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Integrating transit and TNC services to improve job accessibility: Scenario analysis with an equity lens

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Abstract: With the rapid growth of Transportation Network Company (TNC) services and the continued decline of transit ridership, existing research has proposed and some transit agencies have implemented programs that integrate transit and TNC services. This paper expands the research area to examine the equity implications of such integrations, focusing on job accessibility improvements for low-income workers. We develop an analytical framework that compares improvements in accessibility to jobs under different hypothetical scenarios in which TNC travel serves as the last-mile connection of transit services. Using the city of Chicago for the case study, this research confirms that such transit-TNC integration increases job accessibility for all low-income workers throughout the city, but it also pinpoints nuanced differences in the accessibility improvements among workers of different races, ethnicities, and sexes during peak and off-peak hours.

Keywords: Ride-hailing, ridesourcing, Black, Asian, Hispanic, women

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1 Introduction

Transportation Network Companies (TNC), such as Uber and Lyft, have grown significantly in terms of the number of users (Mazareanu, 2020) as well as the service areas (Gehrke, 2020). Along with this growth, research on TNC services has increased exponentially and started to examine these services' socioeconomic impacts, particularly the equity implications. Meanwhile, the continued decline of transit ridership motivates transit agencies and policymakers to consider the feasibility and the implications of integrating TNCs with conventional transit services. With this background, this research develops an analytical framework that examines two research questions: 1) To what extent does the transit-TNC integration, specifically using TNC services as the last-mile connection of conventional transit systems, improve accessibility to low-income jobs? and 2) How are the accessibility benefits of the integration distributed among low-income workers of different sociodemographic groups?

Integrating transit and TNC services has become a popular mobility strategy in the transportation sector and thus requires timely examination of its equity implications. On the one hand, TNC services disproportionally benefit those who can afford the services, i.e., middle-to-high income people, leaving behind disadvantaged groups. It is commonly perceived and often supported by empirical evidence

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that TNCs are less likely to serve low-income low-education people. Exacerbating the mobility inequity, TNC services can substitute for transit travel and reduce transit ridership, worsening the financial situations and the service levels of transit (Graehler et al., 2019). Such disruptive effects are disproportionally shouldered by disadvantaged groups who rely on transit.

On the other hand, a growing amount of research has suggested potential benefits of integrating TNC and transit services, particularly when subsidized TNC travel serves as the last-mile connection for transit riders. Such integrations have been implemented in many cities/regions across the U.S. and increasingly catered to low-income workers and their commuting needs. For example, Pinellas Suncoast Transit Authority (PSTA) of Pinellas County, Florida, and Metro Transit of Minneapolis–Saint Paul, Minnesota, reimburse qualified TNC trips for economically disadvantaged commuters. A more recent example is FlexRide Milwaukee, which partners with Milwaukee Country Transit System (MCTS) to provide a first/last-mile solution to residents living in disadvantaged Milwaukee neighborhoods who work in a neighboring suburban county.

The transit-TNC integrations will undoubtedly improve transit riders' access to opportunities, the most essential of which are jobs. However, no research, to the best of our knowledge, has quantified the accessibility improvements of the transit-TNC integrations, let alone the equity implications of the improvements. This research fills in the gap by investigating the two research questions proposed above.

The contributions of this research are two-fold. First, we develop an analytical framework, particularly through an equity lens, to probe accessibility impacts of policies that integrate transit and TNC services. Second, this framework can facilitate decision-making with scenario analysis. Analysis results of different hypothetical scenarios, categorized by the levels of subsidy ($5, $7.5, and $10) and of service (transfer penalty scenarios of 0, 5, and 10 minutes), can inform these policies' efficiency outcomes—accessibility improvements—and equity outcomes—the distribution of the improvements. As a result, the analytical framework can guide transport policies and identify transit-TNC integration strategies that efficiently and equitably serve disadvantaged groups.

The city of Chicago is the case study area. We first compare transit-based and transit-TNC-based accessibility to low-income jobs and then examine how accessibility improvements by the transit-TNC integration are distributed among racial, ethnic, and sex groups. Results reveal that the transit-TNC integration improves job accessibility for all low-income workers across Chicago, but the extent of the improvements varies among workers of different races, ethnicities, and sexes during peak and off-peak hours.

2 Integrating transit and TNC to improve job accessibility for low-income workers

Although low-income workers, the focus of our study, are less likely to afford TNC travel than other income groups, the transit-TNC integration can potentially address the affordability barriers and improve mobility and subsequently accessibility for these workers.

2.1 Supporting TNC travel for low-income workers

TNC services have improved mobility for travelers who can afford the services. Although TNC riders tend to be white, high-income, and highly-educated (Alemi et al., 2018; Clewlow & Mishra, 2017; Grahn, Harper, et al., 2019; Sikder, 2019; Young & Farber, 2019), researchers have also observed TNC usage among other population groups. For example, TNC usage is not significantly different across racial groups (Grahn, Harper, et al., 2019). However, low-income and low-education persons are still much less likely to use TNC (Grahn, Harper, et al., 2019; Sikder, 2019).

Barriers to using TNC services include monetary barriers of unaffordability (Dillahunt et al., 2017; Dillahunt & Veinot, 2018) as well as non-monetary barriers, which include discrimination (Ge et al., 2016), a lack of services in certain neighborhoods (Thebault-Spieker et al., 2017), and digital illiteracy (Dillahunt et al., 2017; Dillahunt & Veinot, 2018). Therefore, to integrate TNCs into transit services and to serve transit-dependent riders, affordability and other non-monetary barriers need to be addressed.

To reduce the enlarging mobility gaps between those who can and cannot afford TNC travel and to tackle the barrier of unaffordability, this paper assumes scenarios of integrated transit-TNC services in which low-income transit riders receive subsidies for their last-mile TNC trips. Similar strategies have been implemented in many places, e.g., by Los Angeles Metro, San Bernardino County Transportation Authority (SBCTA), Des Moines Regional Transit Authority (DART), and more. Therefore, it is imperative to develop an analytical framework to evaluate these transit-TNC integrations.

2.2 Integrating TNC and transit services

A growing amount of research agrees that TNCs can be integrated into existing transit systems, specifically as last-mile connections in multi-modal trips.

Probably because of the time lag in publishing empirical research, existing research that investigates the relationships between TNC and transit travel tends to assume single-modal travel. Treating transit and TNC travel as separate modes of travel, many studies suggested substitution effects of TNC based on estimated travel time differences (Komanduri et al., 2018) or preference surveys (Yan et al., 2019). Comparing fares and estimated travel times between TNC and transit trips in Chicago, Schwieterman and Livingston (2019) suggested that the substitution effects are larger in places with lower levels of transit service. Other studies, based on reported travel behavior, found modest substitution effects (Rayle et al., 2016), and the effects tend to concentrate on population groups who are likely to use TNC, i.e., young and highly-educated people (Lavieri & Bhat, 2019). Some studies that rely on aggregated city-level data also suggest the substitution effects: based on a longitudinal study of 22 American cities in 2015-2018, Graehler et al. (2019) suggested that TNCs reduce heavy rail ridership by 1.3% and bus ridership by 1.7% each year. Tirachini (2019) reviewed international literature and claimed stronger substitution effects than complementary effects.

Meanwhile, researchers have also found complimentary effects of TNCs on transit, and these studies tend to use the data for the whole U.S., but not for one specific city/region. Using the data from the 2017 National Household Travel Survey, Sikder (2019) estimated a positive association between public transit use and TNC use among travelers. Through a longitudinal analysis of 196 metropolitan areas in the U.S., Hall et al. (2018) declared complementary effects given the finding that transit ridership increases two years after TNCs entered the metropolitan areas. Examining panel data of 379 urbanized areas, Babar and Burtch (2020) suggested complementary effects of TNCs on commuter rail transit services.

Naturally, some studies claimed both complementary and substitution effects. Examining time differences between TNC and transit travel in the city of Toronto, Young et al. (2020) described nuanced complementary or substitution effects during different times of day, for different trip purposes, and at different levels of transit services. Jin et al. (2019) suggested that in the city of New York, TNCs compete with public transit during daytime and in places with good transit services but complement transit at midnight and in places with low levels of transit services.

In the discussion, multi-modal travel, e.g., using TNC trips as the last-mile connection for fixed-route transit services, has increasingly been recognized as an effective and efficient mobility strategy

(Clewlow & Mishra, 2017; Lavieri & Bhat, 2019; Shaheen & Chan, 2016; Sikder, 2019). This strategy is supported by empirical findings that many TNC riders request TNC services at transit stops (Davidson et al., 2017) or around transit stations (O'Brien, 2020), as well as by the information provided by transit agencies and TNC users (Feigon & Murphy, 2016). Moreover, simulation models of transit-TNC integration show significant mobility improvements for all (Chen & Nie, 2017; Stiglic et al., 2018).

In practice, many transit agencies have started collaborations with TNCs (Schwieterman & Livingston, 2019). Programs of discounted TNC (Uber/Lyft) rides from designated transit stops/stations have been implemented in the city of Altamonte Springs, Florida; San Diego County, California; and the southeastern Pennsylvania region. Some transit-TNC integrations aim to address the travel needs of disadvantaged groups. For example, Pinellas Suncoast Transit Authority in Florida and Metro Transit of Minneapolis–Saint Paul reimburse TNC (Uber/Lyft) trips after regular working hours for economically disadvantaged workers (Metro Transit, 2020; Pinellas Suncoast Transit Authority, 2020). A limited number of empirical studies have suggested careful design of the transit-TNC integration to ensure equitable and efficient services for disadvantaged populations (Zhu et al., 2021; Zuniga-Garcia et al., 2022).

Nevertheless, research has not fully examined the accessibility benefits of the transit-TNC integration, let alone the equity implication of the accessibility improvements. With the rapid development and expansion of integrated transit-TNC services, we need timely examine these consequences.

2.3 Improving job accessibility for low-income workers

The mobility improvements associated with the transit-TNC integration undoubtedly increase transit riders' accessibility to various activities and opportunities, the most essential of which are jobs. Job accessibility is an important spatial indicator that has significant impact on the economic prospects of people (Hu, 2019; Jin & Paulsen, 2017; Kawabata, 2003; Merlin & Hu, 2017; Sanchez et al., 2004).

Research has demonstrated significant benefits of enhancing the last-mile connection of transit services, including boosting transit use (Tilahun et al., 2016) and improving job accessibility (Boarnet et al., 2017). Recently, Zuo, Wei and Chen (2020) and Zuo, Wei, Chen, et al. (2020) highlighted that improving the last-mile connection increases transit use of the poor, car-less, and minority population groups.

The accessibility improvements by integrated transit-TNC services could greatly benefit those who rely on transit, particularly low-income and minorities (Grahn, Hendrickson, et al., 2019). Much research has examined the spatial (in)equity in job accessibility by non-automobile travel modes (Kawabata & Shen, 2007; Wang & Chen, 2015; Yan, 2020) for disadvantaged groups (Cui et al., 2019; Deboosere & El-Geneidy, 2018; El-Geneidy et al., 2016; Hu, 2015). Investigating spatial inequity in accessibility and accessibility change is prevalent in the research field (Hu et al., 2020). This paper advances this line of inquiry by considering the potential accessibility benefits of integrating new transportation services, such as TNC.

Research on the job accessibility effects of TNC services, particularly through the lens of equity, is scarce. In this background, this research examines to what extent the transit-TNC integration can improve job accessibility for low-income workers and how the accessibility benefits are distributed among population groups.

3 Data and study area

3.1 Data

Our data come from three sources. First, the City of Chicago publishes Transportation Network Provider trip data after November 2018 (City of Chicago, 2020). We use weekday trip information for the 12-month period from March 1, 2019, to February 29, 2020, before COVID-19 hit the U.S. The trip information includes start and end times, duration, length, fare, and census tract ID of pickup and drop-off locations. The fare information is rounded to the nearest multiple of $2.50. We removed the TNC trip records on weekends and public holidays during the 12-month period.

Second, the Chicago Metropolitan Agency for Planning (CMAP) provides estimated TAZ-to-TAZ (Traffic Analysis Zone) travel time/distance matrices for the year 2020, and the matrices were estimated and published in March 2020 (Chicago Metropolitan Agency for Planning, 2020b). In this research, we use the CMAP transit travel time matrix and automobile travel time/distance matrices. The transit travel time matrix does not differentiate between rail and bus transit. CMAP provides travel time matrices during weekday peak hours (7:00 a.m. to 9:59 a.m.) and off-peak hours (10:00 a.m. to 12:59 p.m.). Accordingly, we focus on TNC trips that start and end in the respective peak and off-peak hours.

Third, we collected data of low-income workers (at residence) and low-income jobs (at workplace) from the 2017 LEHD Origin-Destination Employment Statistics (LODES) (U.S. Bureau of the Census, 2020). The data are provided at the census block level. LODES classify three monthly-earning levels: $1250 or less, $1251- $3333, and greater than $3333. We focus on low-income workers with earnings less than $1250. In the city of Chicago, there were 244,439 low-income workers, accounting for 20.7% of the working population in 2017 (U.S. Bureau of the Census, 2017). One advantage of the LODES data is that it provides cross-tabulations of earning levels and demographic characteristics of race, ethnicity, and sex, allowing us to compare low-income workers of different races, ethnicities, or sexes. Unfortunately, LODES does not provide a cross-tabulation of race and ethnicity, and therefore we cannot compare, for example, non-Hispanic white workers with non-Hispanic Black workers.

The unit of analysis is the census tract, the smallest geographic unit of Chicago Transportation Network Provider data. Data from other sources were converted or aggregated to the census tracts. The CMAP travel matrix data are based on TAZs, whose boundaries largely overlap with census tracts. Therefore, we converted the TAZ-to-TAZ travel matrices to tract-to-tract matrices by connecting the centroids of TAZs with the centroids of the closest census tracts. We aggregated the LODES block-level data to the census tracts.

3.2 The city of Chicago

The study area, the city of Chicago, offers convenient transportation services. Chicago Transit Authority (CTA) operates eight rail lines and nearly a hundred bus routes, establishing an extensive transit network for residents. Metra, the regional (Northeast Illinois) commuter rail system, connects suburban communities with the city of Chicago. Figure 1 shows the study area and its transit network. The level of transit services, naturally, is the highest in and around the Chicago Central Business District (CBD), which is the hub of rail and bus transit services. Transit level of services declines with an increasing distance from the CBD, and the far southeast side of Chicago has the lowest coverage of transit services.

A large number of workers in Chicago have no access to cars and rely on transit. In 2018, 16.3% of workers in the city of Chicago do not have cars in their households (U.S. Bureau of the Census, 2018). Many Chicago workers rely on transit: in 2018, 28.3% of them commuted by public transportation (U.S. Bureau of the Census, 2018), far greater than the 4.9% national average (U.S. Bureau of the Census, 2018). We expect much greater reliance on transit for low-income workers living in Chicago.

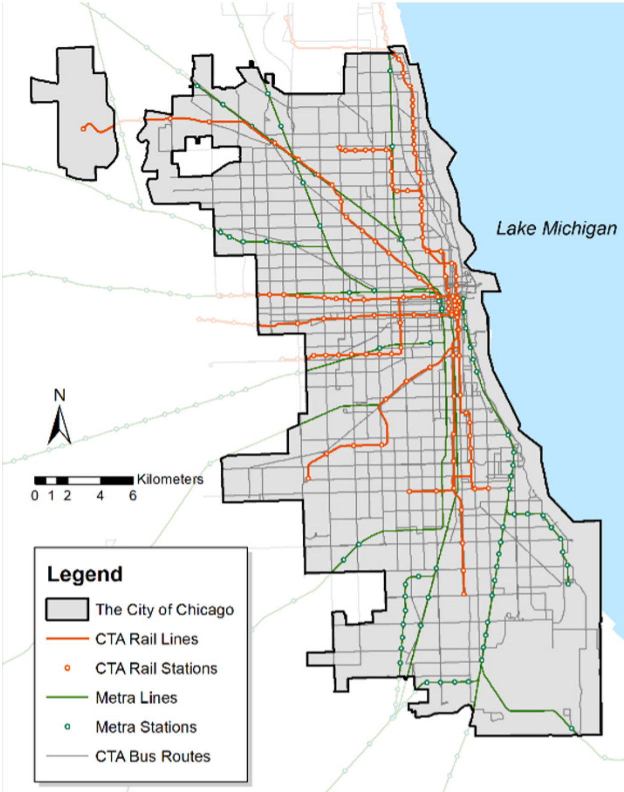

Figure 1. Study area and transit network

Figure 2 shows the distribution of low-income workers (at residence) and low-income jobs (at workplace), based on the LODES data. In total, the city had 244,439 low-income workers and 257,299 low-income jobs.

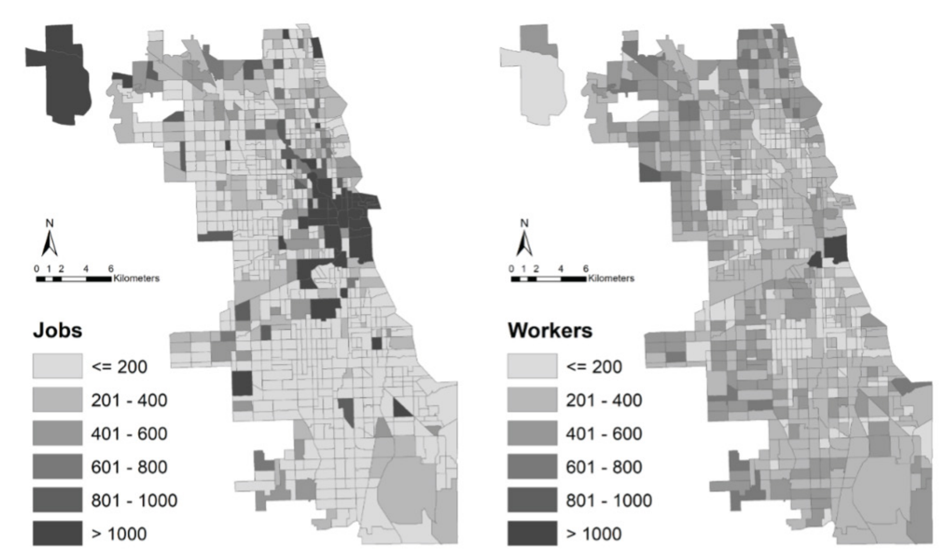

Figure 2. Distribution of low-income workers and jobs

Low-income jobs are spatially more clustered than low-income workers. Low-income jobs concentrate in and around the CBD and O'Hare International Airport. Meanwhile, low-income workers are more dispersed in the city, although they also display some concentrations to the south of the CBD. Considering the concentrated job supply as well as the extensive transit services in the CBD area, we can expect high job accessibility for low-income workers living in and around the CBD.

The spatial locations of low-income workers of different races, ethnicities, and sexes can influence their job accessibility as well as the extent of accessibility improvement by the transit-TNC integration. Figures 3a–3g show their spatial distributions. Racial/ethnic segregation is evident in the city of Chicago, even among low-income workers. White and Black low-income workers (Figures 3a and 3b) live in different parts of the city without many overlaps. Asian low-income workers (Figure 3c) are few, but they show clear clustering in neighborhoods to the southwest of the CBD. Similarly, non-Hispanic and Hispanic low-income workers have different location patterns (Figures 3d and 3e); the places with high concentrations of the respective ethnic group do not have many overlaps. Naturally, male and female workers show correlated distribution patterns, but still, there are more low-income female workers (Figure 3g) than male workers (Figure 3f), and they could have different levels of job accessibility.

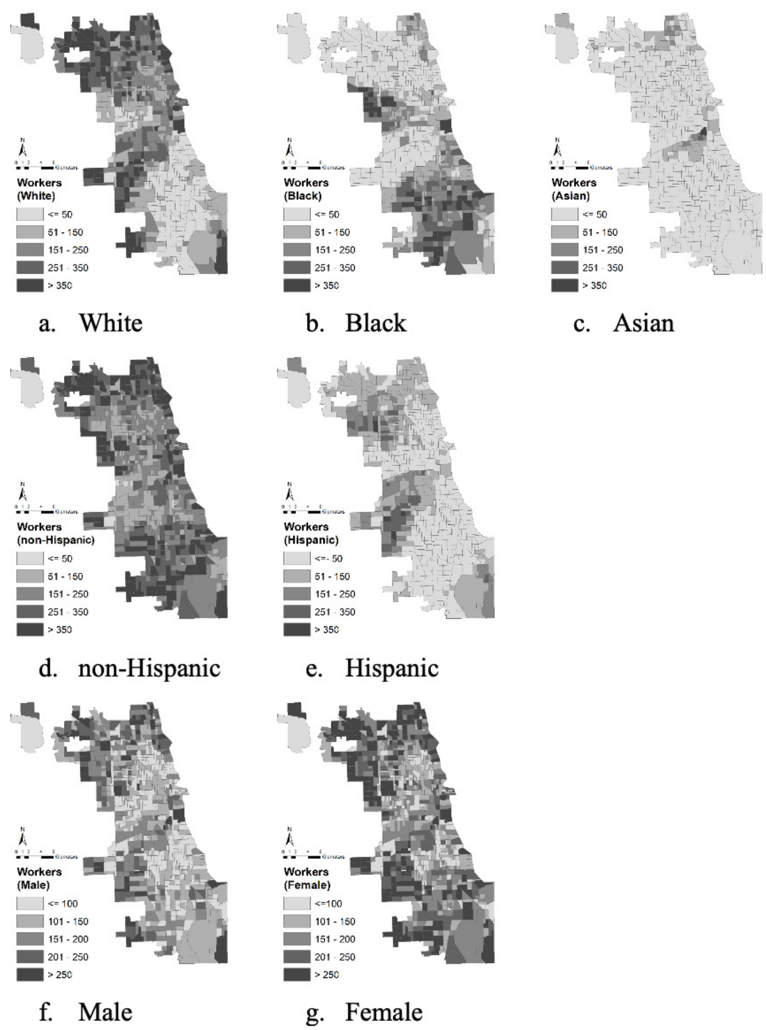

Figure 3. Distribution of low-income workers by race, ethnicity, and sex

4 Analytical framework and methodology

Figure 4 shows the analytical framework to probe the two research questions. The left half shows that transit-TNC integration can improve job accessibility by connecting to more potential job opportunities. The right half shows that accessibility improvements can be unevenly distributed across space and thus benefit to various extents different population groups, who live in different parts of the study areas.

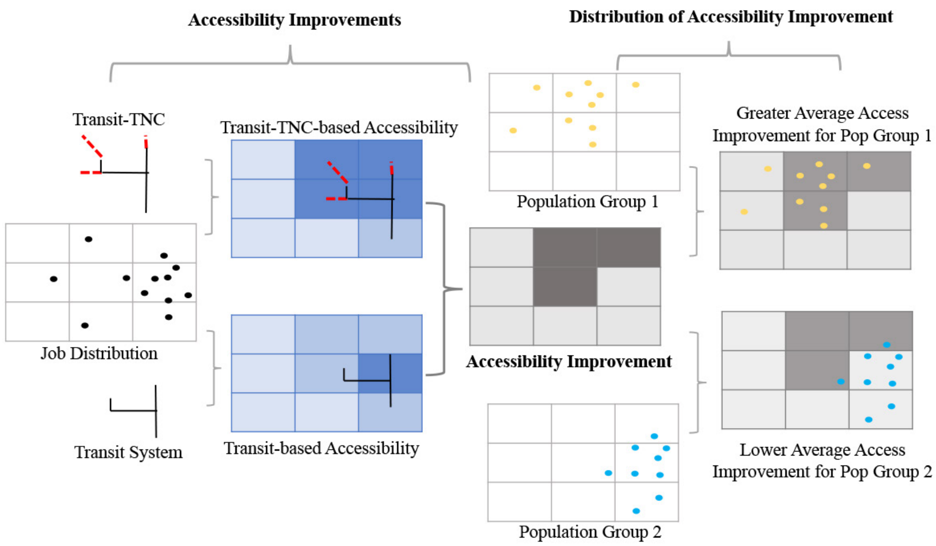

Figure 4. Analytical framework

4.1 Job accessibility

We estimate two sets of job accessibility: transit-based and transit-TNC-based. The latter assumes subsidized last-mile TNC trips within predetermined fare thresholds. We adopt the gravity-based model which discounts jobs that are further away (Hansen, 1959). The model has been widely applied (e.g., Cervero et al., 2002; Foth et al., 2013; Gibb et al., 2014; Levine et al., 2012; Levinson, 1998; Wang & Chen, 2015).

First, *transit-based job accessibility* is estimated in the following way:

$$\text{Job Access}^{\text{transit}}{}_{i} = \sum_{j} E_j f(T^{\text{transit}}{}_{ij}) \quad (1)$$

$$f(T^{\text{transit}}{}_{ij}) = e\hat{}(-bT^{\text{transit}}{}_{ij}) \quad (2)$$

Where

$\text{Job Access}^{\text{transit}}{}_{i}$ = transit-based job accessibility for low-income workers living in census tract *i;*

E_j = the number of low-income jobs located in census tract *j*;

$T^{\text{transit}}{}_{ij}$ = centroid to centroid transit travel time from *i* to *j*, based on CMAP in-vehicle transit travel time;

b = impedance factor = 0.02857 (=1/35). The average commuting time is 35 minutes in the city of Chicago (Chicago Metropolitan Agency for Planning, 2020a)

Next, we estimate *transit-TNC-based job accessibility*, assuming that TNC travel provides the last-mile connection for transit trips within certain fare thresholds.

$$\text{Job Access}^{\text{transit-TNC}}_{i} = \sum_{j} [E_j f(T^{\text{transit-TNC}}_{ij})] \quad (3)$$

Where

$\text{Job Access}^{\text{transit-TNC}}_{i}$ = transit-TNC based job accessibility for workers living in census tract *i*;

$T^{\text{transit-TNC}}_{ij}$ = shortest *i* to *j* travel time among the options of transit and transit-TNC travel (See Figure 5).

All the other notations are the same as in previous equations.

Figure 5 illustrates how to decide the shortest travel time between home census tract *i* and workplace census tract *j*. There are two types of travel modes: transit and integrated transit-TNC travel, and three hypothetical routes: one transit-only (route 2) and two transit-TNC routes (route 1 and route 3). Assuming that route 3 has the shortest travel time, this travel time is used in Equation (3). Of course, there are situations in which the transit-only route is the fastest, and in those cases, the transit travel time is used in the accessibility calculation in Equation (3). Note that since TNC travel is the last-mile connection for transit services, the transit-only route by default is the shortest route for intrazonal trips.

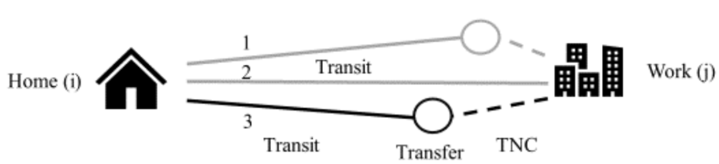

Figure 5. Shortest route among trip options

We estimate nine possible transit-TNC scenarios with three predetermined thresholds of TNC fare subsidies ($5, $7.5, and $10) and three transfer penalty scenarios (0, 5, and 10 minutes). We acknowledge that the 0-minute transfer is unrealistic, but a seamless and effortless transfer is an aspiration for multi-modal travel. The 5- and 10-minute transfers are commonly used in scenario analysis in the literature (Reck & Axhausen, 2019).

4.1.1 TNC fare matrix

To calculate job accessibility with the transit-TNC integration under different scenarios of subsidized TNC travel, we need to estimate census tracts that can be reached within the fare thresholds. In other words, if the fare of a TNC trip is above the threshold, the TNC trip is not considered in the accessibility calculations for that scenario.

We first construct a TNC fare matrix for all potential origin-destination (O-D) pairs. Actual TNC trip data are used to estimate the fare matrix. The city of Chicago contains 801 census tracts and thus 641,601(=801×801) possible O-D pairs. The TNC dataset includes valid trip information of 8,278,618 trips for 194,581 distinctive O-D pairs during the morning peak hours and 5,727,750 trips for 186,218 O-D pairs during the off-peak hours. We first estimate the average fare for the O-D pairs with valid TNC trip information.

TNC fare is calculated mainly based on travel time and distance (Lyft, 2020; Uber, 2020). Using the actual TNC data, we estimate the following regression model for TNC trips from census tract *i* (origin) to census tract *j* (destination). We adopt linear regression models as scatter plots show linear relationships between fare and time/distance, during both peak and off-peak hours. Although travel time and travel distance are highly correlated, the multicollinearity does not affect model prediction or its goodness-of-fit.

$$Fare_{ij}=a_0+a_1*Time_{ij}+a_2*Distance_{ij} + error_{ij} \quad (4)$$

Where

a_0, a_1, and a_2 are all parameters;

$Time_{ij}$ = Average travel time from census tract *i* to census tract *j*;

$Distance_{ij}$ = Average travel distance from census tract *i* to census tract *j*.

After the parameters are estimated, we use CMAP automobile time/distance matrices to extrapolate the TNC fare matrices for all 641,601 O-D pairs in the study area. In the transit-TNC accessibility estimation, we select the O-D pairs within the predetermined TNC fare thresholds. Figure 5 shows that some transit-TNC routes, with the last-mile TNC travel within a certain fare threshold, can have shorter travel time than the transit-only route.

4.2 Job accessibility improvement by population group

After calculating the transit-based job accessibility (based on Equation (1)) and transit-TNC-based accessibility (based on Equation (3)), we investigate to what extent the integrated transit-TNC services can improve job accessibility (Research Question 1) and how the improvement is distributed among low-income workers of different races, ethnicities, and sexes (Research Question 2). To do so, we estimate the weighted average job accessibility by population group:

$$Ratio_{i,p}=N_{i,p}/ \sum_i N_{i,p} \quad (5)$$

$$AveAccess_p= \sum_i (Job\ Access_i * Ratio_{i,p}) \quad (6)$$

Where

$Ratio_{i,p}$ = the percentage of the total number of workers of population group *p*, e.g., Black low-income workers, in census tract *i*. ($\sum_i Ratio_{i,p}$= 100% and $\sum_i N_{i,p}$ = the total number of workers in group *p*).

$N_{i,p}$ = the number of workers of population group *p* in census tract *i*.

$AveAccess_p$= the weighted average job accessibility of population group *p*.

Based on Equation (6), we can compare the average accessibility of population groups with different travel options: transit-only or integrated transit-TNC travel. We also use Equation (6) to calculate the weighted average job accessibility for all low-income workers. In this case, population group p is all low-income workers.

5 Results

5.1 TNC fare matrix

We estimate the regression model based on equation (4) using the actual TNC trip information for the 194,581 O-D pairs during the peak hours and the 186,218 O-D pairs during the off-peak hours. The regression models are as below.

$$Fare^{peak}_{ij}=3.778+0.121*Time_{ij}+0.557*Distance_{ij} \quad (7)$$

$$Fare^{off\text{-}peak}_{ij}=3.580+0.099*Time_{ij}+0.559*Distance_{ij} \quad (8)$$

The regression models have good model fit. All coefficients are significant at the 1% level. The R-squared is 0.711 for the peak-hour model and 0.760 for the off-peak model. For robustness check, we tried two additional models: one with only travel time as the independent variable and the other with only travel distance as the independent variable. These two models have lower R-squared and adjusted R-squared than the final models we use. We also compare the errors between the actual and the estimated fare (using the 194,581 O-D pairs during the peak hours as the reference) and found that for the O-D pairs with the actual average fare lower than \$5, 50.6% of the pairs have errors within \$1 (20% difference of the \$5 fare). Larger fare thresholds yield more accurate estimations: 80.1% and 79.5% O-D pairs have errors within 20% differences from the actual fares with the threshold of \$7.5 and \$10, respectively.

We can expect accessibility improvements with the transit-TNC integration. During peak hours, \$5 TNC trips can cover 22,462, 3.5%, of the 641,601 O-D pairs, and naturally greater fares cover larger areas—62,999 (9.8%) and 112,326 (17.5%) O-D pairs with the fares of \$7.5 and \$10, respectively.

5.2 Job accessibility improvement with transit-TNC integration

In this section, we compare the transit-TNC-based accessibility of nine hypothetical scenarios (3 fare thresholds × 3 transfer penalty scenarios) with the original transit-based accessibility in two time periods (peak and off-peak hours). Because of the limited space, we first use the TNC fare of \$5 during peak hours to visually illustrate the analytical framework that quantifies accessibility improvements by transit-TNC integration. Maps of other scenarios (\$5 fare during off-peak hours, \$7.5 during peak and off-peak hours, and \$10 during peak and off-peak hours) are provided in the Appendix. We then provide full results of accessibility improvements of all nine transit-TNC scenarios in both time periods.

Figure 6 shows transit-based job accessibility (a) and transit-TNC-based accessibility (b, c, and d) assuming \$5 TNC fare and three levels of transfer penalty (0, 5, and 10 minutes) during the peak hours, and Figure 7 shows respective accessibility improvement of the transit-TNC integration. Figures in the Appendix show that spatial patterns of accessibility and accessibility improvements for other scenarios are similar as shown in Figures 6 and 7, although greater TNC fares improve accessibility to a larger extent.

Figure 6 shows that, as expected, accessibility to low-income jobs is the highest in the Chicago CBD area, regardless of the travel mode options. Accessibility declines with an increasing distance from the CBD. Additionally, among the four options, accessibility by transit-TNC travel without any transfer penalty is the highest. This observation is expected as the transfer penalty reduces the time-saving advantages of integrating TNC travel.

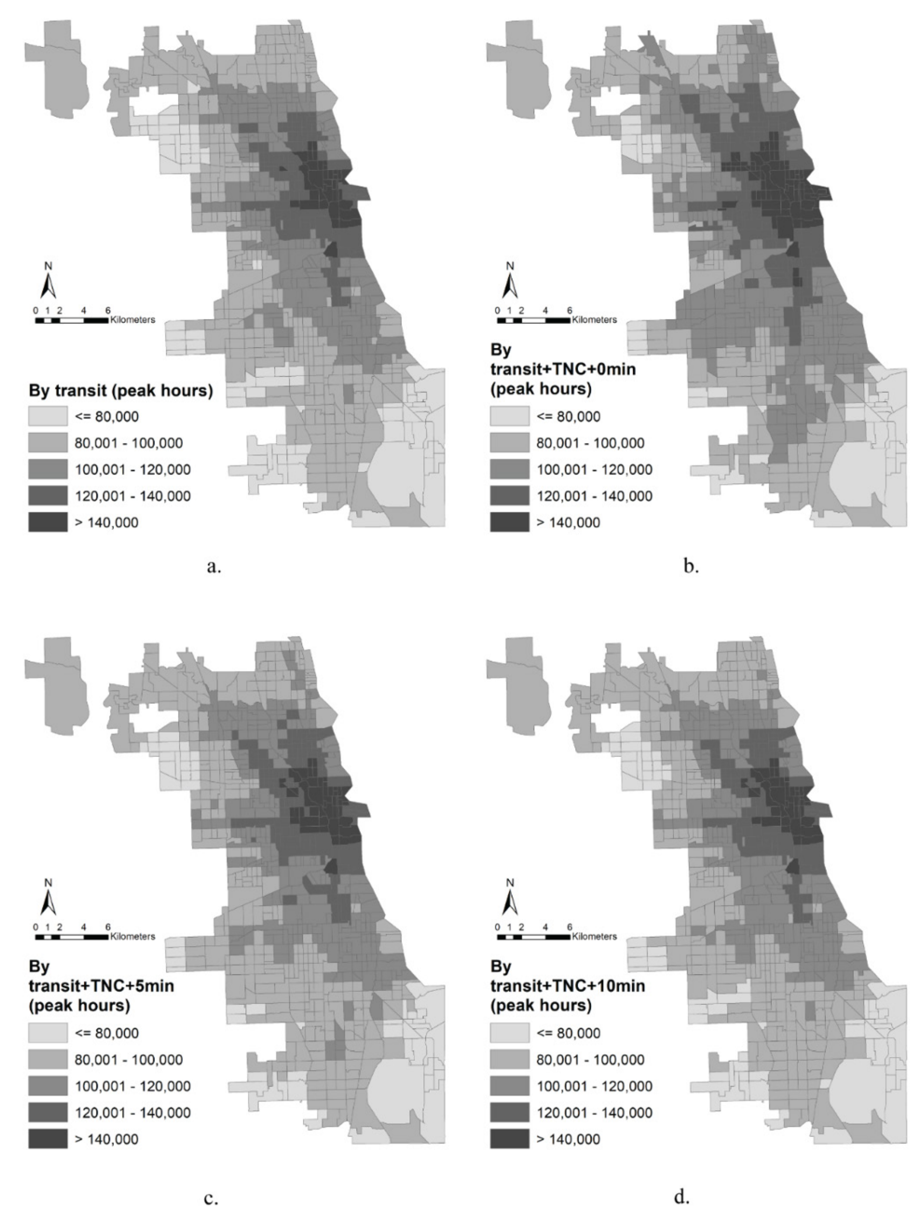

Figure 6. Transit-based and transit-TNC-based accessibility ($5 fare, peak hours)

Figure 7 shows accessibility improvements by the transit-TNC integration, in absolute terms, compared with transit-based accessibility. All census tracts experience some accessibility improvements, and the improvement diminishes with the increasing transfer penalty.

Nevertheless, we do not detect obvious spatial patterns of the accessibility improvement. Census tracts with relatively large accessibility improvement, e.g., greater than 10,000 jobs, are scattered in all three transit-TNC scenarios. In the scenario with the greatest transfer penalty (Figure 7c), the greatest accessibility improvements are observed in both the city center (close to the CBD) and the periphery (the far southeast side). It is difficult to determine which locations gain the greatest or the least accessibility improvements with the transit-TNC integrations.

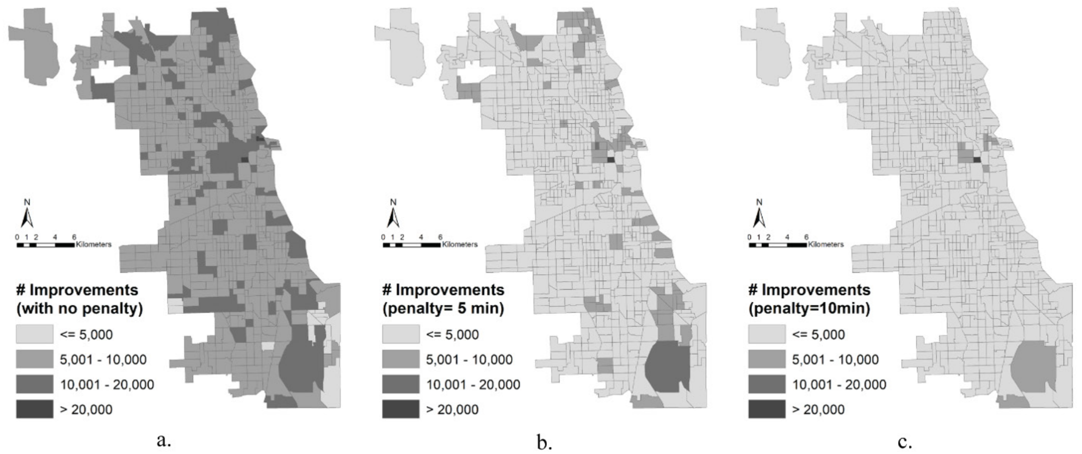

Figure 7. Accessibility improvement with transit-TNC integration ($5 fare, peak hours)

Table 1 shows full results of job accessibility improvement of all scenarios (3 fare thresholds, 3 transfer penalties, and two time periods). The respective top rows of both peak and off-peak hour panels show the weighted average transit-based accessibility, and the other rows show accessibility improvements by the nine transit-TNC scenarios. The improvements are illustrated by changes in the absolute term (number of jobs) and the relative term (percentage difference) in the weighted average accessibility, calculated based on Equation (6).

Accessibility improvements enlarge with the increasing TNC fare but diminish with the increasing transfer penalty. Naturally, the scenario with the greatest improvement has the highest TNC fare of $10 but no transfer penalty, and the scenario with the least improvement has the lowest fare of $5 with the longest transfer penalty of 10 minutes.

Table 1. Accessibility improvement for all low-income workers

Peak Hour			
Transit-based Access		98702	
TNC fare	Transfer Penalty (min)	Ave Access Improvement*	% Improvement
<= \$5.0	0	8832	8.95
	5	3339	3.38
	10	1298	1.32
<= \$7.5	0	11673	11.83
	5	4689	4.75
	10	1765	1.79
<= \$10.0	0	11972	12.13
	5	4845	4.91
	10	1812	1.84
Off-peak Hour			
Transit-based Access		93380	
TNC fare	Transfer Penalty (min)	Ave Access Improvement*	% Improvement
<= \$5.0	0	2627	2.81
	5	1125	1.20
	10	559	0.60
<= \$7.5	0	10938	11.71
	5	4430	4.74
	10	1797	1.92
<= \$10.0	0	14945	16.00
	5	6683	7.16
	10	2669	2.86

* Average Accessibility Improvement=$AveAccess^{transit\text{-}TNC}_p$ - $AveAccess^{transit}_p$ (Based on Equation (6) and population group *p* of all low-income workers).

Regardless, the transit-TNC integration benefits all low-income workers. Even in the scenario of the least accessibility improvement with the \$5 fare and 10-minute transfer penalty, low-income workers on average still gain access to 1298 more jobs, a 1.32% increase, during peak hours and 559 more jobs, a 0.60% increase, during off-peak hours.

Table 2. Accessibility improvement by race

		White		**Black**		**Asian**	
Peak Hour							
Transit-based Access		99755		95373		105942	
TNC fare	Transfer Penalty (min)	Access Improv.	% Improv.	Access Improv.	% Improv.	Access Improv.	% Improv.
<= $5.0	0	8838	8.86	8803	**9.23**	**8879**	8.38
	5	3326	3.33	**3368**	**3.53**	3305	3.12
	10	**1322**	**1.33**	1258	1.32	1307	1.23
<= $7.5	0	11620	11.65	**11747**	**12.32**	11701	11.04
	5	4638	4.65	**4786**	**5.02**	4636	4.38
	10	1765	1.77	**1768**	**1.85**	1761	1.66
<= $10.0	0	11919	11.95	**12052**	**12.64**	11970	11.30
	5	4796	4.81	**4941**	**5.18**	4776	4.51
	10	1813	1.82	**1814**	**1.90**	1803	1.70
Off-peak Hour							
Transit-based Access		95656		87676		101939	
TNC fare	Transfer Penalty (min)	Access Improv.	% Improv.	Access Improv.	% Improv.	Access Improv.	% Improv.
<= $5.0	0	**2684**	2.81	2531	**2.89**	2615	2.56
	5	**1172**	**1.23**	1048	1.20	1115	1.09
	10	**602**	**0.63**	483	0.55	575	0.56
<= $7.5	0	**11257**	11.77	10344	**11.80**	11173	10.96
	5	**4589**	**4.80**	4143	4.73	4522	4.44
	10	**1893**	**1.98**	1620	1.85	1882	1.85
<= $10.0	0	15185	15.87	14477	**16.51**	**15193**	14.90
	5	**6794**	7.10	6491	**7.40**	6694	6.57
	10	**2742**	2.87	2546	**2.90**	2681	2.63

(In each Transit-TNC scenario, the largest absolute and relative improvements among the three racial groups are highlighted with bold numbers.)

Nuanced differences in accessibility improvement between the peak and off-peak hours are observed. Compared with peak hours (the top panel), during off-peak hours (the bottom panel) the transit-TNC integration improves accessibility to a lesser extent with a lower fare threshold ($5) but to a greater extent with a higher fare threshold ($10), in terms of both the absolute and the relative accessibility improvements. We suspect that the reason is associated with the much wider spatial coverage by the large fare of $10 during the off-peak hours than during peak hours. Specifically, the $10 fare covers 112,326 O-D pairs during the peak hours, but in off-peak hours, the number of pairs increases to 182,138, 62.2% more than during the peak hours. Meanwhile, the $5 TNC fare covers, during the off-peak hours, 27,155 O-D pairs, only 20.9% more than the peak hours—22,462 O-D pairs. The comparison results suggest that decision-makers should consider different accessibility outcomes of the same TNC subsidies during the peak and off-peak hours.

5.3 Accessibility improvement by population group

This section investigates accessibility improvement by population group. We start with the three major racial groups: white, Black, and Asian, to illustrate the framework for the comparison. Table 2 shows transit-based job accessibility and accessibility improvement by the transit-TNC integration for the respective racial groups.

Racial disparities exist in the original transit-based accessibility (top row of each panel). Low-income Asian workers have the highest accessibility: an average of 105,942 during the peak hours and 101,939 during the off-peak hours, followed by low-income white workers (99,755 and 95,656), and low-income Black workers have the lowest transit-based accessibility (95,373 and 87,676). It is noteworthy that Black workers have not only the lowest transit-based accessibility but also the steepest drop in accessibility between the peak and off-peak hours, signifying their exacerbated accessibility situation during off-peak hours.

Transit-TNC integration can reduce the original racial gaps in transit-based accessibility during peak hours. The integration can make up for some initial accessibility disadvantages of low-income Black workers. During peak hours Black workers would experience the greatest accessibility gain in both absolute and relative terms in seven out of the nine transit-TNC scenarios. The only two exceptions are the scenarios of $5 TNC fare with 0- and 10-minute transfer penalties. On the other hand, among the three racial groups, low-income Asian workers, who have the highest transit-based accessibility initially, tend to gain the smallest accessibility improvements with the transit-TNC integration. As a result, initial racial gaps in transit-based accessibility are moderated with the transit-TNC integration during peak hours.

However, during the off-peak hours, accessibility benefits of integrated transit-TNC services tend to concentrate on white workers. Among the three racial groups, white workers gain the greatest absolute improvements in all scenarios except for one ($10 TNC fare with no transfer penalty). Meanwhile, Black workers gain the greatest relative improvements in five scenarios. However, the main reason for the greatest relative improvements for Black workers is their low initial transit-based accessibility. In fact, the absolute improvements in accessibility are still the smallest for Black workers in all nine transit-TNC scenarios during off-peak hours. The observation cautions potential equity implications of subsidizing TNC trips for low-income workers during off-peak hours.

Table 3 shows transit-based job accessibility and the accessibility improvement with the transit-TNC integration of two ethnic groups: non-Hispanic and Hispanic. Like racial disparities, ethnic gaps in transit-based accessibility exist. Hispanic workers have lower transit-based accessibility than non-Hispanic workers during both peak and off-peak hours.

Transit-TNC integration does not reduce ethnic gaps in accessibility: Hispanic workers do not enjoy proportional accessibility improvements as non-Hispanic workers do. During the peak hours, integrated transit-TNC services can increase job accessibility, in absolute terms, to a greater extent for non-Hispanic workers than for Hispanic workers. Due to the relatively lower base of transit-based accessibility, Hispanic workers have greater relative improvements in the three scenarios with zero transfer penalty. However, the zero transfer penalty is a mathematical assumption and unrealistic in practice. Similarly, during off-peak hours, the only scenarios under which Hispanic workers gain some advantages are those without transfer penalty. These observations underscore the unequal distribution of accessibility benefits of the hypothesized transit-TNC integrations between Hispanic and non-Hispanic workers.

Table 4 shows the comparison results for male and female workers. Sex differences in transit-based accessibility are observed: female workers have lower accessibility than male workers. The transit-TNC integration can make up for some of the differences in both the absolute and relative terms during peak hours, as female workers gain greater accessibility than male workers in all nine scenarios. However, during off-peak hours, female workers experience greater improvements only in the relative terms but not in the absolute terms.

In general, the above scenario analysis shows that Black, Hispanic, and female workers have lower accessibility to jobs by the transit-only mode when compared with the respective advantaged groups. Integrating TNC and transit services can reduce some of the initial transit-based accessibility gaps for Black and female workers during peak hours but not for Hispanic workers. During off-peak hours, accessibility gains through the transit-TNC integration, particularly in absolute terms, tend to concentrate on advantaged groups of white, non-Hispanic, and male workers.

Table 3. Accessibility improvement by ethnicity

		Non-Hispanic		**Hispanic**	
Peak Hour					
Transit-based Access		99667		95576	
TNC fare	Transfer Penalty (min)	Access Improv.	% Improv.	Access Improv.	% Improv.
<= $5.0	0	**8898**	8.93	8615	**9.01**
	5	**3402**	**3.41**	3134	3.28
	10	**1347**	**1.35**	1141	1.19
<= $7.5	0	**11734**	11.77	11476	**12.01**
	5	**4747**	**4.76**	4504	4.71
	10	**1818**	**1.82**	1593	1.67
<= $10.0	0	**12022**	12.06	11811	**12.36**
	5	**4896**	**4.91**	4684	4.90
	10	**1864**	**1.87**	1645	1.72
Off-peak Hour					
Transit-based Access		93640		92538	
TNC fare	Transfer Penalty (min)	Access Improv.	% Improv.	Access Improv.	% Improv.
<= $5.0	0	2624	2.80	**2635**	**2.85**
	5	**1137**	**1.21**	1086	1.17
	10	**578**	**0.62**	497	0.54
<= $7.5	0	10914	11.66	**11016**	**11.90**
	5	**4458**	**4.76**	4340	4.69
	10	**1856**	**1.98**	1606	1.74
<= $10.0	0	14908	15.92	**15067**	**16.28**
	5	**6685**	7.14	6679	**7.22**
	10	**2713**	**2.90**	2527	2.73

(In each Transit-TNC scenario, the largest absolute and relative improvements between the two ethnic groups are highlighted with bold numbers.)

Table 4. Accessibility improvement by sex

		Male		Female	
Peak Hour					
Transit-based Access		98825		98611	
TNC fare	Transfer Penalty (min)	Access Improv.	% Improv.	Access Improv.	% Improv.
<= $5.0	0	8823	8.93	**8838**	**8.96**
	5	3329	3.37	**3347**	**3.39**
	10	1293	1.31	**1303**	**1.32**
<= $7.5	0	11659	11.80	**11684**	**11.85**
	5	4676	4.73	**4699**	**4.77**
	10	1757	1.78	**1771**	**1.80**
<= $10.0	0	11958	12.10	**11983**	**12.15**
	5	4833	4.89	**4855**	**4.92**
	10	1804	1.83	**1818**	**1.84**
Off-peak Hour					
Transit-based Access		93674		93160	
TNC fare	Transfer Penalty (min)	Access Improv.	% Improv.	Access Improv.	% Improv.
<= $5.0	0	**2629**	2.81	2625	**2.82**
	5	**1128**	1.20	1123	**1.21**
	10	**563**	0.60	556	**0.60**
<= $7.5	0	**10960**	11.70	10921	**11.72**
	5	**4437**	4.74	4425	**4.75**
	10	**1797**	1.92	1796	**1.93**
<= $10.0	0	**14967**	15.98	14928	**16.03**
	5	**6688**	7.14	6679	**7.17**
	10	2668	2.85	**2670**	**2.87**

(In each scenario, the largest improvements are highlighted with bold numbers.)

6 Discussions and conclusion

Some limitations constrain the scope of this research and the generalizability of the results. First, based on the CMAP definition, the off-peak hours are mid-day (10:00 a.m. to 12:59 p.m.). We do not have transit travel time matrices for other off-peak hours, and we acknowledge that close to 30% of low-income workers might need to commute during evenings, nights, and weekends (Enchautegui, 2013). Second, we consider only the last-mile solution to efficiently illustrate this analytical framework, as job accessibility is more relevant for home-based work trips. In this context, a first-mile solution can be more easily coordinated than the last-mile solution as a family member or friend can give a ride from home to transit stops. Still, future research will need to consider both first- and last-mile solutions. Third, we cannot separate rail and transit services since CMAP transit travel time matrices are estimated with both modes included. Fourth, the labor market is regional, but the TNC travel data are available only for the city of Chicago, and thus we cannot estimate job accessibility for low-income workers living outside of the city boundary. Fifth, COVID might have fundamentally changed labor market dynamics and travel behavior, and we do not fully understand these changes yet.

Nevertheless, this study provides an important analytical framework for policy and planning discussion. The research approach that we developed offers a new way to probe imminent questions: Can integrating the rapidly-growing TNCs with conventional transit services improve accessibility? What are the equity implications of this integration?

Our answers to these questions, based on scenario analysis for the city of Chicago, are three-fold. First, integrating TNC travel as the last-mile connection of transit services improves job accessibility for all low-income workers during both peak and off-peak hours. Second, the benefits are distributed unevenly across racial, ethnic, or sex groups. During peak hours, Black and female workers gain greater accessibility improvements with the transit-TNC integration than white and male workers, respectively, reducing initial racial and gender gaps in transit-based accessibility. However, Hispanic workers tend to gain smaller benefits than non-Hispanic workers. Third, the transit-TNC integration is more beneficial for disadvantaged groups during peak hours than the off-peak hours as defined in the research.

Our analytical framework can be expanded for future policy analysis, particularly in the context of the continued decline of transit ridership and the rapid growth of ride-hailing services. For example, the framework can be used to examine accessibility to other essential services and opportunities, including healthcare and grocery stores, and to investigate equity outcomes of various policy strategies, such as TNC services substituting for low-rider transit routes, integrated fare system that reduces transfer penalty, and dynamic pricing mechanisms for TNC subsidies. Timely analysis of these strategies recognizes the growing trend of on-demand mobility services, potentially facilitating complementary effects of TNC on conventional transit services and benefiting disadvantaged groups.

We propose these hypothetical scenarios for research purposes, and we do not advocate for subsidizing private businesses, i.e., TNC. In fact, we want to underscore our caution of subsidizing for-profit TNCs, especially their potentially disruptive effects on public transit services, on which low-income workers disproportionately rely. What we support is flexible and integrative transit services collaborating with private mobility service providers, when the efficiency and equity benefits of these collaborations can be expected.

Indeed, our research demonstrates some efficiency and equity benefits of the transit-TNC integration. We show that the transit-TNC integration benefits all low-income workers and can reduce some of the original transit-based accessibility disadvantages of Black and women workers. These findings call for future research and practices to consider the partnerships between private TNC and public transit services with an equity lens.

Appendix

Appendix available as a supplemental file at https://jtlu.org/index.php/jtlu/article/view/2229.

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