Final Report

# Impact OF COVID-19 on Ridehailing and Other Modes of Transportation

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**16. Abstract**

During the COVID pandemic, a large drop in travel was observed all around the world due to stay-in-place and quarantine orders. Because travelers were concerned about sharing space with others, public transit and ridesharing travel was affected significantly during the pandemic. Bikeshare, a travel mode in open space that can easily maintain the needed social distancing, may become a mode of choice under these special circumstances. In this report, we used the bikeshare data from the City of Chicago in 2019 and 2020 to study the variation in bike trip frequencies, trip lengths, spatial distribution prior to and during the pandemic, and the potential interaction of bikeshare travels and public transit during the pandemic. Our conclusions show that during the pandemic, bikeshare trips rebounded more quickly than other travel modes. The bikeshare trips also increased in length, especially for subscribers, and most trips occurred during peak hours. Spatial analysis showed that travelers used bikeshare more extensively across the city compared to trip patterns prior to the pandemic. About 35% of bikeshare stations that were heavily used were found to be isolated from transit bus stations. About 10% of them were co-located with commuter rail stations. To investigate the intercorrelation of bikeshare with other non-mobile modes, bikeshare data in Chicago on weather-friendly days in 2019 and 2020 were analyzed to investigate the variation in bikeshare travel before and during the pandemic. Our results show that bikeshare trips during the pandemic were much longer than those prior to the pandemic. The increased rate of bikeshare usage was unbalanced spatially and varied significantly for different user types. Bikeshare was used significantly more by casual users than by subscribers, and the increase occurred much more in the outskirts of the city. The increase in bikeshare travel was associated with a reduction in travel by ridehailing and public transit, especially in the urban periphery. The correlation of bikeshare use with the bus system was much less significant than with the rail system. Bike lanes/facilities had a mixed effect on bikeshare travel. Weekend bike trips increased in areas where there was no bike lane. Weekday trips, on the contrary, increased in the vicinity of bike greenways.

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## ABSTRACT

During the COVID pandemic, a large drop in travel was observed all around the world due to stay-in-place and quarantine orders. Because travelers were concerned about sharing space with others, public transit and ridesharing travel was affected significantly during the pandemic. Bikeshare, a travel mode in open space that can easily maintain the needed social distancing, may become a mode of choice under these special circumstances. In this report, we used the bikeshare data from the City of Chicago in 2019 and 2020 to study the variation in bike trip frequencies, trip lengths, spatial distribution prior to and during the pandemic, and the potential interaction of bikeshare travels and public transit during the pandemic. Our conclusions show that during the pandemic, bikeshare trips rebounded more quickly than other travel modes. The bikeshare trips also increased in length, especially for subscribers, and trips occurred during the peak hours. Spatial analysis showed that travelers used bikeshare more extensively across the city compared to trip patterns prior to the pandemic. About 35% of bikeshare stations that were heavily used were found to be isolated from transit bus stations. About 10% of them were co-located with commuter rail stations. To investigate the intercorrelation of bikeshare with other non-mobile modes, bikeshare data in Chicago on weather-friendly days in 2019 and 2020 were analyzed to investigate the variation in bikeshare travel before and during the pandemic. Our results show that bikeshare trips during the pandemic were much longer than those prior to the pandemic. The increased rate of bikeshare usage was unbalanced spatially and varied significantly for different user types. Bikeshare was used significantly more by casual users than by subscribers, and the increase occurred much more in the outskirts of the city. The increase in bikeshare travel was associated with a reduction in travel by ridehailing and public transit, especially in the urban periphery. The correlation of bikeshare use with the bus system was much less significant than with the rail system. Bike lanes/facilities had a mixed effect on bikeshare travel. Weekend bike trips increased in areas where there was no bike lane. Weekday trips, on the contrary, increased in the vicinity of bike greenways.

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# I. Table of Contents

## II. List of Figures

## III. List of Tables

# Chapter 1: Changes in Bikeshare Travel Behavior during the COVID-19 Pandemic: The Chicago Case Study

## INTRODUCTION

Bikeshare has developed rapidly during the last couple of decades, with the number of cities in the world that offer bikeshare services increasing from less than 10 to almost 1,000 [1]. In the U.S. there were 35 million bikeshare trips in 2017 and this number jumped to 84 million in 2018 [2, 3]. Currently, more than 100 cities in the U.S. offer bikeshare services.

Numerous bikeshare studies have been conducted to better understand user behavior and design a bikeshare system that can better serve travel needs. Previous bikeshare-related research has investigated topics including usage patterns, user profiles, barriers to using bikeshare as a routine transportation mode, factors affecting bikeshare usage, fleet rebalancing, bikeshare planning, access analysis, etc. [4-11]. The COVID-19 pandemic started to hit the U.S. in March 2020. During the pandemic, traffic volumes around the world dropped dramatically as non-essential travel was curtailed by governments [12-14]. People who had to travel, such as essential workers, were concerned about the risk of contagion when they used public transit or any other vehicles in which they shared an enclosed space with other passengers.

During the pandemic, bikeshare showed its advantage. A unique feature of the bike mode is that bikers are in the open air and naturally keep a social distance from other travelers. Recent research has sought to investigate changes in bikeshare usage patterns relative to other travel modes in response to the pandemic. Wang and Noland found that while both subway ridership and bikeshare usage plummeted initially, bikeshare usage has nearly returned to normal while subway ridership remains substantially below pre-COVID levels [15]. Their conclusions indicate the potential that bikeshare has as an alternative travel mode during the pandemic given that bikers will naturally distance themselves from other people while riding. In this report, we will concentrate on the variation in bikeshare travel during the pandemic by investigating trip frequency, trip lengths, spatial distributions, and the potential interaction between bikeshare travel and other modes including ridehailing during the pandemic in order to better understand bikeshare travel during the pandemic and propose recommendations to help administrators design a better bikeshare system.

## DATA SOURCES

Table 1 illustrates the data sources used in this report. Bikeshare data were obtained from DIVVY®. Data from 2019 were downloaded from the City of Chicago Data Portal,[1] and the data from 2020 were downloaded from the DIVVY website[2]. Weather data were obtained from GHCN (Global Historical Climatology Network), a composite of climate databases from numerous sources that were merged and then subjected to a suite of quality assurance reviews. The archive includes over 40 meteorological elements, including daily temperature maximum/minimum, precipitation, snowfall, snow depth, evaporation, wind speed, wind maximums, etc.[3] Weather data from two airports (Chicago Midway Airport and Chicago O'Hare International Airport) were selected from multiple weather observation stations and integrated to fill in missing data. To help us understand the changes in bikeshare traveling

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[1] https://data.cityofchicago.org/browse?category=Transportation
[2] https://divvy-tripdata.s3.amazonaws.com/index.html
[3] https://www.ncdc.noaa.gov/ghcn-daily-description

associated with other modes, we also incorporated three other non-personal-vehicle travel modes as comparison baselines: L' stations (passenger rails)[4], buses, and trips served by Transportation Network Companies (TNCs, such as Uber and Lyft), aka ridehailing. These data were downloaded from the Chicago Data Portal as well.

*Table 1 Data Sources and Descriptions*

| DATA | DESCRIPTION | NOTES |
|---|---|---|
| **DIVVY BIKE DATA** | Trip start-end time stamps, locations, user/non-user, bike IDs, number of docks | 2019 – 2020<br>7.4 million |
| **WEATHER DATA** | Daily wind, precipitation, snow depth, temperature, special weather | 2019 – 2020 |
| **L-STATION DAILY RIDERSHIP** | Daily total ridership by L-station | 2019 – 2020<br>238.3 million |
| **BUS DAILY RIDERSHIP** | Daily total ridership by bus routes | 2019 – 2020<br>348.6 million |
| **TNC DAILY RIDERSHIP** | Trip start-end time stamps, locations, fare, number of passengers, etc. | 2019 – 2020<br>154.8 million |

Since previous literature has proven that the travel behavior around the world was heavily affected by local COVID-19 polices, such as shelter in place commands and stay at home orders [15], we included the dates of important COVID-related orders issued in Chicago in our analysis. The dates were obtained from the Department of Health website[5].

*Table 2 Important COVID Dates in Chicago*

| TIME PERIOD | DATES | |
|---|---|---|
| **1** | Before 3/18/2020 | Pre-pandemic |
| **2** | 3/18/2020 | Shelter in Place |
| **3** | 3/26/2020 | Stay-at-home Executive Order - State |
| **4** | 4/8/2020 | Cessation of Alcoholic Liquor Sale |
| **5** | 5/1/2020 | Applying Stay-at-Home Executive Order - City |
| **6** | 7/24/2020 | Gradually resume |
| **7** | 10/23/2020 | Curfew for non-essential business 10pm to 6am - Re-tightening of COVID 19 restrictions |
| **8** | 11/12/2020 | STAY-AT HOME-ADVISORY |

## Data Exploration

During the COVID-19 pandemic, the world observed a dramatic drop in the traffic volumes for all transit modes, with an estimated 40% to 60% reduction in travel volume reported globally [12]. While this overall reduction was similar across the world for personal vehicles, the reduction and variation of bikeshare travel remains unclear: did bikeshare travel have a similar reduction as other travel modes?

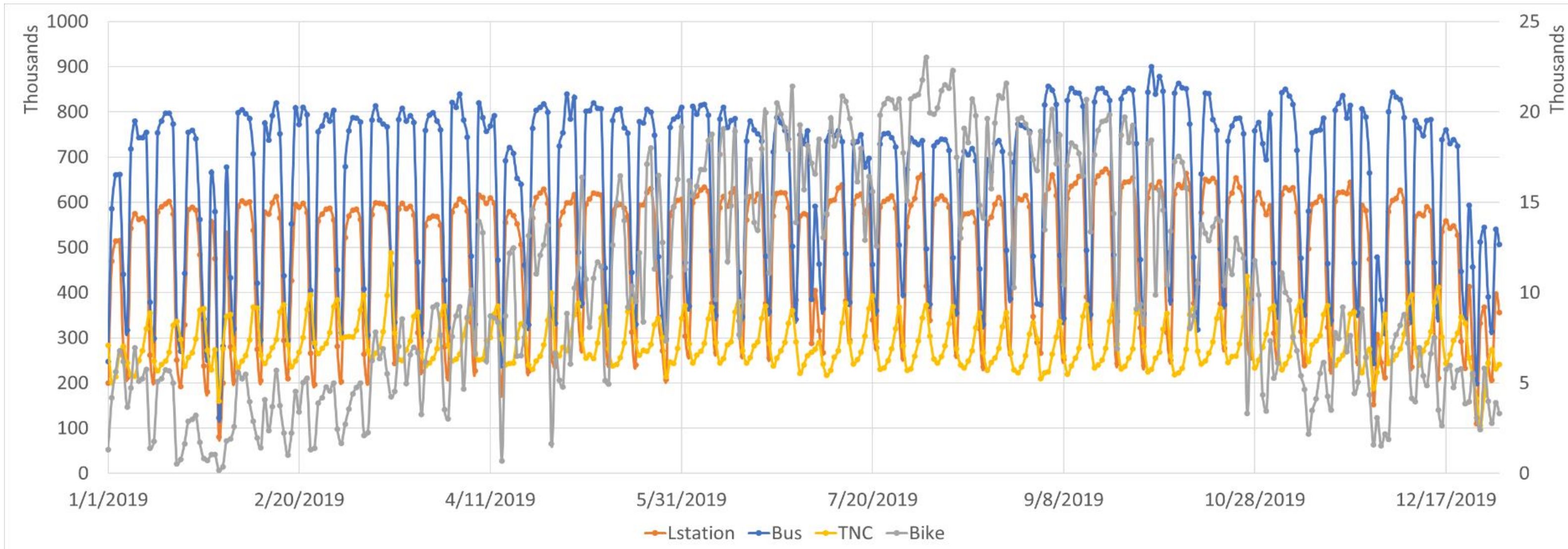
[4] CTA's train system is known as the 'L' (a now-official name originally short for "elevated")
[5] https://www.chicago.gov/city/en/sites/covid-19/home/health-orders.html

How likely were travelers to use bikes as an alternative travel mode when other modes have potential risks of contagion in a closed shared space?

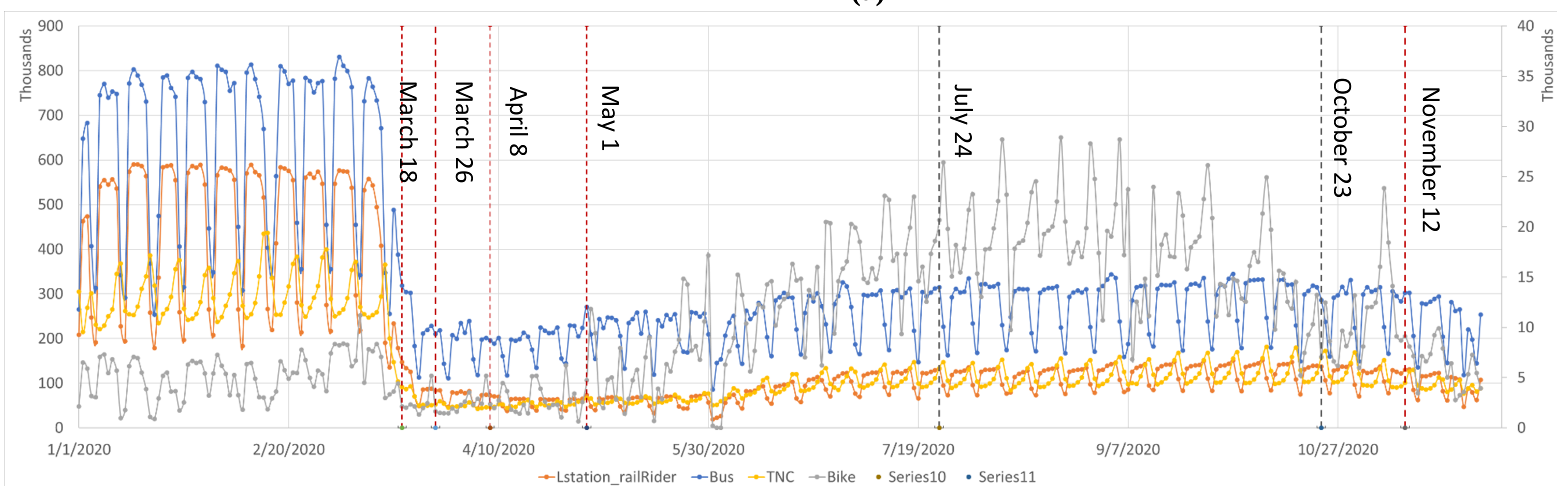
The number of trips made using different travel modes from 2019 – 2020 were plotted in

Figure 1. As the figure demonstrates, travel by buses, rails, and TNCs were consistent through all of 2019. Bikeshare travel, on the contrary, exhibited seasonal variation, with ridership being low in the first couple of months of the year and rising during the warmer months. Bikeshare volume peaked from July to September and dropped when the temperature decreased in winter. When the COVID-19 pandemic started in March of 2020, all travel modes dropped significantly. Like other modes, bikeshare travel remained low until May. While the other modes stayed low; however, bikeshare travel started to increase dramatically, with bike volumes peaking around July and August and remaining high until October. Another peak occurred in November before volumes dropped back to a low level. The bike trips during 2019 and 2020 were then plotted in Figure 2 (a). As the graph indicates, bikeshare travels were significantly higher in 2020 than in 2019 from July to November. These observations indicate that travelers were more likely to switch to bikeshare from other modes during the pandemic. Previous studies have found that subscribers and casual users typically have different travel patterns [1, 16, 17]. Our observations, represented in Figures 2(b) and Figure 2(c), illustrated the travel patterns of subscribers and casual users[6]. Subscribers, indeed, traveled less in 2020 during the pandemic than in 2019. The casual users of bikeshare traveled a lot more. In our next section analysis, we will divide the data into subscribers and casual users to illustrate the differences.

[6] For the DIVVY bike users, subscribers pay $9 per month and the first 45 minutes of a trip will be covered by the membership fee. Additional time will be charged by $0.15 per minute. Casual users pay $3.3 a trip or $15 a day.

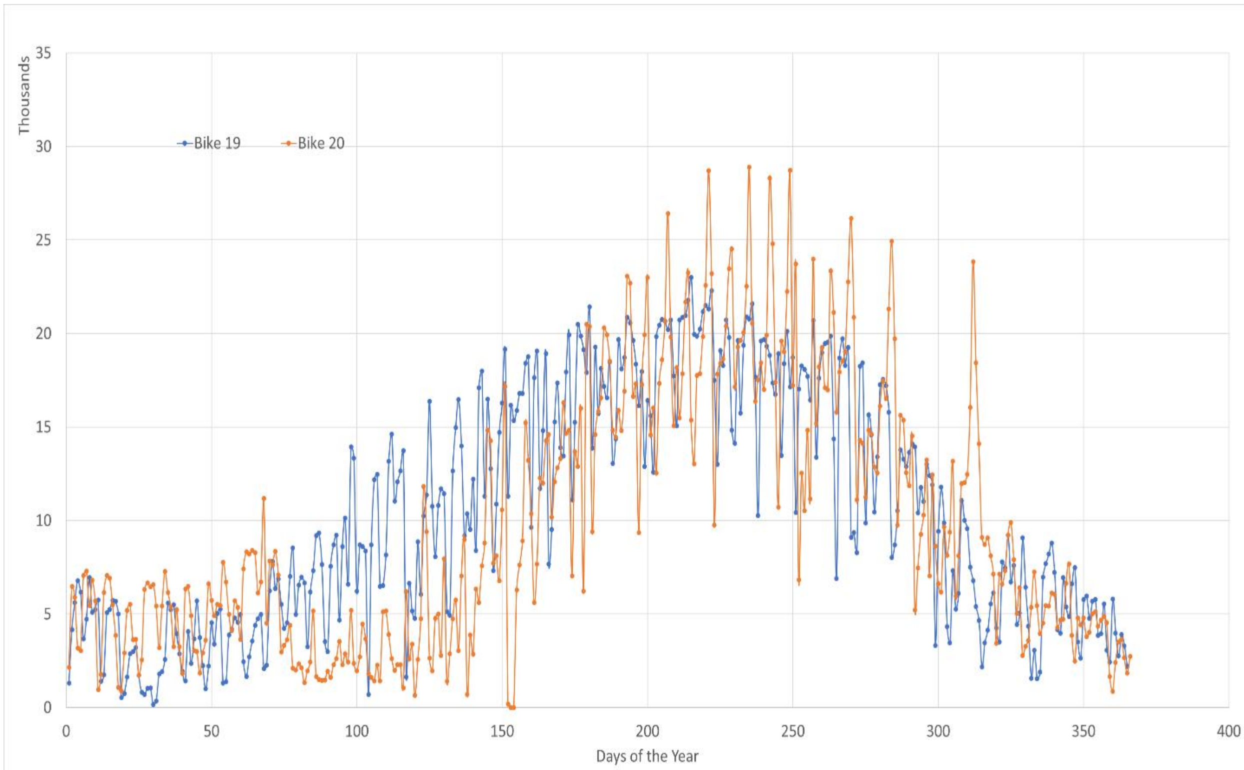



**(a)**




**(b)**

Figure 1 Trip Trend by Modes in 2019 (a) and 2020 (b)


Thousands
35
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20
15
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Bike 19
Bike 20
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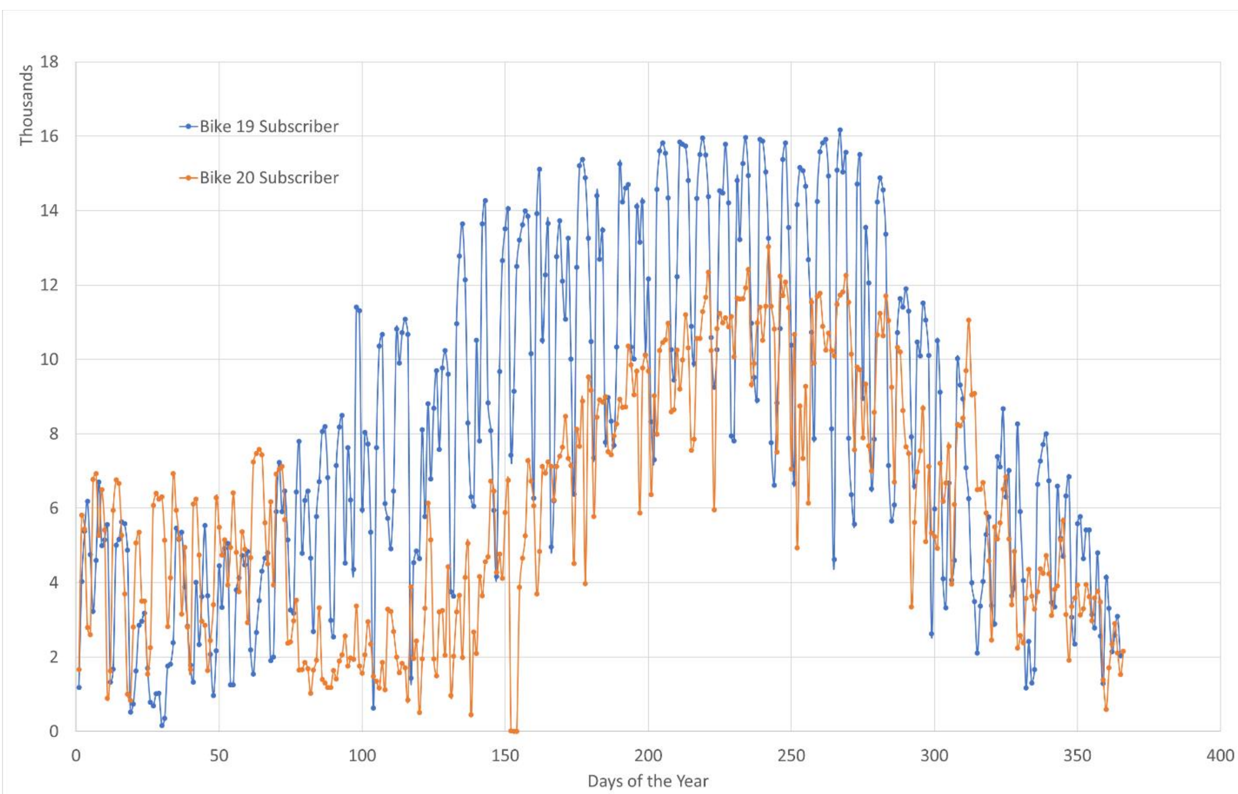
50
100
150
200
250
300
350
400
Days of the Year

(a)


Thousands
18
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Bike 20 Subscriber
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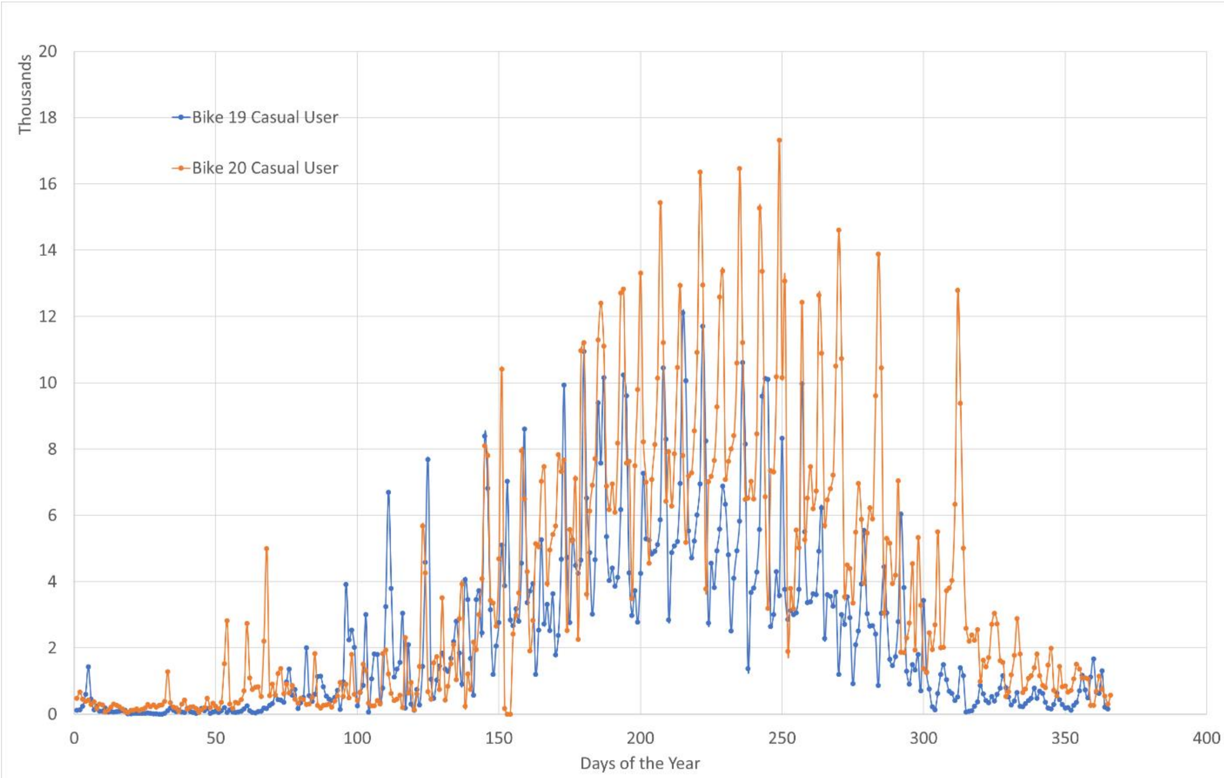
100
150
200
250
300
350
400
Days of the Year

(b)




(c)

*Figure 2 Bikeshare Travel Patterns (a) Overall Trips (b) Subscribers (c) Casual Users*

# DATA ANALYSIS AND MODELING

## Changes in Travel Frequencies and Trip Lengths

We have already asserted that bikeshare usage increased significantly and recovered more quickly during the pandemic than other modes (

Figure 1). We now want to investigate if trip lengths changed as well. A set of T-tests for all trips made by subscribers and casual users as well trips occurring during peak hours (6-10 am and 3-7 pm on weekdays) and nonpeak hours were conducted to compare the bikeshare trip lengths in 2019 versus those of 2020. The results are listed in Table 3. The results show that there was no significant difference between the trip lengths in January 2019 and January 2020. After the onset of the pandemic in March of 2020; however, travel times increased substantially, dwarfing their counterparts in 2019. The most significant increases occurred in May with the average travel time rising by 57%. The increase slowed as the weather got colder until November when the pandemic rebounded and the city issued another stay-at-home advisory (Time period 8 in Table 2). As a result, we noted an increase in trip lengths in November similar to that observed during the summer. Separating trips by subscribers and casual users, Table 3 also shows that subscribers were the primary contributors to the increase in trip lengths. They made longer trips through the pandemic while casual users made trips that were shorter than those taken before COVID. We then compared the length of trips made during peak hours and non-peak hours. While both peak hour trips and off-peak hour trips increased in 2020 compared to 2019, the increase in peak hour trips was a lot more significant than that of off-peak hour trips. Although there is no data of trip purposes available in this study, the fact that subscribers have longer, more frequent trips during peak hours may indicate that travelers used bikeshare for commuting to replace other modes during the pandemic.

*Table 3 Trip Lengths Comparison (Alpha = 0.05)*

| Month | 2019 Trips | 2019 Mean length (min) | 2020 Trips | 2020 Mean length (min) | Change | T-test | P-value |
|---|---|---|---|---|---|---|---|
| 1 | 103192 | 12.441 | 142533 | 12.287 | -1% | 1.307 | 0.191 |
| 2 | 96149 | 11.720 | 137574 | 13.557 | 16% | -14.526 | < 0.01 |
| 3 | 165536 | 13.706 | 138765 | 18.010 | 31% | -36.036 | < 0.01 |
| 4 | 265200 | 17.573 | 83621 | 24.239 | 38% | -47.281 | < 0.01 |
| 5 | 367300 | 19.526 | 197607 | 30.587 | 57% | -92.764 | < 0.01 |
| 6 | 475201 | 21.264 | 337963 | 29.407 | 38% | -81.081 | < 0.01 |
| 7 | 557048 | 22.620 | 542041 | 30.939 | 37% | -92.237 | < 0.01 |
| 8 | 589866 | 22.178 | 608736 | 26.572 | 20% | -57.243 | < 0.01 |
| 9 | 492991 | 19.624 | 521896 | 22.763 | 16% | -42.965 | < 0.01 |
| 10 | 371606 | 16.474 | 379599 | 18.952 | 15% | -31.891 | < 0.01 |
| 11 | 177054 | 13.539 | 255009 | 18.562 | 37% | -49.465 | < 0.01 |
| 12 | 155012 | 13.794 | 129422 | 15.069 | 9% | -10.599 | < 0.01 |
| **Subscriber** | | | | | | | |
| 1 | 98601 | 11.455 | 134858 | 10.831 | -5% | 6.812 | < 0.01 |
| 2 | 93522 | 11.225 | 125375 | 11.081 | -1% | 1.482 | 0.138 |
| 3 | 149659 | 11.262 | 114350 | 13.059 | 16% | -24.414 | < 0.01 |
| 4 | 217531 | 12.470 | 60264 | 18.269 | 47% | -57.980 | < 0.01 |
| 5 | 285793 | 13.235 | 111576 | 19.623 | 48% | -82.575 | < 0.01 |
| 6 | 345135 | 14.044 | 185183 | 18.556 | 32% | -68.906 | < 0.01 |
| 7 | 381615 | 14.349 | 276507 | 17.625 | 23% | -60.928 | < 0.01 |
| 8 | 403241 | 13.864 | 324954 | 16.555 | 19% | -58.221 | < 0.01 |
| 9 | 364004 | 13.184 | 295408 | 15.276 | 16% | -46.138 | < 0.01 |
| 10 | 300717 | 11.993 | 237904 | 13.938 | 16% | -37.175 | < 0.01 |
| 11 | 158401 | 11.093 | 168384 | 13.609 | 23% | -40.006 | < 0.01 |
| 12 | 138647 | 11.035 | 99808 | 12.732 | 15% | -20.994 | < 0.01 |
| **Casual User** | | | | | | | |
| 1 | 4591 | 33.620 | 7675 | 37.867 | 13% | -2.713 | < 0.01 |
| 2 | 2627 | 29.347 | 12199 | 39.000 | 33% | -5.721 | < 0.01 |
| 3 | 15877 | 36.744 | 24415 | 41.195 | 12% | -6.053 | < 0.01 |
| 4 | 47669 | 40.861 | 23357 | 39.641 | -3% | 2.474 | 0.013 |
| 5 | 81507 | 41.584 | 86031 | 44.807 | 8% | -9.794 | < 0.01 |
| 6 | 130066 | 40.423 | 152780 | 42.559 | 5% | -8.579 | < 0.01 |
| 7 | 175433 | 40.612 | 265534 | 44.803 | 10% | -20.387 | < 0.01 |
| 8 | 186625 | 40.143 | 283782 | 38.043 | -5% | 11.793 | < 0.01 |
| 9 | 128987 | 37.800 | 226488 | 32.529 | -14% | 27.719 | < 0.01 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 10 | 70889 | 35.481 | 141695 | 27.371 | -23% | 32.944 | < 0.01 |
| 11 | 18653 | 34.306 | 86625 | 28.189 | -18% | 13.355 | < 0.01 |
| 12 | 16365 | 37.169 | 29614 | 22.947 | -38% | 22.865 | < 0.01 |
| **Peak** | | | | | | | |
| 1 | 59346 | 11.539 | 86404 | 11.718 | 2% | -1.379 | 0.168 |
| 2 | 58153 | 11.338 | 72030 | 11.533 | 2% | -1.394 | 0.163 |
| 3 | 91385 | 12.432 | 66621 | 15.103 | 21% | -19.365 | < 0.01 |
| 4 | 141261 | 14.475 | 29167 | 21.061 | 46% | -38.334 | < 0.01 |
| 5 | 176425 | 15.620 | 55860 | 25.664 | 64% | -58.640 | < 0.01 |
| 6 | 212068 | 17.171 | 112062 | 25.589 | 49% | -62.706 | < 0.01 |
| 7 | 240186 | 17.966 | 185132 | 25.401 | 41% | -65.267 | < 0.01 |
| 8 | 256203 | 17.246 | 191165 | 21.972 | 27% | -48.742 | < 0.01 |
| 9 | 229556 | 15.599 | 188925 | 19.450 | 25% | -44.251 | < 0.01 |
| 10 | 194522 | 13.700 | 144536 | 16.687 | 22% | -32.009 | < 0.01 |
| 11 | 92294 | 12.024 | 91129 | 15.808 | 31% | -32.404 | < 0.01 |
| 12 | 78973 | 11.958 | 51814 | 13.982 | 17% | -13.801 | < 0.01 |
| **Offpeak** | | | | | | | |
| 1 | 43846 | 13.663 | 56129 | 13.162 | -4% | 2.286 | 0.022 |
| 2 | 37996 | 12.305 | 65544 | 15.781 | 28% | -15.261 | < 0.01 |
| 3 | 74151 | 15.277 | 72144 | 20.694 | 35% | -27.318 | < 0.01 |
| 4 | 123939 | 21.104 | 54454 | 25.941 | 23% | -22.359 | < 0.01 |
| 5 | 190875 | 23.136 | 141747 | 32.528 | 41% | -56.947 | < 0.01 |
| 6 | 263133 | 24.563 | 225901 | 31.301 | 27% | -47.771 | < 0.01 |
| 7 | 316862 | 26.148 | 356909 | 33.811 | 29% | -59.736 | < 0.01 |
| 8 | 333663 | 25.965 | 417571 | 28.678 | 10% | -25.020 | < 0.01 |
| 9 | 263435 | 23.132 | 332971 | 24.643 | 7% | -13.911 | < 0.01 |
| 10 | 177084 | 19.521 | 235063 | 20.345 | 4% | -6.852 | < 0.01 |
| 11 | 84760 | 15.188 | 163880 | 20.093 | 32% | -30.926 | < 0.01 |
| 12 | 76039 | 15.702 | 77608 | 15.795 | 1% | -0.507 | 0.612 |

## Significant Factors Affecting Bikeshare Travels During the Pandemic

As stated in previous literature, bike travel varies with the seasons. The most significantly factors are weather and temperatures, which are more significant than topography, infrastructure, land use mix, and peak hours in determining bikeshare usage[7, 18]. Therefore, before further investigating the temporal and spatial characteristics of bikeshare travels, we need to explore seasonal impacts, including temperature, precipitation, wind, etc., as well as the impact of COVID-related orders.

We use a quasi-Poisson model to evaluate the impacts of these factors. The response variables are the daily bike trip counts (2019 to 2020) and are considered generated from a Poisson process. Let $Y_i$ be the $i^{th}$observation of response variable,

$$Y_i \sim Poisson\ (\lambda_i) \tag{1}$$

$$\log(\lambda_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_K X_{Ki} \quad (2)$$

where $X_{ki}$is the $k^{th}$explanatory variable for the $i^{th}$observation and $\beta_k$ is the corresponding regression coefficient. A statistically significant result indicates there is a significant association between the explanatory variable and the response variable.

For binary variables, exp $(\beta_k)$corresponds to the rate ratio between two levels; for continuous variables, exp $(\beta_k)$ indicates the rate ratio for each one unit increase in $X$. As the preliminary results indicated overdispersion, we used the quasi-Poisson model to adjust for the overdispersion effects. The estimated parameters for each variable and the associated statistics are listed in Table 4. As the table indicates, the bike trips made by subscribers are significant with the following factors: all the dates when important COVID-related orders were issued by the state or the city excluding time periods 6 and 7, average temperature, average wind speed, precipitation, special weather (one or more of the following weather conditions: ice pellets, sleet, snow pellets, blowing dust, blowing sand, or hail), and holidays/weekends. For casual users, all the factors are significant.

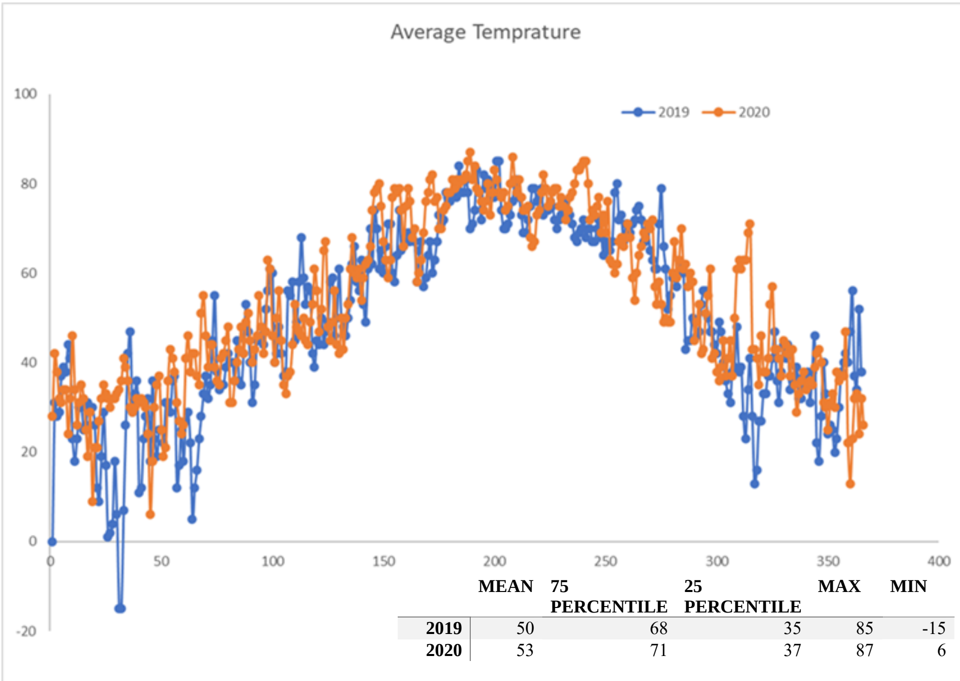
*Table 4 Modeling Results*

| | **Estimated rate ratio** | **STD** | **T-value** | **Pr(>\|t\|)** |
|---|---|---|---|---|
| | | **Subscribers** | | |
| **Time Period 2 vs 1** | 1.23 | 0.05 | 3.93 | < 0.05 |
| **Time Period 3 vs 1** | 0.32 | 0.16 | -7.41 | < 0.05 |
| **Time Period 4 vs 1** | 0.36 | 0.12 | -8.69 | < 0.05 |
| **Time Period 5 vs 1** | 0.61 | 0.06 | -7.67 | < 0.05 |
| **Time Period 6 vs 1** | 1.04 | 0.06 | 0.64 | 0.52479 |
| **Time Period 7 vs 1** | 1.15 | 0.08 | 1.79 | 0.07450 |
| **Time Period 8 vs 1** | 0.82 | 0.07 | -2.75 | < 0.05 |
| **Average temp** | 1.02 | 0.00 | 32.08 | < 0.05 |
| **Average wind** | 0.99 | 0.00 | -4.25 | < 0.05 |
| **precipitation** | 0.65 | 0.05 | -9.41 | < 0.05 |
| **special weather** | 0.84 | 0.08 | -2.06 | < 0.05 |
| **holiday/weekend** | 0.69 | 0.02 | -15.385 | < 0.05 |
| | | **Casual users** | | |
| **Time Period 2 vs 1** | 3.61 | 0.20 | 6.516 | < 0.05 |
| **Time Period 3 vs 1** | 1.26 | 0.32 | 0.716 | < 0.05 |
| **Time Period 4 vs 1** | 1.91 | 0.25 | 2.573 | < 0.05 |
| **Time Period 5 vs 1** | 3.98 | 0.20 | 6.852 | < 0.05 |
| **Time Period 6 vs 1** | 6.35 | 0.20 | 9.236 | < 0.05 |
| **Time Period 7 vs 1** | 7.44 | 0.21 | 9.615 | < 0.05 |
| **Time Period 8 vs 1** | 4.48 | 0.21 | 7.134 | < 0.05 |
| **Average temp** | 1.04 | 0.00 | 35.32 | < 0.05 |
| **Average wind** | 0.97 | 0.01 | -5.178 | < 0.05 |
| **precipitation** | 0.50 | 0.08 | -8.924 | < 0.05 |
| **special weather** | 0.45 | 0.19 | -2.746 | < 0.05 |
| **holiday/weekend** | 1.83 | 0.03 | 20.458 | < 0.05 |

The estimated parameters are all relative to a baseline value of 1. If the parameter is larger than 1, it means that the corresponding factor will generate an increase of (parameter-1)*100% bike trips per one unit of increase of the factor. If the parameter is smaller than 1, it indicates that the corresponding factor will generate a decrease of (1-parameter)*100% bike trips per one unit of increase of the factor. In addition to concluding that bikeshare travels are significantly affected by the wind, temperature, precipitation, and special weather, which is consistent with previous studies, bikeshare travels were also significantly impacted on the dates when several important COVID-related orders were issued. One interesting observation is that casual users' estimated parameters for time period variables are all larger than 1, indicating that casual users increased their usage of bikeshare consistently through the pandemic. Whenever there was a new COVID order issued, more travelers (casual users) decided to travel with bikeshare. Subscribers, on the other hand, limited their travels during time periods 3 through 5 when the pandemic was severe and time period 8 when the temperature dropped. These significant dates were marked in

Figure 1 (b) for subscribers (red dashed lines) and casual users (all dashed lines) to illustrate the division points between time periods for our next step analysis.

To further investigate the changes in spatial distributions of bikeshare trips, we aggregated the trips by bike stations and by time periods in 2020 that have significant impacts on bikeshare travel. To illustrate the changes in 2020 compared to 2019, we decided to use the same months and dates as cut-off dates to divide the bike data from 2019 into multiple time periods simultaneously and use them as a comparison baseline. To do so, we need to ensure that the weather and temperature conditions of the two years are not significantly different. We conducted paired T-tests of average wind and precipitation for 2019 and 2020. The results showed no significant differences (alpha = 0.05) of the two years. For temperature, although the paired T-test rejected the null hypothesis, a close examination showed that the difference was caused by several outliers in 2019 (Figure 3). The mean, 75th percentile, 25th percentile, and maximum average temperature of the two years were indeed not significantly different (shown in the right corner of Figure 3). Therefore, we believe it is reasonable to use the same month and date to divide 2019 data into different time periods in the data analysis in the next section.




| | MEAN | 75 PERCENTILE | 25 PERCENTILE | MAX | MIN |
|---|---|---|---|---|---|
| 2019 | 50 | 68 | 35 | 85 | -15 |
| 2020 | 53 | 71 | 37 | 87 | 6 |

*Figure 3 Average temperatures of 2019 and 2020*

## Changes in Spatial Characteristics of Bikeshare Trips

In this section, we will investigate the spatial patterns of the bikeshare trips to see if travelers are traveling to and from similar locations. If changes occurred in the spatial patterns, did they involve at a time when important COVID-related orders were issued? In other words, did travelers have a different spatial pattern during different time periods? According to our modeling in the previous section, there are five dates during the pandemic that had significant impacts on the bikeshare travels of subscribers (as shown by the red dash lines in

Figure 1) and seven dates that were significant to casual users. We will aggregate the bikeshare trips by station, by significant time periods, and by user types. To remove the bias in trip counts caused by the differences in the lengths of the time periods, we will use $Perc$, the percentage of trips that occurred at a station for each user type during a certain time period, as the responding variable in this section of the report (Equation 3).

$$Perc_{t,s}=\frac{TripCounts_{t,s}}{\sum_{1}^{S} TripCounts_{s}} \qquad (3)$$

Where the dependent variable $Perc_{t,s}$ is the percentage of trips occurring during time period $t$ at station $s$.

Each trip has one origin station and one destination station. After we calculated $Perc_{t,s}$ for origins and destinations separately, we conducted a set of Paired T-tests for $Perc_{t,s}$ for origins and destinations. For all the stations, no significant differences were found between origins versus destinations ($alpha$ = 0.05). Therefore, we will only illustrate the patterns of $Perc_{t,s}$ for trip origins in this section.

We conducted a spatial analysis called Local Bivariate Analysis in ArcGIS Pro®. A local bivariate analysis was used to analyze two variables for statistically significant relationships using local entropy. The basic idea is to measure the joint entropy of two variables, which is equal to the entropy of the first variable plus the entropy of the second variable minus the mutual information of the two variables. The mutual information serves as a useful measure of the level of dependence between the variables spatially [19]. In our case, the spatial pattern of $Perc$ in each of the time periods in both years was compared against one another[7]. The results classify the spatial relationship of two variables into one of the six categories: Positive linear, negative linear, concave, convex, undefined, and not significant. All the analyses have a confidence level of 95%.

Before the pandemic, the bikeshare trips made by subscribers were generally distributed evenly over space. An average of 74% of bikeshare trips are positively linearly correlated during 2019, meaning that a station with a higher percentage of bike trips originating from it at a certain time period is likely to attract a higher percentage of trips during all the other time periods in 2019 and vice versa. Some stations have a concave or a convex relationship at different time periods. None were negatively related, and about 8% did not have a significant relationship. This pattern changed in 2020. Of all the stations, only an average of 59% of stations are positively linearly correlated, while more than 25% of the stations are not significantly related. This observation showed that the spatial distribution of bikeshare trips by subscribers was much less consistent in 2020 across different time periods. Comparing the same time period in 2019 against that of 2020 revealed that usage among different stations during the first time period are much more similar than the rest of the year. The correlation pattern returned to a higher level later in time periods 5-7 and time period 8, indicating that bikeshare travels by subscribers during the later time period of the pandemic were more similar to pre-pandemic patterns. Casual users, on the contrary, exhibit much less spatial correlation among different time periods. In 2019, about 55% of the stations were positively correlated, while more than 30% were not correlated. This means that casual users were more likely to start and end their trips at stations that are more randomly distributed in the city compared to their subscriber counterparts. The randomness of trips made by casual users in 2020 is even more than that of 2019. On average, less than 45% of the stations were positively correlated while about 45% of the stations were not significantly related. When comparing the same periods in 2019 against 2020, casual users consistently had a smaller percentage of stations with a positive linear relation than do the subscribers. During time period 3 (Stay-at-home Executive Order of Illinois state issued on 3/28/2020), stations did not have a statistical correlation between 2019 and 2020 for casual users.

*Table 5 Subscriber Local Bivariate Analysis (All results at $\alpha$= 0.05)*

| | **2019 Time PERIOD 1** | | | | | |
|---|---|---|---|---|---|---|
| | **Positive Linear** | **Negative Linear** | **Concave** | **Convex** | **Un-defined** | **Not significant** |
| **2019 TP 2** | 544 (82.3%) | 0 (0%) | 24 (3.6%) | 35 (5.3%) | 0 (0%) | 58 (8.8%) |
| **2019 TP 3** | 475 (71.9%) | 0 (0%) | 33 (5%) | 95 (14%) | 0 (0%) | 58 (8.8%) |
| **2019 TP 4** | 491 (74.2%) | 0 (0%) | 44 (6.7%) | 72 (10.9%) | 0 (0%) | 54 (8.2%) |
| **2019 TP 5-7** | 471 (71.3%) | 0 (0%) | 45 (6.8%) | 111 (16.8%) | 0 (0%) | 34 (5.1%) |
| **2019 TP 8** | 461 (69.7%) | 0 (0%) | 43 (6.5%) | 97 (14.7%) | 0 (0%) | 60 (9.1%) |
| | **2020 Time Period 1** | | | | | |
| **2020 TP 2** | 413 (62%) | 0 (0%) | 47 (7.1%) | 35 (5.3%) | 0 (0%) | 166 (25.2%) |

[7] https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/learnmore-localbivariaterelationships.htm

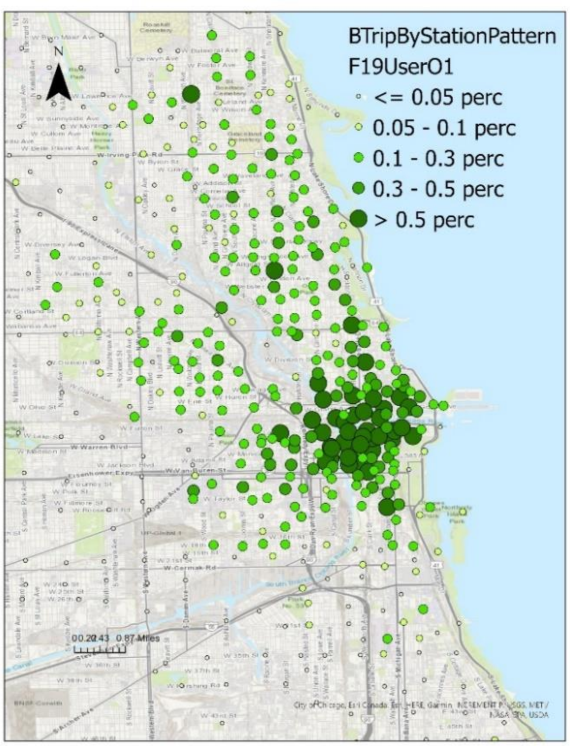
| | | | | | | |
|---|---|---|---|---|---|---|
| **2020 TP 3** | 401 (60.7%) | 0 (0%) | 14 (2.1%) | 50 (7.6%) | 0 (0%) | 196 (29.7%) |
| **2020 TP 4** | 381 (57.6%) | 0 (0%) | 29 (4.4%) | 74 (11.2%) | 2 (0.3%) | 175 (26.5%) |
| **2020 TP 5-7** | 377 (57%) | 0 (0%) | 54 (8.2%) | 87 (13.2%) | 0 (0%) | 143 (21.6%) |
| **2020 TP 8** | 408 (61.7%) | 0 (0%) | 26 (3.9%) | 58 (8.8%) | 0 (0%) | 169 (25.6%) |
| | **2019 Time Period 1** | | | | | |
| **2020 TP 1** | 489 (74%) | 0 (0%) | 37 (5.6%) | 90 (13.62%) | 2 (0.3%) | 43 (6.5%) |
| | **2019 Time Period 2** | | | | | |
| **2020 TP 2** | 303 (45.8%) | 0 (0%) | 33 (5%0 | 34 (5.1%) | 12 (1.8%) | 279 (42.2%) |
| | **2019 Time Period 3** | | | | | |
| **2020 TP 3** | 283 (42.8%) | 0 (0%) | 11 (1.7%0 | 37 (5.6%) | 0 (0%) | 330 (49.9%) |
| | **2019 Time Period 4** | | | | | |
| **2020 TP 4** | 312 (47.2%) | 0 (0%) | 19 (2.9%) | 74 (11.2%) | 3 (0.45%) | 253 (38.3%) |
| | **2019 Time Period 5-7** | | | | | |
| **2020 TP 5-7** | 465 (70.4%) | 0 (0%) | 39 (5.9%) | 100 (15.1%) | 1 (0.15%) | 56 (8.5%) |
| | **2019 Time Period 8** | | | | | |
| **2020 TP 8** | 442 (66.9%) | 0 (0%) | 22 (3.3%) | 52 (7.9%) | 1 (0.15%) | 144 (21.8%) |

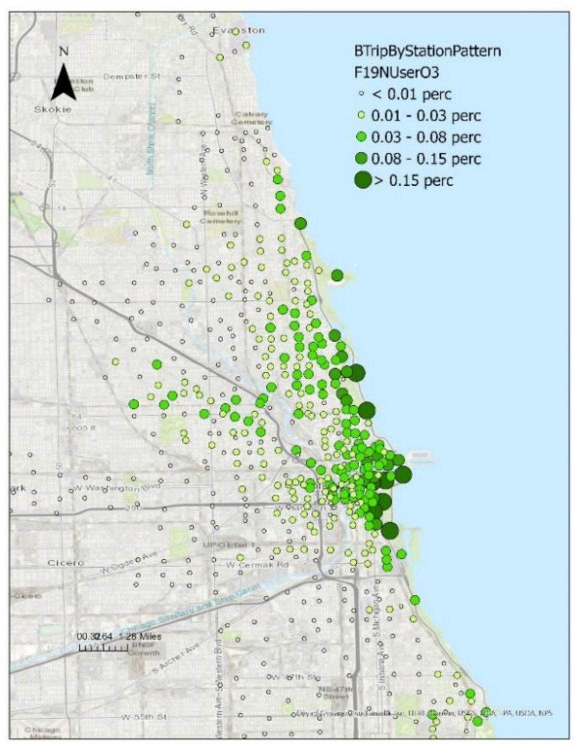
*Table 6 Casual User Local Bivariate Analysis (All results at $\alpha = 0.05$)*

| | **2019 Time Period 1** | | | | | |
|---|---|---|---|---|---|---|
| | **Positive Linear** | **Negative Linear** | **Concave** | **Convex** | **Un-defined** | **Not significant** |
| **2019 TP 2** | 312 (47.2%) | 0 (0%) | 7 (1.1%) | 31 (4.7%) | 2 (0.3%) | 309 (46.8%) |
| **2019 TP 3** | 348 (52.7%) | 0 (0%) | 56 (8.5%) | 57 (8.6%) | 0 (0%) | 198 (30%) |
| **2019 TP 4** | 406 (61.4%) | 0 (0%) | 55 (8.3%) | 42 (6.4%) | 3 (0.45%) | 155 (23.5%) |
| **2019 TP 5** | 431 (65.2%) | 0 (0%) | 51 (7.7%) | 58 (8.8%) | 0 (0%) | 121 (18.3%) |
| **2019 TP 6** | 370 (56%) | 0 (0%) | 49 (7.4%) | 44 (6.7%) | 3 (0.45%) | 195 (29.5%) |
| **2019 TP 7** | 319 (48.3%) | 0 (0%) | 12 (1.8%) | 60 (9.1%) | 10 (1.5%) | 260 (39.3%) |
| **2019 TP 8** | 320 (48.4%) | 0 (0%) | 6 (0.9%) | 48 (7.3%) | 0 (0%) | 287 (43.4%) |
| | **2020 Time Period 1** | | | | | |
| **2020 TP 2** | 181 (27.4%) | 0 (0%) | 13 (2%) | 33 (5%) | 1 (0.15%) | 431 (65.2%) |
| **2020 TP 3** | 67 (10.14%) | 0 (0%) | 1 (0.15%) | 20 (3%) | 6 (0.9%) | 567 (85.8%) |
| **2020 TP 4** | 302 (45.7%) | 0 (0%) | 14 (2.1%) | 31 (4.7%) | 23 (3.5%) | 291 (44%) |
| **2020 TP 5** | 344 (52%) | 0 (0%) | 18 (2.7%) | 77 (11.7%) | 0 (0%) | 222 (33.6%) |
| **2020 TP 6** | 443 (67%) | 0 (0%) | 11 (1.7%) | 86 (13%) | 3 (0.45%) | 121 (18.3%) |
| **2020 TP 7** | 398 (60%) | 0 (0%) | 8 (1.2%) | 109 (16.5%) | 0 (0%) | 146 (22.1%) |
| **2020 TP 8** | 318 (48.1%) | 0 (0%) | 7 (1.1%) | 89 (13.5%) | 0 (0%) | 247 (37.4%) |
| | **2019 Time Period 1** | | | | | |
| **2020 TP 1** | 318 (48.1%) | 0 (0%) | 9 (1.4%) | 73 (11%) | 0 (0%) | 261 (39.5%) |
| | **2019 Time Period 2** | | | | | |
| **2020 TP 2** | 66 (10%) | 0 (0%) | 6 (0.9%) | 19 (2.9%) | 5 (0.8%) | 565 (85.5%) |
| | **2019 Time Period 3** | | | | | |
| **2020 TP 3** | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 661 (100%) |

| | | | | | | |
|---|---|---|---|---|---|---|
| | **2019 Time Period 4** | | | | | |
| **2020 TP 4** | 73 (11%) | 0 (0%) | 2 (0.3%) | 12 (1.8%) | 1 (0.15%) | 573 (86.7%) |
| | **2019 Time Period 5** | | | | | |
| **2020 TP 5** | 454 (68.7%) | 0 (0%) | 14 (2.1%) | 145 (21.9%) | 0 (0%) | 48 (7.3%) |
| | **2019 Time Period 6** | | | | | |
| **2020 TP 6** | 356 (53.8%) | 0 (0%) | 16 (2.4%) | 207 (31.3%) | 0 (0%) | 82 (12.4%) |
| | **2019 Time Period 7** | | | | | |
| **2020 TP 7** | 388 (58.7%) | 0 (0%) | 7 (1.1%) | 88 (13.3%) | 2 (0.3%) | 176 (26.6%) |
| | **2019 Time Period 8** | | | | | |
| **2020 TP 8** | 279 (42.2%) | 0 (0%) | 4 (0.6%) | 52 (7.9%) | 0 (0%) | 326 (49.3%) |

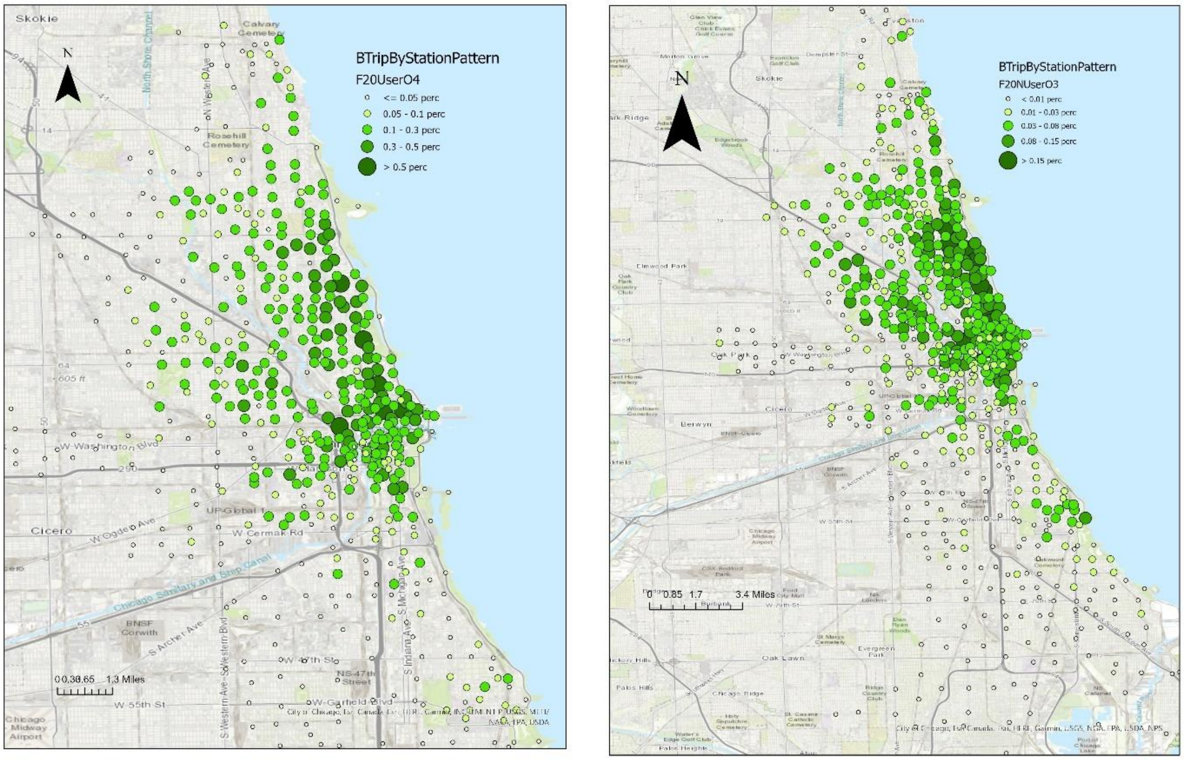
To visually illustrate $Perc$, we plotted $Perc$ using graduated symbols and colors. Figure 4 shows the typical spatial distribution of subscribers and casual users in 2019. Bike stations around Millennium Park attracted more trips by subscribers, while bike stations along the Lake Michigan coastline attract more casual users. Note that both subscribers and casual users exhibited a consistent trend through 2019 in all time periods, although casual users have a weaker spatial consistency than that of subscribers. In 2020, the subscribers exhibited a spatial distribution similar to that of 2019 only in the first time period (TP 1). After COVID hit the city; however, the spatial distribution changed in that: 1, trips by subscribers were much less concentrated around the Millennium Park stations; 2, trips by casual users were much less concentrated along the coastline; and 3, both types of users started to show a more random distribution across the whole city with fewer high-$Perc$ stations (darker green circles) and more median $Perc$ categories (lighter and smaller green circles).




(a) (b)

*Figure 4 Spatial pattern for subscribers in TP 1 (a) and casual users in TP 3 (b), 2019*




(a) (b)

*Figure 5 Spatial pattern for subscribers in TP 4 (a) and casual users in TP 3 (b), 2020*

## Interaction of Bikeshare Trips with Public Transit

The findings we have identified so far indicate that bikeshare trips migrated spatially during COVID, both for subscribers and casual users, through the pandemic. We then explored the relationship between the locations of bike stations with higher $Perc$ and the bus stations or rail stations in the neighborhood to see if there is a correlation. Here, we defined bike stations with higher $Perc$ as stations that have a $Perc$ value larger than the 75th percentile.

A colocation analysis was conducted in ArcGIS Pro®. Colocation analysis is used to measure local patterns of spatial association between two categories using the colocation quotient statistics[8]. A local colocation quotient was calculated using equation (4).

$$Q = \frac{N_{bus\ stop\ or\ rail\ stations \rightarrow bike\ stations\ with\ perc>75\ percentile}}{N_{perc>75\ percentile} / (N_{bike}-1)} \tag{4}$$

Where $N_{perc>75\ pertentile}$ are the number of bike stations that have a $Perc$ that is larger than the 75th percentile of $Perc$. $N_{bus\ stop\ or\ rail\ stations \rightarrow bike\ stations\ with\ perc>75th\ percentile}$ is the spatially weighted average number of bus stops or rail stations that are in the neighborhood of each bike station with $Perc >$

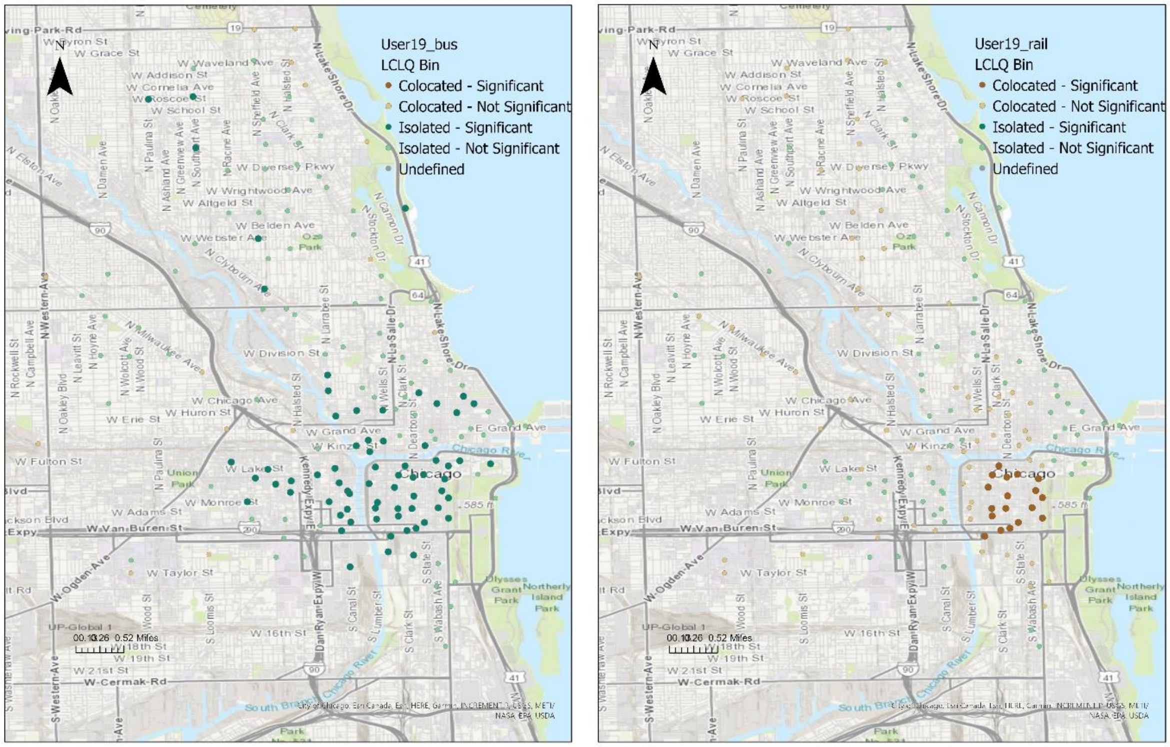
[8] https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/learnmorecolocationanalysis.htm

$75\ percentile$. The weight is calculated using a distance decay function that allows closer features to weigh heavier. In our analysis, we used a distance band of 0.5 mile, which is a reasonable walking distance accepted by most bikeshare users stated in previous research, to define a neighborhood to select close-by neighbor from. In total 170 stations were identified as $N_{perc>75\ pertentile}$.

Overall, more than half of the bike stations did not have spatial correlation with public transit stations, while the other half of bikeshare stations with higher $Perc$ values were more likely to be co-located with rail stations but more isolated from bus stations (Table 7). This indicates that bikeshare users might use bikes to complement trips that were not served by buses. Meanwhile, we also observed that some heavily used bike stations located around the Millennium Park were significantly co-located with the rail stations. This result might indicate that travelers use bikes to connect their rail travels. The co-location relationship of bikeshare stations with both bus stations and rail stations becomes weaker in 2020, with fewer percentage of isolated (to bus stations) or co-located bikeshare stations (to rail stations). This observation is consistent with the conclusion in our previous section that bikeshare trips during the pandemic were spatially distributed more randomly and spread more extensively across the city.

*Table 7 Co-location Analysis with Rail and Bus Stations (All results with a P-value = 0.05)*

| | **Bus Stations** | | **Rail Stations** | |
|---|---|---|---|---|
| | **Co-located** | **Isolated** | **Co-located** | **Isolated** |
| **Subscriber 19** | 0 | 68 (40%) | 18 (11%) | 0 |
| **Casual User 19** | 0 | 64 (38%) | 15 (9%) | 0 |
| **Subscriber 20** | 0 | 58 (34%) | 12 (7%) | 0 |
| **Casual User 20** | 0 | 48 (28%) | 12 (7%) | 0 |




(a) (b)

*Figure 6 Co-location analysis of heavily used bikeshare stations of subscribers with bus stations (a) and rail stations (b)*

## CONCLUSIONS AND DISCUSSIONS

Plummeting traffic volume worldwide was observed during the COVID-19 pandemic in 2020, especially for areas with stay-at-home orders. Only essential travel was permitted, and social distancing was required in most places. This report studied the variation of bikeshare travels in Chicago in terms of trip frequencies, trip lengths, spatial distributions, and the potential interaction of bikeshare travels and the public transit during the pandemic. Our conclusions are as follows:

1. Bikeshare usage dropped along with other modes when the stay-at-home order was issued. However, it quickly rebounded, while all the other mode travel remained low for the rest of the year. As a travel mode that is in open air and naturally creates distance among travelers, bikeshare exhibited an advantage over other travel modes.
2. While subscribers made slightly fewer trips during the pandemic in 2020 relative to 2019 travel, there was a significant increase in trips made by casual users. This significant increase contributed to the rebound in the number of bikeshare trips we observed in May 2020. More travelers who previously were not regular bikeshare users chose bikeshare during the pandemic.
3. Trip lengths and peak hour trips increased significantly for subscribers. , while fewer increases were observed for off-peak trips. For casual users, trip lengths increased for the first half of the year but decreased later on. Although there was no supporting data showing the trip purposes, the fact that trip lengths increased more for subscribers and during the peak time may indicate that travelers used bikeshare for their commuting trips.
4. The regression model we fit showed that bikeshare travel is significantly related to temperature, wind speed, precipitation, and the weekday/weekend. In addition, 5 of the 7 important dates when COVID-related orders were issued were also significant variables that affected the number of

bikeshare trips for subscribers. All 7 dates were found to be significant for casual users. On each date, the number of trips made by casual users significantly increased, showing an increased tendency of travelers to switch to bikeshare from other travel modes in response to the COVID related orders.

5. In 2019, the spatial distribution of bikeshare trips was very consistent, meaning that the bike stations that attracted more trips during one time period were typically highly-used stations throughout the entire year, and vice versa. This is especially significant for subscribers. For subscribers, the majority of the bike stations had a linearly positive relationship with the number of trips at different time periods of the year. However, in 2020, travelers made trips that were spatially located at different locations. Approximately 25% of the stations were not significantly related during the different time periods through the year. For casual users, there were fewer stations that had positive relations to start with in 2019. During the pandemic in 2020, this positive relationship became even weaker. This observation indicated that the spatial distribution of bikeshare trips was more random during the pandemic.
6. When the spatial distribution of the bikes was examined, we observed a different pattern for subscribers and casual users in 2019. For subscribers, more trips occurred around Millionaire Park while casual users traveled more along the Lake Michigan coastline. This pattern was consistent in 2019 as well as before the pandemic in 2020. However, once the COVID pandemic became more serious, both subscribers and casual users were less concentrated in certain areas. Instead, bikeshare trips were more evenly distributed across the city. This observation might indicate that travelers switch to bikeshare from other modes and use it to serve more diversified travel needs.
7. About 35% percent of bikeshare stations with higher $Perc$ were found to be isolated from bus stations while about 10% of them are co-located with rail stations. This spatial correlation was weaker during the pandemic. This is a very interesting observation that deserves further investigation. We believe that bikeshare is complementing public transit in that bikeshare allowed travelers to travel around places that are not served by bus stations and to connect their trips with rail stations. More data are needed to verify this conjecture. We recommend a better design of bikeshare stations along with public transit stations to make the two modes complement each other.

In summary, this report investigated the changes in bikeshare travel patterns during the COVID-19 pandemic in the Chicago Greater Area. We believe that bikeshare is a healthy and green travel mode that has very high potential to be used as a routine travel mode, even after the pandemic. We believe that bikeshare can be used as an alternative mode to serve everyday travel needs in a more routine way. Further studies are needed to help promote the bikeshare system so that it can better serve travel needs, especially the locations of the bike stations, the number of docks needed for each station, as well as a better coordination of bike system and public transit system.

# CHAPTER 2: BIKESHARE INTERACTIONS WITH OTHER TRANSPORTATION MODES DURING THE COVID PANDEMIC

## INTRODUCTION

During the COVID-19 pandemic, the world observed a dramatic drop in the volumes of all traffic modes. Automobile traffic, for example dropped between 40% and 60% [12]. Due to the need to abide by social distancing policies and the concerns about infection, travelers tended to switch to travel modes with lower exposure to the virus. Bikeshare, due to its open -air properties and natural distancing features, became popular. While the reduction of traffic volume for personal vehicles was similar across the world, our study concentrates on the changes in bikeshare usage. Specifically, we identify the variation in bikeshare usage during the pandemic and its interaction with other travel modes by attempting to answer the following questions: How did bikeshare travel vary during the pandemic? How did bikeshare interact with other travel modes? Did all modes have a similar reduction? Will travelers be more motivated to use bikeshare in conjunction with more equitable and sustainable transit modes after the pandemic? To answer these questions, this report obtained and analyzed the travel data of multiple transportation modes before and during the pandemic. Our goal was to identify the variation of bikeshare travel during the COVID-19 pandemic, explore its correlation with other modes, especially public transit, and propose possible policies that can stimulate bikeshare usage. The results of this report will help policy makers better understand the travel behavior of bikeshare users so that they can make effective policies and create a more sustainable and equitable traffic system post pandemic. .

## BACKGROUND AND LITERATURE REVIEW

Bikeshare has developed rapidly since its first appearance as the “white bike” in Amsterdam in the 1960s. Currently, there are 7,469 docking stations and 36 dock-less bikeshare systems in the U.S. Since bikeshare is relatively low in cost and has a minimal carbon footprint, it can be a promising solution for inequities and environmental problems in the traffic system., Previous studies have investigated various aspects of bikeshare travel, including user profiles, weather impacts, and interactions between bikeshare other modes, to better understand the behavior of bikeshare users and promote the usage of bikes. Due to the focus of this report, we will concentrate our literature review on studies that have investigated the relationship between bikeshare and other transportation modes.

Kong et al. found that bikeshare trips can be grouped into three types regarding their relationship with public transit: modal substitution (MS), modal integration (MI), and modal complementation (MC). Bike trip patterns vary by weekend/weekdays and subscribers/casual users. MI trips are typically shorter in distance and occur during the weekdays. MC and MS are more dominant compared to MI. MC often happens during times when public transit is not available. MS made by casual users is much more than subscribers [20]. Welch et al. investigated the role of the built environment and other factors affecting travelers’ choice of mode. Their conclusions found that cost is an important factor. In addition, higher job diversity, and lower density of roads and intersections are positively linked to shared modes (ridesharing or bikeshare) [21]. Shaheen et al. analyzed survey data from four cities and found that bikeshare will both increase and decrease the usage of buses and rail. The percentage of travelers who indicated that they use less public transit due to bikeshare is more than the percentage of users who said they increased public transit travel in three of the cities in the study: Montreal, Toronto, and Washington, D.C. The only city in which more travelers indicated that their usage of public transit increased was the Twin Cities (Minneapolis and Saint Paul, Minnesota). The authors believed that this difference was caused by the density of the city and existing level of service provided by public transit [22].

A more detailed analysis using the same survey data was conducted by Martin and Shaheen. They found that in Washington, D.C., those shifting toward bus and rail transit live on the urban periphery, whereas those living in the urban core tend to use public transit less. In Minneapolis, the shift toward rail extends to the urban core, while the modal shift for bus transit is more dispersed. The conclusion drawn by the authors is that public bikeshare may be more complementary to public transit in small to mid-size cities while acting as a substitution for public transit in larger and denser cities [23]. To analyze the impact on car substitution of bikeshare, Fishman et al. used survey data where bikeshare users from five cities around the world were asked, "Thinking about your last journey on bikeshare, which mode of transport would you have taken had it not existed?". They concluded that for 2012, bikeshare usage was responsible for a decrease in car travel of 115,826 km in Melbourne and 632,841 km in London. However, the authors also found that total vehicle miles traveled increased by 344,446 km when accounting for miles generated from service vehicles rebalancing bikes at different stations when bikeshare replaces car use [24]. Jappinen et al. used data collected from Journey Planner, a public internet service provided by Helsinki Region Transport, to assess information about the optimal route between a given origin and destination by public transit at a given time of a day and study the potential travel time savings that can be offered by bikeshare. Their analysis concluded that a bikeshare system would decrease public transportation travel times. On average, travel time would be 6 minutes shorter when combining public transit with bikeshare than when using public transit alone. The time savings, however, vary according to location. In the city center area, the difference is smaller. The busiest stations were near railway and metro stations. The authors concluded that a large-scale bikeshare system can complement a traditional public transit system [25]. Singleton et al. concluded that transit and cycling were short-term mode substitutes but might be long-term complements [26]. Campbell and Brakewood concluded that bikeshare competed with buses and resulted in a 2.42% decrease in bus trips per thousand docks along a bus route [27]. Ma et al., however, drew the opposite conclusion regarding the relationship between rail and bikeshare. They believe that a 10% increase in annual bikeshare ridership contributed to a 2.8% increase in average daily Metrorail ridership [28]. Fuller et al. studied bikeshare trips during a transit strike in Philadelphia. Their results showed that in the face of a major transportation constraint, large-scale adoption of biking as a transportation mode is possible. Although after the strike bikeshare usage decreased to normal levels, T

he authors believe that bikeshare usage among less-frequent users is likely to increase by enhancing the service on rebalancing bikes [29]. Saberi et al. indicated that when public transportation is constrained, large-scale adoption of cycling can occur, indicating a similarity in the pool of public transportation users and bike users [30].

Since the outbreak of COVID-19, researchers have studied the resulting changes in travel, including bikeshare and other modes [12-14]. Hu et al. found that during the COVID-19 pandemic, bikeshare usage at stations near the city center decreased more than at stations in other places [31]. Teixeira and Lopes found about a 71% decrease in bikeshare trips in New York City. However, compared to the overall 90% drop in the subway system usage, bikeshare appears to be more resilient and rebound more quickly [32]. Using data collected from Budapest, Bucsky concluded that bikeshare became more popular during the pandemic [33]. Song et al. concluded that bikeshare systems may serve as a replacement mode when public transit services are restricted due to lockdown policies and have the potential to facilitate a disease-resilient transport system

[34]. Nikiforiadis et al. analyzed some survey data from Thessaloniki, Greece, and concluded that bikeshare is likely to become preferable mode for people who were previously commuting with private cars as passengers (not as drivers) and existing bikeshare subscribers [35]. A study by Kim and Cho indicated that the COVID-19 pandemic weakened the competitive relationships between bikeshare and bus transit and disrupted modal integration between bikeshare and subway in Seoul, South Korea. They concluded that bikeshare increases the overall resilience of the public transit system to pandemics by providing an alternative to short-term bus trips and long-term subway trips [36]. Jie et al. believed that short trips between transit stations or bus stops may be replaced by shared bikes and thus concluded that bikeshare may have the ability to absorb additional travel demands due to reduced capacities of public transit services [37].

While bikeshare is a promising transit mode with the potential to reduce the carbon footprint of the transportation system, it has not been fully utilized due to the wide availability of other modes. The COVID pandemic provided us with an opportunity to study bikeshare usage when travelers needed to limit their usage of other modes. If we can better understand the travel behavior of bikeshare users during the COVID pandemic and provide travelers with better bikeshare systems, policymakers can encourage people to make a better use of bikeshare and create a more sustainable transportation system.

## DATA EXPLORATION AND ANALYSIS

Because biking is dramatically affected by weather, it is necessary to account for the effects of inhospitable weather on user behavior when identifying the relationships between bikeshare and other travel modes. According to previous studies, temperature, wind speed, and precipitation significantly affect bike travel [38-42]. Weather data were obtained from the Global Historical Climatology Network, a composite of climate databases from numerous sources that were subjected to a suite of quality assurance reviews.[9] Table 8 shows the weather data statistics for Chicago in 2019 and 2020.

*Table 8 Statistics for Weather*

| | YEAR | MEAN | MAX | MIN | STD | 75TH PCTL | 25TH PCTL |
|---|---|---|---|---|---|---|---|
| **AVERAGE WIND (MPH)** | 2019 | 9.80 | 25.17 | 3.36 | 3.47 | 11.97 | 7.38 |
| | 2020 | 9.74 | 22.37 | 3.69 | 3.42 | 11.69 | 7.27 |
| **RAIN (INCH/DAY)** | 2019 | 0.12 | 2.22 | 0.00 | 0.28 | 0.11 | 0.00 |
| | 2020 | 0.11 | 3.39 | 0.00 | 0.32 | 0.05 | 0.00 |
| **AVERAGE TEMPRATURE (F)** | 2019 | 50 | 85 | -15 | 20.34 | 68 | 35 |
| | 2020 | 53 | 87 | 6 | 18.69 | 71 | 37 |
| **SNOW (INCH/DAY)** | 2019 | 0.13 | 5.4 | 0 | 0.588 | 0 | 0 |
| | 2020 | 0.12 | 3.1 | 0 | 0.38 | 0 | 0 |

We used the following criteria as filters to identify days with good weather for bikeshare users based on previous research: temperature above 70 Fahrenheit, wind speed below 7 mph, amount of rain less than 0.1 inch/day, and no snow. Using these criteria, we extracted 48 good-weather days. Among them, 2019 had 20 days (7 weekend days and 13 weekdays) and 2020 had 28 days (6 weekend days and 22 weekdays). Since

[9] https://www.ncdc.noaa.gov/cdo-web/search

previous studies concluded that the behavior of bikeshare subscribers and casual users differs and that bikeshare usage varies between weekdays and weekends, we separated the data into four different categories for data analysis for the rest of the report: subscribers/casual users and weekday/weekend trips.

The following datasets were acquired:

- Bus ridership by route from the city of Chicago data portal[10]
- Rail ridership by station from the city of Chicago data portal[11]
- Bikeshare data were obtained from DIVVY®. Data from 2019 were downloaded from the City of Chicago data portal[10] and the data from 2020 were downloaded from the DIVVY website.[12]
- Trips served by transportation network companies (TNCs; e.g., Uber and Lyft) downloaded from the city of Chicago data portal[13]
- Bike facilities in the city obtained from the Chicago Department of Transportation (CDOT)

Figure 7 illustrates the existing bike facilities in the city of Chicago. Of the total system of 342 miles, neighborhood greenway and protected bike lanes take up 62 miles, buffered bike lanes 113 miles, and the rest of the facilities (shared lane or bike lane) 167 miles. In total, there are 842 bike stations with 12,904 bike docks.

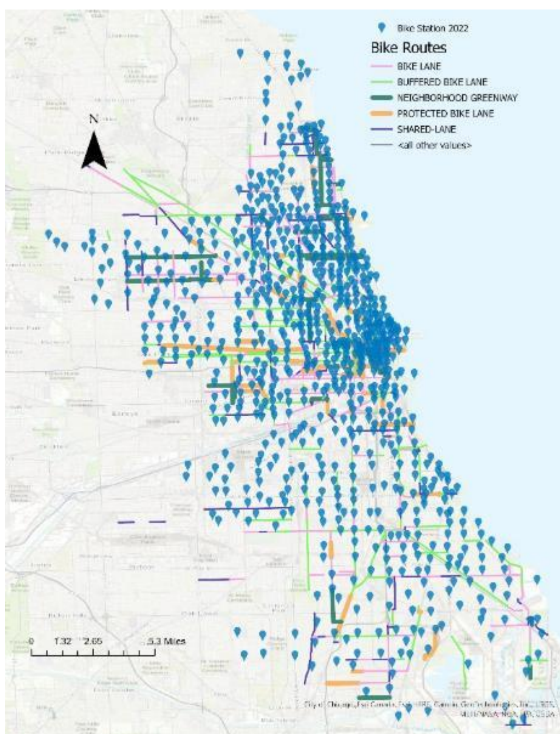



*Figure 7 Bike facilities in Chicago*

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[10] https://data.cityofchicago.org/Transportation/CTA-Ridership-Bus-Routes-Daily-Totals-by-Route/jyb9-n7fm
[11] https://data.cityofchicago.org/Transportation/CTA-Ridership-L-Station-Entries-Daily-Totals/5neh-572f
[12] https://divvy-tripdata.s3.amazonaws.com/index.html
[13] https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips/m6dm-c72p

Table 9 through TABLE 11 illustrate statistics for bikeshare, bus, rail, and ridehailing travel. As can be seen in Table 9, bikeshare travel by casual users on weekdays increased significantly in trip frequency during the pandemic, but no significant change was observed in trip time. On the other hand, Bikeshare travel by casual users on weekends decreased slightly in trip frequency but increased in trip time. For subscribers, trip frequency decreased on both weekdays and weekends. However, there was a significant increase in trip time. The standard deviation for trip time was larger for both casual users and subscribers, indicating a larger variation in the bike trips during the pandemic. As can be seen from Table 10, ridehailing trips dropped significantly on both weekends and weekdays. In 2020, trip lengths increased on both weekends and weekdays while trip times decreased, indicating longer trips by ridehailing users in a less-congested traffic network where the trips could be accomplished in a much shorter time. TABLE 11 provides bus and rail ridership. The use of public transit, for both buses and rail, decreased significantly, especially for rail, where ridership decreased by 77% (weekends) and 81% (weekdays).

*Table 9 Statistics for Bikeshare Trips*

| User Type | Year and Day Type | Average Trips per day | Trip Time Mean (sec) | Trip Time Median (Sec) | STD |
|---|---|---|---|---|---|
| Subscriber | 2019 Weekday | 15,008 | 812 | 636 | 952 |
| | 2019 Weekend | 9,517 | 972 | 743 | 1,353 |
| | 2020 Weekday | 10,050 | 989 | 764 | 1,257 |
| | 2020 Weekend | 6,579 | 1,215 | 957 | 1,687 |
| Casual | 2019 Weekday | 5,118 | 2,307 | 1,506 | 3,258 |
| | 2019 Weekend | 10,184 | 2,595 | 1,714 | 3,260 |
| | 2020 Weekday | 7,912 | 2,376 | 1,366 | 4,007 |
| | 2020 Weekend | 9,063 | 2,958 | 1,716 | 4,519 |

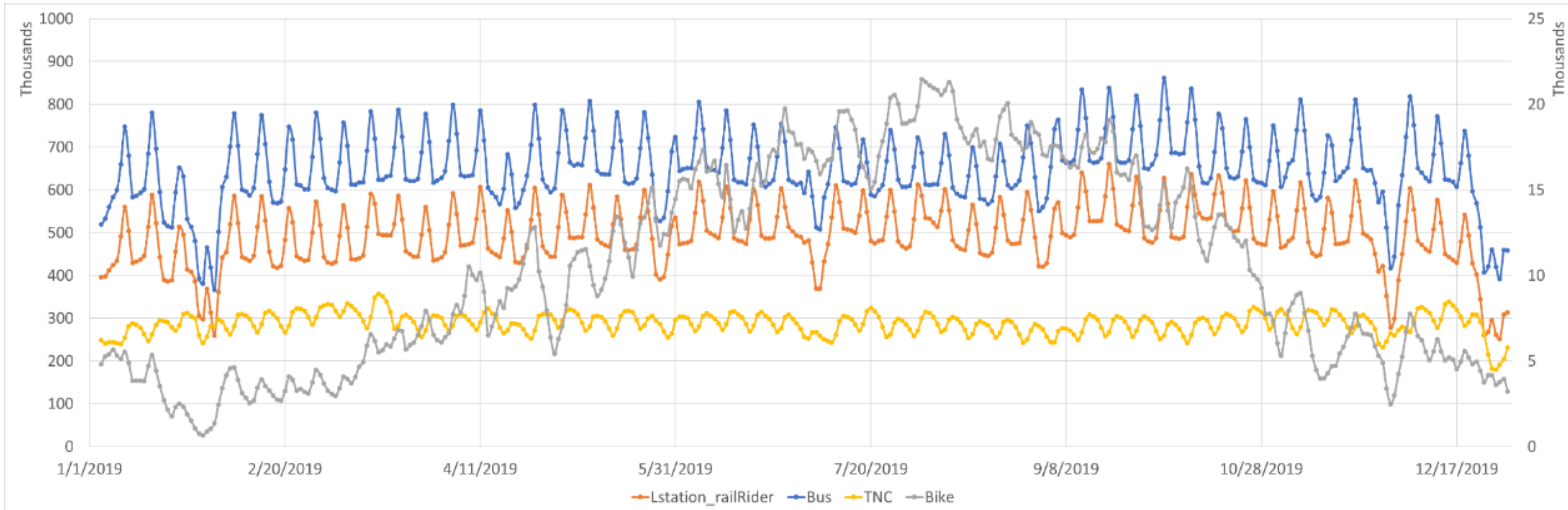
*Table 10 Statistics for Ridehailing Trips*

| YEAR AND DAY | TRIPS PER DAY | TIME MEAN (SEC) | TIME MEDIAN (SEC) | TIME STD | LENGTH MEAN (MILES) | LENGTH MEDIAN (MILES) | LENGTH STD |
|---|---|---|---|---|---|---|---|
| 2019 Weekday | 283,945 | 1,132.81 | 914.00 | 808.36 | 5.91 | 3.60 | 6.54 |
| 2019 Weekend | 314,812 | 985.12 | 827.00 | 652.24 | 5.58 | 3.60 | 6.15 |
| 2020 Weekday | 104,953 | 993.09 | 838.00 | 654.23 | 6.55 | 4.30 | 7.10 |
| 2020 Weekend | 107,108 | 923.26 | 781.00 | 600.01 | 6.56 | 4.20 | 7.26 |

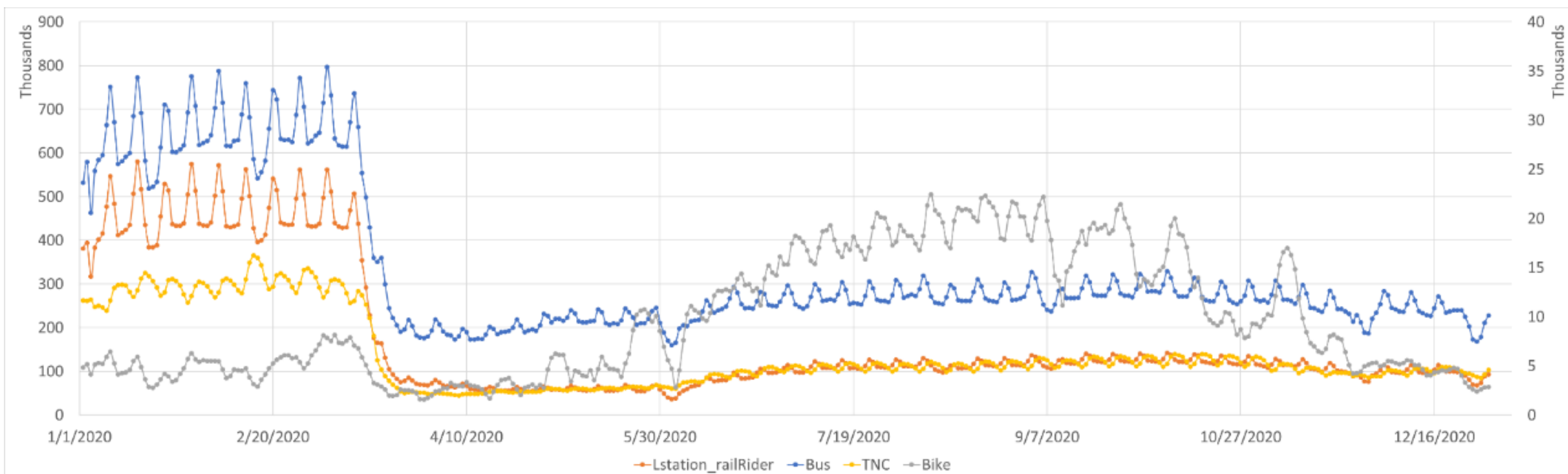
*TABLE 11 Statistics for Public Transit Ridership (Per Day)*

| | YEAR/DAY TYPE | City Sum (thousand) | Mean | Max | Min | Median | STD |
|---|---|---|---|---|---|---|---|
| **Bus (By Route)** | 2019 Weekday | 758 | 6,017 | 23,396 | 4 | 4,281 | 4,281 |
| | 2019 Weekend | 421 | 3,343 | 15,866 | 0 | 1,759 | 3,878 |
| | 2020 Weekday | 306 | 2,431 | 11,546 | 0 | 1,618 | 2,432 |
| | 2020 Weekend | 197 | 1,563 | 8,521 | 0 | 885 | 1,853 |
| **Rail (By Stop)** | 2019 Weekday | 620 | 4,339 | 22,227 | 475 | 3,128 | 3,882 |
| | 2019 Weekend | 326 | 2,281 | 11,396 | 256 | 1,470 | 2,289 |
| | 2020 Weekday | 121 | 843 | 3,660 | 123 | 658 | 642 |
| | 2020 Weekend | 74 | 519 | 2,307 | 75 | 366 | 431 |

Figure 8 shows the seven-day moving average of the number of trips made by different travel modes in 2019 (above) and 2020 (below). It describes the overall trends and changes of modes. As can be seen, travel by bus, rail, and TNC was consistent through all of 2019. Bikeshare travel, on the contrary, exhibited a seasonal variation, starting low in the first couple of months and rising during the warmer months of the year. The volume peaked during the summer from July to September and then dropped when the temperature decreased in winter. In 2020, the pandemic changed these patterns. Bikeshare volumes dropped along with all the other modes when the shelter-in-place order was issued in March. Bikeshare travel volume then started to increase rapidly in May, while the other modes stayed low for the rest of the year. Bikeshare travel peaked in August and stayed high until November. These observations should encourage future researchers to further explore the possibility of using bikeshare as a routine commuting mode and using bikeshare jointly with other modes, especially public transit, after the pandemic.




**(a)**




**(b)**

Figure 8 Trip trend by mode in (a) 2019 and (b) 2020

*Intercorrelation of Bikeshare with Other Modes*

We calculated the percentage of volume changes from 2019 to 2020, $Delta_{m,w,i}$, using the following equation for all the other modes besides bikeshare:

$$Delta_{m,w,i} = \frac{(Vol_{2020,m,w,i} - Vol_{2019,m,w,i})}{Vol_{2019,m,w,i}} * 100\% \qquad (1)$$

where $m$ indicates different modes, $w$ indicates weekdays or weekends, and $i$ delegates the location $i$ in which $Vol_{2020}$ or $Vol_{2019}$ occurred. Location $i$ can be rail stations (for rail), bus routes (for buses), or census tract (for ridehailing).

For bikeshare, the $Delta$ was calculated separately for casual users and subscribers and calculated using equation (2) for each bike station $j$.

$$Delta_{w,user,j} = \frac{(Vol_{2020,w,user,j} - Vol_{2019,w,user,j})}{Vol_{2019,w,user,j}} * 100\% \qquad (2)$$

where $user$ is either subscribers or casual users.

The histogram of $Delta$ for each mode is illustrated in Figure 9. As can be seen, rail and bus ridership decreased significantly. The majority of t rail stations had their ridership decrease by 50% to 100%, and most bus routes had their ridership decrease by 50% - 75%. A similar trend was observed for ridehailing. Decreases in trips made by ridehailing varied across different census tracts. Most of them had more than a 50% reduction. We divided bikeshare trips into two categories: those made by subscribers and by casual users. Overall, subscribers made fewer trips in 2020 than 2019. However, bikeshare trips made by subscribers increased at half of all bike stations. Casual users' trips increased significantly in 2020. Some stations had double or triple the number of trips compared to 2019. The distribution of $Delta$ for casual bikeshare users varied widely across the board from -50% to 500%. In the following section, we will investigate the spatial distributions and variations of different modes.

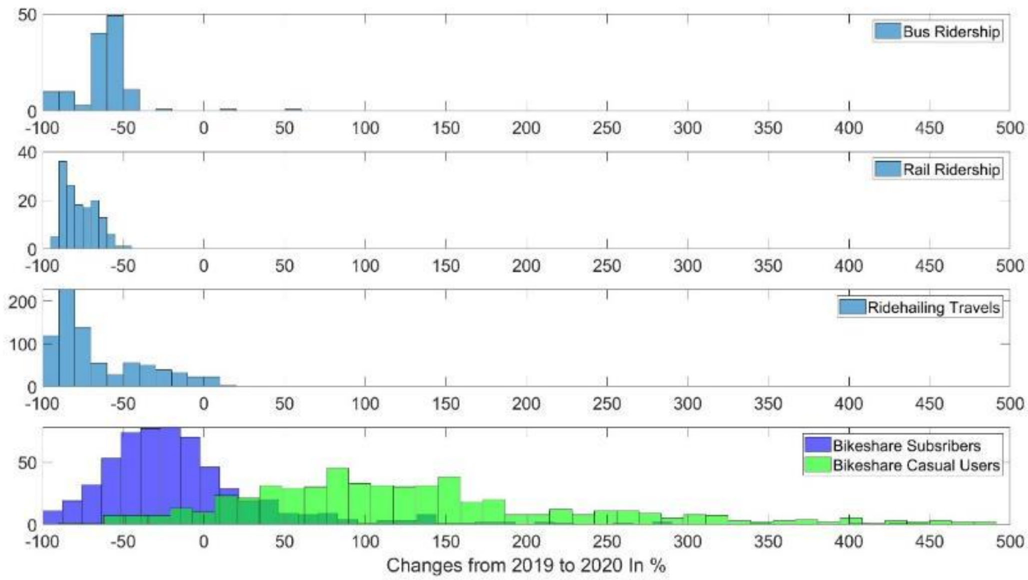



*Figure 9 Histogram of changes in trip volume by mode*

A difference ratio ($DR$) was calculated for each location $i$ of rail station, bus route, or census tract using equation (3). $DR$ is used to represent the relative changes (Difference in Difference) of bikeshare in relation to the change of volumes by another mode.

$$DR_{m,w,user,i} = \frac{Mean(Delta_{w,user,j\in 0.25\ mile\ of\ i})}{Delta_{m,w,i}} \quad (3)$$

where $Mean(Delta_{w,user,j\in 0.25\ mile\ of\ i})$ is the average of $Delta$ all the bike stations that are within 0.25 miles of a location $i$ (rail station, a bus route, or a census tract, and the $DR$ of mode $m$ at location $i$ of weekday or weekend (by casual users or subscribers) to other modes. The threshold value 0.25 mile is selected because this is a reasonable walking distance accepted by most travelers [43]. Due to the large range of the values of $DR$ for different modes, we used different thresholds for a better visualization for the following figures. The threshold values we adopted are illustrated in Table 12. We then plotted the $DR$ of rail, bus, and ridehailing versus bikeshare in the figures below. Note that there is an extremely small number of locations that have both increased volume in bikeshare and the other modes. After a careful examination, we illustrated these cases separately using different legends (as shown in blue and brown lines in Figure 11 or empty census tracts without green or red dots in Figure 12).

*Table 12 Threshold Values for Visualization of DR*

| Mode | $DR$ Threshold Value Range | Legend |
|---|---|---|
| Rail | <= -1.5 | Rail decreases, bike increases significantly |
| | -1.5 - 0 | Rail decreases, bike increases mildly |
| | > 0 | Both decrease |
| Bus | <= -3 | Bus decreases, bike increases significantly |
| | -3 - 0 | Bus decreases, bike increases mildly |
| | > 0 | Both decrease |
| Ridehailing | <= -20 | Ridehailing decreases, bike increases significantly |
| | -20 - 0 | Ridehailing decreases, bike increases mildly |
| | > 0 | Both decrease |

Figure 10 illustrates the $DR$ for bikeshare versus rail. As the left two maps demonstrate, most rail stations saw a decrease in ridership, and the number of trips made by bikeshare subscribers decreased. Bikeshare stations around certain rail stations in the northern part of the city experienced increased trip volumes during weekdays, and some bikeshare stations around rail stations in the South and West saw significantly increases in bikeshare usage. For casual users, the pattern is completely different. Indeed, most rail stations are associated with increased use of nearby bikeshare stations, especially for weekday travel. These observations show that (1) subscribers might use bikeshare to replace some of their rail trips in the outskirt areas of the city; and (2) casual users might use bikeshare to replace the majority of their rail travel, especially during weekdays and at the periphery of the city.

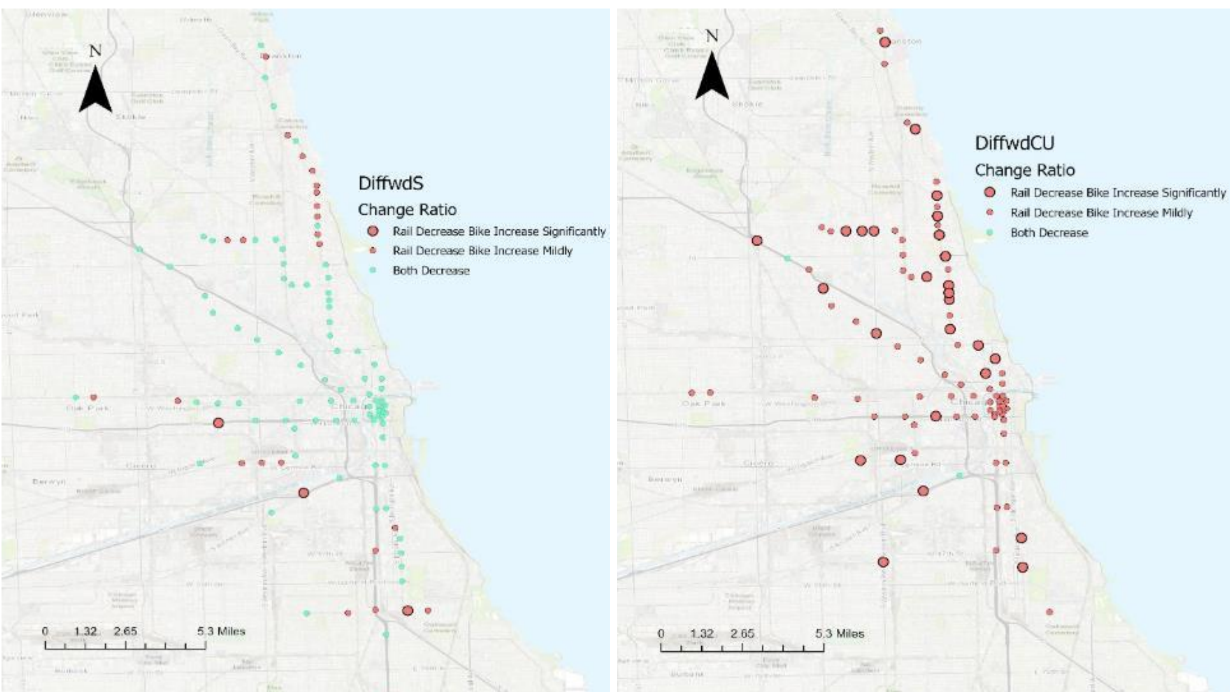



*Figure 10 Rail and bikeshare (left upper: weekday subscribers; left lower: weekend subscribers; right upper: weekday casual users; right lower: weekend casual users)*

Figure 11 shows the relationship between bus ridership and bikeshare usage. The majority of the bus routes had decreased ridership and decreased bikeshare subscriber usage. The exception is located at the outskirts of the city. While some bus routes in the southern part of the city that saw ridership decrease, the surrounding bikeshare stations saw a significant increase in usage by subscribers, indicating that travelers used bikeshare to replace their bus rides in the remote area of the city. On weekdays, bus ridership across the city decreased, but casual bikeshare users significantly increased their bikeshare trips, indicating that they used bikeshare to replace bus riding during the weekdays. For weekends, the increase of bikeshare usage was not as significant. Again, we observed a significant increase in bikeshare usage in the areas other than downtown, especially in the southern parts of the city. As can be seen, there are two sets of bus routes (in blue lines) that have increased ridership along with increased bikeshare usage (both for subscribers and casual users on both weekend and weekdays). These are promising locations that have high potential of integrating bus travels with bikeshare travels. Increasing bike stations in these areas is a valid plan for bikeshare development.

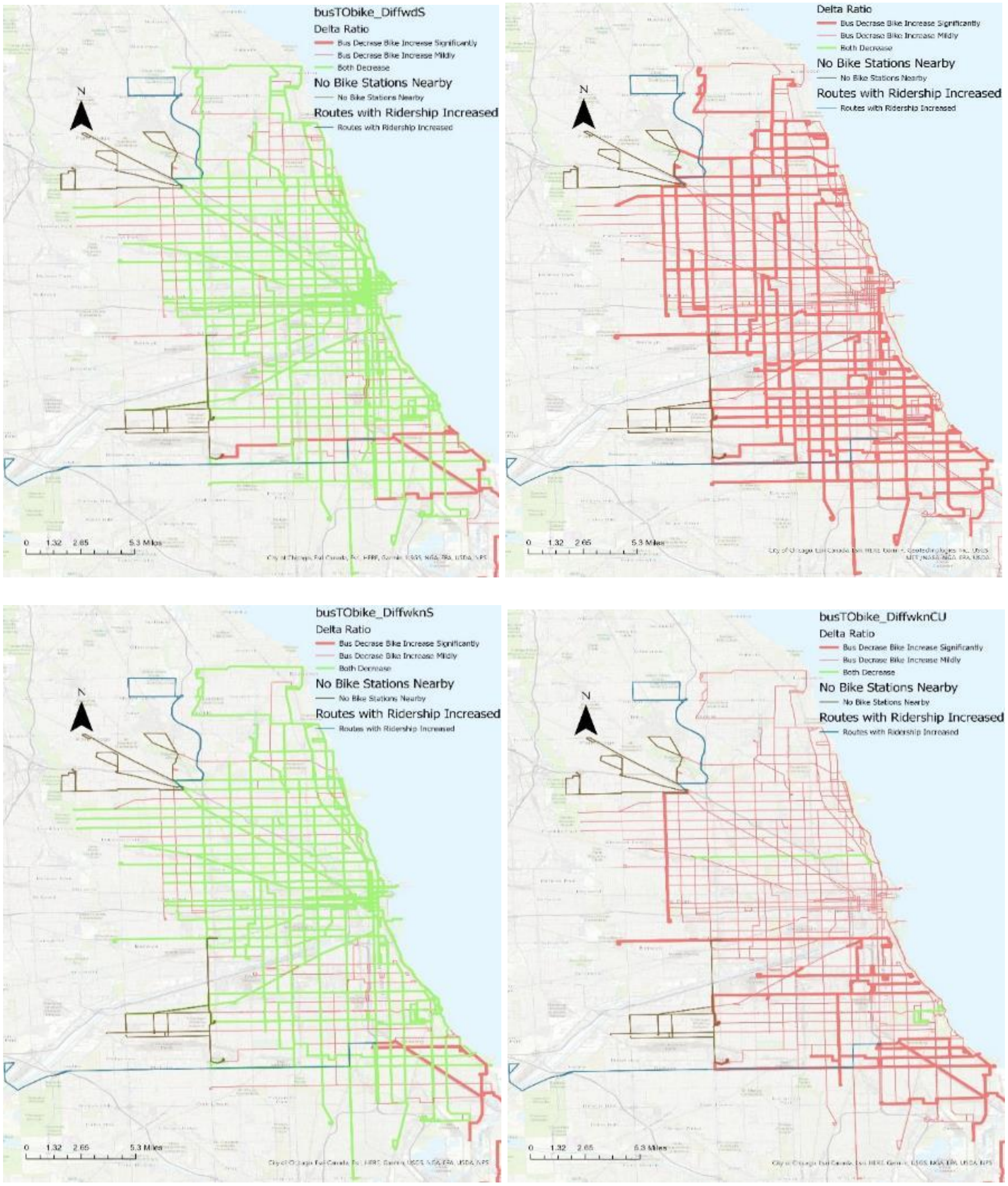



*Figure 11 Bus and bikeshare (left upper: weekday subscribers; left lower: weekend subscribers; right upper: weekday casual users; right lower: weekend casual users)*

Figure 12 shows the interaction between ridehailing and bikeshare travel. Ridehailing travel and bikeshare travel by subscribers decreased in half of the census tracts (left panes). About half of the census tracts saw a slight increase bikeshare travel by subscribers along with a decrease in ridehailing travel. Bikeshare travel by subscribers also significantly increased in several census tracts in the southern part of the city. As for casual users, bikeshare travel increased while ridehailing travel decreased in most census tracts on weekdays. Certain tracts, including the ones in the northern part, west outskirts, and southern part of the city, saw significant increases in bikeshare travel along with decreased ridehailing travel. For weekends, the increase of bikeshare is not as significant as weekdays. However, it is still evident that travelers made many more bikeshare trips than ridehailing trips.

In summary, when comparing the changes in bikeshare travel during the pandemic with changes in other modes, we can see that subscriber bikeshare travel increased significantly as usage of other modes declined in the outskirts areas of the city. Bikeshare travel by subscribers in the center area of Chicago saw a decline in usage similar other modes. For casual users, however, weekday travel by bikeshare increased along with the reduction of other modes. There is not much spatial difference for the $DR$ values in the downtown area, but bikeshare usage increased significantly as trips made with other modes declined in the southern part of the city. On weekends, casual users tended to make significantly more bikeshare trips, along with reduced bus, rail, or ridehailing trips, at the outskirts of the city.

Since we are specifically interested in the relationship between bikeshare travel and public transit trips, we will concentrate on the analysis of bikeshare trips versus travel by bus and rail in the next section.

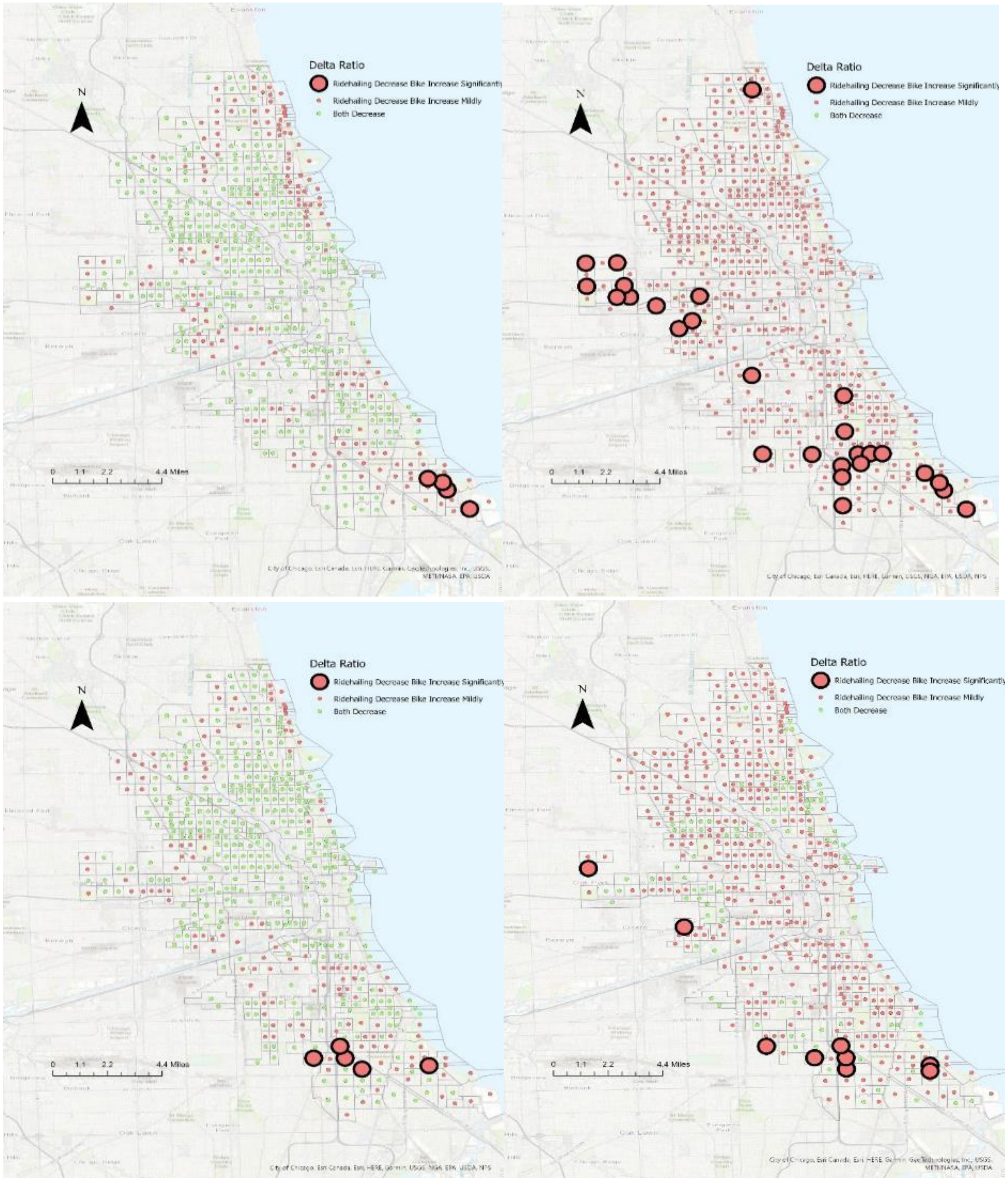



*Figure 12 Ridehailing and bikeshare (left upper: weekday subscribers; left lower: weekend subscribers; right upper: weekday casual users; right lower: weekend casual users)*

### *Bikeshare and Public Transit*

In order to enable more effective public policies that encourage travelers to maximize these sustainable and healthy travel modes, we need to explore the changes between bikeshare usage and public transit. To evaluate this relationship, the locations of bikeshare stations were overlaid on each of the following data layers: bus stops, bus routes, rail stations, and bike facilities (bike lanes shown in Figure 7). The distances between each bike station to surrounding data layer features were categorized into the following five groups: < 200 feet (extremely easy access to bike stations), 200-500 feet (easy access to bike stations), 500-1,320 feet (moderately easy access to bike stations), 1,320-2,640 feet (accessible bike stations), and > 2,640 feet (remote bike stations). The $Delta_{w,user,j}$ are plotted in the boxplots from Figure 13 through Figure 17.

As can be seen from Figure 13, the bike stations that are further away from bike routes had the highest percentage increase for three categories of user and time period. The only exception was for the subscribers on weekdays. Indeed, bikeshare usage slightly increased at bike stations that are located further away from biking facilities. As Figure 7 demonstrates, existing bike routes are not distributed evenly across the city. The downtown and northern parts of the city have a much higher density of bike routes. As illustrated in the earlier section of the report, the bike stations with the highest increases are in the southern part or at the west border of the city. This observation is consistent with the fact that stations at the outskirts of the city have a larger increase in bikeshare usage. Users are employing bikeshare to reach locations that were not traveled by bikeshare users before. The fact that there is no significant difference among different distance categories of bike stations to the closest bike routes for subscribers on weekdays indicates that subscribers were not affected by the availability of bike facilities/routes for their weekday travels. This is a user group that makes bikeshare trips with or without bike lanes on weekdays.

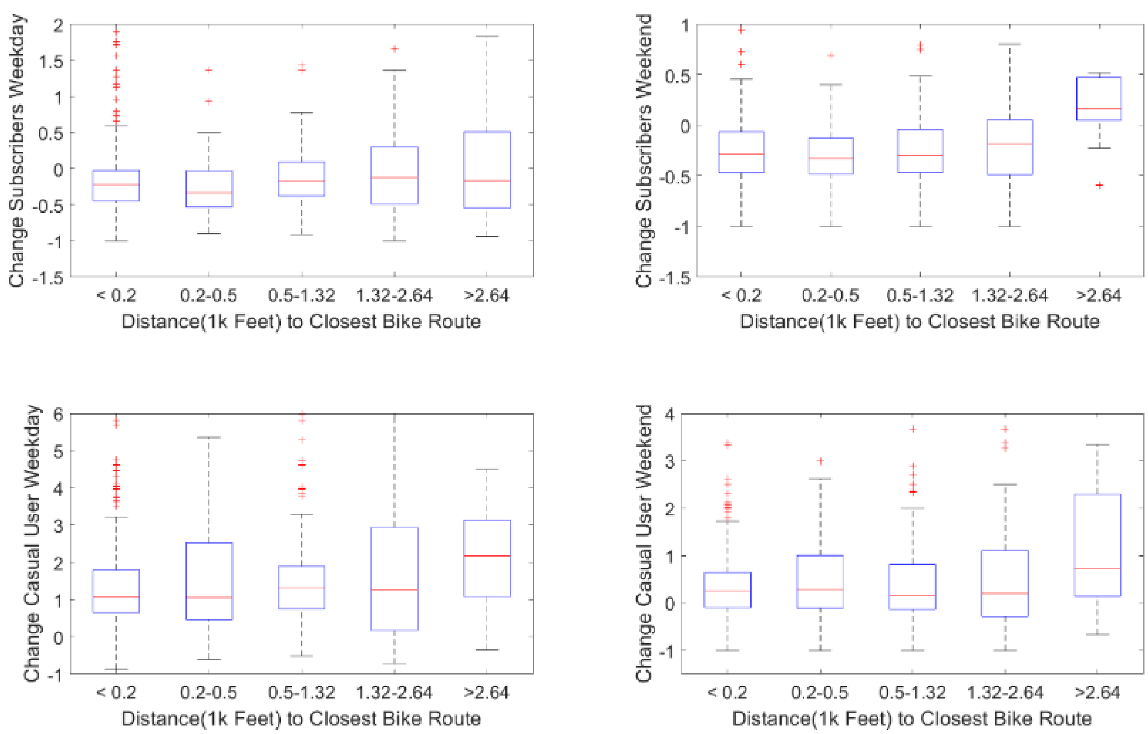



*Figure 13 Changes in bikeshare trips by distance to the closest bike facilities*

There were no significant differences for $Delta_{w,user,j}$ of bikeshare stations located further from or closer to bus stops and bus routes for the majority of user and time categories (Figure 14 and Figure 15). One noticeable fact relates to the trips made by subscribers on weekdays. As can be seen, the ranges for the changes of trips at bike stations that are within 0.25 miles (1.32 k feet) of bus stops are relatively small, indicating more consistency for subscriber workday trips.

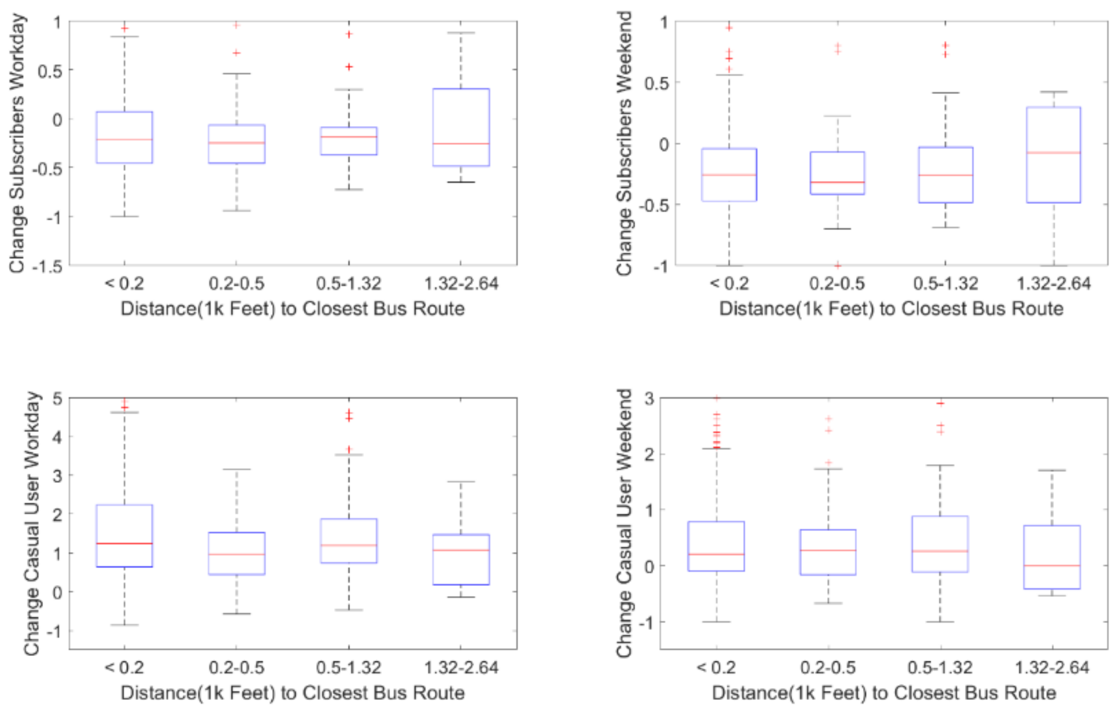



*Figure 14 Changes in bikeshare trips by distance to the closest bus routes*

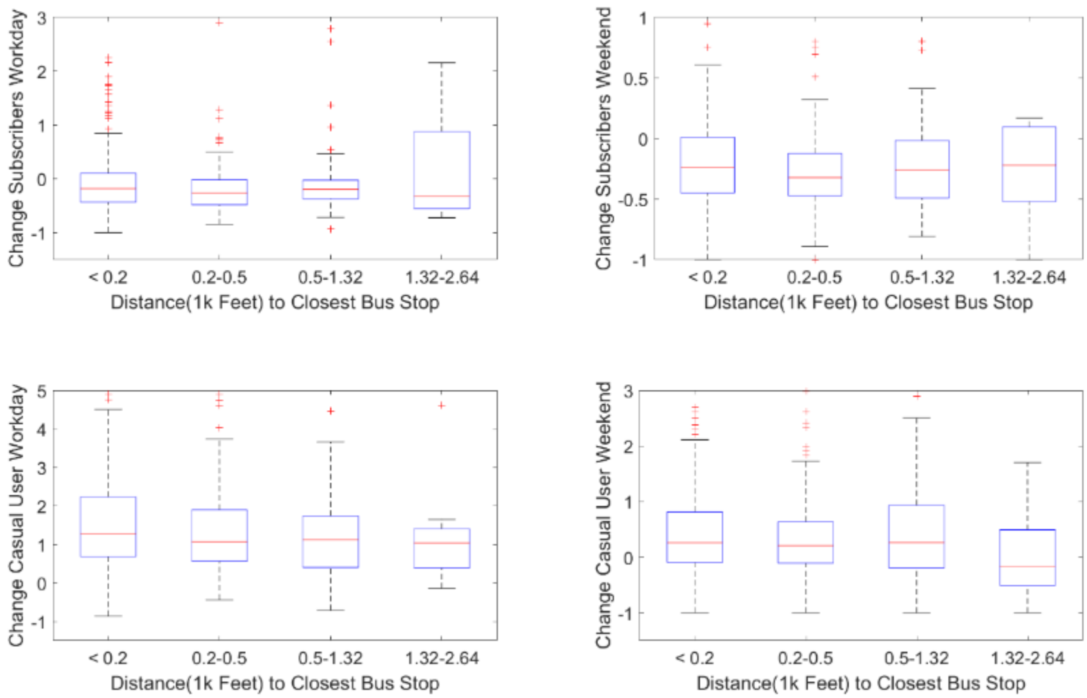



*Figure 15 Changes in bikeshare trips by distance to the closest bus stops*

Figure 16 shows the relationship between changes in bikeshare trips and the distances between bike stations and rail stations. We see an increase in bikeshare trips as bikeshare stations get further away from rail stations for casual users. For subscribers, the decrease in bikeshare trips becomes smaller when the bike stations are located further away from rail stations.

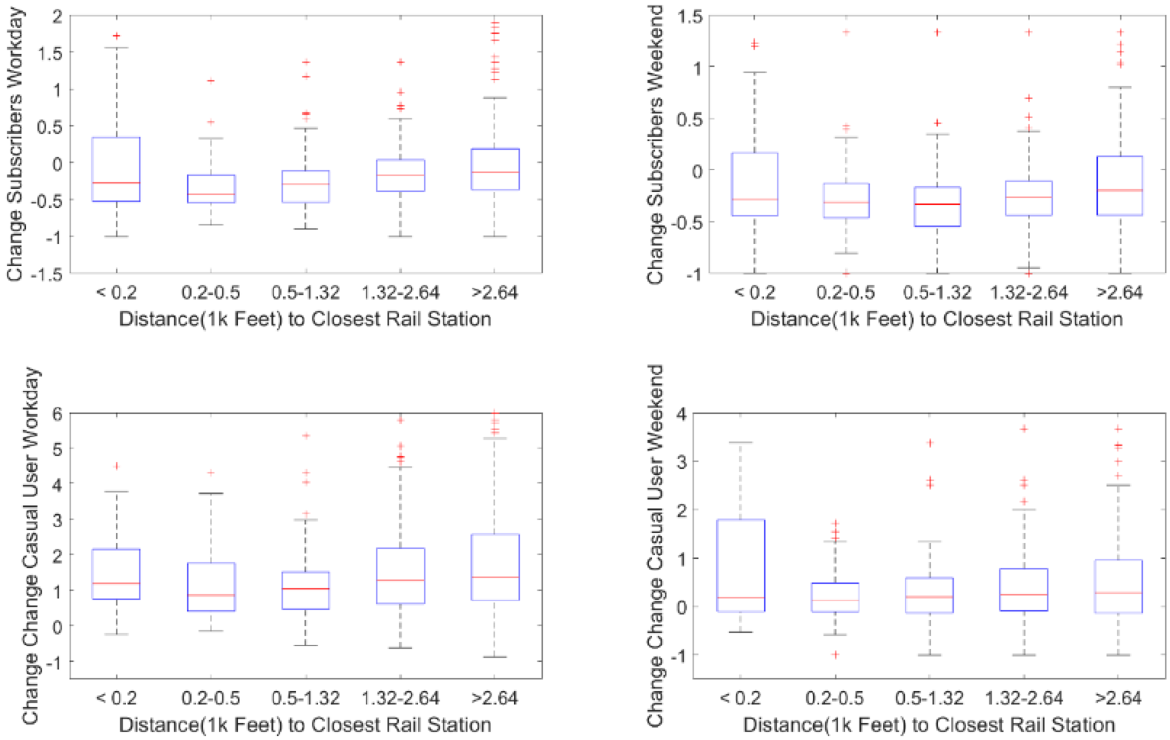



*Figure 16 Changes in bikeshare trips by distance to the closest rail stops*

Figure 17 illustrates the changes in bike usage at bike stations in relation to the type of the closest bike facility. "None" indicates a bike station with no bike facilities within 2 miles. For weekdays, the largest increase occurred at bikeshare stations that have easy access to greenways. While looking at the locations of the greenways (Figure 7), we can see that the majority of greenways are in the downtown area. We may infer that bikeshare users might use bikeshare to serve their commuting needs. However, more survey data are needed to confirm this inference. For weekends, the largest increase occurred at bike stations that do not have any bike facilities close by. One plausible explanation is that weekend bikeshare trips increased more at locations that are not typically served by biking facilities.

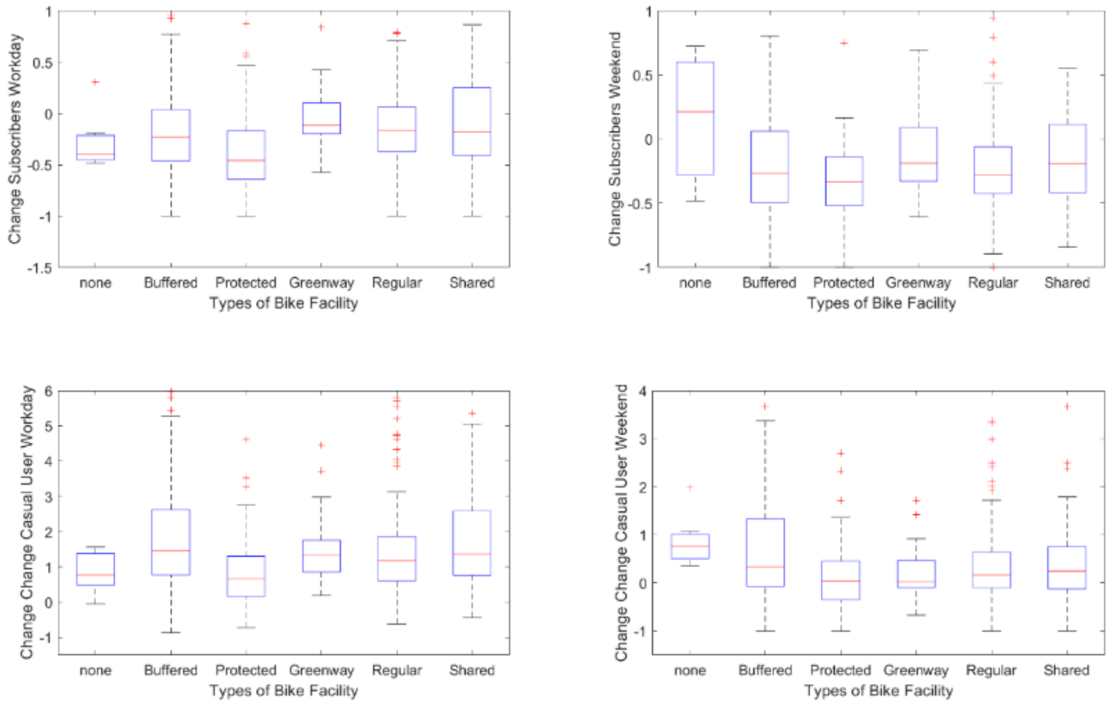



*Figure 17 Changes for stations with the type of the closest bike route ("none" indicates there is no bike facility nearby.)*

To identify all the factors that impact the changes in bikeshare trips, we conducted a 7-way analysis of variance (ANOVA) test to identify significant factors. The results are illustrated in Table 13. As the table demonstrates, bus stops and bus routes have no impact on changes in bikeshare usage. If there is a bike facility close by, the distance from the bike station to a bike facility or a rail station, the user type, and the time (weekday or weekend) that the trips occurred significantly affect changes in bikeshare trips.

*Table 13 ANOVA Results*

| | Sum Square | Degree of Freedom | Mean Square | F-test | Prob>F |
|---|---|---|---|---|---|
| **Bike Facility Type*** | **78.918** | **5.000** | **15.784** | **6.480** | **0.000** |
| **Distance to Bike Facility*** | **28.781** | **4.000** | **7.195** | **2.954** | **0.019** |
| Distance to Bus Stop | 5.144 | 3.000 | 1.715 | 0.704 | 0.550 |
| Distance to Bus Route | 15.633 | 3.000 | 5.211 | 2.139 | 0.093 |
| **Distance to Rail Station*** | **56.237** | **4.000** | **14.059** | **5.772** | **0.000** |
| **User type*** | **1021.619** | **1.000** | **1021.619** | **419.397** | **0.000** |
| **Weekday/Weekend*** | **196.136** | **1.000** | **196.136** | **80.518** | **0.000** |
| Error | 5568.529 | 2286.000 | 2.436 | | |
| Total | 7011.256 | 2307.000 | | | |

*** Significant at 0.05**

# DISCUSSION AND CONCLUSIONS

Biking is a healthy and sustainable means of travel. Bikeshares provide travelers with the opportunity to use this mode without having to worry about the storage and transport of bikes. Although promising, bikeshare is not as widely used in the US compared to countries in Europe. Over the past several decades, numerous studies have been conducted to design policies stimulating active transport and study the effectiveness of such policies [29, 44-48].

During the pandemic, bikeshare usage dropped like other modes of transportation but bounced back quickly and stayed relatively high. Bikeshare has thus proven to be a resilient and equitable transit mode [31]. We see the possibility of using bikeshare as a routine travel mode after the pandemic. Therefore, it is now more important than ever to understand the behavior of bikeshare users, obstacles to using it as a routine commuting mode, feasible and effective policies that can sustain bikeshare usage, and possible policies to encourage the usage of bikeshare together with public transit.

In this report, we studied bikeshare and other non-personal-vehicle travel modes before and during the pandemic in the city of Chicago. By identifying variation and intercorrelation among these modes, we believe that the results can answer some of the questions regarding bikeshare travel and eventually help policy makers to design a biker-friendly traffic system. Two unique features of our study are (1) that all the data analysis is based on data under biker-friendly weather conditions, which we do to exclude the biased impacts of weather on different travel modes; and (2) that the dependent variable we analyzed in this report is the relative change of different modes, $Delta$, before and during the pandemic. By using $Delta$ instead of absolute volumes, we are avoiding the bias created by the varying capacity of different modes.

Our conclusions are as follows. (1) Bikeshares are potentially acceptable for longer trips that may serve as regular commuting trips. As can be seen from our analysis, trip lengths of bikeshare subscribers on weekdays increased significantly during the pandemic. (2) Subscribers have a stable travel demand for bikeshare during weekdays. Whether the bike stations are close to a public transit facility or not will have minimal impact the bikeshare travel of subscribers. (3) The changes in bikeshare travel are heterogeneously distributed over space. Our analysis showed that bikeshare travel increased most significantly in the relatively remote areas. The authors believe that travelers are using bikeshare to reach destinations that were not served as usual bikeshare destinations before the pandemic. This conclusion is in accordance with the fact that bikeshare travel during the pandemic is longer [31, 49], which is consistent with previous studies [23, 30, 31]. It implies that a more connected bikeshare network can be achieved by either increasing the number of stations in remote areas, adjusting the pricing strategy, or optimizing the rebalancing strategy to favor remote areas [45]. Interventions, either fiscal or policy-related, can increase the bikeshare usage if adopted effectively. (4) Bikeshare usage can increase with effective infrastructure design and policy subsidies. Caggiani et al. and Hamidi et al. found that during a lockdown period, people living in underserved areas may need more outdoor activities than those living in wealthier areas. In our study, we also found that the bikeshare stations with the larger changes are in the southern part of the city, where the income level is relatively low. Therefore, we should take equity into consideration when planning bikeshare infrastructure [50, 51]. (5) Weekday bikeshare trips increased at stations associated with biking facilities (greenways) close by, while weekend bikeshare trips had a greater increase at locations without any biking facilities. This observation tells us that on weekdays with heavier traffic flow, travelers would prefer to use bikeshare with biking routes. However, users are still willing to use bikeshare without biking lanes during the weekend when the traffic volume is relatively light to reach more remote locations. Building more biking facilities on the outskirts of the city will create positive incentives for bikeshare users on weekdays. (6) Finally, bikeshare travel is more likely to be correlated with rail travel. There is a minimum connection of bikeshare travel with bus stops or bus routes. This conclusion is consistent with previous studies [27, 49].

A limitation of this study is that the results are only drawn from objective data. In the future, stated preference surveys are needed to collect data regarding the opinions and thoughts of bikeshare users; for example, what are the factors limiting further or more usage of bikeshare? Such data cane complement analysis of objective data, allow us to better understand the behavior of travelers, and improve the resilience of the system.

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