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Impacts of COVID-19 on the usage of public bicycle share in London

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ABSTRACT

The COVID-19 pandemic led to the adoption of many unprecedented measures to slow down the spread of the virus. Such measures have greatly impacted the entire transportation system and individuals' travel behaviors. This paper evaluates the impacts of COVID-19 related policies, including the lockdown and the first lockdown ease on the usage of public bicycle share in London using interrupted time series approach. Our results indicate that the UK's lockdown led to an immediate decrease in the London Cycle Hire (LCH) usage, while the first lockdown ease had no statistically significant immediate impacts. Moreover, during the lockdown period, the LCH usage showed an increasing trend and the first lockdown ease led to a much larger increase rate. Such impacts vary by the trip characteristics (i.e., occurring period and trip duration). The morning peak trips and short duration trips maintained a lower usage level during the lockdown and the lockdown ease period. On the contrary, the number of other LCH trips were much larger than that in normal days. Furthermore, the impacts on the LCH stations near the rail stations, hospitals, and parks also varied differently. The LCH trips near the rail stations reduced more after the imposition of the lockdown policy while those near the hospitals reduced less. The LCH stations near the parks had a much higher increase rate during the lockdown and the lockdown ease period than the general level. Our results provide practical implications for the policy makers and operators of the public bicycle share system.

1. Introduction

The COVID-19 outbreak was first identified in December 2019, which has dramatically influenced our daily life. The World Health Organization (WHO) declared the outbreak a Public Health Emergency of International Concern on 30 January 2020. By mid-July 2020, over 12 million people had been infected and more than 500 thousand had died from the virus (WHO, 2020). Numerous unprecedented measures have been taken to slow down the spread of the virus, including self-isolate, social distancing, and lockdown.

In the UK, the first two COVID-19 cases were diagnosed in the week commencing January 27, 2020 (Moss et al., 2020). After the early spread in February, on March 2 Public Health England announced: widespread transmission of coronavirus in the UK is "highly likely" (BBC, 2020a). Subsequently, on March 12, people with fever or "continuous" cough or high temperature was advised to self-isolate for seven days (BBC, 2020b). By mid-March, it had been reported nearly 500 cases and 23 deaths in London (detailed COVID-19

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cases data in London can be found on https://data.london.gov.uk/).

Restrictions were announced in the UK in late March. On March 20, social distancing measures were strengthened. Entertainment, hospitality, and indoor leisure premises were told to close (Gov.UK, 2020a). On March 23, Prime Minister Boris Johnson announced the lockdown measures (Gov.UK, 2020b). He described COVID-19 as the biggest threat that the country had faced for decades. During the lockdown period, some public facilities remained open, such as parks, supermarkets, food shops, health shops, petrol stations, banks, etc. People were allowed to leave their home for very limited purpose, including (1) shopping for basic necessities, (2) one form of exercise a day, (3) medical need, and (4) travelling to and from work. But people were not allowed to visit friends in their houses or meet family members who do not live in the same household. (Gov.UK, 2020b). The regulations have been amended four times by the Health Protection (Coronavirus, Restrictions) (England) (Amendment) up to present (July 2020) (details can be found on http://www.legislation.gov.uk/). The first step for easing London lockdown started on May 13. During the lockdown ease period, some workers returned to work, but travelers were still told to avoid public transport and wear a face-covering in enclosed spaces (BBC, 2020c; Gov.UK, 2020c). The UK Health Foundation published a *COVID-19 policy tracker* where the timeline of COVID-19 related national policies and health system responses in England can be found. For detailed information, please refer to The Health Foundation, (2020).

The spread of the COVID-19 and previously mentioned measures have created uncertain shocks on various aspects of transport (Ivanov, 2020; Sobieralski, 2020; De Vos, 2020; Mogaji, 2020; Ito et al., 2020). For urban transport, it can be expected that people will travel less, will try to travel by private cars rather than the public transport in times of social distancing. (De Vos, 2020). According to the COVID-19 Mobility Report published by London Datastore (London Datastore, 2020a), social distancing and lockdown in London have resulted in a huge reduction in journeys made by Londoners. However, the impacts on the cyclists are not presented in the COVID-19 Mobility Report. The purpose of our study is to examine the impact of a series of COVID-19 related policies (i.e., lockdown, lockdown ease) on the public bicycle share (London Cycle Hire, LCH) use in London. To estimate such impacts, segmented regression approach based on the interrupted time series design is used to make causal inference. The impacts on LCH trips with various travel duration and occurring period were estimated separately.

This paper is organized as follows. In Section 2, we review the literature on the impacts of COVID-19 on transportation systems. Methods and data used in this analysis are described in Section 3. Results are provided in Section 4, followed by the discussions and conclusions in the final section.

2. Literature review

2.1. Outbreak, restrictions, and the impacts on transportation

Before the COVID-19 outbreak, a number of studies had been conducted on the impacts of pandemic on transportation systems (Ohkusa and Sugawara, 2007; Aro et al., 2009; Lee et al., 2012; Apolloni et al., 2013; Park et al., 2017; Goscé and Johansson, 2018). Most of the above-mentioned researches were carried out under the H1N1 influenza pandemic background. Several critical findings are listed as follows: (1) Traffic movements, especially the movements by public transport have relevance to the infection and spread of diseases. (2) Mobility features and travel behaviors are of vital importance when assessing the emerging pandemic. (3) Pandemics have pronounced impacts on various aspects of the transportation system, including tourism, public transport, daily travel, travel mode choice, etc.

As an unprecedented pandemic, COVID-19 has caused severe disruption and uncertainty all over the world. Numerous studies on the impacts of COVID-19 on transportation systems have been done (e.g., de Haas et al., 2020; Mogaji, 2020; Hotle et al., 2020; Yen et al., 2020; Bucsky, 2020; Tanveer et al., 2020; De Vos, 2020; Lee et al., 2020; Arellana et al., 2020). Since the restrictions on the movements and traffic controls are expected to be the most important counter measures to slow down the spread of the virus (Yen et al., 2020; Lee et al., 2020; Lin et al., 2020), many countries have implemented social distancing and lockdown measures. As a result, travel demand has declined throughout the world, especially the demand for public transport (Tirachini and Cats, 2020; Astroza et al., 2020). Such changes vary across countries and cities due to the differences in the severity of infection and the effectiveness of the counter measures. For example, 80% of 2500 respondents from Netherlands were shown to reduced their outdoor activities, and people were positive towards the car and far more negative towards public transport during the pandemic period (de Haas et al., 2020). In Colombia, the demand reduction during the “mandatory quarantine period” in most of the public transportation systems were between 90% and 80%, but Cartagena experienced a much higher demand loss (96%) due to its particularity (Arellana et al., 2020). The UK was one of the countries with the highest infection level. As shown in Hadjidemetriou et al. (2020), human mobility in the UK gradually decreased and stabilized at a scale of 80% after the national lockdown policy was imposed.

The impacts on cycling, which we focus on in this study, may be different from those on other travel modes. De Vos (2020) suggests that walking and cycling can be important ways to maintain satisfactory levels of health and well-being. An open letter has also stated that walking and cycling could be compatible with social distancing (Wyke et al, 2020). Recent studies by de Haas et al. (2020) and Bucsky (2020) show that people were more likely to choose cycling during the pandemic. Similarly, Teixeira and Lopes (2020) carried out a case study of New York’s Citi Bike. They found that the bike sharing systems had a less significant ridership drop compared to the subway system and the average bike sharing trip duration increased. In addition, they found a modal transfer from some subway users to the bike sharing systems. Earlier work by Fuller et al. (2019) and Saberi et al. (2018) also suggested that in the face of a major transportation constraint, large scale adoption of cycling may occur. According to the data published by Department for Transport (DfT), since the beginning of April 2020, the cycle use in London had reached twice (on weekdays) even three times (on weekends) of that during the equivalent days last year.

2.2. Lessons for the post-COVID-19 era

Since late April 2020, some countries have begun to ease the restrictions and reopen the cities, which again led to a change in travel patterns. For example, a recent Australia study by Beck and Hensher (2020) found that during the restriction ease period, travel activities started to slowly return, in particular by private car, and in particular for the purposes of shopping and social or recreational activities. However, there was still a concern about using public transport, which is risker than private modes of transport because of the closer contact to other people in public vehicles and stations. They concluded two key implications: (1) authorities should be vigilant to the increasing travel demand for the purposes of recreation; (2) work from home might be one behavior that lasts into the longer term. Some other studies further discussed the future direction of transportation systems in the upcoming post-COVID-19 era. Laverty et al. (2020) implied that prolonged limits to public transport capacity presented individuals and governments with opportunities to change previous detrimental travel patterns. Similarly, in Hensher (2020), the "new norm" formed during the COVID-19 pandemic was also considered to offer the opportunities for taming congestion on the roads and crowding on public transport. In addition, Budd and Ison (2020) proposed a new concept called "Responsible Transport", which emphasize the importance of individual choice and actions in collectively delivering socially desired outcomes.

To better understand how the public bicycle share in London responded to the COVID-19 pandemic and the constraint of public transport during the lockdown and the lockdown ease periods, we conducted a thorough quantitative analysis on the trend of LCH usage during the period of January 2020 to June 2020. In the next section, details on the approach and data used in this study are provided.

3. Methodology

Segmented regression model with an interrupted time series design is applied to estimate the impacts of the lockdown and first lockdown ease on the LCH usage. The parameters of interest are the intercepts (level change) and slopes (trend change) of lockdown and first lockdown ease. Furthermore, Bayesian structural time-series (BSTS) model is used for results validation and the estimation of the cumulative impacts during the entire lockdown and lockdown ease periods. In this section, the methods and data used in this study are described.

3.1. Interrupted time series design

Interrupted time series design is a quasi-experimental approach for time series analysis, which is widely used to evaluate the effects of an intervention in longitudinal settings. It has been applied in several transport related studies (Grundy et al., 2009; Fuller et al., 2012; Carnis and Blais, 2013; Bonander et al., 2014; Nazif-Muñoz et al., 2018; Song and Noyce, 2019; Fuller et al., 2019). For example, Fuller et al. (2012) evaluated the impact of a public transit strike on public bicycle share use in London. To assess the impacts and control for other important effects, segmented regression model is commonly used in interrupted time series design (Wagner et al., 2002). In its simplest form, the model includes only the time related variables: time, intervention, and time after intervention as shown in Eq. (1).

$$Y_t = \beta_0 + \beta_1 {}^* time + \beta_2 {}^* intervention_t + \beta_3 {}^* time_{After} + \varepsilon_t \tag{1}$$

Here, Y_t is the outcome variable. *time* is a continuous variable indicating the time point order from the beginning of the observation period. $intervention_t$ is the intervention indicator variable (pre-intervention period: $intervention_t = 0$, post-intervention period: $intervention_t = 1$. $time_{After}$ is similar to *time* which indicating the time point order from the beginning of the intervention. For pre-intervention period, $time_{After} = 0$. Regression coefficient β_0 is the baseline level of the outcome. β_1 is the pre-intervention slope, which quantifies the trend of the outcome before the intervention. β_2 estimates the change in level at the intervention point (immediate impact), and β_3 estimates the change in slope from pre- to post-intervention (trend change).

In our study, we are interested in the impacts of lockdown and the first lockdown ease. Segmented regression approach can also specify more than one intervention introduced at different time. A simplest model for two interventions at two time points can be expressed as follows:

$$Y_t = \beta_0 + \beta_1 {}^* time + \beta_2 {}^* intervention1_t + \beta_3 {}^* time_{After1} + \beta_4 {}^* intervention2_t + \beta_5 {}^* time_{After2} + \varepsilon_t \tag{2}$$

Variables and coefficients have similar meanings to those in Eq. (1). In this analysis, Y_t is the absolute number of daily LCH usage. $intervention1_t$ and $intervention2_t$ are the indicator variables for lockdown and the first lockdown ease respectively. $time_{After1}$ counts the number of days after lockdown, coded 0 before lockdown. $time_{After2}$ counts the number of days after the first lockdown ease, coded 0 before the first lockdown ease.

It is worth noting that the error term ε_t in Eq. (2) consists of a normally distributed random error and an error term at time t that may be correlated to errors at preceding or subsequent time points (Wagner et al., 2002). Thus, segmented regression approach with autoregressive errors is used in this study. An autoregressive model specifies that a value from a time series depends on the previous values from the same time series. Autoregressive errors address the potential autocorrelations between an error term and its previous error terms. An $AR(p)$ process can be expressed as follows (p represents the order of autoregression, or to say, the autoregressive lag):

$$\varepsilon_t = \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \cdots + \varphi_p \varepsilon_{t-p} + \epsilon_t \tag{3}$$

Here, ε_{t-i} is the ith previous error term. φ_i estimates the correlation between the error term at time t and its ith previous error term. ϵ_t is a normally distributed error term, $\epsilon_t \ N(0, \sigma^2)$. The autoregression order p is primarily determined by autocorrelation function (ACF) and partial autocorrelation function (PACF) plots.

Weather conditions are also taken into consideration in this analysis. Rainy or not is included in the model as an indicator variable. The number of daily LCH trips in 2019 is also included as a covariate. Here, the first Monday in January 2019 (January 7, 2019) is matched with the first Monday in January 2020 (January 6, 2020).

Moreover, an alternative approach is needed to validate our results obtained from the segmented regression models. If a proper control group is available, difference-in-difference (DID) models are well suited for the task. However, the nationwide lockdown policy made it impossible to find a control group. Therefore, we use the Bayesian structural time series (BSTS) model, which is designed for time series data. The basic idea behind BSTS model is to make causal inference by predicting a counterfactual outcome via a Bayesian approach. R package **CausalImpact** is used in this study (Brodersen et al., 2015). For details and discussions on this model, please refer to Scott and Varian (2014) and Brodersen et al. (2015).

3.2. Study design

The primary outcome of interest is the daily number of LCH trips per thousand population (trip rates). The general impacts of two focused COVID-19 related policies (lockdown and the first ease of lockdown) on the total daily LCH trips were firstly estimated. Moreover, trips with different travel durations and occurring time might be impacted differently as they are usually targeted at different travel purposes. For instance, the trips occurring in the morning peak periods are most likely to be the commuting trips, especially those with short durations and near rail stations (i.e., 'last mile' connections), which were supposed to be largely impacted by the lockdown policy. Highly infected and low infected areas (determined by the COVID-19 cases data published by London Datastore) might also be impacted differently as they have varied socio-economic characteristics (Trust for London, 2020), and thus have varied demands for public bicycles. Two approaches can be used to investigate these issues. One is a pooled model with interaction terms of treatment indicator and aforementioned variables, and the other is subgroup analysis. A clear problem for the pooled model is the need to adjust significance levels for multiple hypothesis tests which can limit its power. Therefore, subgroup analysis was conducted in this study. Specifically, the LCH trips are divided into three groups by their durations (short duration trips: 0–15 min, middle duration trips: 15–30 min, and long duration trips: 30–60 min). It is worth noting that LCH users can get access to a bicycle for 2 lb for 24 h, but only the first 30 min are free, it costs an extra 2 lb for each additional 30 min. The LCH trips occurring at morning peak, evening peak, and other times (off-peak) were also separately analyzed. Although the peak hours in the lockdown period could be different from those in normal days, for the purpose of comparison, we define the peak hours the same as the busiest times in normal days (morning peak: 6:30–9:30, evening peak: 16:00–19:00, see TfL, 2020a). Finally, a total of 12 sub samples were generated for following evaluations (as shown in Table 1).

Furthermore, the LCH stations near some particular locations need additional focus, especially rail stations, hospitals, and parks. It is reasonable to assume that these LCH stations were impacted differently from others. For simplicity, the overlap issue (e.g., some LCH stations located in parks are also within the buffer areas of rail stations) was not taken into consideration.

(1) *Rail stations*. As an important connection between different modes of transport, public bicycles are commonly used by rail and bus passengers. According to the data published by DfT, the daily TfL tube use after the lockdown was only around 5% of the equivalent day in 2019 (Gov.UK, 2020d). The LCH usage near rail stations (i.e., tube, DLR, London Overground, TfL Rail and Tram) could be seriously impacted. The LCH stations within 400 m of any rail station were aggregated initially for further investigation (Fig. 1A shows an example near Holborn station) as 400 m is often used in guidelines as the key walking distance in public transport network and service planning (Daniels and Mulley, 2013). The sub samples size for rail station 400 m buffer is 420.

(2) *Hospitals*. Hospitals play a very important role during the COVID-19 pandemic. After the outbreak of COVID-19, public transports were largely constrained. Therefore, patients and health workers were more likely to use private cars and bicycles for necessary travels to the hospital. Also, it should also be noticed that NHS workers have free 24-hour access to the LCH, including all journeys under 30 min. In this study, NHS trusts in London were taken into further consideration. The number of NHS trusts

Table 1
Samples for various types of LCH trips.

Highly infected boroughs	**Low infected boroughs**
Westminster, Wandsworth, Kensington & Chelsea, Hammersmith & Fulham, Lambeth, and Southwark	Islington, Tower Hamlets, City of London, Hackney, Camden
Periods (6 groups)	
Morning peak: 6:30–9:30	Morning peak: 6:30–9:30
Evening peak: 16:00–19:00	Evening peak: 16:00–19:00
Other times	Other times
Travel duration (6 groups)	
Short duration: 0–30 min	Short duration: 0–30 min
Middle duration: 15–30 min	Middle duration: 15–30 min
Long duration: 30–60 min	Long duration: 30–60 min

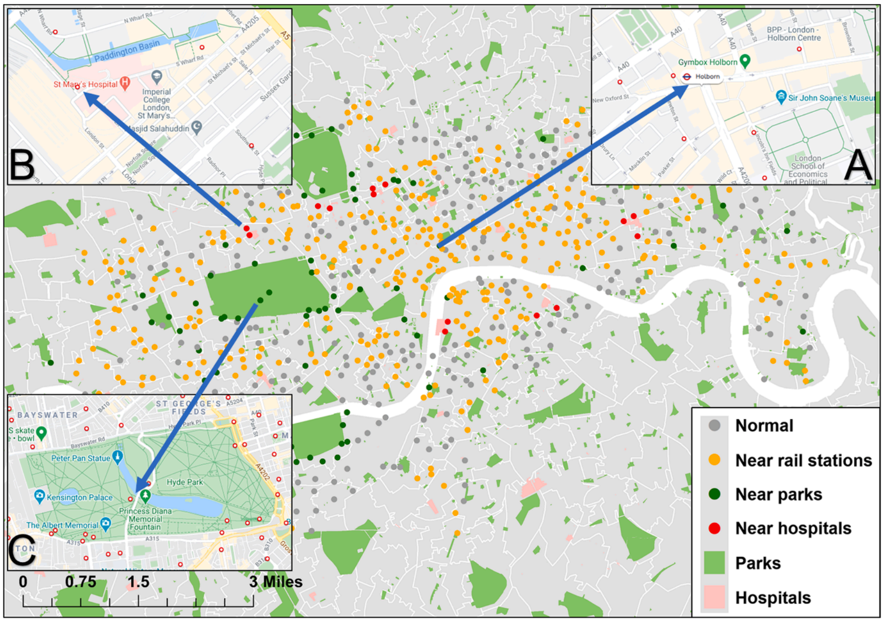

Fig. 1. LCH docking stations near rail stations (A), hospitals (B), and parks (C).

is not as large as the rail stations. Thus, the LCH stations near the hospitals were manually selected from "Find a docking station" driven by Google Map on TfL website (Fig. 1B shows an example near St Mary's hospital). A total of 15 LCH stations are included in this sub sample.

(3) *Parks*. As suggested by De Vos (2020), social distancing may negatively affect the subjective wellbeing and health status. People should be encouraged to walk and cycle to enhance their health. The docking stations near parks were also selected manually. In this study, eight Royal parks in London (Bushy Park, Green Park, Greenwich Park, Hyde Park, Kensington Gardens, Regent's Park, Richmond Park, and St. James's Park) and some other small parks and gardens were included (Fig. 1C shows an example in the Hyde Park). For this sub sample, 75 LCH stations are included.

To conclude, the procedures of this analysis can be illustrated with the following steps:

(1) As mentioned before, on March 23, 2020, Boris Johnson announced a UK-wide lockdown. On May 13, 2020, some workers returned to work as lockdown eased slightly in England. Two variables were created for two events, indicating the pre-lockdown, lockdown, and the first lockdown ease period respectively.
(2) Equivalent daily trips in last year, that is, the number of LCH trips per day in 2019 was included as a covariate. Matching rules: the first Monday in January 2019 (i.e., January 7, 2019) is matched with the first Monday in January 2020 (i.e., January 6, 2020). Weather conditions were also included in the model.
(3) With the data prepared, the model for LCH usage can be specified based on Eq. (2) as:

$$Usage_t = \beta_0 + \beta_1 * time + \beta_2 * lockdown + \beta_3 * lockdown\ ease + \beta_4 * time\_lockdown + \beta_5 * time\_lockdown\ ease + \beta_6 * equivalent\ daily\ trips\ 2019 + \beta_7 * rainy + \varepsilon_t \tag{4}$$

where *lockdown* and *lockdown ease* are the indicator variables for lockdown and the first lockdown ease, coded 0 before the intervention and 1 after the intervention. *time* is the variable counting the number of days from the start of the observation period. *time_lockdown* and *time_lockdown ease* are the variables counting the number of days after the lockdown and the first lockdown ease, coded 0 before the interventions. *rainy* is the indicator variable for rainy or not. *equivalent daily trips 2019* is the number of daily LCH trips on the equivalent days in 2019.

(4) Full samples and sub samples were modelled separately to investigate various impact patterns. BSTS models were used validate the results and estimate the impacts of two interventions in the entire periods (period 1: lockdown, period 2: lockdown ease).

3.3. Data

3.3.1. LCH trips data

A total number of 761 LCH docking stations are included in this study. The transaction records of the LCH are obtained from Transport for London (TfL), which are aggregated at daily level, covering a period from January 2019 to June 2020 (TfL, 2020b). Each transaction record includes the following information: origin and destination, duration, start time and end time as shown in Table 2.

3.3.2. COVID-19 cases data

COVID-19 cases data in London were obtained from London Datastore (London Datastore, 2020b). In this study, eleven boroughs with LCH stations were divided into highly infected and low infected areas based on the total confirmed COVID-19 cases per 100 thousand population by June 14, 2020 for further analyses. Six boroughs with LCH stations were classified into highly infected group (more than 250 cases per 100 thousand population): Westminster, Wandsworth, Kensington & Chelsea, Hammersmith & Fulham, Lambeth, and Southwark. The other five boroughs were classified into the low infected group (less than 250 cases per 100 thousand population): Islington, Tower Hamlets, City of London, Hackney, Camden. Fig. 2 clearly shows the cases per thousand population in London, in which the grey dots represent the LCH docking stations. Population data are the latest mid-year estimates obtained from UK'S Office for National Statistics (ONS).

4. Results

4.1. Descriptive analysis of the LCH usage

Descriptive statistics of the number of LCH trips are presented in Table 3. The average daily number of LCH trips occurring during the pre-lockdown period was close to that of the equivalent period in 2019. While during the lockdown period, the usage was much less than the last year with higher daily variation. More LCH trips occurred during the lockdown ease period than the equivalent period last year, also with higher daily variation.

Figs. 3 and 4 display the trends of daily LCH trip rates (per thousand population) for the total sample, and the sub samples with various occurring day times and travel durations. The sub samples for rail stations, hospitals, and parks do not have corresponding population data, so the average number of LCH trips at the station level are plotted (Fig. 5). It can be seen that although the LCH usage experienced a reduction after the initial introduction of UK's lockdown, a significant increasing trend during the lockdown and the lockdown ease period was observed, except for the morning peak trips. The results of interrupted time series analysis are provided in the following sections.

4.2. Effects of COVID-19 on daily LCH trips

The results for the impacts of COVID-19 on daily LCH trips (per thousand population) in the highly infected boroughs are provided in Table 4. The coefficients of *lockdown* and *lockdown ease* indicate the level changes (immediate impacts) caused by the lockdown and the first lockdown ease measures. And the coefficients of *time_lockdown* and *time_lockdown ease* indicate the trend changes (trend impacts) after the lockdown and the first lockdown ease. It can be concluded that the UK's lockdown led to an immediate reduction in the LCH usage, while the impacts of the first lockdown ease were not statistically significant. However, the trend changes indicate that during the lockdown period and the lockdown ease period, the LCH usage showed an obvious increasing trend, especially after the first lockdown ease.

4.3. Results of sub samples

Further results obtained from the sub samples are shown in Table 5, where only the parameters of interest (level and trend impacts) are provided. Such results reveal the heterogeneity of the impacts. The main findings are listed as follows:

Immediate impacts (level changes):

(1) The immediate impacts of the lockdown were negative, which were statistically significant except for the long duration trips. While the immediate impacts of the first lockdown ease were not significant.
(2) Highly infected boroughs experienced a larger immediate reduction in both absolute numbers and percentages after the lockdown (highly infected boroughs: −5.20, 51.36% vs. low infected boroughs: −2.68, 44.36%). It is worth noting that the percentage changes in this study were calculated as (changes in absolute numbers)/ (average daily number of LCH trips in the pre-lockdown period).

Table 2
Sample of LCH transaction records.

Rental Id	Duration	Bike Id	End Date	EndStation Id	EndStation Name	Start Date	StartStation Id	StartStation Name
96217132	1980	15531	14/04/2020 18:50	333	Palace Gardens Terrace, Notting Hill	14/04/2020 18:17	225	Palace Gardens Terrace, Notting Hill
96105516	4680	10193	10/04/2020 15:44	333	Palace Gardens Terrace, Notting Hill	10/04/2020 14:26	225	Palace Gardens Terrace, Notting Hill
…								

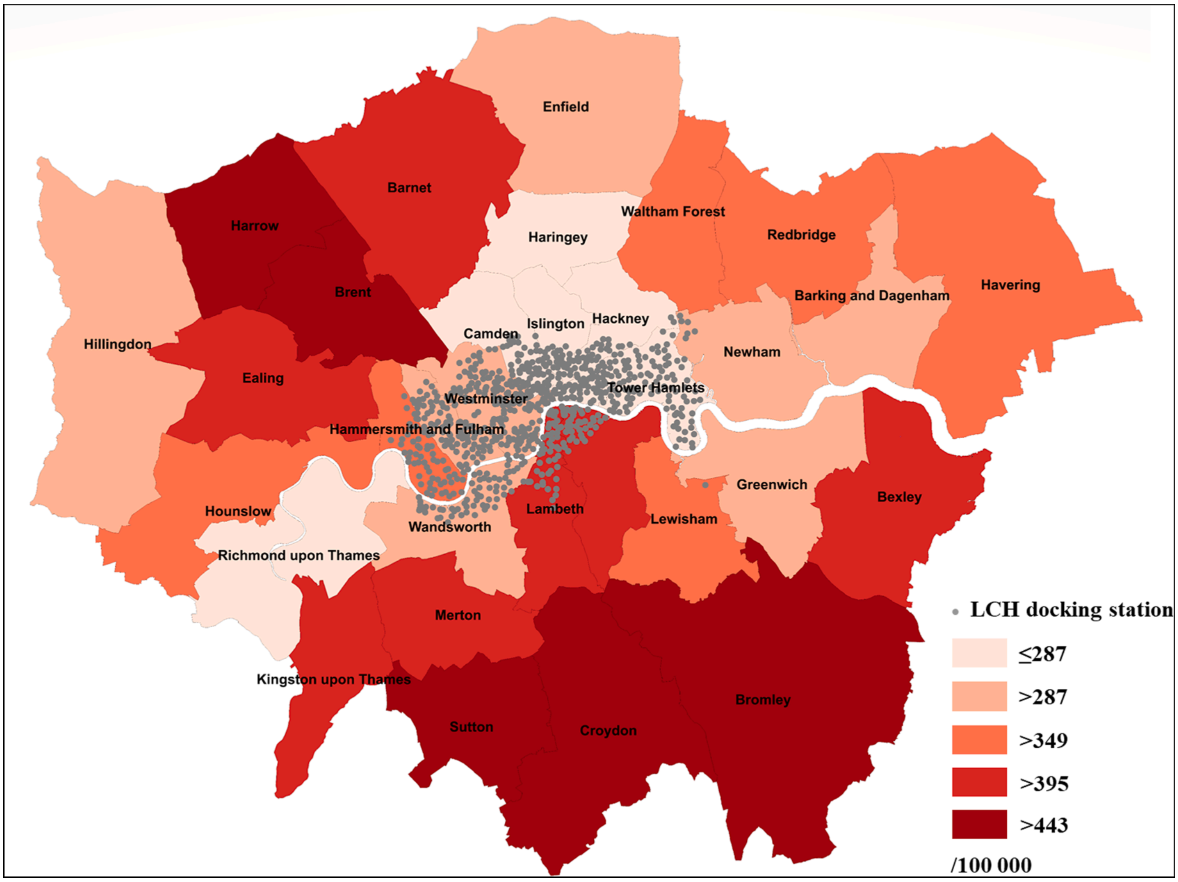

Fig. 2. Confirmed cases per 100 thousand residents by borough.

Table 3
Descriptive statistics of daily LCH trips.

Periods	mean	S.D.	min.	max.
Pre-lock down	21730.75	5683.81	6225	28,702
Lockdown	18391.20	9631.76	4596	45,104
Lockdown ease	36588.00	12638.97	15,954	62,837
Equivalent period of pre-lockdown (2019)	23211.44	5697.18	9246	34,032
Equivalent period of lockdown (2019)	28576.61	5735.52	16,062	37,229
Equivalent period of lockdown ease (2019)	32914.93	5313.95	25,243	39,782

(3) The LCH trips occurring in the morning peak hours had the largest immediate reduction after the lockdown. From the travel duration perspective, the short duration trips decreased much more than the other two groups.

Trend changes:

(1) Generally, during the lockdown and the lockdown ease periods, the LCH trips showed an increasing trend.
(2) Specifically, during the lockdown period, all types of LCH trips increased and the impacts on the trend were statistically significant. While during the lockdown ease period, the trends of short duration and morning peak trips were similar to those of the lockdown period. As to the other types of LCH trips, the increasing trends were all significant. The absolute numbers of daily increases were much larger than those of the lockdown period. As a result, the number of daily LCH trips in the lockdown ease period was much higher than that in the pre-lockdown period.
(3) To make clear comparisons between the trends of various types of LCH trips, the daily increase rates are also calculated (see Table 5). Compared to the low infected areas, the highly infected areas had a lower increase rate during the lockdown period but a higher increase rate during lockdown ease period.

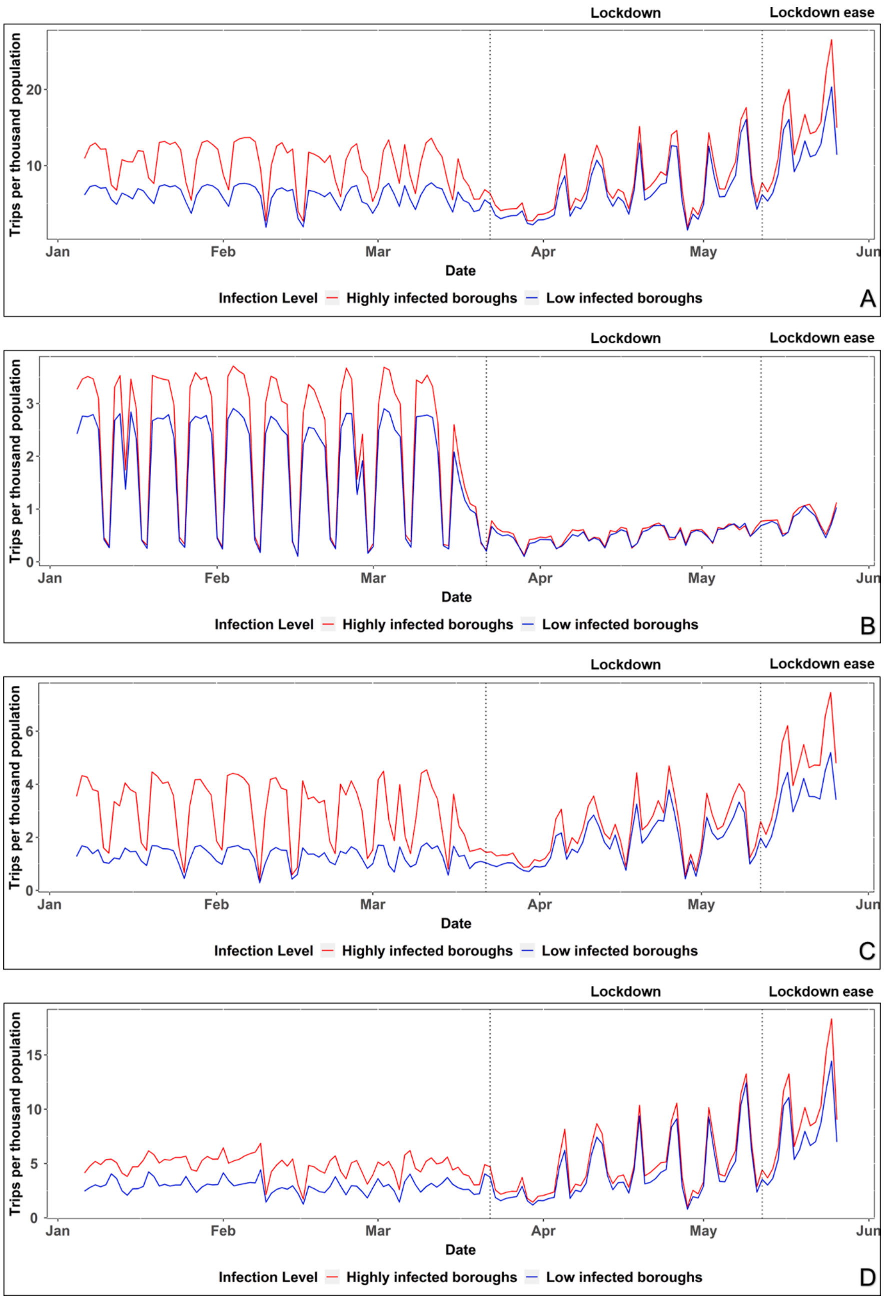

Fig. 3. Trends of the daily LCH trip rates (per thousand population). A: full sample; B: morning peak; C: evening peak; D: other times.

Moreover, as discussed earlier, the LCH stations near selected rail stations, NHS Trusts (hospitals), and parks need further investigation. Table 6 presents the results for these sub samples. In this part, the highly and low infected boroughs are not analyzed separately, otherwise some sub samples would be too small to give conclusive results. The main findings for each sub sample are concluded as follows:

Docking stations near the rail stations:

(1) After the lockdown, the immediate impact on the LCH docking stations near rail stations (16.69%, 52.74%) was larger than the general level for all types of LCH trips. The immediate impact of the first lockdown ease was insignificant.

(2) During the lockdown and the lockdown ease period, the impacts on the trend of LCH trips from this group of docking stations was similar to the general level.

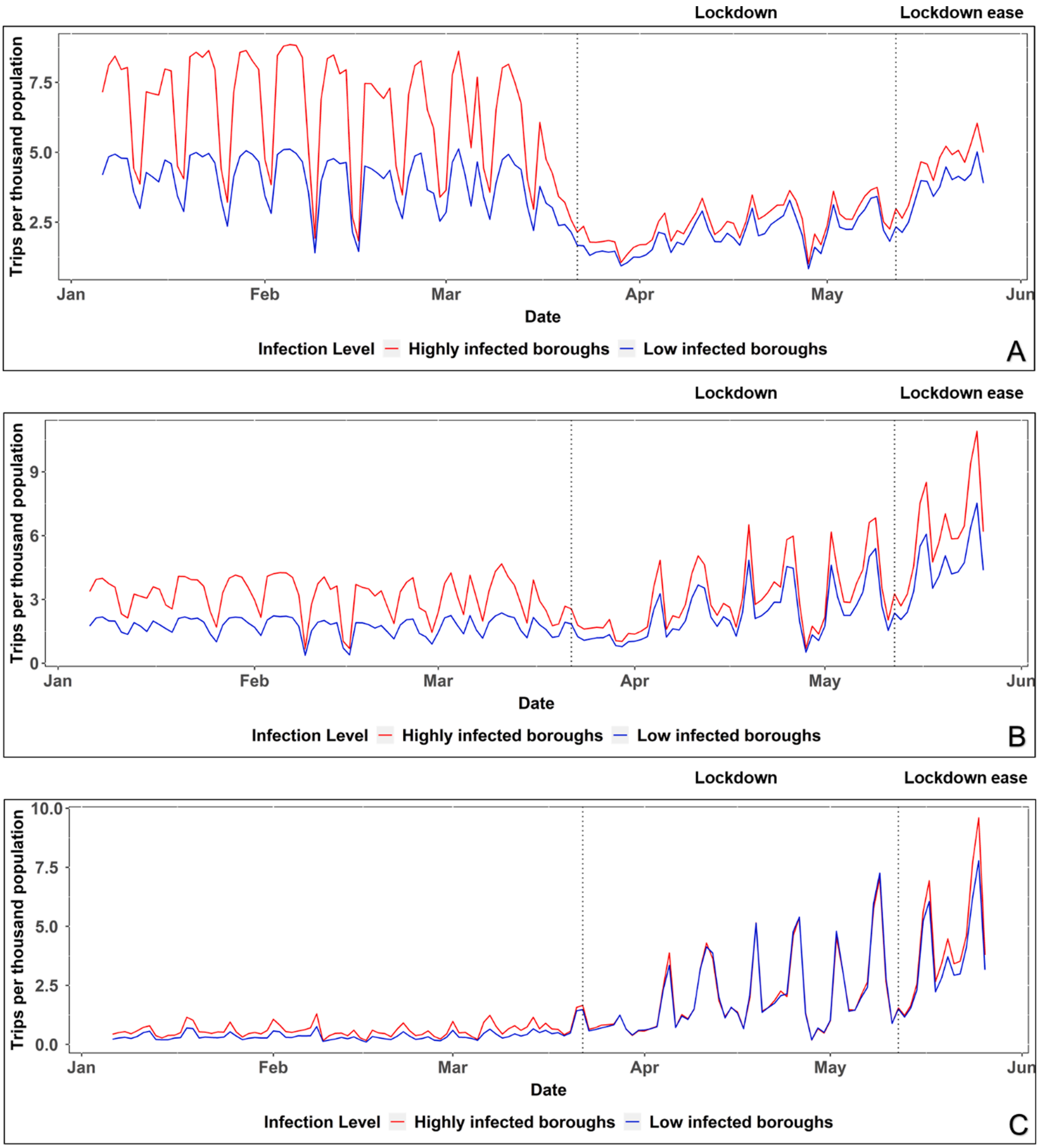

Fig. 4. Trends of the daily LCH trip rates (per thousand population). A: short duration; B: middle duration; C: long duration.

Docking stations near the hospitals:

(1) The immediate impact (18.29, 47.75%) of the lockdown measure was lower for the docking stations near hospitals than the general level.
(2) During the two post-intervention periods, especially the lockdown ease period, the trend impacts (lockdown: 0.56, 1.47%; lockdown ease: 2.05, 7.32%) of this group were much lower than the general level.

Docking stations near the parks:

(1) The immediate impact (−10.60, 36.12%) of the lockdown measure on these LCH stations was the lowest.

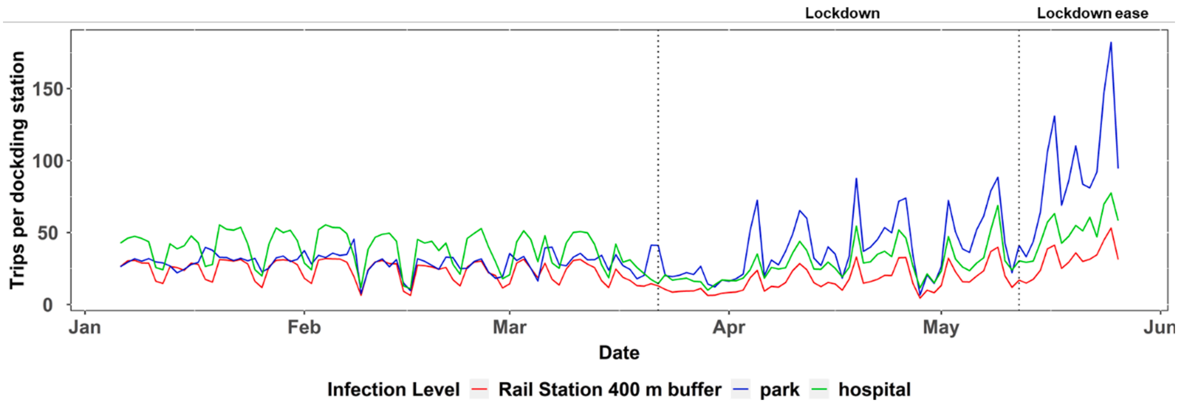

Fig. 5. Trends of the daily LCH trip per docking station.

Table 4
Results of segmented regressions: effects of lockdown and lockdown ease on daily LCH trips in highly infected boroughs.

Variables	Coefficient	Std. Error	*p*-value
intercept	13.627	1.676	<0.001**
lockdown	−5.202	1.220	<0.001**
lockdown ease	–		
time	–		
time_lockdown	0.162	0.034	<0.001**
time_lockdown ease	0.748	0.214	<0.001**
rainy	−1.378	0.632	0.031*
equivalent daily trips 2019	–		
AR parameters: $\varphi_1 = 0.46$, $\varphi_2 = -0.41$, $\varphi_3 = 0.11$, $\varphi_4 = -0.12$, $\varphi_5 = -0.09$, $\varphi_6 = 0.07$, $\varphi_7 = 0.32$.			

Notes: (1) *lockdown* and *lockdown ease* are the indicator variables for lockdown and the first lockdown ease, coded 0 before the intervention and 1 after the intervention. *time* is the variable counting the number of days from the start of the observation period. *time_lockdown* and *time_lockdown ease* are the variables counting the number of days after the lockdown and the first lockdown ease, coded 0 before the interventions. *rainy* is the indicator variable for rainy or not. *equivalent daily trips 2019* is the number of daily LCH trips on the equivalent days in 2019. (2) All models contain 6 dummy variables to control for daily variations (Monday – Saturday). (3) ** 1% significance level; * 5% significance level. (4) "–" indicates insignificant variables.

Table 5
Results of segmented regressions: effects of lockdown and lockdown ease on daily LCH trips with different occurring periods and trip durations.

		Highly infected boroughs		Low infected boroughs	
		Lockdown	Lockdown ease	Lockdown	Lockdown ease
Level	Total	−5.202** (51.36%)	−2.096	−2.682** (44.36%)	−1.864
	Morning peak	−1.537** (66.85%)	0.038	−1.228** (67.04%)	0.358
	Evening peak	−1.405** (46.60%)	−0.110	−0.268 (20.74%)	−0.153
	Other times	−2.315** (48.09%)	−2.162	−1.230* (42.13%)	−1.929
	Short duration	−3.676** (57.93%)	−0.125	−2.172** (55.38%)	−0.021
	Middle duration	−1.510** (47.55%)	−0.765	−0.694* (39.74%)	−0.570
	Long duration	−0.035 (5.74%)	−1.223*	0.146 (38.82%)	−1.309*
Trend	Total	0.162** (1.59%)	0.748** (10.03%)	0.132** (2.18%)	0.507** (8.09%)
	Morning peak	0.017* (0.75%)	0.011 (2.05%)	0.015* (0.83%)	0.007 (1.46%)
	Evening peak	0.044** (1.47%)	0.206** (9.27%)	0.029** (2.20%)	0.132** (7.45%)
	Other times	0.100** (2.07%)	0.541** (11.50%)	0.087** (2.99%)	0.382** (9.54%)
	Short duration	0.061** (0.97%)	0.164 (6.69%)	0.044** (1.13%)	0.114* (5.59%)
	Middle duration	0.060** (1.89%)	0.301** (9.90%)	0.045** (2.58%)	0.190** (8.37%)
	Long duration	0.040** (6.59%)	0.284** (14.41%)	0.042** (11.22%)	0.203** (10.34%)

Notes: ** 1% significance level; * 5% significance level. Because the immediate impacts of the first lockdown ease are not significant, the percentage changes for the level change of lockdown ease are not listed in the table.

Table 6
Results of segmented regressions: effects of lockdown and lockdown ease on daily LCH usage of different types of docking stations.

		Rail 400 m buffer		Hospitals		Parks	
		Lockdown	Lockdown ease	Lockdown	Lockdown ease	Lockdown	
Level	Total	−16.689** (52.74%)	−7.003	−18.289** (47.75%)	−5.445	−10.601* (36.12%)	−9.364
	Morning peak	−5.178** (67.89%)	0.106	−6.723** (69.71%)	−0.014	−3.947** (63.83%)	0.130
	Evening peak	−4.161** (45.72%)	−0.434	−3.153** (31.63%)	0.534	−0.438 (6.38%)	0.223
	Other times	−7.529** (50.48%)	−7.294*	−8.474** (45.34%)	−6.567	−6.273 (38.48%)	−9.318
	Short duration	−11.819** (58.82%)	−0.598	−13.490** (55.21%)	−1.590	−6.815** (45.39%)	0.511
	Middle duration	−4.791** (49.68%)	−2.407	−4.759** (40.51%)	−0.681	−2.908 (27.67%)	−2.826
	Long duration	−0.144 (7.53%)	−4.117*	0.164 (7.76%)	−3.646	−0.905 (23.63%)	−6.663
Trend	Total	0.545** (1.72%)	2.172** (9.20%)	0.562** (1.47%)	2.047** (7.32%)	0.653** (2.23%)	5.664** (14.64%)
	Morning peak	0.061* (0.80%)	0.028 (1.66%)	0.069* (0.71%)	0.024 (1.02%)	0.051** (0.82%)	0.069 (3.23%)
	Evening peak	0.145** (1.59%)	0.580** (8.32%)	0.137** (1.37%)	0.440* (4.90%)	0.150** (2.18%)	1.902** (14.92%)
	Other times	0.339** (2.27%)	1.615** (10.79%)	0.360** (1.93%)	1.644** (9.85%)	0.451** (2.76%)	3.643** (15.29%)
	Short duration	0.208** (1.04%)	0.478 (6.12%)	0.251** (1.03%)	0.720* (6.87%)	0.172** (1.14%)	1.105** (10.14%)
	Middle duration	0.198** (2.05%)	0.855** (9.16%)	0.193** (1.64%)	0.544 (4.81%)	0.270** (2.57%)	2.154** (12.72%)
	Long duration	0.139** (7.30%)	0.848** (13.09%)	0.115** (5.42%)	0.839** (13.57%)	0.216** (5.63%)	2.374** (21.84%)

Notes: ** 1% significance level; * 5% significance level. Because the immediate impacts of the first lockdown ease are not significant, the percentage changes for the level change of lockdown ease are not listed in the table.

(2) During the lockdown and the lockdown ease periods, the trend impacts (lockdown: 0.65, 2.23%; lockdown ease: 5.66, 14.64%) were much larger than the general level.

4.4. Results of BSTS models

The BSTS model was applied to validate our results and estimate the cumulative impacts during the entire lockdown and lockdown ease periods. Since the immediate impact of the first lockdown ease was not significant, it was not estimated in this part. The results of BSTS models are provided in Table 7. In addition, Fig. 6 displays the impacts on the daily LCH usage in highly infected boroughs (A: lockdown; B: lockdown ease). In Fig. 6(A) and (B), the first graph shows the observed (solid line) and the counterfactual (dash line) values of daily LCH trips. The second graph shows the point impact (i.e., the impact in a particular day) and the third graph shows the cumulative impacts.

The immediate impacts estimated by the BSTS models are similar to those estimated by the interrupted time series models (i.e., level impact). For example, the estimated immediate impacts of the lockdown on total daily LCH trips in the highly infected boroughs are 5.20 and 6.28 based on the interrupted time series model and BSTS model respectively. In this section, we mainly focus on the cumulative impacts.

In Table 7, the “lockdown cumulative” and “lockdown ease cumulative” show the cumulative impacts of the lockdown and the first lockdown ease respectively. Generally, the cumulative impacts of lockdown were negative. However, for the long duration trips, such impacts were positive. In the low infected boroughs, the impacts of lockdown also vary by trip characteristics. Moreover, the first lockdown ease led to a significant increase in the LCH usage, except for the short duration trips and morning peak trips, which kept at a low level during the entire lockdown and lockdown ease period. It is worth noting that the lockdown ease period in this study covers only around two weeks. That is, the average daily impact of the first lockdown ease was much larger than the negative impact caused by the lockdown.

The sub samples of rail stations and hospitals generate similar results as the full sample. While for the sub sample for the park LCH stations, a unique pattern was observed. During the lockdown period, the cumulative impacts were positive, except for the short duration and morning peak trips. And the first lockdown ease further increased the LCH usage near the parks. As a result, the LCH usage near the parks was much higher than that in normal days.

5. Discussions and conclusions

COVID-19 has resulted in an ongoing pandemic. To slow down the spread of the virus, numerous policies have been implemented since the outbreak of COVID-19. Social distance and lockdown in the UK have significantly changed the travel behaviors. The objective of this study is to evaluate the impacts of UK’s lockdown and the first lockdown ease on the public bicycle share usage in London. In this

Table 7
Results of BSTS models.

	Highly infected boroughs (per 1 k population)			Low infected boroughs (per 1 k population)		
	Lockdown immediate	Lockdown Cumulative	Lockdown ease Cumulative	Lockdown immediate	Lockdown Cumulative	Lockdown ease Cumulative
Total	−6.280*	−116.4*	103.7*	−3.034*	13.9	76.1*
Morning peak	−2.227*	−86.2*	4.05*	−1.706*	−65.2*	3.66*
Evening peak	−2.195*	−39.4*	34.6*	−0.514*	21.4*	23.3*
Other times	−1.992*	4.65	63.5*	−0.866*	54.9*	47.9*
Short duration	−4.556*	−182.4*	28.0*	−2.417*	−86.9*	23.1*
Middle duration	−1.756*	−3.53	44.0*	−0.736*	24.4*	30.1*
Long duration	0.018	64.0*	31.1*	0.151	74.0*	22.6*
	Rail 400 buffer (per station)			**Hospitals (per station)**		
	Lockdown immediate	**Lockdown Cumulative**	**Lockdown ease Cumulative**	**Lockdown immediate**	**Lockdown Cumulative**	**Lockdown ease Cumulative**
Total	−20.540*	−344.8*	315*	−22.147*	−430.5*	314*
Morning peak	−7.856*	−290.3*	13.4*	−10.530*	−364.8*	15.1*
Evening peak	−6.597*	−105.8*	102.2*	−5.241*	−54.7*	98*
Other times	−6.610*	36.7	194*	−7.274*	−28.4	195*
Short duration	−14.971*	−574*	87.4*	−18.069*	−659*	109.3*
Middle duration	−5.669*	−4.72	131.4*	−4.309*	1.84	117.2*
Long duration	0.057	214.8*	95.1*	−0.177	200.7*	90.7*
	Parks (per station)					
	Lockdown immediate	**Lockdown Cumulative**	**Lockdown ease Cumulative**			
Total	−11.051*	427.6*	743*			
Morning peak	−5.256*	−192.0*	19.4*			
Evening peak	−1.229	255*	278*			
Other times	−4.669	352.8*	443*			
Short duration	−7.414*	−179.3*	177*			
Middle duration	−3.403	291.6*	310*			
Long duration	0.047	322.6*	255*			

Notes: * 5% significance level. Lockdown immediate: the immediate impacts of the lockdown on the LCH usage. Cumulative: cumulative impacts of the lockdown and the first lockdown ease during the entire period (lockdown and lockdown ease).

section, the three major findings of this study are discussed.

The first finding concerns the general impacts of UK's lockdown and the first lockdown ease on the LCH usage. Our results indicate that after the imposition of the lockdown, the LCH usage experienced a significant reduction in the trips with various occurring periods and travel durations, except for the long duration trips. While the first lockdown ease did not have significant immediate impacts. Moreover, during the lockdown period, the LCH usage showed an increasing trend. Results also show that the trend impacts of the first lockdown ease were much larger than the lockdown, which are in line with our expectation. After the imposition of the national lockdown, overall travel demand decreased, leading to the initial reduction in the LCH usage. However, to avoid being infected, people were less likely to choose public transport in pandemic situations. As pointed out by Fuller et al. (2019), when the public transportation is constrained, a large-scale adoption of cycling can occur. Saberi et al. (2018) also provided similar results. Therefore, the public bicycles took on more demand for necessary trips (e.g., shopping for necessities, exercise, medical needs, travelling to and from work), which led to the increasing trend of the LCH usage during the lockdown period, especially the long duration trips. Also, as shown in a news report, the leisure-oriented LCH trips surged after the first lockdown ease (Enfield Independent, 2020), which led to a higher increase rate. Therefore, the public bicycle share operators should make sure that the system is ready for such booming demand.

The second finding relates to the comparison between the impacts in highly and low infected areas. The immediate impact of the lockdown in low infected boroughs was lower than that in highly infected boroughs. While during the lockdown period, the increase rates were much higher in low infected boroughs. And the first lockdown ease led to a larger impact on the trend in highly infected boroughs. Varying impacts on highly and low infected areas could be due to the residents' attitudes toward COVID-19 pandemic and

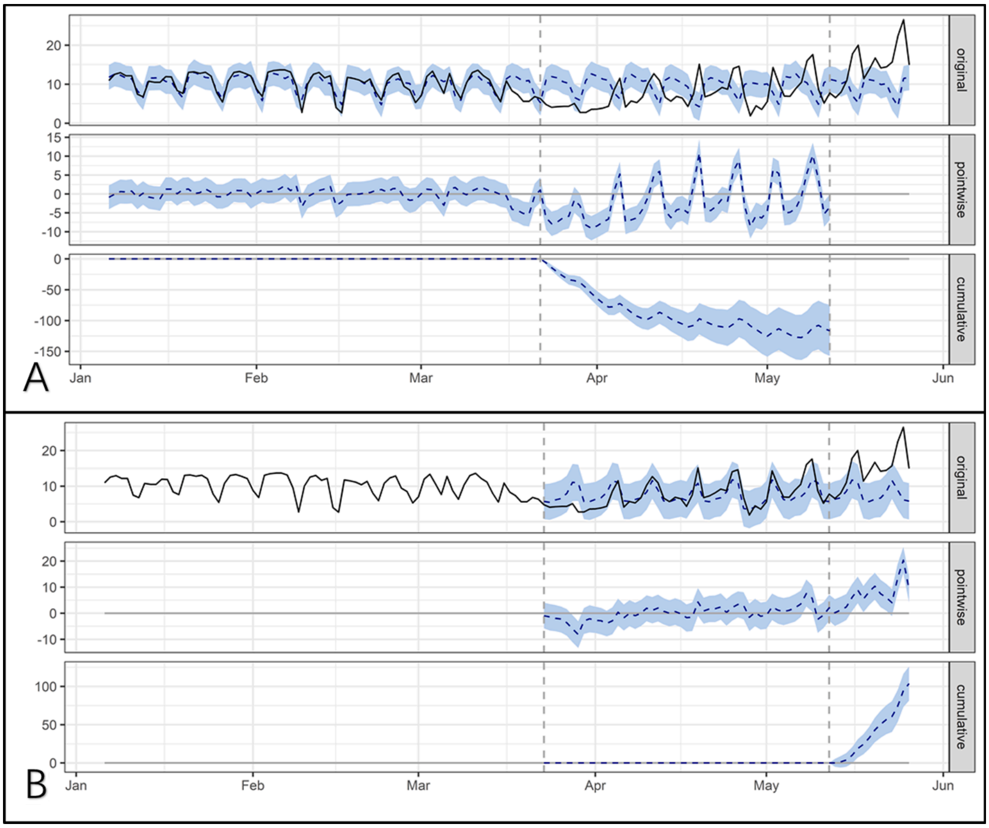

Fig. 6. BSTS models: impacts on the daily LCH usage in highly infected boroughs (A: lockdown; B: lockdown ease).

the local socioeconomic characteristics. It is worth noting that low infected boroughs defined in this study have a relatively high proportion of people living in poverty, except for City of London, according to the poverty rates calculated by Trust for London (Trust for London, 2020). Deprived residents would have higher demand for the public bicycles in face of public transportation constraint, since they have less alternative travel modes to choose than the wealthier. Moreover, as suggested by Guardian analysis, deprived Londoners share less space and have limited access to private gardens (Guardian, 2020). Therefore, during the lockdown period, people living in deprived areas may need more outdoor activities than those living in wealthier areas. Such a fact indicates that the social equality issue should be taken into consideration in cycle infrastructure planning (Caggiani et al., 2020; Hamidi et al., 2019).

Furthermore, the LCH docking stations near the rail stations, hospitals, and parks were influenced differently. The LCH trips near the rail stations reduced more after the imposition of the lockdown policy. The reduction in the commuters related connecting trips was a possible reason. On the contrary, the LCH trips near the hospitals reduced less during the lockdown period probably used by essential health workers. In addition, the LCH stations near the parks experienced the highest increase rate after the lockdown. Although some parks experienced a temporary closure (e.g., on March 25, Tower Hamlets council decided to close Victoria Park because too many people did not obey social distancing orders, for details see Gov.UK, 2020f), they were crucial for exercise and mental wellbeing activities during the pandemic. The eight Royal Parks announced to remain open for visitors to boost physical and mental wellbeing in the pandemic situation (RoyalParks, 2020). De Vos (2020) also suggests that it is important to remain physically active by frequently walking and cycling. Moreover, according to the Mobility Report published by London Datastore, pedestrian activity in parks increased a lot after the lockdown, especially after the first lockdown ease, which was partly due to the fact that the weather was quite good during the lockdown and lockdown ease periods (London Datastore, 2020a).

COVID-19 is an unprecedented pandemic which caused severe disruptions to transportation system. Public transport operation under such situation needs to be based on the best knowledge available of the impacts of COVID-19 on transportation systems. The findings of this study would be helpful to the policymakers and operators of the public bicycle share system. The main implications are provided as follows:

(1) The demand for public bicycles near rail stations and parks have undergone great changes during the pandemic. Strategies for public bicycle rebalancing should be adapted in response to such changes.
(2) Also, our results indicate that reopening the city can lead to a significant increase in the usage of public bicycles, which is even greater than that in normal times. Therefore, the operators should make sure that the public bicycle share system is ready for such booming demand. According to a previous news report, TfL has already set out plans to expand the LCH scheme to keep up

with such unprecedented demand (Intelligent Transport, 2020). In terms of the COVID-19 prevention, public bicycle share facilities, including docking stations and public bicycles should be disinfected regularly. For individuals, social distancing is still of vital importance, and cycling or walking in groups in the parks is not encouraged.

(3) As discussed earlier, the long duration LCH trips increased a lot due to the constraint of other modes of public transportation. Therefore, the original service fee standard should be revised to suit changing travel patterns. Currently, the first 30 min of each journey is free for both 24-hour membership and yearly membership. If the journey is longer than 30 min, £2 are needed for each additional 30 min. Discount policy (e.g., lengthening the free hire duration, 24-hour free access) is recommended, especially for the Oyster Card (seasonal tickets) users. However, no investigation has yet been conducted regarding the public bicycle share pricing strategies in pandemic situations, detailed economic analysis is needed to provide more complete guidelines in the future.

(4) COVID-19 pandemic has greatly reshaped the travel patterns. Governments need to concern about increased private vehicle dependence being sustained after the lockdown ends (WCTRS, 2020). In the post-COVID-19 era, promoting walking and cycling is an important strategy. In the UK, £2 billion package was announced to encourage walking and cycling, and to keep public transport safe (Gov.UK, 2020e). Moreover, walking and cycling are in close relation to social equality. Therefore, in the effort to reopen the city, policymakers should not neglect the support for public bicycle share schemes and cycling infrastructures. In view of the current situation, there is a serious risk that the second outbreak will happen, and a reliable, accessible bicycle system is vital to the urban mobility.

There are also some limitations in this study. First, COVID-19 related policies changed every day, it is difficult to consider all the policy amendments in the models. Therefore, only two major policy modifications, i.e., lockdown and the first lockdown ease were modelled. The second is related to the sample size. The lockdown ease period only covers a period of two weeks (May 13, 2020–May 26, 2020), which is partly due to the data restriction. Another reason is that on June 1, 2020, the second lockdown ease started. To better estimate the impacts of the first lockdown ease, the end point of the lockdown ease period should be selected before June 1. The third limitation is that the spatial attraction of trips has been interpreted in a limited way. The impact mechanisms have not been fully studied, which deserve deeper exploration in the future. As yet it is not known when the COVID-19 pandemic will come to an end, follow-up studies are suggested to monitor its impacts on the various aspects of transportation system from a long-term perspective.

CRediT authorship contribution statement

Haojie Li: Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Yingheng Zhang:** Writing - original draft, Formal analysis, Visualization, Validation. **Manman Zhu:** Software, Formal analysis, Visualization. **Gang Ren:** .

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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