Safety Effects of the London Cycle Superhighways on Cycle Collisions

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ABSTRACT

This paper evaluates the effects of the London Cycle Superhighways (CS) on cycle collisions. A total of 45 CS segments and 375 control segments are observed for a period of 8 years in London. Variables such as road characteristics, crash history and socio-economic information are included in the data set. Traffic characteristics including traffic volume, cycle volume and traffic speed are obtained from Department for Transport. We first estimate the safety effects on the CS routes using Empirical Bayes methods. Then propensity score matching methods are also applied for comparison. The introduction of cycle superhighways caused cycling traffic volumes to increase dramatically along CS routes with no significant impacts on collision rates. Our models find that the increase in traffic was associated with a rise in annual total cycle collisions of around 2.6 per km (38% in percentage). However, when we re-estimate the effects based on cycle collision rates rather than levels, our results also show that the CS routes are not more dangerous or safer than the control roads. Among the four CS routes, CS3 performs the best in protecting cyclists with a large proportion of segregated lanes whilst the cyclists have to share the lanes with motorists on other routes. It is recommended that consistent safety designs should be applied on all CS routes for a safer cycling environment.

Key words: London Cycle Superhighways; Cycle Collisions; Causal Effects

1 INTRODUCTION

Cycling is a sustainable and healthy travel mode, which helps to cut traffic congestion and reduce emissions and parking demand. There has been a dramatic increase in the number of cyclists over the past few decades in European cities, including London. Daily journeys by bicycle in Greater London have increased from 380,000 in 2004 to 610,000 in 2014 (TfL, 2014). The growth in cycling is closely related to a number of policies and the investment in new facilities inspiring the usage of bicycle, including the Barclays Cycle Hire (later renamed Santander Cycles), Biking Boroughs and the Cycle Superhighways (CS), all of which are designed to meet the Mayor’s target of a 400 percent increase in cycling by 2026.

Cycle Superhighways are cycle paths running from outer London into and across central London, aiming to increase commuter cycling, breaking down barriers to commuting by bicycle through a unique package of measures. The first two pilot routes, CS3 and CS7 were opened in July 2010. As reported by TfL (2011b), the Cycle Superhighways scheme has significantly increased the number of cyclists. Cycling has increased by 46 percent along CS7 and 83 percent along CS3 during the first year, while a number of cyclists along both routes experienced more than 100 per cent growth. However, the safety effects of the Cycle Superhighways are not evaluated in the report by TfL (2011b) due to the lack of post-intervention accident data.

The estimation of the impacts of the London Cycle Superhighway can be complicated. On one hand, drivers become more aware and better at anticipating cyclist behavior with increased number of cyclists. Hence injury rates will decrease with increased cycling rates, so called “safety in numbers” (Robinson, 2005; Jacobsen, 2003). On the other hand, there have been continuous critical opinions on the safety of London's cycle superhighways. A frequent criticism is that the Cycle Superhighways are nothing more than blue paint due to a lack of consistent high level of protections for cyclists.

This paper aims to evaluate the safety effects of the London Cycle Superhighways based on panel data from 2007 to 2014. To control for the regression to mean and time trend effects, we employ the widely used Empirical Bayes (EB) method. A common issue with the before-after control study is the justification of the similarity between treated and control groups. Hence propensity score matching (PSM) method is also applied to address this issue and the results are compared with the ones from the EB method. Another issue which has not been fully addressed in previous studies is the lack of traffic exposure. The failure to control for the change in cycle traffic volume could also bias the estimation results. In this study, the cycle volume data is extracted from road traffic statistics produced by Department for Transport.

The paper is organized as follows. The introduction of the London Cycle Superhighways and literature review is presented in the next section. The method and data used in the analysis are described in Section 3 and Section 4. The results are presented and discussed in Section 5. The conclusions are given in the final section.

2 BACKGROUND

Twelve new cycle routes, termed as the Cycle Superhighways, were announced in 2008, aiming to provide safer, faster and more direct cycle journeys into the city. As shown in Figure 1, twelve routes were planned to radiate from central London based on the clock face layout. Two routes (CS6 and CS12) have been cancelled, while CS10 has been replaced by a new East-West route. Only four routes have been put into use by 2015, including CS2

(Stratford to Aldgate), CS3 (Barking to Tower Gateway), CS7 (Merton to the City) and CS8 (Wandsworth to Westminster).

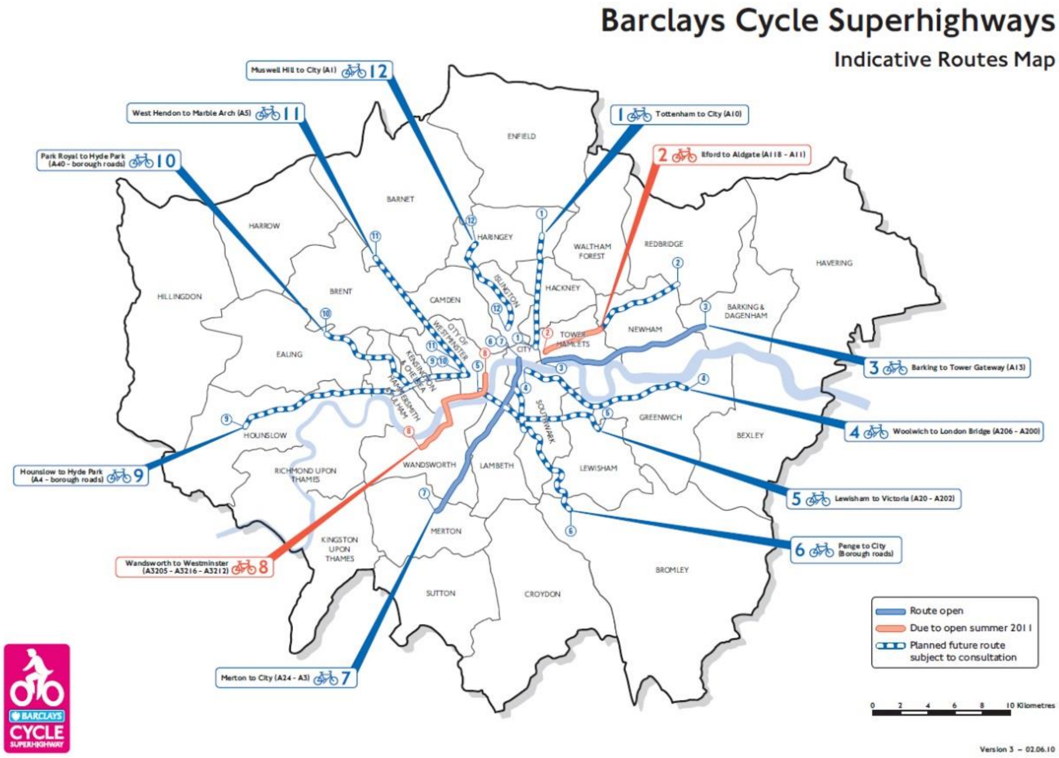

Figure 1 Routes Map of the London Cycle Superhighways

The Cycle Superhighways were chosen to provide good geographic coverage in areas where there are lots of existing cyclists and where there is future potential for people to cycle to work with right facilities. The cycle lanes are at least 1.5 meters wide and use blue surfacing to distinguish them from other existing cycle lanes in London. According to the results of independent customer satisfaction surveys by Transport for London (TfL), 61% of cyclists said that the blue surfacing made them feel safer and encouraged them to use the routes (TfL, 2011b). There are also new signs, road markings and information about journey time and links to other routes. A variety of measures have been undertaken to improve safety for cyclists to commute by bike on the CS routes. These include (TfL, 2011a):

(1) Realigned traffic and bus lanes to create more space for cyclists on busy stretches of the

routes;

(2) Re-designed junctions to make them safer for cyclists (e.g. by removing left-turn slip roads);

(3) Segregated cycle lanes at particular sections of the routes;

(4) Blind spot visibility mirrors at signalized junctions in order to improve the visibility of cyclists to heavy goods vehicles;

(5) New Advanced Stop Lines and extensions to existing ones (to a minimum of 5 meters) in order to help cyclists move away from signals before other traffic.

However, the promised improvements are not consistently met and the superhighways are frequently criticized as “nothing but blue paint”. Table 1 summarizes the characteristics of the four routes in operation. These routes were opened during 2010 and 2011 with an average length of about 10km. The superhighways run between central London and outer London mostly via main roads. Figure 2 shows some examples of the pros and cons of the Cycle Superhighways. Compared to the sporadic designs which provide high level of protection for cyclists (as shown in pictures A, B and C), inadequate functionality (as shown in pictures D, E and F) is more prevalent along these routes. The main issues regarding cycling safety are described below:

(1) Lack of segregated cycle lanes.

(2) Cycle lanes shared with buses and other road users.

(3) Conflicts between cyclists and buses and parked vehicles.

(4) Significant hook risks remains at key junctions, e.g. Bow roundabout in east London.

Table 1 Characteristic of Cycle Superhighways

CS No.	Opening	Length	Route	Cycle Lane Types	Problems
CS 2	2011 July: Aldgate to Bow; 2013 Nov: Extension from Bow to Straford	6.8 km	Aldgate to Stratford via A118 and A11	Original Route: Cycle lanes shared with buses and sometimes pushed to the center of the road; Extension: sporadic segregated lanes	Low level of protection for cyclists on the original route, particularly at key junctions, e.g. Bow roundabout; Cars frequently cross into the bike route.
CS 3	2010 July	12.3 km	Barking to Tower Gateway via A13 and Cable Street	Mostly Segregated cycle lanes and two-way track.	Cyclists have to stop and share the crossings with pedestrians at junctions
CS 7	2010 July	13.7 km	Merton to City via A24, A3 and Southwark Bridge Road	Segregated cycle lanes are rarely seen; mostly one-way tracks.	Parking bays locate on the cycle lane. Cyclists have to share space with buses and other road users.
CS 8	2011 July	8.2 km	Wandsworth to Westminster via A3, A3205 and Vauxhall Cross	Mostly one-way tracks.	Cycle lane shared with parked vehicles; Cycling through busy traffic; Inconsistent lane width.

Figure 2 Pros and Cons (Source: http://www.thisbigcity.net by Joe Peach)

Although the safety effects of the London Cycle Superhighways have been rarely studied, a limited amount of studies have been conducted to examine the impacts of cycle lanes on collisions (e.g. Lusk et al., 2011; Teschke et al., 2012; Reynolds et al., 2009; Park et al., 2015; Zangenehpour et al., 2016; Pulugurtha and Thakur, 2015; Abdel-Aty et al., 2014; Chen et al., 2012). For example, Reynolds et al. (2009) reviewed 23 studies of the impact of transportation infrastructure on cyclist safety. Their results suggest that separated cycle lanes (on-road, off-road, segregated by physical barriers or color paint) can reduce the risk of collisions and injury severities compared to cycling on road with motorists or pedestrians. Another review study by Thomas and DeRobertis (2013) conclude that one-way cycle tracks are generally safer than two-way, and constructing cycle tracks reduces collisions and injuries when effective intersection treatments are employed. Park et al. (2015) employed both before-after with empirical Bayes and cross-sectional methods to determine relationships between the safety effects of adding a bike lane and the roadway characteristics. Ten years data from 2003 to 2012 for Florida is used in this study. The results show that adding a bike lane is more effective in reducing bike crashes than all crashes. Zangenehpour et al. (2016) investigate the safety effects of cycle tracks at signalized intersections using a case-control study based on video data. The results highlight the important role of cycle tracks and the factors that increase or decrease cyclist safety. However, the before-after approach is not applied in this study because no data from the before period is available. Another case-control study conducted in the city of Charlotte shows that bicycle lanes reduce all crashes due to conscious driving on segments with on-street bicycle lane by motorists (Pulugurtha and Thakur, 2015).

Despite the empirical evidence of the positive impacts of cycle lanes on safety, the quantification of such effects can be complicated due to various confounding factors. For example, roads with parked vehicles are expected to have more cyclist injuries compared to roads without parking, because parked vehicles may restrict sight distances and increase the risk of conflict with parking vehicles or car doors (Pai, 2011; Rifaat et al., 2011). Similarly, the presence of public transport stops (e.g. bus and tram) is also expected to increase the risk of cyclist collisions due to frequent bus and pedestrian activities (Pei et al., 2010). In addition, the effects of cycle lanes are also related to risk perception of cyclists as well as motorists. It is suggested the presence of cycle lane may increase cycle use, and the perception that a route contains cycle lanes increases the likelihood that it will be chosen (Noland and Kunreuther, 1995; Hoehner et al., 2005). Parkin and Meyers (2010) conclude that with a cycle lane motor traffic may pass closer to a cyclist than they would if the cyclist and the motor driver were sharing the same lane.

Besides, there are several outstanding issues which have yet to be fully addressed in the previous studies on the safety effects of cycle lanes. Most studies to date have used either before-and-after or case-control methods (Daniels et al., 2008, 2009; Jensen et al., 2007, 2008; Park et al., 2015; Vandenbulcke et al., 2014). In these studies, a comparison group is usually applied in order to account for the general trend in accidents and provide an estimation of counterfactual outcomes for a study group. One consideration is regarding the similarity between treated and comparison groups. Ideally comparison groups should have the same or similar traffic levels and road characteristics, i.e. the comparison group must be representative of the intervention sites. For example, “an effort was made in order to avoid consequences of larger differences between general comparison group and treated roads, where bicycle facilities were applied. Trends for different types of crashes and injuries of the general comparison group were compared” (Jensen et al., 2007). However, in previous research, not only is there insufficient justification of the selection of control groups, how the treatment and control groups are matched is also unclear.

Another major problem for adopting a before-and-after control study in road safety analysis is the lack of exposure data. As pointed out in the review studies on the safety of urban cycle facilities (Thomas and DeRobertis, 2013; Reynolds et al., 2009; Pulugurtha and Thakur, 2015), many analyses did not control for exposure and were therefore biased. The bicycle traffic volume indicates activity level or exposure of bicyclists, however, is seldom available especially at the segment level. Instead, proxy exposure is usually employed, such as annual bicycle crashes per mile or annual bicycle crashes per annual vehicle miles travelled (Pulugurtha and Thakur, 2015). Vandenbulcke et al. (2014) estimate the potential bicycle traffic using “gravity-based index”, which is often correlated with trip generation and closely reflects actual travel behaviors. In addition, cycle track construction may decrease motorized traffic volume and hence reduce collisions. The failure to control for the change in motorized traffic volume could also bias the study results and conclusions. Thomas and DeRobertis (2013) also suggest that fatal and disabling injuries should be separated from minor ones.

3. METHODS

In this study we employ the EB and PSM methods to estimate the safety effects of London Cycle Superhighways. In this section, the EB methods are first introduced, followed by the discussion of the PSM models.

3.1 Empirical Bayes

The EB methods have been introduced and widely used in before-and-after traffic safety countermeasures evaluation (e.g. Hauer, 1997; Hauer et al., 2002; Persaud et al., 2009). In the EB approach, the predicted number of crashes without treatment is derived by combining the observed crash counts in before period and expected number of crashes from Safety Performance Functions (SPFs). The Negative Binomial (NB) model is usually used to develop the SPF. As discussed in the study by Park et al. (2015), there are two types of SPFs mainly used in the literature. The full SPF relates the crash frequency to both traffic and roadway characteristics, while the simple SPF only considers the traffic exposure as an explanatory variable. In this study, the full SPF is used to account for both traffic volume and road segment characteristics.

The SPF used in this study is based on the model proposed by Park et al. (2015), which can be described as:

$$y \sim \mathrm{Poisson}(\mu)$$

$$\ln\mu = \alpha + \beta_1 \mathrm{V} + \beta_2 \mathrm{L} \ldots + \beta_k X_k + \varepsilon$$

Where V is the cycle AADT for each segment, L is the segment length and X_k is the segment characteristics. ε is a Gamma distributed random error term. The covariates included in the SPF will be discussed in the next section.

The EB estimate of total number of crashes $\widehat{\mu_B}$ in a before period of t_B years is

$$\widehat{\mu_B} = t_B \hat{\mu}$$

Then the predicted number of crashes in a before period, $\widehat{M_B}$ can be obtained by

$$\widehat{M_B} = \rho\widehat{\mu_B} + (1-\rho)Z_B$$

Where Z_B is the observed number of crashes in the before period and

$$\rho = (1 + \frac{\widehat{\mu_B}}{\varphi})^{-1}$$

φ is the shape parameter for the NB distribution.

To account for the trend in accidents between the before and after periods, the expected accidents in the after periods are calibrated using a reference group. The estimate of accidents number in the after period had the treatment not occur, $\widehat{M_A}$, can be calculated after adjusting the time trend effect:

$$\widehat{M_A} = (\frac{N_{A\_POP}}{N_{B\_POP}})\widehat{M_B}$$

Where N_{B_POP} and N_{A_POP} are the numbers of crashes for total population in the before and after periods.

To control for the effect of any cycle volume changes due to the treatment, the expected cycle flow in the after period had the treatment not occurred, V'_A can be estimated as

$$V'_A = \left(\frac{V_{A\_POP}}{V_{B\_POP}}\right) V_B$$

Where V_{B_POP} and V_{A_POP} are the cycle flow for the whole population in the before and after periods, V_B is the observed cycle flow in the before period.

The estimate of crashes number in the after period can be refined as

$$\widehat{M'}_A = \left(\frac{V_A}{V'_A}\right)^{\beta_1} \widehat{M}_A$$

Where V_A is the observed traffic flow in the after period.

The treatment effect can be obtained as

$$\delta_{ATT} = \frac{\frac{Z_A}{t_A} - \frac{\widehat{M'}_A}{t_A}}{Z_{B/T_B}}$$

Where Z_A is the observed number of crashes in the after period. Standard errors and confidence intervals can be calculated using the bootstrap.

Compared to conventional before-after control methods, the EB methods not only isolate but also estimate the effects due to the RTM and time trend. However, the validity of the EB approach heavily relies on the availability of a proper comparison group and an inappropriate comparison group can bias the estimation of SPFs. In previous research, not only is there insufficient justification of the selection of control groups, how the treatment and control groups are matched is also unclear. In fact, this issue of similarity is also critical when selecting the control group in conventional before-after methods.

In this study, we tackle this critical issue of similarity between treated and comparison groups by using the PSM method. What makes the PSM method attractive is that it gives a clear criterion by which to select the control group. Similar groups can then be defined clearly as those with similar propensity scores, and by this avoid selection bias to ensure that the difference between the treatment and control groups can be attributed to the treatment. In addition, the comparisons between EB and PSM methods can enhance the validity of the estimation results. The PSM method is discussed in the next section.

3.2 Propensity Score Matching

In the case of a randomized experiment, the treatment status T_i is unconditionally independent of the potential outcomes Y_i. For non-randomized observational data, such independence cannot be achieved due to the confounding factors $\boldsymbol{X}$, that is, covariates that affect both the probability of treatment exposure and potential outcomes. Consequently, simple comparison of mean outcomes between treated and untreated groups will not in general reveal the causal effect. However, conditional independence of potential outcomes and treatment status can be ensured by adjusting for the vector of covariates $\boldsymbol{X}$, then consistent causal estimates of treatment effects can be obtained.

A widely used method called the Propensity Score Matching is applied in this study to evaluate the safety effect of the Cycle Superhighways. The idea behind this method is to construct a control group that is similar to the CS segments in all relevant pre-treatment covariates $\boldsymbol{X}$. Instead of matching directly on all the covariates $\boldsymbol{X}$, PSM has the advantage of reducing the multiple dimension of matching to a single dimension, the propensity score, which is the probability of receiving a treatment. Conditional on the propensity score, differences in observed outcomes between the two groups can be solely attributed to the intervention impacts. In other words, adjusting for the propensity score is enough to eliminate the bias created by all confounding factors.

3.2.1 Notations

The treatment indicator is defined as T_i, where T_i=1 if unit i receives the treatment and T_i =0 otherwise. Let $Y_i(T)$ denote the potential outcome for unit i, where i=1,…, N and N denote the total population. The treatment effect for unit i can be described as:

$\delta_i = Y_i(1) - Y_i(0)$.

In practice, the parameter of interest is usually the average treatment effect on the treated (ATT), which can be defined as:

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

3.2.2 PSM Assumptions

Two crucial assumptions underlying the PSM method are introduced by Rosenbaum and Rubin (1983). The first assumption for an unconfounded assignment is known as the conditional independence assumption, which assumes all observed differences in characteristics between the treated and untreated units are controlled for, and the outcomes that would result in the absence of treatment are the same for both groups.

Rosenbaum and Rubin (1983) proposed the idea of balancing scores, suggesting that if potential outcomes are independent of treatment conditional on covariates $\boldsymbol{X}$, they are also independent of treatment conditional on a balancing score, such as the propensity score. The conditional independence assumption based on the propensity score can thus be described as:

$(Y(1), Y(0)) \perp T|P(\mathbf{X}), \ \forall \mathbf{X}$ (Unconfoundedness given the propensity score)

The second problem is regarding the chance of finding a match for each unit with the same propensity score. It is possible that there is no match in the control group with a similar propensity to that of any treated unit. So it requires that units with the same $\boldsymbol{X}$ values have a positive (non-zero) probability of being in both treated and untreated groups:

$0<P(T=1|X) <1$ (Overlap)

This is called the overlap assumption as it implies that the support of the conditional distribution of $\boldsymbol{X}$ given $T=0$ overlaps completely with that of the conditional distribution of $\boldsymbol{X}$

given *T=1*. In other words, the overlap assumption ensures that there is sufficient overlap in the characteristics of the treatment and control units to find adequate matches. If some units in the treatment group have combinations of covariates ***X*** that cannot be matched by those of units in the control group, it is not possible to construct a counterfactual. Therefore, the treatment effects for this subgroup cannot be estimated.

3.2.3 *Implementing PSM*

The first step when implementing PSM is to estimate the propensity score. Because linear probability models produce predictions outside the [0, 1] bounds of probability, logit and probit models are usually used estimating propensity score. For binary treatment, logit and probit models usually yield similar results, hence the choice between them is not critical. Please refer to the paper by Smith (1997) for further discussion of this point. In this paper, a logit model is used:

$$P\,(T{=}1 \mid X) = \frac{\mathrm{EXP}(\alpha+\beta' X)}{1+\mathrm{EXP}(\alpha+\beta' X)}$$

Where α is the intercept and β' is the vector of regression coefficients. The covariates included in PSM will be discussed in section 4.

After estimating the propensity score, a matching algorithm is selected to construct the control group from non-treated units. There are four mostly used matching algorithms: nearest neighbour matching, caliper and radius matching, stratification and interval matching, kernel and local linear matching. For detailed discussion of these matching algorithms, please refer to the work by Heinrich et al. (2010). Once treated units have found matches from the untreated group, the treatment effect can be evaluated by taking differences in outcomes between treated units and their matches.

4. DATA

The total length of the CS routes studied is approximate 40 km long with a total number of 45 segments. A total of 375 potential control segments were selected randomly along main corridors running from outer London into and across central London. The EB and PSM methods require that the comparison group should be representative of treated units. Regarding the issue of similarity, we will discuss in the next section.

The accident data used cover the period from 2007 to 2014 to ensure that three years data before and after are available for all CS routes. A total number of 33886 cycle-related accidents are recorded in London. The data are based on police records and collected by the UK Department for Transport (DfT) and are known as “Road accident data - GB”, or the STATS 19 data base. The location of an accident is recorded using coordinates which are in accordance with the British National Grid coordinate system. Each individual accident can be located on the road network as shown in Figure 3. The data set also records the severity of accident, e.g. killed and seriously injured (KSI) and slightly injured, the date and time of the accident, and the type of vehicles involved in the accident.

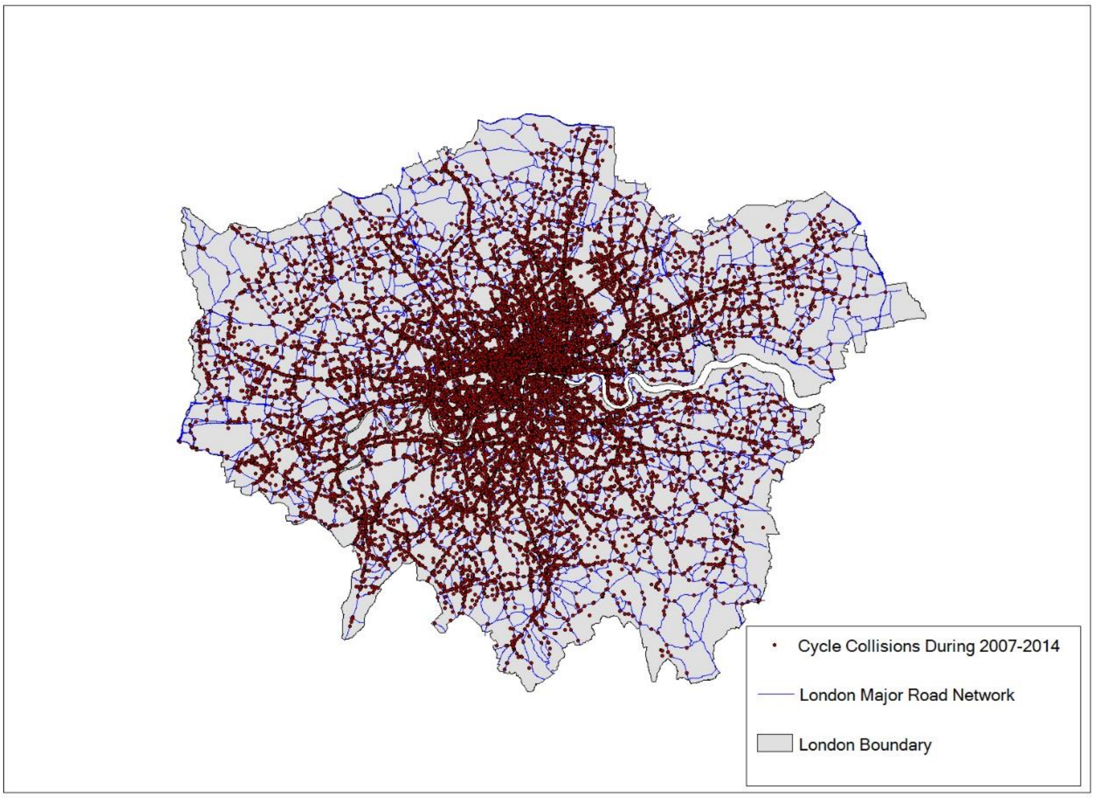

Figure 3 Cycle Collisions in London 2007-2014

It is worth noting that although STATS 19 data provides a detailed source of accident data, it is prone to underreporting, especially for slight injury crashes. The estimated reporting rates also vary across different road user groups. Reasons for the underreporting could be:

- People are unaware that injury accidents should be reported;
- Some people who are affected by drugs or alcohol do not want to report to police;
- The injury is not apparent.

As discussed earlier, it is important to control for the exposure when analyzing the safety effects of cycle lanes. Cycle traffic count is included in the traffic data produced by The Department for Transport (DfT). DfT collects traffic data to produce statistics on the level of traffic on roads in Great Britain. Data are available for each junction to junction link on the major road network as shown in Figure 4. Data are also available for the sample of points on the minor road network. In addition, traffic data are collected from the London Atmospheric

Emissions Inventory (LAEI). A detailed description of the LAEI has been provided in the study by Gulliver et al. (2015). The LAEI data contains traffic flow, composition and speed information. Traffic flows are calculated using data collected from manual classified count (MCC), which are widespread and cover all of the major roads in London (Beevers et al., 2009). In addition, vehicle speed is obtained based upon a combination of TrafficMaster GPS derived and Moving Car Observer speeds (Gulliver et al., 2015).

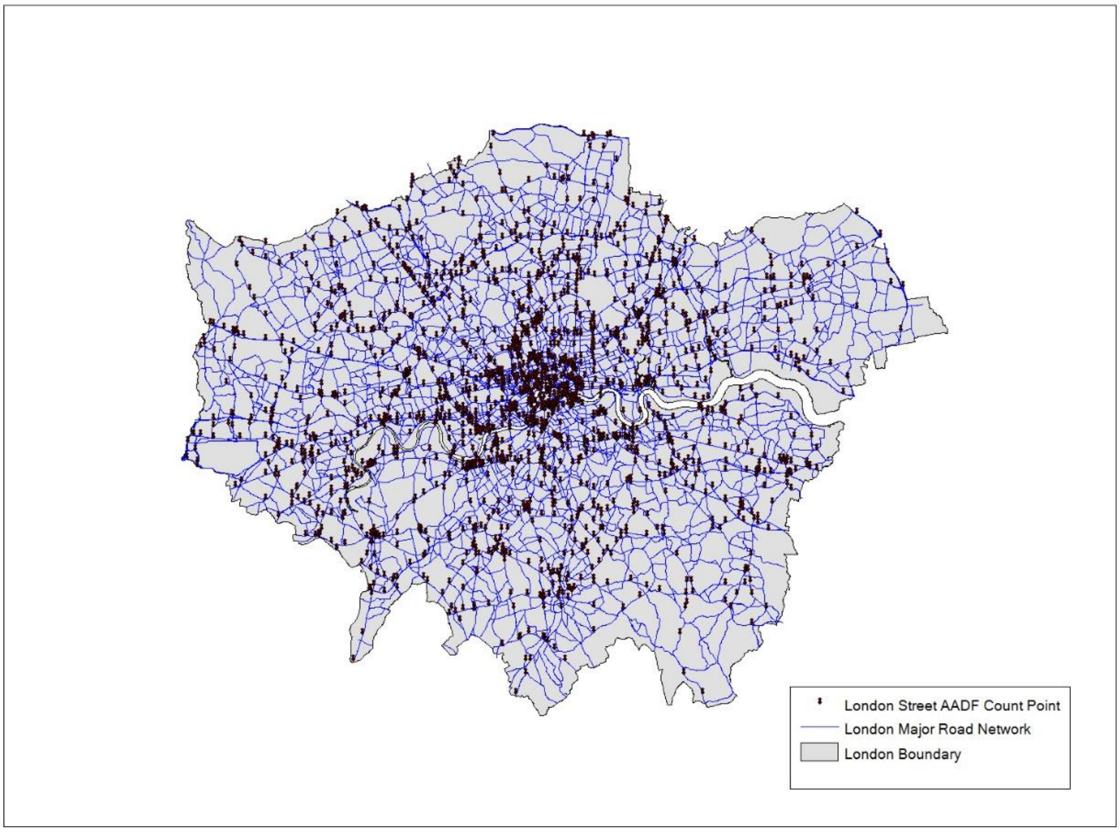

Figure 4 Traffic Count Points in London

In this study we also include variables which may have an impact on the occurrence of cycle collisions. For example, it is suggested that the number of cycle collisions are associated with the number of bus stops and the number of intersections (Pulugurtha and Thakur, 2015). Previous research has also suggested an association between road traffic crashes and socio-demographic characteristics, such as employment, deprivation and land use (Wier et al., 2009; Dissanayake et al., 2009; Graham and Stephens, 2008). To consider this effect, the data for population and employment, as well as the information of land use was obtained from the Office for National Statistics (ONS). In summary, the covariates that included in the model are shown in Table 2.

Table 2 Descriptive statistics of the variables for CS segments

Variables	Description	Mean	S.D.	Min	Max
Total Cycle Collisions (baseline)	Injured cycle collisions in three-years pre-intervention period	5.74	4.12	0.00	14.43
KSI Cycle Collisions (baseline)	Killed and seriously injured cycle collisions in three-years pre-intervention period	0.89	0.84	0.00	3.09
Speed (baseline)	Traffic speed in the pre-intervention period (km/h)	25.97	9.23	15.77	62.02
AADT (baseline)	Annual average daily traffic volume in the pre-intervention period	20905.83	8279.57	8344.32	53802.79
AADB (baseline)	Annual average daily bicycle volume in the pre-intervention period	1696.01	1418.29	22.50	7100.25
Length	Length of road sections (m)	908.89	264.01	508	1494
Road Class	1 =A Road, 0 = B Road and Minor Road	1=94.67%	0=5.33%		
Road Type	1=Dual Carriageway, 0=Single Carriageway	1=16%	0=84%		
Density of Intersections	Number of intersections per m	1.14E-02	5.02E-03	1.63E-03	2.76E-02
Density of Bus Stops	Number of bus stops per m	6.14E-03	3.36E-03	0	1.25E-02
Domestic (%)	Percentage of domestic buildings, e.g. residential area	10.35%	4.85%	2.49%	24.40%
Non-Domestic (%)	Percentage of non-domestic buildings, e.g. business and office district area	13.42%	6.65%	3.02%	29.16%
Road (%)	Percentage of road area	21.17%	4.51%	8.77%	28.08%
IMD	The index of multiple deprivation	34.38	9.37	16.22	55.69
Population Density	Residential population per m2	9.02E-03	3.25E-03	1.38E-03	1.44E-02
Employment Density	Number of employees per m2	4.64E-03	1.88E-03	5.04E-04	8.32E-03

5 RESULTS

5.1 Changes in the Number of Cyclists

According to the report by TfL (2011b), cycling has increased along the Cycle Superhighways. Table 3 summarizes the AADT and AADB for the CS and control segments during pre- and post-intervention periods. It can be seen that there is a small reduction in the AADT for both groups, while the increase in the AADB is significantly higher for the CS segments than the control segments (19.6% and 2.5% respectively).

There are two possible reasons for the increase in the number of cyclists on the CS routes. First, the Cycle Superhighways scheme encouraged existing cyclists to cycle more or switch route to the Cycle Superhighways. For example, the frequency of cycling increased for both CS3 and CS7, with the percentage of those cycling five or more times per week increasing by over two percentage points. Meanwhile, the Cycle Superhighways also attracted new cyclists to take up cycling. For example, two waves of interviews were conducted among people who have the potential to cycle or cycle more before and after the launch of the Cycle Superhighways. The proportions of respondents who have started cycling as a result of the Cycle superhighways are 20 percent for CS3 and 32 percent for CS7 (TfL, 2011b).

While more cycling is good for health, environment and congestion reduction, the increase in cycling traffic brought about by CS means more cycling collisions can be expected. In addition, due to the cycle scheme implemented in London in recent year (e.g. Barclays Cycle Hire and Biking Boroughs), there are more inexperienced cyclists on the road. They may be more prone to use CS routes, which may also induce more collisions on CS routes. In the next section, we evaluate the effect of CS on cycling collisions.

Table 3 Summary of AADT and AADB by groups

	Treated Group		Comparison Group	
	Mean	S.D.	Mean	S.D.
AADT pre-intervention	20905.83	8279.57	16491.4	6432.8
AADT post-intervention	18770.29	7725.92	15727.88	6495.81
Changes (%)	-10.2%	t-value=-10.61	-4.6%	t-value=-5.72
AADB pre-intervention	1696.01	1418.28	827.39	848.01
AADB post-intervention	2027.99	1776.45	848.37	920.17
Changes (%)	19.6%	t-value=4.78	2.5%	t-value=0.98

5.2 Effects of CS on the Number of Cycling Collisions

In this section we first employ the EB method to estimate the effects of CS on cycling collisions in absolute numbers. The SPFs are developed using datasets including traffic characteristics, road section characteristics and socio-economic information. The SPFs are estimated using the NB model with all 375 comparison sections as the reference sites. The SPFs are developed for two severity levels, total cycle collisions and KSI cycle collisions. Table 4 shows that the number of cycle-related collisions is higher for road segments with higher total AADT and AADB at a 95% confidence level. It is also found that higher density of intersections is significantly correlated with more collisions, which is consistent with previous findings (Wei and Lovegrove, 2013). This is probably due to high traffic volume and complex traffic condition at intersections, such as many conflicting turning movements. It is found that bus stops are expected to cause blackspots for cyclists since frequent pedestrian activity occurs around these stops (Pei et al., 2010; Quddus, 2008). The density of bus stops, however, is not significant in this study.

It is worth noting that the collision frequency decreased as the traffic speed increases. A possible reason is that there are fewer cyclists driving on streets with higher traffic speeds. For example, the AADB of control segments with traffic speed higher than 30 km/h is 269, while the AADB for other control segments is 956. Another possible reason is that both cyclists and motorists may allocate more attention to each other on roads with high traffic speed. In addition, the results suggest that the number of total cycle collisions is related to socio-economic characteristics. More cycle collisions are found in area with higher percentages of business and office district. And it is also found that deprived areas with higher IMD scores experienced more cycle collisions. Many previous studies have shown a correlation between traffic crashes and economic status (Graham and Stephens, 2008; Huang et al., 2010; Abdel-Aty et al., 2013). However, most of the variables are not significant in the SPF for KSI cycle collisions, which is probably due to the lower number of KSI cycle collisions.

The EB estimates of cycle collisions in the pre- and post-intervention periods are predicted based on the SPFs. The safety effects of the Cycle Superhighways are then estimated for total and KSI cycle collisions. As shown in Table 5, there is an increase of 2.58 annual cycle collisions per km (37.2% in percentage) on CS routes at a 99% confidence level. KSI cycle collisions increase by 56.8%, although the increase is not significant in absolute numbers. As discussed earlier, an advantage of the EB method is that it can estimate the effects due to the RTM and time trend. The RTM effects are estimated to be significantly negative, which is consistent with the intuition that black spots with high recent crash record tend to have lower accidents rate in subsequent years. In contrast, the results show a significant increase in cycle collisions due to the time trend effects, which is also consistent with the overall trend in cycle collisions in London.

Since the validity of the EB approach relies heavily on the availability of a proper reference group, it is critical to test the suitability of candidate reference groups. One commonly used test compares time trends in accident number for the treatment and reference groups. The time trend of a good reference group should track the one of treatment group very well (Hauer, 1997). As discussed earlier, a good reference group must be representative of the treated entities in terms of the time trends of crash counts, traffic flow and road characteristics. However, the odds ratio approach only takes the historical crash counts into account. To address this issue, the propensity score can be applied to find untreated sites that are similar to treated sites.

Table 4 Results of SPFs estimation

	Total Cycle Collisions (per year*km)			KSI Cycle Collisions (per year*km)		
	Coef.	S.E.		Coef.	S.E.	
AADB	2.93E-04	3.46E-05	***	3.22E-04	9.42E-05	***
Density of Intersections	35.733	8.108	***	43.252	22.185	*
Density of Bus Stops	---			---		
Speed	-0.044	0.008	***	-0.035	0.022	*
AADT	2.48E-05	7.46E-06	***	4.72E-05	1.89E-05	**
Length	---			---		
Domestic (%)	---			---		
Non-Domestic (%)	1.627	0.692	**	---		
Road (%)	---			---		
IMD	0.009	0.004	***	---		
Population Density	---			---		
Employment Density	---			---		
Road Class	0.437	0.153	***	---		
Road Type	-0.531	0.218	**	---		
	Adjusted R^2= 0.53			Adjusted R^2= 0.31		

Notes: Figures are significant at: *90%, **95%, ***99%

We then estimate the effects of the Cycle Superhighway on cycle collisions using the Difference-In-Difference (DID) PSM estimator. The conditional independence assumption is too strong and may not hold when unobserved factors that may influence outcomes are not included in the model. However, the CIA can be relaxed by using the DID matching estimator

(Heckman et al., 1997). Given data from the pre-treatment period, any time-invariant confounder can be controlled for. In the DID matching approach, the dependent variable is the difference between pre-intervention and post-intervention periods. The estimation results of propensity scores and tests of matching quality are detailed in Appendix A, B and C.

Table 6 presents the estimation of effects of the Cycle Superhighways on annual cycle collisions per km. using PSM method. The observed increase in annual total cycle collisions per km is 3.08 in absolute numbers and 47% in percentage. When applying the PSM method, the increase is around 2.65 (38.7% in percentage). In terms of the effect on KSI cycle collisions, the results show an average increase of 55.1%, although the increase is not significant in absolute number. The results are very similar to those from the EB methods, which increase our confidence in the PSM method.

Table 5 Empirical Bayes estimation of safety effects

	Treatment effect			RTM effect			Time trend effect		
	Changes	S.E	95% CI	Changes	S.E	95% CI	Changes	S.E	95% CI
Total Cycle Collisions (per km*year)	2.58	0.81	{0.95, 4.22}	-1.49	0.39	{-2.29, -0.70}	2.5	0.16	{2.16, 2.83}
Total Cycle Collisions (%)	37.2%	0.112	{0.053, 0.509}	-5.5%	0.094	{-0.241, 0.133}	43.6%	0.039	{0.348,0.523}
KSI Cycle Collisions (per km*year)	0.24	0.12	{0.10, 0.78}	-0.41	0.12	{-0.65, -0.17}	0.15	0.01	{0.13, 0.18}
KSI Cycle Collisions (%)	56.8%	0.167	{0.136, 0.844}	-18.0%	0.081	{-0.347, -0.007}	15.0%	0.022	{0.121, 0.187}

Table 6 PSM estimation of safety effects

	Total Cycle Collisions					KSI Cycle Collisions				
	DID estimator of cycle collisions (per year*km)					DID estimator of cycle collisions (per year*km)				
	Treated	Controls	Difference	S.E.	T-stat	Treated	Controls	Difference	S.E.	T-stat
Unmatched Control Model	4.15	1.07	3.08	0.31	9.2	0.32	0.09	0.23	0.07	3.1
PSM Model	4.15	1.50	2.65	0.64	4.14	0.32	0.14	0.18	0.16	1.11
	DID estimator of cycle collisions (%)					DID estimator of cycle collisions (%)				
	Treated	Controls	Difference	S.E.	T-stat	Treated	Controls	Difference	S.E.	T-stat
Unmatched Control Model	72.2%	25.2%	47.0%	0.347	1.16	65.8%	0.2%	65.6%	0.183	3.59
PSM Model	72.2%	33.5%	38.7%	0.173	2.24	65.8%	10.6%	55.2%	0.236	2.04

5.3 Effects of CS on Cycling Collision Rates

As suggested by the majority of recent studies, roads with cycle tracks are either safer or at least not more dangerous than those without cycle tracks (Zangenehpour et al., 2016). However, the results from both the EB and PSM methods indicate that the cycle-related collisions have significantly increased due to the implementation of the Cycle Superhighways. A possible reason pointed out by Thomas and DeRobertis (2013) is that although the bicycle volume was included in the model, the collision results before- and after-intervention periods were not divided by the bicycle traffic volume to assess the change in relative risk. The failure to control for the changes in bicycle volumes may bias the study results and conclusions.

Standard practice when analyzing motor accidents is to calculate motor accident rates relative to traffic volume. This should also apply to bicycle accident analysis. In this study, the cycle collision rate, which has been widely used in the literature (Strauss et al., 2013), was applied as below:

$$\text{Cycle collision rate}=\frac{\text{Annual Collision per km x } 10^6}{\text{AADBx365}}$$

The safety effects of the Cycle Superhighways are then estimated based on cycle collision rate. Table 7 shows the effects of the Cycle Superhighways on cycle collision rate using the PSM methods. The estimation results suggest that there is no significant difference in the relative risk of cycle collisions between the CS and control segments. In other words, the “blue paint” cycle lanes on the CS routes are not more dangerous than other roads. The increase in the number of cycle collisions is probably attributed to the dramatic boost in the use of cycling along the Cycle Superhighways.

Table 7 Estimation of safety effects on collision rate

	Total Cycle Collisions per million cyclists					KSI Cycle Collisions per million cyclists				
	Treated	Controls	Difference	S.E.	T-stat	Treated	Controls	Difference	S.E.	T-stat
Unmatched Control Model	23.65	26.69	-3.05	16.87	-0.18	4.77	2.24	2.52	1.05	2.39
PSM Model	23.65	22.57	1.07	51.96	0.02	4.77	1.73	3.04	2.21	1.37
	DID Total Cycle Collisions per million cyclists					DID KSI Cycle Collisions per million cyclists				
	Treated	Controls	Difference	S.E.	T-stat	Treated	Controls	Difference	S.E.	T-stat
Unmatched Control Model	11.29	5.85	5.43	3.66	1.49	2.94	-0.05	2.99	1.41	2.11
PSM Model	11.29	-0.25	11.54	11.54	1.47	2.94	-1.01	3.96	3.55	1.11

5.4 Comparison of Safety Performance among CS Routes

In this section, we further investigate how the effects of the Cycle Superhighways on cycle collisions vary by different route characteristics. Table 8 shows the effects of four routes on total and KSI cycle collisions respectively. It can be seen that the total cycle collisions have significantly increased on CS2 and CS7 in absolute numbers (4.35 and 3.65 respectively) and percentages (73.7% and 38.4% respectively). Although the results are mostly insignificant for KSI collisions, positive signs are obtained for these two routes, indicating that there might be an increase in KSI cycle collisions due to the Cycle Superhighways. The increase is much smaller and insignificant for CS8. In contrast, we find a reduction in both total and KSI cycle collisions on CS3, although the figures are insignificant. There are several possible reasons, among which the most important one is that CS3 has the highest percentage of segregated cycle lanes. As shown in Table 9, about 78% of the cycle lanes on CS3 are segregated, while the percentages for other routes are significantly lower.

We then examine the proportion of cycle lanes shared with other vehicles. A segment is identified as a cycle lane shared with other vehicles if one of the conditions below is met.

(1) A small blue box is painted on the motor lane instead of a blue painted cycle lane;

(2) The Cycle Superhighways are simply painted on top of the red bus lane, indicating that cyclists have to share space with buses and parked cars during off-peak time.

(3) No signs are provided on the road.

As shown in Table 9, CS2 and CS7 have higher percentages of shared cycle lanes (34% and 49%), suggesting that shared cycle lanes are related to more cycle collisions, which is similar to previous findings (Reynolds et al., 2009; Teschke et al., 2012)

As discussed in the previous section, we also find that the number of cycle collisions increases as the density of intersections increases, which is consistent with the conclusions from previous studies (Wei and Lovegrove, 2013; Pei et al., 2010). The results indicate that it is much safer to cycle on CS3, which has the highest proportion of two-way cycle lanes. However, previous studies suggest that two-way cycle lanes are usually more dangerous than one-way cycle lanes (Thomas and DeRobertis, 2013). This is probably because that all of the two-way cycle lanes on CS3 are segregated lanes, which increases the safety level (Reynolds et al., 2009).

Table 8 Estimation of safety effects by routes

	Total Cycle Collisions						KSI Cycle Collisions					
CS Route No.	Effect	S.E.	T-stat	Effect (%)	S.E.	T-stat	Effect	S.E.	T-stat	Effect (%)	S.E.	T-stat
CS 2	4.35	1.14	3.81	73.7%	0.268	2.78	0.45	0.34	1.33	84.8%	0.988	0.94
CS 3	-0.45	0.93	-0.48	-3.3%	0.521	-0.06	-0.32	0.29	-1.09	-26.0%	0.542	-0.48
CS 7	3.65	1.06	3.46	38.4%	0.173	2.29	0.23	0.26	0.89	74.8%	0.453	1.65
CS 8	1.15	0.53	1.95	12.4%	0.440	0.16	0.29	0.26	1.11	47.2%	0.355	1.31

Table 9 Characteristics of cycle lanes by routes

CS No.	Percentage of Lanes shared with other vehicles	Percentage of Segregated Cycle Lanes	Percentage of Two-way Tracks	Intersection Density (per km)
CS 2	34%	16%	0	13.5
CS 3	22%	78%	78%	7.4
CS 7	49%	2.3%	0	13.4
CS 8	23%	3%	3%	10.9

6 DISCUSSIONS AND CONCLUSIONS

As an important part of the program to support the Mayor's target of a 400 percent increase in cycling by 2026, the London Cycle Superhighways are expected to provide a safe, fast, direct, continuous and comfortable way of getting to central London. A few reports have been done to assess the profile of cycling along and the cyclists' perception of the Cycle Superhighways (TfL, 2011b). However, the safety effect of the Cycle Superhighways has not been evaluated before, because accident data during post-intervention period is not sufficient. This study contributes to the literature by applying causal models to estimate the effects of the London Cycle Superhighways on cycle collisions.

The results found that the introduction of cycle superhighways caused cycling traffic volumes to increase dramatically along CS routes with no significant impacts on collision rates. Cycling on CS routes has significantly increased by 19.6%, because the Cycle Superhighways scheme encouraged existing cyclists to cycle more and also attracted new cyclists to take up cycling. Then the EB and PSM methods are applied to estimate the effects of the Cycle Superhighways on cycling collisions. The SPFs are first developed for the EB methods using a comparison group. It is found that cycle collisions are associated with traffic conditions, the density of intersections, land use characteristics, deprivation and road type. In terms of the estimation of safety effects, although we found an increase in the absolute number of cycle collisions on CS routes, the results suggest no significant difference in cycle collision rates between the CS and control segments after controlling for exposure, implying that the Cycle Superhighways are not more dangerous or safer than other roads. The increase in cycle collisions on the CS routes can be attributed to the dramatic increase in cycling along the CS routes.

The London Cycle Superhighways are frequently criticized as “nothing but blue paint”. In fact, a certain proportion of the CS routes are even not covered by the blue surfacing. Only about two thirds of the lanes are designed exclusively for cyclists. In addition, besides CS3 the segregated cycle lanes are rarely seen on other CS routes. The cyclists have to share the lanes with other motor vehicles in most cases. It is suggested that if cyclists will share space with motor traffic of high volumes, specific safety measures and high quality protected cycle infrastructures should be provided (London Cycling Campaign, 2015). It is obvious that the current safety measures and designs implemented on the Cycle Superhighways cannot provide high level of protection for cyclists.

However, most of the cyclists using the Cycle Superhighways have the perception that it is safer to cycle on the CS routes, and the visibility of the blue surfacing encouraged them to use the routes (TfL, 2011b). Consequently, there is a dramatic increase in the cyclists on the CS routes while the risk of cycling is not effectively reduced, with the exception of CS3. Compared to other CS routes, it is relatively safer to cycle on CS3, since most segments of CS3 are raised from the road and separated from the motor lanes (Reynolds et al., 2009). There would be a safer environment for cycling if such designs can be applied consistently on all other routes. Although the improvements of cycling infrastructure are costly, the environmental and public health benefits can also be tremendous. The cost-effectiveness issue is beyond the scope of this study, however, it could be an interesting topic for future research.

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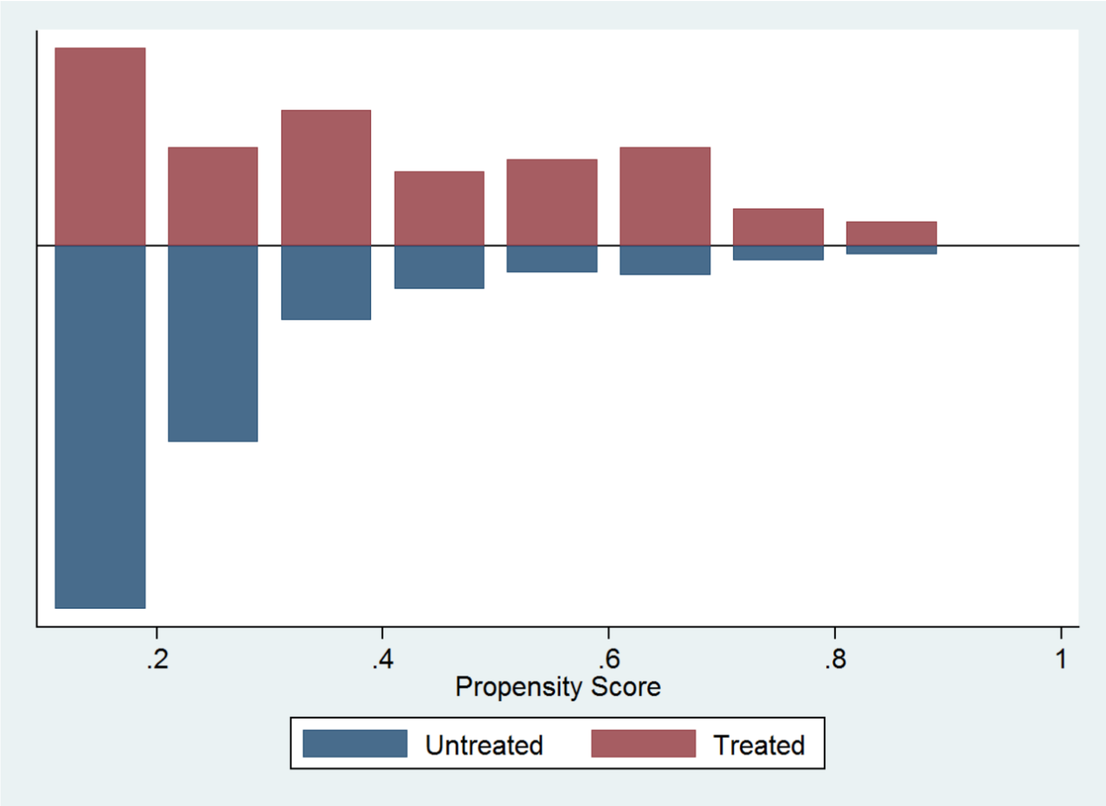
Appendix A Estimation Results of Propensity Score Model

	Coef.	Std. Err.	z	P>|z|
Total Cycle Collisions (baseline)	0.045	0.019	2.38	0.017
KSI Cycle Collisions (baseline)	0.068	0.079	0.85	0.393
Speed (baseline)	-0.025	0.021	-1.2	0.230
Total AADT (baseline)	8.45E-05	1.73E-05	4.89	<0.001
Bus AADT (baseline)	-4.62E-04	2.09E-04	-2.21	0.027
Cycle AADT (baseline)	1.98E-04	1.18E-04	1.68	0.094
Length	2.30E-03	6.36E-04	3.61	<0.001
Road Class	-0.061	0.449	-0.13	0.893
Road Type	-0.087	0.422	-0.21	0.835
Density of Intersections	81.851	26.890	3.04	0.002
Density of Bus Stops	-113.174	40.804	-2.77	0.006
Domestic (%)	-27.071	4.343	-6.23	<0.001
Non-Domestic (%)	6.341	2.233	2.84	0.005
Road (%)	12.116	3.650	3.32	0.001
IMD	0.023	0.013	1.7	0.089
Population Density	-340.073	103.986	-3.27	0.001
Employment Density	841.715	201.112	4.19	<0.001
Obs.=420	Pseudo R^2=0.483			

Appendix B Overlap Test Based on Propensity Score Distribution



Appendix C Balancing test between treated and control groups

	Unmatched	Mean			%reduct	t-test	
Variable	Matched	Treated	Control	%bias	|bias|	t	p>|t|
Total Cycle	U	18.41	9.27	82.2		7.59	<0.001
Collisions (baseline)	M	18.41	19.14	-6.5	92	-0.33	0.744
KSI Cycle Collisions	U	2.79	1.27	72.1		6.88	<0.001
(baseline)	M	2.79	2.70	4.3	94	0.24	0.814
Speed (baseline)	U	25.97	25.26	8.7		0.75	0.453
	M	25.97	24.80	14.2	-64.2	0.77	0.441
AADT (baseline)	U	20906	16491	59.5		5.15	<0.001
	M	20906	21430	-7.1	88.1	-0.33	0.745
AADB (baseline)	U	1696	827.4	74.3		7.11	<0.001
	M	1696	1453.3	20.8	72.1	1.12	0.263
Length	U	1120.1	1034.7	45.3		4.14	<0.001
	M	1120.1	1100.2	10.6	76.6	0.58	0.563
Road Class	U	0.95	0.91	15.3		1.12	0.262
	M	0.95	0.97	-8.2	46.7	-0.64	0.521
Road Type	U	0.16	0.09	20.1		1.73	0.085
	M	0.16	0.19	-10.4	48.0	-0.55	0.581
Density of	U	1.14E-02	1.14E-02	0.1		0.01	0.992
Intersections	M	1.14E-02	1.13E-02	1.6	-150	-1.47	0.143
Density of Bus Stops	U	6.14E-03	7.61E-03	-43.7		-3.44	0.001
	M	6.14E-03	6.63E-03	-14.6	66.6	-0.77	0.44
Domestic (%)	U	0.10	0.13	-47.2		-3.67	<0.001
	M	0.10	0.12	-22	53.3	-1.38	0.171
Non-Domestic (%)	U	0.13	0.10	45		3.51	<0.001
	M	0.13	0.15	-18.3	59.2	-1.05	0.294
Road (%)	U	0.21	0.19	38.8		2.93	0.004
	M	0.21	0.22	-24.3	37.5	-1.53	0.127
IMD	U	34.38	30.55	35.6		2.61	0.009
	M	34.38	33.65	6.8	80.8	0.47	0.639
Population Density	U	9.02E-03	8.22E-03	22.3		1.67	0.096
	M	9.02E-03	9.34E-03	-8.9	59.9	-0.53	0.594
Employment Density	U	4.64E-03	4.19E-03	23.3		1.8	0.073
	M	4.64E-03	4.89E-03	-12.8	45.1	-0.7	0.482

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