# The relationship between Ridehailing and Public Transit in Chicago: a comparison before and after COVID-19

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**ABSTRACT**
As Transportation Network Companies (TNCs) have expanded their role in U.S. cities recently, their services (i.e. ridehailing) have been subject to scrutiny for displacing public transit (PT) ridership. Previous studies have attempted to classify the relationship between transit and TNCs, though analysis has been limited by a lack of granular TNC trip records, or has been conducted at aggregated scales. This study seeks to understand the TNC-PT relationship in Chicago at a spatially and temporally granular level by analyzing detailed individual trip records. An analysis framework is developed which enables TNC trips to be classified according to their potential relationship with transit: complementary (providing access to/from transit), substitutive (replacing a transit alternative), or independent (not desirably completable by transit). This framework is applied to both regular operating conditions and to early stages of the COVID-19 pandemic, to identify the TNC-PT relationship in these two contexts. We find that complementary TNC trips make up a small fraction of trips taken (approximately 2%), while potential independent trips represent 48% to 53% and potential substitution trips represent 45% to 50%. The percentage of substitution trips drops substantially following COVID-19 shutdowns (to around 14%). This may be attributed to a reduction in work-based TNC trips from Chicago's north side, indicated by changes in spatial distributions and flattening of trips occurring during peak hours. Furthermore, using spatial regression, we find that an increased tendency of TNC trips to substitute transit is related to a lower proportion of elderly people, greater proportion of peak-period TNC travel, greater transit network availability, a higher percentage of white population, and increased crime rates. Our findings identify spatial and temporal trends in the tendency to use TNC services in place of public transit, and thus have potential policy implications for transit management, such as spatially targeted service improvements and safety measures to reduce the possibility of public transit being substituted by TNC services.

**Keywords:** Transportation Network Companies, ridehailing, public transit, substitutive, complementary, independent

# 1 Introduction

The public transit (PT) system has been disrupted by the explosive growth of TNC (or ridehailing) services. As a result, recent years have witnessed declining transit ridership and monthly transit pass sales, and TNCs are generally considered one of the contributing factors (Rayle, et al., 2016; Henao, 2017; Graehler, et al., 2019). The Chicago Transit Authority (CTA) has identified this disruption as well, stating in its 2018 Annual Ridership Report that "Ridership in 2018 was affected by relatively low gas prices and competition from ride hailing companies like Uber and Lyft" (CTA Ridership Analysis and Reporting, 2019).

While the convenience of TNCs certainly causes some riders to replace transit trips with TNC trips, there are cases where TNCs might enable easier access to PT or might serve trips that occur at times and places where PT is inaccessible or inefficient (Murphy, 2016; Hall, et al., 2017). This calls for some nuance and specificity to the discussion of the relationship between TNCs and PT. An improved understanding of this relationship could better inform public transit management, to make transit a more competitive option and thereby regain ridership.

Therefore, the goal of this paper is to understand the substitutive, complementary, or independent relationship between TNC and PT services on a spatio-temporally granular scale. Partnering with the Chicago Transit Authority (CTA), this study uses a broad mix of data sources (e.g. TNC trip records, automated transit operating data, transit service schedules, and other geospatial data), and develops a framework to analyze the TNC-PT relationship by classifying each TNC trip as potentially complementary to, substitutive for, or independent from PT. Using this framework, different periods of significance are evaluated and compared to better understand how the TNC-PT relationship has evolved due to the COVID-19 pandemic in March 2020.

Specifically, this study investigates three main topics of research which build incrementally on each other. First, we develop a generally applicable approach which may be used to classify the substitutive, complementary, or independent relationship of TNC trips with public transit, and apply the method to quantify both the aggregate nature of this relationship and spatial and temporal patterns in it under ordinary operating conditions. Second, we apply regression modelling to further examine the nature of the TNC-PT relationship on a more granular scale, assessing explanatory variables in demographics, the built environment, and the TNC and PT networks. Finally, we apply the method to investigate how this relationship evolves during the initial stages of the COVID-19 pandemic in Chicago.

By identifying this relationship between TNC trips and public transit and investigating spatial and temporal trends, this research will facilitate detailed, route-level planning and policy analysis. Strategies such as targeted management of transit services may be employed to encourage transit as an alternative to TNC trips which contribute to congestion and hinder transit operations, while transit routes may be added, frequency may be modified, or safety measures may be implemented to provide a stronger transit alternative in key areas.

The rest of the paper is organized as follows. Section 2 reviews the state of research on the TNC-PT relationship and the impacts of the COVID-19 pandemic on travel behavior for both modes. The data and methods are described in section 3. Section 4 presents and discusses the findings. Finally, Section 5 summarizes the most salient conclusions and sets the stage for future expansion upon this work.

## 2 Literature Review

### 2.1 TNC-PT Relationship

Previous studies have used surveys, statistical models, and simulations to study the TNC-PT relationship, and indicate the complexity of the relationship between TNCs and PT. It seems clear from existing research that the relationship may take many different forms depending on context, and is both highly sensitive to the city's existing infrastructure and to regulatory action taken by local governments.

The concept of substitution, complementarity, and independence of two products/services is well-studied in microeconomics using the concept of cross elasticity of demand[1]. Although effective for distinguishing products at an aggregate scale, it cannot capture the variability of TNC-PT relationship across space and time. To address this challenge, this paper adopts and develops a methodology for investigating this TNC-PT relationship with spatial and temporal granularity.

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

Other research has employed big data analytics and statistical models: Hoffmann et al. (2016) found that TNC trip volumes increase by over 30% when there is a subway disruption; Hall et al. (2017) found that transit ridership increased by 5% within two years after Uber enters the market; while a study by Graehler et al. (2019) estimated a 1.3% decrease in heavy rail ridership and a 1.7% decrease in bus ridership for each year after TNC services enter the market. Erhardt et al. (2021) use aggregated TNC records and APC-inferred transit ridership to form a fixed effects panel data regression model, which estimated that TNC services caused a 10.8% decline in bus ridership in San Francisco in 2015, but no significant impact on light rail ridership. Grahn et al. (2020) also use APC-inferred transit boardings, in conjunction with surge pricing-based data indicating events of high TNC demand, applying a linear regression model to find that four of ten observed locations saw a significant change in bus boardings during periods of high TNC use. Such research is effective in capturing the overall effect of the TNC relationship by studying a large sample, but only captures the aggregate TNC-PT relationship across the whole study area without distinguishing granular spatial or temporal trends. Specifically in Chicago, Barajas & Brown (2021) studied TNC pick-up and drop-off locations to investigate the potential for the

[1] The cross elasticity of demand ($E_{P_A,Q_B}$), calculated as:

$$E_{A,B} = \frac{\partial Q_B}{\partial P_A} \cdot \frac{P_A}{Q_B},$$

where $P_A$ is the price of good A, and $Q_B$ is the quantity demanded for good B. In this framework, substitution is defined as $E_{A,B} > 0$, complementarity is defined by products for which $E_{A,B} < 0$, and independence is the case where $E_{A,B} = 0$.

services to provide access to "transit deserts" (areas not adequately served by public transit). However, the study finds that TNC services are more associated with areas of higher transit coverage and household income than with "transit deserts."

Young et al. (2020) use a sample of 1,578 TNC trip records obtained through the 2016 Transportation Tomorrow Survey in Toronto, to investigate the relationship between TNC services and transit. The study compares travel times with hypothetical transit alternatives and investigates correlations with various factors using OLS and logistic regression models. The paper finds that 31% of TNC trips have a competitive transit alternative, and that these competitive trips are correlated with peak-period and downtown travel. This study builds upon these results by investigating a larger dataset (40,000 trips per day over eight days of analysis) and differentiating TNC trips which may provide a first-mile or last-mile connection to transit services. Methodologically, both studies conduct travel time comparisons between real-world TNC trips and a hypothetical transit alternative using OpenTripPlanner and GTFS transit schedules, however the method of travel time comparison differs. While Young et al. (2020) use both proportional and absolute differences between TNC and transit travel times and apply the two separately, this study uses a combined proportionate and absolute approach based on the travel time of the TNC trip, as described in Section 3.2.1.3. Additionally, this study performs geographic (buffer) analysis and first mile/ last mile analysis to differentiate TNC trips which may connect with a transit station.

To inform TNC regulation and transit management, we examine the TNC-PT relationship at a nuanced spatial and temporal scale. Two previous studies have attempted to understand the substitution effects of each TNC trip on PT on this scale, but both were limited by data availability (Jin et al., 2019; Kong et al., 2020). In this study of Chicago, TNC trip data is available at a spatially granular level, along with comprehensive transit data through General Transit Feed Specification (GTFS). This enables us to examine the TNC-PT relationship thoroughly and to draw confident conclusions which may be operationalized by the transit agency (i.e. CTA) and urban planners. The analysis framework developed in this study aims to determine the potential relationship between each TNC trip and the public transit system (substitution, complementary, or independent) at a disaggregated level, and could be applied generally to other study areas.

## 2.2 Impacts of COVID-19 on Travel

In addition to the immeasurable impacts of COVID-19 on all facets of life in cities, the pandemic has dramatically changed travel behavior in North America. Ridership for major transit agencies has plummeted following its onset, in attempts to enable social distancing and reduce transmission. Following Illinois' stay-at-home order on March 21st, 2020, ridership for the Chicago Transit Authority (CTA) reduced by 84% for rail and 72% for bus from pre-COVID levels by the end of March 2020 (CTA Ridership Analysis and Reporting, 2020).

Transportation Network Companies (TNCs) have also been impacted by COVID-19. Prior to the pandemic, the number of daily TNC trips in Chicago had rested steadily above 400,000 per day, but dropped rapidly following stay-at-home order on March 21st, 2020, to 86,586 on March 24th, 2020 and stabilize below 50,000 for the remainder of March 2020 (Chicago Data Portal, 2020).

Outside of Chicago, many studies have examined the dramatic impacts of COVID-19 on travel behavior. Several studies identified dramatic ridership drops in various major cities, while finding that many socioeconomically disadvantaged communities maintained greater levels of transit ridership during the pandemic, likely due to limited alternative travel options and disproportionate likelihood of working in essential jobs which could not be conducted remotely (Brough, et al., 2021; Wilbur, et al., 2020; Sy, et al., 2020; Hu & Chen, 2021). In a study of New York City and Seattle, Gao et al. also found a dramatic reduction in both transit and traffic demand (2020). Lessened congestion has resulted in higher traffic speeds and higher crash fatality rates, posing new dangers to all road users. Additionally, discrepancies in mode use recovery rates between transit and private vehicles lead the authors to conclude that mode shift has occurred. Based on analysis of Chinese cities which are several months further in their recovery, Gao et al. predict that transit system recovery will be slow (2020).

Although both TNCs and PT have been closely studied during the COVID-19 pandemic, the evolution of their relationship is lacking in academic literature. This study examines the change of TNC-PT relationship in the early stages of COVID-19, to understand the ever-changing landscape of urban mobility during the pandemic and provide implications for regulatory response and PT management.

# 3 Data and Methods

## 3.1 Data and Case Study

The case study was conducted in the City of Chicago to evaluate the change in the TNC-PT relationship under ordinary conditions and over the early stages of the COVID-19 pandemic. Four sample dates before the outbreak of COVID-19 (October 8, 2019, November 19, 2019, January 21, 2020, and January 28, 2020) are used to examine the TNC-PT relationship under regular operating conditions. The dates were chosen across multiple seasons to mitigate the influence of seasonality. Four sample dates after the COVID-19 shutdowns (March 24, 2020, March 31, 2020, May 12, 2020, and June 2, 2020) are used to examine the relationship in the COVID-19 pandemic, first near the beginning of the stay-at-home order (active on March 21, 2020) and later as travelers react to the policy change and adjust their behaviors. In selection of these analysis dates, comparison was kept consistent across day of the week (Tuesday), to avoid influence from any cyclic fluctuations in daily travel behavior. Days with moderate weather (no precipitation or extreme temperatures) were chosen to minimize any external influence, and selected dates were checked by CTA planners to ensure that they did not represent anomalies in system operation or ridership.

Five categories of data were collected for this study, explained as follows:

(1) *TNC trip data* contain timestamps and locations of pick-up and drop-off for trips on major ridehailing companies, at a level of spatial resolution sufficient to perform detailed analysis. A separate, public version of the dataset, with origin and destination locations aggregated, is available through the Chicago Data Portal (2020). The data include all physically completed TNC trips as reported by Transportation Network Companies to the City of Chicago as part of routine reporting required by ordinance. A 40,000-trip subset was randomly sampled for each of the eight selected study dates. The distributions of the selected samples were compared with their respective populations to ensure that results would not be skewed significantly due to the sampling process (Appendix A).

(2) *GTFS transit schedule data* provides stop locations and scheduled vehicle arrival times for transit services.

(3) *Point of Interest (POI) data* was downloaded from OpenStreetMap for the FMLM analysis (see section 3.2.1.2) and regression modeling.

(4) *CTA Parking Lot data* including geographic location and lot capacity was used for FMLM analysis (see section 3.2.1.2) and is provided publicly on the Chicago Data Portal.

(5) *Socio-demographic data* at the census-tract level was used for regression analysis, including race, age, education, vehicle ownership, foreign born, income, and population (from the American Community Survey 2019 5-year estimates),Walkability Index (from the U.S. EPA), and crime rate (from the Chicago Data Portal).

## 3.2 Methods

### *3.2.1 TNC-PT relationship recognition*

This study seeks to adapt and further develop the analysis process introduced by Kong et al. (2020). Thanks to the better data availability and collaboration with the CTA, this paper improves the methodology from three perspectives. Firstly, the previous study is only able to recognize the substitutive TNC-PT relationship, but this paper distinguishes all three types of relationship (i.e. substitutive, complementary, and independent), which could provide more significant policy implications. Second, data limitations on detailed transit scheduling are overcome in this study thanks to a wealth of data access. The COVID-19 pandemic case study also provides an opportunity to examine a dramatic change in travel behavior, and how this change is reflected in the TNC-PT relationship. This research was also developed through ongoing consultation with planning experts at the CTA, which allowed us to develop criteria that reflect significant factors in transportation policy and transit operation.

The overall intention of the method developed is to create a process of analysis which categorizes TNC trips according to their potential relationship with PT: substitution, complementarity, or independence. In effect, these types of relationship are essentially a continuum which varies according to individual experience. For this study, discrete categorizations are employed based on established methods. These three concepts are defined as follows:

- **Substitution**: TNC trips for which PT provides a desirable alternative mode of travel (within a comfortable walking distance to transit and at comparable travel time).
- **Complementarity**: TNC trips which provide a first-/last-mile connection to transit (either bringing passenges to or carrying them from the PT network)
- **Independence**: TNC trips which operate between OD pairs where there is no transit service available. Some researchers describe this situation as complementarity since TNCs fill in the 'transit desert', but in this study we define it as 'independence' to differentiate it from case when TNC serves a first-/last-mile connection to transit.

The overall analysis framework is shown in Figure 1, following a rule-based classification system with three rules. The set of TNC trips is processed through three levels of analysis, comparing each trip with its potential alternative transit trip(s) taken from the same origin to the same destination, at the same time. These three levels of analysis include: buffer analysis (to determine whether a TNC trip is geographically within the transit service area, as described in Section 3.2.1.1), first mile/last mile analysis (to assess whether a TNC trip is providing access to transit connections, as described in Section 3.2.1.2), and service quality analysis (to estimate whether the potential alternative transit trip(s) would provide an acceptable quality of service, as described in Section 3.2.1.3).

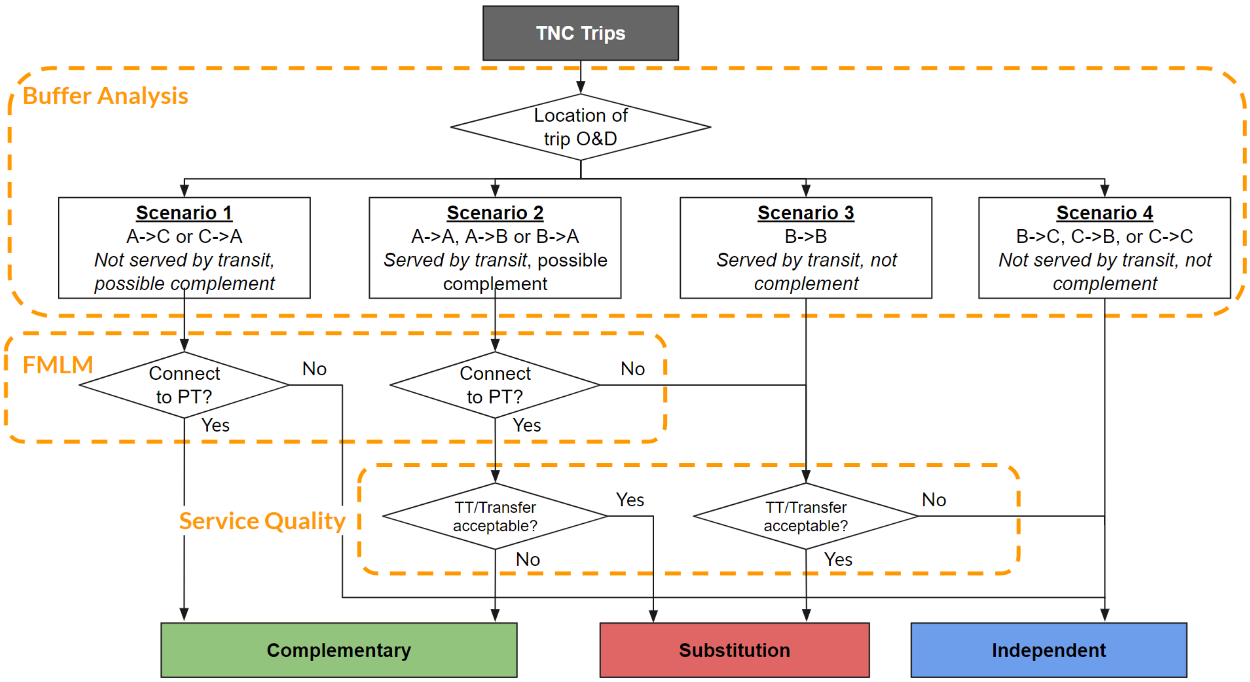


**Figure 1 Overall analysis framework for determining the TNC-PT relationship** ***(Note: 'A', 'B', and 'C' refer to buffer analysis zones, FMLM refers to First Mile/Last Mile Analysis, 'TT' refers to travel time)***

*3.2.1.1 Buffer (Coverage) Analysis*

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

- Scenario 1: A → C, or C → A. The origin of the TNC trip is close enough to transit stop (zone A) that the trip is potentially complementary while the destination is outside of transit service, or vice versa. The trip is thus not served by transit, so FMLM analysis is used to test for complementarity. If this is not the case, the trip is independent since either its origin or destination is not covered by transit.
- Scenario 2: A → A, A → B, or B → A: Origin/destination is close enough to transit service (zone A) that the trip is potentially complementary, and the trip is served by transit. FMLM analysis is used to test for complementarity. Travel time and transfer analysis is used to test for substitution (since both origin and destination are within transit coverage), and if not considered substitution then the result of the FMLM analysis is used.
- Scenario 3: B → B: Origin and destination served by transit but not close enough to be considered complementary, so travel time and transfer analysis is used to test for substitution.

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

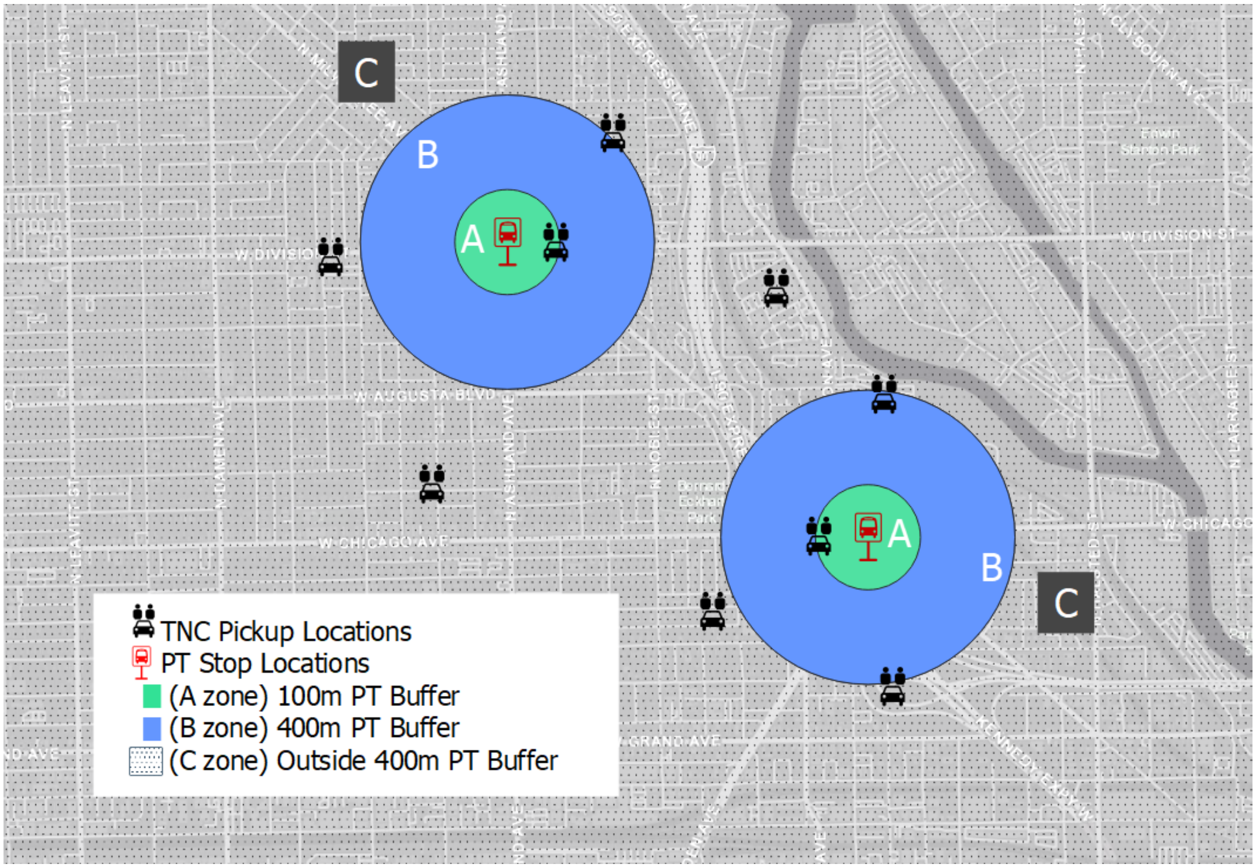


**Figure 2. Sample schematic diagram of buffer analysis zone classifications**

### 3.2.1.2 First Mile/ Last Mile (FMLM) Analysis

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

To estimate the likelihood that a TNC trip is used to connect riders to PT instead of accessing non-transit activities near transit stops, we predict the level of non-transit activity immediately around each station. Open Street Map (OSM) POI data[2] is used for this process. The 'attraction power' (or number of potential attendees) and likely operating hours are assigned to each POI (Appendix B in Supplementary Materials). These values are estimated using professional judgement and in consultation with planners, though admittedly it is a subjective and approximate approach. For each TNC trip, the total

[2] The data is further refined by removing non-significant attractions (e.g. garbage bins, vending machines, mailboxes).

attraction power ($a(POI)$) of all points of interest which are operating at the time of the trip is summed across a 100m buffer around the station ($\Sigma_{100m} a(POI)$). Using this, the likelihood of complementarity ($\%_{comp}$) is assigned between 0 and 1 on a linear scale, according to the fraction of this attraction power compared with a selected 'maximum' attraction power from a downtown station ($a_{downtown}$), at which activity level it would be unlikely for TNC trips to access the transit system:

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

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

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

Due to the subjectivity involved in the FMLM analysis method, the results were further investigated by cross-referencing external sources (i.e., CTA survey data), to ensure that the results fell in sensible ranges and did not constitute an extreme overestimation or underestimation. Additionally, an upper bound on the complementary trips percentage is calculated (provided in Section 4.1). To compute this estimate, all assumptions of the FMLM analysis process are removed. Trips classified in Scenario 1 or Scenario 2 of buffer analysis are assumed to connect to PT. Thus Scenario 1 trips are directly labelled as complementary, and Scenario 2 trips are passed directly to service quality analysis. This provides an approximate ceiling on the estimated number of complementary trips.

#### 3.2.1.3 Service Quality (Travel Time and Transfer) Analysis

The final stage is quality of service analysis, which determines whether a hypothetical transit trip (conducted in place of the TNC trip that was taken) provides an acceptable level of service to be considered a viable alternative. While quality of service may be determined using a wide variety of criteria (such as travel time, transfers, fare costs, vehicle crowding, service frequency, wait times, and reliability), data availability limitations necessitate that this paper approximates quality of service using transit travel time and number of transfers. Thus for the case study application, the analysis is referred to as "travel time and transfer analysis." Additional service quality factors may be incorporated into future research using the same high-level analysis framework.

Travel time and number of transfers were determined using a local instance of OpenTripPlanner, based on daily GTFS schedules. This approach was chosen among alternative approaches developed by Li et al. (2021), including real-time vehicle arrivals from Automated Vehicle Location data, and inferred passenger trip records from Origin-Destination Inference data, due to its ease of implementation and scalability to a large set of trips.

Travel time comparison was conducted using two methods: proportional difference and absolute difference. Proportional difference measures the ratio of the transit travel time ($t_{PT}$) to the TNC travel time ($t_{TNC}$) according to $\Delta t_p = t_{PT}/t_{TNC}$, whereas absolute difference measures the difference between the two, as $\Delta t_a = t_{PT} - t_{TNC}$. Based on sensitivity analysis (Appendix C) and in consultation with CTA planners, a hybrid approach to the threshold for $\Delta t$ was selected: for TNC trips with duration less than 15 minutes, an absolute difference of 15 minutes was used as the threshold, while for TNC trips lasting more than 15 minutes, a proportional difference of double was used.

For the number of transfers, an acceptable limit was set at two transfers, with transit trips requiring more not being considered a competitive alternative.

### *3.2.2 Modeling impacts on the substitution rate*

Four different models are used to evaluate the correlation between various factors and the TNC-PT substitution rate. The models used include: (1) Ordinary Least Squares (OLS) regression model; (2) fractional regression; (3) spatial lag model; and (4) spatial error model.

The dependent variable used in the model is the percent of total TNC trips categorized as substitution, and the analysis unit is census tracts. The independent variables fitted into the model include:

(1) Soceio-demographics: percentage of population identifying as white, percentage aged over 65, percentage aged 25-34, percentage college-educated, percentage of households without a private vehicle, percentage of foreign-born population, median household income;
(2) TNC network: number of TNC trips per km$^2$, TNC average travel time, TNC average fare, percentage of TNC trips during peak hours;
(3) PT network: percentage of commuting by transit, number of PT stops per km$^2$, whether there is a rail stop present;
(4) Built environment: population density, crime rate, walkability index, number of POIs.

The explanatory variables are examined for potential collinearity (correlation matrix provided in Figure F.1 of Supplementary Materials), and median household income was found to strongly correlate with several other factors (including percent white, percent aged 25 to 34, percent college graduate, and percent without a vehicle). It is thus removed from the subsequent regression analysis.

The OLS model is conducted as the base model. Given that the dependent variable is a continuous fraction in the range of [0,1], we further applied fractional regression, which is achieved by fitting the GLM link function to the standard binomial likelihood in R.

The spatial lag model accounts for spatial autocorrelation in the observed data and is constructed as follows:

$$Y = X\beta + \rho WY + \varepsilon \tag{2}$$

Where $Y$ represents the set of response variables (i.e. the TNC-PT substitution rate) for each census tract, $X$ represents the set of explanatory variables, $\beta$ represents the regression coefficients, $\varepsilon$ represents the error terms, $\rho$ is a spatial lag parameter that measures the strength of spatial dependence, and $W$ is a spatial weight matrix for each census tract relative to each other (Chi & Zhu, 2019). This model considers the values of the observed variable ($Y$) in adjacent spatial areas when predicting coefficients for a given area.

The spatial error model produces an error term which considers both spatially lagged errors and normally distributed errors, and is constructed as follows:

$$Y = X\beta + u; u = \rho Wu + \varepsilon \tag{3}$$

Where $u$ is a set of error terms, $\rho$ is a spatial error parameter, and $W$ is a spatial weight matrix for each census tract (Chi & Zhu, 2019).

# 4 Results and Discussions

## 4.1 TNC-PT Relationship Under Regular Conditions

Firstly, we examine the TNC-PT relationship under regular operating conditions (before COVID-19 shutdowns), producing aggregate results shown in Table 1. It is found that potential substitution trips represent approximately 45% to 50% and potential independence trips represent around 48% to 53%. A detailed breakdown of how these percentages were calculated through the analysis process is provided in Appendix D. These results also assert that complementarity plays a minor role in the overall relationship, ranging from 1.9% to 2.2% in ordinary conditions, an estimate which is lower than findings of various earlier papers for other contexts such as King et al. (2020). While the authors acknowledge the inherent subjectivity of decisions in the First-Mile/Last-Mile analysis process, a reasonable upper bound was calculated according to the process described in Section 3.2.1.2, which estimated the complementary trip percentage to be a maximum of 3.8% to 4.2% (depending on analysis date).

**Table 1 Aggregate analysis results for baseline TNC-PT relationship**

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

### *4.1.1 Temporal Trend of TNC-PT Relationship in Regular Conditions*

We further examine the temporal trends of the TNC-PT relationship under regular conditions on January 28, 2020 before the COVID-19 shutdowns (Figure 3). This chart demonstrates morning and evening peak travel periods, as well as spikes in substitution rates during these times. As work-based trips account for a large proportion of trips during the peak, our results indicate that many work-based TNC trips have a viable transit alternative which individuals choose not to take – potentially due to decision-making factors such as crowding on transit lines, aversion to possible delays, or a greater sensitivity to travel time.

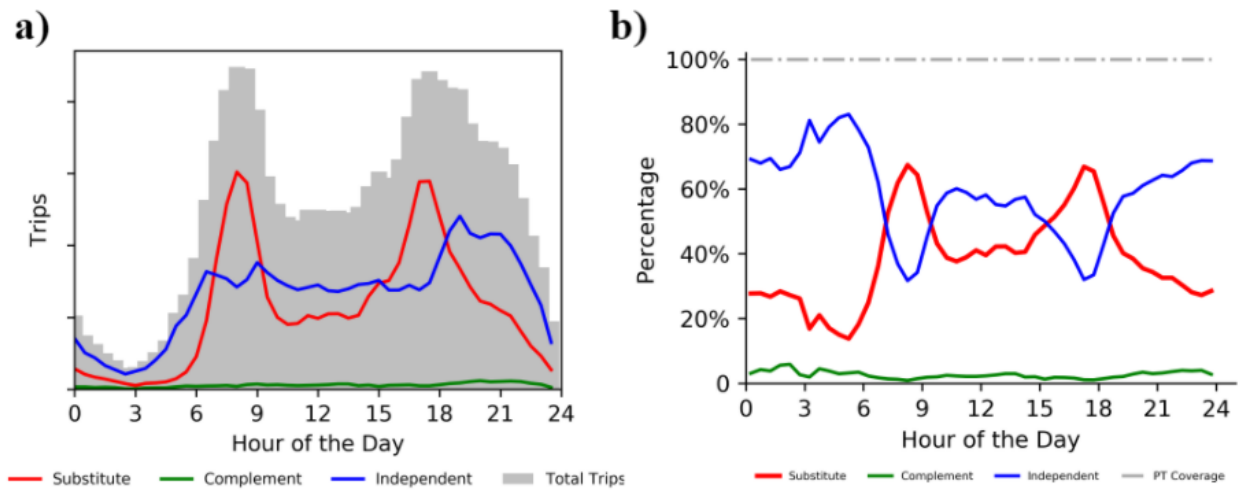


**Figure 3 Temporal trends of (a) volumes and (b) percentage for TNC trips in each category on January 28, 2020**

### *4.1.2 Spatial Distribution of TNC-PT Relationship in Regular Conditions*

We adopt spatial analysis to identify patterns in the TNC-PT relationship. First, distributions of complementarity, independence, and substitution rates by origin census tract[3] are examined, by calculating the proportion of each trip category relative to the total number of TNC trips taken within that tract (Figure 4). Independent trips are prevalent in areas further away from major rail transit. Substitution trips, on the other hand, are most concentrated downtown, and along rail lines. Complementary trips are seen primarily in neighborhoods to the north and northwest of downtown which are served effectively by rail.

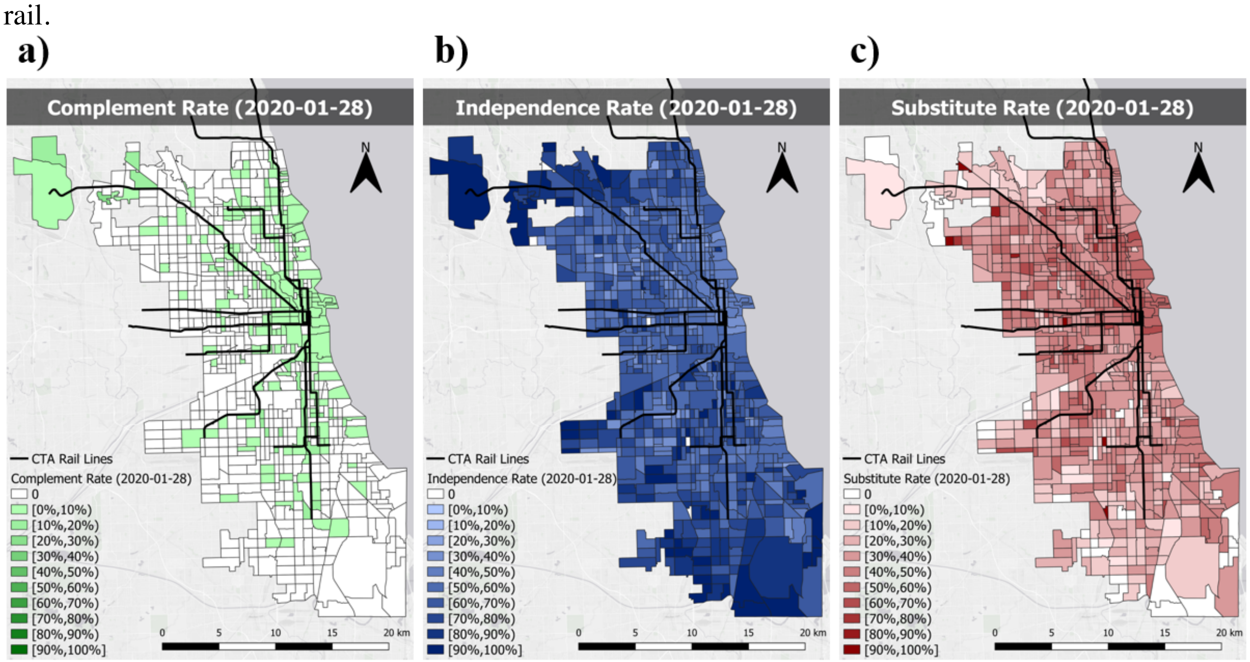


**Figure 4 Spatial distribution of complementarity, independence, and substitution rates for ordinary operation on January 28, 2020**

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[3] More granular analysis is possible with the current data and could be more effective if a smaller area was examined.

The spatial distribution is also examined by identifying clusters of high and low rate for each type of relationship using a local Getis Ord ($G_i^*$) statistic, because the relationship is highly spatially autocorrelated[4]. Tracts found to be part of a hot-spot (dark color) or cold-spot (light color) at 90% confidence are illustrated in Figure 5 for each type of relationship. This shows that the downtown area and some other regions along rail lines experience higher rates of substitution. Additionally, areas which are not well served by rapid transit (particularly on the south side of Chicago) experience consistently low substitution rates, indicating a lack of viable transit alternatives to TNC trips which are taken. This differs from the conclusions reached by Barajas & Brown (2021), who claimed that TNC services do not correlate with use in transit deserts based on observations of TNC ridership by census tract. This different conclusion may come from the stricter criteria used to differentiate the nature (rather than strictly volume) of TNC trips utilized in this study, which identify TNC trips as independent from transit if the transit alternatives require long walking times to access transit or experience very long transit travel times. Complementarity hotspots are located almost entirely around a few major rail stations, potentially indicating areas which are popular first/last mile destinations for linked TNC-PT trips.

In Figure 5, it is also visually clear that many areas which are ‘cold spots’ for substitution are also ‘hot spots’ for independence, and vice versa. This is largely the case because complementary trips make up a very small proportion of the total (less than 5%), and thus most trips fall in one of the other two categories. Intuitively, while the results assert that a majority of TNC trips do not connect to transit services, the two modes maintain service areas and service qualities which overlap in some places (particularly regions with high concentrations of substitution), but differ considerably in other areas (likely those with greater rates of independence).

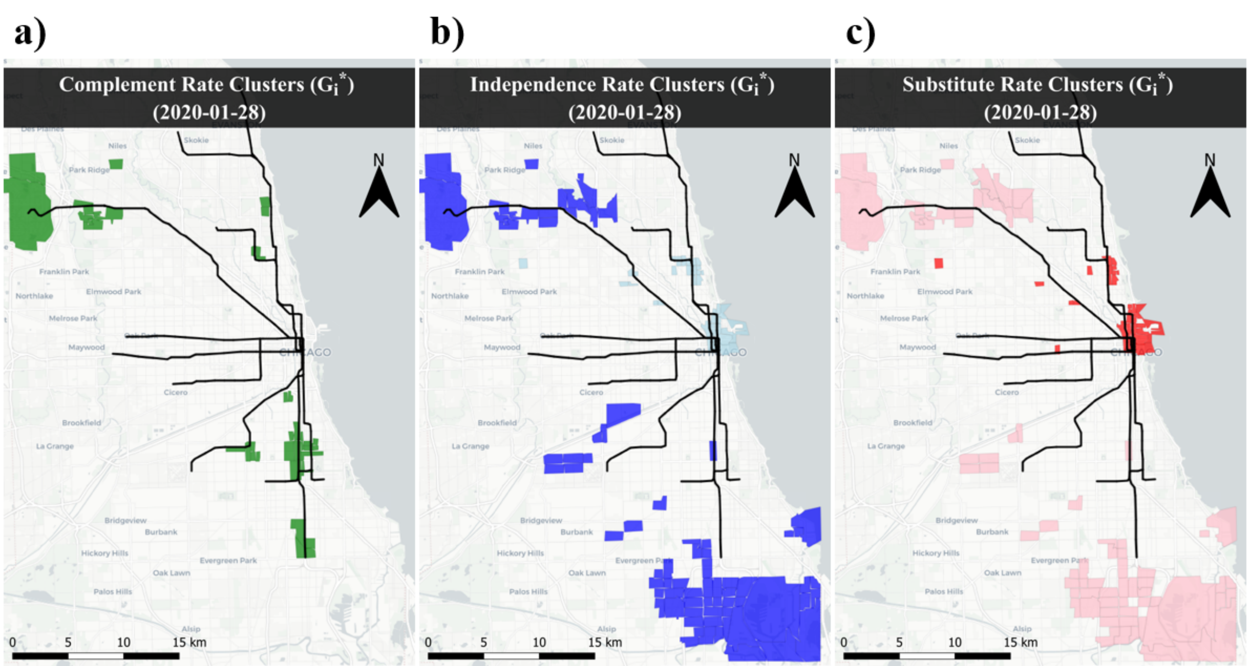


**Figure 5 Identified clusters of high (dark color) or low (light color) rates using local Getis Ord (Gi*) statistic for (a) complementary, (b) independent, and (c) substitution trips**

## 4.2 Factors Influencing the TNC-PT Relationship

[4] The Moran’s I statistic value of substitution rate is 0.258 (variance of 0.00038).

To further evaluate the factors that are associated with the TNC-PT relationship under regular conditions (January 28, 2020), four alternative regression models are used as described in Section 3.2.2. Table F.1 (in Appendix F of Supplementary Materials) provides the descriptive statistics of the variables.

The initial level of spatial autocorrelation of the dependent variable (substitution rate by trip origin census tract) is tested, yielding a Moran's I statistic of 0.313 (with variance of 0.00055). This indicates that the initial results are highly autocorrelated, which must be accounted for in subsequent regression models. While the OLS and fractional regression are inadequate in capturing these spatial effects, both the spatial lag and spatial error models successfully do so. As the spatial lag model produced the minimum AIC, maximum log-likelihood, and greater Lagrange Multiplier value, it better captures the intended effects and was used for interpretation.

As shown in Table 2, the percentage of residents aged over 65 has significant and negative correlation with the TNC-PT substitution rate, indicating that in census tracts with more elderly populations, a lower percentage of TNC trips tend to substitute PT. Areas with a greater percentage of white residents, on the other hand, correlate with a greater likelihood to substitute transit with TNC trips. These results are all supported by previous studies such as those by Rayle et al. (2016) and Young & Farber (2019). These factors expand upon the spatial analysis by providing insight into demographic features, thus helping to better understand the individual decision to take, or not to take, a TNC trip in place of a transit trip.

Areas with high crime rates also substitute transit for TNC trips at increased rates. This indicates safety as a relevant factor for transit system operators, whether that be neighborhood safety or perceived safety on transit. This result was highly significant across all models, and corroborates findings by the Chicago Metropolitan Agency for Planning (2019) and San Francisco County Transportation Authority (2017). These findings build upon previous research by Henao (2017), which identified that lower-income, potentially higher-crime areas have low TNC ridership relative to other portions of cities. This study similarly finds overall ridership to be low in high-crime areas, but the findings which correlate crime rate with TNC substitution rate provide further insight into the nature of ridership which does exist. Specifically, the results may reflect a subset of safety-concerned individuals who choose TNC travel (despite having a public transit option) due to concerns around personal safety. This influence of neighborhood crime rates on TNC substitution percentage indicates a potential for transit operators to regain TNC riders if they are successfully able to improve real or perceived safety levels on the transit system.

Several characteristics of the TNC network are correlated with the substitution percentage. Areas with a greater TNC fare are less likely to substitute TNCs for transit, perhaps indicating a sensitivity of riders to the price difference between services (as transit prices remain constant across the CTA network). Areas with a greater share of peak-period TNC trips are also correlated with greater substitution rates, further indicating that work-based TNC trips may disproportionately substitute for public transit. Additionally, the level of PT network availability also correlated with increased substitution percentage, possibly because areas which are well-served by transit are more likely to have a competitive transit alternative to TNC trips.

**Table 2 Results of regression on rate of substitution by census tract for baseline analysis period (January 28, 2020)**

| Variable | OLS | Binomial Logit | Spatial Lag | Spatial Error |
|---|---|---|---|---|
| (intercept) | 0.193 (*) | -1.269 (.) | 0.111 | 0.189 (.) |
| *Socio-demographics* | | | | |
| Percent white | 0.113 (***) | 0.503 (***) | 0.094 (**) | 0.105 (**) |
| Percent aged over 65 | -0.212 (*) | -0.952 (*) | -0.177 (.) | -0.202 (*) |
| Percent aged 25-34 | 0.109 | 0.402 | 0.081 | 0.114 |
| Percent college grad | 0.049 | 0.221 | 0.028 | 0.047 |
| Percent without vehicle | 0.062 | 0.315 | 0.041 | 0.064 |
| Percent foreign born | -0.027 | -0.087 | -0.034 | -0.033 |
| *TNC network* | | | | |
| TNC trips per km$^2$ | -0.032 | -0.152 | -0.037 | -0.034 |
| TNC avg travel time | 0.235 (***) | 1.074 (***) | 0.182 (***) | 0.202 (***) |
| TNC avg fare | -0.456 (***) | -2.116 (***) | -0.356 (***) | -0.403 (***) |
| TNC percent peak trips | 0.392 (***) | 1.791 (**) | 0.381 (***) | 0.395 (***) |
| *PT network* | | | | |
| Percent commuting by transit | 0.060 | 0.266 | 0.045 | 0.050 |
| PT stops per km$^2$ | 0.110 (***) | 0.479 (***) | 0.102 (***) | 0.102 (**) |
| PT rail stop presence | 0.036 (*) | 0.151 (**) | 0.035 (*) | 0.037 (*) |
| *Built Environment* | | | | |
| Population per km$^2$ | -0.093 | -0.415 (.) | -0.082 | -0.086 |
| Crimes per km$^2$ | 0.398 (*) | 1.708 (**) | 0.355 (*) | 0.382 (*) |
| Walkability index | 0.006 | 0.023 | 0.005 | 0.005 |
| POI count | 0.005 | 0.039 | 0.004 | 0.005 |
| *Summary of Statistics* | | | | |
| Number of observations | 791 | 791 | 791 | 791 |
| Residual Moran's I | 0.066 | 0.090 | -0.039 | -0.003 |
| Log-Likelihood | 421.5 | -426.9 | 433.0 | 425.8 |
| AIC | -805.0 | 889.8 | -826.0 | -811.6 |

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

## 4.3 COVID-19 Impact on the TNC-PT Relationship

The aggregate TNC-PT relationship is shown for selected analysis dates through COVID-19 in Table 2. Unsurprisingly, the overall volume of trips reduces dramatically from pre-COVID levels, down 92% on March 31st, 2020, but recovering somewhat through summer 2020. The spatial distribution of trip volume decreases (shown in Appendix E) is concentrated around Chicago's central business district (the 'loop'), and generally affluent neighborhoods immediately north and northwest of downtown (Dwyer, et al., 2017). This may indicate a decrease in work-based trips, reflecting office jobs which are most likely to be conducted remotely during COVID-19 (Brynjolfsson, et al., 2020). The average length of trips taken also decreases by around 20% from January 28, 2020 to March 31, 2020, potentially attributable to an increased percentage of shorter non-work trips. This length decrease was not, however, accompanied by a proportional decrease in fares. Customers thus paid a greater per-minute price for TNC trips, potentially due to a decrease in supply of drivers willing to complete trips.

**Table 2 Estimated aggregate TNC-PT relationship for selected dates through COVID-19**

| Analysis Date | Total Trips | Avg Length (min) | Avg Fare ($) | Complementary (%) | Substitution (%) | Independent (%) |
|---|---|---|---|---|---|---|
| 2019-10-08 | 429,119 | 17.4 | $14.09 | 2.02 | 46.59 | 51.39 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2020-01-28 | 440,328 | 15.9 | $14.42 | 2.19 | 44.88 | 52.93 |
| 2020-03-24 | 86,586 | 13.1 | $13.82 | 2.89 | 12.67 | 84.44 |
| 2020-03-31 | 37,852 | 12.8 | $13.54 | 2.93 | 13.51 | 83.56 |
| 2020-05-12 | 97,197 | 14.0 | $14.06 | 2.82 | 12.10 | 85.09 |
| 2020-06-02 | 109,006 | 16.2 | $15.32 | 3.19 | 14.51 | 82.30 |

Changes of each type of TNC-PT relationship are also clear. The percent of potential substitution trips decreases dramatically, by close to 70% as COVID-19 shutdowns begin. This loss of substitution trips is absorbed entirely by the potential independent trips, indicating that a greater percent of trips took place in areas not sufficiently served by transit.

### *4.3.1 Temporal Trend of TNC-PT Relationship after COVID-19 Shutdown*

We further examine the temporal pattern of TNC-PT relationship after the COVID-19 shutdowns (Figure 6). Compared with Figure 3, after COVID-19 shutdowns, the number of substitution trips is consistent throughout the day, somewhat proportional to the overall number of trips. This decreased fluctuation of substitution rates could indicate an increased uniformity of trip purpose throughout the day (e.g. grocery shopping), rather than peaks attributable to commuting trips.

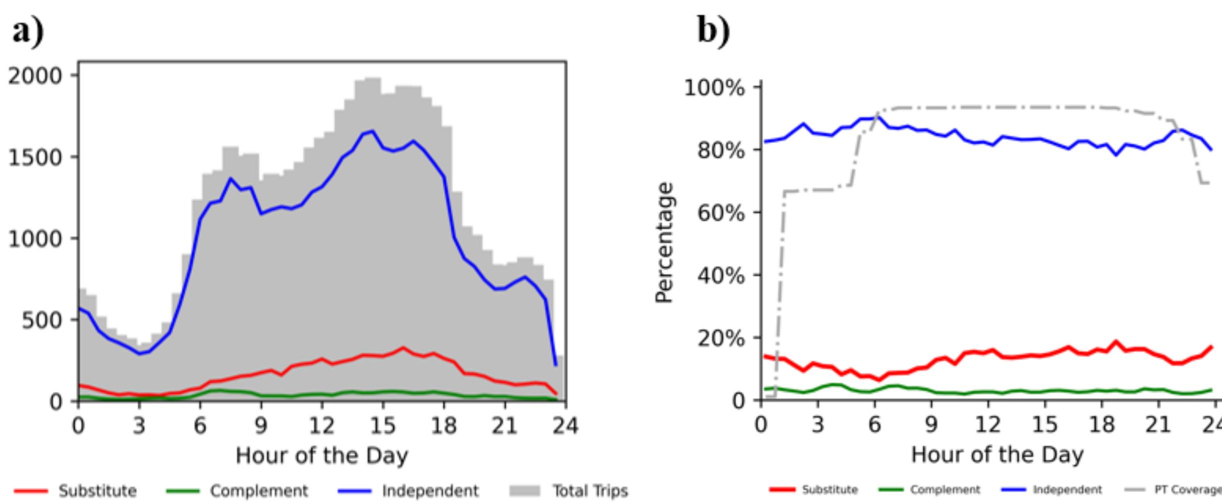


**Figure 6 Temporal (a) trip volumes and (b) substitution rates for TNC trips on March 31, 2020**

### *4.3.2 Impacts of COVID-19 on TNC-PT Substitution Rate*

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

Therefore, the COVID-19 pandemic has dramatically altered the landscape of Chicago's TNC-PT relationship. The changes in the spatial and temporal patterns in substitutive TNC trips indicate that many conventional work-based trips in high-income areas are no longer being conducted, which substituted for transit services before COVID-19.

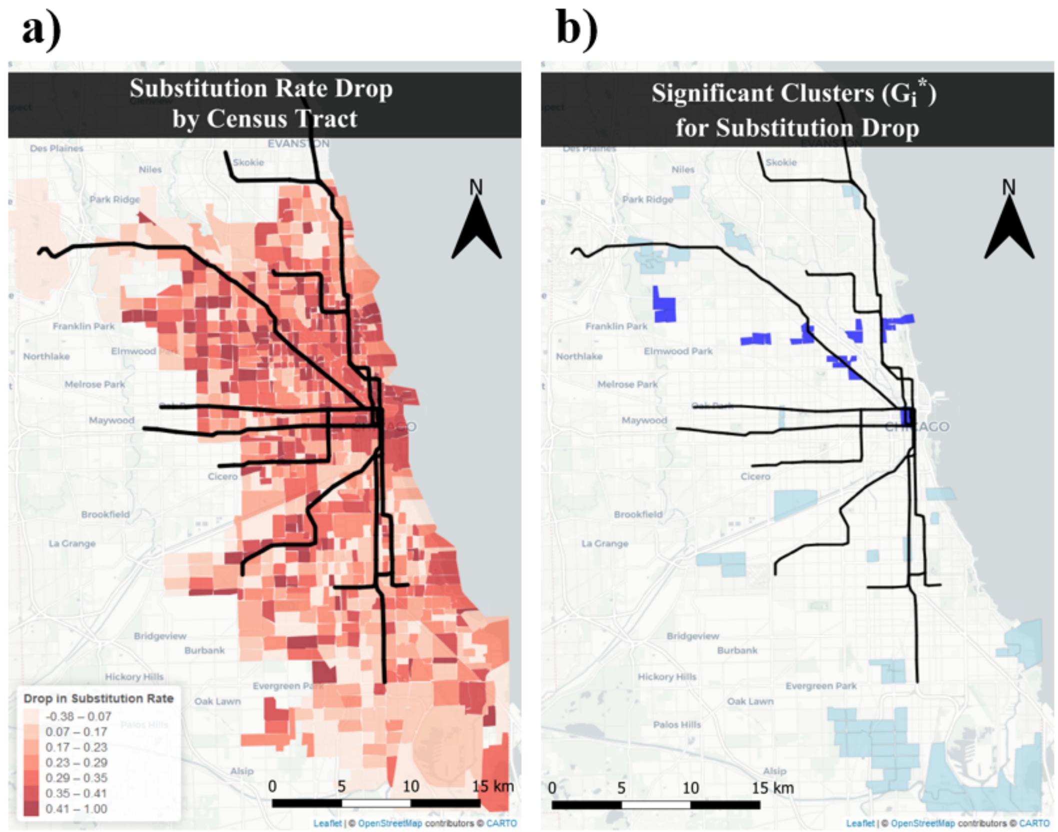


**Figure 7 Drop in substitution rate by (a) census tract, and (b) clusters found with $G_i^*$ statistic, from January 28, 2020 to March 31, 2020**

*4.3.3 Factors influencing the TNC-PT relationship during the COVID-19 shutdown*

To evaluate the factors that are associated with the TNC-PT relationship following the COVID-19 shutdown, the regression models described in Section 3.2.2. are performed for March 31, 2020 (following COVID-19 shutdowns). The model dependent variable is the percent of substitution trips, and the analysis unit is census tracts. Table F.1 (in Appendix F of Supplementary Materials) provides the descriptive statistics of the variables. As shown in Table 3, in comparison with the model conducted for ordinary operating conditions (Section 4.2), the results shift somewhat though some correlated factors remain consistent. While TNC fares, transit stop density, and crime rates remain highly correlated with the tendency to substitute transit trips for TNCs, several additional factors become significant following COVID-19. Population density, number of points of interest, immigration status, and college education are all significant factors in the post-shutdown model. This seems to indicate a tendency for downtown areas (where many of these new factors are prominent) to retain higher rates of substitution following the pandemic, while less-dense areas seemed to decrease both TNC use and the tendency for these TNC trips to substitute transit – perhaps due to fewer work-commute trips.

**Table 3 Results of regression on substitution rate by census tract following COVID-19 shutdowns (March 31, 2020)**

| Variable | OLS | Binomial Logit | Spatial Lag | Spatial Err |
|---|---|---|---|---|
| (intercept) | 0.250 (***) | -0.866 (*) | 0.191 (**) | 0.273 (***) |
| *Socio-demographics* | | | | |
| Percent white | -0.009 | -0.113 | -0.003 | -0.013 |
| Percent aged over 65 | -0.060 | -0.326 | -0.044 | -0.046 |
| Percent aged 25-34 | 0.057 | 0.284 | 0.048 | 0.070 |
| Percent college grad | 0.095 (***) | 0.604 (***) | 0.068 (*) | 0.082 (**) |
| Percent without vehicle | 0.070 (.) | 0.412 (*) | 0.041 | 0.062 |
| Percent foreign born | 0.095 (**) | 0.602 (***) | 0.084 (**) | 0.099 (**) |
| *TNC network* | | | | |
| TNC trips per km$^2$ | -0.077 (**) | -0.412 (**) | -0.068 (**) | -0.072 (**) |
| TNC avg travel time | 0.054 (.) | 0.404 (*) | 0.024 | 0.013 |
| TNC avg fare | -0.216 (***) | -1.541 (***) | -0.161 (***) | -0.178 (***) |
| TNC percent peak trips | 0.110 (.) | 0.664 (.) | 0.098 | 0.096 |
| *PT network* | | | | |
| Percent commuting by transit | 0.084 (.) | 0.504 (*) | 0.068 | 0.080 (.) |
| PT stops per km$^2$ | 0.100 (***) | 0.514 (**) | 0.090 (***) | 0.084 (***) |
| PT rail stop presence | 0.024 (*) | 0.120 (*) | 0.024 (*) | 0.027 (*) |
| *Built Environment* | | | | |
| Population per km$^2$ | -0.193 (***) | -0.986 (***) | -0.198 (***) | -0.194 (***) |
| Crimes per km$^2$ | 0.476 (***) | 2.432 (***) | 0.421 (***) | 0.440 (***) |
| Walkability index | 0.000 | -0.001 | 0.000 | 0.001 |
| POI count | -0.056 (*) | -0.265 (*) | -0.056 (*) | -0.057 (*) |
| *Summary of Statistics* | | | | |
| Number of Observations | 791 | 791 | 791 | 791 |
| Residual Moran's I | 0.121 | 0.139 | -0.016 | -0.009 |
| Log-Likelihood | 729.2 | -219.0 | 746.3 | 742.9 |
| AIC | -1420.3 | 474.0 | -1452.6 | -1445.8 |

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

## 5 CONCLUSIONS

In conclusion, to address the methodolical limitations of earlier studies and provide granular insight into the nature of the TNC-PT relationship, this paper expanded existing methods for analyzing the TNC-PT relationship and applied them to both normal operating conditions and the early stages of COVID-19 in Chicago.

Before the COVID-19 pandemic, around 45% to 50% of TNC trips could potentially substitute for PT, and around 48% to 53% of TNC trips were potentially independent from PT. This result is comparable with previous findings from Young et al. (2020), which estimated the proportion of TNC trips with a competitive transit alternative to be approximately 31% in Toronto. The results differ somewhat, likely due to the varying methodological approaches and case study contexts. Similar to Young et al., this study finds that a greater proportion of TNC trips compete with transit during peak travel periods, and in areas near the downtown.

TNC trips that potentially complement transit make up a very small percentage of the total, showing that generally TNC services are unsuccessful in providing a first or last mile connection to transit. The factors associated with high TNC-PT substitution rate also provide additional insight, including the tendency for older populations not to use TNC trips, as well as greater substitution rates in locations with high crime levels, a greater rate of peak-period TNC use, a higher percentage of white population, and greater transit network availability. The application of the framework to the COVID-19 pandemic indicates a significant change in how TNCs interact with transit services during this period, particularly through increased levels of independence and decreased substitution, likely stemming from a significant reduction in the relative percentage of work-based trips which typically reflected a spike in substitution rates during peak hours.

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

It is also important to acknowledge the limitations of this study, particularly regarding judgement-based decisions made for analysis thresholds. For example, the categorization of complementary TNC trips were estimated by the likelihood of a rider taking the TNC trip to access transit stops, rather than by the complete information of a rider's entire trip chain or travel purpose. Other decisions, such as selected thresholds for buffer analysis or travel time comparison, were made considering reference literature and sensitivity analysis. We acknowledge the limitations and subjectivity in this process, though decisions had to be made to operationalize the methods developed. When applied to other study areas, these thresholds need to be adjusted based on the local context and data availability. Furthermore, the study only analyzes the TNC-PT relationship on several sample dates. Since we have carefully selected the sample dates to avoid the variations in seasons, weather, and days of the week, our results are still representative of the mobility landscape in the period we are interested in. The geographic scope of the case study is also restricted to the City of Chicago, and transit service analyzed includes only the CTA (although both Pace Suburban Bus and Metra rail operate in the Chicago area). This decision was made as the Chicago TNC data sharing agreement (City of Chicago, 2017) only mandates that trips taken within the City of Chicago be reported, and Pace and Metra services operate almost entirely outside of the city boundary. However, given greater data availability, the study may be expanded in the future to analyze the TNC-PT relationship more holistically across the greater Chicago area.

Future research may expand upon this initial study in several different ways. By integrating additional data sources, transit service quality measures could be expanded to capture the impacts of passenger crowding. Furthermore, the method may be used to study the development of the TNC-PT relationship during the recovery phase of the COVID-19 pandemic, and the post-pandemic 'normal'. Transit ridership records (with APC data) and surveys may also be applied to better understand individual decisions to use TNCs in place of public transit, and how transit ridership has changed in response to the introduction of TNC services. Finally, the application of the research may be broadened to assess evolution of the TNC-PT relationship in response to other scenarios, such as TNC tolling and other policy interventions.

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