The impact of Covid-19 pandemic on the mobility pattern of shared bicycles: a case study of London

by

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Declaration

I, Maidi Xu, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is 7505 words in length, from the abstract to reference inclusive, excluding figures.

Signed:

Date: August 20th 2022

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I also wish to thank my parents for their support and encouragement throughout my study.

Abstract

The shock to the pulse and activity of bike-sharing during the pandemic has received increasing attention from academia. It is important to investigate the change of bike-sharing usage using retrospective data in order to deal with potential natural disasters in the future. However, the lack of analysis of bike-sharing activities during the pandemic has made it difficult to understand how to improve bike-sharing activities after the pandemic.

In London, although many authors have used different methods to study the factors that affect sharing bicycles, including the weather, the environment and census tracts, bicycle sharing has been limited in the past two years (2020 and 2021) due to the epidemic. Therefore, this paper aims to investigate whether the spatio-temporal pattern of the Santander bike was affected by the government’s lockdown policy that was implemented in London from 2019 to 2021. Although the turmoil of COVID-19 has passed at the time of writing this paper, it is hoped to inspire more targeted policymaking and planning for urban sharing businesses.

To achieve these goals, this paper uses principal component analysis and spatial data visualisation with eigendecomposition to examine the bicycle-sharing model in relation to the tier three policy during the global epidemic. Platform and bicycle usage patterns in specific areas will be correlated, and the time–use patterns of bicycles will be analysed, as this may exhibit different structural changes in areas of the city.

Contents

List of figures

List of tables

Chapter 1 Introduction

In December 2019, a new infectious virus called COVID-19 emerged and quickly spreaded to almost every country. Like other respiratory viruses, COVID-19 is spread mainly through the respiratory tract, which is highly efficient and contagious; therefore, to prevent COVID-19 infection, people have had to maintain effective social distancing in their daily lives. According to data recorded on the World Health Organization's (WHO) Coronavirus Dashboard, up until 2022, there have been more than 500 million confirmed cases and six million deaths worldwide. Decision-making and response times to the pandemic have varied from country to country, based on when the virus began to spread and the political shape of each country.

Today, there are over 20 million confirmed COVID-19 cases in the UK and almost 200,000 people have died. As COVID-19 initially swept through the UK, the UK government instituted four-tier coronavirus alert restrictions. This study examines whether the bike-sharing model in London changed in the context of the UK government's response to the tier three restriction – Very High Alert. Tier three meant that there were restrictions on meeting others, travelling and working. To clearly observe whether the temporal and spatial characteristics changed, it is necessary to analyse the shared bicycle usage model separately in three stages: before, during and after the pandemic.

Santander Bike is the shared bicycle system regulated by the UK government, and it implements a model of shared bicycles with piles. The shared bicycle system requires users to pick up and return bikes at a fixed location, which has a relatively stable data service because people need to borrow and return shared bicycles at a fixed docking station. Compared with shared bicycles from other service providers, the Santander bike is more in line with the local habits of shared bicycles. The dataset is also completer and more unified.

This study aims to reveal changes in the pulse of cycling activity before and after the pandemic from mainstream docked bike-sharing systems. Time–use patterns of shared bikes in urban areas are reconstructed from millions of bike trips extracted from the Santander Transport for London (TfL) datasets. Eigendecomposition methods are then employed to reveal the hidden temporal structure of these patterns by demonstrating how they resemble or deviate from the basic patterns of cities in different scenarios (before, during and after the pandemic). Then, several critical variable metrics are derived and correlated with bicycle usage patterns. Finally, the spatial distribution of sites is visualised with unique temporal characteristics to gain deep insights into specific docking stations and their surroundings.

While revealing the pulse of the bicycle in different scenarios, the analysis results are also critically referenced and compared with the existing literature. Principal component analysis (PCA) is used to compare various parameters and variables with the existing literature to assume the direction of the results. The difference is that this study focuses more on whether the pulse of docked bikes deviates from or correlates to the basic model of the city in a pandemic-era scenario. Therefore, there is a difference between the existing literature and the results. In the subsequent analysis, the possible factors and conjectures of differentiation will be explained in detail, and extended ideas will be given under the existing conclusions.

Chapter 2 Literature review

2.1 Mobility pattern of shared bicycles before COVID-19

For shared bicycle usage patterns before the epidemic, most of the relevant literature before 2019 can be referred to. These studies focus on understanding the demand for bike-sharing systems by revealing the impact of the built environment, sociodemographic and weather conditions, and policies on bike-sharing services (Chibwe et al., 2021; Eren and Uz, 2020). For example, when comparing the relationship between weather and bike-share rentals, evidence suggests that weather conditions play a crucial role in explaining the demand for bike-sharing systems and the duration of bike rentals. Although this study is limited to bicycles in London, it is still possible to refer to different modes of bicycle sharing in other countries to gain a complete understanding of its purpose and the factors that affect bicycle sharing.

Shaheen et al. (2011) conducted a survey in Hangzhou, China to understand the determinants of bike-sharing and user adoption. The authors developed two different questionnaires for bike-sharing participants and non-participants to examine the potential impact of several factors on bike-sharing use. These factors were grouped into four categories: travel behaviour, sociodemographic and psychographics (the effect on cycling), conditions and environmental issues. The study also considered perceptions of and satisfaction with bicycle sharing. The results showed that bicycle-sharing participants were younger than 45 years old and had a moderate family income, which indicates that these two variables have a remarkable potential impact on shared bicycle use. The study also found that bike-sharing participants were not negatively affected by a high car ownership rate, that is, participants who owned a car would still participate in bike sharing.

The use of shared bikes has been comprehensively studied in past decades; for example, Xu et al. (2019) analysed temporal characteristics (weekdays and weekends, peak hours within 24 hours) and spatial features (the location of the station and the surrounding facilities where the vehicle stops). Most of the shared bicycle data analysis is consistent, especially in developed cities such as London or Singapore. Cars are mostly used during the morning or evening rush hours, and compared to weekends, the use of shared bicycles on weekdays is more regular. This shows that shared bikes are used more during the working week.

According to the literature, Bullock et al. (2017) found that the public bike-share (PBS) programme can improve connections between destinations, including first-mile and last-mile connections between homes, public transport and workplaces. This also shows that the value of shared bicycles complements that of other public transport.

2.2 Temporal and spatial characteristics of shared bicycle use during COVID-19

Teixeira and Lopes (2020) found that infectious respiratory diseases, such as coronaviruses and influenza-type viruses, are transmitted from person to person in three ways: droplets, aerosols and contact. The viruses can be spread either through direct skin contact or indirectly through contaminated surfaces. As the primary route of COVID-19 infection is through respiratory droplets from coughs and sneezes, the physical distance between the uninfected and the infected poses the most risk.

Overall, mobility and riding on public transport have declined remarkably since the start of the pandemic (Teixeira and Lopes, 2020). At the same time, people perceive that the positioning of shared bicycles is healthy, environmentally friendly and sustainable (Zheng et al., 2019; Otero et al., 2018). It can be found that shared bikes are flexible, the decrease in passenger capacity is relatively small and the average travel time increases.

Public transportation, such as buses, subways and taxis, are considered dangerous modes of transportation in the eyes of residents during a pandemic. For example, Fenichel et al. (2013) found that people respond to epidemics by voluntarily engaging in self-protective behaviours. Clearer risk communication could remarkably reduce the cost of an epidemic. People who engage in costly risk-reducing behaviours, such as abandoning non-refundable flights, suggest that they may also make less expensive behavioural adjustments to avoid infection. As a result, they are more likely to choose modes of transportation that limit exposure, such as cycling, driving in a private car or walking (Shamshiripour et al., 2020).

Recent literature assesses the impact of shared bike usage during the COVID-19 pandemic based on the gradual maturation of data and expanding sample size. The information sheets provided by the WHO (2022), as well as information in the existing literature, suggest that the most significant changes may come from changes in how people move (Batty, 2020). Until a vaccine is found – if one is developed that has a good chance of relieving symptoms – then people will be very cautious about staying in close contact with each other. In Beijing, Chai et al. (2020) analysed bike-sharing usage data, which revealed a 60% drop compared to the same period in 2019, with the city centre being the most affected area during and shortly after the outbreak. Taking

Thessaloniki in Greece as an example, Nikiforiadis et al. (2020) estimated that the proportion of bike-sharing trips would not increase. Nonetheless, certain groups (i.e., potential users who may use shared bicycles) would be more inclined to accept shared bikes due to the epidemic.

Additionally, it can be found that during the epidemic, residents' average distance and duration using shared bicycles increased, and their travel purpose was more for leisure rather than commuting. The pandemic also dramatically weakened the connection between sites and reduced the complexity of the bike-sharing network structure. During the epidemic, the relationship between shared bicycles and buses gradually changed from complementary to alternative (Hu et al., 2021).

Heydari et al. (2021) studied the impact of the COVID-19 pandemic on bike-sharing demand and rental time using data that included total monthly bike rentals and average monthly bike rental duration (travel time) from July 2010 (the launch of the London bike-share scheme) to the end of December 2020. They used a Bayesian second-order random walk time-series approach to investigate how the outbreak affected the bike-sharing system in London. Limitations of the study were that it was too short a time, and there was some uncertainty about the methods they used. The dataset used in this paper spans two months and defines three time periods: before the pandemic, during the pandemic and after the pandemic. This expands the sample size of the dataset and makes the output results more convincing. Previous studies did not discriminate for specific stations, only for overall estimation and analysis; therefore, this paper will also conduct discriminative research for specific stations at city halls, in public residential areas and in parks. This indicates that people in different regions may use shared bicycles for different purposes.

Chapter 3 Data and Methodology

This research aims to analyse and compare the patterns of TfL's Santander Cycles of one month from 2019 to 2021. Data from the three periods were based on each shared bicycle's order number, and the start time, start station, station ID and end time, end station and its station ID for each trip were recorded. The purpose of this research is to understand whether people's use of shared bikes during weekdays changed before, during and after the COVID-19 pandemic, and whether the capacity of popular bike-sharing stations changed due to the emergence of the COVID-19 pandemic.

Following data analysis based on code with link:

https://github.com/ucfnmxu/diss_code/blob/main/before-data.ipynb

3.1 Data source and pre-processing

3.1.1 Extracting origin–destination trips from public TfL data

Greater London has a total area of 611 square miles and a population of more than seven million. It has 800 docking stations for around 12,000 bicycles for shared use (Transport for London, 2022). A complete bicycle trip consists of docking stations with origin–destination and the departure and arrival times of the trip; these variables are all available in public TfL data. The dataset provided by TfL makes early data collection more regular and straightforward.

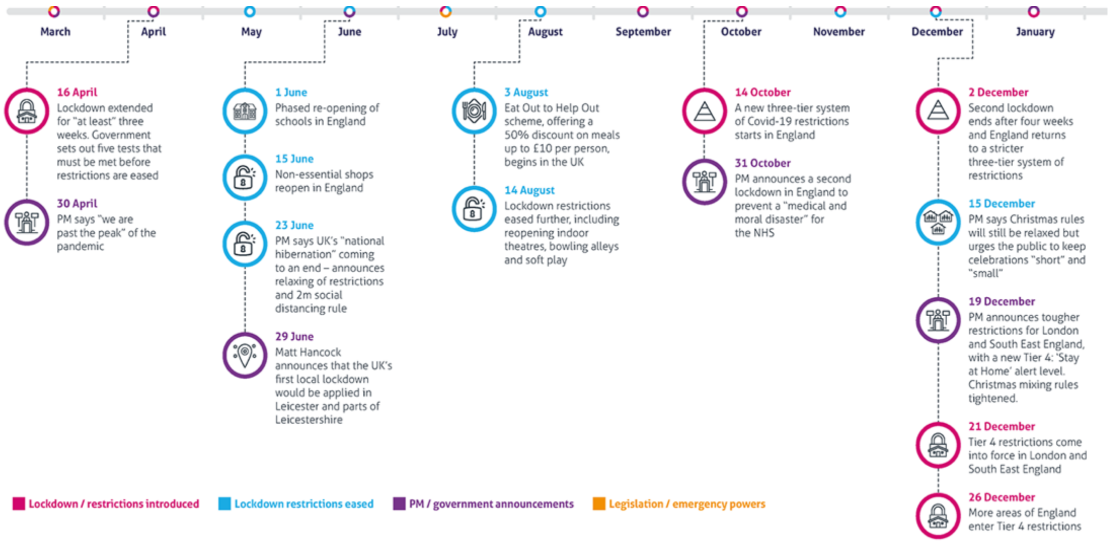


Figure 1: Timeline of UK government coronavirus lockdowns and measures (Source: Institute for Government analysis)

This study aims to compare whether the bike-sharing model in London, based on the city model, had an impact before and after the pandemic. Therefore, relevant data needs to be filtered to explain the three periods before, during and after the pandemic. The timeline in Figure 1 shows that on 14th October 2020, the UK government issued a new three-tier system to curb the spread of COVID-19. In reviewing the literature and news, UK Statutory Instruments details the new tier three restrictions on citizens (Age UK, 2021). For example, it clearly states that:

1. Outdoor activities of up to six people can be carried out in parks or on beaches
2. The recommendation is to work from home as much as possible
3. Outdoor travel should be minimized

These restrictions aligned with the characteristics of this study during the pandemic, so data was selected from 15th October to 15th November 2020. The weather and seasons can impact people's bicycle usage (Kim, 2018); therefore, periods had to be selected before and after the pandemic that had similar weather and seasons to the pandemic. The period selected before the pandemic was 15th October to 15th November 2019, and the period selected after the pandemic was from 15th October to 15th November 2021. Choosing the same months can make the results of data analysis independent of other impacts, such as weather, and reduces the uncertainty. Table 1 presents the complete suite of variables incorporated into this research.

Table 1: Research variables

Category	Variable
Before the pandemic 15th October – 15th November 2019	End Date
	EndStation ID
	EndStation Name
	Start Date
	StartStation ID
	StartStation Name
During the pandemic 15th October – 15th November 2020	End Date
	EndStation ID
	EndStation Name
	Start Date
	StartStation ID
	StartStation Name

After the pandemic 15th October – 15th November 2021	End Date
	EndStation ID
	EndStation Name
	Start Date
	StartStation ID
	StartStation Name

3.1.2 Selection of specific docking stations

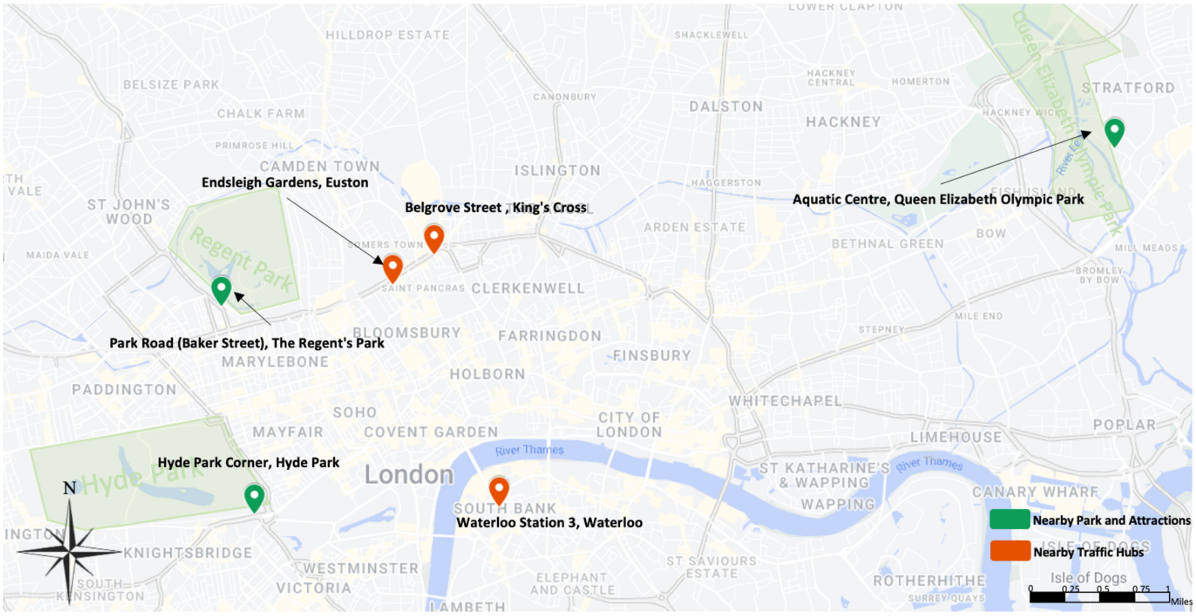


Figure 2: Map of selected docking stations

For further investigation, several specific docking stations are selected, as outlined in Figure 2. Different coloured labels represent the different types of areas the docking stations are located in. The stations coloured red represent important traffic hubs and the stations coloured green represent parks and attractions.

In London, important traffic flow hubs include but are not limited to King's Cross, Euston and Waterloo. The reason these three stations are selected as important transportation hubs in this study is that they all have the National Rail network, which connects outer London and inner London. They also have underground stations; therefore, the daily traffic flow through these stations is substantial. This study's selection of traffic flow hubs does not consider underground-only stations (because there is less traffic than stations with the National Rail network). Table 2 presents the UK's 10 busiest rail stations as recorded in 2020. To achieve data diversity and prevent outliers, this study screened the busiest platform (Waterloo), a relatively busy platform (Euston) and the least busy platform (King's Cross) when selecting essential hubs; these are bold and italic in Table 2.

Table 2: The UK's 10 busiest rail stations in 2020

Station	**Number of entries and exits (millions)**
London Waterloo	***94.2***
London Victoria	74.7
London Liverpool Street Station	69.5
London Bridge	61.3
Birmingham New Street	47.9
London Euston	***46.1***
Stratford	41.2
London Paddington	38.2
London St Pancras International	36
London Kings Cross	***34.6***

Docking stations are placed around each station for citizens to choose from. As there may be a docking station with a small passenger flow that cannot be accurately analysed, when selecting docking stations in different regions, only the docking stations with the biggest passenger flows in the area are chosen. This is shown in Figure 2.

3.2 Illustration of workflows and methods

This study introduces an eigendecomposition approach to analyse the spatiotemporal patterns of cycling activity in London. A similar use case for this method analysed weekdays and weekend activity on dockless bicycle sharing in Singapore (Xu et al., 2019). For this study, the same approach is used to examine if the temporal patterns of bike usage at different bike-share stations resemble or deviate from the basic pattern across the city before, during and after the COVID-19 pandemic.

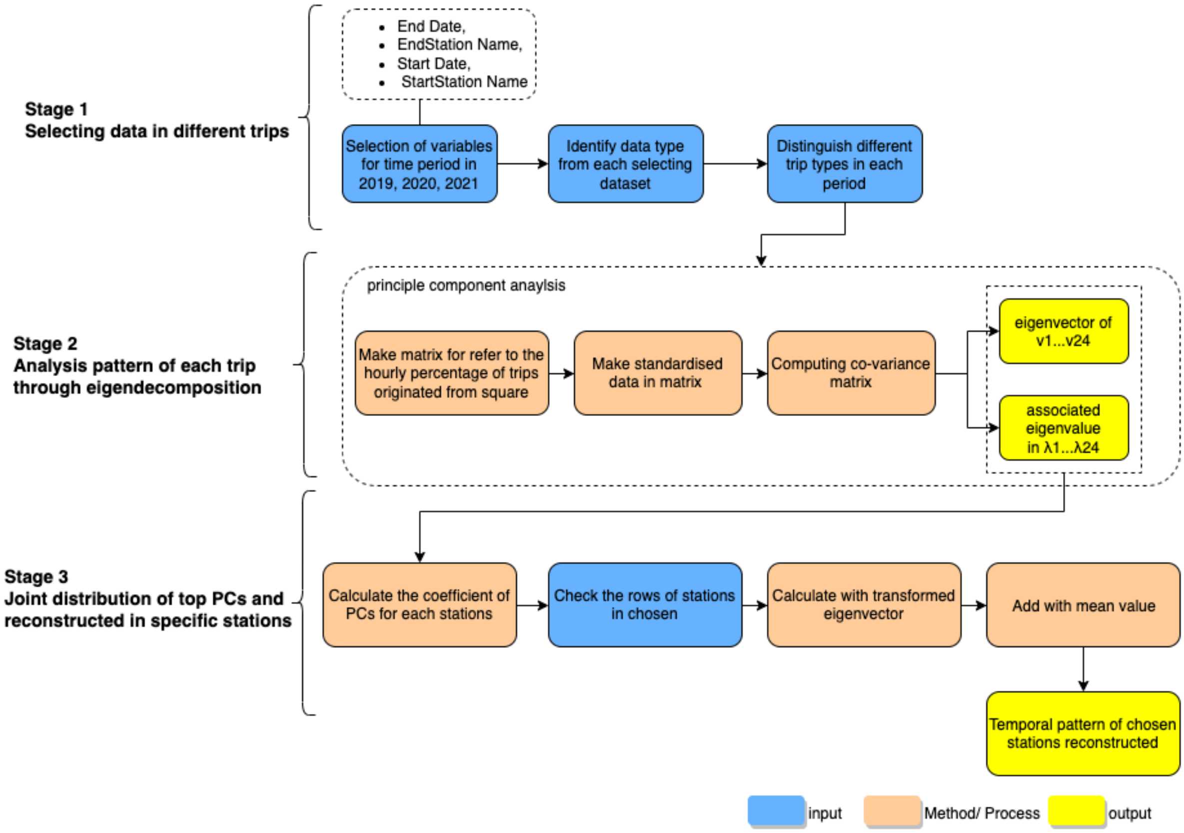


Figure 3: Workflow diagram

3.2.1 Stage 1: Selecting data for different trips

Considering the possible temporal pattern bias between weekdays and weekends, Xu et al. (2019) concluded that bike-sharing in Singapore was more random at weekends, which strays even further from the city-based model in both cities. Therefore, more regular and rhythmic weekdays will be used instead of random weekends when studying this topic. People who originally commute between two points and one line or who only use shared bicycles as transportation to other public transit may spontaneously or passively deviate from their original travel habits due to COVID-19. Therefore, this study performs feature decomposition in six combinations:

(1) pre-pandemic weekday arrival travel

(2) pre-pandemic weekday departure travel

(3) during a pandemic weekday arrival travel

(4) during a pandemic weekday departure travel

(5) post-pandemic weekday arrival travel

(6) post-pandemic weekday departure travel

3.2.2 Stage 2: Analysis of each trip using eigendecomposition

Taking departure trips on weekdays before the pandemic as an example, for all bike-share stations, the average number of trips per hour is calculated across all weekdays and normalised using the stations' average daily total:

$$\sum_{t=1}^{24} r_{i,j} = 1$$

The following equation gives the hourly percentage of departures from a particular i docking station during the time window of j hours:

$$r_{i,j} = \frac{number\ of\ trips\ in\ i\ station\ j\ hour}{average\ number\ of\ trips\ in\ j\ hour}$$

From this, a matrix can be constructed:

$$M = \begin{pmatrix} r_{1,1} & \cdots & r_{1,24} \\ \vdots & \ddots & \vdots \\ r_{N,1} & \cdots & r_{N,24} \end{pmatrix},$$

where N is the number of docking stations and 24 is the number of hours in a day. This matrix describes the deviation of a square's temporal features from the fundamental pattern. From this, covariance matrix C can be calculated:

$$C = \frac{1}{N} M^T M$$

Once the covariance is obtained, you can get the eigenvectors v1...v24, and the relevant eigenvalues in v24 are from 1–24. The eigenvectors of covariance matrix C are the principal components (PCs) of matrix M, and the relevant eigenvalues represent the variance explained by each PC (24 in total). In the new coordinate system, the transformed dataset D of size N×24 is:

$$D = MV^{-1}$$

Interpreted as:

$$D = \begin{pmatrix} d_{1,1} & \cdots & d_{1,24} \\ \vdots & \ddots & \vdots \\ d_{N,1} & \cdots & d_{N,24} \end{pmatrix}$$

$d_{i,j}$ in matrix D can be interpreted at the i^{th} station (N stations in total), the coefficient of the j^{th} PC. It can be found that each row represents all PC coefficients in a docking station.

3.2.3 Stage 3: Joint distribution of top PCs reconstructed at specific stations

The original pattern of each docking station i can be reconstructed using the following equation:

$$PCA\ reconstruction = D_i V^T + \mu,$$

where μ is the mean vector and D_i refers to the i^{th} row vector of matrix D. This explains all the PC coefficients for each docking station. In the subsequent analysis process, the most frequently used PC coefficients are distributed between the first PC and second PC. Hourly trip demand is used to explain the differences between the base modes of various regions and cities.

Chapter 4 Results

Table 3 explains the percentage of variance in the top four PCs per trip (out of six), and each one is different. Criteria based on the existing literature were followed when selecting the top PCs. In his work on PCA, Holland (2019) explains that when investigating how many PCs need to be covered, one of the criteria is that all the PCs should be included to a predetermined total percentage of variance, such as 70–90%.

Although there is some loss of information when performing PCA, Ringnér (2008) points out that PCA aims to identify the directions with the most remarkable variation, not the directions associated with separating the sample classes. In other words, the percentage of variance in the first PC of the Before Pandemic data is relatively more prominent than the data for During Pandemic and After Pandemic, which means that the original data described in Before Pandemic is more complete. Extending to this study, as the data are compared with the urban model, this suggests that the higher percentage of variance in the raw data would be more stable and the overall trips would follow the urban model more closely. With a relatively low percentage of variance, bicycle use tends to be more random and scattered.

Table 3: Percentage of variance explained by the top four PCs

Trip Type	Variance explained by			
	1st PC	2nd PC	3rd PC	4th PC
Before Pandemic & Weekday arrival trips	62.27%	9.65%	8.33%	5.19%
Before Pandemic & Weekday departure trips	61.83%	10.40%	7.17%	6.54%
During Pandemic & Weekday arrival trips	41.76%	12.92%	9.02%	6.72%
During Pandemic & Weekday departure trips	46.90%	11.50%	7.54%	6.17%
After Pandemic & Weekday arrival trips	49.98%	11.93%	8.90%	6.83%
After Pandemic & Weekday departure trips	52.45%	12.26%	7.44%	5.98%

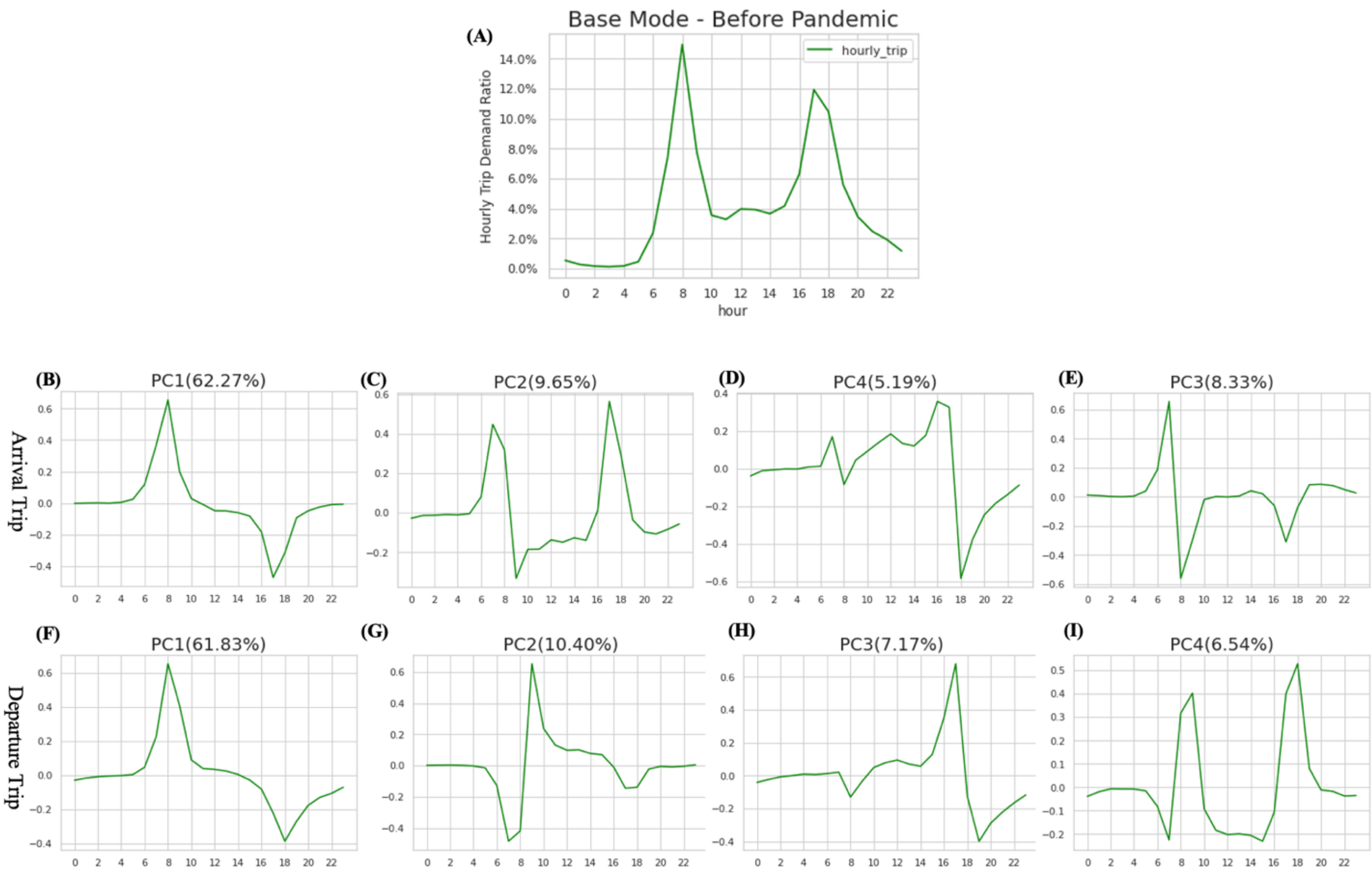
4.1 Comparing temporal characteristics of bicycle use with existing literature

Before the epidemic, most cities used shared bicycles to travel, so London's 2019 epidemic-free bike-sharing model will be compared to Singapore's 2017 model of bike-sharing (Xu et al., 2019). London is around 2.2 times the size of Singapore (as shown in Table 4), but the number of shared bikes is less than in Singapore. .Such a geographical gap may lead to a large deviation from the basic city model in the use of bicycles in London. The results of the eigendecomposition in this study will be compared with the results of the eigendecomposition of working days in the literature (Xu et al., 2019).

	Population (in million)	Size (in km^2)	Number of shared bikes
Singapore	5.7	728.6	~36000
Greater London	9.0	1569	~11500

Table 4: Comparison of London and Singapore in 2020

A time pattern that peaks around 08:00 can be found by examining the first PC in the Before Pandemic data on arrival trips. The structure of this peak (Figure 5B) is almost like the first PC of the weekday arrival travel in the literature. However, there is a big gap between the total variance (62.3%) and the literature (86%). It is speculated that this may have something to do with the urban geographic model because more Outer London people might flock to specific areas in the early morning hours to commute to work, which will lead to a more random structure of shared bicycle arrival trips. In contrast, Singapore, a smaller island nation, has a more dynamic and rhythmic pattern



of arrival trips.

Figure 5: Results of eigendecomposition – Before Pandemic

The first PC for departure trips in the Before Pandemic analysis explains a remarkable and similar total variance (61.8%) to arrival trips as well as similar peaks (Figure 5F). Expanding the discussion, the first PC shows that, regardless of departure or arrival trips, if a bike-share station attracts more trips around 08:00, there will be fewer departure or arrival trips from that station between 16:00 and 18:00. Notably, the second PC arrival trip (Figure 5C) was more active from 06:00 to 08:00 and 16:00 to 19:00. For departure trips (Figure 5G), the total contrast and peaks are explained entirely differently to the literature, as departure trips are more active at 09:00.

Figure 6 presents the During Pandemic data and shows relatively few first PCs. In fact, the overall pattern is like that of weekend trips in the literature in that they are both around 40% (Xu et al., 2019). The peak of the first PC is still identical to Before Pandemic, with a remarkable peak between 07:00 and 09:00 (Figures 6B and 6F), which is also like the model of weekend travel in the literature. This highlights the randomness of people riding during the pandemic and how much the space for cycling has changed. It is worth noting that on the second PC, if more people started their trips from 09:00 to 16:00, then there would be fewer other times (Figure 6G), while arrival trips have the opposite travel model (Figure 6C).

Interestingly, the peak in total variance for During Pandemic is very similar to weekend travel in the literature (Xu et al., 2019), as more people chose to work from home rather than commute to work every day. In this context, it is logical that the feature breakdown structure during a pandemic is more like a weekend trip.

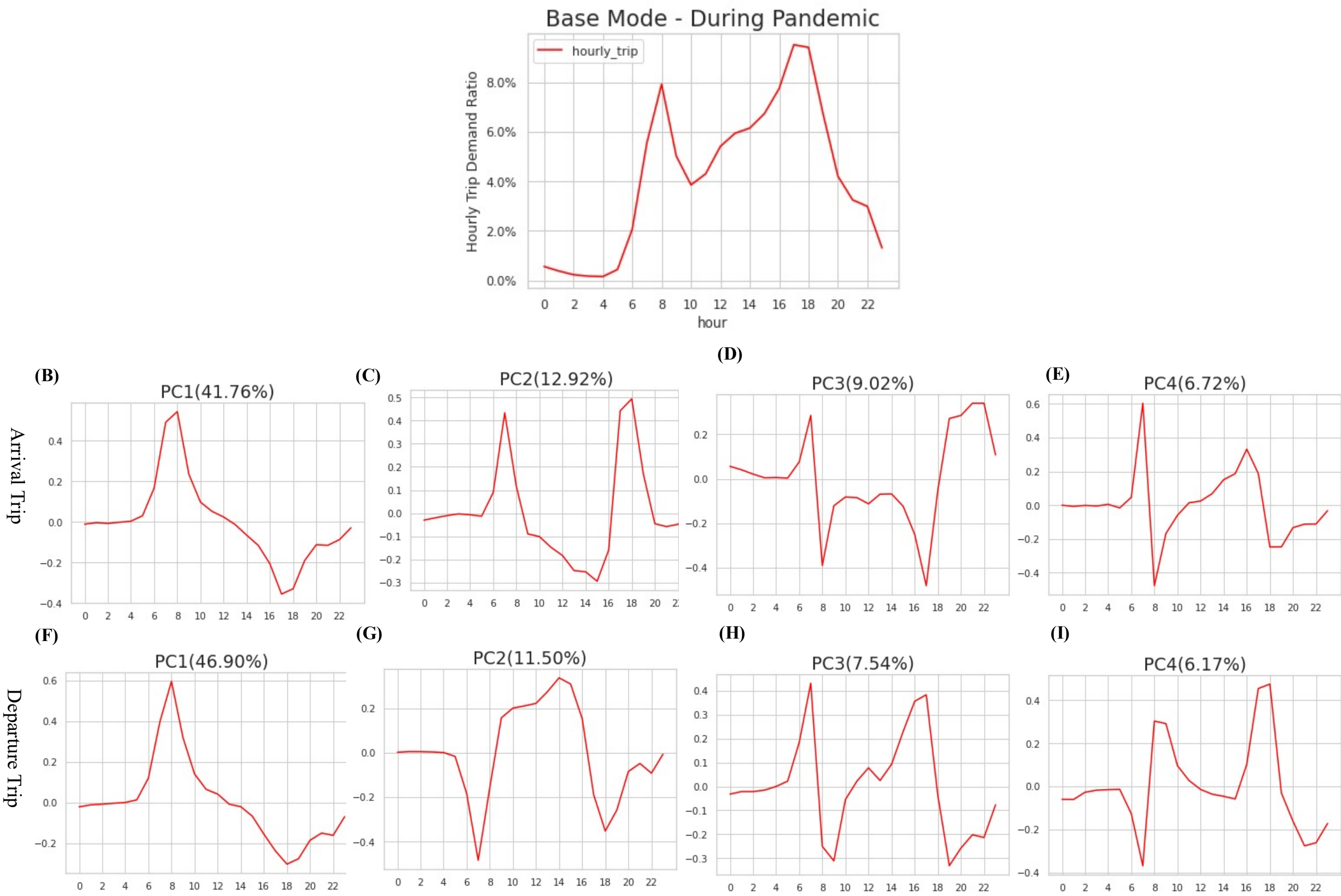


Figure 6: Results of eigendecomposition – During Pandemic

Figure 7 presents the data for After Pandemic and is relative to the total variance of the first PC in During Pandemic (Figures 6B and 6F). This increase explains the rhythm of arrivals and departures after the pandemic. The peaks of departure and arrival trips (Figures 7B and 7F) for the first PC are still similar to the previous ones, with more people departing or arriving from a specific place between 07:00 and 09:00. The second PC explains the total variance of arrival and departure trips and is like that of During Pandemic. The peak of arrival travel (Figures 7B and 7C) and the peak arrival travel during the pandemic are almost the same, which may be because people were still reluctant to undertake prolonged close human-to-human contact in the post-pandemic era. This may lead to some Outer London commuters still choosing to work from home. For departure trips in the second PC, the peak is similar to pre-pandemic, as more people choose to depart between 09:00 and 10:00, but one difference is that, except for this period, several people are still travelling from a particular station from 11:00 to 16:00.

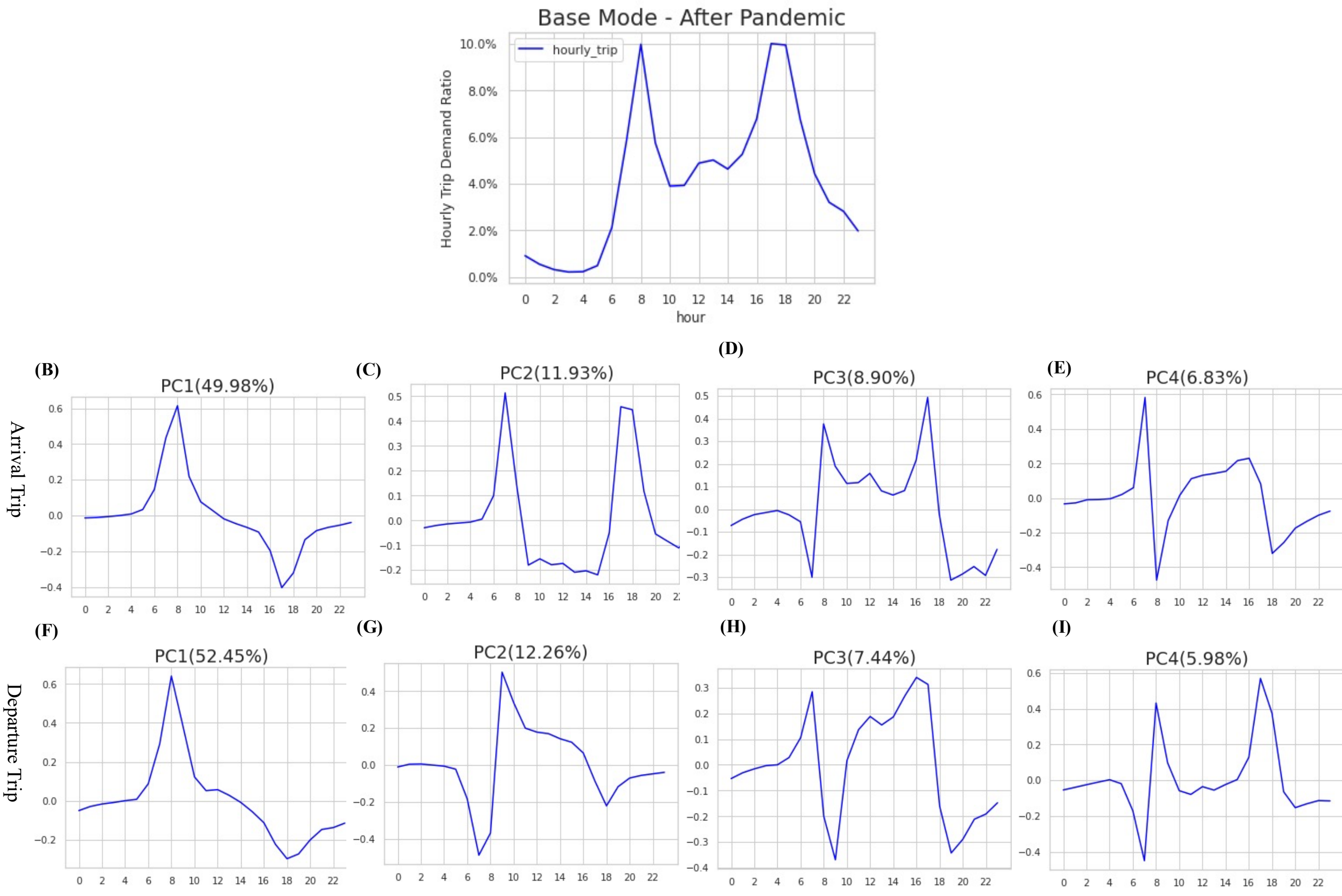


Figure 7: Results of eigendecomposition – After Pandemic

4.2 Joint distribution of top PCs reconstructed at specific stations

4.2.1 Arrival trips

Figure 8A explains the joint distribution of the coefficients of the first two PCs for arrival trips in all stations on weekdays before the pandemic. The figure shows how effective the bike-sharing stations are in six locations: Belgrove Street, King's Cross; Waterloo Station 3; Endsleigh Gardens; Hyde Park Corner; Park Road (Baker Street), Regent's Park; the Aquatic Centre in Queen Elizabeth Olympic Park(ACQ Park). To reconstruct their temporal characteristics, when choosing these bike-share stations, the area was divided into two categories: major public transportation hubs and parks and attractions. In the first category, this study will analyse the areas of King's Cross, Waterloo and Euston. In the second category, the three regions selected are Regent's Park, Hyde Park and Queen Elizabeth Olympic Park. Because of the large number of bike-sharing stations in each area, the stations with the most ridership, that is, the stations with the most trips, will be prioritised.

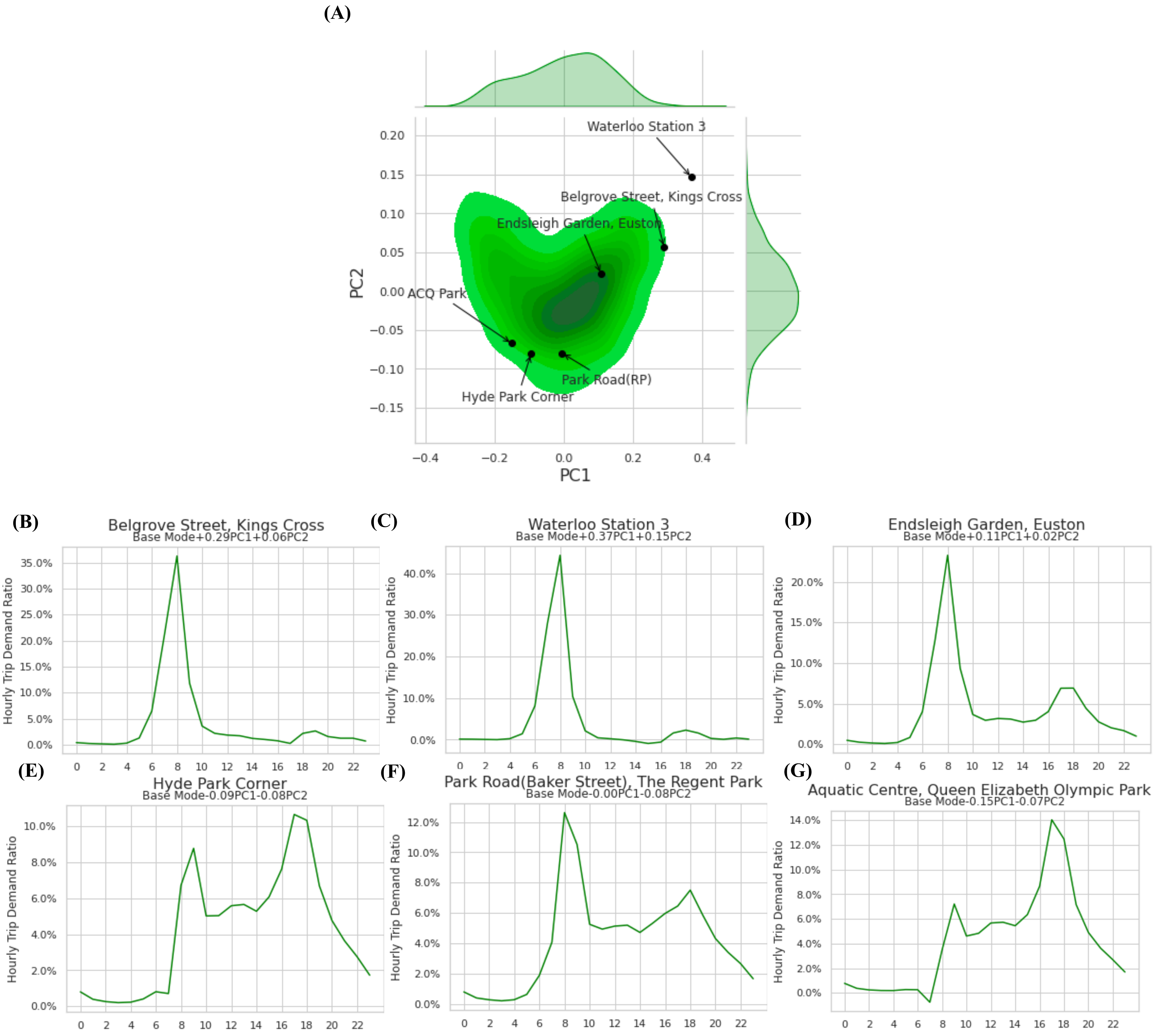


Figure 8: (A) Joint distribution of PC1 and PC2 coefficients of the stations (before pandemic arrival trips); (B–G) Temporal patterns of the six stations reconstructed from these two PCs

The three stations in the first category (Belgrove Street, King's Cross; Waterloo Station 3; Endsleigh Gardens, Euston) are shown in Figures 8B, C and D. These are important public transport hubs for shared bike stations and have positive coefficients for the first and second PCs. These positive tables have higher demand in the early morning compared to base mode and lower arrival trips in the evening than base mode. For the other three bike-sharing stations classified as parks and attractions in Figures 8E, F and G (Hyde Park Corner; Park Road (Baker Street), Regent's Park; the Aquatic Centre, Queen Elizabeth Olympic Park(ACQ Park)), their first and second PCs are both negative, indicating a remarkable demand in the early morning in base mode and the need for these three stations to be concentrated in the evening because several trips occur in the afternoon and at night.

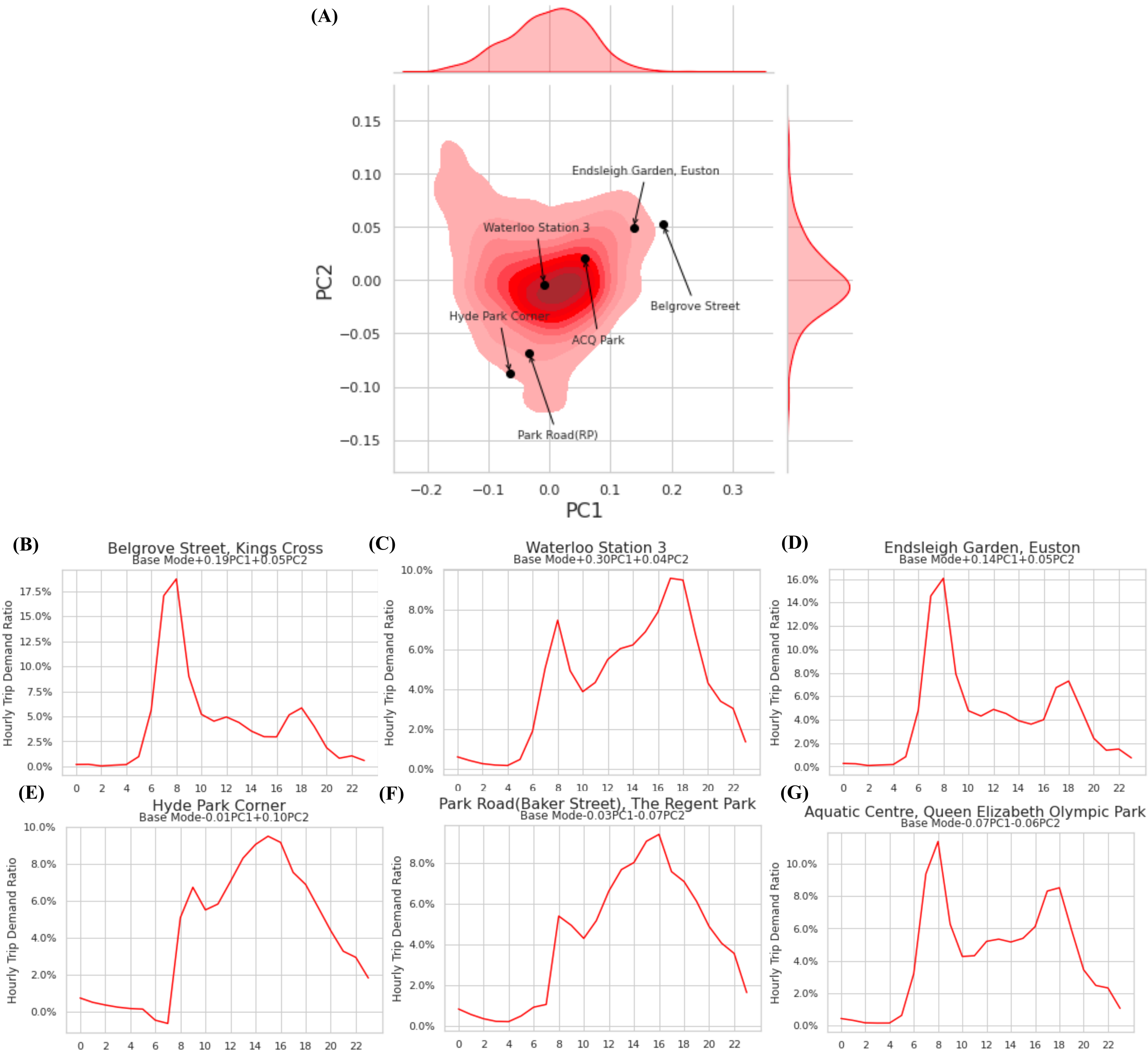


Figure 9: (A) Joint distribution of PC1 and PC2 coefficients of the stations (during pandemic arrival trips); (B–G) Temporal patterns of the six stations reconstructed from these two PCs

For arrival trips during the pandemic, it can be found that most of the positive and negative coefficients of the first and second PCs are like those before the pandemic. However, the positive value in Figure 9C compared with the pre-pandemic value (Figure 8C) produced a remarkable difference. Waterloo Station 3 has seen a shift in bike usage from morning to evening during the pandemic. In the parks and entertainment category, the negative coefficients of Hyde Park Corner and Park Road in Regent’s Park are compatible with the first and second PCs, indicating lower demand in the early morning (07:00) but a remarkable increase in cycling activity in the early afternoon and evening from 14:00–17:00 (Figures 9E and 9F).

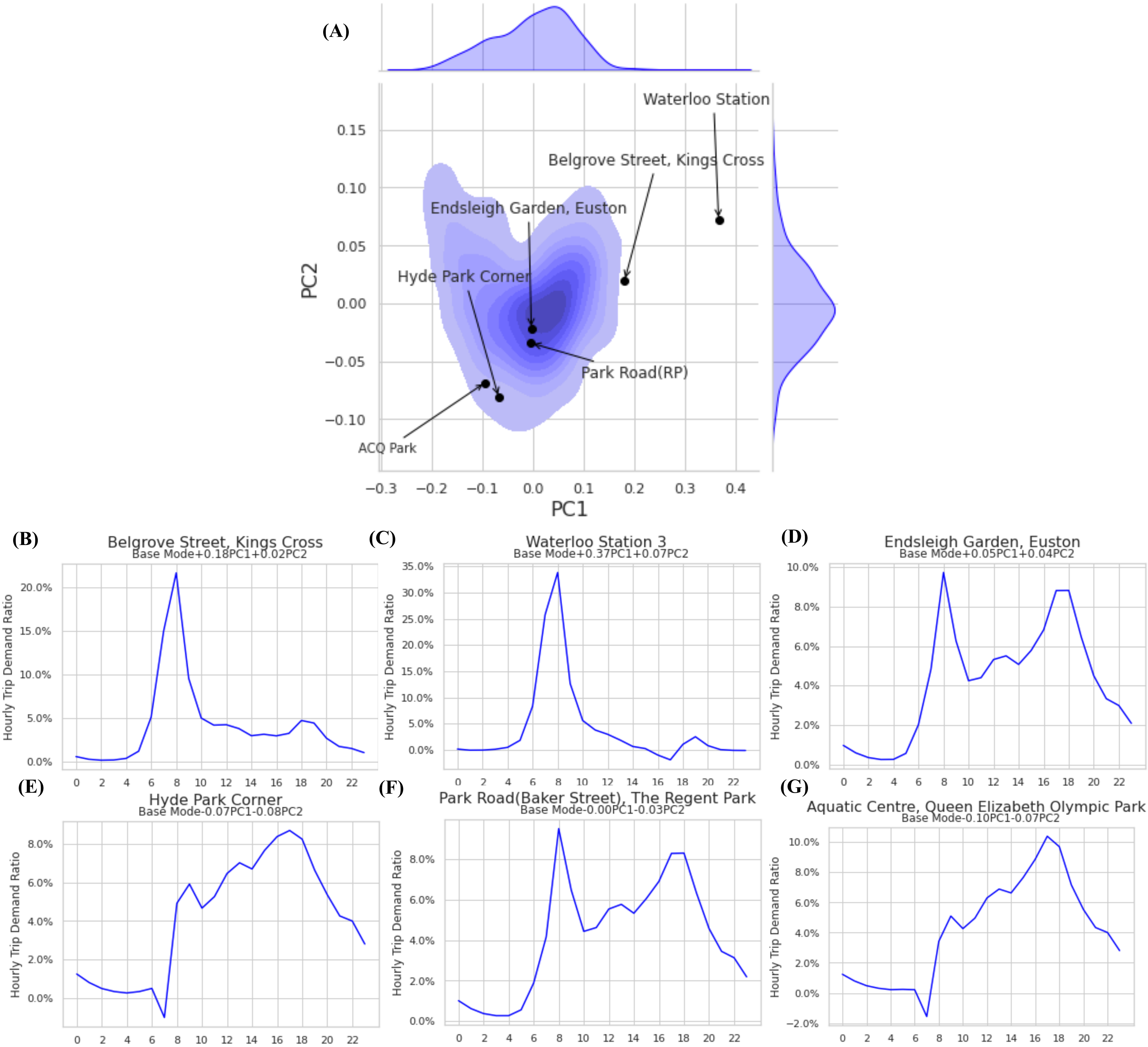


Figure 10: (A) Joint distribution of PC1 and PC2 coefficients of the stations (after pandemic arrival trips); (B–G) Temporal patterns of the six stations reconstructed from these two PCs

After the pandemic, Figure 6 explains that the first and second PC coefficients of most of the stations are similar to those before the pandemic. As a result, actual bike usage at the stations at King's Cross, Waterloo, Hyde Park, Regent's Park and Queen Elizabeth Olympic Park is similar to the pre-pandemic period. However, for Endsleigh Gardens in Euston (Figure 10D), the coefficient of the first PC is reduced, and the dominant role of the second PC results in more arrival travel in the afternoon and evening.

4.2.2 Departure trips

In explaining the pre-pandemic arrival trips for these six locations, the first and second PC coefficients for these stations are inverse to the associated departure trips. For example, on Belgrove Street (Figure 11B), the first and second PCs at King's Cross are -0.17 and -0.05, respectively. Looking back at the arrival trip at the same station, in Figure 8B, the first and second PCs are +0.29 and 0.06, respectively. This indicates that the level of departure travel at night is higher than base mode. The same applies to stations at Waterloo Station 3 (Figure 11C), Endsleigh Gardens (Figure 11D) and the (ACQ Park)Aquatic Centre (Figure 11G). Both the first and second PCs at Hyde Park Corner (Figure 11E) are positive, indicating that the level of departure travel is similar to base mode and is higher in the morning (i.e. 08:00–10:00).

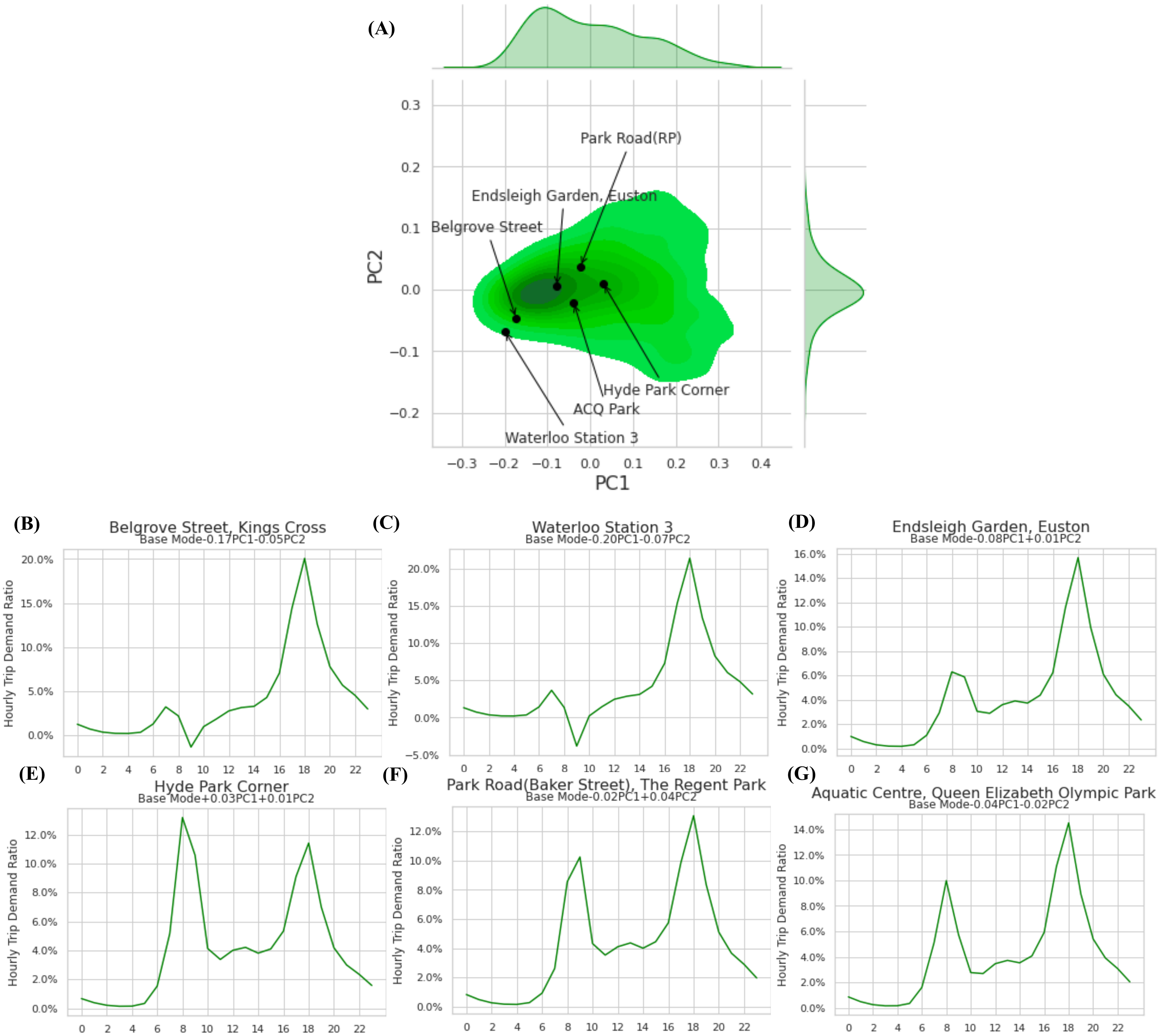


Figure 11: (A) Joint distribution of PC1 and PC2 coefficients of the stations (before pandemic departure trips); (B–G) Temporal patterns of the six stations reconstructed from these two PCs

Notably, the patterns across the six stations show a similar trend for departure trips during the pandemic, with a concentration of departure trips in the afternoon to evening (14:00–19:00). Interestingly, in Hyde Park Corner (Figure 12E) and Park Road (Figure 12F), as the first PC is very close to 0, the second PC plays a dominant role, which also results in two peak periods of departure travel. Although there are two peaks, it is relatively smooth. For the remaining four docking stations, departure trips are focused around 18:00, which may be related to the transportation facilities around them.

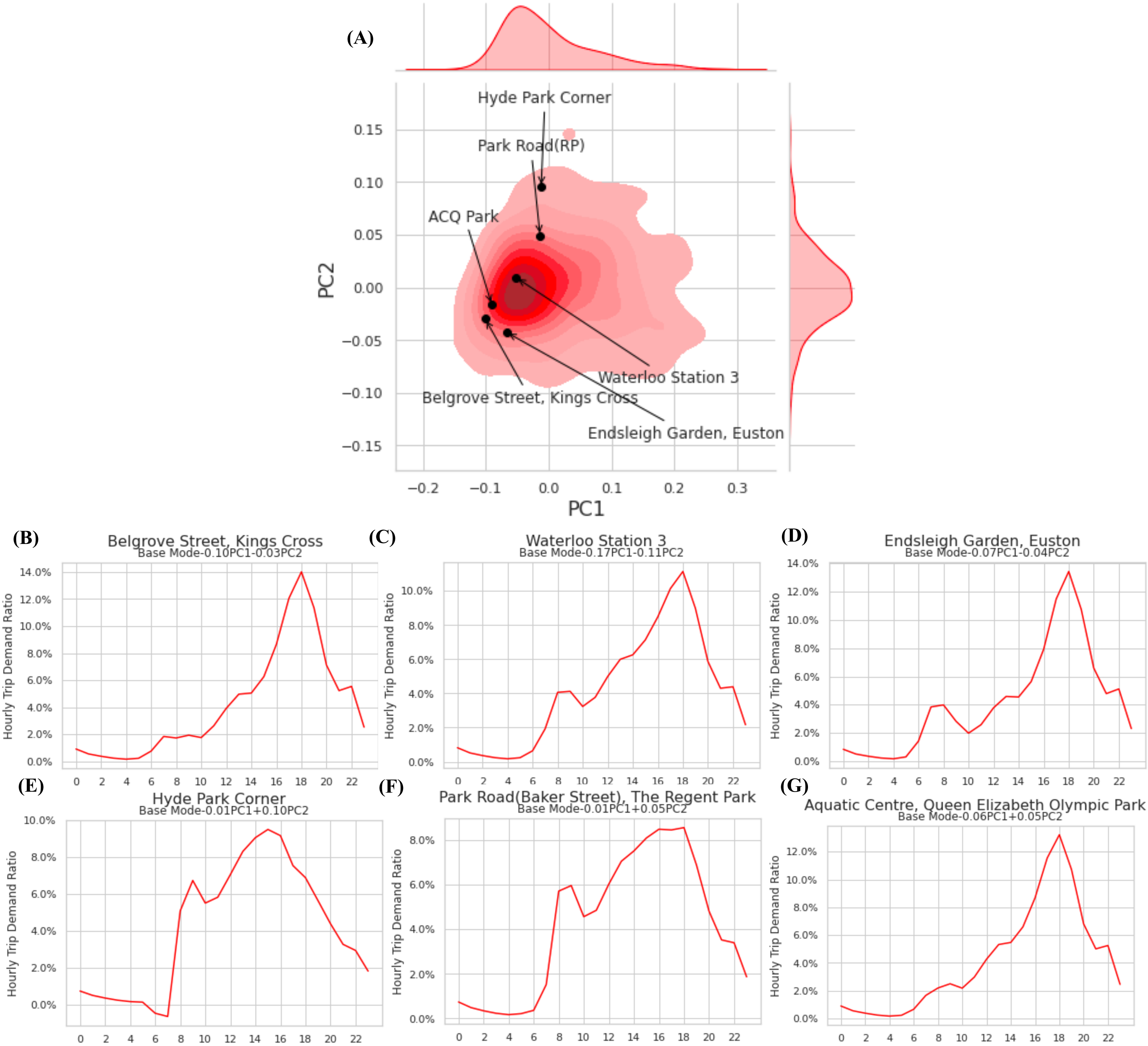


Figure 12: (A) Joint distribution of PC1 and PC2 coefficients of the stations (during pandemic departure trips); (B–G) Temporal patterns of the six stations reconstructed from these two PCs

The coefficients of the first and second PCs at Endsleigh Gardens and the Aquatic Centre are positive and negative. The difference is that Endsleigh Gardens' first PC coefficient is closer to zero. The dominant role of the second PC resulted in the observation of a temporal signature of greater ridership during the day (Figure 13D). In contrast, the first and second PCs for Hyde Park Corner and Park Road (Figures 13E and 13F) are both positive but tend towards zero. This suggests that the observed temporal characteristics are closer to the urban base mode.

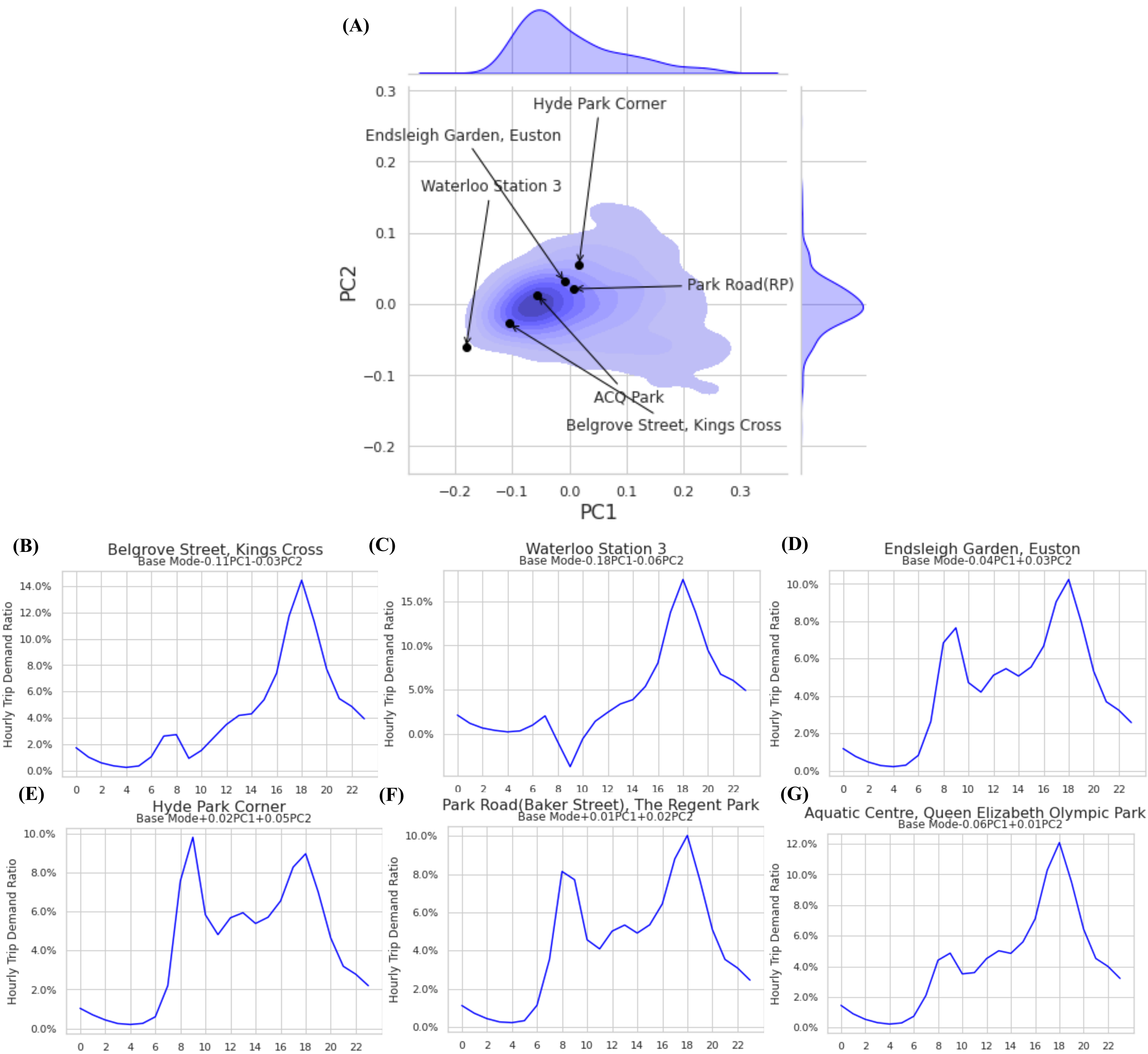


Figure 13: (A) Joint distribution of PC1 and PC2 coefficients of the stations (after pandemic departure trips); (B–G) Temporal patterns of the six stations reconstructed from these two PCs

Chapter 5 Discussion

To date, limited research efforts have been devoted to revealing the spatiotemporal structure of the environment and passenger factors in bike-sharing systems. Even in recent years, with the impact of COVID-19 on bicycle sharing, few people have analysed the spatiotemporal structure of individual sites. To fill this research gap, this study investigated a six-month dataset provided by TfL Santander Cycles in London. Based on data from tens of thousands of bicycle trips, it charts changes in urban bicycle use before, during and after the pandemic as well as temporal changes in bike-sharing at a few more specialised docking stations.

The results show that the use of shared bikes varies before, during and after the epidemic. Before the pandemic, early morning rides played a crucial role in differentiating bicycle usage patterns in different regions. During the pandemic, both departure and arrival cycling activity was less concentrated than before the pandemic, and the overall change in departure and arrival trips was slighter than before the pandemic, indicating temporal characteristics of bicycle use across the city. The distribution was more even. Post-pandemic, PC profiles suggest a return to rhythmic cycling activity but not at pre-pandemic cycling activity levels. This means that cycling activities will become more irregular and rhythmic when the city model faces the epidemic. Even when the government announces that it will open in 2021, it will be challenging to return to the normal pre-pandemic riding mode anytime soon.

According to the first few PC coefficients, the eigendecomposition method effectively describes the temporal characteristics of cycling activities at different locations. It can be observed that, under normal circumstances, places close to subway stations or essential transport hubs in London tend to have a significant attraction in the morning and evening rush hours. The assumption is that people tend to use shared bikes at subway and train stations, and the most likely purpose is to connect the distance between work and subway station and home and subway station, that is, for commuting. People usually reach these places by bicycle during the morning rush hour (Figures 8B, C and D) and evening rush hour (Figures 8E, F and G). From this, it can be inferred that shared bicycles in London had 'first-mile' and 'last-mile' characteristics before the outbreak of the pandemic (Huang et al., 2020). During the pandemic, arrival trips (Figure 9) were more random than departure trips (Figure 11), which shows that the stops close to important transportation hubs had more concentrated departures during the evening peak. Comparing Figures 11 and 12, during the epidemic, the hourly travel demand ratio of these six stops was lower than before the pandemic. That said, during the pandemic, outbound travel was not as concentrated as it was before the pandemic, probably because more and more people opted to work from home. Furthermore, due to the introduction of the new tier three policy, outdoor activities were strictly limited to no more than six people, and the two peaks before the pandemic disappeared during the pandemic. Cycling activity in the park was also less attractive, with an overall smoother and more uniform timing profile.

Interestingly, at the three park stops selected for this study, bicycle use was mainly distributed in the morning and evening peaks but at slightly later times. The stations in these parks, especially Hyde Park and Regent's Park, had more static phases of bike use during the pandemic. In contrast, at the Aquatic Centre, which is close to the major transport hub at Stratford and, therefore, has a larger passenger flow than more scenic spots, it can be speculated that the new tier three policy did not restrict people's attendance at work but precisely limited the maximum number of people who could participate in outdoor activities. Therefore, at the stops close to important transportation hubs, the use of bicycles did not change much, and there was always a more obvious peak in the morning and evening. The stops near the park were hit hard, and the two peak hours that originally appeared soon disappeared. For the Aquatic Centre, because of its geographic proximity to parks and important transport hubs, with passenger flow as a weighting, bike usage patterns were closer to docking stations such as Belgrove Street and Waterloo Station 3.

Chapter 6 Conclusion

This paper used a combination of PCA and geographic information to address the urgent need of gaining a deeper understanding of the pulse of London's docked bike-sharing activity in the context of the pandemic. In identifying, modelling and inferring the pulse of London cycling activity, the results of this analysis can provide decision-makers with the tools to understand and strategically address current and future iterations of dock theory. It is also hoped that this research will inspire future work that experiments with other methods for understanding bike-sharing mobility. Despite this success, this paper acknowledges certain limitations inherent in the analysis that may be improved by future research. First, the study was limited to fixed docking stations and did not include dockless cycling activities. Although much of the bike-sharing activity in London is for docked bikes, it is recognised that bike-sharing patterns may change in the future. Second, as mentioned earlier, the derivation of PCA models inevitably suffers from data loss, which inadvertently affects the accuracy of the results. Potentially, connections can be made to more relevant datasets and other models to further enhance this analysis and the inferences of our model. In the end, London is just one city; therefore, making connections with other cities and comparing the results will provide further insights. However, this intent is also dismissed given the lack of quality data compared to the data used in this paper. Nevertheless, as more and more urban shared bicycle data is standardised, for other towns with shared bicycles, a detailed analysis of the shared bicycle mode of each city, whether docked or dockless, will not be too far away.

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