

Measuring Place-Based Transit Service Equity in Chicago

by

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Abstract

How to equitably distribute public transit service is a highly topical subject facing transit agencies operating in North America. Recent social movements have reignited the debate around Civil Rights on public transit and resulted in increased scrutiny of transit planning practices. While many agencies are striving to incorporate more progressive equity analyses, these equity assessment methods have several shortcomings. For example, they have not addressed important questions such as how service levels can be meaningfully compared between city areas differing in geospatial characteristics (e.g. residential neighborhoods versus Central Business Districts), and what a sufficient level of transit service should be for an area to be considered equitably served.

The goal of this thesis is to develop a new method for assessing place-based equity on a city-wide level, using Chicago and its transit system, the Chicago Transit Authority, as a case study. This method addresses several gaps in literature and practice, using historical passenger trips closely reflective of true system conditions, to measure the state of transit service. This thesis develops a method for determining what an equitable level of transit service should be while accounting for where an area is situated within the greater city geography.

This method is applied to two datasets from different time periods, September 2019 and October 2022. The two time periods are compared to understand if and how service quality has changed. Two types of analyses are performed on the data, one illustrating the service quality of all trips originating in an area, and the other to specific destinations, highlighting the strengths and weaknesses of the transit system. A quantitative equity score for each area in Chicago is presented, demonstrating a full execution of the method. The method is also applied to a project under proposal, the Red Line Extension, quantifying the projected equity benefits, and demonstrating how the method can be applied in different contexts.

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Contents

- 1 Introduction & Background 15**
 - 1.1 Transportation Equity in the United States 15
 - 1.2 Background 18
 - 1.2.1 A Brief History of Chicago 18
 - 1.2.2 The Chicago Transit Authority 23
 - 1.2.3 The Red Line Extension 25
 - 1.3 Objectives 27
 - 1.4 Thesis Structure 27

- 2 Literature Review 28**
 - 2.1 Equity Analysis 28
 - 2.1.1 Title VI Analysis 28
 - 2.1.2 Progressive Equity Analysis Landscape 29
 - 2.1.3 Mobility Analysis 31
 - 2.1.4 Accessibility Analysis 31
 - 2.1.5 Activity Based Analysis 35
 - 2.2 Automatic Fare Collection and Origin Destination Inference 35
 - 2.3 Transit Metrics 37

3	Creating a New Transit Service Equity Framework in Chicago	39
3.1	Defining Equity Goals	39
3.2	Metric Formulation	40
3.2.1	Measure of Need	41
3.2.2	Method of Measurement	45
3.2.3	Method of Comparison	47
3.2.4	Identifying Equitable Service Metrics	52
3.3	Analysis Types	54
3.3.1	Anywhere Trip Analysis	54
3.3.2	Critical Destination Analysis	54
4	Data Selection and Preparation	56
4.1	ODX Selection and Preparation	56
4.1.1	ODX Missing Information Inference	57
4.1.2	Home Trip Identification	58
4.1.3	Waiting Times	58
4.1.4	Data Set Period Selection	60
4.2	Driving Time Calculations	61
4.3	Metric Preparation	63
4.3.1	Bus Metrics	63
4.3.2	Rail Metrics	63
4.4	Combining and Aggregating Data Sources	64

5	Description of Chicago’s Transit Service Landscape	65
5.1	Anywhere Trip Analysis	66
5.2	Discussion of ATA Results	80
5.2.1	Statistical Significance	80
5.2.2	Discussion of Stationarity Between Periods . . .	81
5.3	Critical Destination Analysis	83
6	Identifying Inequity and Application of Method to the Red Line Extension	99
6.1	Exploring Inequity	99
6.2	Application to the Red Line Extension	107
6.3	Discussion	112
7	Conclusion	115
7.1	Summary of Findings	115
7.2	Discussion of Transit Service Quality Landscape of Chicago Findings	116
7.3	Discussion of Equity Analysis Findings	118
7.4	Contributions	119
7.5	Limitations and Future Work	120
7.5.1	Data Limitations	120
7.5.2	Limitations Regarding Travel Time Ratios . . .	122
7.5.3	Limitations to Equity Scoring	123
7.6	Closing Discussion	123
A	Metric Calculation Glossary	125

B	Composition of Different Need Indices	131
C	Neighborhood Ring Cleaning Process	132
D	The ODX Scaling Process	134
E	Complete List of October 2022 Equity Scores	136

List of Figures

1-1	Racial Demographic Distribution of Chicago	19
1-2	Median Household Income in Chicago	20
1-3	Official Chicago Community Areas	21
1-4	The Regions of Chicago	22
1-5	Chicago “L” Map	23
1-6	Red Line Extension Alignment	26
2-1	Screenshot of ROVE Dashboard	38
3-1	EHI map of Chicago	42
3-2	Sample Equity Need Indexes for Chicago	44
3-3	Population Density Map of Chicago (United States Census Bureau, 2022)	49
3-4	Public Transit Modal Share in Chicago (United States Census Bureau, 2022)	49
3-5	Car Ownership Rates in Chicago (Chicago Metropolitan Agency for Planning, 2014)	50
3-6	Final Set of Rings After Manual Adjustment	51
3-7	Ring 4 Neighborhood Group	51
4-1	ODX Preparation Flow	60

5-1	September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, All Modes	68
5-2	September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Mixed Mode	69
5-3	September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Bus Only	70
5-4	September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Rail Only	71
5-5	October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, All Modes	74
5-6	October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Mixed Mode	75
5-7	October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Bus Only	76
5-8	October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Rail Only	77
5-9	Percent Change in Travel Time Ratio September 2019 to October 2022, Anywhere Trip Analysis, Peak Weekday	79
5-10	Travel Time Ratio 95 Percent Confidence Intervals for Anywhere Trip Analysis Travel Time Ratios AM Peak September 2019 and October 2022	80
5-11	Waiting Time Distributions for Bus-Only Trips	82
5-12	Observed Minus Scheduled Frequency for the AM Peak, September 2019 and October 2022	82
5-13	CDA Locations	84
5-14	Loop CDA Analysis, AM Peak, October 2022, All Modes	85

5-15 Loop CDA Analysis, AM Peak, October 2022, Mixed Mode	86
5-16 Loop CDA Analysis, AM Peak, October 2022, Bus Only	87
5-17 Loop CDA Analysis, AM Peak, October 2022, Rail Only	88
5-18 River North CDA Analysis, AM Peak, October 2022, All Modes	89
5-19 River North CDA Analysis, AM Peak, October 2022, Mixed Mode	90
5-20 River North CDA Analysis, AM Peak, October 2022, Bus Only	91
5-21 River North CDA Analysis, AM Peak, October 2022, Rail Only	92
5-22 IMD CDA Analysis, AM Peak, October 2022, All Modes	93
5-23 IMD CDA Analysis, AM Peak, October 2022, Mixed Mode	94
5-24 IMD CDA Analysis, AM Peak, October 2022, Bus Only	95
5-25 IMD CDA Analysis, AM Peak, October 2022, Rail Only	96
6-1 Equity Score, October 2022	100
6-2 Underserved and Adequately Served Neighborhoods . .	103
6-3 Supporting Metrics for ATA, All Modes, October 2022	104
6-4 South Side Trips Using Bus to Reach Dan Ryan and 95th	108
6-5 Projected Post-RLE Equity Score and Travel Time Savings to Dan Ryan	110
C-1 Chicago Neighborhoods Intersected with 2km Rings from the CBD with No Manual Adjustment	133

List of Tables

1.1	Annual CTA System Ridership	24
1.2	Tri-Monthly CTA System Ridership	25
2.1	Litman’s Equity Types	30
3.1	Critical Destination Analysis Locations	55
4.1	Scheduled Headway and Associated Passenger Wait Time	59
4.2	September 2019 and October 2022 Data Summary . . .	61
5.1	September 2019 Anywhere Trip Analysis Peak Period Metrics and Observations	67
5.2	October 2022 Anywhere Trip Analysis Weekday Peak Period Metrics and Observations	73
5.3	Critical Destination Analysis Results Summary By Mode and Location, October 2022	97
6.1	Equity Scores of the Top-20 Highest Need Ring- Neighborhood Areas, October 2022	102
6.2	Results of Linear Regression for 2022 AM Peak ATA Analysis	105

6.3	Supporting Metric Values for Top 10 Neediest Areas	106
6.4	RLE Estimated TTR and Equity Scores	111
6.5	Number of Observations of Far South Side Origins Across Datasets in AM Peak	114
B.1	Demographic Weightings of Different Need Indices	131
E.1	Equity Scores, All Ring-Neighborhood Areas, October 2022	136

Chapter 1

Introduction & Background

1.1 Transportation Equity in the United States

Equity has become an increasingly pressing topic in recent years. Particular emphasis has been placed on ensuring equity within public institutions, with public transit receiving much attention in this regard. Equitable mobility outcomes on public transit are paramount as they critically contribute to equity across other dimensions, from employment to healthcare, and education (Palm and Farber, 2020; Smart and Klein, 2020; Syed et al., 2013).

Despite recent enthusiasm for the subject of transit equity, the question of how to ensure equity in transit is not new. Many school children in the United States can recount the story of Rosa Parks, a Black woman, who on a segregated bus refused to give up her seat for a white passenger. Her act ignited a mass bus boycott which eventually resulted in a Supreme Court ruling, and paved the way for the more far reaching 1964 Civil Rights Act. Title VI of the Civil Rights Act states that “[it] prohibits discrimination on the basis of race, color, or national origin

in any program or activity that receives federal funds or other federal financial assistance” (noa, 1964). In 1970, the Department of Transportation (USDOT) issued an effectuation to transit agencies stipulating that they must comply with Title VI of the Civil Rights Act for them to continue receiving federal funds (Federal Transit Administration, 1970). In 1991, the Inter-modal Surface Transportation Efficiency Act (ISTEA) was signed into law, and gave the power to States to reallocate federal highway funds for public transportation and doubled its funding over 6 years (Dilger, 1992). ISTEA also mandated the creation of Metropolitan Planning Organizations (MPOs) in suburban areas with populations over 50,000, granting them the power to allocate these new funds, thus making them liable to the requisites of Title VI. In 1994, President Clinton signed Executive Order 12898 titled “Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations”, which included provisions to ensure MPOs’ compliance (Clinton, 1994). In 1998, the Transportation Equity Act for the 21st Century (TEA-21) was signed after the expiration of ISTEA funding in late 1997 (Federal Transit Administration, 1998). TEA-21 provided new funding for projects and stipulated new processes for the nascent MPOs, further bolstering Executive Order 12898, which obligated them to “[seek] out and [consider] the needs of those traditionally underserved by existing transportation systems, such as low-income and minority households, who may face challenges accessing employment and other services” (Federal Transit Administration, 1993).

Despite these important federal acts, discrimination on transit is still of great concern. Equity analysis beyond the federally required Title VI analysis has decades of history (Fox, 1983; Krumholz and Forester, 1990; Pucher, 1982), with academics and planners alike recognizing since the 1980s that these federal requirements have not sufficiently

addressed the issue of equity on transit. The murder of George Floyd in summer of 2020 ignited public discourse on discrimination, particularly as it pertained to anti-Black racism, driven largely by the Black Lives Matter movement (BLM). Transit’s role in systemic, anti-Black, racial discrimination was given significant attention in the media (Butler, 2020; Grisby, 2020). BLM succeeded in bringing the issue of transit to the attention of the highest federal levels of office. President Biden issued an Executive Order in his first day of office that declared that the Federal Government should consider equity holistically from a racial perspective (Biden, 2021). The USDOT responded to this with its Equity Action Plan which included plans such as “reinvigorating Title VI analysis” and creating a national transportation cost burden measure (US Department of Transportation, 2022a). The passing of the Bipartisan Infrastructure Law presents a unique opportunity and explicit commitment to enabling equity in public transit across the United States (US Department of Transportation, 2022b) with \$91.2 billion available in mandatory transit funding. On a transit agency level, equity commitments are emerging from the ground-up. A recent report by non-profit think-tank TransitCenter titled *Equity in Transit: A Guidebook for Agencies* highlights the different approaches that several transportation agencies are taking to address equity issues, including Los Angeles Metro, Sound Transit in the Seattle Region, and The Massachusetts Bay Transportation Authority in Boston (TransitCenter, 2021a). There is a clear will amongst agencies and society to address these issues, but how exactly to measure equity is still up for debate and intellectual discussion. This thesis aims to provide an antidote to the current shortcomings in existing equity analyses by developing a new method to measure equity addressing those concerns.

1.2 Background

1.2.1 A Brief History of Chicago

Pre-European settlement, Chicago and the surrounding area was inhabited by the Algonquin People, specifically the Mascouten and Miami tribes, and subsequently the Pottawatomie Peoples as of the 1720s. There was limited permanent non-Indigenous settlement until after the War of 1812. In the late 1800s, Chicago became a major trade center, attracting major development and growth.

By the early 1900s Chicago attracted a large immigrant population consisting mostly of Eastern Europeans. Starting in the 1910s, a period known as the Great Migration saw large groups of Black and African American people moving to northern cities, fleeing racism in the Jim Crow era Southern states, an estimated 500,000 of whom settled in Chicago from 1916-1970. While Black people came North looking for a refuge from racial discrimination, they were not able to escape it. Practices including redlining (Hillier, 2003), and racially restrictive covenants (Plotkin, 2001) relegated African Americans to cycles of generational poverty still felt today (Brown et al., 2019). In more recent years, Chicago demographics have continued to evolve. Migration from Latin countries and Asia led to increases in those populations by 30% and 36% respectively from 2000-2010 (Chicago Metropolitan Agency for Planning, 2015). Although greater protections now exist against racist policies, non-white newcomers have still faced discrimination. For example, the Latin/Hispanic community in Chicago also faced segregation on their arrival (Betancur, 1996). Figure 1-1 shows the geographic racial/ethnic composition of Chicago, and Figure 1-2 shows the median income. It is immediately visible that the more white residents, the higher the median income tends to be. This demonstrates the

deep racial and socio-economic divisions that still exist today. Because Chicago has such concentrated areas of wealth and racialized poverty, questions of equity become particularly important. This makes Chicago well suited to transit equity analysis, as it is clear that inequity in the city is an ongoing and serious issue.

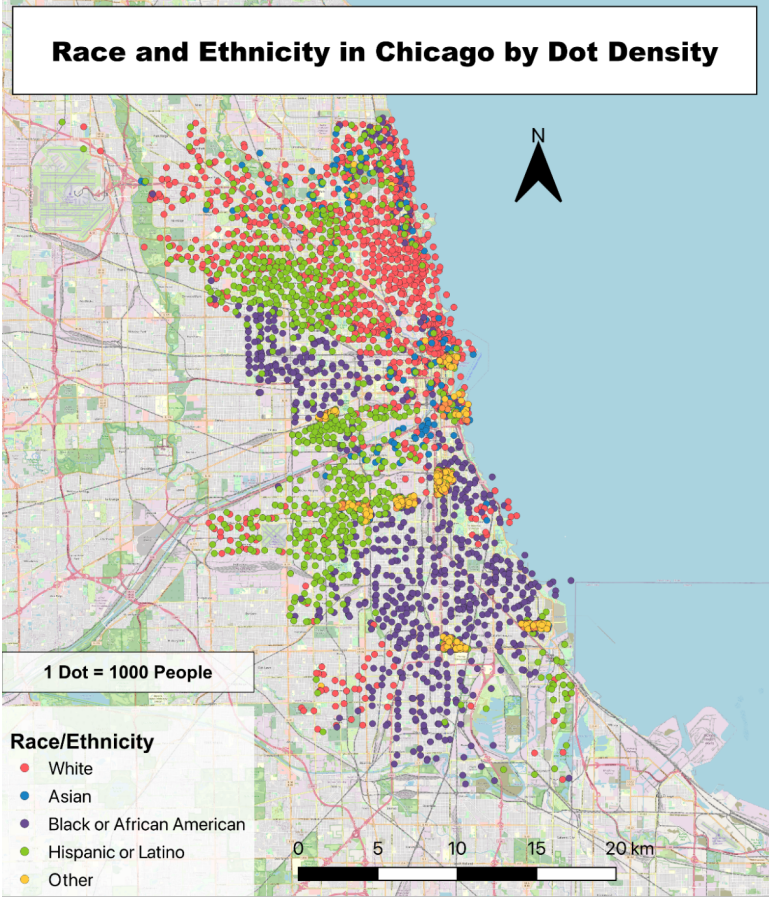


Figure 1-1: Racial Demographic Distribution of Chicago (United States Census Bureau, 2022)

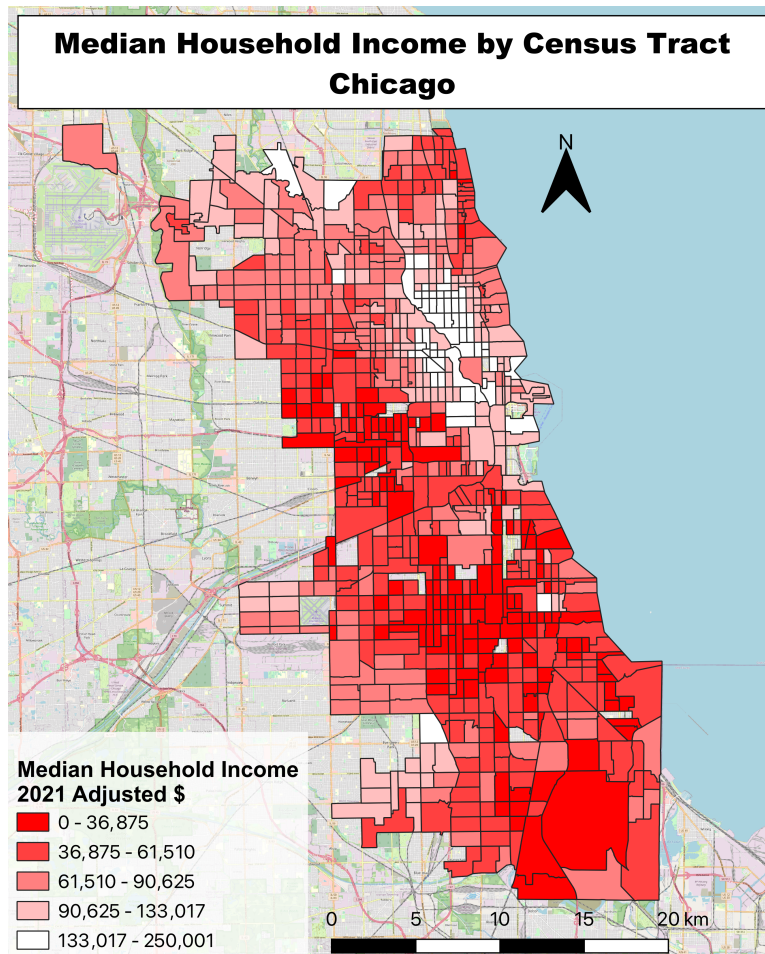


Figure 1-2: Median Household Income in Chicago (United States Census Bureau, 2022)

Today, the geographic areas of Chicago are often characterized in one of two ways. The first is by community area. Community areas in Chicago, referred to henceforth as neighborhoods, are 77 areas of the city that are formally recognized by Chicago’s city government with boundaries that remain static over time (Figure 1-3). The second geographic characterization of Chicago is by “regions”, which are unofficial but widely accepted aggregations of the 77 official community areas to 9 larger areas (Figure 1-4). Although not official, these are widely recognized areas that official entities will acknowledge when speaking about areas of the city, and helpful when discussing the city.

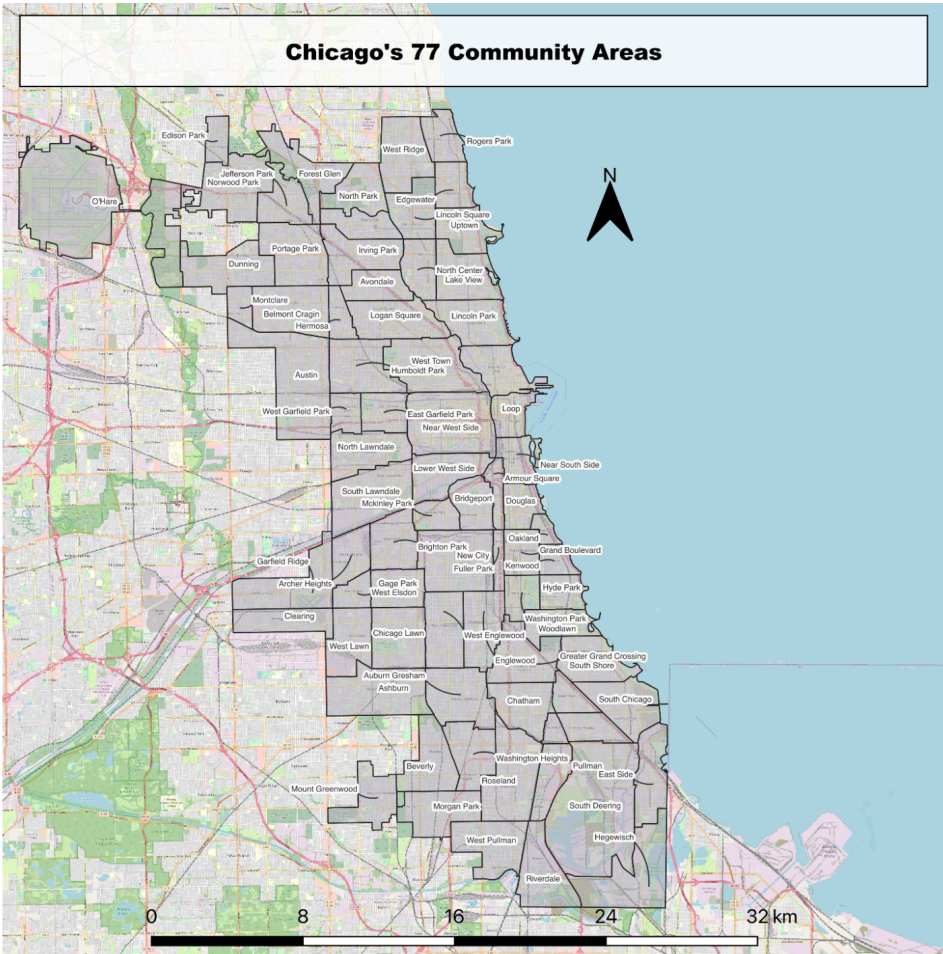


Figure 1-3: Official Chicago Community Areas (City of Chicago, 2018)

1.2.2 The Chicago Transit Authority

The Chicago Transit Authority (CTA) is the second-largest transit agency in North America. Serving Chicago proper and 10 surrounding suburbs, it has a fleet size of 1,864 buses and 1,492 trains (Chicago Transit Authority, 2017), and as of 2021 it provided 774,800 passenger trips per weekday (Chicago Transit Authority, 2022c). The CTA rail system, known as the “L” consists of 145 stations serviced by 8 lines, which can be seen in Figure 1-5.

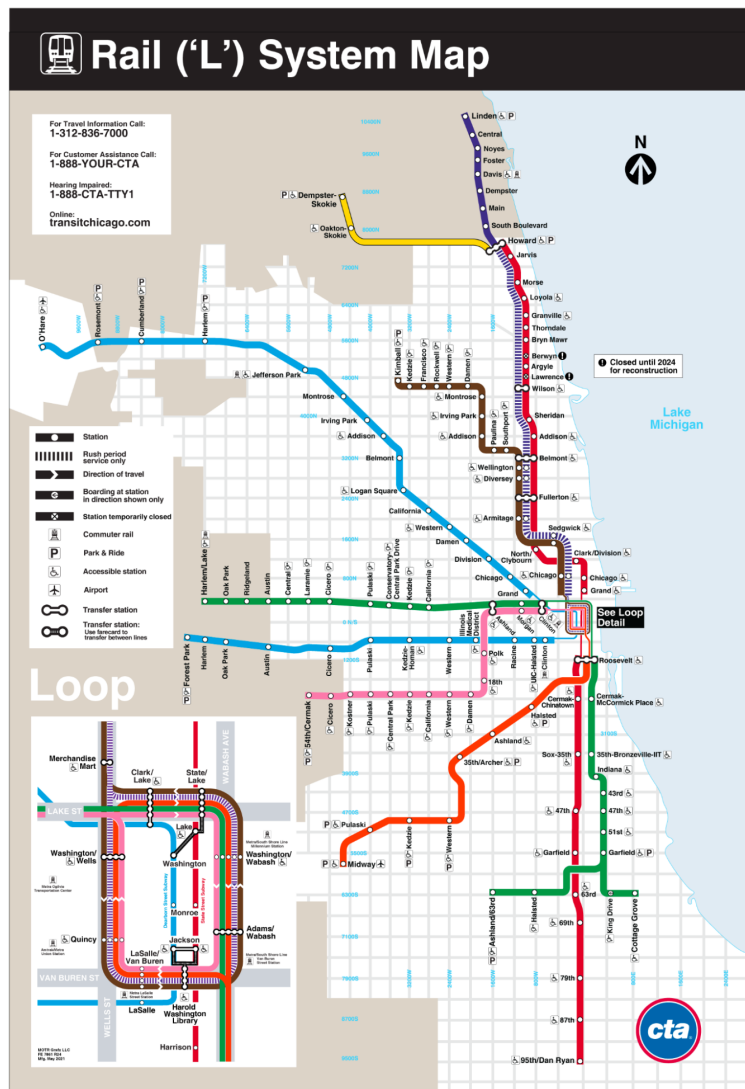


Figure 1-5: Chicago “L” Map (Chicago Transit Authority, 2021)

Prior to March 2020, with the declaration of the Covid-19 pandemic, the CTA saw yearly ridership levels between 545.6-455.7 million between 2012 and 2019 (Table 1.1). After March 2020, the CTA has struggled to recover ridership to pre-pandemic levels, with ridership levels in September 2022 at 57% of what they were in September 2019 1.2.

Table 1.1: Annual CTA System Ridership, (Chicago Transit Authority, 2022c)

Year	System Ridership (millions)
2012	545.6
2013	529.2
2014	514.2
2015	516.0
2016	497.7
2017	479.4
2018	468.1
2019	455.7
2020	197.5
2021	196.0

Emerging from the pandemic, the CTA has grappled with a number of issues. A national transit operator shortage, which affected an estimated with 84% of America’s transit agencies in their ability to provide service, affected the CTA deeply (Foursquare ITP, 2023). For example, in April of 2022, one analysis of the Blue Line (the CTA’s second busiest rail line) found that it was observing only 50% of scheduled arrivals (Greenfield, 2022). In August 2022, the CTA unveiled their “Meeting the Moment” plan, which outlined targeted campaigns to address these issues, with operator hiring being one of the greatest priorities (Chicago Transit Authority, 2022b). At the end of 2022, the CTA had made great progress in some of their goals, such as hiring 420 operators, with a goal of 450, and delivering 85% of bus service, up from 83.1% in September, and 79.5% of rail service, up from 79.3% in September (Chicago Transit Authority, 2022a).

Table 1.2: Tri-Monthly CTA System Ridership (Chicago Transit Authority, 2022c)

System Adjusted Monthly Totals						
	System		Rail		Bus	
	Total	% Change Sept '19	Count	% Change Sept '19	Count	% Change Sept '19
Sep-19	40.5	N/A	19.4	N/A	21.1	N/A
Dec-19	34.8	-14%	16.1	-17%	18.7	-11%
Mar-20	23.2	-43%	9.8	-49%	13.4	-37%
20-Jun	10.2	-75%	2.9	-85%	7.3	-65%
Sep-20	13.1	-68%	4.5	-77%	8.5	-60%
Dec-20	11.0	-73%	3.6	-81%	7.4	-65%
Mar-21	13.5	-67%	4.7	-76%	8.8	-58%
Jun-21	16.5	-59%	6.7	-65%	9.8	-54%
Sep-21	20.9	-48%	8.9	-54%	11.9	-43%
Dec-21	17.3	-57%	7.1	-63%	10.2	-51%
Mar-22	20.2	-50%	8.3	-57%	11.9	-44%
Jun-22	21.3	-48%	9.4	-52%	11.9	-44%
Sep-22	23.3	-43%	10.1	-48%	13.1	-38%

1.2.3 The Red Line Extension

The Red Line Extension (RLE) is a proposed project that would extend the existing Red Line. As proposed it is 5.6-miles long and would add four new stations near 103rd Street, 111th Street, Michigan Avenue, and 130th Street (Chicago Transit Authority). The locations of the stops and track alignment can be seen in Figure 1-6. This extension is highly anticipated. When the Red Line originally opened in 1969, then Mayor Richard Daley promised to extend the Red Line South of Dan Ryan and 95th (its current southern terminus) (Evans, 2022b), but 54 years later it has still not been built. There are strong equity implications for the project. The South East of Chicago also has been the victim of environmental racism (Evans, 2022a), and the area has experienced systemic infrastructure underdevelopment (Sheppard, 2022). There is great hope that the RLE, if successfully funded and built, will help improve not only transportation access, but spur job creation and economic development, benefiting the community.

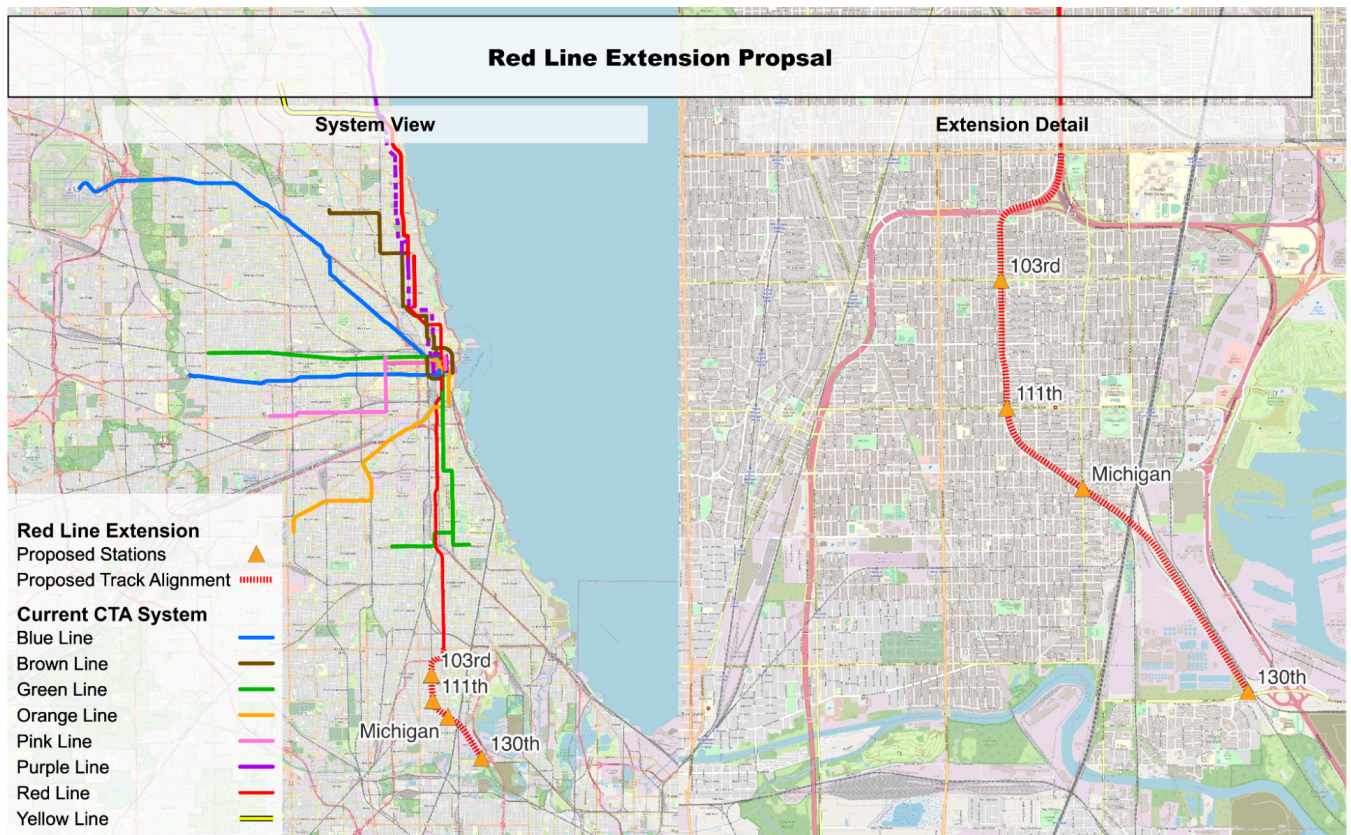


Figure 1-6: Red Line Extension Alignment (Chicago Metropolitan Agency for Planning)

1.3 Objectives

The objectives of this thesis are as follows:

- To develop a method to quantitatively assess transit equity between areas in Chicago
- Use the developed method to determine which areas of Chicago should be prioritized for service improvements
- Identify if and how the equity landscape changed between 2019 and 2022
- Apply the developed equity methodology to assess the equity impacts of the proposed Red Line Extension

1.4 Thesis Structure

The second chapter will review literature pertaining to transit equity metrics, farecard data, and transit service performance evaluation. The third chapter presents the methodology to quantitatively prioritize geographic areas in Chicago for transit service improvements. The fourth chapter will provide details about the data preparation and selection process. The fifth chapter will describe the travel time competitiveness landscape of transit versus auto of Chicago for trips with a range of destinations, characterizing service levels over two time periods. The sixth chapter will present the results of the equity ranking methodology developed in chapter three to make judgments about which neighborhoods should be prioritized for improvements, and provide a preliminary investigation into the possible service quality factors driving these. It will also apply the developed equity methodology to the Red Line Extension, quantifying the estimated equity impacts of the project. The final chapter will summarize findings, identify the key areas of contribution, and discuss limitations and areas for future work.

Chapter 2

Literature Review

2.1 Equity Analysis

2.1.1 Title VI Analysis

There are specific guidelines and stipulations in Title VI for fixed-route transit providers (Federal Transit Administration, 2012). For example, large transit providers (defined as transit providers who operate at least 50 vehicles in peak service, and serve an urban area of at least 200,000 inhabitants) are required to conduct on-board surveys every five years, which must collect certain demographic information (race, gender, English proficiency etc. . .). This demographic information enables additional stipulations aimed at preventing discrimination, including service area maps highlighting where a disproportionate minority population resides in relation to transit service and amenities, and demonstrating that major network redesigns do not overly burden minorities.

As mentioned in the introduction, Title VI analyses are required by federal law. However, they have not prevented the deep inequities that exist in public transit. Title VI is sometimes referred to as the “sleeping giant” of Civil Rights Legislation, as it is far reaching and poten-

tially powerful, but its full potential is not reached (Johnson, 2014). Most Title VI analyses rely on infrequently collected survey data, or use data on populations that live in close proximity to transit service (perpetuating the ecological fallacy, see: (Jargowsky, 2005)), resulting in oversimplified results (TransitCenter, 2021a). For large capital projects, traditional four-step models are often used for planning purposes to forecast future ridership for Title VI analyses, despite those models being increasingly scrutinized for their ability to forecast future passenger behavior (Karner and Niemeier, 2013; Voulgaris, 2019). For these reasons other equity analyses have become favored in literature and in practice.

2.1.2 Progressive Equity Analysis Landscape

Litman’s analysis of equity frameworks demonstrates the great variation in equity definitions and types of analysis. He characterizes them along several distinctions (Litman, 2014). The first is in terms of the type of equity they measure, the main categories of which are horizontal and vertical. Horizontal equity refers to equal treatment, and vertical equity refers to people being treated on the basis of their level of need. Embedded into the horizontal and vertical equity measurements, Litman identifies five other categories; fair share of resources and external costs being horizontal measurements, and inclusivity, affordability, and Social Justice belonging to vertical equity measures. A brief description of each type of equity can be viewed in Table 2.1. The current branch of equity that most agencies are taking interest in is the Social Justice equity measure.

Table 2.1: Litman’s Equity Types (Litman, 2014)

Equity Measure	Equity Type	Description
A fair share of resources	Horizontal	“Get what you pay for and pay for what you get.”
External costs	Horizontal	Minimize costs imposed on other people.
Inclusivity	Vertical	Ensure that transport systems serve everybody. Multimodal planning and Universal design.
Affordability	Vertical	Ensure that everybody can afford basic mobility. Quality of low-price modes. Targeted subsidies.
Social Justice	Vertical	Considers structural injustices

Secondly, Litman divides equity analyses as falling into two categories, mobility and accessibility. Mobility refers to measures such as the total vehicle miles traveled (VMT), journey times, vehicle speeds, etc., while accessibility refers to measuring the number of opportunities a passenger can reach using non-motorized, motorized, and mobility substitute modes. Marten’s 2012 “Justice in transport as justice in accessibility: applying Walzer’s ‘Spheres of Justice’ to the transport sector” (Martens, 2012) and book “Transportation Justice: Designing Fair Transportation Systems” (Martens, 2016) have served as touchstones for the transit equity school of thought. In their earlier work, Martens relates the current transit equity discourse to the justice movement in environmental planning and puts forth a distributive framework for transportation policy, i.e. “how [transportation] benefits and burdens are and should be distributed over members of society”. *Transportation Justice* extends this justice-focused approach, stressing the importance of accessibility analysis, discussed in detail in the forthcoming section.

2.1.3 Mobility Analysis

In his analysis framework discussed in 2.1.2, Litman identified mobility as a commonly calculated type of equity metric. Another commonly calculated type of metrics is a measure of supply (MOS), which we characterize as a mobility metric. MOS tend to look at some quantity of transit (i.e. arrivals (Currie, 2010; Delbosc and Currie, 2011)) and their distribution across a spatial area. While some research has sought to quantify the usefulness of the transit supply in terms of its “connectedness” (Mortazavi and Akbarzadeh, 2017), they mostly show intensity of service, and make no claims about outcomes. Under a MOS definition, a bus that arrives every five minutes to pick up passengers at a station and drives in circles in a parking lot could be hypothetically considered well serviced. In this aspect, they are limited in their usefulness. Additionally, MOS do not account for the realities of spatial distribution. Even with the needs of those residing outside the downtown core, it is not feasible for a suburb to have the same level of transit service as a central business district due to land use patterns.

2.1.4 Accessibility Analysis

Especially in the context of addressing the inadequacies of traditional planning, recent research on transit equity has drawn attention to the importance of service quality and accessibility. Accessibility is defined by Hansen as the “potential of opportunities for interaction” (Hansen, 1959). Accessibility analysis is also sometimes referred to as “freedom” analysis (Walker, 2018). Transit accessibility analyses typically use scheduled General Transit Feed Specification (GTFS) data, which represents the scheduled trips of a transit network, to calculate travel times to a set of destinations such as employment (Allen and Farber, 2019; El-Geneidy et al., 2016), grocery stores ((Farber et al., 2014),

higher education institutions (Ermagun and Tilahun, 2020), and hospitals (Ermagun and Tilahun, 2020).

Accessibility analyses are a powerful tool in assessing a region’s equity landscape, but they have limitations. First is that they are susceptible to inaccurately representing travel times due to real-world conditions. GTFS is usually publicly available, and several high profile accessibility projects have made use of it to calculate accessibility, such as TransitCenter’s Equity dashboard (TransitCenter, 2021b). However, scheduled travel time and realized travel time usually differ. Wessel and Farber used Automatic Vehicle Location (AVL) data, which contains the retrospective movements and actions of buses on a highly granular level, to reconstruct journeys to compare with journey lengths calculated with GTFS (Wessel and Farber, 2019). They found that the AVL calculated journeys, which more accurately reflect the realized transit service, diverged from the GTFS calculated travel times, with areas with lower service levels overall underestimating the experienced travel times. However there is recognition in the literature of these inaccuracies, and methods have been developed to include unreliability in accessibility analyses (Arbex and Cunha, 2020; Bills and Carrel, 2021).

Even when using AVL data or incorporating unreliability in measuring travel times, these calculations are usually performed under the assumption that users will always take the shortest path to reach that opportunity. However, passengers do not always choose to take the transit option that is shortest in time. Berggren et al. used automatic fare collection (AFC) data to reveal that passengers’ route choice on public transit is highly sensitive to service reliability (Berggren et al., 2022). Li et al. compared three travel times for the same origin destination (OD) pairs, calculated using the shortest path with GTFS and AVL data, and using the “real” path reflected in the AFC data (Li

et al., 2021). They found that the respective options were respectively progressively longer in duration, with the AFC-measured trips having higher variability. These examples illustrate that assuming a passenger takes the shortest available path on transit risks underestimating travel times between ODs.

Another limitation with accessibility analysis is that choosing what kind of opportunity to measure introduces a level of bias. Job accessibility is possibly the most commonly calculated accessibility metric in the literature and practice. In contrast, according to the 2017 American Public Transit Association “Who Rides Public Transportation” report, more than 50% of all trips made are for non-work purposes (CJI Research Corporation and Clark, 2017). Through making employment accessibility the de-facto equity standard, populations who use the system for non-commuting purposes (or in addition to commuting) risk being overlooked. Karner makes the similar critique that “accessibility is an imprecise measure [of transit] because it is not linked to the trips that people want or need to make” (Karner, 2022) Furthermore, there is no true “bundle” or weighting of opportunities that represents perfect accessibility for all. Presenting a unified final score to different destinations is difficult for this reason, and when performed, the types of destinations included and the thresholds to be deemed “sufficient” make accessibility scores vary widely (Klumpenhauer et al., 2021; van der Veen et al., 2020). Moreover, there are some critical opportunities and destinations that are almost impossible to measure. For example, access to seeing family members and friends for socialization purposes is very important for overall well-being (Lamanna et al., 2020), but performing an accessibility analysis of this nature for the general population would be difficult.

One other issue with accessibility analysis is how it views improvements. An increase in an accessibility score indicates better potential opportunities for passengers. If systemic barriers prevent travelers from benefiting from those opportunities (e.g. jobs requiring postsecondary education that people do not have, supermarkets being too expensive for people to shop at), the realized service for that population does not improve, all while the accessibility metric suggests an improvement. In this respect, activity-based analyses are useful, and discussed in the forthcoming section. Finding a minimum acceptable accessibility threshold for different destination types (i.e. how many hospitals or grocery stores in a given travel time threshold is good), also described by Martens as “sufficiency” (Martens, 2016), would be a useful benchmark. The development of these standards, while appearing in the literature, is still emerging. The current leading method for determining a sufficient level of opportunities is based on car accessibility alone (van der Veen et al., 2020). For example, one hospital reachable by car in 45 minutes may not be truly sufficient for a population, but under this definition as long as one hospital is reachable for the population by transit it will be defined as “sufficient”. The TransitCenter Accessibility Dashboard also incorporates some degree of threshold setting for opportunities available (TransitCenter, 2021b). For grocery store accessibility, they show the accessibility of the 3rd closest location, acknowledging that a minimum number of opportunities should be considered in our judgements about transit service quality. However, there appear to not be any appropriate widely acknowledged accessibility benchmarks in literature or practice that could be practically implemented.

2.1.5 Activity Based Analysis

Activity-based, also referred to as behavior-based, analyses are equity analyses that consider the realized travel behavior of passengers. Differing from the forecasts resulting from the traditional four-step model, activity based models can examine the historical behavior, usually by utilizing transit rider or onboard surveys, which transit agencies are legally mandated to conduct every five years. Karner argues that activity-based analysis can help agencies truly understand the benefits of transit investment in a way that accessibility cannot, by comparing the results of surveys before and after changes are implemented (Karner, 2022). Bills et al. describe a method for applying activity-based analysis to equity problems (Bills et al., 2012). Karner further suggests short-range forecasts based on these surveys, calibrating a model based on the before/after survey data, can better reflect true passenger behavior compared to long-range models. However, there are severe limitations to transit rider surveys. Firstly, they are costly to conduct and consequently, tend to be small and infrequently performed. Therefore, the sampling bias inherent in most transit rider surveys has the possibility to significantly affect the results (Douglas, 2009). Secondly, passengers tend to provide an inaccurate travel time when self-reporting the duration of their journeys (Varela et al., 2018). Because of these biases, the accuracy of results obtained with activity-based models are also currently limited.

2.2 Automatic Fare Collection and Origin Destination Inference

Since the 1990s, AFC systems have seen widespread adoption across major transit systems (Pelletier et al., 2011). In addition to creating

a more efficient fare collection system, they also collect useful data to understand passenger behavior. AFC systems differ in their design, and are on an “openness” spectrum (Dumas, 2015). Fully closed AFC systems require users to validate their cards at the beginning and end of their trip (and sometimes in the middle, if transferring), regardless of mode. Such systems are often found in Asia. Semi-closed systems require passengers to validate on entry and sometimes upon exit. Such systems can be found in Washington DC and London England. On rail in these cities, passengers are required to tap out of the system, but on buses passengers must only validate upon entering the system.

Origin Destination Transfer (ODX) is an algorithm that infers destinations and transfers of smartcards in open AFC systems. The foundations of ODX were laid in 2002 when the Metropolitan Transit Authority (MTA) in New York used the findings from travel diary surveys that revealed two key rider tendencies and applied those assumptions to get a system wide daily Origin Destination (OD) flows for rail (Barry et al., 2002). The assumptions were that riders return to the destination station of their previous trip before their next trip, and that riders end their final trip of the day at the station where they made their first trip of the day. This approach was adopted by other agencies with open-fare systems (Zhao et al., 2007), and eventually extended to include bus journeys (Gordon et al., 2013). Most recently, ODX was updated to more accurately reflect passenger behavior using a general disutility mode for path and destination choice, including aspects such as in-vehicle time, waiting time, and the number of legs in a passenger’s journey (Sánchez-Martínez, 2017).

ODX provides highly granular trip information, including the origin and destinations of a passenger, total number and location of transfers, the route or line for each journey leg, and overall travel time duration.

Knowing the individual characteristics of trips is helpful in measuring equity, as discussed in Section 2.1.5. Historically, information about individual characteristics of trips has been collected by conducting on-board surveys, which have limitations such as being collected infrequently (also discussed Section 2.1.5). ODX addresses many of these shortcomings as it can be generated for all trips taken across the entire transit system of every day, all day, of the year, providing a high quality, detailed, representative data. These characteristics of ODX make it ideal to perform a large-scale analysis for a transit system.

2.3 Transit Metrics

AVL data is a rich data source for analysis as it provides highly granular data about bus vehicle movements. AVL is an input to ODX itself, and can be used to calculate a large range of metrics helpful to agency's performance management (Kittelston & Associates et al., 2003). ODX and Automatic Passenger Count (APC) data enable even more metrics to be calculated. However, these different data sources are often disparate in their raw forms, and performing complex data calculations from raw sources is challenging for most transit agencies. To make this data readily available for transit agencies, a tool known as the Ridership and Operations Visualization Engine (ROVE) was developed.

ROVE combines AVL, GTFS, ODX, and APC information to calculate 24 metrics, both on the operational and passenger level (Caros et al., 2023). A full list of the metrics it generates can be found in Appendix A. ROVE outputs these 24 metrics into a highly usable format, providing metrics calculated for a month on five time-of-day periods, (corresponding peak and off-peak periods for transit, e.g. AM Peak is 6-10AM) on an interactive, highly visual platform. Figure 2-1 shows a screenshot



Figure 2-1: Screenshot of ROVE Dashboard

of the ROVE dashboard displaying scheduled frequency metrics. It is able to prepare and filter the results of most metrics on the route, stop, or time-point level, making it a granular and rich datasource readily available for analysis.

Chapter 3

Creating a New Transit Service Equity Framework in Chicago

3.1 Defining Equity Goals

In March 2021 TransitCenter, a non-profit think tank dedicated to transit issues, released their report, *Equity in Practice: A Guidebook for Transit Agencies*. This report outlines five equity pillars that transit agencies should adopt to "optimize their service to help people who have been marginalized thrive" (TransitCenter, 2021a). Their fourth pillar is to "measure equitable outcomes for people and the neighborhoods where they live and work. Track outcomes of the transportation system for people who depend on transit and people facing marginalization wherever they live in the region as well as for neighborhoods with a high concentration of residents who depend on transit or who face marginalization" This pillar is ultimately a call to develop transit-service equity metrics.

Many definitions of equity exist. The TransitCenter report references the Urban Sustainability Directors Network report, titled *Equity in Sustainability*, where six types of equity are identified. The definition

that TransitCenter adopted for their fourth pillar is "distributional equity". Distributional equity is defined as "programs and policies result in fair distribution of benefits and burdens across all segments of a community, prioritizing those with highest need" (Park, 2014). In this context, transit service is the burden and benefit levied on populations and geographic areas.

TransitCenter further advises that two sub-types of metrics be developed, the first is "place or neighborhood-focused" measures, which is defined as "how the benefits and harms of transportation accrue to areas". The second type is "person-focused" measures, defined as "how benefits and harms of transportation accrue to people of certain identities, aggregating across residential locations". The primary goal of this thesis is to heed the call of Transit Center's fourth pillar and develop measurements that show the equity of the transit system.

3.2 Metric Formulation

As discussed in Chapter 2, the three major drawbacks to current equity analyses are that 1) potential or anticipated trips are used to measure transit service quality attributes, rather than actual trips, 2) current equity methods do not provide an adequate framework to compare and prioritize areas for increased service beyond socio-demographic indicator, and 3) specific targets for metrics are not routinely set.

To build an equity metric that addresses the three main drawbacks of current equity analysis, three individual components are required. The first is a "measure of need", which is the measure by which we prioritize different areas and populations. The second is a method of measurement, a measure or measures of transit quality that represent the conditions passengers experience, and should be closely reflective

of actual conditions. The final component is a method of comparison, some way to prioritize areas or groups against one another. Combining all three components of the metric, we are able to apply them to an entire city to identify areas that should be prioritized for improvement.

3.2.1 Measure of Need

As discussed in Chapters 1 and 2, Chicago is a city where deep inequalities exist. There are several other possible measures of need that could be applied. However, the spatial distribution of high-need areas tends to remain static despite the measure selected.

A measure of need that is favored by Chicago area organizations is the Economic Hardship Index (EHI) (see: (City of Chicago, 2019,0)). The EHI is an indicator that combines economic information including housing, employment, education, income poverty and dependency to indicate overall levels of need ((United Health Foundation)). Its possible values range from 0 to 100, with a higher score indicating higher need. The median EHI value for a Chicago neighborhood is 46. A map of EHI values for the city of Chicago can be seen in Figure 3-1.

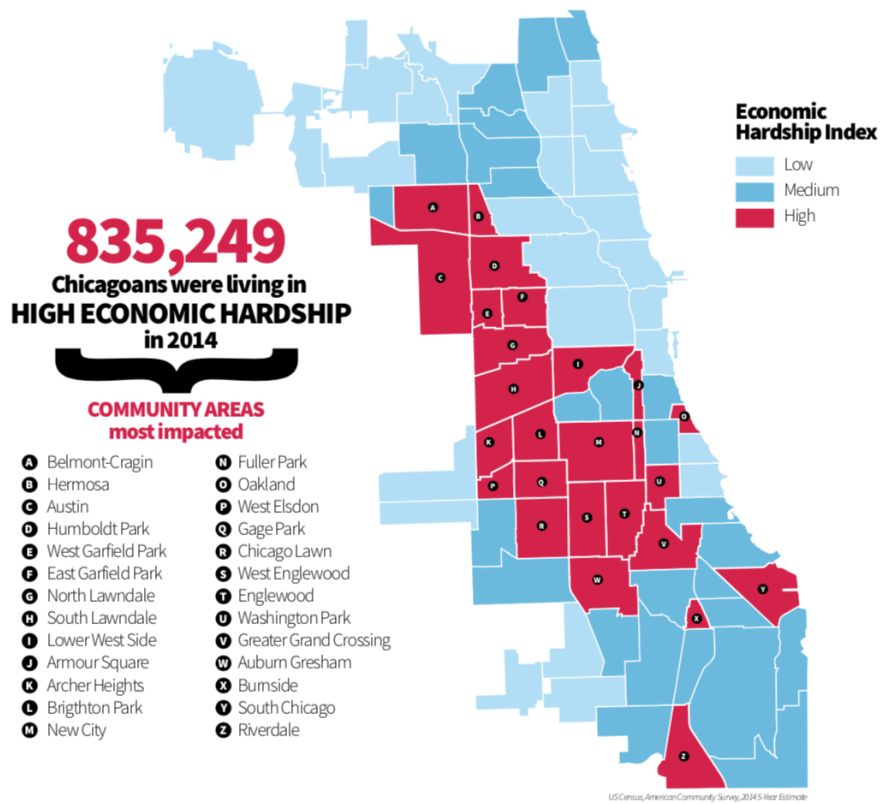


Figure 3-1: EHI map of Chicago

Transit agencies have used many different need indices to identify areas in need. LA Metro in Los Angeles and King County Metro in Washington State use internally developed need indices to measure areas in need, which can be seen applied to Chicago in Figure 3-2. Other need indices exist, such as the index used for federal equity analyses for Title VI analysis. These incorporate demographic information including race, disability, car ownership, etc. . . and weigh attributes differently, differing from the EHI which weighs all 6 indicators equally. Each needs metric's composition and weightings can be found in Appendix B. Figure 3-2 shows a sample of these other metrics alongside EHI. Each score, ranked from 1-5 were calculated based on Jenks natural breaks, with a higher score indicating higher need.

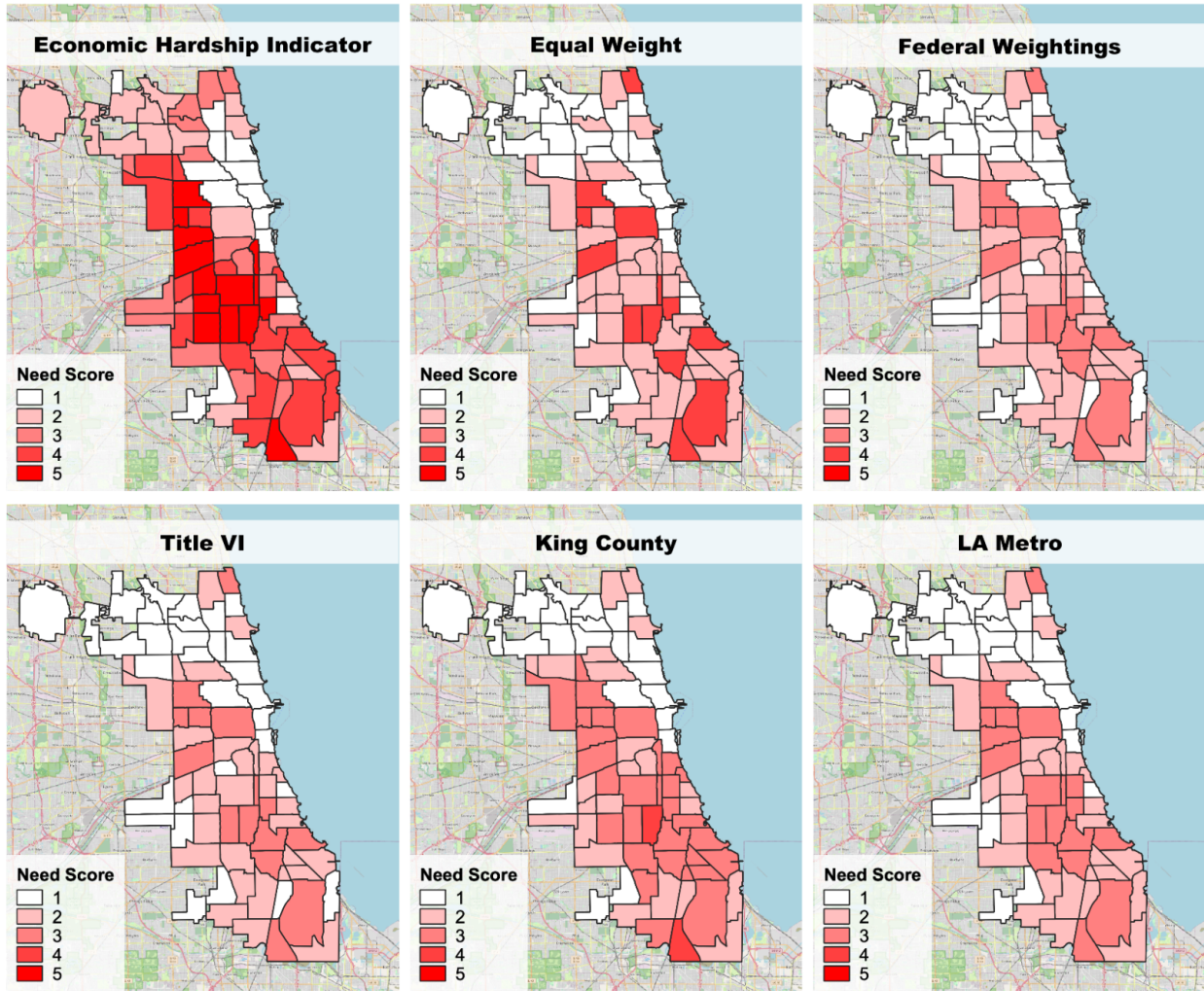


Figure 3-2: Sample Equity Need Indexes for Chicago
(Amanda Madrigal)

It is apparent in Figure 3-2 that there is very little variation in the spatial distribution of need in these maps. The highest need is consistently found in the South and West areas of Chicago. This consistent spatial pattern reveals that the measure of need for Chicago we choose will not meaningfully affect our results. To be consistent with other Chicago agencies, we will use the EHI as our measure of need in our analysis.

3.2.2 Method of Measurement

As discussed in the background, previous accessibility analyses are prone to both underestimating journey times, and not capturing the full range of trips that are made. This necessitates a new method to measure equity that goes beyond the *potential* for opportunity, and begins to look at *realized* opportunity. The proposed solution is to use historical trip data to generate metrics, which we can obtain from ODX. This achieves the desired effect of an activity-based analysis, but with higher quality data than with travel surveys.

Transit service quality metrics fall into two broad categories as described by Redman et al.; physical and perceived. Physical metrics include those measurable without engaging public transit users and include metrics such as reliability and frequency. Perceived metrics require passengers to be engaged and answer questions, and measure aspects such as safety and comfort (Redman et al., 2013). For the scope of this project, we only consider physical metrics for our analysis.

But what physical metrics to use? A 2003 report sponsored by the Federal Transit Administration identified over 400 different performance measures (Kittelsohn & Associates et al., 2003). One challenge with selecting universal metrics for an entire transit system is the difference in relative importance for service-level attributes between different groups.

While different passenger groups (e.g. frequent versus infrequent riders, women, older adults) value certain service attributes differently, there are several service attributes that are highly relevant across groups (Abenzoza et al., 2017; dell’Olio et al., 2010). One of these attributes is the relative journey of public transit versus automobile, also known as the travel time ratio (TTR), which was found to have a greater influence on modal share than transit frequency, with the number of transfers required being an important secondary factor (Lunke et al., 2021). Redman et. al’s review paper, which investigated which service quality attributes were most important to passengers and encouraged modal shift towards transit, found that speed was a critical factor in increasing ridership transit modal share, along with frequency and reliability.

Not only is TTR important to the passenger, but it is the only metric that is affected by all others, including them implicitly. Because we include wait times in the transit portion of the TTR for frequently served routes (≥ 5 scheduled arrivals/hour), we obtain a wait time estimate based on historical frequency data, Equation 3.1. Although transfers may not always cause longer travel times, they are strongly associated with longer and less competitive transit journeys (Krygsman et al., 2004; Lunke et al., 2021), making them similarly implicit in the transit travel time.

$$O(w) = \frac{\mu_H}{2} + \frac{\sigma_H^2}{2\mu_H} \tag{3.1}$$

Where μ_H is the observed headway mean and σ_H is is the observed headway standard deviation.

For our method of measurement, we select TTR as the primary metric for determining equity. Not only is TTR of great importance to passengers, but including a transit journey-time based metric continues

the precedent of emphasizing transit travel times in equity analysis, which accessibility analysis and recent activity-based equity analyses currently use. While TTR will receive most emphasis, our analysis will also include frequency, on-time performance, and average number of transfers as secondary metrics. We include them because of their importance to passengers and intrinsic relationship with TTR. By quantifying the secondary metrics' relationship with TTR, and viewing them alongside the TTR, they can help us glean immediate insights into what might be causing less competitive trips, lending themselves to actionable recommendations for service changes to improve equity.

3.2.3 Method of Comparison

A measurement of service quality is not enough to address inequities. To be actionable, there must be an understanding that different areas should receive differing service levels on the basis of their geospatial characteristics, in addition to level of need. For example, it is reasonable to expect that the downtown core of any city should have a higher level of transit service than a majority residential area, even if the residential area is higher need than the downtown core. The crux of progressive equity undertakings is providing differing levels of service depending on need. To address this issue, we add a level of normalization, classifying areas into “peer” neighborhoods that can be compared against each other.

For this equity study, distance from the Central Business District (CBD) was selected as the method of normalization. This was selected because residential density, transit mode share, and car ownership rates all tend to follow a radial pattern Figures 3-3 – 3-5, imitating the distance from CBD pattern. Although more nuanced peer groupings could be identified by combining two or more of these factors (the residen-

tial density and car ownership patterns are not perfectly radial) for the scope of this project, we will examine distance from the CBD only. In the future, it is recommended that other levels of normalization be examined.

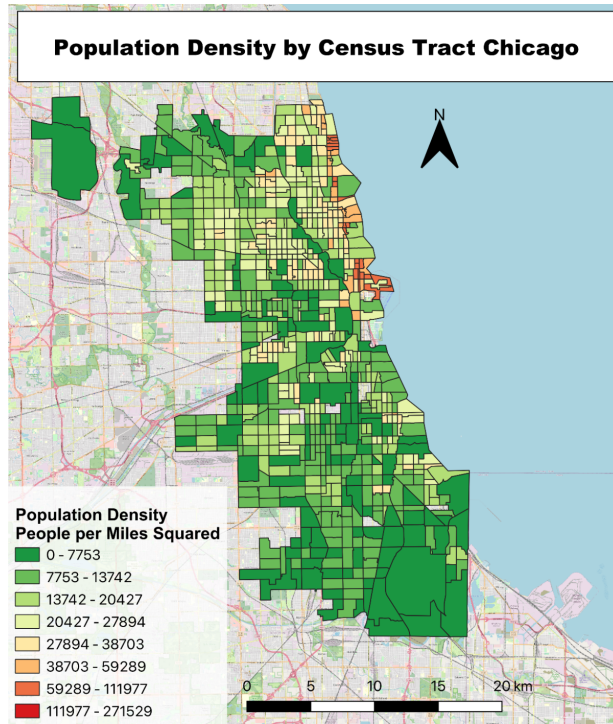


Figure 3-3: Population Density Map of Chicago (United States Census Bureau, 2022)

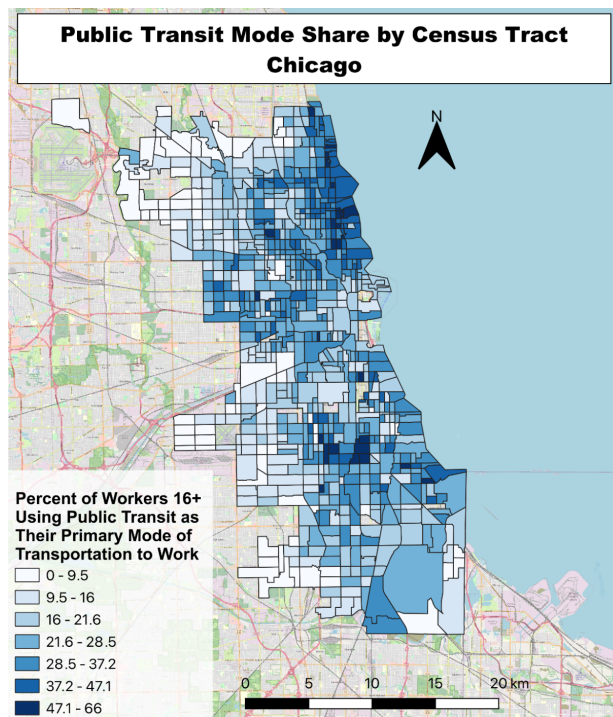


Figure 3-4: Public Transit Modal Share in Chicago (United States Census Bureau, 2022)

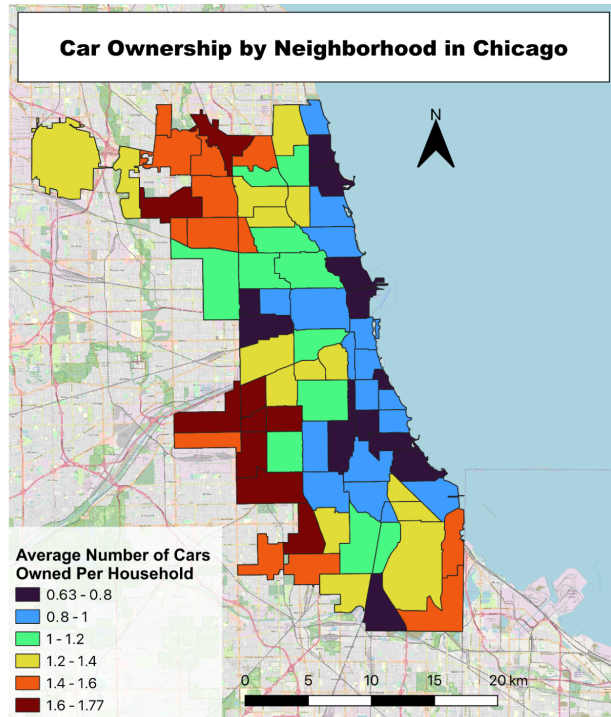


Figure 3-5: Car Ownership Rates in Chicago (Chicago Metropolitan Agency for Planning, 2014)

The final peer neighborhood groupings based on distance from the CBD, also known henceforth as “neighborhood ring areas”, are created by intersecting the 77 Chicago neighborhood areas shown in Figure 3-6 with 2 km wide concentric rings originating in the centroid of the Loop, 220 S Michigan Ave (which is located near the intersection of S Michigan Ave and E Jackson Drive). A full description of how peer groupings are generated and manually adjusted can be found in Appendix C. The process results in 174 neighborhood ring areas, with an example of a single ring shown in Figure 3-7.

3.2.4 Identifying Equitable Service Metrics

After spatial peer groupings are defined, then metrics for each ring-neighborhood area within the same ring can be compared. However, we have not yet defined what an equitable level of service should be for ring-neighborhood areas, which we require in order to make judgements about if they are equitably served. With our method of measurement, we have focused our assessment of the CTA on its performance relative to the automobile due to its relationship with public transit modal share. The goal of transportation is to overcome physical space in an efficient manner. With public transportation, our goal is to facilitate this movement in an efficient manner given the resource constraints imposed by serving a large constituency. But how should we define “sufficiently efficient” to be considered equitably in the context of TTRs?

Echoing the discussion around accessibility benchmarking in Section 2.1.4, developing judgments about ranges of acceptable TTR addresses the question of how efficient they should be. Revisiting the work of Lunke et. al, transit modal shares between 20-30% require TTRs of at most 1.5, and at most 1 transfer. Modal share at higher TTR values was highly dependent on the number of transfers required alongside other factors. TTRs of 2 were associated with modal shares between 15-20%, and around 4 scheduled arrivals per hour (Lunke et al., 2021)). The vast majority of the CTA network serves stops with a frequency of 4 or more scheduled arrivals per hour. With these pieces of information, we make two qualitative judgments; for each ring, we define a target TTR range. The lower bound of this range is the lowest observed TTR of the neighborhood areas in the ring, but not less than 1.5. The upper bound of this range is the highest observed TTR of the areas in the ring, but not more than 2.0. The added constraints reflect our normative judgment that a TTR of 1.5 is sufficiently competitive,

corresponding to transit mode shares of 20-30%, while TTRs above 2.0 reflect unacceptably long journeys.

After establishing acceptable ranges for TTRs for ring sections, the question remains of how to determine what an equitable TTR is for an individual ring-neighborhood area given their EHI. Our equity ethos is that higher need neighborhoods should have higher levels of transit service. Therefore, for an equitable outcome, in each ring, the highest EHI neighborhood-ring should have the lowest TTR. Determining exactly what TTR each neighborhood-ring should have to be considered equitable could take a couple different approaches. The simplest way would be to divide the TTR into equal intervals based on the number of neighborhoods in the ring, and assign each neighborhood, starting from highest EHI, and increasing TTR score incrementing by the interval value. However, this does not take into account that rings may have ring-neighborhood areas with similar EHIs.

A more appropriate method of determining equitable TTRs was to normalize EHI scores between 0 and 1, and then assign TTRs based on the normalized value, also normalized between 0 and 1 for the minimum/maximum TTR for the given ring. This can be seen in Equation 3.2. This is advantageous as it takes into account where there are great or small differences in EHI.

$$ttr_{i,ideal} = (1 - z_i) * ((max(x) - min(x)) + min(x)) \quad (3.2)$$

Where z_i is the normalized EHI value for a ring-neighborhood area i , and x is all the TTR values found in a given ring.

The end result of this process is an “ideal” TTR for each neighborhood-ring area, that can be compared to the observed TTR. By calculating the difference between the ideal TTR and actual TTR, we arrive at a

final equity score, where the greater the negative difference in ideal and observed TTR, the greater the priority should be for increasing service.

3.3 Analysis Types

3.3.1 Anywhere Trip Analysis

As discussed in the background, one of the drawbacks of accessibility analysis is that they cannot fully capture the breadth of trip types riders make. The consequence of this is the service qualities of trips falling outside those narrow categories are excluded from our analysis. By looking at all trips taken originating from a given neighborhood and calculating the associated metrics, it allows us to understand the full picture of service equity for all passenger trips originating in a given area, fulfilling the goal of “place-based” analysis. We christen the analysis in which we look at all trips originating from a ring-neighborhood area "Anywhere Trip Analysis" (ATA)

3.3.2 Critical Destination Analysis

While understanding the overall level of transit service, regardless of destination, is important, understanding service quality to specific locations important to a wide range of travelers can still be valuable. For example, Chicago Loop, the heart of the CBD is not only the location of 339,441 private sector jobs (as of 2018 (Chicago Loop Alliance) but also over 250 cultural assets, major parks, two universities, and the city’s municipal government. Looking at trips to specific destinations, such as the Loop, allows for targeted transit improvements to improve access to populations who may benefit from the range of amenities and opportunities it has to offer. A sample list of destinations similarly ben-

Destination Name	Location
Chicago Loop	Central Chicago
River North	North of Central Chicago
West Loop	West of Loop
O'Hare Airport	North West of Chicago
Midway Airport	Mid-South-West of Chicago
Illinois Medical District	West Side

Table 3.1: Critical Destination Analysis Locations

eficial to study can be found in Table 3.3.2. We refer to the analysis in which we examine trips to a specific destination originating from a ring-neighborhood area "Critical Destination Analysis" (CDA).

The Loop is the first destination we examine for the reasons stated above. Additionally we will look at River North, located directly north of the Loop, which is also a major employment and tourist center with similar destinations to the Loop, but differs in the concentration of transit services. Finally we will examine the Illinois Medical District (IMD). The IMD is a major healthcare center for the entire city (as well as state). Because of the high concentration of medical services, understanding access to this specific destination is helpful because many Chicagoans will likely access it at some point. In addition to medical care, it is also a major employment center covering a range of employment opportunities from high to low wage.

Chapter 4

Data Selection and Preparation

4.1 ODX Selection and Preparation

The ODX algorithm, introduced in Chapter 2 Section 2.2, is an algorithm that infers transit passenger origins, destinations and transfers using farecard data. It is used within transit systems that collect fares at gated stations and ungated stops. The ODX algorithm produces a record of passenger journeys across the transit system. Each record represents one passenger ID for a given service day. Passenger IDs are assigned to Ventra cards (the CTA’s fare card system), allowing passenger behavior to be examined longitudinally. The results of the CTA implementation of the ODX algorithms are referred to simply as “ODX” henceforth.

There are three payment methods for passengers on the CTA. The first is with Ventra, the aforementioned electronic fare payment system used in the city of Chicago and the surrounding suburbs. The second is a paper ticket. Fare gates at rail stations do not accept cash. If a customer does not have a Ventra card, they must either obtain one, or purchase a single-use paper ticket to gain access to the system. The final payment option is cash, which is only accepted on buses. The

ODX algorithm uses passenger journey information from Ventra cards and paper tickets, and estimates journey information about cash trips based on Ventra and paper ticket information.

The ODX algorithm implementation at CTA uses different algorithms to infer information for bus and rail. For bus, ODX is well equipped to handle the common case where bus journeys do not closely adhere to published schedules. A complex but representative calculation is performed within ODX that uses retrospective AVL feeds to find actual times of departures and arrivals of vehicles to account for these schedule deviations. This yields highly accurate travel times between OD pairs that are reflective of the conditions of the system and surrounding environment on any given day. For rail, travel times are calculated differently. Travel times are based on GTFS feeds, under the core assumption that most trains arrive on time. To find travel times, the shortest OD paths between stations in the system are calculated based on published schedules. These are calculated on the hour and half hour mark (i.e., as if a passenger had tapped their card at XX:00 or XX:30 at that station), and represent the entirety of the time spent behind the fare gates, including both in-vehicle and on the boarding platform waiting. These travel times are stored in a look-up table. The ODX algorithm assigns all passenger journeys at rail fare gates to a 30 minute time interval, and based on the inferred destination, assigns the travel time for the given OD stored in the look-up table.

4.1.1 ODX Missing Information Inference

After the ODX algorithm is run, some boarding or alighting stops journeys are unable to be inferred. Additionally, the ODX algorithm does not directly infer information about journeys paid with cash. It also does not have alighting information for journeys paid with paper tick-

ets. A process known as ODX scaling aims to ensure that the total ridership captured by ODX on a given route reflects the ridership estimates given by Automatic Passenger Count (APC) systems, and adds missing information. Scaling accounts for trips made with cash by adding “synthetic” records to the ODX data, creating entries based on the distribution of boarding and alightings for complete trips made with Ventra. Sometimes an ODX record may be missing information, such as an alighting stop. The scaling algorithm once again relies on the distribution of completely specified trips to infer a destination for that trip that is consistent with APC records. More details on the scaling procedure can be found in Appendix C.

4.1.2 Home Trip Identification

Identifying service quality in places where people live is a key component of measuring place based equity according to TransitCenter (TransitCenter, 2021a). It is therefore necessary to use trips that are home-based for analysis, in order to measure transit equity for where residents live. To ascertain if a trip was home-based, a simple method is used; a trip is classified as “home-based” if it was the first trip of the day taken before 2 pm for a given passenger. The 2 pm cutoff is based on passenger segmentation research done by CTA staff which found that non-commuting passengers often take home-based trips later in the day compared to their working peers.

4.1.3 Waiting Times

To rectify the issue with rail trips implicitly including wait time in travel time durations, but not bus, we add the associated wait times to bus trips, making trips consistent in their composition of in and

out-of-vehicle time. For frequently served stops (defined as 5 or more scheduled arrivals per hour), ROVE contains stop-level information about the observed wait time. For frequently served stops we simply add this wait time to the existing trip duration, resulting in a trip record that includes wait time for frequently served bus routes. For infrequently served stops, ROVE does not calculate an observed wait time. However, literature exists that has examined how long passengers arrive before scheduled service. Ingvardson et al. measured passenger arrival times at rail stations with published time tables, and developed an equation for the average wait time based on the headway. For infrequently served stops, we round the scheduled headway for the stop served to the nearest 5 minute mark, and add the associated wait time of that headway to the in vehicle duration for the bus trip.

Table 4.1: Scheduled Headway and Associated Passenger Wait Time, (Ingvardson et al., 2018)

Headway (minutes)	Wait Time (minutes)
10	3.9
15	4.9
20	5.9
25	6.3
30	6.7

A summary flow chart of the steps described in Sections 4.1.1-4.1.3 can be seen in Figure 4-1.

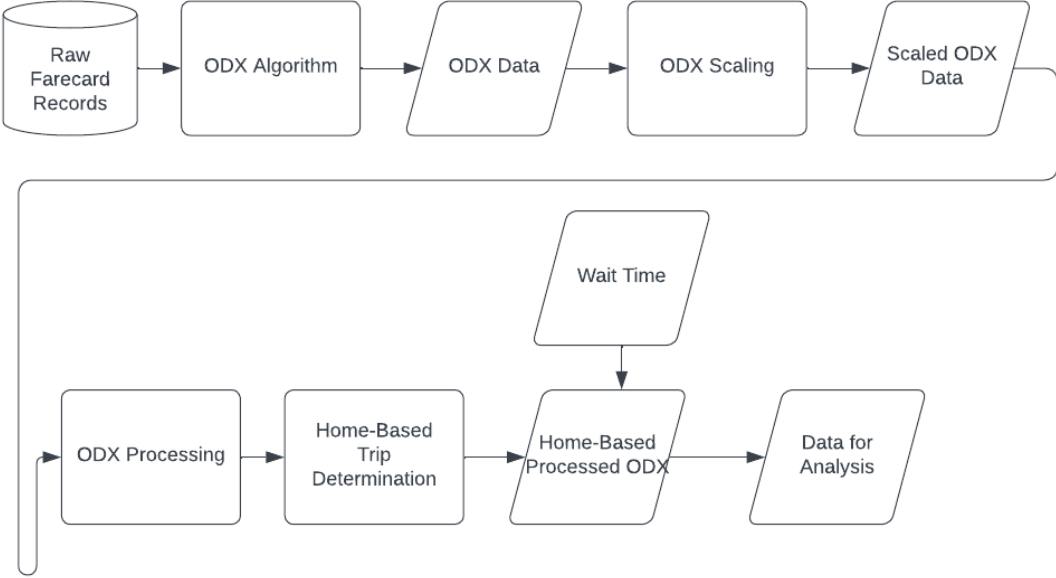


Figure 4-1: ODX Preparation Flow

4.1.4 Data Set Period Selection

One of the main goals of this work is to describe the transit equity landscape of Chicago and determine if and how it changed between September 2019 and October 2022. The September 2019 represents a pre-pandemic scenario and October 2022 represents a post-restriction scenario. Ideally, the month of October should be used for both years to capture the most consistent ridership levels. However, in October 2019 the Chicago Public Schools (CPS) went on a 14 day strike. This made October 2019 an unideal dataset to use as the closure of schools disrupted ridership, and why September 2019 was more appropriate to use. October 2022 was a month in which the CTA experienced several issues, as discussed in Chapter 1. The CTA faced an acute operator

Table 4.2: September 2019 and October 2022 Data Summary, (Chicago Transit Authority, 2022c)

	Total Monthly Valid Scaled ODX Records (Thousands)	Total Valid ODX Journeys (Thousands)	Total Home-Based Journeys (Thousands)	CTA Reported Monthly Unliked Boardings (Thousands)
Sep 2019	36,479	29,771	9,358	40,036
Oct 2022	21,636	16,781	6,785	23,576

shortage, and observed frequency not meeting scheduled frequency for rail and bus. This makes it an interesting time period to examine from an equity perspective, as we will assess the magnitude of these impacts in our analysis. A summary of the 2019 and 2022 datasets can be seen in Table 4.2.

4.2 Driving Time Calculations

In Chapter 3, we established that the ratio between auto and transit travel times should be our primary metric for assessing transit service equality. Representative driving times (i.e. those that reflect traffic conditions, as opposed to simply using free flow speeds) between trip ODs were required to obtain travel time ratios that reflected true conditions. The Google Maps API is a software tool that allows users to make queries to the Google Maps engine and obtain directions and travel times between point coordinates. It uses historical data to give users an estimate of future traffic conditions (Lau, 2020). However, use of the Google Maps API comes with several constraints. The first is that it is only able to calculate travel times for dates in the future. The other is that it is costly and time consuming to run. To address these issues, instead of calculating the driving times for each home-based trip record (i.e. using the latitude and longitude of the origin and egress stop IDs as the OD input, and the time of day of the journey as the

departure time), auto travel times representing an aggregation of trips were calculated.

This was achieved by aggregating journeys both temporally and spatially. Because the home-based trip definition requires trips to be taken before 2 pm on a given day, ODX trips were classified as falling into one of two temporal periods. The first was the peak period, occurring from 5:00:00 to 8:59:59 am, and off-peak, occurring from 9:00:00 am to 13:59:59 pm. The spatial aggregation was based on finding the neighborhood-ring section in which a given stop fell. This was done by spatially joining each stop in the network with the ring neighborhoods with GIS software. A look-up table was constructed, associating each stop id in the network with the ring neighborhood, and then assigning a ring-neighborhood area origin and destination for every ODX record. The transit travel time to auto ratio for a given trip is given by 4.1

$$R(i, j, t, m) = \frac{tr(i, j, t, m)}{A(x(i), y(i))} \quad (4.1)$$

Where i is origin stop, j is the destination stop, tr is the transit travel time using path p connecting i and j at time t using mode m . A is the duration of the auto trip between $x(i)$ and $y(j)$, which are the centroids of the ring-neighborhood areas where i and j lie.

Once each ODX record had been assigned a time period and neighborhood-rings for their origin and destination, a list of the unique time-period, origin neighborhood-ring, and destination neighborhood-ring was found, a representative date and time for each period, and representative coordinates for the origin and destination neighborhood-rings was assigned. For both time periods, September 19th 2023 (a Tuesday) was represented as the departure date, with a departure time of 8am for peak trips, and 12pm for off-peak trips. For the origin and

destination point coordinates, the centroid of each ring-neighborhood area was used. The Google Maps API was then queried for the unique combinations using the representative departure times, and origin and destination locations specified above. For the case of intra-ring travel times, four random points within each ring-neighborhood area were generated using the QGIS random sample function. Driving times between the ring-neighborhood area centroid and the four random points were found and averaged and used to represent the inter-neighborhood-ring driving time for that ring-neighborhood area.

4.3 Metric Preparation

4.3.1 Bus Metrics

As discussed in Chapter 3, ROVE is a bus metric calculation engine used by the CTA. It calculates a range of metrics, including on-time performance and frequency, which we have identified as secondary metrics for equity analysis. ROVE calculates metrics based on a representative Tuesday for a given month. Metrics can be aggregated on the route, timepoint, or stop level, and are provided at the time period level (e.g. am peak), among others. To find the associated observed frequency and on-time performance metrics for journeys that began on bus, a simple lookup table was constructed, linking any given stop id and time period with the median on-time performance and frequency observed at that given stop.

4.3.2 Rail Metrics

For journeys that begin on rail, we do not have ROVE metrics readily available. Calculating rail arrival on-time performance was considered

a low priority and less important as on-time performance for bus, as rail is typically a much more reliable mode. Calculating frequency was straightforward to perform. AVL data for rail is stored separately from the AVL for buses at the CTA, and referred to as SmartTrack data. Observed frequencies are obtained for each period (5am-9am for peak, 9am-3pm for off-peak) by dividing the number of arrivals at a stop obtained from the SmartTrack data divided by the span of service (i.e. active service hours within the time period). These are then stored in a similar fashion to ROVE metrics. A representative Tuesday is used for each month to obtain the observed arrival data.

4.4 Combining and Aggregating Data Sources

After each separate piece of information was gathered (ODX journey records, driving times, bus metrics, and rail mails) they were combined so that each ODX record contains a driving time and the appropriate metrics. Driving times were joined based on period, origin and destination ring-neighborhood area, and metric types were added based on time period, mode, route, and stop id.

After all data was prepared, then the Anywhere Trip Analysis or Critical Destination Analysis was ready to be performed.

Chapter 5

Description of Chicago's Transit Service Landscape

In Chapter 3, we established a method for measuring transit equity using ODX, and in Chapter 4 identified the data periods we wished to compare. While the ultimate goal of our method is to measure equity, one of the other goals of this thesis is to describe the transit service landscape of Chicago. While this is an intermediary step in the equity measurement process, it is a helpful undertaking on its own, as it provides a baseline understanding of service levels in the city.

In addition to ATA and CDA analyses (developed in Chapter 3, Section 3.3), to understand the nuances of transit service, we will disaggregate our trips further by time period and mode. One particularly important reason for disaggregating by mode is that rail is traditionally more competitive than any other mode, as it offers frequent service at high operating speeds. By looking at results by mode we can begin to understand the nuances of service quality and act accordingly when beginning to address potential issues.

5.1 Anywhere Trip Analysis

To begin our ATA analysis, we view the results of the TTR distribution from September 2019 in the peak period (5am-9am). Table 5.1 summarizes the geospatial patterns seen in Figures 5-1 – 5-4. The left map for each mode shows all ratio values, the right shows areas with scores equal 2 or above. This allows us to readily view where transit service is uncompetitive, defined as having a median TTR of 2 or more.

Table 5.1: September 2019 Anywhere Trip Analysis Peak Period Metrics and Observations

Transit Mode(s)	Number of Observations	Median TRR by Ring-Neighborhood Area	Median TRR by Trip	Observations
All	3,945,893	1.93	1.67	Competitive travel times feature most prominently along the Brown, and Red Lines, around the Blue Line ring-neighborhood areas on the O'Hare branch, and around the terminus of the Orange line. Higher TTRs are found across the city, most prominently throughout the South Side, North of the Brown Line terminus, and in areas along the northern portion of the O'Hare Blue Line.
Bus Only	2,186,673	2.03	2.01	Competitive TTRs are not found in any area. High TTRs are found throughout the city, with the exception of some areas between and around the Brown and Blue (O'Hare and Forest Park) lines, and the South-East area near the terminus of the Orange Line.
Mixed Mode	466,080	1.84	1.79	Competitive travel times are few but scattered across the city. High TTRs are most prominent along the Lakeshore South of the CBD, and Far South Side.
Rail Only	1,293,140	1.24	1.15	Competitive travel times are found practically everywhere rail is easily accessible.

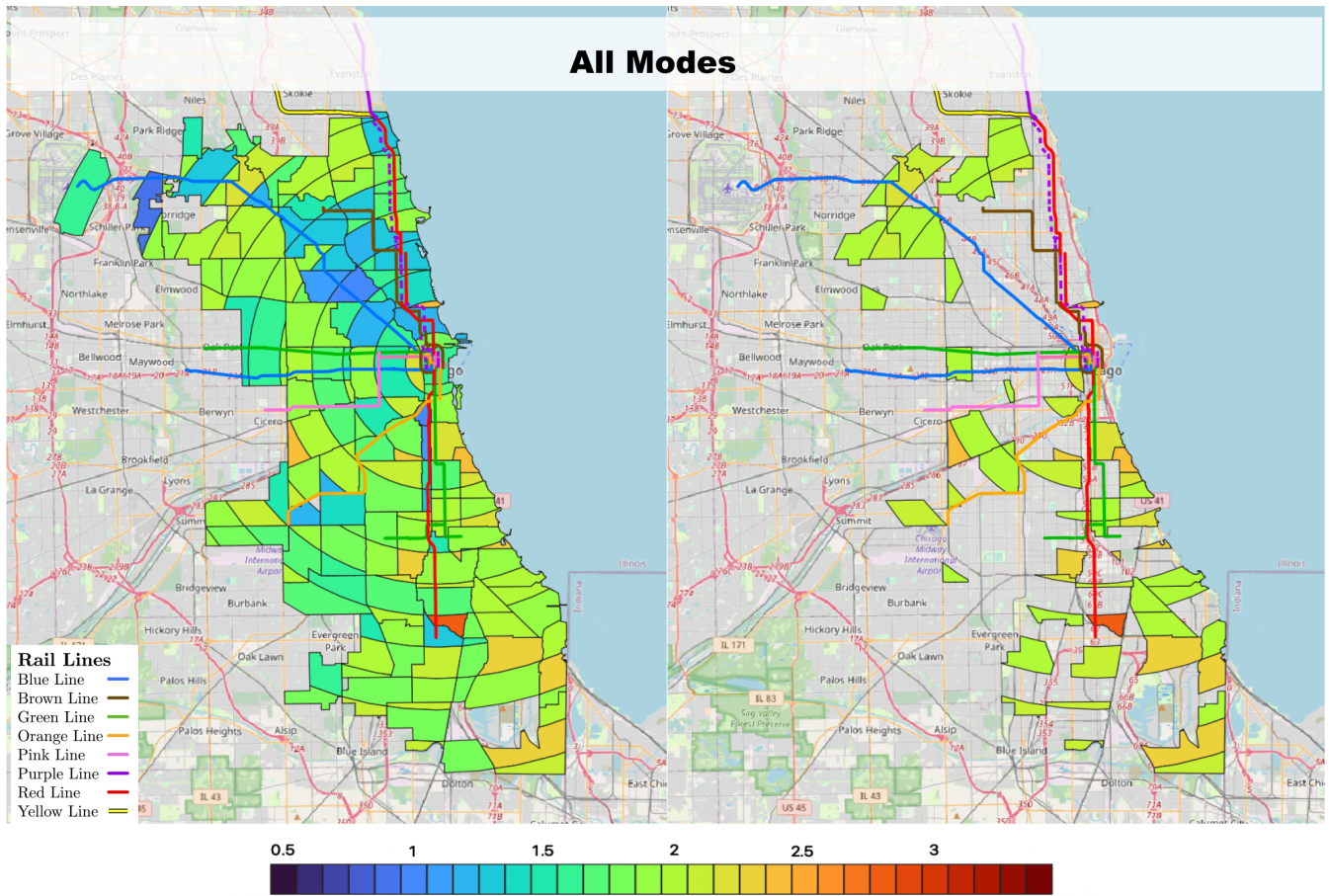


Figure 5-1: September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, All Modes

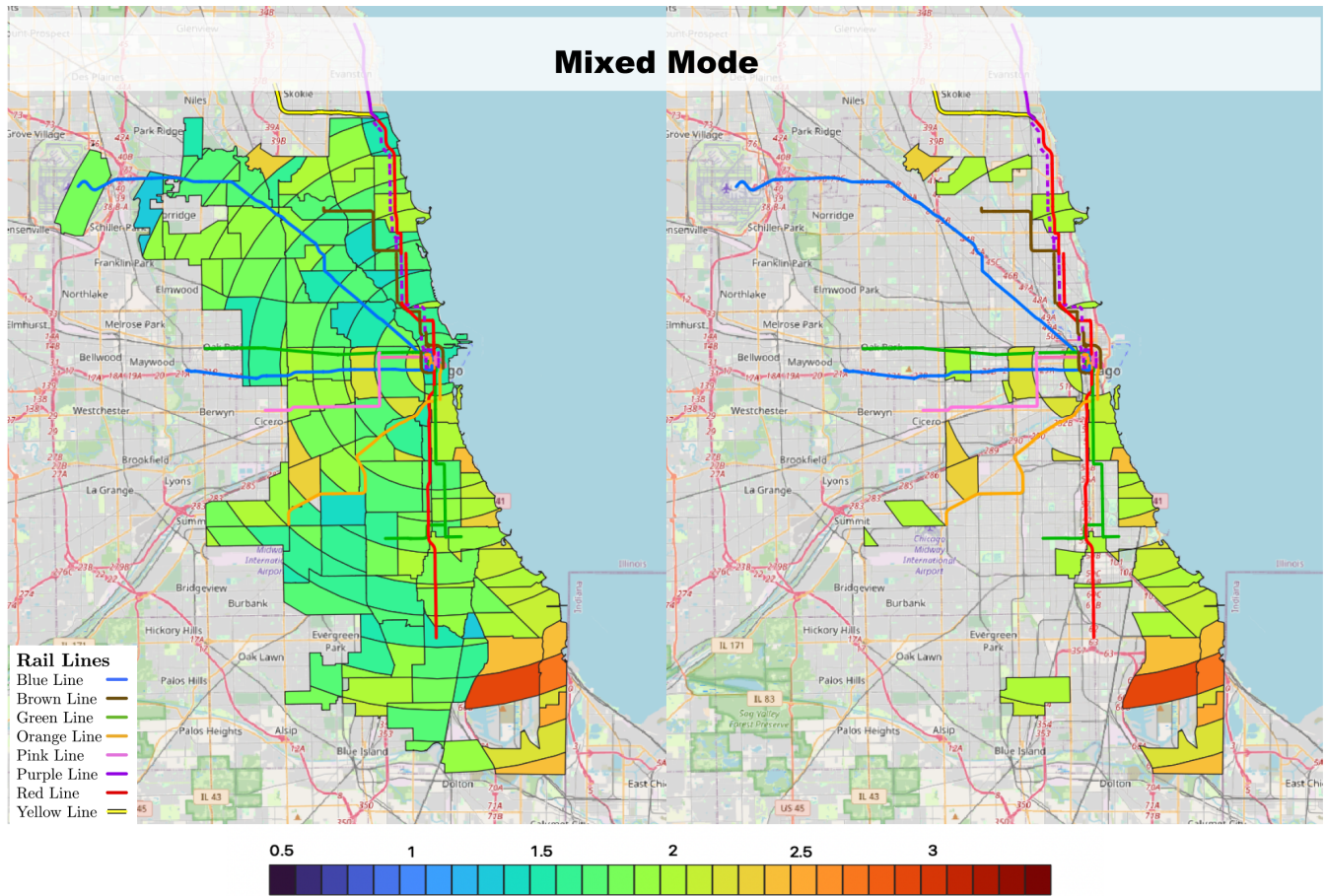


Figure 5-2: September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Mixed Mode

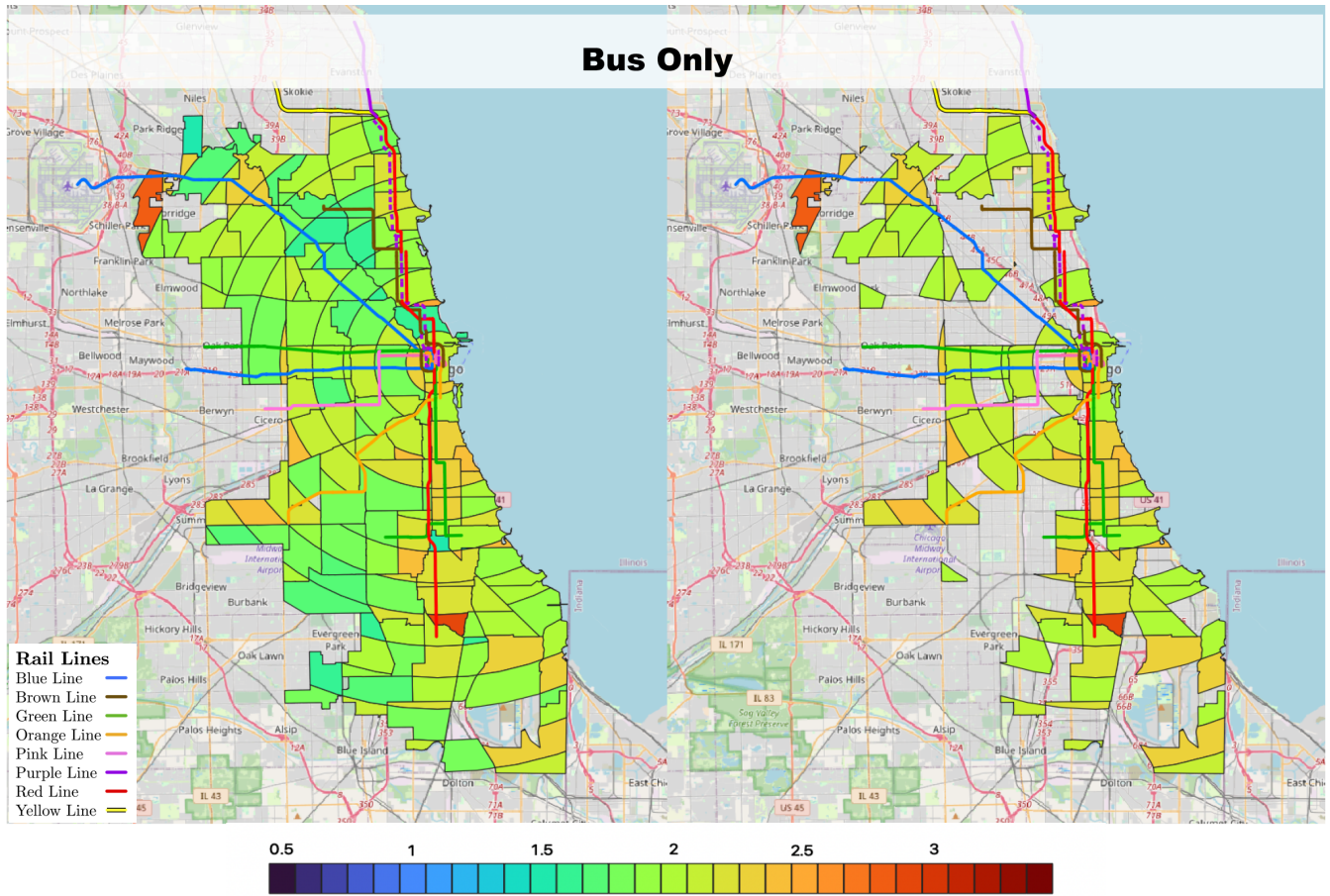


Figure 5-3: September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Bus Only

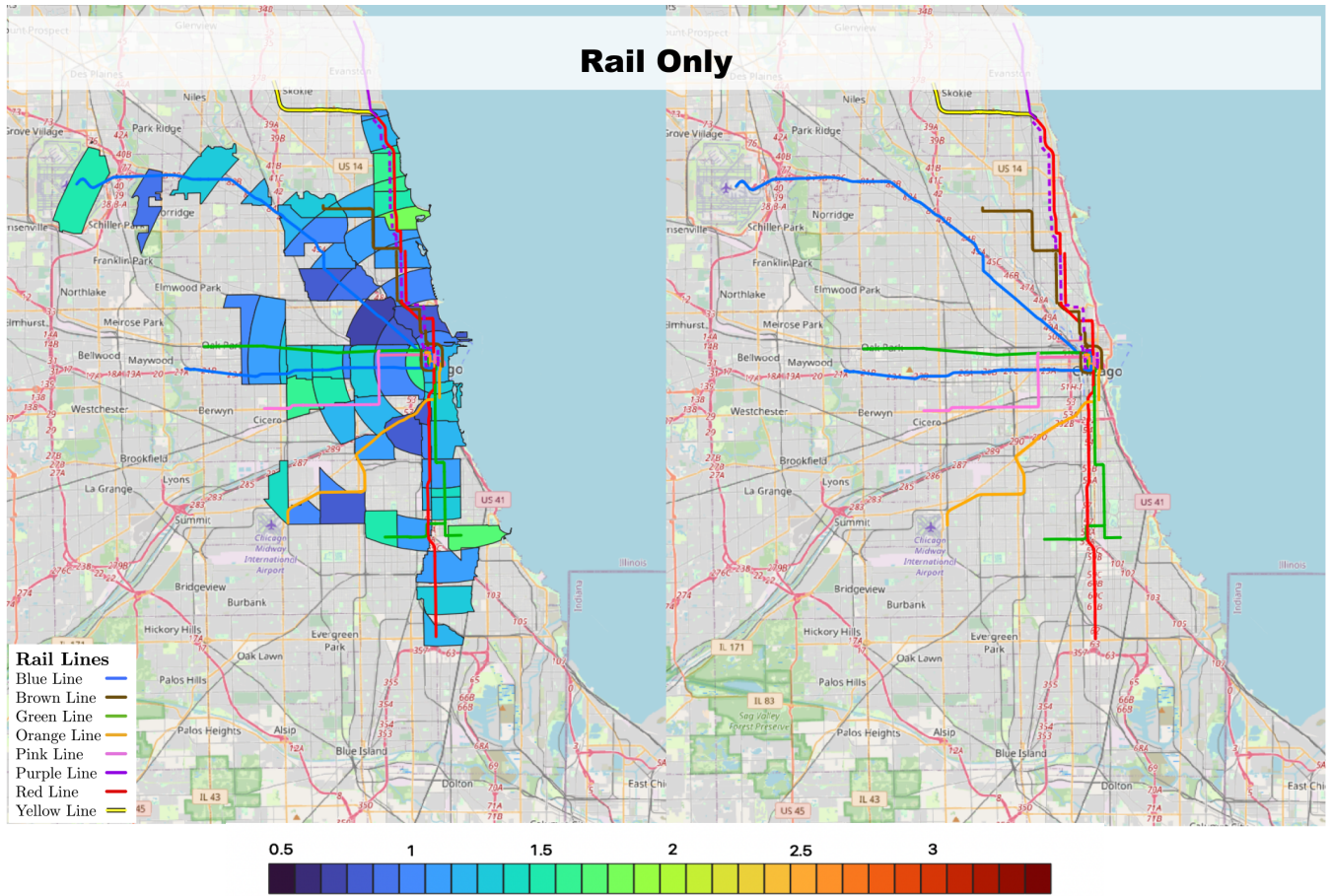


Figure 5-4: September 2019 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Rail Only

Several noteworthy city-wide geospatial trends emerge from the September 2019 ATA analysis. The first is that several clusters of ring-neighborhoods areas appear to have uncompetitive TTRs across modes. The Far South-Side and South Side along the lakeshore consistently have high TTRs. The ring-neighborhood areas along the Orange line also emerge as a grouping that shows high TTR values across modes. The second trend is that bus service is less competitive than other modes city-wide, with most trips being uncompetitive with car travel (i.e., TTR is over 2).

For our second ATA analysis, we view the results for October 2022. Table 5.2 summarizes the observations from Figures 5-5 – 5-8

Table 5.2: October 2022 Anywhere Trip Analysis Weekday Peak Period Metrics and Observations

Transit Mode(s)	Number of Observations	Median TRR by Ring-Neighborhood Area	Median TRR by Trip	Observations
All	2,024,836	1.85	1.71	Competitive travel times along the O’Hare branch of the Blue Line, along the Brown/Red Lines, near the terminus of the Orange line, and scattered along the Far South Side. Uncompetitive travel times are seen on the South Side near the Lakeshore and Green and Red Lines, and in the Far South Side.
Bus	1,275,100	1.95	1.80	Competitive travel times are not prevalent. Uncompetitive trips are found throughout the city, and are most prominent on the O’Hare Branch, in the downtown core, around and between the Pink and Orange Lines, and throughout the South Side.
Mixed Mode (Bus and Rail)	194,683	1.85	1.80	Competitive travel times are not prevalent. Uncompetitive travel times are seen scattered north of the Brown Line, along the O’Hare branch of the Blue Line, and near the terminus of the Orange Line. Uncompetitive travel times feature prominently along the Southern Lakeshore and the Far South Side.
Rail Only	555,053	1.23	1.16	Competitive travel times are found almost everywhere rail is accessible.

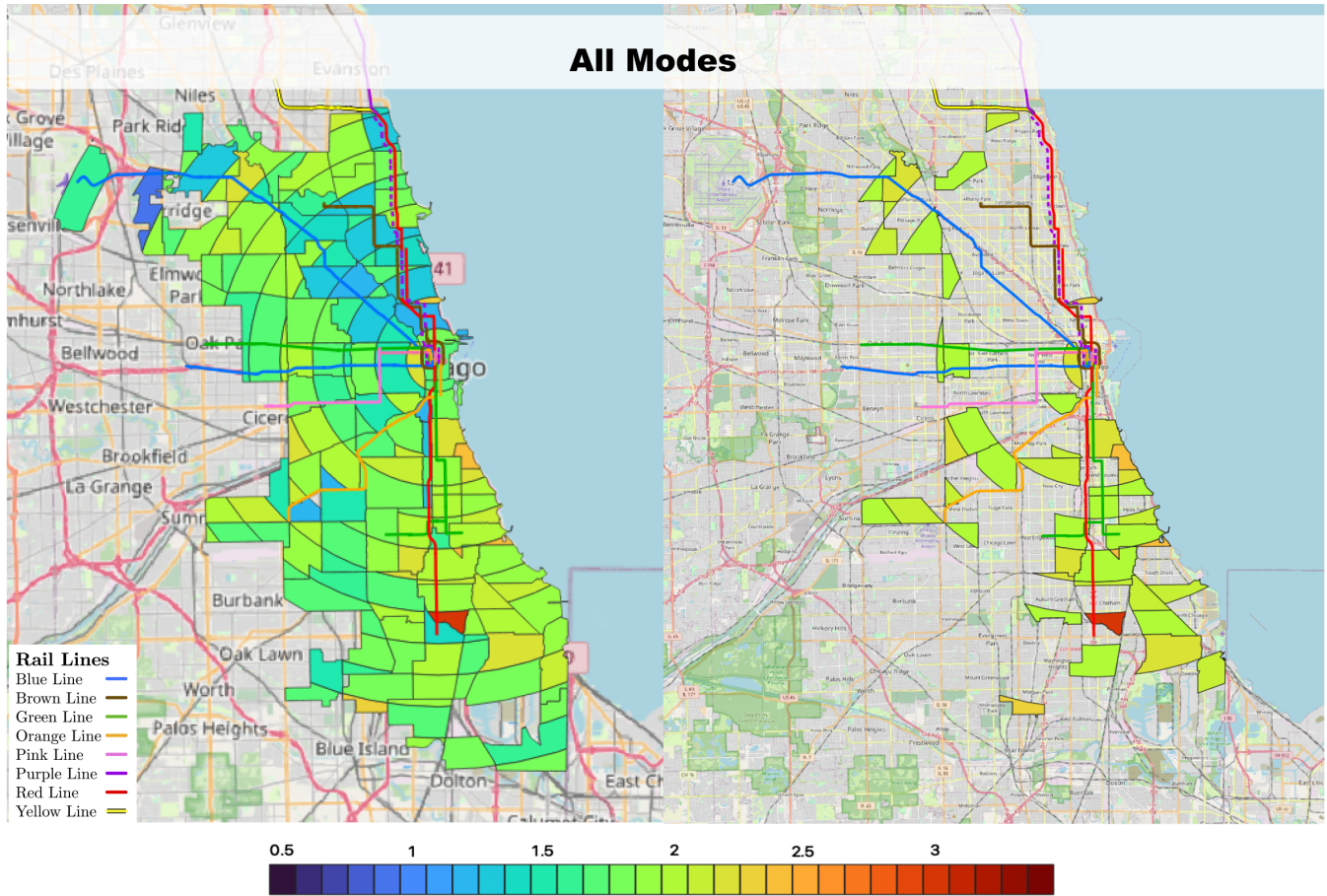


Figure 5-5: October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, All Modes

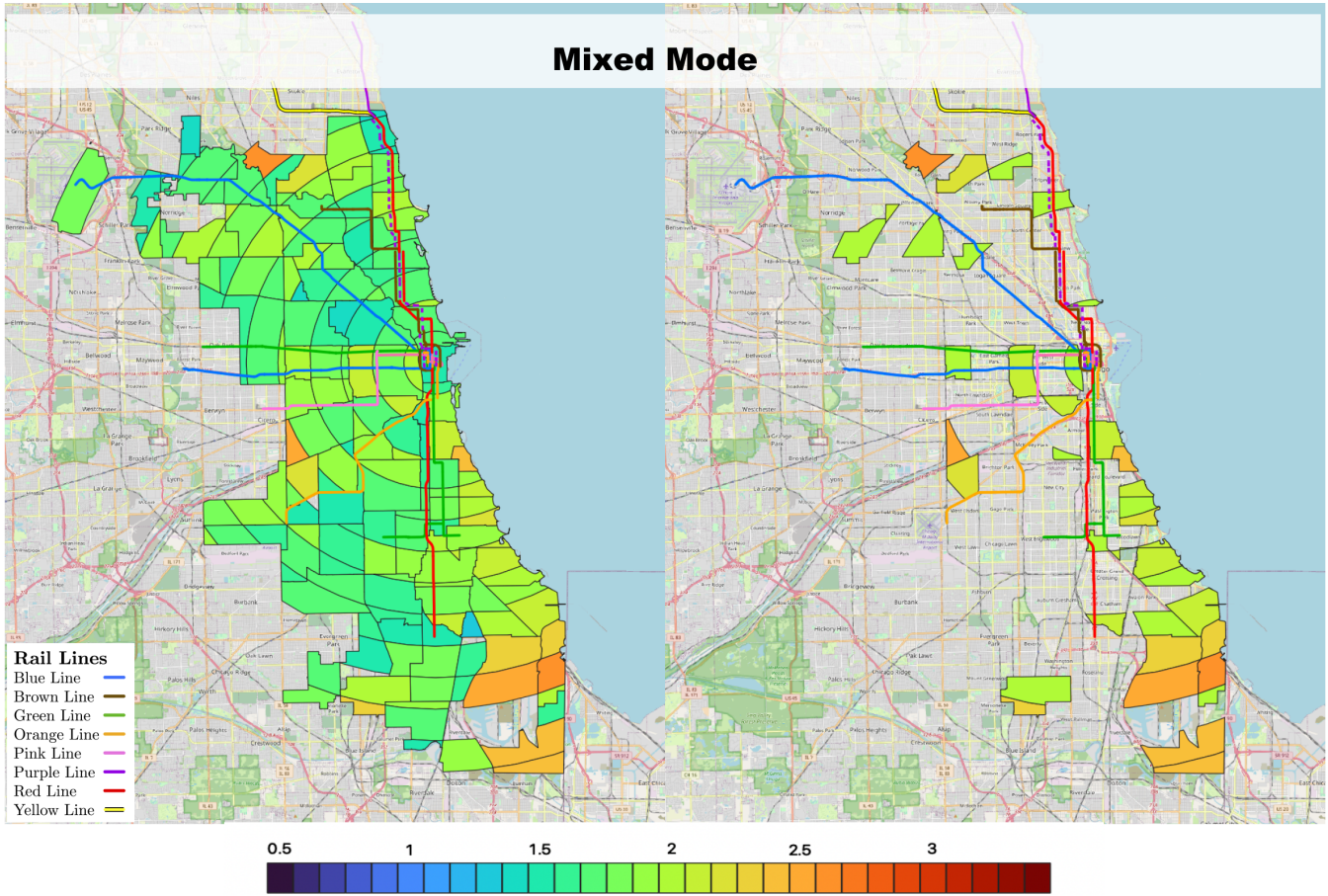


Figure 5-6: October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Mixed Mode

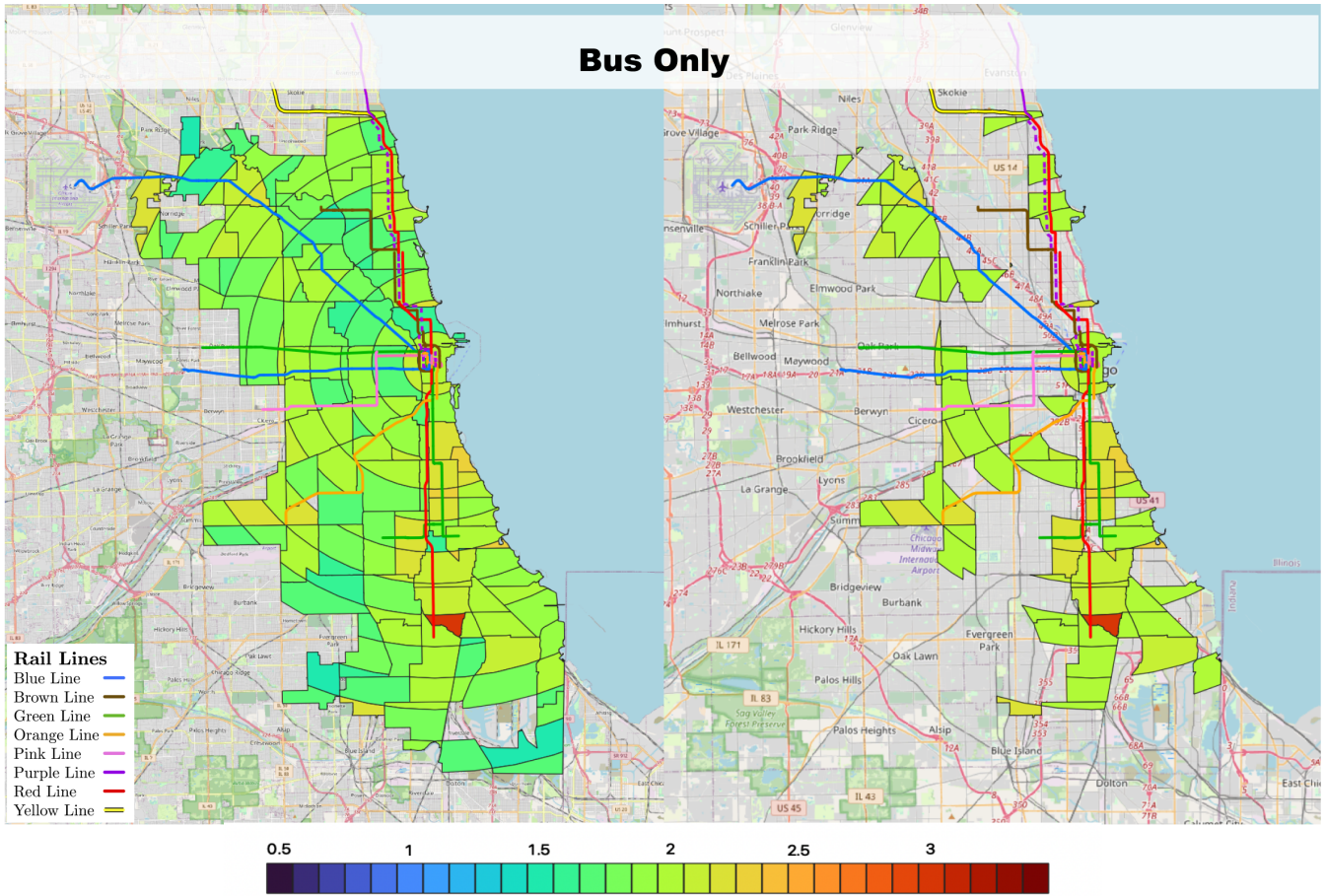


Figure 5-7: October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Bus Only

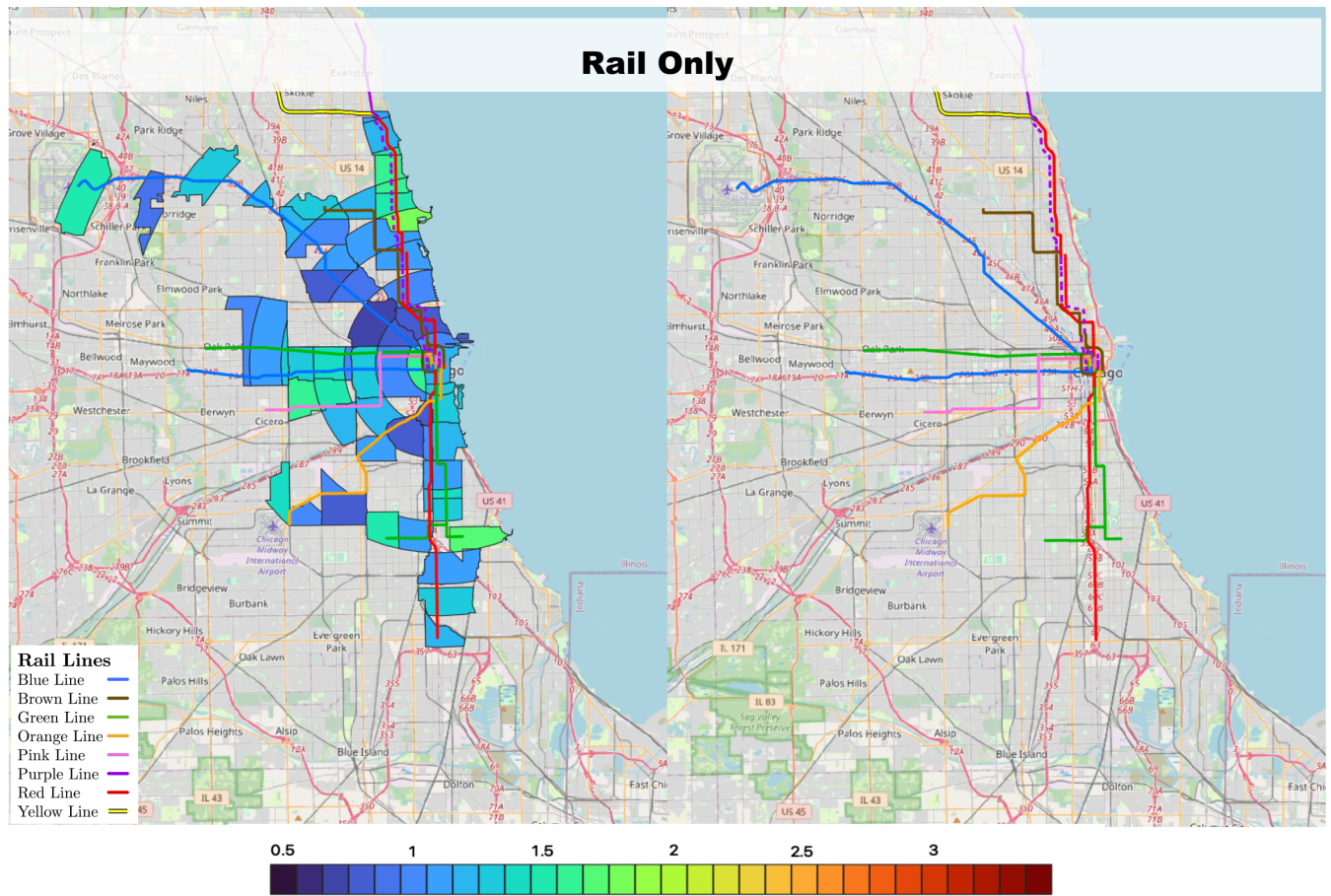


Figure 5-8: October 2022 Peak Weekday Anywhere Trip Analysis of Chicago Transit to Auto Travel Time Ratio, Rail Only

The geospatial patterns that are most prevalent in the October 2022 set are similar to the patterns seen in the September 2019 analysis. Near the terminus of the Orange Line, the far South-Side, and the South Side, particularly along the lakeshore, emerge as three major areas that appear consistently and prominently throughout the different TTR analyses.

Comparing the 2019 and 2022 time periods, it becomes apparent that they do not vary greatly in their overall distributions and TTR. Calculating the percent change in TTR from 2019 and 2022, we can observe that the vast majority (82.7%) of the ring-neighborhood areas see their TTRs change by under 5%. There are some exceptions to this, such as along the O'Hare branch of the Blue Line, which experiences a TTR increase over 15%, Figure 5-9.

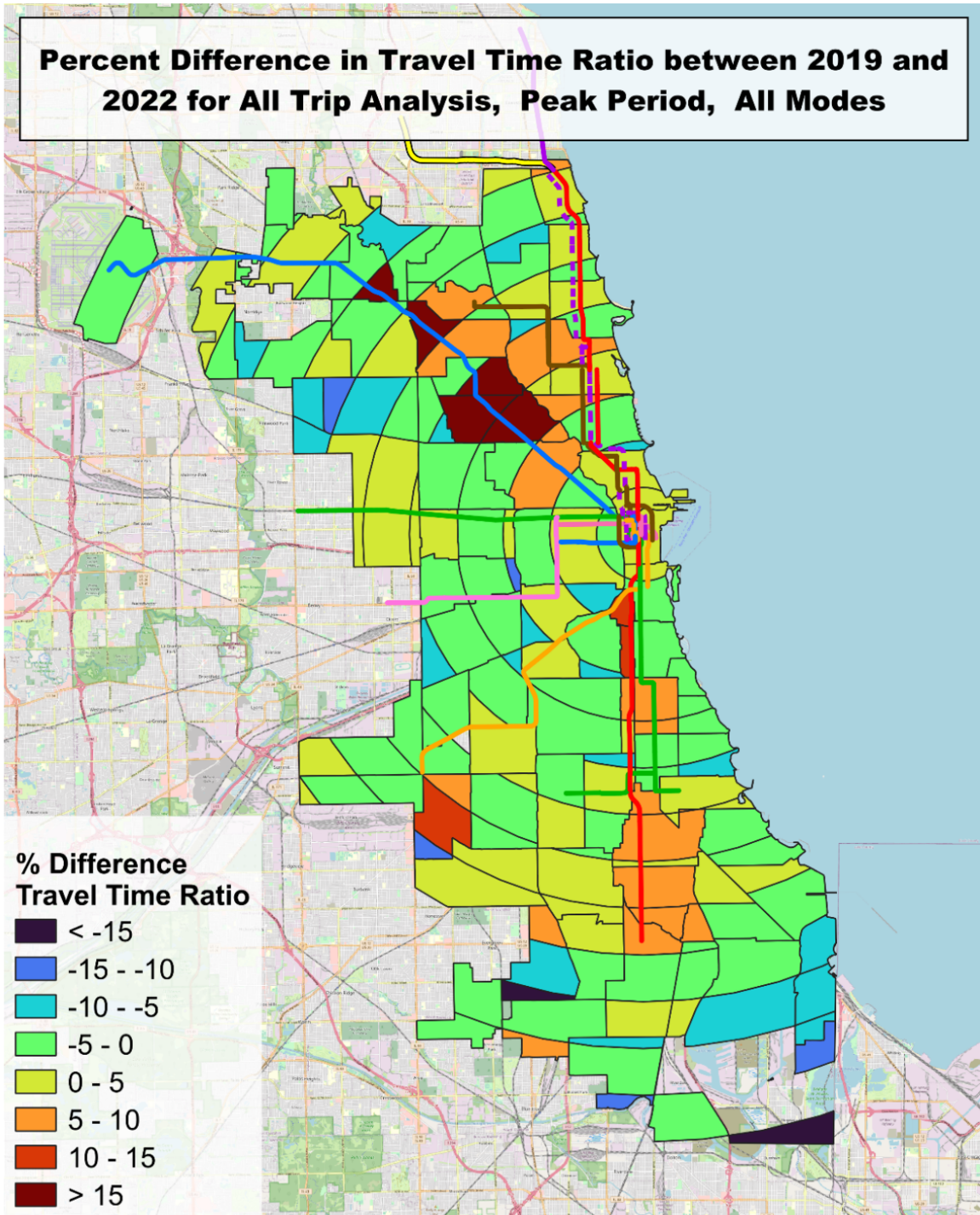


Figure 5-9: Percent Change in Travel Time Ratio September 2019 to October 2022, Anywhere Trip Analysis, Peak Weekday

5.2 Discussion of ATA Results

5.2.1 Statistical Significance

One concern with the results depicted in 5-9 that is the difference in the total number of samples between the two datasets. Reported ridership fell sharply between 2019 and 2022, resulting in a smaller sample size of trips in 2022 and therefore more susceptible to randomness. However, when the confidence intervals for each time period are calculated, they are relatively small for the TTRs across both data sets.

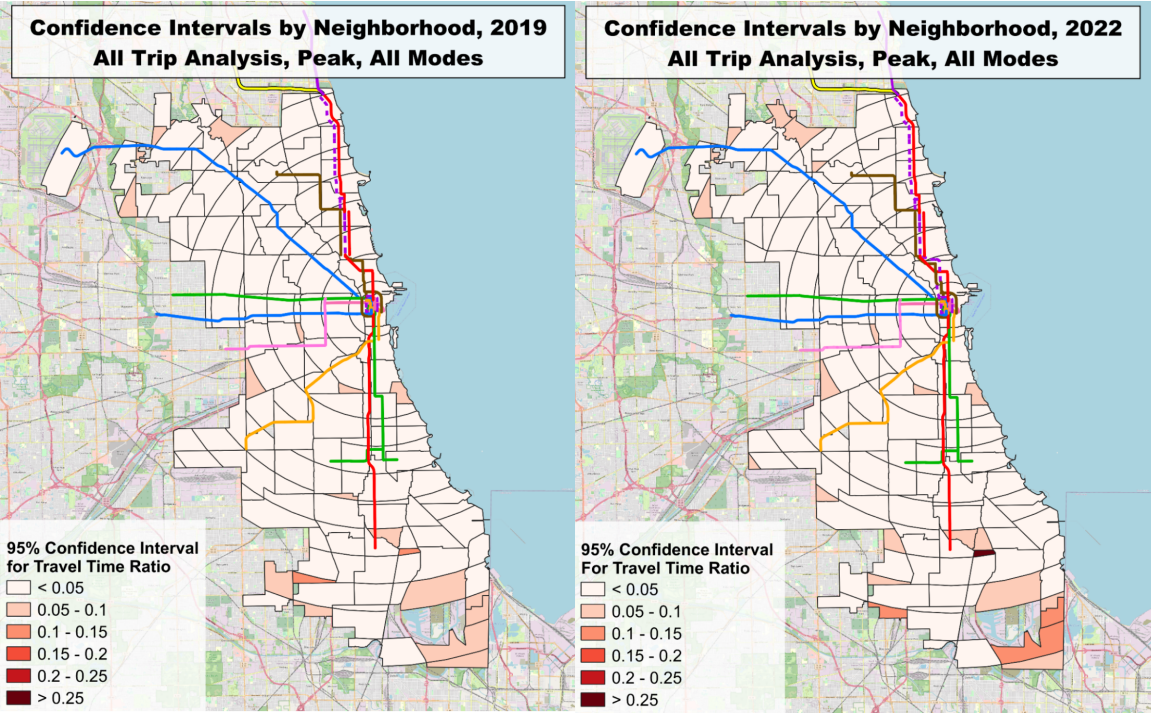


Figure 5-10: Travel Time Ratio 95 Percent Confidence Intervals for Anywhere Trip Analysis Travel Time Ratios AM Peak September 2019 and October 2022

Because of the similarity between the two periods, and their statistical significance, it is reasonable to only perform full equity analysis on one time period, the focus of Chapter 6. October 2022 is more appropriate to include because it is the most recent and therefore relevant, despite its relative number of observations compared to 2019.

5.2.2 Discussion of Stationarity Between Periods

As discussed in Section 4.1, October 2022 was a challenging month for the CTA as the agency was facing an operator shortage and unable to run a significant portion of scheduled service. The stationarity between the 2019 and 2022 datasets may come as a surprise given our understanding of the relationship between less frequent and more unpredictable service and increased TTR (as discussed in Section 3.2.2) and warrants further investigation into the causes of this lack of trend.

Investigating the wait time for bus-only trips (not all mixed-mode and none of the rail-only trips have wait time included explicitly), we can observe that October 2022 sees the upper range of wait times increase significantly, Figure 5-11. However, the median wait-time value remains the same at 5.9 minutes. While it may seem odd that the median remains the same, a 5.9 minute wait time is the associated value for routes serviced by 20-minute scheduled headways. For infrequent routes we simply assign a waiting time value based on values found in literature for scheduled service. For frequent routes, ROVE makes estimated wait times based on historical data and realized headway readily available, leading them to be higher due to the more infrequent service. Hard-coded wait times for infrequently served routes is also the explanation for why the 25th and 50th percentiles are almost identical for October 2022, as there are many trips that are accessing routes with close to 20-minute headways. While the average wait time increases significantly between 2019 and 2022, it remains static because of the use of the median value. In the future, recalculating the TTR using mean waiting time, or modifying infrequent routes to better reflect deviations from the schedule could help better reflect the experienced wait times for passengers.

Another important aspect of the data that may contribute to the con-

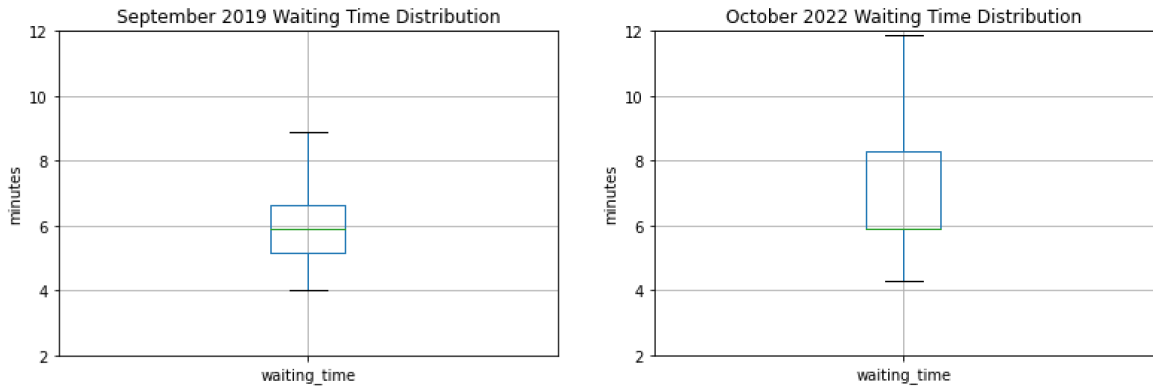


Figure 5-11: Waiting Time Distributions for Bus-Only Trips

sistency in TTR between periods is that trip legs made on rail are calculated based on scheduled data. In October 2022 there were significant issues across rail lines in Chicago including an increase in “slow zones” and the aforementioned operator shortage causing a decrease in service. Figure 5-12 illustrates this problem, as the number of rail stops that see fewer arrivals than scheduled increases greatly in October 2022.

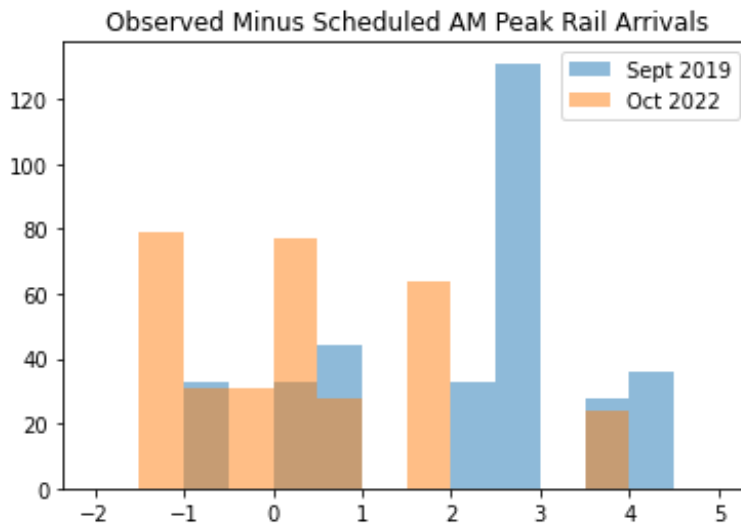


Figure 5-12: Observed Minus Scheduled Frequency for the AM Peak, September 2019 and October 2022

While we capture this discrepancy in frequency for bus trips in our analysis, we do not do so for trips where the first leg is on rail. Therefore, we are not capturing the longer wait times associated with unreliability. In future work, calculating rail-based ODX journeys with AVL would be a useful upgrade and effectively circumvent this issue.

A final aspect to consider is auto travel. When we calculate driving times we use representative travel times from a Tuesday in 2022. This means that our traffic conditions are based on historical averages, and may not reflect the experienced conditions for a day. Additionally, a finer level of analysis could be used when calculating driving times. Currently, it is done on the ring-neighborhood area OD level, with the departure time being the same across all trips. This may also contribute to the stationarity we see, as our representative travel times may not adequately represent true conditions, as they may not be sufficiently granular.

5.3 Critical Destination Analysis

As discussed in Section 3.3, Critical Destination Analysis (CDA) is helpful if we wish to assess the quality of service for a specific destination that has particular importance for equity outcomes. Three such destinations are the Loop (the heart of the CBD in Chicago), the Illinois Medical District (IMD), and River North. CDA stops for each location are shown with a star in Figure 5-13. The results of the CDA analysis for the Loop are shown in Figures 5-14 – 5-17, River North in Figures 5-18 – 5-21, and IMD in Figures 5-22 – 5-25 and are summarized in Table 5.3.

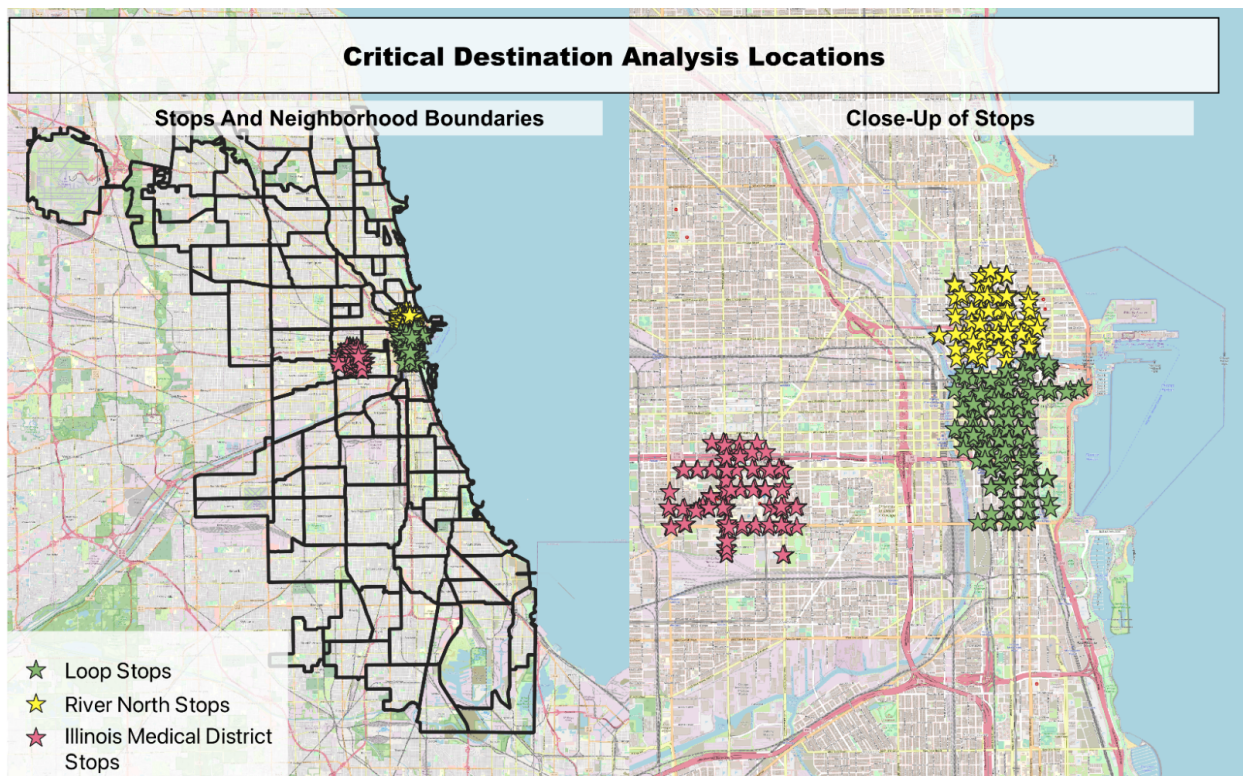


Figure 5-13: CDA Locations

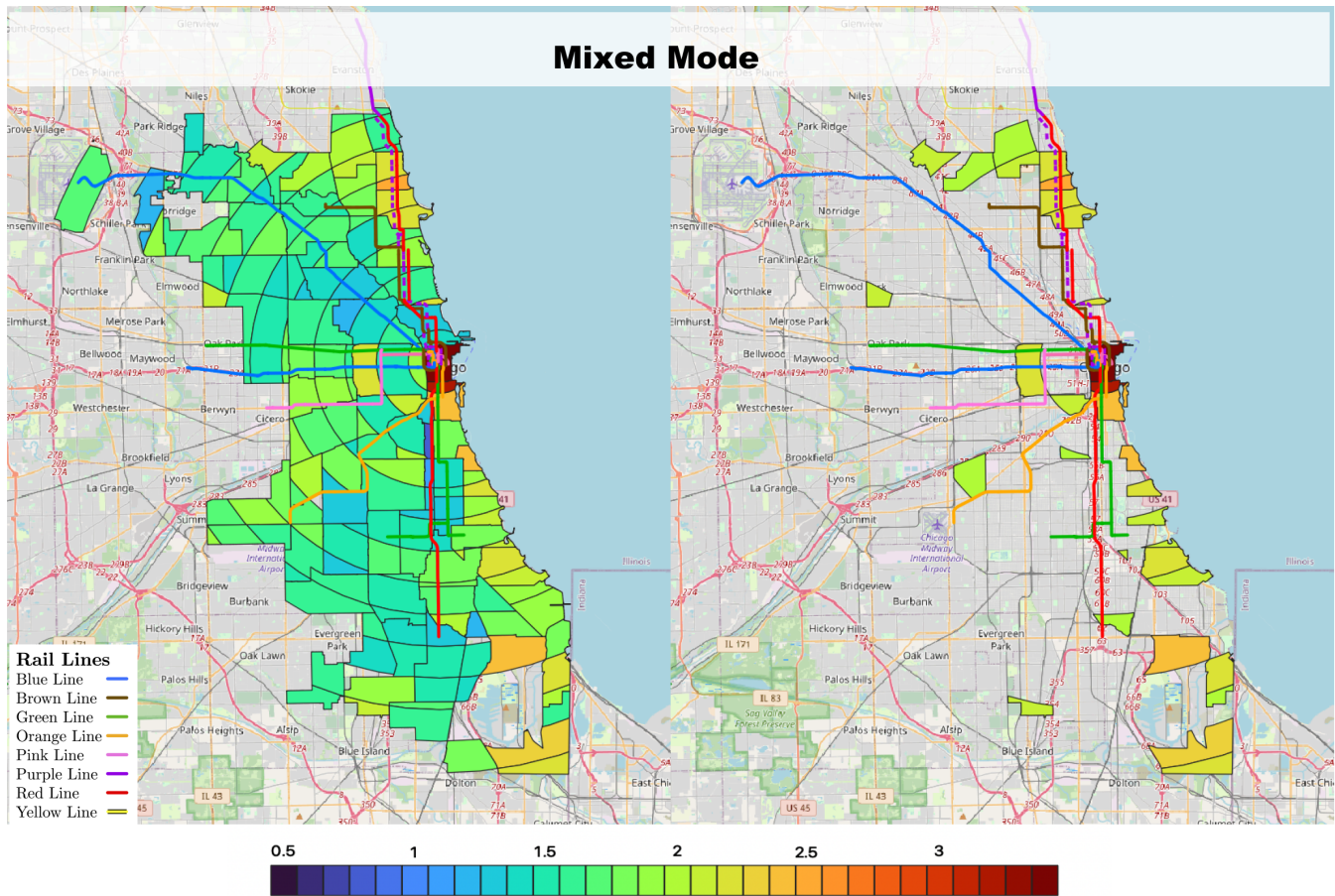


Figure 5-15: Loop CDA Analysis, AM Peak, October 2022, Mixed Mode

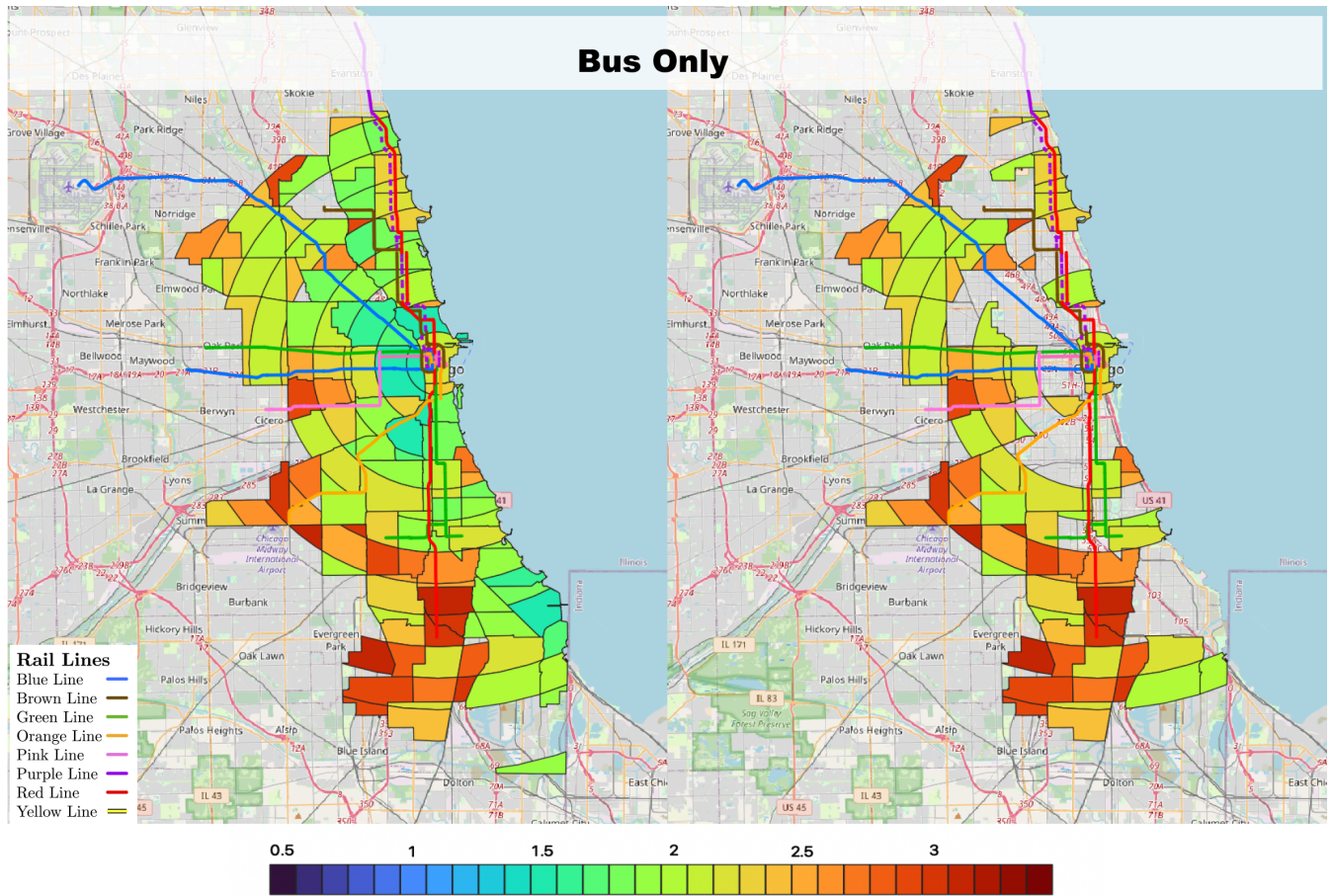


Figure 5-16: Loop CDA Analysis, AM Peak, October 2022, Bus Only

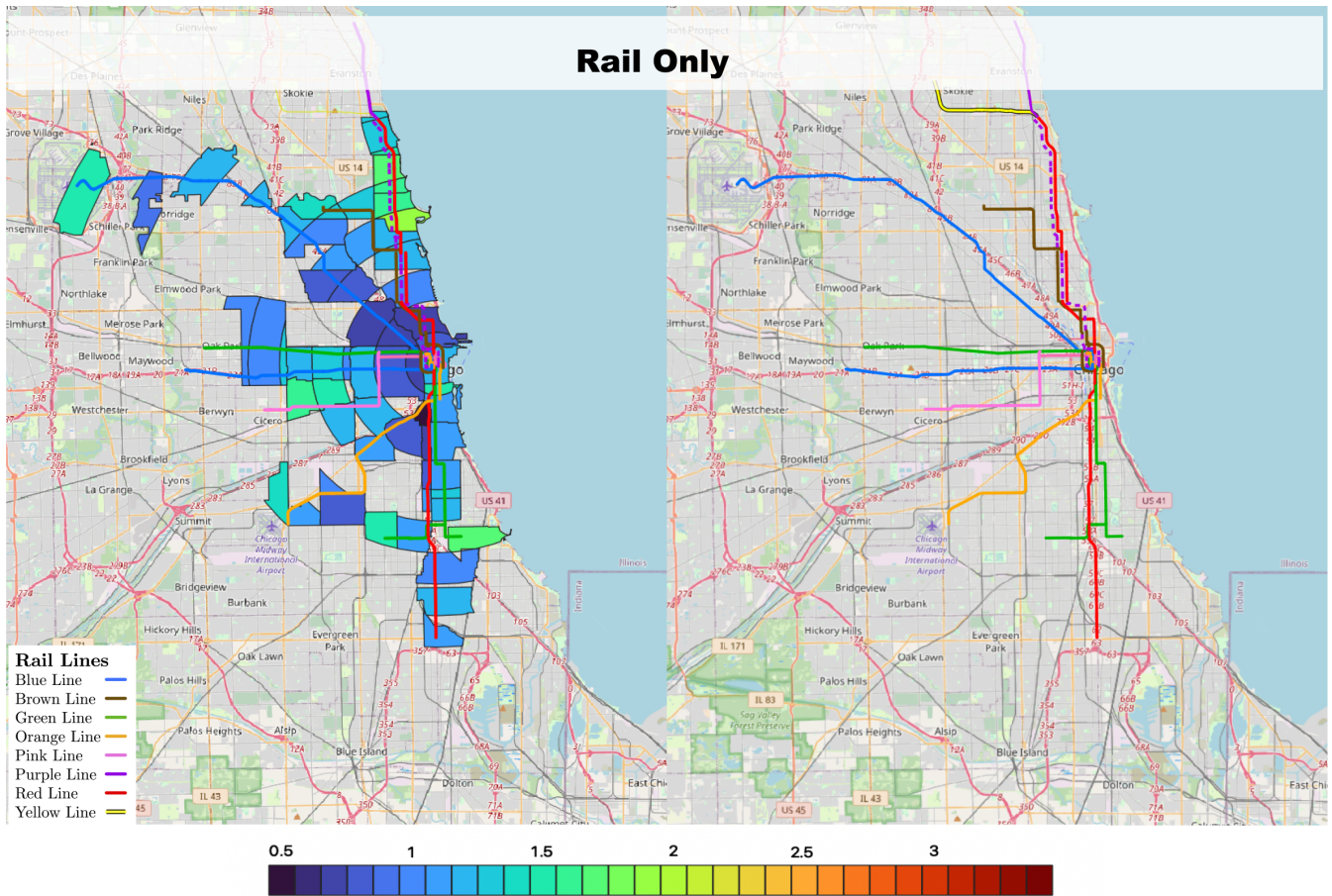


Figure 5-17: Loop CDA Analysis, AM Peak, October 2022, Rail Only

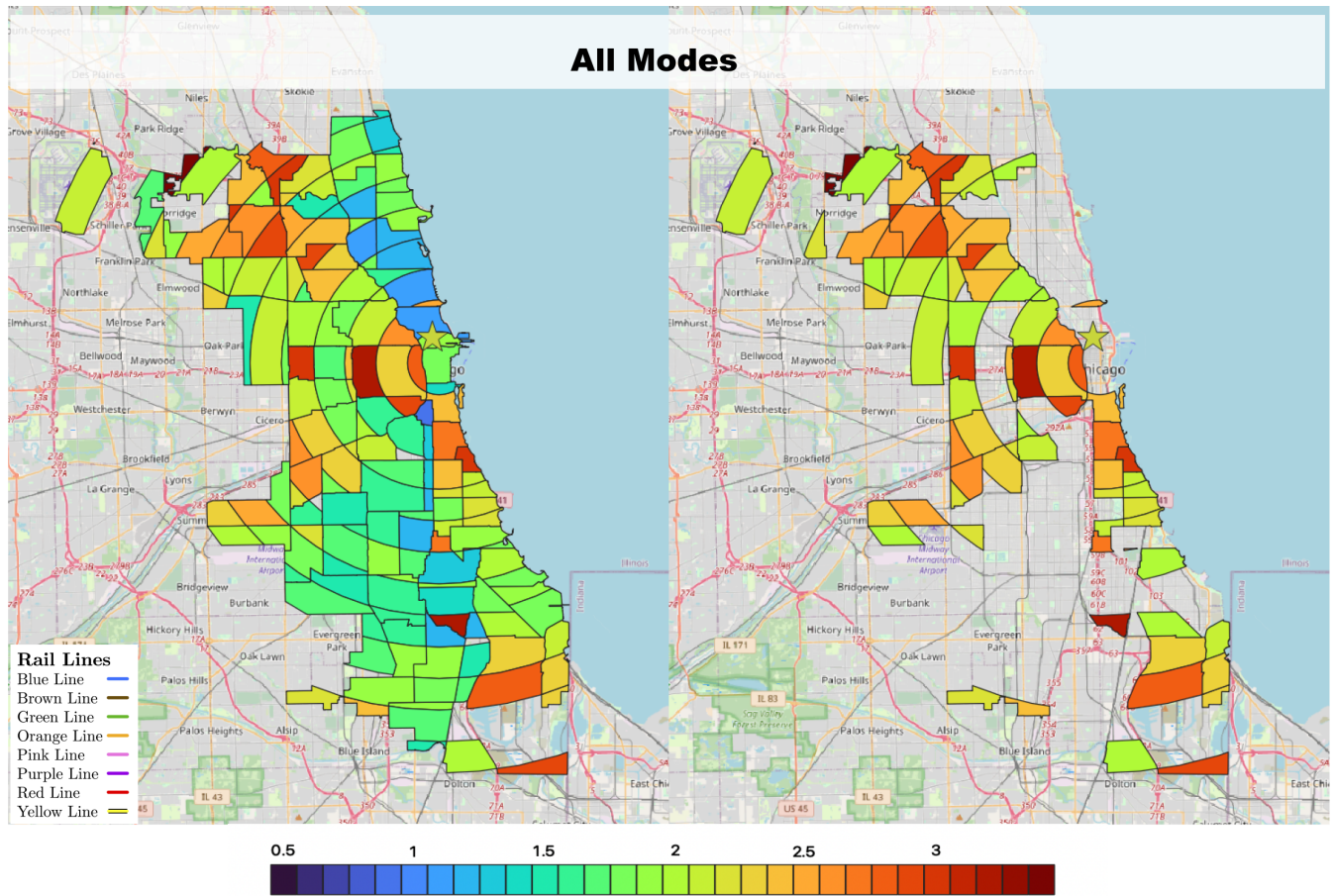


Figure 5-18: River North CDA Analysis, AM Peak, October 2022, All Modes

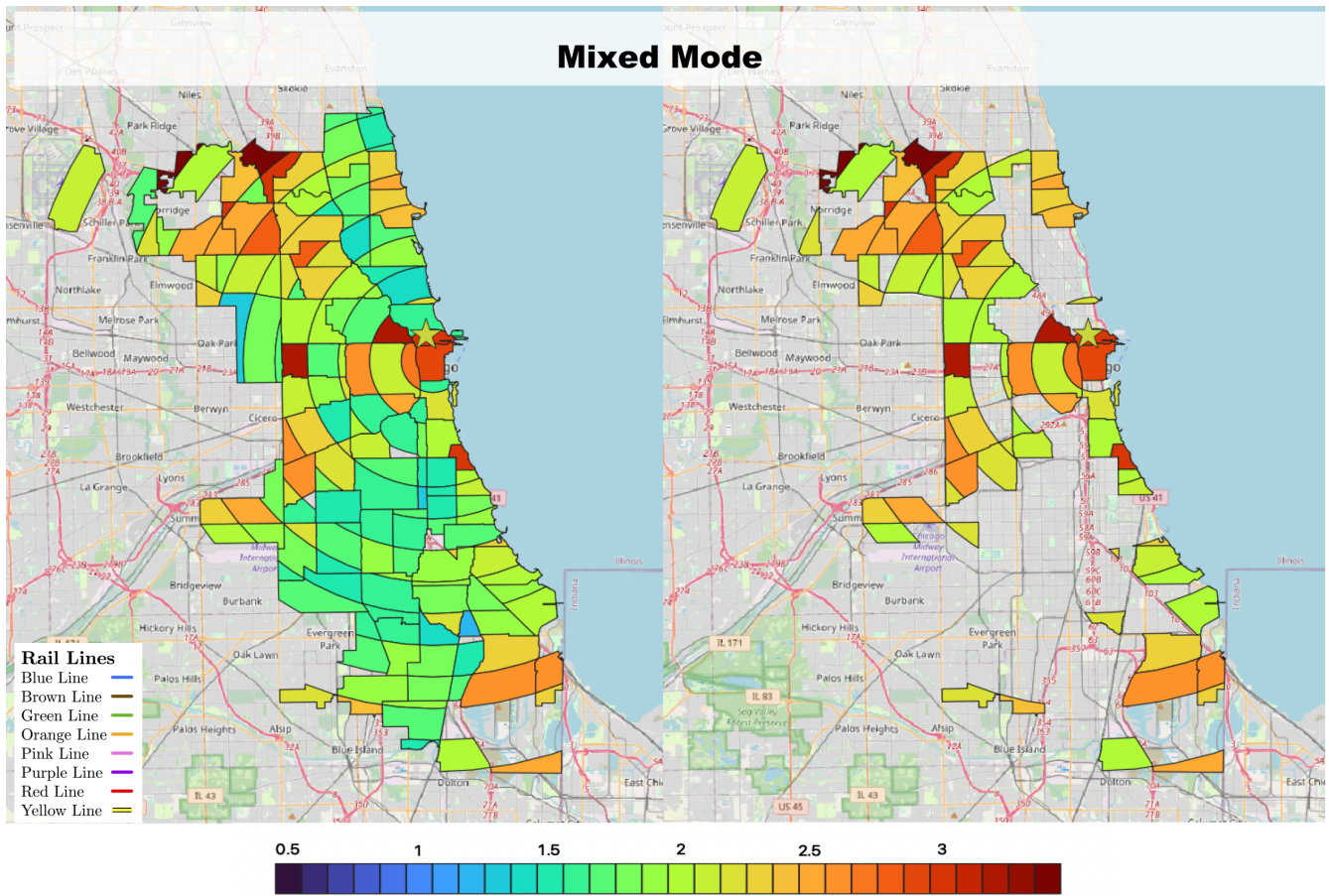


Figure 5-19: River North CDA Analysis, AM Peak, October 2022, Mixed Mode

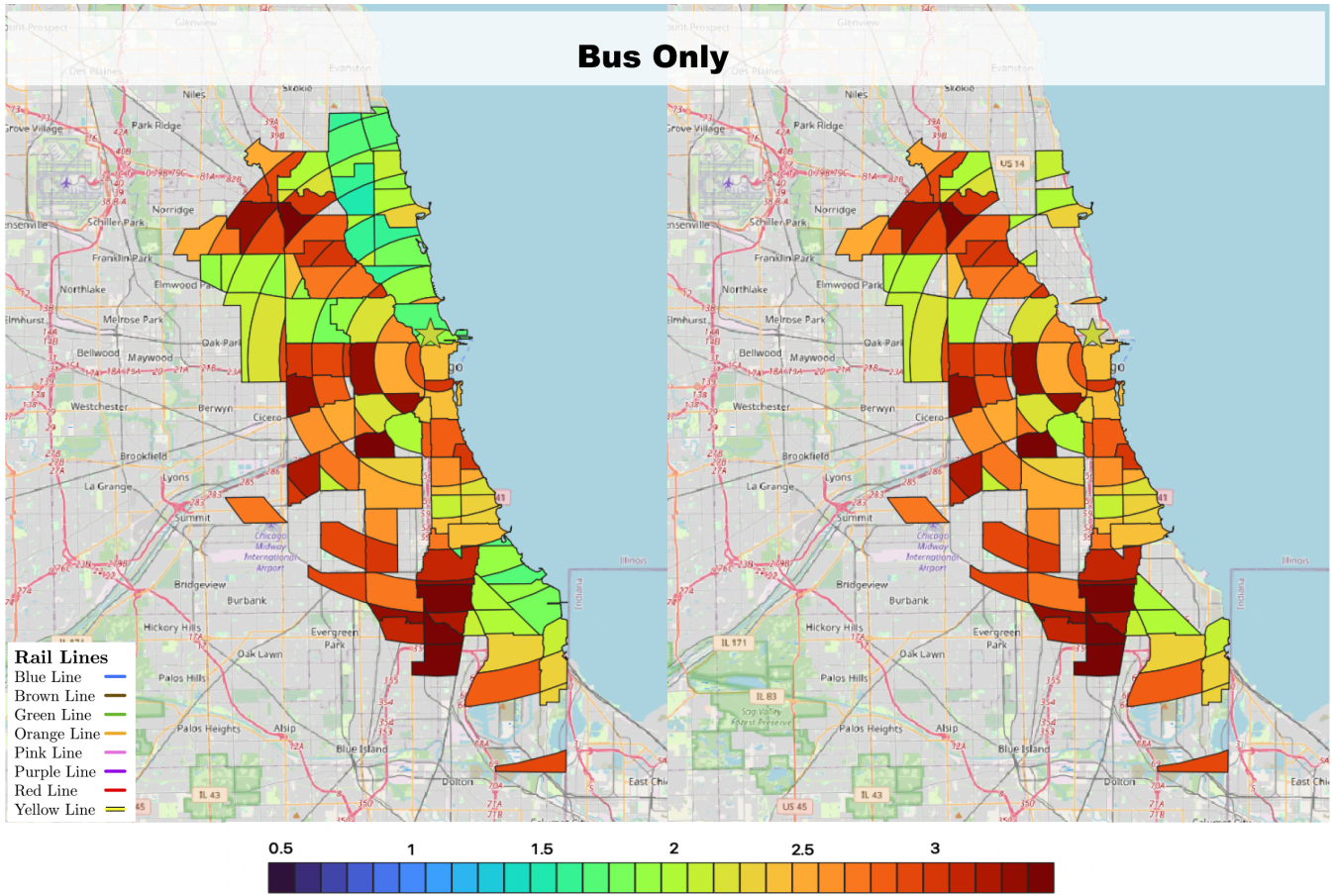


Figure 5-20: River North CDA Analysis, AM Peak, October 2022, Bus Only

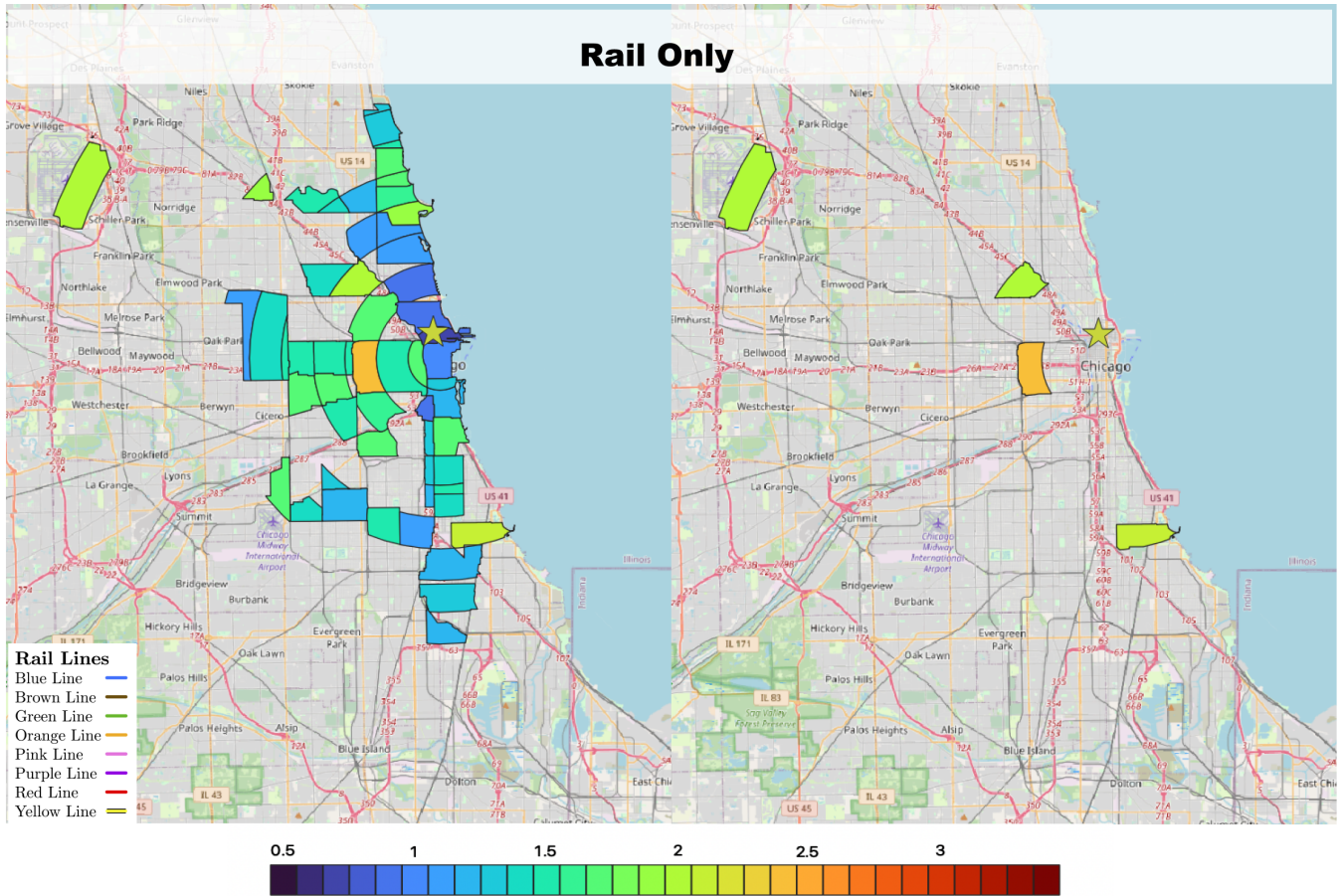


Figure 5-21: River North CDA Analysis, AM Peak, October 2022, Rail Only

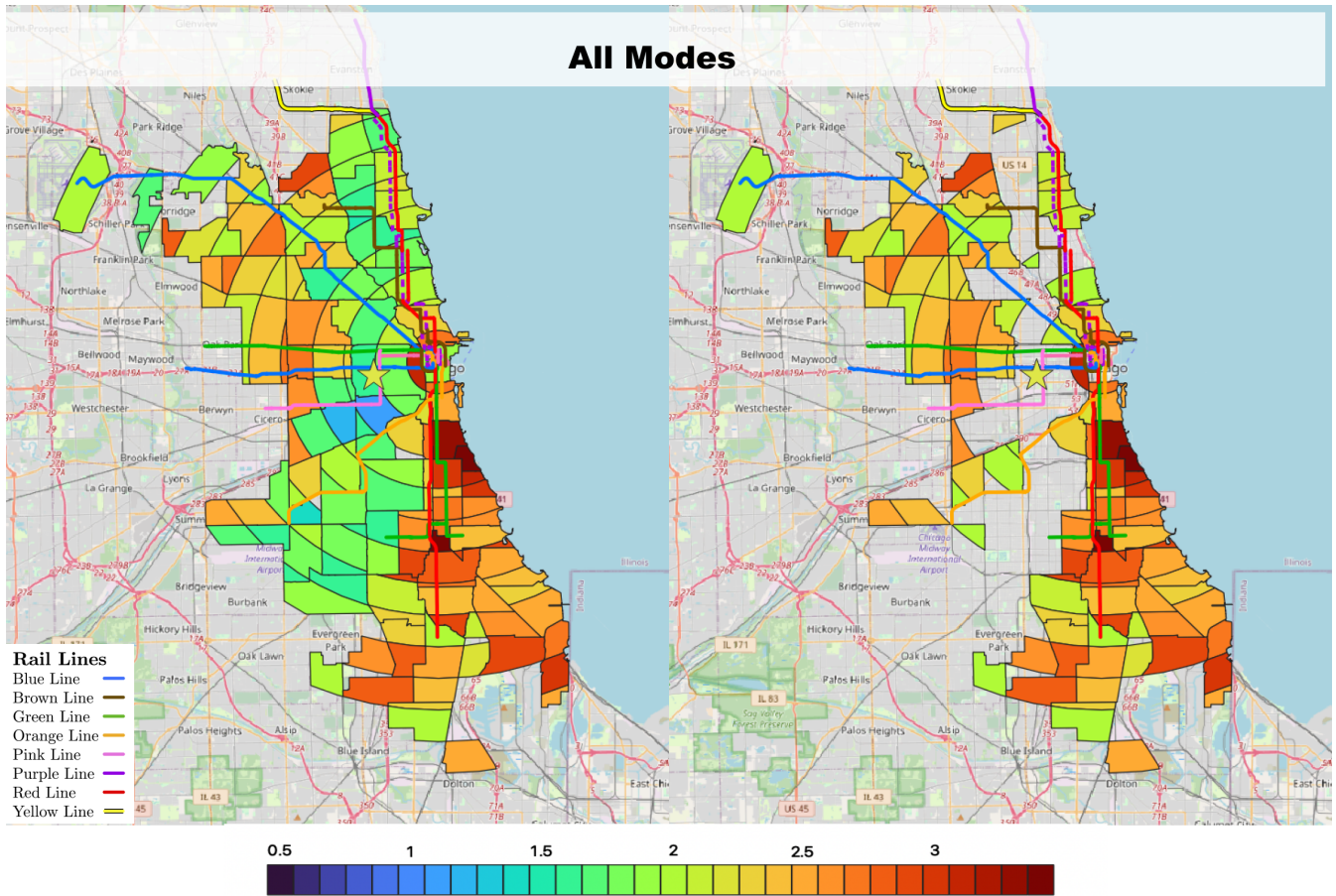


Figure 5-22: IMD CDA Analysis, AM Peak, October 2022, All Modes

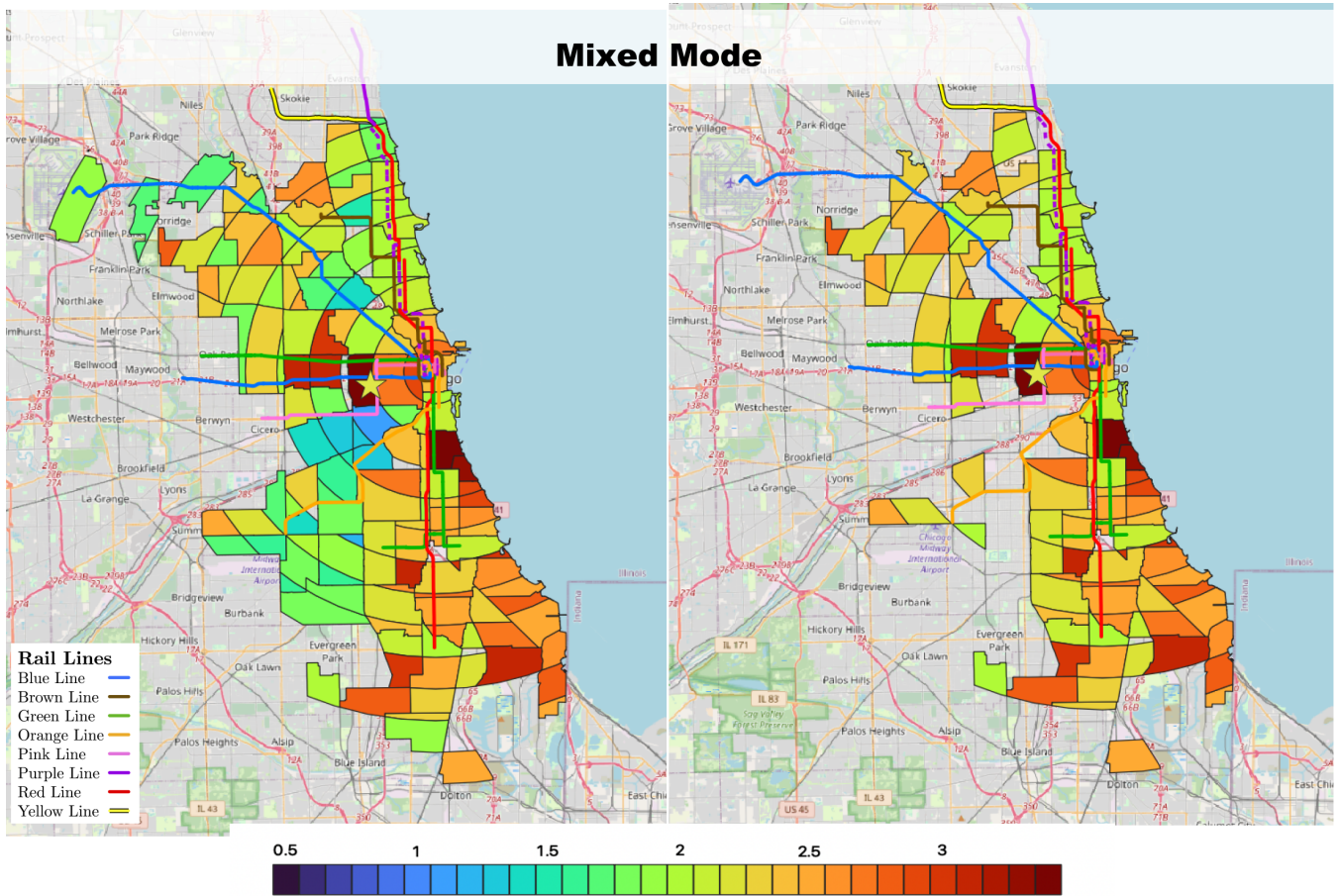


Figure 5-23: IMD CDA Analysis, AM Peak, October 2022, Mixed Mode

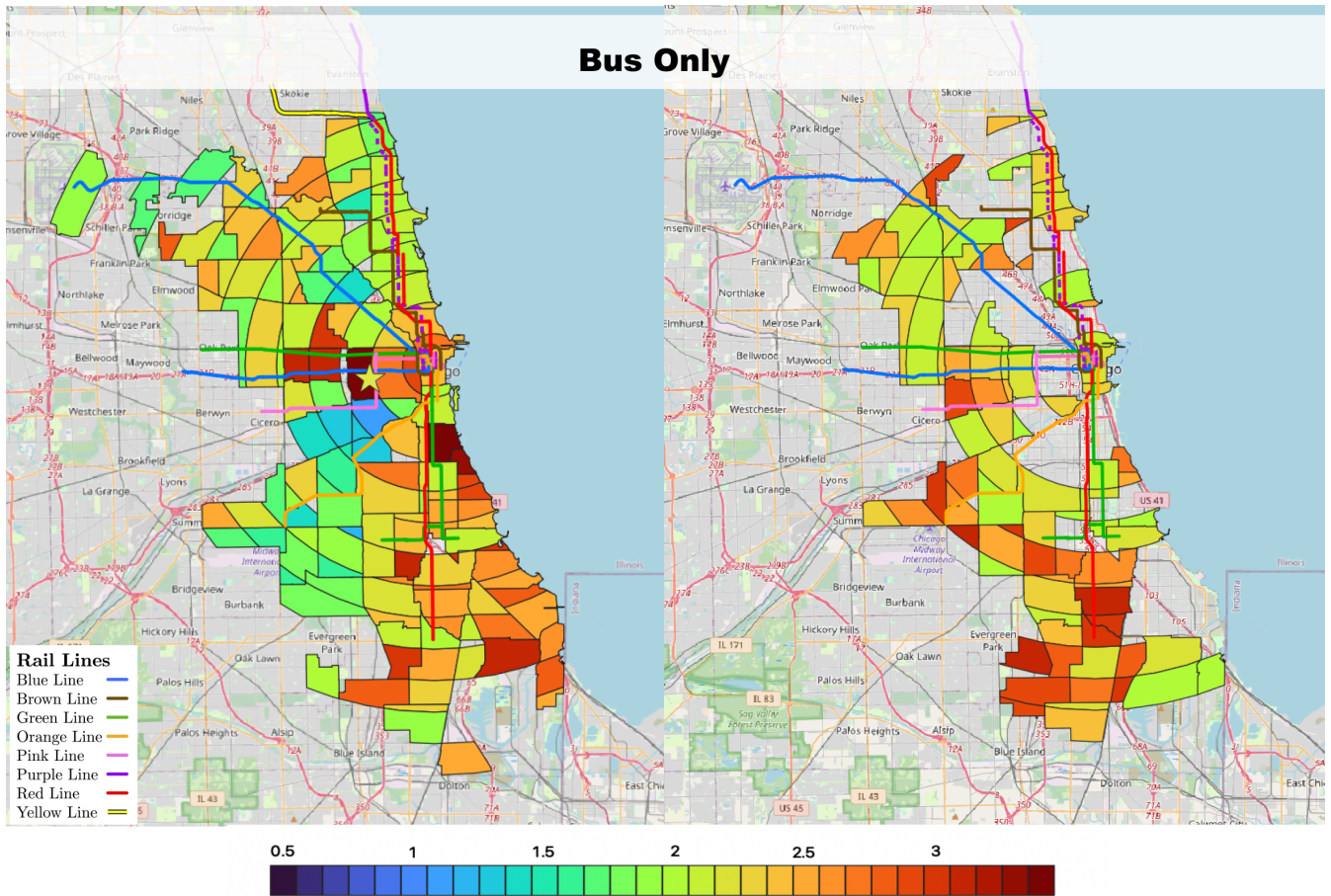


Figure 5-24: IMD CDA Analysis, AM Peak, October 2022, Bus Only

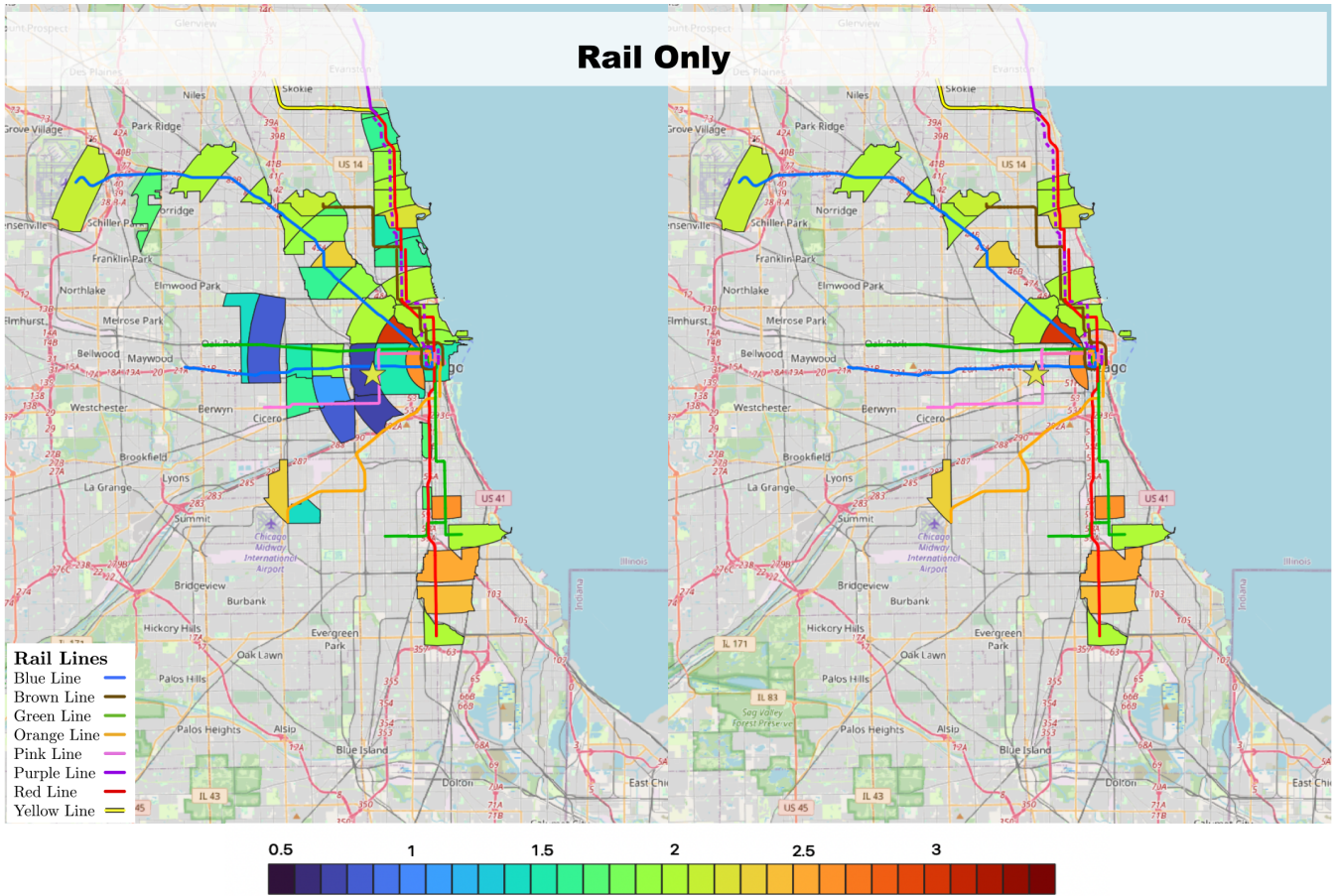


Figure 5-25: IMD CDA Analysis, AM Peak, October 2022, Rail Only

Table 5.3: Critical Destination Analysis Results Summary By Mode and Location, October 2022

Transit Mode(s)	# Observations	Median TRR: Ring-Neighborhood Area	Median TRR: Trip	Observations
Loop				
All	554,718	1.65	1.37	The majority of trips (59%) taken to the Loop are taken using rail only, leading to competitive travel times (median of 1.37 for all trips). However, bus only and mixed-mode trips, comprising 39% of all trips to the Loop, are less competitive, with uncompetitive travel times for mixed mode journeys prominently visible along the lakeshore and Far South Side, and throughout the city for bus only journeys, with the exception of areas along the North portion of the Blue Line, along the Orange Line, and a portion of the Far South Side.
Bus	173,777	2.2	1.96	
Mixed Mode	52,654	1.70	1.65	
Rail Only	328,287	1.21	1.12	
Near North Side				
All	146,544	1.96	1.65	Competitive travel times are seen on rail journeys along rail lines. Mixed mode journeys tend to be uncompetitive across the city. Bus trips are mostly uncompetitive with the exception of areas along the North Lakeshore.
Bus	66,722	2.48	2.08	
Mixed Mode	15,568	1.96	1.9	
Rail Only	64,254	1.49	1.21	
IMD				
All	50,436	2.3	2.02	Uncompetitive travel times are highly concentrated throughout the South Side across modes, with the exception of ring-neighborhood areas in close proximity to the IMD. South-West Side ring-neighborhood areas and some along the Northern portion Blue, Brown, and Red Lines see TTRs either competitive or uncompetitive (between 1.5 and 2). Rail trips not on the Green, Pink, and Western portion of the Blue lines are not competitive.
Bus	31,930	2.53	2.13	
Mixed Mode	5,675	2.28	2.13	
Rail Only	12,831	1.95	1.81	

It is clear from viewing the CDA results that despite each destination evaluated in CDA being located relatively close to the CBD, their TTRs vary widely. Service to the Loop is very good and highly competitive in general. The CTA system is designed radially with the intention of bringing passengers in and out of the core efficiently, and in our results we can determine that the system is performing as it should in this respect. However, for mixed-mode and bus-only trips, the system does not perform competitively in most places. In direct contrast to the Loop, River North, located just north of the Loop, has a very different level of transit service despite their close proximity. Finally, the IMD, despite being a roughly 10 minute drive from the Loop, also has a very different level of transit service. With the exception of ring-neighborhood areas on the West side that have transit service that brings them directly to the IMD, transit service to the IMD is uncompetitive almost everywhere.

In conclusion, this information can be useful to the CTA as it highlights its relative strengths and weaknesses in providing service to different destinations. One major result from this analysis is that access to the Loop is good for the majority of the city, River North service quality is lower than Loop service despite its close physical proximity, and the IMD is currently uncompetitive across most areas of the city.

Chapter 6

Identifying Inequity and Application of Method to the Red Line Extension

6.1 Exploring Inequity

While viewing TTR results on a macro scale is helpful to understand the overarching geospatial and longitudinal distribution of transit service in Chicago, introducing a measure of comparison is critical if we wish to make equity-driven decisions. To achieve this we compare ring-neighborhood areas which are equidistant from the CBD which we defined as “spatial peers” in Chapter 3. Also in Chapter 3, we defined a method for assessing if a ring-neighborhood area was inequitably served based on its observed and ideal TTR.

While Chapter we focused on exploring how TTR varied by mode, time period, and analysis type, to produce an equity analysis to determine which ring-neighborhood areas are in greatest need, we will focus on a single dataset. We will use the “Anywhere Trip Analysis” for all modes in the weekday peak dataset from October 2022 to perform our

analysis. This period was chosen as it includes the greatest number of trips, and therefore inclusive of the greatest portion of the population. However, this equity analysis is easily replicable for the other analysis types and periods explored in Chapter 5.

The result of the equity analysis for the ATA can be seen in Figure 6-1.

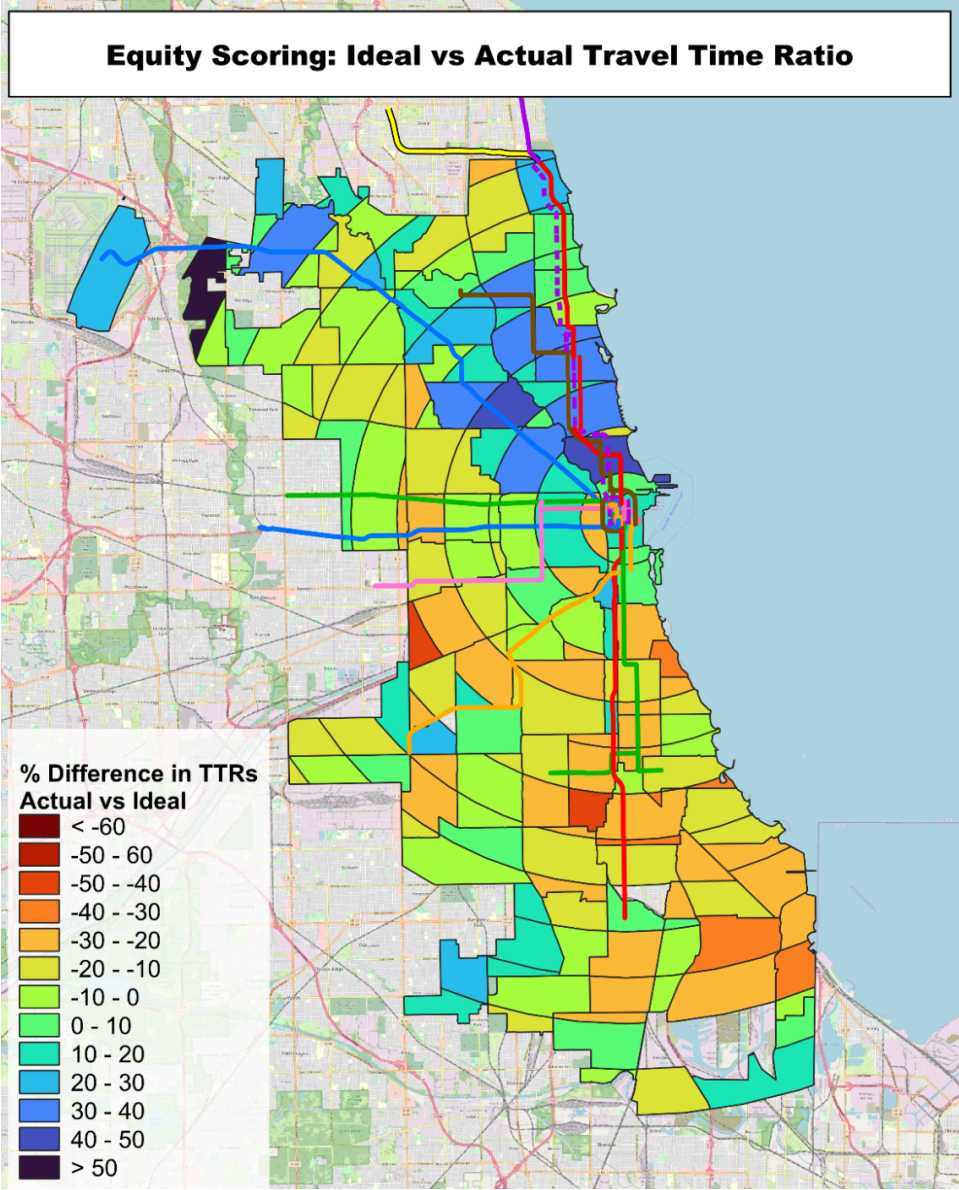


Figure 6-1: Equity Score, October 2022

Viewing the results of our equity score above in Figure 6-1, the overarching geospatial pattern observed in Chapter 5 of the South and West Sides of Chicago being underserved, and the North Side being well served, once again emerges.

On the North Side, the ring-neighborhood areas near the Brown, Red, and Purple lines are well served. Their median TTRs surpass the minimum TTR we set based on their need level derived from the EHI score. Some outer reaches of the North Side, such as West Ridge, are underserved, but overall, the ring-neighborhood area is adequately serviced. Examining the West Side of Chicago, between the two branches of the Blue Line, ring-neighborhood areas including Hermosa, Belmont Cragin, Dunning, Portage Park, Austin, West Garfield Park, and Humboldt Park emerge as underserved. Ring neighborhood areas around the Pink Line such as North Lawndale, and South Lawndale, emerge as underserved. Virtually the entirety of the South Side portion of Chicago is underserved, with exceptions, which are either low EHI (i.e. Beverly, Mouth Greenwood) or closely accessible by rail (Armour Square, Fuller Park, Roseland). Figure 6-2 breaks down Figure 6-1 into under (observed TTR is less than the ideal) and adequately served (observed TTR greater or equal to the ideal TTR).

From this analysis, the result is a list of all ring-neighborhood areas in Chicago ranked by the percent difference in their observed versus ideal TTR. This result has two purposes. The first is that it gives a quantitative ranking to which ring-neighborhood-areas are underserved, while accounting for their distance from the core, and secondly, assigns a value to how underserved the area is based on TTR. A full ranked list of the 174 ring-neighborhood areas can be found in Appendix E. The Top 20 highest need ring-neighborhood areas can be seen in Table 6.1

From Table 6.1, viewing the top 20 neediest neighborhoods as well

Table 6.1: Equity Scores of the Top-20 Highest Need Ring-Neighborhood Areas, October 2022

Need Rank	Ring Neighborhood Area	Number of Observations	Actual TTR	Ideal TTR	% Diff in TTRs	EHI
	<i>Median Across Neighborhood Areas</i>	5773	1.85	1.72	-7.71	43.9
1	9_Chatham	1999	3.09	1.62	-62.7	47.9
2	6_South Lawndale	186	2.30	1.50	-42.1	70.6
3	7_Englewood	5659	2.27	1.50	-40.8	70.5
4	10_South Deering	5495	2.25	1.50	-40	58.1
5	4_Oakland	3323	2.43	1.64	-38.5	53.2
6	7_Woodlawn	5032	2.45	1.71	-35.8	50.4
7	11_East Side	2539	2.14	1.52	-34.1	56.7
8	8_Greater Grand Crossing	7730	2.16	1.58	-31.3	54.3
9	4_New City	3260	2.12	1.57	-29.9	62.6
10	8_South Chicago	4962	2.1	1.57	-29.3	54.9
11	9_Ashburn Gresham	4496	2.09	1.56	-29.1	51.5
12	5_South Lawndale	15032	2.01	1.50	-29.1	70.6
13	6_Englewood	9089	2.01	1.50	-28.9	70.5
14	5_West Garfield Park	10601	2.03	1.52	-28.8	68.3
15	5_Brighton Park	13673	2.04	1.54	-28.2	66.1
16	3_Douglas	15404	2.24	1.70	-27.5	42.5
17	10_Roseland	5499	2.08	1.58	-27.3	52.6
18	9_South Chicago	8247	1.97	1.50	-27.2	54.9
19	7_Ashburn Gresham	877	2.22	1.69	-26.8	51.5
20	1_Near West Side	43784	2.22	1.70	-26.2	26.6

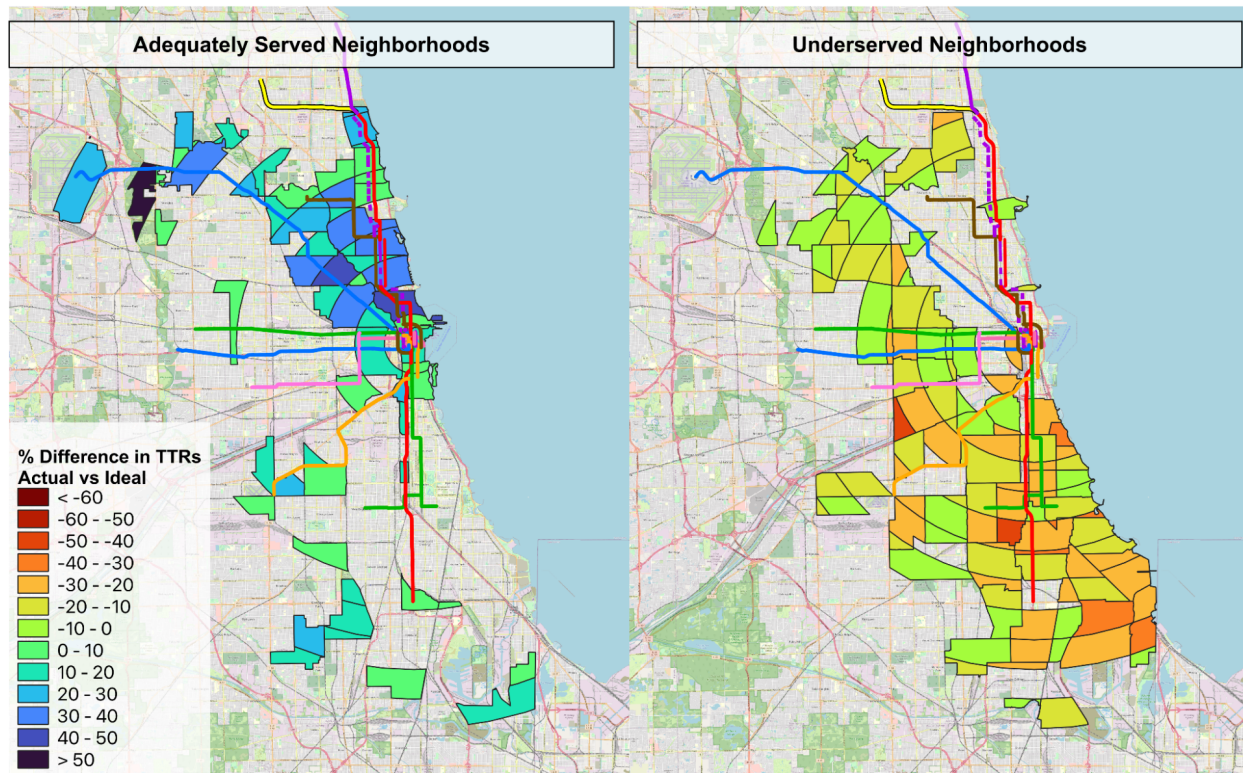


Figure 6-2: Underserved and Adequately Served Neighborhoods

as the median “baseline” value across neighborhoods, we can identify several patterns associated with the high need neighborhoods. Within the top 20, almost all are located on the South Side of Chicago, with a few West Side Neighborhoods (South Lawndale, West Garfield Park, Austin, Near West Side) also included. Their TTRs are all well above the median ring-neighborhood area median, and with a few exceptions (Near West Side, Douglas) the EHI exceeds the city-wide median. While the median percent difference between the observed and ideal TTR is around 8%, all these neighborhoods are off by over -25%. This result is reassuring, as our ranking system appears to be highlighting areas with especially poor service, and high need overall.

While identifying inequitable disparities in TTR is our primary goal, also important is the supporting metrics, frequency, average number of transfers, and on-time performance, that we selected in Chapter 3.

Not only are these three metrics important to passengers, but they give intuition into what might be causing longer TTRs. Understanding these three supporting metrics' relationship with TTR is helpful if we wish to work towards lowering TTRs. Figure 6-3 below presents these metrics on the ring-neighborhood area level.

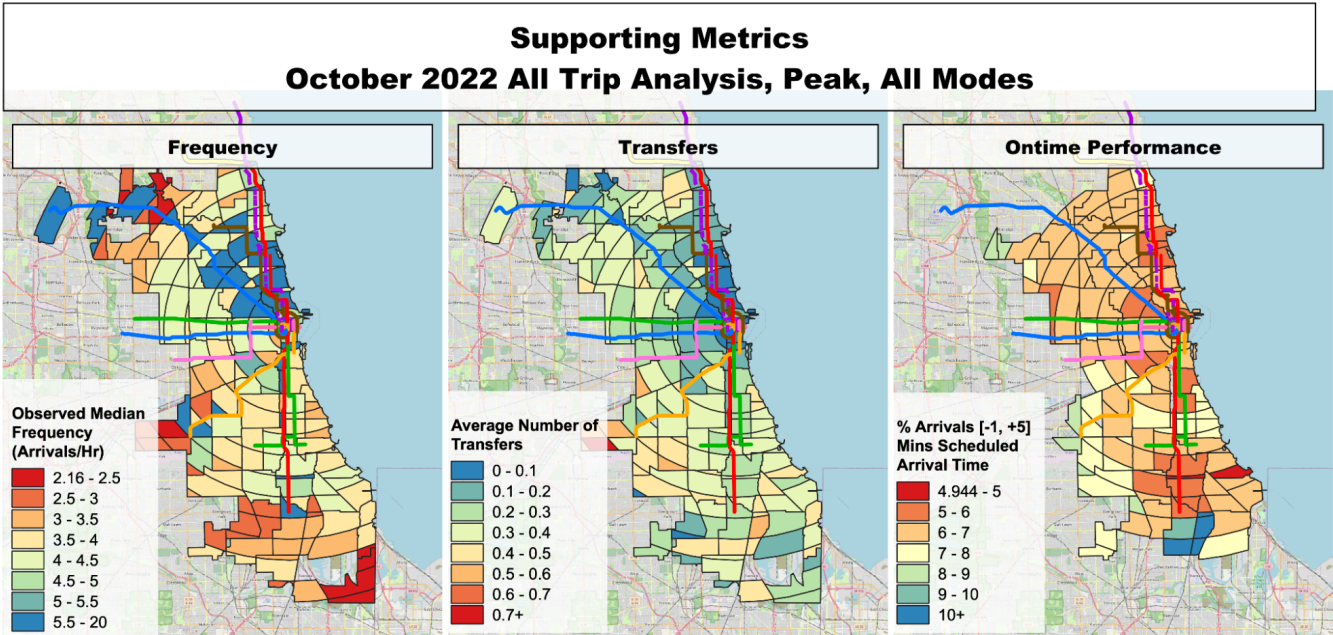


Figure 6-3: Supporting Metrics for ATA, All Modes, October 2022

By examining the supporting metric graphs, certain geospatial patterns emerge. For the average number of transfers, the results appear radial, with the fewest transfers being seen in the core, and increasing towards the outer boundaries of the city. However, the North Side of Chicago (along the Red, Brown, and Purple lines) does not follow these patterns. For median frequency, the most remote edges of the city see the fewest arrivals per hour by far. The rest of the city appears as a “mosaic” of frequencies. As for median on-time performance, areas closer to the core appear to have greater delay.

To best understand how each of these metrics affects the TTR score for each ring-neighborhood area on a statistical level, a linear regression

Table 6.2: Results of Linear Regression for 2022 AM Peak ATA Analysis

<i>Variable</i>	<i>Coefficient Estimate</i>	<i>Standard Error</i>	<i>t-Stat</i>	<i>P-Value</i>
(Intercept)	2.37	0.15	16.00	2.00E-16
Observed Frequency	-0.07	0.01	-6.25	4.66E-09
Number of Transfers	0.58	0.19	3.14	0.00208
On-time Performance	-0.06	0.02	-2.96	0.00364
<i>Summary Statistics</i>				
Adjusted R-squared	0.358			
Multiple R-squared	0.371			
Standard Error	0.220			
Number of Observations (32 removed for completeness)	139			

performed. The results can be seen in Table (6.2). Each of the three metrics shows statistical significance above the 99% level. The sign (i.e. negative or positive) of each coefficient makes intuitive sense - having an extra transfer increases the TTR whereas having access to more frequent service and more on-time buses decreases the TTR. However, the adjusted R-squared value shows that only 36% of all variance in TTRs can be explained by these three secondary metrics.

Despite the limited statistical significance of these metrics in explaining the overall TTR values, to illustrate how supporting metrics can give us intuition into how we might lower TTRs, the top 10 most underserved neighborhoods under each equity definition and their associated metrics are given in Table 6.3. Viewing Table 6.3 and seeing supporting metrics together with the TTR yields immediate insight. For example, trips originating in the area of South Lawndale in the 6th ring take many transfers and there is a low observed frequency. These two metrics give us the intuition that infrequent, indirect service may be causing the high TTRs. However, for other areas, the cause of high TTRs is less obvious. For example, South Chicago in the 8th ring experiences more frequent and direct service than the median, but has a high TTR.

Table 6.3: Supporting Metric Values for Top 10 Neediest Areas

Ring Neighborhood Area	Actual TTR	Observed Frequency	On-time Performance	Number of Transfers	Observation/Intuition
<i>Median Across Neighborhood Areas</i>	<i>1.85</i>	<i>3.88</i>	<i>6.6</i>	<i>0.3</i>	<i>N/A</i>
9_Chatham	3.09	4	5.9	0.36	Higher number of transfers, lower on-time performance
6_South Lawndale	2.3	3.25	N/A	0.56	High number of transfers, low number of observed hourly arrivals
7_Englewood	2.27	4.16	5.99	0.39	Lower on-time performance, higher number of transfers
10_South Deering	2.25	3.71	6.4	0.28	Slightly fewer arrivals per hour than average
4_Oakland	2.43	3.8	7.01	0.44	High number of transfers, slightly lower frequency
7_Woodlawn	2.45	3.78	6.07	0.39	Higher number of transfers, slightly lower frequency
11_East Side	2.14	3.75	N/A	0.33	Slightly higher transfers, slightly lower frequency
8_Greater Grand Crossing	2.16	5.97	4.95	0.32	Number of transfers slightly higher than city-wide median, on-time performance worse than city-wide median
4_New City	2.12	3.65	6.63	0.34	Slightly lower frequency, slightly higher transfers
8_South Chicago	2.1	4.08	6.14	0.25	On-time performance slightly lower than city-wide median

Although the explanatory power of our three secondary metrics may be limited, by ranking areas where TTR is high compared to need and viewing the supporting metrics, we create the opportunity for further research and investigation into what other factors may be at play in causing these long TTRs.

6.2 Application to the Red Line Extension

As discussed in Chapter 1, the RLE (Red Line Extension), is a major CTA infrastructure project currently under review. There is much excitement around this project from an equity perspective because the South Side of Chicago has been historically underserved.

The equity analysis in the previous section confirmed how the Far South Side is currently underserved when compared its spaital peers. Understanding how TTRs and equity scores may change if the RLE goes forward is a good case study for our equity method, and can demonstrate how this can be used practically to advocate for equity-focused transit service interventions and investments.

The particular aspect we are interested in understanding for this case study is the mixed mode trips that originate south of the Red Line that transfer onto the Red Line via bus. As we have explored, the number of transfers required for a trip has a large, negative impact on TTRs. Figure 6-4 below shows the travel times for the pre-Red Line bus leg(s) for trips transferring to the Red line at Dan Ryan and 95th station in October 2022.

To estimate how the TTR will change when the Red Line is introduced, several assumptions were made. The first was that passengers whose original boarding stop was in a 500 meter as-the-crow-flies radius would not use a bus to access the station, and simply use the station

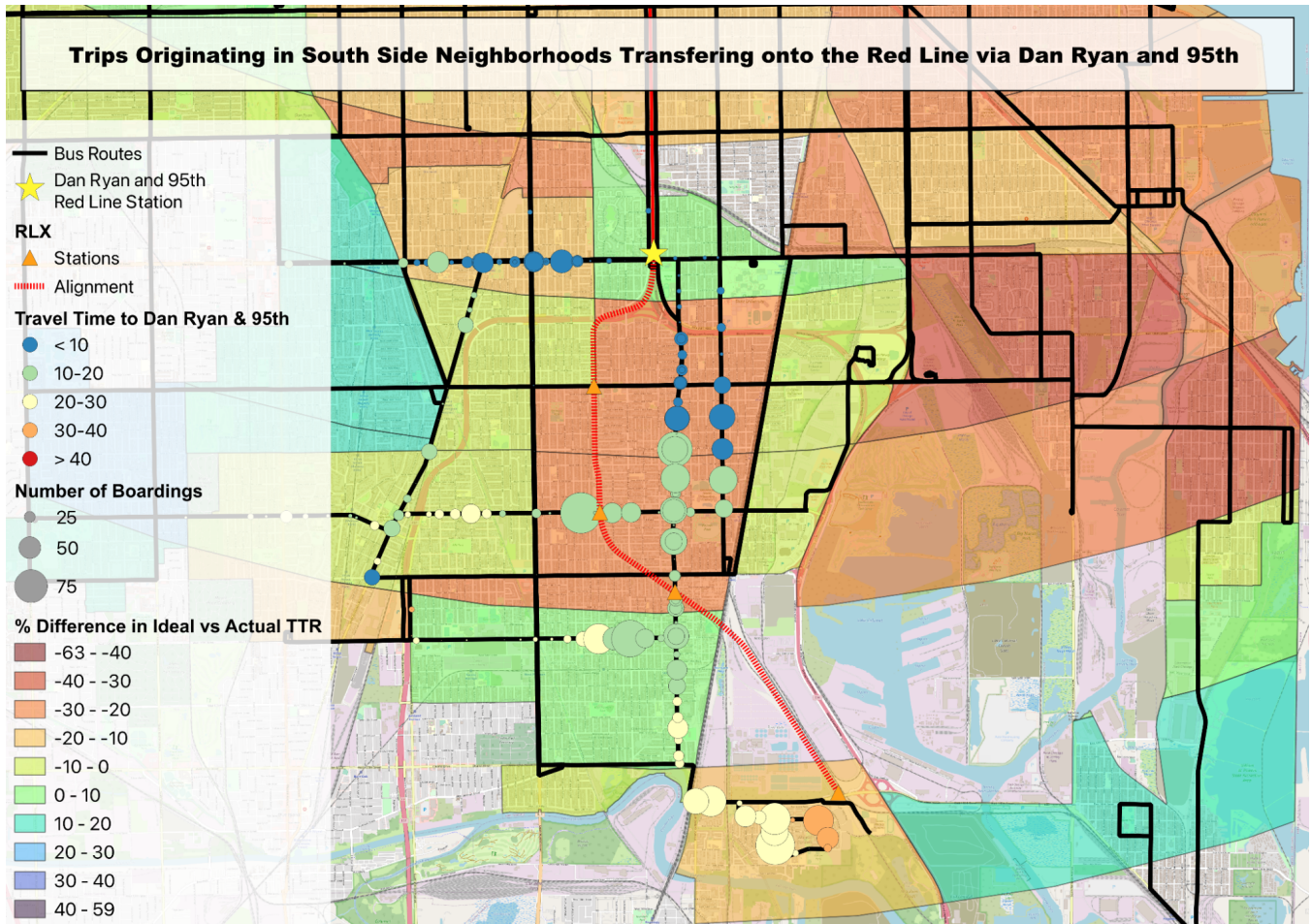


Figure 6-4: South Side Trips Using Bus to Reach Dan Ryan and 95th

in closest proximity to them. The 500 meter range was chosen from a well-known threshold for how far passengers are willing to walk to rapid transit stations, which is typically 400-800 meters (Federal Transit Administration, 2013). A conservative value was chosen to reflect a lower bound of the benefits the RLE could bring.

The second assumption is that if the journey was over 500 meters in distance, the passenger would still use a bus to transfer onto the Red Line, but access the Red Line stop closest to them. To estimate travel times on the new Red line, a representative value was found based on the current Red Line travel conditions between Red Line stations. On average, it takes about 3 minutes to travel between stations. This value was assigned to trips based on how many stations they would travel through on the RLE. For example, if a passenger gets on at the new 130th Subway station, it would take them 12 minutes to reach Dan Ryan and 95th. In the case where the distance to the nearest stop was over 500 meters, a bus leg was added to the closest proposed Red Line stop (or Dan Ryan). The travel time to reach the new Red Line stations was calculated by dividing the as-the-crow-flies distance by the mean speed with dwell for the four highest ridership bus routes in the dataset (34, 119, 111, and 112) which was equivalent to about 12.5 miles per hour, and added to the estimated travel time they would spend on the RLE.

The resulting analysis suggests that travel times to Dan Ryan for neighborhoods along the RLE will improve greatly, especially around the 111th and 130th street stations, as seen in Figure 6-5. In terms of the overall impact on the equity score, Riverdale sees a noticeable improvement in its equity score. This analysis suggests that it will decrease the overall ATA score for October 2022 by over 9%, bringing its current equity score from around -12% to -2%, making it practically equitably

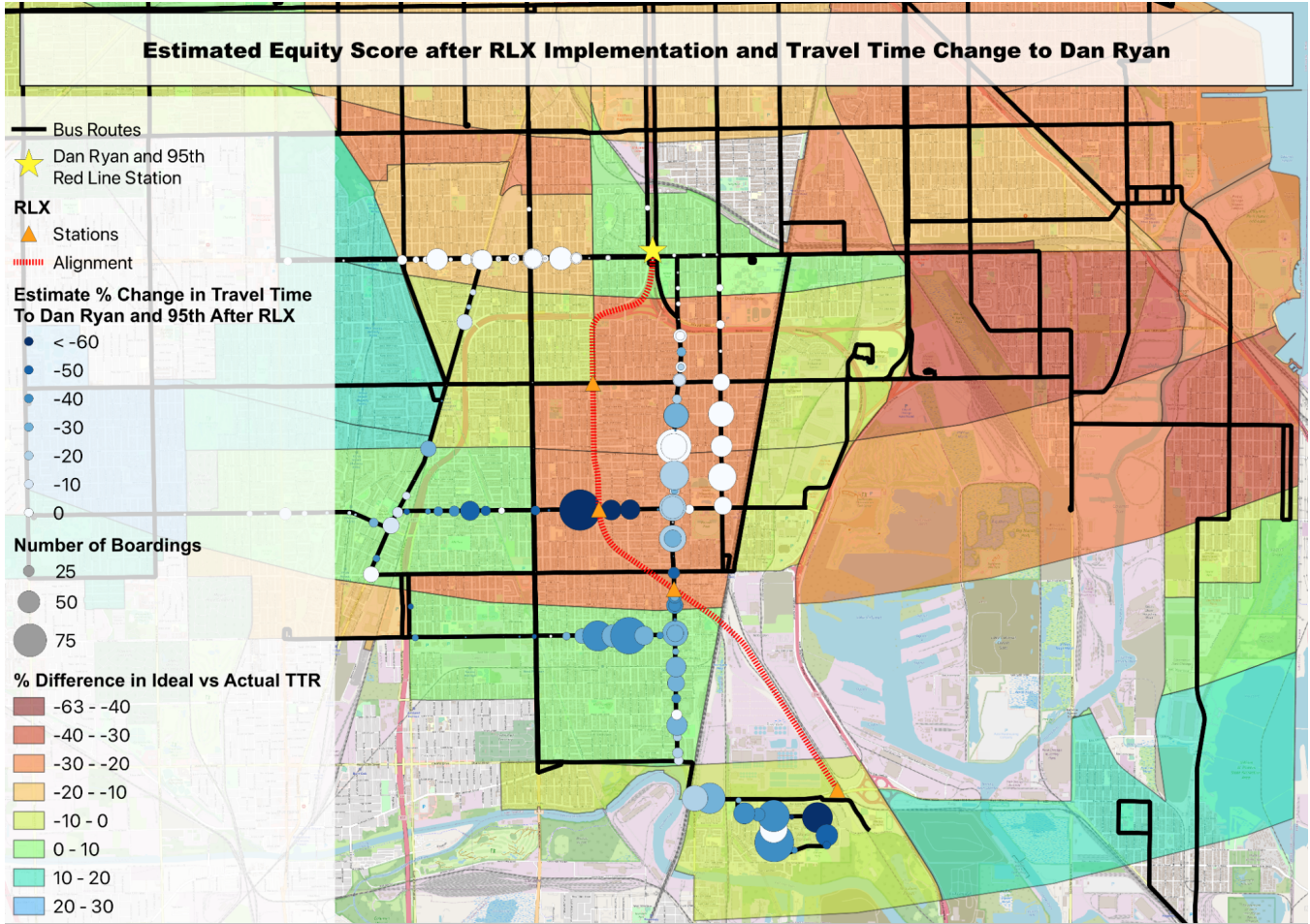


Figure 6-5: Projected Post-RLE Equity Score and Travel Time Savings to Dan Ryan

served under our definition. Other neighborhoods also see noticeable improvements, with the portion of Morgan Park in Ring 11, seeing over a 4% decrease in the overall TTR, bringing the neighborhood from underserved to adequately served. TTRs and the change in equity score for each ring-neighborhood that benefits from the RLE can be seen in Table 6.4.

Table 6.4: RLE Estimated TTR and Equity Scores

Ring	Neigh- borhood Area	Pre-RLE TTR	Estimated RLE TTR	Pre-RLE Equity Score	Post-RLE Equity Score	Change in Equity Score
13_	Riverdale	1.82	1.65	-12.3	-2.46	9.84
11_	Morgan Park	1.82	1.75	-1.56	2.66	4.22
12_	West Pull- man	1.79	1.73	0.25	1.19	0.94
11_	Roseland	1.99	1.95	-23.1	-21.4	1.7
10_	Roseland	2.08	2.06	-27.3	-26.1	1.20
11_	West Pull- man	1.98	1.97	-24.4	-24	0.4
10_	Washington Heights	1.82	1.82	-5.86	-5.5	0.36
12_	Morgan Park	2.33	2.32	-19.1	-19.7	-0.6
9_	Beverly	1.75	1.75	13.3	13.45	0.15
9_	Washington Heights	1.99	1.99	-16.34	-16.2	0.14
11_	Mount Greenwood	1.59	1.59	20.4	20.43	0.03

6.3 Discussion

There are several limitations and aspects of our equity analysis worthy of discussion. The first is connected to the finding in Chapter 5 that the overall equity scores between September 2019 and October 2022 do not change meaningfully. There is concern around this result, because, as discussed in Chapters 1 and 4, in October 2022 the CTA was experiencing major service delivery issues. Underlying shortcomings with the data and method causing this will be discussed in Chapter 7, but the ultimate consequence is that we may be underestimating TTRs, resulting in equity scoring that may not highlight areas where transit service is inequitable, and underestimating the overall difference between observed and ideal TTRs across the city.

Regarding Section 6.2, several assumptions were made in order to conduct the equity analysis that are noteworthy of discussion. First was the assumption that if a passenger's origin bus stop was within a 500 meter buffer of a new RLE stop, the passengers would walk instead of taking a bus. This was a conservative estimate, as research suggests that around 70% of passengers located within that radius will walk, rather than take some form of transit (Federal Transit Administration, 2013). A radius of 800 meters corresponds to around 40% of passengers accessing the station by walking. However, selecting a conservative radius may be beneficial. We used as-the-crow-flies distance as opposed to Manhattan distance, which likely underestimates the distance of the journey, as many passengers will have to walk over 500 meters in network distance to reach the station. The other reason a conservative estimate is warranted is that we have not incorporated information about the walkability of the area surrounding the RLE. There are serious concerns amongst Chicago residents about safety. Lowe et al. conducted interviews with 120 Chicagoians from October 2019 to February 2020

about their lived experiences with public transit (Lowe et al., 2023). Many reported being extremely concerned with the walk associated with taking a public transit trip, expressing severe safety concerns, which ranged from ranging from being caught in cross-gun fire to being racially profiled by police. Additionally, the quality of sidewalks in an area can greatly affect accessibility to transit stations (Woldeamanuel and Kent, 2016). Without understanding the current conditions of the area under study, we are unable to know exactly how far passengers are willing to walk to the subway stop. For this reason, a conservative estimate was appropriate.

In terms of other shortcomings, this particular assessment of the RLE only looked at the effects of the RLE for trips currently using bus to access the Red Line. However, more work to understand what the impacts of trips that will substitute some portion of a bus trip for the Red Line not currently accessing Dan Ryan will need to be conducted to understand the overall scale of the impact. Another concern with this case study is that the percent change in equity score for the RLE case study tends to be small, despite it having a significant impact on riders. This is because the percentage of equity improvement is partially a function of the share of trips originating in the ring-neighborhood area that use the Red Line. For example, a high proportion of all trips originating in Riverdale transfer on to the Red Line (23.6%), and it sees a major improvement in its overall equity score (+9.84%). A similar overall number of trips originating in Roseland in Ring 10 transfer onto the Red Line via bus, but are a smaller portion overall of all trips taken from the neighborhood (12.5%). This makes its impact on the overall equity score small (+1.2%), despite decreasing over TTRs by over 30% for some riders in that area who make the bus-to-Red Line journey.

Table 6.5: Number of Observations of Far South Side Origins Across Datasets in AM Peak

ring_neigh_index	All Trips	Bus-to-Red Line Trips	% of All Trips that are Bus-to-Red
10_Beverly	851	22	2.6%
10_Roseland	5499	685	12.5%
10_Washington Heights	1894	79	4.2%
11_Morgan Park	2667	452	16.9%
11_Mount Greenwood	1224	6	0.5%
11_Roseland	5498	811	14.8%
11_West Pullman	2841	183	6.4%
12_Morgan Park	98	4	4.1%
12_Mount Greenwood	579	2	0.3%
12_West Pullman	4449	747	16.8%
13_Riverdale	2705	638	23.6%
9_Beverly	149	11	7.4%
9_Roseland	17039	114	0.7%
9_Washington Heights	4737	567	12.0%

Chapter 7

Conclusion

7.1 Summary of Findings

This work developed a method to assess place-based equity for public transit systems, addressing several shortcomings and limitations in the equity assessment practices currently used in literature and practice. This equity assessment method has three components: a measure of need, a method of measurement, and a method of comparison. The measure of need makes use of existing social need metrics, in this case, the EHI (Economic Hardship Index), to make judgements about which geographic areas in Chicago should be prioritized for greater transit service on the basis of their social need. The method of measurement focuses on measuring a primary service quality metric, the TTR (travel time ratio), to reflect the service attributes of observed passenger trips, to determine where service quality is poor or adequate. Supporting metrics including frequency, on-time performance, and number of transfers required, were also selected as part of the method of measurement to provide intuition into what factors may be affecting the TTR. Finally, the method of comparison introduced a level of normalization to our process, and acknowledges that areas with different spatial character-

istics should have different levels of transit service. The concept of “spatial peers”, areas of the city equidistant from the core, was selected as the method of comparison for equity analysis.

TTR results for two time periods, pre- and post-pandemic restrictions (September 2019 and October 2022), were presented. Different methods for aggregating trips originating from ring-neighborhood areas were used, one looking at all trips originating from a neighborhood regardless of destinations ATA (Anywhere Trip Analysis), which is helpful in understanding the overall picture of service quality for a given area, and trips to specific destinations, CDA (Critical Destination Analysis), which is helpful for understanding service quality to key destinations. Finally, a full equity analysis of October 2022 was conducted, and the top 20 highest-need neighborhoods were identified. These neighborhoods were concentrated in the South and West Sides of the city. The equity methodology was then applied to the RLE (Red Line Extension) Project, currently under proposal, as a case study. The results demonstrated how the project will help advance equity in the Far South Side of Chicago by lowering TTRs in high-need ring-neighborhood.

7.2 Discussion of Transit Service Quality Landscape of Chicago Findings

Chapter 5 characterized the service quality landscape of Chicago. This analysis examined different subsets of passenger trips, analyzing how service quality changed by mode and destination between September 2019 and October 2022.

Looking at all trips regardless of destination (ATA), spatial and modal patterns as well as overall TTR scores remained fairly consistent between September 2019 and October 2022. Examining results by mode,

rail was the most competitive by far (median TTR of 1.15, 1.16 respectively for 2019 and 2022 by passenger trip) with mixed-mode (1.79,1.80), and bus-only (2.01,1.80) being far less competitive. Aggregating across all home-based journeys taken in the AM Peak, median TTRs of 1.71 and 1.67 were observed for 2019 and 2022, respectively. Uncompetitive mixed mode trips were particularly prominent along the lakeshore on the South Side, and in the West Side of the city. Uncompetitive bus only-trips were seen throughout the city. Because of the similarity between the 2019 and 2022 datasets, it was determined that the remaining analysis should focus on 2022 as it reflected current conditions most closely.

As mentioned, Between September 2019 and October 2022, overall TTRs remained fairly static. This result was unexpected, given the well-publicized and prevalent degradation of service in late 2022. Several reasons for the unexpectedly static results are worthy of discussion. Firstly, the ODX algorithm for rail assumes perfect train schedule adherence to calculate passenger travel times. In October 2022 there were several issues with rail service, the CTA struggled to dispatch all scheduled rail trips, and lines experienced several slow-zones due to track work not reflected in schedules. If true conditions were reflected, we might see TTRs varying much more. Secondly, driving times may have not reflected the true travel time conditions for the time periods. Thirdly, concerns around long bus-time waits were raised by the community during that period, and acknowledged by the CTA publicly. While longer average wait times were observed in our results, the median wait time remained the same across the two periods. The final possibility is that passengers may have been self-selecting for trips. Passengers may have been timing their trips to coincide with better service times (e.g. avoiding rush hour), or simply opting out of trips altogether, either not traveling (e.g. working remotely) or using an al-

ternative mode (e.g. using a car) because the transit option was so poor. Chapter 5 also explored the results of trips to three specific destinations, The Loop, River North, and the IMD. It was found that TTRs to the Loop are highly competitive (with a median passenger TTR of 1.37 across modes), TTRs to River North less so (1.65), and uncompetitive to the IMD (2.02). This result highlights how the CTA system is highly effective at moving passengers to the Loop, but is less adept at providing competitive travel times to other popular locations outside the heart of the Central Business District. Interestingly, River North is directly adjacent to the Loop, but even in the case of mere meters of separation, transit service differs greatly between these areas. Finally, access to the IMD was found to be particularly poor in many areas, which is a potential cause for concern, as it is an important area for both employment and medical care.

7.3 Discussion of Equity Analysis Findings

Chapter 6 focused on applying the equity methodology developed in Chapter 3 to generate a final equity ranking and score for ring-neighborhood areas. This was performed on the peak, weekday ATA October 2022 dataset, and the process is easily replicable for all other datasets. The median ring-neighborhood area was found to have a TTR around 8% higher than it ideally should based on its level of need compared to its spatial peers. The ring-neighborhood areas highlighted by the method as highest-need were high-EHI neighborhoods located in the South and West Sides with high median TTRs over 2. The relationship between TTR and supporting metrics was then explored. A linear regression found that all three were strongly statistically significant with the TTR, with the number of transfers required having the largest negative impact. However, the three supporting metrics were

only able to explain around 35% of all variance in TTR. Viewing the three secondary metrics alongside the TTR helped glean intuition for potential remedies, but more detailed analysis should be done to better understand the factors causing high TTRs in these areas.

The second portion of Chapter 6 focused on applying the equity methodology to the RLE project. This was done by identifying trips in the dataset that currently access the South Side terminal station, 95th and Dan Ryan, via bus, and estimating how much time they are projected to save by using the extension, and recalculating the equity score using the projected decreased TTRs. It was found that the extension will decrease travel times significantly along the proposed alignment route, and have a positive impact on the equity score of most neighborhoods, with significant improvements being seen in Riverdale.

7.4 Contributions

This thesis contributes to work in two distinct sectors. The first is to transit agencies and their staff. One shortcoming of the most commonly used equity analyses employed in practice is that they do not create a definitive ranking of which areas are in highest need of increased service while acknowledging differences in neighborhood characteristics (e.g a residential neighborhood versus CBD). Additionally, these equity analysis methods do not provide an “end goal” for transit agencies to strive towards. For accessibility analysis, barring some recent work, benchmarks or targets are not typically set. This makes measuring equity progress difficult. The equity analysis we have developed in this thesis addresses these issues, and creates a framework that transit agencies can follow to improve equity.

The second contribution of this thesis is to academia. Currently, there are few “activity-based” analyses that can be found in literature. This thesis not only contributes a new activity based analysis, but performs it on a large, high-quality, and comprehensive set of trip data. Additionally, it contributes a new framework for performing this activity-based analysis that could be replicated in a number of different cities. The method is also flexible, and would allow for different measures of need, methods of measurement, and methods of comparison, to be substituted.

7.5 Limitations and Future Work

7.5.1 Data Limitations

One limitation that has appeared repeatedly in this work is the granularity and historicity of the data sources used. While this implementation of ODX provides granular, highly accurate, travel time information for bus, it does not do the same for rail. As discussed previously, service disruptions on rail are an ongoing cause for concern at the CTA, due to service fulfillment issues and “slow zones”. Modifying ODX to use train AVL data in a similar fashion to how it currently uses bus data, or obtaining train travel times in a different way (e.g. through data scraping), would yield a much more realistic picture of rail service. Because rail travel times are idealized in this work, we may be overestimating the quality of CTA rail service, which may have implications for our equity analysis.

Another area that could use improvement is auto travel times. Due to resource constraints, travel times were calculated between ring-neighborhood areas - not origin to destination stop. Additionally, their start time was fixed to a single date and time set in the future, and

based on historical traffic data from the Google Maps API. Calculating auto travel times more granularly (i.e. for the specific time and date for departure, and directly to the origin and destination transit stops) would help give a more accurate picture of true travel time conditions, and provide a more accurate TTR. This could be achieved by making use of historical traffic databases, such as HERE Traffic (HERE Traffic), to calculate these travel times. Finally, in regards to granularity, metrics and wait times could be calculated on a finer temporal resolution level. For the purposes of this work, we made use of the median values for wait time, frequency, and on time performance aggregated on a month-level for a time period. In the future, AVL data could be processed on a shorter time frame, finding the exact wait time, frequency, on-time performance etc... for each ODX record. Another limitation of ODX is that we do not have the true origin and destination locations of passengers. By not including access and egress time to transit stations, we are inherently underestimating TTRs, as walking, the typical mode of access/egress, is low speed. One way to address this would be to link travel survey data to ODX trips. This would allow for the full duration of their trips to be calculated against the associated auto trip, and the true origin and destinations to be revealed. In a similar vein, linking demographic information with ODX trips would address the second portion of the TransitCenter's Fourth Equity Pillar. Calculating how transit service differs by demographics would constitute person-based metrics, which would allow transit agencies and practitioners to understand how transit service quality aggregates to demographics such as gender and race, expanding understanding beyond geographic origin.

7.5.2 Limitations Regarding Travel Time Ratios

One limitation discussed in Chapter 6 is that our understanding of the factors surrounding the TTR is not complete. Our analysis only explained around 35% of all variance in TTR. Including more data points, such as additional transit metrics, land use characteristics, etc. . . in our analysis, as well as using more powerful model selection tools, such as machine learning, could be methods employed in the future to improve our understanding of the factors driving TTR. This would be particularly helpful to transit agencies and practitioners, as it would help them better understand how they could practically decrease TTRs to reach equitable levels in underserved neighborhoods.

An aspect of the method of measurement that has not been explored thus far is the possibility of calculating TTR differently. TTR does not necessarily have to be done with auto travel times, it could be performed with different modes, such as biking or walking. Something else worth considering is assessing service quality with the basic speed of a transit journey. This would address the issue that a low TTR trip does not always mean transit service is high quality - the associated auto journey may just be very slow. Finding a target speed for transit journeys could encourage transit agencies to prioritize making journeys maximally efficient, rather than simply competitive compared to the automobile, as our method suggests. This relates to another aspect of future work, which is benchmarking acceptable TTRs more rigorously. It would be an interesting endeavor to further understand which TTR is “equitable” in itself, decoupled from modal share and results from other cities, which were used to set acceptable TTR thresholds in this work. Understanding how TTR benchmarks differ based on local needs, attitudes, and system capabilities would be an interesting area of further study.

7.5.3 Limitations to Equity Scoring

One aspect of our analysis that we have purposefully ignored is the number of trips originating from each ring-neighborhood area. One reason we do this is the reality of self-selection. If transit service is so poor that passengers find alternatives, we are not penalizing them for this decision. Our equity method focuses on overall need and quality, not optimizing for where demand is greatest. However, we recognize practically that demand is important, and could also have important equity implications. Understanding how this research could be used for utilitarian purposes would be a helpful extension for transit agencies to practically implement these insights to make transit improvements that would benefit the most number of people possible.

In regards to the Method of Comparison, in Chapter 3 various levels of normalization for geographic areas were introduced. There was a brief discussion in that chapter that while most spatial patterns (i.e. density, car ownership) were radial, they were not perfectly so. It is recommended that future work explore the creation of different, more refined spatial peer groupings to understand how equity recommendations may change based on different peer classifications.

7.6 Closing Discussion

Now more than ever, our communities are asking us as academics and professionals to address the deeply harmful, systemic discrimination perpetuated through our public institutions. Public transit, one of those key intuitions, is an engine for opportunity - it can be used to empower or oppress. Transit agencies, including the CTA, are actively grappling with their role in perpetuating and correcting injustices. This thesis provides a framework for determining both the location and magni-

tude of transit service inequity, so that potential remedies can be applied. It also lays the groundwork for transit agencies to practically implement these analyses, and aid them in setting quantitative targets for what constitutes equity in their systems, so that they can measure their progress in achieving them. We hope that this thesis will be the first of many activity-based equity analyses performed with large-scale AFC data, and wish to see goals and measurements derived directly from them routinely reported and utilized in decision-making at transit agencies.

Appendix A

Metric Calculation Glossary (Caros et al., 2023)

These metrics are the complete list of those available from the Ridership and Operations Visualization Engine (ROVE), an open-source bus service and journey visualization performance tool. ROVE combines diverse datasources including GTFS, AVL, APC, and OD data to generate these metrics. To read more about ROVE, or to download it, visit: <https://github.com/jtl-transit/rove>

Operation metrics:

1. Stop spacing (feet)
 - (a) Segment-level: calculate from shapes file generated by map matching
 - (b) Route-level: Average of segments
2. Scheduled frequency (buses/hour)
 - (a) Segment-level: Number of trips per day divided by the span of service within the time period
 - (b) Corridor-level: Number of trips per day divided by the span of service within the time period

- (c) Route-level: Number of trips per day divided by the span of service within the time period
3. Observed frequency (buses/hour): same as scheduled frequency
 4. Running time (minutes)
 - (a) Segment-level: actual running time for segments
 - (b) Corridor-level: actual running time for corridors
 - (c) Route-level: actual running time from first stop to last stop of routes
 - (d) Timepoint-segment-level: actual running time for segments with timepoints
 - (e) Timepoint-corridor-level: actual running time for corridors with timepoints and branch points
 5. Scheduled speed (mph)
 - (a) Segment-level: stop spacing divided by running time
 - (b) Corridor-level: stop spacing divided by running time
 - (c) Route-level: Route length divided by running time
 - (d) Timepoint-segment-level: stop spacing divided by running time for segments with timepoints
 - (e) Timepoint-corridor-level: stop spacing divided by running time for corridors
 - (f) Notice: Keep speed data within [0, 65] range
 6. Observed speed with dwell (mph): same as scheduled speed
 7. Observed speed without dwell (mph): same as scheduled speed
 8. Loads at stop (pax)
 - (a) Number of passengers on buses for segment
 9. Route-level flow at stops (pax/hour)
 - (a) Sum of all passengers on buses for segment per hour (during service time) of a day
 10. Corridor-level flow at stops (pax/hour)

- (a) Sum of all passengers on buses for all trips per hour (during service time) of a day
11. Route-level peak load (pax)
- (a) Maximum passenger loading along the trip
12. Boarding (pax/trip)
- (a) Segment-level: Number of pax get on the bus at first stop of segment per trip
 - (b) Corridor-level: Number of pax get on the bus at first stop of corridor per trip
 - (c) Route-level: Total number of pax get on the bus
 - (d) Timepoint-segment-level: Total boardings for bus stops within segments with timepoints per trip
 - (e) Timepoint-corridor-level: Sum of routes via the corridor defined by timepoints
13. Route-level Revenue hour (hour)
- (a) Daily total vehicle hours
14. Route-level Productivity (pax/hour)
- (a) Daily ridership / monthly revenue vehicles hours
15. Sample size (trip)
- (a) Number of trips used to calculate the metrics monthly
 - (b) Segment-level
 - (c) Corridor-level
 - (d) Route-level
16. Congestion delay (pax-min/mile or min/mile)
- (a) Passenger-weighted and vehicle-weighted congestion delay
 - (b) Congestion-delay: $(\text{travel time} - \text{minimum travel time}) / \text{distance} * \text{weight}(\text{number of vehicles or passengers})$

- (c) Congestion-delay metrics are calculated based on monthly full-day data
- (d) Segment-level
- (e) Corridor-level

17. Boarding Transfer

- (a) Transfer percentage: percentage of passengers transfer from the previous journey stage among all boarding passengers
- (b) Transfer count: total number of passengers transfer from the previous journey stage
- (c) Segment-level/Corridor-level: metric regarding the first stop of the segment/corridor
- (d) Route-level: Total number of transfers from the previous stage and percentage of transfers

18. Boarding Transfer Alighting Transfer

- (a) Transfer percentage: percentage of passengers transfer to the next journey stage among all alighting passengers
- (b) Transfer count: total number of passengers transfer to the next journey stage
- (c) Segment-level/Corridor-level: metric regarding the second stop of the segment/corridor
- (d) Route-level: Total number of transfers to the next stage and percentage of transfers

Metrics that do not change between 50th and 90th percentile: Stop spacing, Segment and corridor-level flow, Route-level Revenue hour, Route-level Productivity, scheduled frequency, observed frequency, sample size, congestion delay, transfer.

Passenger service level metrics: Metrics for all types of routes:

1. Crowding (%)
 - (a) Segment-level: Segment-level occupancy / vehicle capacity
 - (b) Corridor-level: Aggregate of segment-level crowding
 - (c) Route-level: Peak load / vehicle capacity
2. On-time performance (seconds /
 - (a) On-time: actual arrival time within [-1, +5] time window of scheduled arrival time from GTFS data
 - (b) Segment-level: arrival delay at the first stop of the segment. $\text{Max}(0, \text{actual arrival time} - \text{scheduled arrival time})$
 - (c) Route-level: percentage of stops with arrival time within [-1, +5] time window regarding to GTFS arrival time
3. Journey-based delay (minutes)
 - (a) Route-level only
 - (b) Percentile of journey-based delay for a specific route and direction
 - (c) Journey-based delay: excess waiting time at boarding stop + excess running time

Metrics for high-frequency routes only (Scheduled frequency ≥ 5 buses/hour):

1. Scheduled expected wait time (minutes)
 - (a) Segment-level: calculated based on scheduled headway distribution at the first stop of the segment
 - (b) Route-level: calculated based on scheduled headway distribution at the first stop of the route
2. Actual expected wait time (minutes)
 - (a) Segment-level: calculated based on scheduled headway distribution at the first stop of the segment

(b) Route-level: calculated based on scheduled headway distribution at the first stop of the route

3. Excess wait time (minutes)

(a) Segment-level: $\text{Max}(0, \text{actual segment-level expected wait time} - \text{scheduled segment-level expected wait time})$

(b) Route-level: $\text{Max}(0, \text{actual route-level expected wait time} - \text{scheduled route-level expected wait time})$

Metrics that do not change between 50th and 90th percentile: Scheduled expected wait time, Actual expected wait time, excess wait time, on-time performance

Appendix B

Composition of Different Need Indices

Table B.1: Demographic Weightings of Different Need Indices (Amanda Madrigal)

Need Index	Demographics							
	Poverty	Youth	Senior Citizen	Female-Led Household	Disabled	Minorities	Zero Car	
Equal Weights	13%	13%	13%	13%	13%	13%	13%	
Federal Policies	20%	5%	5%	5%	20%	20%	5%	
Income & Vehicle Ownership	25%	8%	8%	8%	8%	8%	25%	
Race & Income 50%	25%	8%	8%	8%	8%	25%	8%	
King County Metro	30%	5%	5%	5%	5%	40%	5%	
Race / Income 60% - LEP/Vehicles Ownership 20%	30%	5%	5%	5%	5%	30%	10%	
Less Emphasis on age with high preference on race and income	25%	5%	5%	10%	10%	25%	10%	
LA Metro	20%	8%	8%	8%	8%	20%	20%	

Appendix C

Neighborhood Ring Cleaning Process

To practically implement distance from the core, Chicago's 77 neighborhoods are superimposed onto a series of concentric 2 kilometer rings radiating from the Chicago Loop, the heart of the CBD, which is known as "The Loop". The 2 kilometer ring specification was arrived at qualitatively and could be changed in future analysis. Each neighborhood-ring overlap will be treated as its own unit of analysis, increasing the number from 77 to 239. By breaking neighborhood areas into smaller portions it allows us to more easily compare neighborhoods and find spatial peer groupings. Neighborhood groups are "peers" if they lie within the same ring. Figure C-1 shows Chicago's 77 neighborhoods superimposed with these rings.

However, this imposition of rings makes some units of analysis impractically small, making them useful for analysis. To remedy this, if a neighborhood-ring section is less than 0.5 kilometers square in terms of area, then it is adjoined to the larger portion of the neighborhood that it is adjacent to, making the rings "clean" for analysis. The result of this cleaning process can be seen in 3-6 in 4.

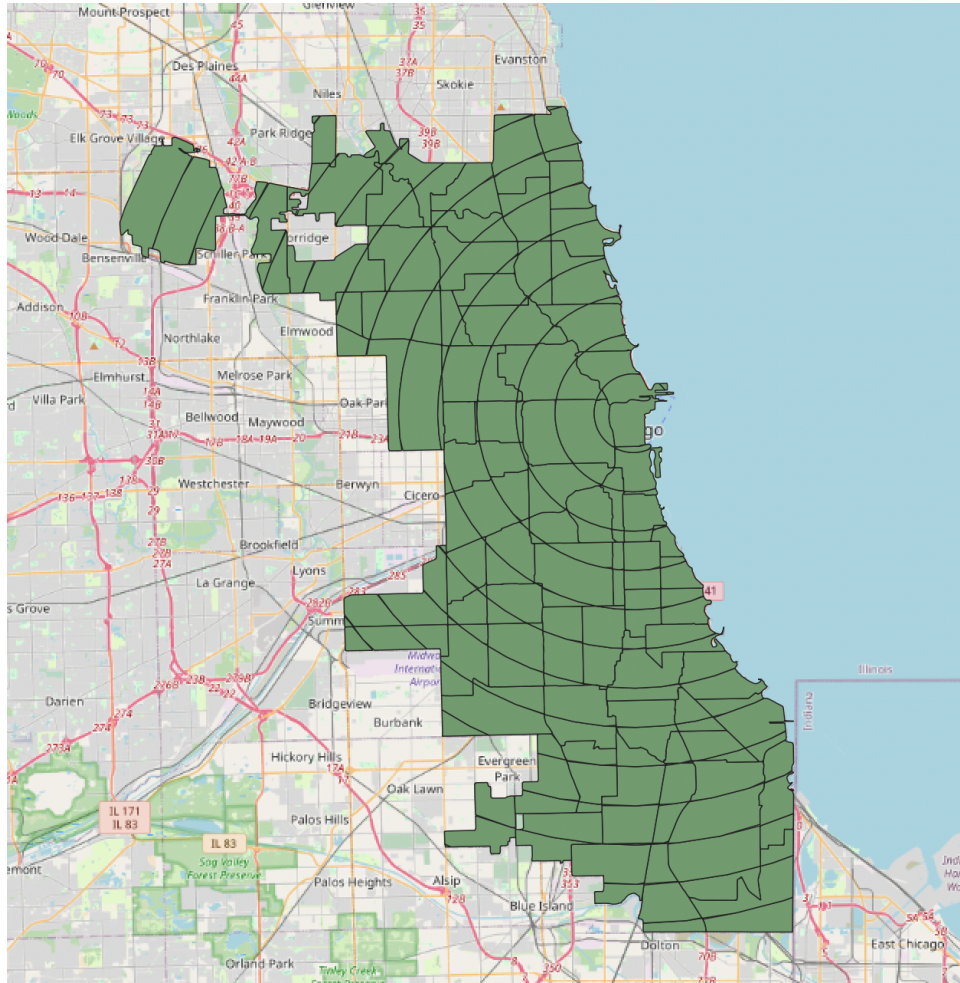


Figure C-1: Chicago Neighborhoods Intersected with 2km Rings from the CBD with No Manual Adjustment

Appendix D

The ODX Scaling Process

ODX scaling is divided into three stages. Stage zero is the most involved as it serves two functions, and is different because it infers information for bus transactions only. As outlined previously, rail journeys will always have an associated boarding location because of the fixed location of the fare gate. Buses move, necessitating inference based on location information. The first step of stage zero is to infer missing boarding stops from bus journeys. Every journey transaction has a transaction time and a vehicle identification number. The scaling script searches for another transaction with a boarding stop on the same vehicle within a 15 minute timeframe. If one is found, that boarding stop is used for the missing journey record. Otherwise, the journey is not assigned a boarding stop at all. The second function of stage zero is to create “synthetic” records in the ODX dataset for journeys paid for in cash. The number of cash boardings to be added is determined by a “cash factors” table that gives the percent of total boardings on a given route that are paid for in cash. This information is gathered by the bus operator, who pushes a button whenever a passenger boards and pays with cash. Stage zero infers a boarding stop, trip id, and boarding time.

The final two stages infer an alighting stop and time. Stage one infers

alighting for rail and bus journeys that share boarding information for a complete transaction, in other words, there was at least one other passenger who boarded at the same stop as the passenger with missing information, and that passenger had a recorded alighting stop. The alighting stop for the missing transaction is sampled from the distribution of alightings for their boarding cohort. Stage two handles journeys that do not share identical boarding information with journeys with valid alighting stops. In these kinds of journeys, only one passenger boarded at the given stop or station. Therefore, the alighting stop is sampled from the overall alighting distribution of the system conditionally.

Appendix E

Complete List of October 2022 Equity Scores

Table E.1: Equity Scores, All Ring-Neighborhood Areas,
October 2022

Need Rank	Ring Area	Neighborhood	Number of Observations	Actual TTR	Ideal TTR	% Diff in TTRs	EHI
1	9_Chatham		1999	3.09	1.62	-62.7	47.9
2	6_South Lawndale		186	2.30	1.50	-42.1	70.6
3	7_Englewood		5659	2.27	1.50	-40.8	70.5
4	10_South Deering		5495	2.25	1.50	-40	58.1
5	4_Oakland		3323	2.43	1.64	-38.5	53.2
6	7_Woodlawn		5032	2.45	1.71	-35.8	50.4
7	11_East Side		2539	2.14	1.52	-34.1	56.7
8	8_Greater Grand Crossing		7730	2.16	1.58	-31.3	54.3
9	4_New City		3260	2.12	1.57	-29.9	62.6
10	8_South Chicago		4962	2.10	1.57	-29.3	54.9

11	9_Ashburn Gresham	4496	2.09	1.56	-29.1	51.5
12	5_South Lawndale	15032	2.01	1.50	-29.1	70.6
13	6_Englewood	9089	2.01	1.50	-28.9	70.5
14	5_West Garfield Park	10601	2.03	1.52	-28.8	68.3
15	5_Brighton Park	13673	2.04	1.54	-28.2	66.1
16	3_Douglas	15404	2.24	1.70	-27.5	42.5
17	10_Roseland	5499	2.08	1.58	-27.3	52.6
18	9_South Chicago	8247	1.97	1.50	-27.2	54.9
19	7_Ashburn Gresham	877	2.22	1.69	-26.8	51.5
20	1_Near West Side	43784	2.22	1.70	-26.2	26.6
21	7_Archer Heights	2250	2.14	1.65	-26	56.1
22	9_West Ridge	3514	2.11	1.63	-26	47.3
23	10_East Side	841	1.97	1.52	-25.8	56.7
24	5_Washington Park	6516	2.05	1.59	-25.7	60.2
25	11_West Pullman	2841	1.98	1.55	-24.4	54.3
26	8_Avalon Park	4274	2.13	1.67	-23.9	47.9
27	9_Burnside	1216	1.98	1.56	-23.7	51.2
28	11_Roseland	5498	1.99	1.58	-23.2	52.6
29	2_Lower West Side	7409	2.05	1.62	-23.1	50.1
30	8_West Lawn	3555	1.99	1.58	-22.7	53.7
31	7_West Englewood	6402	1.98	1.57	-22.7	63.3
32	11_South Deering	409	1.88	1.50	-22.4	58.1
33	5_Englewood	2459	1.88	1.50	-22.4	70.5
34	7_West Lawn	2688	2.09	1.67	-22.4	53.7
35	4_Bridgeport	413	2.17	1.74	-22.2	41.9
36	4_Kenwood	2855	2.24	1.80	-22.1	34.6
37	5_Grand Boulevard	2736	2.07	1.67	-21.1	49.8
38	7_Greater Grand Crossing	19230	2.05	1.67	-20.8	54.3
39	5_Austin	4931	2.02	1.64	-20.7	53.1

40	6_ Washington Park	3522	1.96	1.60	-20.6	60.2
41	6_ Hermosa	6596	2.02	1.65	-20.3	54.3
42	4_ Brighton Park	845	1.87	1.54	-19.8	66.1
43	8_ South Shore	15832	1.97	1.62	-19.6	51.4
44	12_ Morgan Park	98	2.33	1.92	-19.1	36.7
45	9_ Portage Park	654	2.18	1.81	-18.5	36.2
46	6_ Woodlawn	14279	2.03	1.69	-18.4	50.4
47	6_ Belmont Cragin	12746	1.96	1.64	-18	55.9
48	5_ Humboldt Park	24747	1.89	1.58	-17.8	60.3
49	8_ Garfield Ridge	2573	2.15	1.82	-17	38.7
50	5_ North Lawndale	10972	1.87	1.59	-16.5	59.8
51	9_ Washington Heights	4737	1.99	1.69	-16.3	43.3
52	3_ North Lawndale	384	1.81	1.53	-16.2	59.8
53	4_ Humboldt Park	15510	1.86	1.58	-16.1	60.3
54	8_ Austin	1246	1.87	1.59	-16.1	53.1
55	4_ South Lawndale	13024	1.76	1.50	-16	70.6
56	6_ Archer Heights	2085	1.92	1.64	-16	56.1
57	9_ West Lawn	1057	1.78	1.52	-15.8	53.7
58	2_ Lincoln Park	5773	2.32	1.98	-15.7	10.3
59	9_ Jefferson Park	3682	2.21	1.89	-15.7	31.3
60	8_ West Ridge	18214	1.96	1.68	-15.4	47.3
61	5_ New City	18180	1.83	1.57	-15.4	62.6
62	9_ Garfield Ridge	1405	2.06	1.77	-15.3	38.7
63	8_ North Park	2837	2.03	1.75	-14.8	42.8
64	4_ Grand Boulevard	11963	1.94	1.67	-14.7	49.8
65	8_ Dunning	5227	2.19	1.90	-14.3	33.4
66	6_ West Englewood	10013	1.81	1.57	-14.2	63.3
67	9_ Calumet Heights	5896	2.04	1.77	-14	38.4
68	7_ South Shore	21610	1.95	1.70	-13.8	51.4
69	6_ Chicago Lawn	1400	1.84	1.61	-13.6	59.2

70	8_Chatham	20963	1.90	1.67	-12.8	47.9
71	8_Belmont Cragin	6951	1.76	1.55	-12.4	55.9
72	13_Riverdale	2705	1.82	1.61	-12.3	84.2
73	7_West Ridge	7049	1.97	1.74	-12.3	47.3
74	5_Kenwood	7369	2.02	1.80	-11.8	34.6
75	4_Fuller Park	5660	1.74	1.55	-11.7	64.9
76	7_Belmont Cragin	28050	1.85	1.65	-11.5	55.9
77	8_Ashburn Gresham	17206	1.80	1.62	-10.4	51.5
78	10_Clearning	341	1.98	1.79	-10.2	38.8
79	7_North Park	5965	1.97	1.78	-9.9	42.8
80	4_East Garfield Park	12599	1.76	1.60	-9.9	58.9
81	7_Portage Park	15275	2.04	1.85	-9.9	36.2
82	7_Chicago Lawn	18745	1.78	1.62	-9.9	59.2
83	11_Pullman	517	1.88	1.70	-9.6	43.3
84	6_Hyde Park	2576	2.11	1.92	-9.1	25.3
85	8_Albany Park	780	1.86	1.71	-8.5	45.7
86	8_Chicago Lawn	1671	1.62	1.50	-7.9	59.2
87	4_McKinley Park	11378	1.79	1.66	-7.7	51.5
88	3_East Garfield Park	4206	1.67	1.54	-7.6	58.9
89	8_Portage Park	14460	2.00	1.85	-7.4	36.2
90	5_Hermosa	4613	1.76	1.63	-7.4	54.3
91	9_Dunning	7338	1.97	1.85	-6.2	33.4
92	6_Avondale	14196	1.91	1.80	-6.1	38.6
93	3_Bridgeport	14723	1.81	1.70	-6	41.9
94	10_Washington	1894	1.82	1.72	-5.9	43.3
	Heights					
95	4_North Lawndale	16435	1.68	1.59	-5.5	59.8
96	4_Lower West Side	1409	1.76	1.67	-5.4	50.1
97	8_Montclare	7212	1.83	1.74	-5.4	43.9
98	5_Uptown	36952	1.92	1.82	-5.1	31.5

99	6_Austin	40934	1.74	1.66	-4.3	53.1
100	5_Hyde Park	9260	1.95	1.87	-3.9	25.3
101	9_Norwood Park	951	2.01	1.94	-3.8	28.2
102	13_West Pullman	319	1.90	1.84	-3.1	54.3
103	9_Ashburn	4472	1.78	1.73	-2.8	40.8
104	10_O'Hare	342	1.91	1.86	-2.8	33.8
105	3_Near West Side	17250	1.89	1.85	-2.2	26.6
106	10_Pullman	1437	1.76	1.72	-2.1	43.3
107	9_Forest Glen	520	2.00	1.96	-1.8	26.7
108	11_Morgan Park	2667	1.82	1.79	-1.6	36.7
109	12_East Side	226	1.81	1.78	-1.5	56.7
110	6_Greater Grand Crossing	1555	1.66	1.65	-0.5	54.3
111	9_Clearing	2449	1.77	1.76	-0.1	38.8
112	12_West Pullman	4449	1.79	1.80	0.3	54.3
113	6_Uptown	25360	1.83	1.86	1.7	31.5
114	9_Pullman	50	1.66	1.69	1.8	43.3
115	11_Norwood Park	94	1.86	1.91	2.7	28.2
116	6_Gage Park	18736	1.50	1.55	3.2	65.3
117	3_Lower West Side	26577	1.57	1.63	3.3	50.1
118	7_Lincoln Square	8183	1.93	2.00	3.3	21.7
119	8_Clearing	2263	1.75	1.81	3.6	38.8
120	9_Roseland	17039	1.48	1.54	3.8	52.6
121	7_Edgewater	34716	1.85	1.93	3.8	28.9
122	7_Albany Park	25008	1.69	1.75	4	45.7
123	12_Hegewisch	72	1.84	1.92	4	37
124	7_Austin	16545	1.61	1.68	4.2	53.1
125	10_Dunning	1129	1.78	1.87	4.8	33.4
126	6_Edgewater	23224	1.80	1.89	5	28.9
127	3_Logan Square	1901	1.76	1.86	5.1	25.6

128	2_Near South Side	13044	1.88	1.98	5.1	11.2
129	8_Ashburn	3794	1.69	1.78	5.2	40.8
130	1_Near North Side	29859	1.84	2.00	8.4	8.6
131	1_Near South Side	16066	1.79	1.96	9	11.2
132	10_Beverly	851	1.81	2.00	10.2	24.5
133	10_Forest Glen	265	1.78	1.97	10.3	26.7
134	5_Fuller Park	3064	1.39	1.55	10.4	64.9
135	12_Mount Greenwood	579	1.78	2.00	11.5	25.6
136	3_Armour Square	5751	1.32	1.50	12.4	63.5
137	5_Avondale	29256	1.55	1.76	13	38.6
138	9_Beverly	149	1.75	2.00	13.3	24.5
139	4_North Center	1979	1.69	1.94	13.7	16.9
140	2_Near West Side	34275	1.59	1.84	14.2	26.6
141	4_Lincoln Park	8952	1.72	2.00	14.6	10.3
142	8_Forest Glen	852	1.71	2.00	15.4	26.7
143	7_Rogers Park	9695	1.56	1.82	15.6	39.4
144	1_Loop	82567	1.70	1.99	15.8	9
145	13_Hegewisch	159	1.69	1.98	15.8	37
146	7_Garfield Ridge	19986	1.54	1.83	16.9	38.7
147	6_North Center	1202	1.69	2.00	17	16.9
148	11_Beverly	31	1.64	1.96	17.8	24.5
149	4_West Town	11850	1.60	1.93	18.4	18.7
150	2_West Town	20344	1.58	1.91	18.7	18.7
151	7_Irving Park	11104	1.55	1.89	19.5	32.3
152	6_Brighton Park	7822	1.26	1.54	19.9	66.1
153	11_Mount Greenwood	1224	1.59	1.95	20.4	25.6
154	8_Jefferson Park	27721	1.56	1.93	21.2	31.3
155	2_Armour Square	6966	1.21	1.50	21.4	63.5
156	13_O'Hare	4164	1.61	2.00	21.5	33.8
157	9_Rogers Park	9102	1.40	1.75	22.3	39.4

158	6_ Albany Park	13396	1.35	1.73	24.7	45.7
159	6_ Irving Park	32328	1.45	1.86	24.9	32.3
160	8_ Rogers Park	24955	1.39	1.80	26	39.4
161	11_ Edison Park	553	1.51	2.00	28.1	21.8
162	7_ West Elsdon	11041	1.28	1.72	29.2	49.2
163	5_ Logan Square	38828	1.36	1.87	31.7	25.6
164	4_ Lake View	138101	1.44	2.00	32.6	9.9
165	3_ West Town	60910	1.36	1.92	34.1	18.7
166	10_ Norwood Park	10125	1.37	1.94	34.9	28.2
167	5_ Lake View	34928	1.40	2.00	35.5	9.9
168	6_ Lincoln Square	31894	1.36	1.96	35.9	21.7
169	5_ North Center	18606	1.34	1.94	36.6	16.9
170	3_ Lincoln Park	61881	1.38	2.00	36.9	10.3
171	4_ Logan Square	44662	1.21	1.87	42.7	25.6
172	2_ Near North Side	68428	1.29	2.00	43.2	8.6
173	11_ O'Hare	10262	0.99	1.83	59.4	33.8
174	10_ Ashburn	1		1.76		40.8
175	14_ Hegewisch	267	1.85			37

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