - 300	9:00	17:00
3	hotel	200	9:00	22:00
4	public attraction	10-200	9:00	22:00
5	playground	50	9:00	22:00
6	Ice rink	100	9:00	22:00
7	Community center	300	9:00	22:00
8	library/museum/park	100-200	9:00	17:00
9	Theme park	500	9:00	22:00
10	sightseeing	10-50	9:00	22:00
11	convenience	10	0:00	24:00
12	restaurant	20-30	7:00	22:00
13	food court	100	7:00	19:00
14	school	200-300	8:00	16:00
15	university	700	8:00	22:00
16	college	500	8:00	22:00
17	hospital	500	0:00	24:00
18	service-based retail	10-20	9:00	17:00
19	supermarket	300	9:00	22:00
20	small shops	10-20	9:00	19:00
21	shop	50	9:00	22:00
22	mall	500	9:00	22:00

B.3 Programming Model for TNC+PT Regression

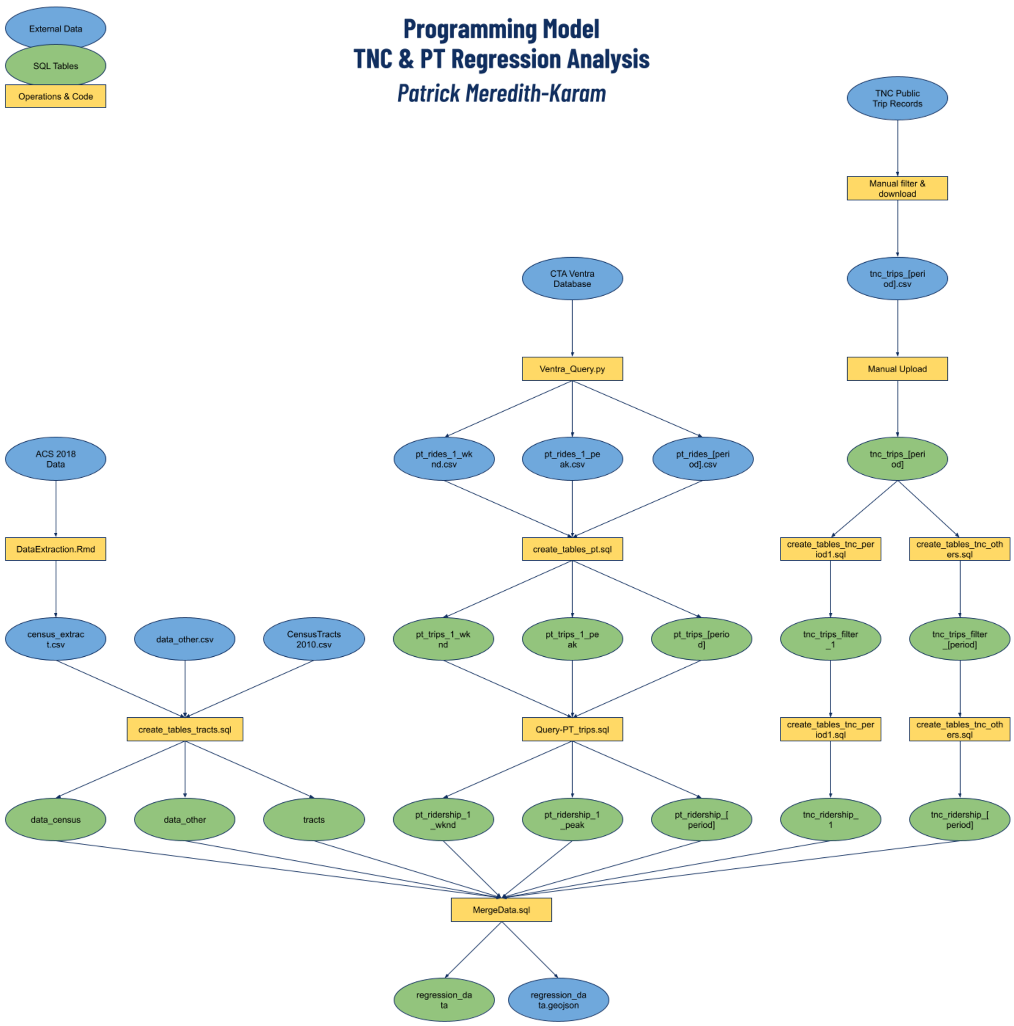


Figure B-1: Programming model for TNC and PT regression analysis

B.4 Programming Model for TNC-PT Relationship

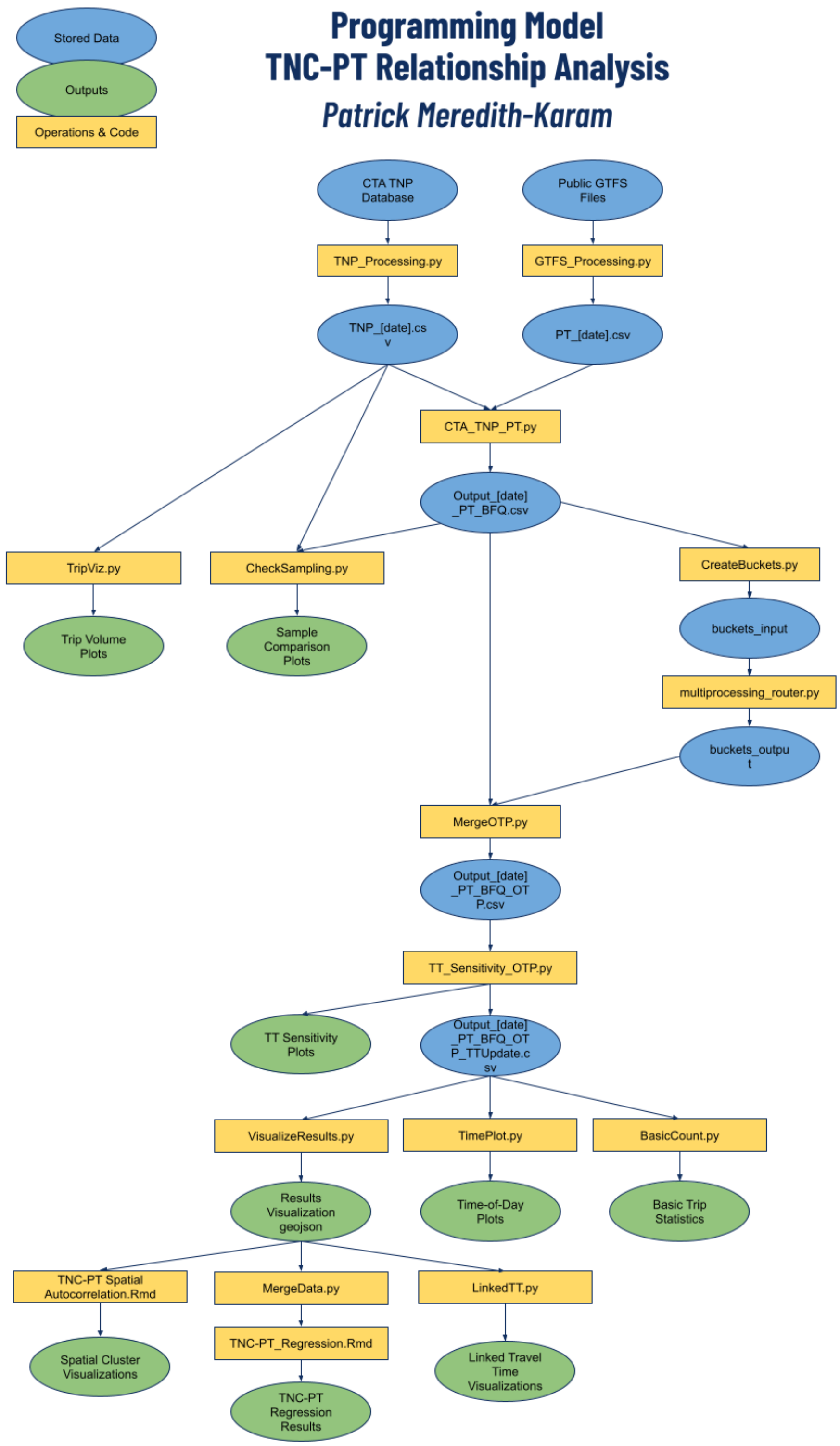


Figure B-2: Programming model for TNC-PT relationship analysis

Appendix C

Additional GTT Case Study Results

This appendix provides additional results for analysis conducted in the GTT case study, as referenced in Chapter 5.

C.1 Additional Exploratory Analysis Results

Additional results from the exploratory analysis conducted in Section 5.3 are provided in this section, covering different time periods for comparison.

Table C.1: Exploratory analysis of trip volumes in GTT-affected areas from December 2019 to January 2020 (aggregate growth rate = 1.0144)

Type	**Area**	**Trip Volume (2019-12)**	**Projected Trips (2020-01)**	**Trip Volume (2020-01)**	**% Difference from Projection**
Pickup	McCormick	64,399	65,327	62,033	- 5.0%
	Navy Pier	23,298	23,634	20,054	- 15.1%
	O'Hare	151,199	153,377	152,241	- 0.7%
	Midway	39,211	39,776	32,121	- 19.2%
	Downtown (North)	645,394	654,690	649,534	- 0.8%
	Downtown	1,253,353	1,271,406	1,277,104	+ 0.4%
Dropoff	McCormick	70,667	71,685	61,761	- 13.8%
	Navy Pier	19,792	20,077	16,825	- 16.2%
	O'Hare	183,838	186,486	183,124	- 1.8%
	Midway	41,058	41,649	34,855	- 16.3%
	Downtown (North)	618,169	627,073	626,271	- 0.1%
	Downtown	1,258,941	1,277,074	1,291,333	+ 1.1%

Table C.2: Exploratory analysis of trip volumes in GTT-affected areas from February 2019 to February 2020 (aggregate growth rate = 1.0008)

Type	**Area**	**Trip Volume (2019-02)**	**Projected Trips (2020-02)**	**Trip Volume (2020-02)**	**% Difference from Projection**
Pickup	McCormick	60,563	60,612.29	67,538	+ 11.4%
	Navy Pier	21,177	21,194.23	24,082	+ 13.6%
	O'Hare	126,235	126,337.73	153,605	+ 21.6%
	Midway	29,989	30,013.41	34,476	+ 14.9%
	Downtown (North)	685,167	685,724.61	692,059	+ 0.9%
	Downtown	1,356,205	1,357,308.72	1,375,405	+ 1.3%
Dropoff	McCormick	61,778	61,828.28	68,588	+ 10.9%
	Navy Pier	17,857	17,871.53	20,491	+ 14.7%
	O'Hare	155,655	155,781.68	181,509	+ 16.5%
	Midway	32,334	32,360.31	35,198	+ 8.8%
	Downtown (North)	661,380	661,918.25	671,716	+ 1.5%
	Downtown	1,376,054	1,377,173.87	1,387,826	+ 0.8%

C.2 Additional Ridership and Surcharge Change Charts

Additional charts highlighting the change in ridership and TNC trip surcharge by census tract are provided here, to expand upon those included in Section 5.3.

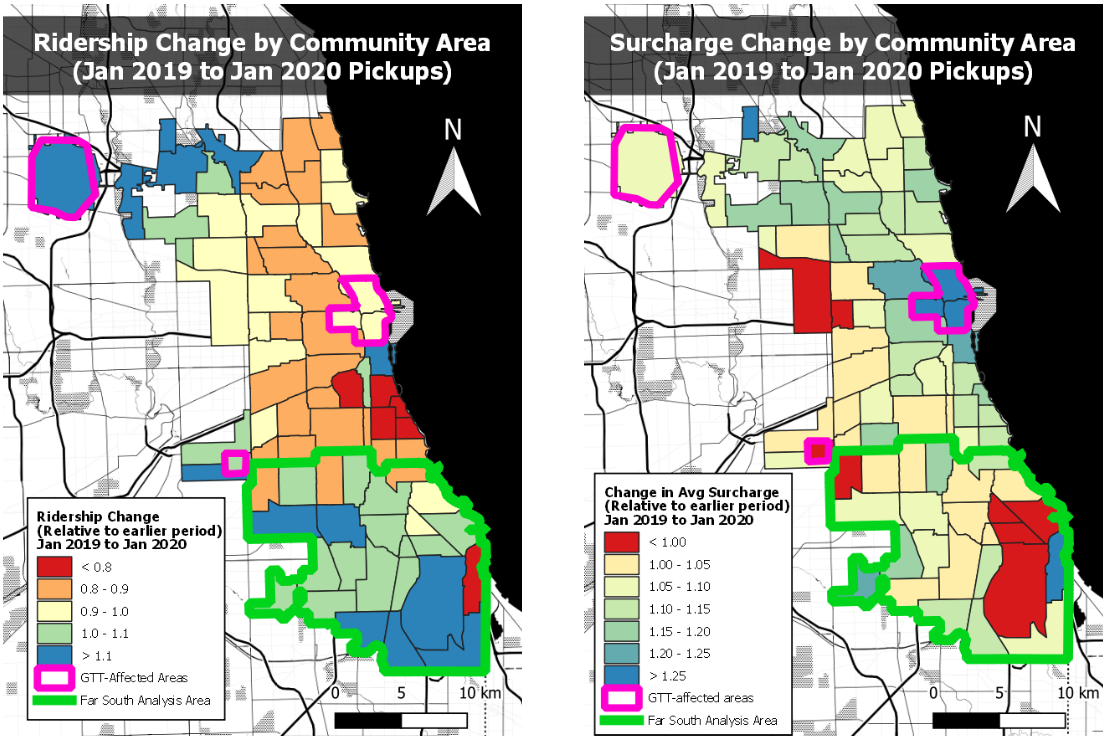


Figure C-1: Percentage change in ridership (left) and average surcharge (right) by pickup adjusted community area from January 2019 to January 2020

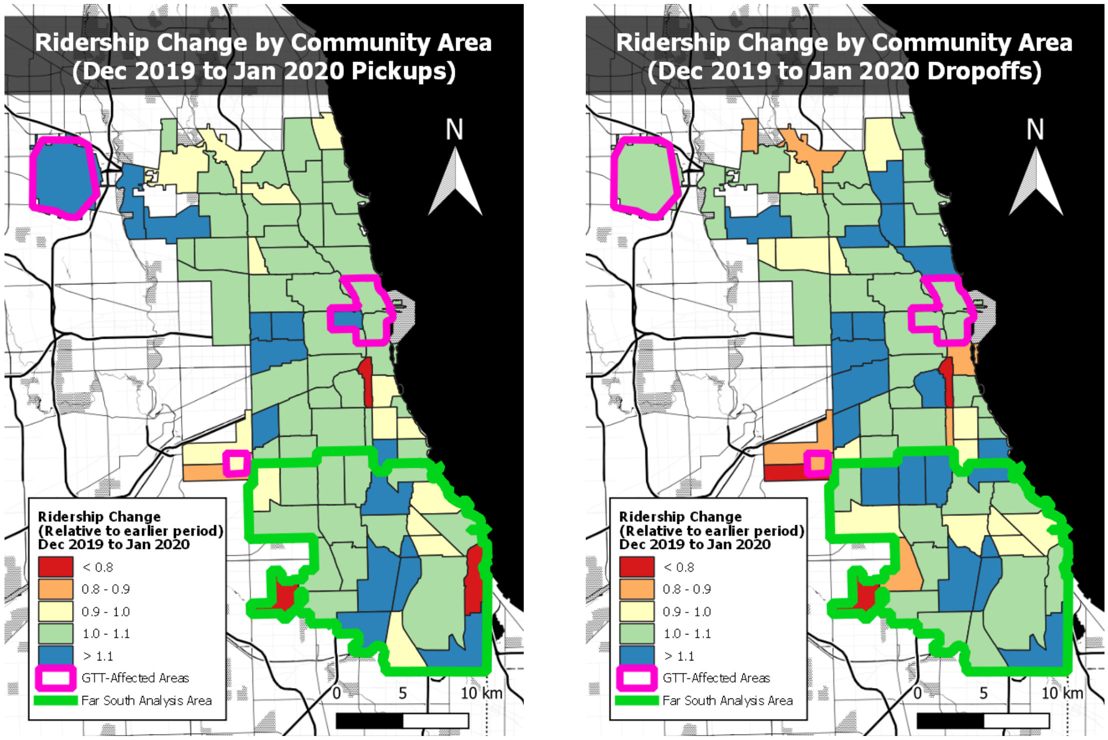


Figure C-2: Percentage change in ridership by pickup (left) and dropoff (right) adjusted community area from December 2019 to January 2020

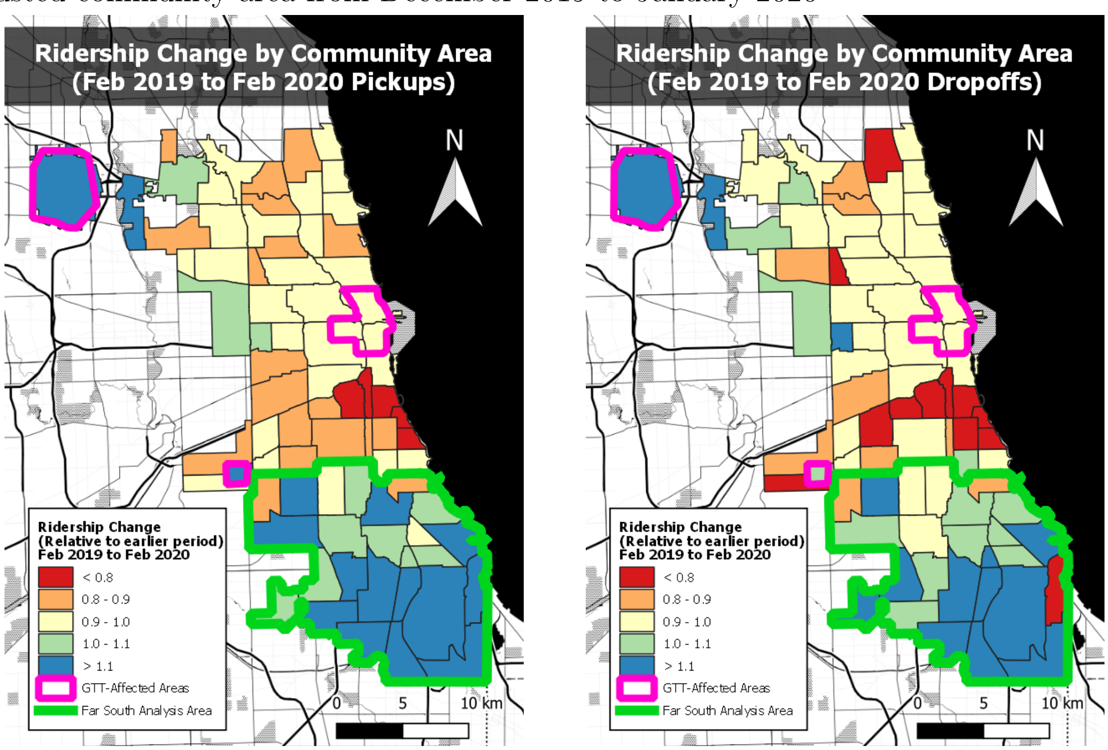


Figure C-3: Percentage change in ridership by pickup (left) and dropoff (right) adjusted community area from February 2019 to February 2020

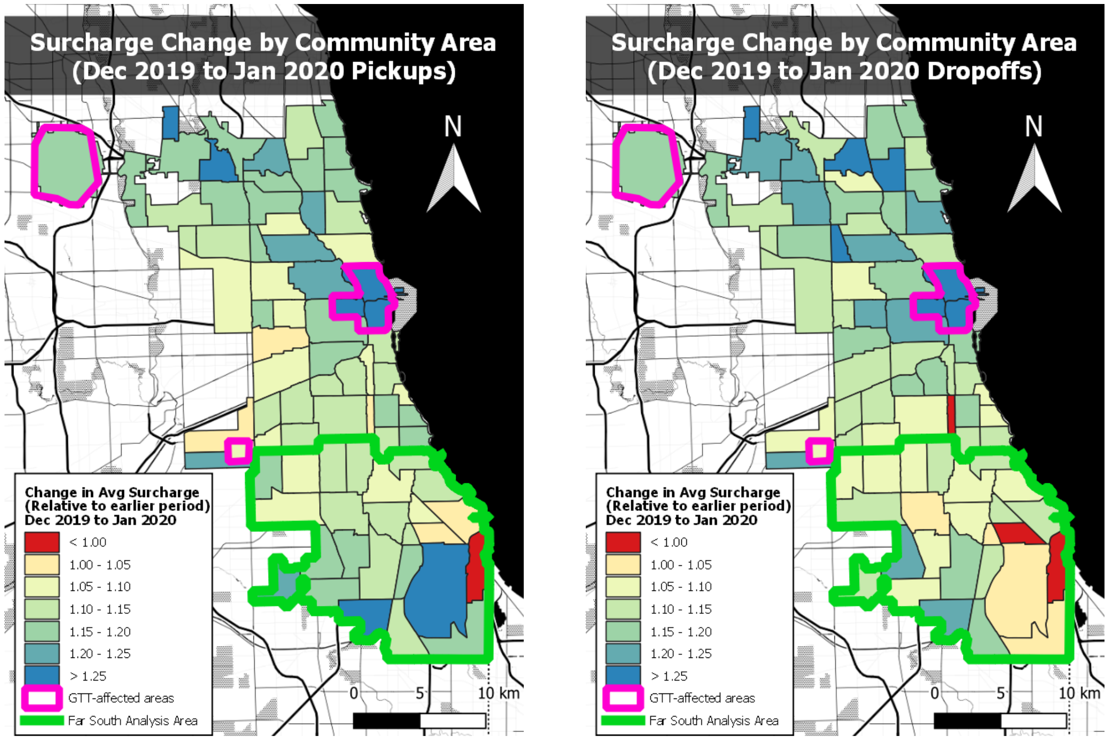


Figure C-4: Percentage change in average surcharge by pickup (left) and dropoff (right) adjusted community area from December 2019 to January 2020

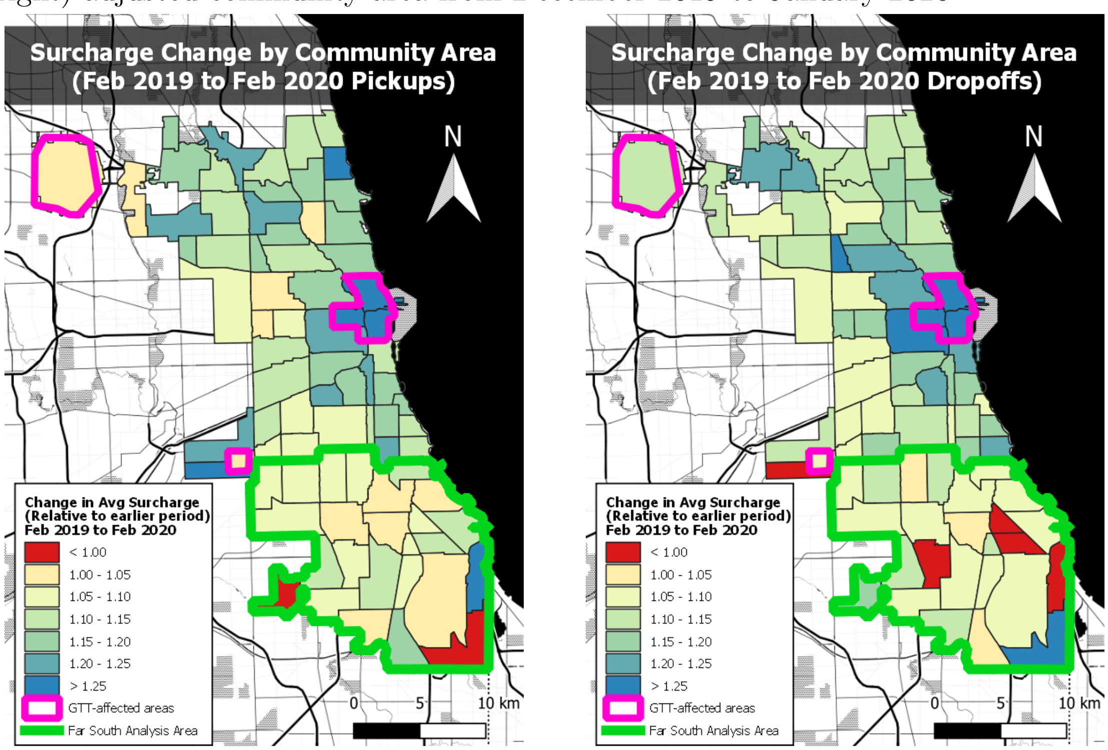


Figure C-5: Percentage change in average surcharge by pickup (left) and dropoff (right) adjusted community area from February 2019 to February 2020

C.3 Additional Spatial Investigation Plots

Additional charts developed comparing ridership change for trips originating and terminating in the Far South analysis area are provided here, to expand upon those included in Section 5.3.

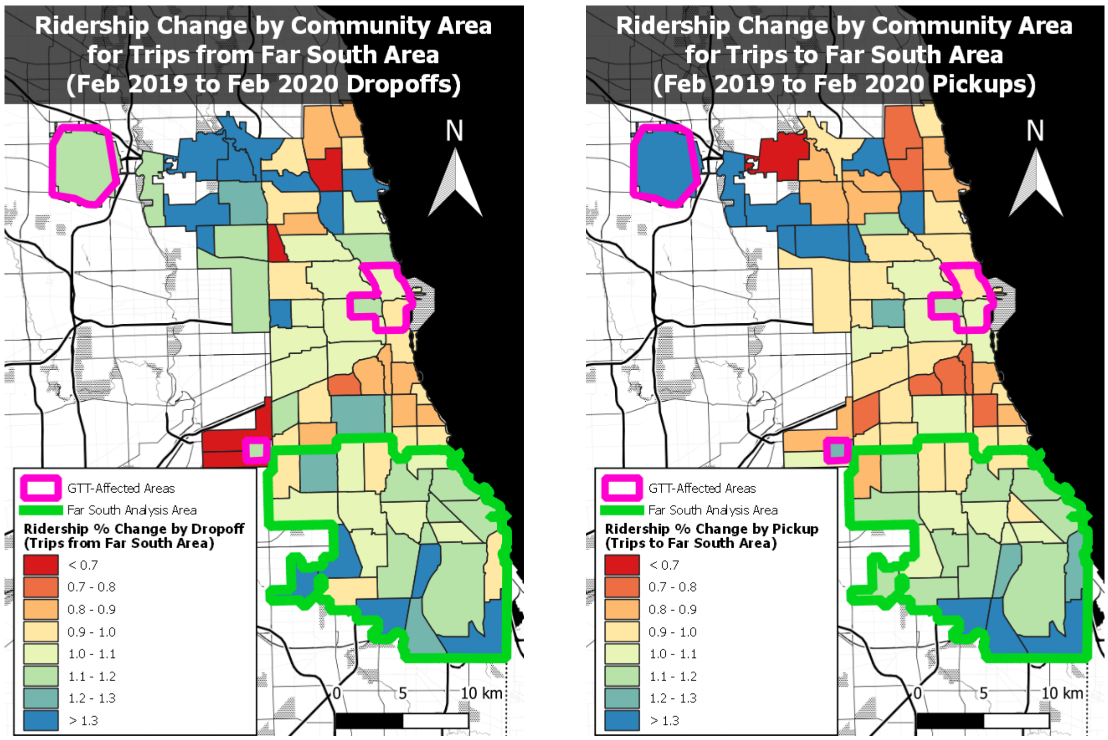


Figure C-6: Spatial distribution of ridership change for trips originating (left) and terminating (right) in the Far South analysis area (from February 2019 to February 2020)

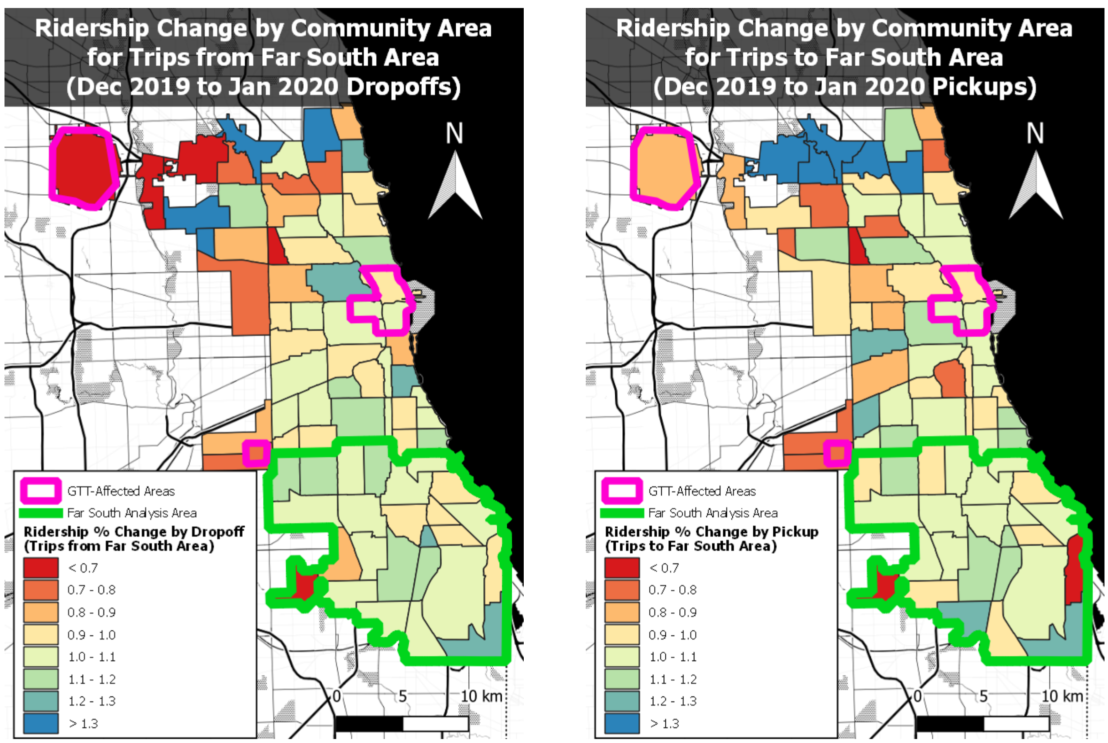


Figure C-7: Spatial distribution of ridership change for trips originating (left) and terminating (right) in the Far South analysis area (from December 2019 to January 2020)

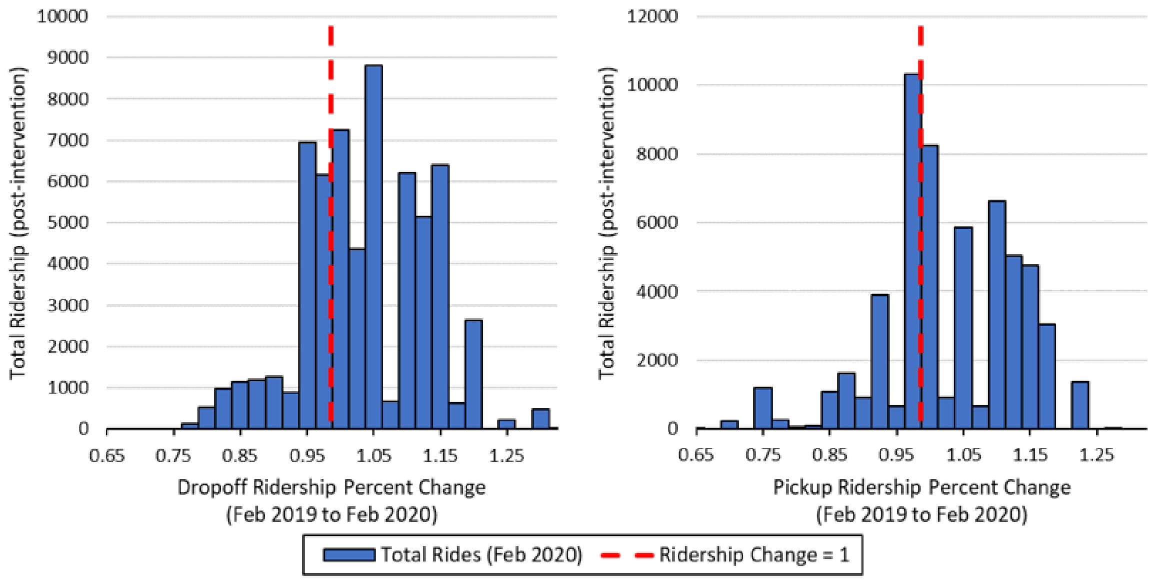


Figure C-8: Distribution of ridership change for trips originating (left) and terminating (right) in the Far South analysis area (from February 2019 to February 2020)

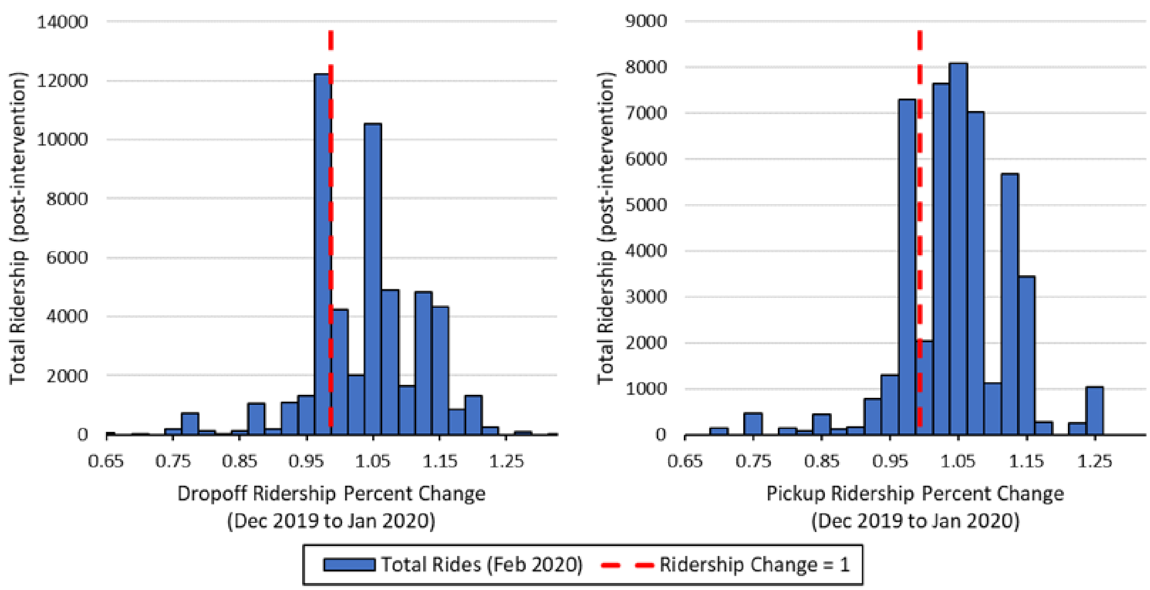


Figure C-9: Distribution of ridership change for trips originating (left) and terminating (right) in the Far South analysis area (from December 2019 to January 2020)

Appendix D

Additional COVID-19 Case Study Results

This appendix provides additional results for analysis conducted in the COVID-19 case study, as referenced in Chapter 6.

D.1 Additional Results for Regression Analysis

Table D.1: Results of Moran's I tests for spatial distribution of ridership change

Mode	**Period**	**Moran's I**	**Variance**
TNC	2	0.0980	0.000632
TNC	3	0.2738	0.000636
TNC	4	0.1162	0.000636
TNC	5	0.1765	0.000649
PT	2	0.6708	0.000637
PT	3	0.3619	0.000632
PT	4	0.3685	0.000636
PT	5	0.3276	0.000648

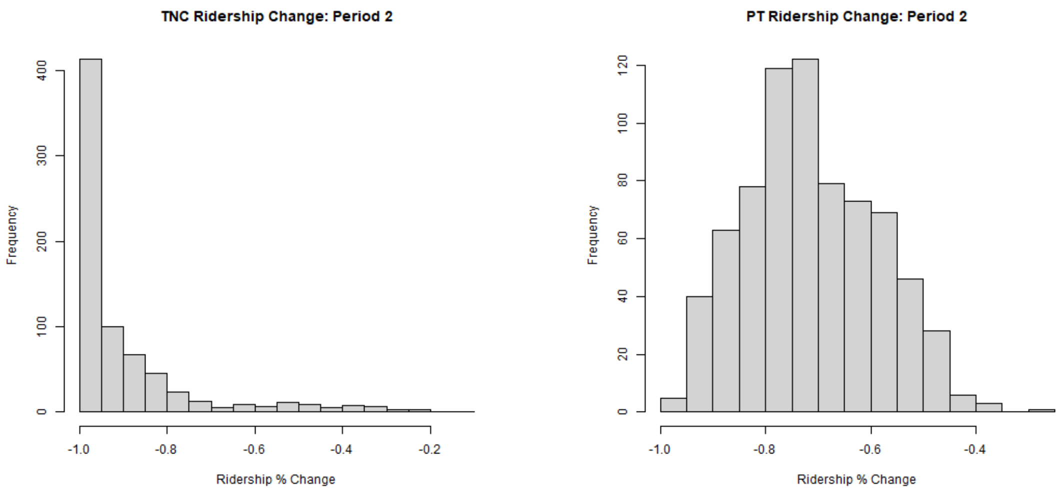


Figure D-1: Ridership change distributions for Period 2 relative to baseline

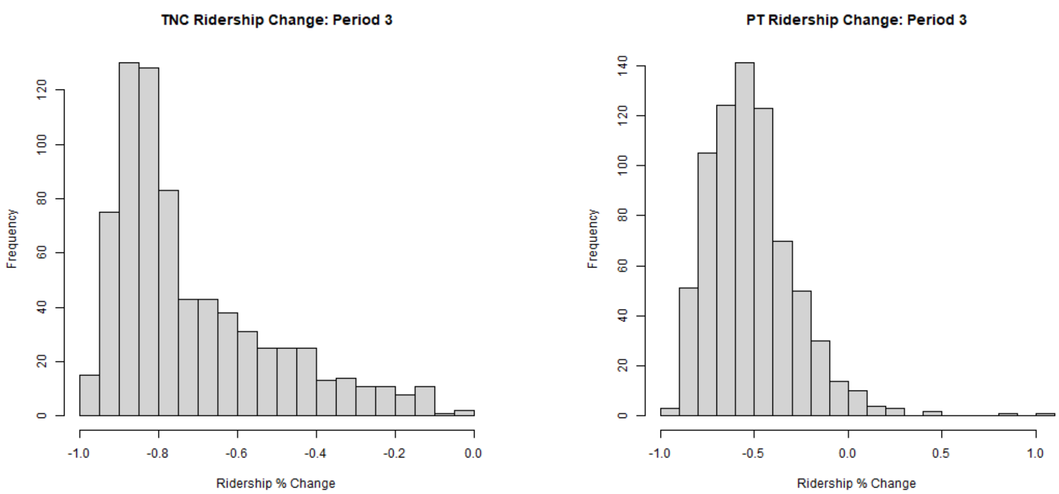


Figure D-2: Ridership change distributions for Period 3 relative to baseline

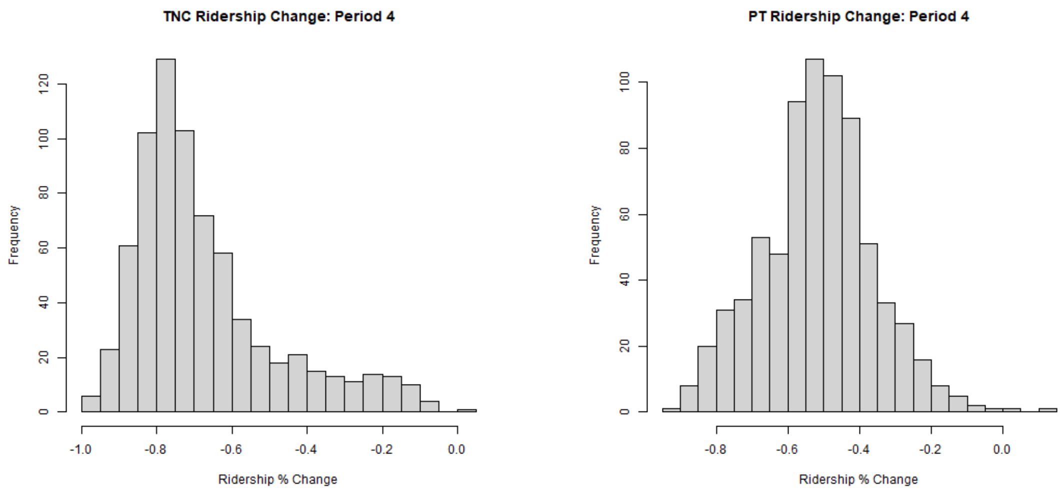


Figure D-3: Ridership change distributions for Period 4 relative to baseline

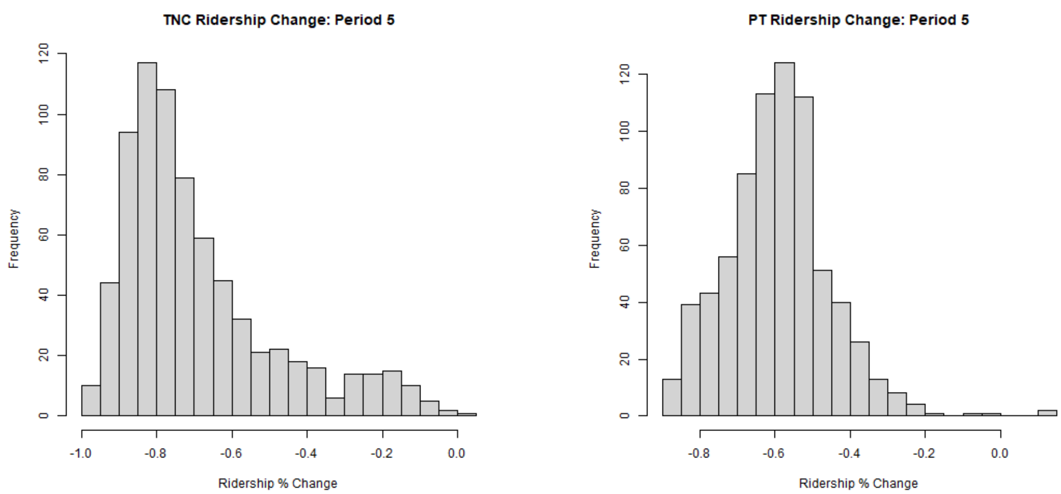


Figure D-4: Ridership change distributions for Period 5 relative to baseline

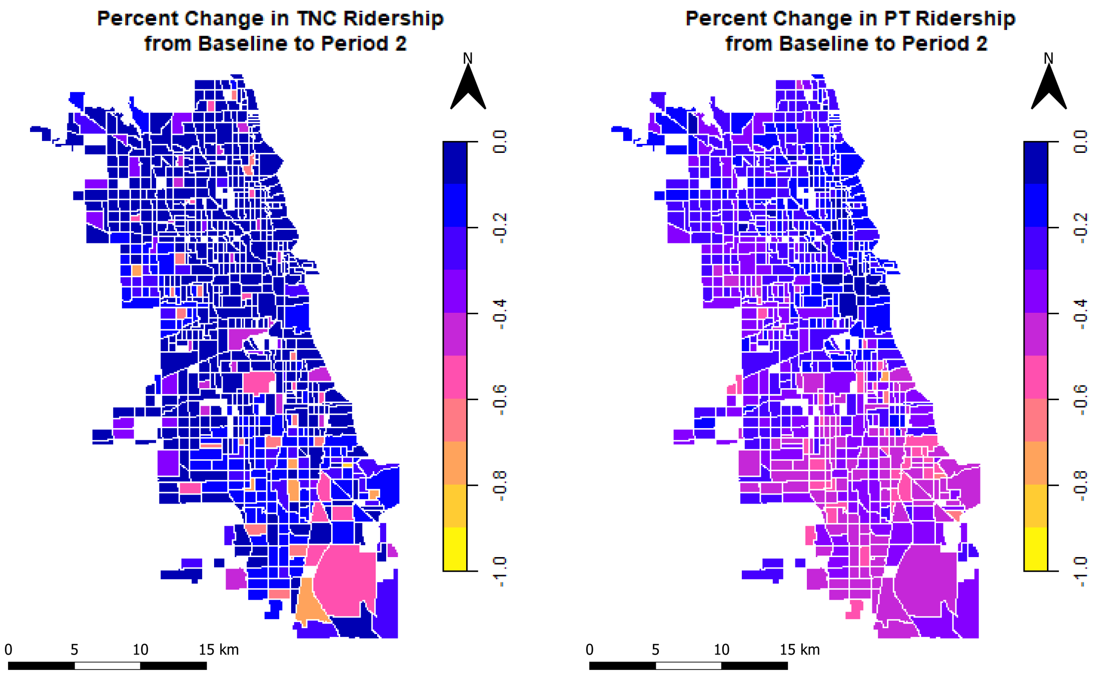


Figure D-5: Spatial distributions of ridership change for Period 2 relative to baseline

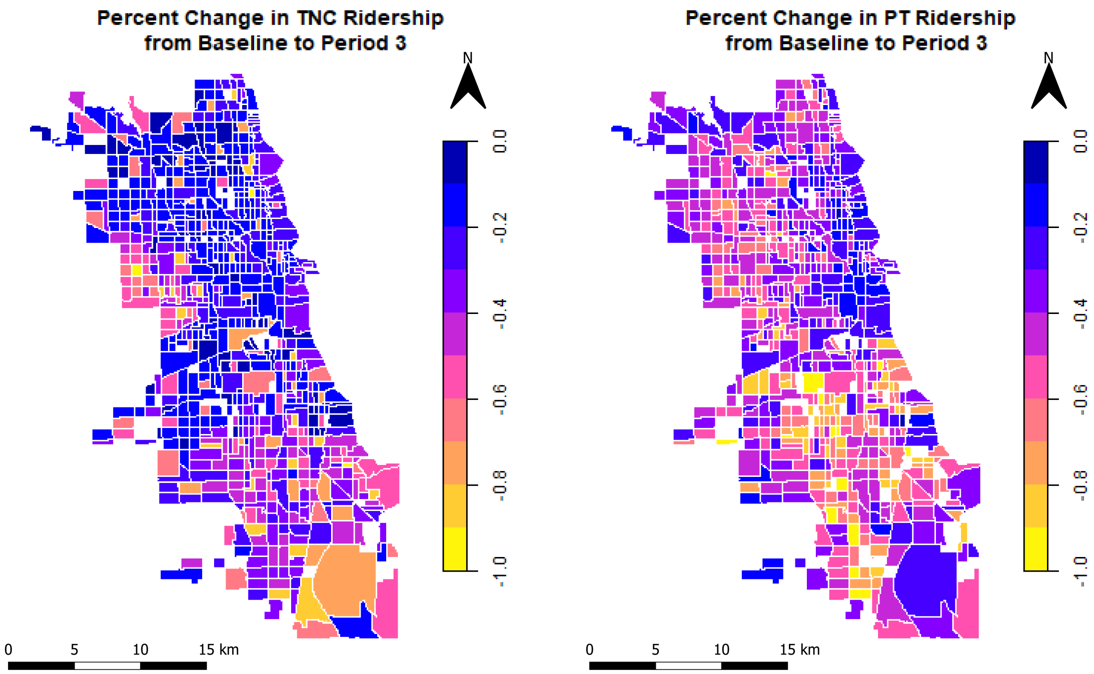


Figure D-6: Spatial distributions of ridership change for Period 3 relative to baseline

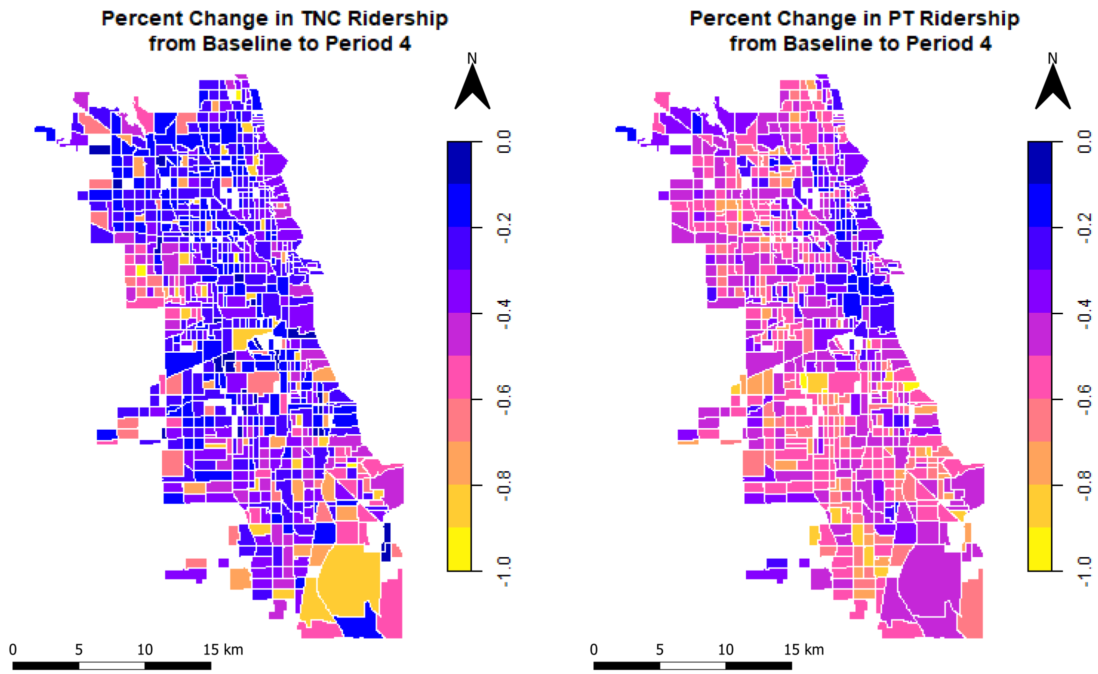


Figure D-7: Spatial distributions of ridership change for Period 4 relative to baseline

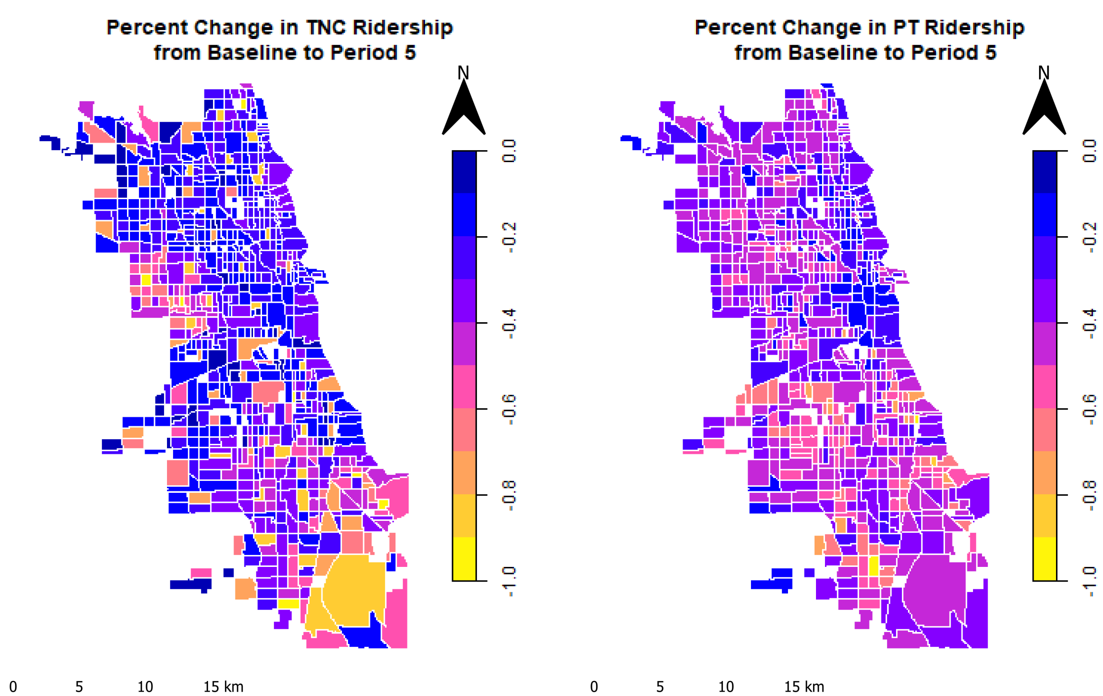


Figure D-8: Spatial distributions of ridership change for Period 5 relative to baseline

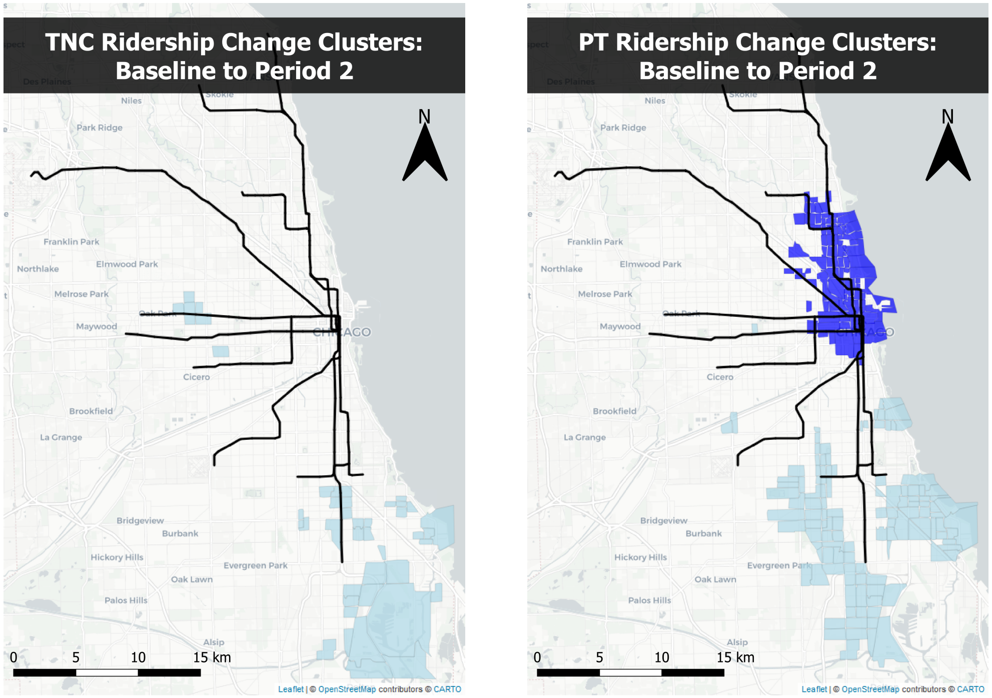


Figure D-9: Clusters of high (dark color) and low (light color) ridership change for Period 2 relative to baseline

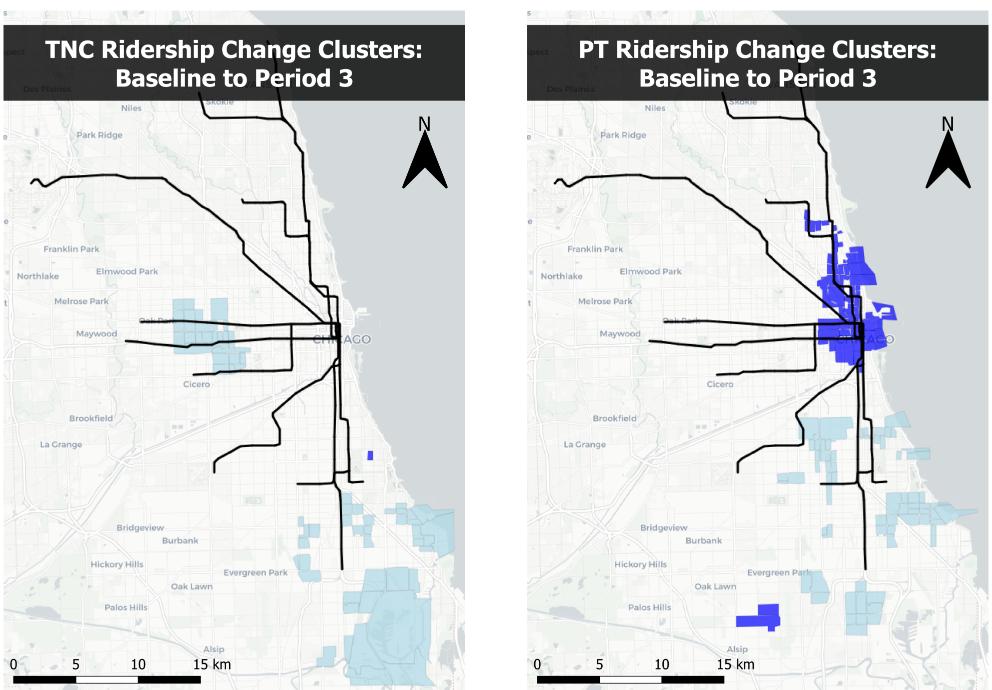


Figure D-10: Clusters of high (dark color) and low (light color) ridership change for Period 3 relative to baseline

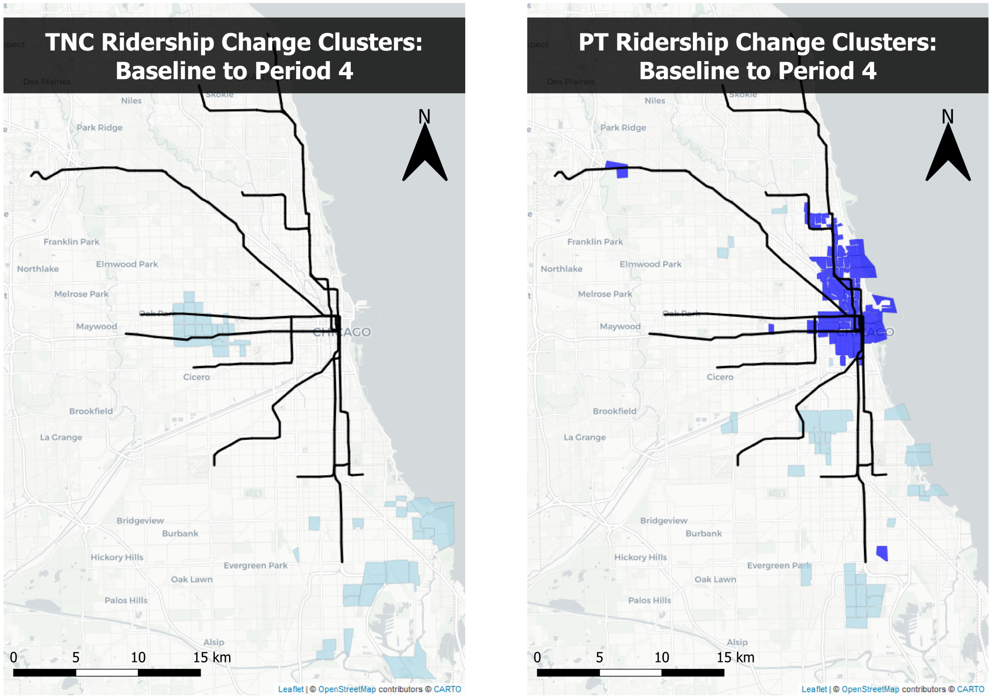


Figure D-11: Clusters of high (dark color) and low (light color) ridership change for Period 4 relative to baseline

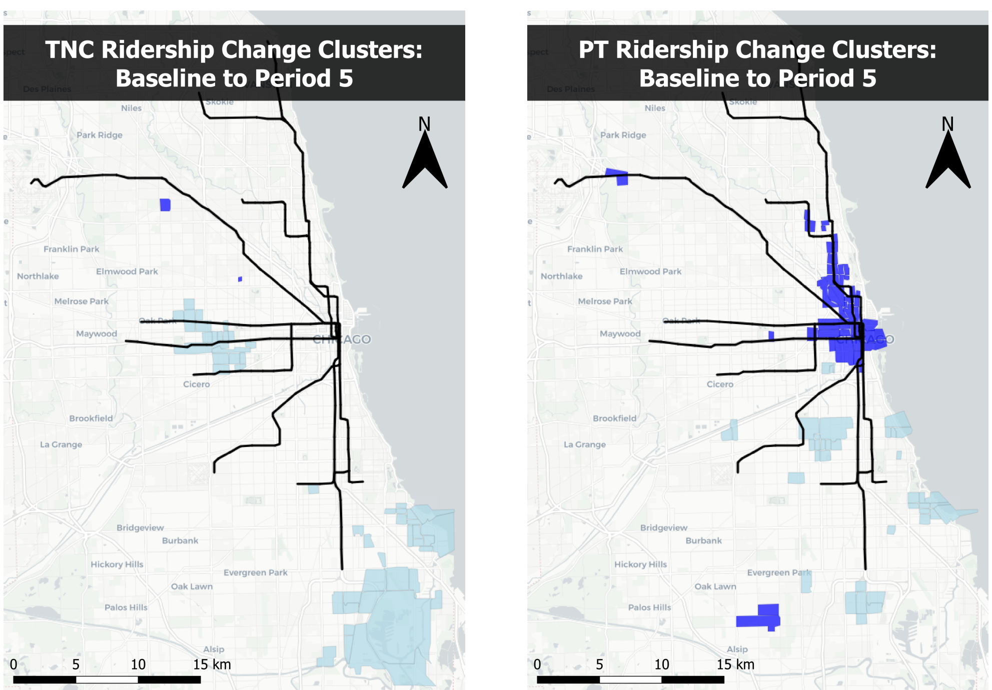
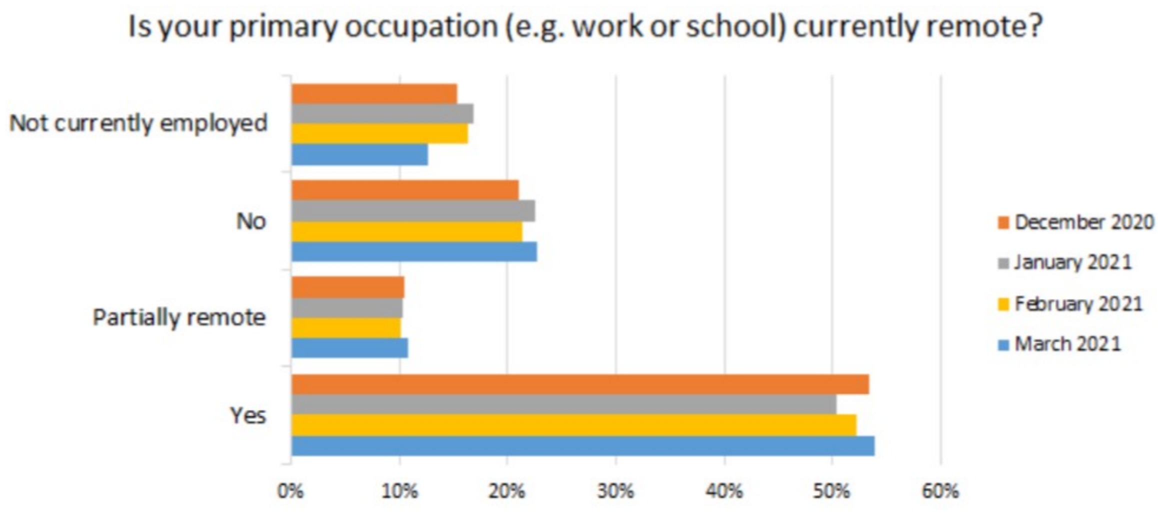


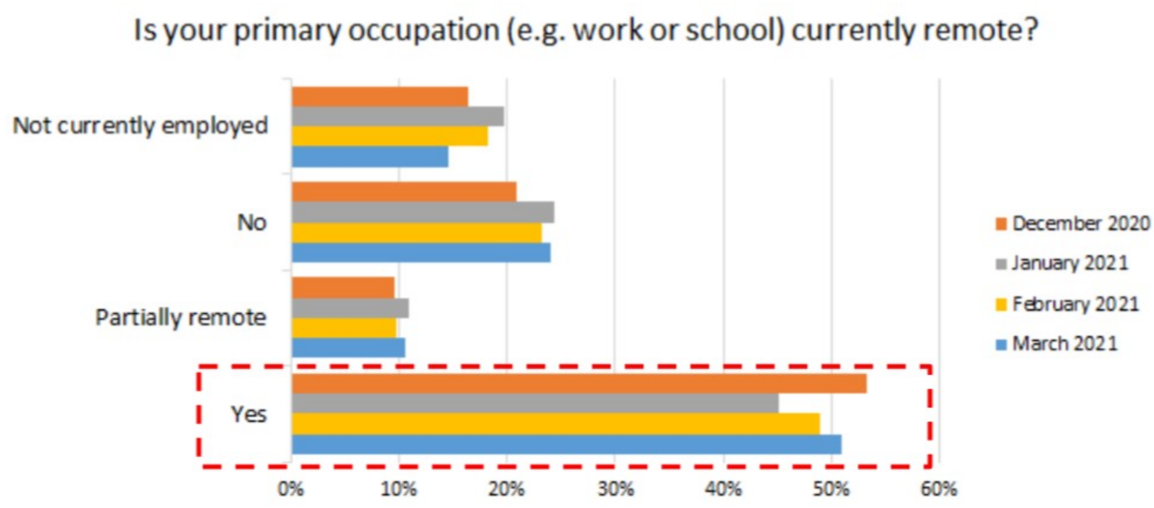
Figure D-12: Clusters of high (dark color) and low (light color) ridership change for Period 5 relative to baseline

D.2 Comparison of Weighted and Unweighted Survey Results

Survey response weighting was conducted according to the process detailed in Chapter 6. The process of weighting did not significantly change the distribution of responses, or resultant conclusions, for any survey question. Weighted and unweighted versions of one survey question most significantly impacted by weighting are provided in Figure D-13.



(a) Unweighted survey result



(b) Weighted survey result

Figure D-13: Sample comparison of weighted and unweighted survey responses

Appendix E

Additional TNC-PT Case Study Results

This appendix provides additional results for analysis conducted in the TNC-PT Relationship case study, as referenced in Chapter 7.

E.1 TNC Trip Sample and population comparison for selected analysis dates

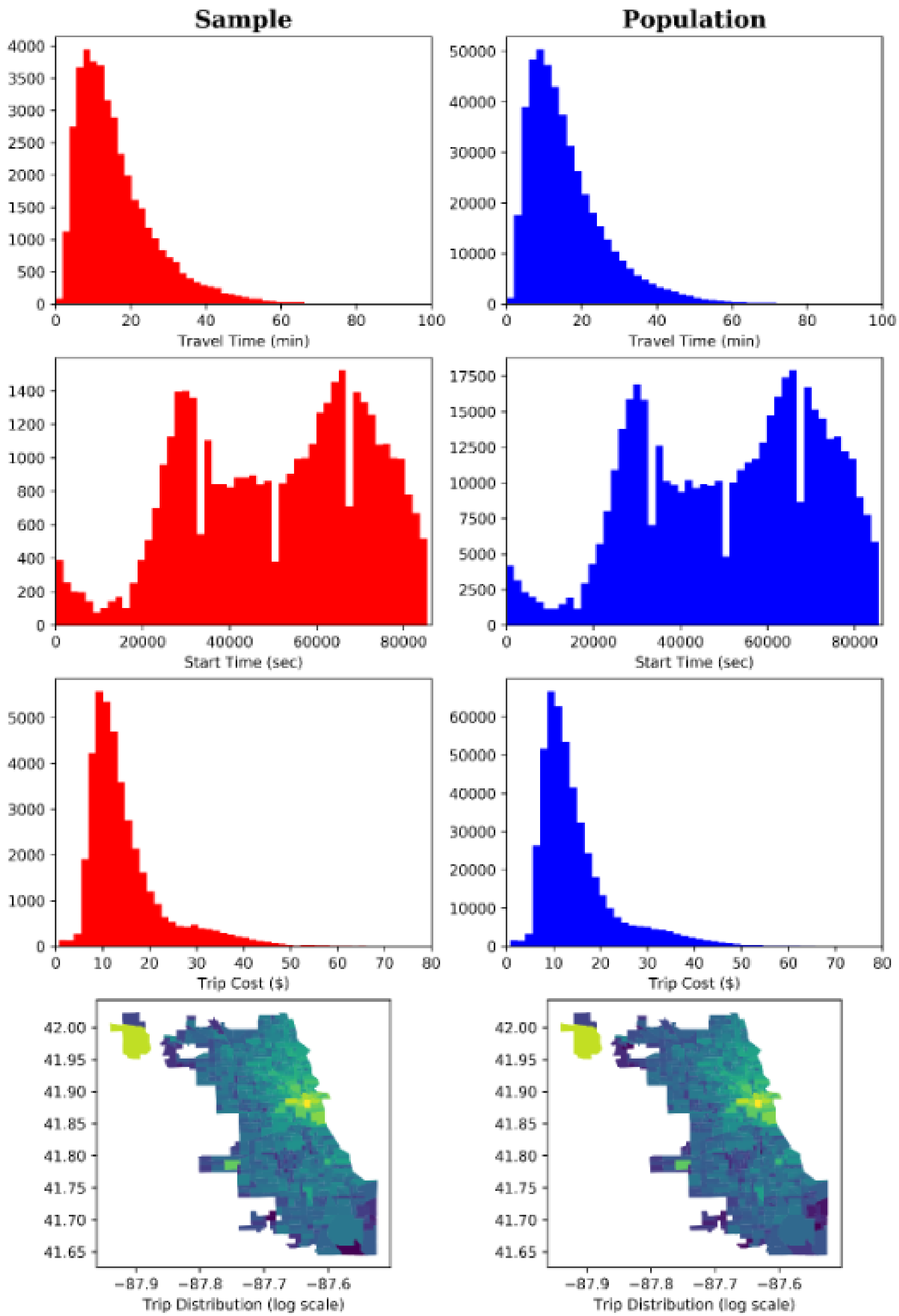


Figure E-1: Sample and population comparison for October 8, 2019

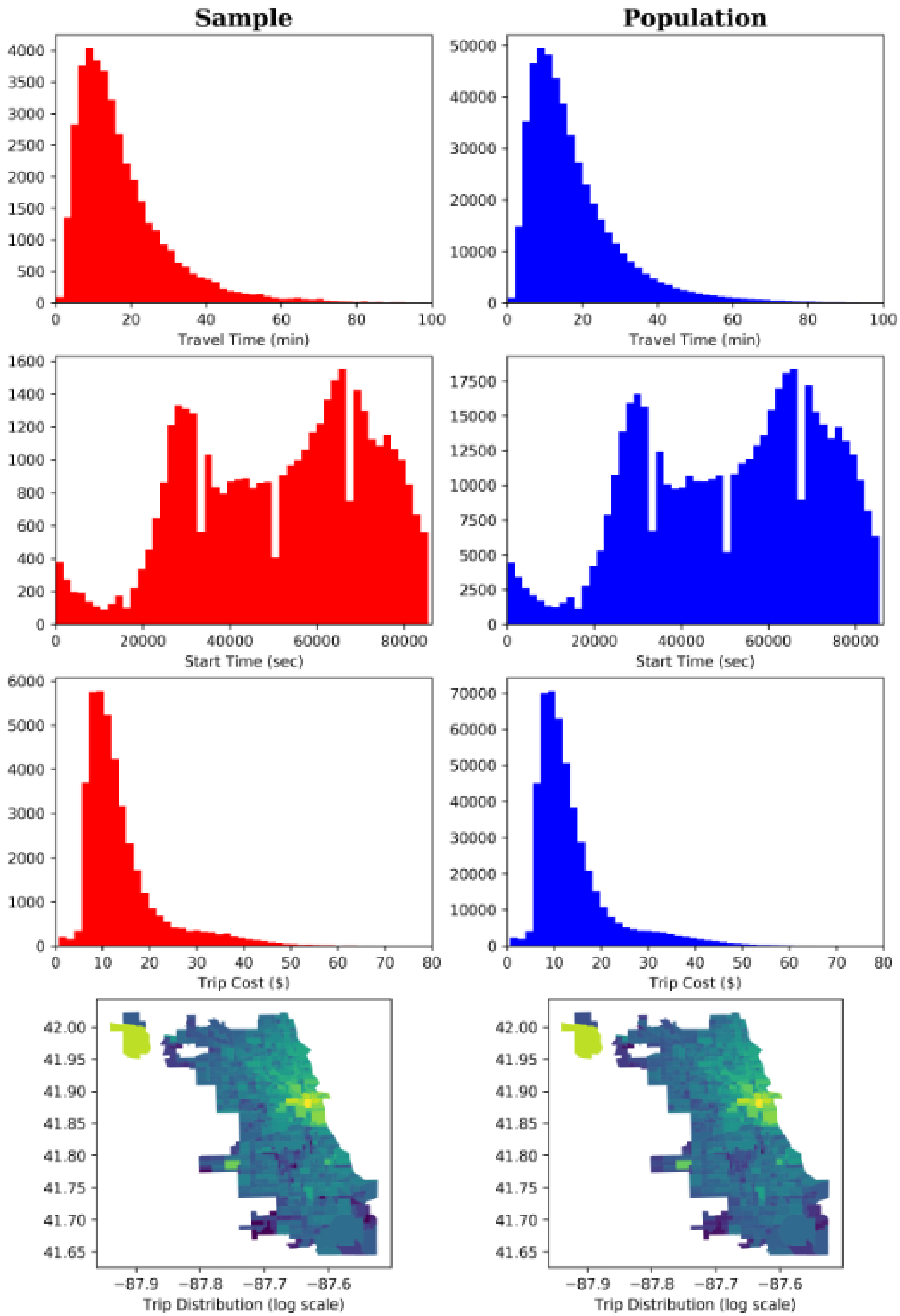


Figure E-2: Sample and population comparison for November 19, 2019

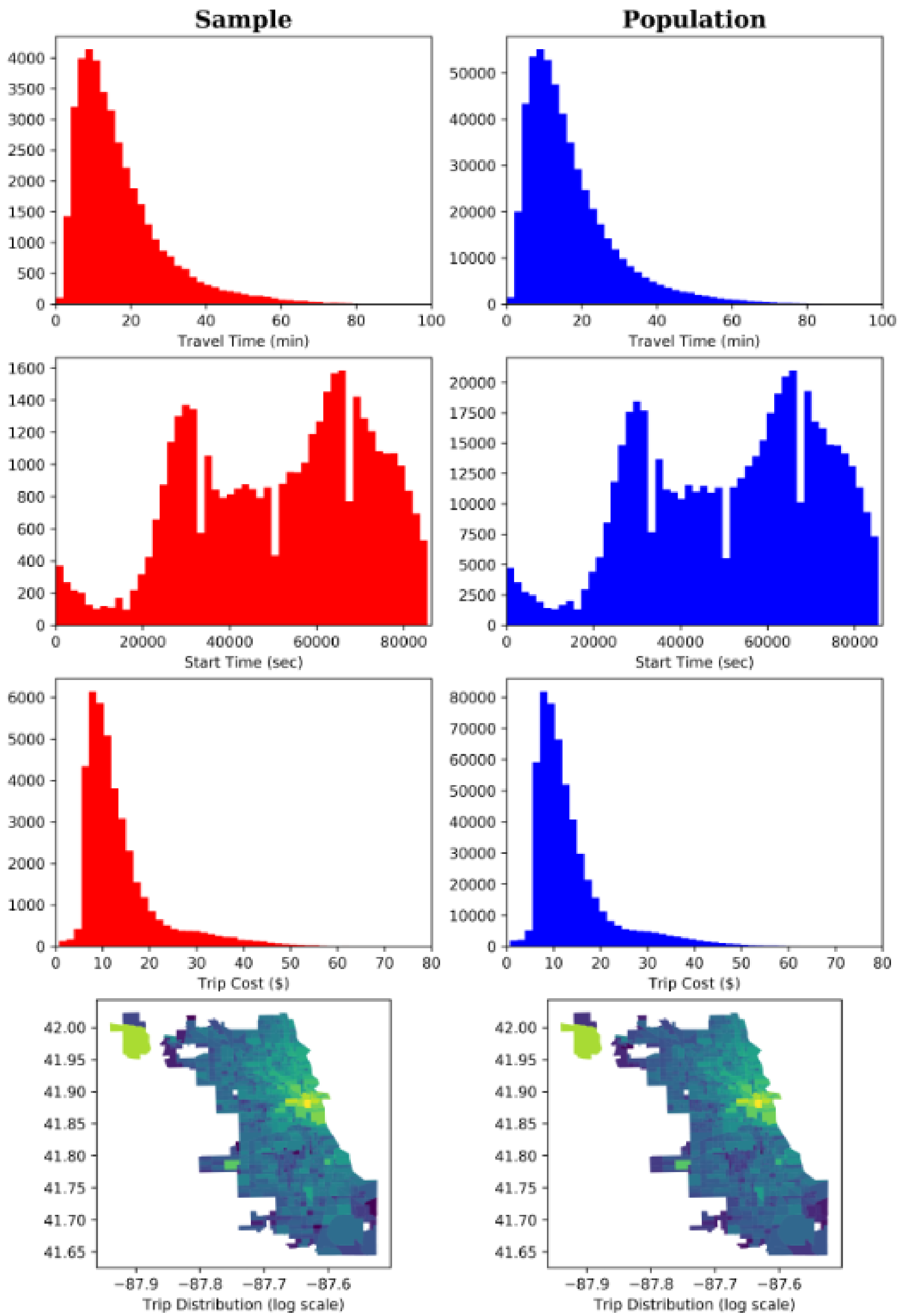


Figure E-3: Sample and population comparison for December 10, 2020

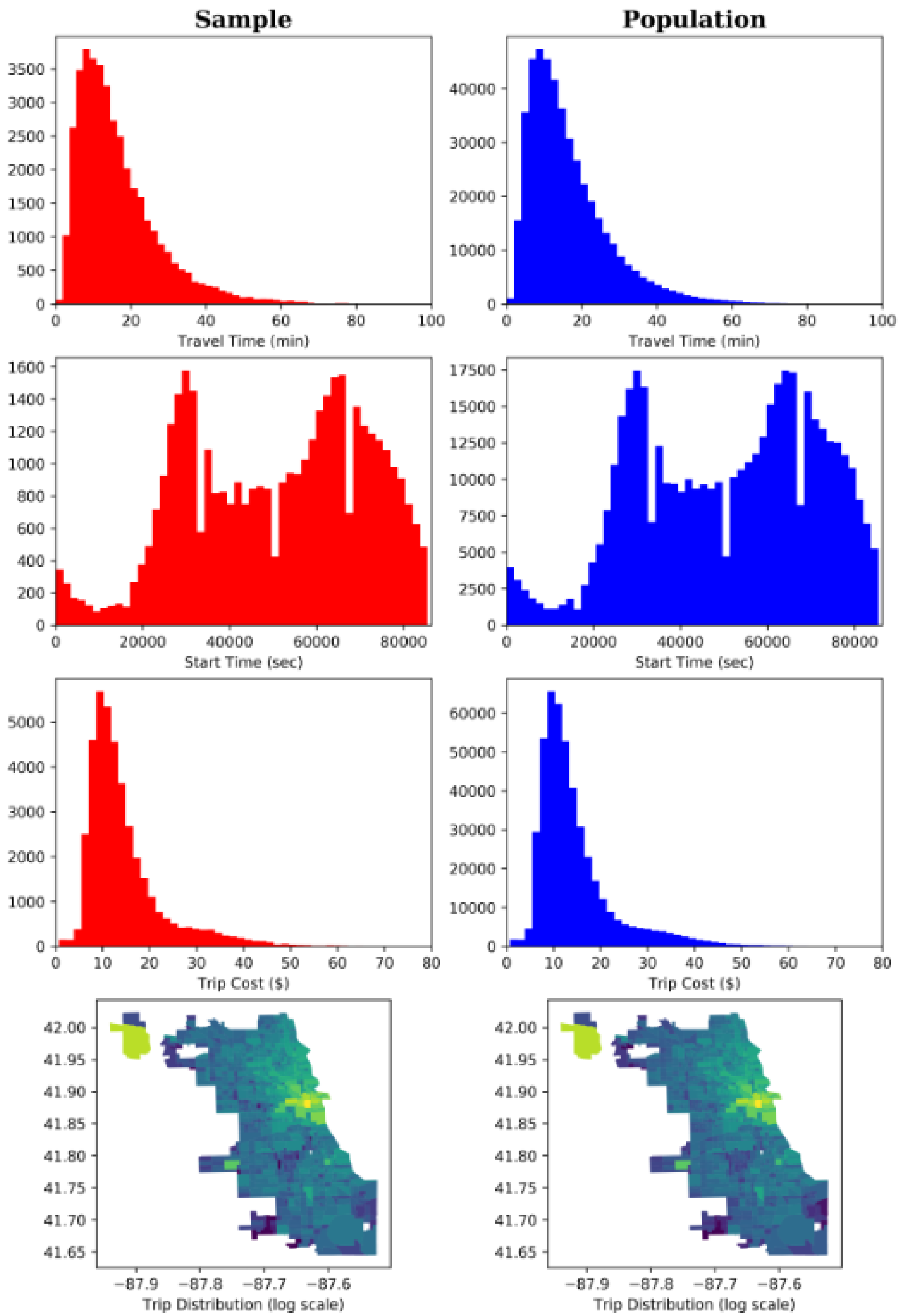


Figure E-4: Sample and population comparison for January 21, 2020

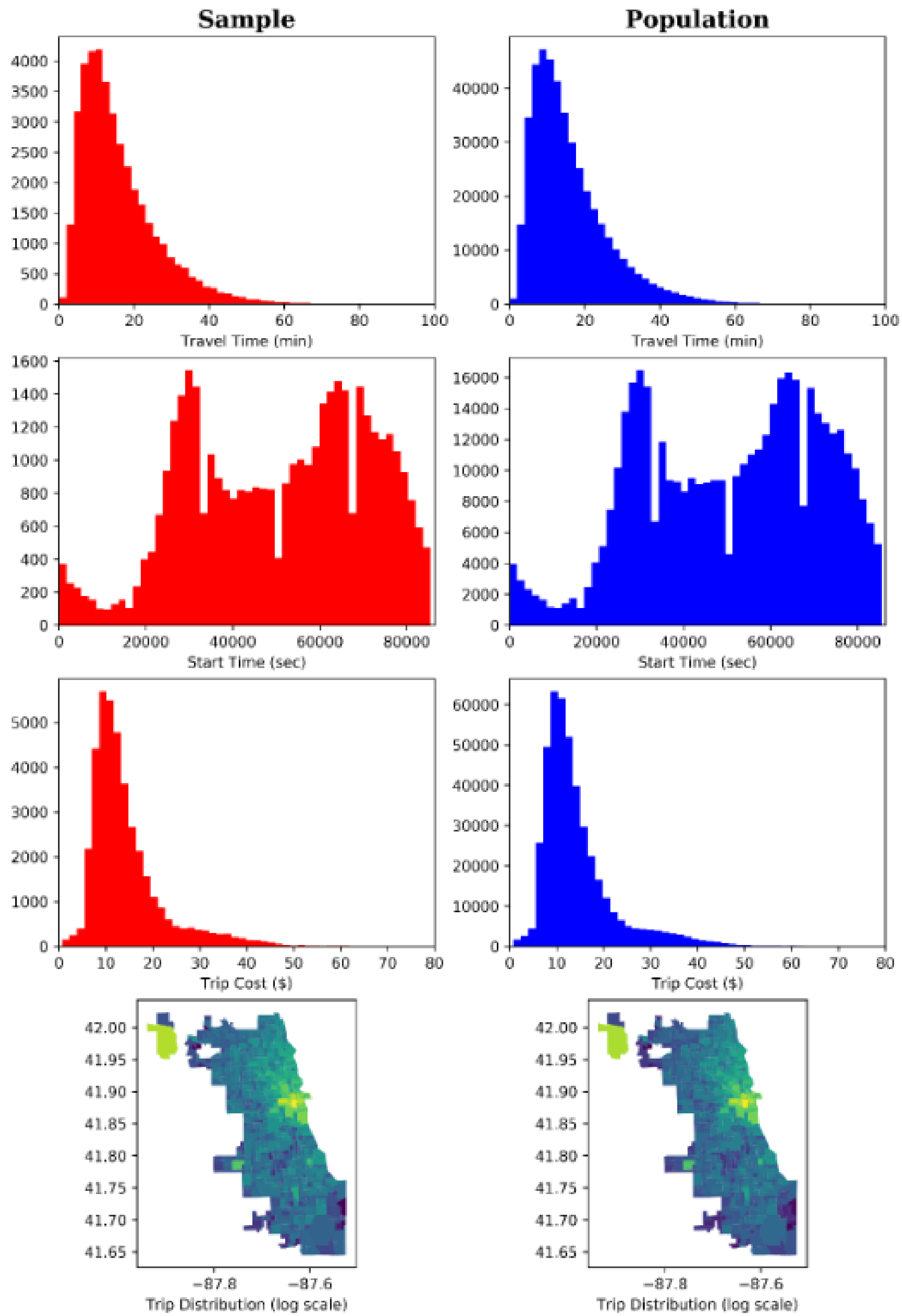


Figure E-5: Sample and population comparison for January 28, 2020

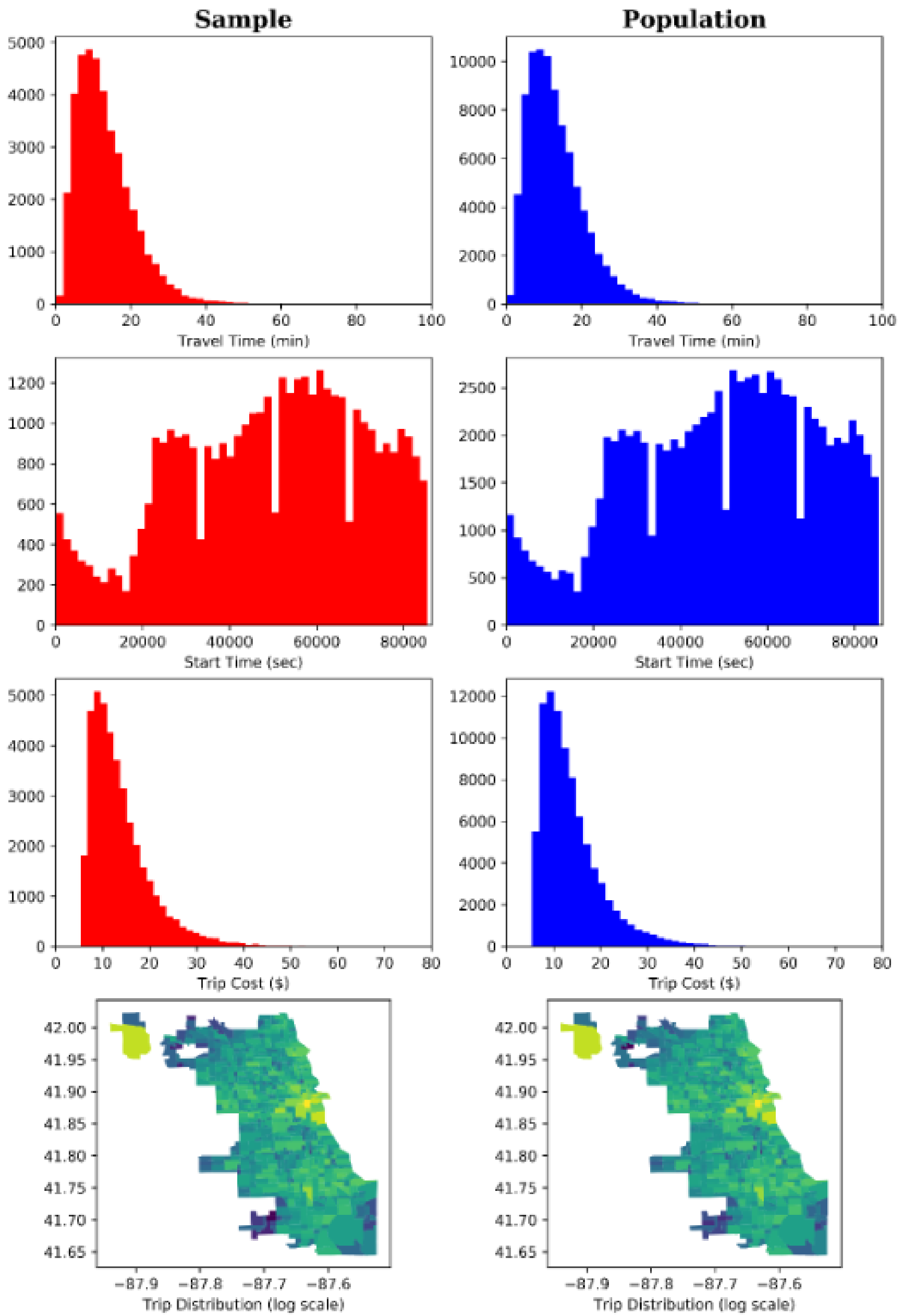


Figure E-6: Sample and population comparison for March 24, 2020

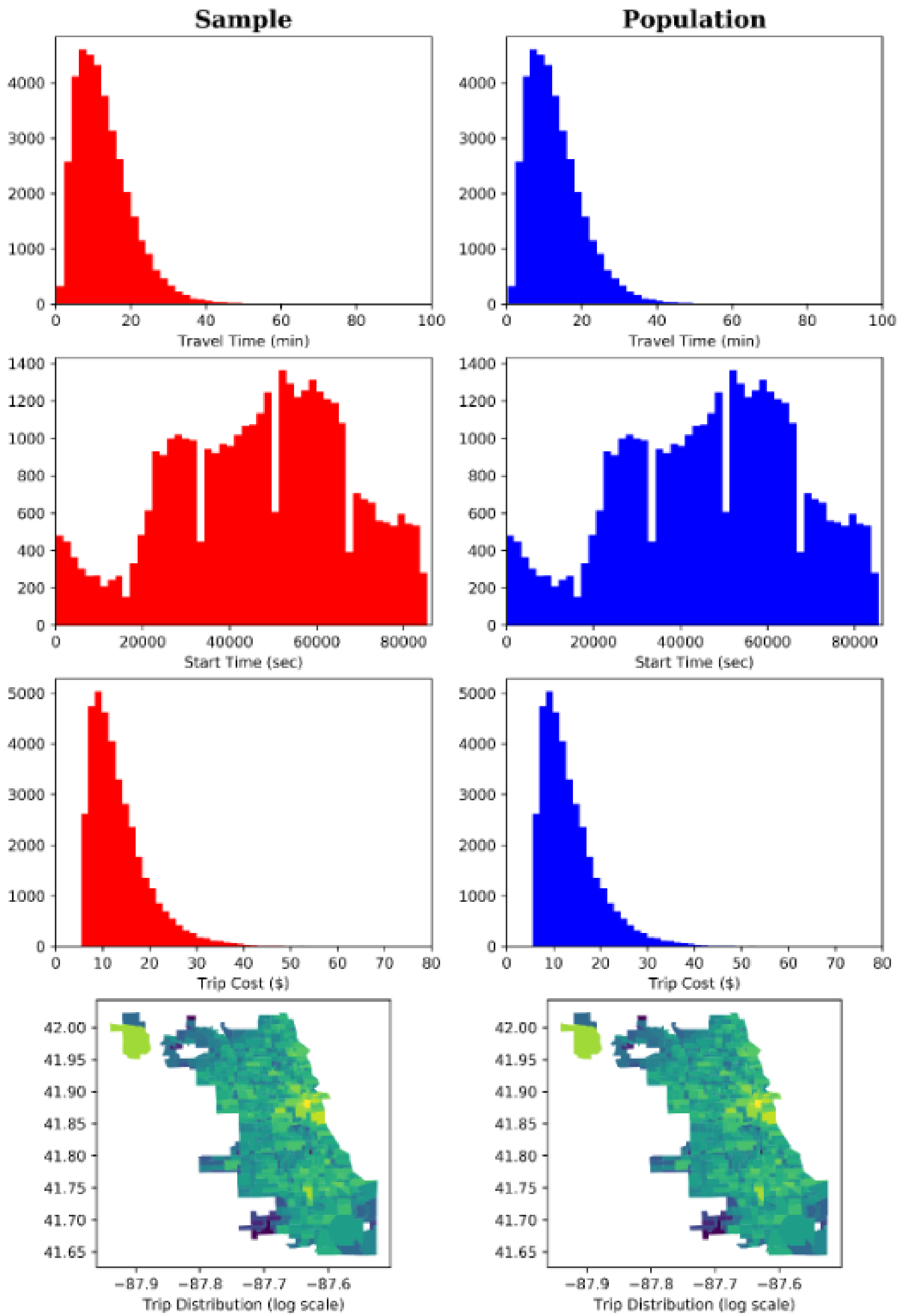


Figure E-7: Sample and population comparison for March 31, 2020

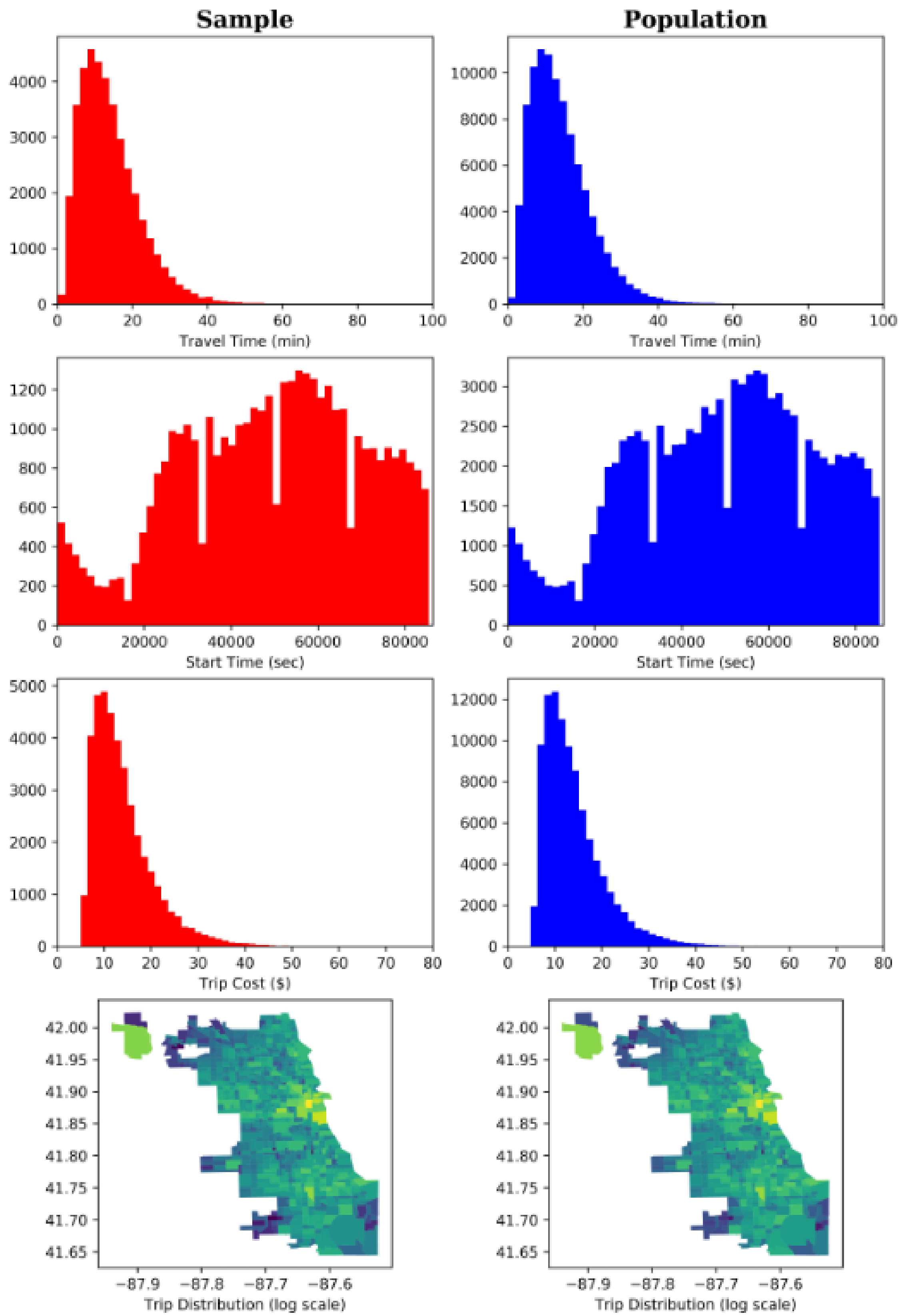


Figure E-8: Sample and population comparison for May 12, 2020

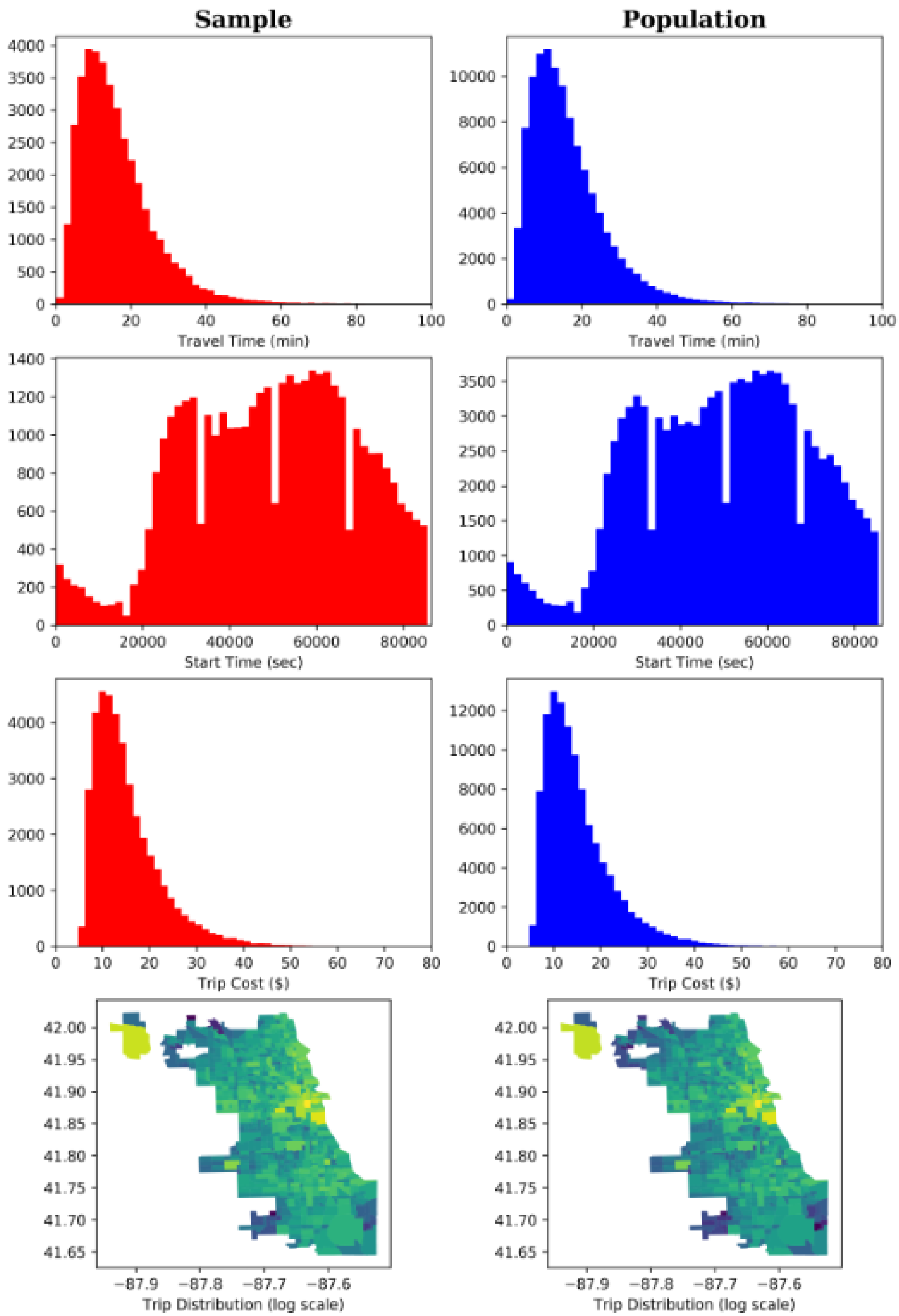


Figure E-9: Sample and population comparison for June 2, 2020

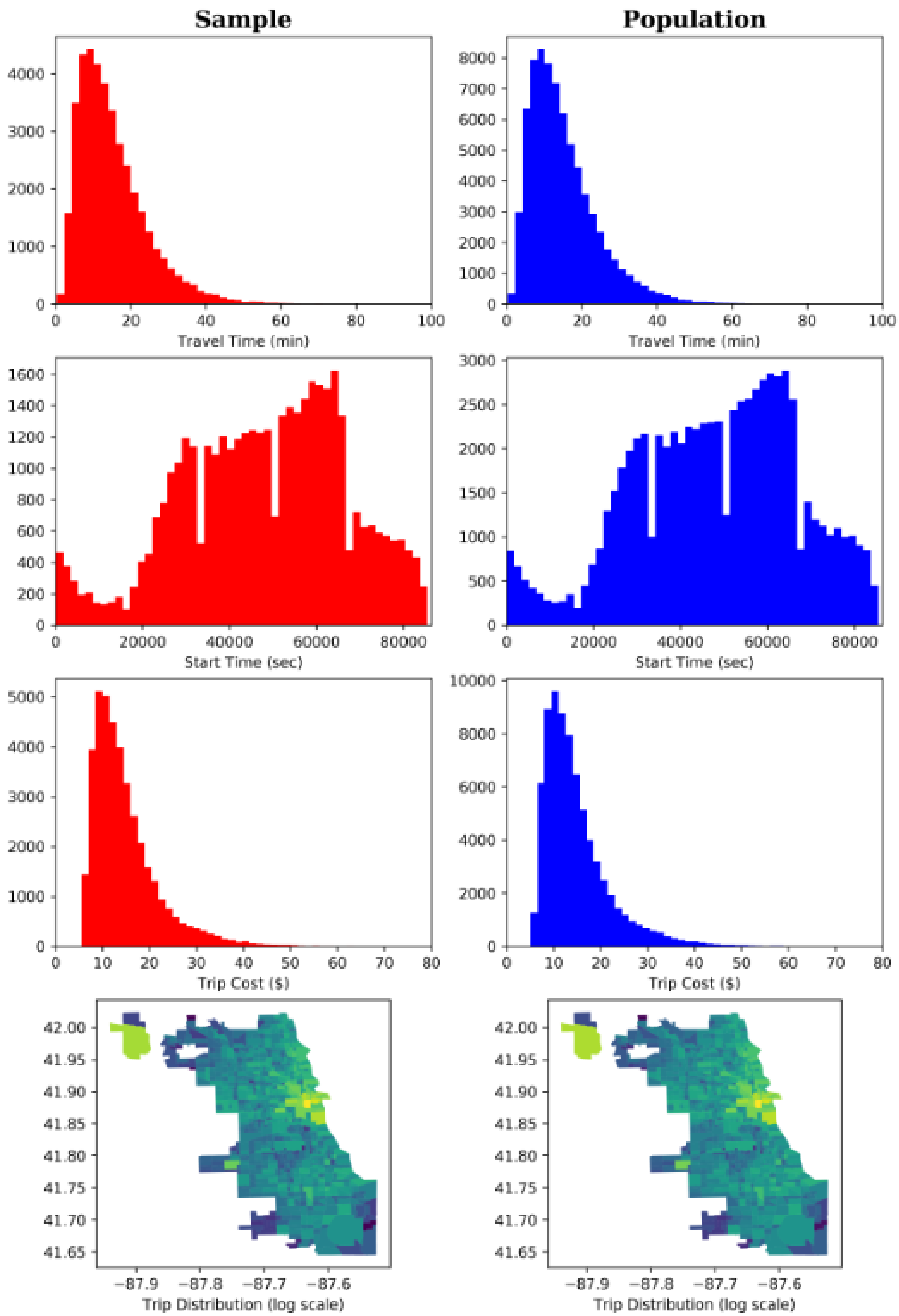


Figure E-10: Sample and population comparison for June 30, 2020

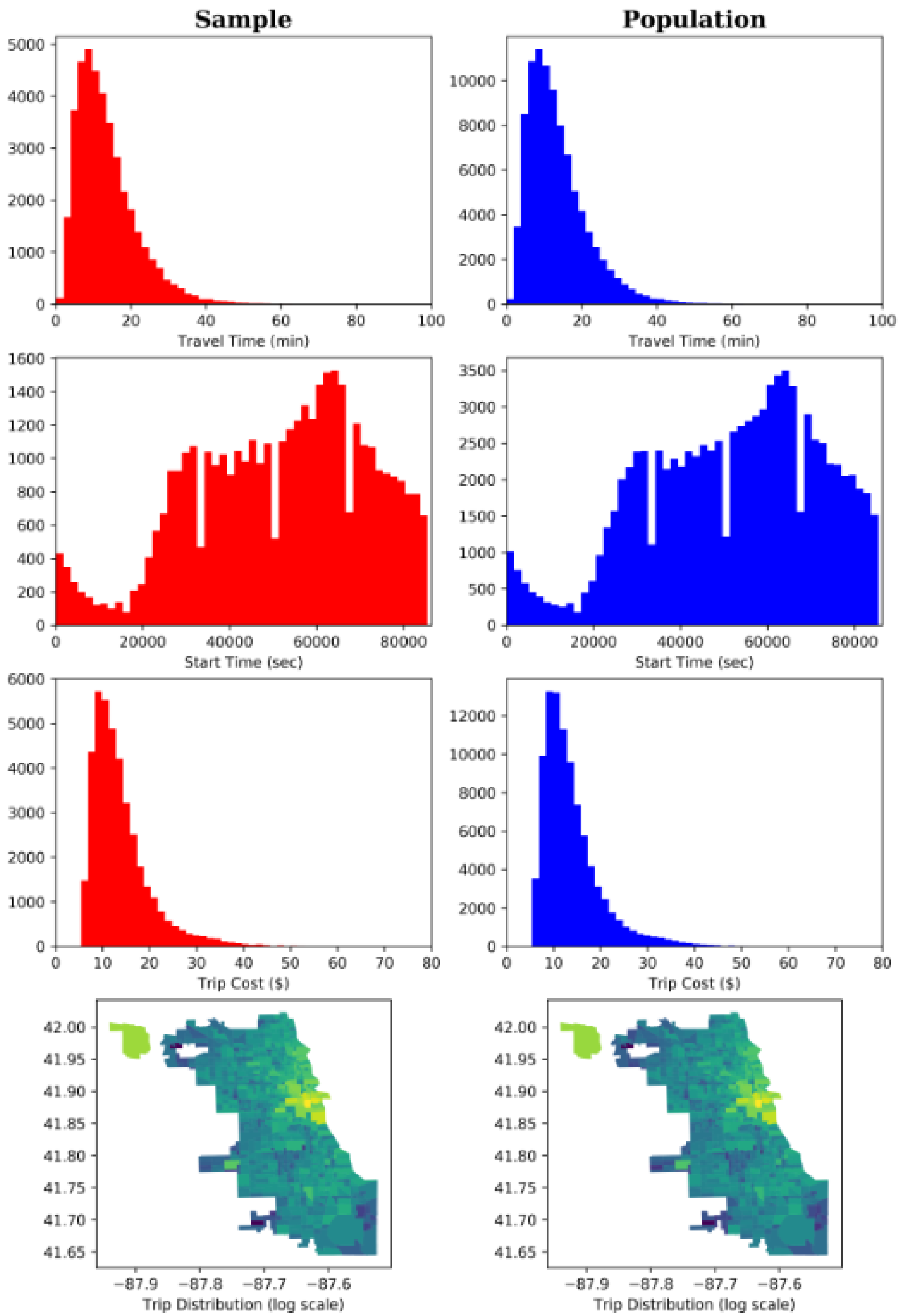


Figure E-11: Sample and population comparison for July 28, 2020

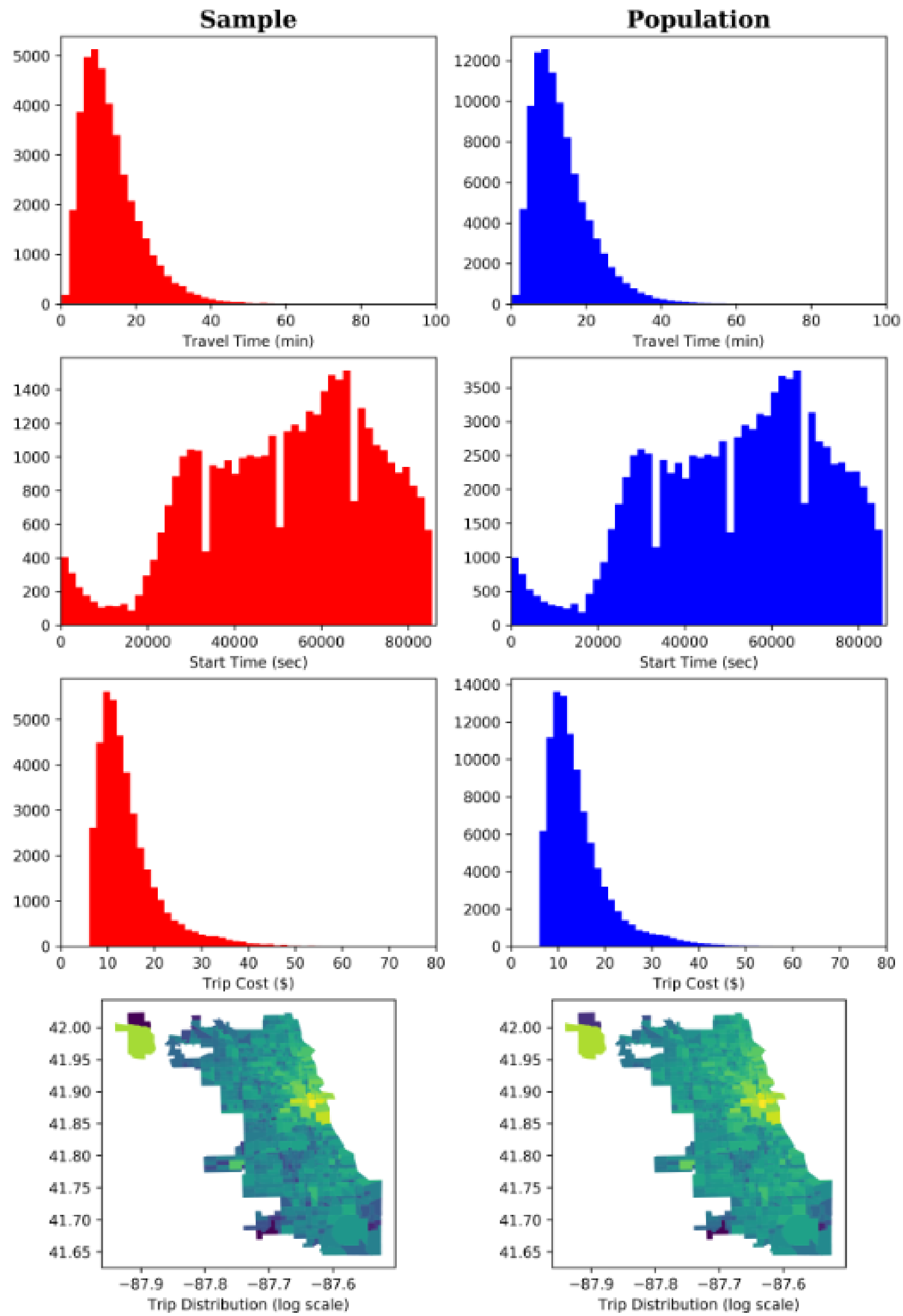


Figure E-12: Sample and population comparison for August 25, 2020

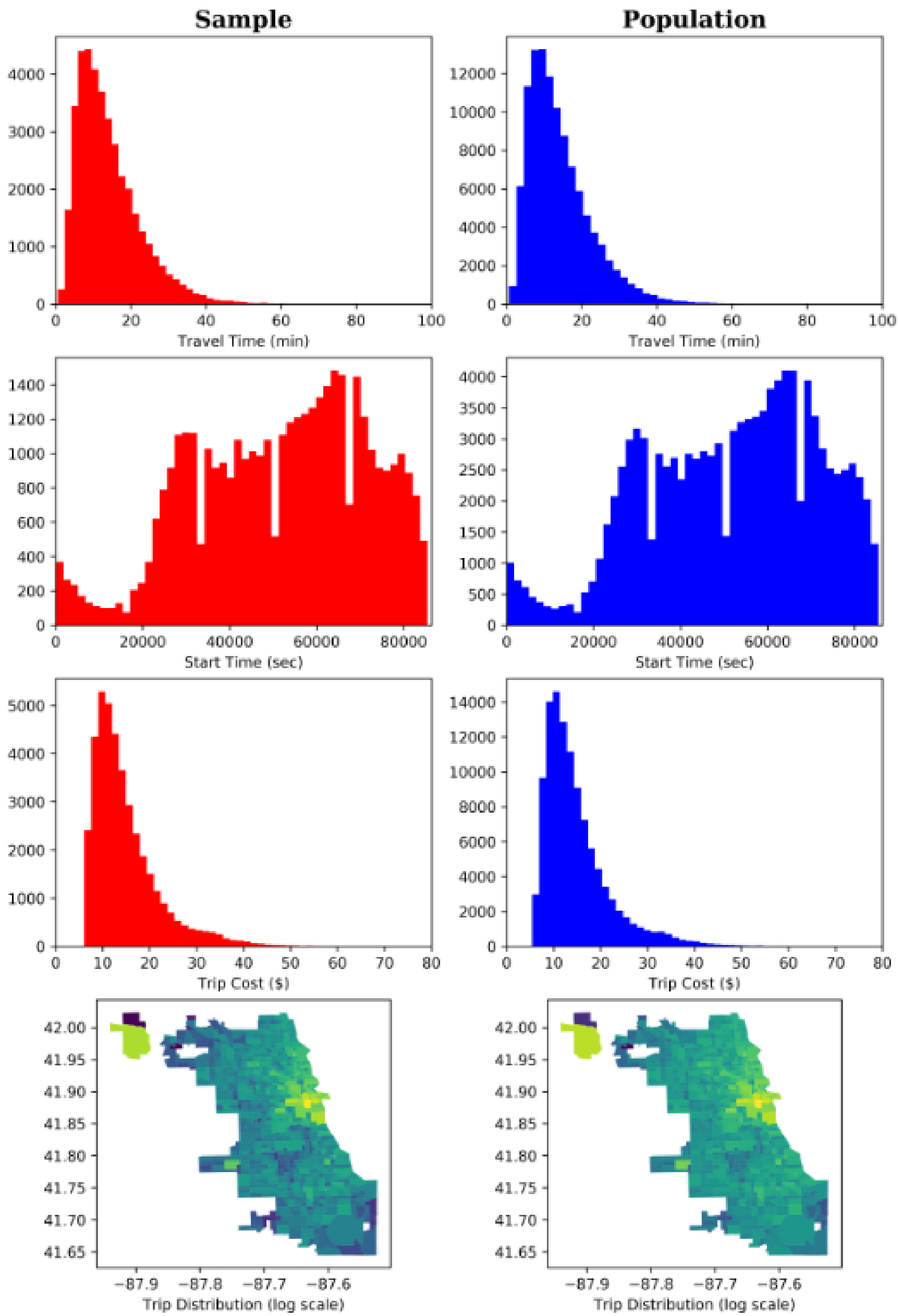


Figure E-13: Sample and population comparison for September 29, 2020

E.2 Additional Analysis Results

This section provides additional results of spatial and temporal analysis for all time periods considered, to expand upon the sample of images provided in Chapter 7. Temporal trip distributions are provided in Section E.2.1, spatial distributions of trip volumes are provided in Section E.2.2, and cluster analysis of the TNC-PT relationship is provided in Section E.2.3.

E.2.1 TNC Trip Temporal Distributions

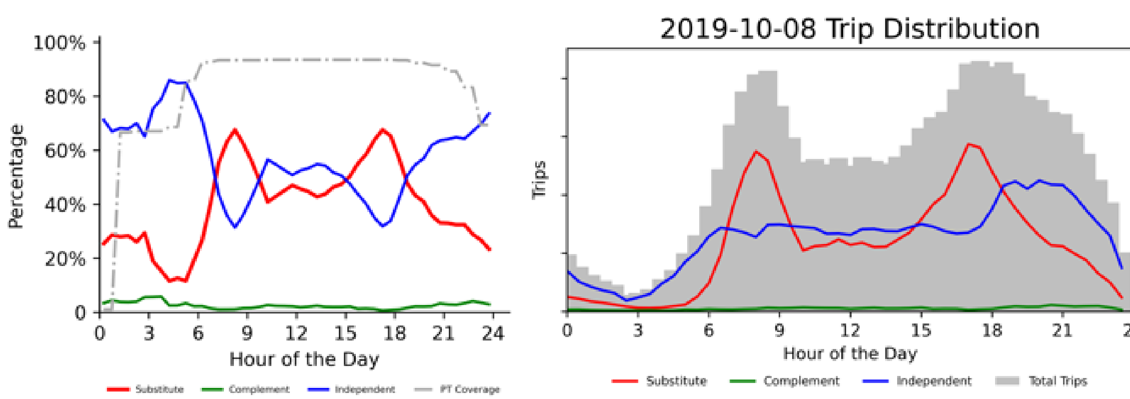


Figure E-14: Temporal trip volumes and rates for October 8, 2019

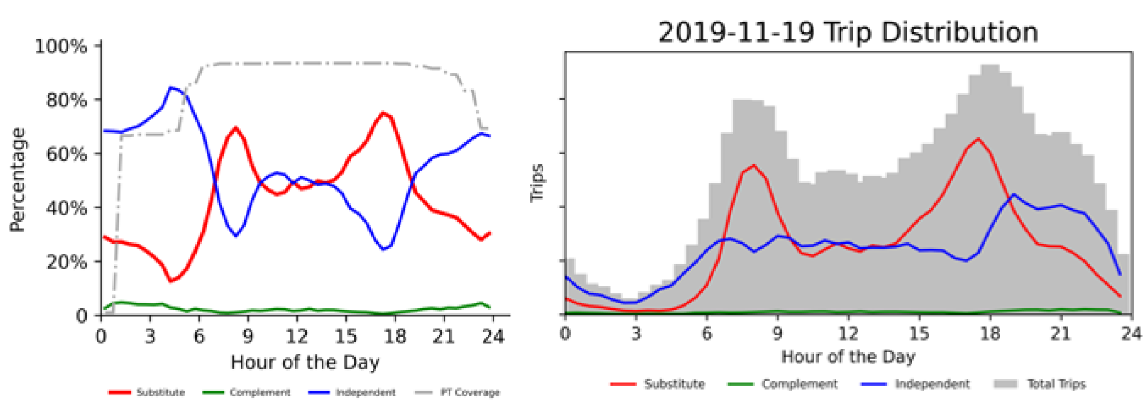


Figure E-15: Temporal trip volumes and rates for November 19, 2019

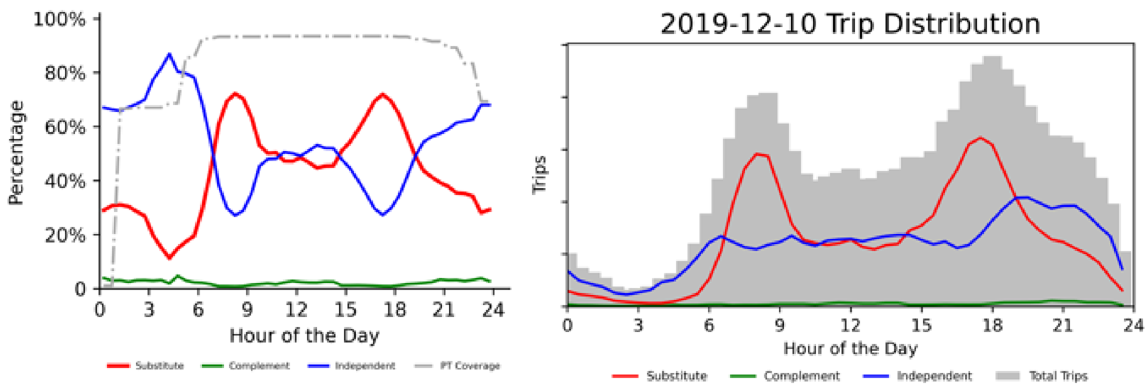


Figure E-16: Temporal trip volumes and rates for December 10, 2019

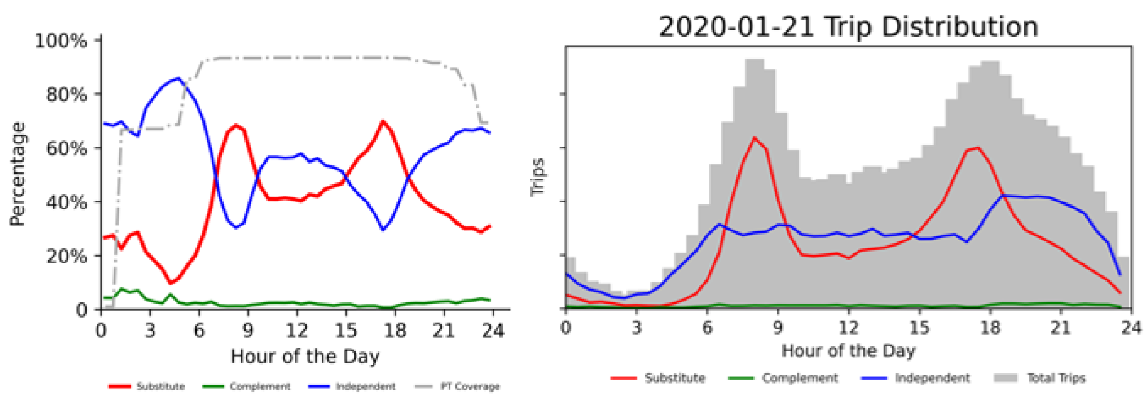


Figure E-17: Temporal trip volumes and rates for January 21, 2020

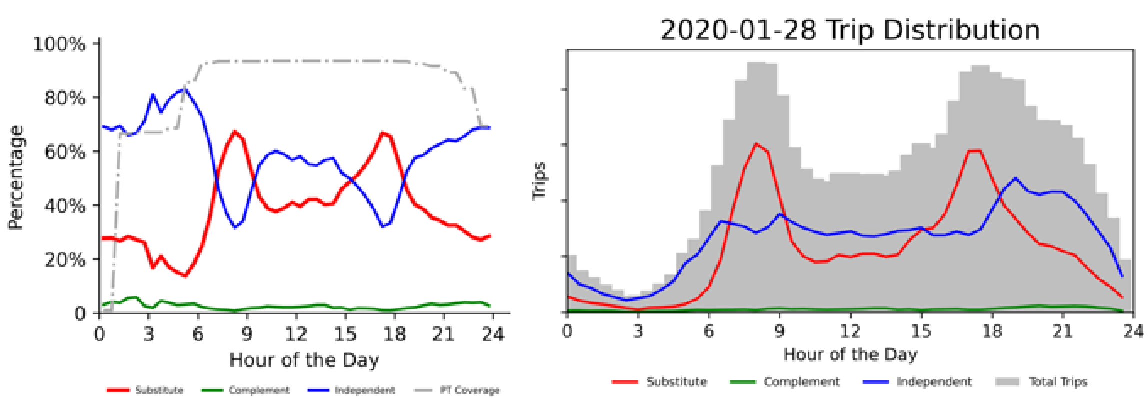


Figure E-18: Temporal trip volumes and rates for January 28, 2020

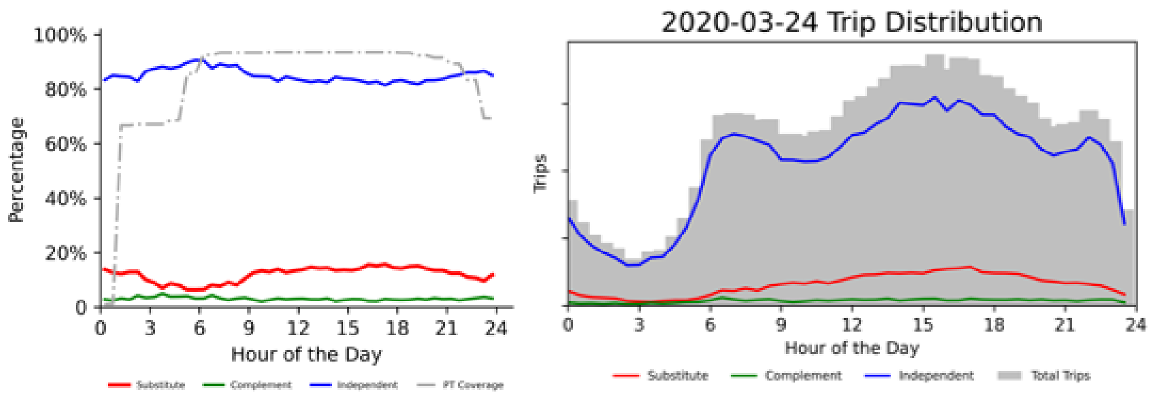


Figure E-19: Temporal trip volumes and rates for March 24, 2020

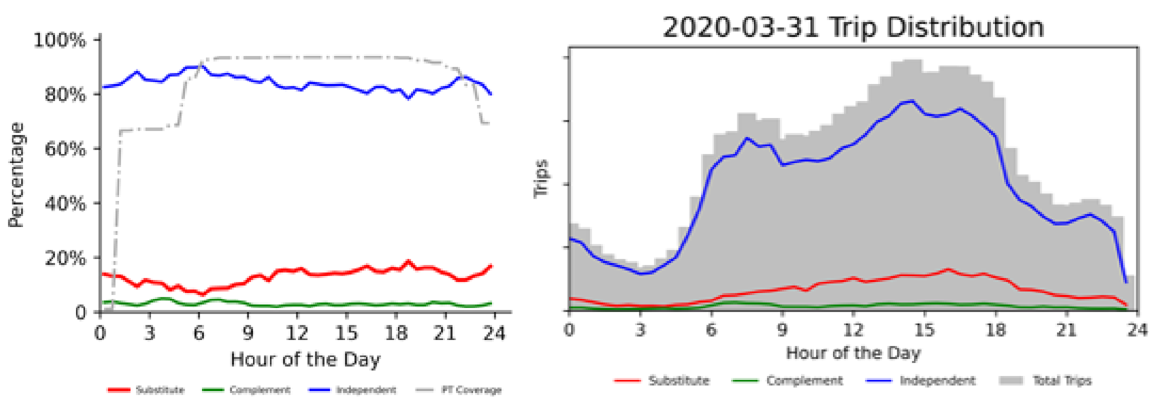


Figure E-20: Temporal trip volumes and rates for March 31, 2020

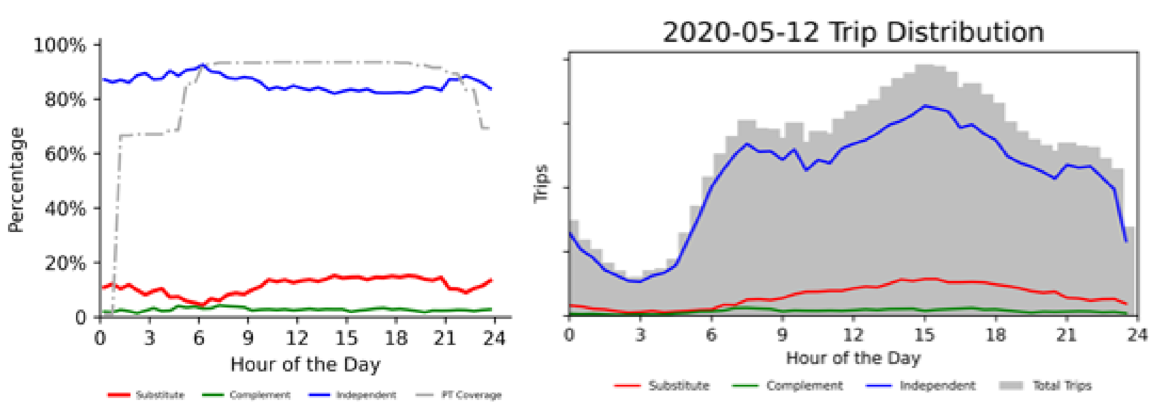


Figure E-21: Temporal trip volumes and rates for May 12, 2020

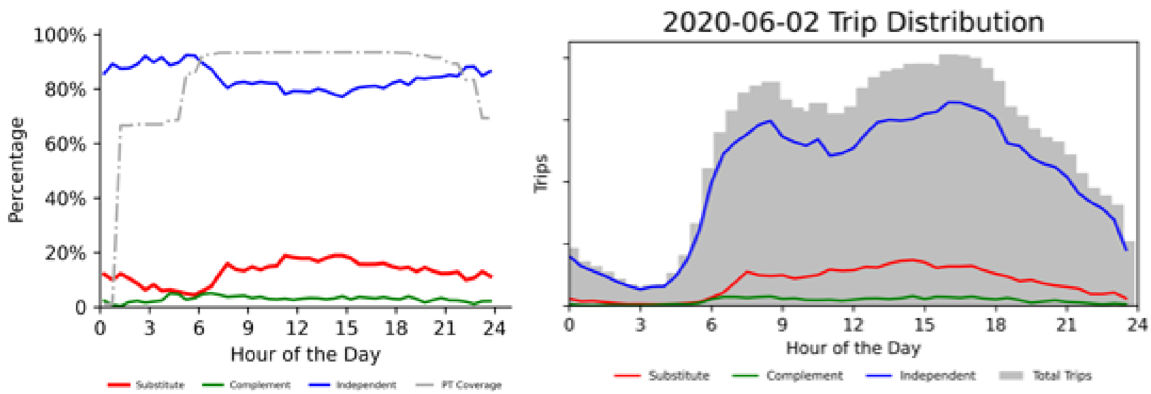


Figure E-22: Temporal trip volumes and rates for June 2, 2020

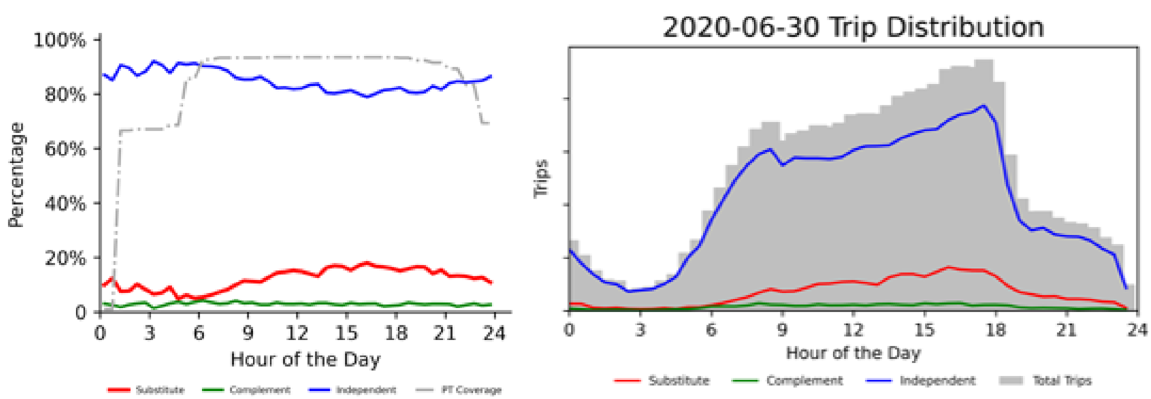


Figure E-23: Temporal trip volumes and rates for June 30, 2020

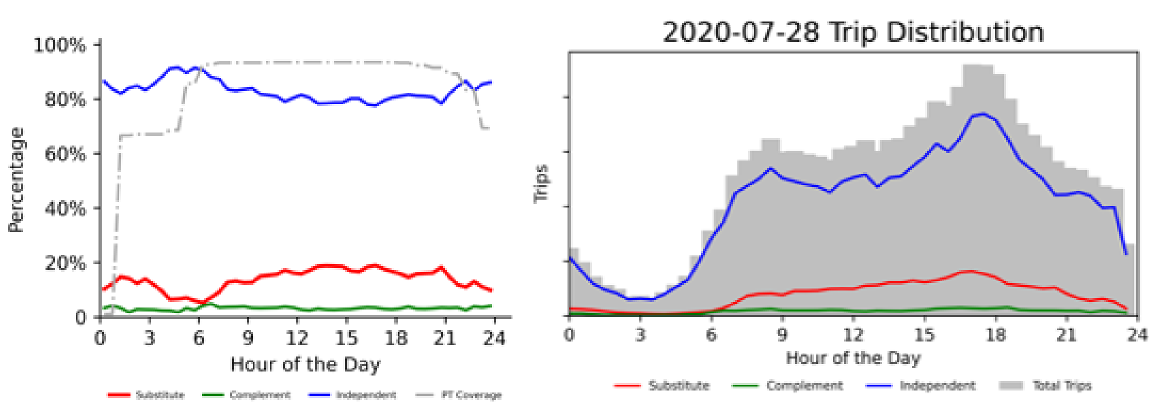


Figure E-24: Temporal trip volumes and rates for July 28, 2020

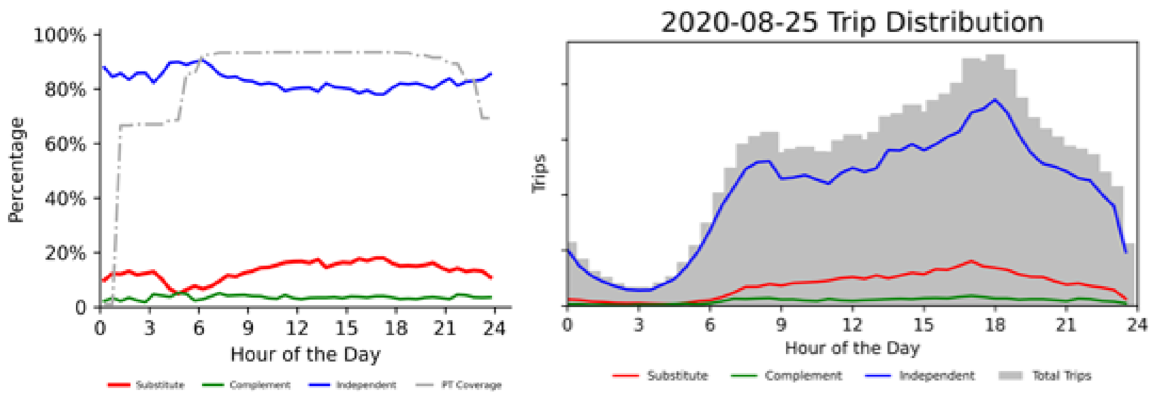


Figure E-25: Temporal trip volumes and rates for August 25, 2020

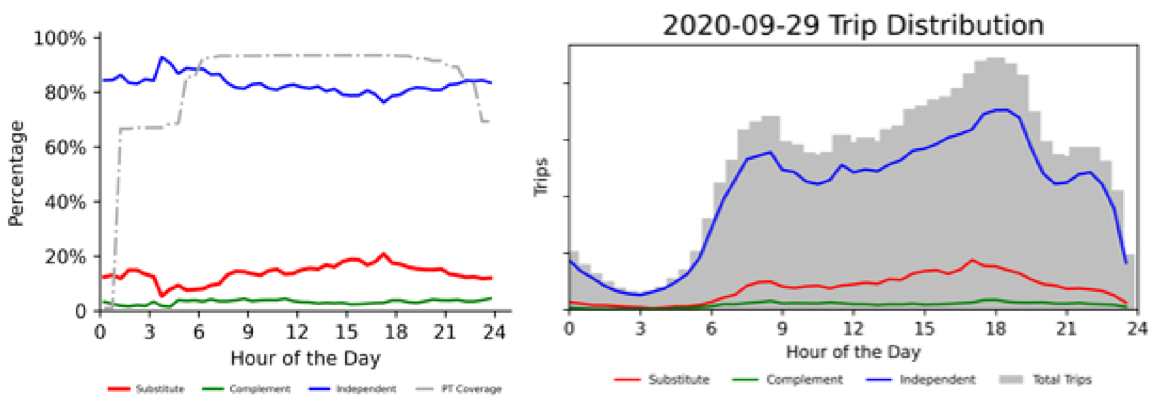


Figure E-26: Temporal trip volumes and rates for September 29, 2020

E.2.2 TNC Trip Spatial Distributions

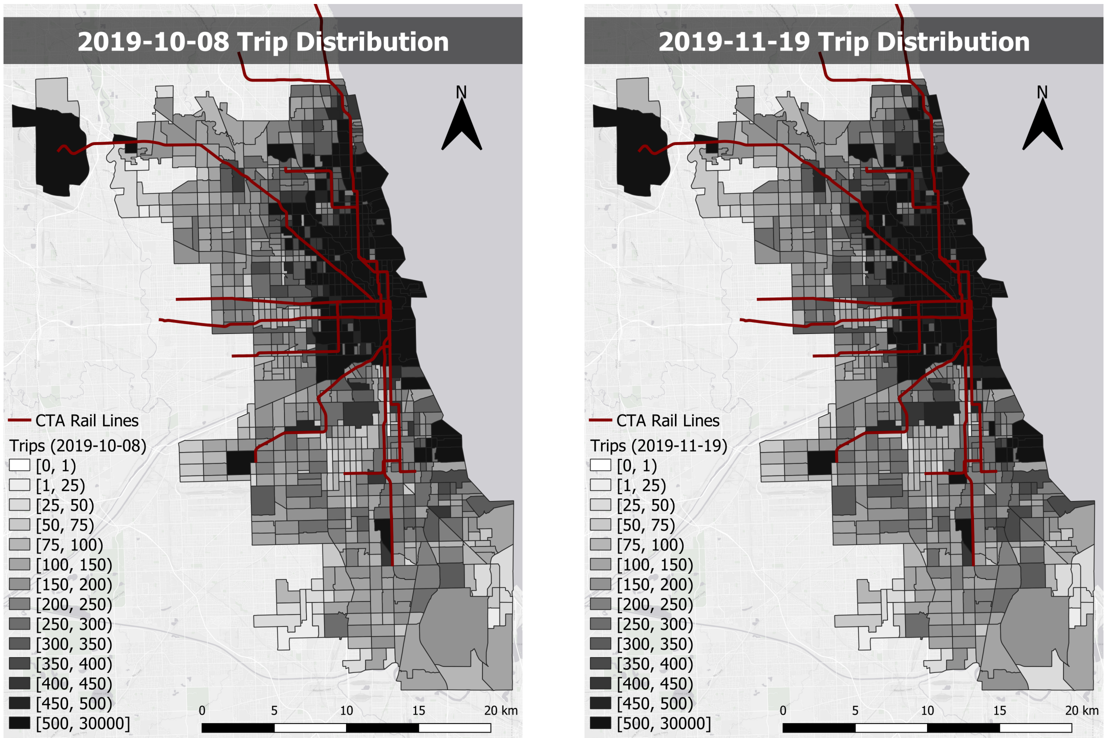


Figure E-27: Spatial distribution of TNC ridership for October 8, 2019 (left) and November 19, 2019 (right)

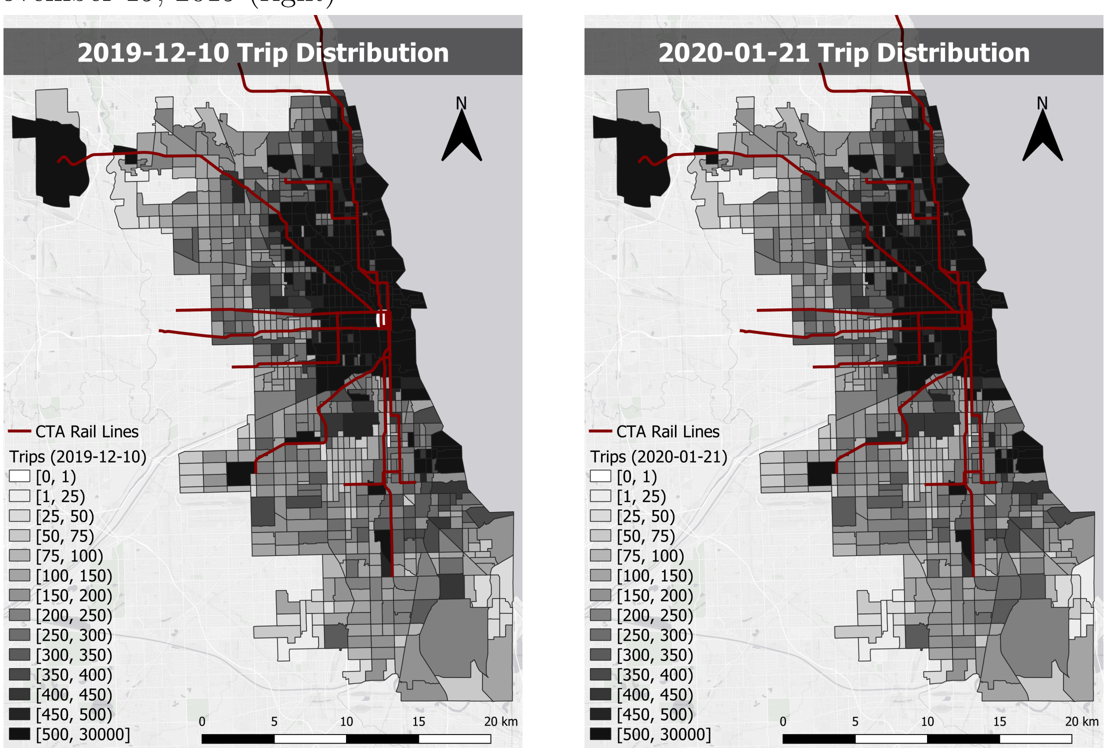


Figure E-28: Spatial distribution of TNC ridership for December 10, 2019 (left) and January 21, 2020 (right)

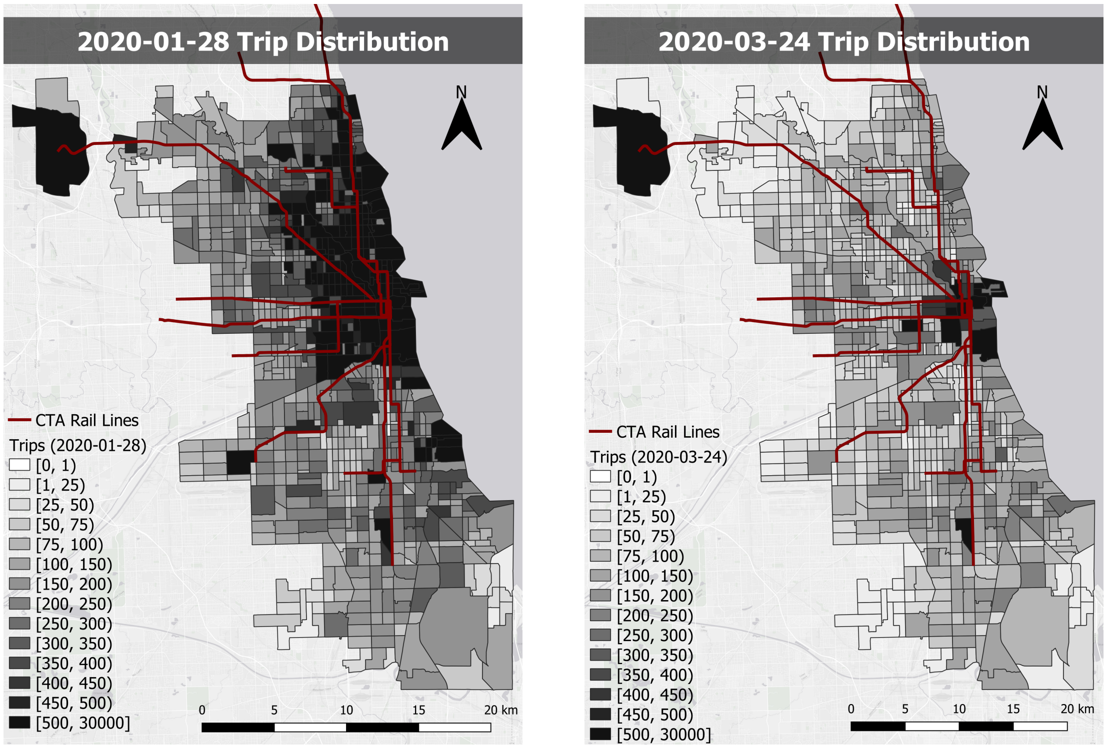


Figure E-29: Spatial distribution of TNC ridership for January 28, 2020 (left) and March 24, 2020 (right)

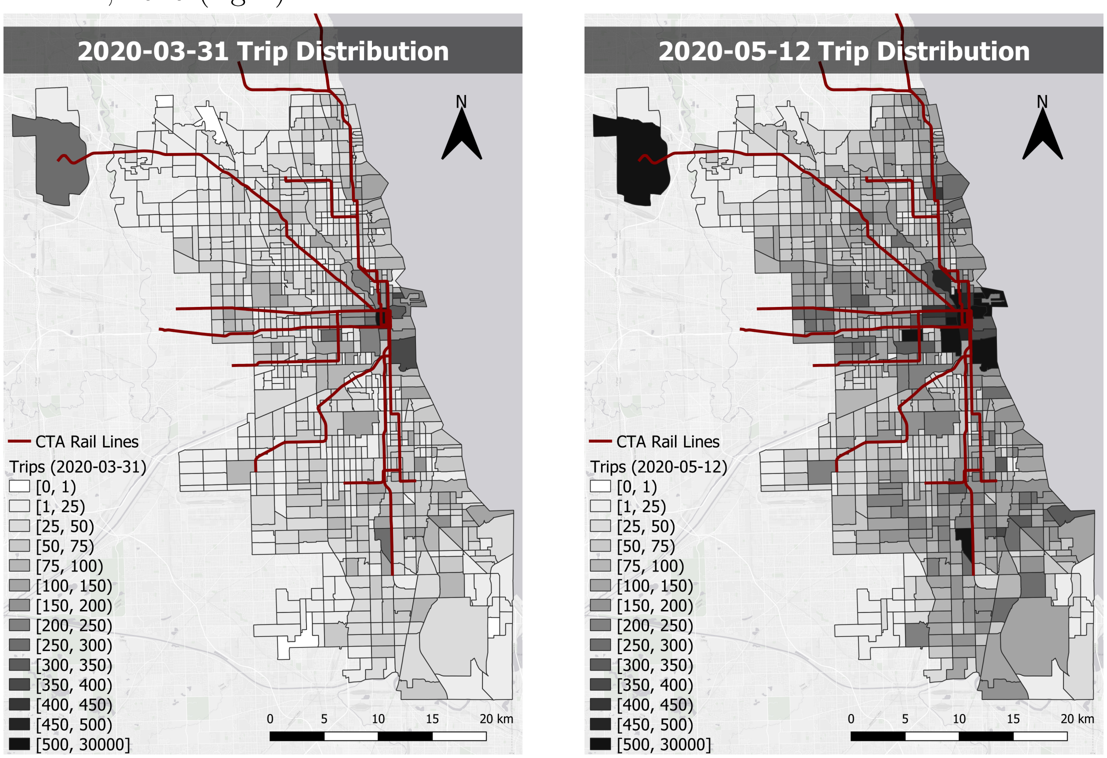


Figure E-30: Spatial distribution of TNC ridership for March 31, 2020 (left) and May 12, 2020 (right)

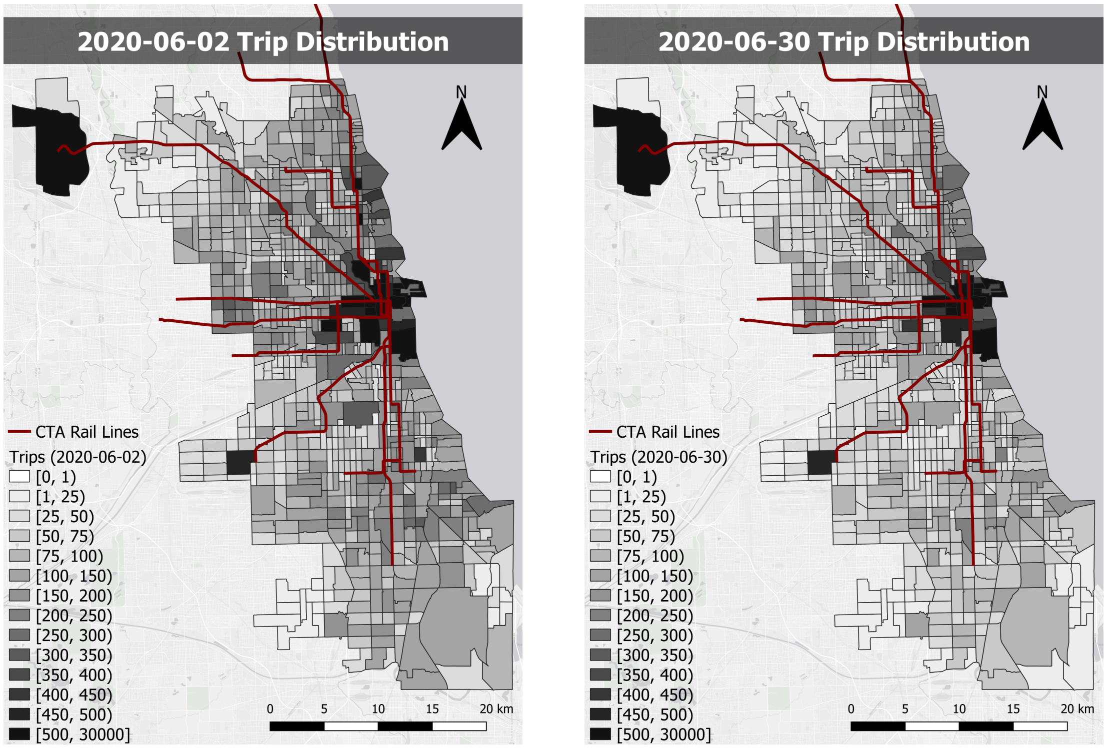


Figure E-31: Spatial distribution of TNC ridership for June 2, 2020 (left) and June 30, 2020 (right)

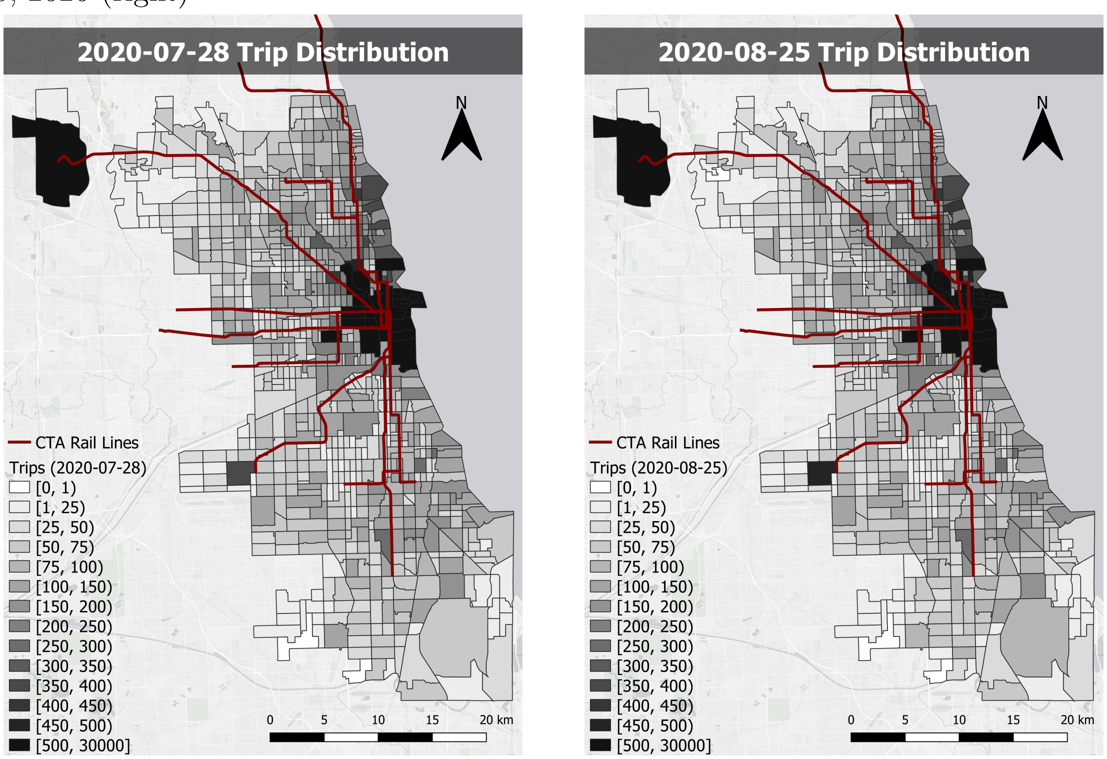


Figure E-32: Spatial distribution of TNC ridership for July 28, 2020 (left) and August 25, 2020 (right)

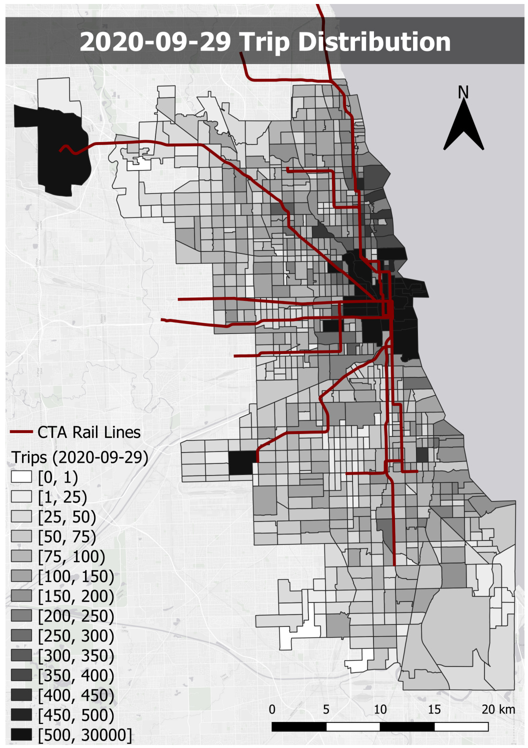


Figure E-33: Spatial distribution of TNC ridership for September 29, 2020

E.2.3 Cluster Analysis of TNC-PT Relationship

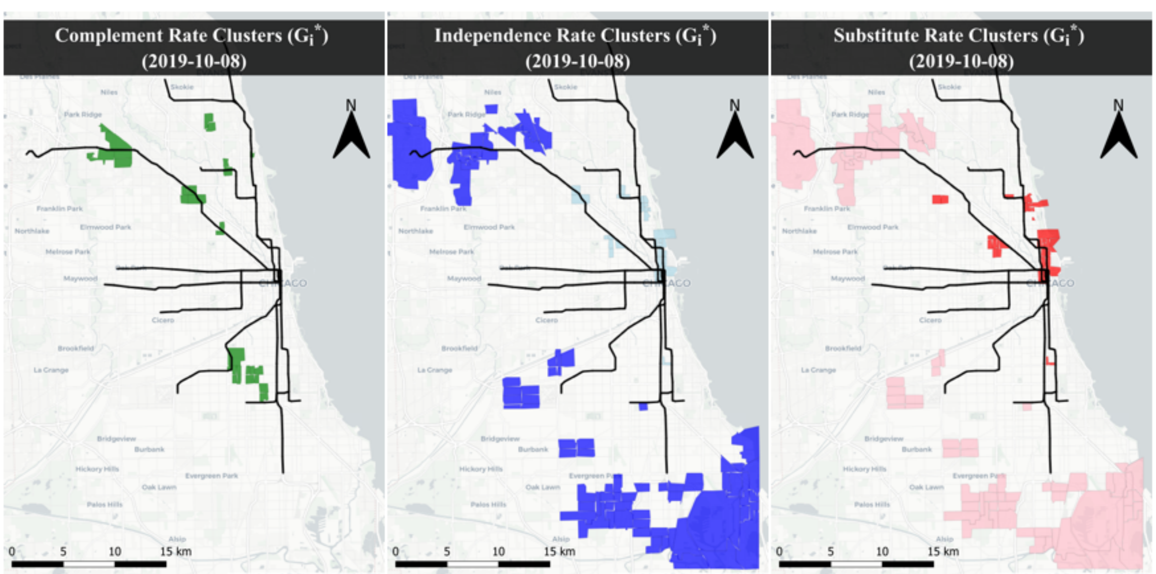


Figure E-34: Spatial cluster analysis for October 8, 2019

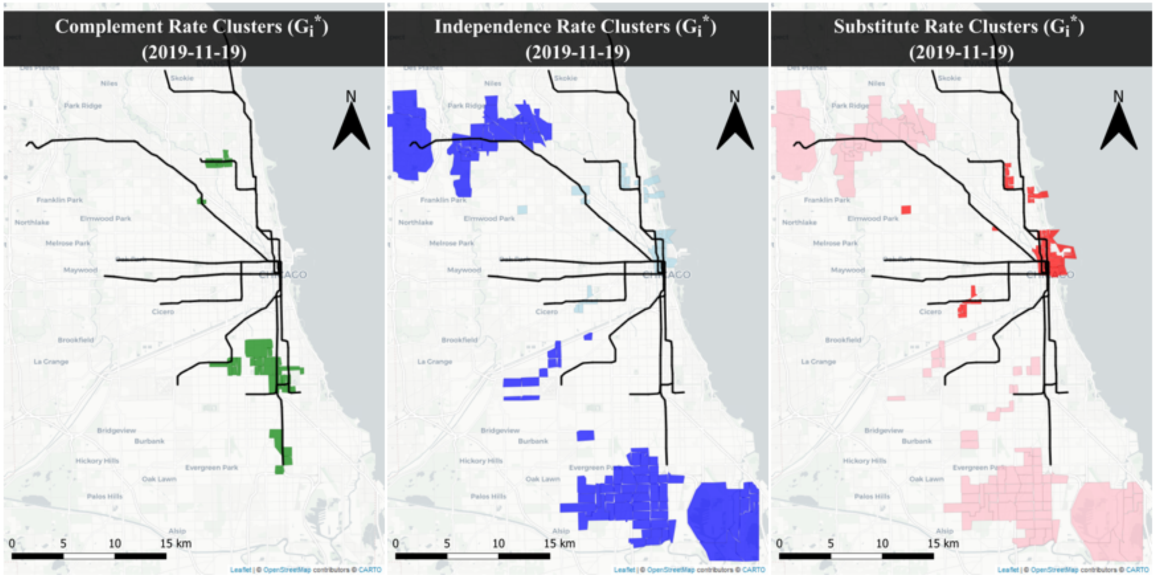


Figure E-35: Spatial cluster analysis for November 19, 2019

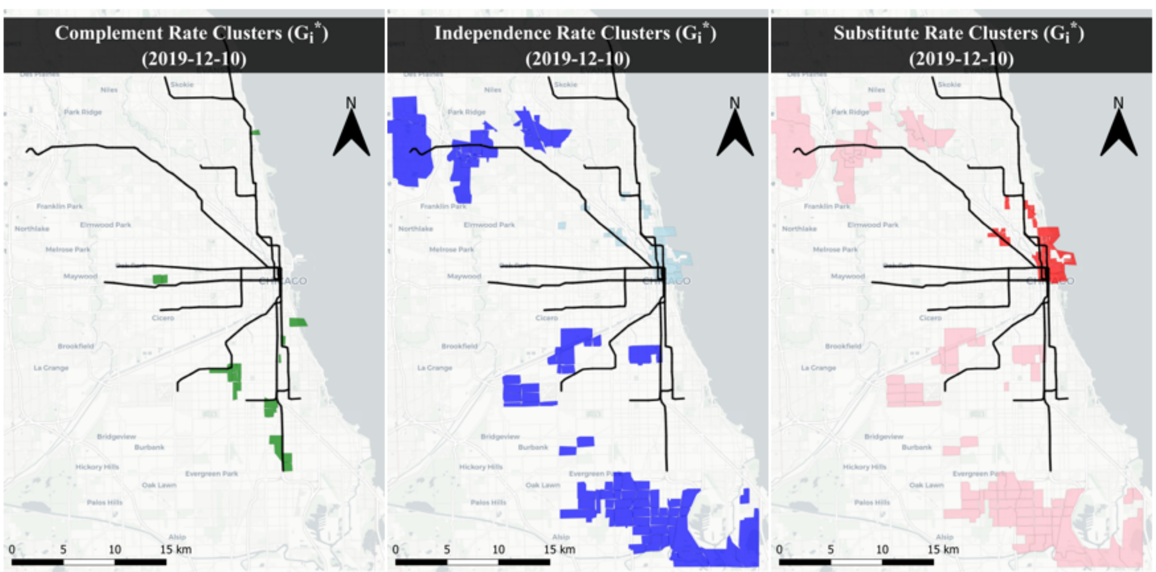


Figure E-36: Spatial cluster analysis for December 10, 2019

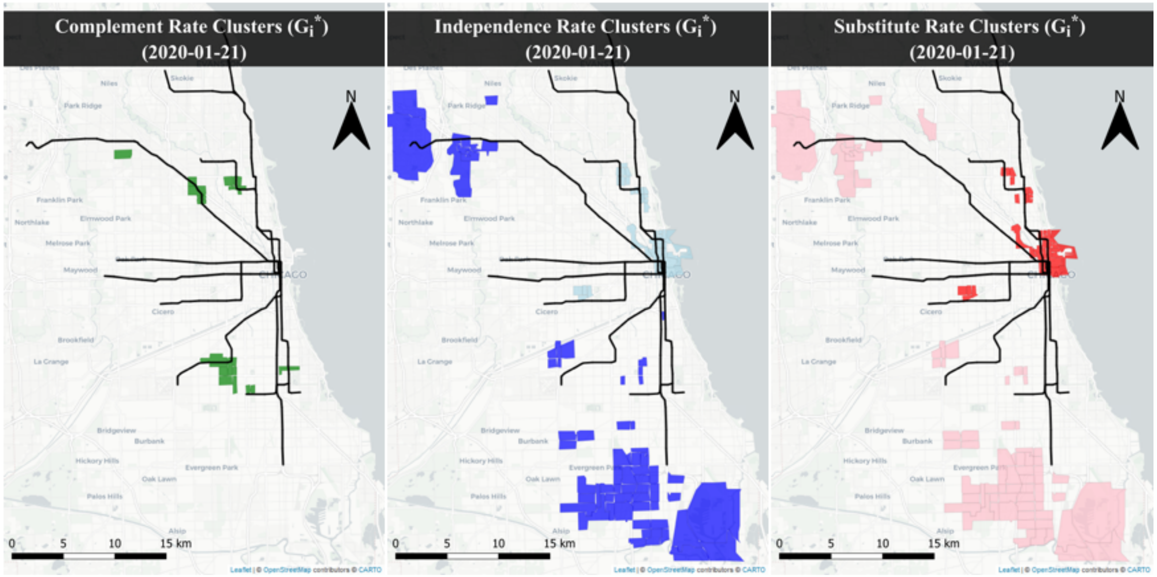


Figure E-37: Spatial cluster analysis for January 21, 2020

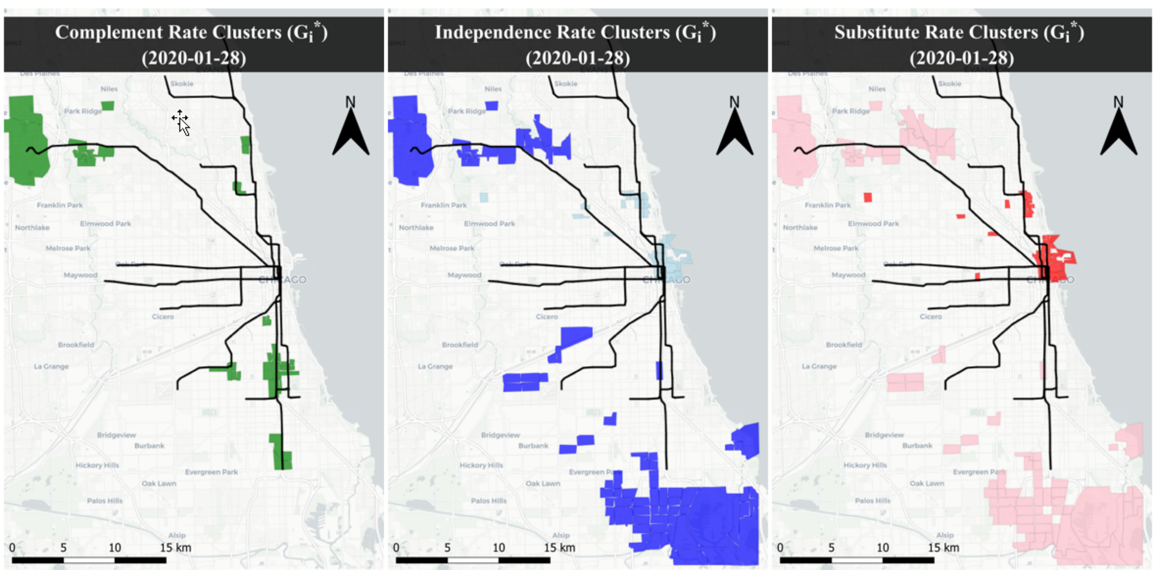


Figure E-38: Spatial cluster analysis for January 28, 2020

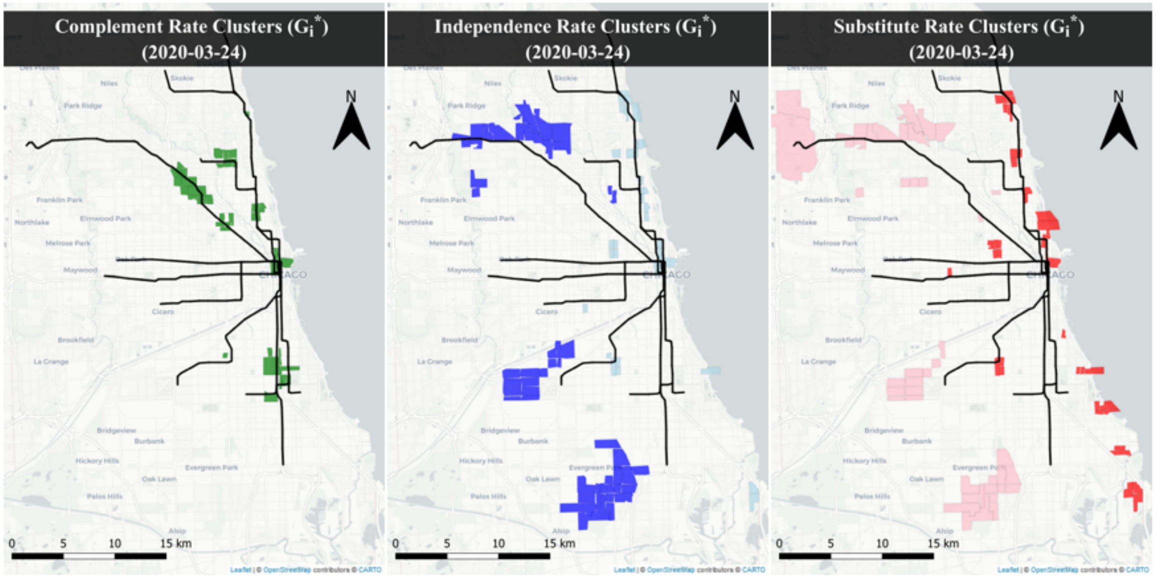


Figure E-39: Spatial cluster analysis for March 24, 2020

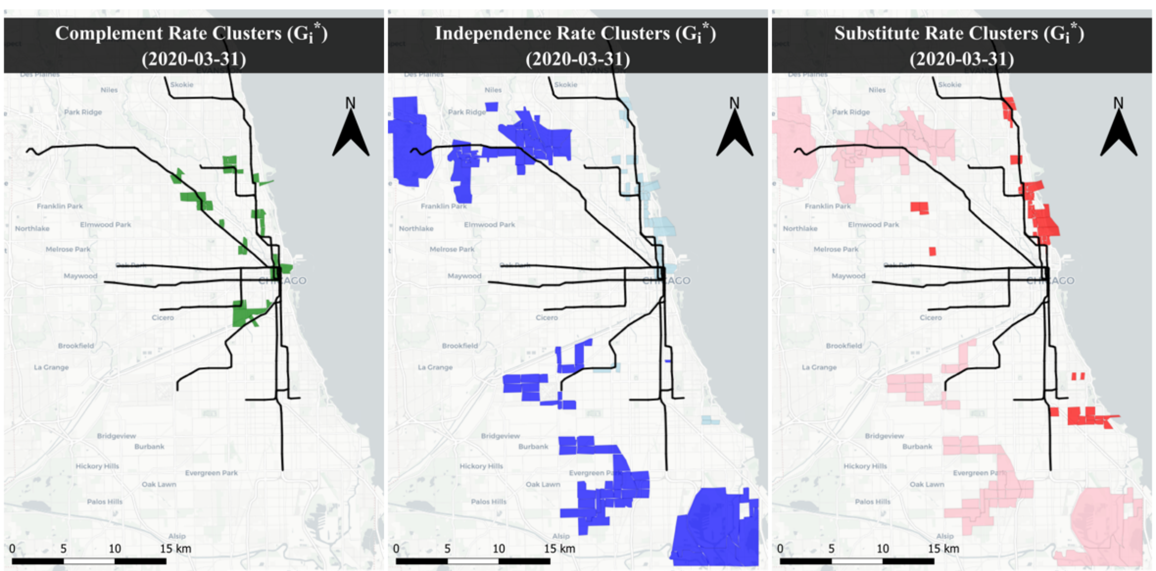


Figure E-40: Spatial cluster analysis for March 31, 2020

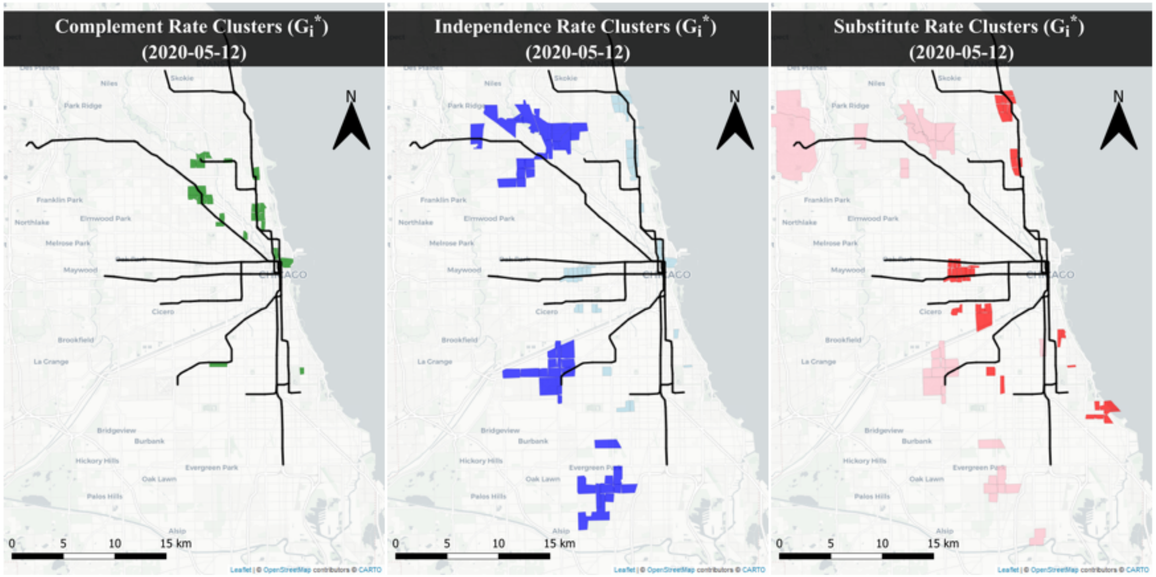


Figure E-41: Spatial cluster analysis for May 12, 2020

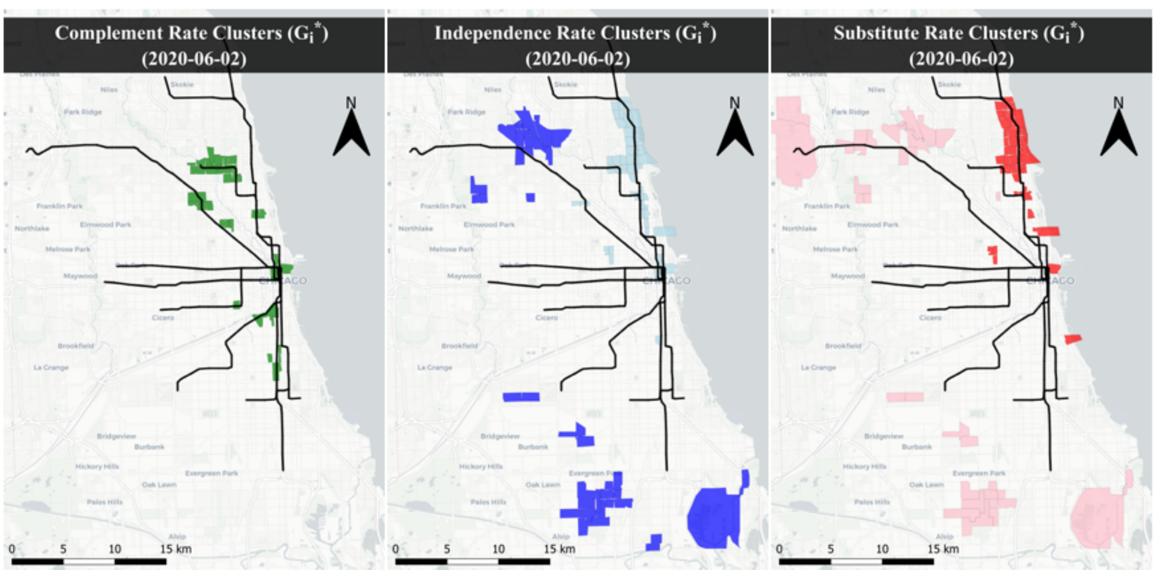


Figure E-42: Spatial cluster analysis for June 2, 2020

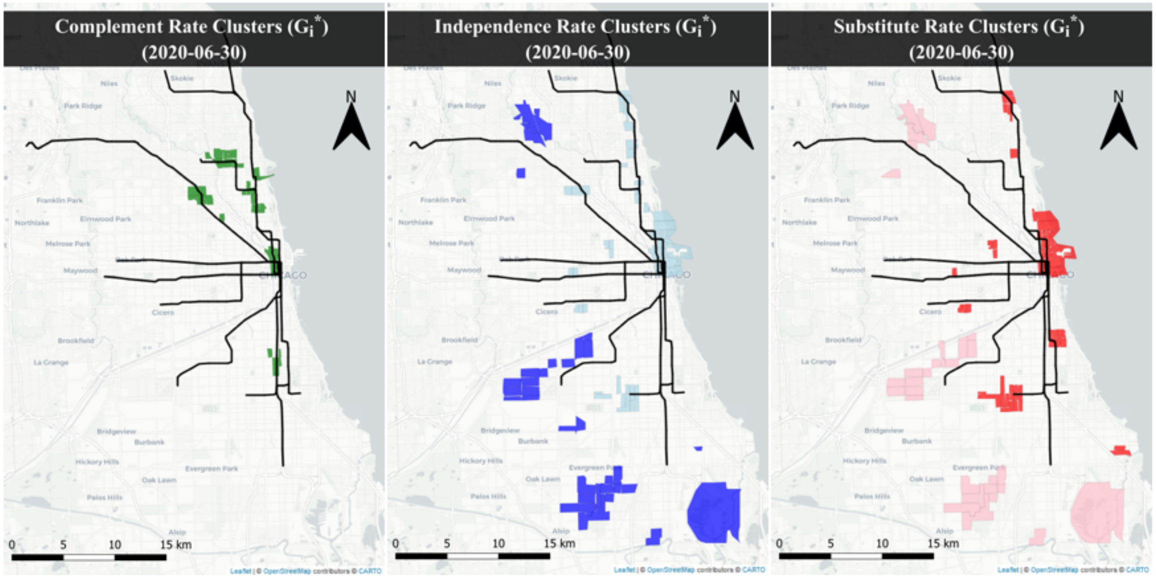


Figure E-43: Spatial cluster analysis for June 30, 2020

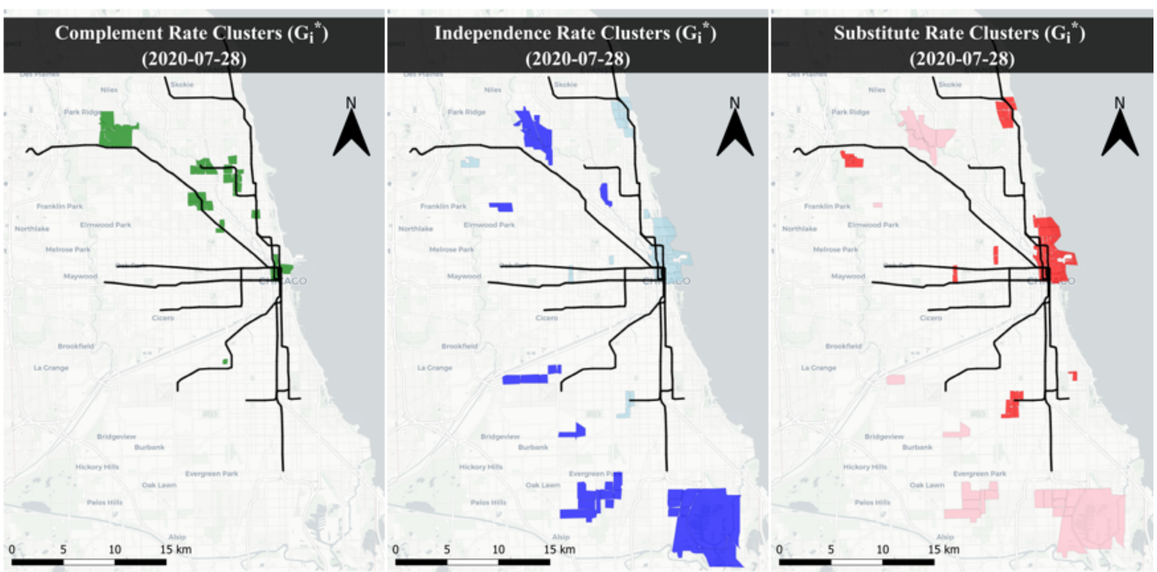


Figure E-44: Spatial cluster analysis for July 28, 2020

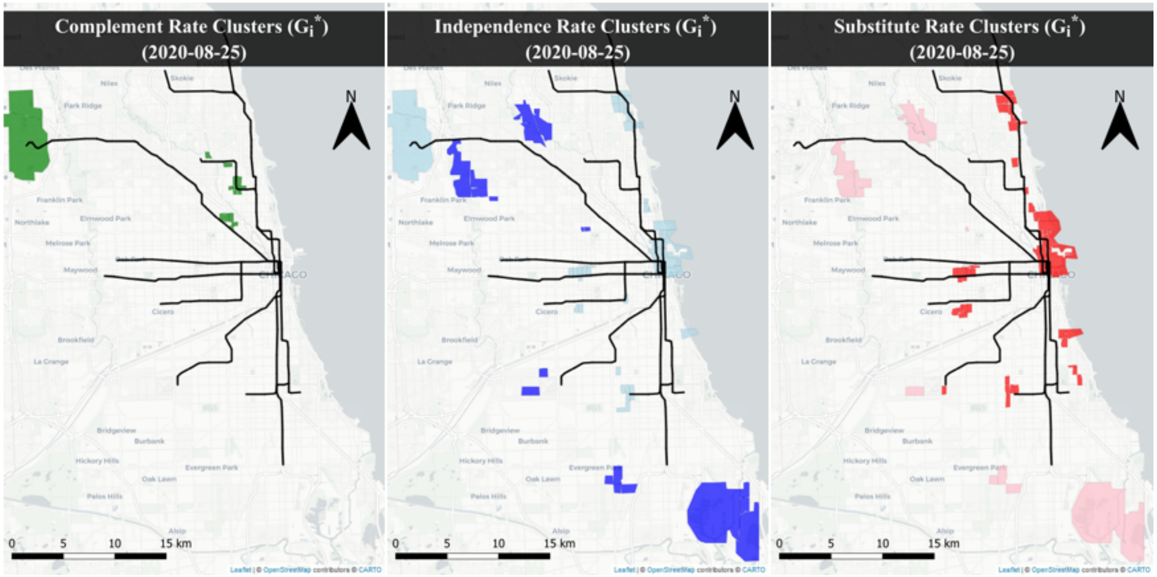


Figure E-45: Spatial cluster analysis for August 25, 2020

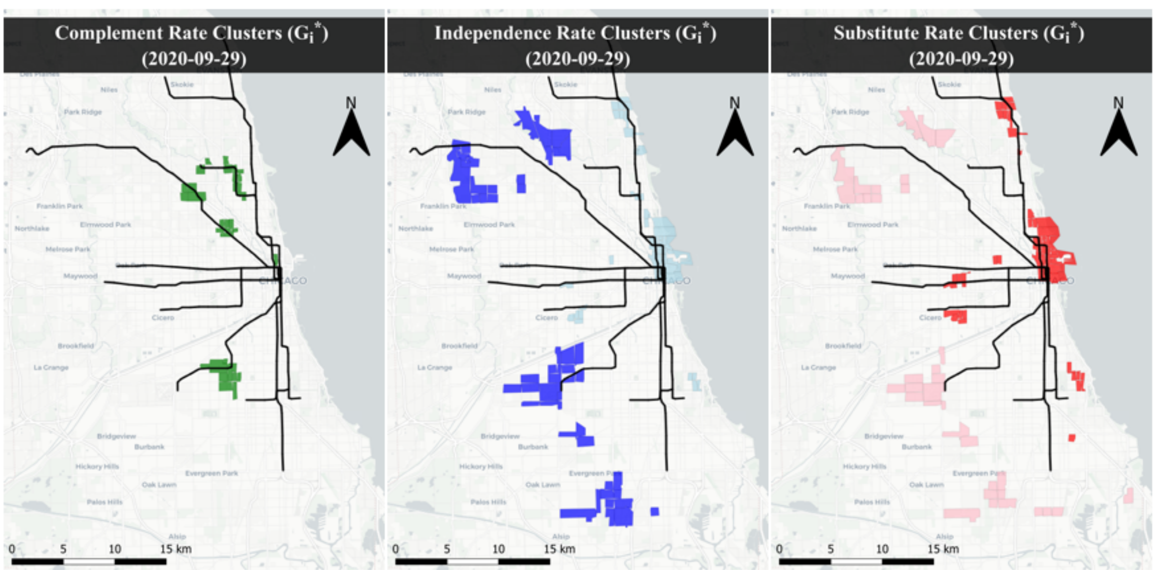


Figure E-46: Spatial cluster analysis for September 29, 2020

Bibliography

Angrist, J D and J Pischke [2008]. "Chapter 5: Parallel Worlds: Fixed Effects, Differences-in-differences, and Panel Data". In: *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, pp. 165–185.

Barajas, J M and A Brown [2021]. "Not Minding the Gap: Does Ride-Hailing Serve Transit Deserts?" In: *Journal of Transport Geography* 90.

Basu, R et al. [2018]. "Automated Mobility-on-Demand vs. Mass Transit: A Multi-Modal Activity-Driven Agent-Based Simulation Approach". In: *Transportation Research Record*. `https://doi.org/10.1177/0361198118758630`.

Beer, R et al. [2017]. "Qualitative Analysis of Ride-Hailing Regulations in Major American Cities". In: *Transportation Research Record* 2650. `https://doi.org/10.3141/2650-10`, pp. 84–91.

Bolton, C [2020]. *CMAP, ATA, and CDOT discuss pandemic transportation challenges, and the way forward*. Streetsblog Chicago, `https://chi.streetsblog.org/2020/09/24/cmap-ata-and-cdot-discuss-pandemic-transportation-challenges-and-the-way-forward/`.

Brail, S [2018]. "From Renegade to Regulated: The Digital Platform Economy, Ride-hailing and the Case of Toronto". In: *Canadian Journal of Urban Research* 27. `https://www.jstor.org/stable/26542036`, pp. 51–63.

Brough, R, M Freedman, and D C Phillips [2021]. "Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic". In: *Journal of Regional Science*. `https://doi.org/10.1111/jors.12527`.

Brown, A [2020]. "Not All Fees Are Created Equal: Equity Implications of Ride-hail Fee Structures". In: *OSF Preprints*. `https://doi.org/10.31219/osf.io/cpsqu`.

Brynjolfsson, E et al. [2020]. “COVID-19 and Remote Work: An Early Look at US Data”. In: *National Bureau of Economic Research* NBER WORKING PAPER SERIES. https://www.nber.org/papers/w27344.

CDOT [2021a]. *Leadership*. City of Chicago, https://www.chicago.gov/city/en/depts/cdot/auto_generated/cdot_leadership.html.

— [2021b]. *Public Transportation and Stations*. Chicago Department of Transportation, https://www.chicago.gov/city/en/depts/cdot/provdrs/transit_facilities.html.

Chen, S [2013]. “The Relationship between Rail Transit Ridership and Built Environment and Transportation System”. Master’s Thesis. Department of Civil and Environmental Engineering: Massachusetts Institute of Technology.

Chi, G and J Zhu [2019]. “Models Dealing With Spatial Dependence”. In: *Spatial Regression Models for the Social Sciences*. SAGE Publishing, pp. 55–83.

Chicago Data Portal [2010a]. *Boundaries - Census Blocks - 2010*. Chicago Data Portal, https://data.cityofchicago.org/Facilities-Geographic-Boundaries/Boundaries-Census-Blocks-2010/mfzt-js4n.

— [2010b]. *Boundaries - Census Tracts - 2010*. Chicago Data Portal, https://data.cityofchicago.org/Facilities-Geographic-Boundaries/Boundaries-Census-Tracts-2010/5jrd-6zik.

— [2013]. *CTA - Park and Ride - kml*. Chicago Data Portal, https://data.cityofchicago.org/Transportation/CTA-Park-and-Ride-kml/2cys-9ux7.

— [2020a]. *Crimes - 2019*. Chicago Data Portal, https://data.cityofchicago.org/Public-Safety/Crimes-2019/w98m-zvie.

— [2020b]. *Transportation Network Providers - Trips*. Tech. rep. https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips/m6dm-c72p. Chicago: City of Chicago.

Chicago Historical Society [2005]. *Aldermanic Privilege*. Encyclopedia of Chicago, http://www.encyclopedia.chicagohistory.org/pages/2197.html.

Chicago Metropolitan Agency for Planning [2019]. *New Data Allows an Initial Look At Ride Hailing in Chicago*. Tech. rep. Chicago: CMAP.

Chicago Transit Authority [2017]. *Facts at a glance*. Chicago Transit Authority, https://www.transitchicago.com/facts/.

— [2019]. *Rail ('L') System Map*. Tech. rep. https://www.transitchicago.com/assets/1/6/ctamap_Lsystem.pdf. Chicago: Chicago Transit Authority.

— [2020a]. *Coronavirus (COVID-19) info*. Chicago Transit Authority, https://www.transitchicago.com/coronavirus/.

— [2020b]. *Financial Statements and Supplementary Information, Years Ended December 31, 2019 and 2018*. Tech. rep. Chicago: Chicago Transit Authority.

— [2020c]. *Monthly Ridership Report: March 2020*. Tech. rep. https://www.transitchicago.com/assets/1/6/Monthly_Ridership_2020-03.pdf. Chicago: Chicago Transit Authority Ridership Analysis and Reporting.

— [2020d]. *Monthly Ridership Report: November 2020*. Tech. rep. Chicago: Chicago Transit Authority Ridership Analysis and Reporting.

— [2020e]. *Ridership*. Chicago Transit Authority, https://www.transitchicago.com/ridership/.

— [2021]. *More Fun, Less Fare!* Chicago Transit Authority, https://www.transitchicago.com/summer-2021-passes/.

Chow, W [2014]. "Evaluating Online Surveys for Public Transit Agencies Using a Prompted Recall Approach". Master's Thesis. Department of Civil and Environmental Engineering: Massachusetts Institute of Technology.

City of Chicago [2017]. *Transportation Network Providers Rules*. Tech. rep. https://www.chicago.gov/content/dam/city/depts/bacp/rulesandregs/TNPRulesAmendedeffJan1201 pdf. Chicago: Department of Business Affairs and Consumer Protection; Department of Aviation.

— [2019]. *Transportation Network Providers and Congestion in the City of Chicago*. Tech. rep. https://www.chicago.gov/content/dam/city/depts/bacp/Outreach%20and%20Education/MLL_10-18-19_PR-TNP_Congestion_Report.pdf. Chicago: City of Chicago.

City of Chicago [2020a]. *City of Chicago Congestion Pricing*. City of Chicago, https://www.chicago.gov/city/en/depts/bacp/supp_info/city_of_chicago_congestion_pricing.html.

— [2020b]. *Transportation Network Providers (Ride-Hail Companies)*. City of Chicago, https://www.chicago.gov/city/en/depts/bacp/supp_info/transportation-network-providers.html.

— [2021a]. *About Chicago*. City of Chicago, https://www.chicago.gov/city/en/about.html.

— [2021b]. *Chicago Ward, Community Area and Neighborhood Maps*. City of Chicago, https://www.chicago.gov/city/en/depts/dgs/supp_info/citywide_maps.html.

Data USA [2018]. *Chicago, IL: Housing & Living*. Tech. rep. https://datausa.io/profile/geo/chicago-il. Data USA.

Demetsky, M J and B Bin-Mau Lin [1982]. "Bus stop location and design". In: *Transp. Eng. J. ASCE 108 (4)*, pp. 313–327.

Dwyer, A, J McGregor, and S Gasulla [2017]. *Chicago's Wealth Divide*. Tech. rep. https://www.chicagobusiness.com/static/section/chicagos-wealth-divide.html. Chicago: Crain's Chicago Business.

Erhardt, G D et al. [2021]. "Do transportation network companies increase or decrease transit ridership? Empirical evidence from San Francisco". In: *Transportation*. https://doi.org/10.1007/s11116-021-10178-4.

Fissinger, Mary Rose [2020]. "Behavioral Dynamics of Public Transit Ridership in Chicago and Impacts of COVID-19". Master's Thesis. Department of Civil and Environmental Engineering: Massachusetts Institute of Technology.

Freund, S [2020]. *Chicago's new ride-hailing tax begins now, and it's the country's highest fee*. Curbed Chicago, https://chicago.curbed.com/2019/12/2/20992472/chicago-transportation-tax-uber-lyft-taxi.

Furcher, T et al. [2020]. *How consumers' behavior in car buying and mobility is changing amid COVID-19*. McKinsey & Company, https://www.mckinsey.com/

business-functions/marketing-and-sales/our-insights/how-consumers-behavior-in-car-buying-and-mobility-changes-amid-covid-19.

Gan, Z et al. [2019]. "Analysis of Metro Station Ridership Considering Spatial Heterogeneity". In: *Chinese Geographical Science* 29. https://doi.org/10.1007/s11769-019-1065-8, pp. 1065–1077.

Gao, J et al. [2020]. *The Effects of the COVID-19 Pandemic on Transportation Systems in New York City and Seattle, USA*. Tech. rep. 2020: C2 SMART.

Gehrke, S R, A Felix, and T Reardon [2018]. *Fare Choice: A survey of ride-hailing passengers in Subway Boston.* Tech. rep. http://www.mapc.org/wp-content/uploads/2018/02/Fare-Choices-MAPC.pdf. MAPC Research Brief.

Gertler, P J et al. [2016]. "Chapter 7: Difference-in-Differences". In: *Impact Evaluation in Practice*. 2nd. World Bank Group, pp. 129–142.

Getis, A and J K Ord [1992]. "The Analysis of Spatial Association by Use of Distance Statistics". In: *Geographical Analysis* 24, p. 192.

Graehler, M, A Mucci, and G D Erhardt [2019]. "Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes?" In: *Transportation Research Board Annual Meeting.*

Grahn, R et al. [2020]. "Are travelers substituting between transportation network companies (TNC) and public buses? A case study in Pittsburgh". In: *Transportation* 48, pp. 977–1005.

Greenfield, J [2019a]. *Once again Chicago leads the way, passing a tax to help get Uber and Lyft under control.* Streetsblog Chicago, https://chi.streetsblog.org/2019/11/26/once-again-chicago-leads-the-way-passing-a-ride-hail-tax-to-help-get-uber-and-lyft-under-control/.

— [2019b]. *Why Lori's Order to End Aldermanic Prerogative Is Good for Sustainable Transportation.* StreetsBlog Chicago, https://chi.streetsblog.org/2019/05/20/why-loris-executive-order-to-end-aldermanic-prerogative-is-good-for-sustainable-transportation/.

Greer, J L [2014]. “Historic Home Mortgage Redlining in Chicago”. In: *Journal of the Illinois State Historical Society* 107. https://www.jstor.org/stable/10.5406/jillistathistsoc.107.2.0204, pp. 204–233.

Hall, J D, C Palsson, and J Price [2018]. “Is Uber a substitute or complement for public transit?” In: *Journal of Urban Economics* 108. https://doi.org/10.1016/j.jue.2018.09.003, pp. 36–50.

Hawas, Y E, M N Hassan, and A Abulibdeh [2016]. “A multi-criteria approach of assessing public transport accessibility at a strategic level”. In: *Journal of Transportation Geography* 57, pp. 19–34.

Henao, A [2017]. *Impacts of Ridesourcing-Lyft and Uber-on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior*. Tech. rep. University of Colorado at Denver.

Henao, A et al. [2018]. *Airport Analyses Informing New Mobility Shifts: Opportunities to Adapt Energy-Efficient Mobility Services and Infrastructure*. Tech. rep. https://www.nrel.gov/docs/fy18osti/71036.pdf. Golden, CO: National Renewable Energy Laboratory.

Hoffmann, K, P Ipeirotis, and A Sundararajan [2016]. “Ridesharing and the Use of Public Transportation”. In: *International Conference on Information Systems (ICIS)*.

Hu, S and P Chen [2021]. “Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership”. In: *Transportation Research Part D* 90.

Irvin, E [2019]. *Who Will Really Pay The Most for New Ride Hailing Fees?* Center for Neighborhood Technology, https://www.cnt.org/blog/who-will-really-pay-the-most-for-new-ride-hailing-fees.

Jin, S T, H Kong, and D Z Sui [2019]. “Uber, public transit, and urban transportation equity: A case study in New York City”. In: *The Professional Geographer* 71, pp. 315–330.

Kepaptsoglou, K, A Stathopoulos, and M G Karlaftis [2017]. “Ridership estimation of a new LRT system: Direct demand model approach”. In: *Journal of Transport*

Geography 58. https://doi.org/10.1016/j.jtrangeo.2016.12.004, pp. 146–156.

Kim, S J and R Puentes [2018]. *Taxing New Mobility Services: What's Right? What's Next?* Tech. rep. https://trid.trb.org/view/1526430. Washington, DC: Eno Center for Transportation.

King, D A, M W Conway, and D Salon [2020]. "Do For-Hire Vehicles Provide First Mile/Last Mile Access to Transit?" In: *Transport Findings*. https://doi.org/10.32866/001c.12872.

Kong, H, X Zhang, and J Zhao [2020]. "How does ridesourcing substitute for public transit? A geospatial perspective in Chengdu, China". In: *Journal of Transport Geography* 86.

Li, T et al. [2021]. "Comparison of Door-to-Door Transit Travel Time Estimation Using Schedules, Real-Time Vehicle Arrivals, and Smartcard Inference Methods". In: *Transportation Research Record*. https://doi.org/10.1177/03611981211023768.

Lightfoot, L E [2019]. *Sixty-Day Report on Implementation of Executive Order No. 2019-2*. Tech. rep. Chicago: City of Chicago.

Liu, L, H J Miller, and J Scheff [2020]. "The impacts of COVID-19 pandemic on public transit demand in the United States". In: *PLoS ONE* 15. https://doi.org/10.1371/journal.pone.0242476.

Luo, R, J Moody, and J Zhao [2020]. *AVOIDING TRAVEL TO WORK AND BY SHARED MODES AS PREVENTIVE ACTIONS IN RESPONSE TO COVID-19: A MATCHED PRE- / POST- LOCKDOWN STUDY IN SINGAPORE*. Tech. rep. MIT Transit Lab (Working Paper).

Marquet, O [2020]. "Spatial distribution of ride-hailing trip demand and its association with walkability and neighborhood characteristics". In: *Cities* 106. https://doi.org/10.1016/j.cities.2020.102926.

Martin, D et al. [2018]. "Origin-destination geodemographics for analysis of travel to work flows". In: *Computers, Environment and Urban Systems* 67. https://doi.org/10.1016/j.compenvurbsys.2017.09.002, pp. 68–79.

Metra [2021a]. *Operations and Ridership Data.* Metra Rail, https://metrarail.com/about-metra/reports-documents/operations-ridership-data.

— [2021b]. *Our History.* Metra Rail, https://metrarail.com/about-metra/our-history.

Meyer, M D and E J Miller [2001]. "Chapter 5: Transportation Demand Analysis". In: *Transportation Planning: A Decision-Oriented Approach.* McGraw-Hill, pp. 1–85.

Murphy, C [2016]. *Shared Mobility and the Transformation of Public Transit.* Tech. rep. ttps://www.apta.com/resources/reportsandpublications/Documents/APTA-Shared-Mobility.pdf. American Public Transportation Association.

Murray, A T et al. [1998]. "Public transportation access". In: *Transp. Res. Part D: Transp. Environ. 3 (5)*, pp. 319–328.

National Weather Service [2021]. *All Local Events.* National Oceanic and Atmospheric Administration, weather.gov/lot/events.

NBC Chicago [2020]. *Chicago Ride-Share Tax Hikes Take Effect Monday.* NBC Chicago, https://www.nbcchicago.com/news/local/chicago-politics/chicago-ride-share-tax-hikes-take-effect-monday/2196000/.

O'Sullivan, D and D J Unwin [2010a]. "Chapter 7: Area Objects and Spatial Autocorrelation". In: *Geographic Information Analysis.* 2nd. John Wiley & Sons, Inc., pp. 187–214.

— [2010b]. "Chapter 8: Local Statistics". In: *Geographic Information Analysis.* 2nd. John Wiley & Sons, Inc., pp. 215–237.

OpenMobilityData [2020]. *CTA GTFS.* OpenMobilityData, https://transitfeeds.com/p/chicago-transit-authority/165.

Pace Suburban Bus [2021]. *About Pace.* Pace Suburban Bus, https://www.pacebus.com/about.

Pritzker, J B [2021]. *Executive Order 2021-12.* State of Illinois Coronavirus Response, https://coronavirus.illinois.gov/resources/executive-orders/display.executive-order-2021-12.html.

Rao, L [2011]. *Uber Brings Its Disruptive Car Service To Chicago*. TechCrunch, https://techcrunch.com/2011/09/22/uber-brings-its-disruptive-car-service-to-chicago/.

Rayle, L et al. [2016]. "Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco". In: *Transport Policy* 45, pp. 168–178.

Rodriguez, S [2013]. *Lyft, a ride-sharing app service, expands to Chicago*. Los Angeles Times, https://www.latimes.com/business/technology/la-fi-tn-lyft-chicago-name-change-20130509-story.html.

RTA [2020]. *RTA COVID-19 Recovery Scenario Planning*. Tech. rep. Chicago: Chicago Regional Transportation Authority.

— [2021a]. *About Us*. Regional Transportation Autority Chicago, https://www.rtachicago.org/about-us.

— [2021b]. *Operating Revenue and Funding*. Regional Transportation Autority Chicago, https://www.rtachicago.org/finance-management/operating-revenue-and-funding.

— [2021c]. *Operating Revenue and Funding*. Regional Transportation Autority Chicago, https://rtachicago.org/finance-management/operating-revenue-and-funding.

RTAMS [2021]. *Transit Data for Northeastern Illinois*. Regional Transportation Authority Mapping and Statistics, https://www.rtams.org/.

Rudick, R [2020]. *Understanding Transit Needs of Essential Workers*. Streetsblog SF, https://sf.streetsblog.org/2020/12/17/understanding-transit-needs-of-essential-workers/.

Salon, D et al. [2020]. *COVID-19 and the Future Survey*. Tech. rep. Arizona State University.

San Francisco County Transportation Authority [2017]. *TNCs Today: A Profile of San Francisco Transportation Network Company Activity*. Tech. rep. San Francisco: San Francisco County Transportation Authority.

Schwerdt, G and L Woessmann [2020]. “Chapter 1 - Empirical methods in the economics of education”. In: *The Economics of Education*. 2nd. Academic Press, pp. 3–20.

Shamshiripour, A et al. [2020]. “How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago”. In: *Transportation Research Interdisciplinary Perspectives* 7.

Slowik, P, S Wappelhorst, and N Lutsey [2019]. *How Can Taxes and Fees ON Ride-Hailing Fleets Steer Them to Electrify?* Tech. rep. https://www.researchgate.net/profile/Nicholas-Lutsey/publication/336148064_How_can_taxes_and_fees_on_ride-hailing_fleets_steer_them_to_electrify/links/5d92dd88a6fdcc2554a97ec6/How-can-taxes-and-fees-on-ride-hailing-fleets-steer-them-to-electrify.pdf. The International Council on Clean Transportation.

Souza Silva, L A de, M O de Andrade, and M L Alves Maia [2018]. “How does the ride-hailing systems demand affect individual transport regulation?” In: *Research in Transportation Economics* 69. https://doi.org/10.1016/j.retrec.2018.06.010, pp. 600–606.

Stiglic, M et al. [2018]. “Enhancing urban mobility: Integrating ride-sharing and public transit”. In: *Computers & Operations Research*, pp. 12–21.

Sy, K L et al. [2020]. *Socioeconomic Disparities in Subway Use and COVID-19 Outcomes in New York City*. Tech. rep. Oxford University Press.

The Global Grid [2018]. *Urbanism and the Peculiarity of Aldermanic Privilege*. Smart Cities Dive, https://www.smartcitiesdive.com/ex/sustainablecitiescollective/peculiarity-aldermanic-privilege/165461/.

TransitCenter [2020]. *Transit Is Essential: 2.8 Million U.S. Essential Workers Ride Transit to Their Jobs*. TransitCenter, https://transitcenter.org/2-8-million-u-s-essential-workers-ride-transit-to-their-jobs/.

US Census Bureau [2019]. *American Community Survey: 5-Year Estimates*. United States Census Bureau.

— [2020]. *When to Use 1-year, 3-year, or 5-year Estimates*. US Census Bureau, https://www.census.gov/programs-surveys/acs/guidance/estimates.html.

Watkins, K E et al. [2011]. “Where Is My Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders”. In: *Transportation Research Part A: Policy and Practice* 45, pp. 839–848.

Welle, B, G Petzhold, and F M Pasqual [2018]. *Cities Are Taxing Ride-Hailing Services Like Uber and Lyft. Is This a Good Thing?* Tech. rep. https://www.wri.org/insights/cities-are-taxing-ride-hailing-services-uber-and-lyft-good-thing. World Resources Institute.

Wilbur, M et al. [2020]. *Impact of COVID-19 on Public Transit Accessibility and Ridership*. Tech. rep. Cornell University.

Williams, R [2017]. *How Uber works together with Southern California’s growing rail network*. Medium, https://medium.com/uber-under-the-hood/how-uber-works-together-with-southern-californias-growing-rail-network-fa8b1aba03b4.

Wilson, M and M Daly [1997]. “Life expectancy, economic inequality, homicide, andreproductive timing in Chicago neighbourhoods”. In: *BMJ* 314. https://doi.org/10.1136/bmj.314.7089.1271.

Wu, C and A T Murray [2005]. “Optimizing public transit quality and system access: the multiple-route, maximal covering/shortest-path problem”. In: *Environ. Plan. B 32 (2)*, pp. 163–178.

Xu, W [2021]. “Legacies of Institutionalized Redlining: A Comparison Between Speculative and Implemented Mortgage Risk Maps in Chicago, Illinois”. In: *Housing Policy Debate*. https://doi.org/10.1080/10511482.2020.1858924.

Young, M, J Allen, and S Farber [2020]. “Measuring when Uber behaves as a substitute or supplement to transit: An examination of travel-time differences in Toronto”. In: *Journal of Transport Geography* 82. https://doi.org/10.1016/j.jtrangeo.2019.102629.

Young, M and S Farber [2019]. “The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey”. In: *Transportation Research Part A: Policy and Practice* 119, pp. 383–392.

Zhang, Y [2011]. “Boundaries of Power: Politics of Urban Preservation in Two Chicago Neighborhoods”. In: *Urban Affairs Review* 47. https://doi.org/10.1177/1078087411400376, pp. 511–540.

Zhao, J, W Deng, et al. [2014]. “Analysis of Metro ridership at station level and station-to-station level in Nanjing: an approach based on direct demand models”. In: *Transportation* 41. https://link.springer.com/article/10.1007/s11116-013-9492-3, pp. 133–155.

Zhao, J Z, C Fonseca, and R Zeerak [2020]. “Revenue Usages, Pricing Schemes, and Media Discussions for Taxing Ridesourcing Services”. In: *Transportation Research Record* 2674. http://dx.doi.org/10.1177/0361198120927403, pp. 191–201.

Zheng, S et al. [2016]. “Transit development, consumer amenities and home values: Evidence from Beijing’s subway neighborhoods”. In: *Journal of Housing Economics* 33. https://doi.org/10.1016/j.jhe.2016.05.003, pp. 22–33.