THE IMPACTS OF FIRST/LAST-MILE MOBILITY PRICING SOLUTIONS ON JOB ACCESSIBILITY

BY

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THESIS

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ABSTRACT

In the past few years, many cities in the Unites States have adopted mobility-on-demand (MOD) and ride to transit (R2T) services to address the mobility needs of their disadvantaged, typically carless populations. When integrated with public transit, these services can help to increase accessibility and alleviate the last-mile problem by reducing travel times to important destinations like employment centers, however, their ability to do so has not been properly evaluated in the transportation planning literature using experimental methods. This study attempts to shed light on the efficacy of an R2T in promoting low-wage job accessibility by combining Census tract-level accessibility scores with data from a state-of-the-art randomized control trial (RCT) that provides subsidized R2T Uber trips in the Chicago Metropolitan Area. By analyzing the interaction between the subsidy treatment and participants' accessibility, I attempt to answer the following questions: First, how large is the disparity between transit- and auto-based low-wage job accessibility in the Chicago Metropolitan Area? Then, to what extent can transit-linked Uber trips alleviate any accessibility gaps? And lastly, how do the accessibility gains one achieves through FLM connectivity play a role in determining their take up of a subsidized R2T program? My results serve to help planners in determining where and for whom R2T program usage is highest and whether job accessibility is a useful metric for predicting program uptake.

ACKNOWLEDGMENTS

I would first like to give a big thank you to all my committee members that took time out of their busy schedules to provide feedback on my research. You held my work to a rigorous academic standard and challenged me to think more critically about my methodology, results, and the conclusions at which I arrived. I am especially indebted to my advisor, Professor Peter Christensen for his faith in my research design and analytical skills. Without his encouragement to continue pursuing the last-mile research I began in my undergrad; I probably would not have ended up sticking around at the University and realizing my passion for economic research.

I would also like to extend a special thanks to Gustavo Nino for his patience in answering my many questions about the Uber Chicago research design and for assisting me with adapting the treatment effect regression code to my own purposes. In addition, I would like to express my gratitude to Craig Heither and Nicholas Ferguson at the Chicago Metropolitan Planning Agency for assistance in interpreting and working with their organization's travel demand model output data.

Of course, none of this would have been possible without the continued support of my friends and family throughout the past year and a half. Whether you sat with me through a defense practice run, or a casual conversation about the last-mile problem, tour interest in my work kept me motivated to continue to dig deeper into the transportation problems that our cities face and reminded me why I decided to pursue a degree in higher education in the first place.

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CHAPTER 1: INTRODUCTION

It is well known that low-income households in American cities are less likely to own a personal vehicle and are thus more reliant on public transit services for their commutes. The consensus in the transportation planning literature however is that job accessibility by transit is many magnitudes lower than accessibility by car, even in the parts of metropolitan areas with the densest transit service (Boarnet et al., 2017; Grengs, 2010; Kawabata & Shen, 2007; Kim & Lee, 2019). Moreover, while these low-income households are predominantly located in transit-dense urban areas, there is no guarantee that the fixed route nature of transit services will geographically coincide with their residents ' commuting origins or destinations (Brown et al., 2021; Jiao & Wang, 2021). This aspect of public transit has led to considerable research into the effect of the first- last-mile (FLM) on ridership (Boarnet et al., 2017; Chen et al., 2021; Ha et al., 2023). The first- last-mile is the 1/2 to 1-mile radius outside of the core transit service area in which people commonly decide that traveling to transit stations is either too time consuming, unsafe, or cumbersome, and choose instead to opt for personal vehicle travel (U.S. Census Bureau & Dowell, 2020). Because not all households have reliable access to a personal vehicle, many have highlighted the need for reduced cost mobility options to improve FLM connectivity, especially among low-income groups (Boarnet et al., 2017; Franklin, 2018).

Following their explosion in popularity over the past decade, transportation modes such as bike sharing, ridesharing, and micro transit services have been suggested by researchers, planners, and the private sector as a way to reduce FLM travel times (Brown et al., 2021; Greenawalt, 2021; Shaheen & Chan, 2016; Witek et al., 2020). Boarnet et al. (2017) finds that the gap in low-wage job accessibility between rail transit and car can decrease significantly if a car is used as a complement to transit, making up the FLM distance. Few studies have tried to estimate the degree of complementarity that exists between micro transit and public transit, and what little evidence they do find points to very small positive effects, though typically for those with higher incomes who are already adequately serviced by transit (Barajas & Brown, 2021; Brown et al., 2021; Ma et al., 2015; Martin & Xu, 2022; Sabouri et al., 2020). Despite this, many cities have partnered with mobility-on-demand MOD service providers like Uber, Lyft, and Via to adopt micro transit services, which provide their residents with reduced-cost shared rides, and ride-to-transit (R2T) services, a similar type of ride hailing that restricts trip purpose to first- last-mile transit connectivity (Greenawalt, 2021). To my knowledge, Brown et al. (2021) is the only study that has attempted to empirically evaluate the success of such a program in bridging the FLM gap. They analyze data from Los Angeles' MOD pilot program, but are limited by a lack of experimental design, an inability to link trip data to user demographic information, and difficulties with surveying frequent riders. Beyond studying the coincidence of MOD trip origins and destinations with low-income Census tracts, the authors do not reach any definitive conclusions regarding the equity and welfare impacts of the pilot.

This study attempts to address the identification problems mentioned previously by combining Census tract-level measures of low-wage job accessibility with data from a state-of-the-art randomized control trial (RCT) that examines the effects of a program which provides subsidized R2T connectivity in the Chicago Metropolitan Area. The experiment, developed by Christensen, Lehe, & Osman from the University of Illinois Urbana-Champaign, provides treated individuals with a 50% fare price subsidy for their transit-linked Uber trips. In the first part of my paper, I calculate zone-level accessibility scores that account for transit station access and egress time. In doing so, I establish that the use of a car to traverse the first- and/or last-mile of a transit commute can greatly increase the transit-based low-wage job accessibility experienced by the Chicago area's low-income populations. The Chicago context is a useful comparison to Boarnet et al.'s (2017) San Diego results because it sheds light on the extent to which FLM connectivity increases accessibility in a larger, more transit-oriented, yet economically segregated, metro area. The second part of my analysis evaluates these zone-level accessibility scores in determining how they influence the treatment effects of the R2T program. I use travel survey data collected at the mid and endline of the RCT to develop a set of treatment effect models that estimate an average treatment effect (ATE) on trips taken in the previous day using a personal vehicle, car, and various types of transit. Each model includes a term that interacts the treatment variable with a measure of the increase in the accessibility achieved by linking transit with ride hail trips. Given available data, I find that transit-based accessibility to low-wage jobs does not significantly increase treatment effects, though the direction of the coefficients indicates the potential for positive effects on trips taken using transit and increased Uber utilization. These results are very relevant to planners and government officials that are considering R2T programs as a way to meet equity and sustainability goals in their city. This accessibility framework can also help to identify areas and populations for which a program would have the strongest effects for the purposes of targeted implementation and welfare analysis.

The rest of this paper will proceed as follows: Chapter 2 reviews the literature on job accessibility, the first- last-mile problem, and the relationship between ride hailing and transit, while also highlighting experimental and quasi-experimental transportation planning studies; Chapter 3 describes the study area and the demographic composition of Chicagoland; Chapters 4 and 5 provide the respective methodologies for and results of the accessibility and regression analyses; and in Chapter 6, I interpret these results and discuss their policy implications.

CHAPTER 2: LITERATURE REVIEW

2.1 Spatial Mismatch and Accessibility

Understanding the disparity in job accessibility faced by low-income groups first requires a discussion of the spatial mismatch hypothesis. Spatial mismatch was first proposed in 1968 by economist John F. Kain, who posited that disproportionate levels of unemployment among poor urban black populations could be explained by the various residential segregation mechanisms that had increased their geographical distance from job centers (Kain, 1968). More recent tests of the spatial mismatch hypothesis have studied the shift of employment centers into the suburbs in American metros, away from urban areas where low-income groups tend to concentrate (U.S. Census & Dowell, 2020). This body of literature is driven by skeptics in the transportation planning field, who question how much physical distance plays a role in determining employment outcomes. Taylor & Ong (1995) were the first to argue that employment outcomes among low-income populations could be traced back to a "modal-mismatch", or a lack of personal vehicle ownership as opposed to physical distance. This finding implies that travel time is the primary barrier to opportunity rather than distance. Successive studies have generally supported this finding, characterizing it as a problem of accessibility (Blumenberg, 2002; Grengs, 2010; Kawabata, 2003; Kawabata & Shen, 2007). Many job accessibility studies have investigated the correlation between zone-level transit-based accessibility scores and socioeconomic problems relevant to this research (Kawabata, 2003; Kim & Lee, 2019; Owen & Levinson, 2015). Kawabata (2003) finds transit-based accessibility to be positively associated with the probability that a carless worker in Boston, Los Angeles, and San Francisco is employed. Using binary logistic models and a utility-based definition of accessibility, Kim & Lee (2019) find that increases in Census tract-level ratios of transit- to auto-based accessibility are significantly associated with higher transit commuting shares in the Chicago Metropolitan Statistical Area (MSA).

If spatial mismatch is at its core, an accessibility problem as the literature would suggest, then approaches that reduce low-income residents' travel times to large employment destinations could help alleviate the problem. In light of this, some have argued for policies that aid carless people in gaining access to automobiles (Blumenberg, 2002; Grengs, 2010)., Putting more cars on the road, however, runs contrary to common goals set by cities to reduce congestion and reduce emissions from their transportation sectors. Transit agencies may also pursue headway reductions – reducing the time between vehicles at a given stop – to cut down on the amount of time a traveler would spend waiting for their vehicle to arrive. In an era of shrinking transit agency budgets and rising infrastructure costs, running more buses and trains is rarely an option, even on high ridership routes (Regional Transit Authority, 2022). Another avenue for improving accessibility lies in decreasing overall travel times through interventions that address the FLM (Boarnet et al., 2017; Huang & Boarnet, 2022; Lu et al., 2021).

2.2. First- Last-mile Solutions

While first- last-mile transit access is often cited as an obstacle to increasing transit ridership in Chicago and other U.S. cities (Chandra et al., 2013; Regional Transit Authority, 2022), it is not always accounted for in current models of accessibility to jobs and services (Boarnet et al., 2017). Even though the FLM distance is intrinsic to a commuter's specific trip origin and destination and thus hard to generalize for zonal-accessibility analysis, Krygsman et al. (2004) finds that it can account for a large share of transit travel times, warranting its inclusion in travel behavior models. Boarnet et al. (2017) find that the first- last-mile plays a large role in the provision of adequate transit-based job accessibility for very-low-income residents of San Diego, and that its omission from travel time modeling can severely overestimate job access. Conversely, they find that this modal disparity can be reduced by 58.2% if a car is used to complete the transit access and egress portion of a commute. In such a scenario, these transit-linked car trips would act as an economic complement to transit, contributing to a multimodal trip rather than directly substituting for it. Policies that reduce FLM travel times (Boarnet et al., 2017; Krygsman et al., 2004) and associated costs (Franklin, 2018, Bryan et al., 2014, Phillips, 2014) can thus improve accessibility by transit by reducing modal-mismatch.

2.3 Ridesharing Literature

In light of decreasing transit ridership in U.S. cities, and the increasing prevalence of ride sharing, much of the ridesharing/transit literature intuitively focuses on the potential for the former substitute for the latter (Hall et al., 2018; Malalgoda & Lim, 2019; Mallett, 2018; Puentes, 2017). Some find that ridesharing services are increasingly used for trips that otherwise would have been completed using more sustainable modes (Gehrke, 2020; Gehrke et al., 2019; Sabouri et al., 2020). Using a multi-level modeling approach, Gehrke (2020) finds that growth in Census tract level Uber activity in the morning peak period in Boston, San Francisco and Washington D.C. is most concentrated in employment-dense and transit-dense areas, indicating that Uber may compete with transit services. Work from Sabouri et al. (2020) produces similar findings with trip-level data from 24 U.S. cities, showing that Uber demand tends to cluster around areas with high transit-stop density. Interestingly, the authors also observe negative correlations with both auto- and transit-based job accessibility which they attribute to the fact that alternative modes may maintain a competitive advantage over ridesharing services in certain areas, while Uber is used as a "last resort" option.

Ridesharing services can theoretically complement public transit systems in two ways; via FLM connectivity on a trip-by-trip basis, and in a more city-wide sense by filling in the gaps created by the fixed-route nature of transit services (Hall et al., 2018). While addressing the needs of mobility deprived populations, ride sharing services have been found to do a poor job of addressing so called "transit deserts" or urban areas where transit access is low (Barajas & Brown, 2021; Jiao & Wang, 2021). Using hotspot analysis, Barajas & Brown (2021) report that clusters of ride-sharing trip origins and destinations in the city of Chicago tend to not be spatially correlated with any measure of transit service deficiency, but instead with higher median household incomes. When controlling for income and other socioeconomic characteristics as well as urban form variables, they find a negative effect on overall transit station density, but a positive effect on rail station proximity, indicating that rail transit could be a better candidate for FLM connectivity. Meredith-Karam et al. (2021) provide one of the few studies that directly examine ridesharing as a potential FLM solution. They classify Uber trips made in Chicago into three relationship bins: complement, substitute, or independent of transit, using factors such as proximity to light rail transit, transit schedule data, and nearby points of interest as criteria. Their model reveals that only 2% of the Uber trips taken in the city in 2019 act as complements to transit. Hall et al. (2018) take a more disaggregated approach, sacrificing the ability to distinguish between a trip-level and system-wide effect in favor of estimating a causal impact. Using a difference in differences model to determine the effect of Uber arrival and market penetration on transit ridership in U.S. cities, they reveal a significant complementary effect, with the arrival of Uber increasing the ridership of the average transit agency by 5% over the course of two years. Their results are highly heterogenous with the strongest effects seen in agencies in large cities, smaller transit agencies, and rail agencies, providing causal support for the claim made by Barajas & Brown (2021).

Taken together, the FLM literature tends to corroborate Boarnet et al.'s (2017) claim that policy incentives for micro mobility may be necessary for encouraging multi-modal transit trips, especially among lower-income populations. It should be underscored that the FLM studies reviewed above have used either observational, stated preference, or in the best case, quasi-experimental methods. While Meredith-Karam et al. (2021) provide one of the best frameworks for estimating the impact of ride sharing on public transit, their classification of trip-purpose is still just an estimation. A hypothetical trip that satisfies the "complement" criteria, may just be mimicking a trip with a first- last-mile purpose and, is a substitute for transit. This study addresses this limitation by making first- last-mile trip purpose intrinsic to its design.

2.4 Pricing of Urban Transportation and Experimental Methods

While there are some notable exceptions, randomized control trials (RCTs) are rarely used to study travel behavior and even less frequently to study ride hailing (Christensen & Osman, 2021; Merlin et al., 2022; Rosenfield et al., 2020). In most planning studies, assignment to treatment is a product of self-selection – participants choose where they live and what modes they use to travel (Bagley & Mokhtarian, 2002; Cao et al., 2009; Merlin et al., 2022). This self-selection can lead to fundamental unobservable differences between treatment and control groups that impede the identification of program impacts. Randomization deals with these differences by balancing the averages of observable characteristics between treatment and control given a sufficiently large sample size. In doing so, unobservable factors, like an individual's propensity to take public transit for example, become balanced as well. In terms of experimental design, intervention cost is often another prohibitive factor to studying the impacts of new transportation systems on welfare (Asher & Novosad, 2020). Building new transportation infrastructure is an expensive undertaking while close coordination with local government agencies regarding project timelines is typically required for baseline data collection on demographics and travel behavior. Thirdly, transportation RCT designs are limited in their ability to prevent spillover effects. Put simply, you cannot easily prevent a control group from using new infrastructure or certain transportation modes without providing significant incentives.

Mobility pricing approaches to studying travel behavior are well suited to a randomized design and have the potential to circumvent all three of these issues. Mobility pricing refers to policies and programs that either increase or decrease individuals' transportation costs. The ubiquity of smartphones and advances in GPS technology in recent years have made it easier than ever for researchers to employ such methods (Christensen & Osman, 2021). Charging different prices to different individuals can be done easily using a digital platform, reducing the chance for spillover effects, while the collection of GPS-accurate travel data can deal with recall bias (Christensen & Osman, 2021; Dixit et al., 2017; Merlin et al., 2022). Christensen, Osman, and Lehe's Uber Chicago study utilizes these technological improvements by collecting participants' trip data through Google Timeline and constraining subsidy application to treated individuals' Uber trips made within a 200-meter buffer of transit stops.

Recent studies have employed randomization to study the impacts of transportation pricing on welfare outcomes, through rarely in a developed country context (Christensen & Osman, 2021; Franklin, 2018; Phillips, 2014). Phillips (2014) attempts to answer a similar question to the one I pose, applying a randomized pricing approach to the question of whether transportation subsidies can improve the job search intensity of unemployed and carless jobseekers in Washington D.C. He finds that the subsidy treatment increases seekers' search intensity by 19% on average, with this effect more than doubling to 40% for those living the furthest from employment centers. His results indicate that reducing transportation cost has welfare effects that increase with distance, an important implication for economically disenfranchised populations living outside the FLM boundary that I will attempt to characterize in this paper.

CHAPTER 3: STUDY AREA

3.1 Demographics

The Chicago-Naperville-Elgin MSA encompasses eight counties in northeastern Illinois, four counties in northwest Indiana, and Kenosha County in Wisconsin. Because my primary interest is in identifying improvements in transit-based accessibility, this analysis will be limited to the regions' counties that receive transit service: Cook County, home to the city of Chicago, and its five "collar" counties - DuPage, Kane, Kendall, McHenry, Lake, and Will. Residents of these counties were also the primary targets for Uber Chicago recruitment. Chicagoland counties are the six most populous counties in the state; the region was home to 8,483,267 people in 2019, according to American Community Survey 5-year estimates. It also supports 4,240,993 jobs according to data from the Census' Longitudinal Employer-Household Dynamics program and had a median household income of $69,827.50 in 2019 as well. For demographic, travel time, and accessibility calculations, I use Census tracts (with 2010 boundaries) as my unit of analysis along with demographic data from the 2019 American Community Survey 5-year estimates. The study area contains 1,985 Census tracts, but I drop 4 tracts with either 0 population or 0 jobs to avoid underestimating summary statistics and accessibility calculations (n=1,981).

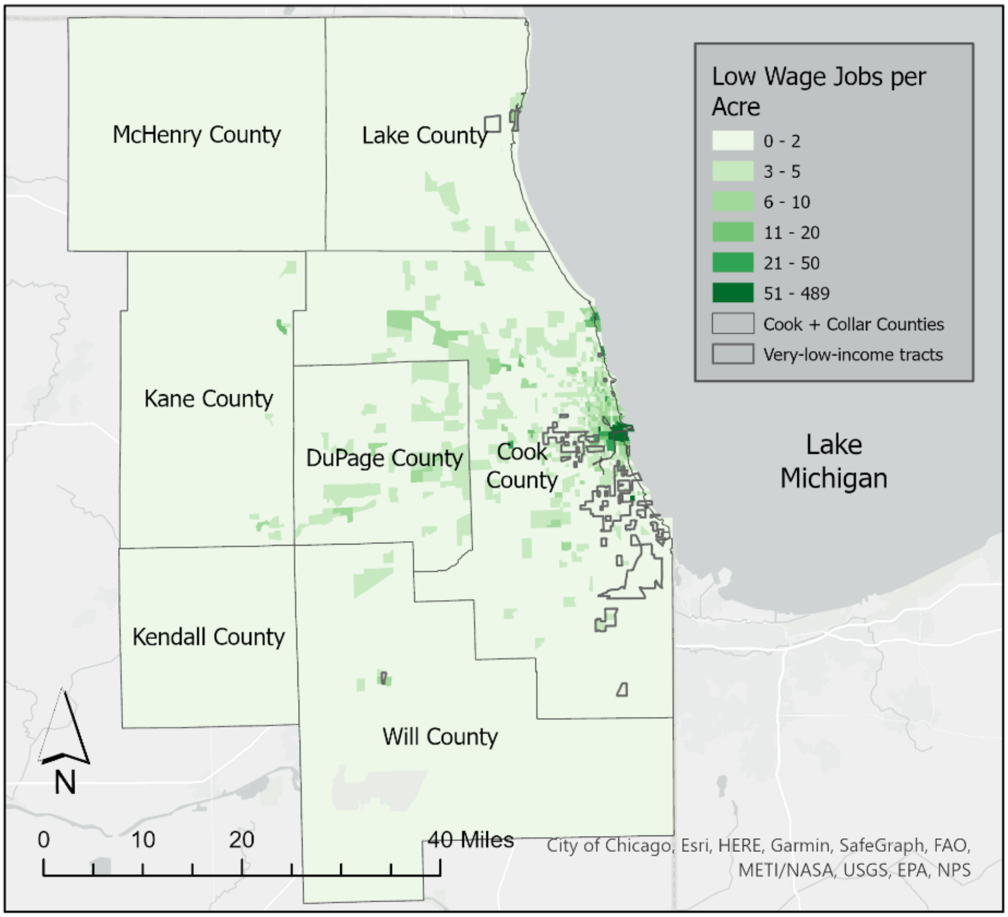
The first part of this paper seeks to measure the increase in transit-based accessibility that can be achieved by a R2T program, and whether benefits are felt equally by low-income populations. To isolate the region's population that may be low-wage job and transit reliant, I use the Department of Housing and Urban Development's (HUD) definition of very-low-income households – areas with a median household income less than or equal to half of the MSA's median, $35,885 in 2019. 229 of the 1,981 Census tracts in the study area meet the established very-low-income threshold. A demographic comparison of these very-low-income tracts with the entire region can be seen in *Table 1*. *Figure 1* displays the location of these very-low-income tracts along with tract-level low-wage job densities.

As evidenced by the clustering of very-low-income tracts on the City's West and South sides, Chicago is consistently ranked as one of the top five cities in terms of segregation on the grounds of both race and income (Acs et al., 2017). For a breakdown of the past and present mechanisms that enabled this segregation, see (Barajas & Brown, 2021). While poverty is predominantly concentrated in urban areas, pockets of low-income earners are found in parts of Lake, Will, and south suburban Cook County as well. The average annual median household income of these tracts is almost 3 times lower than that of the region at $26,433.30, while their poverty and unemployment rates are 23.4% and 11% higher respectively. The average share of zero-vehicle households is 38.9% in very-low-income tracts, illustrating a large gap in car-ownership and a potential for transit dependency.

Table 1: Demographic and Employment Characteristics of Study Area Census Tracts

	All tracts			Very low		
	N	*Average*	*Std. dev*	*N*	*Average*	*Std. dev*
Population density (acres)	1981	16.0	19.5	229	20.1	14.0
Median household income	1976	$ 76,509.30	$ 38,366.53	229	$ 26,433.32	$ 6,039.46
Poverty rate	1977	13.4	11.6	229	36.5	10.6
Unemployment rate	1978	7.2	6.5	229	18.2	8.7
Pct. households with no vehicle	1977	14.1	14.6	229	38.9	13.7
Pct. of car commuters	1978	74.0	18.9	229	60.6	15.3
Pct. of transit commuters	1981	15.6	14.3	229	29.8	13.5
Total jobs	1981	2.5	14.2	229	1.2	2.2
Job density	1981	6.3	35.7	229	2.7	4.8
Low wage jobs	1981	847	3367	229	228	502
Low wage job density	1981	2.5	14.2	229	1.2	2.2

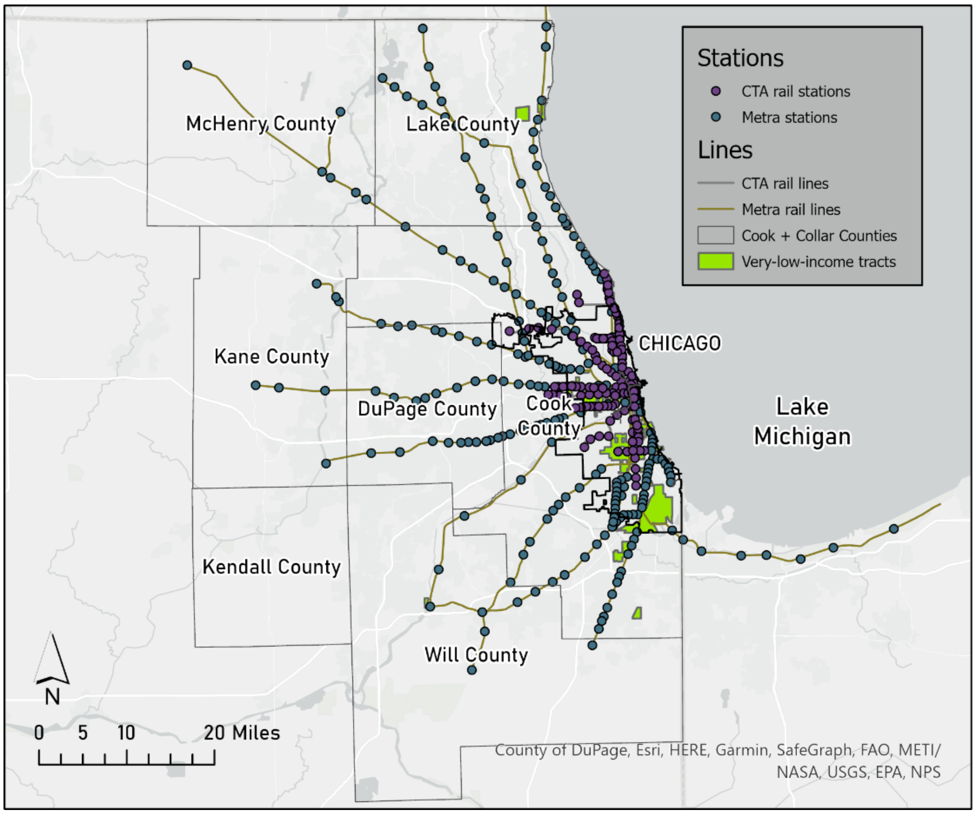
Figure 1: Tract-level low-wage job density



3.2 Transit Services

The Chicago MSA has four main transit services. The Chicago Transit Authority (CTA) operates an elevated light rail train, the "L," as well as a bus service in the City of Chicago and parts of its inner ring suburbs. The larger metropolitan area is served by Metra, a heavy rail commuter train and the Pace bus, both of which operate throughout the Chicago suburbs, providing crucial connections to downtown job centers. These public transit services are well-used within the region: 15.6% of commuters used transit in 2019, though this share increases to roughly 21% when only considering Cook County, and to 29.8% when using the subset of by very-low-income tracts whose residents are on average, much more transit reliant. When compared to other MSAs, Chicagoland is very transit oriented: In 2019, the L and Metra were the 3rd and 4th largest rail transit systems by ridership in the country (Dickens & APTA, 2019).

Figure 2: Transit Services in Chicagoland



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Transit investment in the City of Chicago has historically favored white collar and upper middle-class Chicagoans, while infrastructure that serves low-income neighborhoods on the west and south sides has languished. This became very apparent in the early 2000s when the city made massive investments with the express purpose of attracting and retaining creative-class workers by improving rail service in the city's central business district ,The Loop, increasing connectivity to Metra, the city's two airports, and affluent northside neighborhoods. The CTA's red line extension project, which was intended to increase transit service to Chicago's far southside, only recently received adequate funding after having been held up by political and budgetary concerns for more than five decades. A map of the extension's proposed path can be seen in *Figure A.1* of Appendix A.

CHAPTER 4: ACCESSIBILITY MODELING ANALYSIS

4.1 Defining Access to Low Wage Jobs

The first part of this research seeks to compare the Chicago MSA's very-low-income population to the larger region to determine whether this population has comparatively reduced job access, and whether potential gaps in access can be lessened with FLM interventions. To investigate this, I calculate two measures of low-wage job accessibility using the demographic, employment, and travel time data that will be discussed in more detail in the following sections. The first measure is a computation of cumulative opportunity, or absolute job access, that measures the total number of jobs that can be reached in a vector of destination Census tracts *"j"* from a given origin tract *"i"* in under 30 minutes.

$$JA_i^{transit} = \sum_{i,j} lw\ jobs_j \tag{1}$$

This 30-minute threshold was chosen because it is near the region's average commute time of 32 minutes and facilitates comparison between the accessibility provided by various travel modes. Given increases in computing power and data availability, the accessibility literature has proposed a number of improvements to the cumulative opportunity measure (Kim & Lee, 2019; Lee & Miller, 2019; Owen & Levinson, 2015; Shen, 1998, 2001), though it remains popular among planners for its ease of interpretation (Merlin & Hu, 2017). Perhaps one of the most popular modifications comes from Shen (1998, 2001) who argues that job accessibility cannot be accurately measured without considering the demand generated by other potential job seekers. He takes a relative approach to accessibility through calculating a ratio between cumulative opportunity and labor market demand. Shen weights the cumulative opportunity index of each origin tract's 30-minute commuting shed by the amount of potential low-wage job seekers traveling by auto and by transit that also live within that commuting shed. To illustrate the usefulness of this measure, consider a very-low-income tract on the west side of Chicago. The tract has a high transit-based absolute accessibility score but is surrounded by tracts with many low-wage job seekers. Relative transit-based accessibility is calculated as seen in *Equation 2:*

$$A_i^{transit} = \sum_j \frac{E_j^{transit}}{\sum_{k1} L_{k1} * \alpha_{k1} + \sum_{k1} L_{k1} * (1 - \alpha_{k1}) + \sum_{k2} L_{k2} * (1 - \alpha_{k2})} \quad (2)$$

Where $E_j^{transit}$ is the total number of low wage jobs reachable in destination j; *k1* is a vector of tracts for which the travel time between *k1* and *j* is ≤ 30 minutes by either transit or car; *k2* is a vector of tracts for which the travel time between *k2* and *j* is ≤ 30 minutes by car but ≥ 30 minutes by transit; α_{k1}, α_{k2} are the percentage of transit commuters in each set of tracts; and L_{k1}, L_{k2} are the number of potential job seekers in tracts *k1* and *k2*.

4.2 Low-wage Job and Job Seeker Definitions

The U.S. Census' Longitudinal Employer-Household Dynamics (LEHD) program provides job counts by sector at the Census block level. I opt to focus on low-wage jobs for this analysis because they provide a representation of the opportunities that are commensurate with very-low-income job seekers' experience levels. To estimate what share of these jobs are considered low-wage, I apply Boarnet et al.'s (2017) method of estimating low wage jobs in each North American Industrial Classification (NAIC) employment sector using National Industry-Specific Occupational Employment and Wage Estimates (OEWS) from the U.S. Bureau of Labor Statistics. Using the mean and standard deviation of each sector's wage distribution, I calculate the probability that a given job falls below the national median hourly wage, $19.33/hour in 2019. I then multiply each sector's probability by its total number of jobs. To get total tract-level employment, I aggregate the block level data to the tract level using ArcGIS.

The resulting low wage job concentrations can be seen in *Figure 2*, with darker areas indicating higher density. As expected, the highest low-wage job densities are concentrated in downtown Chicago, which has an average of 4.6 low-wage jobs per acre. It should be noted that 77% of total low-wage jobs are found outside of the city, which indicates a need for reliable urban to suburban commuting modes, given the clustering of very-low-income tracts in Chicago. These tracts, outlined in gray, are on average less than half as low-wage job dense as the region.

$$\boldsymbol{lw\ jobs_i} = \sum_{\boldsymbol{i}} \boldsymbol{Emp_{i,j}} * \mathbf{pr}(\boldsymbol{wage_j} \leq \$\mathbf{19.33}/\boldsymbol{hr}) \tag{3}$$

To quantify demand from potential jobseekers, L_{k1} and L_{k2}, I take the percentage of low-income households in each tract, defined by the U.S. HUD as those that make 80% or less than their MSA's median household income, and multiply that percentage by the size of the tract's working-age labor force. In the relative measure, these totals are weighted by the share of transit and auto commuters in each tract. Using the low-income threshold instead of very-low-income accounts for a potentially wider range of job seekers that may compete for low-wage jobs.

4.3 Travel Time Data

4.3.1 Auto Times

Auto travel times were calculated at the Census tract level using a highway network shapefile exported from the Chicago Metropolitan Agency for Planning's (CMAP) Travel Demand Mode (Chicago Metropolitan Agency for Planning, 2018) . The dataset is composed of nodes and roadway links that contain an impedance value that represents the time it would take a driver to traverse that link during peak roadway congestion (7:00-9:00 AM). Link impedance is calculated based on several factors such as time of day, speed limit, number of road lanes, parking availability, and allowable vehicle types (Chicago Metropolitan Agency for Planning, 2018). After constructing a network dataset in ArcGIS, I calculate an origin-destination (OD) cost matrix that contains travel times for the shortest network path between pairs of Census tract centroids ($n*(n-1) = 3{,}922{,}380$ pairs). Peak congestion travel times are used because they provide a more accurate representation of what a commuter would experience when trying to get to work, as well as a more conservative travel time estimate for accessibility calculations. Because the CMAP dataset of roadway links does not include all local roads and does not neatly align with tract centroids, I use the time it would take for a car traveling 20 mph, which is common on the region's residential roads, to travel the straight-line distance from each tract centroid to the nearest node in the road network. Because tract to tract travel times are approximations of the impedance faced by a given household in the origin tract, I do not view it as necessary to compute network times using more granular road data.

4.3.2 Transit Times

The transit travel time matrix was constructed using Emme skim files from CMAP that contain estimated wait, transfer, and in-vehicle times for origin-destination pairs of transit stations stored as traffic analysis zones (TAZs). CMAP computes zone to zone travel times in the peak period using GTFS schedule data from a representative weekday (Chicago Metropolitan Agency for Planning, 2018). Peak period travel times are estimated as a weighted average of the travel time of all trips departing within the 7:00 AM-9:00 AM window. These trips can be made using one or more of the L, Metra, or bus, though routes using rail transit are weighted more highly. To make these transit travel times compatible with Census tract level job counts; each TAZ is first assigned to the Census block group with which it has the most geographic overlap using Python's GeoPandas package. Block groups are used for this assignment procedure because they are closer in size to TAZs than tracts, thus proving a better spatial representation of travel time pairs. Of these block group to block group pairs, the pair with the shortest travel time is chosen to represent the travel time between each corresponding Census tract pair. Thus, as in Boarnet et al. (2017), the methods used provide a lower bound estimate of transit travel time, but are likely reflective of the times that transit-commuters, who tend to live closer to transit stations, experience (Guerra et al., 2012). Transit station access and egress times were estimated similarly to the impedance on the connector links in the auto travel scenario. I use the straight-line distance between each Census block centroid and its nearest transit stop multiplied by the average speeds of various modes (3 mph for walking, 8 mph for biking, and 20 mph for driving).

Transit travel times are computed for six different scenarios to model the changes in job accessibility that result from the use of different access/egress modes or changes to transit service. ”Walk/walk”, bike/bike, “auto/walk”, and “auto/auto” refer to transit station access/egress modes, while “25Hdwy” and “50Hdwy” represent percent reductions to transit line headway times, another policy intervention commonly used to reduce travel time and promote job access. Later, I compare each of these scenarios and their effectiveness in achieving parity with auto-based job accessibility.

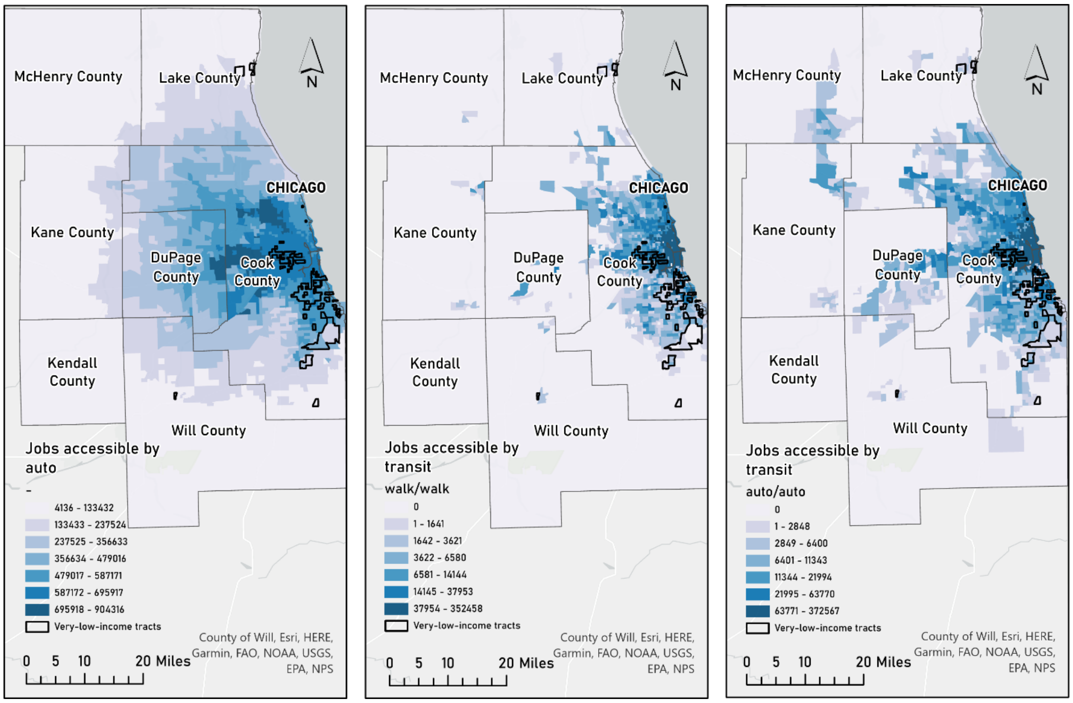
4.4 Results

4.4.1 Spatial Distribution of Accessibility

From left to right, *Figure 4* displays the number of low-wage jobs accessible in 30 minutes or less by car, transit with walking access and egress, and transit with auto access and egress. Scores are mapped in seven quantiles, with higher levels of accessibility shown in darker shades. As predicted, there is a very large disparity in access between the two modes. This is illustrated by the fact that the Census tract with the highest transit-based score in the “walk/walk” scenario, with 352,458 low-wage jobs, would only fall into the third quantile of auto-based accessibility. The highest levels of auto-based accessibility can be seen in Chicago's northwest neighborhoods, as well as its inner ring suburbs. The cluster of very-low-income tracts on Chicago's west side also tend to fall within these top quantiles of auto access, while southside tracts have scores that are closer to the middle of the range in quantiles three and four. Very-low-income Census tracts in the suburbs are very disadvantaged when compared to their urban counterparts, falling within the lowest two quantiles. Transit-based accessibility is much more concentrated in the region's urban areas, though switching from "walk/walk" to "auto/auto" access/egress drastically increases the size of suburban clusters, typically in conjunction with the location of Metra stations and greater low-wage job densities (refer to *Figures 1* and *2*).

The highest concentrations are found downtown, where rail transit and low-wage jobs are densest, and slightly further from near-downtown neighborhoods on the north and west sides of the city. Like auto accessibility, transit-based access is lower for very-low-income tracts on Chicago's south side than those on its west side, with some parts of the southside falling into the lowest of the two quantiles and below the regional average. Very-low-income tracts in the suburbs tend to have higher transit accessibility than those in the south and west sides, but nowhere near as much as the aforementioned urban tracts.

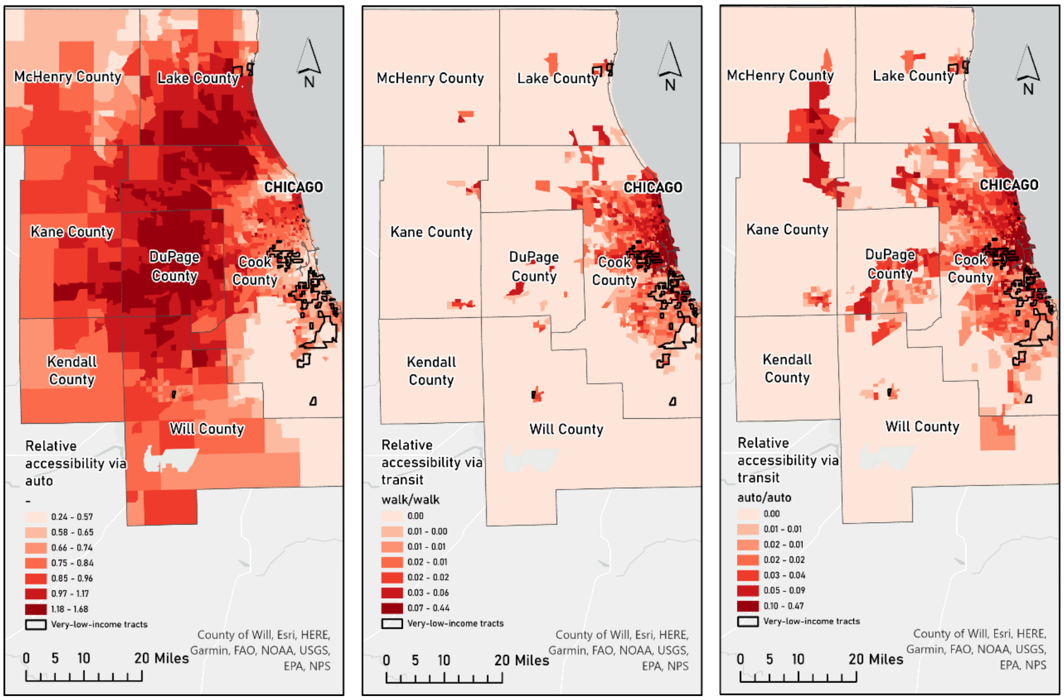
Figure 3: Absolute low-wage job accessibility by car and by transit ("walk/walk", "auto/auto")



4.4.2 Relative Accessibility

The use of the relative measure drastically changes the spatial distribution of auto-based job accessibility as shown in Figure 4. The highest auto scores are now found outside of the city, in suburban parts of DuPage, Lake, and Cook County. Very-low-income tracts are much worse off than they were before, rarely falling into the upper quantiles of relative access. This difference in absolute and relative score distribution indicates that the jobs accessible from very-low-income neighborhoods in urban areas are subject to more labor market demand than their suburban counterparts. Absolute and relative transit access scores are similarly distributed across space, with high access found in downtown Chicago and its north and west sides. Islands of accessibility are still found in DuPage County suburbs like Wheaton, Naperville, and Oak Brook. Very-low-income tracts are once again split along geographical lines, with tracts on the south side seeing much lower access to low-wage-job opportunities than those on the west side. The disparity between transit and auto is even higher than that of absolute access, with the highest quantile of transit-based access only overlapping with the lowest quantile of auto-based access.

Figure 4: Relative accessibility scores by car and transit (walk/walk, auto/auto)



To test the similarity of the absolute and relative access measures, I calculate simple correlation coefficients between the two variables. I find the relative and absolute measures of both the "walk/walk" and "auto/auto" transit scenarios to be highly correlated, with coefficients of 0.98 and 0.97 respectively. In contrast, absolute and relative auto access exhibit a very low correlation of -0.03.

4.4.3 Comparison of Transit Access and Egress Scenarios in Very-Low-Income Tracts

Figures 1 and *4* provide a useful visual analysis of the distribution of low wage jobs and job accessibility in relation to the locations of very-low-income Census tracts: In virtually all tracts, a car is superior to transit for either measure of low-wage job access, especially for low-income populations. I now quantify this modal disparity specifically for very-low-income tracts in

Tables 2 and *3*, which compare auto-based accessibility with each of the six transit scenarios. I also estimate a scenario without access-egress times to illustrate their importance to accurate measurement.

Table 2: Absolute Job Accessibility Provided by Various Travel Time Scenarios

	Car	no access/egress	walk/walk	bike/bike	auto/walk	auto/auto	25% headway reduction	50% headway reduction
Total jobs reachable								
Mean	536526.1	57934.1	30091.4	46730.4	44065.1	53247.6	55343.1	89056.8
Median	561836.0	10663.0	3368.0	7149.0	6155.0	8538.0	8658.0	20168.0
Std. Dev	153054.1	86151.7	62798.0	76381.1	74594.4	82089.5	85684.2	105411.6
Ratio of car and transit access								
Mean	–	9.3	17.8	11.5	12.2	10.1	9.7	6.0
Median	–	52.7	166.8	78.6	91.3	65.8	64.9	27.9
Std. Dev	–	1.8	2.4	2.0	2.1	1.9	1.8	1.5
Percent change of ratio between auto and transit access								
Mean	–	–	–	35.6%	31.7%	43.5%	45.6%	66.2%
Median	–	–	–	52.9%	45.3%	60.6%	61.1%	83.3%
Std. Dev	–	–	–	17.8%	15.8%	23.5%	26.7%	40.4%

By calculating ratios between auto access and the access provided by the various transit scenarios, I determine to what degree each transit stop access/egress mode can close the gap between transit and auto travel. The third set of results in the table show the percent change in the auto to transit ratio when shifting from “walk/walk” to the other scenarios. On average, job seekers in very-low-income areas can reach a far greater number of jobs when commuting by car; 17.8 times as many as the “walk/walk” scenario, 12.2 times more than “auto/walk”, and 10.1 times more than “auto/auto”. Using a bike for transit stop access and egress is more effective than using a car for access and can lower the auto/transit ratio by 35.59%, though using a car to cover the FLM distance can lower the ratio by an average of 45.4%. A 25% headway reduction is slightly more effective at reducing travel time, even when access and egress time is not accounted for, while a 50% headway reduction would narrow the gap in transit and job accessibility by almost three times making it by far the most effective method.

Table 3: Relative Job Accessibility Provided by Various Travel Time Scenarios

	Car	**no access/egress**	**walk/walk**	**bike/bike**	**auto/walk**	**auto/auto**	**25% headway reduction**	**50% headway reduction**
Total jobs reachable								
Mean	0.67	0.06	0.03	0.05	0.04	0.05	0.06	0.09
Median	0.64	0.01	0.00	0.01	0.01	0.01	0.01	0.03
Std. Dev	0.13	0.08	0.06	0.07	0.07	0.08	0.08	0.10
Ratio of car and transit access								
Mean	–	11.4	22.9	14.4	15.3	12.5	12.1	7.2
Median	–	46.9	146.7	65.7	86.1	55.5	52.2	24.8
Std. Dev	–	1.6	2.3	1.9	1.9	1.7	1.6	1.3
Percent change of ratio between auto and transit access								
Mean	–	–	–	37.2%	33.0%	45.4%	47.2%	68.5%
Median	–	–	–	55.2%	41.3%	62.2%	64.4%	83.1%
Std. Dev	–	–	–	19.6%	17.3%	26.8%	28.9%	45.2%

CHAPTER 5: REGRESSION ANALYSIS

The accessibility scores I presented in Chapter 4 made several necessary assumptions about travel times, jobs, and job seekers, and as such, may not exactly replicate real-world job accessibility at the individual level. Moreover, travel time and cumulative opportunity are not the only variables that factor into the utility of using a given travel mode (Kim & Lee, 2019). Even so, the computation of simple zone-level accessibility scores is a useful and common practice in the field of urban planning. Accessibility scores can help planners answer questions such as how frequently trains should run at a given station, whether the construction of a new employment center can improve accessibility and for whom (Spielman, 2022), and whether the installation of new bike-sharing stations can improve FLM connectivity to transit routes serving higher education facilities (Lord, 2017). In Chapter 5, I attempt to use accessibility scores to predict heterogeneity in the average treatment effects of subsidized R2T ride hailing using data from Christensen, Osman, and Lehe's on-going Uber Chicago study.

5.1 Uber Chicago Data

Recruitment for the Uber Chicago study was carried out by Uber, which sent emails to a random selection of its regular users in the Chicago metropolitan region asking them to participate in a mobility study conducted by the University of Illinois. Participants were then randomized into two groups, one of which was provided with a treatment of 50% off their transit-linked Uber trips for 2-months. Transit-linked trips are defined as those with a pick-up or drop-off location within 200 meters of a Chicagoland transit station, which is the buffer distance the Uber app uses in determining subsidy allocation. The experiment collected data through three mechanisms. Surveys were sent out to every participant via mobile at the baseline, midline, and endline of the study period to collect demographic information, their home and work locations, employment status, as well as an itinerary of their trips taken in the previous day. Uber also provided administrative data on participants including number of trips taken, the pickup and drop off location of their trips, and fare prices. Participants submitted Google Timeline data at the midline and endline, which described their trips at the segment level - origin and destination, longitude and latitude, beginning and end time, mode, and distance. Due to difficulties in identifying instances of bus vs. personal vehicle used in the Google Timeline data, I focus my

Table 4: Uber Chicago Balance Table

Variables	Control	Treatment	Diff
Male	0.46	0.46	0.00
	(0.50)	(0.50)	(0.05)
Female	0.54	0.54	0.00
	(0.50)	(0.50)	(0.05)
Age	33.19	32.40	-0.80
	(9.53)	(9.50)	(1.04)
Married	0.27	0.24	-0.03
	(0.44)	(0.43)	(0.05)
Currently Working	0.84	0.83	-0.01
	(0.37)	(0.38)	(0.04)
Car Owner	0.50	0.42	-0.08
	(0.50)	(0.49)	(0.06)
Household Size	2.16	1.93	-0.23
	(1.36)	(1.28)	(0.15)
Children in Household (under 16)	0.21	0.23	0.02
	(0.56)	(0.65)	(0.07)
College Education	0.81	0.73	-0.08
	(0.39)	(0.44)	(0.06)
High School	0.17	0.22	0.06
	(0.37)	(0.42)	(0.04)
Mobility Constraints	0.01	0.01	-0.01
	(0.11)	(0.08)	(0.01)
Trips Taken Yesterday (Uber Excluded)	1.38	0.91	-0.45
	(6.34)	(1.86)	(0.20)
Observations	162	169	331
F statistic	1.05		
P-value	(0.41)		

Notes: Table reports baseline characteristics for participants assigned to control and treatment conditions. Third column reports mean and standard error of differences between the groups. Table also reports the F-statistic and p-value of a test of joint significance in all baseline characteristics.
*** p<0.01, ** p<0.05, * p<0.1

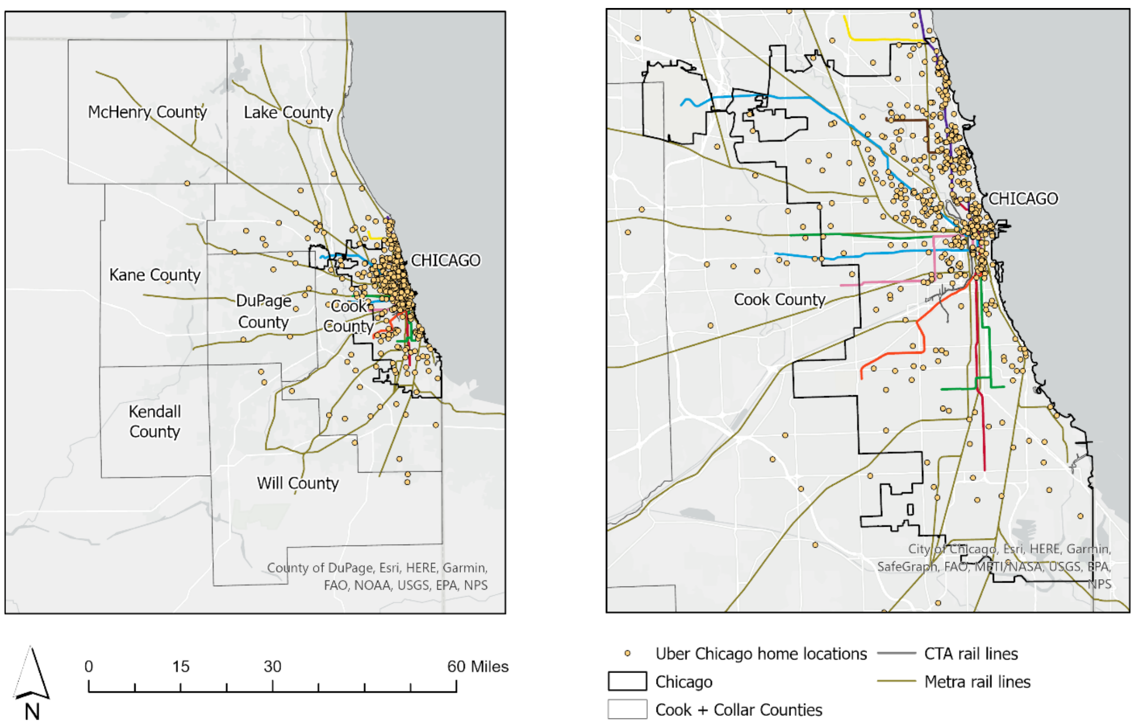
regression analysis on the survey results. The spatial distribution of participants' home locations can be seen in *Figure 5*.

Randomized control trials are an incredibly attractive form of impact evaluation because they allow researchers to deal with the selection and heterogenous treatment effect biases that impact the average treatment effect (ATE). If characteristics among the treatment and control groups are adequately balanced, then both biases should equal 0, producing a reliable estimate of the counterfactual. The Uber Chicago sample was successfully randomized into treatment and control groups with similar average characteristics, the results of which can be seen in *Table 4*.

While sample randomization is relatively straightforward, there are a few small but necessary assumptions that need to hold true for selection and omitted variable bias to be equal to 0. Randomization assumes stable unit treatment values (SUTVA) which means there is no potential for treatment spillover into the control group, and that outcomes for one individual are independent of all others. In a hypothetical scenario, an individual in treatment is already acquainted with someone in the control group and uses their subsidy to transport both to a transit station at a reduced cost. Because Uber randomized recruitment emails, the chance of this occurring is incredibly small, validated by the fact that no survey participants share home or work locations. An unbiased RCT also assumes full program compliance, though there are two possible sources of noncompliant behavior in my design. In the first, participants have the potential to "game" the program, by using Uber for a single mode trip to a destination that happens to be within the 200-meter station buffer. The second form of noncompliance involves a treated individual ordering a subsidized Uber for a friend or acquaintance, and not actually using it themselves. Having Google Timeline data collected via GPS and administrative data from

Uber has the benefit of allowing me to identify both instances of noncompliance: Trips where a subsidized Uber segment is not followed up by a trip made using bus, Metra, or L can be considered an example of the first, while the timeline data can be cross-referenced with the Uber admin data to identify occurrences of the second, where a charge on a participant's account is not followed up by an Uber trip segment. Only ten instances of these behaviors were found in the data, indicating that it is not a major concern from an internal validity standpoint.

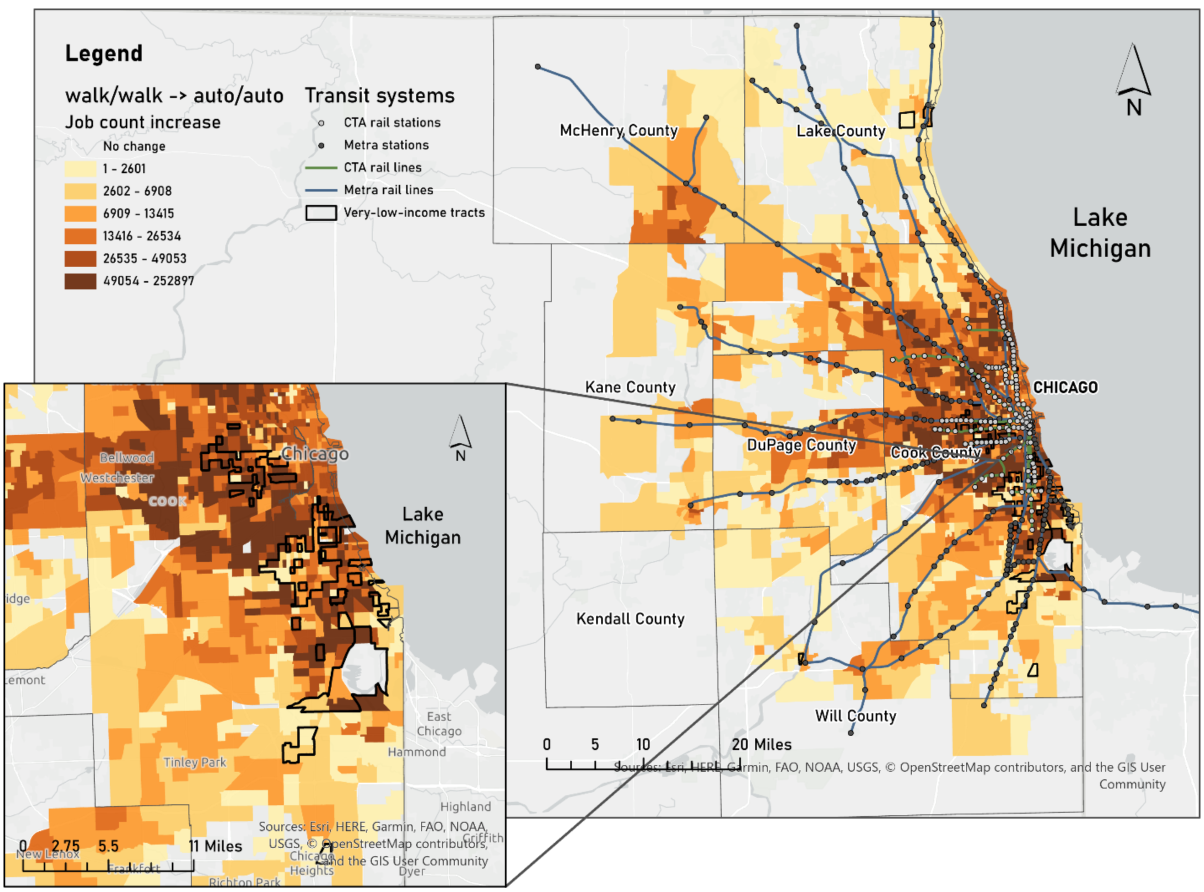
Figure 5: Uber Chicago Study Home Locations



5.2 Differenced Transit-Based Accessibility

When contemplating the impact of a real-world R2T program, the largest benefits would theoretically be accrued by those who do not own a personal vehicle and experience most gains in accessibility to high value destinations within the city. To capture these gains, I create a variable that is the difference in the "auto/auto" and "walk/walk" scenarios of transit-based accessibility using a 45-minute commuting threshold. (A 30-minute accessibility threshold was used previously primarily to facilitate comparisons between modes and because it is a close approximation of the region's average commute time of 32 minutes (U.S. Census Bureau, 2019). As previously established, very-low-income households are much less likely to have access to a personal vehicle. Thus, it is reasonable to assume that a commuter without a vehicle is not comparing auto and transit travel times when determining trip mode choice and is basing their perception of travel time on something closer to the region's average transit commute time of 50.1 minutes (U.S. Census Bureau, 2019). The increases, shown in *Figure 6,* model an upper

Figure 6: Modeled Accessibility Increases



bound of R2T program effects by assuming a traveler uses it to traverse both the access and egress leg of their transit trip. The tracts that are not shown on the map did not have their transit-based low-wage job accessibility increased by switching their accessibility scenario to "auto/auto". A computation of the results using only R2T for station access can be seen in Appendix A.

Figure 6 reveals that accessibility increases tend to be spatially correlated with the locations of transit stations, though tracts with the highest scores form "rings" around the tracts that intersect routes and stations directly. This image offers a striking depiction of how R2T alleviates the first- last-mile problem, providing the most benefit to tracts just outside the buffer of walkability where first-mile times disqualify participants from reaching jobs in certain destination tracts. Almost all very-low-income Census tracts see an increase in low-wage job accessibility, though west side tracts tend to see greater gains on average.

5.3 Fixed Effects Regression Model

To examine the differences in mode-share outcomes that can be attributed to the low-wage job accessibility of individuals' home locations, I propose a set of seven fixed effects models that interact the tract-level accessibility increase of participants' home locations with a treatment dummy variable. Due to large differences in units and the differing magnitudes of auto- and transit-based accessibility scores, this variable was standardized to have a mean of 0 and a unit standard deviation after assignment to participant home locations. Coefficients on interaction terms then measure the change in trips taken using a given mode that can be attributed to a one standard deviation increase in accessibility. Due to the extremely high correlation between absolute and relative transit-based accessibility scores, and the simplicity of the absolute measure, I do not estimate a regression that uses the relative scores for the interaction term.

The dependent variables of the seven models can be defined as the change in total trips, trips taken by bus, walking or biking, car (non-Uber), Uber, L, and Metra from baseline travel behavior. Multimodal trips contribute to the treatment effect on all modes used in the trip. It is important to note that the Uber trip dependent variable sums all a respondents' Uber trips taken in the previous day, with or without the subsidy. Thus, the ATE in this regression cannot be interpreted as a direct measure of treatment utilization. This highlights an important aspect of interpretation: the coefficients presented in *Tables 5* and *6* should be interpreted as the effect of *providing* the subsidy on trips taken using a given mode.

The nature of the experimental design warrants the inclusion of cohort and month fixed effects in each of the seven models. These effects account for time invariant factors that may have resulted in differences in characteristics between cohorts. Since the data collection process spans two months, and the surveying process for each cohort began at different times, an opportunity for time-varying differences between cohorts is created. Month fixed effects are intended to account for differences in weather, school and work schedules, and the occurrence of holidays.

Individual rail transit stations intrinsically provide differing levels of service based on factors like headways times between trains, whether they enable transfers to multiple service lines, and the destinations they allow a commuter to reach. Thus, I assume treatment effects will vary as different stations can affect travel outcomes heterogeneously. Rail transit station fixed effects are added to the model to account for this, with a given station dummy taking a value of 1 if it is the closest to a participant's home location. The base treatment effect model that I use to study mode-shift is shown in *Equation 4:*

$$\boldsymbol{Y_i = \beta_0 \lambda_i + \beta_1 T + \theta_{st} + \gamma_t + \delta_c + \varepsilon_i} \tag{4}$$

Where Y_i is the outcome of interest; *T* is the treatment dummy variable; λ_i is a vector of control variables; γ_t is a vector of month fixed effects; δ_c is a vector of cohort fixed effects intended to control for time invariant factors; and θ_{st} represents Metra and L station fixed effects. Since the survey data includes both midline and endline observations, standard errors are clustered around participants' login IDs. Before estimating the coefficients, I hypothesize that the decreased FLM transportation costs provided by the treatment will increase participants' overall Metra, L, and Uber usage, reduce number of trip segments made using a personal vehicle and on foot , and having a negligible effect on bus usage. Busses are generally regarded as inferior to rail services due to traffic impeding their reliability and because they stop more frequently. The benefit of these frequent stops is that a given stop is more likely to coincide with a traveler's trip origin or destination, which creates the potential for bus transit to be superior to rail from a FLM perspective. R2T connectivity largely invalidates this advantage by providing more seamless travel to transit stations, and because of this, I suspect that rail stations will be the primary target for transit-linked trips.

The specification for the model that includes the differenced accessibility score is as follows in *Equation 5*:

$$\boldsymbol{Y_i = \beta_0 \tau_i + \beta_1 T + \beta_2 * (T * (JA^t_{aa} - JA^t_{ww})) + \theta_{st} + \gamma_t + \delta_c + \varepsilon_i} \quad (5)$$

Where JA^t_{ww}, JA^t_{aa} are the standardized tract-level job accessibility scores achieved by transit for a participant's home location with walking and auto access/egress respectively, and τ_i is a vector of controls containing the variables from *Equation 4's* λ_i term in addition to JA^t_{ww}, and JA^t_{aa}. I hypothesize that participants living in Census tracts that experience larger modeled increases in accessibility due to R2T connectivity should see higher treatment utilization and a greater ATE on trips taken using Uber, L, and Metra. In terms of identification, using the difference of the two transit-based accessibility scores as opposed to one or the other, is intended to capture transit trips taken using the R2T service for those whom the FLM is a barrier rather than unlinked trips made by travelers within easy walking distance of transit.

Before moving on to the results, it should be noted that the Uber Chicago study is still in its early stages. While response rates to the midline and endline surveys were high, the sample size of trip days is still relatively small compared to similar studies like Christensen & Osman (2021), where observations consisted of each participant's Uber trips taken in a given week of a 12-week study (n = 16,440). Recognizing this, the researchers have plans to expand their study, and recently received funding to study travel behavior in two more cities to increase their sample size and analyze heterogeneity across metros and transit systems. As such, the treatment effects shown should be treated as preliminary and are best interpreted as indicators that the program, at its full scale, could drive mode-shift.

5.4 Regression Results

Because treatment effects are hypothesized to affect a variety of travel behaviors, tables in this section are formatted to show the ATE on each of the seven outcomes of interests; trips made on foot, trips made using the bus, a personal vehicle, Uber, the subway (L), Metra, and total trips made. Recall that participants' trip totals were collected on a representative weekday at the midline and the endline of the survey. I interpret these observations as a proxy for average weekday travel behavior in the presence of treatment rather than the effect on trips taken on a specific day. The first row of values displays point estimates for each outcome, while the standard errors associated with those estimates are shown below each estimate in parentheses. As stated earlier, a randomized control trial design assumes that the averages of all observed and unobserved characteristics are equal across treatment and control. Thus, I omit coefficient estimates for controls from the tables shown because they do not influence the size of the treatment effect and serve only to increase its precision.

An estimation of the parameters outlined in *Equation 3* can be seen in *Table 5.* The treatment effect in each of the 7 regressions goes in the expected direction, and more clarity is provided when each of the dependent variables are interpreted in the context of their control means. Statistically significant effects can be found in the regressions predicting daily car and subway trips at the 0.05 and 0.1 level respectively: On average, the 50% off subsidy program reduces daily car trips taken by 0.22 and increases subway trips taken by 0.12 from baseline levels. Recall that the Uber outcome variable is a measure of all Uber trips taken, not just those with the subsidy. Summing the Uber and L effects with their respective control means yields a roughly equivalent number of daily trips, 0.35 and 0.36 respectively. These figures suggest that R2T linked transit trips potentially substituted for treated individuals' unsubsidized Uber trips. The coefficient on Metra, while positive, is not statistically significant. This, and the low control mean of 0.06 further validate what I suspected after mapping participants' home locations, that a lack of Metra trips taken in the sample would lead to a lack of power for estimating a statistically significant effect.

Table 5: Base Regression Model Results

	Dependent variable:						
	Bus	Walking	Car	Uber	L	Metra	Total
Treatment	-0.05	0.06	-0.23*	-0.08	0.15**	0.04	-0.12
	(0.07)	(0.12)	(0.12)	(0.09)	(0.07)	(0.03)	(0.25)
Control Mean	0.27	0.77	0.91	0.43	0.21	0.06	2.65
Observations	884	884	884	884	884	884	884
Adjusted R^2	0.18	0.03	0.20	-0.00	0.01	0.33	0.13
Note:					*p<0.1; **p<0.05; ***p<0.01		

Table 6 displays coefficient estimates for the models specified in *Equation 5* that predict a heterogeneous response to treatment based on accessibility increases. Due to a relatively low

Table 6: Accessibility Term Interaction Model Results

	Dependent variable:						
	Bus	Walking	Car	Uber	L	Metra	Total
Treatment	-0.05	0.06	-0.23*	-0.08	0.15**	0.04	-0.12
	(0.07)	(0.12)	(0.12)	(0.09)	(0.07)	(0.03)	(0.25)
Treatment* acs_inc_45	0.07	0.13	-0.12	0.21*	0.02	-0.01	0.30
	(0.06)	(0.14)	(0.12)	(0.11)	(0.06)	(0.02)	(0.29)
Control Mean	0.27	0.77	0.91	0.43	0.21	0.06	2.65
Observations	884	884	884	884	884	884	884
Adjusted R^2	0.18	0.03	0.20	-0.00	0.01	0.33	0.13
Note:					*p<0.1; **p<0.05; ***p<0.01		

number of observations, the size and significance of the coefficients should not be taken too literally. That said, I am beginning to see significant positive effects on transit and Uber usage in areas where accessibility increases are larger. The overall effect on average daily Uber trips taken becomes positive when a 1standard deviation increase in accessibility gains is added to the base treatment effect. While I am currently unable to determine if this average increase in Uber usage can be attributed to subsidized trips, no other external factors could have driven this increase, leading me to believe that they were taken to serve a FLM purpose. The interaction terms in the Metra, L, and bus models are not significant, though their signs indicate that there is a potential for accessibility to positively affect the treatment response to transit and reduce the number of car trips taken.

The low-wage job accessibility increase variable measures the increase in jobs accessible when a car is used to complete both the station access and egress portion of a transit trip. However, the coefficients and control means shown in *Tables 5* and *6* indicate that on average, treated individuals are probably not using the subsidy frequently. *Table A.2* in Appendix A estimates a regression with an interaction term that is calculated as the difference between the "auto/walk" and "walk/walk" which has the dual purpose of providing a more conservative estimate of treatment utilization and isolating the effect of first mile R2T connectivity. Using this variable leads to slightly lower magnitudes on all the treatment effects, indicating that two-way R2T is potentially a better predictor of utilization.

CHAPTER 6: DISCUSSION AND POLICY IMPLICATIONS

The first part of this research focuses on determining whether the gap between transit- and auto-based low-wage job accessibility can be alleviated through services that provide FLM connectivity. I establish that very-low-income populations are much more reliant on transit for their commutes than the region on average, are less than half as likely on average to own a vehicle and live in census tracts with low employment densities. While physical distance to transit is not necessarily a barrier for very-low-income Census tracts, their transit-based job accessibility is far lower than households with automobiles, which puts households without cars at a significant disadvantage. Comparing the average accessibility scores between access/egress scenarios, I find that using a car to access ("auto/walk") and/or egress ("auto/auto") can help to close the low-income cumulative job access gap between transit and car by 31.7% and 43.5% respectively, indicating that a program like Uber Chicago could be very effective in increasing low-income households' access to low wage jobs.

Relative accessibility results highlight how the usefulness of very-low-income individuals' high transit-based accessibility is potentially reduced when accounting for job market competitors with access to cars. After analyzing these scores, I find a high correlation between the relative and absolute transit measures, and almost no correlation for the two auto measures. This implies that the average relative auto/transit disparity is slightly larger than that of the absolute measure, though faster access/egress modes are shown to reduce the gap by a few percentage points more. Though the literature lacks consensus on which measure of accessibility is superior, the relative measure indicates that a cumulative opportunity score potentially understates both the auto/transit access disparity as well as the ability of faster access/egress modes to alleviate it.

A simple regression analysis of the data collected through the Uber Chicago program shows that subsidizing the cost of ride hailing for first- and last-mile travel can lead to significant mode-shift outcomes. The treatment increased the average L usage by 0.15 trips per day and reduced the number of driving trips by 0.23. After combining the accessibility scores calculated in the first part of my analysis with the Uber Chicago data, I determined that modeled transit-based low-wage job accessibility is not a statistically significant determinant in the uptake of a program that subsidizes the cost of FLM ride hailing. Despite this lack of significance, my results show that individuals who experience larger gains in accessibility from R2T connectivity are more likely to use Uber and may also use more L and bus.

6.1 Limitations:

While this work seeks to measure the potential for R2T services to provide low-income populations with better access to employment opportunities, there are several aspects of the Uber Chicago RCT study that prevent me completely addressing this question. Because the program represents a temporary (2-month) reduction in transportation costs, the results cannot be used to draw any conclusions about long-term employment outcomes. Moreover, the study lacks data on trip purpose, and there is currently no way to determine whether R2T trips are actually being used to facilitate transit-based commuting trips. Increasing the study duration would obviously provide more insight into changes in long-term employment trends though program cost could quickly become an issue. Currently, researchers' best option is to use these short-term changes in travel behavior to predict longer-term responses.

A second concern comes from the fact that data collection for Uber Chicago did not explicitly target low-income populations. As seen in *Figure 3,* home locations of the sample tend to be concentrated in downtown Chicago and more affluent neighborhoods on the city's north side, with only 25 participants living in the very-low-income Census tracts identified in the demographic analysis. This raises a large question of external validity as low-income earners are the most likely to be seeking low wage jobs. To ensure that the lack of significance on the interaction term coefficients is not due to a mischaracterization of the population of interest, I estimated regressions that interact treatment with the increase in accessibility to all jobs provided by R2T and find little change in the coefficients. Very-low-income travelers may also have a different willingness to pay (WTP) than the Uber Chicago sample, leading to heterogenous mode-choice responses. Even a trip with a 50% reduction in fare price may still be too expensive for a traveler to justify, let alone make on a regular basis as a part of their commute. The MOD pilot program studied by Brown et al. (2021) offered rides for $1.75 at its outset, before eliminating fares altogether at the beginning of the fourth month of its roughly year-long duration. Combining the rigor and last-mile requirement of the Uber Chicago experimental design with the provision of a more equity-driven mobility service could be the next logical step for researchers in evaluating the effectiveness of R2T.

Considering these factors, I recommend that readers interpret the low-wage job accessibility regression variable as a proxy for how easily an individual can travel around the region rather than as a predictor of employment outcomes. To this end, low-wage job accessibility serves as a suitable indicator of access to other attractive destinations like food and retail businesses, grocery stores, and entertainment destinations. To measure the robustness of this claim, further research could calculate composite accessibility scores that factor in the presence of these other destinations.

6.2 Policy Implications

R2T programs enacted through public-private partnerships often have limited budgets, and it is difficult for government officials to justify the continuation of costly programs without knowledge of their causal impacts. My results provide politicians and urban and regional planners with a picture of how ride-to-transit services can increase low-wage job accessibility for disadvantaged groups in Chicago, and an understanding of the role accessibility can potentially play into mode-shift responses to a fully implemented program. Modeled accessibility scenarios reveal that R2T connectivity provides accessibility enhancements that are comparable to headway reductions and is most likely a cheaper intervention. While reducing the cost of first-last-mile ride hailing has been found to significantly increase the average number of weekday L trips taken by Uber Chicago study participants, the influence of absolute low-wage job accessibility is less clear, despite what accessibility scores may indicate. In evaluating R2T and MOD program design, planners should seek to implement experimental evaluation methods as well as continue to study the impact of accessibility measures. Going forward, I recommend that planners develop more comprehensive measures of accessibility incorporating things like network travel times for access and egress measurement, the quality of the built environment near stations, considerations of traveler preferences, and measurements of transit service quality to determine significant effects.

REFERENCES

Acs, G., Pendall, R., Trekson, M., & Kahre, A. (2017). *The Cost of Segregation*.

Asher, S., & Novosad, P. (2020). Rural Roads and Local Economic Development. *American Economic Review*, *110*(3), 797–823. https://doi.org/10.1257/aer.20180268

Bagley, M. N., & Mokhtarian, P. L. (2002). The impact of residential neighborhood type on travel behavior: A structural equations modeling approach. *The Annals of Regional Science*, *36*(2), 279–297. https://doi.org/10.1007/s001680200083

Barajas, J. M., & Brown, A. (2021). Not minding the gap: Does ride-hailing serve transit deserts?*Journal of Transport Geography*, *90*, 102918. https://doi.org/10.1016/j.jtrangeo.2020.10298

Blumenberg, E. (2002). On the Way to Work: Welfare Participants and Barriers to Employment. *Economic Development Quarterly*, *16*(4), 314–325. https://doi.org/10.1177/089124202237196

Boarnet, M. G., Giuliano, G., Hou, Y., & Shin, E. J. (2017). First/last mile transit access as an equity planning issue. *Transportation Research Part A: Policy and Practice*, *103*, 296–310. https://doi.org/10.1016/j.tra.2017.06.011

Brown, A., Manville, M., & Weber, A. (2021). Can mobility on demand bridge the first-last mile transit gap? Equity implications of Los Angeles' pilot program. *Transportation Research Interdisciplinary Perspectives*, *10*, 100396. https://doi.org/10.1016/j.trip.2021.100396

Cao, X. (Jason), Mokhtarian, P. L., & Handy, S. L. (2009). Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings. *Transport Reviews*, *29*(3), 359–395. https://doi.org/10.1080/01441640802539195

Chen, S., Yan, X., Pan, H., & Deal, B. (2021). Using big data for last mile performance evaluation: An accessibility-based approach. *Travel Behaviour and Society*, *25*, 153–163. https://doi.org/10.1016/j.tbs.2021.06.003

Chicago Metropolitan Agency for Planning. (2018). *CMAP ON TO 2050 Travel Demand Model Documentation*. Chicago Metropolitan Agency for Planning. https://www.cmap.illinois.gov/documents/10180/911391/FINAL+Travel+Demand+Model+Documentation+Appendix.pdf/f3b1322c-2e60-2513-720f-38ee68b799d1

Christensen, P., & Osman, A. (2021). The Demand for Mobility: Evidence from an Experiment with Uber Riders. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3803723

Dickens, M., & APTA. (2019). *ESTIMATED UNITED STATES UNLINKED TRANSIT PASSENGER TRIPS*.

Dixit, V. V., Ortmann, A., Rutström, E. E., & Ukkusuri, S. V. (2017). Experimental Economics and choice in transportation: Incentives and context. *Transportation Research Part C: Emerging Technologies*, *77*, 161–184. https://doi.org/10.1016/j.trc.2017.01.011

Dowell, E. K. P. (n.d.). *Job Sprawl Results in Unemployment for Low-Income Urban Residents*. U.S. Census Bureau. https://www.census.gov/library/stories/2020/03/spatial-mismatch- when-workers-can-not-get-to-jobs-in-suburbs.html

Franklin, S. (2018). Location, Search Costs and Youth Unemployment: Experimental Evidence from Transport Subsidies. *The Economic Journal*, *128*(614), 2353–2379. https://doi.org/10.1111/ecoj.12509

Gehrke, S. R. (2020). Uber service area expansion in three major American cities. *Journal of Transport Geography*, *86*, 102752. https://doi.org/10.1016/j.jtrangeo.2020.102752

Gehrke, S. R., Felix, A., & Reardon, T. G. (2019). Substitution of Ride-Hailing Services for More Sustainable Travel Options in the Greater Boston Region. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*(1), 438–446. https://doi.org/10.1177/0361198118821903

Greenawalt, A. (2021, February 11). Is on-demand public transit now mainstream in the US? *Via*. https://ridewithvia.com/resources/articles/is-on-demand-public-transit-now- mainstream-in-the-us/

Grengs, J. (2010). Job accessibility and the modal mismatch in Detroit. *Journal of Transport Geography*, *18*(1), 42–54. https://doi.org/10.1016/j.jtrangeo.2009.01.012

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

Ha, J., Ki, D., Lee, S., & Ko, J. (2023). Mode choice and the first-/last-mile burden: The moderating effect of street-level walkability. *Transportation Research*

Part D: Transport and Environment, *116*, 103646. https://doi.org/10.1016/j.trd.2023.103646

Hall, J. D., Palsson, C., & Price, J. (2018). Is Uber a substitute or complement for public transit? *Journal of Urban Economics*, *108*, 36–50. https://doi.org/10.1016/j.jue.2018.09.003

Huang, J., & Boarnet, M. G. (2022). Analyzing the Potential Impact of Docked Bikeshare on Transit First-Last Mile Accessibility in East Los Angeles. *Findings*. https://doi.org/10.32866/001c.33140

Jiao, J., & Wang, F. (2021). Shared mobility and transit-dependent population: A new equity opportunity or issue? *International Journal of Sustainable Transportation*. https://doi.org/10.1080/15568318.2020.1747578

Kawabata, M. (2003). Job Access and Employment among Low-Skilled Autoless Workers in US Metropolitan Areas. *Environment and Planning A: Economy and Space*, *35*(9), 1651– 1668. https://doi.org/10.1068/a35209

Kawabata, M., & Shen, Q. (2007). Commuting Inequality between Cars and Public Transit: The Case of the San Francisco Bay Area, 1990-2000. *Urban Studies*, *44*(9), 1759–1780. https://doi.org/10.1080/00420980701426616

Kim, J., & Lee, B. (2019). More than travel time: New accessibility index capturing the connectivity of transit services. *Journal of Transport Geography*, *78*, 8–18. https://doi.org/10.1016/j.jtrangeo.2019.05.008

Krygsman, S., Dijst, M., & Arentze, T. (2004). Multimodal public transport: An analysis of travel time elements and the interconnectivity ratio. *Transport Policy*, *11*(3), 265–275. https://doi.org/10.1016/j.tranpol.2003.12.001

Lee, J., & Miller, H. J. (2019). Analyzing collective accessibility using average space-time prisms. *Transportation Research Part D: Transport and Environment*, *69*, 250–264. https://doi.org/10.1016/j.trd.2019.02.004

Lord, S. (2017, October 31). Aurora-area bike sharing program gets boost from planning agency. *Aurora Beacon News*. https://www.chicagotribune.com/suburbs/aurora-beacon-news/ct- abn-bike-regional-trails-st-1101-20171031-story.html

Lu, Y., Prato, C. G., & Corcoran, J. (2021). Disentangling the behavioural side of the first and last mile problem: The role of modality style and the built environment. *Journal of Transport Geography*, *91*, 102936. https://doi.org/10.1016/j.jtrangeo.2020.102936

Ma, T., Liu, C., & Erdoğan, S. (2015). Bicycle Sharing and Public Transit: Does Capital Bikeshare Affect Metrorail Ridership in Washington, D.C.? *Transportation Research Record: Journal of the Transportation Research Board*, *2534*(1), 1–9. https://doi.org/10.3141/2534-01

Malalgoda, N., & Lim, S. H. (2019). Do transportation network companies reduce public transit use in the U.S.? *Transportation Research Part A: Policy and Practice*, *130*, 351–372. https://doi.org/10.1016/j.tra.2019.09.051

Mallett, W. J. (2018). *Trends in Public Transportation Ridership: Implications for Federal Policy*.

Martin, R., & Xu, Y. (2022). Is tech-enhanced bikeshare a substitute or complement for public transit? *Transportation Research Part A: Policy and Practice*, *155*, 63–78. https://doi.org/10.1016/j.tra.2021.11.007

Merlin, L. A., Freeman, K., Renne, J., & Hoermann, S. (2022). Clustered randomized controlled trial protocol of a Mobility-as-a-Service app for College campuses. *Transportation Research Interdisciplinary Perspectives*, *14*, 100572. https://doi.org/10.1016/j.trip.2022.100572

Merlin, L. A., & Hu, L. (2017). Does competition matter in measures of job accessibility? Explaining employment in Los Angeles. *Journal of Transport Geography*, *64*, 77–88. https://doi.org/10.1016/j.jtrangeo.2017.08.009

Owen, A., & Levinson, D. M. (2015). Modeling the commute mode share of transit using continuous accessibility to jobs. *Transportation Research Part A: Policy and Practice*, *74*, 110–122. https://doi.org/10.1016/j.tra.2015.02.002

Phillips, D. C. (2014). Getting to work: Experimental evidence on job search and transportation costs. *Labour Economics*, *29*, 72–82. https://doi.org/10.1016/j.labeco.2014.07.005

Puentes, R. (2017, June 1). Ghosts of Transit Past: What Can We Do About Declining Transit Ridership? [Think tank]. *Eno Center for Transportation*. https://www.enotrans.org/article/ghosts-transit-past-can-declining-transit-ridership/

Rosenfield, A., Attanucci, J. P., & Zhao, J. (2020). A randomized controlled trial in travel demand management. *Transportation*, *47*(4), 1907–1932. https://doi.org/10.1007/s11116-019-10023-9

Sabouri, S., Park, K., Smith, A., Tian, G., & Ewing, R. (2020). Exploring the influence of built environment on Uber demand. *Transportation Research*

Part D: Transport and Environment, *81*, 102296. https://doi.org/10.1016/j.trd.2020.102296

Shaheen, S., & Chan, N. (2016). Mobility and the Sharing Economy: Potential to Facilitate the First- and Last-Mile Public Transit Connections. *Built Environment*, *42*(4), 573–588. https://doi.org/10.2148/benv.42.4.573

Shen, Q. (1998). Location characteristics of inner-city neighborhoods and employment accessibility of low-wage workers. *Environment and Planning B: Planning and Design*, *25*(3), 345–365. https://doi.org/10.1068/b250345

Shen, Q. (2001). A Spatial Analysis of Job Openings and Access in a U.S. Metropolitan Area. *Journal of the American Planning Association*, *67*(1), 53–68. https://doi.org/10.1080/01944360108976355

Spielman, F. (2022, August 1). *Discover Financial Services call center opens in former Target store in Chatham*. https://chicago.suntimes.com/city-hall/2022/8/1/23287903/chatham-target-closed-discover-call-center-chatham-bobby-rush

U.S. Census Bureau. (2019). *American Community Survey 2019 5-Year Estimates S0801 COMMUTING CHARACTERISTICS BY SEX*. U.S. Census Bureau. https://data.census.gov/table?q=commuting&tid=ACSST5Y2019.S0801

Witek, C., Neagu, E., Kappeyne, A., Johansson, A., Bermthal, R., Murphy, C., & Schady, He. (2020). *Village of Bedford Park Last Mile Mobility Action Plan*. Shared Use Mobility Center.

https://learn.sharedusemobilitycenter.org/wpcontent/uploads/VOBP_Action

PlanLayout-5.28.2020-single-page_Optimized.pdf

APPENDIX A: SUPPLEMENTAL TABLES AND FIGURES

Figure A.1 CTA Planned Red Line Extension

Table A.2 Interaction Term Model Results ("auto/walk" – "walk/walk")

	Dependent variable:						
	Bus	Walking	Car	Uber	L	Metra	Total
Treatment	-0.05	0.05	-0.24*	-0.06	0.15**	0.04	-0.11
	(0.07)	(0.12)	(0.12)	(0.09)	(0.07)	(0.03)	(0.24)
Treatment*ww_to_aw_inc_45	0.07	0.14	-0.08	0.17	0.00	0.00	0.30
	(0.06)	(0.14)	(0.12)	(0.11)	(0.06)	(0.01)	(0.29)
Control Mean	0.27	0.77	0.91	0.43	0.21	0.06	2.65
Observations	884	884	884	884	884	884	884
Adjusted R^2	0.19	0.04	0.20	0.00	0.01	0.33	0.13