Impact of e-scooter sharing on bike sharing in Chicago

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Impact of e-scooter sharing on bike sharing in Chicago

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Abstract: As a new type of shared micromobility, e-scooter sharing first appeared in the United States and became popular worldwide. Considering e-scooter sharing and bike sharing have similar service attributes, the ridership of bike sharing may be affected by the introduction of e-scooter sharing. To date, studies exploring this impact are limited. In this study, we seek to analyze the impact of e-scooter sharing on the usage of bike sharing from trip data of e-scooter sharing and bike sharing in Chicago for a total of 30 weeks. We rely on a difference-in-differences modeling approach based on the propensity score matching method. We found that the average duration of e-scooter trips is shorter than that of bike trips. The introduction of e-scooter sharing reduced the overall bike sharing usage by 23.4 trips per week per station (10.2%). bike sharing usage of non-members and members decreased by 18.0 (34.1%) and 5.4 (4.0%) trips, and that of male and female members decreased by 3.3 (3.1%) and 2.0 (7.3%) trips, respectively. Furthermore, the volume of short-, medium-, and long-duration trips of bike sharing decreased by 10.9 (7.5%), 5.4 (9.6%), and 3.4 trips (20.5%), respectively. Finally, bike sharing use during non-peak hours decreased but was not affected during peak hours.

Keywords: Micromobility, Shared E-scooter, Bike sharing, Difference-in-differences, Propensity score matching

1. Introduction

E-scooter sharing has developed rapidly worldwide since 2017. In 2019, shared e-scooter trips doubled from 2018 and now make up 2/3 of all shared micromobility trips in the US (NACTO, 2020). Nearly one-fourth of Parisians used shared e-scooters in 2019 (Lime, 2019a). In Los Angeles, the e-scooter sharing operator Lime provided 3 million trips from 2017 to the beginning of 2019 (Lime, 2019b). In Austin, the cumulative number of shared e-scooter trips reached 5 million in July 2019, greatly exceeding that of bike sharing trips (Austin, 2019). Being dockless means that an e-scooter can be parked anywhere within the service area instead of being returned to the designated stations. Moreover, as a powered vehicle, e-scooters can be used to travel for longer distances with less physical effort. Both features reduce some of the barriers associated with bike sharing systems. The growth of e-scooter sharing has been fueled by private investment and is faster than bike sharing. Notably, bike sharing has a longer history, and approximately 1,000 cities worldwide have bike sharing systems. The appearance of e-scooter sharing has brought a new micromobility option to urban travel but the role of e-scooter sharing in urban transportation systems is still unclear (Tuncer et al., 2020). In particular, e-scooter sharing and bike sharing are both shared micromobility modes and are usually used for short-distance travel. Thus, they are likely to compete for riders. It is important for government agencies to understand how the advent of ESS influences the ridership of bike sharing so they find ways to coordinate the two systems to better serve the public and expend public resources. Some examples include relocating bike sharing stations, adjusting the capacities of different stations, pricing, and determining the e-scooter sharing operation areas. This topic has not been explored in depth by previous studies. In this study, we aim to quantify the impact of e-scooter sharing on the ridership of bike sharing.

In our study, the data of Chicago is adopted and analyzed because this city has both e-scooter sharing and bike sharing systems and the trip data of both systems are open to the public. The e-scooter sharing pilot program in Chicago began on June 15, 2019. During the nearly four-month period, 2,500 e-scooters were deployed, which generated more than 800,000 trips (CDOT, 2019). The Chicago bike sharing system began operation on June 27, 2013, with 75 stations and 750 bicycles. By December 2019, the number of stations had increased to 612, and the number of bicycles exceeded 6,000. The usage had also increased year by year. We aim to quantitatively analyze the impact of the e-scooter sharing on the usage of bike sharing. A difference-in-differences (DID) model based on the propensity score matching (PSM) method is used for this analysis.

This paper is further structured as follows. Section 2 introduces the literature review on e-scooter sharing and bike sharing. Section 3 describes the Chicago e-scooter sharing and bike sharing data and performs a comparative analysis. Section 4 presents the method used in this article. Section 5 presents the analysis and discusses the results. Section 6 concludes and discusses the limitations of this study.

2. Literature Review

In this study, we aim to explore the impact of the advent of dockless e-scooter sharing on the usage of station-based bike sharing. In this section, we describe the literature on the role of bike sharing and e-scooter sharing in the transportation system, followed by a review of the studies exploring the interaction between station-based bike sharing and dockless e-scooter sharing.

Factors that influence the demand for bike sharing include the "5D" built environment, trip characteristics, user characteristics, and weather (Faghih-Imani and Eluru, 2016; Wu et al., 2021; Yang et al., 2020). Because the demand profiles often follow morning and afternoon peak hours, commuting is regarded as one of the major trip purposes of bike sharing (Bordagaray et al., 2016; Lathia et al., 2012; McKenzie, 2019; Zhao et al., 2015). Other scholars have done work on the interaction between bike sharing and other modes of transportation (Campbell and Brakewood, 2017; Gu et al., 2019; Guo and He, 2021; Kong et al., 2020; Li et al., 2019; Ma et al., 2019). Three types of interactions have been defined between bike sharing and other modes of transportation: substitution, integration, and complementarity (Kong et al., 2020). Most often, bike sharing mainly replaces public transit (Campbell and Brakewood, 2017; Ma et al., 2019). In these studies, the difference in difference (DID) methods are commonly used. For example, Campbell and Brakewood (2017) and Ma et al. (2019) used the DID approach to analyze the changes in bus ridership before and after the emergence of bike sharing. The results show that the emergence of bike sharing can reduce bus ridership.

Early research on e-scooter sharing relied on questionnaire-based stated preference surveys to collect data. Those studies link demographic characteristics of shared e-scooter users and their intention to use shared e-scooters (Aguilera-García et al., 2020; Eccarius and Lu, 2020; Laa and Leth, 2020; Mitra and Hess, 2021; Sanders et al., 2020). Men and people with higher education tend to be more likely to use shared e-scooters (Aguilera-García et al., 2020; Laa and Leth, 2020; Mitra and Hess, 2021; Nikiforiadis et al., 2021).

When e-scooter sharing trip data became available, many studies analyzed the impact of the built environment on behavior (Bai and Jiao, 2020; Bai et al., 2021; Caspi et al., 2020; Hawa et al., 2021; Huo et al., 2021). These studies found that e-scooter sharing is most heavily used around university campuses and in downtown areas, and deployment patterns follow this demand. The peak hours for shared e-scooter trips are usually in the afternoon. In terms of replaced transport modes, Laa and Leth (2020); Mitra and Hess (2021); Nikiforiadis et al. (2021) found that e-scooter sharing mainly replaced walking and public transportation, while Sanders et al. (2020) found that e-scooter sharing replaced many walking and bicycling trips. On the other hand, PBOT (2018) found that a large proportion of shared e-scooter trips (around 34%) replaced car-based trips.

Some studies explored the interaction between e-scooter sharing and bike sharing and their findings are relevant to the topic of this study. For example, Zhu et al. (2020) analyzed bike sharing and e-scooter sharing in Singapore and found that bike sharing is often used for commuting while e-scooter sharing mainly serves recreation or tourism activities in the downtown area. This finding is consistent with that of McKenzie (2019) and Zamir et al. (2019), both of which are based on the analysis of bike sharing and e-scooter sharing, trips in Washington D.C.. Reck et al. (2021) analyzed the choice behavior of the four shared micro-mobility modes (docked e-bike, docked bike, dockless e-scooter, dockless e-bike) and found that docked modes are more preferred for commuting than dockless. Reck and Axhausen (2021) surveyed the residents of Zurich and found that the demographics of e-scooter sharing users are more similar to those of the residents than bike sharing users, which indicates that e-scooter sharing users are more representative of the residents. Younes et al. (2020) analyzed the determinants of demand for e-scooter sharing and bike sharing in Washington DC and the interaction between the two modes. They found that the usage of e-scooter sharing has a possible competitive relationship with the usage of bike sharing by non-members and a complementary relationship with the usage of bike sharing by members. However, they acknowledge the lack of causality in their study.

As a result, to our best knowledge, no research has analyzed the impact of e-scooter sharing on the usage of bike sharing using long-term data. Therefore, we perform this study aiming to answer the following three questions: (1) Whether e-scooter sharing impacts the usage of bike sharing; (2) Whether the impact is different among different bike sharing user types; (3) Whether the impact is different among different types of trips (happening in different time periods or are different durations)?

3. Data

3.1 Background

On June 15, 2019, ten companies (Bird, Bolt, Grüv, Jump, Lime, Lyft, Sherpa, Spin, VeoRide, and Wheels) obtained permits to operate e-scooter sharing in the Chicago Department of Business Affairs and Consumer Protection. Altogether, 2,500 e-scooters were allowed to be operated in designated areas in the northwest of the city. The e-scooter sharing pilot program in Chicago aimed to provide residents with a fair, safe, and sustainable travel mode while testing the performance of e-scooter systems and providing equitable access. The northwest area was designated as the pilot program area because of the area's many different demographic groups and a variety of transportation modes (CDOT, 2019). Table 1 shows the number of e-scooter trips reported by 10 operating companies during the pilot (spanning four months). By comparing the trip data reported by various operators, Bird, Lime, Lyft, and Jump have a higher market share than the other operators. Each operator sets its own price. Generally, the price is one dollar to start the trip and 15 cents for every minute of use (CURBED, 2019).

Table 1 E-scooter sharing operators and number of trips provided

Provider	Number of trips	Proportion
Bird/Sherpa	178,134	21.7%
Lime	121,131	14.7%
Lyft	119,116	14.5%
Jump	100,528	12.2%
VeoRide	75,559	9.2%
Grüv	68,620	8.4%
Wheels	57,740	7.0%
Spin	55,463	6.8%
Bolt	45,324	5.5%

The Chicago Divvy bike sharing was first launched on June 27, 2013, and was operated by Motivate, which was later bought by Lyft. More than 612 stations and 6,000 bikes exist now. In 2019, Divvy's average daily ridership was approximately 10,460, and each bike is used approximately 1.74 times per day. The membership includes three types; annual member, 15-day member, and non-member. Non-member users pay $3 per trip, and the trip duration is limited to 30 minutes. Beyond 30 minutes, the price increases by $0.15 for every additional 1 minute. Figure 1 shows the location and number of docks of bike stations. Stations are primarily located in the downtown area of Chicago, with less dense distributions beyond the urban core. In 2016, more than 10 million trips used Divvy bike sharing.

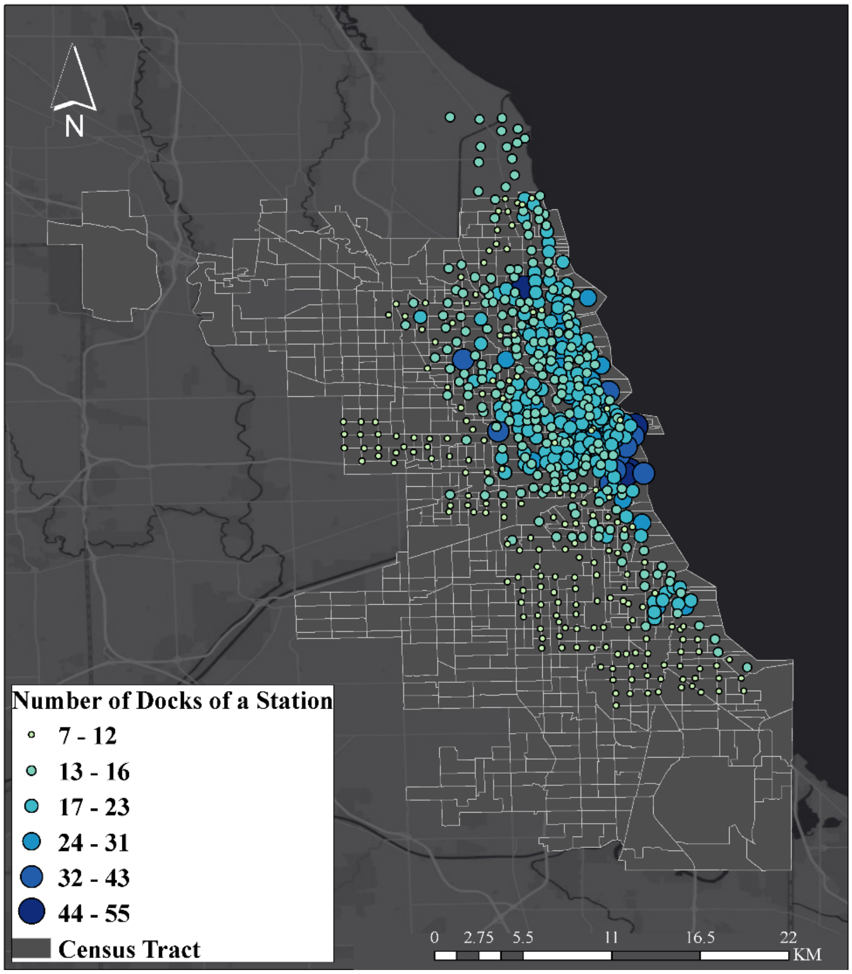

Figure 1 Location of bike sharing stations and e-scooter sharing pilot program area

3.2 Data Description

The data used in this study include three datasets, Divvy bike sharing ridership data[1], e-scooter sharing ridership data[2], and the Smart Location Database[3]. There were more than 2,870,000 bike sharing trips from March 2019 to October 2019. The trip-related information includes starting and ending time, starting and ending station, trip duration, type of user (annual members, 15-day members, and non-members), and age and gender of annual and 15-day members (the demographic information of non-members is unknown). The bike sharing data also contain the coordinates and capacity of each bike station.

E-scooter sharing ridership data are from June 15, 2019, to October 15, 2019. There were 812,615 reported shared e-scooter trips during that time period across operators (CDOT, 2019). Only 664,975 disaggregated trips are stored and provided to the public for the time period between June 15 and October 15. Among them, a significant portion of the trips does not have latitude or longitude information. Those trips are deleted, leaving 560,449 trips. We further deleted the trips shorter than 100 m, longer than 10 km, less than 60 seconds, or longer than 2 hours, leaving 557,462 trips to be analyzed (deleted 0.54% of the trips). These criteria are consistent with many

[1] https://www.divvybikes.com/system-data
[2] https://data.cityofchicago.org/Transportation/E-Scooter-Trips-2019-Pilot/2kfw-zvte
[3] https://www.epa.gov/smartgrowth/smart-location-database-technical-documentation-and-user-guide

previous studies (Huo et al., 2021; Shen et al., 2018). When we further cleaned the data, we found that the data from October 1 to October 14 were missing. As a result, we set the study period as June 17- September 29 (15 weeks). The number of trips during the study period is 538,287.

E-scooter sharing trip data include the census tract of trip origin and destination, trip starting and ending time, trip duration, and distance. In addition, socio-economic and built environment covariates around each bike station were collected to control the effects of those covariates. The built environment covariates include the "5Ds" covariates (i.e., density, diversity, design, distance to transit, and destination accessibility) (Ewing and Cervero, 2010), which were obtained from the Chicago data portal (2018)[4]. Then, the socio-economic variables were drawn from the Smart Location Database (Ramsey and Bell, 2014) and the US Census Bureau[5].

3.3 Data Analysis

3.3.1 Divvy bike sharing ridership analysis

Table 2 The usage of bike sharing in different time periods

		Time period (trips/hours)					**Weekday or weekend**		**Sum**
		00:00-05:59	06:00-10:59	11:00-15:59	16:00-18:59	19:00-23:59	Week day	Week end	
Gender	**Male**	10,393	132,889	115,268	252,815	67,845	1936,634	464,186	2,400,820
	Female	2,970	45,598	46,764	86,723	23,636	641,414	216,564	857,978
User type	**Member**	12,282	169,359	135,962	310,267	81,253	2,393,963	543,404	2,937,367
	Non-member	3,773	22,844	72,674	78,461	29,005	502,402	378,235	880,637
Age	**55-73**	2,618	19,746	14,791	18,887	4,211	212,687	84,166	296,853
	41-54	4,764	43,631	25,772	46,177	9,716	451,566	179,182	630,748
	31-40	7,507	76,122	45,502	95,911	26,430	821,525	327,353	1,148,878
	25-30	9,099	68,136	50,444	107,032	38,381	845,272	336,045	1,181,317
	19-24	2,551	16,169	18,269	31,419	14,921	251,924	100,147	352,071

Table 2 lists bike sharing ridership in each period by gender, user type, and age group. According to the temporal distribution of ridership, the time period is divided into five parts: AM peak hours (6:00–10:59), Midday (11:00–15:59), PM peak hours (16:00–18:59), Evening (19:00–23:59), and Night (0:00–5:59). We can see that trips made by male users are roughly triple those

[4] https://data.cityofchicago.org/

[5] https://data.census.gov/cedsci/

made by female users. Regarding the user type, trips made by members are more than triple those made by non-members. The period with the highest number of trips for members is from 16:00 to 18:59, and for non-members is from 11:00 to 15:59. Regarding age, the highest number of trips is made by the 25–30 age group, followed by the 31–40 age group. Notably, the highest number of trips for users of age 19–54 is in the evening peak hours from 16:00 to 18:00, whereas for users of age 55 to 73 is from 06:00 to 10:00. This finding may indicate that users of age 19–54 mainly use bike sharing for commuting, whereas users of age 55–73 mainly use bike sharing for non-commuting activities.

3.3.2 Distribution of trip duration of bike sharing and e-scooter sharing

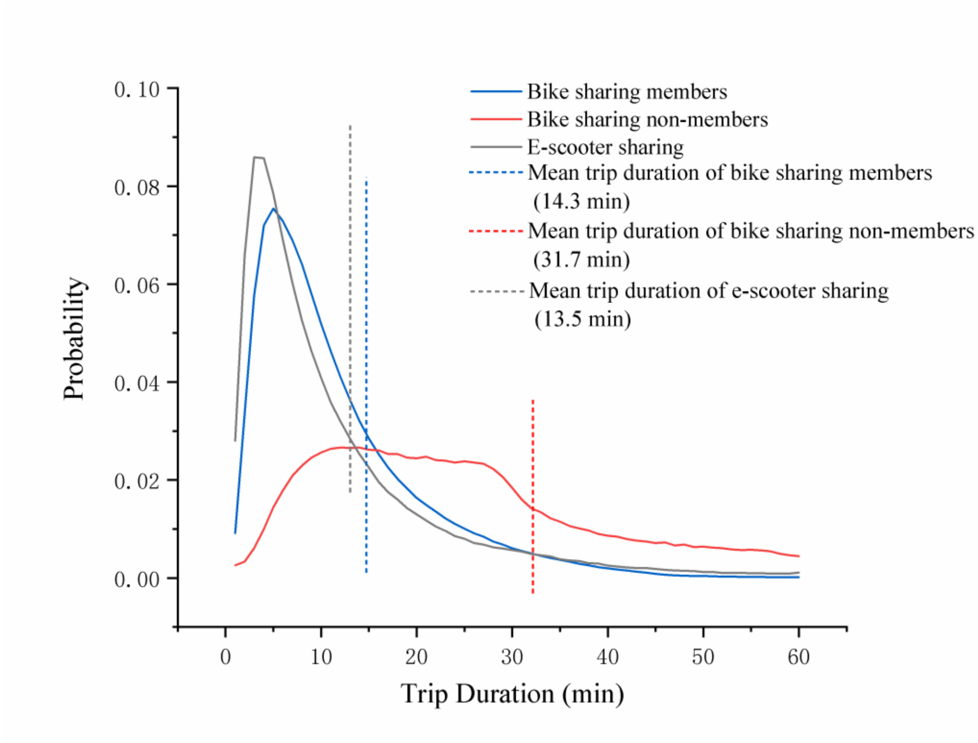

Figure 2 Distribution of trip duration of bike sharing and e-scooter sharing

In Figure 2, we plotted the distribution of trip duration of bike sharing and e-scooter sharing. The average duration of bike sharing trips made by non-members is twice that of members. The duration of e-scooter trips appears to be similar to that of bike trips made by members.

3.3.3 Temporal distribution of ridership of bike sharing and e-scooter sharing

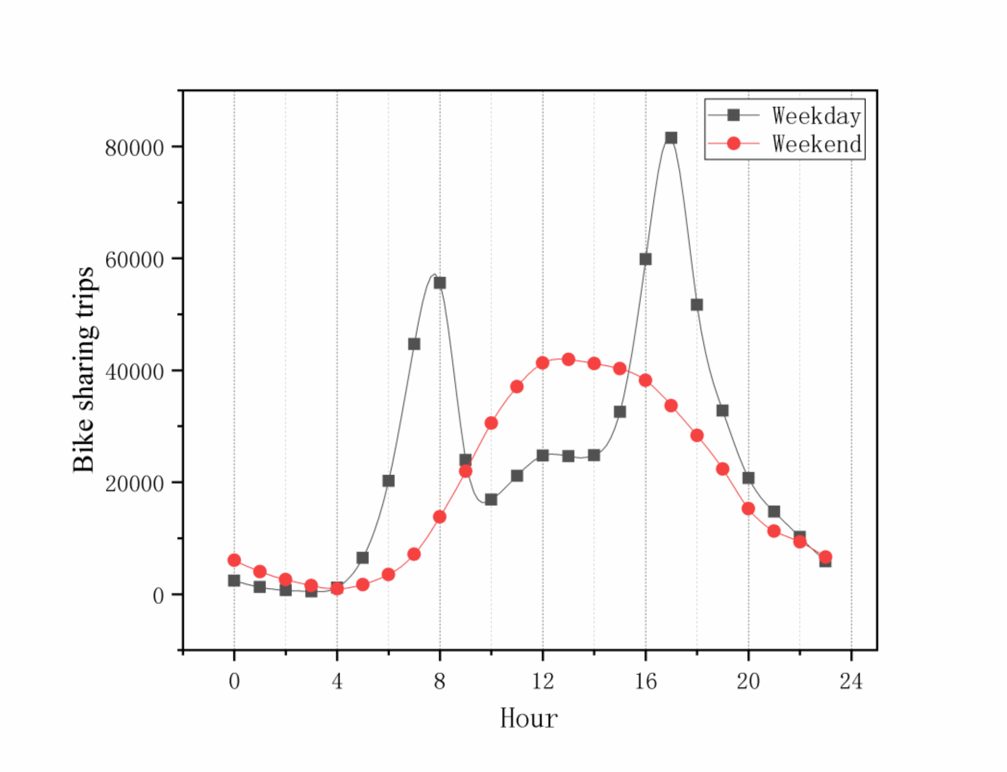

Figure 3 Number of bike sharing trips by hour

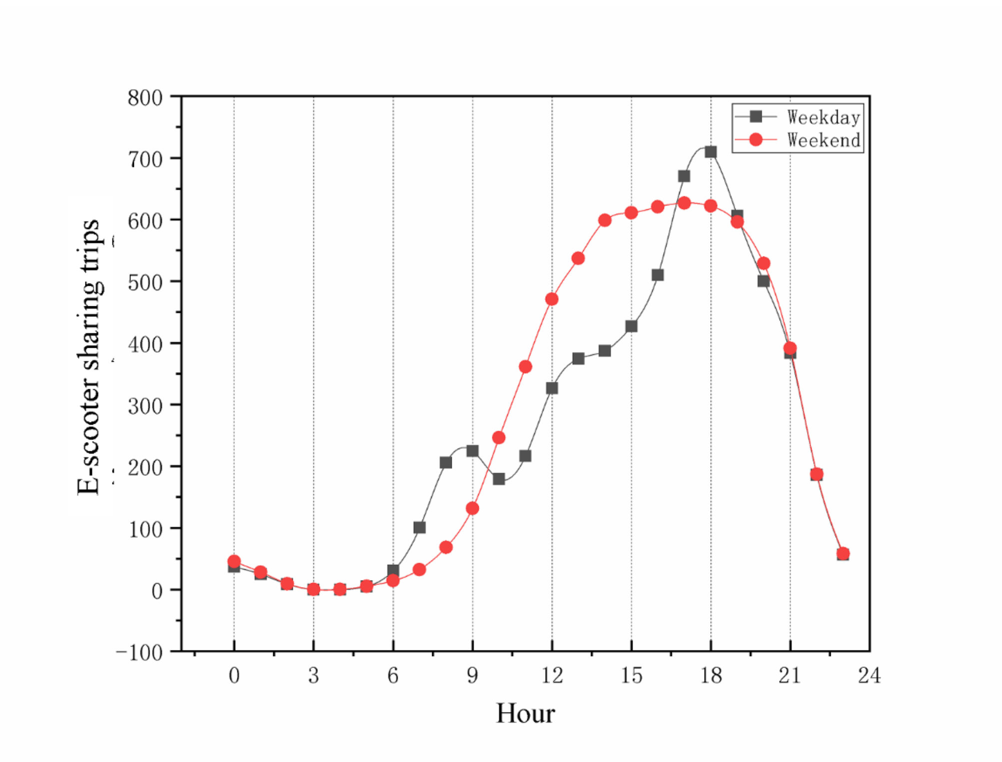

Figure 4 Number of e-scooter sharing trips by hour

As expected, the temporal distribution of bike sharing ridership is different on weekdays and weekends (Figures 3 and 4). On weekdays, the ridership has two peak periods, that is, morning and afternoon peak hours, indicating that that bike sharing is an important transportation mode for commuting, particularly for members. From a different perspective, the ridership of e-scooter sharing on weekdays and weekends are similar, both without the two-peak weekday commute pattern. The peak occurs late in the afternoon, between 16:00 and 20:00 on weekdays and 14:00 and 19:00 on weekends. The weekday peak includes typical afternoon commute hours.

4. Research Design and Method

4.1 Method

Difference-in-difference (DID) is a widely used statistical method to infer a causal relationship in social science to mimic an experimental research design using observational data (Ashenfelter and Card, 1984; Li et al., 2018; Li et al., 2012; Li et al., 2019), particularly when a randomized experiment is impossible as in our case. The basic premise is to divide all the studied units into treated and untreated units. The former receives treatment, which is the influence of the e-scooter sharing in our study, whereas the latter does not receive treatment. The effect of the treatment is estimated by comparing the change of the outcome (usage of bike sharing in this study) over time (before and after the launching of e-scooter sharing) of the treated units to the change of the outcome of the untreated ones. This could mitigate the effects of extraneous factors (e.g., systematic changes in demand).

However, the results of the DID method could suffer from selection bias, which means that the units in the treated group are inherently different from those in the untreated group. This would make the treated and untreated units not comparable, and the results of the DID analysis unreliable. In Propensity Score Matching (PSM), the propensity score refers to the probability that a unit with certain characteristics belongs to the treated or untreated units. The scores can be used to reduce or eliminate potential selection bias by balancing the characteristics of the units between the treated and untreated ones. PSM creates matched sets of treatment and control groups in the treated and untreated units. A matched set consists of at least one unit in the treatment group and one unit in the control group with a similar propensity score. This method could ensure that the outcome is independent of the division of the treatment and control groups. After matching, the difference in the outcomes observed between the treatment and control groups can be completely attributed to the treatment (Rosenbaum and Rubin, 1983).

4.2 Theoretical framework for DID-PSM

The "psmatch2" package of the Stata software is used to implement the DID-PSM (Leuven and Sianesi, 2003). The following sections describe the steps to implement DID-PSM.

(1) Propensity score estimation

Given that the propensity score indicates the probability that a unit belongs to the treated units, logit and probit models are usually used to construct the relationship between the covariates (characteristics of the units) and the group category. In this study, the logit model is selected:

$$P(T=1|\,X) = \frac{EXP(\alpha+\beta X)}{1+EXP(\alpha+\beta X)} \qquad (4-1)$$

where X represents the covariates, T represents the group category with 1 indicating treated units and 0 indicating untreated units, α is the intercept, and β is the vector of regression coefficients.

(2) Matching algorithm and balance detection

After obtaining the propensity score, we need to use matching algorithms to select observations from the untreated units to construct the control group. Common matching algorithms include k-nearest neighbor, caliper matching, radius matching, and kernel matching. To date, no conclusion exists on which is the best matching algorithm. Generally, when the sample size is large, the results of all the matching algorithms should be similar (Li et al., 2013). More details on the matching algorithms can be found in (Heinrich et al., 2010). Usually, multiple matching algorithms are used and compared to increase the reliability of the results. In this study, we use balance detection to test the reliability of matching results. If no significant difference exists in the covariates used for matching between the two groups, then the matching covariates and matching methods selected are suitable, and the matching result is good. We use the following equation to calculate the standardized difference δ:

$$\delta = \frac{\bar{\chi}_T - \bar{\chi}_C}{\sqrt{s_T^2 / s_C^2}} \qquad (4-2)$$

where: $\bar{\chi}_T$ and s_T represent the mean and standard deviation of a covariate of the treatment group, respectively; $\bar{\chi}_C$ and s_C represent the mean and standard deviation of a covariate of the control group. Some studies suggest that when the difference $\delta \leq 10\%$ for all covariates, it passes the balance test and the result is acceptable (Wang and Cao, 2017).

(3) Treatment effect estimation

After the balance test is passed, the average difference between the treatment and control groups is reflected by the average treatment effect (ATE). Considering that the t-value of ATE is not provided in Stata, we choose the average treatment effect on the treated (ATT) to represent the change of bike sharing usage after the launching of e-scooter sharing. The equation of ATT is as follows:

$$ATT = \frac{1}{N^T}\sum_{i\epsilon T}\Delta y_i^T - \frac{1}{N^T}\sum_{i\epsilon T} w_j \Delta y_i^C \qquad (4-3)$$

where T and C represent the treatment and control groups, respectively; Δy_i represents the difference in the usage of shared bikes before and after the treatment for the i_{th} station; w_j represents the weight of the j_{th} station, which is obtained by various matching methods.

4.3 Treated units and study period

We study the impact of e-scooter sharing on the use of bike sharing using the DID model based on the PSM method. Hence, we first need to divide the bike sharing stations into treatment and control units. Treated units refer to the stations for which the usage of bike sharing is influenced by the e-scooter sharing, whereas the untreated units refer to the contrary.

We regard the bike sharing stations located in the e-scooter sharing pilot program with no less than 100 shared e-scooter trips within the 400-meter buffer area around the station as the treated units. Since only the census tract of the shared e-scooter trip origin is known, we regard the shared e-scooter trips to be uniformly distributed in the census tract so as to calculate the number of shared e-scooter trips within the buffer area. The reason for choosing the 400-meter buffer area is that previous studies have concluded that 400 meters is considered an acceptable walking distance to access the bike sharing station (Daniels and Mulley, 2013; Hoehner et al., 2005; Li et al., 2019; McCormack et al., 2008; Pangbourne, 2019; Pikora et al., 2003). The number of units in the treated and untreated units is 150 and 461, respectively, with a ratio of approximately 1:3, which is considered sufficient to ensure the quality of the matching.

Figure 6 shows the location of bike sharing stations and spatial variation of e-scooter trips. The red dots represent stations in the treated units, whereas the blue ones represent stations in the untreated units. The figure also shows the number of e-scooter trips of each census tract.

The outcome variable is the difference in the change in usage before and after the launching of e-scooter sharing. To obtain a reliable estimation of the effect of the treatment, we select the time period of 15 weeks before and after the launching of e-scooter sharing, from March 2, 2019, to September 29, 2019. The period of 15 weeks before the launching of e-scooter sharing is regarded as the pre-treatment period, and that after the launching of e-scooter sharing is regarded as the post-treatment one.

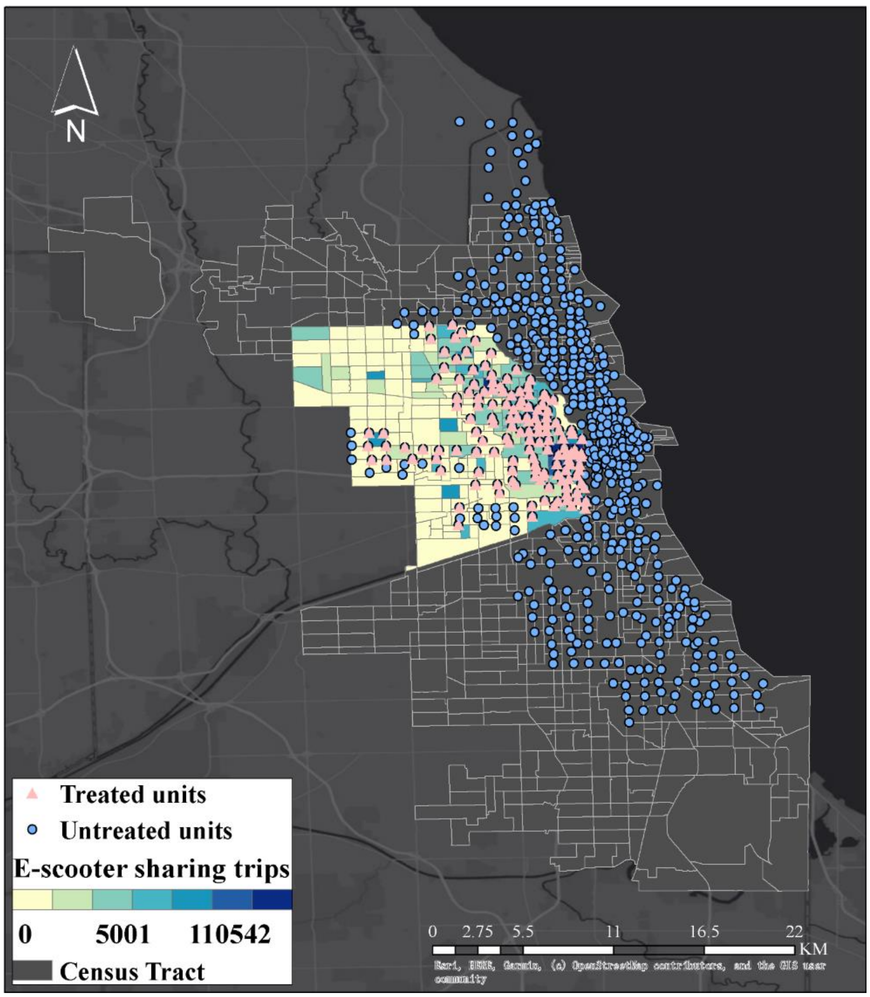

Figure 6 Location of bike sharing stations and spatial variation of e-scooter trips

4.4 Covariates

The PSM method requires covariates to capture as many potential confounding factors as possible. Therefore, the model should include covariates that affect bike sharing trips. However, adding a covariate that has no impact on the outcome in PSM would increase the variance of the estimated treatment effect (Brookhart et al., 2006). Thus, all the covariates that were associated with outcomes should be included regardless of whether they influence the treatment assignment (Brookhart et al., 2006; Li et al., 2017).

The selection of covariates in our study is based on previous studies that explored factors affecting bike sharing usage (Faghih-Imani and Eluru, 2016; Faghih-Imani et al., 2014; Fishman et al., 2014; Li et al., 2018; Li et al., 2019). Previous studies have shown that socio-economic covariates, such as population density, income, and employment density, affect the usage of bike sharing (Faghih-Imani and Eluru, 2016; Wang et al., 2018; Yang et al., 2020). Other studies found that land use factors and transportation infrastructure-related covariates also influenced the usage of bike sharing (Yang et al., 2020). Therefore, we choose to include three types of covariates: socio-economic, land use, and transportation infrastructure. A buffer with a radius of 400 meters is drawn around each station. The reason for choosing 400 meters is as follows. First, Daniels and Mulley (2013); Noland et al. (2016) recommended that 400 meters is generally considered as the distance threshold for residents to walk to public transportation and bicycle stations. Second, when the distance is too low, the surrounding variable attributes may not be captured since the resolution of the census tracts is larger than very short walking distances. The value of each variable is extracted from the buffer area. Given that the boundary of the census block group (CBG) is not the same as the buffer, residents and jobs are assumed to be uniformly distributed in the CBG. Thus, the values of these covariates for each station could be calculated based on this assumption.

Based on previous studies, the following covariates are selected (Table 3). Socioeconomic covariates include population density, employment density, and average income. Land use covariates include residential area, commercial area, industrial area, park area, and distance to the city center. Transportation infrastructure covariates include bike trail density, major road density, number of bus stops, passenger volume of nearby subway stations within the 400-m buffer, number of docks of nearby bike stations within the 400-m buffer, and traffic volume (average daily traffic volume of the road closest to the station, or AADT) of the road closest to the bike station (Zhang et al., 2017).

Table 3 Descriptive statistics of covariates to calculate propensity score

Covariates	Description	Mean	Min	Max	Std
Bike trips	Weekly bike sharing trips	130	1.000	4,172	206
E-scooter trips	Weekly e-scooter sharing trips	4,202	51,946	68,611	19,854
Population density	Population density within the 400m buffer	4,240	312	18,500	2,637
Employment density	Employment density within the 400m buffer	8,657	11.637	175,768	24,798
Average income	Average annual income of residents within the 400m buffer (dollar)	79,807	2,223	834,629	93,878
Bike trail density	Density of bike trail within the 400m buffer (km/km^2)	1.648	0.000	6.477	1.458
Major road density	Density of major road within the 400m buffer (km/km^2)	0.043	0.000	0.499	0.064
Bus stop	Number of bus stops within the 400m buffer the 400m buffer	8.913	0.000	27.000	4.970

Subway ridership	Number of inbound passengers of subway stations within the 400m buffer	535,794	0.000	16,916,972	1,614,785
Number of docks	Total number of docks of stations within the 400m buffer	27.601	7.000	170.000	28.846
Residential area	Proportion of residential area within the 400m buffer	0.290	0.000	0.633	0.167
Commercial area	Proportion of commercial area within the 400m buffer	0.130	0.000	0.802	0.120
Industrial area	Proportion of industrial area within the 400m buffer	0.031	0.000	0.543	0.075
Park area	Proportion of park area within the 400m buffer	0.062	0.000	0.954	0.141
AADT	Average daily traffic volume of the road closest to the station	10,111	154.075	28,700	6,102
Distance to city center	Distance from the station to city center (m)	4,240	312	18,500	2,637

5. Results

5.1 Initial analysis

In this section, we perform an initial analysis of the usage of bike sharing in Chicago. Figure 7 shows the average weekly number of bike sharing trips in the treated and untreated units over time. The average usage of the untreated stations was lower than that of the treated stations before e-scooter sharing was introduced and became higher than that of the treated units after e-scooter sharing was introduced.

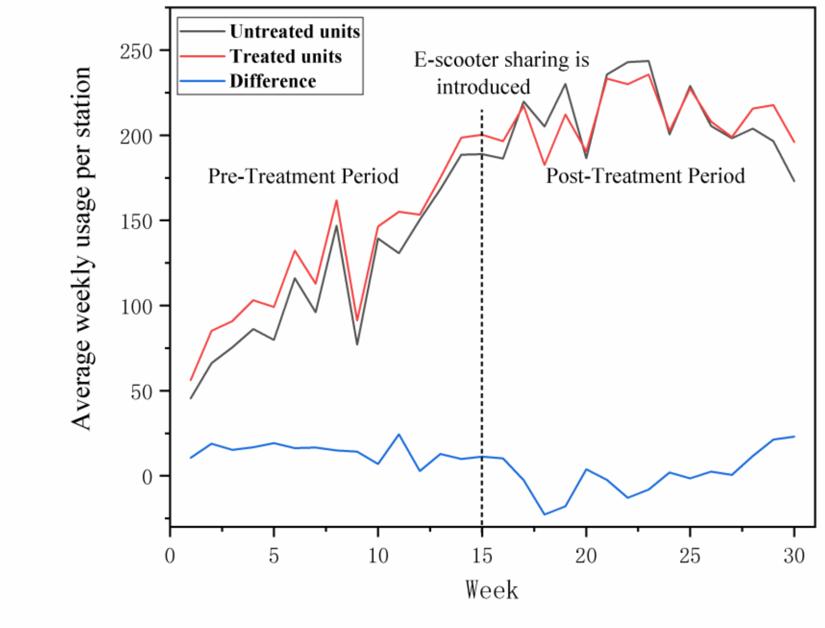

Figure 7 Bike sharing average weekly usage before and after the introduction of e-scooter sharing.

5.2 PSM quality evaluation

It is crucial to make sure the units in the control group have similar characteristics to the units in the treatment group. The overlap test is a routine test that is performed to evaluate whether the units in the two groups are similar. The validity of the PSM results is evaluated by visually inspecting the distribution of propensity scores of units in the treatment and control groups, which is shown in Figure 8. If there are both treated units and untreated units in a column, those units are called “on support.” Otherwise, those units are called “off support” and should be deleted before further analysis (Li et al., 2018). Figure 8 shows that all the units are “on support” and could be used for further analysis.

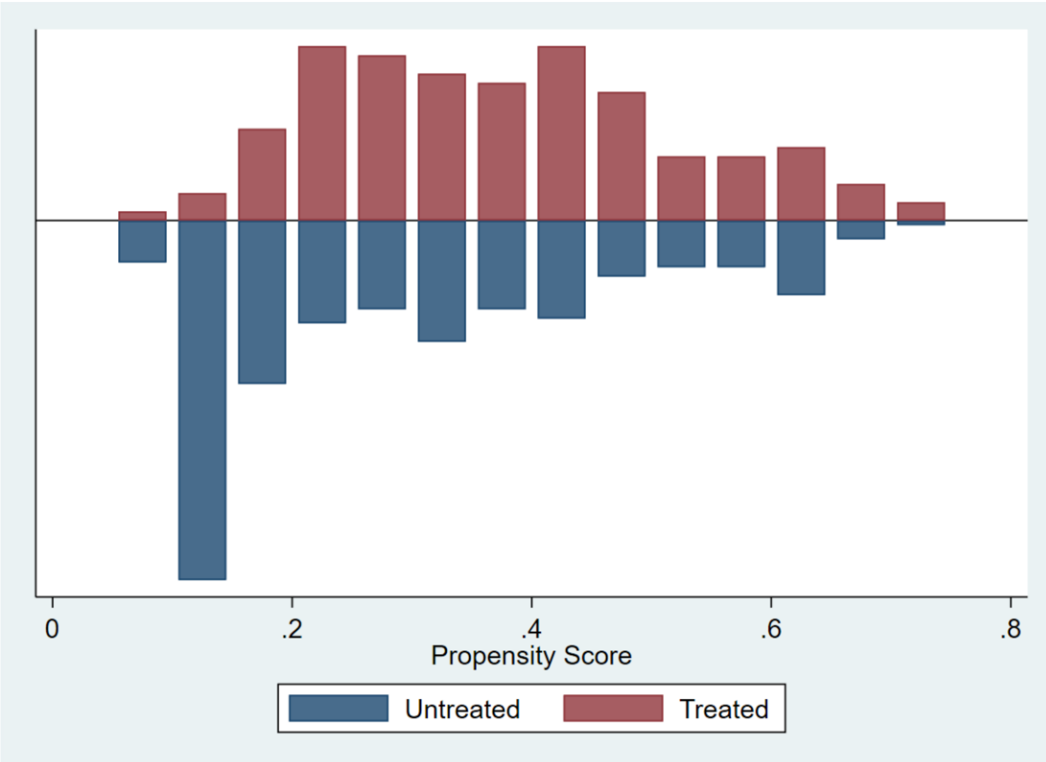

Figure 8 Results of overlap test based on propensity score

A balancing test is performed to check whether the stations in the treatment and control groups are similar after matching, which could mean that no significant difference exists in the mean values of covariates between the stations in the treatment and control groups. Table 4 shows the t-test results of the difference in the mean values of covariates before and after matching. The results show that significant differences exist in most of the mean values of covariates between units of the treatment group and groups before matching ($p < 0.05$). After matching, no significant difference is observed.

Table 4 Balancing test results

Variable	Unmatched or matched	Mean of treatment group	Mean of control group	% bias	% |bias| reduced	t-stat	p value
Population density	U	4,209.700	4,429.300	-9.400		-2.290	0.022
	M	4,209.700	4,127	3.600	62.300	0.930	0.353
Employment density	U	2,184.700	10,634	-42.500		-9.120	0.000
	M	2,184.700	2,091.700	0.500	98.900	0.740	0.458
Mean income	U	73,461	87,267	-17.100		-3.980	0.000
	M	73,461	74,492	-1.300	92.500	-0.390	0.695
Bike trail density	U	1.805	1.597	15.100		3.990	0.000
	M	1.805	1.770	2.500	83.200	0.550	0.585
Major road density	U	0.038	0.041	-5.200		-1.550	0.120
	M	0.038	0.038	-0.200	96.300	-0.040	0.964

Bus stop	U	7.377	9.135	-37.600		-9.840	0.000
	M	7.377	7.449	-1.500	95.900	-0.360	0.717
Subway passengers	U	200,000	630,000	32.100		-7.070	0.000
	M	200,000	220,000	-1.100	96.600	-0.560	0.577
Number of docks	U	20.164	29.758	-40.000		-9.060	0.000
	M	20.164	20.746	-2.400	93.900	-0.980	0.326
Residential area	U	0.339	0.291	30.200		8.140	0.000
	M	0.339	0.333	3.600	88.100	0.770	0.444
Commercial area	U	0.126	0.133	-5.800		-1.520	0.128
	M	0.126	0.132	-4.900	15.600	-1.060	0.289
Industrial area	U	0.038	0.022	23.400		6.520	0.000
	M	0.038	0.039	-2.700	88.300	-0.480	0.629
Park area	U	0.032	0.072	-31.200		-7.680	0.000
	M	0.032	0.033	-1.000	96.300	-0.310	0.759
AADT	U	11,946	11,080	13.500		3.800	0.000
	M	11,946	11,444	7.800	42.100	1.610	0.108
Distance to center	U	7,803	10,660	-56.000		-12.900	0.000
	M	7,803	7,725	1.500	97.300	0.500	0.616

5.3 Impact of e-scooter sharing on the usage of bike sharing

5.3.1 Overall impact

In this section, we evaluate the impact of e-scooter sharing on the usage of bike sharing. When using the PSM method for analysis, a variety of matching methods are used to verify the validity of the results. In our study, the matching methods used include K-nearest neighbor, kernel, and radius matching. Table 5 shows the results of those matching methods. After e-scooter sharing is introduced, the average weekly usage of bike sharing is reduced substantially (by 10.2%). Moreover, the matching results of different methods are similar, ranging from 9.7% to 11.3%. In the following analysis, we report the results of the kernel matching analysis.

Table 5 The impact of e-scooter sharing on weekly bike sharing usage

Models	Sample	Treatment Group	Control Group	Difference	t-stat
K-nearest neighbors matching (K = 3)	PSM model	68.197	90.759	-22.562	-4.970*
K-nearest neighbors matching (K = 5)	PSM model	68.197	90.440	-22.243	-5.160*
Radius matching (caliper = 0.01)	PSM model	68.309	90.603	-22.295	-3.780*
Radius matching (caliper = 0.1)	PSM model	68.197	95.054	-26.858	-5.790*
Kernel (bandwidth=0.05)	PSM model	68.197	92.081	-23.884	-5.240*

* |t-stat| >1.96

5.3.2 Impact on the usage of bike sharing by type

Table 6 Effect of e-scooter sharing on different user types of bike sharing

Type	Group	Sample	Treatment Group	Control Group	Difference	t-stat	Effect
Membership	Member	PSM model	48.193	53.544	-5.350	-2.316*	-3.95%
	Non-member	PSM model	20.206	38.235	-18.029	-6.572*	-34.0%
Member-Gender	Male	PSM model	30.576	33.897	-3.321	-2.095*	-3.1%
	Female	PSM model	17.569	19.548	-1.979	-2.246*	-7.3%
Member-Age	19-24	PSM model	9.569	11.759	-2.190	-3.520*	11.4%
	25-30	PSM model	19.358	21.058	-1.700	-2.695*	3.3%
	31-40	PSM model	12.128	12.310	-0.182	-0.423	
	41-54	PSM model	3.398	3.9271	-0.529	-0.491	
	55-73	PSM model	3.740	4.490	-0.750	-0.300	
Trip duration	0-15 min	PSM model	36.204	49.119	-12.915	-6.070*	-15.8%
	15-30 min	PSM model	23.388	28.826	-5.438	-2.890*	-21.2%
	30-60 min	PSM model	5.164	8.592	-3.428	-2.810*	-16.1%
Different time periods	Weekday peak hours	PSM model	38.311	42.892	-4.581	-1.830	
	Weekday non-peak hours	PSM model	15.289	23.549	-8.261	-4.940*	-7.5%
	Weekend peak hours	PSM model	7.182	13.984	-6.802	-5.340*	-9.6%
	Weekend non-peak hours	PSM model	7.414	11.404	-3.99	-4.090*	-20.5%

Table 6 shows the impact of e-scooter sharing on the usage of bike sharing by the member type (member and non-member). In general, after e-scooter sharing is introduced, the usage of bike sharing by members and non-members decreased by 5.4 (3.95%) and 18.0 (34.0%) trips per week per station, respectively. e-scooter sharing had a much larger impact on non-member ridership. The age and gender of non-member bike sharing riders are unknown. However, in this study, we focus on the impact of e-scooter sharing on the usage of bike sharing members by gender and age group. Table 6 shows the influence of e-scooter sharing on the usage of bike sharing members by gender. The results show that after e-scooter sharing was introduced, ridership of male and female members decreased by 3.3 and 2.0 trips per week, respectively. We categorize age into five groups:

19-24, 25-30, 31-40, 41-54, and 55-73, which corresponds with the age range usually used in previous studies (Lee et al., 2019; Newbold and Scott, 2017, 2018; Rahimi et al., 2020; Wang et al., 2018; Wang, 2019). Age groups may be as important, or more important, than other generational factors. Table 6 shows the impact of e-scooter sharing on bike sharing usage of members of different age groups. The results show that after the introduction of e-scooter sharing, the bike sharing usage of the age group 19-30 decreases significantly. Other age groups did not see large or significant changes. This is probably because e-scooter sharing is more attractive to young users (age 19-31) than others (Mitra and Hess, 2021; Shaheen et al., 2013).

Based on the temporal variation of bike sharing trips, on weekdays, the morning and evening peak hours are 6:00–10:00 and 16:00–19:00, respectively. On weekends, there is a relatively uniform peak from 10:00 to 18:00. The results show that the introduction of e-scooter sharing does not have a significant impact on the use of bike sharing during peak hours on weekdays. However, we saw reductions in trips per week during non-peak hours on weekdays (8.3 (7.5%)) and peak (6.8 (9.6%)) and non-peak hours (4.0 (20.5%)) on weekends. Thus, only trips of bike sharing during commute hours are not affected by the introduction of e-scooter sharing.

Non-member bike sharing is priced at 3 dollars for a 30-minute trip and 0.15 dollars for every additional minute. Therefore, we use 30 minutes as the division interval. We divide bike sharing trips into three groups based on the trip duration: short-duration trips (0–15 min), medium-duration trips (15–30 min), and long-duration trips (30–60 min). In this study, we find that the number of short-, middle-, and long-duration trips decrease by 12.9 (15.8%), 5.4 (21.2%), and 3.4 (16.1%), respectively.

6. Discussion

Our results show that, on average, the weekly usage of bike sharing decreases by 10.2%. The weekly usage of bike sharing of members decreases by 4.0% and that of non-members decreases by 34.0%. Younes et al. (2020) concluded that e-scooter sharing had a complementary relationship with bike sharing for bike sharing members and a competitive relationship with bike sharing for bike sharing non-members. Our finding refutes the first part of the finding of Younes et al. (2020). We found that e-scooter sharing also has a competitive relationship with bike sharing members and the competition is more intense for bike sharing non-members.

Because only the gender and age of members are known, we can only study the impact of the advent of e-scooter sharing on the usage of members of different genders and age groups. All of the changes of bike sharing ridership come from younger riders; ridership of members of the 19-41 age group decreased by 3.4%, while ridership of other age groups was not significantly impacted. This result is consistent with the finding of previous studies that e-scooter sharing users are more likely to be young (Huo et al., 2021; Mitra and Hess, 2021; Shaheen et al., 2013). The bike sharing ridership of male and female members decreased by 3.1% and 7.3%, respectively.

Short, medium, and long duration bike sharing trips decreased by 15.8%, 21.2%, and 16.1%, respectively. This contrasts with the effects of dockless bike sharing on station-based bike sharing shown by (Li et al., 2019), which shows that only short duration trips decreased, while the ridership of middle and long duration trips was not significantly influenced.

We compared the average daily trips of e-scooter sharing and bike sharing on weekdays and weekends and found that the peak hours for shared e-scooter trips on weekdays or weekends are about the same, late afternoon (16:00–18:00), whereas the peak hours for bike sharing trips are 6:00–9:00 and 17:00–18:00 on weekdays (reflecting commute-oriented trips) and 11:00–16:00 on weekends. We also observed that the introduction of e-scooter sharing does not have a significant impact on the usage of bike sharing during peak hours on weekdays. But for non-peak hours on weekdays, peak hours on weekends, and non-peak hours on weekends, the bike sharing usage decreases by 7.5%, 9.6%, and 20.5%, respectively. Again, e-scooter sharing has the largest impact on the weekend or non-commute-oriented trip patterns. This likely reflects the larger marginal cost of use from e-scooter sharing that is more akin to recreation or visitor bike sharing trips, compared to bike sharing subscription rates that result in a very low marginal cost that caters to repeat or habitual commute patterns. This finding is consistent with the finding of previous studies that commuting is not the major trip purpose of e-scooter sharing (Caspi et al., 2020; Reck et al., 2021).

7. Conclusions

e-scooter sharing is newly developed shared micromobility travel mode. its advent could possibly influence the ridership of bike sharing. In this study, we try to answer the question of whether the advent of e-scooter sharing influences the ridership of bike sharing and to quantify the influence on the bike sharing ridership of different user groups and types of trips. The e-scooter sharing and bike sharing trip data of Chicago are used in this study. The PSM-DID method is adopted to rule out the effect of exogenous factors on the study results. Results show that the bike sharing ridership declines by 10.2% in the e-scooter sharing operation area due to the advent of e-scooter sharing. Bike sharing operators should anticipate a decrease in the usage of bike sharing when e-scooter sharing is introduced and lower the expectation of ridership and revenue; specifically, non-commute-oriented trips and trips with a higher marginal revenue stream will likely erode. Based on the quantification of the impact of e-scooter sharing on bike sharing usage, the bike sharing operators could adjust the allocation of resources for operation and maintenance of bike sharing, as well as the pricing scheme to maximize the utility of bike sharing. But the bike sharing in Austin could still continue to operate because 90% of the existing ridership remains.

The ridership of bike sharing members and non-members decreases by 4.0% and 34.0% respectively. When e-scooter sharing and bike sharing are both under operation in the same area, the locations and capacities of the stations of bike sharing could be adjusted to focus more on the member users. The bike sharing ridership by members of the age group 19-40 decreases by 3.4% while that of the other age groups does not decrease significantly. Regarding the ridership of different time periods, the ridership during weekday non-peak hours, weekend peak hours, and weekend non-peak hours decreases by 7.5%, 9.6%, and 20.5%, respectively, while the ridership during weekday peak hours does not change significantly. Commuting is not one of the major purposes of shared e-scooter trips (Caspi et al., 2020; Huo et al., 2021; Noland, 2019). These results reveal that the decrease of bike sharing ridership is not uniformly distributed among different user groups or types of trips. The locations and capacities of bike sharing should be adjusted to accommodate for the change caused by the advent of e-scooter sharing.

This study also has some limitations. First, this study is based on the Chicago case under the specific local settings of the e-scooter sharing and bike sharing system and specific characteristics of Chicago's e-scooter sharing trial. Chicago's e-scooter sharing program specifically aimed to reduce overlap between the systems, so it is possible that other less regulated systems may experience more competition. The result could be influenced by characteristics of the e-scooter sharing system, such as the price of using shared e-scooters, how large the e-scooter sharing operation area is, and the number of e-scooters that are placed in the operation area. With a lower price of using e-shared e-scooters, larger operation area, and higher number of e-scooters, one may observe larger decreases of bike sharing ridership. However, bike sharing systems that have responded to e-scooter sharing by changing their pricing structure to be more competitive with the price of using shared e-scooters could stem some of the competitive impacts of ridership (Venigalla et al., 2020). Secondly, whether the results of this study could be applied to other cities is not clear. Yet, our results are clear. In this context, e-scooter sharing has a competitive relationship with the bike sharing system instead of a complementary relationship. E-scooter sharing significantly and substantially eroded ridership of the bike sharing system, particularly among the non-members. Bike sharing system operators should anticipate a decline in bike sharing ridership and revenue when the e-scooter sharing is implemented in the city and should adjust the locations and capacities of the bike sharing stations and pricing to accommodate for this change. In this study, we propose a framework to analyze the impact of e-scooter sharing on the usage of bike sharing. Future research could use this framework to perform similar analyses based on data from other cities to obtain more insights.

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References

Aguilera-García, Á., Gomez, J., Sobrino, N. (2020) Exploring the adoption of moped scooter-sharing systems in Spanish urban areas. *Cities* 96, 102424.
National Bureau of Economic Research (1984) *Using the longitudinal structure of earnings to estimate the effect of training programs*.
Austin (2019) What 5 Million Scooter Rides in Austin Tell Us About the Future of Micromobility.
Bai, S., Jiao, J. (2020) Dockless E-scooter usage patterns and urban built environments: a comparison study of Austin, TX, and Minneapolis, MN. *Travel behaviour and society* 20, 264-272.
Bai, S., Jiao, J., Chen, Y., Guo, J. (2021) The relationship between E-scooter travels and daily leisure activities in Austin, Texas. *Transportation Research Part D: Transport and Environment* 95, 102844.
Bordagaray, M., dell'Olio, L., Fonzone, A., Ibeas, Á. (2016) Capturing the conditions that introduce systematic variation in bike-sharing travel behavior using data mining techniques. *Transportation Research Part C: Emerging Technologies* 71, 231-248.
Brookhart, M.A., Schneeweiss, S., Rothman, K.J., Glynn, R.J., Avorn, J., Stürmer, T. (2006) Variable selection for propensity score models. *American journal of epidemiology* 163, 1149-1156.
Campbell, K.B., Brakewood, C. (2017) Sharing riders: How bikesharing impacts bus ridership in New York City. *Transportation Research Part A: Policy and Practice* 100, 264-282.
Caspi, O., Smart, M.J., Noland, R.B. (2020) Spatial associations of dockless shared e-scooter usage. *Transportation Research Part D: Transport and Environment* 86, 102396.
(2019) *E-Scooter Pilot Evaluation*, https://www.chicago.gov/content/dam/city/depts/cdot/Misc/EScooters/E-Scooter_Pilot_Evaluation_2.17.20.pdf.
CURBED (2019) Everything you need to know about electric scooters in Chicago.
Daniels, R., Mulley, C. (2013) Explaining walking distance to public transport: The dominance of public transport supply. *Journal of Transport and Land Use* 6, 5-20.
Eccarius, T., Lu, C.-C. (2020) Adoption intentions for micro-mobility–Insights from electric scooter sharing in Taiwan. *Transportation Research Part D: Transport and Environment* 84, 102327.
Ewing, R., Cervero, R. (2010) Travel and the built environment: A meta-analysis. *Journal of the American planning association* 76, 265-294.
Faghih-Imani, A., Eluru, N. (2016) Incorporating the impact of spatio-temporal interactions on bicycle sharing system demand: A case study of New York CitiBike system. *Journal of Transport Geography* 54, 218-227.
Faghih-Imani, A., Eluru, N., El-Geneidy, A.M., Rabbat, M., Haq, U. (2014) How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (BIXI) in Montreal. *Journal of Transport Geography* 41, 306-314.
Fishman, E., Washington, S., Haworth, N., Mazzei, A. (2014) Barriers to bikesharing: an analysis from Melbourne and Brisbane. *Journal of Transport Geography* 41, 325-337.
Gu, T., Kim, I., Currie, G. (2019) Measuring immediate impacts of a new mass transit system on an existing bike-share system in China. *Transportation research part A: policy and practice* 124, 20-39.

Guo, Y., He, S.Y. (2021) The role of objective and perceived built environments in affecting dockless bike-sharing as a feeder mode choice of metro commuting. *Transportation Research Part A: Policy and Practice* 149, 377-396.
Hawa, L., Cui, B., Sun, L., El-Geneidy, A. (2021) Scoot over: Determinants of shared electric scooter presence in Washington D.C. *Case Studies on Transport Policy*.
Heinrich, C., Maffioli, A., Vazquez, G. (2010) A primer for applying propensity-score matching. *Inter-American Development Bank*.
Hoehner, C.M., Brennan Ramirez, L.K., Elliott, M.B., Handy, S.L., Brownson, R.C. (2005) Perceived and objective environmental measures and physical activity among urban adults. *American Journal of Preventive Medicine* 28, 105-116.
Huo, J., Yang, H., Li, C., Zheng, R., Yang, L., Wen, Y. (2021) Influence of the built environment on E-scooter sharing ridership: A tale of five cities. *Journal of Transport Geography* 93, 103084.
Kong, H., Jin, S.T., Sui, D.Z. (2020) Deciphering the relationship between bikesharing and public transit: Modal substitution, integration, and complementation. *Transportation Research Part D: Transport and Environment* 85, 102392.
Laa, B., Leth, U. (2020) Survey of E-scooter users in Vienna: Who they are and how they ride. *Journal of Transport Geography* 89, 102874.
Lathia, N., Ahmed, S., Capra, L. (2012) Measuring the impact of opening the London shared bicycle scheme to casual users. *Transportation Research Part C: Emerging Technologies* 22, 88-102.
Lee, Y., Circella, G., Mokhtarian, P.L., Guhathakurta, S. (2019) Heterogeneous residential preferences among millennials and members of generation X in California: A latent-class approach. *Transportation Research Part D: Transport and Environment* 76, 289-304.
Leuven, E., Sianesi, B. (2003) PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing.
Li, H., Ding, H., Ren, G., Xu, C. (2018) Effects of the London Cycle Superhighways on the usage of the London Cycle Hire. *Transportation research part A: policy and practice* 111, 304-315.
Li, H., Graham, D.J., Liu, P. (2017) Safety effects of the London cycle superhighways on cycle collisions. *Accident Analysis & Prevention* 99, 90-101.
Li, H., Graham, D.J., Majumdar, A. (2012) The effects of congestion charging on road traffic casualties: A causal analysis using difference-in-difference estimation. *Accident Analysis & Prevention* 49, 366-377.
Li, H., Graham, D.J., Majumdar, A. (2013) The impacts of speed cameras on road accidents: An application of propensity score matching methods. *Accident Analysis & Prevention* 60, 148-157.
Li, H., Zhang, Y., Ding, H., Ren, G. (2019) Effects of dockless bike-sharing systems on the usage of the London Cycle Hire. *Transportation Research Part A: Policy and Practice* 130, 398-411.
Lime (2019a) Nearly 1/4 Million Parisians Are Using Dockless Electric Scooters, Study Finds.
Lime (2019b) Los Angeles First In US To Break 3 Million Electric Scooter Rides.
Ma, X., Zhang, X., Li, X., Wang, X., Zhao, X. (2019) Impacts of free-floating bikesharing system on public transit ridership. *Transportation Research Part D: Transport and Environment* 76, 100-110.
McCormack, G.R., Giles-Corti, B., Bulsara, M. (2008) The relationship between destination proximity, destination mix and physical activity behaviors. *Preventive Medicine* 46, 33-40.
McKenzie, G. (2019) Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, DC. *Journal of transport geography* 78, 19-28.

Mitra, R., Hess, P.M. (2021) Who are the potential users of shared e-scooters? An examination of socio-demographic, attitudinal and environmental factors. *Travel Behaviour and Society* 23, 100-107.
NACTO (2020) Shared Micromobility in the U.S.: 2020. *National Association of City Transportation Officials*.
Newbold, K.B., Scott, D.M. (2017) Driving over the life course: The automobility of Canada's Millennial, Generation X, Baby Boomer and Greatest Generations. *Travel Behaviour and Society* 6, 57-63.
Newbold, K.B., Scott, D.M. (2018) Insights into public transit use by Millennials: The Canadian experience. *Travel Behaviour and Society* 11, 62-68.
Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Raptopoulou, A., Kostareli, A., Basbas, S. (2021) Analysis of attitudes and engagement of shared e-scooter users. *Transportation Research Part D: Transport and Environment* 94, 102790.
Noland, R.B. (2019) Trip patterns and revenue of shared e-scooters in Louisville, Kentucky. *Findings*, 7747.
Noland, R.B., Smart, M.J., Guo, Z. (2016) Bikeshare trip generation in New York City. *Transportation Research Part A: Policy and Practice* 94, 164-181.
Pangbourne, K. (2019) Disrupting Mobility: Impacts of Sharing Economy and Innovative Transportation in Cities. Lecture Notes in Mobility, G. Meyer, S. Shaheen (Eds.), Springer, Cham (2017). Elsevier.
Pikora, T., Giles-Corti, B., Bull, F., Jamrozik, K., Donovan, R. (2003) Developing a framework for assessment of the environmental determinants of walking and cycling. *Social Science & Medicine* 56, 1693-1703.
Rahimi, A., Azimi, G., Jin, X. (2020) Investigating generational disparities in attitudes toward automated vehicles and other mobility options. *Transportation Research Part C: Emerging Technologies* 121, 102836.
Ramsey, K., Bell, A. (2014) Smart location database. *Washington, DC*.
Reck, D.J., Axhausen, K.W. (2021) Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. *Transportation Research Part D: Transport and Environment* 94, 102803.
Reck, D.J., Haitao, H., Guidon, S., Axhausen, K.W. (2021) Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. *Transportation Research Part C: Emerging Technologies* 124, 102947.
Rosenbaum, P.R., Rubin, D.B. (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70, 41-55.
Sanders, R.L., Branion-Calles, M., Nelson, T.A. (2020) To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. *Transportation Research Part A: Policy and Practice* 139, 217-227.
Shaheen, S.A., Cohen, A.P., Martin, E.W. (2013) Public bikesharing in North America: Early operator understanding and emerging trends. *Transportation research record* 2387, 83-92.
Shen, Y., Zhang, X., Zhao, J. (2018) Understanding the usage of dockless bike sharing in Singapore. *International Journal of Sustainable Transportation* 12, 686-700.
Tuncer, S., Laurier, E., Brown, B., Licoppe, C. (2020) Notes on the practices and appearances of e-scooter users in public space. *Journal of Transport Geography* 85, 102702.
Venigalla, M., Rayaprolu, S., Brennan, T., Kaviti, S. (2020) Could Value-based Pricing Improve Economic Sustainability of Bikeshare? *Journal of Modern Mobility Systems* 1, 131-137.

Wang, D., Cao, X. (2017) Impacts of the built environment on activity-travel behavior: Are there differences between public and private housing residents in Hong Kong? *Transportation Research Part A: Policy and Practice* 103, 25-35.
Wang, K., Akar, G., Chen, Y.-J. (2018) Bike sharing differences among millennials, Gen Xers, and baby boomers: Lessons learnt from New York City's bike share. *Transportation research part A: policy and practice* 116, 1-14.
Wang, X. (2019) Has the relationship between urban and suburban automobile travel changed across generations? Comparing Millennials and Generation Xers in the United States. *Transportation Research Part A: Policy and Practice* 129, 107-122.
Wu, C., Kim, I., Chung, H. (2021) The effects of built environment spatial variation on bike-sharing usage: A case study of Suzhou, China. *Cities* 110, 103063.
Yang, H., Zhang, Y., Zhong, L., Zhang, X., Ling, Z. (2020) Exploring spatial variation of bike sharing trip production and attraction: A study based on Chicago's Divvy system. *Applied geography* 115, 102130.
Younes, H., Zou, Z., Wu, J., Baiocchi, G. (2020) Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, DC. *Transportation Research Part A: Policy and Practice* 134, 308-320.
Zamir, K.R., Bondarenko, I., Nasri, A., Brodie, S., Lucas, K. (2019) Comparative Analysis of User Behavior of Dock-Based vs. Dockless Bikeshare and Scootershare in Washington, DC. *arXiv preprint arXiv:1907.11526*.
Zhang, Y., Thomas, T., Brussel, M., Van Maarseveen, M. (2017) Exploring the impact of built environment factors on the use of public bikes at bike stations: case study in Zhongshan, China. *Journal of transport geography* 58, 59-70.
Zhao, J., Wang, J., Deng, W. (2015) Exploring bikesharing travel time and trip chain by gender and day of the week. *Transportation Research Part C: Emerging Technologies* 58, 251-264.
Zhu, R., Zhang, X., Kondor, D., Santi, P., Ratti, C. (2020) Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility. *Computers, Environment and Urban Systems* 81, 101483.