https://doi.org/10.1016/j.tbs.2020.10.002

EFFECT OF LONDON CYCLE HIRE SCHEME ON BICYCLE SAFETY

Hongliang Ding
[a] Department of Civil and Environmental Engineering
The Hong Kong Polytechnic University
Hung Hom, Kowloon, Hong Kong
Email: hongliang.ding@connect.polyu.hk

N.N. Sze (Corresponding author)
[a] Department of Civil and Environmental Engineering
The Hong Kong Polytechnic University
Hung Hom, Kowloon, Hong Kong
Tel: +852 2766-6062; Email: tony.nn.sze@polyu.edu.hk

Haojie Li
[b] School of Transportation, Southeast University, China
[c] Jiangsu Key Laboratory of Urban ITS, China
[d] Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, China
Email: h.li@seu.edu.cn

Yanyong Guo
[b] School of Transportation, Southeast University, China
[c] Jiangsu Key Laboratory of Urban ITS, China
[d] Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, China
Email: guoyanyong@seu.edu.cn

September 2020

Acknowledgments

The work that is described in this paper was supported by the grants from the Research Grants Council of Hong Kong (15209818) and Research Committee of the Hong Kong Polytechnic University (1-ZE5V).

EFFECT OF LONDON CYCLE HIRE SCHEME ON BICYCLE SAFETY

ABSTRACT

This study evaluates the effect of London Cycle Hire scheme (LCH) on bicycle crashes, based on the data from 333 Lower Layer Super Output Areas (LSOAs) in the period 2011-2012. The Propensity Score Matching method (PSM) is applied to evaluate the effects of policy interventions ('treatment') on bicycle safety, with which the effects of confounding factors on the treatment effects are accounted, using the systematically established untreated groups. Covariates including land use, traffic and population characteristics are considered when selecting the untreated group for each treated unit. Results of PSM indicated that numbers of overall and slight injury bicycle crashes increased by 37.7% and 31.8% when LCH was introduced. Additionally, the interaction by another transport management policy – London Congestion Charging scheme (LCC) - on the effects of LCH on bicycle crash was estimated. Numbers of overall and slight injury bicycle crash further increased by 59.1% and 57.8% because of the implementation of LCC. For the killed or seriously injured (KSI) bicycle crashes, increases were observed in both cases (i.e. 81% for LCH and 66% for LCC), despite that they are not statistically significant. Results are indicative to the design and planning of bicycle infrastructure that could enhance the overall bicycle safety in London.

Keywords: Bicycle crash, London Cycle Hire scheme (LCH), London Congestion Charging scheme (LCC), Propensity Score Matching method (PSM)

1. INTRODUCTION

Car dependency has been an issue in sustainable urban development. It leads to a number of problems including air pollution, climate change, traffic congestion, road safety and physical health (Ruiz et al., 2018; Johnson and Silveira., 2014). Therefore, it is of essence to promote alternative transport modes including public transport, cycling and walking. In particular, cycling has been increasingly promoted as a green transport mode. It does not only alleviate the problem of traffic congestion and traffic-related emission, but also enhances the overall social well-being (Li et al., 2019; Guo et al., 2018b). In recent years, many policy interventions were introduced to promote cycling round the world. For example, residents in London suggested that they were inspired by the London Cycle Hire (LCH) program that was launched in July 2010 to start cycling (ITV, 2014). In 2010, there were 5,000 bicycles and 315 docking stations for the LCH program. As of the end of 2018, number of bicycles was increased to 11,500 and number of docking stations was increased to 750 respectively. The docking stations spread across Southwestern London and several royal parks in Central London (TfL, 2018a). Location of LCH docking stations is shown in **Figure1**.

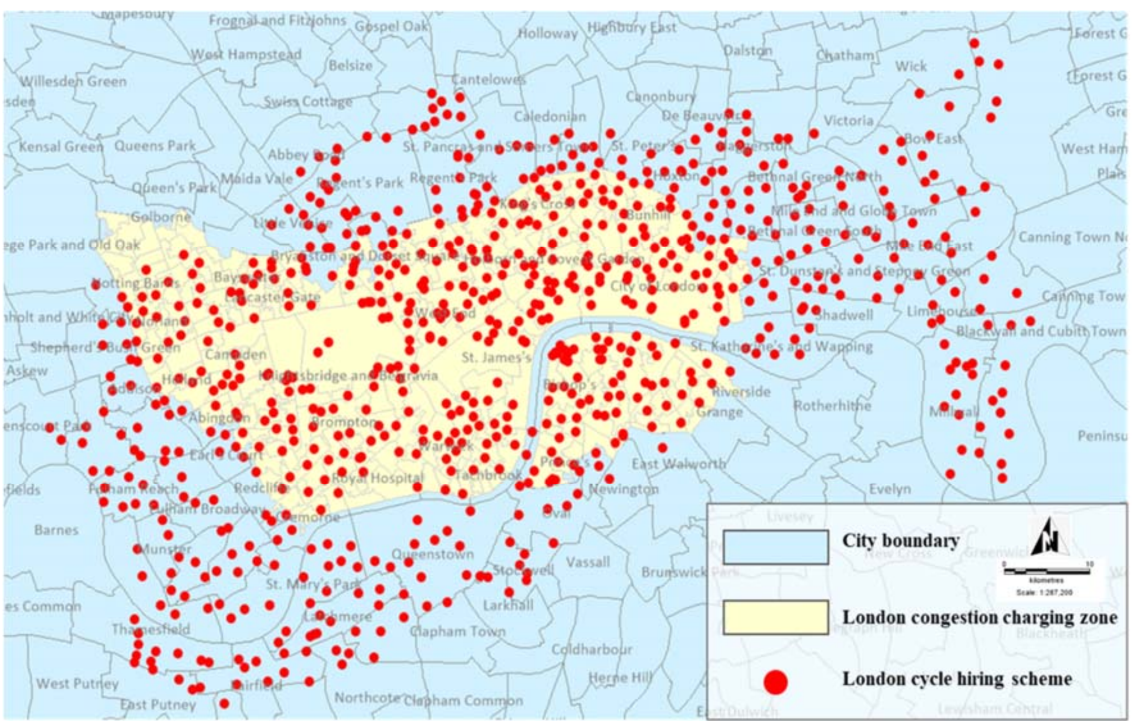

Figure 1 Locations of bicycle docking stations in London

Most of the previous studies focused on the environmental benefits of cycle hire scheme (Woodcock et al., 2014; O'Brien et al., 2014; Li et al., 2019; Fishman et al., 2014a, b; Zhang et al., 2017; Campbell et al., 2016). It is rare that the safety effects of cycle hire scheme are attempted. However, bicyclists are vulnerable to road injuries, compared with motor vehicle occupants (Nikitas et al., 2014). We hypothesize that the overall bicycle crash may increase after the introduction of LCH program since there are more new bicyclists on the roads. For instance, 49% of LCH users were encouraged by the scheme to start cycling in London (ITV,2014). Hence, it is of essence to evaluate the effect of LCH scheme on bicycle safety. On the other hand, some of the LCH docking stations are in the congestion charging area. London Congestion Charging scheme (LCC) was introduced in February 2003. LCC covered an area of 21 km^2 (also shown in **Figure 1**) and accounted for about 1.3% of total area of Greater London. A few studies indicated that congestion charging was associated with the reduction in motor vehicle crash but the increase in bicycle crash (Li et al., 2012). Therefore, it would be interesting to examine the role and impact of multiple policies on bicycle safety. Contribution of this paper is twofold. First, change in the bicycle crash frequency because of the introduction of LCH is evaluated. Second, the interaction effect by LCC on the association between LCH and bicycle crash frequency is examined.

This paper is organized as follows. Literature reviews are presented in section 2. Section 3 and Section 4 describe the analysis method and data respectively. Results are presented in section 5. Section 6 provides the concluding remark.

2. LITERATURE REVIEW

2.1 Cycle hire scheme

In recent years, several studies had attempted to evaluate the environmental and social benefits of cycle hire scheme, with which the effects on transport mode share and bicycle usage were considered (Woodcock et al., 2014; O'Brien et al., 2014; Li et al., 2019; Fishman et al., 2014a, b; Zhang et al., 2017; Campbell et al., 2016). For instances, cycle hire scheme was found to have favourable effects on overall health and environmental conditions of the society (Woodcock et al., 2014; Zhang and Mi, 2018), and the health benefits of male and older cyclists were more remarkable, as compared to other cyclists (Woodcock et al., 2014). Effects of cycle hire scheme on transport mode shares were similar across different studies. It stimulated the mode shift to green transport alternatives and promoted the sustainable transportation in highly developed urban cities (O'Brien et al., 2014; Caulfield et al., 2017; Fishman et al., 2014a; Midgley, 2011; Aldred, 2019).

Factors contributing to bicycle usage and mode share were revealed. The key factors were population density and characteristics including gender, age, education, employment and income level (Li et al., 2019; Campbell et al., 2016; Fishman et al., 2014a, b; Jain et al., 2018; Woodcock et al., 2014; Scott and Ciuro., 2019; Abasahl et al., 2018; Piatkowski and Marshall., 2015). Additionally, distribution of bicycle docking station and built environment that was characterized by land use, road network and bicycle infrastructure could also affect the bicycle usage (Zhang et al., 2017; García-Palomares et al., 2012; Gutiérrez et al., 2020). Moreover, bicycle usage could be modified by the weather conditions (Campbell et al., 2016; Gebhart and Noland, 2014).

A few studies have attempted the safety effects of cycle hire scheme; however, findings are controversial. For example, presence of cycle hire scheme is found associated with reduced risk of bicycle injuries. Likelihoods of fatal and severe injuries of bike share users are lower than that of other bicyclists (Fishman and Schepers, 2016, 2018). In contrast, road users tend to consider bicycle as unsafe in general, considering the vulnerability, instability and invisibility in the traffic of bicycles. Hence, safety concern is an issue that hinder the wider adoption of cycle hire scheme (Nikitas et al., 2014; Sun 2018; Hess and Schubert, 2019). Nevertheless, rigorous analysis of bicycle crash risk associated with bike sharing is crucial to decision makers regarding the introduction and expansion of cycle hire scheme.

2.2 Bicycle safety

For bicycle safety, previous studies have attempted the relationship between factors including built environment and land use, traffic attributes and population characteristics and bicycle crash risk at the macroscopic level (Siddiqui et al., 2012; Wei and Lovegrove, 2013; Chen, 2015; Pulugurtha and Thakur, 2015; Guo et al., 2018a, 2018b; Vanparijs et al., 2015). For example, bicycle crash frequencies of industrial and commercial areas are higher than that of other areas (Chen, 2015; Narayanamoorthy et al., 2013). In addition, bicycle crash frequency is associated with the number of intersections (Aldred et al., 2018; Pulugurtha and Thakur, 2015; Wei and Lovegrove, 2013; Siddiqui et al., 2012), presence of cycle lane (Hamann and Peek-Asa, 2013; Wei and Lovegrove, 2013; Reynolds et al., 2009) and presence of traffic signal (Chen, 2015; de Geus et al.,2012). Lastly, population demographic and socio-economic characteristics including age, gender and income are associated with the bicycle crash risk (Aldred and Woodcock, 2015; Wei and Lovegrove, 2013). However, it is rare that the frequency of bicycle trips, which can be influenced by different transport demand management policies, e.g. bike sharing and bike-and-ride, are considered in the bicycle safety analysis (Ding et al., 2020). It is necessary to examine the influences of transport policies on bicycle use, and therefore, the intervention on the relationship between bicycle crash risk and possible risk factors.

2.3 Congestion charging scheme

To resolve the traffic congestion problem, congestion charging scheme was introduced in many cities like Singapore, London and Stockholm. Studies have been conducted to evaluate the effectiveness of congestion charging scheme from the perspectives including public perception (Santos, 2004; Eliasson and Jonsson., 2011), traffic congestion (Xie and Olszewski, 2011; Santos and Bhakar, 2006), vehicle emissions (Atkinson et al., 2009; Percoco, 2015) and economy (Santos, 2004; Givoni, 2012). Not only the favorable effects on vehicular speed, traffic flow and vehicle emission, but also the safety influences could be revealed after the introduction of congestion charging (Transport for London, 2005). Congestion charging is effective in relieving the traffic congestion problem by reducing the overall traffic volume, shortening the travel time and increasing the vehicular speed. This could then in turn affect the road safety level (Xie and Olszewski, 2011; Lord et al., 2005). Studies indicated that number of motor vehicle crash was reduced after introducing the congestion charging scheme in London (Green et al., 2016; Quddus, 2008a, 2008b; Noland et al., 2008). However, number of bicycle casualties was increased (13.3%) at the same time (Li et al, 2012). Yet, it was not well studied whether such increase was attributed to the increase in bicycle trips or other factors like traffic volume, vehicle mix and vehicular speed. Also, it is necessary to consider the effects of confounding factors that may affect the association between congestion charging and bicycle safety.

2.4 The current paper

Previous studies on cycle hire scheme mainly focused on travel behavior, transport mode share and environment benefits. It was rare that the effect of cycle hire scheme on bicycle safety was investigated. Indeed, bicycle safety is an important metric that affect the planning and design of bicycle network. Additionally, transport policies including congestion charging can also affect the flow volumes of different transport modes, e.g. private car, bus, bicycle and walking, etc., and in turn affect the bicycle safety. Therefore, effects of multiple policies on bicycle crashes should be estimated. In this paper, the Propensity Score Matching (PSM) method is applied to evaluate the influences of policy interventions (i.e. cycle hire and congestion charging schemes) on bicycle crash, with which the effects of confounding factors on the treatment effects (i.e. policy interventions) are accounted using a systematically established 'untreated' group. Findings of this study are indicative to the decision making of transport planners that can improve the design of bicycle network and enhance the overall bicycle safety.

3. METHOD

To measure the effect of an intervention (known as 'treatment') on an entity, it is crucial to account for the effects of possible confounding factors other than the 'treatment' at the same instance. For the experimental studies, it is possible to select 'treated' and 'untreated' groups using randomized design. Therefore, presence of 'treatment' and possible outcomes are independent. However, for the road safety studies, presence of 'treatment' is usually dependence to the prevailing operation and safety record of an entity. Selections of 'treated' and 'untreated' groups are seldom random. Additionally, association between treatment and outcome can be intervened by possible confounding factors including traffic flow and weather conditions (Wood et al., 2015a; Li et al., 2017; Guo et al., 2020). To resolve the fundamental problems of how to account for the non-randomized intervention and possible confounding factors in empirical studies, PSM can be applied (Sasidharan and Donnell., 2013; Wood et al., 2015b; Wood and Donnell, 2017).

In the PSM, similarity between the treated and untreated groups is assured based on all possible covariates $\boldsymbol{X}$. A single dimension 'propensity score' that reflect the probability of receiving a 'treatment' can be deduced based on the multi-dimension matching scores. Therefore, bias by non-random treatment assignment and possible confounding factors can be eliminated.

3.1 Notation

In this study, $y_i(D)$ denotes the outcome of unit i, where i = 1,2, …and N, and N is the total number of units (i.e. zone). Set D_i as treatment indicator, where D_i = 1 if unit i is treated, and D_i = 0 otherwise. Treatment effect for unit i can be specified as,

$$\delta_i = y_i(1) - y_i(0) \tag{1}$$

In practice, the parameter of interest is Average Treatment Effect (ATT) of all treated units. It can be specified as

$$\delta_{ATT} = E(\delta|T = 1) = E(Y(1)|T = 1) - E(Y(0)|T = 1) \tag{2}$$

3.2 Assumption

There are three critical assumptions for PSM (Rosenbaum and Rubin, 1983): (1) Stable Unit

Treatment Value Assumption (SUTVA): Treatment does not have any impact on the control groups; (2) Conditional Independence Assumption (CIA): Probability of receiving treatment and outcome are independent and all observed factors are controlled. CIA can be specified as

$$(Y(1), Y(0)) \perp T|X \quad (3)$$

; and (3) Common Support Condition (CSC): This is also known as 'overlap assumption'.

There is sufficient overlap between 'treated' and 'untreated' groups to guarantee that units with similar propensity scores are matched. CSC can be specified as

$$0 < P(T = 1|X) < 1 \quad (4)$$

3.3 Model formulation

To implement PSM, propensity score of every unit is first calculated using the conventional discrete outcome approaches including logit and Probit models (Smith, 1977; Guo et al., 2018a). An early study indicated that there was no significant difference in the estimation results between the two models (Smith, 1977). In this study, logit model is adopted to calculate the propensity score and is specified as follow,

$$P(T = 1|X) = \frac{EXP(\alpha+\boldsymbol{\beta}'\boldsymbol{X})}{1+EXP(\alpha+\boldsymbol{\beta}'\boldsymbol{X})} \quad (5)$$

where α is the intercept and $\boldsymbol{\beta}'$ is the vector of parameters for covariate $\boldsymbol{X}$.

After estimating the propensity score, an untreated group is constructed for each treated unit. In this study, four common matching algorithms: (1) K-nearest neighbors matching; (2) caliper and radius matching; (3) kernel and local linear matching; and (4) stratification and interval matching, are adopted for the construction of control groups (Heinrich et al., 2010). Finally, treatment effect is estimated by comparing the difference in the outcomes between treated group and corresponding untreated group. In this study, the treatment effect is estimated using the software package Psmatch2 of STATA (Leuven and Sianesi, 2003).

3.4 Illustrative example

An example is given in **Table 1** to illustrate the mechanism for the matching of treated and untreated groups using PSM. In this example, there are five untreated units (a, b, c, d, and e) and four treated units (f, g, h, and i). For each treated unit, an untreated group is matched based on the propensity scores (i.e. the nearest values), as shown in the fourth column of Table 1. Then, the treatment effects (the sixth column of Table 1) are estimated by comparing the differences in the outcome (i.e. crash frequency in this example) between treated unit and corresponding untreated group. As shown in Table 1, overall treatment effect is estimated at (2 + 2 + 3 + 2) / 4 = 2.25. Interested readers may refer to Li et al. (2018)'s study for more details.

Table 1. A numerical example of applying the PSM

Observation unit	Treatment	Propensity score	Untreated units matched	Number of crashes	Treatment effect
a	Untreated	0.1	Not applicable	2	Not applicable
b	Untreated	0.3	Not applicable	3	Not applicable
c	Untreated	0.5	Not applicable	5	Not applicable
d	Untreated	0.6	Not applicable	6	Not applicable
e	Untreated	0.8	Not applicable	2	Not applicable
f	Treated	0.1	a	4	4 – 2 = 2
g	Treated	0.6	d	8	8 – 6 = 2
h	Treated	0.8	e	5	5 – 2 = 3
i	Treated	0.4	b, c	6	[(6 – 3) + (6 – 5)]/2 = 2

4. DATA

4.1 Covariate

Validity of PSM largely depends on the unconfoundedness assumption. Unfortunately, level of confoundedness is not assessable. To avoid the violation of unconfoundedness assumption, more covariates should be considered when calculating the propensity score. In this study, as the outcome is bicycle crash frequency, all possible factors that contribute to bicycle safety will be considered to achieve the optimal precision and minimize the bias when estimating the propensity score (Brookhart et al., 2006). Yet, too many covariates can increase the variability of estimate.

In this study, observation unit is Lower Super Output Area (LSOA). LSOA is the primary unit of population census, home affair administration and election in the United Kingdom. Each LSOA has a population of 1,500 on average. One of the 'interventions' under investigation is LCC scheme, which is in force during the period from 7:00 am to 6:00 pm on weekdays only. Hence, bicycle crashes occurred in the evenings and on the weekends would be excluded in the subsequent analysis. Bicycle crash data is obtained from the dataset maintained by Department for Transport (DfT). It provides the information on crash location, casualty age, casualty gender and vehicle type of every bicycle crash involving personal injury.

There are currently no specific criteria for the selection of confounding factors in PSM. In this study, covariates are primarily derived from those revealed in conventional bicycle crash prediction models. Hence, the possible covariates are population characteristics including proportions of different genders and age groups, and household income (Li et al., 2012; Lee et al., 2015; Wang et al., 2017; Guo et al., 2018b; Sze et al., 2019; Guo et al., 2019). In this study, information on population demographic and socioeconomic characteristics are obtained from the Office for National Statics (ONS)[1] database.

Additionally, built environment, land use and transport infrastructure can also affect bicycle safety (Guo et al., 2018a, b; Narayanamoorthy et al., 2013; Wei and Lovegrove, 2013). Therefore, land use (i.e. residential, commercial, green area and transport infrastructure) data is obtained from the Greater London Authority (GLA)[2]'s database and transport network data (i.e. Class A road, Class B road and minor road lengths, traffic volume, bicycle flow and bus stop, etc.) is obtained from the Department for Transport (DfT)[3] database. Moreover, bicycle

[1] Office for National Statistics (ONS): https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates

[2] Greater London Authority (GLA): https://data.london.gov.uk/dataset/land-use-ward

[3] Department of Transport (DfT): https://roadtraffic.dft.gov.uk/downloads

infrastructure can also affect bicycle safety (Li et al., 2018). Since 2008, eight Cycle Superhighways have been built in Greater London to provide safer, faster and more direct routes for bicyclist (Li et al., 2018). In this study, length of Cycle Superhighway is also considered in the analysis.

The aforementioned bicycle crash incidence, population characteristics, land use and transport infrastructure data are mapped into the corresponding LSOAs using the geographical information system (GIS) approach. In particular, the software package MapInfo is used for the mapping. **Table 2** summarizes the covariates considered in the proposed PSM model.

Table 2. Summary statistics of land use, transport and population characteristics

Factor	**Attribute**	**Mean**	**S.D.**	**Min.**	**Max.**
Number of observations = 333 (LSOA)					
Bicycle crash frequency	Total bicycle crash	3.06	6.01	0	132
	Killed and severely injured crash	0.45	1.10	0	21
	Slightly injured crash	2.61	5.16	0	111
Population density	Population per km^2	13.06	5.98	0.62	49.85
Gender	Proportion of male	0.50	0.03	0.40	0.63
	Proportion of female	0.50	0.03	0.37	0.60
Age	Proportion of age above 64	0.09	0.04	0.02	0.21
	Proportion of age below 16	0.16	0.05	0.03	0.33
Income	Annual average household income (€)	50,626	18,444	26,140	153,420
Land use	Proportion of residential area	23.50	12.09	2.29	202.59
	Proportion of business and office area	27.58	49.24	0.48	1,041
	Proportion of green area	70.75	92.11	4.39	1,291
	Proportion of road, railway and footpath area	49.54	49.44	7.46	672.11
Road density	Class A road (km per km^2)	4.29	3.01	0	18.21
	Class B road (km per km^2)	0.60	1.44	0	13.40
	Minor road (km per km^2)	0.75	1.27	0	6.60
Traffic flow	Annual average daily traffic	16,110	11,847	42.5	108,828
Bicycle flow	Annual average daily bicycle flow	825	787	0	5,458
Density of bus stop	Bus stop per km^2	0.04	0.03	0	0.22

Factor	Attribute	Mean	S.D.	Min.	Max.
Cycle superhighway	Length of Cycle Superhighway (km)	1.41	1.45	0	6.22

4.2 Treated and untreated groups

333 LSOAs are considered in this study. As shown in **Table 3**, LCC was imposed in 33 LSOAs and LCH was introduced in 132 LSOAs respectively. Since PSM is a 'data-hungry' approach that a large sample of treated and untreated units is required, as shown in **Table 3**, 201 LSOAs that have no LCH nor LCC are considered to ensure sufficient overlap (Wood and Donnell, 2017; Wood et al., 2015b). To increase the sample size, two-year data (i.e. 2011 and 2012) are used. Therefore, total number of analysis unit is 666. In this study, safety effect of LCH only (Analysis I) and marginal safety effect of LCC on LCH (Analysis II) would be evaluated. For Analysis I, treated units refer to those that have LCH only and untreated units refer to those that neither LCH nor LCC is imposed respectively. For Analysis II, treated units refer those that have both LCH and LCC and untreated units refer to those that have LCH only respectively. This justifies the Stable Unit Treatment Value assumption (SUTVA). **Figure 2** illustrates the spatial distributions of treated and untreated units for the two analyses.

Table 3. Study design of proposed analysis

Characteristics of LSOA	Number of LSOA	Analysis	
		I. LCH only	II. Marginal effect of LCC
LCH only	99	Treated units	Untreated units
LCH and LCC	33	N/A	Treated units
Neither LCH nor LCC	201	Untreated units	N/A

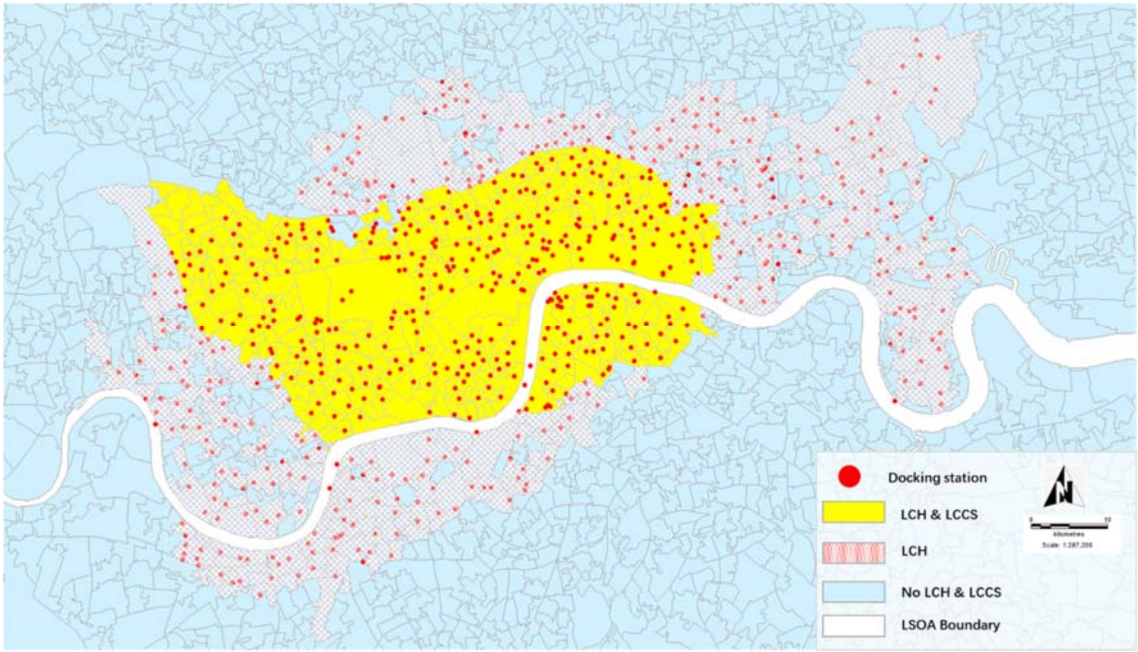

Figure 2. Distribution of LSOA by policy interventions

5. RESULTS AND DISCUSSION

5.1 Validity of PSM Model

Prior to the evaluation of treatment effect on bicycle crash incidence, it is necessary to construct an appropriate 'untreated' group for every 'treated' unit using PSM approach. Firstly, a balancing test would be conducted to assess the validity of PSM, so that propensity of receiving 'treatment' is independent from the outcome. **Table 4** presents the results of balancing test. As shown in Table 4, the 'treated' and 'untreated' groups were imbalanced for all covariates at the 5% level of significance before matching (U- Unmatched). Favorably, bias on effectiveness evaluation can be eliminated by refining the untreated groups using the proposed matching algorithm. The 'treated' and 'untreated' groups are balanced for all covariates after matching (i.e. M - Matched). This justifies the Conditional Independence Assumption (CIA).

Table 4. Results of balancing test for treated and untreated groups

Covariate	Unmatched (U)/ Matched (M)	Mean		% reduction		t-test	
		Treated	**Untreated**	**% bias**	**bias**	***t* -statistics**	***p*-level**
Income	U	49,514	45,063	35.7	97.0	3.90	0.000*
	M	49,514	49,646	-1.1		-0.09	0.928
Population density	U	13.12	13.23	-1.9	-566.3	-0.21	0.836
	M	13.12	13.90	-13.0		-1.20	0.233
Male	U	0.499	0.493	25.4	60.5	2.86	0.004*
	M	0.499	0.501	-10.0		-0.92	0.359
Age above 64	U	0.089	0.089	0.4	-2082	0.04	0.965
	M	0.089	0.086	8.6		0.84	0.401
Age under 16	U	0.162	0.183	-44.4	91.6	-4.78	0.000*
	M	0.162	0.161	3.7		0.35	0.730
Business and office area	U	25.26	19.00	22.2	74.1	2.29	0.023*
	M	25.26	23.64	5.8		0.39	0.695
Road area	U	47.15	45.63	4.0	-102.9	0.42	0.678
	M	47.15	44.07	8.1		0.76	0.447
Green area	U	71.52	88.11	-17.3	80.0	-1.95	0.052
	M	71.52	74.82	-3.5		-0.36	0.717
Class A road	U	4.479	3.771	23.3	38.8	2.62	0.009*
	M	4.479	4.046	14.3		1.41	0.160
Class B road	U	0.489	0.604	-8.0	60.9	-0.83	0.405
	M	0.489	0.534	-3.1		-0.36	0.719
Minor road	U	0.493	1.001	-41.2	75.7	-4.17	0.000*
	M	0.493	0.618	-10.0		-1.17	0.243
Traffic flow	U	18,103	14,559	29.5	65.5	3.21	0.001*
	M	18,103	19,327	-10.2		-0.80	0.426
Bicycle flow	U	880.3	561.3	49.8	92.0	5.57	0.000*
	M	880.3	854.8	4.0		0.33	0.744
Cycle Superhighway	U	0.069	0.024	21.4	74.3	2.53	0.012*
	M	0.069	0.058	5.5		0.44	0.661

** Statistical significance at the 5% level*

Additionally, validity of PSM can be assessed graphically based on the propensity score distributions of treated and untreated groups. Overlap area in the frequency distribution of propensity score indicates 'common support'. Units that are in the region of common support are referred as 'on support', and 'off-support' otherwise. As shown in **Figure 3**, overlaps of treated and untreated groups are enough, and all units are 'on support'. Hence, the Common Support Condition (CSC) assumption is justified.

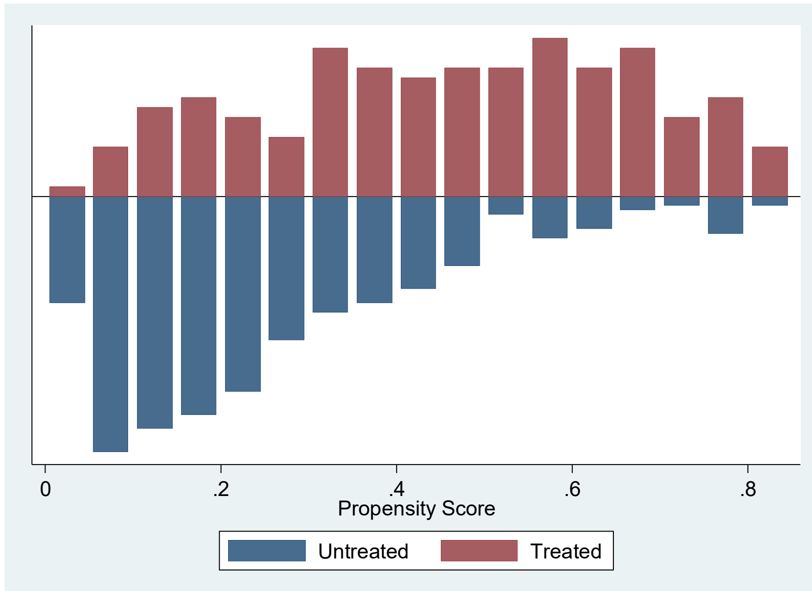

Figure 3. Results of overlap test

5.2 Safety effect of London Cycle Hire scheme

Table 5 illustrates the estimation results of the effect of LCH on (i) overall bicycle crash; (ii) killed and severely injured (KSI) bicycle crash; and (iii) slightly injured bicycle crash. As shown in Table 4, overall bicycle crash (37.7%) and slightly injured crash (31.8%) increased significantly when LCH is implemented, both at the 5% level, after controlling the possible confounding factors using PSM. It could be because of the increase in the number of cyclists on the roads. Indeed, 49% of bicyclists in London admitted that they were encouraged to cycle by the LCH (ITV, 2014). To this end, we also evaluated the change in bicycle usage in the treated LSOAs. As shown in **Table 6**, increase in bicycle usage (when LCH was present) was remarkable at the 5% level. Such increase in bicycle usage (37.3%) was comparable to that of overall bicycle crash and slight bicycle crash (32-38% as shown in Table 4). This justified that the unfavorable safety effect by LCH could be attributed to the increase in bicyclists on the roads (Transport for London, 2018b). Moreover, the results indicated that there is no significant difference in the occurrence of KSI bicycle crash between treated and untreated LSOAs. It could be because majority of bicycle docking stations are in the area which the speed limits are usually lower than 30 mph. Therefore, it is unlikely that the injury risk be elevated (Li and Graham, 2016).

Table 5. Effect of LCH on bicycle crash incidence

Outcome	Sample	Treated	Untreated	Difference	Standard error	t-statistic	Effect
Overall bicycle crash	Unmatched	3.10	1.74	1.35	0.21	6.32	37.7%*
	ATT	3.10	2.25	0.85	0.28	3.01	
Slight bicycle crash	Unmatched	2.61	1.51	1.10	0.18	5.98	31.8%*
	ATT	2.61	1.98	0.63	0.24	2.62	
KSI bicycle crash	Unmatched	0.48	0.23	0.25	0.06	4.08	Insignificant
	ATT	0.48	0.27	0.22	0.08	1.64	

** Statistical significance at the 5% level*

Table 6. Results of PSM for bicycle usage (LCH only)

Outcome	Sample	Treatment	Control	Difference	S.E.	t-stat	Effect
Bicycle usage	Unmatched	980	561	418	63.0	6.65	37.3%*
	ATT	980	713	266	83.4	3.20	

** Statistically significant at the 5% level*

5.3 Marginal effect of London Congestion Charging scheme

Some LSOAs have both LCH and LCC schemes introduced. Since the patterns of traffic flow and speed could be changed in the areas that have LCC, it is crucial to estimate the marginal effect of LCC on bicycle crashes. As shown in **Table 7**, the marginal effects of LCC on overall bicycle crash (59.1%) and slightly injured bicycle crash (57.8%) were significant, both at the 5% level. However, as shown in **Table 8**, the traffic volume in the LSOAs that have both LCC and LCH are 21% lower than that have LCH only. This could be because of the dramatic increase in bicycle in the treated LSOAs (74.9% as shown in **Table 8**) because of the mode shift after the introduction of congestion charge (Li et al., 2012; Xie and Olszewski, 2011; Tang, 2016). Again, increase in KSI bicycle crash (66%) can be observed, though it is not significant. It could be because of the expansion of the bicycle infrastructure, particularly the Cycle

Superhighways in the area (Li et al., 2017).

Table 7. Marginal effect of LCC on bicycle crash

Outcome	Sample	Treated	Untreated	Difference	Standard error	t-statistic	Effect
Overall bicycle crash	Unmatched	5.92	3.11	2.81	0.58	4.84	59.1%*
	ATT	5.92	3.72	2.20	0.87	2.52	
Slight bicycle crash	Unmatched	5.02	2.61	2.42	0.50	4.83	57.8%*
	ATT	5.02	3.18	1.84	0.74	2.48	
KSI bicycle crash	Unmatched	0.89	0.51	0.38	0.14	2.84	Insignificant
	ATT	0.89	0.54	0.36	0.19	1.85	

** Statistical significance at the 5% level*

Table 8. Results of PSM for traffic flow and bicycle usage (LCH and LCC)

Outcome	Sample	Treatment	Control	Difference	S.E.	t-stat	Effect
AADT	Unmatched	14916	16857	-1941	1508	-1.29	-21.3%*
	ATT	14684	18670	-3985	1862	-2.14	
Bicycle usage	Unmatched	1572	912	669	116	5.74	74.9%*
	ATT	1572	898	673	153	4.38	

** Statistically significant at the 5% level*

6. CONCLUSION

To promote the bicycle use, policy strategies including bicycle infrastructure development and bicycle sharing scheme have been implemented round the world. In London, a public bicycle hiring scheme (LCH) was introduced in 2010. Despite that public bicycle rental system was effective in promoting green transport and improving the physical well-being of community (Woodcock et al., 2014; Zhang and Mi, 2018; Heinen et al., 2018), it was rare that the safety effect of bicycle sharing was investigated. This study contributes to the literature by estimating the effects of LCH on bicycle crash incidence, with which the possible confounding factors are considered using the PSM approach. Results of this study indicated both the overall (38%) and slight bicycle crashes (32%) in the areas with LCH introduced were remarkably higher than those with no LCH. However, no significant effect on KSI bicycle crash could be revealed. This could be attributed to effective traffic control measures and development of bicycle infrastructures.

Moreover, this study also contributes to the literature by exploring the marginal effect of congestion charging scheme (LCC) on the LCH. Our results suggested numbers of overall (59.1%) and slight bicycle crash (57.8%) in the areas with both LCC and LCH introduced were remarkably higher than those with LCH only. It could be because of the possible mode shift (to active transport modes including cycling and walking) because of congestion charging scheme (Li et al., 2012; Green et al., 2016; Quddus, 2008a, 2008b; Noland et al., 2008). Also, no significant changes could be found in the KSI bicycle crash.

The above findings are indicative to the decision making of transport planner, particularly striking the balance between environmental benefit, physical health, traffic safety and societal impact when promoting green transport. Also, effective countermeasures like bicycle warning signs and road markings can be introduced to improve the safety perception and awareness of bicyclists. Hence, overall bicycle safety and level of service of the bicycle network could be enhanced (Sze et al., 2011; Wong et al., 2013). However, it is noteworthy that the current approach does not take into account the differences in crashes between the treated and untreated groups that might exist before the introductions of LCH and LCC. In the extended study, it is worth exploring the mediation effects by possible factors before and after the interventions. Moreover, possible influences by the weather conditions and seasonal effects on the association are not considered in this study. It is worth exploring the interactions by weather conditions on the safety effect of bicycle sharing scheme when more comprehensive data are available in the future study (Ding et al., 2020).

REFERENCES

Abasahl, F., Kelarestaghi, K.B., Ermagun, A., 2018. Gender gap generators for bicycle mode choice in Baltimore college campuses. Travel Behaviour and Society. 11, 78-85.

Aldred, R., 2019. Who caused that congestion? Narrating driving and cycling in a changing policy context. Travel Behaviour and Society. 16, 59-69.

Aldred, R., Goodman, A., Gulliver, J., Woodcock, J., 2018. Cycling injury risk in London: A case-control study exploring the impact of cycle volumes, motor vehicle volumes, and road characteristics including speed limits. Accid Anal Prev. 117, 75-84.

Aldred, R., Woodcock, J., 2015. Reframing safety: An analysis of perceptions of cycle safety clothing. Transport Policy. 42,103-112.

Atkinson, R.W., Barratt. B., Armstrong, B., Anderson, H.R., 2009. The impact of the congestion charging scheme on ambient air pollution concentrations in London. Atmospheric Environment. 43, 5493–5500.

Brookhart, M.A., Schneeweiss, S., Rothman, K., Glynn, R., Avorn, J., Stürmer, T., 2006. Variable selection for propensity score models. Am. J. Epidemiol. 163, 1149–1156.

Campbell, A.A., Cherry, C.R., Ryerson, M.S., Yang, X., 2016. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. Transp. Res. Part C 67, 399-414.

Caulfield, B., O'Mahony, M., Brazil, W., Weldon, P., 2017. Examining usage patterns of a bike-sharing scheme in a medium sized city. Transportation Research Part A: Policy and practice. 100, 152–161.

Chen, P., 2015. Built environment factors in explaining the automobile-involved bicycle crash frequencies: a spatial statistic approach. Saf. Sci. 79, 336–343.

de Geus, B., Vandenbulcke, G., Int Panis, L., Thomas, I., Degraeuwe, B., Cumps, E., et al., 2012. A prospective cohort study on minor accidents involving commuter cyclists in Belgium. Accid. Anal. Prev. 45, 683–693.

Ding, H., Sze, N.N., Li, H., Guo, Y., 2020. Roles of infrastructure and land use in bicycle crash exposure and frequency: A case study using Greater London bike sharing data. Working paper.

Eliasson, J., Jonsson, L., 2011. The unexpected ''yes'': Explanatory factors behind the positive attitudes to congestion charges in Stockholm. Transport Policy. 18, 636–647.

Fishman, E., Schepers, P., 2016. Global bike share: What the data tells us about road safety. Journal of Safety Research. 56, 41-45.

Fishman, E., Schepers, P. 2018. The Safety of Bike Share Systems. ITF Discussion Papers, International Transport Forum, Paris.

Fishman, E., Washington, S., Haworth, N., 2014a. Bikeshare's impact on active travel: evidence from the United States, Great Britain, and Australia. J. Transp. Heal. 2, 135–142.

Fishman, E., Washington, S., Haworth, N., Watson, A., 2014b. Factors influencing bike share membership: an analysis of Melbourne and Brisbane. Transportation Research Part A: Policy and practice. 71, 17–30.

García-Palomares, J.C., Gutiérrez, J., Latorre, M., 2012. Optimizing the location of stations in bike-sharing programs: A GIS approach. Applied Geography. 35, 235-246.

Gebhart, K., Noland, R.B., 2014. The impact of weather conditions on bikeshare trips in Washington, DC. Transportation (Amst) 41, 1205–1225.

Givoni, M., 2012. Re-assessing the Results of the London Congestion Charging Scheme. Urban Studies. 49, 1089–1105.

Green, C.P., Heywood, J. S., Navarro, M., 2016. Traffic accidents and the London congestion charge. Journal of Public Economics journal. 133, 11–22.

Guo, Y., Osama, A., Sayed, T., 2018a. A cross-comparison of different techniques for modeling macro-level cyclist crashes. Accid Anal Prev. 113, 38–46.

Guo, Y., Li, Z., Wu, Y., Xu, C., 2018b. Exploring unobserved heterogeneity in bicyclists' red-light running behaviors at different crossing facilities. Accid Anal Prev. 115, 118-127.

Guo, Y., Sayed, T., & Zaki, M. H., 2019. Evaluating the safety impacts of powered two wheelers on a shared roadway in China using automated video analysis. Journal of Transportation Safety & Security, 11(4), 414-429.

Guo, Y., Zheng, L., & Sayed, T., 2020. A comparison of collision-based and conflict-based safety evaluation of left-turn bay extension. Transportmetrica A: Transport Science, 16(3), 676-694.

Gutiérrez, M., Hurtubia, R., Ortúzar, J.D.D. 2020. The role of habit and the built environment in the willingness to commute by bicycle. Travel Behaviour and Society 20, 62-73.

Hamann, C., Peek-Asa, C., 2013. On-road bicycle facilities and bicycle crashes in Iowa, 2007–2010. Accid Anal Prev. 56, 103-109.

Heinrich, C., Maffioli, A., Vázquez, G., 2010. A Primer for Applying Propensity-Score Matching. Spd Working Papers. 59, 147-164.

Hess, A.K., Schubert, I., 2019. Functional perceptions, barriers, and demographics concerning e-cargo bike sharing in Switzerland. Transportation Research Part D: Transport and Environment. 71,153-168.

ITV., 2014. Boris Bikes extended to south-west London. http://www.itv.com/news/london/2013-04-04/boris-bikes-extended-to-south-west-london/

Jain, T., Wang, X., Rose, G., Johnson, M., 2018. Does the role of a bicycle share system in a city change over time? A longitudinal analysis of casual users and long-term subscribers. J. Transp. Geogr. 71, 45–57.

Johnson, F.X., Silveria, S., 2014. Pioneer countries in the transition to alternative transport fuels: Comparison of ethanol programmes and policies in Brazil, Malawi and Sweden. Environmental Innovation and Societal Transitions. 11, 1-24.

Lee, J., Abdel-Aty, M., Choi, K., Huang, H., 2015. Multi-level hot zone identification for pedestrian safety. Accid. Anal. Prev. 76, 64–73.

Leuven E., Sianesi B., 2003. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Version: 4.0.4 10 nov2010. Available: http://ideas.repec.org/c/boc/bocode/s432？001.html. Accessed 2014 Feb 09.

Li, H., Ding, H., Ren, G., Xu, C., 2018. Effects of the London Cycle Superhighways on the usage of the London Cycle Hire. Transportation Research Part A: Policy and practice. 111, 304–315.

Li, H., Graham, D.J., 2016. Quantifying the causal effects of 20 mph zones on road casualties in London via doubly robust estimation. Accid Anal Prev. 126, 65-74.

Li, H., Graham, D.J., Liu, P., 2017. Safety effects of the London cycle superhighways on cycle collisions. Accid. Anal. Prev. 99, pp. 90–101.

Li, H., Graham, D.J., Majumdar, A., 2012. The effects of congestion charging on road traffic casualties: A causal analysis using difference-in-difference estimation. Accid Anal Prev. 49, 366–377.

Li, H., Zhang, Y., Ding, H., Ren, G., 2019. Effects of dockless bike-sharing systems on the usage of the London Cycle Hire. Transportation Research Part A: Policy and practice. 130, 398–411.

Lord, D., Manar, A., Vizioli, A., 2005. Modeling crash-flow-density and crash-flow- V/C ratio relationships for rural and urban freeway segments. Accid. Anal. Prev. 37, 185–199.

Midgley, P., 2011. Bicycle-Sharing Schemes: Enhancing Sustainable Mobility in Urban Areas. Comm. Sustain. Dev. 19th Sessi, 1–26.

Narayanamoorthy, S., Paleti, R., Bhat, C.R., 2013. On accommodating spatial dependence in bicycle and pedestrian injury counts by severity level. Transportation Research Part B. 55, 245-264.

Nikitas, A., Michalakopoulos, N., Wallgren. P., 2014. Bike-sharing: Is safety an issue adversely affecting its potential for being embraced by urban societies? Proceedings of the 3rd International Cycling Safety Conference, 18-19 November, Gothenburg, Sweden.

Noland, R.B., Quddus, M.A., Ochieng, W.Y., 2008. The effect of the London congestion charge on road casualties: an intervention analysis. Transportation. 35, 73–91.

O'Brien, O., Cheshire, J., Batty, M., 2014. Mining bicycle sharing data for generating insights into sustainable transport systems. J. Transp. Geogr. 34, 262-273.

Piatkowski, D.P., Marshall, W.E. 2015. Not all prospective bicyclists are created equal: The role of attitudes, socio-demographics, and the built environment in bicycle commuting. Travel Behaviour and Society. 2, 166-173.

Percoco, M., 2015. Environmental Effects of the London Congestion Charge: A Regression Discontinuity Approach. Working paper.

Pulugurtha SS., Thakur V., 2015. Evaluating the effectiveness of on-street bicycle lane and assessing risk to bicyclists in Charlotte, North Carolina. Accid Anal Prev. 76, 34-41.

Quddus, M.A., 2008a. Modelling area-wide count outcomes with spatial correlation and heterogeneity: an analysis of London crash data. Accid. Anal. Prev. 40, 1486–1497.

Quddus, M.A., 2008b. Time series count data models: an empirical application to traffic accidents. Accid. Anal. Prev. 40, 1732–1741.

Reynolds, C., Harris, M., Teschke, K., Cripton, P., Winters, M., 2009. The impact of transportation infrastructure on bicycling injuries and crashes: a review of the literature. Environ. Health. 8 (1), 47.

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika. 70, 41–55.

Ruiz-Padillo, A., Pasqual, F.M., Larranaga Uriarte, A.M., Cybis, H.B.B., 2018. Application of multi-criteria decision analysis methods for assessing walkability: A case study in Porto Alegre, Brazil. Transportation Research Part D: Transport and Environment. 63, 855-871.

Santos, G., 2004. Preliminary results of the London congestion charging scheme. Public Works Management & Policy. 9, 164–181.

Santos, G, Bhakar, J., 2006. The impact of the London congestion charging scheme on the generalised cost of car commuters to the city of London from a value of travel time savings perspective. Transport Policy. 13, 22–33.

Sasidharan, L., Donnell, E., 2013. Application of propensity scores and potential outcomes to estimate effectiveness of traffic safety countermeasures: exploratory analysis using intersection lighting data. Accid. Anal. Prev. 50, 539–553.

Scott, D.M., Ciuro, C., 2019. What factors influence bike share ridership? An investigation of Hamilton, Ontario's bike share hubs. Travel Behaviour and Society. 16, 50-58.

Smith, H., 1997. Matching with multiple controls to estimate treatment effects in observational studies. Sociol. Methodol. 27, 325–353.

Sun Y., 2018. Sharing and Riding: How the Dockless Bike Sharing Scheme in China Shapes the City. Urban science. 2(3), 68.

Siddiqui, C., Abdel-Aty, M., Choi, K., 2012. Macroscopic spatial analysis of pedestrian and bicycle crashes. Accid Anal Prev. 45, 382-391.

Sze, N.N., Tsui, K.L., Wong, S.C., So, F.L., 2011. Bicycle-related crashes in Hong Kong: Is it possible to reduce mortality and severe injury in the metropolitan area? Hong Kong Journal of Emergency Medicine 18, 136-143.

Sze, N.N., Su, J., Bai, L., 2019. Exposure to pedestrian crash based on household survey data: Effect of trip purpose. Accid Anal Prev. 128, 17-24.

Transport for London, 2018a. Find a docking station (accessed on November 12, 2018). https://tfl.gov.uk/modes/cycling/santander-cycles/find-a-docking-station.

Transport for London, 2018b. Travel in London, report. http://content.tfl.gov.uk/travel-in-london-report-11.pdf

Transport for London, TfL., 2005. Central London congestion charging scheme: impact monitoring. Available: http://www.tfl.gov.uk.

Tang, C.K., 2016. Traffic externalities and housing prices: evidence from the London congestion charge. SERC Discussion Papers 0205, Spatial Economics Research Centre, LSE.

Vanparijs, J., Panis, L.I., Meeusen, R., de Geus, B., 2015. Exposure measurement in bicycle safety analysis: A review of the literature. Accid. Anal. Prev. 84, 9-19.

Wang, J., Huang, H., Zeng, Q., 2017. The effects of zonal factors in estimating crash risks by transportation modes: motor vehicle, bicycle and pedestrian. Accid. Anal. Prev. 98, 223–231.

Wei, F., Lovegrove, G., 2013. An empirical tool to evaluate the safety of cyclists: community based, macro-level collision prediction models using negative binomial regression. Accid. Anal Prev. 61, 129–137.

Wong, S.C., Sze, N.N., Loo, B.P.Y., Tsui, K.L., So, F.L., 2013. Final Report for Bicycle Injury Prevention Program in Tuen Mun District: Analysis of Bicycle Accident Hot Zones and Site Investigation. Prepared for the Hong Kong Transport Department, Hong Kong. (Unpublished)

Wood, J., Donnell, E., 2017. Causal inference framework for generalizable safety effect estimates. Accid. Anal. Prev. 104, 74–87.

Wood, J., Donnell, E., Porter, R.J., 2015a. Comparison of safety effect estimates obtained from empirical Bayes before–after study, propensity scores-potential outcomes framework, and regression model with cross-sectional data. Accid. Anal. Prev. 75,144–154.

Wood, J., Gooch, J., Donnell, E., 2015b. Estimating the safety effects of lane widths on urban streets in Nebraska using the propensity scores-potential outcomes framework. Accid. Anal. Prev. 82, 180–191.

Woodcock, J., Tainio, M., Cheshire, J., O'Brien, O., Goodman, A., 2014. Health effects of the London bicycle sharing system: health impact modelling study. BMJ 348, 1–14.

Xie, L., Olszewski, P., 2011. Modelling the effects of road pricing on traffic using ERP traffic data. Transportation Research Part A: Policy and practice. 45, 512–522.

Zhang, Y., Mi, Z., 2018. Environmental benefits of bike sharing: a big data-based analysis. Appl. Energy 220, 296–301.

Zhang, Y., Thomas, T., Brussel, M., van Maarseveen, M., 2017. Exploring the impact of built environment factors on the use of public bikes at bike stations: Case study in Zhongshan, China. J. Transp. Geogr. 58, 59–70.