Human mobility in response to COVID-19: a study of weekend travel demand in London

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Contents

Chapter 1

Introduction

The COVID-19 pandemic has changed the established urban mobility patterns, as lockdown, work from home and social distancing measures have been imposed around the world.

On the one hand, the transformations might benefit our cities through the boost of active mobility as some cities reallocated road space to pedestrians and cycling and through the reduced crowding as more employers allow remote work. On the other, some of the industries are highly dependant on people's movement patterns. High street economy is one of them.

In London, the recovery of high streets was named one of the nine post-pandemic priorities in London (Mayor of London 2020). This move indicates the importance of this activity to the city.

This study intends to contribute to the ongoing research of the global pandemic yet-to-be-determined influence on urban environment through an investigation of movement change in London.

The research question of this study is the following: *Which factors influenced bus and bike* *sharing ridership before and during COVID in London?*

To answer this question, a spatial econometrics approach described by Morton et al. (2021) is used to evaluate the link between features of local environment and the mobility change before and during the COVID-19 pandemic in central London.

Two modes of transportation were analysed: public transport trough the example of buses and cycling through the example of London's Cycle Hire Scheme (LCHS).

Three time periods were used to evaluate the change:

- June 2019 for pre-pandemic mobility,
- June 2020 for lockdown mobility,
- June 2021 for lockdown easing period.

The following objectives are set in the study:

1. To review the change of temporal patterns for different days of week and hours of the day in London overall,
2. To assess the spatial differentiation of mobility recovery in different boroughs and locations in London,
3. To build a spatial regression model for each time period and transportation mode to analyse what influences the trip distribution and how the influence changed over time.

Chapter 2

Literature Review

2.1 Post-pandemic cities

The impact of COVID-19 on cities is currently widely discussed and studied, but is still hugely a matter of speculation as the pandemic itself is far from over, so are we far from assessing its long-term implications.

The pandemic has already changed the way we live, work, communicate, shop and travel. The transformation is happening in many domains, but what most researchers and policy makers agreed on is that the key changes will take place in the way we move around (Batty 2020).

As Kleinman (2020) forecasts, many people will continue to work from home and mass commuting will not return to previous levels, online shopping will force high streets to evolve into mixed-use environments hosting more housing and employment. With urban mobility, he continues, there are currently two opposite trends. Road spaces around the world are reallocated to cyclists and pedestrians; yet pandemic caused 'fear of transit', thus people are avoiding underground and prefer private motor vehicles (Wright 2020).

Batty (2020) emphasises that rising demand for car travel poses a risk to the dominance of compact city and transit-oriented development policies gaining momentum since late 20th century and describes decentralised and sprawling low-density urban future.

2.2 High streets challenges and policy

One of the largest casualties of these scenarios is the traditional brick-and-mortar retail and the high street industry based on density.

In London, for instance, there are more than 600 high streets providing 28% of all jobs and hosting 41% of all businesses in the city (Greater London Authority 2017). Not only they are essential to the city's economy, but also invaluable to the local communities and the importance of the latter has been growing in the recent years. The global pandemic might force the role of retail to decrease even further as people get used to online retail and long-term staying local guidelines might influence the way people access and use high streets.

These changes are also in line with the new mobility paradigm which suggests that people will be willing to travel despite the advancement in digital and mobile technologies (Sheller & Urry 2006). The trips become more individual and overall movement, not statis, is considered to be the benchmark of social relationship.

Besides the widely discussed switch to online-shopping (Relihan et al. 2020), the performance of retail is also highly dependant on people's mobility patterns. Evidence from UK shows that city centres are suffering the most with a 4.3% decline of retail stores number compared to -3.0% and -2.3% in town and villages respectively (Local Data Company 2021). And within London the City and West End are performing worse than suburban neighbourhoods.

Yet it is not just COVID-19 that commenced this changes. We detected similar discussions about the challenges high streets face in numerous pre-COVID reports. Hall (2011) emphasises the volatility caused by global financial crisis in 2008. In 2013 the Centre for Retail Research predicted that from 2013 to 2018 the stores numbers in the UK would have fallen by 22% and that share of consumer spending happening on high streets would have declined from 50% in 2000 to 40.2% by in 2018 (Centre for Retail Research 2013). And a 2010 study commissioned by Design for London reported that many of London's high streets have been in longterm decline since the 1970s suffering from disinvestment, traffic and poor management (Scott 2010). To sum it up, the notion of high street decline has been around for decades already. The pandemic has just accelerated the trends.

In any case, there is an agreement that the challenges need to be addressed. The recovery of high streets was named one of the nine post-pandemic priorities in London (Mayor of London 2020). The so-called High Streets for All mission aims at supporting existing activity centres to adapt to the changing realities, bring new functions to the underused buildings and, in the end, bring people to high streets and public spaces.

This underpins the need of understanding what currently brings people to these activity centres, how they access, use and move around which is fundamentally the goal of urban mobility analytics.

2.3 Understanding urban mobility

Kandt & Batty (2021) point out that among different applications including energy or policing, transport is perhaps the most established application of urban analytics nowadays. They discuss traffic management with its the largest number of applications with high frequency data streams and real-time solutions and also cover the existing practices of smart card data analytics.

There is a growing number of data sources and techniques are used to analyse mobility patterns of daily activity (Hasan et al. 2013). Traditionally travel surveys were used to question individuals in detail about their travel patterns. In addition, numerous big data sources have recently emerged which help evaluate everyday movement at a massive scale: from mobile phone traces (Calabrese et al. 2013) to smart cards (Reades et al. 2016) to the most unconventional sources like social media which are used as a proxy when transport data is unavailable (Hawelka et al. 2014).

With a growing amount of data, the number of methods and applications is enormous and way beyond the scope of this research. What we are interested in is measuring flows of people in specific locations and understanding what drives this demand.

In transport modelling a traditional approach to do so is the four-step model (FSM) (McNally 2007). The steps include:

1. Trip generation to evaluate the total daily travels.
2. Trip distribution to generate production-attraction pairs.
3. Mode choice to produce mode-specific estimations.
4. Route choice to reflect specific paths usage.

The first step, trip generation, might be performed either knowing origins and destinations of trips and, thus, producing OD matrices or separately for trip production and trip attraction. The latter case helps independently estimate what factors influenced those trips (Morton et al. 2021), but limits the understanding of accessibility measures (McNally 2007). However, a huge advantage of this method is possibility to work with count transport data when origins-destinations are not given which is often the case.

Trip generation analysis is usually performed through the family of regression models (Cardozo et al. 2012). For example, in a 2015 study in California two linear regression were used to estimates of automobile trip-generation separately for morning and evening peak hours (Schneider et al. 2015).

However, traditional linear regressions are based on several assumptions including the independence of variables. In transportation this is not always true. For example, if a bus stop is overcrowded passengers might walk to the next one. In terms of regression, it means that the performance of one observation would be affected by the performance of another. This phenomenon is called spatial non-stationary effect in spatial econometrics (Yang et al. 2020). The spatial econometrics approach is essentially a way to introduce the peculiarities of spatial dimension to the traditional statistical models (Anselin & Bera 1998). This includes dealing with spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models (Anselin et al. 2001).

Consequently, spatial regression models are gaining popularity for trip generation studies. For instance, semi-parametric geographically weighted regression (S-GWR) model was used to understand what factors influences bike sharing ridership in Chicago (Yang et al. 2020). A London-based study used spatial lag model (SLM) for the same purpose (Morton et al. 2021).

This study attempts to contribute to the body of trip generation studies using the spatial econometrics approach through the following enhancements. First, we analyse two different modes of transportations: buses to represent transit and bike sharing to active mobility. Trip productions are analysed for buses and trip attractions for cycling. Second, we apply the methodology to evaluate the mobility change before, during and after COVID-19 related restrictions in London. Finally, we are interested in high street economy and therefore distinguish weekday and weekend travel and focus on the latter while most studies mentioned above cover weekday patterns. Overall, this research aims at applying the well-established methodology transport analysis to the non-commute mobility in London.

Chapter 3

Methodology

In previous chapter, we covered the existing discussion of COVID-19 influence on urban mobility and the possible dangers to urban density, high street economy and public transit. These three domains lie in the centre of compact development agenda and their performance will largely affect whether we recover into sustainable walkable cities with healthy economy. Overall, this study aims at understanding what drives bus and cycling mobility grounded into local London context. This chapter describes the study area choice, data used for the analysis, its preprocessing and overall methods used for the analysis.

The code used in this research can be accessed here: `https://github.com/alvova/london-covid-mobility/`.

3.1 Study area

This research focuses on mobility in London, the UK's largest city and economic centre, and further narrows down the area to 154 MSOAs in Zones 1 and 2.

As was described in previous chapter, large cities have been largely affected by the pandemic. Shifting to work from home and lockdown restrictions made core urban areas less attractive and could cause a long-term exodus (Nathan & Overman 2020). The size, status of financial and cultural hub which make London a distinguishable dragon king within the UK urban system also make it more more vulnerable to the negative consequences of the pandemic. The most recent 2021 data shows that city centres continue to be more exposed to the pandemic ramifications than suburban areas (Local Data Company 2021). As Anderson et al. (2020) point out many of the city's key sectors either rely on proximity, agglomeration economies and externalities or rest on continuous migration flows. In essence, these peculiarities all comes down to footfall and mobility patterns.

For London to recover it is crucial to locate areas that generated activity expressed in public transport and bicycle trips and to better understand what helped them stay afloat even during the lockdown.

The geographic extent of this study was additionally narrowed to 154 MSOAs to capture two modes of transportation. The availability of travel data will be covered in more detail in subsection 3.2.2. The MSOAs are situated in in Zones 1 and 2 within 12 boroughs.

As data collected for the study came attributed to points, street segments and polygons, two spatial units were considered for aggregation: polygons like administrative or statistical boundaries or street segments. Ultimately, it was decided to use polygons as the aggregation process would be easier and clearer. The spatial level used for the analysis is MSOA (middle layer super output area). Data associated to street segments was overlaid with polygon boundaries and aggregated.

3.2 Data

To perform the analysis data about high streets extent, human mobility, features of the built environment and socio-economic context was required. Overall, it was obtained from various open and proprietary sources. An overview of sources and variables obtained from them is reported in table 3.1. A significant and time-consuming part of the study was dedicated to searching, requesting and choosing relevant datasets. Some of the steps and decisions will be covered in the subsections below.

3.2.1 High street boundaries

Despite the high street extensive contribution to the economy (Greater London Authority 2017), there is no universal definition for high street in the UK. Thus, geographical, economical, financial information related to high streets varies depending on the data holders' interpretation of high streets.

First, Consumer Data Research Centre (CDRC) holds a publicly available national level dataset with retail centre boundaries and centroids (Consumer Data Research Centre 2017). The boundaries were based on an adapted DBSCAN clustering algorithm (Pavlis et al. 2018).

However, in 2021 CDRC released a new dataset based on new spatial techniques (hexagons) and new methodology (Consumer Data Research Centre 2021). Overall, there was no backward compatibility between the versions and the documentation for the new one was not available at the time of inquiry.

Second, in 2019 Office for National Statistics (ONS) and Ordnance Survey (OS) collected detailed geographical information about high streets: address, building and road attributes to create street based retail clusters which resulted in a report (Office for National Statistics 2020) and an interactive map Ordnance Survey (2020) which were both updated in 2020. This dataset is experimental and not publicly available, however was obtained through an agreement with OS.

Finally, Greater London Authority (GLA) has recently published a High Street Boundaries dataset London Datastore (2021). Regrettably, it does not specify high street locations within the Central Activities Zone (CAZ) partially covered in this study. Additionally, these boundaries were created to support the recently launched high streets data service

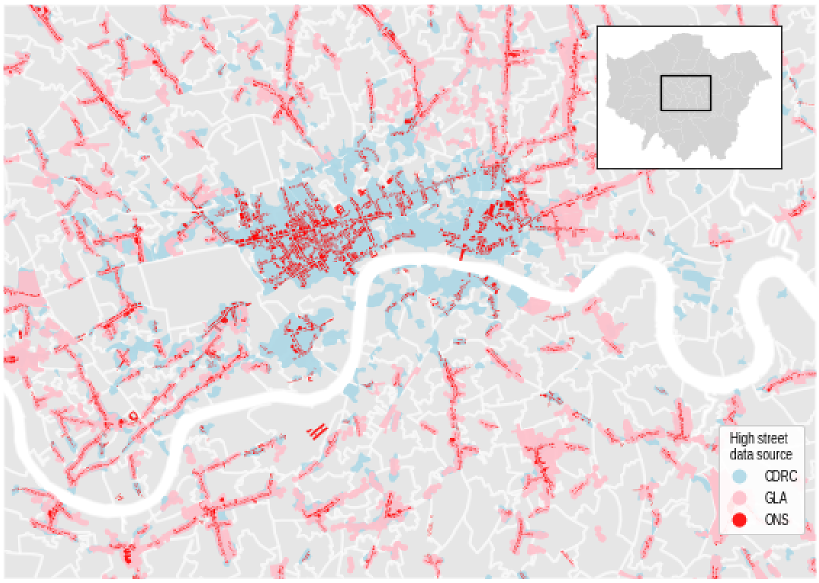


Figure 3.1: Spatial extent of high street boundaries from different sources.

(London Datastore n.d.) and to serve as attributes about high street spend and footfall data. The latter sources are not publicly available and could not be obtained for the purpose of this study. The status and availability of the high streets data service will be additionally covered in the Discussion chapter.

The spatial extent of the datasets listed above is shown in figure 3.1. It can be observed that CDRC dataset show in light blue is very unspecific in the city centre while GLA shown in pink, on the contrary, totally excluded central areas. ONS/OS data shown in red has both good coverage and granularity showing specific buildings at high streets. After comparison, the OS boundaries were chosen as the most granular and detailed despite its experimental and unofficial nature. It was used to construct a predictor variable with the square meter area in each MSOA covered with high streets.

3.2.2 Mobility data

Two key sources were used to represent mobility in London: boarding counts for bus stops in Greater London and public bike-sharing scheme data including trip origins, destinations and travel time.

Bus data had information about the number of passengers boarding by hour at each bus stop in London between between January 2018 and June 2021.

To analyse the impact of COVID three periods were picked: June 2019 to represent before pandemic situation, June 2020 to represent the lockdown and June 2021 to represent the easing of coronavirus restrictions.

Though the bus count data covers the whole London, it only contains passenger loads: how many people entered the bus at each stop, but neither where or how far they went, nor how many people exited at the bus stop. Therefore this information focuses on departures from certain locations, not arrivals.

This research focuses on mobility attractors – what makes people travel to certain locations, specifically high streets? For this purpose, either OD data or arrival counts would be more useful. This information was extracted from the cycling usage dataset. As its spatial extent is smaller than the one for buses, it was chosen as the common denominator for this study.

No pedestrian count data is publicly available. While there are several proprietary sources, they do not provide consistency in spatial and temporal granularity. For example, CDRC footfall data was requested for this research, however after certain consideration it was decided not to use it The reason is that from approximately 300 GPS trackers recording footfall in London only 60 locations had records after March 2020 when the first lockdown started. They are shown on figure 3.2. Such amount of observations unevenly spread around Greater London would not allow to properly perform travel demand analysis.

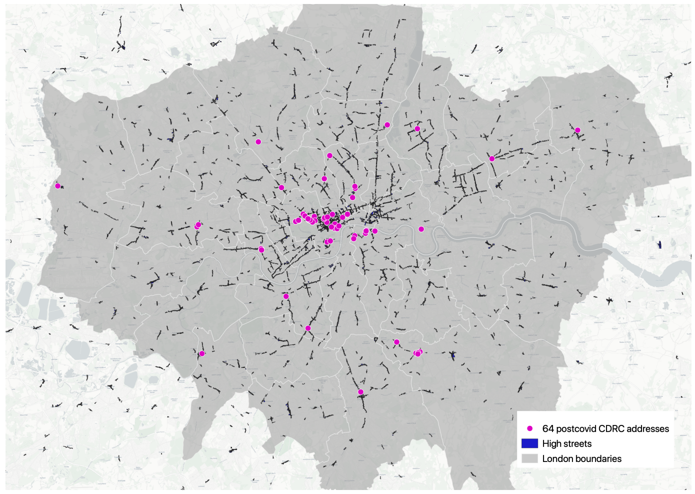


Figure 3.2: Locations of CDRC footfall data with records after March 2020

3.2.3 Other data sources

Socio-economic, built environment and transport system variables were identified through the literature review and constructed from several data sources

Demographic variables including residential and employment density, and deprivation levels were retrieved from official data sources.

Street network measures were calculated using OSMnx Python library (Boeing 2017). First, betweenness centrality was chosen to represent street centrality as it is considered to be the most relevant centrality type in transportation systems. It demonstrates the significance of a street to the flow of people through the network and highlights the value of transfer or transit in a node (Derrible 2012). To calculate weighted edge (street segment) betweenness centrality, pedestrian graph from OpenStreetMap was used. Then, median centrality measure was calculated for each MSOA. Second, street length measure was picked to represent the transit potential. It was calculated as the edges sum in the undirected representation of the graph.

Commercial data was requested from Whythawk company which holds quarterly commercial location data collected via Freedom of Information requests. Raw data included property address with postcode and street, category and subcategory, floor area, rates and occupation status from most local authorities in England and Wales. Data preparation included the following steps. First, properties were joined, first, with national postcode dataset to extract coordinates and, second, with MSOAs. Each of the four categories (Office, Retail, Industrial, Leisure) was aggregated by territory. Total number of properties was calculated too. Additionally, three most popular retail subcategories were aggregated: high street retail, restaurants and cafes, superstores and retail warehouses.

OpenStreetMap POI data with tourist attractions downloaded through Overpass turbo web service was aggregated in the same manner.

Table 3.1: List of data sources used in the study

Data	**Description**	**Variables**	**Source**
Geographic			
Greater London boundaries	Cropped from national dataset. Used to crop other spatial data sources	-	ONS Open Geography portal
MSOA boundaries	Spatial unit	-	London Datastore
Postcodes	Cropped from national dataset. Used to geocode commercial property dataset	-	ONS Open Geography portal
High streets	Spatial extent and profile of high streets across GB	total high street area	Provided by OS upon request
Mobility			
Boarding counts for bus stops		mean total passenger counts during weekend	Provided by TfL upon request

Bike-sharing usage	Weekly files with trip origins, destinations and travel time	mean total arrivals during weekend, mean total departures during weekend	TfL Open Data Portal
Socio-economic			
Population	2018-based housing-led population projections by GLA	number of residents	London Datastore
Employment	Residents aged 16 to 74 in employment in the area the week before the Census	number of employees	ONS Nomis
Index of multiple deprivation	Cropped from 2019 national dataset	deprivation score	National Statistics GOV.UK
Transport system			
Street network	Street graph was obtained to calculate graph measures for each street segment	edge betweenness centrality, street length	OSMnx package
Bus stops	Used to get coordinates for bus boarding data and for independent variable generation	number of bus stops	TfL Open Data Portal
Bike stations	Added 11 missing stations manually and dropped 2 incorrect outliers. Used to get coordinates for bike docks and for independent variable generation	number of bike stations	Provided by TfL upon request
Built environment			

Commercial property	Quarterly reports by local authorities in England with property address, classification and occupancy	number of offices, industrial, leisure places and retail places also split into restaurants and superstores	Provided by Whythawk
Tourism attractions	Open data on tourist attractions	number of POIs	OSM
Greenspace areas	Cropped from national dataset	total greenery area	OS Open Greenspace

The descriptive statistics for each variable are summarised in table 3.2. As variation in commercial property variables has not changed significantly over years, only one year variables descriptive stats are given.

3.3 Ethical evaluation of data

This section elaborates on the ethical implications of the study which can be narrowed down to two areas: dealing with potentially sensitive sensitive information about individuals and using proprietary data sources.

Though this study aims to understand how people's mobility patterns have changed over lockdown, its interest is beyond the individual. We are concerned with understanding the consequences of the travel choices expressed in aggregated trip counts. Not only sensitive data which could potentially violate one's privacy was not used, but also it is generally is outside the interest of this study.

Most of the data used in this research is open and publicly available. Several proprietary data sets were provided by request and are not accessible to the general public.

First, bus boarding data for 2018–2021 was requested from TfL. The data for each bus stop was aggregated into hourly counts on the side of the provider. Only boarding data was included, no potentially sensitive information about trips destinations, purposes or durations was provided. If bus counts were less than 5, they have been rounded up to 5 to avoid the potential risks to link the information with specific individuals. The process was fully performed by TfL as they are obliged to do in accordance with British data protection legislation. The requested data was similar in its structure with other mobility data published by TfL under FOI requests.

Bicycle sharing data was obtained from TfL Open Data Portal and is regularly updated and accessible to general public. It includes unaggregated information about specific trips including their length, start and finish timestamps and dock stations. However, no information associated with users is included.

Second, commercial property database collected by Whythawk was used for this study. Data provider derives the commercial property ratepayer data through regular FOI requests to local authorities and then processes, merges with open data and aggregates it. Only locations and categorisation of businesses were used for this study, neither financial nor occupancy data were utilised.

Third, high street data which only includes non-personal geographic information was requested from Ordnance Survey. The dataset is new and has only been developed during recent two years, thus certain errors could potentially evolve from it. However, the visual comparison with two other public data sources did not reveal them.

The code used for the study is published on github. The original datasets which were provided for the study by request are not published, however we provide values aggregated for the spatial units of this study to assist reproducibility of the research.

3.4 Analysis

Figure 3.3 summarises the overall pipeline of this study.

3.4.1 Temporal and spatial patterns of trips

Mobility data was initially visualised. First, time series plots were created depicting hourly change of average trips counts for buses and bicycles. Second, trip numbers were separated by days of week to compare work-related and leisure-related mobility. Third, average weekend trips were mapped.

3.4.2 Spatial autocorrelation

Local indicators of spatial association (LISA) were used to measure spatial dependance in the trips for each mode and period Anselin (1995). The spatial weights matrix was created using the queen criterion of contiguity which defines polygons to be neighbours if they share either a common edge or a vertex Anselin et al. (2010). Weights were row-standardised and Local Moran's I statistic was calculated. Then, so called hot and cold spot analysis was performed as four clusters displaying different forms of spatial association were identified using 5% threshold for statistical significance and mapped.

3.4.3 Model specification

After calculating global Moran's I statistic a spatial regression model was specified. A spatial lag model (SLM) with maximum likelihood estimation was chosen over Spatial Error Model (SEM) as it is based on a general assumption that the dependant variable might be influenced not only by independent factors, but also but neighbouring results. In our case, the amount of trips in one location influences the amount of trips in the neighbouring one. To simplify, it makes perfect sense as people want to travel somewhere avoiding crowding or looking for a free dock station for bike. Therefore we believe that SLM is more suitable for our research question.

Secondly, a multiple linear regression, SLM and SEM were built for one response variable (bus trips in 2019). SLM had the best performance with the lowest mean squared error

(MSE) and the highest R-squared values.

The SLM includes a spatial lag of the dependent variable into the equation and can be summarised as follows:

$$y_i = \beta_0 + \beta_1 x_i + \rho w_i y_i + \epsilon_i \tag{3.1}$$

where:

y_i is the dependent variable,

β_0 is the model intercept,

β_1 is the slope parameter,

x_i is an independent variable,

ρ is a spatial autocorrelation coefficient, positive value indicates that areas are expected to generate/attract more trips if their neighbours, on average, have high trip amounts,

$w_i y_i$ is the spatial lag of y,

ϵ_i is the non-spatial random error.

The dependent variables are the average trips by bus from each MSOA and trips by bike to each MSOA for three time periods.

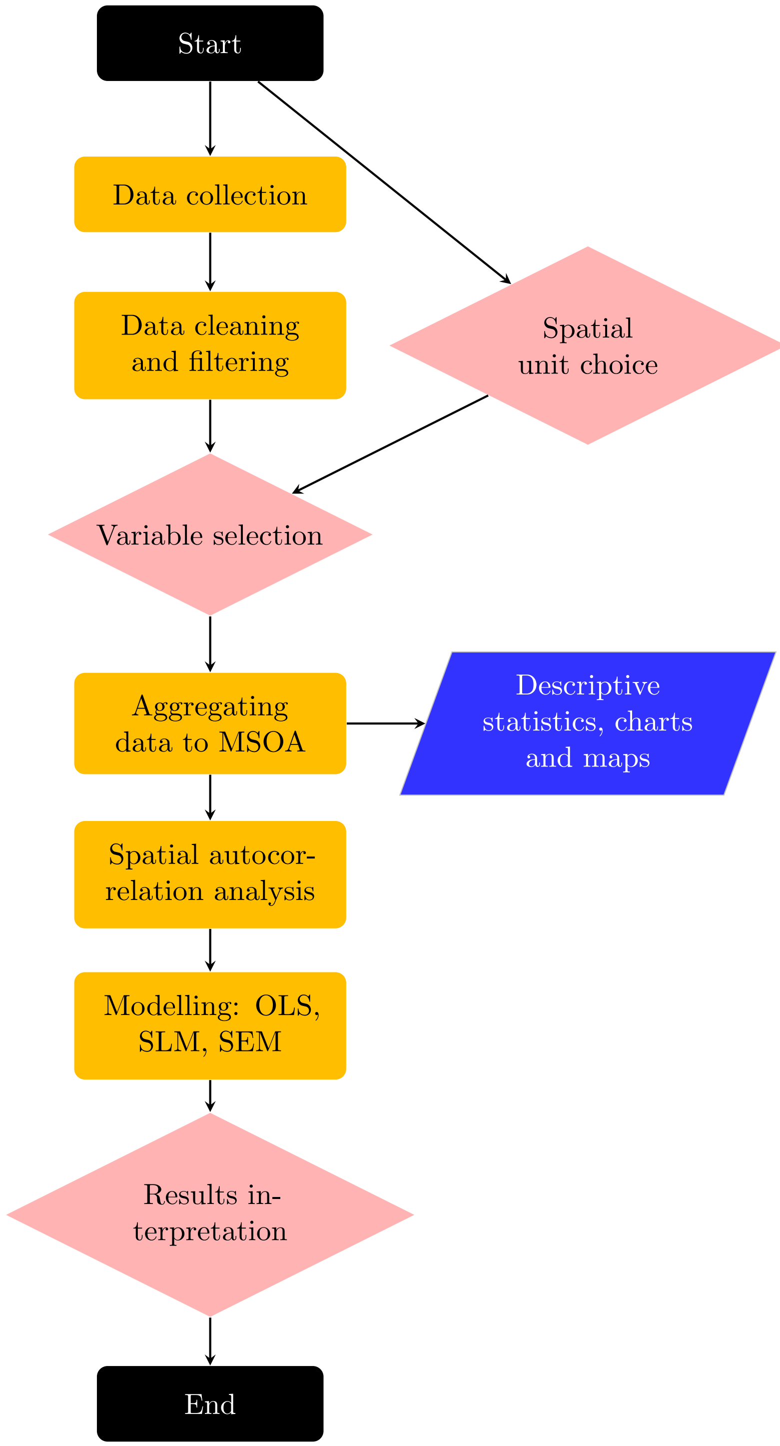
The independent variables come in three groups: related to demographics, built environment and to transport system per se.

All variables except deprivation level have positively skewed distributions and therefore were transformed into their natural logarithms to meet the regression assumptions. As some variables like *number of offices* include zero values a constant was added, so that $log(x + 1)$ transformation was performed.

Table 3.2: Descriptive statistics of variables

Category	Variable	Min.	Max.	Mean	Std. dev.
Travel demand	bus trips 2019	868.50	54,545	8361.43	8742.17
	bus trips 2020	296.75	13,189	2177.81	2111.72
	bus trips 2021	506.00	33,398	5468.88	5919.80
	cycle arrivals 2019	0.00	67631.00	5530.27	8248.58
	cycle arrivals 2020	0.00	47689.00	6161.56	6463.23
	cycle arrivals 2021	0.00	44949.00	5130.23	6515.09
Socio-economic	population	5829	24,964	9298	2516
	employment	919.00	356,706	13276	34950
	deprivation	7.50	49.70	23.90	9.01
Transport system	n of bus stops	3.00	109.00	17.34	12.30
	n of bike docks	1.00	43.00	5.49	5.29
Built environment	street length	7522.40	140,254	24,016	17,007
	median ebc	1488.00	34,574	6769.62	4723.67
	msoa area	293,825	3589,007	731,869	474,813
	green area	0.00	2285,941	93,487	218,650
	tourism poi	0.00	56.00	3.27	6.82
	high street area	0.00	537,540	31,992	65,667
	total properties 19	70.00	21,427.00	899.96	2124.48
	office 19	5.00	16,484.00	522.82	1604.90
	retail 19	19.00	3844.00	250.75	424.30
	leisure 19	0.00	144.00	11.57	18.58
	industrial 19	0.00	516.00	47.08	69.81
	other 19	7.00	927.00	67.74	105.37
	restaurants 19	0.00	583.00	45.13	82.94
	superstores 19	0.00	371.00	7.18	31.32

Figure 3.3: Flowchart of the overall analysis



Chapter 4

Results

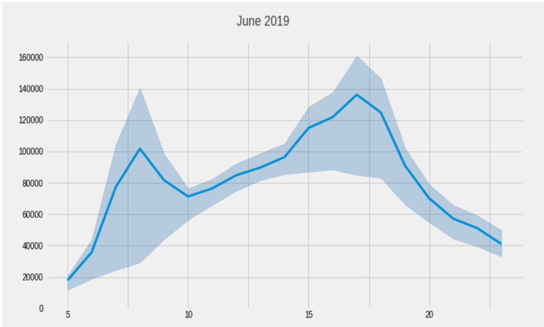
4.1 Temporal and spatial patterns of trips

The initial step of the analysis is spatiotemporal visualisations of data which help us detect some evident changes in mobility rhythms in London over lockdown.

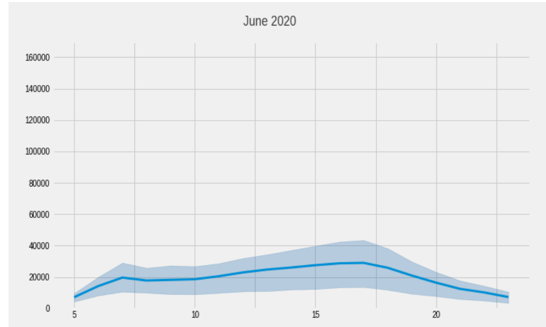
4.1.1 Bus trips

Figure 4.1 shows daily amount of passengers entering a bus across all stops (N= 2636) in the study area. The blue line represents average value and light blue area is the 10 - 90% confidence interval.

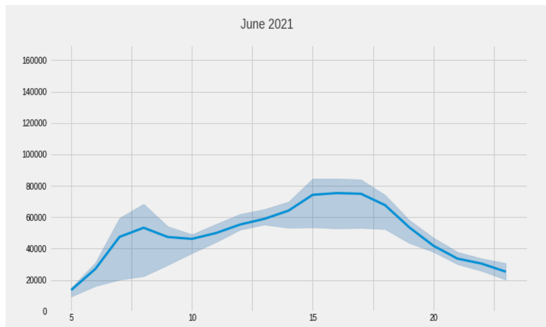
Though all days of the week are aggregated into one average day for this graph, June 2019 shows two evident peaks: morning 7–9 and evening 16–18 traditionally associated with commute. In June 2020, in the midst of the first lockdown, the passenger volume had dropped dramatically, the morning peak disappeared completely and the curve flattened. By June 2021 the peaks were back, but the total volumes have not restored to the pre-COVID levels.



(a) 2019



(b) 2020



(c) 2021

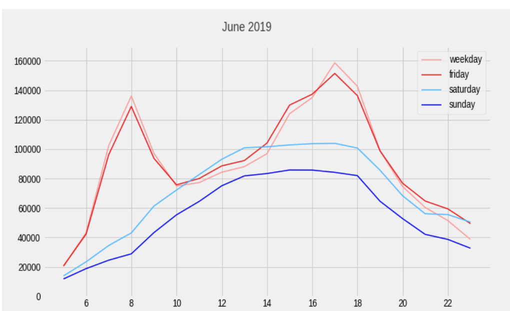
Figure 4.1: Mean daily amount of bus passengers for 3 study periods.

To analyse the high street performance commute should be separated from other trips. As trip destination and purpose were unknown, the data was aggregated into different days of the week to compare the temporal patterns. Four week days from Monday to Thursday were aggregated into one average weekday. It was assumed that Friday trip patterns might differ from previous days as people leave work earlier, however the plots at Figure 4.2 demonstrate there is no significant difference: pink (average Monday to Thursday) and red (Friday) lines are almost indistinguishable during all three time periods. Saturday and Sunday profiles, shown in light blue and blue respectively, have similar bell shapes, but Saturday volumes are higher than Sunday ones.

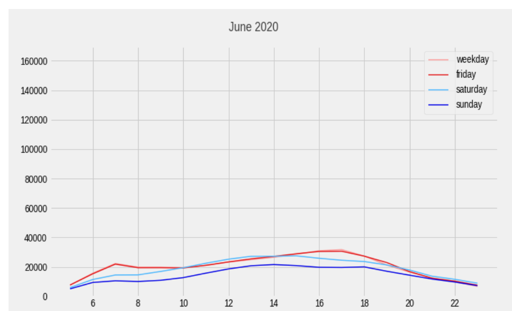
Figure 4.2a for June 2019 looks similar to plot 4.1a with trips aggregated into one day. There are two peak periods in the morning and in the evening. The amount of trips during the weekday peak hour is almost twice larger that the weekend volumes at the same period.

The trip patterns for June 2020 are shown twice in separate graphs with different scales. Figure 4.2b has the same y-axis scale as graphs for 2019 and 2021 for general comparability, while figure 4.2c is zoomed in to see the local variation in more details.

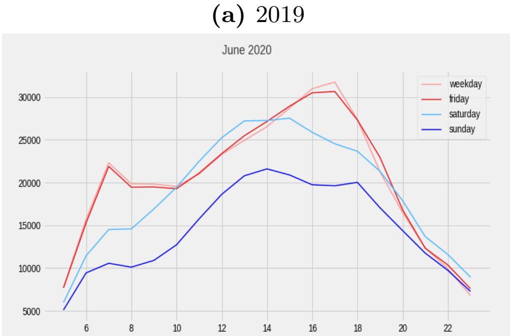
As it is evident from figure 4.2c in 2020 the amount of weekday trips dropped up to 5 times in comparison with previous year and became almost equivalent to the weekend volumes. The morning peaks dropped larger than evening ones. As for weekends, the shape has slightly changed too. Before COVID the trips on average reached their high by 1pm and then their amount stayed flat till 6pm. In 2020 the volumes started declining after 3pm. It can be observed that in 2021 the 1–6pm line started flattening back, but is still slightly askew.



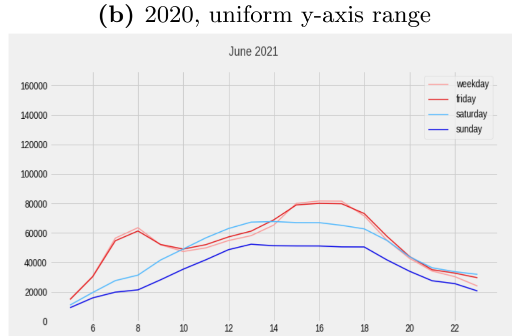
(a) 2019



(b) 2020, uniform y-axis range



(c) 2020, dynamic y-axis range

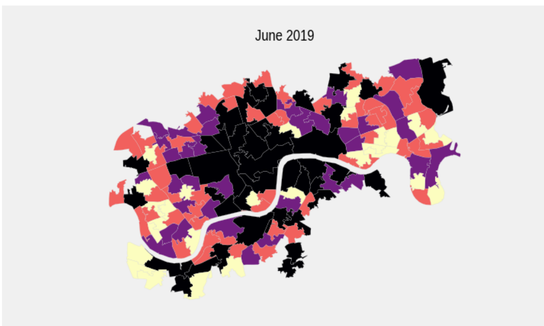


(d) 2021

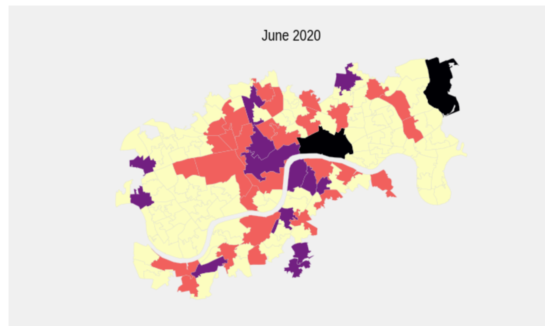
Figure 4.2: Mean daily amount of bus passengers by day of the week for 3 study periods.

Finally, bus trips were aggregated by spatial units and mapped. The maps demonstrate concentric nature of trip distribution with most trips starting in Westminster and City of London over all periods of study. Western areas including Kensington and Chelsea and Eastern areas including Tower Hamlets borough demonstrate the largest trip reduction in 2020 in 2021.

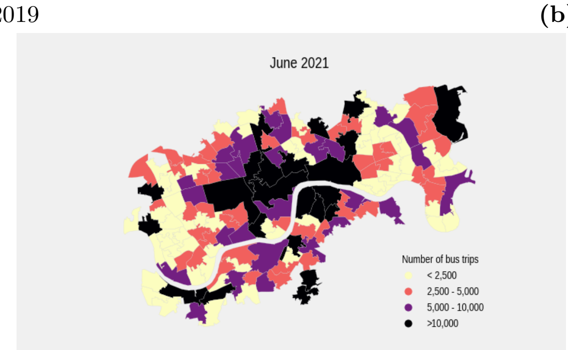
The geographical pattern will be examined in more detail in section4.2 to determine whether the overall spatial distribution is random or has a certain structure.



(a) 2019



(b) 2020



(c) 2021

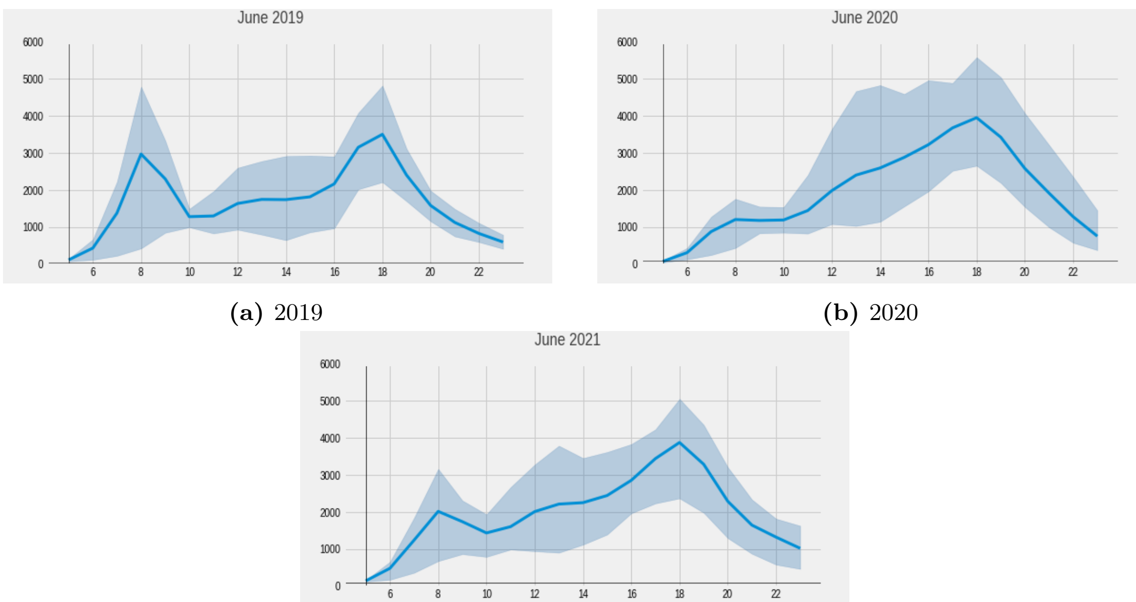
Figure 4.3: Average weekday bus passengers aggregated by MSOA

4.1.2 Bike trips

While bus mobility dropped in 2020 and started to recover in 2021, the cycling demonstrates a different dynamics. The lockdown generally increased the popularity of cycling as most locations and time periods demonstrate a demand surge.

As it is evident from figure 4.4, the 2019 time series plot for cycling has 2 major peaks and therefore is similar to the bus plot for the same period described in the previous subsection. While evening bus peaks outperformed morning ones, the bike peaks were almost similar in size. It might indicate that buses used to be less popular in the morning as they are slower than underground, while the bikes are equally popular as the last mile transportation.

The shape of 2020 plot changed dramatically as morning peaks disappeared completely and the variation in data increased for evening periods.



(a) 2019

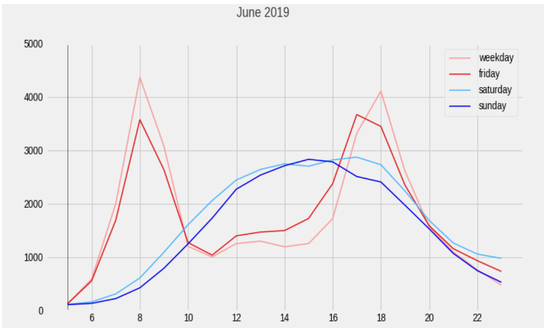
(b) 2020

(c) 2021

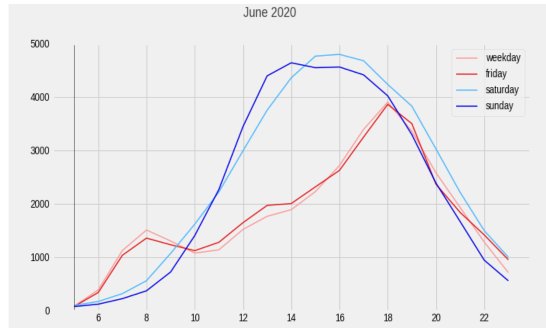
Figure 4.4: Mean daily amount of cycle hire trips for 3 study periods.

Splitting the data into different days helps understand this change better. Figure 4.5b illustrates that the weekend cycling activity outperformed the weekdays during both day and evening periods and caused the widening of the confidence interval.

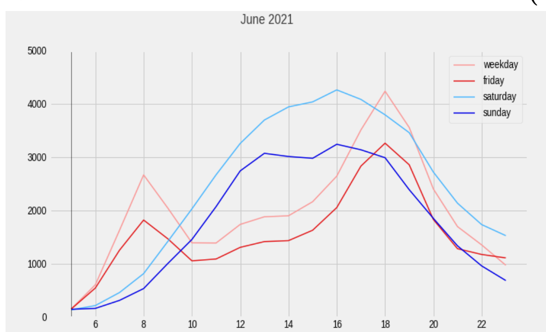
It is noteworthy that in June 2021 the average weekend number of bike trips slightly decreased in comparison to 2020 however was still higher than June 2019 levels.



(a) 2019



(b) 2020

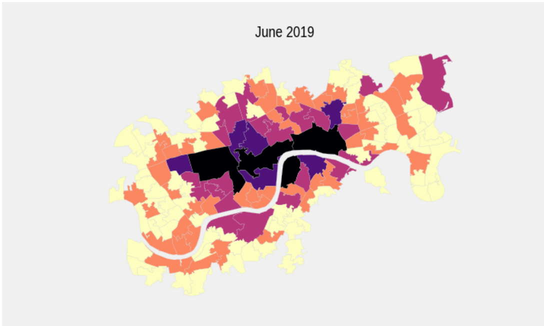


(c) 2021

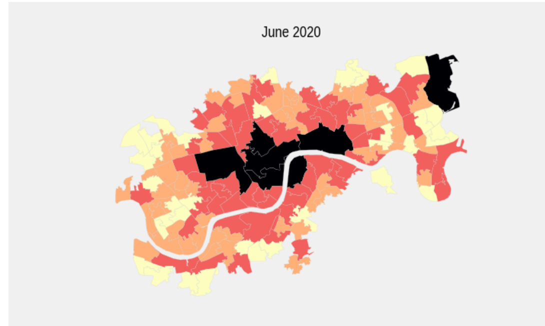
Figure 4.5: Mean daily amount of cycle hire trips by day of the week for 3 study periods

The maps with weekend trip arrivals aggregated by MSOAs show that the key attraction increase of 2020 was located in Westminster and City. However, further areas with previously low demand also managed to grow. Surprisingly, the middle and frontier parts of the study area demonstrate higher demand expressed in solid orange color in map 4.6b.

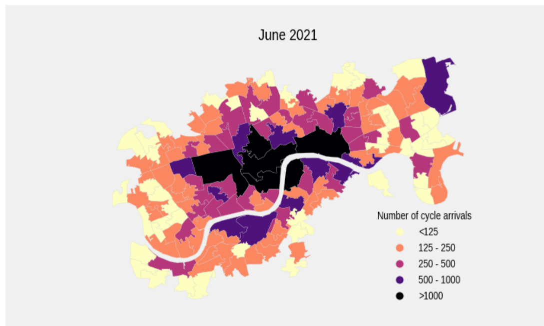
It might indicate that before COVID people had specific reasons to travel to certain locations. As most businesses were closed, the reasons to travel presumably changed and the distribution of trips became more homogeneous.



(a) 2019



(b) 2020



(c) 2021

Figure 4.6: Average weekday cycle hire trips aggregated by MSOA

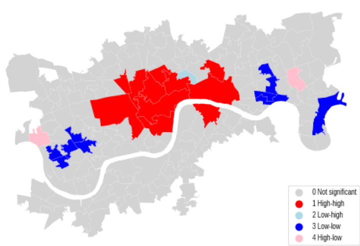
4.2 Spatial autocorrelation

The results of the LISA analysis are shown in maps 4.7 and 4.8. There are two types of positive (High-High and Low-Low) and two types of negative autocorrelation (High-Low and Low-High). Red areas represent the first type respectively or hot spot cluster where unusually high levels of trips are surrounded by neighbours with also high levels. On the contrary, bright blue stands for cold spots or Low-Low areas. Pink areas represent the so called diamond cluster where high values are surrounded by low ones. Light blue territories are called 'doughnut' cluster as low values are surrounded by high values.

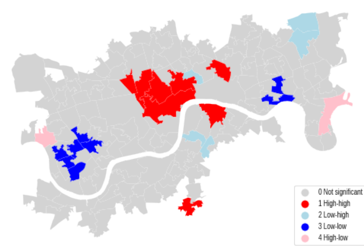
For buses before COVID the most central London areas were clearly the main activity centres, however they shrank during the 2020 lockdown. The most touristic and popular leisure destinations like Victoria and St James Park, Belgravia, Hyde Park surroundings, City of London, Camden lost the status of activity centres. South of Thames, there is only one unit being an activity centre. This is a territory in Southwark where Borough Market is situated. The analysis shows that this area managed to be a stable weekend trip generator even during the pandemic.

The maps also show consistent cold spots situated in Fulham, Earl's Court and South Kensington. This phenomenon might be explained by two hypotheses: 1) these are affluent residential areas which do not have many attractions to non-residents; 2) locals might avoid using public transport.

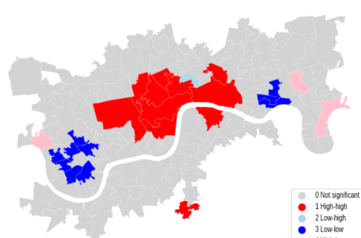
Overall for buses, the 2020 map looks like a disruption of traditional mobility patterns with decreased activity which have been reestablishing back to normal in 2021.



(a) 2019



(b) 2020

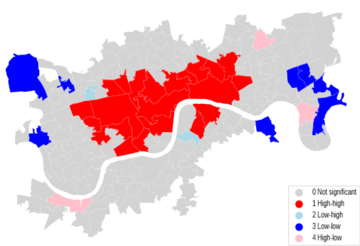


(c) 2021

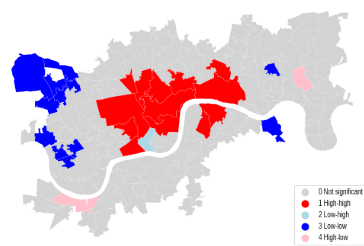
Figure 4.7: Local Moran cluster map for average bus departures on a weekday

For cycling hires, the maps demonstrate same dynamics for hot spots: the number of central activity centres has dropped almost twice in 2020, but bounced back in 2021. As for cold spots the north-western part of the study area showed a decline of values with the blue cluster expanding in Shepard's Bush and Notting Hill. The cluster can still be observed in the 2021 indicating that the territories could not reinstate their weekend potential.

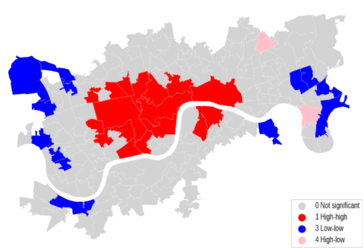
It is also notable, that a cold spot cluster in Tower Hamlets including Poplar and Bow Common territories has disappeared in 2020, but re-emerged in 2021. That might indicate that during lockdown people became more willing to travel to areas that had previously not specifically attractive and that the demand became distributed more evenly from the spatial perspective.



(a) 2019



(b) 2020



(c) 2021

Figure 4.8: Local Moran cluster map for average cycle arrivals on a weekday

4.3 Spatial regression

Finally, to understand which features shape the observed mobility patterns 9 spatial lag model were run: for 3 variables (bus departures, bike arrivals and bike trip length) of each period. The results are presented in tables 4.1, 4.2.

The pseudo coefficients of determination (squared correlation between actual and predicted dependent variable) demonstrate relatively good levels for bus and bike count data varying between 0.60 and 0.75. Yet this measure does not account for spatial autocorrelation and induced heteroskedasticity, therefore alternative measures of fit are used for spatial models (Anselin & Rey 2014).

The Log Likelihood value can be used to to compare the models. The higher it is, the better fit for the data. We can see that for each variable 2019 and 2021 values are more similar and 2020 stands out. For bus departures 2020 model performed worse that 2019 and 2021, while for bike arrivals, on the contrary, log likelihood is higher in 2020.

The Akaike Information Criterion (AIC) is an alternative way to compare models through the out-of-sample prediction error estimation. The lower it is, the better the fit. Again, for bikes cumulative arrivals are lower in 2020, while bus volumes are better predicted in 2019 and 2021.

4.3.1 Demographic variables

Neither resident population, nor employment population demonstrated statistically significant relationship with the trips generation. At the same time, deprivation score manifested its influence on the trips. The relationship is positive for bus departures and negative for bike arrivals. In other words, bus passengers tend to leave deprived territories and bike users avoid arriving there. Though the coefficient is relatively small, for buses it grew from 0.011 in June 2019 to 0.017 in June 2020 and then slightly decreased to 0.015.

4.3.2 Transport system

In accordance with other studies (Mateo-Babiano et al. 2016*a*,*b*) , there is a solid link between the supply of transport infrastructure and its usage. For buses beta-coefficient varies between 0.7–08 and for cycles between 1.3–1.6. Morton et al. (2021) use the bike sharing example and warn not to overstate this possibly chicken or egg situation as infrastructure planners probably allocated dock stations closer to potential demand and therefore it might be difficult to distinguish causes from effects.

Notoriously, the bus trips revealed positive association with dock stations in 2019 and 2021, but not in 2020. Our intuitive interpretation is that during non-lockdown periods these two modes could be part of same journeys as bike sharing systems are often considered to solve the 'last mile problem' and connect people with public transportation. Shaheen & Chan (2016)

4.3.3 Built environment

During lockdown areas with more high street areas demonstrated positive relationship with bus departures and negative with bike arrivals. Furthermore, total amount of businesses displayed negative relationship within all time frames, amount of offices had positive relationship, while retail and leisure properties have not demonstrated statistically significant links with mobility volumes. These results turned out to be somewhat counterintuitive, as we would expect people not to travel to office zones and rather travel to environments with retail and leisure amenities. A further investigation is required to explain the causality of these observations. For example, origin-destination analysis could be appropriate to understand which zones generate flows to these attractors.

Table 4.1: SLM results for bus counts

	Bus trips 2019 (ln)			**Bus trips 2020 (ln)**			**Bus trips 2021 (ln)**		
	Beta	**S.E.**	$P > \|t\|$	**Beta**	**S.E.**	$P > \|t\|$	**Beta**	**S.E.**	$P > \|t\|$
CONSTANT	1.775	2.478	0.474	-1.74	2.284	0.446	-0.132	2.415	0.956
population (ln)	0.044	0.191	0.816	0.222	0.179	0.215	0.181	0.186	0.332
employment (ln)	-0.033	0.101	0.747	-0.048	0.095	0.617	-0.028	0.1	0.776
deprivation	0.011*	0.005	0.042	0.017*	0.005	0.001	0.015*	0.005	0.003
n of bus stops (ln)	0.794*	0.123	0.0	0.725*	0.116	0.0	0.77*	0.121	0.0
n of bike docks (ln)	0.225*	0.11	0.04	0.19	0.103	0.065	0.228*	0.107	0.033
street length (ln)	-0.274	0.296	0.354	-0.213	0.278	0.444	-0.029	0.29	0.919
median ebc (ln)	-0.101	0.114	0.376	-0.149	0.108	0.169	-0.131	0.113	0.248
msoa area (ln)	0.526	0.282	0.062	0.464	0.264	0.078	0.304	0.276	0.272
green area (ln)	-0.018	0.021	0.4	-0.013	0.02	0.504	-0.011	0.021	0.594
tourism poi (ln)	-0.029	0.059	0.626	-0.079	0.055	0.153	-0.057	0.058	0.328
hs area (ln)	0.032	0.017	0.06	0.038*	0.016	0.02	0.029	0.017	0.08
total prop (ln)	-1.187*	0.325	0.0	-1.118*	0.298	0.0	-1.08*	0.311	0.001
office (ln)	0.442*	0.129	0.001	0.391*	0.119	0.001	0.389*	0.126	0.002
retail (ln)	0.703	1.084	0.516	1.107	1.07	0.301	1.029	1.098	0.349
leisure (ln)	0.042	0.06	0.482	0.019	0.057	0.736	0.032	0.059	0.591
industrial (ln)	0.051	0.049	0.29	0.052	0.046	0.253	0.046	0.047	0.332
other prop (ln)	0.161	0.14	0.248	0.288*	0.13	0.027	0.204	0.135	0.131
restaurants (ln)	0.045	0.189	0.813	-0.061	0.199	0.759	-0.03	0.206	0.883
superstores (ln)	-0.043	0.065	0.504	-0.088	0.062	0.156	-0.051	0.063	0.415
Spatial interaction									
W	0.028	0.082	0.733	0.16*	0.081	0.047	0.087	0.08	0.276
Model fit									
AIC	233.918			215.146			227.533		
Log likelihood	-94.959			-85.573			-91.766		
Pseudo R-squared	0.7402			0.7313			0.7509		

Table 4.2: SLM results for cycle arrivals

	Cycle arrivals 2019 (ln)			**Cycle arrivals 2020 (ln)**			**Cycle arrivals 2021 (ln)**		
	Beta	**S.E.**	$P > \|t\|$	**Beta**	**S.E.**	$P > \|t\|$	**Beta**	**S.E.**	$P > \|t\|$
CONSTANT	8.082*	3.263	0.013	4.553	3.682	0.216	9.391*	3.405	0.006
population (ln)	-0.188	0.25	0.451	-0.121	0.285	0.671	-0.247	0.259	0.341
employment (ln)	0.039	0.132	0.765	0.019	0.152	0.899	0.048	0.138	0.73
deprivation	-0.016*	0.007	0.025	-0.017*	0.008	0.031	-0.017*	0.007	0.022
n of bus stops (ln)	-0.058	0.161	0.72	-0.016	0.184	0.932	0.003	0.167	0.987
n of bike docks (ln)	1.587*	0.143	0.0	1.338*	0.162	0.0	1.534*	0.147	0.0
street length (ln)	-0.192	0.386	0.62	-0.351	0.441	0.427	-0.157	0.401	0.695
median ebc (ln)	0.087	0.149	0.559	0.137	0.169	0.419	0.164	0.155	0.29
msoa area (ln)	-0.057	0.372	0.879	0.379	0.42	0.367	-0.074	0.385	0.848
green area (ln)	0.021	0.028	0.446	0.012	0.032	0.701	0.015	0.029	0.609
tourism poi (ln)	0.137	0.078	0.08	0.089	0.088	0.312	0.145	0.081	0.071
hs area (ln)	-0.023	0.022	0.299	-0.053*	0.026	0.04	-0.04	0.023	0.087
total prop (ln)	-0.821	0.425	0.054	-1.222*	0.475	0.01	-1.361*	0.432	0.002
office (ln)	0.302	0.169	0.075	0.389*	0.19	0.04	0.465*	0.175	0.008
retail (ln)	-0.715	1.416	0.614	0.29	1.7	0.865	-0.492	1.52	0.746
leisure (ln)	0.154	0.079	0.051	0.159	0.09	0.077	0.246*	0.082	0.003
industrial (ln)	0.151*	0.064	0.018	0.174*	0.073	0.016	0.206*	0.066	0.002
other prop (ln)	-0.404*	0.182	0.027	-0.246	0.206	0.232	-0.377*	0.187	0.044
restaurants (ln)	0.206	0.247	0.404	0.052	0.317	0.869	0.196	0.286	0.492
superstores (ln)	0.102	0.085	0.229	0.111	0.099	0.261	0.113	0.088	0.197
Spatial interaction									
W	-0.014	0.088	0.872	-0.066	0.098	0.496	-0.06	0.089	0.499
Model fit									
AIC	316.584			357.787			328.196		
Log likelihood	-136.292			-156.894			-142.098		
Pseudo R-squared	0.7325			0.6016			0.7123		

Chapter 5

Discussion

5.1 Spatiotemporal patterns of trips

We observed that bus travel demand decreased dramatically and is far from pre-COVID levels. This results corresponds with the trends described in 2.1 and might indeed imply the emergence of the 'fear of transit'.

At the same time the cycling weekend demand managed to outperform not only the weekday volumes at that period, but even pre-COVID weekday volumes. The 2021 weekend levels almost did not changed in comparison with 2020 which might indicate the potential long-term endurance of this demand which, again, goes in line with the prevalent opinions.

5.2 Spatial autocorrelation

The other trend discovered in cycle demand has not managed to establish a foothold yet. The LISA analysis demonstrated that during lockdown cold spots at underused Eastern docks disappeared, possibly indicating a smoother distribution of trip arrivals and an increased propensity to travel to a variety of localities. However the cold spot reemerged in

2021.

This kind of analysis might be implemented into the city policy evaluation as an indicator of place attractiveness. As many researchers discuss possible exodus from the city centres to small towns and suburbs (Nathan & Overman 2020), it is important to look closely at the reliability of this trend.

5.3 Model Interpretation and Policy Implications

Our trip generation model proved that there is a strong relationship between the supply of transport infrastructure and the demand for trips which supports previous studies in different cities. Interestingly, the was a drop of positive association between bus trips and amount of cycling dock stations in 2020. Our idea, yet totally speculative, is that the status of cycle hire as the last-mile change could have changed during that period. This idea builds upon the temporal patterns showing the weekend demand overtaking the weekend one. However, this idea needs to be investigated further.

Surprisingly for us, the built environments factors showed mixed results. Our model showed that total amount of businesses had a negative effect on travel, amount of offices had positive relationship, retail and leisure properties have not demonstrated statistically significant effects at all.

At the same time, deprivation level showed s significant link with trip generation. The Index of Multiple Deprivation comprises income, employment, crime risks, quality of education, health and environment. It essentially means that supporting local communities, not only businesses, should be an integral part of London strategy to support high streets. It is not attracting new visitors, it is rather not losing those you have.

GLA broadly divide high street use into three categories: essential shopping, leisure and socialising, serious shopping and entertainment (Greater London Authority 2020).

As was discussed in Chapter 2 the role of the first category is declining. And for the last two, need to be ‘pleasant and aesthetic to encourage people to visit and stay longer’ (Greater London Authority 2020, slide 8).

Our results go in line with this statement: we demonstrate that area’s deprivation level as a proxy of its general attraction are more important in generating weekend mobility than simply density of retail properties.

5.4 Limitations

There were several limitations to this research.

First, analysis only covers 154 MSOAs predominantly in central London. As was discussed in 3.1 COVID established a reallocation of resources between urban centre and periphery (Local Data Company 2021), therefore a deeper look into mobility of far-from-centre neighbourhoods would be of interest.

Second, the research was narrowed down to weekend mobility as trip purposes for aggregated travel data are not given. Additionally to analyse high street performance pedestrian data would be the most suitable source of information.

Thirdly, origin-destination data would be of high use to understand the movement patterns change. The ’new mobility paradigm’ prescribes that the trips become more individual and despite the rise of technologies people still want to travel (Sheller & Urry 2006). Origin-destination data could help investigate whether the trends described in the ‘new mobility paradigm’ were accelerated by the pandemic through the look at movement as a set of spatiotemporal characteristics such as trip length, speed and regularity.

Finally, occupancy data would be of use for the high street study. The Whythawk dataset includes this information, but several boroughs like Islington, Hackney and Westminster refuse to disclose this information. Excluding them from the analysis would make the study area too small.

Overall, this research gave an overview of the influence of COVID-19 on weekend mobility, but the presented amount of data does not allow to fully use the potential of the urban mobility analysis in the context of high streets.

These challenges could be addressed with the new high streets data service developed by GLA (London Datastore n.d.). However, being advertised as a tool for public good this source is not publicly available and at this point cannot be accessed for academic purposes.

Chapter 6

Conclusion

This research contributes to the ongoing analysis of the influence of COVID-19 on human mobility in cities.

A spatial lag model proved to be useful to evaluate the link between features of local environment and the mobility change before, during and after the lockdown in 154 MSOAs in London. The model demonstrated significant negative relationship between trip production and deprivation levels and total amount of businesses and positive relationship with the transport system infrastructure.

Certain insights could be obtained from the spatiotemporal analysis. It demonstrated, for instance, that weekend cycling outperformed weekday activity, while bus usage is still low possibly indicating the establishment of ‘fear of transit’ trend.

Overall, this results could be beneficial to urban policy makers, transport planners and businesses as the city recover programs are being developed.

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