Cycling Towards Cleaner Cities? Evidence from New York City's Bike Share Program*

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Abstract

What is the impact of cycling on air quality in cities? This paper leverages the staggered rollout of New York City's bike share program to estimate the effect of cycling on air pollution concentrations. I combine the universe of bike share trips with ground-level, high-resolution observational air pollution measures between 2010 and 2019. Through a routing algorithm, I use the location of bike share stations to map areas where road traffic is expected to decrease after the introduction of bike share. I compare these areas with others where traffic was likely unaffected using a staggered difference-in-differences strategy to retrieve causal estimates. I find that the deployment of bike share is associated with a 3% reduction in black carbon and 13% reduction in nitric oxide concentrations, both pollutants associated with road traffic. In addition, I investigate potential mechanisms and show that the introduction of bike share is associated with a decrease in short taxi trips in areas served by bike share, which I interpret as suggestive evidence that bike share substitutes road traffic.

Keywords: Air pollution, Urban transit, Mode substitution, Cycling, Bike share
JEL Classification: R4, Q53, I1

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1 Introduction

Air quality is a central issue in cities: with a majority of the world's population living in urban areas, increased exposure to air pollutants has negative impacts on health, and is associated with substantial social and economic costs. Road transportation is an important emitter of urban air pollutants, contributing close to 40% of concentrations (EEA, 2021), leading many cities to implement novel policies aiming to lessen the burden of motor vehicles. Bike share is one such intervention, a network of automated stations where public bicycles are rented for short periods and returned. With over three thousand systems installed worldwide in the past 20 years, bike share has become a ubiquitous sight in cities. By making cycling more convenient and cheaper, bike share has the potential to replace trips previously made by internal-combustion-engine (ICE) vehicles, thus improving air quality. Despite its popularity and potential, very little is known about the impact of bike share on road transportation and air pollution.

In this paper, I identify the causal effects of bike share on air pollution concentrations in New York City (NYC). While previous research has examined the impact of other policies on pollution abatement from road transportation, such as, for example, low-emission zones (Jiang et al., 2017; Wolff, 2014; Zhai and Wolff, 2021), congestion charge (Green et al., 2020; Tonne et al., 2008) and the opening of new subway lines (Chen and Whalley, 2012; Gendron-Carrier et al., 2022), the impact of cycling on air pollution has received much less attention. Existing research relies heavily on hypothetical rates of substitution towards cycling to estimate bike share's environmental impact (Fishman et al., 2014; Médard de Chardon, 2016; Qiu and He, 2018; Ricci, 2015; Zhang and Mi, 2018; Zheng et al., 2019). Two recent studies have taken a causal approach to estimate the impact of bike share on a related outcome, traffic congestion (Hamilton and Wichman, 2018; Wang and Zhou, 2017). Shr et al. (2022) are the first to use a causal identification strategy to study air quality, and do not find a robust effect of bike share in Taiwan. Nevertheless, there is a notable scarcity of studies investigating the causal impact of bike share on air quality using observational data.

The main challenges in causally estimating this relationship are (1) the availability of high-resolution pollution data over long periods and (2) a credible identification strategy. I address these challenges by using the staggered rollout of NYC bike share stations and combining it with the NYC Community Air Survey (NYCASS), a high-resolution spatial dataset of air pollutants' concentration in NYC over ten years. While bike share is not implemented randomly (to ensure success, city planners choose to deploy bike share in busy areas first, where a large demand for transportation guarantees sufficiently high usage), I argue that the timing and spatial extent of each roll-out wave are as good as random, conditional on a set of covariates. The staggered rollout of bike share provides quasi-random variation in cycling accessibility and costs allowing me to estimate the causal effect of bike share on air pollution concentrations using a difference-in-differences (DD) strategy.

I find that concentrations of pollutants associated with road transportation reduce by 3 to 13% with respect to pre–bike-share mean concentrations, depending on the pollutant. These results are robust to a battery of specifications and hold when using novel DD estimators accounting for variation in treatment timing. The main channel through which bike share is expected to reduce pollution runs through the substitution of road transportation trips, reducing emissions and thus local pollutants. This paper examines the evidence on the substitution mechanism using the universe of taxi trips and finds that, in areas served by bike share, short taxi trips (most similar to typical bike share trips) decrease faster than longer ones, indicating that bike share did substitute trips from road transportation.

These findings are highly relevant when set in the context of the significant health impact of air pollution. In the United States (US), between 100 and 200 thousand yearly deaths are associated with air pollution (Burnett et al., 2018). Excessive concentrations of air pollutants have been linked to asthma incidence and crises, costing upwards of $135mio per year in emergency room visits alone (Anenberg et al., 2018; Qin et al., 2021).[1] Air pollution has also been negatively associated with a host of non-medical outcomes such as cognitive performance, crime rates, labour productivity and supply, and decision-making ability (Aguilar-Gomez et al., 2022; Klingen and van Ommeren, 2021). As this literature highlights, the benefits associated with improving air quality are large and broad in scope.

Road transportation is one the largest sources of air pollution: in NYC, up to 30% of concentrations of local air pollutants are attributed to ICE vehicles. Reducing the impact of road traffic has thus become a priority in pollution abatement strategies of cities. Cities can either make vehicles less polluting, or reduce the number of trips (or kilometres driven). In the latter option, one strategy is to replace road transportation trips with other, less pollution modes. To get road transportation users to substitute trips, policymakers may decide to increase the cost of using road transportation (e.g., congestion zones, carbon tax), or increase the availability (and decrease the price) of substitutes (public transit, cycling infrastructure). By implementing bike share on a large scale, NYC effectively made cycling easier, more convenient and cheaper in vast areas of the city. The sudden improvement of an alternative to road transport has the potential to divert road transportation users to cycling, reducing the kilometres driven and congestion, and ultimately reducing air pollutants associated with ICE vehicles.

This paper contributes to two main strands of the literature. First, it extends the environmental economics literature on the impacts of transportation policies on air quality. Jiang et al. (2017), Wolff (2014), and Zhai and Wolff (2021) evaluate the impact of low-emission zones (LEZ) on pollution concentrations and find that on average, pollution decreases in areas with LEZ. Tonne et al. (2008) and Green et al. (2020) both

[1] Air pollution also affects other chronic respiratory diseases, leading to the yearly loss of an estimated 371 thousand disability-adjusted life years in the US (Murray et al., 2020). Other medical outcomes affected include newborn birth weights and mortality (Currie et al., 2014).

examine the effect of the London congestion charge on concentrations of air pollutants and find statistically and economically significant decreases. Chen and Whalley (2012) and Gendron-Carrier et al. (2022) check whether subway lines openings decreased air pollution, with Chen and Whalley (2012) focusing on the opening of the Taipei subway, and Gendron-Carrier et al. (2022) combining satellite measures of pollution and 58 subway openings around the world. Chen and Whalley (2012) find that pollution decreases significantly after the opening, while the results reported by Gendron-Carrier et al. (2022) indicate that only the most polluted cities see an improvement in air quality when a new subway line opens. Bike share systems have now been deployed in more than three thousand cities around the world, and are often portrayed as tools to reach pollution abatement objectives (DeMaio, 2009; Médard de Chardon, 2016), despite the limited evidence. This paper aims to fill that gap in our understanding of the environmental impacts of bike share.

Second, an emerging 'cycling' literature examines the effects of bike share on the environment and congestion. Most studies on the impact of bike share on the environment rely on hypothetical rates of substitutions from ICE vehicles to bike share, limiting their validity. For example, Médard de Chardon (2016), Qiu and He (2018), Ricci (2015), and Zhang and Mi (2018) assume that all or nearly all bike share trips replace ICE vehicles, and estimate unrealistically large reductions in emissions of greenhouse gases. Fishman et al. (2014) take a more realistic approach by grounding their rates of substitution on surveys of bike share users, and combine them with emissions from bike share service providers when rebalancing stations. Most cities in their sample saw an overall decrease in the total distance traveled by ICE vehicles. Zheng et al. (2019) go a step further and estimate the emissions associated with the whole life-cycle of bike share (i.e., including manufacturing), and take into account multiple environmental dimensions (e.g., global warming, fossil depletion). Using hypothesised substitution rates, they find that bike share reduces the environmental footprint along most of the dimensions.

My study contributes to this literature by providing causal estimates of the impact of bike share on air pollution using observational air quality data. As such it relates to an emerging literature, attempting to produce causal estimates of the impact of bike share and cycling infrastructure on congestion. For example, Bhuyan et al. (2021) find that segregated cycling paths in London reduce congestion, while Graham et al. (2022) find a 1% decrease in traffic speed due to new bike lanes in NYC. Examining e-scooters in Atlanta, Asensio et al. (2022) show that restrictions on e-scooters increase urban travel time by 9 to 11%. Wang and Zhou (2017) look at congestion in 96 US cities, and find that bike share reduced congestion in large cities, but increased it in richer ones. Hamilton and Wichman (2018) take the case of Washington D.C. and find that bike share reduced congestion by upwards of 4%, mostly in congested areas. Recently, Shr et al. (2022) estimate the willingness-to-pay for bike share systems in Taiwan, finding a robust increases in rental prices nearby bike share stations. They also investigate the impact on air pollution, but do not find robust evidence that bike share improves air quality. This literature highlights that the effects of cycling infrastructure on congestion and air quality are not obvious. While congestion might be negatively associated with air pollution, Asensio et al. (2022), Hamilton and Wichman (2018), and Wang and Zhou (2017) do not estimate the effect of cycling infrastructure on air quality. Focusing on air quality, Shr et al. (2022) do not find an impact on air pollution in Taiwan, underscoring the uncertainty around the potential effect, and suggesting that the local transport context (such as existing transport habits and transport options) may be a crucial mediator between bike share and air quality. By specifically focusing on air pollution concentrations in NYC, I omit the congestion question and estimate the direct relationship between bike share and air quality in a global city with its unique local transport context.

The rest of the paper is organised as follows: section 2 develops the conceptual framework linking bike share to air pollution, section 3 the empirical strategy and section 4 presents the data, section 5 presents the results, section 6 explores the substitution mechanism, and section 7 concludes.

2 Conceptual framework

This section introduces a simple model of transport choice that will formalise the relationship between bike share and the propensity to choose cycling as a mode of transport. I then describe the main channel through which bike share may change air pollution concentrations (other channels are presented later in section 6.3).

2.1 Transport mode choice

The toy model described below is adapted from McFadden (1974b) and McFadden (1974a), as presented in Small and Verhoef (2007). For a given trip within the city, each individual n faces a menu of transport options $j = 1, ..., J$ (e.g., walking, public transport, taxi). Each option j is associated with costs c (e.g., ticket purchase, purchase or rent of a vehicle), travel time t and ease of access a (i.e., how far does the individual need to travel on foot to access mode j) for a given pair of origin-destination locations l. Utility is composed of a systematic utility $V(\cdot)$ which incorporates the characteristics of transport options as described above, and an unobservable component of utility ϵ_{jn} which captures idiosyncratic individual preferences. Individuals choose the transport option j that maximises their total utility:

$$U_{jln} = V(c_{jl}, t_{jl}, a_{jl}) + \epsilon_{jn} \tag{1}$$

The introduction of bike share abruptly increases the systematic utility of cycling in areas served by bike share: cycling is cheaper and more accessible. In other words, for areas L where bike share is implemented at time T, the utility of cycling ($j = J$) increases: $V_{t<T}(c_{JL}, t_{JL}, a_{JL}) < V_{t\geq T}(c_{JL}, t_{JL}, a_{JL})$. For individuals to switch to cycling after bike share, the utility associated with cycling after T needs to be greater than utilities for all other transport options:

$$\begin{aligned} \text{at } t > T: \quad & U_{JLn} > U_{jLn} && \text{for all } j \neq J \\ = \quad & V_{JL} + \epsilon_{Jn} > V_{jL} + \epsilon_{jn} && \text{for all } j \neq J \\ = \quad & \epsilon_{Jn} - \epsilon_{jn} > V_{jL} - V_{JL} && \text{for all } j \neq J \end{aligned}$$

If that condition is satisfied, and $j_{t<T} \neq J_{t<T}$ (i.e., the individual was not already cycling before bike share), then the individual will have switched to cycling thanks to bike share.

2.2 Substitution and impact on air quality

Having established the conditions that enable an individual to switch to cycling due to the availability to bike share, we now turn to how that translates into improving air quality. The change in air pollution is highly dependent on the mode of transport used in $t < T$: if the individual switched from a polluting mode of transport (i.e., an ICE vehicle), replacing those polluting trips with cycling will have an impact on air pollution concentrations. The substitution effect of bike share towards cycling is operative on air quality conditional on the previous mode of transport. On the other hand, if the individual switched to cycling from public transport or walking, the effect will be minimal.[2]

The key takeaway from this simple model is that the substitution mechanism implies that pollution reduces in areas where less polluting vehicles are driven after the implementation of bike share. In section 3, I use this spatial property of the substitution effect to construct a credible measure of where ICE traffic might have reduced thanks to bike share. This is used as the treatment variable in the empirical analysis to identify the causal impact of bike share on air pollution.

3 Empirical strategy

There are several empirical challenges to estimating the causal impact of bike share on air pollution concentrations. The first challenge is that air quality depends on a multitude of factors other than bike share. In addition, other changes that could be happening at the same time with the expansion of bike share could also change pollution concentrations.

[2] Bike share may still have an indirect positive effect by decongesting public transport, which becomes more attractive to some ICE vehicle users who now switch to now less-congested public transport, thus reducing emissions. Another form of indirect substitution occurs when bike share and public transit are taken as complementary modes of transport: if bike share helps connect transportation hubs (e.g., railway or subway stations) to final destinations, a composite bike-share–public-transit transportation good might become a more attractive alternative to ICE vehicle users, inducing substitution.

In this section, I present the identification challenges and how my empirical strategy overcomes these challenges.

The main challenge to identifying the causal relationship between bike share and air pollution is that bike share stations are not randomly placed across the city. From a city planning perspective, this makes sense: one has to ensure that the bike share program will be successful by reaching a large enough transport market. In the case of NYC, that meant that bike share was deployed first in Manhattan south of 60th street and downtown Brooklyn.[3] In subsequent years, bike share was expanded north on the island of Manhattan, and, across the East River, deeper into Brooklyn and Queens (gradual rollout is mapped in Figure A.1).

The second identification challenge is that NYC is a large, heterogenous city, constantly evolving. A myriad of policies that might affect pollution concentrations are enacted every year, which could contaminate the estimate of the impact of bike share.

I address these challenges using a staggered difference-in-differences (DD) strategy. The empirical strategy compares areas affected by bike share with areas less affected, before and after the deployment of bike share. It takes advantage of the gradual rollout of the bike share program to sequentially identify treated and control areas. It then aggregates the estimated treatment effect of bike share over the several expansion waves to yield an overall average treatment effect.

I further define the treatment indicator by carefully identifying the areas where bike share is expected to affect pollutant concentrations the most, making it is less sensitive to the placement of bike share stations. As discussed below in greater detail, I define the treatment areas as areas where fewer cars are expected to drive, thus covering a larger tract of land than the stations themselves. This approach exploits the fact that bike share's *area of influence* changed over the years at a seemingly random pace.

More specifically, recall that the units of analysis are 300 by 300-metre cells, for a total of 9,760 cells across NYC. Each of these cells will be considered treated if it lies on the route between two bike share stations that exchanged a bike during a given year. In other terms, the treated cells are the cells through which ICE traffic is expected to decrease, which, because cars tend to be constrained by the road network, includes many cells where bike share stations are not accessible. This constitutes the first element that introduces variation on the spatial scale that is unrelated to the placement of bike share stations.

Furthermore, the expansion of the bike share network was carried out in a staggered and irregular fashion. The history of NYC's bike share deployment makes for a fitting illustration. Bike share's first deployment in NYC was originally scheduled for Summer 2012, but due to major software issues it was delayed first to Fall 2012 and then Spring

[3]The highest concentration of transportation trips in NYC is located in the southern third of the island of Manhattan, which contains Midtown and Lower Manhattan, the city's most important business districts. While that area as a whole is fairly heterogenous, it does contain the major business centres and transportation hubs (Pennsylvania Station, Grand Central Station, Port Authority Bus Terminal), and generates an important share of NYC's transport demand.

2013. At the same time, the spatial extent of the initial launch was significantly scaled down as a result of extensive damages from Hurricane Sandy in October 2012.[4] The first expansion of the system was similarly pushed back by a year to 2015 because of remaining software issues.[5] Thus, while the *order* through which areas of the city received bike share is arguably not random, the *exact timing* (i.e., the year it received bike share) and the *precise spatial extent* of the extension (e.g., why stop at 59th street and not 79th street?) are relatively random. Combined with the fact that the treatment definition used in this study is a superset of the area where stations are deployed based on car itineraries, the precise timing and extent of the treatment variable provides enough variation to act as a valid treatment definition for a DD setting. In section 5.3, I perform several tests to back up these claims.

In addition to a credible treatment, the empirical strategy relies on two main assumptions. First, control and treatment areas must follow parallel trends in terms of pollution concentrations before the deployment of bike share. In other words, the difference in concentrations between the treated and control group should be stable before treatment. This central DD assumption is necessary in order to take the post-treatment trend of the control group as a credible counterfactual for the post-treatment trend of the treatment group had bike share not been implemented. I test for parallel trends in section 5.1.2 using a dynamic DD specification.

Second, staggered DD assumes that no other concomitant policy that could have affected pollution concentrations was enacted at the same time and place as/where bike share was rolled out. This assumption requires that there are no omitted and concurrent policies that might explain the change in air quality. This means that treated areas (the areas where bike share is expected to lower traffic emissions) should not have been subjected to policies that could have reduced air pollution. While many policies and programs are enacted every year in NYC, it appears unlikely that these policies would have targeted the precise areas where bike share is expected to reduce pollution, and not the others. For example, the city introduced a new type of taxi in 2013, the boro taxi. Launched to increase transport options in neighbourhoods outside Manhattan, boro taxis can only pick up passengers North of 100th street in Manhattan and everywhere else in the other boroughs. While the launch date closely matches the opening of the bike share program, the boro taxis program, if it affected traffic and pollution, affected it in areas different from the ones I code as treated by bike share. It is therefore unlikely that a policy followed the same spatial and temporal pattern as bike share's extension.

[4]Originally planned to extend up to 79th street, the launch finally covered areas south of 59th street only.

[5]The considerable reworking of plans and schedule was reported at the time by the press (see for example https://archive.ph/jZl4 and https://www.wnyc.org/story/284420-breaking-citibank-is-sponsor-of-nyc-bike-share-citibike/), and confirmed during several private conversations I had with people involved in the planning of NYC's bike share program. Apart from major software issues and Hurricane Sandy, they also noted that the initial lack of enthusiasm for the program on the part of Bill De Blasio (NYC's new mayor in 2014) decreased available resources for further expansions in the short run.

One of the central requirements for this estimation strategy is the precise identification of areas where pollution concentrations might have been affected by bike share. Using the bike share trips dataset, I construct a new variable to capture the impact of bike share on air pollution. As described in section 2, the impact of bike share on air quality depends on the substitution away from ICE vehicles as a result of bike share. If there is any substitution away from ICE vehicles, we would expect air pollution concentrations to decrease in areas where fewer vehicles are driven because of bike share.

To identify those areas, I use the bike share trip data to first compute the unique origin-destination pairs of stations (i.e., pairs of stations that exchanged at least one bike during a given year). Using the `r5r` package in R, a routing algorithm able to take into account the road network at different periods (Pereira et al., 2021), for each pair of stations I compute the optimal car route that would have been driven if the bike trip between these stations would have been made by car. For each year, there are on average 24K unique origin-destination pairs of bike share stations, totalling 500K computed car routes.[6]

This exercise produces the optimal car routes between unique pairs of bike share stations for each year. Next, I intersect these car routes (including a 150-meter buffer on both sides) with the grid cells, identifying the cells crossed by a car route. Finally, I input the number of bike share trips associated with each pair of stations to the car routes, and sum the number of bike share trips for each cell that are crossed by car routes. I end up with a dataset of cells that measure the total bike share traffic, but in areas where cars would have been driven. In other words, I now have a yearly variable that captures where (at the extensive margin) we would expect air pollution to reduce after bike share, and, where we would expect it to reduce the most (at the intensive margin) as captured by the number of bike share trips. The result is displayed as a map in Figure A.2.[7]

The econometric specification used to estimate the staggered DD is described by equation 2. It is a standard two-way fixed effects (TWFE) model with multiple treatment periods:

$$Y_{ct} = \beta \cdot Treat_{ct} + \phi_t + \gamma_c + C_{ct_0} + \varepsilon_{ct} \tag{2}$$

Y_{ct} denotes the concentration of a given pollutant in cell c at time t; $Treat_{ct}$ is a binary variable indicating whether cell c is treated by bike share at time t; ϕ_t and γ_c are

[6]The r5r routing algorithm is well-suited to this application for several reasons. First, contrary to the Google Maps API, it takes into account the road network in place at a given time, letting me compute realistic routes across my sample period. Second, it is run on a local computer, which greatly reduces computational time. Finally, it is free and open-source, which makes the algorithm and processing transparent and reproducible.

[7]Alternatively, I define treatment for a given cell during a given year as (1) being within 300 metres of a bike share station, or (2) being contained within the smallest convex polygon encompassing all stations. The first alternative definition is based on the proximity to the bike share system, while the second is also based on proximity but incorporates areas *between* treated areas as being treated, even though they might be far from a station. Both, however, do not model the footprint of cars that might be substituted as a consequence of bike share expansion.

year and cell fixed effects, respectively, which control for any invariant cell characteristics and time trends; C_{ct_0} is a vector of controls for cell c at period t_0 right before treatment; ε_{ct} is the error term. Standard errors are clustered at the community district level,[8] and in a robustness check I follow Conley (1999) to compute standard error robust to spatial dependence.

The coefficient of interest is β, which represents the average treatment effect on the treated for the whole post-treatment period. In other words, it is the average change in pollution concentration for a cell being crossed by a car route. If the treatment is continuous (i.e., the number of bike share trips), β is interpreted as the effect of an additional bike share trip on pollution concentration for an average treated cell.

The average treatment effect is a valuable metric, but one might, however, also be interested in the dynamic effect of treatment with respect to time. The dynamic DD specification, also known as an event study, plots the treatment effect for all periods. The dynamic specification also allows us to test for differential pre-tends between groups: by plotting the difference between treatment and control in the pre-treatment period, we will be able to evaluate the validity of the parallel trends assumption.

The specification for the dynamic DD is given in equation 3:

$$Y_{ct} = \sum_{k=-9}^{-2} \beta_k \cdot Treat_{ck} + \sum_{k=0}^{6} \beta_k \cdot Treat_{ck} + \phi_t + \gamma_c + C_{ct_0} + \varepsilon_{ct} \tag{3}$$

where k denotes the relative time to the first year of treatment, and the other terms are the same as in the previous specification. The coefficients of interest are β_k, which are then plotted against relative time. In this setting, the reference period is relative time $k = -1$, therefore the plotted β_k denote the relative difference between treatment and control groups compared to the period right before treatment.

A recent strand of the econometric literature has brought into question the TWFE estimator with multiple treatment times. In particular, Goodman-Bacon (2021) shows that TWFE reports biased average treatment effects, and those distortions are particularly pronounced when (1) the size of the control group is small, and (2) the average treatment effect varies over time. Several robust estimators have since been proposed in the literature, with notable contributions including Borusyak et al. (2022), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021). While my setting does not suffer from a small control group, I cannot rule out that the average treatment effect varies across cohorts. To confirm the results obtained from the TWFE model, I use the estimator developed by Borusyak et al. (2022). This estimator has several advantages compared to alternative robust estimators, the main one being its high efficiency in computing standard errors.

[8] Community districts are local, within-borough neighbourhood advisory boards. There are 59 such districts across NYC, plus 12 non-district areas (e.g., parks, beaches, airports), for a total of 71 clusters.

4 Data

This section describes the data used to carry out the main analysis and the testing of the substitution mechanism.

4.1 Air pollution

Spatial-temporal concentrations of air pollutants are the main outcome variables of the analysis. The New York City Department of Health and Mental Hygiene (NYCDOH) provides yearly, high-resolution air pollution data covering the city's territory, divided into 9,670 300-metre square cells since 2009. This subsection describes these data.

The project known as the New York City Community Air Survey (NYCCAS) has been conducted by the NYCDOH and Queens College since December 2008. It aims to evaluate air quality at the street level by measuring six major air pollutants: fine particulate matter (particles smaller than 2.5 micrometres, i.e. PM 2.5), black (or elemental) carbon (BC), nitric oxide (NO), nitrogen dioxide (NO_2), ozone (O_3) and sulfur dioxide (SO_2).[9] Up to 150 monitors are distributed around the city every year, with 80% percent of sites selected randomly, while the remainder are purposefully chosen near areas of interest and to guarantee minimal coverage of neighbourhoods. The data collected from the monitors is then processed and used to calibrate a land-use regression (LUR) model which in turn produces the final raster grid dataset. Each of the 9,670 300-metre cells measures the annual average concentration of a given pollutant in that cell. Details on air pollutant measurements and the LUR model are presented in Clougherty et al. (2013) and Matte et al. (2013).

Several features make the NYCCAS a relatively unique air quality dataset. First, it offers measurement for a wide range of air pollutants. Second, pollution concentrations are given at a high spatial resolution (300-metre cells, when satellite-based resolutions range from 1 to 2 kilometres, see for example Gollin et al. (2021) or Gendron-Carrier et al. (2022)), enabling much more detailed analysis within the city. Finally, the NYCCAS is continuously available before and after the start of bike share, making pre and post-bike-share comparisons possible.

I focus on a subset of pollutants measured by the NYCCAS. Two criteria were used to select pollutants: (1) the pollutant should be associated with ICE vehicles, and (2) it should be measured close to its emission source. Criterium (1) ensures that the pollutant is relevant to the main mechanism (i.e., substitution), while (2) is necessary to narrow down the potential area of influence of bike share. The selected pollutants are nitrous oxides (NO and NO_2), and particulate matter (PM 2.5 and BC). Nitrous oxides are gases and common markers of ICE vehicle traffic, with 30% of concentrations attributed to on-road vehicles. Nitrous oxides have a relatively steep concentration gradient, which means that concentrations decrease faster the further away from the emission source.

[9] O_3 is measured during the Summer season only. SO_2 was measured in Winter only until 2017, when its measurement was discontinued due to concentrations below detection limits.

PM 2.5 captures all the particles that are smaller than 2.5 micrometres (about 1/20th the diameter of a human hair). Its health impacts have been extensively studied, which makes it a popular pollutant to focus on. BC (also called soot or elemental carbon) is a subset of PM associated with Diesel engine emissions.

4.2 Bike share

The bike share data is publicly available on the website of the service provider, Citi Bike.[10] The data consists of the universe of bike share trips made on the system since its start in May 2013, as required by the service agreement with the city of New York. Each trip is characterised by origin and destination station (unique ID, name and geographic coordinates), departure and arrival timestamps, and an indicator variable for subscriber riders. If the rider is a subscriber, year of birth and gender are reported. Several cleaning operations are made on trip data to remove potentially problematic observations: temporary and service stations are removed using identified keywords; round trips (i.e., identical origin and destination station) are removed; and trips under three minutes and over six hours are dropped. The final dataset contains about 100 million trips from May 2013 to December 2019.[11] The gradual rollout of the bike share stations is mapped in Figure A.1.

4.3 Spatial and time-varying variables

I collect several spatially distributed and time-varying control variables. The location and type of cycling lanes are obtained from the New York City Department of Transportation (NYCDOT). A large amount of data cleaning and manual processing was necessary in order to correctly classify changes in cycling-lane types. Cycling lane lengths per type were then computed for each 300-metre cell.

The American Community Survey (ACS) is used to gather socio-demographic variables. I use the ACS 5-year, which collects data on a rolling 5-year basis and delivers estimates at the census tract resolution. Census tract values are then imputed to the 300-metre cells using the areal interpolation functions from the `areal` R package (Prener and Revord, 2019).[12] Variables extracted from the ACS include population, median household income, and level of tertiary education.

Zoning and building information are sourced from the New York City Department of City Planning (NYCDCP) and its PLUTO dataset, which provides detailed land use and geographic data at the tax lot level. These data are also aggregated at the 300-metre cell level using areal interpolation.

Finally, I obtain the map of community districts from the NYC Open Data portal,

[10] https://ride.citibikenyc.com/system-data/, accessed 2022-10-20.

[11] I described the building of the bike share treatment variable using these data in section 3.

[12] Each cell takes the weighted average of census tracts with weights given by the share of each tract's area covering the cell.

and assign each cell to one of the 59 community districts (and 12 remaining areas, usually parks) its area covers the most.

4.4 Summary statistics

The variables used in the analysis are summarised in Table 1. The yearly counts of cells crossed by a car route (main treatment variable) are displayed in Table 2.

5 Results

In this section, I report the average treatment effect of bike share on air pollution concentrations obtained from the TWFE estimation. Event studies plotting the dynamic impact of bike share on concentrations are presented, for both standard TWFE and the Borusyak, Jaravel and Spiess (BJS) estimator. Tests on the validity of the empirical setting are then presented.

5.1 TWFE results

5.1.1 TWFE Average treatment effects

The results are presented for each selected pollutant in turn in Tables 3 to 6. Standard errors are clustered at the community-district level.[13] My preferred specification includes cell and year fixed-effects with baseline controls (Column 2).

Table 3 shows the impact on NO concentrations for a cell being on a car route between bike share stations. In my preferred specification with baseline controls (Column 2), concentrations of NO decrease on average by 2.7 parts per billion for cells on a car route. This coefficient represents a 13.4% decrease with respect to mean concentrations for the whole sample before 2013. Table 4 reports the average treatment effect of bike share on NO_2 concentrations. Bike share significantly reduces NO_2 concentrations in areas where fewer cars are likely to be driven. The decrease in NO_2 represents about 6.2% of pre-treatment concentrations. The impact on BC is reported in Table 5. For BC also, concentrations reduce in areas where fewer cars are expected to be driven due to bike share. The coefficient represents a 2.8% decrease compared to BC concentrations before the first implementation of bike share in 2013. Finally, the effect on PM 2.5 is shown in Table 6. The effect of bike share on PM 2.5 concentrations is indistinguishable from zero, but has the expected negative sign. From these results, it appears that bike share has reduced the concentration of NO, NO_2 and BC by 2.8 to 13.4%, but had no effect on PM 2.5 concentrations.

Tables 3 to 6 investigate the extensive margin of the impact of bike share, with the treatment being an indicator variable taking the value of 1 if the cell is crossed by a car route, and zero otherwise. These results do not take into account the intensity of bike

[13] Conley (1999) standard errors robust to spatial dependence are reported in Appendix B.

Table 1: Summary statistics

	Mean	SD	Min	Max
Treatment group				
Bike share trips	184,432.4	425,979.5	0	3393072
NO (parts per billion)	22.36	9.27	8.89	71.85
NO2 (parts per billion)	23.28	4.44	11.25	47.46
PM 2.5 (microgram per cubic metre)	9.45	1.61	5.99	17.63
BC (absorption)	1.11	0.3	0.47	2.61
College graduates (count)	592.12	679.39	0	4,815.52
Population	1,589.34	1,161.32	0	7,311.22
Population over 25	1,149.99	880.62	0	5,832.03
Median household income (2019 $)	69,168.22	44,223.59	0	272,587.4
Protected cycle lane (ft)	318.34	579.58	0	3,522.82
Painted cycle lane (ft)	425.09	710.55	0	4,540.39
Cycle route (ft)	156.77	384.82	0	2,946.44
At-least-painted cycle lane (ft)	743.43	887.22	0	5,729.1
Built surface (sq ft)	1,451,731	1,744,487	0	22,156,429
Office area (sq ft)	296,846.4	1,079,304	0	13,503,541
Residential area (sq ft)	784,423.6	821,027.6	0	5,625,712
Commercial area (sq ft)	641,170.4	1,386,116	0	19,326,407
Retail area (sq ft)	78,493.02	169,277.3	0	3,790,754
Other floor area (sq ft)	2.79	16.26	0	1,047.57
Control group				
Bike share trips	0	0	0	0
NO (parts per billion)	14.86	5.22	5	80.52
NO2 (parts per billion)	16.62	4.15	5.38	32.27
PM 2.5 (microgram per cubic metre)	7.94	1.3	5.36	13.2
BC (absorption)	0.78	0.24	0.17	3.23
College graduates (count)	132.32	158.72	0	1,910.09
Population	734.29	837.89	0	7,394.62
Population over 25	492.46	551.1	0	4,916.74
Median household income (2019 $)	63,418.2	37,975.29	0	293,774.6
Protected cycle lane (ft)	101.97	373.93	0	6,913.87
Painted cycle lane (ft)	105.04	368.01	0	3,974.35
Cycle route (ft)	53.82	233.34	0	3,086.08
At-least-painted cycle lane (ft)	207.01	525.26	0	7,911.46
Built surface (sq ft)	382,765.3	516,905.7	0	49,915,505
Office area (sq ft)	16,346.77	52,503.43	0	1,046,949
Residential area (sq ft)	284,622.9	338,853.6	0	2,919,417
Commercial area (sq ft)	93,149.03	250,471.1	0	10,218,426
Retail area (sq ft)	17,338.82	46,285	0	1,103,965
Other floor area (sq ft)	0.75	6.83	0	992.49

Table 2: Treatment yearly summary

Year	Cell on car route	Count	Percent
2013	0	8510	92.79
	1	661	7.21
2014	0	8512	92.81
	1	659	7.19
2015	0	8165	89.03
	1	1006	10.97
2016	0	7903	86.17
	1	1268	13.83
2017	0	7599	82.86
	1	1572	17.14
2018	0	7547	82.29
	1	1624	17.71
2019	0	7442	81.15
	1	1729	18.85

Table 3: Effect of bike share on NO concentrations

	NO	
	(1)	(2)
On-car-route	-2.5360***	-2.7281***
	(0.8595)	(0.8543)
Baseline controls		✓
Cell FE	✓	✓
Year FE	✓	✓
Mean concentration pre-treat.	20.322	20.353
% mean concentration pre-treat.	-12.479	-13.404
Observations	91,710	90,898
R^2	0.906	0.908
Within R^2	0.049	0.066

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Effect of bike share on NO2 concentrations

	NO2 (1)	NO2 (2)
On-car-route	-1.1489***	-1.2554***
	(0.2771)	(0.2759)
Baseline controls		✓
Cell FE	✓	✓
Year FE	✓	✓
Mean concentration pre-treat.	19.950	20.007
% mean concentration pre-treat.	-5.759	-6.275
Observations	91,710	90,898
R^2	0.978	0.979
Within R^2	0.081	0.123

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Effect of bike share on BC concentrations

	BC (1)	BC (2)
On-car-route	-0.0253*	-0.0280**
	(0.0128)	(0.0129)
Baseline controls		✓
Cell FE	✓	✓
Year FE	✓	✓
Mean concentration pre-treat.	1.015	1.017
% mean concentration pre-treat.	-2.494	-2.757
Observations	91,710	90,898
R^2	0.956	0.956
Within R^2	0.006	0.011

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Effect of bike share on PM concentrations

	PM	
	(1)	(2)
On-car-route	-0.0097	-0.0320
	(0.0686)	(0.0688)
Baseline controls		✓
Cell FE	✓	✓
Year FE	✓	✓
Mean concentration pre-treat.	9.433	9.441
% mean concentration pre-treat.	-0.103	-0.339
Observations	91,710	90,898
R^2	0.978	0.979
Within R^2	0.000	0.018

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

share activity and produce an average treatment effect on the treated, irrespective of the level of treatment. Next, I investigate the impact of treatment intensity on pollution concentrations. Recall from section 3, I compute, for each car route between pairs of bike share stations, the number of bike share trips for that pair. I then aggregate the number of bike share trips for each cell. In Tables 7 to 10, I report the effect of the number of bike share trips in cells crossed by car routes. I present the results for both the number of bike share trips measured in 10,000 and the inverse hyperbolic sine transformation of the number of bike share trips.[14]

For NO (Table 7), 10,000 additional bike share trips through a cell crossed by a car route reduce concentrations by 0.086 parts per billion, or 0.4% of the pre-2013 mean NO concentration. For a 1% increase in bike share trips, NO concentration would decrease by 0.003 parts per billion, or 0.015% of pre-2013 mean concentrations. The impact of an additional 10,000 bike share trips is smaller for NO_2 but still statistically significant (Table 8): concentrations would reduce by 0.13% with respect to the pre-2013 mean. The impact of a 1% increase in bike share trips would result in a 0.006% decrease from the pre-treatment mean. BC concentrations would reduce by 0.1% for ten thousand additional bike share trips, and 0.003% for a 1% increase. Finally, PM concentrations decrease by 0.035% for 10,000 additional bike share trips (statistically significant), but a 1% increase in bike share trips does not significantly reduce concentrations.

[14] The inverse hyperbolic sine (IHS) is a type of log transformation, particularly suited for variables with a large share of zeros (Bellemare et al., 2013; MacKinnon and Magee, 1990). The IHS value is given by $IHS(x) = ln\left(x + \sqrt{x^2+1}\right)$. Its interpretation is the same as a typical log transformation: the coefficient divided by 100 represents the change in the outcome variable when the independent variable increases by 1%.

Table 7: Effect of bike share on NO concentrations

	NO			
	(1)	(2)	(3)	(4)
Trips (10K)	-0.0839***		-0.0860***	
	(0.0115)		(0.0114)	
Trips (IHS)		-0.2758***		-0.2947***
		(0.0850)		(0.0845)
Baseline controls			✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean concentration pre-treat.	20.322	20.322	20.353	20.353
% mean concentration pre-treat.	-0.413	-1.357	-0.423	-1.448
Observations	91,710	91,710	90,898	90,898
R^2	0.927	0.909	0.929	0.911
Within R^2	0.257	0.077	0.279	0.097

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Effect of bike share on NO2 concentrations

	NO2			
	(1)	(2)	(3)	(4)
Trips (10K)	-0.0253***		-0.0263***	
	(0.0034)		(0.0033)	
Trips (IHS)		-0.1119***		-0.1218***
		(0.0256)		(0.0254)
Baseline controls			✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean concentration pre-treat.	19.950	19.950	20.007	20.007
% mean concentration pre-treat.	-0.127	-0.561	-0.131	-0.609
Observations	91,710	91,710	90,898	90,898
R^2	0.981	0.979	0.982	0.980
Within R^2	0.188	0.103	0.231	0.147

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Effect of bike share on BC concentrations

	BC			
	(1)	(2)	(3)	(4)
Trips (10K)	-0.0010***		-0.0010***	
	(0.0002)		(0.0002)	
Trips (IHS)		-0.0032***		-0.0035***
		(0.0012)		(0.0012)
Baseline controls			✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean concentration pre-treat.	1.015	1.015	1.017	1.017
% mean concentration pre-treat.	-0.097	-0.316	-0.100	-0.342
Observations	91,710	91,710	90,898	90,898
R^2	0.958	0.957	0.958	0.957
Within R^2	0.046	0.014	0.052	0.019

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Effect of bike share on PM concentrations

	PM			
	(1)	(2)	(3)	(4)
Trips (10K)	-0.0031***		-0.0033***	
	(0.0011)		(0.0011)	
Trips (IHS)		-0.0036		-0.0057
		(0.0067)		(0.0067)
Baseline controls			✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean concentration pre-treat.	9.433	9.433	9.441	9.441
% mean concentration pre-treat.	-0.033	-0.038	-0.035	-0.060
Observations	91,710	91,710	90,898	90,898
R^2	0.979	0.978	0.979	0.979
Within R^2	0.033	0.001	0.055	0.020

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

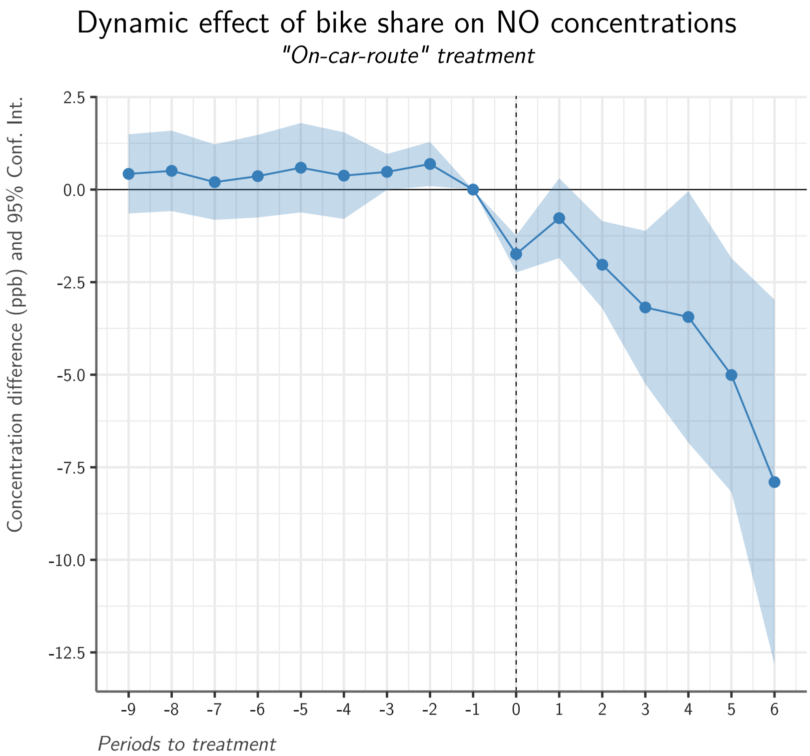

Figure 1: Dynamic effect of bike share on NO concentrations

5.1.2 TWFE Dynamic effects

I now report the estimates for the dynamic TWFE specification. In this specification, I estimate the impact of bike share on pollution concentrations for every period relative to treatment. Plotting the results yields an event study, which lets us evaluate the parallel trends before treatment assumption (i.e., no statistically significant differences in the trends of pollution concentrations between the control and treatment group before the treatment), and observe the dynamics of the effect over time. The estimates plotted control for baseline covariates, with standard errors clustered at the community district level.

Figure 1 plots the dynamic effect of being crossed by a car route between two bike share stations on the concentration of NO. In the period leading up to treatment (the left half of the plot), we notice no statistically significant differences in pollution concentrations between the treated and control group, providing good support for the parallel trends assumption. A decreasing trend after treatment indicates that treated cells see their NO concentrations drop after bike share is implemented and are crossed by car routes. The effect gets larger and is persistent over time. Turning to NO_2 in Figure 2, we also notice and significant decrease post-bike-share introduction. In the period leading to treatment, however, treated cells displayed a statistically significant difference in NO_2 concentration with control cells, which does not support the parallel trends assumption. Dynamic

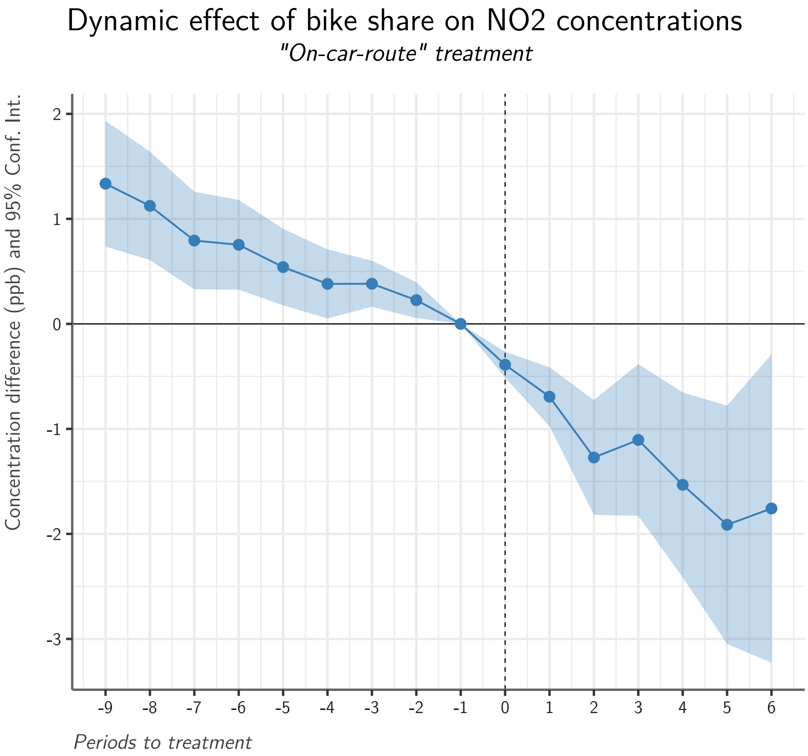

Figure 2: Dynamic effect of bike share on NO_2 concentrations

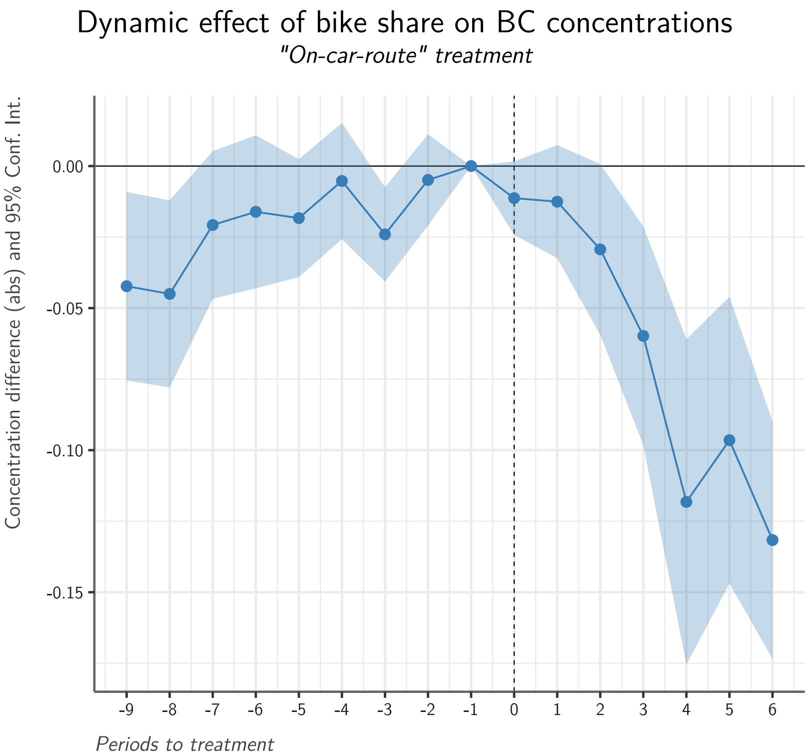

Figure 3: Dynamic effect of bike share on BC concentrations

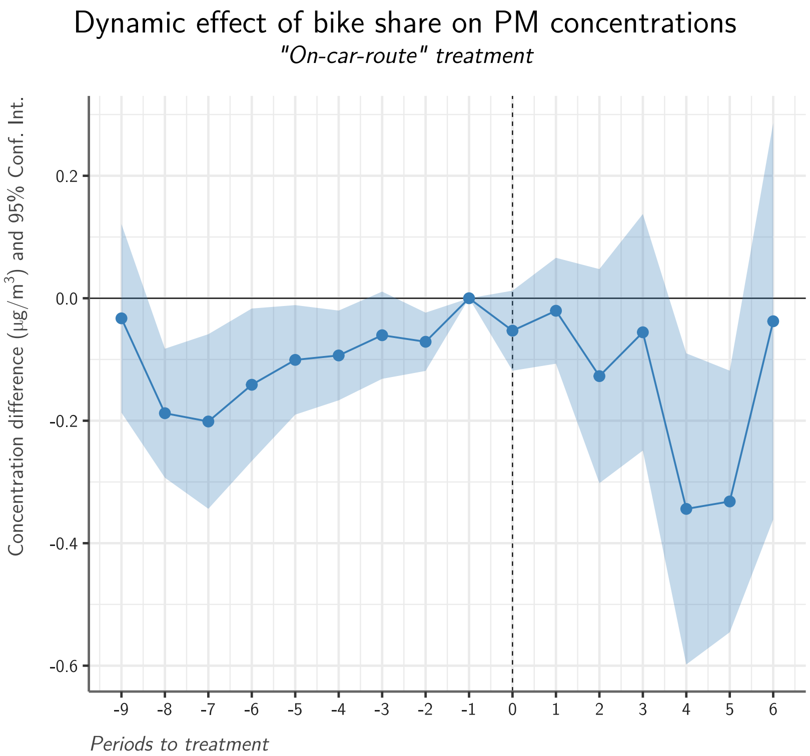

Figure 4: Dynamic effect of bike share on PM 2.5 concentrations

effects of bike share on BC are displayed in Figure 3. The parallel trends assumption seems reasonably supported by the data, and there is a statistically significant and persistent decrease in BC concentrations after bike share introduction. Finally, there are no discernible patterns of the impact of bike share on PM 2.5 concentrations (Figure 4).

5.2 Borusyak, Jaravel and Spiess (2022) Dynamic effects

Under some conditions, TWFE estimates have been shown to be biased for settings with multiple treatment periods. While the present setting does not suffer from the worst pitfalls of TWFE (e.g., small or non-existent never treated), TWFE is still subject to potential bias if the ATT varies over time. To mitigate these concerns, I report the dynamic effects of bike share on pollution concentrations using the Borusyak et al. (2022) (BJS) estimator.

Figure 5 shows the dynamic effect of being crossed by a car route for cells at each period relative to treatment on the concentration of NO. In the pre-treatment period, we notice a slight negative pre-trend for the treated group, which may indicate that treated cells were not following a parallel trend in NO concentration before treatment. In the post-period, we see a decrease, persistent in time, for the treated group. NO_2 (Figure 6) now displays reasonable parallel trends between groups prior to treatment, and a significant and persistent decrease in NO_2 concentration for the treated group

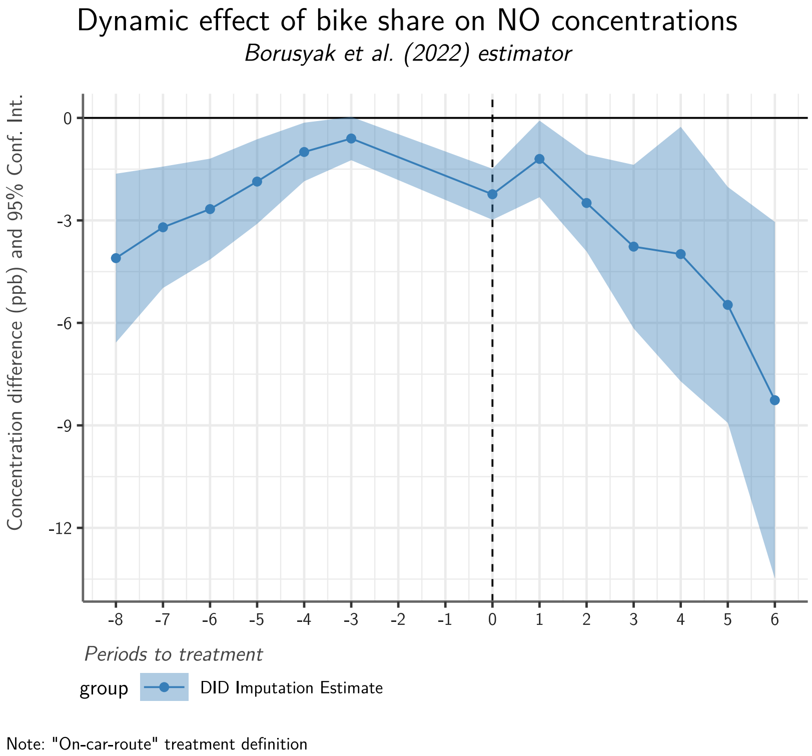

Figure 5: Dynamic effect of bike share on NO concentrations, BSJ estimator

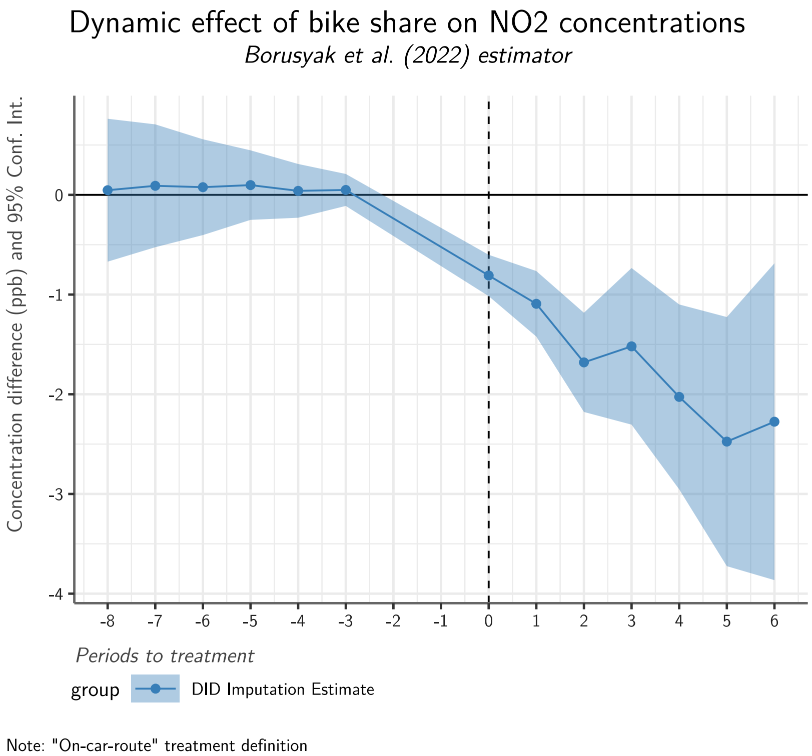

Figure 6: Dynamic effect of bike share on NO_2 concentrations, BSJ estimator

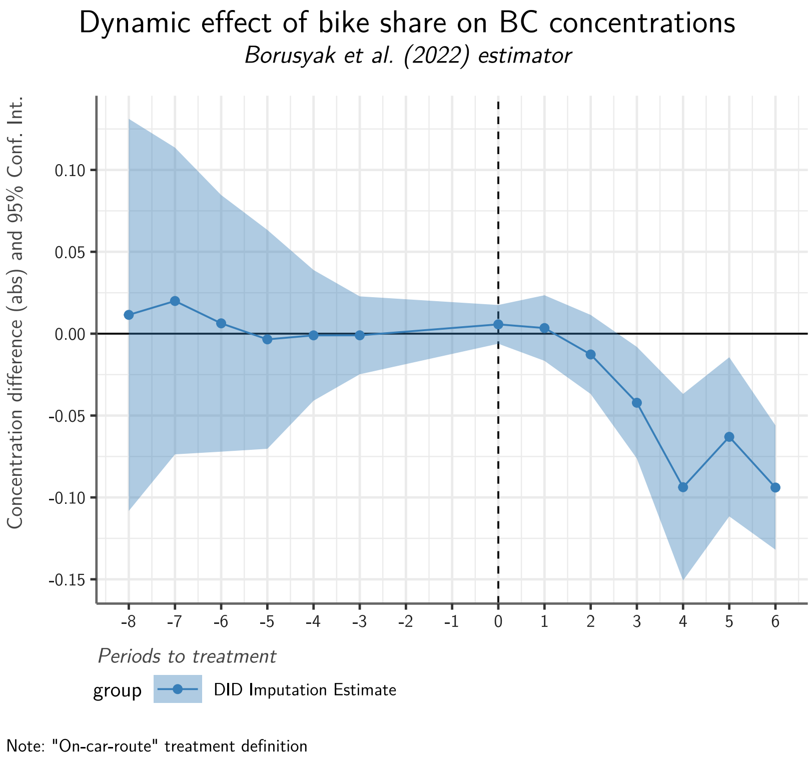

Figure 7: Dynamic effect of bike share on BC concentrations, BSJ estimator

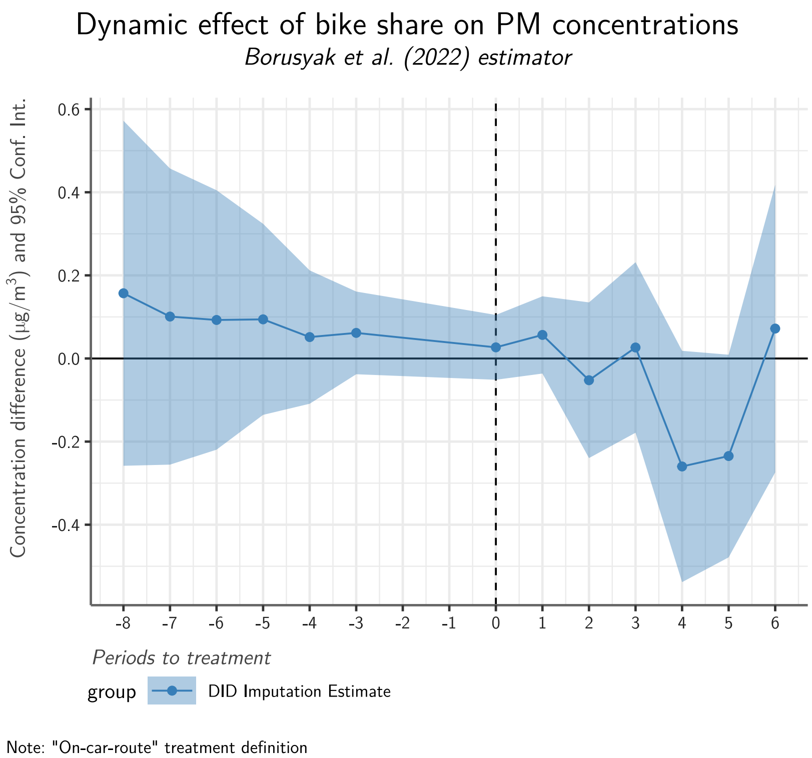

Figure 8: Dynamic effect of bike share on PM 2.5 concentrations, BSJ estimator

after treatment. BJS dynamic effects (Figure 7) confirm TWFE results for BC, with pre-trends consistent with the parallel trend assumption and a negative and persistent effect of bike share on BC concentrations. Finally, the effects of bike share on PM 2.4 (Figure 8) remain indistinguinshable from zero.

5.3 Testing treatment exogeneity

DD estimations rely on the assumption that treatment status and timing are orthogonal to covariates. I now turn to the testing of the exogeneity assumption, both on the cross-sectional level and the temporal level. To check for the cross-sectional exogeneity of treatment, I run a linear probability model on the treatment status, using a battery of covariates averaged for years before 2013. The estimating equation takes the form of

$$Y_i = \beta_0 + \beta X_{i\bar{t}} + \gamma_b + \varepsilon_i \tag{4}$$

where Y_i is the binary treatment status (0 if never treated, 1 if eventually treated) of cell i, $X_{i\bar{t}}$ the vector of covariates average over the pre-treatment period $\bar{t}$ (i.e., before 2013), β the vector of coefficients associated with the covariates, and γ_b are borough fixed effects.

Results of the linear probability model are reported in Table 11. Magnitudes are in general fairly small, but a handful of covariates are systematically associated with a higher probability of a cell having a car route crossing it. In preferred specifications with borough fixed effects (columns 3 and 4), higher levels of residential built area, office area and general built area are associated with a higher probability of treatment. Bike lane length seems to be associated with a higher probability of treatment, but the different types take varying statistical significance depending on the specification.[15] Population and median income are predictors of treatment in specifications without borough fixed effects, but their predictive power vanishes when adding them. Finally, higher counts of college graduates per cell are associated with a higher probability of treatment.

Table 12 estimates the same model as in 4, with the year of treatment now taking the role of the dependent variable. The goal of this estimation is to check whether covariates are good predictors for the timing of treatment. Negative coefficients are interpreted as covariates that make treatment occur earlier. The extent of residential area is thus associated with slightly later treatment, while total built area is a predictor of earlier treatment. Cycle routes and painted cycle lanes are also associated with earlier treatment, while protected lanes do not appear to be a predictor of treatment. In preferred specifications with borough fixed effects, population and median income are not statistically significant predictors of treatment timing. Finally, college graduates are associated with earlier treatment.

Given their statistical significance in predicting both treatment status and the timing

[15] These measures of bike lanes are highly correlated to each other, and might be relatively collinear.

Table 11: Effects of baseline covariates on probability of treatment

	Probability of being treated			
	(1)	(2)	(3)	(4)
Constant	0.1003***	0.1003**		
	(0.0092)	(0.0475)		
Other floor area (sq ft)	0.0007	0.0007	0.0017	0.0017
	(0.0015)	(0.0029)	(0.0020)	(0.0018)
Retail area (sq ft)	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Residential area (sq ft)	0.0000	0.0000	0.0000*	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Office area (sq ft)	0.0000***	0.0000*	0.0000*	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Commercial area (sq ft)	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Built area (sq ft)	0.0000	0.0000	0.0000*	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
At-least-painted cycle lanes (ft)	-0.0012	-0.0012	0.0000***	0.0000
	(0.0010)	(0.0009)	(0.0000)	(2.8020)
Cycle route (ft)	0.0001***	0.0001*	0.0001	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Painted cycle lanes (ft)	0.0014	0.0014	0.0001***	0.0001
	(0.0010)	(0.0009)	(0.0000)	(2.6784)
Protected cycle lanes (ft)	0.0015	0.0015*	0.0000	0.0000
	(0.0010)	(0.0009)	(0.0000)	(2.8896)
Population over 25	-0.0002***	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Population	0.0001***	0.0001	0.0001	0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Median household income	0.0000***	0.0000**	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
College graduates	0.0005***	0.0005***	0.0003**	0.0003***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Borough FE			✓	✓
Standard-errors	Robust	Cluster CD	Cluster CD	Conley (0.59km)
Observations	9,089	9,089	9,089	9,089
Squared Correlation	0.277	0.277	0.391	0.391
Pseudo R^2	0.288	0.288	0.506	0.506
BIC	6,473.067	6,473.067	4,568.309	4,568.309

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Robust indicate heteroskedasticity-consistent standard errors, *Cluster CD* denote standard errors clustered at the community district, and *Conley* are standard errors robust to spatial dependence computed following Conley (1999).

Table 12: Effects of baseline covariates on timing of treatment

	Year of treatment			
	(1)	(2)	(3)	(4)
Constant	9,199.0699***	9,199.0699***		
	(82.7379)	(380.8176)		
Other floor area (sq ft)	-5.8446	-5.8446	-13.6360	-13.6360
	(14.7006)	(26.0137)	(15.8736)	(14.1585)
Retail area (sq ft)	0.0003	0.0003	0.0003	0.0003
	(0.0007)	(0.0011)	(0.0008)	(0.0007)
Residential area (sq ft)	0.0026	0.0026	0.0043*	0.0043**
	(0.0064)	(0.0052)	(0.0025)	(0.0021)
Office area (sq ft)	0.0011***	0.0011	0.0009*	0.0009**
	(0.0004)	(0.0007)	(0.0005)	(0.0005)
Commercial area (sq ft)	0.0012	0.0012	0.0032	0.0032
	(0.0064)	(0.0052)	(0.0025)	(0.0022)
Built area (sq ft)	-0.0027	-0.0027	-0.0043*	-0.0043**
	(0.0064)	(0.0052)	(0.0025)	(0.0021)
At-least-painted cycle lanes (ft)	15.9987	15.9987	-0.6707***	-0.6707
	(33.4240)	(28.2850)	(0.1279)	(29,801.1007)
Cycle route (ft)	-0.5449***	-0.5449	-0.4542	-0.4542**
	(0.1906)	(0.4194)	(0.3013)	(0.2287)
Painted cycle lanes (ft)	-15.3254	-15.3254	-0.3133*	-0.3133
	(33.4210)	(28.4746)	(0.1598)	(30,109.0169)
Protected cycle lanes (ft)	-13.5124	-13.5124	0.1876	0.1876
	(33.4204)	(28.3052)	(0.1434)	(29,933.4526)
Population over 25	1.6746***	1.6746	1.6433	1.6433
	(0.6230)	(2.3883)	(1.7218)	(1.1214)
Population	-0.9936***	-0.9936	-0.9489	-0.9489
	(0.3711)	(1.3676)	(0.9755)	(0.6694)
Median household income	0.0065***	0.0065*	0.0017	0.0017
	(0.0008)	(0.0034)	(0.0031)	(0.0014)
College graduates	-3.6981***	-3.6981***	-2.3044**	-2.3044***
	(0.3124)	(1.0816)	(0.9850)	(0.5169)
Borough FE			✓	✓
Standard-errors	Robust	Cluster CD	Cluster CD	Conley (0.59km)
Observations	9,089	9,089	9,089	9,089
R^2	0.013	0.013	0.391	0.391
Within R^2			0.112	0.112

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Robust indicate heteroskedasticity-consistent standard errors, *Cluster CD* denote standard errors clustered at the community district, and *Conley* are standard errors robust to spatial dependence computed following Conley (1999).

of treatment, I control for residential area, office area, total built area, at-least-painted cycle lanes, median household income and count of college graduates in my specifications.

5.4 Robustness checks

I perform the same analysis with two alternative treatment definitions: (1) the cell is within 300 metres of a bike share station, (2) the cell is within the smallest convex polygon that includes all bike share stations. These treatment definitions are less well suited to capturing the areas where fewer cars might have been driven due to bike share, and are more closely associated with the areas of bike share implementation, which might make treatment less exogenous to other factors. Conditional on these limitations, I find comparable results using the alternative treatment definitions (see Appendix C).

Finally, I compute standard errors robust to spatial dependence following Conley (1999) (Appendix B). For most specifications, this improves statistical significance.

5.5 Discussion

Results presented in this section indicate that bike share has reduced the concentration of NO by up to 13.4% and BC by up to 2.7% with respect to pre-2013 mean concentrations in NYC. The dynamic estimates shown in the event study plots provide support for the parallel trends assumption for both pollutants, and lead me to conclude that the decreasing effect of bike share on NO and BC is likely causal. The pre-treatment trends displayed by NO_2 in its event study plot call for caution when interpreting the statistically significant negative coefficients as causal. When analysing NO_2 with the BJS estimator, however, the parallel trends assumption seems better supported by the graphical evidence. The impact of bike share on NO_2 is thus uncertain, although it is important to note that NO and NO_2 are often highly correlated and have similar emission sources. As we have seen, the impact on PM 2.5 of bike share is relatively noisy, and we cannot conclude that bike share had a significant impact on PM 2.5 concentrations in NYC.

Comparing these results with related literature is challenging, as most studies focus on other pollutants such as PM 2.5, PM 10 and carbon monoxide (CO). Low-emission-zones studies have found that PM 10 decreases by 5.5 to 9% (Wolff, 2014; Zhai and Wolff, 2021), while Jiang et al. (2017) finds very limited impacts on nitrogen oxides. Some of the literature on congestion charge has found significant decreases in NO_2 and PM 10 (Tonne et al., 2008), while others registered an increase in NO_2 but a decrease in NO (Green et al., 2020). Finally, subway and urban railway expansions have been associated with a reduction of aerosol particulates (similar to PM) of 4% (Gendron-Carrier et al., 2022) and CO by 5 to 15 percent (Chen and Whalley, 2012). The results I obtain, although for different pollutants, are of similar magnitude.

Shr et al. (2022) is the only other study examining the impact of bike share on air pollution using causal inference. Their setting is a two-period DD in Taiwan's second-biggest city. They find moderate decreases in CO of around 2.0%, but no statistically significant decrease in NO or NO_2. They note that CO is the only pollutant they observe of which a significant share may be attributed to two-wheeled ICE vehicles. This suggests that some substitution might have occurred for this class of vehicles, and highlights that the impact of bike share on air quality is highly dependent on the transport modes it substitutes. As we will see in the next section, I argue that taxis play an important role in NYC's transport environment, and find suggestive evidence that bike share substitutes taxi service.

6 Mechanism

In section 2, I discussed the main mechanism through which bike share might have impacted air pollution concentrations, which is the substitution away from internal-combustion-engine (ICE) vehicles in favour of cycling. In this section, I explore the available evidence to support this mechanism. I start by reviewing the literature and policy reports before turning to the data and analysing the evolution of taxi trips in areas served by bike share.

6.1 Introduction

The main hypothesis for bike share to reduce pollution is that the introduction of bike share reduces the relative price of (and increases the accessibility to) cycling. This change in the relative attractiveness of the cycling transport option will induce some trips to be substituted away from other transport modes. If these previous transport modes were ICE vehicles, then bike share will have reduced emissions associated with these vehicles. In the previous section, we saw that the concentrations of key pollutants generated by ICE decreased in areas where fewer vehicles are likely to have been driven due to bike share. Importantly, the previous section has shown a decrease in a harmful *by-product* of traffic, air pollution. Here, I examine there is direct evidence that traffic itself decreased.

To tackle this question, I turn to taxis. Taxis are a useful measure of traffic and ICE vehicles for several reasons. First, taxi trips have been identified by previous research to be good proxies for overall road traffic (Castro et al., 2012; Kan et al., 2019; Kong et al., 2016). Second, taxi riding is a popular mode of transport in NYC. In 2014, taxis made on average 485 thousand trips per day, transporting 236 million passengers per year (New York City Taxi and Limousine Commission, 2014).

Taxi rides in NYC also exhibit many characteristics that make them good substitution candidates for bike share. First, an average taxi ride is similar to an average bike share ride: 55% of taxi trips are less than 3 kilometres long, while around 80% of bike share trips are less than 3 kilometres. Rider demographics are also reasonably comparable, with 70% of taxi riders below 35 years old, while the median age of a bike share subscriber is 33. In addition, bike share was implemented in areas with heavy taxi use: 95% of traditional "yellow" taxi pick-ups occurred in Manhattan below 96th street, an area that

(a) Location of Midtown

(b) Fares and travel time camparison

Figure 9: Bike share vs Taxi service in Midtown, 2019 NYC Mobility Report

bike share served by 2016. Finally, the 2019 NYC Mobility Report presents a compelling case study, comparing taxi service and bike share in Midtown (see Figure 9). In Midtown, where close to 50% of all counted vehicles were taxis or ride-hailing cars, a bike share ride was consistently faster than a taxi ride for trips ranging from 0.5 to 2 miles, and came at a fraction of the taxi fare (see Figure 9b), further hinting towards the substitution potential of bike share for taxi service.

Beyond similar characteristics and substitution potential, previous research has revealed a direct substitution relationship between bike share and taxi rides. Molnar and Ratsimbazafy (2017) show that, following the outage of a bike share station, taxi pickups increase in its vicinity. Moreover, they estimate the long-run substitution of taxis due to bike share of 3 to 4%, with taxi drivers operating in the bike share area seeing a relative decline in revenue.

6.2 Testing the substitution mechanism

Based on the anecdotal and empirical evidence presented above, I further investigate the relationship between bike share and taxi service using the universe of taxi trips from 2009 to 2019 provided by the NYC Taxi & Limousine Commission (NYC T&LC). There are on average 170 million taxi trips per year, for a total of about 1.1 billion trips during my study period. Each trip is characterised by origin and destination locations, start and end time and date, distance driven, fares, and other variables. Using these data, I identify taxi trips most likely to be substitutable by bike share. I use the taxi trip's travel distance, and define substitutable trips as those which are five kilometres or less, based on the fact that 85% of bike share trips are less than five kilometres. I aggregate short (i.e., less than five kilometres) and long taxi trips at the taxi zone of pickup.[16] I then specify a dynamic staggered DD estimation that captures the effect of bike share deployment on the level of short and long taxi trips. The estimating equation is given by:

$$Y_{itd} = \sum_{k=-9}^{-2} \beta_k \cdot Treat_{ik} + \sum_{k=0}^{6} \beta_k \cdot Treat_{ik} + \phi_t + \gamma_i + \eta_{it} + \varepsilon_{it} \tag{5}$$

where Y_{itd} is the number of taxi trips of length d (i.e., short or long) in taxi zone i in month t. Unlike the main analysis, the treatment variable $Treat_i$ is defined, for each taxi zone, as being within 300 metres of a bike share station. In the present context, it is most likely that the impact of bike share on taxi pickups will be most prominent close to bike share stations. Finally, ϕ_t, γ_i and η_{it} denote time, taxi-zone, and borough-time fixed effects, respectively, while ε_{it} serves as the error term.

The β_k coefficients are plotted in Figure 10, separately for short trips (green, circles) and long trips (orange, triangles). In the periods leading to treatment, there are no significant differences in taxi pickups for both short and long taxi trips between taxi zones close to bike share stations and the others. Following treatment, areas served by bike share see a decrease in the number of pickups. Notably, the decrease is larger for short trips compared to long trips. I interpret this as suggestive evidence that bike share reduces taxi trips taken, and more so for taxi trips that are most similar to bike share trips.

6.3 Other mechanisms

While I expect substitution to be the main channel through which bike share impacts pollution, other channels may come into play. I identify three additional channels through which bike share may affect air pollution: the crowding effect, the efficiency externality and the strength-in-numbers virtuous cycle.

The crowding effect describes the effect of increasing the number of bikes on the streets. Although they take much less space per traveler, bikes may still create congestion on streets, especially due to lower travel speeds which may force other vehicles to slow down, creating congestion and increasing pollution emissions. Bike lanes, by removing lanes for other road vehicles, may have a similar effect. On the other hand, the crowding effect may lead ICE vehicles to drive alternative routes to avoid newly congested areas, displacing air pollution rather than reducing it. Evidence from Hamilton and Wichman (2018), however, indicates that congestion tends to decrease in areas served by bike share, and suggests limited road traffic displacement to adjacent areas. Importantly, the

[16] There are 263 taxi zones defined by the T&LC, see Figure A.3. Their size varies, with smaller zones in southern Manhattan and larger ones in Staten Island, likely related to the level of taxi traffic in each zone.

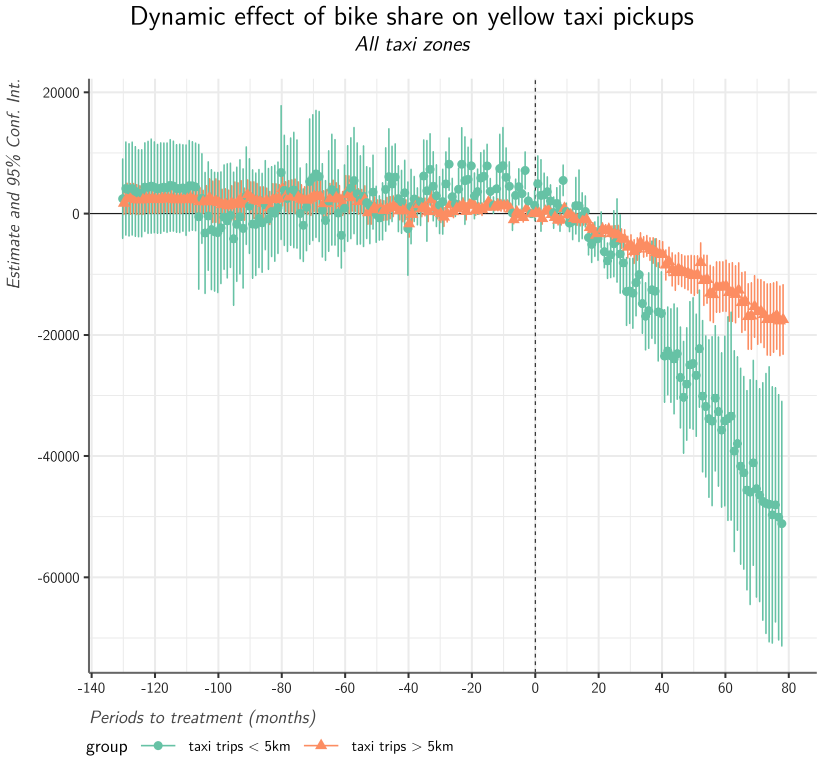

Figure 10: Dynamic effect of bike share on yellow taxi pickups

crowding out effect would go against me finding an impact of bike share on air pollution.

Usage of bike share varies across time and space. Popular origin stations experience a high demand for bikes, while docks at popular destination stations are sometimes full. To ensure a sufficient level of service, bikes need to be rebalanced between stations. This need for efficiency, however, may create externalities. Rebalancing in NYC is done with "bike trains" (an e-bike that can carry 12 to 16 bikes) and ICE vehicles. The trips made by the latter, especially during highly congested periods, increase emissions and congestion, creating an efficiency externality. While little data is available on the scope and frequency of rebalancing, I expect the induced increase in driving and congestion to have a relatively small effect on air pollution due to its relatively small footprint compared to total traffic. Increased air pollution due to station rebalancing would bias the estimates of bike share downwards.

Finally, increasing the number of bike trips made in the city through bike share may create a virtuous cycle: by making bikes more ubiquitous and accessible, the attitude of ICE vehicles towards bikes may change over time. More cyclists on the streets create a "safety-in-numbers" effect and lessen the perceived danger of cycling for potential cyclists, a crucial factor for cycling take-up identified by the literature (Pucher and Buehler, 2012). More bike trips also mean a shift in the perception of cycling, contributing to making cycling a more acceptable transport option. This all leads, at the margin, to more people switching to cycling, further decreasing air pollution if their previous modes of transport were ICE vehicles. The virtuous cycle initiated by bike share would overestimate the effect of bike share if the increase in non–bike-share cycling was spatially correlated with the bike share area.

7 Conclusion

In this paper, I investigate the effect of the implementation and gradual rollout of the NYC bike share program on air pollution concentrations. Leveraging the gradual expansion of the system and a treatment variable capturing areas most likely to be affected by bike share, I find that bike share reduced concentrations of NO_2 by up to 13.4% and BC by up to 2.7% compared to pre-implementation mean concentrations.

These effects differ from estimates made in the previous literature. In particular, Shr et al. (2022) find no impact of bike share on nitrogen oxides and only limited decrease in carbon monoxide in Taipei's second-largest city. The disparity between the two results might stem from different likely sources of substitution. In NYC, the analysis of taxi trips suggests that the substitution away from taxi service might explain the decrease in pollution levels. In Taipei, as Shr et al. (2022) have noted, most of the substitution may come from public transport riders, pedestrians and some two-wheeled-vehicle riders (hence the decrease in carbon monoxide). This highlights the importance of identifying the source of substitution, as it will determine the environmental impact of sustainable transport policies and micromobility services.

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A Additional maps

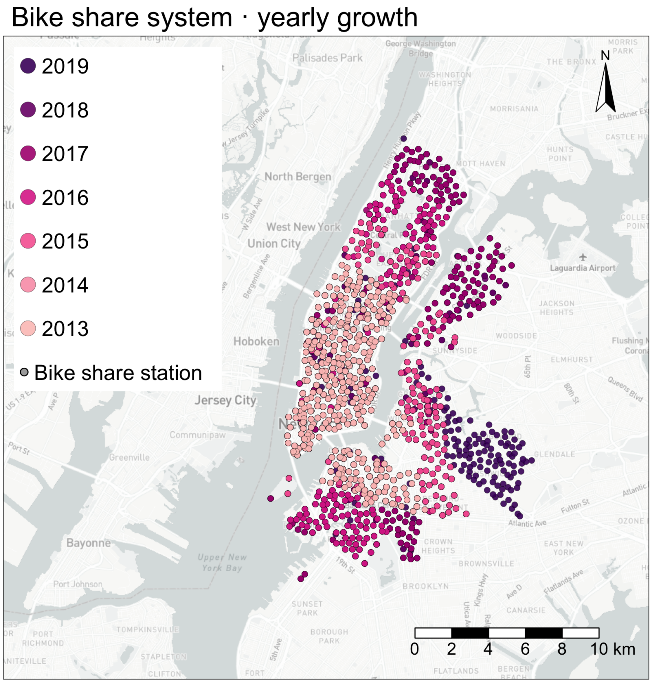
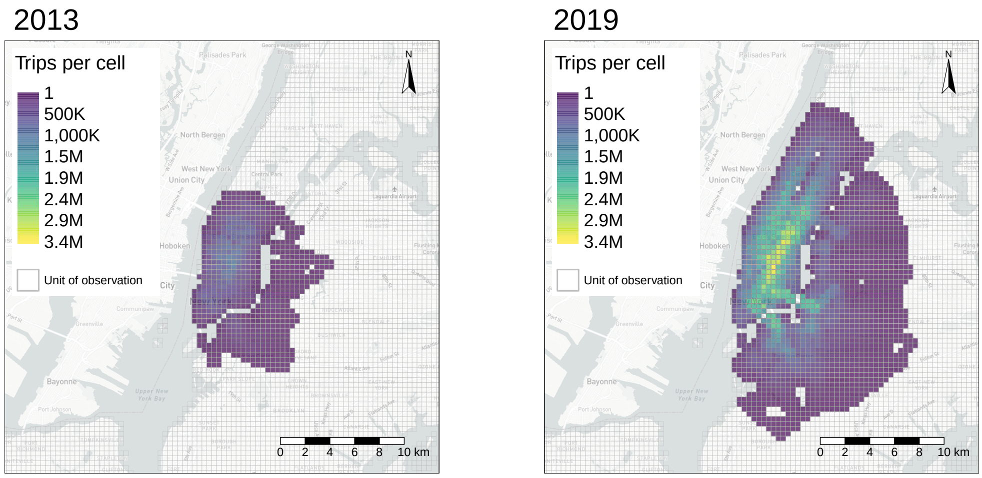
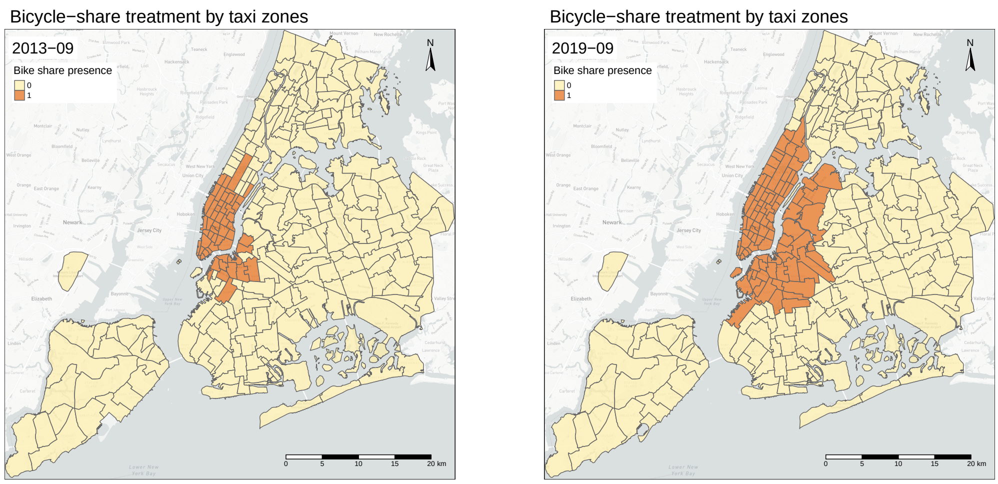


Figure A.1: Gradual rollout of bike share stations in NYC



(a) 2013 (b) 2019

Figure A.2: Spatial extent of treatment and imputed trips per cell at bike share implementation and last study period



(a) 2013 (b) 2019

Figure A.3: Map of taxi zones in proximity of bike share stations

B Conley standard errors

I compute standard errors robust to spatial dependence following Conley (1999) for all specifications.

B.1 TWFE Average treatment effects

Table B.1: Effect of bike share on NO concentrations

	NO			
	(1)	(2)	(3)	(4)
On-car-route	-2.5360***	-2.7281***	-1.0262***	-0.6398***
	(0.3540)	(0.3507)	(0.1957)	(0.1996)
Baseline controls		✓	✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Year-Community district FE			✓	
Year-Borough FE				✓
Mean concentration pre-treat.	20.322	20.353	20.353	20.353
% mean concentration pre-treat.	-12.479	-13.404	-5.042	-3.144
Observations	91,710	90,898	90,898	90,898
R^2	0.906	0.908	0.960	0.937
Within R^2	0.049	0.066	0.013	0.010

Conley (0.59km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B.2: Effect of bike share on NO2 concentrations

	NO2			
	(1)	(2)	(3)	(4)
On-car-route	-1.1489***	-1.2554***	-0.2010***	-0.4141***
	(0.0967)	(0.0955)	(0.0647)	(0.0629)
Baseline controls		✓	✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Year-Community district FE			✓	
Year-Borough FE				✓
Mean concentration pre-treat.	19.950	20.007	20.007	20.007
% mean concentration pre-treat.	-5.759	-6.275	-1.005	-2.070
Observations	91,710	90,898	90,898	90,898
R^2	0.978	0.979	0.994	0.985
Within R^2	0.081	0.123	0.012	0.026

Conley (0.59km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B.3: Effect of bike share on BC concentrations

	BC			
	(1)	(2)	(3)	(4)
On-car-route	-0.0253***	-0.0280***	-0.0078	-0.0097**
	(0.0057)	(0.0057)	(0.0052)	(0.0047)
Baseline controls		✓	✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Year-Community district FE			✓	
Year-Borough FE				✓
Mean concentration pre-treat.	1.015	1.017	1.017	1.017
% mean concentration pre-treat.	-2.494	-2.757	-0.771	-0.952
Observations	91,710	90,898	90,898	90,898
R^2	0.956	0.956	0.979	0.970
Within R^2	0.006	0.011	0.001	0.002

Conley (0.59km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B.4: Effect of bike share on PM concentrations

	PM			
	(1)	(2)	(3)	(4)
On-car-route	-0.0097	-0.0320	-0.0091	0.0538***
	(0.0262)	(0.0260)	(0.0174)	(0.0184)
Baseline controls		✓	✓	✓
Cell FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Year-Community district FE			✓	
Year-Borough FE				✓
Mean concentration pre-treat.	9.433	9.441	9.441	9.441
% mean concentration pre-treat.	-0.103	-0.339	-0.096	0.569
Observations	91,710	90,898	90,898	90,898
R^2	0.978	0.979	0.992	0.984
Within R^2	0.000	0.018	0.003	0.016

Conley (0.59km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Alternative treatment definitions

In this appendix, perform the TWFE estimations using alternative treatment definitions.

C.1 Stations within 300m of cell

Table C.1: Effect of bike share on NO concentrations

	NO		
	(1)	(2)	(3)
Station	-3.8915***	-2.1059***	-1.5368***
	(1.1872)	(0.5868)	(0.5721)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	20.353	20.353	20.353
% mean concentration pre-treat.	-19.120	-10.347	-7.551
Observations	90,898	90,898	90,898
R^2	0.910	0.960	0.937
Within R^2	0.089	0.028	0.021

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C.2: Effect of bike share on NO2 concentrations

	NO2 (1)	(2)	(3)
Station	-1.4994***	-0.4007***	-0.5309***
	(0.3277)	(0.1384)	(0.1807)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	20.007	20.007	20.007
% mean concentration pre-treat.	-7.494	-2.003	-2.654
Observations	90,898	90,898	90,898
R^2	0.979	0.994	0.985
Within R^2	0.122	0.018	0.028

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C.3: Effect of bike share on BC concentrations

	BC (1)	(2)	(3)
Station	-0.0404**	-0.0170*	-0.0153
	(0.0162)	(0.0098)	(0.0093)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	1.017	1.017	1.017
% mean concentration pre-treat.	-3.978	-1.668	-1.506
Observations	90,898	90,898	90,898
R^2	0.957	0.979	0.970
Within R^2	0.015	0.002	0.003

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C.4: Effect of bike share on PM concentrations

	PM		
	(1)	(2)	(3)
Station	-0.1002	-0.0942**	0.0090
	(0.0788)	(0.0419)	(0.0514)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	9.441	9.441	9.441
% mean concentration pre-treat.	-1.061	-0.997	0.095
Observations	90,898	90,898	90,898
R^2	0.979	0.992	0.983
Within R^2	0.022	0.007	0.014

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C.2 Cells within the convex hull

Table C.5: Effect of bike share on NO concentrations

	NO		
	(1)	(2)	(3)
Convex polygon	-2.7534**	-0.1855	-0.3325
	(1.0736)	(0.6438)	(0.5012)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	20.353	20.353	20.353
% mean concentration pre-treat.	-13.528	-0.911	-1.633
Observations	90,898	90,898	90,898
R^2	0.907	0.959	0.936
Within R^2	0.058	0.008	0.008

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C.6: Effect of bike share on NO2 concentrations

	NO2 (1)	(2)	(3)
Convex polygon	-1.1882***	0.0989	-0.2136
	(0.3380)	(0.1864)	(0.2059)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	20.007	20.007	20.007
% mean concentration pre-treat.	-5.939	0.494	-1.067
Observations	90,898	90,898	90,898
R^2	0.979	0.994	0.985
Within R^2	0.100	0.010	0.016

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C.7: Effect of bike share on BC concentrations

	BC (1)	(2)	(3)
Convex polygon	-0.0379**	-0.0170***	-0.0167*
	(0.0143)	(0.0051)	(0.0093)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	1.017	1.017	1.017
% mean concentration pre-treat.	-3.729	-1.669	-1.638
Observations	90,898	90,898	90,898
R^2	0.957	0.979	0.970
Within R^2	0.015	0.002	0.004

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C.8: Effect of bike share on PM concentrations

	PM		
	(1)	(2)	(3)
Convex polygon	-0.0353	0.0399	0.0748
	(0.0802)	(0.0378)	(0.0535)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	9.441	9.441	9.441
% mean concentration pre-treat.	-0.374	0.423	0.792
Observations	90,898	90,898	90,898
R^2	0.979	0.992	0.984
Within R^2	0.018	0.004	0.018

Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*