The impact of cycling segregated lanes on road users

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1 Introduction

The world's major cities have built cycling infrastructures in the last decades. Active travel, including walking and cycling, is encouraged to reduce motorised traffic, bring health benefits and reduce air pollution. In addition, these modes can provide relief to congestion of public transport in central areas. However, these benefits are conditional on doing more than merely displacing bike users from one lane to another, as well as generating a genuine shift in modal share and not only capturing the population's growth in these areas.

Although major cities have spent considerable amounts on increasing the number of cyclists, segregated cycling lanes have not been studied by economists as extensively as other infrastructures such as segregated bus lanes. London's cycling policy reflects other large metropolitan areas in implementing bike-sharing systems, segregated lanes and encouraging users to avoid car traffic. However, bikes represent still only 2.5% of trips in London. London Mayor's strategy is to reach 5% by 2026 (Transport for London 2018). The current strategy aims at convincing more people to cycle. Safety concerns are the first deterrent for cycling in London. Segregated cycling lanes aim directly at improving safety by separating traffic from cars and providing safe junctions. Their design - large straight roads from outer London to Central London - was chosen to be easily recognizable and offer a fast and simple way to travel across central London.

This paper examines whether building cycling infrastructure increases cycling flows in large cities such as London. The program's roll-out between 2008 and 2020 is used to address identification issues. In 2008, Mayor Ken Livingstone announced London's Cycle Superhighways scheme (CSH) as shown in Figure 6.B.1. By 2010, the first lanes were built[1], but they were perceived as unsafe by users. In response to the criticism, in 2012,the first segregated cycle lanes were built[2]. Most of the subsequent lanes were completely separated from the car traffic[3]. The analysis focuses on the second generation of segregated cycling lanes for practical reasons (I do not observe pre-trends in the first generation of lanes) and to narrow the analysis to mainly segregated lanes.

The paper finds evidence of a net increase in cycling flows for three years following the launch of the program. There is not enough data to estimate longer time effects. As soon as the facility

[1] CS3, CS7 in 2010 and CS2, CS8 in 2011

[2] CS5, upgrade of CS2, the extension of CS3, CS6, CS1 + "Better junctions"

[3] I show the differences between the two generations of lanes in Figure 6.B.2 and 6.B.3. The lane number, e.g. CSH8/CSH5, corresponds to the original plan number and not the order of construction; some lanes are called "CS" and others "CSH"

opens, cycling flows increase by about 25%, and then by 20% per year after that. From the empirical design, I find that the increase is not driven by population growth in these areas. I also pay particular attention to the possibility of cycling lanes displacing other traffic. Indeed, the increase in cyclist flow on CSHs could be driven by cyclists choosing safer lanes to do their usual trips. While not a bad outcome in itself, the main goal of the CSH was to create incentives for people to cycle and do more trips cycling. I find no evidence of cycling displacement around the new segregated cycling lanes. The lack of displacement indicates that the increase in traffic in segregated lanes is likely to contribute significantly to the net increase of cycling flow in London, rather than shifting existing flows from other routes. It makes sense as cycling trips are generally short[4], and any additional detour would significantly decrease the advantage of using a bike.

I reproduce the analysis using the London cycle hires - London's public bicycle hire scheme opened under Boris Johnson's mayorship - and show a similar pattern. Following the opening, trips starting or ending at CSHs show an increase while stations further away do not.

Another form of displacement could be car traffic. The reduced effects on pollution would be voided. To disentangle these effects, I analyse the impact of the segregated cycling lanes on cycling at different distances of the lanes. I do not find evidence of decreased car flow or bus flow in the lanes that have been reduced to accommodate the segregated cycling lanes nor in the adjacent lanes.

Finally, I look at the underlying mechanism for the increase in cycling, such as the increased safety of cyclists in segregated lanes. I find that these infrastructures bring direct benefits by decreasing the number of car-cycle accidents and reducing accidents per cyclist.

The main contribution of this paper is to capture that segregated cycling lanes do not offer only a one-time increase in cycling at opening but also put cycling flow on a higher growth path. I further demonstrate that the increase is not due to the displacement of cyclists. I also show that the main argument against segregated cycling lanes - disruption of car traffic - did not manifest in London. Finally, I find a significant decrease in accidents after the opening of lanes - explaining the success of the programme.

This paper has clear policy implications. First, the findings imply that building cycling infrastructure has an immediate impact on traffic flows and that this impact is growing over time. The impact is more prominent for fully segregated lanes but still considerable for partially non-segregated lanes. A cost-benefit analysis should take into a large time frame to evaluate these programmes. Additionally, cycling lanes are also often criticised for increasing congestion. However, in the analysis, I find little evidence of change in traffic flows around the cycling lanes. Finally, in line with the previous literature, this paper provides evidence of safety in numbers for cyclists. Not only does the number of accidents per cyclist on the road decrease, but the number of total accidents also drops after the construction of the cycling lanes. Most importantly, the degree of segregation is crucial in reducing traffic accidents.

The rest of the paper is structured as follows. First, I review the literature on transport in London and cycling in Section 2. I then present the empirical analysis in Section 3 and the datasets I use in the analysis in Section 4. In Section 5, I decompose the results between cycling

[4]22 min on average in London (LTDS, 2018)

flows on the new segregated lanes, the displacement analysis on neighbouring roads and the traffic accidents analysis. Finally, I summarise the results and alleys for future research in Section 6.

2 Literature review

Transport economists are no strangers to London's setting. London is famous for experimenting with a central congestion charge in the early 2000s. The effects of the congestion charge were wide-ranging: reduced motorised traffic, decreased air pollution and accidents, increased housing prices and increased traffic outside the congestion zone. Leape (2006) summarises the early implementation of the London congestion charge reduced all motorised traffic by 12% and up to 34% for cars. Green, Heywood, and Navarro (2018) show evidence that London's Congestion Charge reduced traffic accidents and air pollution in the tolled zone. Keat Tang et al. (2016) uses a partial equilibrium to find an elasticity of housing values with respect to traffic of -0.3. More recently, Herzog (2020) uses a general equilibrium model to show that the congestion charge reduces both the number of commuters and their propensity to drive inside the congestion zone but increases driving among untolled drivers. This paper contributes to the economic literature by evaluating the impact of new transport infrastructure on transport mode and its general impact on motorised traffic.

On segregated cycling lanes, studies have shown they are safer for cyclists (Cohen 2013; Li, Graham, and Liu 2017; Mulvaney et al. 2015; Reynolds et al. 2009; Aldred et al. 2018). These studies highlight a few caveats that are worth noting. First, there is a learning period when new lanes are introduced as users learn how to use them safely. Second, there is safety in numbers, meaning that cycling infrastructure might be particularly useful to sustain a higher cycling growth rate. Third, safer infrastructure is also more inclusive: women, young people or the elderly are more likely to cycle when cycling routes are separated from car traffic. Finally, these studies do not consider that there could be endogeneity in cycling lanes placement and existing pre-trends. Therefore, it is essential to show that these results hold even when pre-existing trends are considered.

In London specifically, Aldred et al. (2017) review the literature on cycling provisions separated by motor traffic. They find that even though all users prefer separation, women have stronger preferences. In a follow-up paper, Aldred and Dales (2017) show that the lack of infrastructure in London and the high-level of perceived danger is a deterrent for most casual users. A study by Li et al. (2018) relates an increase in cycle hire near the CSHs. I generalise the analysis to cyclists using their own bikes, as cycle hire users differ from the general population - cycle hires are used more by tourists and casual users. Li, Graham, and Liu (2017) find no impact of the programme on traffic accidents in the first phase of the programme (2007-2014). They note that a significant drawback of the CSH programme is the lack of separation between cars and cyclists. This paper focuses on the programme's second phase when most routes were built with a physical separation from the motorised traffic in reaction to the early criticism. I find a substantial impact on the reduction of traffic accidents per cyclist.

3 Estimation strategy

In this paper, I study the impact of the construction of the CSHs on cycle traffic in London using an event study analysis. The treatment group is sites with an active CSH; the control group is not yet treated sites and treated late (sites that opened in 2020).

The set-up behind this paper is that individuals in London have a large set of options regarding modal choice. They can choose to walk, cycle, take public transport, hire taxis or private cars. The determinants of modal choice depend on the individuals, trips and the modes' characteristics. Intuitively, building segregated cycling lanes reduces the cost of travelling by bike. It might also increase the cost of travelling by car by reducing road capacity. In consequence, it should increase the demand for cycling and potentially create a substitution with other modes.

One way to investigate this increase in demand would be to use travel diaries. They exist for London (London Travel Demand Surveys from Transport for London), but unfortunately, the level of geographic disclosure is too aggregated to perform this analysis. In this paper, I thus present results on cycling demand increase, but I cannot comment on substitution or general equilibrium effects.

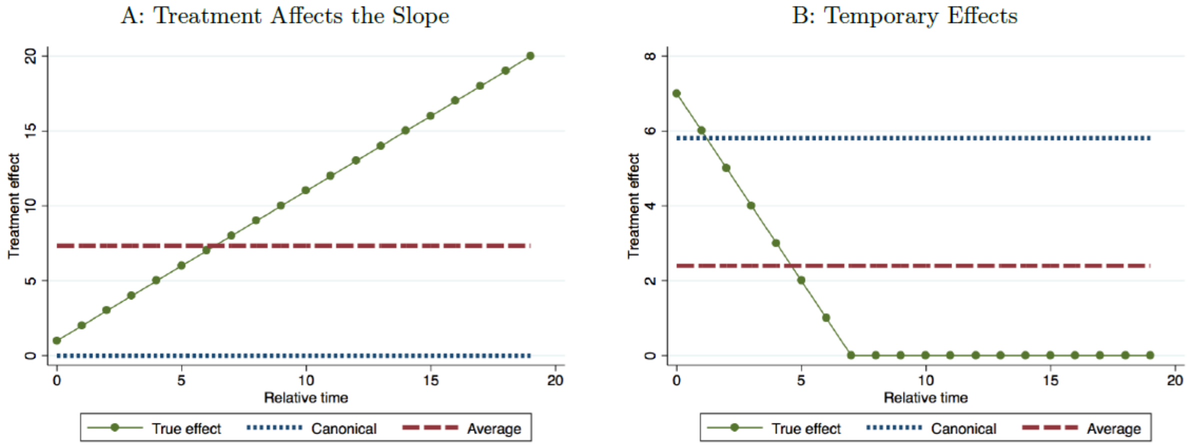
To conduct the analysis, I use the cycle monitoring programme created by Transport for London. It contains various yearly and quarterly surveys available from 2014 to 2019 to track cycling volume across Central London over time. To measure the impact on motorised traffic, I use a similar geocoded survey produced by the Department for Transport road counts for Greater London from 2000 to 2019. I also use the STATS19 dataset from the Department of Transport that records all road accidents with police involvement in the past decades. These datasets contain the exact geo-coordinates of the counting sites and accidents that I spatially relate to the CSHs routes.

The programme's specific design allows overcoming some of the issues highlighted by the recent literature on the difference in differences (DiD) in staggered adoption (Sun and Abraham 2018; Borusyak and Jaravel 2018; De Chaisemartin and D'Haultfoeuille 2018; Goodman-Bacon and Marcus 2020). The canonical difference in differences estimator has two time periods: before and after implementation, and two groups: treatment and control. It identifies the average treatment effect on the treated (ATT) under the (conditional) parallel trend assumption. Many studies use variation across groups that receive the treatment at different times similarly to the cycle superhighway programme. However, in the case of growing effects, using a classic regression with a treatment dummy and panel fixed effects does not recover a reasonable average of the treatment effects (Borusyak and Jaravel 2018). Concretely, in the case of increasing traffic, comparing different routes underestimates long-term effects as it evaluates lanes that just opened to lanes where traffic has been growing for a few years. Obtaining an average would confound the effect on lanes that have been opened for a year, three years, or more. Additionally, there is no meaningful "average treatment effect" as the different lanes' construction has happened at different times.

In more general terms, in the canonical DiD, the difference between the pre-treatment outcome is extrapolated to the post-treatment as a counterfactual. In a staggered DiD, the difference when the staggered groups have been treated also serves to identify the difference in level between groups. However, when the effects are not homogenous in time, then the $\hat{\beta}$ under-estimate long-term effects. Borusyak and Jaravel (2018) show that in the case where openings are distributed uniformly across time, the sample size weighted average treatment effect and the canonical regression estimand differs more and more as the effects become more dynamic (affecting the growth rate, see Figure 3.0.1 from Borusyak and Jaravel (2018)).

Another issue with the two-way DiD is that it overweights cohorts in the middle of the treatment and gives smaller weights to cohorts that opened first or last. A recent paper by Goodman-Bacon

Figure 3.0.1: Difference in differences bias with dynamic effects



and Marcus (2020) shows that this estimator does not recover the ATT but a weighted estimator that depends on group size and variance in treatment. Again, it is mainly a problem if the effect changes over time (in the case of cycling lanes, increasing each year after opening). Other papers such as Borusyak and Jaravel (2018) describe this problem as "negative weighting" of the later cohorts.

Faced with this issue in the staggered difference in differences fixed-effect model, I use the programme's specificity to adopt an alternative identification strategy. I use an event study analysis to capture the impact of the opening of the lanes on cycling flows, car flows and accidents at various distances from the segregated lanes. The roll-out of the CSHs with segregated lanes is concentrated between 2015 and 2019, which allows me to estimate the effect up to 3 years after opening. I present the event study results with the constructed lanes only, as well as the lanes opened in 2020 as a control group. Assuming that the CSHs effect on traffic is stable across cohorts (they all receive the same impact at the opening and each year afterwards), then the event study estimates should be non-biased. In the summary statistics, I compute the socio-economic characteristics of the areas around the different cohorts of segregated lanes to look for differences that could impact the treatment. I do not find major differences in characteristics between cohorts.

Different endogeneity issues could arise in this setting. The first one would be that the timing of the opening is endogenous to the growth potential of the routes. Differences in the timing of opening were due to security concerns over the original design - it should not be related to the potential for cycle growth in the respective routes. The original plan was announced in 2008. It consisted of radial 12 roads linking to Central London.

The first lanes were built in 2010 and focused on improving the readability of the infrastructure. The lanes were visible using "blue paint" on the surface. They were not separated from the traffic and were perceived as unsafe. In response, TfL organised user consultations and small experimentations using the International Cycling Infrastructure Best Practice Study. The safety recommendations were integrated into the "Mayor's cycling vision" and led to higher safety standards. One major drawback of the higher standard of infrastructure was the substantial delays in implementing the CSH programme (London 2014). The second generation of lanes was physically separated from car traffic. It often involved reducing the number of car lanes to fit the 4 meters wide cycling lanes (compared to the non-separated 2m wide original design). There is no indication that the cycling potential was a factor in the timing of the roll-out.

The second endogeneity issue is that the routes could compete with each other for cyclists. The CSHs have been created to be radial roads spanning the London network. They are connecting different parts of London to the centres. The different routes are thus not substitutable. However, there might be a possibility that they are complementary - the more connected the network of segregated lanes, the more valuable they are for Londoners that can now travel safely for greater parts of their journey.

In all the regressions, I cluster the standard errors using two-way clustering at the CSHs route and year level. The general approach for an event study is to cluster at the unit or treatment level. If the error correlations are due to common shocks across observations, then the year-fixed effects will absorb all within-year clustering, and inference needs only to control for clustering on the unit. However, if these shocks have a large route-level component, contemporaneous error correlations across routes will remain. I thus choose two-way clustering at the route and year level.

4 Data

I construct a dataset of cycling traffic flow, car traffic flow, and accidents for a representative set of counting sites along the Cycle Superhighway routes and their surrounding areas. Most of these points are located in Central London (inside the Congestion zone - where car traffic is tolled). For the displacement analysis, I consider locations close to these lanes (up to 600 meters).

CSH data - I use the Cycle Superhighway dataset from the Transport for London cycling monitoring programme. The counting sites are shown with the lines opening year in Figure 4.0.1. The CSH dataset has 320 count sites over 11 planned routes[5] [6]. For each site, I have their exact location and yearly count. These counts are based on daytime ridership and conducted annually; they are adjusted for seasonal variations and represent annual averages. It starts in 2014 and ends in 2019, but not all sites are surveyed every year: I have a balanced panel, pre and post-treatment counts for C1, CS2, CS3, CS5 and C6, which corresponds to 84 counting sites in the treatment.

London cycling- I use the Central/Inner/Outer London Cycle Monitoring programme dataset for the cycle displacement analysis. It starts in 2014 and ends in 2019. Each counting site is monitored quarterly and observed in all directions. They are shown in Figure 4.0.2. For each site, I calculate the distance to the CSHs and group them by distance bands. This dataset has been sampled to be representative of London's cycling roads and traffic.

Road traffic - I use the Department for Transport Road Traffic Counts dataset for the car displacement analysis. It starts in 2002 and ends in 2019. It is observed yearly but with gaps. The road traffic data is available for every major road and some minor roads. The counters are represented in Figure 4.0.3. Similarly to the cycle analysis, I calculate the distance from each monitoring site to the CSH lines. As the data is not available every year, I use the provided

[5] I assign the route reference to counting sites based on the planned network map

[6] Each count site is observed in all directions

Table 4.0.1: Summary statistics 2011 census (treatment group)

	2015	2016	2018
Household size	1.9	2.22	1.95
	(0.2)	(0.58)	(0.28)
Population	268.2	360.47	336.94
	(34.62)	(75.42)	(89.59)
Age	39.71	33.02	35.57
	(6.03)	(3.5)	(3.79)
Median age	37.98	29.49	32.11
	(6.65)	(4.98)	(4.92)
Share highly educated	56.61	48.41	52.31
	(2.31)	(18.34)	(14.17)
Bike to work (per 1000)	40.08	35.34	29.94
	(30.47)	(28.16)	(10.5)
Distance to work	8.71	8.75	7.9
	(2.21)	(2.52)	(1.68)
Total cycles	2047.36	1425.74	1603.28
	(830.95)	(1136.6)	(1019.97)
Counting sites #	N= 2	N= 20	N= 20

imputed values for the missing years[7].

Traffic accident - Finally, I use the Road Safety Data (STATS19) from the Department for Transport to collect all incidents involving cars and bikes near the CSHs before and after opening. The data is precisely geocoded, which allows me to capture accidents on cycling lanes. The data only reports accidents with the police involved - it is thus likely to be missing non-serious accidents. There is no reason to think that the rate of reporting has changed over time. The data contains information on the severity of the accident. However, it is difficult to analyse by severity as the severity reporting was changed in 2016.

Table 4.0.1 shows the main census characteristics for a 150m buffer around the monitoring sites in my treatment groups. Columns 1, 2 and 3 correspond to routes opened in 2015, 2016 and 2018 respectively. As the number of monitoring sites observed for six years is low for the 2015 routes, I reproduce the results dropping that cohort and find similar results. The opening date does not correlate with demographic characteristics or total cycle traffic flow (in both directions). However, the earlier routes are a bit more central, leading to a slightly shorter travel time to work and a lower population. In Table 4.0.2, I present the same variables for the treatment groups (2015-2018) and the control group (never treated). The two groups' areas are similar in demographics and distance to work, but the treatment groups have a higher population overall and a slightly higher proportion of people biking to work.

[7]I do not allow imputation if the gap between two actual counts contains the year of construction

Figure 4.0.1: Map of the CSH counting sites

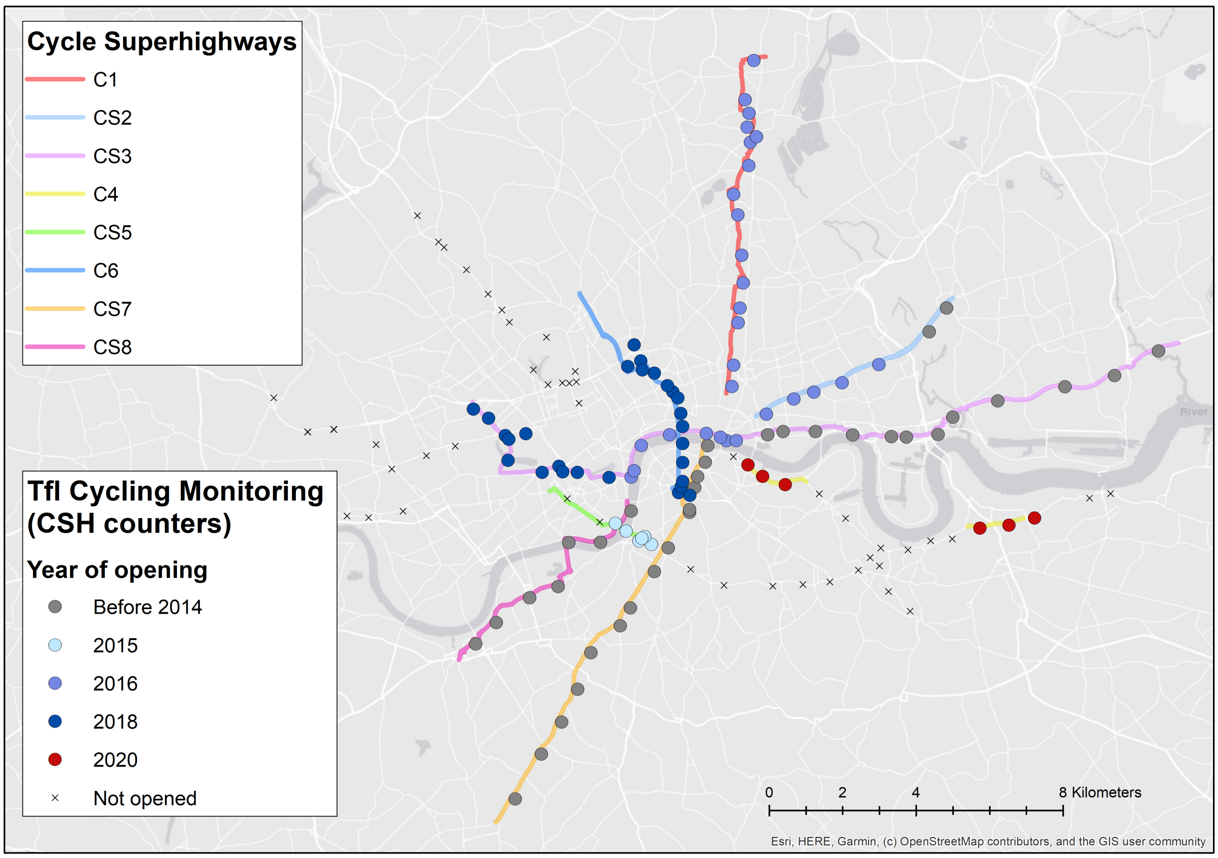


Figure 4.0.2: Map of the cycling monitoring programme counting sites

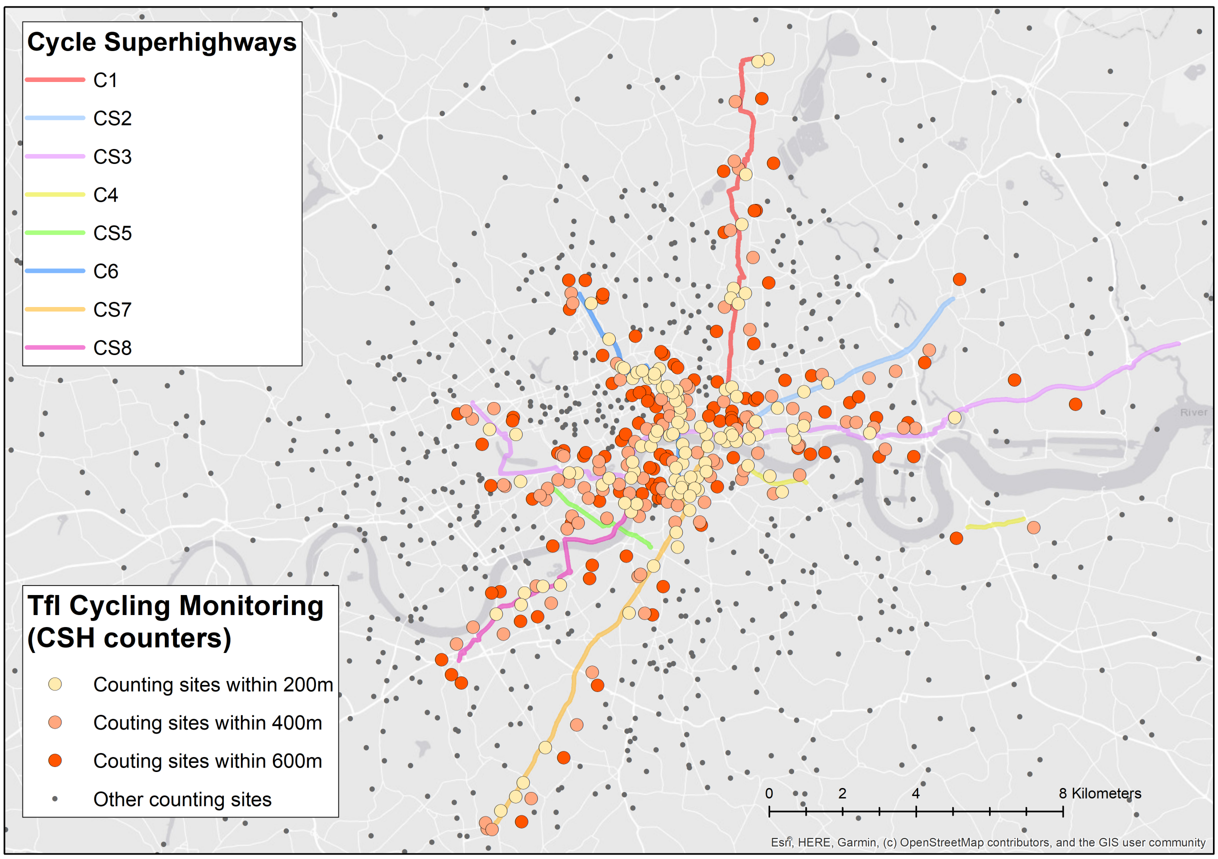


Figure 4.0.3: Map of road traffic counting sites

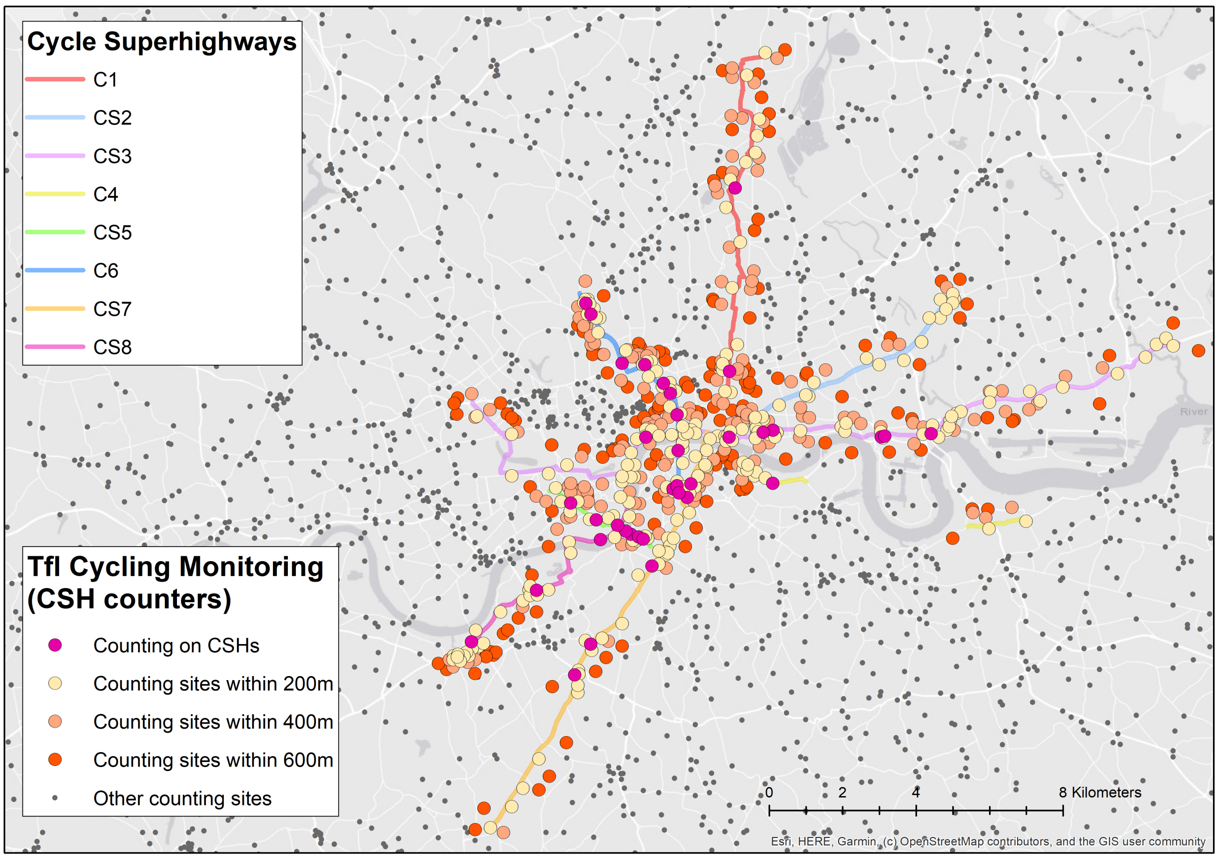


Table 4.0.2: Balance table 2011 census (treatment versus control)

	Treated	Control	Treated=Control
Household size	2.08	2.21	p=0.24
	(0.46)	(0.21)	
Population	344.87	302.32	p=0.02
	(82.59)	(27.21)	
Age	34.56	32.88	p=0.24
	(4.02)	(2.87)	
Median age	31.14	30.31	p=0.48
	(5.28)	(1.93)	
Share highly educated	50.66	41.89	p=0.18
	(15.95)	(13.09)	
Bike to work (per 1000)	32.99	25.01	p=0.08
	(21.24)	(7.05)	
Distance to work	8.34	8.56	p=0.79
	(2.13)	(1.71)	
Total cycles	1539.89	1571.89	p=0.91
	(1057.59)	(540.27)	
Counting sites #	N= 42	N= 6	

5 Empirical analysis and results

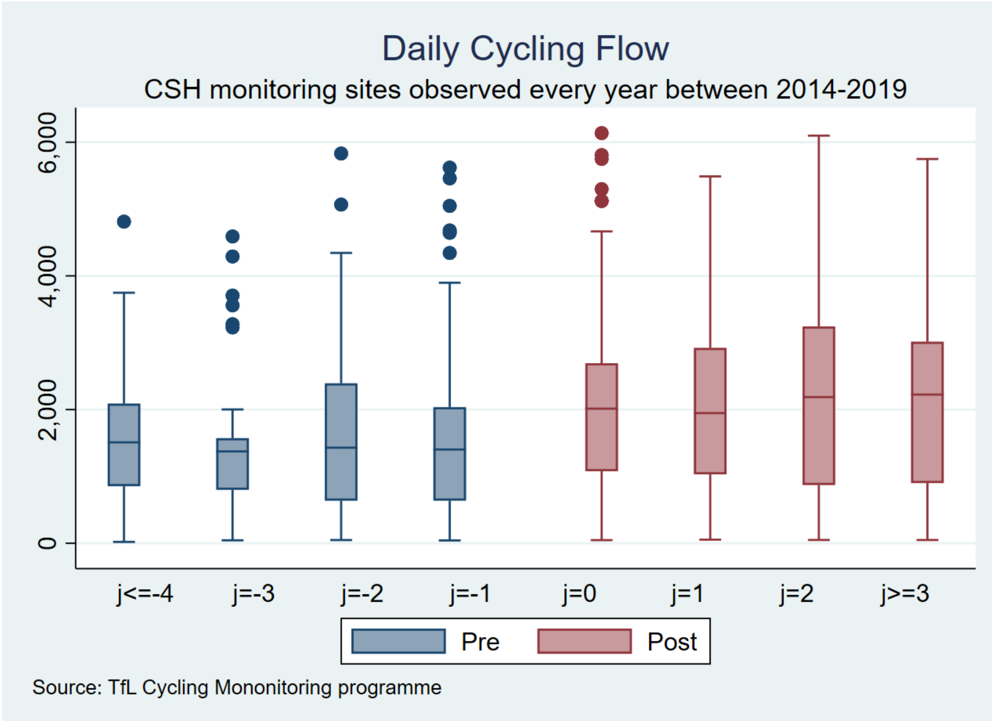
To introduce the analysis, Figure 5.0.1 plots the raw count of the average daily cycling flow for the treated sample for each year pre and post-treatment. The average pre-treatment is about 1,600 counted daily in the monitoring sites, against 2,100 post-treatment. The lower and upper whiskers show that some counting stations average low numbers daily (the minimum is 20 pre-treatment and 46 post-treatment while the busiest monitoring stations register up to 5,830 and 6,136 cyclists counted daily pre-and post-treatment, respectively). These results do not consider the overall growth trends and site heterogeneity but still show a significant jump at opening.

5.1 Dynamic effects estimation

The results from the plot indicate that it would be appropriate to conduct an event study on the CSH openings. I use a fully dynamic specification to analyse the treatment heterogeneity across time. Unlike the two-way fixed effect DiD, the event study coefficient should not be affected by a negative bias as long as the increase is similar across cohorts (cohorts receive the same increase at the opening and every year afterwards). I only include sites for which I have six years of observation in the sample. The treatment group is CSH sites after opening in 2015, 2016 and 2018. The control group is sites that have not opened yet and CSH sites that opened in 2020. The dependent variable is the log flow of cyclists.

$$\ln(TotalCycles_{it}) = \sum_{j=-4}^{J} \theta^j Treat_{it}^j + \gamma_i + \delta_t + \eta_{it}$$

Figure 5.0.1: Daily cycling flow



with $ln(TotalCycles)_{it}$ the average daily flow recorded in counter i and year t. As I use a log-linear model and the coefficients for years of opening are quite large, I exponentiate them in the text. $Treat_{it}^{j} = \mathbb{1}\{j = t - Opening_i\}$ is a categorical variable for years since opening $Opening_i$ $j = \{-3, -2, ..., 4\}$: I use $j = -1$, the year before opening, as a base level, θ_j for $j \geq 0$ captures dynamic effects of j years relative the cycle superhighway opening, finally γ_i and δ_t site and year fixed effects.

I show the result in Table 5.1.1. In column 1, I only include sites for which I have pre and post-treatment years and six years of observation. In column 2, I add the CSH that opened in 2020 (I do not observe the flows after opening as my panel stops in 2019). The coefficients are slightly larger than in column 1 but still within the confidence interval of each other. I illustrate the results of column 1 in the upper left graphs of Figure 5.2.1. There is a short decrease before opening, probably due to construction, a large jump of 24% at the opening, and then a further average increase of 19% per additional year. From the author's calculation, the average construction time is 14 months, which can explain the slight decrease up to two years before opening[8]. The estimates with the control group are a bit larger but also less precisely estimated. I also estimate an average treatment effect on the treated using a difference in differences estimator which I show in the Appendix in Table 6.C.1 and the corresponding Goodman-Bacon decomposition in Figure 6.C.1. Both confirms that there is a large increase after the opening of the CSHs. The effects are increasing over time.

[8]CS3 from Tower Gateway to Parliament Square took 13 months to be built and opened in March 2016. CS3 from Parliament Square to Lancaster gate started in April 2016 and ended in September 2018 (18 months). CS5 Kennington Lane to Victoria took eight months. CS1 took eight months between was built between July 2015 and April 2016. CS6 started in March 2015 and finished in September 2018. CS2 extension started in February 2015 and ended in December 2016 (21 months)

Table 5.1.1: Cycling flow after CSH opening

	Treated	Treated + Control
j<=-4	-0.309	-0.299
	(0.174)	(0.212)
j=-3	-0.118	-0.126
	(0.0767)	(0.149)
j=-2	-0.166***	-0.135**
	(0.0322)	(0.0447)
j=0	0.215***	0.260***
	(0.0397)	(0.0315)
j=1	0.345***	0.400***
	(0.0208)	(0.0283)
j=2	0.494***	0.562***
	(0.0416)	(0.104)
j>=3	0.595***	0.696***
	(0.0185)	(0.105)
N	504	528
Rsquared	0.949	0.949
Year FE	Yes	Yes
Site FE	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

5.2 Traffic displacement

In the next part of the analysis, I reproduce the event study on traffic flow for cycles and cars close to the newly constructed CSH. The estimating equation is the same as above but uses cycle traffic around the CSH as an outcome. To this aim, I use the Cycle monitoring dataset from Transport for London for Central, Inner, and Outer London presented in Figure 4.0.2. I keep all counting sites opened between 2015 and 2020 for the analysis and use the year before opening as the baseline.

The results from the event study on cycle counters 20-200m, 200-400m, and 400-600m away are presented in Table 5.2.1 and in the last 3 plots of Figure 5.2.1. I keep all counting sites that I observe for all quarters. While the coefficients after opening are larger closer to CSHs - meaning that the cycling traffic could be increased close to the CSHs, there are no significant results. The effects could be linked to cyclists getting on and off the segregated lanes. On average, cycle trips are short (20min) and fast, so there is not much gain for the average cyclist to take a large detour to get on a cycle superhighway.

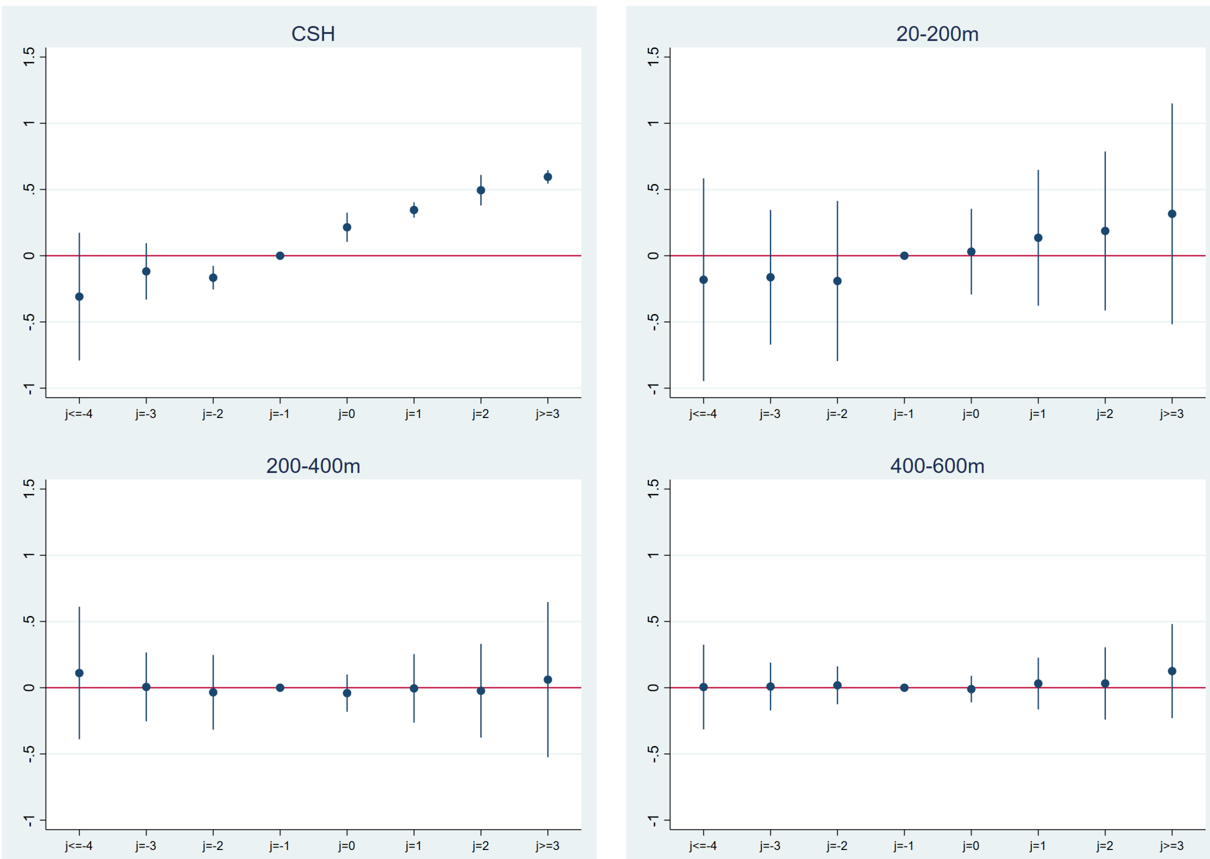
Table 5.2.1: Cycle displacement

	20-200m	200-400m	400-600m
j<=-4	-0.181	0.111	0.00487
	(0.178)	(0.157)	(0.115)
j=-3	-0.163	0.00582	0.00909
	(0.118)	(0.0818)	(0.0649)
j=-2	-0.191	-0.0350	0.0180
	(0.141)	(0.0888)	(0.0514)
j=0	0.0308	-0.0408	-0.0105
	(0.0752)	(0.0443)	(0.0360)
j=1	0.135	-0.00498	0.0316
	(0.119)	(0.0813)	(0.0703)
j=2	0.187	-0.0230	0.0323
	(0.139)	(0.111)	(0.0984)
j>=3	0.316	0.0608	0.125
	(0.194)	(0.184)	(0.128)
N	1426	2415	3151
Rsquared	0.898	0.909	0.932
Quarter FE	Yes	Yes	Yes
Site FE	Yes	Yes	Yes

SD clustered at year and cycle superhighway route level
* $p < .1$, ** $p < .05$, *** $p < .01$

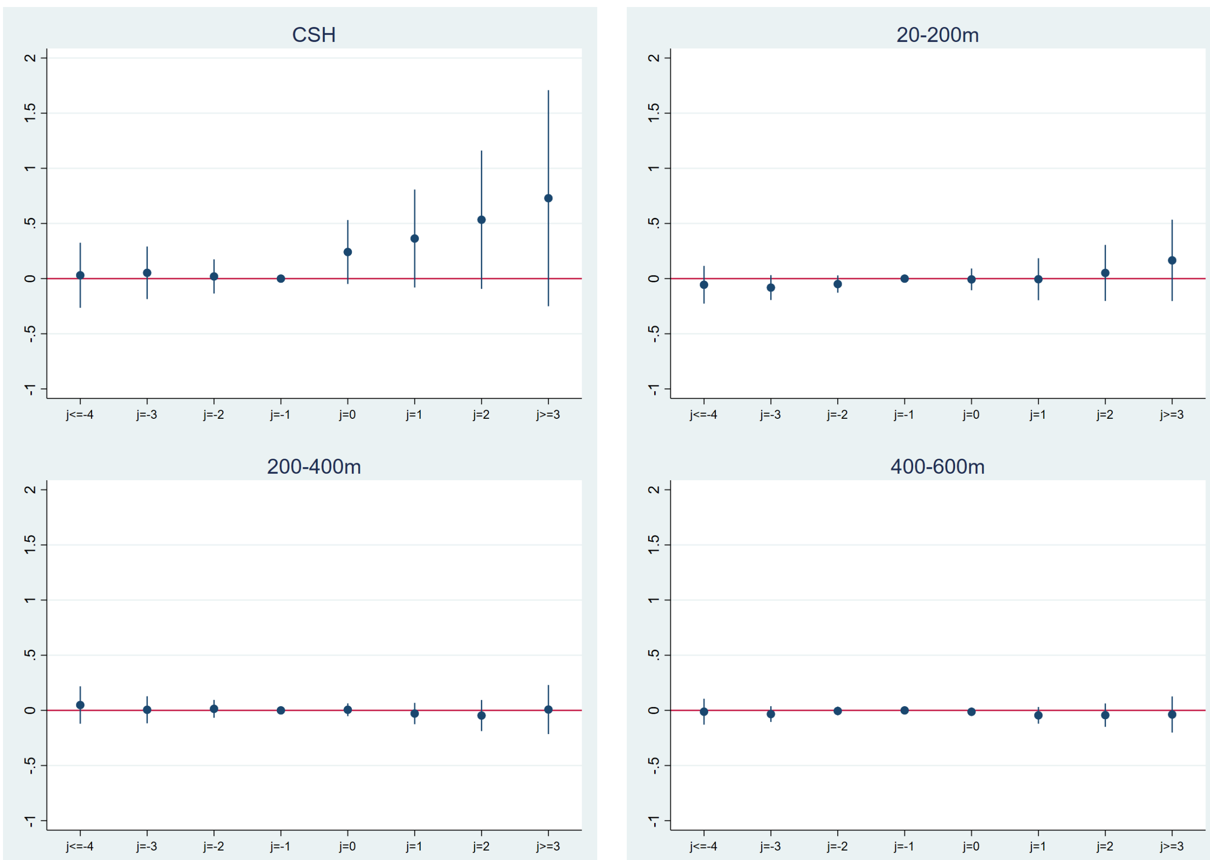
A drawback of the Transport for London cycling surveys is that there are only conducted

Figure 5.2.1: Cycling flows near CSHs using TfL cycling surveys



annually. That is why I also do a robustness check on the impact of the segregated lanes on cycling using the cycle hires data provided by Transport for London. The dataset has all journeys done by hire bikes in London from 2012 to March 2020 (more recent data is available, but I wanted to exclude any changes due to lockdowns). I restrict the analysis to the stations near lanes opened after 2014. The dependent variable is the logged number of journeys starting or ending near segregated lanes. I subset the sample to stations on the segregated lanes (0-20m) and then 20-200m, 200-400m and 400-600m away. I present the results in the appendix in Table 6.D.1 and 6.D.2 , and graphically in Figure 5.2.2 and 5.2.3. I find the same increase in hire starting or ending near segregated lanes, but the effect disappears for stations more than 200m away.

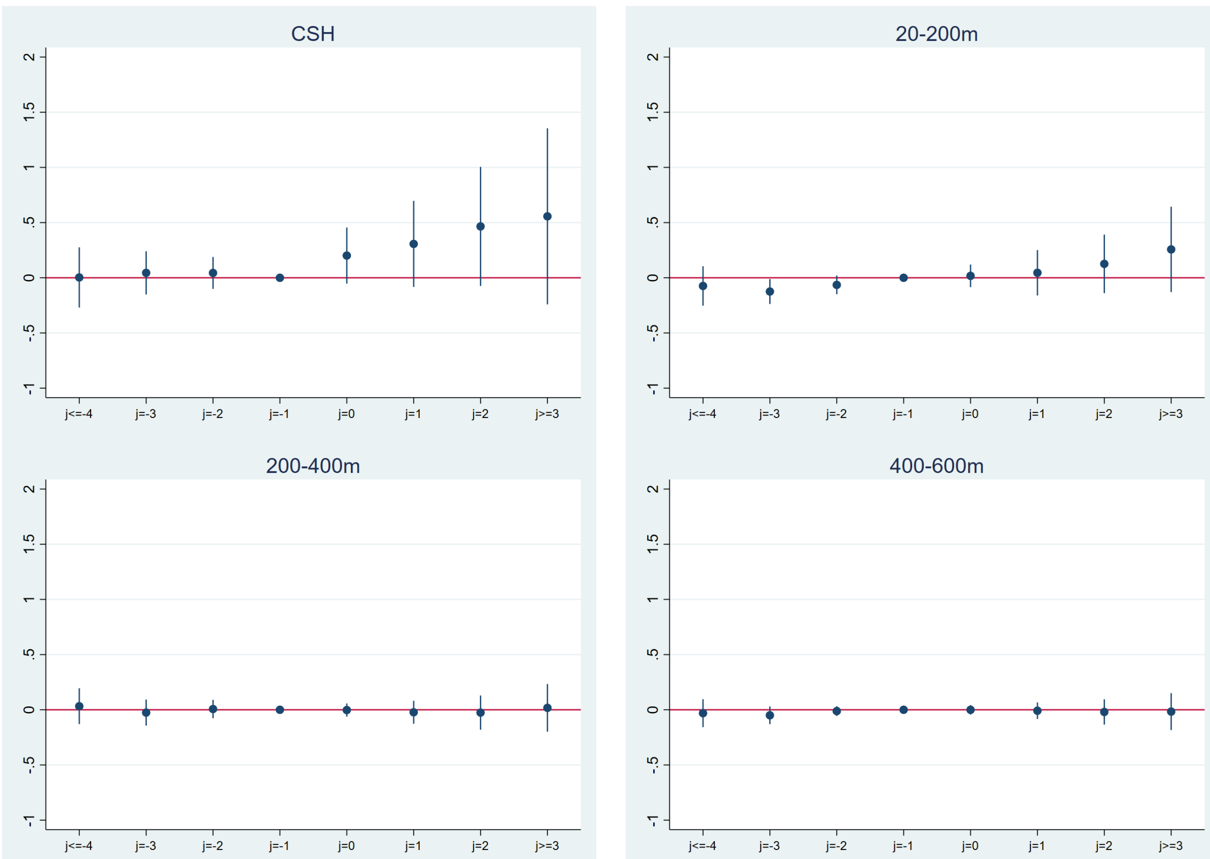
Figure 5.2.2: Cycle hire journeys starting near CSHs



Linked the Cycle Hire Scheme, another limitation of the survey analysis is that I cannot distinguish the impact of the segregated lanes from the two other major cycling policies happening during the same period: the Biking Boroughs project and the roll-out of the London Cycle Hire Scheme. The Biking Borough projects was aimed at Outer London Boroughs - it is thus a different geographical zone to the CSHs which are concentrated in Central London. I can exclude that they have a direct impact on the CSHs.

The London Cycle Hire Scheme opened in 2010 with a second major extension in 2012. Most

Figure 5.2.3: Cycle hire journeys ending near CSHs



of their implementation is thus prior to the development of the segregated lanes. 97% of my CSH survey points have a cycle hire station within 200m. I plot an histogram of the date of opening of the cycle hire stations within 200m of the CSHs compared to the opening of the cycling lanes in Appendix 6.D.1. I find that 75% of the cycle hire stations opened before the CSHs' openings. There is a clear stop of two years during the CSHs' constructions and then after opening, the implementation continues on the same decreasing trend. However, to rule out that cycle hire stations openings contribute significantly to the increase of cycling flows after the segregated lanes opening, I analyze the impact of getting a new cycle hire station within 200m on the segregated lanes. I find no significant impact of getting a new station in appendix Table 6.D.3. I can not do an event study for the opening of the stations as I do not observe enough openings.

The CSHs and the cycling hire are two very effective policies for increasing cycling flows. Clearly, neither the placement of the cycle hire stations nor the placement of the segregated lanes was random. They have both been selected to bolster cycling usage in roads with high potential. However, I argue that the increase that I observe in the CSHs event analysis is solely due to the segregation of the lanes as I do not observe any pre-trends in the CSHs and the cycling hire analysis. Getting additional stations does not increase massively the traffic on the segregated lanes - probably because most of the stations were already built by the time the lanes got constructed. The pre-opening levels, however, probably reflect the already high flows of these lanes and the impact of the cycle hire scheme.

I then reproduce the same event study for cars' and buses' displacement. The outcome is the logged number of total cars (or buses) counted at each survey point. To this aim, I use the yearly counts provided by the Department for Transport. The dataset is available for all of England, but I concentrate on counters on a CSH route (road segment where the lanes were built by reducing car lane capacity, 0-20m) or close to it (20-200m, 200-400m and 400-600m distance buffers). The car traffic dataset provided by TfL relies on imputed data (all counters are not observed each year and the data is interpolated from past years). I present the results using an unbalanced panel in Table 5.2.2 and Figure 5.2.4. I also show the results for the interpolated balanced panel in the appendix Table 6.E.1 for cars and in appendix Table 6.E.2 for buses.

Both tables are fairly similar. The coefficients are slightly higher and positive on the roads with the CSH but not statistically significant.

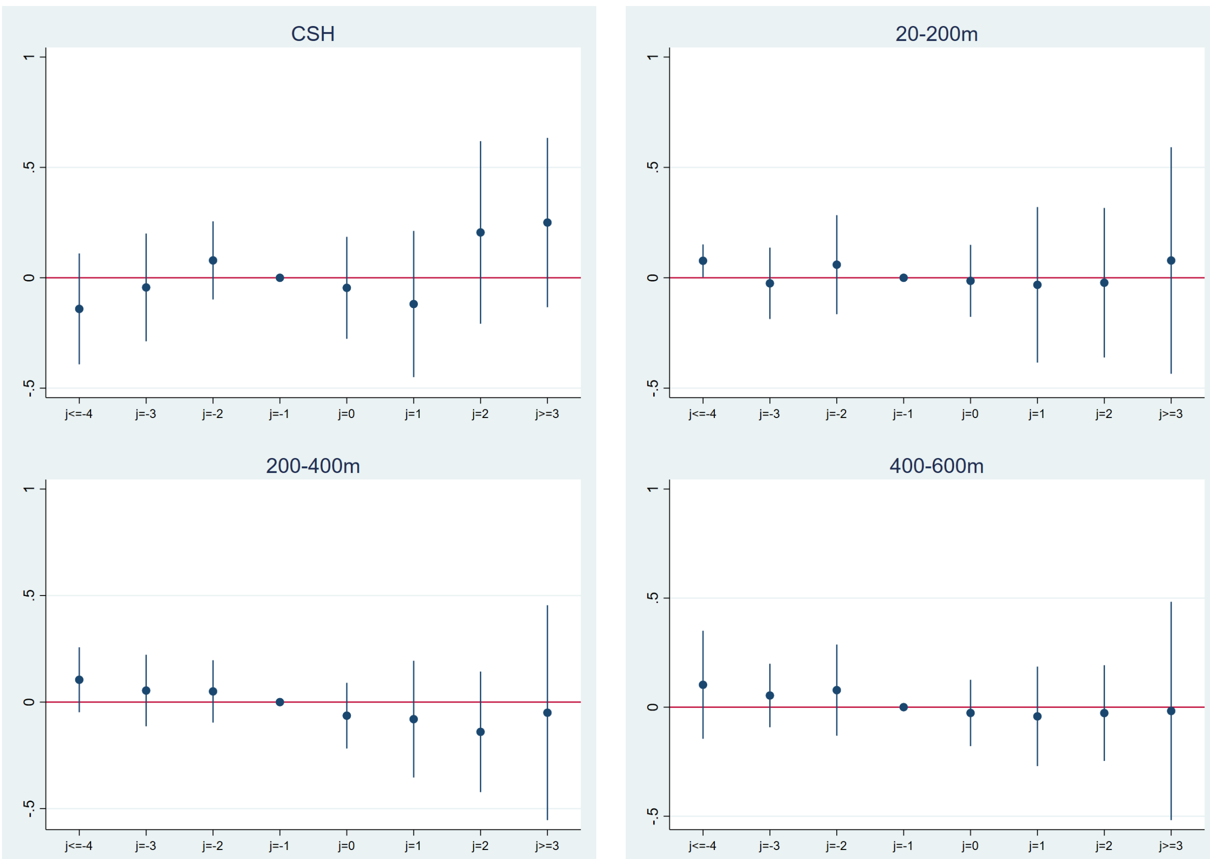
Table 5.2.2: Car displacement near CSH

	CSH	20-200m	200-400m	400-600m
j<=-4	-0.141	0.0770**	0.105	0.103
	(0.0905)	(0.0288)	(0.0593)	(0.0964)
j=-3	-0.0437	-0.0251	0.0543	0.0535
	(0.0879)	(0.0629)	(0.0653)	(0.0566)
j=-2	0.0787	0.0593	0.0501	0.0781
	(0.0638)	(0.0873)	(0.0569)	(0.0813)
j=0	-0.0456	-0.0139	-0.0637	-0.0266
	(0.0832)	(0.0634)	(0.0600)	(0.0592)
j=1	-0.119	-0.0319	-0.0800	-0.0422
	(0.119)	(0.137)	(0.107)	(0.0887)
j=2	0.205	-0.0224	-0.140	-0.0271
	(0.149)	(0.132)	(0.110)	(0.0854)
j>=3	0.250	0.0783	-0.0498	-0.0175
	(0.138)	(0.200)	(0.196)	(0.195)
N	212	510	782	988
Rsquared	0.974	0.967	0.968	0.983
Year FE	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

Figure 5.2.4: Cars flows near CSHs



5.3 Accidents reduction

In the last part of the analysis, I look at accidents' reduction on CSHs. First, I use the STATS 19 datasets that record the location of traffic accidents involving the police in England. Next, I add traffic flow for the average DfT counting sites on the CSHs. The set of monitoring points with traffic data is small, but the results are consistent across specifications.

I include all accidents located on CSH lanes constructed after 2014. In Table 5.3.1 and Figure 5.3.1, I look at the difference between painted lanes and lanes fully segregated by a kerb (the car traffic is physically separated from the cycling lanes). The reduction in accidents seems to be driven by the latter, even though a small sample size might also be at play here.

In Table 5.3.2, I present the results for total accidents involving cyclists, total accidents involving cyclists divided by cycling flow, total accidents involving cyclists divided by cars' flow and total accidents involving cars divided by cars' flow.

In column 1, there is a significant decrease in total accidents after a CSH opening. The results even hold when looking at the number of cycling accidents per cyclist in column 2. In line with the literature, these results indicate that separating cyclists from motorised traffic reduces the number of accidents. Both the number of accidents per cyclist and the absolute number of accidents decrease, indicating that there is safety in numbers - cars are more likely to expect cyclists if they see cycling infrastructures.

In column 3, I look at cycle accidents by car flow. The coefficients become negative after the lanes' opening - but they are not significant at the standard significance level. In columns 4 and 5, I look at car accidents after the opening of the segregated lane. There is no significant pattern emerging. The lanes do not seem to have made traffic safer for cars.

Table 5.3.1: Bike accidents over bike flow by lane segregation

	Painted Bike acc./bike flow	Fully segregated Bike acc./bike flow
j<=-8	2.625	0.0152
	(1.718)	(0.154)
j=-7	2.046	-0.0536
	(1.554)	(0.304)
j=-6	1.539	0.0701
	(1.068)	(0.262)
j=-5	0.406	0.102
	(1.094)	(0.185)
j=-4	1.137	-0.135
	(0.647)	(0.151)
j=-3	-0.205	0.288
	(0.720)	(0.145)
j=-2	-0.436	0.271
	(0.742)	(0.173)
j=0	-1.673	0.0439
	(0.905)	(0.197)
j=1	-0.891	-0.125
	(0.826)	(0.245)
j=2	-2.460	-0.478*
	(1.161)	(0.180)
j=3	-1.455	-0.725**
	(0.696)	(0.225)
j>=4		-1.286***
		(0.202)
N	55	154
Rsquared	0.692	0.811
Year FE	Yes	Yes
Site FE	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

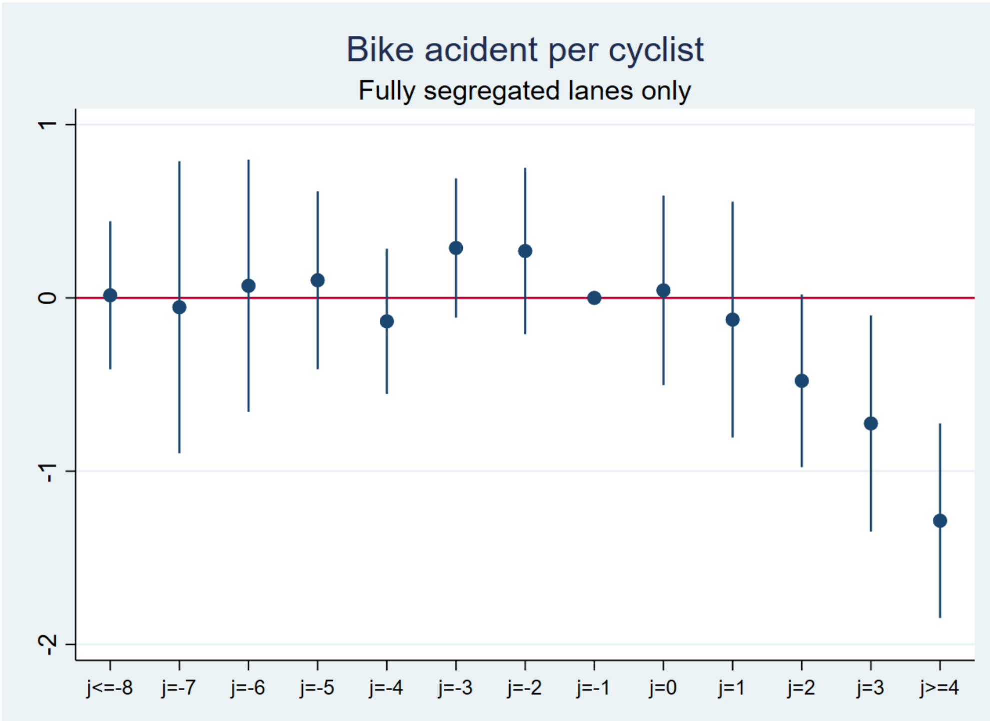
Table 5.3.2: Traffic accidents

	Bike acc.	Bike acc. vs bike flow	Bike acc. vs car flow	Car acc.	Car acc. vs car flow
j<=-8	1.350	0.808	0.505	-0.613	-0.916
	(0.975)	(1.066)	(0.852)	(0.706)	(0.580)
j=-7	1.071	0.651	0.415	-0.653	-0.889*
	(0.710)	(0.838)	(0.699)	(0.480)	(0.390)
j=-6	0.834	0.460	0.260	-0.419	-0.619
	(0.542)	(0.483)	(0.307)	(0.422)	(0.336)
j=-5	0.611	0.286	0.125	-0.678*	-0.838**
	(0.418)	(0.540)	(0.452)	(0.253)	(0.190)
j=-4	0.504	0.209	0.0653	-0.364	-0.507
	(0.356)	(0.348)	(0.268)	(0.442)	(0.405)
j=-3	0.324	0.0360	-0.0611	-1.033*	-1.130**
	(0.177)	(0.257)	(0.244)	(0.401)	(0.366)
j=-2	0.264	0.128	0.124	-0.0817	-0.0863
	(0.160)	(0.188)	(0.202)	(0.161)	(0.166)
j=0	-0.268**	-0.280**	-0.146	-0.263	-0.129
	(0.0871)	(0.0965)	(0.0943)	(0.343)	(0.315)
j=1	-0.545	-0.380	-0.148	-0.108	0.123
	(0.356)	(0.444)	(0.508)	(0.365)	(0.326)
j=2	-0.995**	-0.789**	-0.497	-0.310	-0.0175
	(0.224)	(0.242)	(0.343)	(0.539)	(0.398)
j=3	-1.283**	-0.875*	-0.551	0.153	0.477
	(0.348)	(0.407)	(0.590)	(0.596)	(0.471)
j>=4	-1.978***	-1.401**	-1.227*	0.250	0.423
	(0.354)	(0.431)	(0.525)	(0.598)	(0.467)
N	209	209	209	209	209
Rsquared	0.751	0.715	0.723	0.609	0.617
Year FE	Yes	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

Figure 5.3.1: Bike accident after CSH opening



6 Conclusion

The cycle superhighway programme is associated with a large increase in cycle traffic. The treatment effect at opening represents an increase of about 25% in ridership. The effect increases over time by about 20% a year. Most of this increase is due to new cyclists and increased cycling frequency as there is no evidence of cyclist displacement or car traffic displacement. One of the factors investigated in this analysis to explain the rise in ridership is an increase in safety due to a larger number of cyclists and safer lanes. These findings are essential for policymakers as they show that infrastructures like cycling lanes should not be evaluated by the immediate impact but also by the continuous growth after opening. The agglomeration effects of the lanes are an essential factor to consider - the more lanes, the more cyclists, the safer they are, and the more likely people will take up cycling.

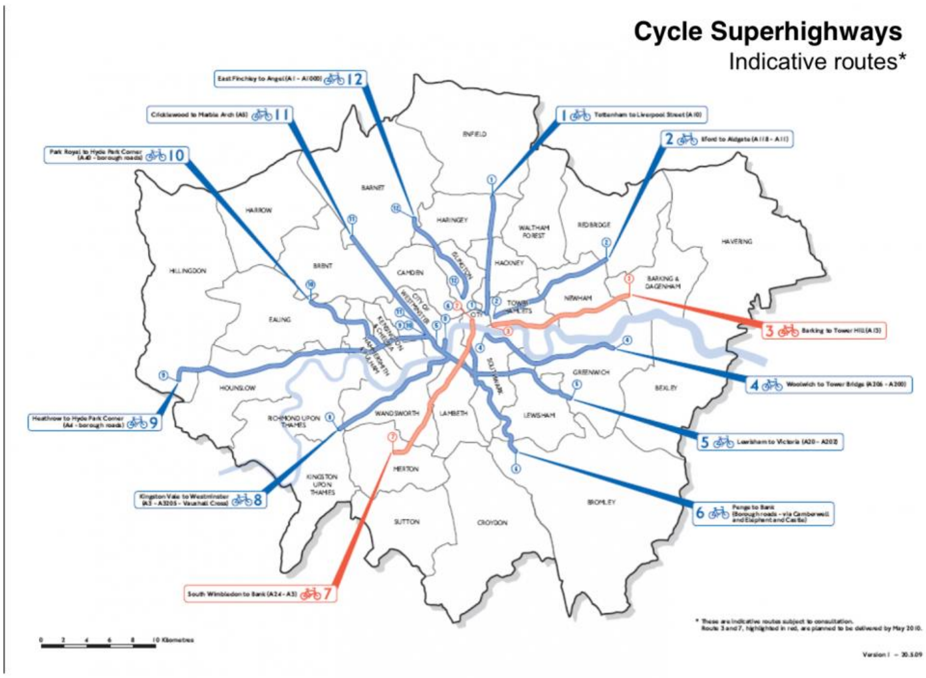
These results are essential to justify the construction of segregated lanes on major roads to encourage cycling. Moreover, in cities like London, where one of the main obstacles to cycling is safety perception, cycling lanes are essential to convince people to take up cycling. Tfl surveys show indeed that new cyclists - for example, new e-bikes users - are particularly sensitive to these infrastructures as they provide safety and clear directions to connect to central parts of the city. The lanes provide a good infrastructure start to sustain cycling growth.

An interesting alley for research would be to investigate how the connectivity and the spread of these lanes participate in increasing cycling usage. The ability to reach most of Copenhagen or Berlin via safe cycling paths is essential to their success. The current growth of the network offers an opportunity to study this phenomenon as it develops. The new “cycleways” programme launched in late 2019 aims to unify London’s cycling projects (CSHs network, quiet ways and minihollands) to provide the best cycling routes between key destinations as part of a connected and unified network. It is an exciting venue for future research on cycling networks.

Appendix

6.B Illustration of the first and second phases of the cycle superhighways

Figure 6.B.1: Original cycle superhighways network map in 2009



6.C Difference in differences

In this appendix, I present the difference in differences approach and the Goodman-Bacon decomposition on cycling flows.

I report the results for the OLS and the difference in differences using two ways fixed effect in Table 6.C.1. I only include sites for which I have six years of observation in my sample. The treatment group is CSH sites that opened in 2015, 2016 and 2018. The control group is CSH sites that were planned but not opened yet and sites that opened in 2020.

The dependent variable is the flow of cyclists logged, I interpret the coefficient on the opening of the segregated lane $CSH_{i,t}$ as the variation in the percentage of the conditional mean of the regressand. As the coefficients are quite large, I exponentiate them in the text. In columns 1, and 2, I only use only treated sites (the ones opened between 2015 and 2018). In columns 3 and 4, I add the routes or part of routes that have been planned but not built and the ones that have been built later in 2020 [9]. In the OLS estimation, I control for the local borough.

[9] CS9, CS10 and CS11 were planned but were not constructed as of 2019 and CS9 opened in 2020, part of CS4 and CS5 did not get constructed; I never include routes that were constructed before 2014

Figure 6.B.2: Cycle Superhighway 8 - Opened in 2011 - Painted lane

Figure 6.B.3: Cycle Superhighway 5 - Opened in 2015 - Segregated lane

In column 1, the naive OLS effect is quite large, a 48% increase, but could be suffering from bias from differences between sites. The impact of getting a CSH is reduced to 17% once site fixed effects are included; however, this specification is likely to suffer from significant bias in a staggered setting; it is a weighted average of the different lengths of exposure with a downward bias as it compares late to early treated.

In column 3, I add a control group using the route opened in 2020 and never constructed. Introducing a control group allows the bias introduced by the late treated to the early treated to be slightly reduced. While the OLS results between columns 1 and 3 are similar, the coefficient for the two ways FE in column 4 is closer now to 30% compared to 17% without the control group. It is consistent with the two-way FE DiD estimator being biased in case of increasing heterogeneous effect in time.

Table 6.C.1: OLS and FE estimations

	Treated		Treated + Control	
	OLS	FE	OLS	FE
Post	0.394***	0.159	0.357**	0.264*
	(0.0833)	(0.0892)	(0.102)	(0.105)
N	504	504	576	576
Rsquared	0.650	0.948	0.637	0.945
Year FE	No	Yes	No	Yes
Site FE	No	Yes	No	Yes
Controls	Yes	No	Yes	No

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

I then present the results of the decomposition of the difference in differences fixed effects in a staggered setting.

The first comparison group is easily understandable: for each cohort, it compares the treated cohorts (e.g. opening in 2015, 2016, 2018) with the control group (routes that opened in 2020 or were never opened). As long as the control group is a good counterfactual for the treated groups, these differences capture the impact of the segregated lanes. The estimates are represented by grey triangles in the graph.

The next comparison - early treated versus late as control is also fairly straightforward as long as there is no anticipation of the treatment. For example, it compares the sites opened in 2015 with sites opened later but before they were opened. We thus get three comparisons: 2015 with 2016, 2015 with 2018 and 2016 with 2018. The estimates are represented by grey crosses the graph.

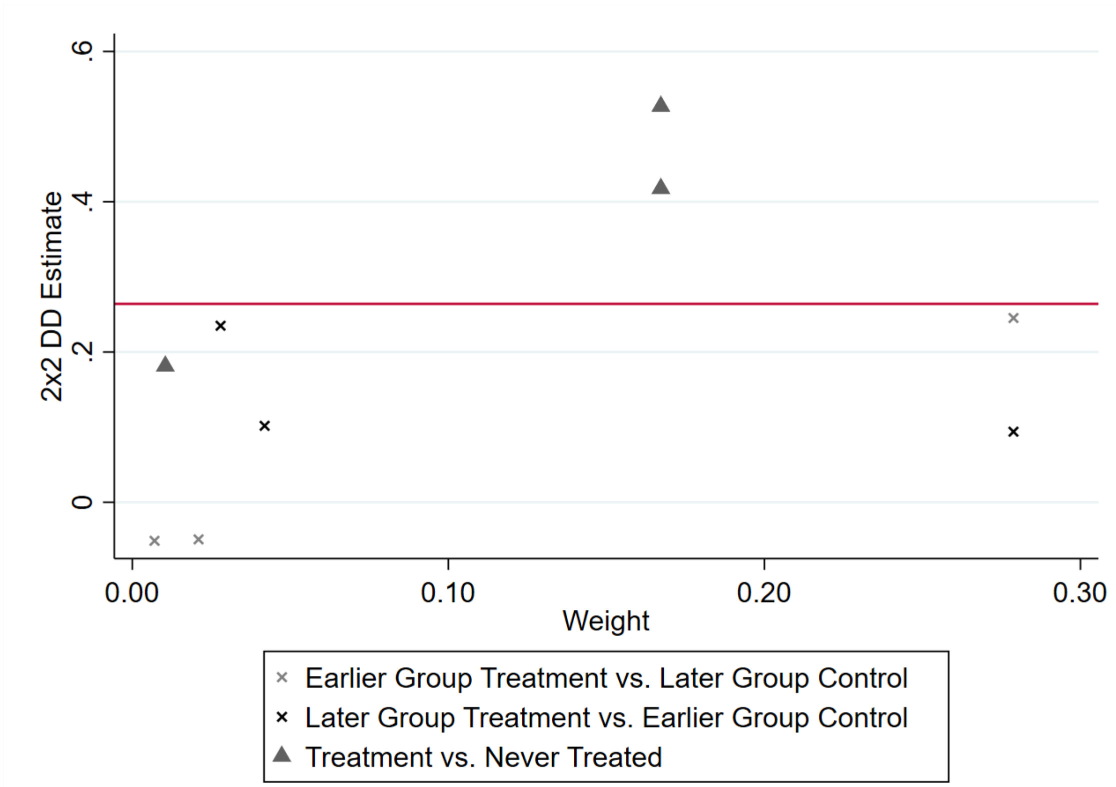
The last set of comparisons is the problematic one. They compare early treatment versus late as control (after late gets treated). It assumes that the pre-treatment difference should be equal to the post-treatment. But if there is maturation in treatment (as in the case of the cycling lanes), the after gap is likely to be larger as the early treated have more time to grow, and it will overall underestimate the treatment effect. In general, treatment effects change (monotonically) over time, the

DiD estimate is biased away from the sign of the true effects. The coefficients are represented by the black crosses.

I present the result for cycling flows on CSHs in Figure 6.C.1. The red line corresponds to the DiD estimator of Table 6.C.1 column 5. The overall estimator for earlier group versus later group control is 0.22 (cohorts opened in 2015 vs 2016 and 2018, and 2016 against 2018). The black crosses correspond to the latter group as treatment versus the earlier group as control after opening. The Later treatment vs Earlier control overall estimator is only 0.11. It is the estimator likely to be biased in case of increasing treatment effect in time. Finally, the treatment versus never treated is represented by the triangles. The corresponding coefficient is 0.46 (cohorts opened in 2015, 2016 and 2018 vs 2020 and never opened).

The x-axis in Figure 6.C.1 shows the weight allocated to each comparison based on group size and time in treatment.

Figure 6.C.1: Goodman-Bacon Decomposition



These figures indicate that the CSHs have been successful in attracting users after opening. I do a robustness check by checking the degree of segregation around the counting sites using the first difference approach. One of the main critics of the CSH scheme is that parts of the lanes are not fully segregated by a kerb, but only painted in blue, sometimes with bollards to delineate their locations. Using the London's Cycling Infrastructure Database (CID) created in 2018, I look at the impact of the degree of segregation of the lanes. In Table 6.C.2, I reproduce the DiD two-ways fixed effects estimate of Table 6.C.1 column 4 using not yet treated or never treated as a control. I find in column 1 that painted only lanes still see a large increase in cycling traffic, but the effect is only significant for fully segregated lanes.

I also repeat the event study analysis using the fully segregated lanes only (I can not do it on the painted lanes only, there is not enough observations for each year after treatment). I find similar coefficients than on the full sample - slightly lower for the last two years. These results seem to indicate that the increase in traffic flow is not only driven by the full segregation but also by other factors brought by the programme such as better visibility of cyclists and network effects.

Table 6.C.2: Lane segregation

	Painted	Fully segregated
Post	0.256	0.278*
	(0.151)	(0.127)
N	276	300
Rsquared	0.971	0.903
Year FE	Yes	Yes
Site FE	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

6.D Cycle hire analysis

I also do a robustness check of the impact of the segregated lanes on cycling using the cycle hires data provided by Transport for London. I use the same event study approach. The dataset has all journeys done by hire bikes in London from 2012 to March 2020 (more recent data is available but I wanted to exclude any changes due to lockdowns). I restrict the analysis to the lanes opened after 2014. The dependent variable is the logged number of journeys starting or ending near segregated lanes. I subset my sample to stations on the segregated lanes and then 200m, and 400m away. Contrary to the counting sites analysis, I do not know if the cyclists have used the segregated lanes, only that the journeys have started or ended near a segregated lane.

I find a similar (but less significant) increase on the segregated lanes (within 20 meters) but no effect further away. The standard errors for the groups further away are quite small, which gives confidence that the absence of displacement is real and not due to a lack of data.

Table 6.C.3: Cycling flow after CSH opening by segregation

	All	Fully segregated only
j<=-4	-0.309	-0.333
	(0.174)	(0.171)
j=-3	-0.118	-0.0512
	(0.0767)	(0.0661)
j=-2	-0.166***	-0.137*
	(0.0322)	(0.0519)
j=0	0.215***	0.262***
	(0.0397)	(0.0532)
j=1	0.345***	0.290***
	(0.0208)	(0.0530)
j=2	0.494***	0.370***
	(0.0416)	(0.0716)
j>=3	0.595***	0.441***
	(0.0185)	(0.0189)
N	504	264
Rsquared	0.949	0.905
Year FE	Yes	Yes
Site FE	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6.D.1: Cycle hire journeys starting near CSH

	CSH	20-200m	200-400m	200-600m
j<=-4	0.0303	-0.0557	0.0486	-0.0121
	(0.139)	(0.0841)	(0.0835)	(0.0578)
j=-3	0.0525	-0.0813	0.00538	-0.0335
	(0.112)	(0.0556)	(0.0604)	(0.0351)
j=-2	0.0197	-0.0494	0.0138	-0.00541
	(0.0731)	(0.0386)	(0.0398)	(0.0197)
j=0	0.241*	-0.00690	0.00545	-0.0127
	(0.137)	(0.0485)	(0.0284)	(0.0192)
j=1	0.364	-0.00550	-0.0287	-0.0451
	(0.209)	(0.0937)	(0.0476)	(0.0373)
j=2	0.534*	0.0515	-0.0468	-0.0434
	(0.296)	(0.125)	(0.0694)	(0.0522)
j>=3	0.729	0.165	0.00747	-0.0374
	(0.462)	(0.181)	(0.109)	(0.0806)
N	595	1820	2205	2730
Rsquared	0.870	0.808	0.893	0.866
Quarter FE	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6.D.2: Cycle hire journeys ending near CSH

	CSH	20-200m	200-400m	200-600m
j<=-4	0.00315	-0.0741	0.0325	-0.0306
	(0.129)	(0.0880)	(0.0798)	(0.0622)
j=-3	0.0447	-0.125**	-0.0252	-0.0499
	(0.0922)	(0.0555)	(0.0581)	(0.0394)
j=-2	0.0439	-0.0645	0.00682	-0.0119
	(0.0682)	(0.0414)	(0.0410)	(0.0216)
j=0	0.201	0.0174	-0.00258	-0.000451
	(0.120)	(0.0503)	(0.0294)	(0.0212)
j=1	0.307	0.0453	-0.0226	-0.00850
	(0.184)	(0.101)	(0.0513)	(0.0369)
j=2	0.465*	0.126	-0.0256	-0.0197
	(0.254)	(0.130)	(0.0763)	(0.0563)
j>=3	0.557	0.257	0.0174	-0.0164
	(0.376)	(0.190)	(0.106)	(0.0824)
N	595	1820	2205	2730
Rsquared	0.900	0.835	0.911	0.883
Quarter FE	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

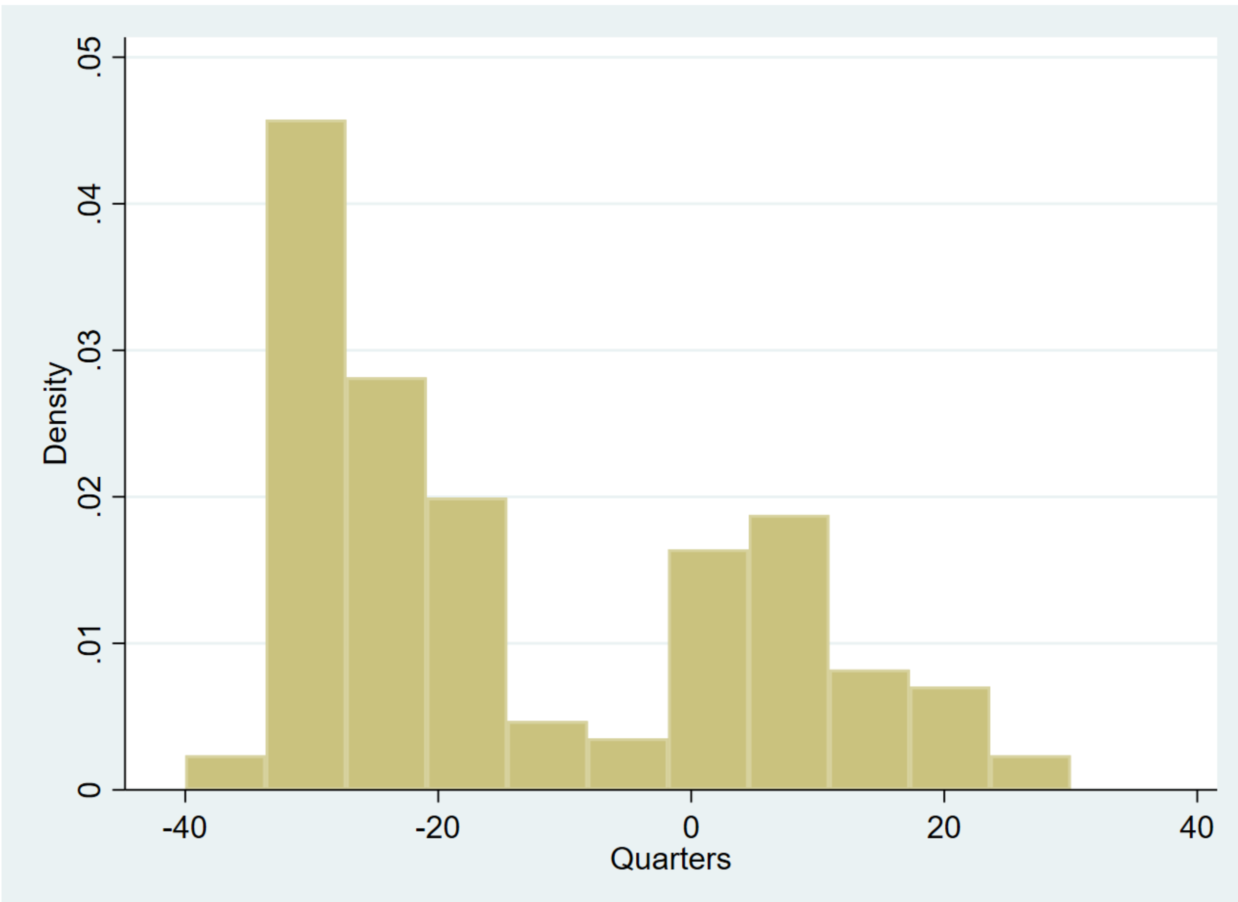
Table 6.D.3: Cycling flow after a new cycle hire station opening

	Ln Total Cycle
New cycle hire station	-0.0142
	(-0.33)
N	340
Rsquared	0.925
Year FE	Yes
Site FE	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

Figure 6.D.1: Opening of cycle hire stations before and after the construction of CSH



6.E Car displacement

I show below the event study for car and bus displacement after the opening of the lanes. The dataset of car counts in London provided by Transport for London uses a large number of imputed values. I remove all values where the imputation happens at the opening of the cycle lanes, and I only keep the values where I have a count before and after treatment. I present in Table 6.E.1 the results. The outcome is the logged number of cars or buses observed at each counting site on a typical day. The counting sites are observed every quarter. The dependent variable is the number of years before and after opening. The base level is the year before opening. As for the unbalanced panel, there is no evidence that cars' or buses flows have changed after the opening of the segregated lanes.

Table 6.E.1: Car displacement near CSH

	CSH	20-200m	200-400m	400-600m
j<=-4	-0.242**	-0.136**	-0.0535	0.000599
	(0.0621)	(0.0422)	(0.0544)	(0.0847)
j=-3	-0.0788	-0.0631***	-0.0247	-0.00462
	(0.0430)	(0.0149)	(0.0138)	(0.0413)
j=-2	-0.0900	-0.0439**	-0.0236	0.00201
	(0.0544)	(0.0119)	(0.0177)	(0.0451)
j=0	-0.0183	-0.0118	-0.0204	-0.0242
	(0.0606)	(0.0276)	(0.0247)	(0.0351)
j=1	0.0146	0.0265	-0.00286	-0.0323
	(0.0864)	(0.0531)	(0.0509)	(0.0758)
j=2	0.0554	-0.00281	-0.0508	-0.0667
	(0.166)	(0.117)	(0.0972)	(0.110)
j>=3	0.156	0.0557	-0.0235	-0.0878
	(0.182)	(0.119)	(0.102)	(0.141)
N	612	1496	2312	2890
Rsquared	0.896	0.915	0.915	0.919
Year FE	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes

SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6.E.2: Bus displacement near CSH

	CSH	<200m	<400m	<600m
j<=-4	-0.182	-0.216	-0.238	-0.255
	(0.197)	(0.193)	(0.279)	(0.225)
j=-3	-0.0867	-0.0712	-0.0894	-0.120
	(0.0730)	(0.0764)	(0.116)	(0.0906)
j=-2	-0.0615	-0.0695	-0.0784	-0.0888
	(0.0539)	(0.0564)	(0.0910)	(0.0722)
j=0	-0.0448	0.0596	0.105	0.0679
	(0.0456)	(0.0630)	(0.0779)	(0.0378)
j=1	-0.0326	0.128	0.173	0.140
	(0.102)	(0.118)	(0.156)	(0.129)
j=2	-0.0248	0.175	0.215	0.171
	(0.146)	(0.159)	(0.189)	(0.128)
j>=3	-0.0504	0.238	0.286	0.273
	(0.161)	(0.206)	(0.273)	(0.224)
N	604	1488	2301	2876
Rsquared	0.882	0.909	0.885	0.896
Year FE	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes

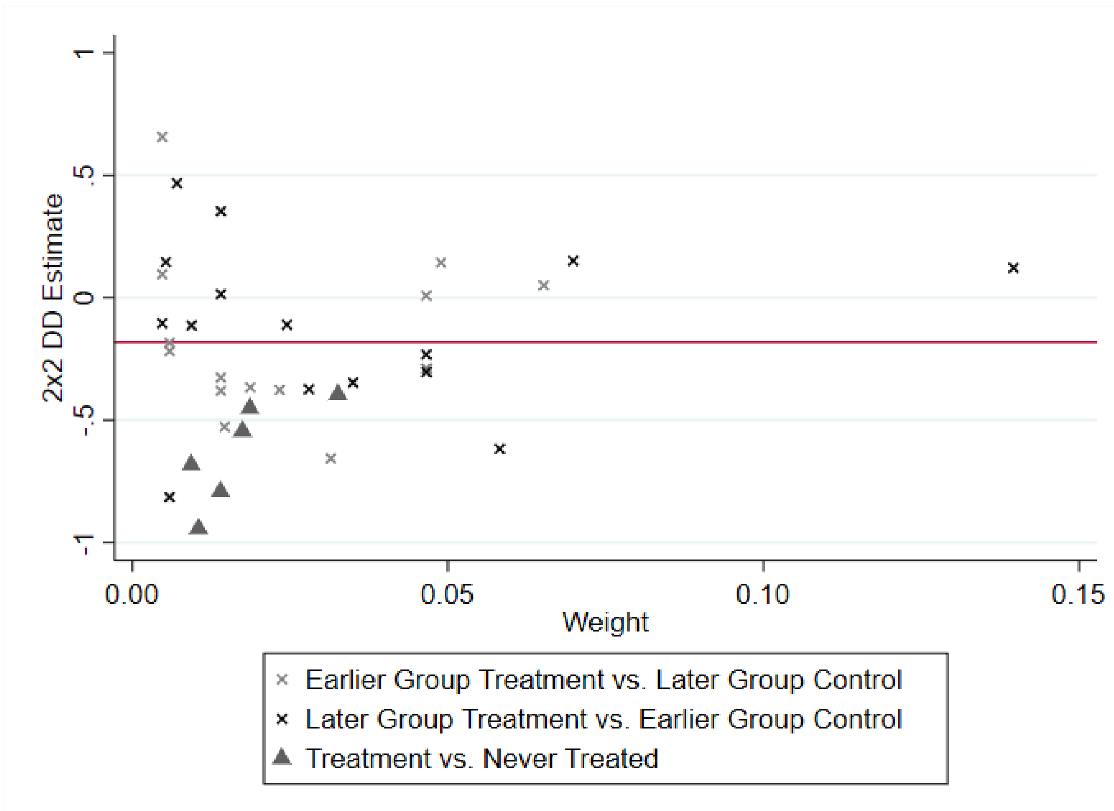
SD clustered at year and cycle superhighway route level

* $p < .1$, ** $p < .05$, *** $p < .01$

6.F Accidents reduction

I further use the Goodman-Bacon decomposition to analyse the different components of the DiD estimator for bike accidents divided by cycling flow after a CSH opening. I find an overall ATT of -0.08, which is decomposed on an Earlier Treatment vs Later Control of -0.079, Later Treatment vs Earlier Control of 0.015 and Treatment vs Never treated of -0.573. The respective weights are 0.332, 0.559 and 0.109. All estimates (expect from the problematic Later Treatment vs Earlier Control) are negative, which indicates that the cycling lanes are quite effective in reducing accidents and the effect is increasing in time.

Figure 6.F.1: Decomposition of DiD estimate for bike accidents



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