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Effect of the COVID-19 pandemic on bike-sharing demand and hire time: Evidence from Santander Cycles in London

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Abstract

The COVID-19 pandemic has been influencing travel behaviour in many urban areas around the world since the beginning of 2020. As a consequence, bike-sharing schemes have been affected—partly due to the change in travel demand and behaviour as well as a shift from public transit. This study estimates the varying effect of the COVID-19 pandemic on the London bike-sharing system (Santander Cycles) over the period March–December 2020. We employed a Bayesian second-order random walk time-series model to account for temporal correlation in the data. We compared the observed number of cycle hires and hire time with their respective counterfactuals (what would have been if the pandemic had not happened) to estimate the magnitude of the change caused by the pandemic. The results indicated that following a reduction in cycle hires in March and April 2020, the demand rebounded from May 2020, remaining in the expected range of what would have been if the pandemic had not occurred. This could indicate the resiliency of Santander Cycles. With respect to hire time, an important increase occurred in April, May, and June 2020, indicating that bikes were hired for longer trips, perhaps partly due to a shift from public transit.

Introduction

Cycling as a sustainable mode of travel is proven to be associated with several benefits such as reducing motorised traffic in urban areas, reducing greenhouse gas emissions, reducing the need for parking spaces, and improving mental and physical health due to an increase in physical activity [1–6]. In recent years, several interventions and policy instruments have been devised to reduce the negative externalities of motorised traffic and encourage more people to cycle [1, 2, 7]. Bicycle-sharing is one of the key policy interventions integrated into many urban transportation networks across the world, with the aim of promoting cycling [7, 8]. In the past two decades, bike-sharing systems, which allow for flexible and environmentally-friendly travel, have been gaining popularity in many cities around the world.

The London bike-sharing scheme (Santander Cycles), one of the largest schemes in Europe, was launched in Central London on 30 July 2010 with 5000 bikes available at 315 docking stations located in 8 boroughs [9]. Over the last decade, the scheme has rapidly expanded to other areas of the city, covering around 100 square kilometres [9]. As of January 2020, the London bike-sharing system had more than 12,000 bicycles [9]. In terms of travel demand, more than 87 million cycle hires were made within 10 years from its launch, and there were more than 1.7 million cycle hires in 2019 [9].

Due to the COVID-19 pandemic, many countries introduced stringent measures to contain the spread of the virus. This resulted in important changes in travel behaviour [10], especially in urban settings; for example, as a consequence of restrictions on travelling, and safety concerns regarding travelling on public transit [11–13], and reduction in the frequency of public transport services. In this regard, for example, Noland [14], discusses the relationship between mobility and the reproduction rate of COVID-19. Also, previous studies showed that public transport disruptions either internally (e.g., maintenance and strikes) or externally (e.g., natural disasters and outbreak of communicable diseases) have spillover effects on the demand for bike-sharing schemes [15–17]. In fact, such disruptions often cause a temporary increase in the demand for other modes of transport, including bike-sharing schemes. This said, we would expect important changes in the London bike-sharing system due to the recent pandemic.

Literature review

Over the last decade, several studies investigated various aspects of bike-sharing schemes [2, 5, 7, 8, 18–23]. These studies mostly focus on understanding the demand for bike-sharing systems by revealing the impact of built environment, sociodemographic, weather conditions, and policies on bike-sharing services. In fact, multiple factors such as weather conditions and disruptions in public transport services affect the number and duration of cycle hires [7, 8, 12, 15, 16, 24–26]. Evidence shows that weather conditions play a key role not only in explaining the demand for bike-sharing systems, but also in explaining the duration of cycle hires. Previous studies suggest that, in general, there is a positive relationship between temperature and the number of cycle hires [7, 27, 28]. For example, Morton [29] and Chibwe et al. [8], found that the demand for bike-sharing systems increases as temperature increases. However, research shows that temperatures exceeding 30 C reduce the demand for bike-sharing systems in some regions [7, 30]. With respect to trip duration, Gebhart and Noland [26], investigating the impact of weather on bike-share trips in Washington D.C., found that shorter trip durations occur at lower temperatures between 10 F and 49 F, compared to higher temperatures between 50 F to 59 F. Faghih-Imani and Eluru [24], examining Citi Bike in New York, found that trip duration for non-member users are longer than the member users in favourable weather conditions.

With respect to the demand for bike-sharing schemes, several previous studies suggest that hire numbers decrease as rainfall, wind speed, and humidity increase [7, 26, 27, 29, 30]. For example, El-Assi et al. [27], found that rainfall and high humidity are unfavourable weather conditions for the Toronto bike-sharing system. Similarly, Morton [29] found a negative correlation between the demand for the London bike-sharing system and rainfall, wind speed, and humidity. Gebhart and Noland [26] found that wind speed and humidity had a negative impact on the demand for the Capital bikeshare scheme. Chibwe et al. [8] found that rainfall, wind speed, and humidity were negatively associated with the demand for the London bike-sharing system.

As discussed by Wang and Noland [12], bike-sharing schemes help improve the resilience of urban transportation networks since they serve as a substitute for public transport services when these are disrupted. This is in accordance with previous research that shows public transport disruptions (including safety concerns) shift the demand from public transit to bike-sharing systems [13, 16, 31]. Therefore, not only the change in travel behaviour due to the COVID-19 pandemic affects bike-sharing systems, but also changes in public transport (e.g., lower frequency and safety concerns relating to the danger of contracting the virus) have an impact on bike-sharing.

For example, Saberi et al. [16] examining the impacts of a London Tube strike on the London bike-sharing system found that trip duration increased by 88% from an average of 23 minutes to 43 minutes per trip. They also found that due to this disruption the bicycle trip counts increased by 85% from an average of 38,886 trips per day to 72,503 trips per day [16]. Fuller et al. [32] investigating the effect of London Tube strikes on 6 September and 10 October 2010 on the London bike-sharing system, found that these strikes did not cause any significant increase in mean trip duration. However, a statistically significant increase in the total number of cycle hires per day was observed [32]. Both studies concluded that changes in the system caused by the above-mentioned disruptions were temporary. Similarly, Younes et al. [15] investigated the impact of three planned disruptive events in Washington D.C. metro services on Capital bikeshare. They found that, while disruptions had increased bike ridership significantly, the change in the mean hire duration was insignificant because the increase in the hire numbers for trips longer than 2.5 miles were relatively small.

Previous studies on understanding the effect of the outbreak of communicable diseases on bike-sharing schemes are relatively limited [8, 12, 33–41] A study conducted by Wang and Noland [12] examined the effect of the lockdown and the subsequent phases of reopening on Citi Bike in New York, analysing two years of data, 2019 and 2020. The authors used a Prais-Winsten regression model that accommodates serial correlation given the time-series nature of their data. They found that the demand for the Citi Bike system decreased sharply after the lockdown, but it started to return normal afterwards. Another recent study conducted by Li et al. [41] found that travellers, in Zurich, preferred to use micro-mobility services (including bike-sharing services) during the COVID-19 pandemic, and that these services were used for longer trips. Chibwe et al. [8] found that the first national lockdown, introduced in March 2020, in England decreased the demand for the London bike-sharing system by around 22%. They considered data from 2012 to June 2020 and used a generalised negative binomial regression, conducting an exploratory analysis, while using lockdown as a categorical variable in their model. Therefore, the method did not allowed for estimating the varying effect of lockdown and other pandemic-related policies over time. Li et al. [38] analysing the demand for the London bike-sharing system over the period January 2019 to June 2020, estimated the effect of the first lockdown and lockdown ease on the number of daily trips. They found that the number of trips decreased after the lockdown, but then the demand showed an increasing trend. A more recent study conducted by Lei and Ozbay [40] used regression discontinuity and the propensity score method to estimate the short- and long-term impacts of the stay-at-home policy on CITI bike in Manhattan. Table 1 provides a summary of relevant literature.

The current paper

In this research we investigate the effect of the COVID-19 pandemic on the London bike-sharing scheme. While previous research in this context is limited and mostly focuses on understanding the effect on the number of trips, we estimate the impact of the pandemic on both hire time (trip duration) and hire numbers in London, UK. Also, while previous studies provide valuable insights, they mostly use pandemic-related policy interventions as explanatory variables in regression models to estimate the effect of these interventions on bike-sharing

Table 1. Summary of relevant literature.

Study	Location	Dependent variable	Data	Methodology	Results
Wang and Noland [12]	New York (US)	Number of cycle hires	Bikeshare usage data: January-September 2019 and January-September 2020	Prais-Winsten regression with lockdown-related policies as regression covariates	Demand decreased sharply after the lockdown; demand returned normal afterwards
Lei and Ozbay [40]	Manhattan (US)	Number of cycle hires	Bikeshare usage data: March-June 2019 and March-June 2020	Regression discontinuity design and propensity score matching	Demand decreased after lockdown; demand for Citi Bike customers increased in May and June
Li et al. [41]	Zurich (Switzerland)	Number of cycle hires and hire time	Bikeshare usage data: 2020	Spatial-temporal-semantic analysis	Demand decreased significantly during lockdown; Bikes were used for longer trips
Li et al. [38]	London (UK)	Number of cycle hires	Bikeshare usage data: January 2019 to June 2020	Interrupted time-series with lockdown-related policies as regression covariates (causal study)	Demand decreased after lockdown; observed an increasing trend after lockdown ease; demand decreased during morning peak hours and for shorter trips; demand increased for other types of trips
Kubaľák et al. [34]	Kosice (Slovakia)	Number of cycle hires and hire time	Bikeshare usage data: 2019 and 2020	Non-model-based analysis comparing observed data	Bike hires increased during 2020 pandemic compared to 2019. Hire time was longer during the pandemic compared to the pre-pandemic period
Hu et al. 2021. [33]	Chicago (US)	Number of cycle hires	Bikeshare usage data: March-July 2019 and March-July 2020	Generalised additive (mixed) models	Bike sharing is a resilient transport system. The proportion of commuting trips witnessed significant decrease; however, proportion of casual trips increased significantly during the pandemic
Jobe and Griffi [37]	Major cities in US	Number of cycle hires	Questionnaire survey 2020	Mixed qualitative and quantitative (descriptive) method	43% of the respondents who were unemployed due to the pandemic experienced increase in the use of bike share; 36% of employed respondents reported decrease in the use of bike share
Chibwe et al. [8]	London (UK)	Number of cycle hires	Bikeshare usage data: January 2012 to June 2020	Generalised negative binomial model with lockdown as a regression covariate	Demand reduced by around 22% during the after lockdown period until June 30th 2020
Padmanabhan et al. [35]	New York, Boston, and Chicago (US)	Number of cycle hires and hire time	Bikeshare usage data: October 1st 2019 to May 31st 2020	Ordinary Least Square regression	COVID-19 negatively impacted bike ridership; average trip duration increased during COVID-19
Nikiforiadis et al. [36]	Thessaloniki (Greece)	Number of cycle hires	Questionnaire survey 2020	Ordinal regression model	COVID-19 does not affect number of bicycle hires; however, bikeshare systems can be a viable and more attractive option than the motorised vehicles.
Teixeira et al. [39]	New York (US)	Number of cycle hires and hire time	Bikeshare usage data: February and March in 2019 and 2020	Mann-Whitney U tests and Ordinary Least Square regression	Bikesharing was more resilient than subway; the demand for bikeshare decreased; hire time (trip duration) increased

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systems mostly based on relatively short time spans (from a few months to one or two years of data).

In this study, however, considering time-series data from 2010 to 2020, we use a Bayesian second-order random walk time-series model to predict what would have happened in terms of demand and trip duration if the COVID-19 pandemic had not occurred; that is, the counterfactual. The model accounts for time dependency in our time-series data as well as the non-linear effect of time on the outcomes of interest: hire time and hire numbers. We then compare the observed hire numbers and hire time (trip duration) with their respective counterfactuals to estimate the varying effect of the COVID-19 pandemic over the period March-December 2020. This allows us to understand the varying effect of the pandemic on hire numbers and hire time during the latter period as various pandemic-related policies came into force. The method implemented is one of the most valid approaches used in biostatistics and medical research; for example, to estimate excess mortality during the recent pandemic [42]. The rest of the paper is structured as follows. The following section discusses materials and methods, explaining the data and our statistical approach. Under the section of statistical analysis we introduce the Bayesian second-order random walk model and our leave-one-year-out cross-validation exercise. We report and discuss the results in the section of results and discussion. Conclusions and implications are provided in the last section.

Materials and methods

Bikeshare data

The data set used in this study is related to the London bike-sharing system and was obtained from Transport for London (TfL). The data set contains average monthly hire time (trip duration) and total monthly cycle hire numbers over an 11-year period from the introduction of the scheme in July 2010 to December 2020. Note that the data used here — which was readily available on TfL's website — is at an aggregate level; i.e., for the entire London bike-sharing system at a monthly level. The study period therefore covers 126 months in total. To control for the size of the system, we obtained time-series of the number of docking stations from TfL, aggregated at a monthly level. Also, weather-related variables (rainfall, temperature, humidity, and wind) were obtained from UK Met Office Integrated Data Archive System and NW3 weather website, and were aggregated at a monthly level to be in accordance with the aggregation level of the outcomes of interest (hire duration and hire numbers). Table 2 provides the summary statistics of the data. Fig 1 displays time-series of the outcomes. This figure implies no major change in the pattern of the cycle hires in 2020 compared to the previous years. However, we see that the pattern changes drastically for hire time in 2020.

Fig 2 takes a closer look into the year 2020, displaying the observed trend in hire numbers and hire time as well as some of the major events (policies) relating to the COVID-19 pandemic. These events are obtained from the Institute for Government Analysis [43]. The first lockdown in England was implemented on 23 March 2020, and since then several changes to restrictions were made by the Government. In May, people who could not work from home were told to go to work, avoiding public transit. Other similar changes to the pandemic-related policies were made over the period May-December 2020. Perhaps, the most important one being the second lockdown that came into force on 5 November 2020, ending on 2 December 2020. It can be seen that the outcomes of interest follow two different trends. Fluctuations in the graph are partly due to seasonal effects and partly due to the implemented policies. It is therefore important to distinguish between the two major sources that influence the London bike-sharing system — which we will discuss in the next section.

Table 2. Summary of descriptive statistics (July 2010–December 2020).

Variable	Mean	Std. Dev.	Min	Max
Average monthly hire time (minutes)	19.28	3.63	13.78	36.00
Monthly number of cycle hires	785,366.00	237,647.80	12,461.00	1,253,102.00
Monthly number of docking stations	687.56	158.47	315.00	834.00
Temperature (°C)	12.14	4.85	2.01	22.11
Rainfall (mm)	1.73	0.99	0.13	5.37
Wind (mph)	4.90	1.01	2.77	8.67
Humidity (%)	75.54	8.12	60.06	90.33

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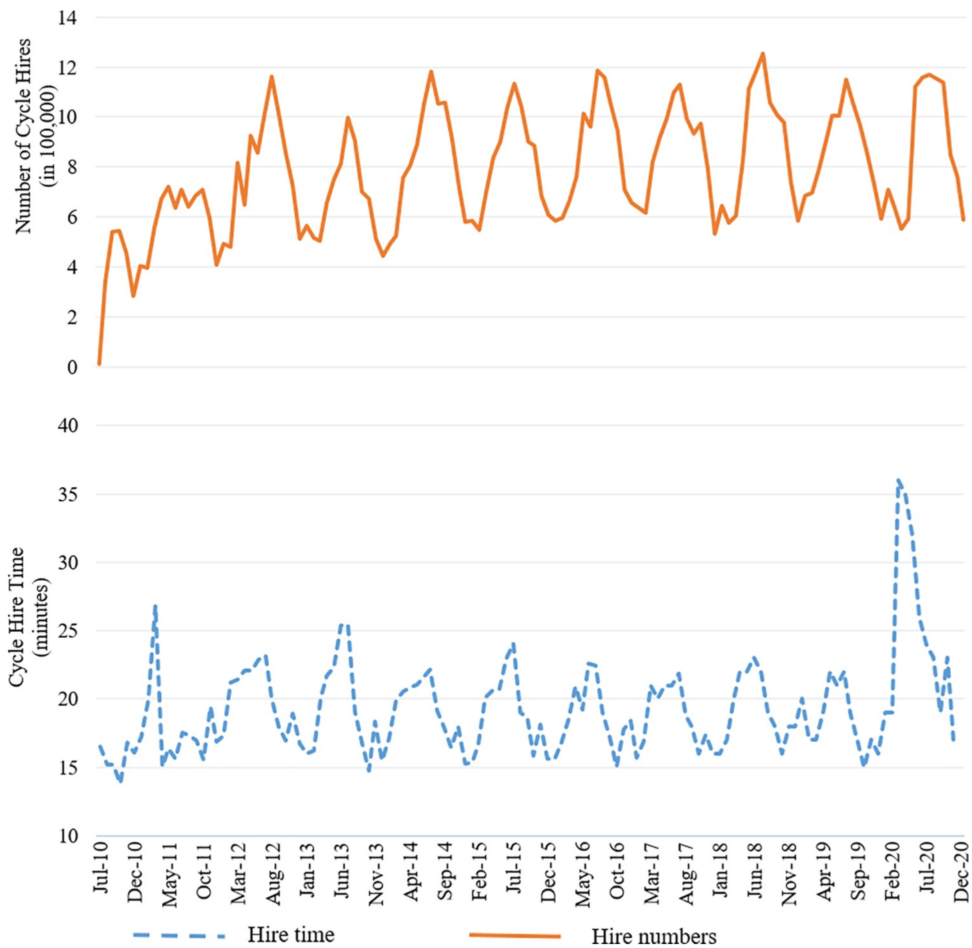

Fig 1. London bike-share time-series of monthly hire numbers and average monthly hire time.

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Statistical analysis

To estimate the change in the London bike-sharing system in terms of both hire number and hire time, we used the pre-lockdown period data from July 2010 to the end of February 2020 (training data) to calibrate our statistical models. We used Bayesian hierarchical models with a second-order random walk specification to account for the temporal correlation in our time-series data. We then used the data from March 2020 to December 2020 to predict hire numbers and hire time for each month had the pandemic not occurred; that is, counterfactuals. To help predictions, we considered a set of covariates including the meteorological variables, number of docking stations, and different lagged versions of the outcome (1, 2, 6, and 12-month lag) based on the previous literature and association with the outcomes of interest (based on parsimony grounds). Finally, comparing the counterfactuals with the observed data in the post-lockdown period, we were able to understand how the recent pandemic affected the London bike-sharing system March-December 2020. A schematic view of the method is displayed in Fig 3.

Bayesian hierarchical second-order random walk model. Hire time is a continuous variable while the monthly cycle hire numbers are large counts. To make the monthly cycle hire numbers continuous and help the convergence, we standardised it (subtracted its mean and divided by its standard deviation) and back-transformed the posterior distribution of the predictions.

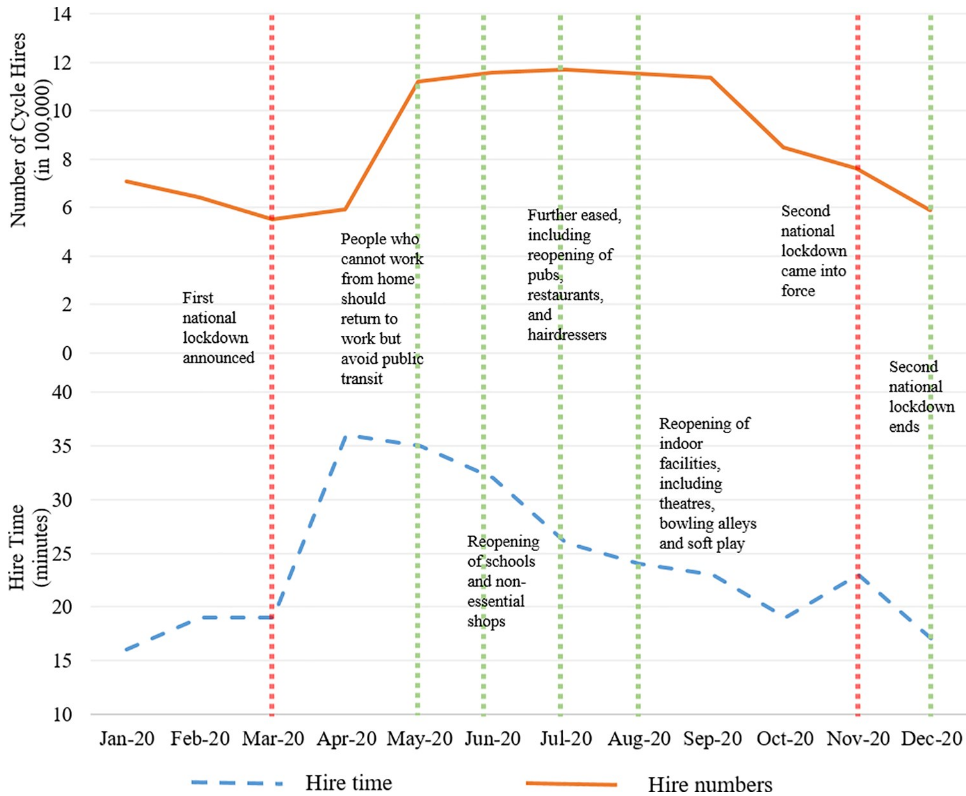

Fig 2. Time-series of observed data in 2020 and pandemic-related events.

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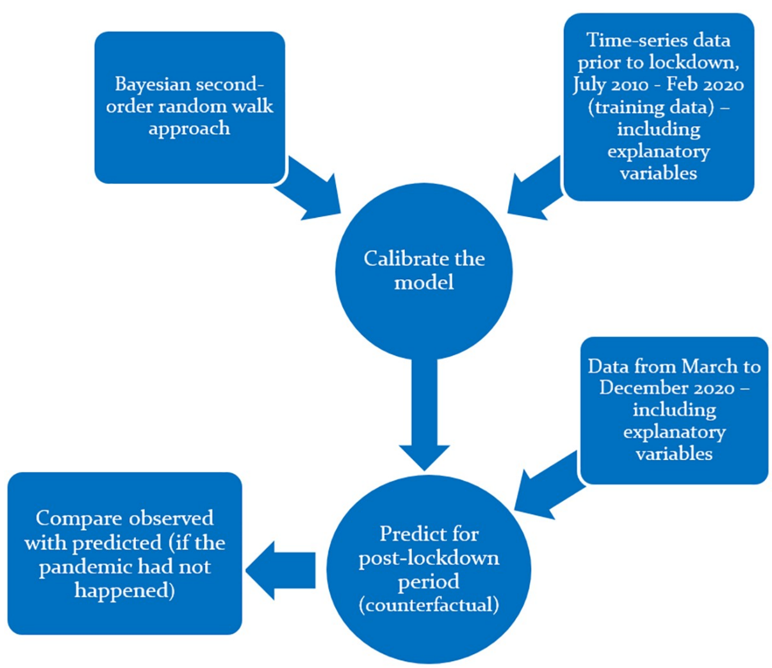

Fig 3. Schematic view of the methodological approach.

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Let y_t denote the observed outcome of interest (e.g. hire time or standardized hire numbers) for the t-th month ($t = 1, 2, \ldots, T$). We assumed that y_t follows a normal density with the mean λ_t and variance v. Note that it can be implied from Table 2 that the distribution of hire time, for example, is skewed. In fact, previous research highlights this [18, 44]. Assuming a normal distribution for hire time, however, would not cause any major bias here as long as we make sure that the model residuals are normal. Also, as we discuss in Section 3.2., the appropriateness of our models can be evaluated through a cross-validation exercise. Let $X_t = (X_{1t}, X_{2t}, \ldots, X_{kt})$ be the vector of k explanatory variables (e.g., weather conditions) for the t-th observation with their corresponding regression coefficients $\beta = (\beta_1, \beta_2, \ldots, \beta_k)$. Let β_0 be an intercept term, and y_{t-12} be the 12-month lag of the t-th outcome with its associated coefficient γ. We can write

$$\begin{aligned} y_t &\sim Normal(\lambda_t,\ v) \\ \lambda_t &= \beta_0 + X_t.\beta + \gamma.y_{t-12} + u_t \end{aligned} \tag{1}$$

where u_t — specified in (2) — is a structured error term that follows a second-order random walk (RW2) process [45], accommodating temporal correlation in the time-series data. Note that u_t allows for non-linearity in the effect of time on the outcome of interest.

$$p(u_t|u_{-t}, v_e) = \begin{cases} Normal(2u_{t+1} - u_{t+2}, v_e) \ \ for\ t = 1 \\ Normal\left(\frac{2}{5}u_{t-1} + \frac{4}{5}u_{t+1} - \frac{1}{5}u_{t+2}, v_e/5\right) \ for\ t = 2 \\ Normal\left(-\frac{1}{6}u_{t-2} + \frac{2}{3}u_{t-1} + \frac{2}{3}u_{t+1} - \frac{1}{6}u_{t+2}, v_e/6\right) \ \ for\ t = 3, \ldots, T-2 \\ Normal\left(-\frac{1}{5}u_{t-2} + \frac{4}{5}u_{t-1} + \frac{2}{5}u_{t+1}, v_e/5\right) \ \ for\ t = T-1 \\ Normal(-u_{t-2} + 2u_{t-1}, v_e) \ \ for\ t = T-2 \end{cases} \tag{2}$$

Where u_t depends on values of u at times different than t; v_e is the associated variance and depends on the number of temporal neighbours (up to two neighbours in the second-order random walk); the more the neighbours, the more the information and thus the smaller the variance v_e. Such a relatively complex temporal structure allows the model to borrow strength from the second order neighbours in time, thereby addressing unobserved heterogeneity [46], specifically temporally-structured heterogeneity, more fully.

We specified non-informative priors Normal(0, 1000) for the regression coefficients, and Gamma densities with shape 1 and rate 0.01 for v and v_e. The rationale behind this selection is to have an adequate mass at zero, making sure that a more complex model is not forced to the data, but driven by the data. We report median and 95% credible intervals (95% probability that the true value lies within the interval) of the model predictions and the regression coefficients. The covariates were standardised to help convergence and back-transformed to facilitate interpretation as we report in Section 4. We estimated the models using Nimble, which allows writing statistical models in the BUGS language from R [47]. Further details are provided in the first section of the S1 File.

Checking model adequacy: Leave-one-year out cross-validation. Besides confirming the normality of the residuals, we employed a comprehensive multiple fold cross-validation approach to investigate model performance. In this approach, we focused on the years 2010–2019 and fit the aforementioned models leaving one year out each time. We then predicted hire number and hire time for each month for the year left out and compared the predicted with the observed values. As metrics, we calculated the adjusted R^2 and the 95% coverage probability, which is the probability that an observed value lies within the 95% credible intervals of the predictions. Doing so, we were able to confirm whether our assumptions and models were appropriate and supported by the data. Note that conducting such a comprehensive cross-validation exercise is rare if non-existent in the extant bikesharing literature.

Results and discussion

We discuss the results in the following five subsections, covering different aspects of our analyses.

Cross-validation results

Following our cross-validation exercise, the adjusted R^2 values were 0.69 and 0.30 for the models representing cycle hire number and hire time, respectively. These values are satisfactory when comparing with previous research. For example, the adjusted R^2 value for trip duration was less than 0.19 in an important study conducted by Gebhart and Noland [26]. The 95% coverage probabilities were 0.86 and 0.94 for the hire number and hire time models, respectively. The coverage probability indicates the proportion of the observed data that falls within the predicted 95% credible intervals. We are therefore satisfied with the performance of the developed models. As an example, Figs 1 and 2 in the supplementary material display the observed vs. predicted hire numbers and hire time for the year 2019 based on the data from 2010 to 2018.

Posterior densities of regression coefficients

Although the focus of our study is on predicting what would have happened if the COVID-19 pandemic had not occurred, we provide the regression coefficient estimates (back transformed to the original scale) for both hire time and hire number models in Table 3. This allows identifying explanatory variables that are statistically important in explaining monthly cycle hires and hire time. In accordance with previous research (e.g., Chibwe et al. [8] and Gebhart and Noland) [26], we found that weather-related variables have an important effect on the demand and trip duration. While temperature is positively associated with these two measures, rainfall, humidity, and wind are negatively associated with cycle hire numbers and hire time. This is in accordance with previous research (e.g., Chibwe et al. [8] and Gebhart and Noland [26]). Also, we found that the lag of 12 (i.e., y_{t-12}) was an important predictor for both outcomes. This can be explained by the fact that for each month, for example, travel patterns and weather conditions are similar to that month's observations in the previous year.

Observed post-lockdown data vs. counterfactuals

Fig 4 displays the observed and predicted (counterfactual) trends for cycle hire numbers in 2020. Specifically, the observed and predicted cycle hire numbers with their 95% credible

Table 3. Posterior summary of the regression coefficients.

	Monthly cycle hire numbers			Average monthly hire time		
		95% credible intervals			95% credible intervals	
Variables	**Median**	**lower limit**	**upper limit**	**Median**	**lower limit**	**upper limit**
Temperature	30,733	26,498	34,863	0.240	0.160	0.310
Rainfall	-30,227	-40,878	-19,608	-	-	-
Wind	-17,212	-27,744	-6,483	-	-	-
Humidity	-	-	-	-0.090	-0.140	-0.040
Lag 12	0.160	0.060	0.260	0.240	0.110	0.380

https://doi.org/10.1371/journal.pone.0260969.t003 intervals (the shaded area) are shown in Fig 4 over the period January-December 2020. Recall that the first lockdown came into force in March 2020 in England. As it can be seen in Fig 4, the number of cycle hires decreased in March and April, which is expected following the city shut down as of March 23rd. It is interesting that the demand in March experienced a relatively important decrease although the lockdown started on 23 March 2020. This could be explained partly due to the lockdown and partly because of the fact that some travellers started to work from home (or reduced their number of trips) in March 2020 even prior to the UK Government's lockdown policy comes into force.

After this reduction, the demand rebounded from May 2020, and remained in the expected range of what would have been if the pandemic had not occurred. This could be an indication that the London bike-sharing scheme has been a resilient transport system during the year 2020 in spite of the pandemic. Previous studies highlighted the resiliency of bikesharing, for example, in New York [12, 39]. In May 2020 some of the restrictions were eased; for example, people who could not work from home were told to go to work, avoiding public transport if they can. Therefore, while public transit suffered in terms of ridership [48, 49], we see a slight increase in the number of cycle hires in May and June 2020. In the period May-December 2020, the larger decrease in the demand was observed in November and December after the second lockdown came into force on 5th November.

Fig 5 shows the observed and predicted average monthly hire time with their associated 95% credible intervals. The pattern differs from the one in Fig 4. In March while the average hire time increased slightly following the first lockdown on 23rd March, an important increase occurred in April, May, and June. Then, from July 2020, the average hire time remained within the posterior distribution of the predicted hire time; therefore, no statistically distinguishable change was observed. Interestingly, in October 2020 hire time became very similar to what it would have been if the pandemic had not happened. Then, following the second lockdown introduced during the first week of November, there was another jump in hire time. The second lockdown ended on 2nd December, and the average hire time in December became similar to its corresponding counterfactual.

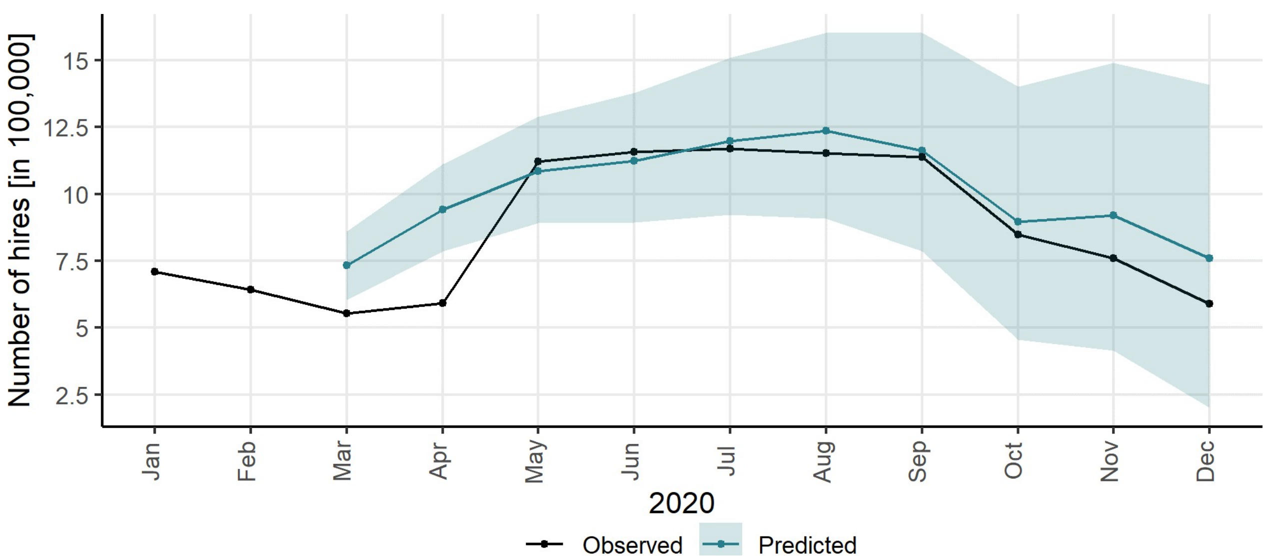

Fig 4. Observed hire numbers vs. predicted hire numbers (counterfactuals). Note: the shaded area indicates the 95% credible intervals around counterfactuals. See the electronic version for a colour view.

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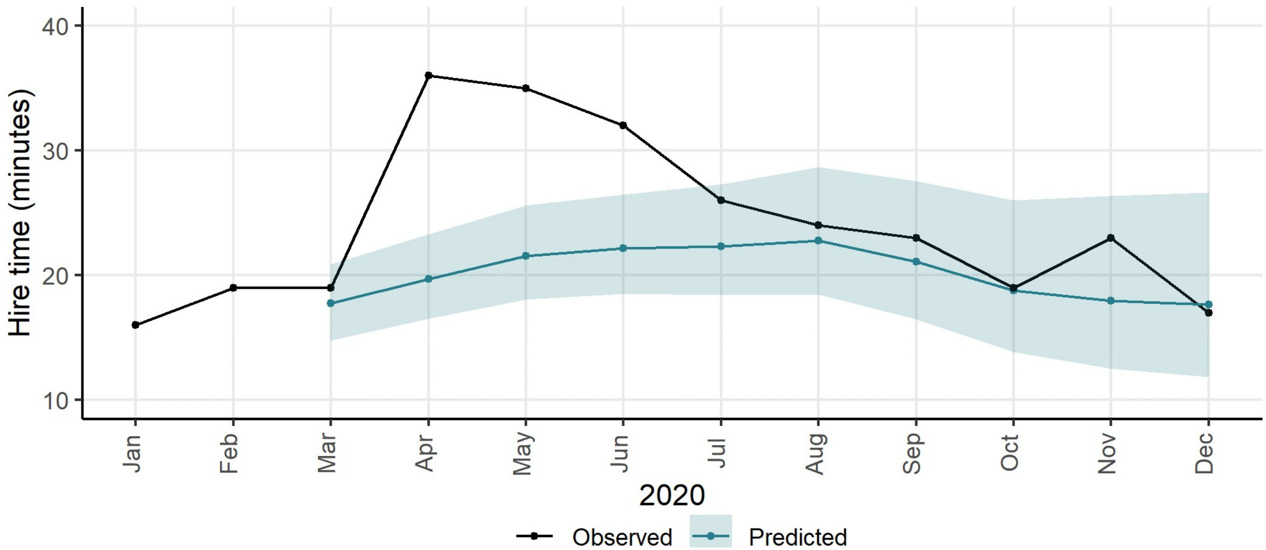

Fig 5. Observed hire time vs. predicted hire time (counterfactuals). Note: the shaded area indicates the 95% credible intervals around counterfactuals. See the electronic version for a colour view.

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The increase in hire time could be partly associated with the fact that perhaps some travellers hired bikes for longer trips, avoiding tube and buses in London. As indicated by previous research, there has been a shift from public transit to other modes of travel including bikeshare; for instance, in New York due to the fear of contacting the Coronavirus while travelling on public transport [12, 39]. Another reason for the observed increase in hire time could be partly associated with an increase in casual users. For example, this might be due to an increase in the number of Londoners who used Santander Cycles for recreational activities including exercising. On the other hand, note that according to official statistics, the number of tourists were lower compared to the previous years over the same period [50].

Magnitude of the change in hire numbers and hire time

To clearly understand the magnitude of the change in hire numbers and hire time during 2020, we obtained posterior densities of the estimated changes (See Table 4). With respect to the total number of monthly cycle hires, Table 4 indicates that the largest decrease occurred in April with around 360,000 fewer bikes being hired, followed by March with around 184,000 fewer bikes being hired. Looking at the 95% credible intervals, the reductions in March and April 2020 are statistically important.

With respect to hire time, the largest statistically important change in trip duration occurred in April with an excess of 16.48 minutes (CI[12.97, 19.18]), followed by May with an excess of 13.72 (CI[9.88, 17.42]) minutes, and then June with an excess of 10.11 (CI[5.86, 13.95]) minutes. The 95% intervals indicate the level of uncertainty around the estimates. Note that the interpretation is different from classical confidence intervals. A 95% credible interval indicates that there is 95% probability that the estimated value (median) is in that interval. In July the excess hire time decreased to 3.96 (CI[-0.72, 8.25]) minutes. Although the latter interval includes zero, a larger proportion of the posterior distribution is on the positive side. The same trend is observed in November 2020 when the second national lockdown came into force.

Table 4. Estimated change in the London bike-sharing scheme.

	Monthly cycle hires (numbers)			Monthly average cycle hire time (minutes)		
		95% credible intervals			95% credible intervals	
Month 2020	**Median**	**Lower limit**	**Upper limit**	**Median**	**Lower limit**	**Upper limit**
March	-183,849	-311,416	-57,143	1.39	-1.72	4.44
April	-359,531	-525,787	-202,016	16.48	12.97	19.8
May	25,377	-179,939	220,883	13.72	9.88	17.42
June	21,602	-232,512	254,274	10.11	5.86	13.95
July	-46,989	-350,991	233,979	3.96	-0.72	8.25
August	-106,165	-464,076	227,011	1.52	-3.87	6.31
September	-50,532	-480,584	333,468	2.24	-3.67	7.45
October	-74,784	-567,513	366,869	0.6	-5.96	6.28
November	-191,748	-743,497	311,631	5.47	-1.98	11.75
December	-204,757	-830,529	363,241	-0.19	-8.23	6.43

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Strengths and limitations of the study

Our method allowed us to understand the varying effect of the COVID-19 pandemic on the London bike-sharing system over the period March-December 2020, using a rigorous time-series model. Specifically, based on our approach, we were able to investigate how the London bike-sharing scheme was affected by various Government policies (i.e., introduction of the lockdown and the easing of restrictions in various stages) that came into force in relation to the COVID-19 pandemic. The Bayesian approach is advantageous as it allows for the propagation of uncertainties in all layers of the model and predictions [51]. Also, the predictions under the second-order random walk approach are smoother (using more neighbouring time periods), which makes it appealing in the context of our study in which the focus is on prediction [52]. Lastly, the leave-one-year-out cross-validation approach adopted here allowed us to ensure the suitability of the models and predictions. In general, using such cross-validation approach is rare if non-existent in the bikesharing literature. Also, while previous research mostly focused on a relatively limited time span in studying bikesharing systems, we considered an eleven-year study period, from the launch of the London bike-sharing scheme to the end of December 2020.

To provide more evidence and better understand the magnitude of the shift from public transport to bikesharing, analysing public transit data together with the bikeshare data is needed. Also, the data used in this study was at an aggregate level in terms of both user type and docking station level. Firstly, analysing the data relating to subscriber and casual users (two different segments of the users) helps understand the impact of the recent pandemic on the London bike-sharing system more fully. Secondly, another important improvement will be achieved by investigating the change at station level. Doing so, it is possible to understand how the effect of the pandemic varies from one docking station to another. For instance, we expect that docking stations in proximity to offices where most users are employees, working mostly from home, are more affected by the pandemic compared to the docking stations located in commercial or residential areas.

Conclusions and implications

The aim of our study was to investigate the impact of the COVID-19 pandemic on the London bike-sharing system, which is one of the largest bike-sharing schemes in the world. To this end, we focused on the readily available data available on TfL's website. The data contained the total number of monthly cycle hires and the average monthly cycle hire time (trip duration) from July 2010 (launch of the London bike-sharing scheme) to the end of December 2020. In addition, we obtained weather-related data and time-series of docking stations from various sources. Using a Bayesian second-order random walk time-series approach, we calibrated a model using the pre-lockdown data (July 2010–February 2020). Then, we predicted what would have been if the pandemic had not occurred; that is, counterfactuals for both hire numbers and hire time for the post-lockdown period from March to December 2020. Comparing the observed data during the post-lockdown period with the counterfactuals and their associated 95% credible intervals, we examined how the London bike-sharing system was affected by the pandemic. Statistically distinguishable changes occurred in March and April with respect to hire numbers, and in April, May, and June with respect to hire time.

The interactions of travellers and travel mode characteristics in London would give rise to how the Government's COVID-related policies has affected the London bike-sharing system. The fact that some travellers might have shifted from public transit to bikeshare has important implications as this could result in a permanent (or at least relatively long-term) change in their travel behaviour, a success that could have not been achieved easily if the pandemic had not happened or if the pandemic-related policies had not been introduced. A discussion on the possibility that this behavioural change may become permanent is provided by Wang and Noland [12]. To reveal the underlying mechanisms behind such behavioural changes, conducting travel surveys would provide valuable insights.

Note that a part of the shift from public transport may have been towards driving alone, especially where active travel is less favourable. Therefore, our recommendation is to extend bikesharing in a way that it covers the entire Greater London area. The fact that the number of cycle hires has not experienced any statistically important reduction from May to December 2020 would indicate that the London bike-sharing scheme has been a resilient transportation system during the pandemic. Therefore, it is important to integrate micro mobility (e.g., bike-sharing schemes) in urban transportation systems not only to increase their resiliency but also to improve air quality; and consequently, human health. At the same time, promoting active modes of travel, cycling and walking should become a priority in urban areas.

Supporting information

S1 File.
(DOCX)

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