

Cycling toward cleaner cities? Evidence from New York City's Bike Share Program*

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Abstract

What is the impact of cycling on cities' air quality? This paper leverages the staggered roll-out 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 2009 and 2019. The bike share data is used to map areas served by bike share, which I compare to unserved areas using a staggered difference-in-differences strategy to retrieve causal estimates. I find that the arrival of bike share is associated with a 3 to 13% reduction in the concentrations of pollutants associated with road traffic. In addition, I 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 reduces 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, 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 some 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, Heywood, and Navarro Paniagua, 2020; Tonne et al., 2008) and the opening of new subway lines (Y. Chen and Whalley, 2012; Gendron-Carrier et al., 2022), the impact of cycling on air pollution has received much less attention. Existing research on the topic relies heavily on hypothetical rates of substitution towards cycling to estimate bike share's environmental impact (Fishman, Washington, and Haworth, 2014; Médard de Chardon, 2016; Qiu and He, 2018; Ricci, 2015; Y. Zhang and Mi, 2018; Zheng et al., 2019). There is a notable dearth of studies investigating the causal impact of bike share on air quality using observational data. 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), while (Shr, Yang, and Y.-S. Chen, 2022) look directly at air quality in Taiwan and do not find a robust effect of bike share. The main challenges in causally estimating this relationship are the availability of high-resolution pollution data over long periods and a credible identification strategy. I address these challenges by using the staggered roll-out of the NYC bike share system 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), the timing and spatial extent of each roll-out wave are as good as random. The staggered roll-out 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. These results are robust to a battery of specifications and hold when using novel DD estimators robust to 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 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), qin2021].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 shown by this literature, 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 cities' pollution abatement strategies. The two (non-exclusive) options are either making vehicles less polluting, or reducing the number of trips (or kilometers driven). In the latter option, one strategy is to replace road transportation trips with other 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 wide scale, NYC effectively made cycling easier, more convenient and cheaper in large 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 kilometers 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, Heywood, and Navarro Paniagua (2020) both examine the effect of the London congestion charge on air pollutants' concentrations and find statistically and economically significant decreases,

¹Air 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).

with Tonne et al. (2008) valuing the decrease as 1888 years of life saved. Y. Chen and Whalley (2012) and Gendron-Carrier et al. (2022) check whether subway lines openings decreased air pollution, with Y. 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. Y. Chen and Whalley (2012) finds that pollution decreases significantly after the opening, while the results from 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 bike share's environmental impacts.

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 Y. Zhang and Mi (2018) assume that all or nearly all bike share trips replace ICE vehicles, and estimate unrealistically large reductions in greenhouse gases emissions. Fishman, Washington, and Haworth (2014) take a more realistic approach by basing 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. The present 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. 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, Yang, and Y.-S. Chen (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, Yang, and Y.-S. Chen (2022) do not find an impact on air pollution in Taiwan, underscoring the uncertainty around that outcome, 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 New York City, 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 together, section 4 presents the data and section 3 the empirical strategy, 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. Next, I 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 $j = 1, \dots, J$ (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:

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

The introduction of bike share suddenly 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:

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

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

After establishing the conditions that enable an individual to switch to cycling thanks to bike share, we 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 substitution mechanism implies that pollution reduces in areas where less polluting vehicles are driven after the implementation of bike share. In the 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. In the estimation, I use it as the treatment variable 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. At the same time, other changes that could be happening concurrently with the expansion of bike share could also change pollution concentrations. In this section, I present the identification challenges and how my empirical strategy mitigates the pitfalls.

²It 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.

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.

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.

The staggered DD addresses the concerns around the identification of a causal relationship between bike share and air quality. First, by carefully identifying the areas where bike share is expected to affect pollutant concentrations the most, it is less sensitive to the placement of bike share stations. As we will see below in greater detail, the treatment area is given by the area where fewer cars are expected to drive. That area covers a larger tract of land than the stations themselves. Second, the identification relies on the differential timing of the bike share expansion. It exploits the fact that bike share's area of influence changed over the years at a seemingly random pace.

What does that mean in detail? 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 itinerary 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 is not accessible. This constitutes the first element that introduces variation on the spatial scale that is unrelated to the precise placement of bike share stations.

On the other hand, 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 2013. At the same time, the spatial extent of the initial launch was significantly

³The highest concentration of 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 (Penn Station, Grand Central, Port Authority Bus Terminal), and generates an important share of NYC's transport demand.

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 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 and based on car itineraries, I argue that 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 ??, 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 be following 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 has to remain 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 (which, you will recall, are 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.

One of the central requirements for this estimation strategy is the precise identification

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

⁵The considerable reworking of plans and schedule was reported at the time in the press (see for example <https://archive.ph/jZ14> 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.

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, a routing algorithm able to take into account the road network at different periods (Pereira et al., 2021), I compute, for each pair of stations, 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 model with multiple treatment periods:

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

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 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;

⁶The 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.

⁷Alternatively, 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.

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 event study, plots the treatment effect for all periods. The dynamic specification also allows us to test for differential pretrends 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:

$$Y_{ct} = \sum_{k=-9}^{-2} \beta_k \cdot Treat_{ck} + \sum_{k=0}^6 \beta_k \cdot Treat_{ck} + \phi_t + \gamma_c + C_{ct0} + \varepsilon_{ct} \quad (3)$$

where k denotes the relative time to the first year of treatment, the other terms being 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, Jaravel, and Spiess (2022), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfoeuille (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, Jaravel, and Spiess (2022). This estimator has several advantages compared to alternative robust estimators, the main one being its high efficiency in computing standard errors.

⁸Community 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 air pollutants' concentrations are the main outcome variables of the analysis. The New York City Department of Health and Mental Hygiene (NYC DOH) provides yearly, high-resolution air pollution data covering the city's territory, divided into 9670 300-meter square cells since 2008. This subsection describes these data.

The project known as the New York City Community Air Survey (NYCCAS) is conducted by the NYC DOH and Queens College since 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 micrometers, 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). Several dozens of monitors are distributed around the city, with eighty percent of sites selected randomly, while twenty percent are purposefully chosen near areas of interest and to guarantee minimal coverage of neighborhoods. 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 9670 300-meter 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-meter cells), when satellite-based resolutions range from 1 to 2 kilometers (see for example Gollin, Kirchberger, and Lagakos (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.

In the present paper, I choose to 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, (2) it should be measured close to its emission source. Criterion (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. PM 2.5 captures all the particles that are smaller than 2.5

micrometers (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.⁹ 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, 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. I describe the building of the bike share treatment variable using these data in section 3.

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-meter 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-meter cells using the areal interpolation functions from the areal R package (Prener and Revord, 2019).¹⁰ Variables extracted from the ACS include population, median household income, and tertiary education level.

Zoning and building information is 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 subsumed at the 300-meter cell level using areal interpolation. The main variable used is the total building area.

Finally, I obtain the map of community districts from the NYC Open Data portal, and assign each cell to one of the 59 community districts its area covers the most.

⁹<https://ride.citibikenyc.com/system-data/>, accessed 2022-10-20.

¹⁰Each cell takes the weighted average of census tracts with weights given by the share of each tract's area covering the cell.

4.4 Summary statistics

The variables used in the analysis are summarised in Table 4.4. The yearly counts of cells crossed by a car route (main treatment variable) are displayed in Table 4.4.

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. Event studies from the Borusyak, Jaravel and Spiess (BJS) estimator are provided, followed by tests on the validity of the empirical setting.

5.1 TWFE results

5.1.1 TWFE Average treatment effects

The results are presented for each selected pollutant in turn. Standard errors are clustered at the community district level.¹¹ My preferred specification includes cell and year fixed-effects with baseline controls (Column 2). These results are robust to computing Conley standard errors account for spatial dependence (see Appendix B.1).

Table 5.1.1 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), NO concentrations 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 5.1.1 reports the average treatment effect of bike share on NO₂ concentrations. Bike share significantly reduces NO₂ concentrations in areas where fewer cars are likely to be driven. The decrease in NO₂ represents about 6.2% of pre-treatment concentrations. The impact on BC is reported in Table 5.1.1. For BC as well, concentrations reduce in areas where fewer cars are expected to be driven thanks 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 5.1.1. 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, NO₂ and BC by 3 to 13%, but had no effect on PM 2.5 concentrations.

Tables 5.1.1 to 5.1.1 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 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

¹¹Conley standard errors robust to spatial dependence are reported in Appendix B.

Table 1: Summary statistics

Treatment		Mean	SD	Min	Max
Treated	Bike share trips	184,432.4	425,979.5	0	3,393,072
	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	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*** (0.8595)	-2.7281*** (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

	NO ₂	
	(1)	(2)
On-car-route	-1.1489*** (0.2771)	-1.2554*** (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)	(2)
On-car-route	-0.0253* (0.0128)	-0.0280** (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 (0.0686)	-0.0320 (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

concentrations. Recall from section 3, I input, for each car route between pairs of bike share stations, the number of bike share trips for that pair. I then aggregated the number of bike share trips for each cell. In Tables 5.1.1 to 5.1.1, I report the effect of bike share trips in cells crossed by car routes. The coefficients displayed represent (1) ten thousand bike share trips and (2) the inverse hyperbolic sine transformation of the number of bike share trips.¹²

For NO (Table 5.1.1), ten thousand additional bike share trips through a cell crossed by a car route reduce concentrations by 0.086 parts per billion, or 0.4% of 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 10K bike share trips is smaller for NO₂ but still statistically significant (Table 5.1.1): 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 10K additional bike share trips (statistically significant), but a 1% increase in bike share trips does not significantly reduce concentrations.

Table 7: Effect of bike share on NO concentrations

	NO			
	(1)	(2)	(3)	(4)
Trips (10K)	-0.0839*** (0.0115)		-0.0860*** (0.0114)	
Trips (IHS)		-0.2758*** (0.0850)		-0.2947*** (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*** (0.0034)		-0.0263*** (0.0033)	
Trips (IHS)		-0.1119*** (0.0256)		-0.1218*** (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*** (0.0002)		-0.0010*** (0.0002)	
Trips (IHS)		-0.0032*** (0.0012)		-0.0035*** (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*** (0.0011)		-0.0033*** (0.0011)	
Trips (IHS)		-0.0036 (0.0067)		-0.0057 (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

Dynamic effect of bike share on NO concentrations
"On-car-route" treatment

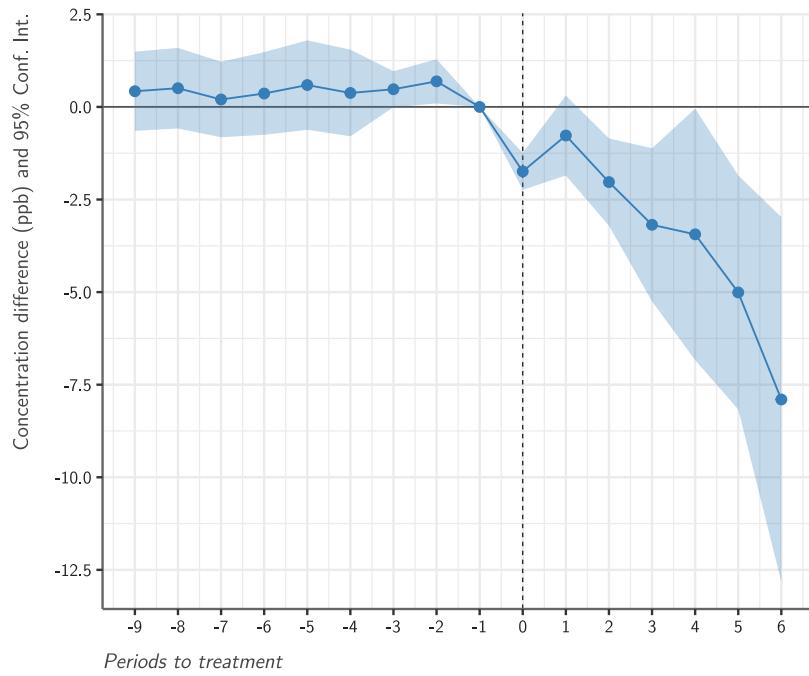


Figure 1: Dynamic effect of bike share on NO concentrations

Dynamic effect of bike share on NO₂ concentrations
"On-car-route" treatment

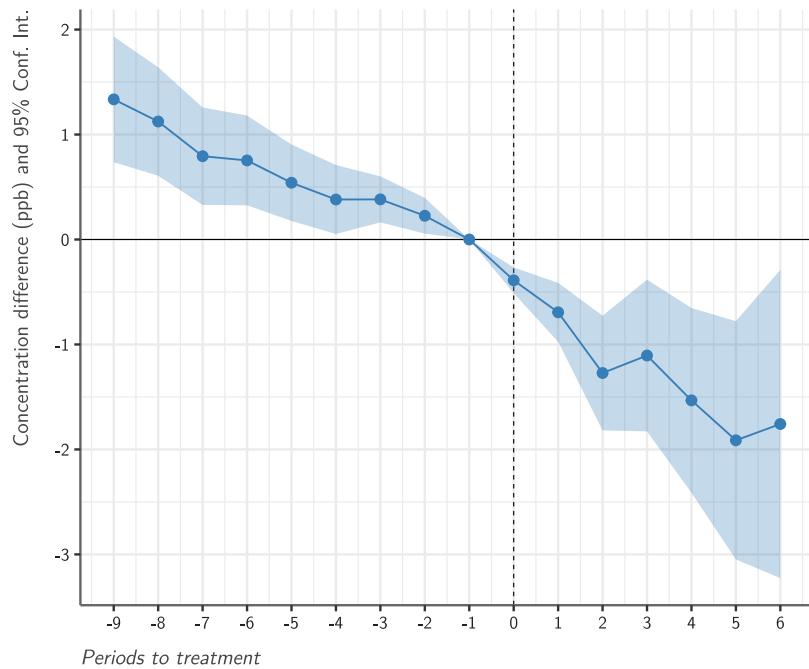


Figure 2: Dynamic effect of bike share on NO₂ concentrations

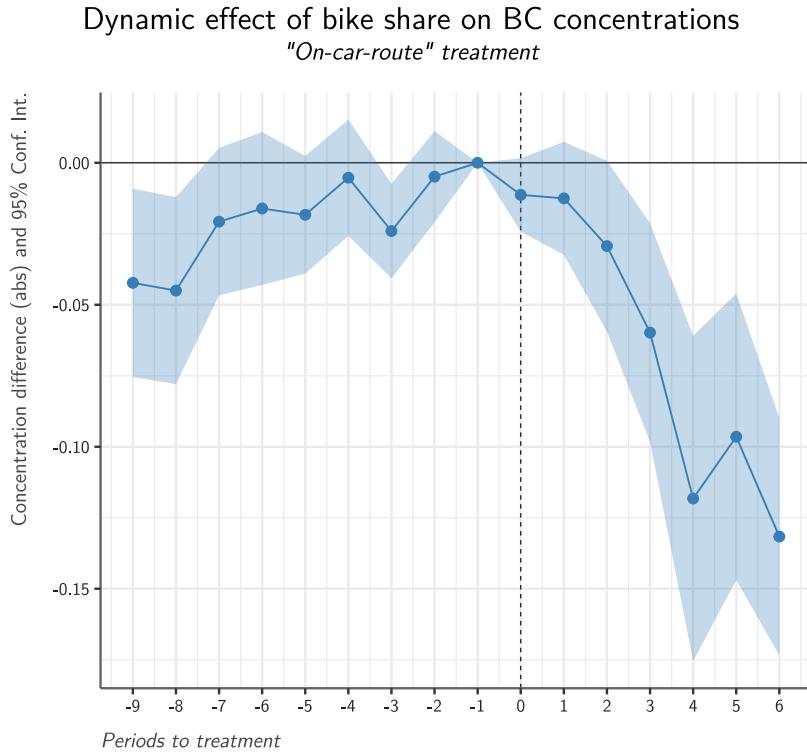


Figure 3: Dynamic effect of bike share on BC concentrations

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 they get crossed by car routes.

¹²The inverse hyperbolic sine (IHS) is a type of log transformation, particularly suited for variables with a large share of zeros (Bellemare, Barrett, and Just, 2013; MacKinnon and Magee, 1990). The IHS value is given by $IHS(x) = \ln(x + \sqrt{x^2 + 1})$. 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%.

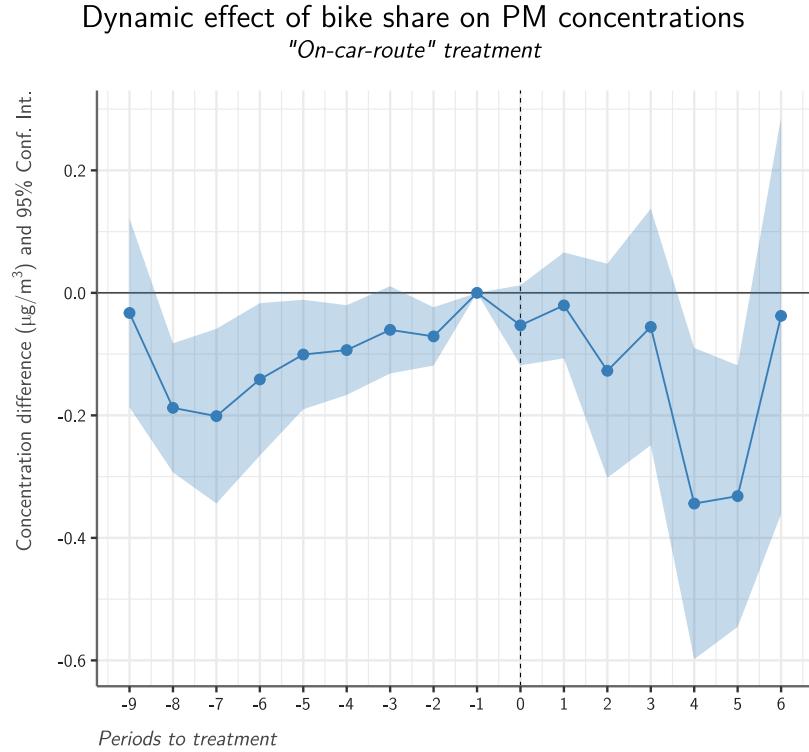


Figure 4: Dynamic effect of bike share on PM 2.5 concentrations

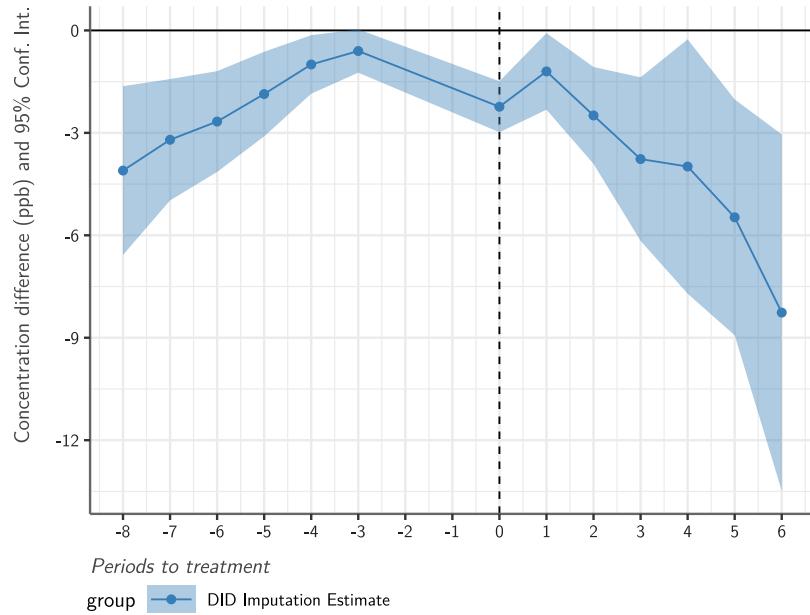
The effect gets larger and is persistent over time. Turning to NO_2 in Figure 2, we also notice and significant decrease post-bike-share introduction. In the period leading to treatment, however, treated cells displayed a statistically significant difference in NO_2 concentration with control cells, which does not support the parallel trends assumption. Dynamic 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, Jaravel, and Spiess (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,

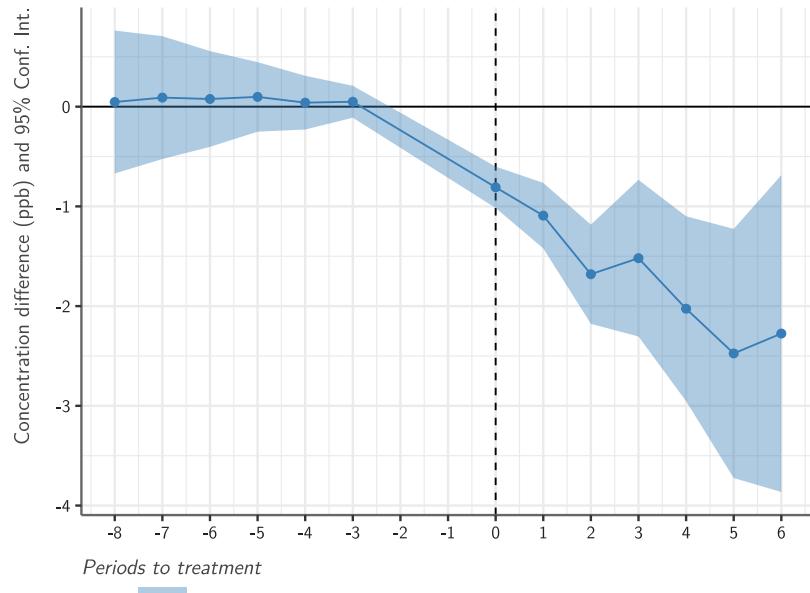
Dynamic effect of bike share on NO concentrations
Borusyak et al. (2022) estimator



Note: "On-car-route" treatment definition

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

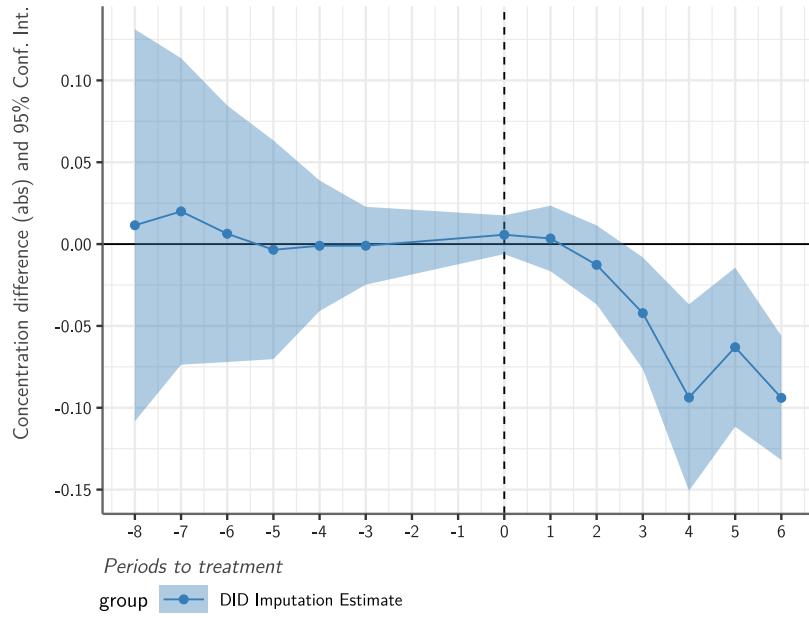
Dynamic effect of bike share on NO₂ concentrations
Borusyak et al. (2022) estimator



Note: "On-car-route" treatment definition

Figure 6: Dynamic effect of bike share on NO₂ concentrations, BSJ estimator

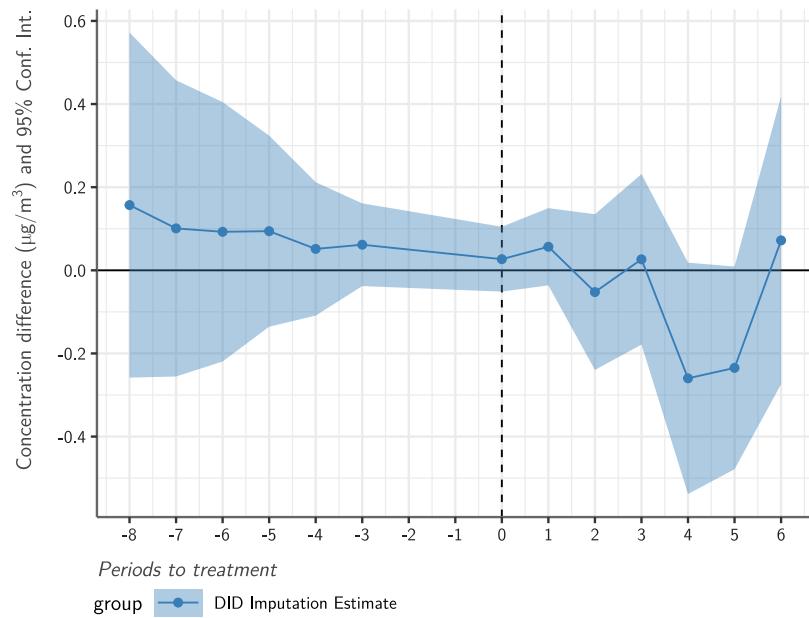
Dynamic effect of bike share on BC concentrations
Borusyak et al. (2022) estimator



Note: "On-car-route" treatment definition

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

Dynamic effect of bike share on PM concentrations
Borusyak et al. (2022) estimator



Note: "On-car-route" treatment definition

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

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. NO₂ (Figure 6) now displays reasonable parallel trends between groups prior to treatment, and a significant and persistent decrease in NO₂ concentration for the treated group after treatment. BJS dynamic effects (Figure 7) confirm TWFE results, 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 indistinguishable 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

$$Y_i = \beta_0 + \beta X_{i,\bar{t}} + \gamma_b + \varepsilon_i \quad (4)$$

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), and 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 5.3. 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.¹³ 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 5.3 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

¹³These 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*** (0.0092)	0.1003** (0.0475)		
Other floor area (sq ft)	0.0007 (0.0015)	0.0007 (0.0029)	0.0017 (0.0020)	0.0017 (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 (0.0010)	-0.0012 (0.0009)	0.0000*** (0.0000)	0.0000 (2.8020)
Cycle route (ft)	0.0001*** (0.0000)	0.0001* (0.0000)	0.0001 (0.0000)	0.0001** (0.0000)
Painted cycle lanes (ft)	0.0014 (0.0010)	0.0014 (0.0009)	0.0001*** (0.0000)	0.0001 (2.6784)
Protected cycle lanes (ft)	0.0015 (0.0010)	0.0015* (0.0009)	0.0000 (0.0000)	0.0000 (2.8896)
Population over 25	-0.0002*** (0.0001)	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0001)
Population	0.0001*** (0.0000)	0.0001 (0.0001)	0.0001 (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*** (0.0000)	0.0005*** (0.0001)	0.0003** (0.0001)	0.0003*** (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*** (82.7379)	9,199.0699*** (380.8176)		
Other floor area (sq ft)	-5.8446 (14.7006)	-5.8446 (26.0137)	-13.6360 (15.8736)	-13.6360 (14.1585)
Retail area (sq ft)	0.0003 (0.0007)	0.0003 (0.0011)	0.0003 (0.0008)	0.0003 (0.0007)
Residential area (sq ft)	0.0026 (0.0064)	0.0026 (0.0052)	0.0043* (0.0025)	0.0043** (0.0021)
Office area (sq ft)	0.0011*** (0.0004)	0.0011 (0.0007)	0.0009* (0.0005)	0.0009** (0.0005)
Commercial area (sq ft)	0.0012 (0.0064)	0.0012 (0.0052)	0.0032 (0.0025)	0.0032 (0.0022)
Built area (sq ft)	-0.0027 (0.0064)	-0.0027 (0.0052)	-0.0043* (0.0025)	-0.0043** (0.0021)
At-least-painted cycle lanes (ft)	15.9987 (33.4240)	15.9987 (28.2850)	-0.6707*** (0.1279)	-0.6707 (29,801.1007)
Cycle route (ft)	-0.5449*** (0.1906)	-0.5449 (0.4194)	-0.4542 (0.3013)	-0.4542** (0.2287)
Painted cycle lanes (ft)	-15.3254 (33.4210)	-15.3254 (28.4746)	-0.3133* (0.1598)	-0.3133 (30,109.0169)
Protected cycle lanes (ft)	-13.5124 (33.4204)	-13.5124 (28.3052)	0.1876 (0.1434)	0.1876 (29,933.4526)
Population over 25	1.6746*** (0.6230)	1.6746 (2.3883)	1.6433 (1.7218)	1.6433 (1.1214)
Population	-0.9936*** (0.3711)	-0.9936 (1.3676)	-0.9489 (0.9755)	-0.9489 (0.6694)
Median household income	0.0065*** (0.0008)	0.0065* (0.0034)	0.0017 (0.0031)	0.0017 (0.0014)
College graduates	-3.6981*** (0.3124)	-3.6981*** (1.0816)	2.3044** (0.9850)	-2.3044*** (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).

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.

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 thanks to bike share, and are more closely associated with the areas of bike share implementation, which might make treatment less exogenous to other factors. Despite these limitations, I run the same analysis and find comparable results (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 to 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.

Comparing these results with related literature is challenging, as most studies focus on other pollutants such as PM 2.5 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, Heywood, and Navarro Paniagua, 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 (Y. Chen and Whalley, 2012). The results I obtain, although for different pollutants, are of similar magnitude.

Shr, Yang, and Y.-S. Chen (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 by 1.9 to 2.0%, but no statistically significant decrease in NO or NO₂. They note that CO is the only pollutant they observe which may be attributed, for a significant share, to two-wheeled ICE vehicles. This suggests that some substitution might have occurred for this class of vehicles, and highlights that bike share’s impact 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 3, 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

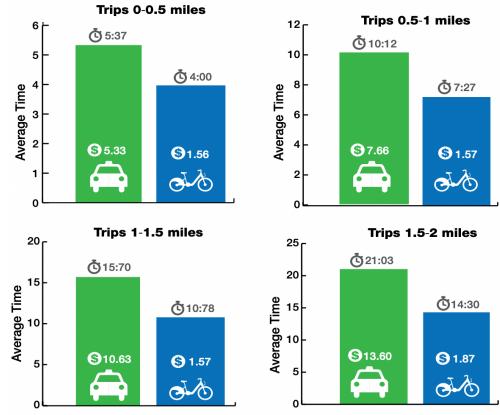
You will recall that the main hypothesis for bike share to reduce pollution is that the introduction of bike share reduces the relative price of (and increases the accessibility to) cycling. This change in the relative attractiveness of the cycling transport option will induce some trips to be substituted away from other transport modes. If these previous transport modes were ICE vehicles, then bike share will have reduced their emissions. 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 thanks to bike share. Importantly, the previous section has shown a decrease in a harmful *by-product* of traffic, air pollution — is there any direct evidence that traffic itself decreased?

To tackle this question, I turn to taxis. Taxis are a useful measure of traffic and ICE vehicle substitutes for several reasons. First, taxi trips have been identified by previous research to be good proxies for overall road traffic (Castro, D. Zhang, and Li, 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



(a) Location of Midtown



(b) Fares and travel time comparison

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

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 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 by 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 distinguish taxi trips most likely to be substitutable with bike share from others. 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.¹⁴ 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:

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

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,

¹⁴There 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.

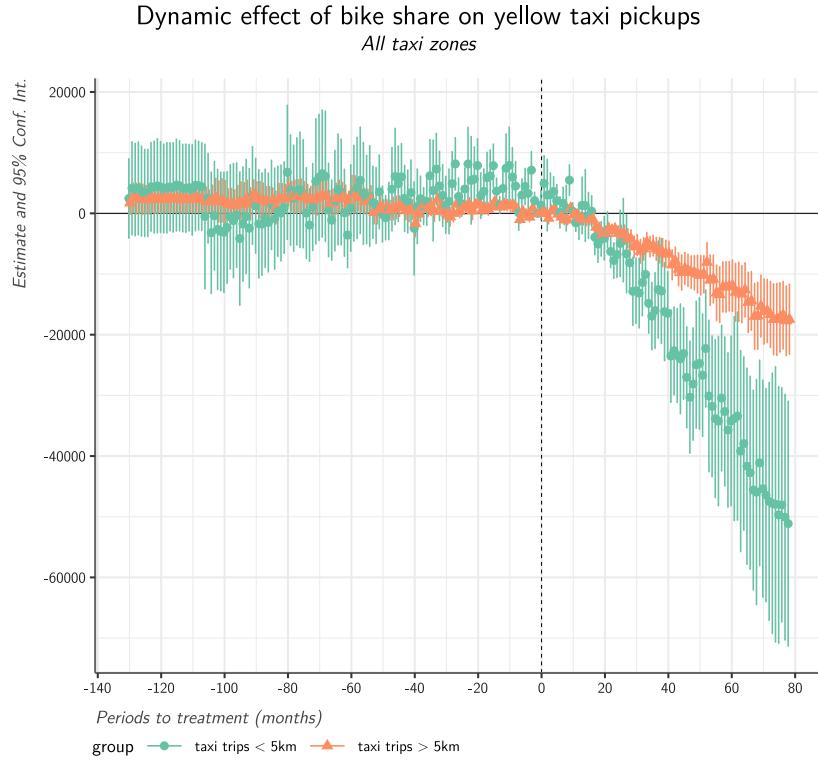


Figure 10: Dynamic effect of bike share on yellow taxi pickups

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.

Usage of bike share varies with 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.

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. 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.

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 NO₂ 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. Shr, Yang, and Y.-S. Chen (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 the different likely source of substitution, a factor of transportation options available before bike share. 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, Yang, and Y.-S. Chen (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

A.1 Gradual rollout of bike share

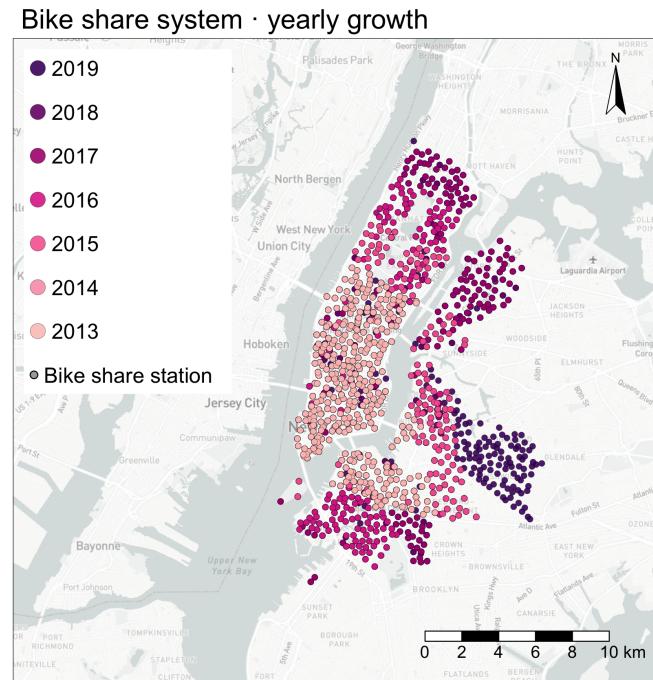


Figure A.1: Gradual rollout of bike share stations in NYC

A.2 Spatial extent of treatment

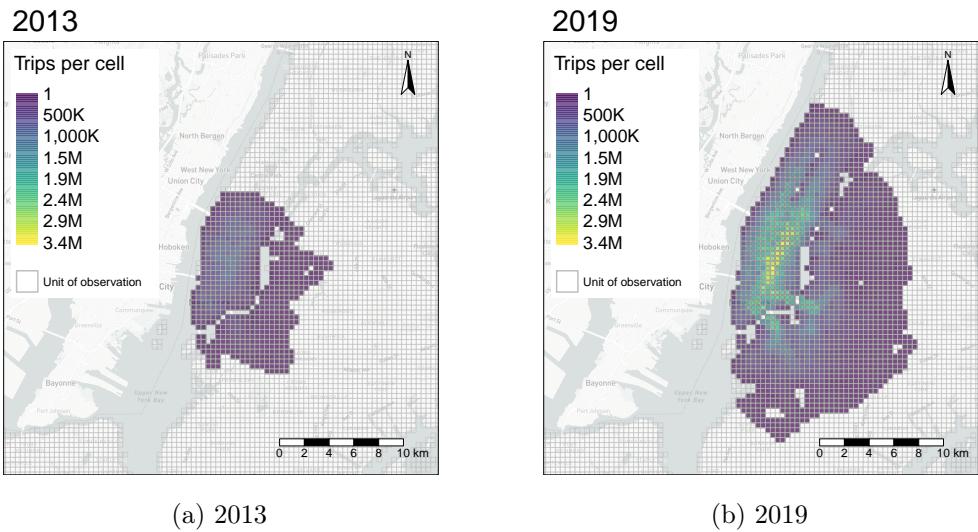
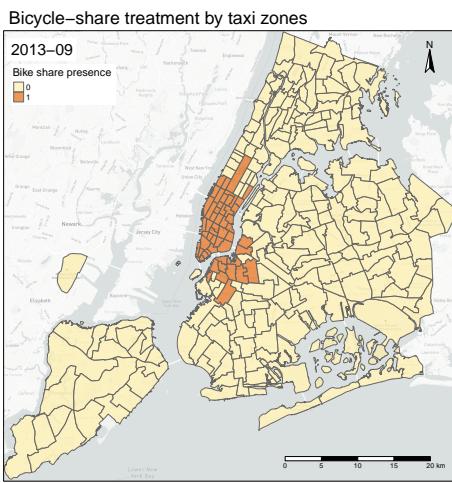
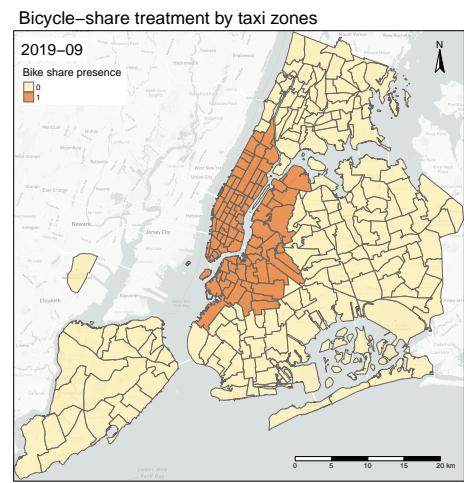


Figure A.2: Spatial extent of treatment and imputed trips per cell at bike share implementation and last study period

A.3 Taxi zones



(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*** (0.3540)	-2.7281*** (0.3507)	-1.0262*** (0.1957)	-0.6398*** (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*** (0.0967)	-1.2554*** (0.0955)	-0.2010*** (0.0647)	-0.4141*** (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*** (0.0057)	-0.0280*** (0.0057)	-0.0078 (0.0052)	-0.0097** (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 (0.0262)	-0.0320 (0.0260)	-0.0091 (0.0174)	0.0538*** (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*** (1.1872)	-2.1059*** (0.5868)	-1.5368*** (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*** (0.3277)	-0.4007*** (0.1384)	-0.5309*** (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** (0.0162)	-0.0170* (0.0098)	-0.0153 (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 (0.0788)	-0.0942** (0.0419)	0.0090 (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** (1.0736)	-0.1855 (0.6438)	-0.3325 (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*** (0.3380)	0.0989 (0.1864)	-0.2136 (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** (0.0143)	-0.0170*** (0.0051)	-0.0167* (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 (0.0802)	0.0399 (0.0378)	0.0748 (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