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What Is the Impact of a Dockless Bike-Sharing System on Urban Public Transit Ridership: A View from Travel Distances

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Abstract: Recently, the rapid development of the bike-sharing system (BSS) has dramatically influenced passengers' travel modes. However, whether the relationship between the BSS and public transit is competitive or complementary remains unclear. In this paper, a difference-in-differences (DID) model is proposed to figure out the impact of the dockless BSS (DBSS) on bus ridership. The data was collected from Shanghai, China, which includes data from automatic fare collection (AFC) systems, automatic vehicle location (AVL) systems, DBSS transaction data, and point-of-interest (POI) data. The research is based on the route-level, and the results indicate that shared bikes have a substitution impact on bus ridership. Regarding all the travel distance, each shared bike along the route leads to a 0.39 decrease in daily bus ridership on the weekdays, and a 0.17 decrease in daily bus ridership on the weekends, respectively, indicating that dockless shared bikes lead to a stronger decrease in bus ridership on weekends compared to weekdays. Additionally, the substitution effects of shared bikes on bus ridership gradually decays from 0.104 to 0.016 in daily bus ridership on weekends, respectively, with the increase in the travel distance within 0–3 km. This paper reveals that the travel distance of passengers greatly influences the relationship between the DBSS and public transit on the route level.

Keywords: dockless bike-sharing system; DID; automatic fare collection system; transit ridership

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1. Introduction

The appearance of a bike-sharing system (BSS) provides city residents with a new way to commute during daily life. Compared with other transportation modes, the BSS is more environmentally friendly and flexible, especially for short trips. In recent years, the BSS has attracted the attention of passengers and governments and has been widely operated in large numbers of countries all over the world, especially in China. There are mainly two types of BSSs, docked and dockless, which are deployed at present. The docked BSS requires physical stations to place shared bikes, and its users have to rent and return bikes at designated stations, while the dockless BSS (DBSS) does not require expensive, space-hungry docking stations [1]. The DBSS typically utilizes GPS technology and intelligent lock devices on their bikes [2]. These features allow users to easily locate and unlock bikes using a mobile app or by other means of authentication, which thereby provides convenience, security, and accountability in dockless bike-sharing systems. Furthermore, they enable users to easily access and return bikes at their desired locations, while also deterring theft and unauthorized use of the bikes. The GPS technology also allows the bike-sharing company to track the bikes, monitor their usage patterns, and optimize their operations. Due to these characteristics, the DBSS gradually dominated the BSS market in

China for its convenience of renting or returning and is considered as an effective solution to meet the need of the last-mile problem.

The BSS has developed rapidly all over the world in recent years. Generally, the shared bike is identified as one short-distance and medium-distance travel mode, while public transit is regarded as a medium-distance and long-range travel mode [3]. However, the relationship between the BSS and public transit is controversial. Conventionally, several researchers believe that cycling is an alternative to public transport [4], and that the BSS might reduce public transit use by competing with the bus and rail transits [5–7]. They were worried in that the BSS would have a negative impact on the development of the transit system as the BSS could act as a substitute for short-distance travel. Campbell and Brakewood [8] found that the expansion of the bike-sharing system has led to a significant reduction in bus ridership in New York City. Liu et al. [9] examined the modal preferences for the last-mile connection to urban rails in Beijing, China, focusing on the choice between the bus and bike-sharing systems. However, they only focused on moderate distances (0.5–3 km) and found that bike-sharing is a rival and suitable alternative to the bus. Fishman et al. [10] also found that BSSs not only replaced car trips, but also reduced public transit to some extent. Brakewood et al. [11] found the Citi Bike bike-sharing program had a significant negative impact on bus ridership at the route level. The proliferation of shared bikes may have resulted in a reduction of over 500 trips per route for bus ridership in Manhattan, where there are more shared bicycle stations. In Brooklyn, which has fewer shared bicycle stations, the average bus ridership per route on weekdays was approximately 375 trips. Ma et al. [12] observed the impacts of the modal shift by considering different kinds of bike-sharing systems and stated that users of shared bikes reduced their use of the bus/tram, car, private bike, and walking. The findings of Kim and Cho [13] suggested that shared bikes can compete with public transit, especially in non-residential areas. At the same time, they can enhance connectivity with rail transit, regardless of the land-use characteristics. Chen et al. [14] examined the potential modes of substitution behavior influenced by dockless bike-sharing for four travel purposes: commuting for work or education, sports and leisure, grocery shopping, and shopping/dining, among other recreational activities. Their results indicated that for most respondents, the DBSS had the potential to replace walking or public transit. The study also revealed that younger respondents of dockless shared bikes were more likely to replace recreational activities that involved public transit with the dockless shared bikes.

Other researchers have noticed that the BSS could be beneficial to the supplement of public transit. Ma et al. [15] found a positive correlation between public transit and shared bicycle usage at the station level, whereby a 10% increase in bicycle trips resulted in a 2.8% increase in public transit ridership. Fuller et al. [16] found that during a public transit strike, the usage of shared bikes increased by 57%, indicating that shared bikes can serve as a complementary mode of public transit during such strikes. Ashraf et al. [17] utilized Poisson-gamma models to examine the impacts of the Citi Bike—a bike-sharing program—on the subway ridership in New York City (NYC). Their results revealed that bike-sharing trips within a quarter-mile radius of subway stations were significantly associated with an increase in subway ridership. For every 10% increase in bike-sharing trips, the average daily subway ridership increased by 2.3%, respectively. Jin et al. [3] conducted a case study of Beijing to evaluate the substitution of bike-sharing ridership on public transit based on the operating data of bike-sharing schemes and public transit data. Their results indicated that the BSS did not cause an overall reduction in public transit ridership. However, within 2 km, public transit ridership did decrease, while transfers increased with the rising shared bike usage. They also observed that the decrease in short-distance transits and the increase in near transfers were highly relevant to the spatial distribution of the shared bikes. The usage and distribution of shared bikes are important for efficiency, and thus BSS enterprises and traffic management departments first need to understand the competitive and cooperative relationship between the BSS and public transit, especially in how the BSS influences short-distance public transit usage [6].

A few studies have suggested that the relationship between bike-sharing and public transport is complex. Shaheen et al. [18] discussed the modal shift that resulted from individuals participating in four public bike-sharing systems in North America. Three of the four largest cities experienced a decrease in bus and rail usage due to shared bikes. In Montreal, Toronto, and Washington D.C., 50%, 44%, and 48% of respondents, respectively, said they had reduced their use of the railways. But in the Twin Cities, 15% of respondents reported an increase in their use of the railways, while only 3% said that their use of railways had decreased. Martin and Shaheen [19,20] assessed the use of shared bikes and public transport in Washington, D.C. and Minneapolis, and they found that in the urban central environment with a high population density, shared bikes, and public transit were competitive, and that the use of shared bikes reduces the travel frequency of public transport. In lower-density regions on the urban periphery, the complementary relationship can be further strengthened. Kong et al. [21] proposed three types of relationships between bike-sharing and public transit: mode substitution, mode integration, and mode complementarity, and investigated the factors affecting their relationship. Their results revealed that it was not where the bike-sharing trip takes place that predominantly determines its relationship with public transit, but rather the bike-share users' travel characteristics. Cui et al. [22] also proposed three relationships between bike-sharing and public transit: competition, integration, and complementation. Their results demonstrated that bike-sharing can significantly compete with public transit in New York City. The existence of this competition benefits socioeconomically disadvantaged commuters, and ultimately promotes a certain degree of transportation equity.

Despite lots of work in researching the influence of the docked BSS on public transit, the impact of the DBSS on public transit systems is still ambiguous. Since the DBSS can remove the limitation of the physical stations, and its users can drop off shared bikes almost everywhere and anytime, it is therefore much more attractive to passengers, and thus has a greater influence on bus ridership when compared with the traditional docked BSS. On the one hand, with dockless shared bikes, riders can reach nearby transit stations faster and easier to take public transit, which may contribute to the usage of public transit. On the other hand, the DBSS may lead to the modal shift of passengers from public transit to bike-sharing and cause direct competition with the public transit system. This study aimed to figure out whether DBSS complements or competes with public transit, and how this relationship changes with the passenger's travel distance. Thus, an advanced statistical approach termed the difference-in-differences (DID) was developed to examine the relationship between the DBSS and the transit system in Shanghai using the check-in/check-out data of the DBSS along with public transportation card data from the automatic fare collection (AFC) systems.

With the rapid development of the DBSS all over the world, it is rather essential to figure out the impact of DBSS on public transit for the public transportation department, DBSS operators, and urban managers to improve the bike distribution strategy and adjust the policy on DBSS management.

The major contributions of this study can be summarized as follows:

(1) The impact of the DBSS on public transit ridership at route levels with different travel distances is measured using multi-source data;

(2) A set of DID models are proposed to deal with the endogenous factor between the different bus stations and routes.

The remainder of this paper is organized as follows. Section 2 provides the description of the multi-source data and describes the methods used in this study. Results of the models at the route-level are illustrated in Section 3, followed by the conclusions and discussions in Section 4. Section 5 demonstrates the main findings and future research direction.

2. Materials and Methods

2.1. Study Area

Shanghai, which is located on the southern estuary of the Yangtze River, is one of the four direct-administered municipalities of China. As one of the world's largest cities, it serves as a global financial center, a major hub for trade and commerce. As of 2021, the population of Shanghai has been estimated to be over 24 million people, making it the most populous city in China and one of the most populous in the world. Shanghai has a land area of approximately 6340 square kilometers (2448 square miles), and consists of 16 administrative districts, as shown in Figure 1. The Huangpu River runs through the city, dividing it into two main areas: Puxi and Pudong. The seven districts in Puxi (shown on the right side in Figure 1), along with the Lujiazui area in Pudong, are regarded as the core areas of Shanghai. These districts encompass the central and most developed parts of the city, featuring a blend of historical sites, commercial centers, cultural landmarks, and residential areas.

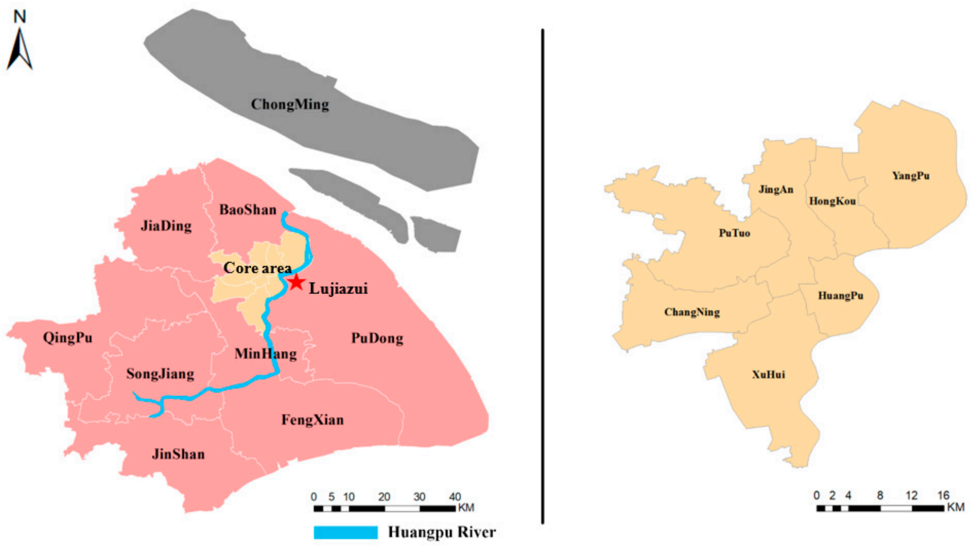

Figure 1. Administrative division of Shanghai.

The public transit system in Shanghai is well-developed, and includes an extensive network of metro lines, buses, and taxis. The metro system, in particular, is highly efficient, and is widely used by both residents and visitors alike for commuting and traveling around the city. As of December 2021, there are 20 metro lines operational with 508 stations in Shanghai. Furthermore, there are more than 300 bus lines with more than 6000 bus stations operated to transfer more than 1 million passengers every day. All these buses have installed an AFC system so that passengers can use their public transportation cards to pay their fee conveniently instead of using cash. Non-motor vehicles, such as bikes and bike-sharing services, also play a significant role in Shanghai's transportation landscape. Bike-sharing services, especially the DBSS, have gained popularity in recent years, providing a convenient and eco-friendly option for short-distance travel. According to the 2017 Shanghai Comprehensive Transportation Annual Report, the public transit system accounted for 33.2% of travel in Shanghai, while non-motor vehicles, including bike-sharing, made up 16.3%, respectively.

2.2. Dataset

There are three types of datasets in this paper: (1) DBSS transaction data from Mobike Technology Co., Ltd., Beijing, China (2) bus location data from the automatic vehicle location (AVL) systems, and bus ridership data from Shanghai Public Transport Card Co., Ltd., Shanghai, China and (3) point-of-interest (POI) data. The collected bus location data only includes data from the Pudong District. Therefore, in this paper, the data scope of all kinds of data has been limited to within the Pudong District.

The DBSS dataset was collected from Mobike, which is a well-known bike-sharing operator that was founded in China in 2015. It launched its services in Shanghai, and quickly expanded to other cities and countries worldwide. This dataset covered the bike-sharing trip orders made from 1 August to 31 August in 2016, respectively, and contains 17,684 unique users, 306,926 bikes, and 1,023,603 orders, respectively. As shown in Table 1, each trip order contained the following information:

➢ Trip characteristics, including the trip start and end time, and latitudes and longitudes of the start and end locations;
➢ Trajectory-related information, including a temporal range of the trajectory and a sequence of intermediate GPS points;
➢ Other information, such as order ID, bike ID, and user ID.

Table 1. Part sequence of Mobike's bike-sharing transaction records.

Order ID	Start time	Start GPS	End time	End GPS	Trajectory
940184	2016/8/26 8:21	121.54, 31.161	2016/8/26 8:30	121.532, 31.149	121.532,31.149 121.533,31.149 ……
940185	2016/8/26 8:21	121.454, 31.223	2016/8/26 8:33	121.451, 31.234	121.450,31.233 121.451,31.232 ……
940186	2016/8/26 8:21	121.488, 31.212	2016/8/26 8:27	121.492, 31.207	121.488,31.211 121.489,31.211 ……
940187	2016/8/26 8:21	121.458, 31.168	2016/8/26 8:29	121.461, 31.172	121.458,31.167 121.458,31.168 ……
940188	2016/8/26 8:21	121.357, 31.107	2016/8/26 8:36	121.366, 31.104	121.357,31.107 121.357,31.108 ……

Before further analysis, orders with abnormal durations were removed. Previous research have suggested that bike-sharing orders with trip durations of less than 2 min or greater than 120 min, respectively, should be filtered out [23]. These orders may have been made due to two situations: firstly, some users may just want to check the status of their accounts rather than ride the bike; secondly, they may have difficulty in picking up or returning the bike on time [24]. Additionally, orders with abnormal start and end locations that are beyond the administrative boundaries of Shanghai were also be excluded from the dataset.

Bus ridership data originated from the Shanghai AFC (auto fare collection) and AVL (automated vehicle location) systems in April 2015 and August 2016, respectively. It contained bus trip orders made from 1 April to 30 April in 2015, respectively, which encompassed 3,706,097 unique users, and 33,775,443 orders, and from 1 August to 31 August in 2016, which contained 3,482,130 unique users, and 31,074,774 orders, respectively.

As shown in Table 2, each trip order from the AFC data contains the date, boarding time, bus line, and user ID. However, the boarding location is not included as the AFC data was not originally designed for transit performance measures. To find out the bus transit ridership at the station level, it is necessary to estimate the boarding location of each bus trip.

Table 2. Part sequence of the AFC data records.

User ID	Date	Boarding Time	Line
200154	2016/8/1	16:15:50	991
101584	2016/8/5	7:24:00	174
101585	2016/8/9	17:20:06	782
200169	2016/8/23	9:09:32	581
190897	2016/8/24	20:18:48	796

Note: User IDs are not fully presented in the table to guard the privacy of bike-sharing users.

Based on the approach proposed by Ma et al. [25], we can estimate the passengers' boarding location and correspondingly calculate the stop-level bus ridership by matching the bus arrival time from the AVL system and the passenger boarding time from the AFC system (see Figure 2). Table 3 shows the detailed information of AVL system, including terminal station ID, line number, station ID and so on. The proposed algorithm is applied as follows:

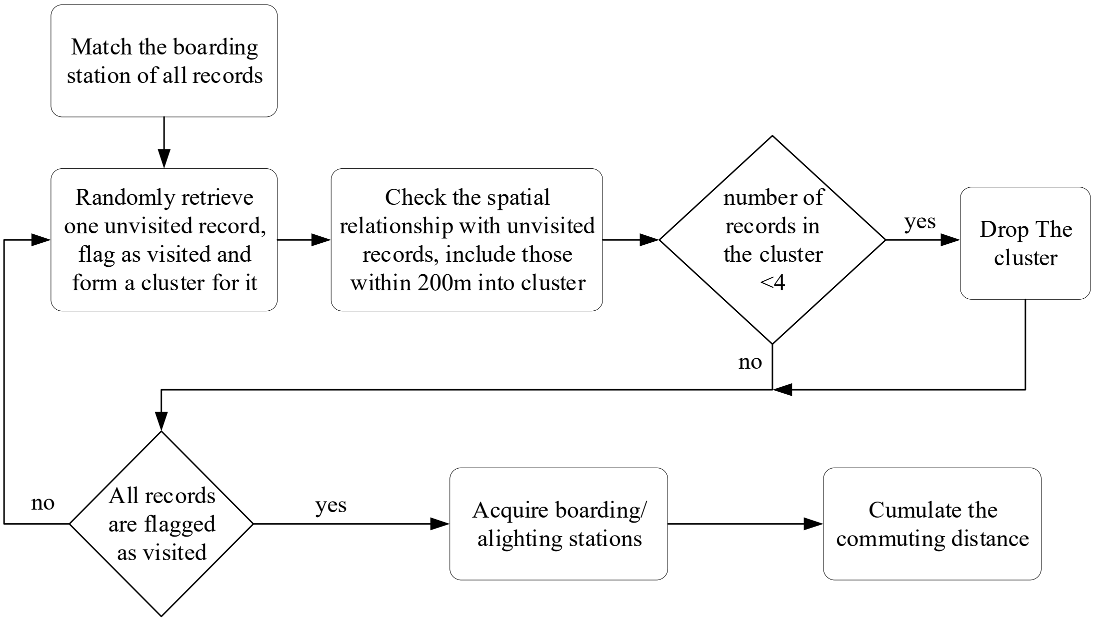

Figure 2. Flow chart of the matching algorithm.

Table 3. Part sequence of AVL data records.

Terminal	Line	Status	Station	Direction	Gateway
050A0025	614	0	70860001	1	2016/8/1 7:27
050A0025	614	1	70860001	1	2016/8/1 7:29
050A0025	614	0	73850000	1	2016/8/1 7:31
050A0025	614	1	73850000	1	2016/8/1 7:32
050A0025	614	0	74830001	1	2016/8/1 7:33

Step 1: for each publication transportation card record, use the route name, the boarding time, and the AVL records to match the boarding stations;

Step 2: randomly retrieve one record that is flagged as unvisited. Flag this record as visited and form a cluster for this record;

Step 3: check the spatial relationship between the last visited record and other unvisited records. If a spatial relationship exists (within 200 m), then this record is included in the cluster formed in Step 2 and flagged as visited;

Step 4: if the number of total records is less than 4, then these records of this card are flagged as noise and dropped; otherwise, the new cluster is confirmed;

Step 5: continue to process the unvisited rest records from Step 2 through Step 4 until the records are all flagged as visited;

Step 6: boarding/alighting stations can be acquired by utilizing the most frequent way within each cluster;

Step 7: for each record, figure out the passing stations using the boarding station, the alighting station, and the bus route information from the AFC system. Cumulate the distance between two adjacent stations to obtain the corrected trip distance of the record.

To figure out the impact of buildings/infrastructures nearby the bus station, point-of-interest (POI) data was collected from the Gaode Map application programming interface (API). A number of studies have shown that the frequencies of POIs are able to disclose and classify the urban land use and the built environment [2,26]. Similar to Ma et al. (2019), the POIs were selected by the rule of thumb. As a result, the POIs considered in this study include restaurants, shopping malls, enterprises, public facilities, hotels, and transport facilities, which are in a 100 m buffer around each bus stop. External stations refer to traffic service-related POIs, such as long-distance bus stations, taxi stops, ferry stations, import/export ports, railway stations, airports, and parking lots.

2.3. Methodology

To figure out the influence of the DBSS on bus ridership, we can directly compare bus ridership before and after the DBSS was operated widely. However, the endogenous factor between these different bus stations and routes, such as economic development, geographic location, and travel demand may lead to an inaccurate evaluation of the influence of the DBSS. Thus, in this paper, we used difference-in-differences (DID) to examine the difference in bus routes ridership with different amounts of shared bikes nearby. The DID method has been widely used to evaluate the impact of policy interventions by comparing the variation of outcomes between the treated groups and the control groups. We used this approach to remove the inherent biases from comparisons over the ridership of bus stations and routes. Figure 3 shows the overall logical flow of the adopted methodology. Firstly, the stop-level bus ridership was obtained by matching the bus arrival time from the AVL system and the passenger boarding time from the AFC system, and then aggregated them into the route-level bus ridership. Secondly, the number of shared bikes and different POIs within a 100 m buffer of each bus station was obtained based on the bus station's coordinates. Thirdly, the bus ridership data was divided into the treated groups and the control groups based on the number of shared bikes along the route, while the POI data was treated as control variables that may impact the bus ridership. Lastly, the route-level DID model was established to examine the impact of dockless bike-sharing on bus ridership, and the impact of the DBSS on bus ridership with different travel distances was also considered.

To be specific, for the route-level DID model, the treated group refers to the bus routes with shared bikes along the routes, and the control group includes bus routes without the shared bikes. The standard to classify with or without shared bikes is a threshold of the number of shared bikes along the route. Each station's shared bike number refers to the number of shared bikes within a 100 m buffer, and the number of shared bikes along the route is the aggregation of the station's number at the route level. In this case, the treated group included 198 bus routes with more than 50 shared bikes along the route, and the control group included the remaining 109 bus routes, respectively. The influence of the shared bikes on the bus routes was acquired using the following DID model to compare the variation in bus ridership between the treated groups and the control groups:

Equation (1):

$$\begin{aligned} \text{BusRiders}_{it} = {} & \alpha + \beta_0 TimeIndicate_t + \beta BikeIndicate_i \\ & + \beta TimeIndicate_t \times BikeIndicate_i \times BikeRiders_{it} + \mu Controls_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where t is the date index; i is the bus route index; $BusRiders_{it}$ and $BikeRiders_{it}$ refer to the daily bus route ridership and the number of shared bikes along the routes, respectively; $TimeIndicate_t$ is a dummy variable which indicates whether the DBSS is operated;

$BikeIndicate_i$ is a dummy variable that equals to 1 if the number of shared bikes along the route is greater than 50; $Controls_{it}$ represents a set of control variables that may impact bus ridership; β indicates the difference in ridership of different bus routes; α is the constant intercept; and ε_{it} is the Gaussian error term.

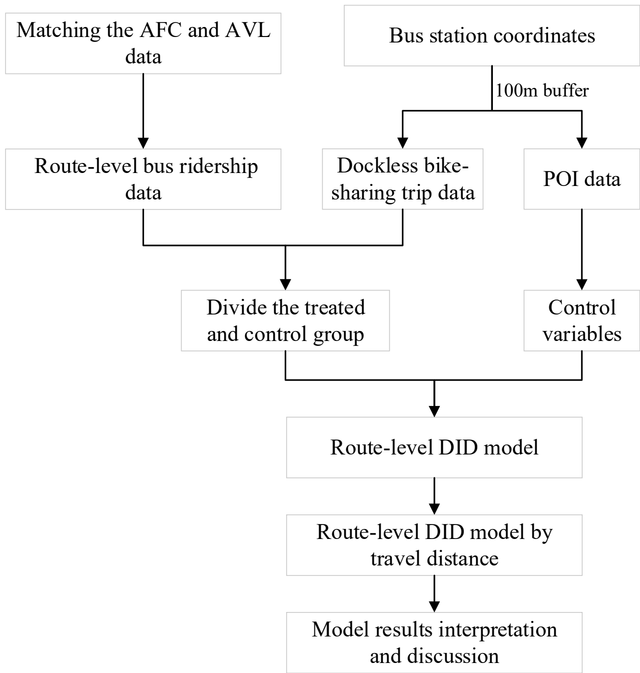

Figure 3. Flowchart of the overall logical flow of the methodology.

3. Results

A route-level DID model was proposed to figure out the influence of shared bikes and other control variables on bus ridership. Table 4 shows the descriptive statistics of the variables in the DID model. The average daily bus ridership at the route level, sharing bike usage along routes, the number of bus stations, and the number of different POIs (i.e., residences, restaurants, shopping malls, education centers, enterprises, subway stations, external traffic facilities, and service places) around each route were all counted. Bus ridership at the route level refers to the total ridership of all the buses with the same route ID. Table 4 indicates that the average daily bus ridership on the weekdays was more than twice in comparison with the weekends, and bus ridership on the weekdays was also found to have a more significant standard deviation. However, in contrast to bus ridership, the average number and standard deviation of daily bike ridership on the weekdays were both fewer than that on the weekends, indicating that the usage trend between the shared bike and bus has been reversed.

Table 4. Descriptive Statistics of Variables.

Variable	Mean	Std. dev	Min	Max
Bus riders	1433.9	1849.01	1	13,805
Busriders (weekday)	1670.21	2134.69	1	15,588
Bikeriders (weekday)	6.44	19.19	0	196
Busriders (weekend)	784.02	1083.55	0	8903
Bikeriders (weekend)	6.61	19.82	0	197
Station_amount	39.17	27.25	2	146
Enterprise	130.96	181.57	0	923

Table 4. *Cont.*

Variable	Mean	Std. dev	Min	Max
Shopping	332.66	358.51	0	1914
Restaurant	269.85	268.81	0	1284
Subway	5.69	8.27	0	52
External station	36.21	38.36	0	205
Service	19.99	23.17	0	100
Residence	40.53	43.7	0	210
Education	37.36	39.58	0	205

3.1. Results of the Route-Level DID Model

In this paper, the route-level DID model, as displayed in Equation (1), was estimated in four cases to figure out the impact of the weekday and weekend situations, along with the control variables (POI). Considering that the POIs that were located along the route greatly contributed to bus ridership, the control variables were subsequently included in both Case (b) and Case (d), while they were not incorporated in Case (a) and Case (c). Table 5 shows the regression results of the DID model in these four cases.

Table 5. Impact of variables on bus ridership within all travel distances.

Variable	Case (a) Weekday without Control Variables	Case (b) Weekday with Control Variables	Case (c) Weekend without Control Variables	Case (d) Weekend with Control Variables
TimeIndicate	−161.937 ***	−72.571 *	−201.483 ***	−53.450 **
BikeIndicate	2002.561 ***	891.856 ***	1035.214 ***	232.483 ***
β (DID)	−0.362 **	−0.390 **	−0.100 ***	−0.172 ***
Enterprise	-	0.264	-	0.498
Shopping mall	-	−0.973 **	-	−0.039
Restaurant	-	3.915 ***	-	2.197 ***
Subway	-	35.459 **	-	31.930 **
External station	-	−11.056 ***	-	−13.869 ***
Service	-	−1.539	-	−0.981
Residence	-	7.386 ***	-	6.692 ***
Education	-	13.361 ***	-	8.629 **
Intercept	549.490 ***	90.276	335.943 ***	−63.376
R2	0.170	0.517	0.130	0.453

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

Table 5 shows that shared bikes reduced bus ridership in all the cases, especially in Case (b) and Case (d), which both included the control variables. When it comes to Case (a) and Case (c), which excluded the control variables, the impact of shared bikes turned out to be decreased. The low R-squared values of Case (a) and Case (c) indicate an endogeneity issue when the DID model excluded the control variables. In Case (b), each shared bike along the route led to a 0.39 decrease in daily bus ridership on the weekdays. Meanwhile, each shared bike led to a 0.17 decrease in daily bus ridership on the weekends. These results indicate that shared bikes have a substitution effect on the bus transit, whether on the weekdays or the weekends. Furthermore, passengers were more likely to use shared bikes instead of taking buses on the weekdays than on the weekends. The dummy variables TimeIndicate in all cases were negative and indicated that the daily average bus ridership at the route level in 2016 decreased by 72 on the weekdays and 53 on the weekends, respectively, influenced by the time factor. In Case (b) and Case (d), enterprise and service variables were both found to be insignificant, indicating that the number of enterprises and service places along the bus route has no significant impact on the bus ridership. Educational institutes, such as schools, universities, and libraries, generated an average of 13.4 and 8.6 of daily trips on each route on the weekdays and the weekends, respectively. Meanwhile, residential areas generated an average of 7.4 and 6.7 daily trips per route on the weekdays and the weekends, respectively. The two above-mentioned coefficients were determined to be significant as passengers often transport by buses near to these education and residential areas, especially on the weekdays. The number of subway stations also had a great impact on bus ridership, which indicates that passengers are more likely to take buses with an increasing number of subway stations along the route. Each subway station contributes to average increases of 35.5 and 31.9 bus ridership per route on the weekdays and weekends, respectively.

3.2. Result of Travel Distance Analysis on the Route Level

In this paper, the impact of the DBSS on bus ridership with different travel distances was also considered. Figures 4 and 5 show the travel distances of the total shared bike trips and bus ridership within 5 km. Figure 5 shows that the number of shared bike trips within 2–3 km on the weekdays was significantly higher than that on the weekends. However, there was no notable gap between trips on the weekdays and trips made on the weekends within other travel distances. Figure 4 shows that both on the weekdays and weekends, the amount of bus ridership within the different travel distances in April 2015 was larger than that of August 2016 in general. The gap of ridership within 2–3 km, and between April 2015 and August 2016 on the weekdays, respectively, was significantly higher than that on the weekends. These results indicate that the travel distance is also a critical factor for passengers to consider their travel methods. Thus, in this paper, another set of DID models was estimated to figure out the impact of the travel distance on the influence of shared bikes. Table 6 shows the regression results of the DID model based on different travel distances on the weekdays/weekends.

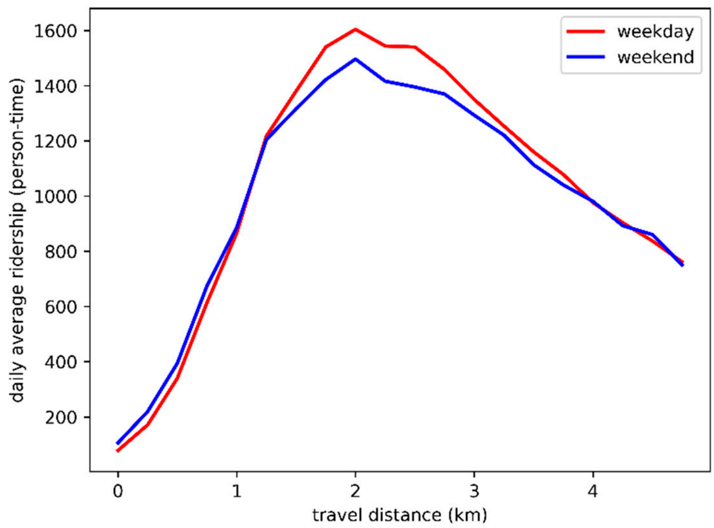

Figure 4. Travel distance distribution of the shared bikes.

Cases (e), (g), (i), (k), and (m) were based on the data on the weekdays, while Cases (f), (h), (j), (l), and (n) were based on the data on the weekends, respectively. Cases (e) and (f), Cases (g) and (h), Cases (i) and (j), Cases (k) and (l), and Cases (m) and (n) separately include the ridership with a travel distance range from 0–1 km, 1–2 km, 2–3 km, 3–4 km, and 4–5 km, respectively.

Table 6 includes the cases within 0–3 km, and shows that shared bikes reduce bus ridership within 0–3 km. In Case (e), each shared bike along the route led to a 0.104 decrease in daily bus ridership while the decrease in Case (f) was only 0.051, respectively. Such a difference was also found to exist between Case (g), Case (h), Case (i), and Case (j). These results indicate that the substitution effect of shared bikes on bus ridership is weakened on the weekends. Meanwhile, by comparing the decrease in these six cases, it is shown that the substitution effect of shared bikes on bus ridership was also reduced when the travel distance increases. Restaurants generated an average of 1.435 and 0.851 daily trips on each route on the weekdays and the weekends based on the ridership within 1 km, respectively. Educational institutes also show a positive effect on the ridership within 1 km, which generated an average of 9.167 and 6.242 daily trips per route on the weekdays and the weekends, respectively. Meanwhile, residences generated 9.167 daily trips on the weekdays, 6.242 on the weekends within 1 km, and 0.567 on the weekdays and 0.091 on the weekends within 2 km, respectively. These variables above can generate ridership significantly within a short distance but can hardly generate ridership when the travel distance gets larger. However, the subway can generate ridership regardless of the travel distance. Each subway along the route can generate ridership ranging from 6.224 to 15.694 on the weekdays, and 2.721 to 7.648 on the weekends, respectively. Other variables, including enterprises, shopping malls, restaurants, and services have no significant influence on bus ridership.

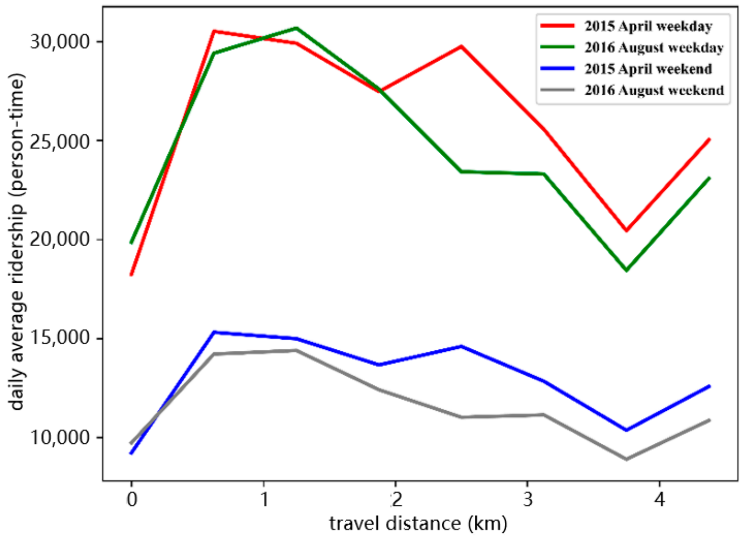

Figure 5. Travel distance distribution of bus ridership.

Table 6. Impact of variables on bus ridership within 0–3 km travel distance.

Variable	Case (e) 0–1 km Weekday	Case (f) 0–1 km Weekend	Case (g) 1–2 km Weekday	Case (h) 1–2 km Weekend	Case (i) 2–3 km Weekday	Case (j) 2–3 km Weekend
TimeIndicate	−58.411 **	−33.502 **	21.023 **	13.231 **	14.817	5.708
BikeIndicate	490.093 ***	224.854 ***	94.687 ***	40.929 ***	94.107 ***	32.877 ***
β (DID)	−0.104 **	−0.051 **	−0.041 ***	−0.025 ***	−0.037 ***	−0.016 ***
Enterprise	0.821 **	0.262	0.011	0.042	0.070	−0.006
Shopping mall	−0.150	−0.086	0.029	0.004	−0.075	−0.032
Restaurant	1.435 **	0.851 ***	0.097	0.035	0.200 *	0.092 *
Subway	15.694 **	7.648	6.378 ***	2.721 **	6.224 ***	3.144 ***
External station	−8.901 ***	−4.800 ***	−0.844 *	−1.476 **	−1.159	−0.860 ***
Service	−0.727	−0.786	−0.280 *	0.043	−0.017	0.043
Residence	7.513 ***	4.377 ***	0.811 ***	1.271 ***	0.526	0.455 **
Education	9.167 ***	6.242 ***	0.567 *	0.091	0.789	0.627 **
Intercept	0.465	9.236	3.247	−10.547 *	6.128	4.031
R2	0.502	0.466	0.206	0.182	0.247	0.335

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

Table 7 includes the cases within 3–5 km. These results indicate that each shared bike has no significant impact on bus ridership within 3–5 km, both on the weekdays and the weekends. Other variables such as residences, subways, and restaurants have a positive influence on bus ridership. Each external station decreases the ridership along each route.

Table 7. Impact of variables on bus ridership within 3–5 km travel distance.

Variable	Case (k) 3–4 km Weekday	Case (l) 3–4 km Weekend	Case (m) 4–5 km Weekday	Case (n) 4–5 km Weekend
TimeIndicate	−4.631	−4.002	3.640	−0.386
BikeIndicate	38.539	12.563 **	45.030 ***	21.391 ***
β (DID)	−0.013	−0.007	−0.010	−0.004
Enterprise	0.055	0.015	0.117	0.037
Shopping mall	−0.018	−0.006	0.026	0.014
Restaurant	0.167 **	0.101 **	0.393 ***	0.198 ***
Subway	4.441 ***	2.400 ***	3.882	1.391 **
External station	−0.475	−0.335 **	−1.347 ***	−0.793 ***
Service	−0.056	−0.028	−0.472 *	−0.204 **
Residence	0.904 ***	0.521 ***	0.635 ***	0.399 ***
Education	0.129	0.148	0.770 ***	0.476 ***
Intercept	13.315	3.210	5.884	−0.072
R2	0.326	0.397	0.324	0.406

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

These results indicate that the travel distance of passengers strongly impacts the relationship between bike-sharing usage and bus ridership.

4. Discussion

The results of these regress experiments show that whether on the weekdays or the weekends, the usage of shared bikes decreases bus ridership in Shanghai. DID models were proposed to figure out the relationship between shared bike usage and bus ridership on the route level. These route-level models also included some potential control variables (POIs) along the routes.

From the result of the proposed models, we can conclude that shared bike usage has a substitution impact on bus ridership. This result is largely consistent with previous findings concerning docked bike-sharing research [13,14]. Chen et al. [14] found that the majority of respondents were found to potentially substitute dockless bike-sharing systems for walking or public transit. Considering all the ridership, the reduction in bus ridership was more significant on the weekdays than on the weekends. This result may be caused by passengers' different travel purposes. On the weekdays, most passengers travel for commuting. To avoid traffic jams and get shorter commuting times, passengers are more likely to use shared bikes instead of taking buses to commute short distances or for the last-mile connection to the urban rails. Thus, the substitution impact of shared bikes on bus ridership was significantly stronger on the weekdays than on the weekends in short travel distances. This result also confirmed what Shaheen et al. proposed [18] in that it is important to distinguish between commuting trips, utility-oriented trips, and leisure travel purposes when assessing the bike-sharing mode substitution.

The substitution impact of shared bikes on bus ridership gradually decayed in daily bus ridership with the increase in travel distance to within 3 km. This result is consistent with Liu et al. in that bike-sharing is a rival and suitable alternative to the bus on a moderate distance (0.5–3 km) [9]. Additionally, shared bikes have no impact on bus ridership if the travel distance is between 3 km and 5 km, respectively. This is intuitive in that if the travel distance is too long, traveling by a shared bike will be exhausting and time-consuming compared with a bus. As a result, the substitution effect of shared bikes on the bus was deemed to not be significant.

Limitations also exist in the proposed model. Firstly, only data collected from Shanghai was utilized in this paper. Secondly, there was no uniform identity system between the DBSSs and the AFC systems, meaning it was difficult for us to capture the transfer activities between the shared bikes and buses. These research limitations call for future improvements. One research direction would be to validate the model in other research areas (e.g., Beijing, China, and New York, USA). Another improvement in the future could also be to examine the impact of other traffic modes on public transit ridership by utilizing new data, especially emerging traffic modes, for example, self-driving taxis [27].

5. Conclusions

To figure out whether DBSSs are complementary or competitive to the public bus transit, this paper proposed route-level DID models to capture the impact of shared bikes and POIs nearby the route on bus ridership. These DID models were used to find out the difference in bus ridership before and after the large-scale operation of the shared bikes. POIs, including subways, restaurants, and residences along the bus routes were taken into consideration in the proposed DID model as control variables.

A case study was conducted on 2015–2016 transit smart data and dockless sharing bike data in Shanghai, China. The number of bus ridership decreased after the operation of the shared bikes, and route-level bus ridership with shared bike usage significantly decreased compared with the ridership without shared bike usage. The proposed route-level DID model thereby shows that there is a competitive relationship between the DBSS and public transit, and that shared bikes have a substitution impact on bus ridership on both the weekdays and the weekends. In addition, the relationship between the DBSS and public transit was also affected by passengers' travel distance. With each increase in the number of shared bikes, bus ridership significantly decreased on weekdays by 0.104, 0.041, and 0.037 within 0–1 km, 1–2 km, and 2–3 km, respectively. In contrast, this decrease tended to be lower on the weekend. This result shows that shared bikes have a degressive substitution impact on bus ridership with the increase in the travel distance. Moreover, when the travel distance is more than 3 km, shared bikes have no significant impact on bus ridership.

This paper estimated a comprehensive model to analyze the impact of the date, environment along the route, and shared bikes on bus ridership in Shanghai, China. The results of this paper can further help the public transportation department and the DBSS operators to adjust their management strategy and relocate the location of these shared bikes on the weekdays and the weekends.

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