Exploring the Impact of Dockless Bikeshare on Docked Bikeshare—A Case Study in London

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Abstract: As a green and sustainable travel mode, the bikeshare plays an important role in solving the “last-mile” problem. The new dockless bikeshare system (DBS) is widely favored by travelers, and the traditional docked bikeshare system (BS) is affected to a certain extent, but the specific circumstances of this impact are not yet known. To fill the knowledge gap, the objective of this study is to measure the impacts of DBS on London cycle hire, which is a type of BS. In this study, the travel data of 707 docking stations in two periods, i.e., March 2018 and March 2017, are included. A spatial-temporal analysis is first conducted to investigate the mobility pattern changes. A complex network analysis is then developed to explore the impact of DBS on network connectivity. The results suggest a significant decrease of 64% in the average trip amounts, with both origins and destinations in the affected area, and the trips with short and medium duration and short and medium distances are mainly replaced by DBS. DBS also has a considerable impact on the structure and properties of the mobility network. The connectivity and interaction strength between stations decrease after DBS appears. We also concluded that the observed changes are heterogeneously distributed in space, especially on weekends. The applied spatial-temporal analysis and complex network analysis provide a better understanding of the relationships between DBS and BS.

Keywords: dockless bikeshare; docked bikeshare; London cycle hire; spatial-temporal analysis; causal effects; complex network analysis

1. Introduction

With the development of cities, environmental pollution and traffic congestion have become worldwide problems [1,2]. As an important part of the public transportation system, the docked bikeshare system (BS) plays an important role in solving the “last-mile” problem [3]. Simultaneously, as a healthy and sustainable mode of transportation, BS is used in many cities, including London, Hangzhou and New York. In July 2010, London cycle hire is established, and many policies and invested facilities are used to improve the convenience of cycling travel, including London cycle hire and the London Cycle Superhighways (CS).

In 2017, dockless bikeshare systems (DBS) appeared in London for the first time, including Mobike, Ofo and Urbo. Due to its freedom and convenience, DBS is loved by many citizens, and it has gradually become a useful shared travel. According to Li et al. [4], since Mobike entered London in 2017, it had been widely loved by locals and had maintained a high usage rate. According to Gu et al. [5], congestion, financial sustainability, vandalism and sleepy fleets were the main problems of DBS operation, and the development prospect of DBS needed to be further explored. BS can solve these problems, but the relationship between the two bikeshare systems is not yet known. It will be important to explore the impacts of DBS on BS, by absorbing the advantages of DBS, and taking advantage of BS to improve the service quality of cycling travel.
As a healthy and low-cost way to travel, BS has been widely studied by researchers [3,5–13]. Simultaneously, many studies have shown that DBS has a great impact on other modes. However, it did not show in detail whether it had any influence on BS [14]. The purpose of this article is to explore the specific impact of DBS on London cycle hire. First, spatial-temporal analysis of trips count trip distance and trip duration in the BS system, before and after the arrival of DBS, and this is used to better understand the impacts of the DBS. Then, we provide a comparative network theoretic analysis of the London cycle hire mobility network before and after the arrival of DBS. The combined spatial-temporal analysis and the complex network methodology [11,15] used here provide a unique view of the effects of DBS on BS.

The remainder of the paper is organized as follows. The introduction of BS and DBS is shown in Section 2. Study area and data are separately illustrated in Section 3. The spatial-temporal analysis and complex network-theoretic approach are shown to increase our understanding of the mobility characteristics in Section 4, followed by conclusions in the final section.

2. Background

The development of BS and DBS is first introduced in this section. Then, we review the literature on both bikeshare systems.

2.1. Docked Bikeshare System

According to Bachand-Marleau et al. [16], the development of BS could be divided into 4 generations. London cycle hire belongs to third-generation products that can normally be rented and returned by smart or credit cards. In July 2010, London cycle hire arrived in London, with 5000 bicycles and 315 docking stations. By 2018, there were more than 13,351 bicycles and 762 docking stations between 300 m and 500 m intervals, and London cycle hire has achieved over 60 million hires [17]. Cyclists have two ways of hiring Santander bikes. It costs 2 GBP for 24 hours or 90 GBP per year, and is free for the first half hour, and 2 pounds every 30 minutes [18]. Students studying in London will get 25% off yearly membership. Figure 1 shows London cycle hire docking stations in March 2020. The London cycle hire stations are located across the city of London and parts of its boroughs (London is composed of the city of London and 32 boroughs).

![Figure 1. London cycle hire docking stations (source: Google Maps).](image-url)
As a healthy and environmentally friendly mode of transportation, BS has been extensively studied by researchers. Measuring the factors affecting the usage of bikeshare systems is a hot topic [19–21]. Campbell et al. [22] conducted a stated preference survey and employed multinomial logit to examine the factors affecting the choice of bikeshare and e-bikeshare. The result showed that travel distance, temperature, precipitation, and air quality were the major factors that affected bikeshare demand. According to Kim [23], weather conditions and temporal characteristics had different influences on different stations over the different time periods within a day, by using clustering analysis. Nickkar et al. [21] explored a temporal-spatial analysis of BS, considering land use and gender. Zhang et al. [24] used a multiple linear regression model to find that population land-use types, bike lanes and population density had positive effects on the ratio of demand to supply and trips demand.

As the key to solving the “last-mile” problem, the combination of cycling and metro has been extensively studied. Many papers have summarized a range of cycling-metro integration topics, including expanding the effects of metro station service coverage [25], the determinants of general cycling-metro integration [10,26–29], the accessibility of cycling-metro [30,31], and the travel characteristics of cycling-metro integrated trips [9,32]. The health and environmental benefits of bikeshare were also studied by Zhang and Mi [33].

Although previous studies have suggested that other travel modes did have impacts on BS, such as the effects of the London Cycle Superhighways [34], the effects of the metro [7,11,35], the effect of DBS on BS is rarely studied in the literature. The effects of DBS on BS usage and characteristics of the BS trips were studied [8]. However, complex networks and traffic patterns have not been studied before. In the following section, DBS will be introduced.

2.2. Dockless Bikeshare System

In early 2017, a new type of DBS was widely used in major cities in China. Then, it quickly became popular all over the world, including in London. It is a kind of bicycle that is very different from the traditional BS. It has many advantages, such as easy access to DBS, convenience to park and pick, relatively low price to use [5], and is widely welcomed by young people. Subsequently, London has introduced DBS, such as oBike, Mobike, Ofo, and Urbo. Figure 2 shows three main bikeshare systems in London.

Figure 2. Bikeshare systems in London. (a) Santander bikes (source: https://www.londoncyclist.co.uk/london-cyclist-is-hibernating); (b) Mobike (source: https://mobike.com/global); (c) Ofo (source: http://www.ofo.so).

Mobike was the first DBS to enter London on July 31, 2017, cooperating with the government. On September 7, Ofo arrived in Hackney with 200 bikes. Cyclists can pay 50 P for 30 minutes to ride Ofo and Mobike, but Mobike requires a 29 GBP deposit to join the scheme. In July 2017, Singapore’s oBike ran in London, without coordinating with local boroughs. The effect of oBike cannot be taken into consideration, because this system releases around 400 bikes in all of London, and this does not affect the results significantly. Table 1 shows the arrival date of DBS and the number of DBS
launched in different boroughs. After DBS arrived, the local government was very supportive because they believed that DBS would help residents travel environmentally and improve urban sustainable development [36]. However, due to disagreement in some boroughs, DBS can only be ridden in a specific area, thus bringing the fragmented distribution of DBS.

| Borough          | Launching       | Firm      | Number of Launched Dockless Bikes |
|------------------|-----------------|-----------|----------------------------------|
| Hackney          | September 2017  | Ofo       | 200                              |
| Islington and City of London | November 2017 | Ofo       | 100 (Islington) and 100 (City)  |
| Islington        | November 2017   | Mobike    | 200                              |
| Southwark        | March 2018      | Ofo and Mobike | 200 (Mobike) and 200 (Ofo) |
| Newham           | March 2018      | Mobike    | 300                              |
| Camden           | June 2018       | Ofo       | 200                              |
| Wandsworth       | June 2018       | Ofo       | No detailed information          |
| Camden           | July 2018       | Mobike    | No detailed information          |

In a previous study, the demand for forecast and rebalancing for the bikeshare system was studied by many academic scholars [37]. Xu et al. [12] used the deep learning approach to develop a dynamic demand forecasting model for DBS. The result showed that the spatial and temporal demand of bikeshare trips was imbalanced. Dell’Amico et al. [38] developed stochastic programming models to solve the bikeshare rebalancing problem with stochastic demands. Zhang et al. [39] developed a dynamic pricing scheme with negative prices to achieve bike relocation. In this paper, a user equilibrium dynamic traffic assignment model was developed to capture travelers’ mode-path choice behavior.

With the widespread use of DBS, the differences between DBS and BS are studied. Ji et al. [40] applied binary logistic models to reveal the impacts of travel characteristics and built environment factors on the regularity of bikeshare usage. The results showed that regular users and occasional users share similar riding times and distances, while there were significant differences in the spatial-temporal distribution for both bikeshare systems. According to Albinski et al. [14], by analyzing the number of trips taken and reservations from DBS and BS, 90 percent of the trips were made from DBS and DBS made the system more attractive. Some studies focus on the factors influencing the usage of DBS [21,41,42].

3. Study Area and Data

3.1. Study Area

London is the capital of the United Kingdom, and the largest city in the United Kingdom, with a population of 13.62 million. In order to build a smart city, some series of sustainable transportation measures have been applied in London, including a comprehensive subway and bus network; pedestrian and bicycle lanes have been established, and public bicycles and shared bicycles have been put into use. As of 2020, London has built a 402 kilometers of the subway network, of which 160 kilometers are underground, and there are 11 lines, 270 stations in operation, and an average of 3.04 million passengers per day. At the same time, London’s bus network is one of the largest in the world, operating 24 hours a day, with approximately 8500 buses, more than 700 bus lines and nearly 19,500 bus stops. London cycle hire is the second largest BS in Europe, and the authorities have applied many measures to improve the convenience of bicycle travel, including the London Cycle Superhighways (CS) [43]. CS was put into use in 2008 and twelve routes were planned to radiate from the center to the surrounding Boroughs. By the end of 2018, a total of six routes had been put into use, including CS1(2016), CS2(2011), CS3(2010), CS5(2015), CS7(2010), CS8(2011) [34].
3.2. Data Description and Preprocessing

This article’s cycling transaction data come from Transport for London (TfL) [18]. In the selection process of the data, we use the data of the London cycle hire in three areas such as Hackney and Islington and City of London as research, and compare the data of the London cycle hire in other areas that DBS had not released before March 2018. A total number of 707 docking stations are included in this study, 113 of them are in the area affected by DBS. The records of each station are aggregated at the day level, which cover two periods, March 2017 and March 2018. Table 2 shows the transaction record, including rental ID, duration, end date, end station ID, end station name, start date, start station ID, and start station name.

| Rental Id  | Duration | End Date   | End Station Id | End Station Name       | Start Date   | Start Station Id | Start Station Name       |
|------------|----------|------------|----------------|------------------------|--------------|-------------------|------------------------|
| 62787069   | 540      | 03/03/2017 | 779            | Houndsditch, Aldgate    | 03/03/2017   | 55                | Finsbury Circus, Liverpool Street |
| 62727993   | 420      | 01/03/2017 | 104            | Crosswall, Tower        | 01/03/2017   | 101               | Queen Street 1, Bank     |
| 62871700   | 420      | 07/03/2017 | 104            | Crosswall, Tower        | 07/03/2017   | 101               | Queen Street 1, Bank     |
| 62842683   | 360      | 06/03/2017 | 104            | Crosswall, Tower        | 06/03/2017   | 101               | Queen Street 1, Bank     |

However, there are some extra information and errors, so there are the following pre-processing steps. The first preprocessing step deletes transaction records with missing values and the same starting and ending stations. The lack of part of the information will reduce the accuracy of the data, and the passengers’ travel itinerary will not be known when the starting and ending stations are the same, but the relatively small number of these parts will not affect the results.

Then, for the bikeshare transactions, a minimum journey duration of 1 min and a maximum journey duration of 60 min are used for data screening similar to Li et al. [4], because such movements might not be associated with an actual cycling activity. According to the household interview travel survey (HITS) of 2012, 99.7% of the HITS trips were finished within one hour. Simultaneously, London cycle hire is free for the first half hour, and then charges 2 GBP every 30 minutes, so it is enough to complete the trip within an hour.

Finally, only global positioning system (GPS) movements with a great-circle distance longer than 100 meters and shorter than 5 kilometers as valid bike trips are selected similar to Shen et al. [42]. We geocode the latitude and longitude of the starting and ending stations to calculate the road network travel distance, using Google Maps. The results are summarized in Figure A1; almost all the trips are longer than 100 meters, and trips longer than 5.0 kilometers are identified as outliers. The short distance may be because the travelers come on a round trip and return to the starting station. At the same time, long-distance driving caused by cycling activities such as fitness has an impact on the accuracy of the research results. We thus select only GPS movements with a distance longer than 100 meters and shorter than 5 kilometers as valid cycling trips.

After excluding these extra information and errors, we have obtained valid trip records of 1,712,520, accounting for 97.5% of the original dataset in 2017 and 983,041, accounting for 98.3% of the original dataset in 2018.

4. Result and Discussion

In this section, the cycling trips are divided into four types: trips with both the origins and destinations in the unaffected area (Type 1); trips with the origins in the affected area (Type 2); trips
with the destinations in the affected area (Type 3); trips with both the origins and destinations in the affected area (Type 4).

4.1. Trend Analysis in about Two Years

In this section, we first conduct the trend analysis on daily temporal distribution of trip amount and travel time. In Figure 3, it shows the time trend of the average trip amount of the London cycle hire, and the Y-axis value represents the average amount of travel per day. After DBS arrives, it is not obvious how DBS affects the use of the London cycle hire, but it will fluctuate depending on the weather and holidays. As can be seen from Figure 3, the usage trends of Type 2 and Type 3 almost overlap, and the effect of DBS on these two types may be similar.

![Figure 3](image1)

Figure 3. Time trend of the average trip amount of the London cycle hire. Trips with both the origins and destinations in the unaffected area (Type 1); Trips with the origins in the affected area (Type 2); Trips with the destinations in the affected area (Type 3); Trips with both the origins and destinations in the affected area (Type 4) (source: Santander Bike System Data, 2020).

Figure 4 shows the comparison between 4 types in terms of average travel time distribution. Similar to Figure 3, the travel time did not change much before and after DBS arrived, but was affected by the weather and holidays in Figure 4. The average daily travel time per person has remained basically the same for two years. Compared to the higher travel time of Type 1 (20 min) and the lower travel time of Type 4 (10 min), Type 2 and Type 3 maintain almost the same duration (15 min). This means that DBS has similar effects on Type 2 and Type 3. The specific impact of DBS on BS will be described in detail below.

![Figure 4](image2)

Figure 4. A comparison between four types in term of average travel time distribution (source: Santander Bike System Data, 2020).
4.2. Spatial-Temporal Analysis

Temporal analysis of bike usage can reveal the dynamics in, and characteristics of, London cycle hire. In Figure 5, we can see the temporal travel patterns in London of the average data within four weeks in four types. Figure 5 shows the use of bicycles in the two periods. It shows that they have similar temporal patterns, with one difference in trip amounts. On weekdays, you can clearly see two peaks; the morning peak and the evening peak. The morning peak is between 7:00 and 9:00 for two hours, and the evening peak is between 16:30 and 18:30, and an hour peak at 12 o’clock may be caused by lunch time. All four types have a peak around 15 o’clock on weekends. According to the study of Gu et al. (2019a), the use of London cycle hire is mostly for commuting, and the weekend is a rest day, so there is no morning and evening peak.

However, the morning peak of Type 2 is lower than the evening peak, and the other types are the opposite. In addition to Type 4, the morning and evening peaks of the other three types all overlap, while Type 4 rarely overlaps. It shows that the type whose starting stations are in the affected area is greatly affected by DBS, and the usage is much lower, but the pattern has not changed. At the peak time of Type 4, the reduction in the use of London cycle hire in 2018 compared to 2017 is much larger; the reduction is about 64%, while the reductions of Type 1, Type 2, and Type 3 are 40%, 46%, 40%. For trips with the origins in the affected area, an increase in the ridership is also observed, although it is not significant. For trips with the destinations in the affected area, the impact of DBS is almost the same as trips with both the origins and destinations in the unaffected area.

Figure 5. Cont.
By using the online map function of ArcGIS (Geographic coordinate system), Figure 6 shows that the spatial distribution of trip amounts significantly changes in the affected area (Hackney and Islington and City of London). However, stations in the affected area show a large reduction compared to the unaffected areas, as expected. Simultaneously, in some areas where DBS is not available, stations close to the center of London (such as Westminster and K and C) decrease more, and peripheral areas decrease less. The network heterogeneity may be caused by the imbalance of available bikes at the stations.
4.3. Causal Effects of DBS on London Cycle Hire

In Figure 7, we can find that London cycle hire cycling travel for the four types is significantly reduced, especially for Type 4. In Type 4, the total SPBS ridership reduces from 151039 to 53915, at a rate of 64.30% from March 2017 to March 2018. Average trips decrease by 63.12% and 70.18% on weekdays and weekends. On weekends, the use of London cycle hire is even more reduced. In other words, after the arrival of DBS, people use DBS more for leisure activities on weekends, and DBS can replace commuter cycling instead of more non-commuter cycling. Simultaneously, the trips with the origins in the affected area (Type 2) and the trips with the destinations in the affected area (Type 3) have little change from the trips with both the origins and destinations in the unaffected area (Type 1). This may be the reason for local policy restrictions (only DBS can be parked in the area where DBS are placed).

Figure 6. Spatial distribution of the London cycle hire stations. Color of circles represent the change in the trip amounts hired at each station in 2017 compared to 2018 (source: Google Maps).

Figure 7. Decreasing rate of trips of London cycle hire (source: Santander Bike System Data, 2020).
As can be seen from the previous sections, Type 4 is the most affected, so this section compares Type 1 and Type 4. In addition, we investigated the effect of DBS on the different travel time of London cycle hire. Because the first 30 minutes of the London cycle hire are free, and every subsequent 30 minutes will be charged 2 GBP, and Ofo and Mobike will charge 50 pennies every 30 minutes, 30 minutes is a key point. Simultaneously, as a manpower travel mode, few single trips last for more than one hour. This article divides the duration into three segments for analysis, short-duration trips (0–15 min), middle-duration trips (15–30 min), and long-duration trips (30–60 min). It can be seen from Table 3 that the impact of DBS on London cycle hire is mainly concentrated between short and medium durations. From 0 to 15 minutes, Type 4 decreases by 63.27%, while Type 1 decreases by 36.14%, and Type 4 decreases significantly. From 15 to 30 minutes, Type 4 decreases by 67.98%, while Type 1 decreases by 44.58%, and Type 4 decreases significantly. Long duration trips show no significant changes. In Table 4, we can find that the average travel time is less affected and has no significant effect. In summary, DBS mainly replaces short and medium duration travel.

Table 3. Effect of DBS on the average hire duration (seconds) of the London cycle hire.

| Travel Duration | Type | 2017       | 2018       | Effect   | Effect (%) |
|-----------------|------|------------|------------|----------|------------|
| 0–15 min        | Type 1 | 433,203    | 276,627    | 156,576  | 36.14%     |
|                 | Type 4 | 133,484    | 49,023     | 84,461   | -63.27%    |
| 15–30 min       | Type 1 | 237,768    | 131,780    | 105,988  | -44.58%    |
|                 | Type 4 | 49,023     | 15,695     | 33,328   | -67.98%    |
| 30–60 min       | Type 1 | 40,653     | 16,640     | 24,013   | -59.07%    |
|                 | Type 4 | 1,860      | 418        | 1442     | -77.53%    |

1 Trips with both the origins and destinations in the unaffected area (Type 1). 2 Trips with both the origins and destinations in the affected area (Type 4).

Table 4. Effect of DBS on the monthly usage of the London cycle hire.

| Type | 2017 | 2018 | Effect | Effect (%) |
|------|------|------|--------|------------|
| Type 1 | 14.19 | 13.12 | 1.07   | -7.54%     |
| Type 4 | 9.35  | 8.80  | 0.55   | -5.88%     |

In terms of the travel distance, we divide the total trips into three parts: short-distance trips (0–1 km), middle-distance trips (1–3 km), and long-distance trips (over 3 km). From Table 5 and Figure 8, we can see that DBS has the greatest impact on short and medium distances (0–1 km and 1–3 km). The reductions are 63.60% and 64.50%, respectively. Table 6 shows that the average travel distance does not have statistically significant changes. The reason may be that only the Euclidean distance between origins and destinations is studied.

Table 5. Effect of DBS on the monthly usage of London cycle hire.

| Distance(O-D) | Type | 2017       | 2018       | Effect   | Effect (%) |
|--------------|------|------------|------------|----------|------------|
| 0–1 km       | Type 1 | 157,567    | 98,409     | 59,158   | -37.54%    |
|              | Type 4 | 52,559     | 19,129     | 33,430   | -63.60%    |
| 1–3 km       | Type 1 | 398,395    | 235,574    | 162,821  | -40.87%    |
|              | Type 4 | 94,768     | 33,645     | 61,123   | -64.50%    |
| Over 3 km    | Type 1 | 125,729    | 73,740     | 51,989   | -41.35%    |
|              | Type 4 | 3712       | 1141       | 2571     | -69.26%    |
A link is the channel between the stations; it will be drawn only when the number of trips between the quantile, median and third quantile of the degree distribution in 2018 are lower than those in 2017. The connectivity of the system is reduced, especially during non-working days.

On weekdays, the average node degree $<k>$ is 52.16 in 2018, which is 93% in 2017. On weekends, $<k>$ is 27.38, which is 79% in 2017. The arrival of DBS reduces the connection of the London cycle hire stations and has a greater impact on weekends.

It can be seen from the above sections that DBS has an impact on trips, with both the origins and destinations in the affected area (Type 4), so the complex network analysis only compares Type 4 before and after, and conducts separate studies on weekdays and weekends. This article selects the period from 3.6 to 3.12 in 2017 and from 3.5 to 3.11 in 2018, to analyze the impact of the emergence of DBS on the characteristics of complex London cycle hire networks.

In this section, we will use a complex network method to make a supplementary analysis of the impact of DBS on London cycle hire. We will select the statistical characteristics of the London cycle hire network for analysis. The connection of many independent nodes is considered a network, and the interconnection between nodes is called a link. From the perspective of a complex network, the stations in the BS are regarded as nodes $i$ or $j$ in the network, and the sum of all the stations is called $N$. A link is the channel between the stations; it will be drawn only when the number of trips between the two stations is at least one. $L$ is the total number of links in the network. The number of trips from node $i$ to node $j$ per unit of time is represented by a nonnegative weight on the link $w_{ij}$. $a_{ij}$ represents the adjacency matrix associated with the network.

4.4. Complex Network Analysis

Table 6. Effect of DBS on the average travel distance (meters) of London cycle hire.

| Type    | 2017  | 2018  | Effect | Effect (%) |
|---------|-------|-------|--------|------------|
| Type 1  | 1.93  | 1.91  | 0.02   | $-1.04\%$ |
| Type 4  | 1.38  | 1.36  | 0.02   | $-1.45\%$ |

4.4.1. Complex Network Statistical Properties

In Table 7, it summarizes the statistics of the bicycle network in the week of 2017 and 2018. In the case where $N$ is basically unchanged, the connection between sites in 2018 is relatively reduced to 95%, and the reduction on weekends is even greater, reduced to 79%. It means that the arrival of DBS reduces the connection of the London cycle hire stations and has a greater impact on weekends.

The degree $k_i$ of a node is defined as the number of links connecting one node in the network,

$$k_i = \sum_j a_{ij}$$  \hspace{1cm} (1)

On weekdays, the average node degree $<k>$ is 52.16 in 2018, which is 93% in 2017. On weekends, $<k>$ is 27.38, which is 79% in 2017. The connectivity of the system is reduced, especially during non-working days.

Figure 9a shows the box plot of node degree between the two periods. On weekdays, the first quantile, median and third quantile of the degree distribution in 2018 are lower than those in 2017.
On weekends, although the first quantile in two years is the same, the average, median, and third quantile are all lower than in 2017. Combined with Figure 9b, it can be shown that, in 2017, it is more likely to observe a high node degree, and the change on the weekend of two years is higher than that on weekdays.

Node flux $F$ is the sum of all trips departing or arriving at a node,

$$F_{ij} = \sum_j w_{ij}$$

Node flux $F$ shows the attractiveness of a node and its ability to connect other nodes in the network. On weekdays, the average node flux $<F>$ is 171.26, which is 89% in 2017. On weekends, the average node traffic $<F>$ is 51.83, which is 69% in 2017. Those changes indicate that the arrival of DBS has caused the demand for London cycle hire to be reduced. The variability of $k$ is reflected in the coefficient of variation CV($k$) and the node flux variability, which is reflected in CV($F$), is reduced on weekends and weekdays, indicating that the difference between connectivity and interactivity between stations has eased, which means that the imbalance between the starting stations and the ending stations has eased due to the reduced connectivity. The node flux CDF (cumulative density function) in Figure 9c suggests that there is a lower probability of nodes, with a smaller flux in 2018. These changes describe the decreased attractiveness of some stations, as well as their interaction strength in connection to other stations in the London cycle hire network.

The link weight $<w>$ is defined as the number of trips on the link. Relative to the average node degree $<k>$ which decreases by 11%, and the average node flux $<F>$, which decreases by 7%, the link weight $<w>$ decreases by 6%, which is the maximum reduction. On weekends, the link weight $<w>$ decreases by 13%, which is the smallest reduction, compared with a 31% reduction in the average node degree $<k>$ and a 20% reduction in the average node flux $<F>$. It may be that the DBS leads to a reduction in the links between the stations and the total number of trips at each station, but some fixed travel links have not decreased much, such as fixed OD station connections to and from the workplace, that is, features, such as the system pricing policy, the average distance traveled by users, and limited availability of bicycles at each station, play a major role in the BS network, and DBS has a limited impact on London cycle hire’s $<w>$. However, the spatial variation of link weights across the network CV($w$) is relatively larger than CV($F$) and CV($k$) on weekends and weekdays. Compared with 2017, CV($w$) becomes smaller, indicating that, the same as the previous two features, the heterogeneity between networks has been alleviated. It can be seen from Figure 9d that the weekends have changed a lot, indicating that the number of trips between connected stations has changed greatly due to the disappearance of commuting cycling, and the network heterogeneity has also changed greatly, relative to the weekdays, while their trends are similar.

The clustering coefficient $c$ represents the degree of stricter interaction between the nodes in the network cluster and other nodes outside the cluster,

$$c_i = \frac{\text{number of pairs of neighbors of } i \text{ that are connected}}{\text{number of pairs of neighbors of } i},$$

On weekdays, the mean clustering coefficient $<c>$ is 0.15, a reduction of 6%. On weekends, the mean clustering coefficient $<c>$ is 0.09, a reduction of 25%. In 2018, local connections become loose, especially on weekends.
Table 7. Statistical properties of the London cycle hire mobility network.

| Proportion | Weekday | Ratio | Weekend | Ratio |
|------------|---------|-------|---------|-------|
| N          | 103     | 1.00  | 104     | 0.99  |
| L          | 2757    | 0.95  | 1814    | 0.79  |
| L/N        | 26.77   | 0.95  | 17.44   | 0.80  |
| δ          | 0.52    | 0.95  | 0.34    | 0.27  |
| T          | 9930    | 0.89  | 3901    | 0.68  |
| <F>        | 192.82  | 0.89  | 75.02   | 0.69  |
| <k>        | 55.26   | 0.93  | 35.75   | 0.79  |
| <w>        | 3.49    | 0.94  | 2.10    | 0.87  |
| CV(F)      | 0.61    | 0.96  | 0.66    | 0.61  |
| CV(k)      | 0.30    | 1.07  | 0.41    | 1.05  |
| CV(w)      | 1.09    | 0.95  | 0.99    | 0.83  |
| <c>        | 0.16    | 0.94  | 0.12    | 0.09  |

Figure 9. (a) The box plot of node degree; (b) The distribution of node degree; (c) The distribution of node flux; (d) The distribution of link weight.

4.4.2. Spatial Analysis of Network Properties

Unlike other biological and technological networks, the bikeshare networks have spatial characteristics. It is close to the conclusion of the statistical distribution of node degrees. In Figure 10, it can be clearly seen that the node degrees at different locations are also different, and the node degree in central London is higher, and the node degree on weekends is significantly lower than weekdays. The heterogeneity of the London cycle hire after the arrival of DBS has eased at the daily degree, which is the same as the above conclusion. Figure 11 shows the changes of node degree k on weekdays and weekends. On weekdays, the changes of different stations show strong heterogeneity. Moreover, 63.1% of the node degrees are decreasing, and the amount of reduction is large; 6.8% of the node degrees remain unchanged, and 30.1% of the node degrees are increasing, and the amount of increase is large. On weekends, the changes of different sites make the display still very heterogeneous. Overall, 86.4% of node degrees are decreasing and the amount of reduction is larger; 3.88% of node degrees remain unchanged, and 9.7% of node degrees are increasing. Compared with weekdays, the percentage of node degrees that decrease has changed significantly, and the amount of node degrees has also
increased significantly, indicating that the effect of DBS on weekends is much greater than on weekdays, and the impact of different stations is different.

Figure 10. Spatial distribution of node degree k: (a) 2017—Weekday; (b) 2017—Weekend; (c) 2018—Weekday; (d) 2018—Weekend (source: Google Maps).

Figure 11. The changes of node degree k on weekdays and weekends. (a) Changes on weekdays; (b) Changes on weekends (source: Google Maps).

4.4.3. Degree and Clustering Coefficient

The relationship between degree and clustering coefficient is an important statistical index item for discovering deep-level laws of the system network. Figure 12 shows the diagram of node degree and clustering coefficient distribution. With the increase of the degree value of the London cycle hire network, the clustering coefficient is gradually decreasing, but the decrease is relatively slow. The trend in 2018 is almost the same as that in 2017, while the clustering coefficient in 2018 is relatively small. On weekends, the distribution gap between the two years is greater and the distribution is more scattered.
5. Conclusion

In order to capture the impacts of the DBS on London cycle hire mobility patterns, spatial-temporal analysis and geostatistical analysis are applied to an in-depth exploration of travel behavior and the laws of urban mobility, and to show more intuitive changes in urban time and space. The presented comparative analysis has led to an in-depth understanding of the structure, interactions, and evolution of London cycle hire mobility patterns in connection with public transportation, by considering the changes in the spatial patterns after the arrival of the DBS.

Major findings from the spatial-temporal analysis and causal effects include:

- The temporal distributions of trip amounts, which follow a similar pattern, with one difference in trip amounts;
- The observed reduced bicycle trip counts are not homogeneous across the network;
- Trips with both the origins and destinations in the effect area (Type 4) decreased by 64% and the effect on Type 4 is the most significant;
- Compared with the weekdays, the use of London cycle hire is even more reduced on weekends;
- DBS mainly replaces short (0–15 min) and medium (15–30 min) duration travel;
- DBS has the greatest impact on short (0–1 km) and medium (1–3 km) distances;
- The applied supplementary network-theoretic analysis also provides further insights on the impact of the DBS on London cycle hire;
- The arrival of the DBS results in smaller connectivity in the London cycle hire network and a decrease in interaction strength between bicycle stations;
- The network heterogeneity has eased after the arrival of DBS because of the reduction of the use of London cycle hire;
- Due to the disappearance of commuting traffic, network statistical properties change greatly on weekends;

Some policies and planning implications emerge from the findings presented in this study. First, more attention should be paid to the improvement of stations in the same district, because the effects on the trips with both the origins and destinations in the affected area (Type 4) are most significant. Second, it can be concluded that the effect of DBS on different stations is uneven in the network analysis. The analysis of the impact factors of the use of DBS in the areas with less impact and the areas with greater impact should be carried out, so that DBS and BS can be joint to maximize the quality of cycling services.

There are several limitations to this paper. First, the data analyzed in this paper come from a short period of time; one month each in 2018 and 2017. Longer research time will be a suitable research plan.
Second, this article does not consider the effects of temperature and weather. According to Kim [23], temperature and weather have significant effects on bikeshare demand. Third, the data acquisition procedure is only able to obtain simple information, which do not include gender, age and income. Personal characteristics are also important in choosing DBS or BS. Such shortcomings are commonly found in cycling research [7,8,35]. In summary, the focus of the paper has been more on measuring the impact of the DBS, which is the first step towards a full understanding of the relationship between DBS and BS.

However, there is more to be done on the socio-demographics. Understanding socio-demographics in the bikeshare system is complex and requires ongoing research and data collection. Therefore, future work should explore the differences of socio-demographics characteristics on the impact of DBS on BS, such as income, age, gender, land use. Simultaneously, expanding time coverage of data to explore the impact of DBS will be good research content.

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Appendix A

Figure A1. Bike trips from Transport for London (Tfl). (a) Box plot of cycling distance; (b) Distribution of cycling trips by cycling distance.
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