The Demand for Cycle Sharing: Examining the links between weather conditions, air quality levels, and cycling demand for regular and casual users

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Abstract
This paper examines temporal variation in the demand for cycling to understand how environmental conditions may promote or hinder active travel. The role of environmental conditions is considered in terms of the prevailing weather as well as concentration levels of local air pollutants. Using data derived from the London Bicycle Sharing Scheme, a set of autoregressive distributed lag models are specified to explore these relationships. The models distinguish casual cyclists from regular cyclists to allow the analysis to consider the demand profiles of these two market segments separately rather than jointly. The analysis makes use of an open science approach, with the data inspected, the models applied, and the results derived being made freely available to interested parties through an online repository.

The results of the models indicate that the demand of casual cyclists is more strongly linked to concurrent weather condition as compared to the demand of regular cyclists, though regular cyclists seem to be more inclined to delay trips to avoid inclement weather. The associations between cycling demand and air quality levels is mixed, with high concentrations of ozone linked with lower levels of demand from regular cyclists while high concentrations of particulate matter 10 are positively related to both regular and casual cycling demand. The findings of this paper could provide benefits to bicycle sharing system managers such as in planning the schedule of maintenance work as well as highlighting the need to inform cyclists about the actions they can take to reduce their exposure to local air pollutants.

Keywords
Cycling demand, environmental determinism, active travel, weather, air quality, time series analysis

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1. Introduction

The promotion of active travel practices such as cycling represents a primary pillar of strategies aimed at shifting urban transport systems onto sustainable trajectories. The potential benefits of expanding urban cycling are extensive, covering reductions in the emission of local and global air pollutants, improvements to public health and wellbeing, and enhancing the liveability of cities (Lindsay et al. 2011; Lowe 1990). To support a shift to cycling, research has considered the efficacy of policies intended to promote cycling (Maibach et al. 2009; Fishman et al. 2013; Handy et al. 2014; Ursaki and Aultman-Hall, 2015) as well the factors that underpin cycling demand profiles (Shaheen et al. 2010; Parkes et al. 2013; O'Brien et al. 2014; Caulfield et al. 2017; Nikitas, 2018; Caspi and Noland, 2019; Scott and Ciuro, 2019). This paper contributes to this later issue of demand profiles by evaluating how environmental conditions are linked to the volume for cycling.

Cyclists are routinely exposed to environmental conditions throughout their travel. As a result of this, cyclists tend to modify their behaviours according to the prevailing environmental conditions (Böcker et al. 2013; Koetse and Rietveld, 2009). This behavioural adaptation generally involves avoiding conditions which lead to unpleasant cycling experiences and seeking those conditions that are linked with enjoyable rides. This response connects with a principal concept in geography, being that the actions of humans are affected by the environments in which they inhabit. Two sets of environmental conditions are considered in this paper. The first are weather patterns such as air temperature and precipitation which have been examined extensively in the existing literature (Miranda-Moreno and Nosal, 2011; Singhal et al., 2014; Zhao et al., 2018b; Kutela et al. 2019). The second is air quality levels covering the concentration rates of local air pollutants such as nitrogen oxides.

The link between air quality and cycling demand represents a topic which has received much less attention in the literature. Plausible arguments can be proposed for both a positive and negative relationship to be present. For example, with cities introducing air quality alerts to notify citizens of high concentrations of local air pollutants, it is plausible that cyclists may curtail their activities or change their mode to limit their exposure. Conversely, the rigid social structures that motivate both cycling and motor traffic (e.g. patterns of work and family life) may promote a positive link between local air pollutant concentrations and cycling demand as citizens find it difficult to alter their travel patterns. In this sense, this paper considers whether cycling demand is curtailed due to poor air quality or if the demand follows the general pattern of motorised traffic.

Through an evaluation of the operation of the London Bicycle Sharing Scheme, this paper builds a set of timeseries autoregressive distributed lag models to consider the links between cycling demand and environmental conditions. Furthermore, this paper evaluates the linkages between environmental conditions and cycling demand across regular and casual cyclists. This distinction allows the analysis to disentangle the response of these two market segments to changes in environmental conditions and provide insights on the behaviour of different types of cyclists in regard to weather patterns and air quality levels.

The following section provides an overview of the existing work that has evaluated the linkages between environmental conditions and cycling demand in order to demonstrate the contribution this research makes to the existing knowledge on the topic. After this, the methodology applied to pursue the research is detailed and the results of the analysis are presented. To conclude, the findings of the analysis are interpreted to consider how they further knowledge in this area and what insights they offer for system management.

2. Background

2.1 Weather and Cycling

Due to the nature of the activity, cyclists are keenly aware of the environmental conditions present during their travel. This awareness is most apparent during inclement weather, where adverse conditions may motivate a behavioural response from cyclists (Heinen et al. 2010). Such a response can take a number of different forms. First, cyclists may displace their trip to an alternative mode of transport which shelters them from the weather. Second, cyclists may postpone their trip until the inclement weather passes such as during bouts of rainfall (Cools and Creemers, 2013). Third, cyclists may curtail their activity by deciding not to travel. The option chosen by a cyclist will likely depend on their specific situation such as the availability of alternative modes and the level of discretion they have regarding the trip being undertaken.

Two research approaches are commonly applied to consider the relationship between weather conditions and cycling activity. The first involves the analysis of observed cycling demand profiles measured on the transport system such as hourly or daily cyclist volume. This may involve data derived from traffic counters positioned on cycle paths or from usage data of a public bicycle sharing scheme. The second covers the behaviour of cyclists with regard to weather conditions through either the application of surveys or travel diaries (Saneinejad et al. 2012; Helbich et al. 2014; Meng et al. 2016). A large proportion of the survey literature has focused on barriers to cycling to work, with exposure to weather patterns representing a salient issue for individuals in terms of how frequently they cycle and their overall engagement with this form of commuting (Gatersleben and Appleton, 2007; Muñoz et al. 2013).

The nature of the research reported in this paper sits within the first of these approaches, where the focus is on the assessment of observed demand profiles for a public bicycle sharing scheme. A common set of weather conditions are typically evaluated regarding their link with observed cycling demand covering temperature, precipitation, windspeed, and relative humidity. For temperature, warmer conditions are generally found to be linked with increased rates of cycling (Miranda-Moreno and Nosal, 2011; Zhao et al. 2018b; Ashraq et al. 2019). However, this link may not be entirely linear, with Ahmed et al. (2012) finding the effect of temperature on cycling tends to diminish once temperatures exceed 20 degrees Celsius. For precipitation, past research indicates that a negative relationship exists between rainfall and the demand for cycling (Ahmed et al. 2012; Corcoran et al. 2014). A similar set of findings is observed for other adverse weather conditions, with cycling demand tending to be lower during episodes of high windspeed (Ermagun et al. 2018; Zhao et al. 2018b) and relative humidity (Miranda-Moreno and Nosal, 2011; El-Assi et al. 2017; Kim, 2018).

The work of Ermagun et al. (2018) typifies the examination of how weather patterns affect cycling activity through a detailed inspection of response across 13 US cities with varying climates (e.g. marine and humid). The findings of this analysis indicate that such conditions as precipitation, wind speed, and temperature have consistent directions of effect in the different climates but that the magnitude of the effects display substantial variations. This suggests that the elasticity of response of cycling volumes to weather conditions is affected by the prevailing climate.

2.2 Air Quality and Cycling

With cyclists often sharing the same road space as motorised vehicles, their proximity to emission sources (i.e. exhausts) is heightened. High concentrations of local air pollutants can have immediate implications for physical health such as inflaming asthmatic symptoms as well as longer-term effects which increase the rate of mortality in a population (Royal College of Physicians, 2016). These adverse consequences may generate behavioural responses from cyclists, such as the adoption of protective measures (i.e. actions to reduce exposure to local air pollutants such as wearing face masks) or activity curtailment.

Cyclist can become aware of air quality levels through two mechanisms. The first mechanism is personal perception, where cyclists detect the presence of local air pollutants through their own senses. An obvious example of this is the visual detection of tropospheric ozone which manifests as smog. In a study on the ability of people to detect air quality levels, Fosberg et al. (1997) found a positive correlation between exposure to nitrogen dioxide concentrations and perceived annoyance with traffic fumes. This connection has been corroborated in later studies (Rotko et al. 2002; Jacquemin et al. 2007), indicating that cyclists can perceive episodes of poor air quality. The second mechanism is the application of air quality alerts. To inform cyclists (and other citizens) about the occurrence of high air pollution events, some local authorities have adopted air quality alerts which are activated when concentrations exceed certain thresholds. Bickerstaff and Walker (1999) found that around half of individuals state that they would reduce outdoor activities during episodes of high local air pollution. Such a response has also been found amongst female cyclists, who are more likely than their male counterparts to make the shift to public transport during episodes of high air pollution (Zhao et al. 2018a). Activity curtailment of this nature has been identified using observed traffic volumes, with Saberian et al. (2017) finding that air quality alerts reduce the volume of cycling by 14-35% through a case study based in Sydney, Australia.

However, the impact of air quality levels on outdoor activities has been questioned in a number of projects. In a qualitative assessment of attitudes towards urban air pollution in Beijing, Xu et al. (2017) found that individuals expressed a feeling of powerlessness towards air quality levels and that behavioural responses are ineffective at limiting exposure. As active travel infrastructure (e.g. bicycle lanes and sharing schemes) tends to be co-located with motorised transport, there might be little opportunity for cyclists to avoid exposure to local air pollutants if they do not have the ability to shift to an alternative mode of transport. Such a situation is partially revealed in the work of Strauss et al. (2012), who found that volumes of cyclists tend to be positively related to concentration levels of local air pollutants at city intersections. This could indicate that the response of cyclists to air quality levels is dependent on the situation present, such as if the activity being considered is discretionary or mandatory as well as the presence of alternatives which provide an effective substitute for the mode.

2.3 Research Focus

As outlined in the work of Harden (2012), geographical examinations of the human – environment link can occur in multiple ways which, in part, depend on the context of the study and the epistemological views of the researcher. In this project, an environmental determinism approach is adopted which presupposes that human action (i.e. the demand for cycling) is partly affected by environmental conditions which are present (i.e. weather and air quality). This paper provides two contributions to the existing literature on the topic of how cycling demand is linked with environmental conditions.

The first contribution is an extension of the behavioural response to consider the relationships between cycling demand, weather patterns, and air quality levels. To date, the majority of the research in this area has focused exclusively on the response of cyclists to weather patterns, with relatively few projects (Strauss et al. 2012; Saberian et al. 2017; Zhoa et al. 2018) having considered how concentrations of local air pollutants may also be connected to cycling demand.

The second contribution is to consider how the response might differ by cyclist type. There is a tendency in the literature to treat cyclists as a homogenous market, rather than a diverse group of individuals that practice a type of mobility (Dill and McNeil, 2013). Preliminary work by Brandenburg et al. (2007) indicates that recreational cyclists display a stronger response to weather patterns as compared to commuter cyclists. This finding has been supported in recent work (Faghih-Imani and Eluru, 2016; Hyland et al. 2018) which demonstrates that the relationship between environmental conditions and cycling demand may vary between members and non-members of a bicycle sharing scheme. The same distinction is made in this paper, with members and non-members characterised as regular and casual cyclists respectively.

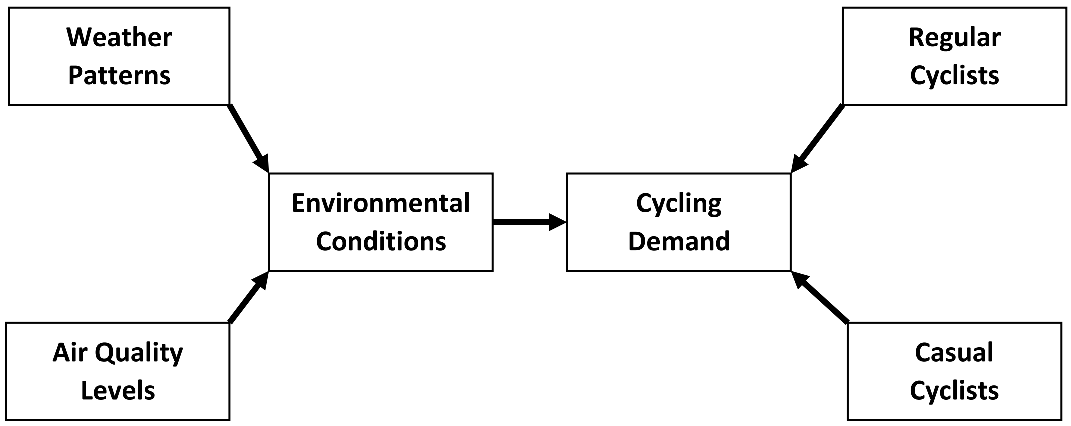

Figure 1: The research framework applied in this work whereby environmental conditions, which comprise of weather patterns and air quality levels, affect the demand for cycling which is disaggregated into casual and regular cyclists

These contributions are illustrated in the research framework displayed in Figure 1. The expectation is that inclement weather (e.g. cold temperatures and rain) will both supress cycling demand during the time period in which it is experienced and shift cycling demand to later time periods due to trip postponement. For air quality levels, the link is less clear as there are plausible explanations which would lead to a negative or positive link being present. If cyclists tend to be aware of high concentration levels, believe that these levels will adversely impact their health, and have the ability to easily shift to another mode of transport, it is reasonable to expect a negative relationship while if cyclists hold the opposite views then a positive relationship may exist. The responses to environmental conditions across regular and casual cyclists may assist in unpicking these links. For instance, it is reasonable to expect that regular cyclists are less affected by variances in environmental conditions as compared to casual cyclists due to the habits and experiences they share as well as the nature of their travel.

3. Methods

3.1 Case Study

Bicycle hire data from the London Bicycle Sharing Scheme (LBSS) in the United Kingdom is used to measure daily cycling demand. The LBSS became operational in 2011 and covers a return-to-base model which allows users to hire bicycles from docking stations spread throughout the centre of the city. Users who hire cycles from the LBSS can either pay an annual membership fee of £90 which allows members to make unlimited hires of up to 30 minutes or else pay a £2 daily access charge which provides unlimited hires for up to 30 minutes for a 24-hour period.

During 2012 and 2013, the scale of the LBSS was enlarged through the installation of new docking stations and an expansion in the number of cycles available for hire. Presently, the scheme comprises 748 docking stations and has circa 11,500 bicycles in circulation. The spatial configuration of the LBSS is illustrated in Figure 2, noting the location of docking stations. The footprint of the scheme is primarily located north of the river Thames and covers much of the urban core including the City of London and Westminster.

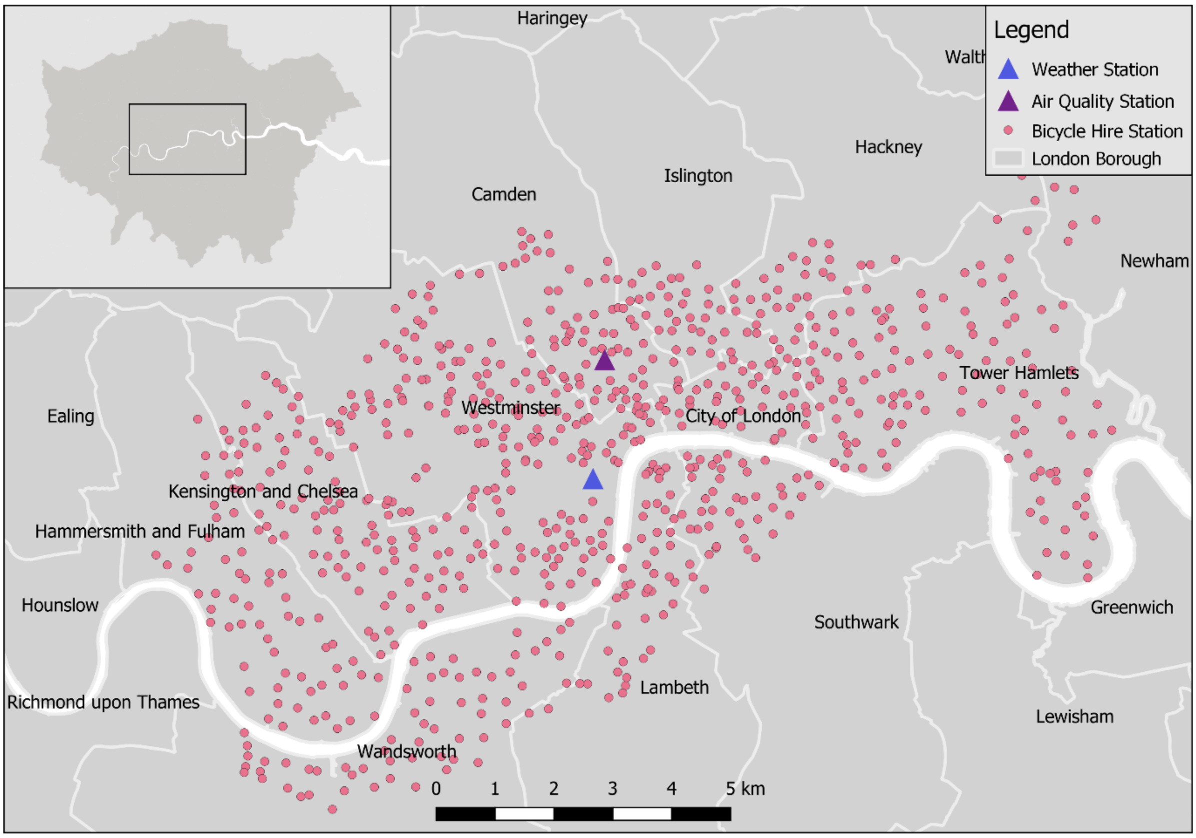

Figure 2: The location of docking stations which comprise the London Bicycle Sharing Scheme alongside the position of the weather and air quality sensors

3.2 Data Sources

The data covering cycle hires, weather conditions, and local air pollutant concentrations has been observed at daily intervals between 1st of January 2012 to 1st of January 2018. These data are combined into a dataset, with each variable included in the analysis being summarised in Table 1. The number of cycle hires on the LBSS has been extracted from Transport for London's system management platform which provides public access to disaggregated trip data for research purposes (https://cycling.data.tfl.gov.uk/). Data of this variety is readily available for similar bicycle sharing schemes, with the bikedata package developed by Padgham and Ellison (2017) providing a universal access point to trips across several schemes.

Separate demand levels have been recorded, with the first noting the number of cycle hires by members of the LBSS (i.e. individuals that have paid the annual subscription) and the second measuring the number of cycle hires by debit or credit card payment (i.e. individuals that have paid the £2 daily charge). These separate records are used to differentiate user type, with members being a proxy for regular cyclists while individuals making payment by debit or credit are used as a proxy for casual cyclists.

Weather conditions covering maximum air temperature (Temp), mean wind speed (Wind), mean relative humidity (Humid), and precipitation have been sourced from the Centre for Environmental Data Analysis which acts as the store of all Met Office weather stations in the UK. Data from the weather station located in St James Park (reference number: 697), London, has been extracted from the SYNOP message. The mean concentration level of local air pollutants including ozone (O3), nitrogen oxides (NOX), and particulate matter 10 (PM10) have been obtained from the Department for Food, Environment, and Rural Affairs' monitoring station located in London Bloomsbury (reference number: UKA00211). This station is part of the Automatic Urban and Rural Network and provides background readings for central London.

Table 1: Descriptive statistics for the variables included in the analysis

Variable	Mean	Std. Dev.	Min.	Max.	Number	Missing
Regular Users (number)	10157.41	5014.96	96	19445	2191	1
Casual Users (number)	10711.48	6182.23	890	45170	2190	2
Maximum Air Temperature (°C)	14.24	5.76	0.30	32.25	2192	0
Precipitation (mm)	1.70	3.83	0.00	47.20	2192	0
Relative Humidity (%)	74.72	10.05	22.75	99.92	2111	81
Average Wind Speed (knot)	8.32	3.23	1.30	23.54	2192	0
Daylight (seconds)	44170.95	10803.62	28183	59900	2192	0
Ozone (µg/m3)	27.64	15.32	0	85	2160	32
Nitrogen Oxides (µg/m3)	78.52	49.21	7	557	2135	57
Particulate Matter 10 (µg/m3)	18.68	10.48	4	89	1987	205

3.3 Data Transformation

Observations of transport demand patterns often display complex forms of seasonality. These patterns may incorporate non-stationarity (i.e. the central tendency and dispersion of the variable changes through time) and serial dependence (i.e. current observations of the variable are strongly related to past observations), which can bias the results of multivariate analysis. In order to address these issues, variables included in the analysis are transformed into their daily residuals following the procedure outlined by Kalkstein et al. (2009) and recently applied to bicycle demand by Zhao et al. (2018b). This daily residual represents the percentage difference between the value of a variable observed in any given day and a 9-term moving average for that variable. The first step in this transformation is the calculation of the 9-term moving average which follows the procedure summarised in equation 1. The moving average calculation uses a weekly index (τ), meaning that the observed value (D_t) on a given day (e.g. a Tuesday) is compared to the same day in the preceding and proceeding 4 weeks.

$$D_t^{MA\pm4} = \frac{\sum_{\tau=-4}^{4} D_{t+7\tau}}{9} \quad (1)$$

The second step in the transformation is the calculation of the residual which follows the procedure summarised in equation 2.

$$\Delta D_t = \frac{D_t - D_t^{MA\pm4}}{D_t^{MA\pm4}} \quad (2)$$

The efficacy of this transformation is evident in Figure 3, where the daily residual (displayed in panel 2 for regular users and panel 4 for casual users) corrects for the apparent seasonality displayed in the original variables. The same transformation has been conducted for the variables measuring concentration levels of local air pollutants and weather conditions except for precipitation. As there are occurrences of days where no rainfall is recorded, the specification of daily residuals for this variable is inappropriate. With this in mind, precipitation is included in the analysis as two dummy variables, with light rainfall (LPrecip) denoted by precipitation between the bands of 0.1 and 4.9 milometers and heavy rainfall (HPrecip) classified as precipitation of 5 milometers or higher.

3.4 Statistical Analysis

The analysis of the dataset progresses through three stages. Each of these stages has been applied in the R statistical programming environment, with the data and code available at the following GitHub repository (https://github.com/clmorton). With similar data being publicly available for bicycle sharing schemes around the world, the code developed in this project could be applied internationally to evaluate how environmental conditions effect the demand for cycling in other regions.

Stage One: involves the illustration of the cycling demand profiles for regular and casual LBSS users, weather conditions, and concentration levels of local air pollutants. This provides insight on the temporal patterns that are present for these variables.

Stage Two: covers the conduct of Spearman's rank correlation analyses between the variables of the dataset. The relationships identified by this stage of the analysis will provide guidance on the specification of the multivariate analysis (i.e. stage three).

Stage Three: the final step in the analysis comprises the specification of time series regression models, which follow an autoregressive distributed lag (ADL) structure and utilise the ordinary least squares estimation method. Applications of ADL models are common in the examination of how cycling demand responds to environmental conditions (Gallop et al. 2011; Nosal and Miranda-Moreno, 2014; Zhao et al. 2018b), allowing the results of this research to be easily compared to past findings. Two sets of models are estimated, with the first using the daily residual for regular user demand for the LBSS as the dependent variable while the second has the daily residual for casual user demand for the LBSS as the dependent variable. The independent variables are the same across both sets of models and comprise the daily residuals for weather conditions, local air pollutant concentrations, as well as a dummy variable which controls for the occurrence of public holidays (Holiday). A one-day lag for all environmental conditions is included in the models to account for trip postponement, where cycling demand gets shifted to the next day if weather conditions or air quality levels in the preceding day are adverse.

A phased entry procedure is used for the independent variables, where weather conditions are entered in the first phase, local air pollutant concentrations in the second phase, followed by an in integrated model of both weather conditions and local air pollutant concentrations in the third phase. The structure of the integrated model is summarised in equation 3.

$$\begin{aligned}\Delta D_t = {} & \beta\Delta D_{t-1} + \beta\Delta Temp_t + \beta\Delta Temp_{t-1} + \beta\Delta Wind_t + \beta\Delta Wind_{t-1} + \beta\Delta Humid_t \\ & + \beta\Delta Humid_{t-1} + \beta LPrecip_t + \beta LPrecip_{t-1} + \beta HPrecip_t \\ & + \beta HPrecip_{t-1} + \beta\Delta Daylight_t + \beta\Delta O3_t + \beta\Delta O3_{t-1} + \beta\Delta NOX_t \\ & + \beta\Delta NOX_{t-1} + \beta\Delta PM10_t + \beta\Delta PM10_{t-1} + \beta Holiday_t + \varepsilon\end{aligned} \quad (3)$$

The quality of each of the models specified is evaluated by the calculation of the variance inflation factor (VIF), the Durbin Watson test, and the Breusch Pagan test to consider the occurrence of multicollinearity, autocorrelation, and heteroskedasticity respectfully.

3.5 Limitations

A number of the variables included in the analysis have missing observations, which occur periodically throughout the time series (summarised in Table 1). These missing observations are most severe for relative humidity and particulate matter and are caused by sensor dropouts. The calculation of 9-term moving average residuals magnifies this issue, as any missing observation will lead to the calculation being unable to compute the value. As a result of these missing observations, the multivariate analysis is applied to a reduced dataset of 923 complete observations.

4. Results

4.1 Time Series

The pattern of demand for the LBSS hour-by-hour and day-by-day for both regular and casual users is summarised in Figure 3. It is apparent that regular users of the LBSS concentrate their use of the scheme in the traditional morning and afternoon peaks for road traffic, with higher utilisation rates on weekdays as compared to weekends. This indicates that regular users are primarily using the scheme for commuting, which corresponds to the findings of survey analysis on this user group (Morton, 2018). Casual users display markedly different demand patterns, preferring to make use of the scheme during the early afternoon to the late evening and with a higher utilisation on weekends.

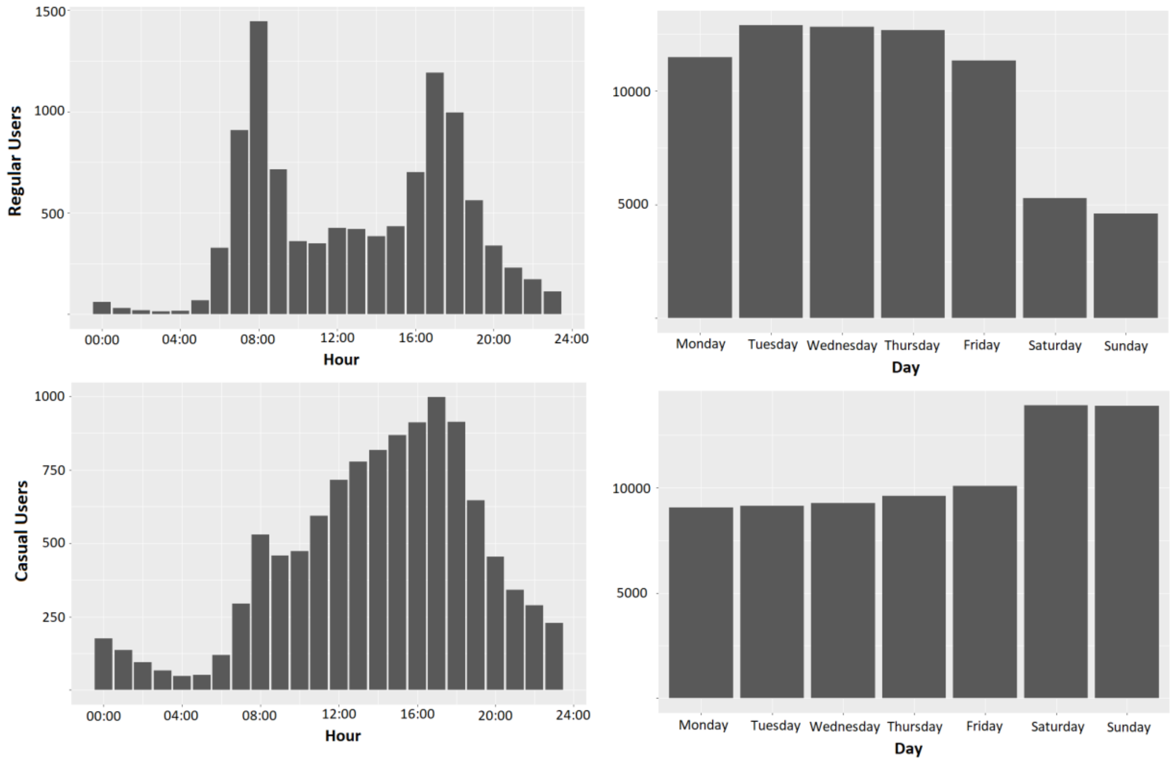

Figure 3: Trip volumes aggregated by [panel 1] hour of the day for regular users, [panel 2] day of the week for regular users, [panel 3] hour of the day for casual users, and [panel 4] day of the week for casual users

The weekly seasonality of regular users is also clear in the time series displayed in Figure 4, with the repeated pattern of high demand during the weekdays and low demand at weekends being evident. The seasonal pattern displayed by casual users is more attuned to meteorological seasons, with demand being low in the winter months, increasing in spring, peaking in summer, and declining through autumn. This patterning suggests that casual user demand may be aligned to leisure trips by locals or tourists to London during the fair-weather periods throughout the year. The spike in casual user demand in late December corresponds to Christmas day, when all other public transport services operated by Transport for London are closed.

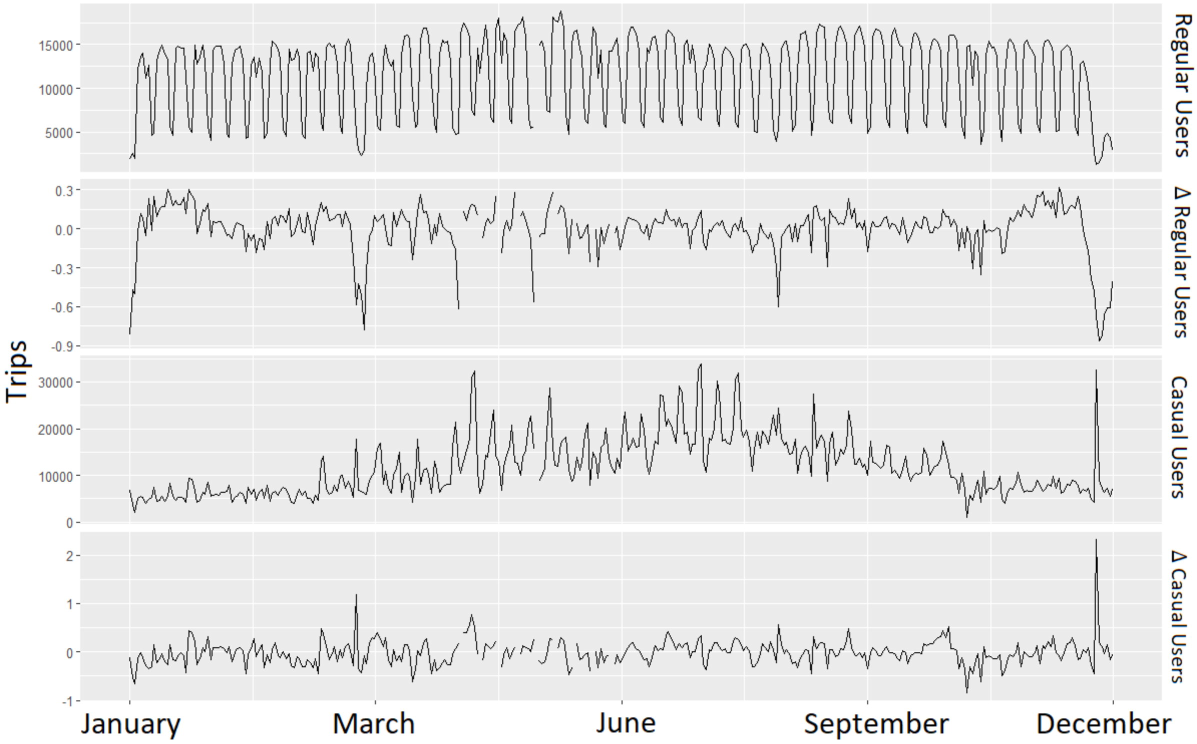

Figure 4: Daily time series for 2016 for [panel 1] number of regular users, [panel 2] daily residual for regular users, [panel 3] number of casual users, and [panel 4] daily residual for casual users

London experiences a temperate oceanic climate, with the time series for the metrological elements illustrated in Figure 5. Maximum air temperatures tend to be highest during the months of July and August and are at their lowest in January and February with the opposite pattern being observed for relative humidity. Storm periods are generally experienced during the winter, which corresponds with average wind speeds tending to display larger variations in the first months of the year. The distribution of rainfall does not display any apparent seasonality.

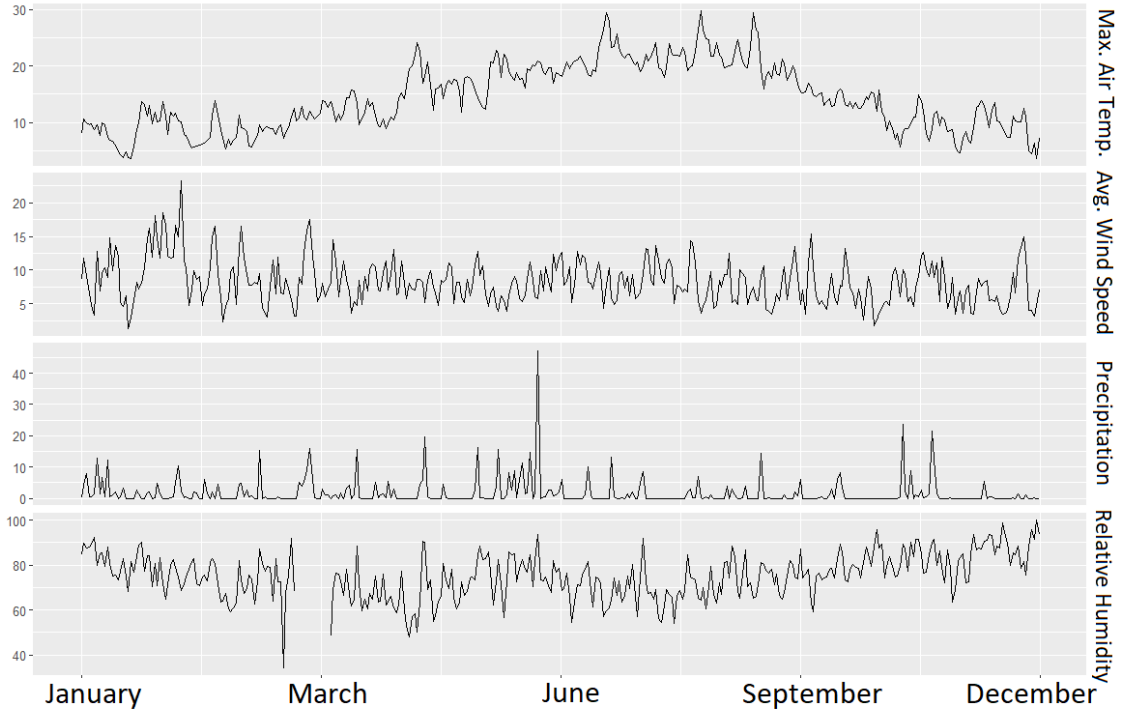

Figure 5: Daily time series for 2016 for [panel 1] maximum air temperature, [panel 2] average wind speed, [panel 3] precipitation, and [panel 4] relative humidity

The final set of time series graphs displayed in Figure 6 cover observations of the concentration rates of local air pollutants. In this instance, there is little seasonality evident in the observations, though there are some notable spikes in both nitrogen oxides and particulate matter 10 during the late autumn and winter.

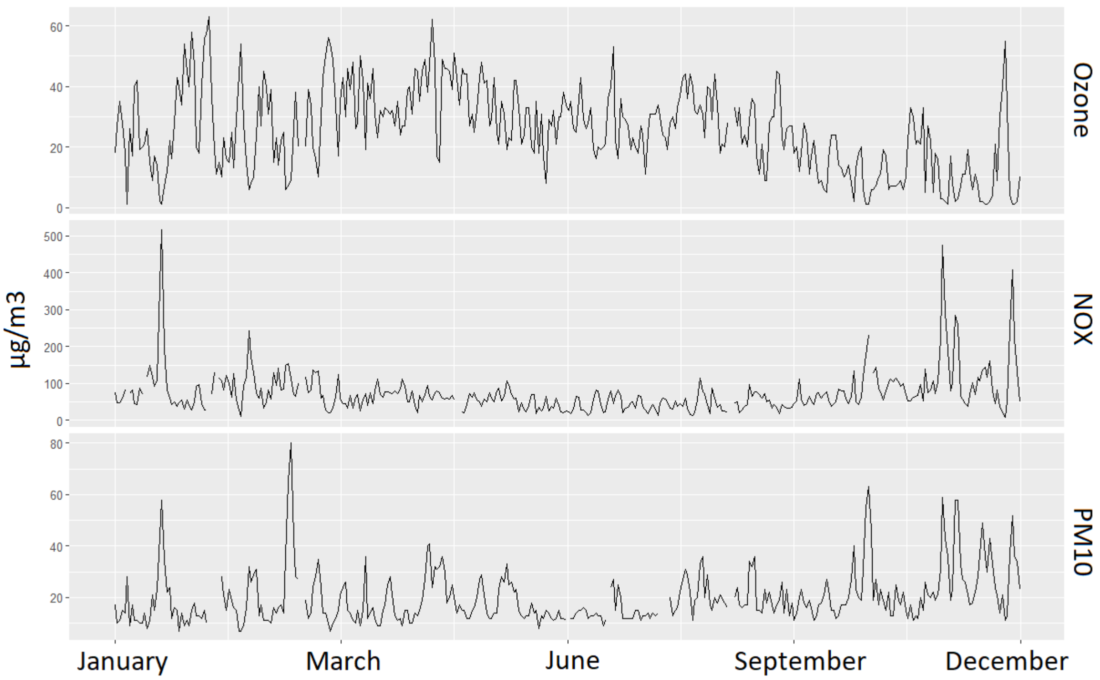

Figure 6: Daily time series for 2016 for [panel 1] mean ozone, [panel 2] mean nitrogen oxides, and [panel 3] mean particulate matter 10

4.2 Correlation Analysis

The results of the correlation analyses between cycling demand across the two user groups, weather conditions, and local air pollutant concentrations are summarised in Table 2. In terms of weather conditions, the cycling demand of both user groups is significantly connected to all of the meteorological elements evaluated. The rate of casual user demand displays marginally larger correlation coefficients with weather conditions as compared to regular user demand. The difference between the two user groups is most apparent for maximum air temperature, where the demand from casual users (r_s: 0.469) is more strongly connected with this weather condition as compared to the demand from regular users (r_s: 0.167). In terms of local air pollutants, the cycling demand of both user groups displays weak positive correlations in all instance except for the association between regular user demand and ozone concentrations, where the correlation is weak and negative.

Table 2: Results of the Spearman's correlation analysis between cycling demand, weather conditions, and local air pollutant concentrations

	Regular	Casual	Max. Temp.	Percip.	Rel. Humid	Avg. Wind	Daylight	Ozone	NOX	PM10
Regular	1.000									
Casual	.487**	1.000								
Max. Temp.	.167**	.469**	1.000							
Percip.	-.405**	-.502**	-.041	1.000						
Rel. Humid	-.359**	-.482**	-.113**	.470**	1.000					
Avg. Wind	-.214**	-.242**	.077**	.199**	-.063**	1.000				
Daylight	-.062**	.099**	.055*	-.099**	-.045*	.026	1.000			
Ozone	-.090**	.102**	.373**	.054*	-.356**	.584**	.089**	1.000		
NOX	.206**	.073**	-.292**	-.179**	-.030	-.616**	.052*	-.716**	1.000	
PM10	.305**	.274**	.032	-.255**	.037	-.510**	.031	-.460**	.518**	1.000

* - p:value < .05; ** - p:value < .01

4.3 Regression Models

The ADL regression models for regular user and casual user cycling demand are summarised in Table 3 and 4 respectively. For both sets of models, the largest VIF is 4.27 which indicates that multicollinearity is not unduly affecting the analysis. The Durbin Watson test returns an insignificant result, implying that the transformation of variables into daily residuals has avoided the occurrence of autocorrelation. However, the result of the Breusch Pagan test is significant, suggesting that the analysis is subject to hetroskedasticity. To correct for this, robust standard errors have been calculated using the technique outlined by Zeileis (2004) to produce heteroskedasticity consistent estimators.

Table 3: Results of the Autoregressive Distributed Lag model for regular bikeshare user demand

	Model 1		Model 2		Model 3	
	Beta	**Std. Err.**	**Beta**	**Std. Err.**	**Beta**	**Std. Err.**
Intercept	0.019**	0.004	0.009*	0.005	0.016*	0.008
Lagged Dependent						
Regular Users $_{t-1}$	0.585**	0.025	0.598**	0.031	0.577**	0.034
Weather Conditions						
Maximum Air Temperature	0.081**	0.017			0.143**	0.028
Maximum Air Temperature $_{t-1}$	-0.043**	0.017			-0.065*	0.027
Light Precipitation	-0.031**	0.005			-0.019*	0.009
Light Precipitation $_{t-1}$	0.020**	0.006			0.020*	0.010
Heavy Precipitation	-0.145**	0.011			-0.141**	0.018
Heavy Precipitation $_{t-1}$	0.100**	0.011			0.117**	0.017
Average Wind Speed	-0.070**	0.009			-0.067**	0.017
Average Wind Speed $_{t-1}$	0.016	0.009			0.034*	0.017
Relative Humidity	-0.441**	0.031			-0.543**	0.060
Relative Humidity $_{t-1}$	0.329**	0.030			0.356**	0.054
Daylight	-0.015	0.217			0.336	0.304
Air Pollution						
Ozone			0.016	0.016	-0.049**	0.017
Ozone $_{t-1}$			-0.029	0.016	0.006	0.017
NOX			0.025	0.018	-0.021	0.018
NOX $_{t-1}$			0.001	0.018	0.027	0.016
PM10			0.058**	0.018	0.047**	0.016
PM10 $_{t-1}$			-0.056**	0.015	-0.042**	0.012
Calendar Events						
Public Holiday	-0.459**	0.020	-0.467**	0.024	-0.443**	0.027
Model Fit						
Adjusted R^2	0.723		0.637		0.763	
AIC	-3312.093		-1071.136		-1416.534	
Model Diagnostics						
Durbin Watson	2.116		2.246		2.138	
Breusch Pagan	275.290**		83.106**		115.530**	

* - p:value < .05; ** - p:value < .01

The results of the integrated model (i.e. model 3) for both the regular and casual user models provide insights on the associations that exist between weather conditions, local air pollutant concentrations, and cycling demand.

All the weather conditions included in the models display significant concurrent effects on demand for both regular and casual users. The direction of the effects is in keeping with expectations, with maximum air temperatures associated with higher rates of demand while the occurrence of precipitation, average wind speed, and relative humidity are all negatively connected. Similar to the results of the correlation analysis, weather conditions appear to be more important in the demand of casual users as compared to regular users. For example, maximum air temperature holds a substantially larger beta coefficient in the casual cycling demand model (β: 0.484) than the regular cycling demand model (β: 0.143). The lagged variables for all of the weather conditions in the regular cycling demand model display significant effects which are opposite in direction to their concurrent counterparts. For instance, the dummy variable denoting heavy rainfall holds a concurrent negative effect (β: -0.141) and a lagged positive effect (β: 0.117). For the casual cycling demand model, none of the lagged weather conditions displays a significant effect. This finding indicates that regular users are more likely to postpone trips to later days if weather conditions are poor.

The local air pollutants display a number of significant affects in the regular user cycling demand model. Concentration levels of ozone are negatively connected (β: -0.049) with regular cycling demand while particulate matter 10 holds a positive concurrent association (β: 0.047) and a negative lagged association (β: -0.042). For the casual cycling demand model, only the variable measuring particulate matter 10 displays a significant positive affect (β: 0.129). The magnitude of the beta coefficients indicates that the importance of the local air pollutant variables across both models is low, implying that air quality levels do not have a substantial impact on the demand of cycling.

Table 4: Results of the Autoregressive Distributed Lag model for casual bikeshare user demand

	Model 1		**Model 2**		**Model 3**	
	Beta	**Std. Err.**	**Beta**	**Std. Err.**	**Beta**	**Std. Err.**
Intercept	0.041**	0.009	-0.021*	0.008	0.035*	0.017
Lagged Dependent						
Casual Users $_{t-1}$	0.135**	0.047	0.279**	0.067	0.033	0.063
Weather Conditions						
Maximum Air Temperature	0.416**	0.039			0.484**	0.074
Maximum Air Temperature $_{t-1}$	0.059	0.049			0.119	0.093
Light Precipitation	-0.078**	0.012			-0.069**	0.021
Light Precipitation $_{t-1}$	0.002	0.012			0.003	0.019
Heavy Precipitation	-0.229**	0.021			-0.249**	0.035
Heavy Precipitation $_{t-1}$	0.012	0.019			0.006	0.034
Average Wind Speed	-0.203**	0.020			-0.267**	0.042
Average Wind Speed $_{t-1}$	0.003	0.022			0.041	0.035
Relative Humidity	-0.963**	0.053			-1.023**	0.115
Relative Humidity $_{t-1}$	0.201**	0.070			0.039	0.113
Daylight	-0.221	0.505			-0.386	0.846
Air Pollution						
Ozone			0.136**	0.046	0.019	0.051
Ozone $_{t-1}$			-0.003	0.042	0.005	0.040
NOX			0.024	0.047	-0.066	0.043
NOX $_{t-1}$			0.024	0.039	0.058	0.032
PM10			0.215**	0.038	0.129**	0.031
PM10 $_{t-1}$			-0.068*	0.034	-0.052	0.028
Calendar Events						
Bank Holiday	0.431**	0.111	0.370*	0.168	0.486**	0.151
Model Fit						
Adjusted R^2	0.540		0.196		0.543	
AIC	-719.939		413.167		-76.971	
Model Diagnostics						
Durbin Watson	1.958		1.968		2.069	
Breusch Pagan	177.230**		125.870**		134.070**	

* - p:value < .05; ** - p:value < .01

5. Discussion and Conclusions

The research reported in this paper focuses on how environmental conditions are linked with the demand for cycling through a study of hire data derived from the London Bicycle Sharing Scheme. The paper extends the understanding of this link in two ways which are outlined in more detail in section 2.3.

The first extension involves the link between cycling demand and air quality levels. In this instance, the findings of the appraisal paint a mixed picture. Concentration levels of ozone are found to have a small negative effect on regular cycling demand, indicating that the presence of smog deters this group of users. As smog is a particularly visible aspect of air quality, this could be the motivating factor for this negative affect. However, concentration rates of particulate matter 10 are positively linked to both regular and casual cycling volume. These findings go against the simple expectation that adverse environmental conditions will tend to reduce cycling demand and support the results of Strauss et al. (2012) that concentrations of local air pollutants and cycling volume are positively related. On further reflection, this observed positive relationship has a number of plausible explanations. First, due to the boundary in which the LBSS operates, the scheme tends to service short distance trips of 2 kilometres or less (Beecham, et al. 2014). As a result of this, the dose of air pollutants that a cyclist receives during a ride is likely to be minimal, which reduces the need for activity curtailment. Second, empirical research which examines the trade-off between the health benefits and costs of cycling has generally found that the advantages substantially outweigh the risks (de Hartog et al. 2010; Tainio et al. 2016). With research of this variety being disseminated widely through the mainstream media, it is plausible that cyclists believe they are better-off on their bikes than in alternative modes of transport. Third, regular cyclists of the LBSS tend use the scheme to conduct non-discretionary commuting trips, where the cost of changing modes might be seen as higher than the benefits of reduced exposure to local air pollutants.

The second extension concerns the disaggregation of cycling demand by user groups, with regular and casual cyclists considered separately rather than jointly. The results of the analysis corroborate the findings of past work on this issue (Faghih-Imani and Eluru, 2016; Hyland et al. 2018; Caspi and Noland, 2019), implying that casual and regular users of bicycle hire schemes have distinct demand profiles and responses to environmental conditions. Specifically, the results indicate that casual cycling demand tends to be more strongly affected by concurrent weather conditions. This finding could be due to casual users of the LBSS being more inclined to use the scheme for leisure trips whereas regular users tend to use the scheme for commuting trips. As commuting is less discretionary than recreational trips, it is reasonable to expect that casual cycling demand will be more responsive to immediate weather conditions. The opposite affect is true for lagged weather conditions, where regular cycling demand is affected while casual cycling demand is not. This implies that regular cyclists tend to postpone trips depending on the weather, with the lags of adverse conditions such as rainfall and relative humidity being positively linked to demand. This result is slightly surprising, as the initial expectation was that casual cyclists would tend to postpone trips as their journey purposes are likely to be more flexible.

The insights derived through this analysis have the potential to be of use for both the management of bicycle sharing schemes and urban cycling policy more generally. In terms of scheme management, the patterns of cycling demand for regular and casual users can provide guidance on when maintenance activities could be scheduled to minimise disruption. For instance, cycle hire stations that primarily serve regular users could have their maintenance scheduled for Bank Holidays or during the later hours of the evening when demand tends to be lower. Similarly, system managers can make use of past volume data and weather forecasts to make predictions on the level of demand likely to be observed over the next few days. Such predictions could prove useful in load management for days when demand is expected to peak, such as through the distribution of reserve bikes and stations.

In terms of urban cycling policy, the positive associations identified between cycling demand and particulate matter 10 concentrations suggest that cyclists may need to be better informed regarding the occurrence of high levels of local air pollutant concentrations to minimise the doses they receive. For example, cyclists could provide the scheme with their intended destination which then informs them of the potential routes which are available. These routes could be characterised by their journey times, level of congestion, and exposure to local air pollutants to allow cyclists to understand how different routes score on important trip criteria. Such a route optimisation approach has already been developed by Ehrgott et al. (2012), which could be implemented either at the stations through a user touch screen or integrated to the scheme's existing smartphone application. In addition, the results of the analysis could provide civil servants with evidence to support the provision of complimentary cycling policies intended to limit exposure to local air pollutants. Such policies could include the implementation of low emission zones which have been found to reduce the concentration levels of particulate matter 10 (Boogaard et al. 2012) or the development of cycling infrastructure intended to reduce exposure such as detaching the infrastructure from conventional roads or using barriers (e.g. green walls) to limit the diffusion of emissions. Tools are being developed for such purposes, with the Propensity to Cycle Tool (Lovelace et al. 2017) having the ability to advise transport planners on suitable locations for new bicycle lanes to promote a shift from private cars to active travel to service commuting trips.

The examination of how environmental conditions impact the transport behaviours of citizens represents an area that is particularly fertile with research opportunities. Future research has the potential to build on the work reported in this paper, with the following issues being noteworthy. First, the willingness of cyclists to detour in order to reduce their dose of local air pollutants is an area that could provide insights on the trade-off between exposure and convenience. Second, the responsiveness of different categories of cyclists (e.g. by sex or age) to varying weather conditions could provide further insights on how cumulative cycling demand can be partitioned. Third, the decision of cyclists to alter their cycling behaviours (e.g. trip lengths and speeds) to varying environmental conditions would allow the analysis of cycling demand profiles to progress from examining cumulative volumes to a more nuanced perspective of trip attributes. Fourth, the models specified in the project can be utilised in other contexts to examine the link between cycling demand and environmental conditions. Such investigations can assist in developing a detailed picture of how the specific environmental conditions present in different locations need to be considered for the effective promotion of active travel practices. Fifth, the analysis could be extended to other modes of transport such as through investigations on activity curtailment amongst pedestrians resulting from poor air quality or the willingness of car drivers to switch to public transport if episodes of high local air pollutant concentrations are expected.

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