IMPACTS OF CONGESTION PRICING ON RIDE-HAILING RIDERSHIP: EVIDENCE FROM CHICAGO

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ABSTRACT

To combat congestion, promote sustainable forms of transportation, and support the public transit system, Chicago introduced a congestion pricing policy targeting transportation network company (TNC) services on January 6, 2020. This policy aimed to discourage single-occupant and peak-period TNC travel, particularly in high-congestion areas. Using TNC trip record data collected from the Chicago Data Portal, we quantify the impacts of the congestion pricing policy on TNC ridership in Chicago, differentiating between shared and single-occupant trips. Employing a Difference-in-Differences identification strategy, we find that the implementation of the congestion pricing policy led to an increase in shared TNC trip counts and a much larger decrease in single-occupant trip counts. Overall, the policy implementation is associated with a 7.1% reduction of total TNC pickup trips, a 16.4% increase of shared TNC pickup trips and a 11% reduction of single TNC pickup trips. Given the estimated policy effects, we find that the price elasticity of the TNC trip volume in the downtown areas is roughly -0.48. In terms of spatial variation, we find that the lost TNC trips were mainly trips that began and ended in the central business district. The south side of Chicago, which has a high proportion of African-American and low-income residents, shows evidence of single trip reduction for trips that began or ended in the downtown areas due to the policy implementation, but the policy did not seem to incentivize pooling to or from the downtown areas as effectively in the south side as in other regions of Chicago. Regarding the time-of-day variation, we find that the policy is more effective in encouraging trip sharing for off-peak travels than for peak-time travels. Our research provides local planners and policymakers with valuable insights into the impacts of the congestion pricing policy. The method and findings of this research can also be used for other cities that are considering adopting congestion pricing policies on TNCs in the future.

Keywords: Transportation Network Company (TNC), ride-hailing, congestion pricing, regulatory policy, pooling, Difference-in-Differences, natural experiment

1. INTRODUCTION

The rise of transportation network companies (TNCs) like Uber and Lyft has dramatically affected urban transportation across the United States and abroad. While TNC services offer customers convenient and flexible transportation services, they have been criticized for negative externalities such as increases in traffic congestion, vehicle miles traveled (VMT), and GHG emissions. To address the negative impact of TNCs, several strategies have been adopted across the U.S. at both the state and the local levels, such as congestion surcharges and vehicle registration fees. Although many studies have analyzed the operation and management strategies of TNC platforms, to the best of our knowledge, no existing literature has tried to empirically quantify the impacts of these regulatory strategies on ride-hailing ridership. As such, in this study we aim to identify and measure the causal effect of the implementation of a ride-hailing congestion pricing policy on TNC trip volumes, and differentiate between pooled trips and ride-alone trips.

This research specifically focuses on the impact of Chicago's Ground Transportation Tax (GTT), which took effect on January 6, 2020. The GTT initiative is a form of ride-hailing congestion pricing, which applies a greater surcharge to TNC trips that start or end in a special area including airports and two special zones, and levies an additional Downtown Zone surcharge for trips that begin or end in the Downtown Zone area between 6:00 am and 10:00 pm, Monday to Friday. Single-occupant TNC trips are also priced at a higher rate than shared trips. We hypothesize that the implementation of such policy would discourage people from taking TNC trips to or from the downtown areas due to the increased trip cost, and may incentivize TNC users to share rides with others as the shared rides are taxed less than the single rides. We are also interested in how the impacts of GTT vary across different areas of the city. As such, we propose the following research questions:

- Did the GTT cause a significant change in TNC ridership in impacted areas following its implementation?
- How does the impact of the GTT implementation on TNC ridership differ between shared and non-shared rides?
- How does the impact of the GTT implementation vary across space and time?

This study uses census tract-level TNC data and the Difference-in-Differences (DID) approach to isolate the causal effect of the GTT implementation on TNC ridership. We estimate the treatment effect by measuring the change of TNC ridership over time between the treated census tracts which lie in the downtown areas and the control census tracts that are outside the downtown areas but are geographically close to the treated census tracts. The effects of the policy shock are examined for various types of TNC trips, including dropoff and pickup trips, shared trips, and single trips, as well as for different communities within the City of Chicago. Based on the estimated effects, we also calculate the price elasticity of the TNC trip volume in the downtown areas.

The rest of the paper is organized as follows. Section 2 reviews prior work and identifies the research gap. Section 3 provides background information on the Chicago GTT policy. Section 4 and 5 describe data, models and our identification strategy. In Section 6, we present the results. Section 7 describes the limitations and future research. We conclude in Section 8.

2. LITERATURE REVIEW

2.1 On-demand shared mobility and its potential externalities

In recent years, TNCs have emerged as new travel mode that has changed mobility patterns for millions of people. TNCs adopt online platforms to connect passengers with drivers using their private vehicles based on real-time information (*9*). The growth of ride-hailing companies such as Uber, Lyft and Didi chuxing has been extraordinary around the globe. For instance, Didi chuxing, the dominant ride-hailing company in China, currently has more than 450 million registered users and more than 400 cities in China (*8*). As of 2018, Uber was already operating in over 800 cities worldwide, while Lyft was in over 300 U.S. cities (*18, 41*). The 2022 user penetrations of the ride-hailing service are 15.7% and 27.8% in Europe and U.S., respectively (*39, 40*). Ride-hailing is not as widespread in Europe as in the U.S. because of the generally higher population density, more extensive public transit supply and stricter regulations on ride-hailing operations in European cities than in U.S. cities (*15*).

The adoption of ride-hailing service benefits society in various ways. With the support of GPS technology and routing algorithms, passengers are provided with information about their drivers, real-time vehicle location, pricing, and estimated travel time. Passengers can easily request or cancel a ride, and drivers can be matched with passengers more efficiently (*30*). However, these benefits do not come without a cost. Existing literature has pointed out several negative impacts TNCs can have on transportation network and urban sustainability. For instance, previous research showed that TNCs have led to a diversion from public transit and a considerable increase in vehicle miles traveled (VMT) in large dense metropolitan areas of the United States (*34, 35*). The VMT generated by TNCs is comprised of two types of trips – passenger hauling trips and deadheading trips. Passenger hauling trips are trips made while transporting passengers towards the destinations, and deadheading trips refer to trips made without a passenger in the vehicle. The excessive VMT consequently leads to increased road congestion, energy use and greenhouse gas emissions (*9, 22, 23, 42*). On the other hand, though sharing of trips can greatly reduce road traffic (for instance, previous literature showed that sharing of trips through taxis in NYC could reduce taxi traffic by 40% or more (*1*)), the growth of shared ride-hailing services has been much more limited than that of single-occupant ride-hailing (*41*). As of December 2017, only 20% and 40% of the total Uber and Lyft rides were pool rides (*36*).

2.2 TNC regulations and surge pricing

To cope with the negative externalities of TNCs, several cities in the U.S. have applied regulatory policies for TNC services. For example, New York State's congestion surcharge charges a $2.75 fee to all single TNC trips and $0.75 fee to all shared TNC trips that begin in, end in, or pass through Manhattan, south of and excluding 96th Street (*29*). San Francisco's rideshare tax imposes a 3.25% surcharge on all single rides and a 1.5% surcharge on shared rides that originate in San Francisco. Trips are taxed for the portion of the ride that happens in San Francisco (*33*). In this study, we focus on the Ground Transportation Tax (GTT) in Chicago, which is a type of congestion surcharge for TNC trips.

Much of the existing literature has focused on the preliminary policy questions surrounding TNC services, particularly whether companies should be allowed to operate at all in cities and how they may be regulated and monitored as a new entrant to the mobility system. Beer et al. (2017) identified and compared various regulatory mechanisms used for TNC services in U.S. cities and states (*2*). The authors evaluated driver related policies such as background checks, driver's licenses, vehicle registrations, business licenses, and external vehicle displays, as well as company related policies including the number of vehicles operating in the metro area, a list of current drivers being provided to the city, and data on trips completed in the city. The authors found that regulation varies considerably by context, and no standard approach has yet been developed in the United States. Brail (2018) conducted a case study which documents the process of legislation and regulation of TNC companies in Toronto, Canada (*3*). The author noted that the impacts of TNC services are borne not only by direct competitors (such as taxi companies) but by the broader city mobility network, and thus states that cities must consider whether regulatory policies are effectively designed to enable inclusive growth and avoid worsening inequity in cities (*3*).

Regarding the previous work that focused on the impacts of congestion charges on TNCs, most studies sought to evaluate or design the TNC pricing schemes using various economic models. For instance, Li et al. (2021) proposed a market equilibrium model to assess the impact of the imposition of a congestion charge and a driver minimum wage (*25*). Slowik et al. (2019) introduced a hypothetical ride-hailing fee system with consistent average revenue per vehicle that would steer ride-hailing fleets to transition to electric vehicles in the 2025 time frame (*37*). Brown (2020) assessed the equity implications of various TNC fee structures in the Chicago context, and found that flat fees are less equitable when compared with percentage-based fees. However, it remains largely unclear regarding whether the existing TNC surge pricing strategies efficiently curb TNC use and whether the differential TNC pricing is sufficient to incentivize pooling. Although several previous studies tried to understand TNC demand among different populations (*9*), these studies predominately relied on surveys of TNC users that were highly dependent on when, where and how the data was collected (*23, 45*). Also, these studies focused on people's preferences towards ride-hailing usage in general, but did not examine the influence of real-world congestion pricing policies. To fill this research gap, we aim to empirically assess the impact of TNC congestion surcharge policies on urban transportation. Specifically, we adopt a DID method to quantify the causal effect of the GTT adoption on TNC ridership for both shared and single TNC trips. The DID method is a quasi-experimental research design which has been widely adopted to measure the causal effect of policy shocks (*47, 48*). Based on the estimated GTT effects derived from the DID estimation, we also contribute to the previous literature by computing the price elasticity of the TNC demand in the downtown areas.

3. BACKGROUND

Based on research conducted by the transportation analytics company INRIX, Chicago was ranked as the second most congested city in the United States in 2019 (*31*). The 2019 average driving time between 6:00am and 10:00pm on workdays in Chicago were 30.8% longer than during the baseline non-congested conditions (*20*). As stated by Mayor Lightfoot, one driver of the intense congestion is the considerable number of ride-hailing rides, especially the single-occupant ones, in the downtown areas (*13*). In response to perceived contributions to traffic congestion by TNC providers, the city of Chicago imposed the Ground Transportation Tax (GTT) starting from January 6, 2020. The GTT initiative replaces a previous flat TNC trip fee of \$0.72, which was applied to all trips regardless of origin or destination. The City of Chicago estimates that the new GTT initiative will raise \$40 million per year in additional revenue, which will be used to improve bus service through dedicated bus lanes, provide financial help to cab owners by lowering the license renewal fee, and supplement the city general fund (*6, 12*).

The rationale behind this tax expresses concern about rapid growth of TNC services and their role in the city's congestion levels, stating that the policy will "combat the plague of congestion, promote sustainable forms of transportation and support our essential public transit system, while making shared rides cheaper in the neighborhoods" (*7*). The GTT levies a greater surcharge for trips which begin or end in a special area, including airports, Navy Pier, and McCormick Place, and applies an additional Downtown Zone Surcharge for trips which begin or end in the Downtown Zone Area (shown in Figure 1) between 6:00am and 10:00pm, Monday to Friday. Single-occupant TNC trips are also priced at a higher rate than shared trips (those which are conducted through UberPool or Lyft Shared services). For example, a single-occupant trip from O'Hare Airport to the Willis Tower on a weekday would incur a surcharge of $8.00, while a shared ride for the same trip would incur a surcharge of $6.25. The full pricing scheme is provided in Table 1. The aim of this approach is to disincentivize downtown and single-occupant trips relative to other TNC travel options and other modes of travel. In this research, we exclude the two airport areas from our analysis and only investigate the policy impacts on trips that started or ended in Downtown Zone and the two special areas: Navy Pier and McCormick Place. We define these areas as the GTT-impacted areas.

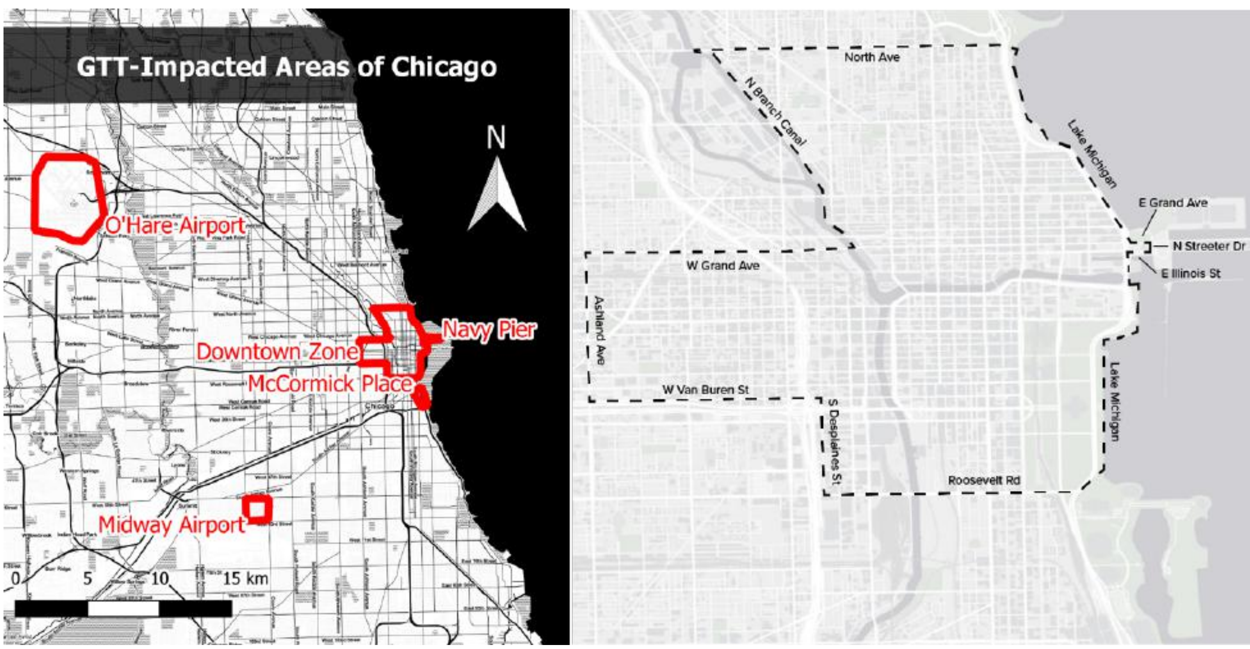


FIGURE 1: All areas charged higher fees under the GTT (left), and boundaries of the "Downtown Zone Area" (right) (*7*)

TABLE 1: GTT pricing policy (*7*)

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

4. DATA

Chicago's TNC trip data is obtained through the Chicago Data Portal (*32*). The data contains both pickup and dropoff time and location for trips made by major ride-hailing companies. The data also contains information about whether a trip is requested as a shared trip or a single-occupant trip. Trips are reported at the census tract level to a temporal resolution of 15 mins. In this study, we aggregate the data to obtain the daily trip counts for each census tract. We analyze all the TNC trip data in Chicago for the period November 1, 2018 (the earliest date that the data is available) to March 8, 2020 (before COVID-19 restrictions began), excluding observations from holidays, which usually show abnormal patterns. The TNC ridership trends are shown in Figure 2.

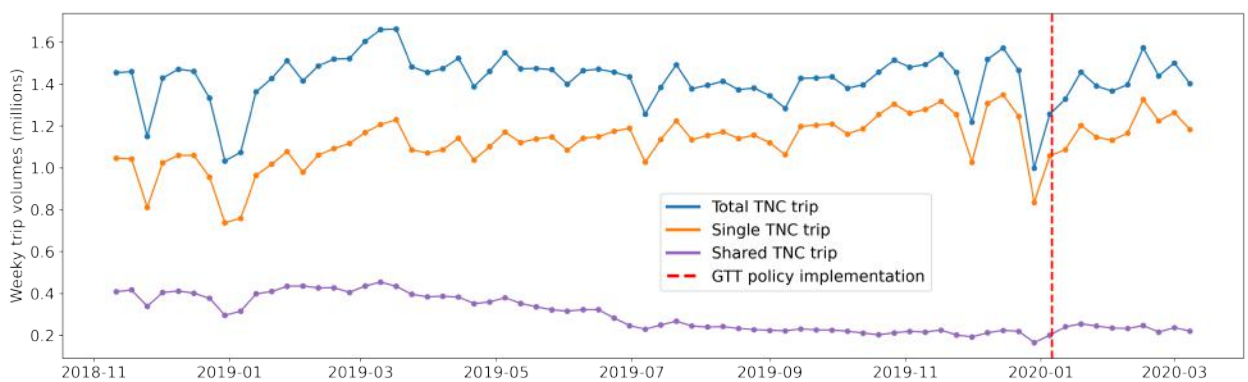


FIGURE 2: TNC ridership Trend

Precipitation is an important factor impacting TNC demand, as previous research showed that precipitation could increase the demand for TNC (*4, 14*). Therefore, we also include precipitation as a predictor for TNC demand in this research. Precipitation data is obtained from the website of National Centers for Environmental Information (*11*). A map of Chicago and census tract boundaries are publicly available from the public data portal of the City of Chicago. Descriptive statistics of the data are reported in Table 2, with the treated and control tracts defined in Section 5.1.1.

In Table 3, we report the average costs for trips started/ended in the treated tracts which are used for the TNC trip demand elasticity calculation. The cost for each trip is calculated as the sum of the trip fare (which is rounded to the nearest $2.50) and the additional charges (including the taxes, fees and any other charges for the trip). The trip cost data is obtained from the Chicago Data Portal (*32*).

TABLE 2: Descriptive statistics with treatment and control tracts defined based on geographic coverage

Name	Mean	Std.dev	Min	Max	Name	Mean	Std.dev	Min	Max
Number of pick-up trips					**Number of drop-off trips**				
Treated tracts, pre-intervention (n=8033)					*Treated tracts, pre-intervention (n=8033)*				
Total trips	2980.40	2568.96	144	16725	Total trips	3102.65	3141.83	78	21567
Morning rush	658.63	392.97	18	2769	Morning rush	1066.33	1661.08	3	12641
Evening rush	1186.65	1221.34	69	8975	Evening rush	1010.55	789.28	12	5529
Shared trips	421.74	427.20	25	3585	Shared trips	446.95	487.87	15	4418
Single trips	2558.67	2220.33	117	15177	Single trips	2655.70	2719.63	58	18349
Treated tracts, post-intervention (n=1247)					*Treated tracts, post-intervention (n=1247)*				
Total trips	2807.66	2550.56	248	15830	Total trips	2916.59	3015.80	226	20468
Morning rush	629.35	372.20	80	2134	Morning rush	1048.12	1661.05	21	10259
Evening rush	1120.37	1220.42	78	7708	Evening rush	924.99	732.01	41	4521
Shared trips	330.14	290.20	29	1709	Shared trips	349.63	340.87	27	2303
Single trips	2477.52	2276.05	189	14163	Single trips	2566.96	2687.11	188	18165
Control tracts (1km boundary), pre-intervention (n=6094)					*Control tracts (1km boundary), pre-intervention (n=6094)*				
Total trips	358.02	487.51	11	2825	Total trips	374.31	549.01	2	2943
Shared trips	95.75	176.37	0	1181	Shared trips	98.12	183.85	0	1269
Single trips	262.27	332.43	10	1957	Single trips	276.19	383.45	2	2244
Control tracts (1km boundary), post-intervention (n=946)					*Control tracts (1km boundary), post-intervention (n=946)*				
Total trips	351.06	491.28	11	2573	Total trips	373.03	557.09	13	2755
Shared trips	67.71	137.81	0	815	Shared trips	70.29	144.88	0	832
Single trips	283.35	362.09	9	1881	Single trips	302.74	420.75	11	2157
Control tracts (2km boundary), pre-intervention (n=16897)					*Control tracts (2km boundary), pre-intervention (n=16897)*				
Total trips	318.32	411.44	0	2825	Total trips	326.34	450.87	0	2943
Shared trips	80.57	130.32	0	1181	Shared trips	82.63	136.50	0	1269
Single trips	237.75	301.34	0	1957	Single trips	243.71	332.56	0	2244
Control tracts (2km boundary), post-intervention (n=2623)					*Control tracts (2km boundary), post-intervention (n=2623)*				
Total trips	312.86	413.39	0	2573	Total trips	322.70	451.53	0	2755
Shared trips	54.92	98.33	0	815	Shared trips	56.65	103.26	0	832
Single trips	257.93	325.29	0	1881	Single trips	266.05	358.04	0	2157
Control tracts (3km boundary), pre-intervention (n=31855)					*Control tracts (3km boundary), pre-intervention (n=31855)*				
Total trips	241.29	332.22	0	2825	Total trips	242.74	360.81	0	2943
Shared trips	59.47	103.72	0	1181	Shared trips	60.20	108.19	0	1269
Single trips	181.83	244.98	0	1957	Single trips	182.55	267.70	0	2244
Control tracts (3km boundary), post-intervention (n=4945)					*Control tracts (3km boundary), post-intervention (n=4945)*				
Total trips	235.49	333.10	0	2573	Total trips	239.04	361.20	0	2755
Shared trips	39.81	76.89	0	815	Shared trips	40.63	80.44	0	832
Single trips	195.67	264.81	0	1881	Single trips	198.41	288.99	0	2157
Precipitation					**Precipitation**				
Pre-intervention (days=277)					*Post-intervention (days=43)*				
Amount (tenths of mm)	0.13	0.28	0.00	1.77	Amount (tenths of mm)	0.03	0.06	0.00	0.25
No. of Prcp. days	167	/	/	/	No. of Prcp. days	23	/	/	/
Percent of Prcp. days (%)	60.29	/	/	/	Percent of Prcp. days (%)	53.49	/	/	/

Note: the morning rush hours are on workdays between 6:00am and 10:00am, and the evening rush hours are on workdays between 3:00pm and 7:00pm.

TABLE 3: Average costs for trips started/ended in the treated tracts

Period	Pickup Trips			Dropoff Trips		
	Total trips	Shared trips	Single trips	Total trips	Shared trips	Single trips
Pre-intervention	\$12.05	\$7.74	\$12.73	\$11.77	\$7.71	\$12.42
Post-intervention	\$13.58	\$8.85	\$14.19	\$13.47	\$8.84	\$14.08

5. METHODS

In this study, we use the Difference-in-differences (DID) models to estimate the effect of the GTT implementation on TNC trip counts. A DID model quantifies the causal effect of a policy by comparing the outcome between the treatment and control groups (*24*). The average treatment effect of the GTT on the TNC trip counts can be expressed as:

$$\begin{aligned} ATT = &(E[TripCount_{it}|i \in G_1, t = 1] - E[TripCount_{it}|i \in G_1, t = 0]) - \\ &(E[TripCount_{it}|i \in G_0, t = 1] - E[TripCount_{it}|i \in G_0, t = 0]) \end{aligned} \tag{1}$$

Where ATT denotes the average treatment effect, which will be estimated using the regression approach (specified in Section 5.1.2). $TripCount_{it}$ represents the trip count in tract i at time t, with $t = 0$ denoting the pre-treatment period and $t = 1$ denoting the post-treatment period. G_0 and G_1 represent the control and treatment groups, respectively.

In this section, we will first introduce our main DID specification, then introduce several alternative specifications for the robustness tests. We then explain how we calculate the elasticity of the TNC demand and investigate the spatial and time-of-day variations of the policy effects.

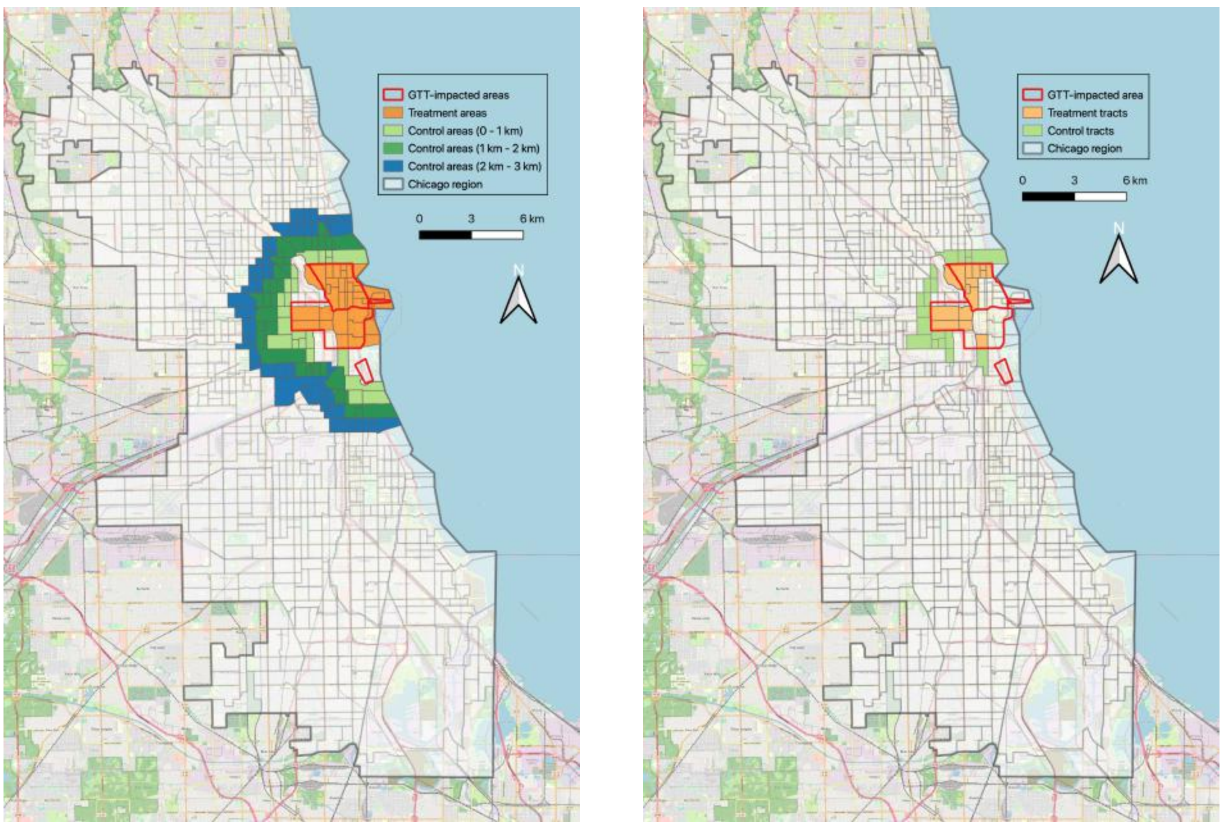
5.1 Main DID specification

This section will first describe how we define the treatment and control groups, then explain our main model specification used to estimate the policy effects on TNC ridership.

5.1.1 Treatment and control groups selections

For our main DID specification, we select the treated census tracts and the control census tracts as shown in Figure 3a. The treated census tracts (highlighted in orange) are those tracts that are at least 50% covered by the GTT-impacted areas. Instead of using all the non-treated census tracts in Chicago as the control group, we consider the census tracts that are outside but close to the GTT-impacted areas as the control group; these census tracts should be more similar to the treatment census tracts in terms of the pre-intervention TNC ridership than census tracts in other parts of the city, owing to their close proximity to the treatment areas. However, we exclude those non-treated tracts that are partially covered by the GTT-impacted areas, since they may have been affected by the GTT intervention, thus are not considered “clean” enough to be included in the control group. Also, for each of the control census tracts, we exclude trips that ended in the treatment census tracts when counting the number of pickup trips, and exclude trips that began in the treatment census tracts when counting the number of dropoff trips, since these two types of trips were also subject to the congestion surcharges. In the end, we have 29 treatment census tracts in total.

We define our control census tracts as those tracts that are within 1 km from the boundary of the GTT-impact areas. Given that the choice of the boundary can be somewhat uncertain, we also test the sensitivity of our models to this choice of control group boundary. In addition to the 1 km boundary, we also specify models with 2 km and 3 km boundaries when defining the control group. The light green, dark green, and blue colors in Figure 3a respectively denote the control census tracts that are within 1 km, between 1 and 2 km, and between 2 and 3 km from the boundary of the GTT-impacted areas, which give 22, 61 and 115 control census tracts respectively. Descriptive statistics for daily ridership data for the treatment and control areas are summarized in Table 2.



(a) Main DID specification

(b) Near-boundary DID specification

FIGURE 3: Geography of treated and control areas

5.1.2 Difference-in-differences research design

We use the DID approach to estimate the effect of the GTT implementation on TNC ridership. We only include observations that took place during workdays (Monday - Friday, excluding holidays) because the Downtown Zone TNC surcharge was only in effect on workdays. Our filtered sample includes 277 days pre-intervention and 43 days post-intervention. The model is expressed mathematically as in Equation 2.

$$\begin{aligned} Y_{it} = &\rho_0 + \rho_1 * Treatment_i * After_t + \rho_2 * After_t + \rho_3 * Trend_t + \rho_4 * Trend_t * Treatment_i + \\ &\alpha_1 * Precipitation_t + \mathbf{c}_i + DayOfWeekFE_t + MonthFE_t + DayOfWeek\text{-}TreatmentFE_{it} + \\ &Month\text{-}TreatmentFE_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

Where Y_{it} refers to the number of TNC trips on date t for census tract i; $Treatment_i$ is a dummy variable that is 1 for the treatment census tracts and 0 otherwise; $After_t$ is a dummy variable index for dates on or after Jan 6, 2020 (the effective date of the GTT); $Trend_t$ measures the time interval between the date t and the GTT effective date (i.e. $t-$Date [Jan 6, 2020]). We control for the heterogeneity in time trend across the treatment and control groups by incorporating $Trend_t * Treatment_i$. $\mathbf{c}_i$ denotes the census tract fixed effect. We also include the day of week fixed effect ($DayOfWeekFE_t$) and the month fixed effect ($MonthFE_t$). Given that the day of week and month dummies can affect the outcome differently across the treatment and control groups, we also include the interaction between $Treatment_i$ and the day of week dummies ($DayOfWeek\text{-}TreatmentFE_{it}$), as well as the interaction between $Treatment_i$ and the month dummies ($Month\text{-}TreatmentFE_{it}$).

5.2 Robustness tests

To test the robustness of our DID estimation results, we employ the following three strategies. First, we test the sensitivity of our estimated treatment effect to the variation of the control group boundary. Second, we deploy a near-boundary DID estimation. Third, we estimate the treatment effect using the workday data as the treatment group and the weekend data as the control group. These three strategies are explained as follows.

5.2.1 Sensitivity analysis regarding the control group boundary

In our main DID specification, we define the control census tracts as those tracts that are within 1 km from the boundary of the GTT-impact areas. We test the sensitivity of our models to 2 km and 3 km boundaries when defining the control group, and examine how the estimated treatment effect varies.

5.2.2 Near-boundary DID specification

Though we can check validity of the DID specification by testing the parallel trends of the treatment and the control groups, we recognize that there may be some confounding factors that affect the TNC ridership change differently across the treatment and control groups after the GTT was implemented. For instance, infrastructure conditions and economic development may vary between the treatment and control areas; thus the unobserved factors may not be identical across the two groups. To address this concern, we define a new set of treatment and control groups by selecting only census tracts that are close to the boundary of the GTT-impacted area, so that other location differences of the census tracts in the treatment and control groups are minimal, except for the policy difference. These alternate treatment and control groups are shown in Figure 3b. In this setting, the treatment and control tracts are limited to those within 0.7 km of the north, south or west boundary of the GTT-impacted downtown region. The east boundary of the GTT-impacted downtown region is ignored because no control census tracts are adjacent to the east boundary. As with the main DID specification, tracts that are partially covered (less than 50% of their total area) by the GTT-impacted areas are excluded from both the treatment and the control groups. Because the new treatment and control census tracts are close in space, differences in unobserved location characteristics can arguably be cancelled out. This gives us 14 treated tracts and 19 control tracts in total. With the new treatment and control groups, we implement the same DID regression as specified in Equation 2.

5.2.3 Alternative specification with the weekend data as the control group

Although we try to address the unobserved difference between the treatment and control census tracts by including only the census tracts that are close to the boundary of the treatment area, the unobserved spatially correlated characteristics may still impose an impact similar to the GTT policy on TNC ridership if they took place at the beginning of 2020, since the treated census tracts are not randomly located in space. Though we found no evidence of such events that could have affected the TNC demand in the treatment area other than the GTT implementation, we acknowledge that from a methodological perspective, this is not as good as if the treated areas were randomly assigned; we therefore test one additional specification of treatment and control groups.

To address the potential endogeneity that arises from the spatially-related omitted variables, we use a different set of control and treatment groups based on the day of week information. Since the GTT levied a greater surcharge for trips that begin or end in the Downtown Zone Area on workdays (Monday to Friday), weekend trips should not be affected by the GTT policy. Therefore, for TNC trips that began or ended in the GTT-impacted area (i.e. the treatment area in Figure 3a), we use weekend TNC trips as an alternative control group and compare it to workday TNC trips as the treatment group. The descriptive statistics of these alternative treatment and control groups are summarized in Appendix A.1. The average numbers of daily pickup/dropoff trips in the pre-intervention and post-intervention periods are both around 3000.

Looking at TNC trips across different days of week alleviates the concern that census tracts within and outside the GTT-impacted area are essentially different. With this new setting, the treatment and control observations are now exposed to the same land use, economics, demographics and other location-based changes for which the main specification does not strictly control. In this alternative specification, the observations included in the analysis are daily TNC ridership for both workdays and weekends in the treated census tracts as specified in Figure 3a during the same analysis period (November 1, 2018 - March 8, 2020). The new model is given by:

$$\begin{aligned} Y_{it} = & \rho_0 + \rho_1 * Workday_t * After_t + \rho_2 * After_t + \rho_3 * Trend_t + \rho_4 * Trend_t * Workday_t + \\ & \alpha_1 * Precipitation_t + \mathbf{c}_i + DayOfWeekFE_t + MonthFE_t + CensusTract\text{-}WorkdayFE_{it} + \\ & Month\text{-}WorkdayFE_t + \varepsilon_{it} \end{aligned} \tag{3}$$

Where Y_{it}, $After_t$, $Trend_t$, $Precipitation_t$, $\mathbf{c}_i$, $DayOfWeekFE_t$, $MonthFE_t$ have the same definitions as those in the main model (Equation 2). $Workday_t$ is a dummy variable that is encoded as 1 when the date t is among Monday to Friday, and is encoded as 0 when t is a weekend day. Given that the gap of TNC ridership between workdays and weekends can be different in different census tracts, we include the interaction between the census tract dummies and $Workday_t$ ($CensusTract\text{-}WorkdayFE_{it}$). We also control for the heterogeneity in the month fixed effects across weekends and workdays by including $Month\text{-}WorkdayFE_t$. Our variable of interest is $Workday_t * After_t$, which compares the TNC ridership in workdays to that in weekends for census tracts in the GTT-impacted area.

5.3 Elasticity of TNC demand

Based on the estimated GTT treatment effects, we measure the price elasticity of the TNC demand regarding the congestion charging, which is calculated as the percentage change of TNC trip volumes in response to a percentage change in the trip costs induced by the congestion charging. This can be expressed as:

$$E_{direct} = \frac{(D_y - D_x)/0.5(D_y + D_x)}{(C_y - C_x)/0.5(C_y + C_x)} \tag{4}$$

Where x refers to the pre-intervention state and y refers to the new state. D_x and C_x represent the TNC trip demand and average trip cost before the GTT implementation. D_y and C_y represent the new TNC trip demand and average trip cost in response to the GTT.

5.4 Regional variation

To better understand the spatial heterogeneity of the GTT policy's impacts, we conduct DID estimations for different regions of Chicago separately. We first divide the city of Chicago into 7 regions as shown in Figure 4 based on the guideline provided by Office of Policy & Planning in Chicago Department of Public Health (*5*). We also present the income and race distributions in Chicago in Figure 5. Figure 5 (left) shows the logarithm of median household income, while Figure 5 (right) shows the percentage of African-American population by census tract within the city. We can observe a bimodal distribution of African-American population from the map, with the vast majority of areas having African-American population below 20% or above 80%. For the income distribution, we can see that the lower-income population is mainly clustered in the far west side and the south side of the city. This current spatial segregation in race and income is a result of centuries of discriminatory policies, particularly as the Great Migration saw an influx of African-American people from southern states, along with a movement of white residents to Chicago's suburbs (*17, 27*). Practices such as "redlining" barred African-Americans from suburban housing and posed major barriers to home ownership through federally-insured mortgages (*27*). These policies have contributed to racial segregation and a wealth gap that persist to present day (*44*).

In the modeling phase, when analyzing how pickup trips were affected by the GTT policy, we group the trip records based on the regions that the TNC trips ended in and deploy the DID estimation for each of the 7 dropoff regions using the main DID specification as shown in Section 5.1. Similarly, when analyzing dropoff trips, we group the trip records based on the pickup regions of the TNC trips. In light of the history of discrimination against residents of the southern parts of

FIGURE 4: Seven Chicago regions

the Chicago region, we specifically investigate how the treatment effects vary between the south side (i.e. the Southwest, the South and the Far South regions) and the remaining regions in the city. The descriptive statistics of the TNC trips by region are shown in Appendix A.2.

5.5 Time-of-day variation

To see how the treatment effects vary by time of day, we estimate the treatment effects for the morning and evening rush hours separately. We define the morning rush hours as 6:00am - 10:00am on workdays, and the evening rush hours as 3:00pm - 7:00pm on workdays based on the Chicago traffic data (*19*). The descriptive statistics shown in Table 2 suggest that the treated tracts have more pickup trips in the evening rush hour than in the morning rush hour, whereas these tracts have more dropoff trips in the morning rush hour than in the evening rush hour. This pattern makes intuitive sense as many people commute to downtown for work in the morning while go back home from downtown in the evening.

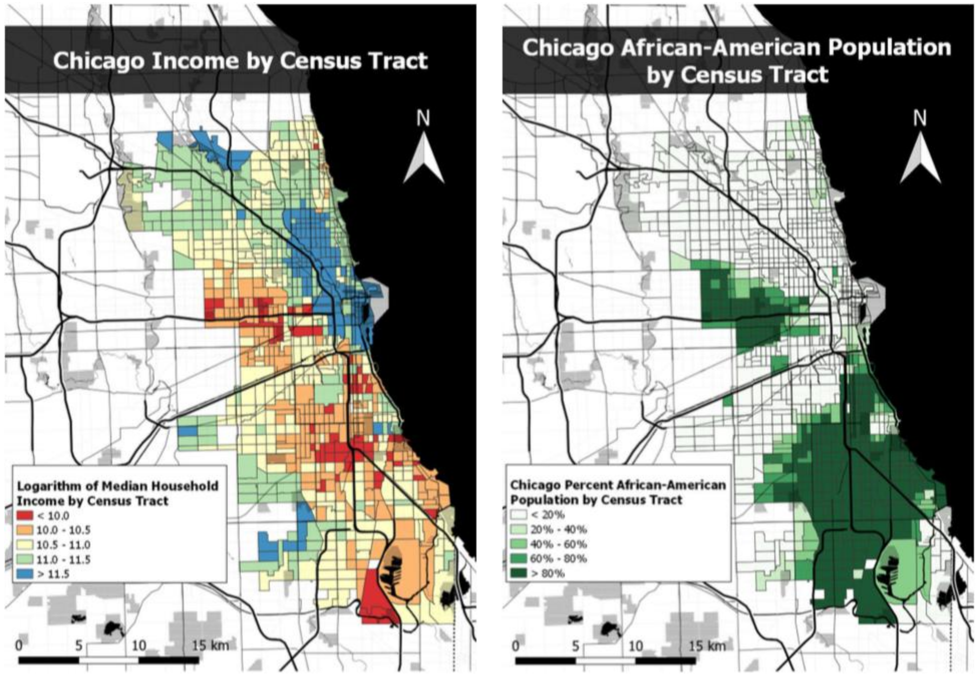


FIGURE 5: Maps of logarithm of median household income (left) and percent of African-American population (right) by census tract for the city of Chicago (data: US Census Bureau 2019 (*43*))

6. RESULTS

In this section, we will present the results of our main DID estimations evaluating the effects of the GTT implementation on the TNC ridership in the GTT-impacted areas, the robustness tests, the estimated TNC demand elasticities and the spatial and time-of-day variations of the policy effects.

6.1 Main results

6.1.1 Main DID estimation

Table 4 presents the result of our main estimation of the GTT effect on the number of TNC trips, based on the method specified in Section 5.1. The TNC ridership in a specific census tract can be represented by either pickup trips or dropoff trips. Therefore, we test the policy effect on both pickup trip counts and dropoff trip counts for the GTT-impacted areas. For each of these two types of trips, we specify three outcome variables: the number of shared trips, the number of single trips (i.e. non-shared trips) and the number of total trips. Table 4 shows the result of the estimation that defines the control group as census tracts that are within 1 km from the boundary of the GTT-impacted areas.

Columns (1) and (4) in Table 4 indicate that the GTT program implementation led to a reduction of roughly 213 pickup trips and 230 dropoff trips per day per GTT-impacted tract. Dividing these numbers by the total daily trip counts per GTT-impacted tract in the pre-treatment period for pickup and dropoff trips, the effects of the GTT policy translate to approximate 7.1% reductions of total daily pickup trips and 7.7% reductions of total daily dropoff trips in the GTT-impacted areas. This reduction is the net result of an increase in shared trips and a larger decrease in non-shared (single) trips. Specifically, Column (2) and (5) show that the GTT caused an increase of roughly 69 shared pickup trips (16.4%) and 77 shared dropoff trips (18.2%) in the GTT-impacted areas. On the contrary, column (3) and (6) indicate that the GTT is associated with a reduction of 282 non-shared pickup (11%) trips and 306 non-shared dropoff trips (12%).

TABLE 4: Effect of GTT on number of TNC trips (1 km)

	Pickup Trips			Dropoff Trips		
	Count: total	Count: shared trips	Count: single trips	Count: total	Count: shared trips	Count: single trips
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment∗After	-212.783^{***}	69.055^{***}	-281.838^{***}	-229.624^{***}	76.587^{***}	-306.211^{***}
	(33.132)	(10.794)	(41.034)	(51.738)	(14.782)	(63.614)
After	-12.587^{***}	3.195	-15.781^{***}	-17.958^{***}	3.294	-21.252^{***}
	(2.316)	(3.903)	(4.271)	(4.311)	(4.850)	(7.177)
Trend	0.024	-0.175^{***}	0.199^{***}	0.041^{*}	-0.173^{***}	0.215^{***}
	(0.021)	(0.054)	(0.066)	(0.023)	(0.055)	(0.076)
Trend∗Treatment	0.286^{***}	-0.764^{***}	1.050^{***}	0.260^{***}	-0.782^{***}	1.043^{***}
	(0.099)	(0.169)	(0.221)	(0.100)	(0.188)	(0.240)
Precipitation	42.613^{***}	13.446^{***}	29.167^{***}	65.551^{***}	15.512^{***}	50.038^{***}
	(10.520)	(2.193)	(8.677)	(15.187)	(2.809)	(12.764)
Observations	16,320	16,320	16,320	16,320	16,320	16,320
R^2	0.971	0.903	0.967	0.971	0.913	0.968
Adjusted R^2	0.971	0.902	0.967	0.971	0.913	0.968

Note: Standard errors in parentheses are clustered on census tracts. Census tract fixed effects, day of week fixed effects, month fixed effects, treatment−month fixed effects, treatment−day of week fixed effects are included in all regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Overall, our results indicate an increase in number of shared TNC trips and a reduction in number of single TNC trips. The reduction in single trips was about four times of the increase in shared trips. These ridership changes are all statistically significant. These results make intuitive sense since under the GTT pricing scheme, single-occupant TNC trips were subject to a higher surcharge than shared trips.

Comparing pickup trips and dropoff trips, we observe that the policy effects were greater for the dropoff trips. Specifically, the GTT led to a larger increase in the shared trip counts and a larger decrease in the single trip counts, and consequently caused a larger reduction of total trip counts for the dropoff trips. This result may suggest that trips originating from the GTT-impacted areas were less sensitive to the policy change than trips destined to the GTT-impacted areas.

In addition, the coefficients for $Trend$ and $Trend * Treatment$ in Column (2), (3), (5) and (6) of Table 4 show that in general, the shared trip counts were declining whereas the single trip counts were increasing over the years, and each of these trends is larger for the treatment group than for the control group. However, our estimations of the treatment effects show that the GTT implementation shifted these trends. The significantly positive coefficients for $Precipitation$ indicate a positive correlation with TNC ridership, which makes intuitive sense as people tend to choose TNC over other modes such as public transit, walking or bicycling on rainy days.

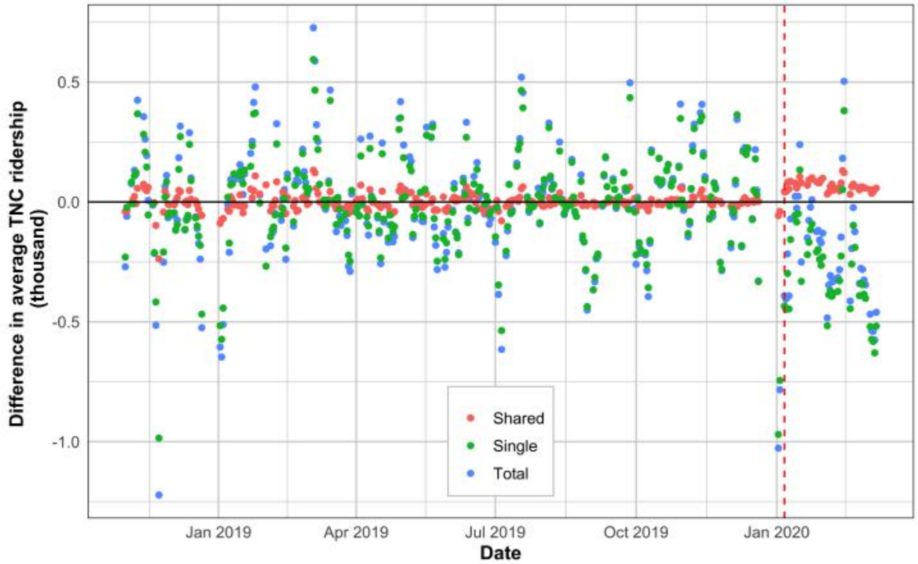


FIGURE 6: Difference in TNC pickup trip counts between the treatment and control groups, after controlling for trend, trend × treatment, precipitation and all the fixed effects

6.1.2 Parallel trend assumption

The validity of the DID estimation relies on the assumption that the treatment and control group should follow a parallel trend if the policy was not implemented. In other words, the difference in TNC ridership between these two groups should not be caused by the intrinsic difference between these two groups. Figure 6 plots the difference in pickup trip counts between the treatment and control groups over the study period while factoring out the control variables including trend, trend × treatment, precipitation and all the fixed effects (i.e. fixed effects regarding census tract, day of week, month, the interaction between treatment and month as well as the interaction between treatment and day of week) based on the estimation results of the main specification in Table 4. All three subfigures in Figure 6 show that prior to the implementation of the GTT on Jan 6, 2020, which is denoted by the red dotted vertical line, the ridership differences between the treatment and control groups after factoring out the control variables were quite stable and centered around zero, which verifies the parallel trend assumption. After Jan 6, 2020, the treatment group began to show a reduction in ridership compared with the control group for total TNC trips and single TNC trips as indicated by the blue and green dots, whereas shared TNC trips began to witness a relative increase in trip counts for the treatment group as indicated by the red dots. We conduct the same analysis on dropoff trips and report the results in Appendix A.3. The results indicate that the parallel trend assumption still holds and our findings are consistent with the dropoff trip analysis.

6.2 Robustness tests

We test the robustness of our estimation results in Table 4 following the three strategies outlined in Section 5.2, and the results are explained below. The treatment effects estimated from different specifications, which correspond to the estimated coefficients for $Treatment * After$ or $Workday * After$ in these specifications, are summarised in Table 5.

TABLE 5: Summary of the estimate treatment effects in various specifications

Model		Pickup Trips			Dropoff Trips		
		Count: total (1)	Count: shared trips (2)	Count: single trips (3)	Count: total (4)	Count: shared trips (5)	Count: single trips (6)
Main (1km boundary)	Treatment*After	-212.783***	69.055***	-281.838***	-229.624***	76.587***	-306.211***
		(32.954)	(10.163)	(40.687)	(51.363)	(14.034)	(62.985)
	Adjusted R^2	0.971	0.902	0.967	0.971	0.913	0.968
2km boundary	Treatment*After	-211.673***	70.665***	-282.337***	-232.920***	77.946***	-310.866***
		(33.132)	(10.794)	(41.034)	(51.738)	(14.782)	(63.614)
	Adjusted R^2	0.976	0.914	0.972	0.975	0.922	0.972
3km boundary	Treatment*After	-213.754***	71.507***	-285.260***	-235.037***	79.017***	-314.053***
		(32.844)	(10.037)	(40.551)	(51.214)	(13.906)	(62.789)
	Adjusted R^2	0.978	0.921	0.975	0.976	0.928	0.973
Near-boundary	Treatment*After	-100.440***	66.068***	-166.509***	-104.954***	65.607***	-170.560***
		(27.561)	(17.038)	(36.690)	(33.268)	(19.713)	(43.747)
	Adjusted R^2	0.974	0.922	0.970	0.961	0.930	0.954
Weekend as the control	Workday∗After	-195.022***	56.846***	-251.868***	-219.517***	61.218***	-280.736***
		(32.552)	(7.982)	(38.384)	(48.253)	(11.005)	(57.226)
	Adjusted R^2	0.948	0.875	0.941	0.946	0.889	0.940

Note: Standard errors in parentheses are clustered on census tracts. All control variables, census tract fixed effects, day of week fixed effects, month fixed effects, treatment−month fixed effects, treatment−day of week fixed effects are included in all regressions.

*p<0.1; **p<0.05; ***p<0.01

6.2.1 Sensitivity analysis regarding the control group boundary

We test the sensitivity of our estimation results in Table 4 to the boundary distance used to define the control census tracts. Table 5 reports the estimated treatment effect when the control group boundary is 1 km and when it is increased to 2 km and 3 km. We can see that when the control group boundary changes from 1 km to 2 km and 3 km, the estimated treatment effects on the TNC trip counts are still significant for total trip counts, shared trip counts and single trip counts, and for both pickup trips and dropoff trips. Also, the magnitudes of the treatment effects do not change much when we increase the control group boundary. These results indicate that our estimation of the GTT treatment effects is robust to the selection of the control group boundary.

6.2.2 Near-boundary DID estimations

In this section, we use the method introduced in Section 5.2.2 to compare outcomes for the treated and control census tracts that are close to the boundary of the GTT-impacted area shown in Figure 3b. The sample size is smaller, relative to the results reported in Table 4, because we now focus on only a subset of the treated tracts and control tracts. The result (model "Near-boundary" in Table 5) shows that under this circumstance, the GTT implementation led a daily reduction of roughly 100 pickup trips for the treated tracts compared with the control tracts, which is comprised of a reduction of 167 daily single pickup trips and an increase of roughly 66 daily shared pickup trips. In terms of the dropoff trips, the estimated coefficients show that the GTT led to a reduction of 105 total daily trips, which can be decomposed into a reduction of 171 single dropoff trips and an increase of 66 shared dropoff trips. The estimated coefficients for the treatment effects are all significant, showing the robustness of our DID results. Note that the absolute values of the treatment effects are smaller than those in the main model (Table 4), which could be explained by two potential reasons. One is that this near-boundary DID specification helps mitigate the omitted variable problems we may have when including all the treated census tracts in the treatment group. However, this hypothesis is not very likely to be valid since the underlying assumption of the omitted variable problem is that even if the policy intervention is absent, the smaller treatment effect in the near-boundary estimation suggests that the areas in the GTT-impacted regions would experience a systematically slower TNC ridership growth than areas outside the GTT-impacted regions after Jan 6, 2020 due to some unobserved factors. Nevertheless, we can not identify any factors that could have led to this pattern. Another possibility is that the treated tracts that are not included in this analysis (i.e. treated tracts that are not within 0.7 km from the north, west or south boundary of the GTT-impacted area) are associated with larger treatment effects; by excluding these treated tracts, the estimated treatment effects become smaller. This hypothesis is likely to be true, since the treated tracts that are not included in the near-boundary estimation are closer to the center of the Downtown Zone area, thus are associated with higher ride-hailing demand overall. As a result, the reduction of TNC trips due to the GTT policy also tends to be larger. By excluding these census tracts, the coefficients for $Treatment * After$ reported in Table 5 (model "Near-boundary") can be interpreted as the lower bound estimations of the GTT treatment effects on different types of TNC ridership in the GTT-impacted area.

6.2.3 Results using the weekend data as the alternative control group

In the analysis using weekend trips as the control group and workday trips as the treatment group, we also observe significant treatment effects for census tracts in the GTT-impacted area. The results for model "Weekend as the control" in Table 5 show that for census tracts in the GTT-impacted area, compared with weekend TNC trips which were not affected by the GTT policy, workday TNC trips are associated with a daily decrease of roughly 195 pickup trips and 220 dropoff trips. The reduction of the total pickup trips comprises a daily increase of roughly 57 shared pickup trips and a daily decrease of roughly 252 single pickup trips, whereas the reduction of the total dropoff trips comprises a daily increase of 61 shared dropoff trips and a daily reduction of 281 single dropoff trips. All these treatment effect coefficients are significant, and the magnitudes of the effects are very close to the estimated treatment effects in our main DID estimation (the coefficients for model "Main (1km boundary)" in Table 5), which further supports the robustness of our DID estimation.

We also test the parallel trend assumption on these alternative treatment and control groups defined based on day of week. Figure 7 shows the difference in daily average TNC pickup trip counts between workdays and weekends grouped by weeks over the study period, after factoring out the control variables including trend, trend $\times$ treatment, precipitation and all the fixed effects. The red dotted vertical line denotes the GTT implementation date. This figure show that before the GTT implementation, the daily TNC ridership difference between the treatment (workday) group and control (weekend) group fluctuates around zero, which validates the pre-treatment parallel trend assumption. After the policy was implemented, the blue and green dots in Figure 7 show that the total and single pickup trip counts in the treatment group became systematically smaller than those in the control group, whereas the red dots show that the shared pickup trip counts in the treatment group significantly increased compared with the control group. These findings are all consistent with our DID estimation results presented in Table 5 (model "Weekend as the control"). We also report the difference in TNC dropoff trips between the treatment and control groups in Appendix A.4, which validates the parallel trend assumption for the dropoff trip analysis as well.

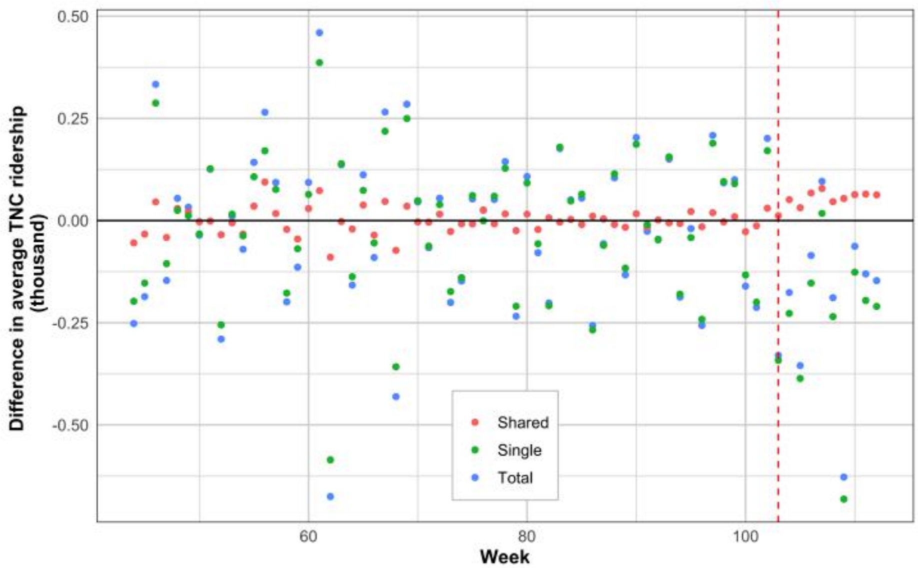


FIGURE 7: Difference in daily average TNC pickup trip counts between workdays and weekends, after controlling for $Trend$, $Trend * Workday$, $Precipitation$ and all the fixed effects

6.2.4 Summary

To summarize and visually compare the treatment effects estimated from various models, we plot Figure 8. The coefficients in Figure 8 correspond to the coefficients for $Treatment * After$ or $Workday * After$ from the five models reported in Table 5. The error bars represent the 95% confidence intervals of the coefficients. The results show that the treatment effects in models regarding 1 km, 2 km and 3 km control group boundaries are statistically indistinguishable with each other. The treatment effects derived from the analysis using the weekend data as the control group are somewhat smaller, but are generally consistent with the treatment effects estimated from the main model. The treatment effects in the near-boundary estimation are only about half of those estimated from the main model. As we've mentioned in Section 6.2.2, this discrepancy is probably due to the exclusion of census tracts that are close to the center of the Downtown Zone, which are likely associated with larger treatment effects.

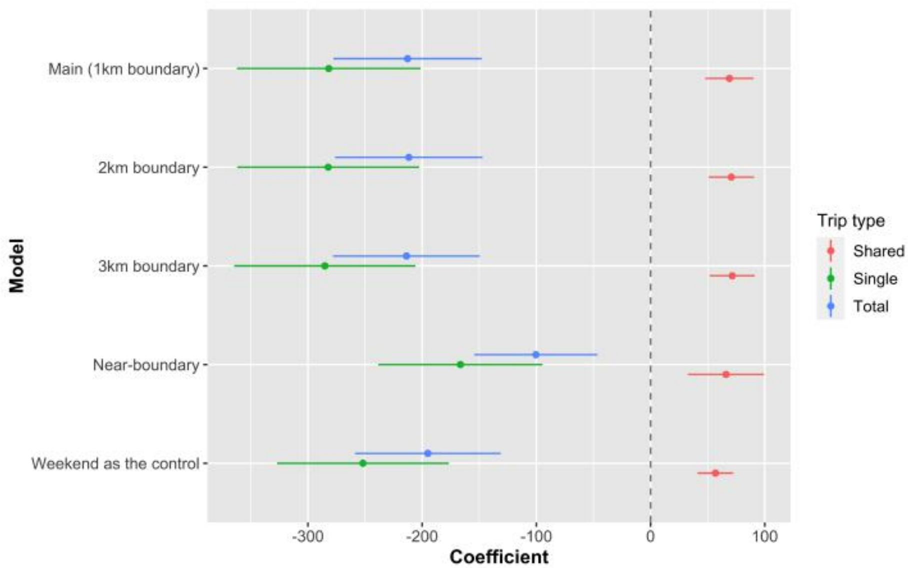


FIGURE 8: Comparison of the treatment effects across models

6.3 Elasticity of TNC demand

Table 6 reports the elasticity of the total TNC trip volume in the GTT-impacted areas in response to the GTT. Regarding the input variables for the elasticity calculations, the trip volumes and the average trip costs in the pre-treatment state are calculated from the Chicago's trip data obtained through the Chicago Data Portal. The changes in the trip volume due to the GTT are the treatment effects estimated from the main DID specification (Table 4). In terms of the change in the average trip cost, before the GTT implementation, a \$0.72 tax was applied to every TNC ride in Chicago. Therefore, compared with the pre-treatment period, each trip that started from or ended in the Downtown Zone was affected by an extra \$2.28 (for single trips) or \$0.53 (for shared trips) after the GTT was implemented. Given the actual shares of single trips and shared trips taken place in the GTT-impacted areas during the pre-treatment period, we get that the GTT induced an extra \$2.03 for each trip started or ended in the GTT-impacted areas on average (Table 6). The trip volumes and the average trip costs in the new state are the sum of those in the pre-treatment state and the amount of changes induced by the GTT.

Based on the values of these input variables and the formula for the elasticity calculation specified in Section 5.3, we get that the elasticities of the total TNC trip volume in the GTT-impacted areas in response to the GTT are -0.476 and -0.484 for the pickup and dropoff trips, which indicate that if the TNC trip costs increase by 1%, the demand for traveling out of and into the GTT-impacted areas by TNC decreases by 0.476% and 0.484%. This result aligns with a previous study investigating the 2003 London's central area congestion charge which shows that the the elasticity of car trip demand in response to the introduction of the £5 congestion charge is -0.55 (*10*).

6.4 Regional variation

Table 7 presents the treatment effects (the coefficient for $Treatment * After$ in Equation 2) of the GTT implementation on TNC ridership by region. Columns (1)-(3) in Table 7 examine how the

TABLE 6: Elasticity of the total TNC trip volume in the GTT-impacted areas in response to the GTT

	Pickup Trips		Dropoff Trips	
	Trip volume	Trip cost	Trip volume	Trip cost
Pre-treatment state	2980.40	$12.05	3102.65	$11.77
Change due to the GTT	-212.78	$2.03	-229.62	$2.03
New state	2767.62	$14.08	2873.03	$13.80
Percent change (%)	-7.40	15.54	-7.69	15.86
Elasticity	**-0.476**		**-0.484**	

pickup trips were affected by the GTT policy for different dropoff regions. To clarify, in the previous main specification, the outcome variable of interest is the number of trips that are picked up in each tract, and the treatment effect is obtained through comparing the average change over time of this outcome between the treated tracts and the control tracts. In that case, we do not make any restrictions on the dropoff places of the trips counted (except that trips starting in the control tracts and ending in the GTT-impacted areas are excluded). But now, we want to see how the treatment effect varies across different dropoff regions of the trips. Therefore, for each of the 7 regions, we study only the TNC trips ending in that region, and examine the differential effect of the treatment on the number of trips per tract that are picked up in the control tracts and the number of those that are picked up in the treated tracts through deploying the DID estimation using the main DID specification outlined in Section 5.1. Similarly, when analyzing the dropoff trips (Column (4)-(6) in Table 7), we group the trip records based on the pickup regions of the TNC trips and report the treatment effects for each region. The result shows that the treatment effects for total, shared and single trips are all significant for the Central, North and Northwest regions. Across all regions, the Central region constitutes the majority of the treatment effect, whereas the magnitudes of the treatment effects are relatively small for the South, Southwest and Far South regions. The magnitudes of the effects have large regional variation, mostly because the average daily TNC trip counts differ across space.

To give a sense of the relative impact of the policy on trips to and from the GTT-impacted areas across different regions with different baseline ridership, we further divide each treatment effect by the corresponding baseline TNC trip count, namely the average daily count of trips that began or ended in the GTT-impacted areas during the pre-treatment period. This approach gives a relative treatment effect for each region, which can be interpreted as the percentage of trips to or from the downtown areas that were lost/gained due to the GTT policy in each region. The result is presented in Table 8. In addition to the relative treatment effects for each region, we also report the relative total treatment effects regardless of the region differences, which are obtained by dividing the estimated treatment effects in Table 8 by the average daily counts of trips that began or ended in the GTT-impacted areas during the post-treatment period. We plot the treatment effects and the relative treatment effects across different regions in Figure 9.

TABLE 7: Treatment effects of the GTT implementation on TNC ridership by region

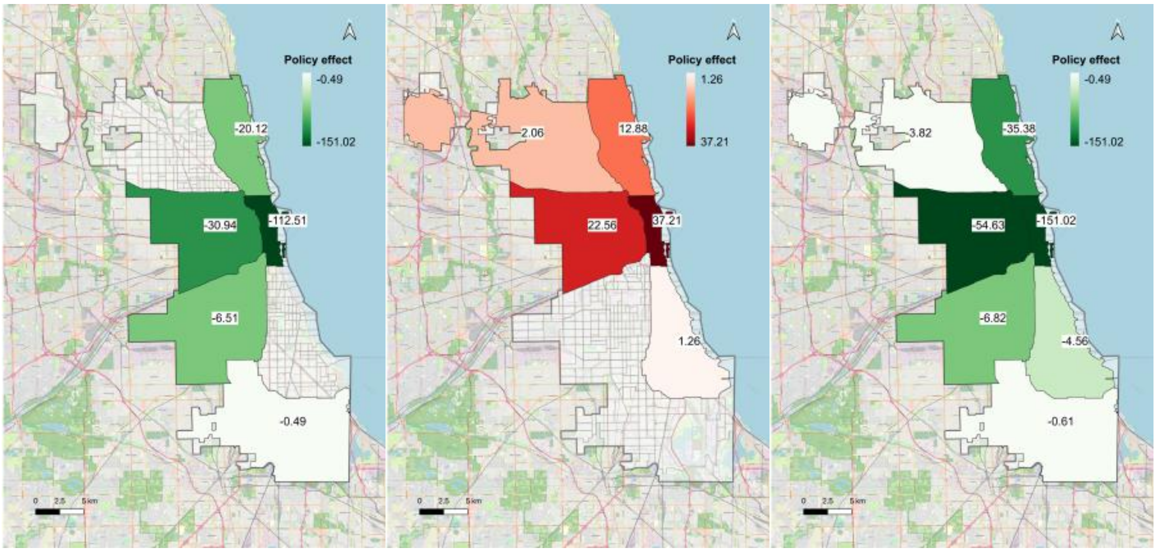
	Pickup Trips			Dropoff Trips		
	Count: total	Count: shared trips	Count: single trips	Count: total	Count: shared trips	Count: single trips
	(1)	(2)	(3)	(4)	(5)	(6)
Central	-116.342^{***}	37.210^{***}	-153.552^{***}	-112.510^{***}	38.427^{***}	-151.017^{***}
	(20.044)	(5.177)	(24.033)	(25.194)	(6.969)	(30.716)
North	-10.166^{***}	12.877^{***}	-23.043^{***}	-20.117^{***}	15.237^{***}	-35.384^{***}
	(3.746)	(2.300)	(3.773)	(4.313)	(3.335)	(6.853)
Northwest	-3.155	2.064^{***}	-5.218	-1.205	2.591^{***}	-3.817^{***}
	(3.415)	(0.597)	(3.279)	(1.542)	(0.785)	(1.405)
West	-23.257^{***}	22.562^{***}	-45.820^{***}	-30.942^{***}	23.649^{***}	-54.632^{***}
	(5.726)	(4.260)	(8.820)	(8.652)	(5.192)	(13.038)
South	-1.104	1.262^{***}	-2.366^{**}	-2.634	1.918^{***}	-4.556^{**}
	(0.941)	(0.359)	(0.947)	(1.882)	(0.744)	(2.194)
Southwest	-5.805^{***}	-0.030	-5.775^{***}	-6.513^{***}	0.299	-6.819^{***}
	(1.603)	(0.360)	(1.446)	(1.808)	(0.363)	(1.633)
Far South	-0.097	-0.137	0.040	-0.495^{**}	0.115	-0.610^{**}
	(0.148)	(0.087)	(0.126)	(0.246)	(0.160)	(0.254)

Note: Standard errors in parentheses are clustered on census tracts. *p<0.1; **p<0.05; ***p<0.01

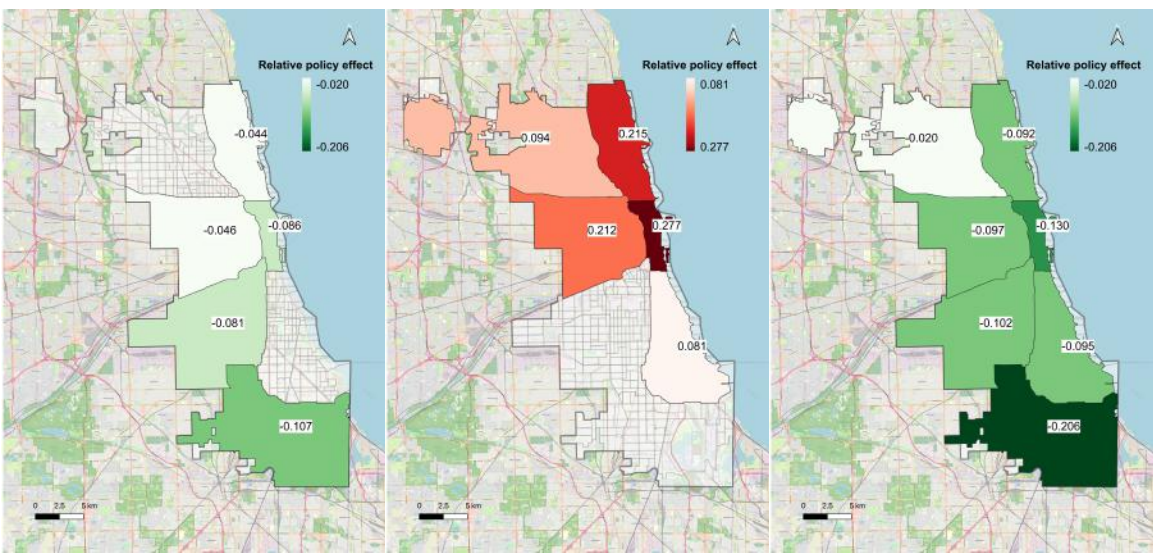
TABLE 8: The ratio of estimated TNC ridership change to the average TNC ridership due to the GTT implementation by region and trip type

	Pickup Trips			Dropoff Trips		
	Count: total	Count: shared trips	Count: single trips	Count: total	Count: shared trips	Count: single trips
	(1)	(2)	(3)	(4)	(5)	(6)
Central	−0.090	0.268	−0.133	−0.086	0.277	−0.130
North	−0.024	0.184	−0.066	−0.044	0.215	−0.092
Northwest	−−	0.082	−−	−−	0.094	−0.020
West	−0.037	0.220	−0.087	−0.046	0.212	−0.097
South	−−	0.063	−0.064	−−	0.081	−0.095
Southwest	−0.080	−−	−0.094	−0.081	−−	−0.102
Far South	−−	−−	−−	−0.107	−−	−0.206
Total*	−0.071	0.164	−0.110	−0.077	0.182	−0.120

Note: For each column, the number is calculated as the magnitude of the treatment effect divided by the average daily count of trips that ended (in the case of pickup trips) or began (in the case of dropoff trips) in the GTT-impacted areas during the pre-treatment period for each region, which can be interpreted as the percentage of trips that were lost/gained due to the GTT policy in each region; (*) the results for the total TNC ridership are obtained through dividing the estimated treatment effects in Table 4 by the average daily counts of trips that began or ended in the GTT-impacted areas during the pre-treatment period. The entries that are associated with insignificant treatment effects are not reported (i.e. denoted as "−−").



(a) Effect size: total trips (b) Effect size: shared trips (c) Effect size: single trips



(d) Relative effect size: total trips (e) Relative effect size: shared trips (f) Relative effect size: single trips

FIGURE 9: The GTT policy effects (corresponding to Table 7) and the relative policy effects (corresponding to Table 8) regarding various types of dropoff trips. Only the significant effects are shown.

The results show that the treatment effects are significant for most of the regions, and the treatment effects for shared trips are always positive, whereas those for total trips and single trips are always negative. These results indicate the directional consistency of the policy treatment effects across space. In terms of magnitude, we observe that the Central region is associated with higher relative treatment effects compared to total ridership in terms of all types of TNC trips. This finding makes intuitive sense since the GTT-impact areas take up a great proportion of the Central region, thus the Central region was affected by the GTT policy the most. The south side of the city has witnessed a great proportional reduction in single-occupant TNC ridership for trips that began or ended in the GTT-impacted areas due to the GTT. Specifically, 9.4% single pickup trips and 10.2% single dropoff trips were lost in the Southwest region, 6.4% single pickup trips and 9.5% single dropoff trips were lost in the South region, and 20.6% of single dropoff trips were lost in the Far South region. As mentioned above, the Southwest and South regions are associated with a higher proportion of ethnic minority and low-income population. Therefore, our findings of great single trip reductions due to the GTT policy in these regions align with previous research showing that the ride-hailing trips are often more expensive than transit and thus are unaffordable to many low-income households (*45*), and the disadvantaged populations are often the most price sensitive TNC users (*23*). However, the GTT policy did not seem to incentivize trip sharing between the GTT-impacted areas and the south side of Chicago, as only the South region experienced an increase in shared TNC ridership for trips that began or ended in the GTT-impacted areas (6.3% for shared pickup trips and 8.1% for shared dropoff trips), which is also relatively small compared to the increase of shared trip counts between other regions and the GTT-impacted areas. One potential cause for the ineffectiveness of encouraging TNC sharing in the south side of Chicago is the lack of service supply. The south side of Chicago is likely to be associated with a lower supply of TNCs, given that ride-hailing companies typically tend to provide more frequent services to places with more demand (e.g. wealthier neighborhoods and neighborhoods with a high density of potential riders) to gain more profit (*21, 26, 38, 49*). In addition, the disadvantaged neighborhoods in the south side are geographically far from the downtown areas. Therefore, travellers in the south side have to wait longer for vehicles to arrive (*21*), and it is also more challenging to find passengers that can share trips in this area. This spatial disparity may limit the effects of the GTT policy in terms of encouraging ride-sharing, and should be brought to the attention of planners and policymakers.

6.5 Time-of-day variation

Table 9 presents the results for both the treatment effect and the relative treatment effect (i.e. the ratio of the treatment effect to the corresponding average TNC ridership in the pre-pandemic period). We find that for the downtown pickup trips, the GTT policy induces a larger effect during the evening rush hours compared with the morning rush hours. Conversely, for the downtown dropoff trips, the policy generally induces a larger effect during the morning rush hours regarding the total and single trips, whereas the effects on the shared trips are relatively the same during these two periods.

In terms of the relative treatment effect, we find that it generally remains stable between the morning and evening rush periods for total and single trips. For shared trips, the relative treatment effects are higher for the morning pickup trips and evening dropoff trips. This result indicates that the policy is more effective in encouraging trip sharing for off-peak travels (i.e. trips coming out of the Downtown Zone in the morning rush and trips entering the Downtown Zone in the evening rush) than peak-time travels, which makes intuitive sense as riders making off-peak travels may have a higher travel time tolerance, thus are associated with a higher probability of taking the shared rides.

TABLE 9: Estimated treatment effects during the morning rush and evening rush periods

	Pickup Trips			Dropoff Trips		
	Count: total	Count: shared trips	Count: single trips	Count: total	Count: shared trips	Count: single trips
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effects:						
Morning rush	-64.402^{***}	14.416^{***}	-78.818^{***}	-93.987^{***}	27.102^{***}	-121.090^{***}
	(9.119)	(2.112)	(10.304)	(30.039)	(7.370)	(36.128)
Evening rush	-89.519^{***}	29.329^{***}	-118.847^{***}	-72.115^{***}	27.837^{***}	-99.952^{***}
	(17.256)	(5.373)	(21.285)	(10.149)	(4.441)	(13.367)
Relative treatment effects:						
Morning rush	−0.098	0.185	−0.136	−0.088	0.143	−0.138
Evening rush	−0.075	0.145	−0.121	−0.071	0.202	−0.115

Note: Standard errors in parentheses are clustered on census tracts. The relative treatment effects are the ratios of estimated treatment effects to the average TNC ridership in the pre-pandemic period. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

7. LIMITATIONS AND FUTURE RESEARCH

In this section, we identify several limitations of our work and propose future research directions accordingly. First, one key limitation of this study is the relatively short post-intervention period we can analyze. Following the adoption of widespread policies to limit the spread of COVID-19 in March 2020, TNC ridership in Chicago changed dramatically, thus could not be used to study the GTT treatment effect. Though we show evidence of the policy effects on TNC ridership in the GTT-impacted areas pre-pandemic, whether these effects will persist after the pandemic is over remains to be seen. Therefore, once TNC ridership reaches a post-pandemic normal, analysis could be conducted to examine the GTT effects on TNC ridership in the post-pandemic world. In that way we can see if the policy effects we find in this research are long-term effects or only reflect the transient state of response to the policy.

Secondly, though we have empirically quantified the causal effect of the GTT policy at the aggregate level, it remains unclear how the policy effects vary across populations. Our study has examined the income and racial variations of the policy effect at the zonal level, but disaggregate analyses can provide more granular insights into what population segments were more likely to be affected by the policy, and how different populations reacted to the policy. As such, qualitative analysis methods such as interviews, focus groups and surveys can be deployed to develop an in-depth understanding of TNC users' attitudes and behaviors regarding the GTT policy.

Thirdly, as stated by the City of Chicago, the GTT policy was deployed to "combat the plague of congestion, promote sustainable forms of transportation and support our essential public transit system, while making shared rides cheaper in the neighborhoods" (*7*). As such, future research can explore whether the deployment of GTT influenced trips related to other travel modes such as public transit and bikesharing. In addition, the fact that the GTT-impacted areas saw fewer TNC trips does not necessarily mean that congestion in the downtown areas was alleviated. Therefore, future research can also look into the association between the GTT adoption and congestion levels in the downtown areas. In this regard, future research should also examine what proportion of the increased shared TNC trips requested by the passengers were successfully matched, since the unsuccessfully matched shared trips are no different from single-occupant trips regarding their impacts on congestion and pollution (*46*). Besides, it will also add great value if future research could explore the impacts of the policy on people's travel mode choice and their consumer surplus, which may enable a better assessment of whether the surcharge is socially beneficial or not.

Fourth, this study considered only the effects of surcharge, not total price of trips, which TNCs vary dynamically. TNCs could have reduced their pricing to offset the effective surcharge borne by passengers. Further research into the salience of the different pricing components (e.g. separately shown tax), as well as their effects on the pickup and dropoff location choices, could be fruitful.

8. CONCLUSION

Congestion pricing of TNC services has become an emerging tool to cope with the negative externalities of TNCs, but the effectiveness of this policy initiative has been understudied (*41*). In this paper, we contribute to the existing literature by quantifying the effects that Chicago's congestion pricing policy has had on TNC ridership using a Difference-in-Differences estimation strategy. Our preferred model indicates that the implementation of GTT policy is associated with an average of 213 fewer daily TNC pickup trips and 230 fewer daily TNC dropoff trips per census tract, for downtown census tracts in GTT-impacted areas. These numbers translate to about 7.1% and 7.7% reductions of total daily TNC trips for pickup trips and dropoff trips respectively. The result of our parallel trend examination shows that the difference in TNC ridership between the treatment and control groups after the GTT was implemented was not due to the systematic difference between the two groups in the pre-treatment period. Based on the estimated policy effects, we get that the price elasticity of the TNC trip volume in the congestion pricing zone is roughly -0.48.

To test the robustness of our DID estimations, we employ three strategies. First, we test the sensitivity of our estimated policy effects to the control group boundary. Second, we conduct our DID estimation by including only the treated and control census tracts that are close to the boundary of the GTT-impacted areas, so as to make sure the location differences of census tracts between the treatment and control groups are tiny. Third, we select the treatment and control groups based not on geographic coverage, but on the day of week characteristics. Since the Downtown Zone surcharge was only in effect on workdays, we use weekend TNC trip data for GTT-impacted census tracts as the control group, and workday TNC trip data for the same set of census tracts as the treatment group, thus eliminating the potential endogeneity that may arise from the spatially-related omitted variables. In all these alternative specifications, we find that the estimated policy effects are still significant. The magnitudes of the estimated effects do not significantly differ from our main DID estimation, except for the near-boundary estimation which gives a treatment effect that is about half of the treatment effect derived from the main model. These results show the robustness of our main DID estimation.

In terms of spatial heterogeneity, we examine how the influences of the GTT policy on the number of TNC trips that began or ended in the GTT-impacted areas vary across seven regions of Chicago, and find that the treatment effects are significant for most of the regions. Across all regions, the treatment effects were the largest in the Central region. Between the GTT impacted areas and the south side of Chicago, which has greater populations of low-income and African-American people, there was a relatively large percent reduction in single TNC trips and a relatively small percent increase in shared TNC trips due to the GTT. The lack of effectiveness in encouraging shared rides between downtown and the south side may be attributable to longer trips or lower TNC supply in these regions. Regarding the time-of-day variation, we find that the GTT reduces more pickup trips in the evening rush than in the morning rush, and reduces more dropoff trips in the morning rush than in the evening rush. With respect to the relative treatment effect, our result indicates that the GTT is more effective in encouraging trip sharing for off-peak travels than peak-time travels.

As cities identify negative externalities from relatively new TNC services (such as low vehicle occupancy, mode shift away from sustainable alternatives, use of valuable downtown curb space, and contribution to increased traffic congestion and thereby worsened bus speed and reliability), they will need to react to mitigate these downsides while realizing the potential benefits of expanded mobility options. Chicago's GTT pricing initiative provides a leading North American example of a responsive policy that was spatially targeted. However, since the GTT was first proposed, the response to this new fee was mixed. At the time of the tax's implementation, some downtown residents voiced frustration with the new pricing scheme, calling it a "revenue grab" by the city which would have little impact on travel choices (*28*). Sustainable transportation advocates generally applauded the initiative, stating that it would encourage riders to switch to more sustainable options such as shared TNC trips and transit services (*16*). Though there have been heated debates surrounding the policy, no previous studies have empirically estimated the impact of the policy on urban transportation. Our research provides valuable evidence that the GTT effectively disincentivized single TNC trips and promoted shared TNC trips. By quantifying the TNC ridership effect of the GTT, our findings can be used to assess the impacts of the initiative and to provide feedback which might be incorporated into future adjustments to the policy. In terms of the policy goals, our results show that the GTT successfully incentivized trip sharing to and from the Downtown Zone, and though we were not able to measure the policy-induced traffic congestion change due to the data unavailability, we assume that the GTT also helped alleviate downtown traffic congestion to some degree by reducing the total TNC trips.

This research has two additional policy implications. First, our results show that, though in general, the GTT has incentivized shared TNC trips to and from the downtown areas, the stimulation of shared rides between the South side of Chicago and the downtown areas is limited, whereas the discouragement of single trips is relatively large. If the City of Chicago wants to encourage TNC pooling in the disadvantaged regions, it can consider reducing the GTT for shared downtown TNC trips that began or ended in the disadvantaged regions. Second, beyond Chicago's borders, the analysis framework presented in this paper could be used to the benefit of many cities who hope to address pressing challenges such as traffic congestion, inequities in transportation, and the allocation of roads and other public spaces as finite resources. While many policies are designed with stated goals of addressing these challenges, the Difference-in-Differences approach in this paper provides a means of retrospectively understanding whether the policy achieved its goals.

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APPENDIX

A.1 Descriptive statistics for the data used in the alternative DID specification

Table 10 summarizes the statistics of the data used in Section 5.2.3, where only the census tracts in the treatment area shown in Figure 3a are considered. The TNC trips took place on workdays (Monday - Friday) form the treatment group, whereas the TNC trips took place on weekends form the control group.

TABLE 10: Descriptive statistics with treatment and control groups defined based on day of week

Name	Mean	Std.dev	Min	Max
Number of daily pick-up trips				
Workdays, pre-intervention (n=8033)				
Total trips	2980.40	2568.96	144	16725
Shared trips	421.74	427.20	25	3585
Single trips	2558.67	2220.33	117	15177
Workdays, post-intervention (n=1247)				
Total trips	2807.66	2550.56	248	15830
Shared trips	330.14	290.20	29	1709
Single trips	2477.52	2276.05	189	14163
Weekends, pre-intervention (n=3422)				
Total trips	2614.32	1817.44	62	13237
Shared trips	292.85	233.14	5	1919
Single trips	2321.47	1649.32	57	11864
Weekends, post-intervention (n=522)				
Total trips	2493.17	1773.07	84	9509
Shared trips	189.04	133.93	5	637
Single trips	2304.12	1662.64	78	8906
Number of daily drop-off trips				
Workdays, pre-intervention (n=8033)				
Total trips	3102.65	3141.83	78	21567
Shared trips	446.95	487.87	15	4418
Single trips	2655.70	2719.63	58	18349
Workdays, post-intervention (n=1247)				
Total trips	2916.59	3015.80	226	20468
Shared trips	349.63	340.87	27	2303
Single trips	2566.96	2687.11	188	18165
Weekends, pre-intervention (n=3422)				
Total trips	2745.66	2109.51	66	15657
Shared trips	324.22	267.66	2	2064
Single trips	2421.44	1906.84	61	14184
Weekends, post-intervention (n=522)				
Total trips	2646.54	2105.20	68	12649
Shared trips	210.91	162.89	2	721
Single trips	2435.63	1969.79	64	11928
Weather (days=320)				
Precipitation (tenths of mm)	0.12	0.26	0	1.77

A.2 Descriptive statistics for regional TNC trip data

Table 11 and 12 report the summary statistics of the TNC trips by region. Table 11 shows the results for the treated tracts, whereas Table 12 shows the results for the control tracts. To clarify, in Table 11, the left panel describes the number of trips originated in treated tracts for different regions. For instance, “Central, pre-intervention” in the left panel summarizes the total number of daily trips that originated in treated tracts and ended in central regions during the pre-intervention period, divided by the number of treated tracts. In the right panel, “Central, pre-intervention” summarizes the total number of daily trips that originated in central regions and ended in treated tracts during the pre-intervention period, divided by the number of treated tracts.

TABLE 11: Descriptive statistics for TNC trips originated/ended in treated tracts by region

Name	Mean	Std.dev	Min	Max	Name	Mean	Std.dev	Min	Max
Number of trips originated in treated tracts					**Number of trips ended in treated tracts**				
Central, pre-intervention (n=7975)					*Central, pre-intervention (n=7975)*				
Total trips	1292.29	1068.44	110	7412	Total trips	1301.39	1364.29	33	10202
Shared trips	138.89	137.30	6	1356	Shared trips	138.97	157.38	2	1490
Single trips	1153.40	957.22	92	6770	Single trips	1162.26	1228.69	24	9310
Central, post-intervention (n=1247)					*Central, post-intervention (n=1247)*				
Total trips	1196.96	1034.75	98	7247	Total trips	1212.23	1287.50	94	8943
Shared trips	118.19	99.34	11	711	Shared trips	119.49	117.74	10	848
Single trips	1078.77	939.51	74	6536	Single trips	1092.74	1172.50	79	8095
North, pre-intervention (n=7975)					*North, pre-intervention (n=7975)*				
Total trips	420.37	385.43	17	2647	Total trips	454.46	477.12	13	3717
Shared trips	70.04	73.47	1	591	Shared trips	70.98	80.47	0	1150
Single trips	350.33	325.63	11	2329	Single trips	383.42	407.86	8	3023
North, post-intervention (n=1247)					*North, post-intervention (n=1247)*				
Total trips	400.26	401.32	38	2397	Total trips	417.19	451.27	26	2788
Shared trips	50.51	46.83	1	270	Shared trips	50.53	51.11	1	287
Single trips	349.75	357.48	27	2148	Single trips	366.66	402.52	20	2516
Northwest, pre-intervention (n=7975)					*Northwest, pre-intervention (n=7975)*				
Total trips	235.11	246.58	9	1848	Total trips	216.08	221.78	4	1389
Shared trips	25.23	26.22	0	312	Shared trips	27.53	27.59	0	327
Single trips	209.89	225.64	7	1604	Single trips	188.50	198.56	4	1291
Northwest, post-intervention (n=1247)					*Northwest, post-intervention (n=1247)*				
Total trips	219.55	249.76	12	1730	Total trips	207.48	220.59	8	1356
Shared trips	18.58	18.53	0	185	Shared trips	20.84	20.25	0	160
Single trips	200.97	233.28	12	1628	Single trips	186.64	202.36	7	1285
West, pre-intervention (n=7975)					*West, pre-intervention (n=7975)*				
Total trips	627.56	598.93	39	4151	Total trips	676.42	762.57	17	5182
Shared trips	102.40	114.88	1	1066	Shared trips	111.32	135.03	1	1397
Single trips	525.16	502.04	24	3506	Single trips	565.02	642.97	12	4342
West, post-intervention (n=1247)					*West, post-intervention (n=1247)*				
Total trips	617.49	616.89	44	3699	Total trips	661.36	763.92	41	5061
Shared trips	83.54	83.54	2	492	Shared trips	89.63	98.79	3	688
Single trips	533.95	535.92	34	3207	Single trips	571.74	666.94	28	4373
South, pre-intervention (n=7975)					*South, pre-intervention (n=7975)*				
Total trips	56.68	74.81	0	516	Total trips	71.81	102.52	0	776
Shared trips	19.97	30.88	0	273	Shared trips	23.75	38.08	0	377
Single trips	36.71	48.04	0	353	Single trips	48.05	68.22	0	520
South, post-intervention (n=1247)					*South, post-intervention (n=1247)*				
Total trips	55.32	70.38	0	403	Total trips	69.16	95.47	0	646
Shared trips	13.10	17.37	0	115	Shared trips	15.89	22.26	0	154
Single trips	42.22	54.16	0	320	Single trips	53.27	74.00	0	492
Southwest, pre-intervention (n=7975)					*Southwest, pre-intervention (n=7975)*				
Total trips	72.47	82.04	0	611	Total trips	80.27	90.94	0	563
Shared trips	11.10	15.71	0	140	Shared trips	13.57	18.18	0	170
Single trips	61.38	69.73	0	507	Single trips	66.69	75.80	0	454
Southwest, post-intervention (n=1247)					*Southwest, post-intervention (n=1247)*				
Total trips	56.15	67.43	0	523	Total trips	66.99	78.62	0	504
Shared trips	6.70	8.86	0	69	Shared trips	9.10	11.79	0	86
Single trips	49.45	59.65	0	461	Single trips	57.89	67.77	0	429
Far South, pre-intervention (n=7975)					*Far South, pre-intervention (n=7975)*				
Total trips	3.11	4.92	0	58	Total trips	4.64	7.34	0	78
Shared trips	1.26	2.44	0	34	Shared trips	1.68	2.97	0	34
Single trips	1.85	2.96	0	30	Single trips	2.96	4.85	0	54
Far South, post-intervention (n=1247)					*Far South, post-intervention (n=1247)*				
Total trips	3.85	5.91	0	49	Total trips	5.62	8.98	0	84
Shared trips	1.18	2.09	0	17	Shared trips	1.81	3.17	0	24
Single trips	2.67	4.21	0	33	Single trips	3.81	6.19	0	63

TABLE 12: Descriptive statistics for TNC trips originated/ended in control tracts by region

Name	Mean	Std.dev	Min	Max	Name	Mean	Std.dev	Min	Max
Number of trips ended in control tracts					**Number of trips ended in control tracts**				
Central, pre-intervention (n=6050)					*Central, pre-intervention (n=6050)*				
Total trips	17.53	23.62	0	332	Total trips	17.07	23.26	0	381
Shared trips	3.24	4.12	0	57	Shared trips	3.05	3.84	0	34
Single trips	14.29	20.96	0	275	Single trips	14.03	20.75	0	369
Central, post-intervention (n=946)					*Central, post-intervention (n=946)*				
Total trips	15.04	20.98	0	239	Total trips	15.88	24.67	0	330
Shared trips	1.93	2.68	0	29	Shared trips	1.87	2.54	0	21
Single trips	13.11	19.11	0	211	Single trips	14.02	22.80	0	309
North, pre-intervention (n=6050)					*North, pre-intervention (n=6050)*				
Total trips	75.25	111.54	0	798	Total trips	73.95	116.06	0	965
Shared trips	14.04	17.98	0	124	Shared trips	13.09	17.37	0	129
Single trips	61.21	97.06	0	734	Single trips	60.86	101.83	0	854
North, post-intervention (n=946)					*North, post-intervention (n=946)*				
Total trips	69.81	102.46	0	655	Total trips	68.47	105.55	0	749
Shared trips	8.55	10.57	0	56	Shared trips	7.54	9.22	0	57
Single trips	61.26	93.06	0	615	Single trips	60.93	97.35	0	703
Northwest, pre-intervention (n=6050)					*Northwest, pre-intervention (n=6050)*				
Total trips	39.60	50.99	0	818	Total trips	35.32	37.67	0	278
Shared trips	6.28	7.33	0	119	Shared trips	6.18	6.53	0	47
Single trips	33.32	45.91	0	710	Single trips	29.13	32.76	0	252
Northwest, post-intervention (n=946)					*Northwest, post-intervention (n=946)*				
Total trips	37.54	45.36	0	778	Total trips	35.76	38.86	0	473
Shared trips	4.09	4.60	0	26	Shared trips	4.16	4.40	0	26
Single trips	33.45	42.30	0	761	Single trips	31.60	35.57	0	447
West, pre-intervention (n=6050)					*West, pre-intervention (n=6050)*				
Total trips	82.85	75.10	0	606	Total trips	89.19	98.33	0	745
Shared trips	22.58	28.37	0	285	Shared trips	23.34	30.92	0	316
Single trips	60.27	52.95	0	348	Single trips	65.85	72.68	0	617
West, post-intervention (n=946)					*West, post-intervention (n=946)*				
Total trips	85.10	81.72	0	480	Total trips	92.24	106.85	0	621
Shared trips	15.15	17.55	0	118	Shared trips	15.71	19.13	0	114
Single trips	69.95	66.08	0	379	Single trips	76.53	89.15	0	540
South, pre-intervention (n=6050)					*South, pre-intervention (n=6050)*				
Total trips	11.63	15.98	0	229	Total trips	13.25	19.68	0	228
Shared trips	5.01	7.19	0	82	Shared trips	5.25	7.89	0	58
Single trips	6.62	9.86	0	148	Single trips	8.00	12.78	0	174
South, post-intervention (n=946)					*South, post-intervention (n=946)*				
Total trips	11.45	15.48	0	164	Total trips	13.25	19.75	0	211
Shared trips	3.23	4.56	0	28	Shared trips	3.71	5.67	0	34
Single trips	8.22	11.54	0	136	Single trips	9.55	14.68	0	177
Southwest, pre-intervention (n=6050)					*Southwest, pre-intervention (n=6050)*				
Total trips	15.57	26.10	0	368	Total trips	16.35	23.37	0	230
Shared trips	3.86	5.85	0	58	Shared trips	4.38	6.34	0	48
Single trips	11.71	22.54	0	345	Single trips	11.97	18.82	0	207
Southwest, post-intervention (n=946)					*Southwest, post-intervention (n=946)*				
Total trips	13.00	17.47	0	210	Total trips	14.78	20.15	0	163
Shared trips	2.39	3.62	0	22	Shared trips	2.95	4.53	0	28
Single trips	10.61	14.97	0	201	Single trips	11.83	16.79	0	158
Far South, pre-intervention (n=6050)					*Far South, pre-intervention (n=6050)*				
Total trips	1.00	2.03	0	19	Total trips	1.39	2.82	0	38
Shared trips	0.47	1.10	0	13	Shared trips	0.60	1.35	0	14
Single trips	0.53	1.26	0	12	Single trips	0.79	1.81	0	30
Far South, post-intervention (n=946)					*Far South, post-intervention (n=946)*				
Total trips	1.45	2.84	0	19	Total trips	1.91	3.81	0	22
Shared trips	0.53	1.21	0	9	Shared trips	0.61	1.34	0	9
Single trips	0.92	1.94	0	13	Single trips	1.30	2.78	0	19

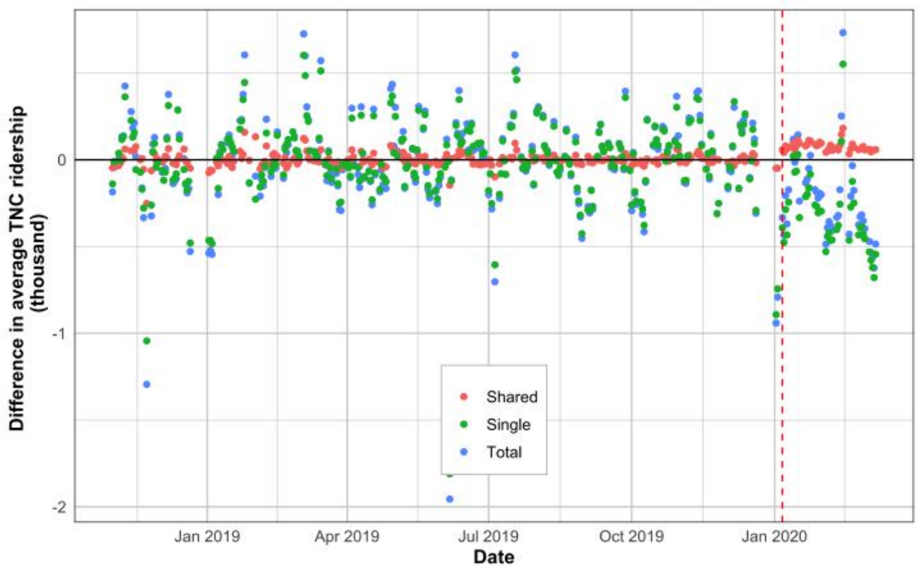

FIGURE 10: Difference in TNC dropoff trip counts between the treatment and control groups, after controlling for trend, trend × treatment, precipitation and all the fixed effects

A.3 Parallel trend examination for TNC dropoff trips analysis in the main DID estimation

Based on the estimation results for the dropoff trips using the main DID specification (Table 4), Figure 10 plots the difference in dropoff trip counts between the treatment and control groups over the study period while factoring out the control variables including trend, trend × treatment, precipitation and all the fixed effects. Similar to the results for the pickup trips, all three subfigures in Figure 10 show that prior to the implementation of the GTT on Jan 6, 2020, which is denoted by the red dotted vertical line, the ridership differences between the treatment and control groups were quite stable and centered around zero, which verifies the parallel trend assumption. After Jan 6, 2020, the treatment group began to show a reduction in ridership compared with the control group regarding the total TNC trips (the blue dots) and the single TNC trips (the green dots), whereas the shared TNC trips began to show a relative increase in trip counts for the treatment group as indicated by the red dots.

A.4 Parallel trend examination for TNC dropoff trip analysis in the alternative DID estimation

Based on the estimation results for the dropoff trips with the alternative DID specification, Figure 11 plots the difference in daily average TNC pickup trip counts between workdays and weekends grouped by weeks over the study period, while factoring out the control variables including trend, trend × treatment, precipitation and all the fixed effects. Similar to the results for the pickup trips, all three subfigures in Figure 11 show that prior to the implementation of the GTT on Jan 6, 2020, which is denoted by the red dotted vertical line, the ridership differences between the treatment and control groups were quite stable and centered around zero, which verifies the parallel trend assumption. After Jan 6, 2020, the treatment group began to show a reduction in ridership compared with the control group regarding the total TNC trips (the blue dots) and the single TNC trips (the green dots), whereas the shared TNC trips began to show a relative increase in trip counts for the treatment group as indicated by the red dots.

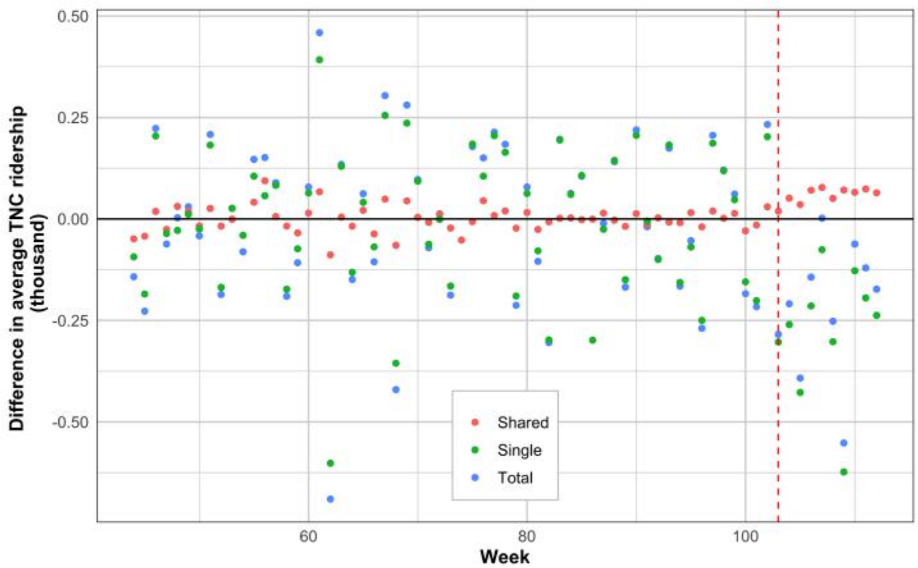

FIGURE 11: Difference in daily average TNC dropoff trip counts between workdays and weekends, after controlling for trend, trend × treatment, precipitation and all the fixed effects

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