An exploratory analysis of the trend in the demand for the London bike-sharing system: from London Olympics to Covid-19 pandemic

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Abstract

It is important to understand variations in the demand for bike-sharing systems to help guide policy aimed at promoting bike-sharing schemes. We conducted an exploratory analysis of the trend in the daily number of cycle hires in London (UK) from January 2012 to June 2020. In particular, we investigated the association between unemployment rate and the trend in the demand for the London cycle hire system. Other explanatory variables included in our analysis were weather-related (e.g., rainfall) and temporal factors (e.g., types of days) as well as the number of docking stations. The study employed a generalised negative binomial model in which the over-dispersion parameter varied across the sample. Using such a model for the first time in investigating the trend in bike-sharing systems, allowed us to understand how uncertainty around the demand varies in the system. We found that unemployment rate, being negatively associated with cycle hires, played an important role in the demand for the London bike-sharing system. Unlike temperature and the number of docking stations, rainfall, humidity and wind had a negative impact on cycle hires. Finally, our analysis revealed significant variations in the demand across various types of days (e.g. lockdown and weekdays).

1.0 Introduction

In recent years, cities around the world have observed a resurgence of cycling as an essential mode of travel. Cycling is recognised to have many benefits including relieving traffic congestion, reducing greenhouse gas emissions and improving public health by increasing levels of physical activity (Bullock, Brereton, and Bailey 2017; de Hartog et al. 2010). After the invention of bicycle-sharing systems, it is not surprising that these systems have grown rapidly and become an important part of urban transport systems (Eren and Uz 2020). Currently, there are more than 9 million bicycles in such systems in more than 2000 cities worldwide (Meddin et al. 2020), although not all of them can be described as successful systems (Médard de Chardon, Caruso, and Thomas 2017). Bike-sharing systems help normalizing utilitarian cycling and broadening the cycling demographic (Goodman, Green, and Woodcock 2014) and increasing road safety and drivers' awareness (Fishman and Schepers 2016). By freeing users from the need to secure their bicycles, bike-sharing systems provide a convenient alternative for one-way or round trips. Further, decisions to make a trip by bike-sharing schemes can be made in a short time frame, providing a quick affordable and healthy transport mode for users. A well designed bike-sharing system could enhance access to public transport system by improving first and last mile connectivity, and hence improve the overall urban transport systems (Jäppinen, Toivonen, and Salonen 2013; Sun and Zacharias 2017; Tarpin-Pitre and Morency 2020).

The first widely-known large bike-sharing systems were initiated in France in cities of Lyon and Paris in late 2000's and have since increased across the world both in terms of numbers and size (Shaheen, Guzman, and Zhang 2010). Given this substantial growth, there is considerable interest in understanding how these systems evolve over time. Further, questions remain about factors that are contributing to bike-share usage and how these factors change as the system evolves and grows. Many bike-sharing systems have now offered service for nearly a decade, potentially allowing us to investigate their evolution and to analyse their usage trend over time.

London bicycle-sharing system, Santander Cycles, is one of the largest systems in the world that was launched in 2010 with 5,000 bicycles available across 315 docking stations in the capital of the United Kingdom. Since opening, the scheme has continued to expand with over 100 km^2 of London having access to a bike-sharing systems station (Reynolds 2020). In 2020, the system contained over 780 docking stations with more than 11,500 bicycles. This initiative has so far achieved more than 87 million trips in the first decade of the program. The number of hires naturally varies across stations and time of the year due to numerous factors affecting the bike-sharing systems users' travel behaviour. London's bike-sharing system is particularly well-used for commuting trips and often is a part of multi-modal trips with a significant number of bikes rented from major train stations (O'Brien, Cheshire, and Batty 2014). Not only the cycle hire scheme in London expanded in the past decade, but also the transport network has changed with cycling infrastructure and segregated cycleways installed across the city. It is important to highlight that cycling intensity is much higher in Central London with a significant number of short trips than in other areas where trips tend to be longer.

The London's bike-sharing scheme is a mature system that has been in service for a decade and can provide enough data for investigating the factors influencing its usage over time and how stable these effects are. This paper examines the impact of several weather and non-weather-related variables (such as unemployment rate, number of stations, and contextual variables including seasonal and type of day variables) on the trend in the demand for the London bike-sharing scheme over the period 2012-2020. Of particular interest is understanding the association between unemployment rate and cycle hires in London. To our knowledge, the later has not been investigated previously in analysing trend in the demand for bike-sharing systems. Besides explaining the variation in the demand, our study investigates and explains the uncertainty around the demand using a generalised negative binomial model, providing further insights into the variance of the demand. This is rare if non-existent in the extant bike-sharing literature. The paper is structured as follows. Section 2 provides a summary of previous studies. Section 3 gives an overview of the data. In section 4, we introduce our statistical approach. Section 5 presents the results and discussions. Section 6 presents our conclusions.

2.0 Literature Review

With the rapid growth of bike-sharing systems over the past few years, we have also observed a rapid increase in the research on these systems. There have been several literature review papers summarising the research done in this field (Eren and Uz 2020; Médard de Chardon 2019; Teixeira, Silva, and Moura e Sá 2020). The research on bike-sharing systems can be broadly categorised as follows:

I. Studies that look at supply-side of the system such as identifying problematic stations, finding the optimal size of stations or proposing methods to improve the efficiency of operator rebalancing program (Forma, Raviv, and Tzur 2015; Fricker and Gast 2016; Reynaud, Faghih-Imani, and Eluru 2018; Soriguera and Jiménez-Meroño 2020);

II. Studies that investigate the bike-sharing systems users adoption, attitudes and preferences (Faghih-Imani and Eluru 2020; Maioli, de Carvalho, and de Medeiros 2019; Manca, Sivakumar, and Polak 2019; Nikitas 2018; Tarpin-Pitre and Morency 2020; Wang et al. 2018); and

III. Studies that analyse the demand and usage of the system (Eren and Uz 2020; Faghih-Imani et al. 2014; Hyland et al. 2018; Kaviti et al. 2020). This last group of studies, of particular relevance to our study, typically characterises bike-sharing systems demand at different temporal level, e.g. hourly, weekly, monthly, or annually, as well as different spatial level, e.g. station level, zone level, or system level. By developing quantitative frameworks, these studies aim to identify contributing factors influencing bike-sharing systems demand using real operation data provided by the bike-sharing systems operator.

Earlier studies found a substantial relationship between bike-sharing systems demand with bike-sharing systems variables, quality of cycling infrastructure, land use and built environment attributes, road and public transport network characteristics, as well as temporal and meteorological attributes. For example, the characteristics of bike-sharing systems such as the number or capacity of stations have been found to significantly impact the bike-sharing systems usage (Faghih-Imani and Eluru 2016a; Hyland et al. 2018; Wang and Chen 2020). Studies indicated that the more cycling infrastructure (such as bike lanes and segregated cycle routes) installed in a city, the more usage its bike-sharing system experiences (Faghih-Imani and Eluru 2016b; González, Melo-Riquelme, and de Grange 2016; Lu, Scott, and Dalumpines 2018; Stenneth et al. 2011; Wang et al. 2016). Stations in areas with a higher number of point of interests (such as retail stores and universities), as well as areas with higher population and job density, tend to observe higher usage (Faghih-Imani and Eluru 2020; Mateo-Babiano et al. 2016; Rixey 2013). These studies highlighted that stations located in areas where fewer job opportunities exist or employment rates are low (indicated by low job density and unemployment rate variables for that area) observe lower usage (Etienne and Latifa 2014; Faghih-Imani and Eluru 2020; Hyland et al. 2018). In fact, a recent study of Chicago bike-sharing system highlighted that employment rate is one of the most important factors to increase system demand in disadvantageous communities (Qian and Jaller 2020).

The relationship between bike-sharing systems usage and public transport system is found to be more complex than expected. Several studies demonstrate that bike-sharing systems have a complementary effect on public transport ridership (Faghih-Imani and Eluru 2016b; González et al. 2016; Noland, Smart, and Guo 2016) while a few studies indicate a substitution effect exists between the two systems (Campbell and Brakewood 2017). In fact, one study suggests the effect is complementary for regular members of bike-sharing systems but substitutional for customers with temporary passes (Faghih-Imani and Eluru 2015).

Further, the weather attributes have been shown to have a significant impact on overall cycling as well as bike-sharing systems usage. Several earlier research efforts highlighted that adverse weather conditions such as rainy and snowy days, extreme temperatures and high humidity all reduce the demand for bike-sharing systems (Faghih-Imani et al. 2014; Gebhart and Noland 2014; Hyland et al. 2018). Bike-sharing systems usage follows temporal patterns. Studies exploring operation data demonstrated pattern of daily commute to work and time-of-day and day-of-week effects, as well as monthly and seasonal patterns (Hyland et al. 2018; Noland et al. 2016; O'Brien et al. 2014). Several studies examined the effect of special events on the bike-sharing systems usage. Several studies investigated the effects of public transport disruptions and strikes on bike-sharing systems usage and found that disruption in public transport system results in a statistically significant increase in bike-sharing systems usage both in terms of number of the trips and duration of the trips (Fuller et al. 2012; Kaviti et al. 2020; Saberi et al. 2018; Younes et al. 2019). This observed increase, however, is not homogenous across the system.

While the bike-sharing systems literature grows and systems around the world become more mature, majority of the studies so far have focused on either cross-sectional data or limited panel data (e.g., a week, a month or a year of data) to analyse the bike-sharing systems usage. Only a handful of studies looked at several years of data in their analysis. Using a dataset of 8-year trips of Montreal's bike-sharing systems, Tarpin-Pitre and Morency (2020) examined the typology of users who use bike share for their access or egress leg of their metro trips (Tarpin-Pitre and Morency 2020). They found six types of users who combine their bikeshare and transit trips and while they are growing in number (although still a very small share of overall bike-sharing systems users), their characteristics are stable over time. Another study explored factors impacting bike-sharing systems usage by casual users and long-term subscribers over a 6-year period for the Melbourne's bike-sharing system (Jain et al. 2018). Their analysis indicated that demand has been gradually increasing with the primary role of the system has been shifting towards casual users with decreasing use by long-term subscribers. Xu et al. (2020) examined the impact of building bike lanes or system expansion on the bike-sharing systems usage over time, using a 3-year worth of data from the New York City's bike-sharing system (Xu and Chow 2020). They concluded that on average, 102 and 43 trips per day, respectively, could be added to the system by the installation of one additional mile of bike lanes, and adding one more docking station to the system. These studies all highlighted the need for more research on longitudinal usage trends for bike-sharing systems around the world to help us better understand the role bike-sharing systems play in a city and how it is changing over time.

3.0 Data

All the variables investigated in the study and their respective descriptive statistics are presented in Table 1. The bicycle hire data used in the study was obtained from Transport for London (Transport for London, 2020). The data comprised the daily total number of bicycles hired at an aggregate level (i.e., for the entire bike-sharing system in London) for the period from January 2012 to June 2020 (3,104 days). Several independent variables classified as weather and non-weather related were examined in our analysis. Unlike bicycle hire data that was obtained from a single source, weather data was obtained from different sources. The hourly temperatures, measured in Degrees Celsius (ºC), provided by the UK Met Office Integrated Data Archive System, were used to estimate the mean daily temperatures for the period January 2012 to December 2017. The mean daily temperature data for the period 2018 to 2020 was obtained from the NW3 Weather website together with data for wind speed, average humidity, and atmospheric pressure. Wind speed, humidity and pressure were measured in miles per hour (MPH), percentage, and hectopascal (hPa), respectively. Average daily rainfall data, measured in millimetres, was sourced from the UK Environmental Agency dataset. The average daily temperatures recorded for the period of analysis ranged from -4.1 to 28.4 ^{o}C with an average of 11.94^{o}C. The average daily rainfall and wind speeds were 1.74mm and 4.92 MPH, respectively.

Table 1: Descriptive statistics of the data

Variable	Mean	Std. Dev.	Min	Max
Dependent Variables				
Cycle hire numbers	27,054.18	9,266.32	3,531	73,094
Independent Variables (continuous)				
Temperature (^{o}C)	11.94	5.47	-4.10	28.40
Rainfall (mm)	1.74	3.65	0.00	36.50
Wind (MPH)	4.93	2.40	0.20	16.40
Humidity (%)	75.17	11.22	39.00	98.00
Pressure (hPa)	6.39	1.73	4.20	10.30
Unemployment rate (%)	6.35	3.45	1.00	12.00
Number of stations in the system	720.42	92.19	395	790
Independent Variables (categorical)				
Weekday (2218)	0.71	0.45	0	1
Weekend (886)	0.29	0.45	0	1
Bank holiday (86)	0.03	0.16	0	1
Special Event (49)	0.02	0.12	0	1
Lockdown (99)	0.03	0.18	0	1
Winter (763)	0.26	0.44	0	1
Spring (828)	0.27	0.44	0	1
Summer (746)	0.24	0.43	0	1
Autumn (767)	0.23	0.42	0	1

Note: value in the parenthesis is frequency for categorical variables

Non-weather-related data included unemployment rate, number of docking stations, and several temporal variables to capture trend, seasonality, and variations in types of days (weekday, special event, etc.). Data on the monthly average number of docking stations in the system was estimated from the Transport for London Cycle Hire Availability database that contains the number and coordinates of the operational cycle hire docking stations (Transport for London, 2020). Of particular interest in our study was investigating the impact of unemployment rate on cycle hire demand over the period 2012-2020. It has been shown by previous research that unemployment rate has a significant impact on bike-sharing membership and usage (Qian and Jaller 2020; Ricci 2015). To this end, monthly unemployment rate for the population aged sixteen and over was obtained from the UK Office for National Statistics (Office for National statistics, 2020).

With respect to temporal factors, a categorical variable representing the four seasons (winter, spring, autumn, and summer) was included to study how the cycle hire demand varies across seasons. Also, we created a categorical variable to capture differences between different types of days. This included weekday, weekend, bank holiday, special event, and lockdown due to the Covid-19 Pandemic. Special events were included in the study to investigate their impact on cycle hires. Over the study period, examples of such events included the London Olympics in 2012, strikes on the London underground, and the Royal Wedding. A variable for lockdown was included in our analysis to establish whether there was a statistically significant association between lockdown and the number of cycle hires. The UK was under Covid-19 lockdown from 23rd March to 30th June, 2020. It should be noted that the most restrictive lockdown (stay home order) lasted until 10th May 2020 beyond which less restrictive measures remained in place. To obtain more reliable statistical inferences in this regard, we did not disaggregate this variable into two groups (of restrictive and less restrictive lockdown periods) as the number of observations in each group is relatively small; and therefore, insufficient. In our analysis, we considered weekday as the base (reference) group for the categorical variable representing the type of day.

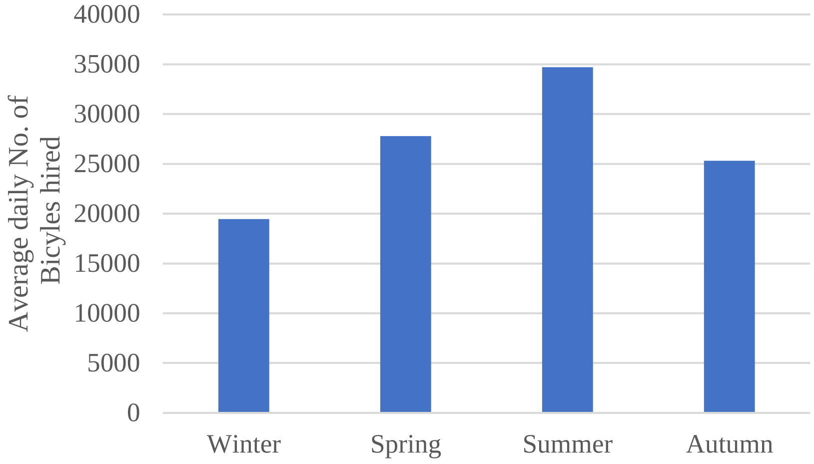

Figure 1: Seasonal variation in London cycle hires over the period 2012-2020

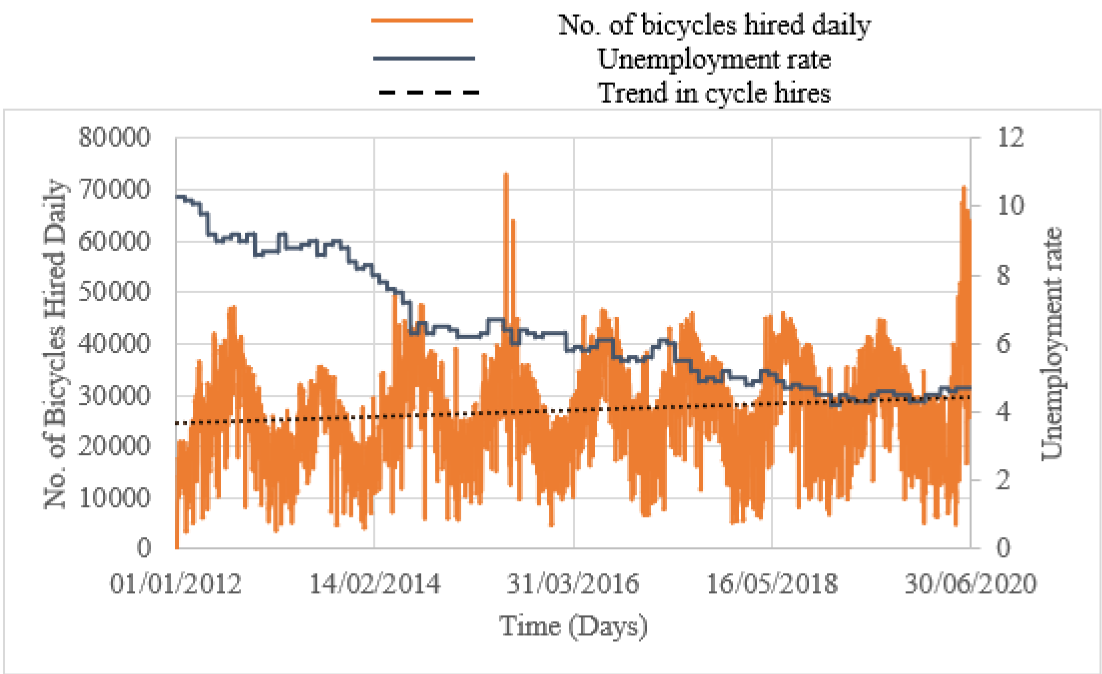

Figure 2: Time series of cycle hires and unemployment rate

Figure 1 displays a bar chart of the average daily number of cycles hired—disaggregated according to the four seasons. As expected, the average daily number of bicycles hired in summer is the highest. Figure 2 displays time series of unemployment rate and the daily number of bicycle hires for the London cycle hire scheme over the period 2012-2020. It can be inferred from Figure 2 that, while there is a decreasing trend in the unemployment rate, there is an increasing trend in cycle hires during the study period. The trend in the unemployment rate is, however, much more pronounced compared to that in the cycle hires.

4.0 Statistical modelling

Since the study sought to investigate the trend of daily cycle hires (a discrete variable) for the period under consideration, we used a count regression to model the number of daily cycle hires. Count models have been previously used to investigate bicycle-sharing system usage (Gebhart and Noland 2014; Wang et al. 2016). Specifically, we employed a negative binomial model, which in contrast to Poisson regression can account for over-dispersion (Washington et al. 2020). To capture unobserved heterogeneity more fully, we used a generalised negative binomial model in which the over-dispersion parameter varies across the sample (instead of being fixed as in the negative binomial regression) as a function of explanatory variables available in the data. This allowed us to identify variables that increase or decrease the variance in the cycle hire demand, providing further insights into uncertainties around the demand. Let y_i and θ_i denote the observed and the expected number of cycle hires for days ($i = 1, 2, \ldots, n$). Let $X = (X_1, X_2, \ldots, X_k)$ be the vector of covariates with the corresponding regression parameters $\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_k)$, excluding the constant term η. A generalised negative binomial model can be specified as:

$$
\begin{aligned}
y_i &\sim Poisson\ (\theta_i) \\
\theta_i &= \lambda_i * e^{\epsilon_i} \\
log(\lambda_i) &= \eta + \boldsymbol{\gamma X_i} \\
log(\theta_i) &= \eta + \boldsymbol{\gamma X_i} + \epsilon_i \\
e^{\epsilon_i} &\sim Gamma(1/\alpha_i, \alpha_i) \\
log(\alpha_i) &= a + \boldsymbol{\beta Z_i}
\end{aligned}
\qquad (1)
$$

where α_i is a varying over-dispersion parameter; $Z = (Z_1, Z_2,\ldots, Z_k)$ is the vector of covariates, capturing variations in the over-dispersion parameter, with the corresponding regression parameters $\beta = (\beta_1, \beta_2,\ldots, \beta_k)$; and a is the constant term. As it can be seen in (1), α varies from one observation to another, in contrast to the commonly used negative binomial model, resulting in a generalised negative binomial specification.

5.0 Results and discussions

The independent variables were tested for high collinearity prior to specifying the model. The unemployment rate, the number of docking stations and month (the variable ranging from 1 to 102, the total number of months over the study period, capturing trend) were highly correlated. Therefore, we developed separate models for each of these independent variables, allowing us to identify the variable that can serve as a better predictor of the trend in the demand for the London bike-sharing system. The parameter estimates for the three separate models are reported in Tables 2–4. All the variables are statistically significant at a 5% level of confidence. Table 2 indicates that as the number of stations increases in the London cycle hire scheme, cycle hires increase. This finding is in accordance with previous research; e.g., (Gebhart and Noland 2014), and is expected since more stations mean more bikes are available to Londoners and larger areas of the city are covered by the bike-sharing system. As reported in Table 3, the variable month, which captures the trend in the demand, is positively associated with cycle hires, confirming the presence of an increasing trend in the demand from 2012 to 2020. We further explored interaction of this variable (as well as a dummy variable representing each year) with other variables to test for temporal stability of estimated coefficients. None of the interaction terms were statistically significant, indicating that the effects are mostly stable over the 2012-2020 period.

Table 2: Model 1 - Generalised negative binomial model with number of stations

Variable	Coef.	Std. Err.	z	[95% Conf. Interval]	
In (No. of stations)	0.416	0.021	20.110	0.376	0.457
Temperature	0.026	0.001	31.520	0.024	0.028
Rainfall	-0.023	0.001	-15.700	-0 .025	-0.020
Wind	-0.015	0.001	-11.550	-0.017	-0.012
Percent Humidity	-0.006	0.000	-18.170	-0.006	-0.005
Weekend	-0.182	0.009	-21.100	-0.199	-0.165
Bank holiday	-0.244	0.033	-7.390	-0.308	-0.179
Special event	0.231	0.026	9.000	0.181	0.281
Lockdown	-0.176	0.045	-3.910	-0.264	-0.088
Spring	0.089	0.011	7.990	0.067	0.111
Autumn	0.121	0.011	11.470	0.101	0.142
Summer	0.089	0.013	6.630	0.062	0.115
Constant	7.659	0.137	55.710	7.389	7.928
Over-dispersion equation					
ln (No. of stations)	-0.683	0.198	-3.460	-1.070	-0.296
Temperature	-0.030	0.008	-3.990	-0.045	-0.015
Rainfall	0.091	0.008	10.940	0.075	0.108
Wind	0.052	0.011	4.810	0.031	0.073
Percent Humidity	0.024	0.003	7.890	0.018	0.030
Weekend	1.100	0.059	18.690	0.985	1.215
Bank holiday	1.609	0.153	10.500	1.308	1.909
Special event	0.543	0.207	2.630	0.138	0.948
Lockdown	2.869	0.147	19.490	2.580	3.157
Spring	-0.701	0.092	-7.620	-0.881	-0.520
Autumn	-0.561	0.077	-7.270	-0.712	-0.410
Summer	-0.533	0.116	-4.580	-0.761	-0.305
Constant	-0.897	1.309	-0.690	-3.462	1.668
Model Fit					
AIC	60935.91	-	-	-	-
BIC	61092.96	-	-	-	-

Table 3: Model 2 - Generalised negative binomial model with variable month to capture trend

Variable	Coef.	Std. Err.	z	[95% Conf. Interval]	
Month	0.002	0.000	22.770	0.002	0.002
Temperature	0.027	0.001	33.810	0.025	0.028
Rainfall	-0.022	0.001	-15.560	-0.025	-0.019
Wind	-0.017	0.001	-13.210	-0.019	-0.014
Percent Humidity	-0.006	0.000	-20.260	-0.007	-0.006
Weekend	-0.195	0.009	-21.960	-0.213	-0.178
Bank holiday	-0.254	0.033	-7.760	-0.319	-0.190
Special event	0.232	0.027	8.480	0.178	0.285
Lockdown	-0.287	0.045	-6.310	-0.376	-0.198
Spring	0.084	0.011	7.840	0.063	0.106
Autumn	0.125	0.010	12.390	0.105	0.145
Summer	0.072	0.013	5.470	0.046	0.097
Constant	10.331	0.027	376.140	10.277	10.385
Over-dispersion equation					
Month	-0.006	0.001	-6.010	-0.007	-0.004
Temperature	-0.019	0.007	-2.600	-0.034	-0.005
Rainfall	0.093	0.008	11.140	0.076	0.109
Wind	0.043	0.011	4.030	0.022	0.064
Percent Humidity	0.022	0.003	7.320	0.016	0.028
Weekend	1.209	0.059	20.510	1.094	1.325
Bank holiday	1.698	0.153	11.090	1.398	1.999
Special event	0.524	0.205	2.550	0.121	0.926
Lockdown	3.205	0.156	20.590	2.900	3.510
Spring	-0.905	0.092	-9.830	-1.085	-0.725
Autumn	-0.703	0.078	-9.040	-0.855	-0.551
Summer	-0.501	0.116	-4.320	-0.728	-0.274
Constant	-5.060	0.283	-17.910	-5.613	-4.506
Model Fit					
AIC	60854.710	-	-	-	-
BIC	61011.770	-	-	-	-

Table 4: Model 3 - Generalised negative binomial model with unemployment rate

Variable	Coef.	Std. Err.	z	[95% Conf. Interval]	
In (unemployment rate)	-0.255	0.010	-24.360	-0.275	-0.234
Temperature	0.027	0.001	34.060	0.025	0.028
Rainfall	-0.022	0.001	-15.760	-0.025	-0.019
Wind	-0.016	0.001	-12.720	-0.018	-0.013
Percent Humidity	-0.006	0.000	-20.430	-0.068	-0.056
Weekend	-0.192	0.009	-21.880	-0.209	-0.175
Bank holiday	-0.253	0.033	-7.770	-0.317	-0.189
Special event	0.236	0.027	8.630	0.183	0.290
Lockdown	-0.246	0.045	-5.440	-0.335	-0.157
Spring	0.088	0.011	8.190	0.067	0.109
Autumn	0.122	0.010	12.150	0.102	0.142
Summer	0.072	0.013	5.570	0.047	0.098
Constant	10.899	0.035	311.680	10.831	10.968
Over-dispersion equation					
In (unemployment rate)	0.566	0.101	5.620	0.369	0.764
Temperature	-0.024	0.007	-3.250	-0.038	-0.010
Rainfall	0.095	0.008	11.440	0.079	0.112
Wind	0.045	0.011	4.220	0.024	0.066
Percent Humidity	0.022	0.003	7.110	0.160	0.280
Weekend	1.226	0.059	20.820	1.110	1.341
Bank holiday	1.702	0.153	11.110	1.402	2.002
Special event	0.589	0.205	2.870	0.187	0.991
Lockdown	3.111	0.150	20.700	2.816	3.405
Spring	-0.892	0.092	-9.690	-1.072	-0.711
Autumn	-0.717	0.077	-9.270	-0.868	-0.565
Summer	-0.514	0.116	-4.430	-0.741	-0.286
Constant	-6.309	0.355	-17.750	-7.006	-5.613
Model Fit					
AIC	60780.600	-	-	-	-
BIC	60937.650	-	-	-	-

Considering the three separate models discussed above, we selected the best model in terms of fit based on two model-fitting criteria: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model with the lowest AIC and BIC values is preferred in terms of goodness of fit. The model-fitting results indicated that the model with the variable unemployment rate provided the best fit, having the smallest BIC and AIC values of 60937.650 and 60780.600, respectively (see Tables 2-4). This is an interesting finding indicating that the demand for the London bike-sharing scheme is more sensitive to the city's unemployment rate than to the number of docking stations available in the system. Although we do not discuss the other two models further, it does not mean that the other two variables, especially the number of docking stations, are irrelevant.

In terms of choosing between a standard negative binomial model and a generalised negative binomial model, note that both BIC and AIC values increased significantly when standard negative binomial models were used. For example, BIC and AIC values increased to 62259 and 62174, respectively, under the model that includes the unemployment rate in its set of covariates. This supports the use of a generalised negative binomial model, especially when several explanatory variables are statistically important in explaining over-dispersion in the data as reported in Tables 2–4.

5.1 Interpretation of the effects of explanatory variables

To interpret the regression coefficients (the effect of explanatory variables on the trend in the London bike-sharing system usage), we used elasticities and relative risk, respectively, for continuous and categorical variables (see Table 5). Average daily temperature, wind speed, humidity, and rainfall were found to be statistically significant in explaining the fluctuations in the cycle demand for the London cycle hire scheme. Temperature had a positive association with demand while the rest of the weather-related variables were found to have a negative impact on the number of bicycles hired. The estimated elasticity of 3.18% for temperature is the expected increase in the demand for bicycles given a 10% rise in the average daily temperature. The estimated reduction in the number of bicycles hired daily given a 10% increase in humidity was estimated to be 4.67%. Similarly, a 10% increase in rainfall and wind speed results in about 0.38% and 0.78% reduction in the cycle demand, respectively. Several previous studies also found similar results with respect to weather-related variables (Gebhat & Noland, 2014; Gallop & Tse, 2012; Nosal & Miranda-Moreno, 2014; Helbich, et al., 2014). The negative association of rainfall, wind speed and, humidity is expected since bicycles do not provide protection for the users from weather elements. However, despite the negative effect of adverse weather on scheme usage, some days of either high rainfall, humidity or wind speed still recorded relatively high numbers of cycle hires. For instance, there were about 79 days in the dataset with average rainfall of over 5mm on which the number of bicycles hired exceeded the overall daily average of 27,054.18. This may suggest that a significant number of trips are for utilitarian purposes that were previously found to be less susceptible to weather variations (Helbich, Böcker, and Dijst 2014; Nosal and Miranda-Moreno 2014; Thomas, Jaarsma, and Tutert 2013) as well as the role of intraday weather variations and use of bike-sharing systems for one-way and short trips.

The unemployment rate and a number of temporal variables were also found to be statistically significant in explaining variations in the bike-sharing system demand in London. The unemployment rate had a negative association with the number of bicycles hired in the scheme. Specifically, the model results demonstrate that a 1% increase in the unemployment rate, resulted in about 0.26% reduction in ridership in the scheme. Caution should be taken in interpreting the effect of unemployment rate on the demand since the number of docking stations, being highly correlated with unemployment rate, would contribute to this effect too. This may indicate that a considerable number of trips undertaken in the scheme are utilitarian associated with commuting trips in London. This is further supported by the observed data showing a significantly higher number of bicycles hired during working weekdays compared to weekends and bank holidays. Further, unemployed people are less likely to become a member of bike-share systems and thus the increase in unemployment rate should result in a decrease in the system usage, which is properly highlighted by our estimated parameter for unemployment rate variable. This result is also in agreement with cross-sectional studies that found bike-sharing stations in neighbourhoods with higher unemployment rates observe fewer ridership (Hyland et al. 2018; Qian and Jaller 2020).

Table 5: Average elasticities and relative changes

Model with Unemployment Rate	
Continuous Variables	*Elasticities*[1]
Unemployment rate	-2.55%
Temperature	3.18%
Rainfall	-0.38%
Wind	-0.78%
Percent Humidity	-4.67%
Categorical Variables	*Relative Change*
Weekend	-17.47%
Bank holiday	-22.35%
Special event	26.62%
Lockdown	-21.81%
Spring	9.20%
Autumn	12.98%
Summer	7.47%

1 Elasticities are based on a 10% increase in continuous variables.

Relative risk (and consequently relative change) is convenient in understanding the impact of categorical variables, representing different seasons and types of days on the daily demand for bicycles in the scheme. The magnitude of the change in the number of bicycles hired was estimated by calculating relative risk; i.e., the exponent of the regressions coefficients and subtracting one from the result prior to multiplying by 100% (i.e., [(exp$^{\gamma}$-1)*100%]). For the seasons, winter was taken as the reference category against which the change in the ridership in the scheme was estimated for spring, summer, and autumn (see table 5). The impacts of spring, summer, and autumn on the cycle demand were estimated to be higher than in winter (Table 4). Specifically, the number of bicycles hired in autumn, summer, and spring was on average, respectively, 13.0%, 7.5%, and 9.2% higher compared to winter. For the type of day, weekday was the reference category against which the relative change in demand for the other types of days was estimated. The daily number of cycle hires on weekends, bank holidays, and during the Covid-19 lockdown was on average, respectively, 17.4%, 22.4%, and 21.81% lower relative to weekdays. On the other hand, the demand for bikes in the scheme on days with special events (e.g., London Olympics) was on average 26.6% higher relative to weekdays.

5.2 Practical implications of the varying over-dispersion parameter

Since our statistical model allowed the over-dispersion parameter to vary across the sample as a function of explanatory variables, we were able to investigate the impact of these variables on the variability (in terms uncertainty around the expected mean estimate) of the demand in the London bike-sharing system. The higher the over-dispersion, the more dispersed the demand for bike-sharing. This implies a higher level of demand uncertainty that is not captured by the explanatory variables available in the data or present in the mean function (see Eq. 1). Table 4 indicates that as rainfall, wind speed, and humidity increase, the demand becomes more dispersed. However, as temperature increases, the demand becomes less dispersed. With respect to the categorical variables, the system usage is less dispersed during weekdays compared to all other types of days. Specifically, the demand during the Covid-19 lockdown days is the most dispersed, implying that unmeasured/unknown factors (variables other than those present in our data) had a bearing on the demand during lockdown. Finally, the demand in winter is more dispersed compared to all other seasons.

6.0 Conclusions

This study employed data from the London cycle hire scheme for the period January 2012 - June 2020, with the aim of exploring the variability in the demand for the London bike-sharing system over the study period. One of the key objectives of the study was to understand the impact of unemployment rate on cycle ridership in the London bicycle hire scheme. The model estimation results largely agreed with the findings of previous studies on the subject. With respect to weather related variables, the study revealed that bicycle demand in the London bicycle share scheme is impacted negatively by an increase in the average daily rainfall, wind speed, and humidity. However, an increase in the overall average daily temperature was found to have an increasing impact on the overall demand.

Non-weather variables were also investigated and found to be statistically important in affecting the cycle demand. Interestingly, we found that the rate of unemployment was a key factor in explaining the demand for the London cycle hire scheme. Note that, since the unemployment rate and the number of docking stations were highly correlated, we developed separate models for each of these variables. Our results indicated that the model including the unemployment rate provided a much better fit to the data compared to the one including the number of docking stations. In this regard, our finding reveals that a high proportion of bike-sharing trips in London is due to commuting to work trips. Since work commuters unlike leisure users, are less sensitive to changes in weather factors, this may also help explain why even on days when there are adverse weather conditions, there is still a relatively high level of demand for the London bike-sharing scheme. Further, some of the variability in the ridership in the scheme was found to be attributed to the different seasons, with the demand being the lowest in winter. The temporal stability of the coefficients indicated that the effects of contributing factors are mostly stable over the analysis period. Using a generalised negative binomial model instead of the commonly used negative binomial model, we captured variability (uncertainty) in the demand, in addition to the demand itself, using the same set of explanatory variables available in the data. The latter approach provided further insights into the uncertainty around the demand for the London bike-sharing system. The results of the study provide useful insights for policy makers on the magnitude of the impact of several variables such as rainfall and humidity that are known to have adverse impacts on cycling in general. Further, the understanding of the impact of unemployment may explain differences in bicycle demand in share schemes in different places with similar characteristics. This would be useful for bike-share scheme planners.

Conflict of interest statement

The authors declare no conflicts of interest.

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