Bicycle-share systems: cycling toward cleaner cities?*

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Abstract

What is the impact of increasing the supply of bicycles on air pollution in cities? Little is known about the impact of cycling on urban transport systems and their environmental benefits. As a non-polluting alternative to public and private transport, cycling has the potential to alleviate cities of the burdens of pollution and congestion. This paper takes advantage a well-defined, both in time and space, cycling policy to estimate the causal impacts of cycling on local air pollution. Using New York's gradual roll-out of bicycle-share, I map the areas treated by bicycle-share and compare them to untreated areas, using difference-in-differences estimators robust to variation in treatment timing. I find that air pollutants associated with road traffic decrease faster in areas with bicycle-share compared to control areas. These results are robust to alternative treatment definitions.

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1 Introduction

Air pollution is a major source of health issues around the world. Yearly excess deaths caused by air pollution are estimated between 3.3 million (Lelieveld et al., 2015) and 10.2 million (Vohra et al., 2021). Air pollution is ranked as the fourth-worst risk factor by the Global Burden of Disease yearly report (Abbafati et al., 2020), causing around 12 percent of all annual deaths. In addition to direct deaths, air pollution is behind a host of negative impacts: chronic respiratory diseases such asthma (Guarnieri and Balmes, 2014), affecting the size and weight of newborns (Currie and Walker, 2011; Schembari et al., 2015), worsening of mental health (Chen et al., 2018) and decreasing labor supply (Hanna and Oliva, 2015; Aragón et al., 2017), to name a few.

In response to these challenges, governments and communities have implemented a whole range of policies. Cities are particularly exposed, as they concentrate high volumes of economic activity (including transport) in a relatively confined space, and do register higher concentrations of air pollutants when compared to rural areas (Strosnider et al., 2017). A notable source of air pollution, especially in urban areas, is motor land vehicles powered by internal combustion engines, henceforth motor vehicles (Nriagu, 2011). The reduction of this type of traffic is thus the focus of many of the policies with the goal of alleviating air pollution.

One avenue explored to tackle urban motor traffic is the promotion of alternative modes of transport, notably public (bus, subway) and active (walking, cycling) transport. In the past 15 years, cities around the world have promoted the use of bicycles through the implementation of affordable bicycle-share systems, which are public bicycles docked at stations spread around the city. By making cycling accessible to many and with fewer constraints, these networks of public bicycles effectively reduce the price of cycling in the city. The price reduction is identifiable both in space (the public bicycles can only be used within the area that contains the stations) and time (the bicycles are useable only after the system is implemented or expanded).

Following this price decrease, one might expect that some users of motor vehicles or taxis in the area now served by the bicycle-share system switch to bicycles for some trips. This switch would imply a decrease in pollution following the arrival of the bicycle network in the service area. The objective of this paper is to assess whether pollution concentrations actually decrease in the service area following the introduction of bicycle-share, and quantify the hypothetical reduction.

To evaluate the impact of bicycle-share, I combine a dataset of the universe of trips made on New York City's bicycle-share system Citi Bike with yearly high-resolution spatial data on local pollution in New York City, from 2008 to 2018. Joining these, I am able to identify which areas of the city are treated by bicycle-share each year, and link that treatment status to the observed level of pollution.

I use a staggered difference-in-differences (DiD) strategy that leverages the property described above: the impact of the bicycle-share on the relative price of cycling is identifiable both in time and space. In practice, this method compares the areas with bicycle-share to those without, before and after the implementation of the system. Under some key assumptions, this method retrieves the average treatment effect on the treated and lets me causally evaluate the impact of bicycle-share on pollution concentrations.

Focusing on the pollutants most likely to originate from motor vehicles (black carbon, nitric oxide and particulate matter), this paper finds that the arrival of the bicycle-share in New York City and its gradual expansion significantly decreased the concentration of black carbon and nitric oxide, while leaving particulate matter levels unaffected. I show that these results remain stable when using complementary definitions of areas served by the network (treated areas).

To the best of my knowledge, this paper provides the first causal estimates of the impact of a bicycle-share system on measures of pollution. Previous literature has relied on a range of assumptions to compute the expected impacts of bicycle-share: assumptions on the substitution rate between bicycles and motor vehicles; on the type of motor vehicle (e.g., fuel consumption) and commuting pattern (e.g., kilometers traveled); on the number of bicycle trips and distances traveled on the system once opened; etc (Pierce et al., 2013; Fishman et al., 2014, 2015; Hamilton and Wichman, 2018; Kou et al., 2020). The present paper frees itself from making any of those assumptions by solely relying on observational data to estimate the effect of bicycle-share on pollution.

Gendron-Carrier et al. (2021) assess the impact of the opening of subway lines on urban particulate matter (PM) concentrations. They find that new lines decrease PM in the most polluted cities and have important economic benefits for society, taking advantage of high-resolution and frequent satellite measures of pollution. The present paper carries on this important line of research evaluating the impact of large-scale transport interventions on cities, using the case of New York City and its bicycle-share system.

There are important reasons why one would like to empirically estimate the causal impacts of bicycle-sharing on pollution. Measuring the decrease in pollution-induced by bicycle-share lets us compute the associated health benefits on a much firmer basis than the assumptions used in other studies. These health benefit estimates become key elements when it comes to compare pollution-reduction policies and evaluate their relative cost-benefit ratio. More precise and accurate information on the different alternative policies available to policymakers is a clear enhancement over the current state of knowledge, and could potentially help improve the living conditions of millions of city dwellers around the world.

The next sections are organized as follow: section 2 presents urban air pollution followed by bicycle-share systems; section 3 outlines the mechanisms through which bicycle-share might impact urban air pollution and describes the treatment definitions; section 4 describes the data sources and transformations necessary for the analysis; section 5 then lays down the empirical strategy and presents the paper's results; finally, section 6 concludes.

2 Setting

2.1 Urban air pollution

Air pollution is the idea that the air contains substances in concentration that may negatively impact the health of those who breathe it. Many different types of pollutants can be found in the air, coming from different sources and with various health implications. In this subsection, I will introduce the main air pollutants, where they come from, and what are their impacts on human health.

Air pollutants may be divided into two broad categories: gases and particulates. Nitrogen oxides (NOx), ozone (O_3), sulfur dioxides (SOx), carbon monoxide (CO) and carbon dioxide (CO_2) are all gases found in various concentrations in ambient air. Particulate matter (PM), or aerosols, are solid elements in suspension in the air, commonly subdivided by their size in microns (μm): 2.5μm or less (fine particles), 10μm or less (coarse particles). Black carbon (sometimes referred to as soot) is a type of fine particulate matter formed by the incomplete combustion of hydrocarbons. Volatile organic compounds (VOCs) are molecules with low boiling points, such as methane, hydrocarbons and solvents, present in the air in vapor forms (Nriagu, 2011).

This paper focuses on the pollutants measured by the New York City Community Air Survey (NYCCAS, see section 4.1). The NYCCAS is a unique pollution dataset for its high spatial definition, but is limited to measuring concentrations of NO, NO_2, O_3, SO_2, PM 2.5 and black carbon (BC). The remainder of this section will focus on these pollutants.

The two main sources of anthropogenic air pollution are stationary (e.g., factories, power stations, buildings, houses) and mobile (land, air and maritime vehicles). Pollution may also result from controlled burns, which is not a very relevant source in the present urban setting.

Source apportionment (i.e., the ability to measure each source's share in pollutants' emissions) of the pollutants is not straightforward. Nriagu (2011) provides some estimates for the substances measured by the NYCCAS: in the United Kingdom (UK), an estimated 50 percent of all NOx originates from motor vehicles. O_3 derives from decaying NOx reacting with VOCs. It forms in the span of a few days, under stable and good weather conditions, and is therefore uncommon around roads. Only an estimated 2 percent of SO_2 in the UK comes from vehicle exhaust, the industrial sector being the main source. The majority of particles emitted by motor vehicles are PM 2.5, which makes it a good marker of traffic pollution. Finally, BC principally derives from the incomplete combustion of diesel fuel.

Long-term exposure to these pollutants has been shown to increase the risk of cardiovascular diseases, as well as respiratory system and lung ailments (Nriagu, 2011). Short-term exposure may create respiratory irritation and other symptoms. The health issues created by the pollutants have concrete public health consequences: several studies have shown that air pollution was associated with increased morbidity and mortality (Hoek et al., 2002; Chay and Greenstone, 2003; Currie and Walker, 2011; Lelieveld et al., 2015; Kheirbek et al., 2016; Arceo et al., 2016; Knittel et al., 2016; Anderson, 2020), Lelieveld et al. (2015) estimating that three million deaths every year can be attributed to air pollution. A recent study by Vohra et al. (2021) focusing on PM 2.5 alone revised previous estimates upwards, with long-term exposure to PM 2.5 causing more than 10 million yearly deaths globally, among which 355 thousand in the United States, representing about 13 percent of all deaths, a figure matched by the most recent Global Burden of Disease report (Abbafati et al., 2020). In addition to the direct loss of lives, air pollution decreases the quality of life of those most exposed to it, burdening them with chronic diseases such as asthma (Guarnieri and Balmes, 2014), affecting the size and weight of newborns (Currie and Walker, 2011; Schembari et al., 2015), mental health (Chen et al., 2018), and making the environment and the outdoors inhospitable, preventing its enjoyment by inhabitants. Air pollution has also been shown to impact important economic outcomes such as labor supply (Hanna and Oliva, 2015; Aragón et al., 2017).

As will be discussed more in detail in section 4.1, the NYCCAS measures concentrations of NO, NO_2, O_3 (in summer only), SO_2 (in winter only), PM 2.5 and BC. Of those, I select a subset that, from my reading of the literature, is the most likely to be related to local road traffic. Since the NYCCAS measures concentrations at a high spatial definition and the empirical strategy specifically compares areas with the bicycle-share to those without, the pollutants of interest must have been likely affected by the arrival of the bicycle-share. In other words, measuring the change in pollutants that travel extensively across space would not make sense, as pollution might be coming from outside the bicycle-share area. I also exclude those pollutants weakly linked to motor vehicles.

I thus focus on NO, PM 2.5 and BC. NO_2 is the product of NO alteration after emission and may linger for some time in the atmosphere and thus travel from one area to another. O_3 follows a similar pattern as it is the product of NOx oxidation after a few days, in which case it likely traveled from the original emission location. Finally, SO_2, as discussed earlier, mostly originates from stationary sources and is only measured in winter when fewer bicycles are used.

2.2 Bicycle-share system

New York City opened its bicycle-share system Citi Bike in 2013 with 360 stations. In 2018, the system consisted of more than 800 stations in four of the city's five boroughs. This section describes the system, its implementation and expansion.

Bicycle-share systems are short-term rental bicycle schemes implemented in cities.

Set up by city councils, sometimes in partnership with private capital, these systems are generally cheaper than classic rental bicycles and are geared towards commuters as well as visitors. The current generation of bicycle-share systems came to prominence in Europe in the early 2000s, and most major cities around the world now have their own network.

The majority of the systems are so-called third-generation bicycle-share systems, characterized by automatic docking stations. To use a bicycle, users may either register for an annual subscription plan, swipe their credit card at the station's kiosk for a daily pass, or use the Citi Bike app to purchase a single ride. The station then unlocks a bicycle, which the user rides until she finds a free dock at her destination station. The first 30 to 45 minutes (depending on the subscription plan) are included for each ride, with additional costs per extra minute charged to users.

Fourth-generation "dockless" bicycles are taking root in many urban areas, but are absent from the New York City landscape and are therefore not considered in the analysis.[1]

Bicycle-share in New York City began in 2009 with a feasibility study commissioned to the city's Department of City Planning (New York City Department of City Planning, 2009). The report was based on the experience gathered in the first large-scale systems at the time: Paris' Vélib, Barcelona's Bicing, and Montreal's Bixi, amongst others. From these early systems, the Department of City Planning was able to define best practices and key implementation parameters, such as station density per square-mile and station placement.

New York City opened its bicycle-share system Citi Bike in 2013, delayed by a year due to Hurricane Sandy damaging equipment, and issues with stations' software. At launch, 362 stations were installed in Lower Manhattan (south of Central Park) and western Brooklyn (figure 1). The system did not expand in 2014, as the service provider and the city's Department of Transportation (NYCDOT) were focused on improving the quality of the service. Expansion resumed between 2015 and 2017, with stations installed further north on Manhattan, and deeper into Brooklyn and western Queens. The service area did not expand in 2018, with NYCDOT focusing on filling in the service area with more stations and adapting the system to demand. 2019 and 2020 saw the bicycle-share system covering the entire island of Manhattan and reaching southern parts of the Bronx, with continued expansion planned for the coming years. Unfortunately, this last round expansion is not included in the analysis, as pollution data was not yet available for these periods at the time of writing.

The bicycle-share system of New York City, like many others around the world, is the result of a public-private partnership. Beyond the planning stages, no public funds were spent on the implementation and operation of the system. Funding relies on sponsors and revenue from subscriptions and short-term rentals. The main sponsor

[1]A dockless system is planned for Staten Island, the city's most isolated borough, but launch has been delayed by the Covid-19 pandemic.

is Citibank, while the operations are run by Motivate, a subsidiary of the ride-hailing app Lyft. Public-private partnerships are not uncommon for this type of venture but might raise questions about the incentives at play when expanding the system. According to the NYCDOT and private correspondence with current and past planners, the private interests of sponsors and operators do not seem to play a role in the roll-out process. The NYCDOT retains full autonomy on the roll-out process and is only limited in the timing of the expansion by the funding constraints from private partners.

How are the bicycle-share stations placed in New York? We can identify two steps in the process of deciding the location of stations. First is the definition of the service area, i.e. the area where the city government wants stations implemented. In the case of New York, this started with the area on Manhattan south of Central Park and the western parts of Brooklyn. These areas were selected first because of their high concentration potential riders, the location of major business centers, transportation hubs, universities and other high transport demand locations. The second step is the placement of stations at their final location on the streets, within the defined service area, according to a predefined station density per square mile. Final placement on the street is the result of a participative process between local stakeholders and the NYCDOT, where residents and local business associations provide proposals and feedback on potential station locations (New York City Department of Transportation, 2013). In section 3.2, I exploit these features to construct a set of treatment definitions.

3 Conceptual framework

This section discusses the relationship at play between bicycle use and air pollution and then describes the different treatment definitions selected.

3.1 Bicycle-pollution relationship

With the arrival of the bicycle-share network, the price of riding a bicycle significantly decrease in the areas served by the system. From an economics perspective, consumers of transport within the areas should respond to the change in relative cost between transport options, and the marginal riders (i.e., those for which the relative price of cycling is now lower than their current transport option) are expected to switch to riding a bicycle. I first describe the likely components of the price of urban cycling, then describe how bicycle-share changes these price components, and what are the likely consequences of these changes on the commuter's choice of urban transport.

3.1.1 Costs and benefits of cycling

The price of acquiring or renting a bicycle might be the most important cost, to which we must add maintenance costs. Storing and securing the bicycle is another major expenditure, especially in cities where real-estate is expensive and flats tend to be smaller, making indoor bicycle storage more difficult. Security and the risk of robbery stem from the previous cost item: buying a good lock is costly but doesn't even guarantee with absolute certainty that the bicycle will not be stolen. Storing a bicycle outdoors because of lack of space in the household also increases maintenance costs as the bicycle is subject to weather and degradation. Adding to the risk dimension, the hazards associated with road accidents and increased exposure to pollution are perceived costs for many riders. The inability to use travel time in other ways (e.g., working, reading, listening to a podcast, making a phone call) represents an additional opportunity cost of cycling versus other transport means. Exposure to bad weather during travel also adds to the cost of riding.

Physical activity required to travel by bicycle and its corollaries (e.g., sweating) may be both a cost (e.g., need to shower at destination, packing an extra set of clothes) and a benefit (e.g., physical exercise improves health). Whether one effect dominates the other will depend on the specific circumstances of each commuter (e.g., availability of showers at destination, changing rooms, etc). Physical activity's cost and benefit may be muted down by the use of electric bicycles.

Social acceptability and culture may also play a role in the decision to ride. As cycling becomes more prevalent in society (or within specific groups), the tendency to imitate peers and/or pressure to conform to the group increase. The trend towards more environmentally friendly lifestyles may also act as an underlying cultural trend decreasing cycling's implicit cost. In some communities, however, increased ridership might have the opposite effect, with car drivers or pedestrians bitterly annoyed and opposed to bicycle expansion.

3.1.2 Bicycle-share's impact on cycling costs

Bicycle-share impacts the relative cost of riding a bicycle on several dimensions. First, it substantially decreases the acquisition, rental and maintenance cost for frequent short rides or infrequent longer ones. An annual subscription starts at $179 (excluding any discounts) and comes with unlimited 45-minute rides. In comparison, according to Bike New York (a bicycle advocacy group), a refurbished secondhand bicycle costs around $350, and an entry-level commuter bike around $400.[2] The entry cost for bicycle-share is substantially lower, includes maintenance[3] and makes locks or storage space unnecessary.

Second, as more bicycles are released on the streets, the more they are present in daily traffic. Previous research has shown that bicycle-related fatalities are negatively related to the number of bicycles in circulation (Jacobsen, 2003; Fishman and Schepers, 2016; Elvik and Bjørnskau, 2017). Moreover, more bicycles in public spaces added to institutional endorsement by local governments can improve social acceptability, and

[2] https://www.bike.nyc/blog/news/the-real-cost-of-a-recycled-bicycle/

[3] Some commentators remark that this may come at the cost of lower general bicycle quality compared to a privately owned bike due to user abuse.

thus lower the relative cost. This creates a price-decreasing feedback loop as ridership increases. If bicycle-share is shown to reduce pollution, it will imply a decrease in pollution exposure, further strengthening the feedback loop. These effects would both impact bicycle-share ridership but also private bicycle ridership.

Third, bicycle-share is often implemented alongside additional bicycle infrastructure improvements, such as the extension of the protected cycle lane network. Bicycle infrastructure improvements have been shown to lower both the perceived and true accident risk for riders, contributing making cycling more attractive (Reynolds et al., 2009; Pucher et al., 2010; Winters et al., 2011; Buehler and Pucher, 2012).

Lastly, bicycle-share availability can be an issue if bicycles are not optimally distributed within the network and shortages of either bicycles or free docks prevent usage. In these circumstances, private bicycle ownership offers more certainty and reliability.

3.1.3 Bicycle-share and other transport modes

To understand the relationship of bicycle-share with other transport modes and how that relationship plays a role in cycling adoption, it is useful to think in terms of complements and substitutes. Some of cycling's comparative advantages are (1) faster than walking, (2) may be faster than a car, motorcycle, taxi, or public transport on short distances (less than five kilometers) and congested roads, (3) cheaper than car, motorcycle, taxi or public transport, (4) more flexible than public transport (no schedules, no predefined routes), (5) physical activity. Bicycle-share enjoys most of these advantages, with the limitations already discussed above. Reducing the price of cycling in the city increases the salience of these advantages, and is expected to induce some degree of substitution from other modes of transport to bicycle-share.

Simultaneously, cycling is an acknowledged complement of public transport (Krizek and Stonebraker, 2010; Heinen and Bohte, 2014) and walking (which is itself a complement of public transport). Bicycles complement public transport well when it comes to accessing the public transport departure station and from the arrival station to the final commute destination. Commuters travel fast and safely on long distances using public transport, but the last-mile connection to their final destination is (e.g., a few kilometers) is often lacking or inefficient, in which case cycling can successfully bridge the gap. The bicycle–public transport combination is itself a substitute to private cars, motorcycles and taxis, with its own set comparative advantages: (1) speed and reliability (depending on the route), (2) cost, (3) ability to use travel time for other activities.

3.1.4 Substitution and impact on pollution

The substitution rates between cycling and the bicycle–public transport combination on one hand, and polluting modes of transport (i.e., cars, motorcycles, taxis) on the other will determine the pollution reduction as the price of cycling decreases on account of the bicycle-share implementation and expansion. To the best of my knowledge, previous research has not estimated either substitution rates, although some surveys documented self-reported number of car trips replaced by bicycle-share users (Bührmann, 2007).

Quantitative estimates of substitution remain spotty and are likely highly dependent on the transport landscape and culture unique to each city. However, bicycle-share should in principle substitute some polluting modes of transport, and, if not directly through current commuters (which appears unlikely), at least by means of the modeling of transport habits of newcomers and their acceptance of cycling as a legitimate transport option.

In the context of New York City, anecdotal evidence indicates that bicycle-share displaced polluting transport traffic from taxis. In 2014 (one year after the launch of Citi Bike), the New York City Taxi & Limousine Commission published its 2014 Taxicab Fact Book (Taxi & Limousine Comission, 2014). The average distance traveled by cab was 4.2 kilometers (20 percent of trips were less than 1.6 kilometers), a distance in the range of a bicycle ride. Moreover, the demographic of taxi passengers was relatively young, wealthy and based in Manhattan,[4] three factors that match typical bicycle-share demographics.[5]

More work is necessary to find out whether the bicycle-share–public transport combination decreased the number of cars entering the city (and thus pollution), but the arguments presented above do suggest that this has likely happened to some degree, especially when considering the sizable price decrease of cycling that bicycle-share has ushered.

3.2 Treatment definitions

Like any other type of transport infrastructure, bicycle-share is a fundamentally spatial phenomenon: individuals have to be located around or come to the stations in order to use the system and have a potential impact on pollution through their mobility choice. With this in mind, it comes to no surprise that treatment definitions include an intrinsic spatial dimension. The spatial dimension, however, may be defined in a variety of ways. Taken together, these definitions help paint a more complete picture of the impact of bicycle-share on urban pollution.

In this section, I present the set of treatment definitions used in the analysis. For the sake of clarity, is worth briefly describing the bicycle-share system's raw data (section 4.2 gives full details). The raw data are the universe of trips made on the system since the opening. Each row includes the date, time and location of both the trip's start

[4]70 percent of taxi passengers are aged 35 or below, while only representing 50 percent of New York City's population. 42 percent of taxi passengers have an annual household income of $100,000 or higher, while that proportion in city population is 24 percent.

[5]https://rstudio-pubs-static.s3.amazonaws.com/562792_a5e5d1698c3b4574b7a7fd093465ccd0.html. See also Hosford et al. (2018).

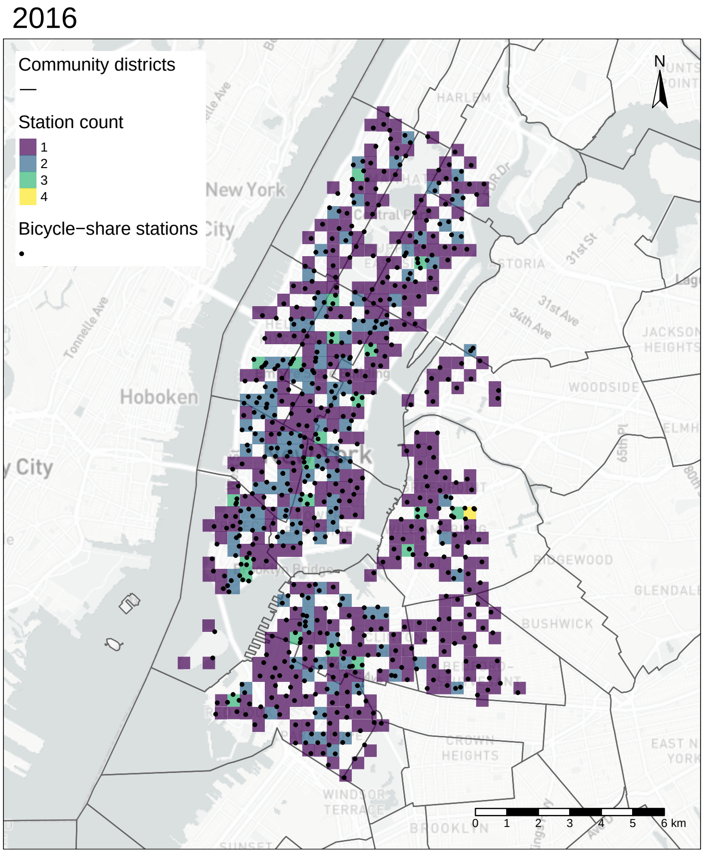

Figure 1: Map of station treatment in 2016 with stations points. Close-up on the treated area. Cells are given by the NYCCAS pollution maps and are the units of observation.

and end, as well as type of rider (subscriber or one-off customer), age and gender (only if the rider is a subscriber). The treatment definitions are based on two complementary attributes of the raw bicycle-share data: stations' locations and routes between any given pair of stations (and the associated number of trips taken on each route) computed with a routing algorithm. Both attributes are complementary and shed light on different aspects of bicycle-share's impact.

A word on the spatial scale: this paper uses cells measuring 300m by 300m from a grid covering the entire city as its units of analysis. The grid is given by the pollution data source, which will be thoroughly described in section 4.1. For the present section, suffice to say that treatment will be defined at the cell level, even though the underlying data is defined in different spatial units (e.g., points, lines).

To better understand the treatment effects' interpretations described below, it is also worth bearing in mind the empirical strategy that will use these treatment definitions. In a nutshell, this paper will use staggered DiD to estimate the average treatment effect on the treated cells. This approach effectively compares treated cells before and after the treatment with never-treated cells. The empirical strategy is presented thoroughly in section 5.1.

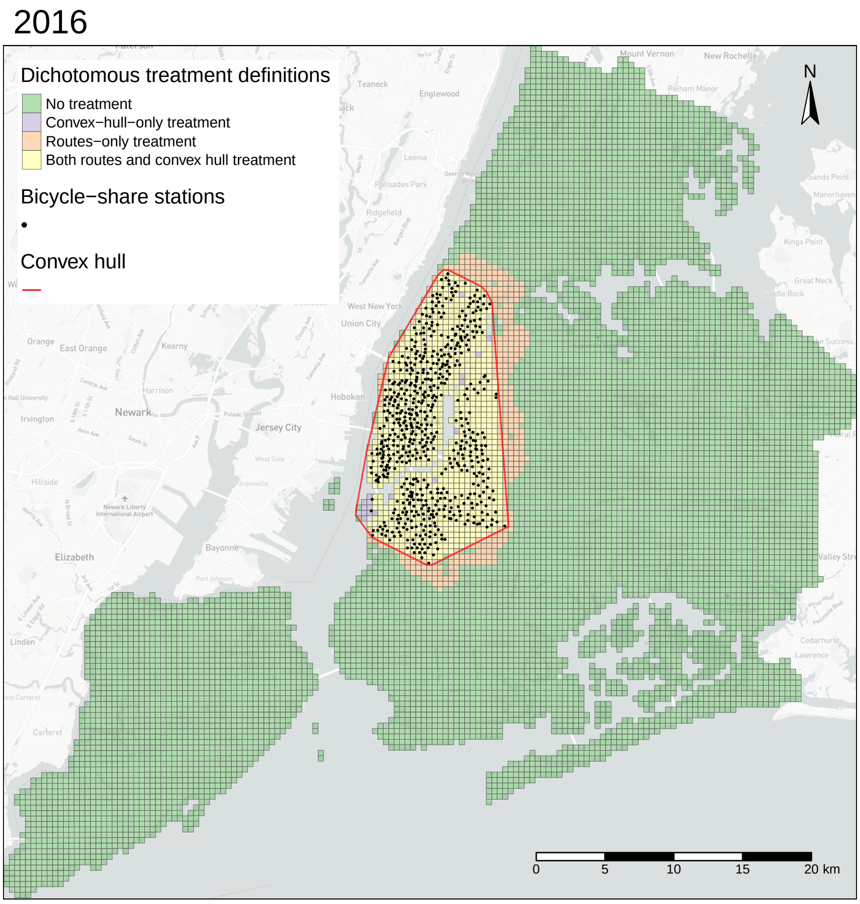

Figure 2: Map of dichotomous treatments in 2016 with stations and the convex hull. Cells are given by the NYCCAS pollution maps and are the units of observation.

3.2.1 Stations

The first attribute taken into account is the locations of stations. Locations of stations are arguably the simplest (and computationally light) proxy to examine the effect of bicycle-share at the very local level. The surroundings of the stations are the areas that have the easiest access to the bicycle-share network, and thus provide an approximation of the locations where individuals might substitute their transport choices out of cars and taxis to bicycle-share.

I start by plotting, for each year, all the system's active stations (see section 4.2 for the criteria for active stations) and overlay the grid given by the pollution data. From there, I identify three treatment definitions that I will develop in the next paragraphs: dichotomous, count and service area.

The *dichotomous* treatment defines treated cells as containing at least one station. The cell containing a station represents the area immediately adjacent to the station, and thus the one that has the best access to it. To capture the magnitude of bicycle-share accessibility, I *count* the number of stations present in each cell: this is the second

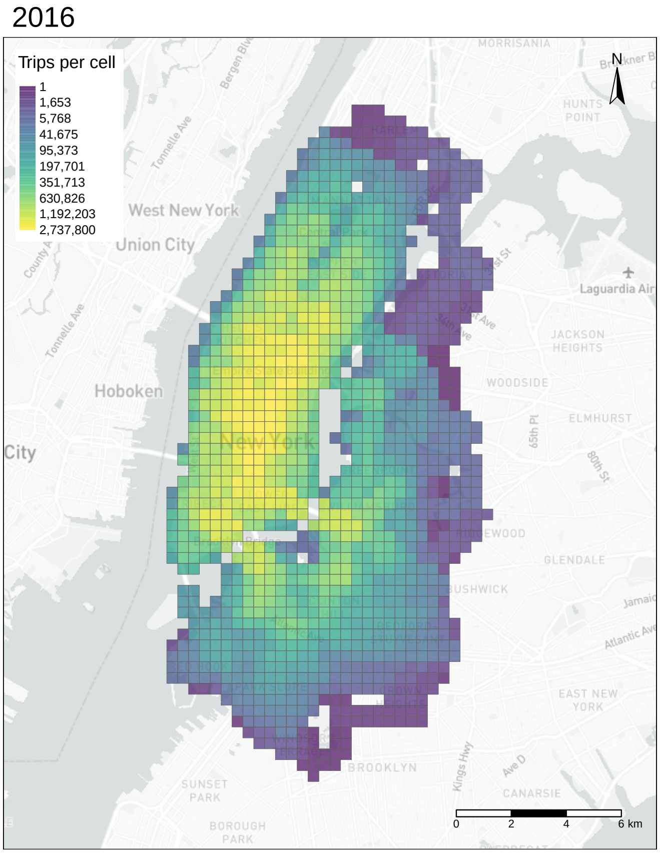

Figure 3: Map of trips-per-cell treatment intensity. Close-up on the treated area. Cells are given by the NYCCAS pollution maps and are the units of observation.

treatment definition. Both treatment definitions for 2016 are depicted in figure 1 (2013 and 2018 can be found in appendix A).

How to interpret the coefficients from those treatments? The dichotomous indicator of station presence estimates the difference in pollution due to bicycle-share stations of treated cells, before and after the arrival of stations in the cells. The count treatment estimates the impact of one additional station on the pollution level of treated cells.

The dichotomous and count treatment definitions are simple to visualize and compute. However, they might imperfectly capture the areas effectively impacted by the arrival of bicycle stations. One might think that cells without stations but surrounded by cells with stations might equally well access the bicycle-share system. As a result, one might expect their pollution levels to decrease as the result of some degree of substitution out of cars and taxis. To capture these cells within what I name the *service area*, I define as treated all the cells that are in-between stations (figure 2).

In technical terms, I build a polygon that encompasses all the cells that have at least one station, and consider all the cells within that polygon to be treated. This polygon is the smallest convex polygon containing all the stations, and is also known as the convex hull of the set of stations. Here is another way to visualize the convex hull: if one were to travel in a hypothetical straight line between any pair of stations (i.e., ignoring streets and buildings), that line would always fall within the convex hull polygon. Taken together, those straight lines between stations, especially the ones linking the stations at the edges of the network, would actually delineate the service area and define it as a convex polygon.

With the yearly locations of stations describe earlier, I construct the convex hull for each year, and define as treated by the bicycle-share system all the cells falling within it. The set of treated cells for a particular year constitute that year's service area.

The interpretation of this treatment definition is similar to the dichotomous treatment: the coefficient of the service area captures the average effect of bringing the bicycle-share system to the treated cells on these cells' pollution level. The only difference is the extent to which we deem a station can treat cells: in the dichotomous treatment, the extent was limited to the area of the cell containing the station; in the service area definition, the extent covers all cells that are surrounded by stations, i.e., the convex hull of stations.

3.2.2 Routes

The service area is an elegant and practical measure of the extent of the bicycle-share's area of influence at a given period. I hinted earlier that this definition assumes a straight line of travel between any pair of stations. This assumption, however, might not be a good representation of travel within the city, with its specific network of streets, buildings blocks, parks and rivers. In other words, taking into account the geography and road network of the city lets me build a more precise picture of the areas affected by the bicycle-share system.

Moreover, the service area definition assumes a constant intensity of treatment across treated cells; a simple attribute of dichotomous variables. Yet, we might want to assess the intensive margin of bicycle-share: does riding more bicycles in a certain area lead to a higher decrease in pollution? To answer this question, we can make full use of the raw bicycle-share trip data and count the number of trips taken within each cell, and estimate the impact of an additional bicycle trip on pollution. This section describes this exercise and the treatment definitions that it enables.

Taking into account the city's streets and natural obstacles, I am able to more precisely map the influence area of bicycle-share. Instead of assuming straight lines of travel between stations, I use the actual network of roads to compute the routes and map these routes onto cells. Using the universe of bicycle-share trips for a given year, I reduce the dataset to unique origin-destination pairs of stations with at least one trip between them, adding a variable counting the number of trips for each pair. By only selecting stations' pairs with at least one trip, I also drop the assumption that the bicycle-share system's impact area extends between *all* pairs of stations: during a given year, it might be the case that two stations did not "exchange" any bicycles, leaving the area between them untreated, whereas that area would have been mechanically coded as treated under the service area definition.

Once the pairs of "exchanging" stations are established, I feed the origin-destination locations to the r5r routing engine (Pereira et al., 2021), which outputs the route between the stations using a specified transport mode (more on that later), taking into account the road network in use that year. The route is provided as a vector line, an arguably narrow definition of the area affect by the passage of a bicycle or car: I therefore add a 150-meter buffer around the line. I then compute, for each cell, all the routes that intersect it. For each cell, I now have the list of all intersecting routes, and the number of bicycle-share trips associated with each of them. The final step is to construct, for each cell, two treatment variables: a routes-dichotomous variable equal to one if the cell is crossed by at least one route and zero otherwise (figure 2 for 2016, other years in appendix A), and a trips-per-cell count variable that sums the bicycle-share trips from all the routes crossing the cell (figure 3). I end up with two new variables: the equivalent of an enhanced service area treatment (routes-dichotomous), and an intensity of treatment (trips-per-cell).

These two new treatment variables take into account the city's geography to provide more spatially accurate treatment definitions. In addition, the trip-per-cell variable fully exploits the bicycle-share trip data and lets me account for the magnitude of bicycle-share trips going through a given area of the city. This last point raises the issue of which routes should we be computing. In and of themselves, bicycles do not produce clean air: as detailed in the previous section, cycling reduces pollution only through the substitution of a polluting mode of transport (either a car or taxi trip) it may induce. Moreover, between any given origin-destination point in the city, cars and taxis may not follow the exact same route as bicycles, due to traffic restrictions, tunnels or bridges, one-way streets and cycle lanes, for example.

To measure the impact of bicycle-share on pollution, the case can be made that the *car* rather bicycle routes between the pairs of stations better capture the reduction in pollution induced by the substitution. When and if bicycles replace cars, the pollution decreases in the areas where cars would have driven under the status quo. Therefore, we should take car routes into account when mapping out the routes between stations, as we assume that a fraction of the bicycle-share trips substitute for car or taxi trips, therefore decreasing pollution in areas previously traveled by cars and taxis.[6]

The interpretation of the routes-dichotomous treatment definition is: we assume that, for each pair of stations, the area where pollution is most likely to decrease is the cells crossed by the optimal car route between the stations. The opening of a new pair of stations might treat new cells, which then are expected to be more likely to see their

[6]Note that it is not assumed that *all* bicycle-share trips are substituting car or taxi trips, simply that the area affected, if any, is *most likely* the one on the routes taken by cars to travel from one bicycle-share station to another. The rate of substitution does not need to be assumed either: the observational data speak for themselves.

Table 1: Treatment definitions summary

Type	Treatment	Data
Dichotomous	Station present	Cell contains at least one station
	Service area	Cell is within the smallest convex polygon containing all the stations
	Routes	Cell is crossed by a car route (or its 150m buffer) going from a station to another, the pair of station having at least one trip between each other
Intensity	Station count	Number of stations within a cell
	Trips per cell	Number of bicycle-share trips converted into car trips passing through a cell when summing trips from all routes between all stations

pollution concentrations decrease. The trips-per-cell definition starts from the same premise but takes into account the volume of bicycle trips between each pair of stations to measure the expected substitution's impact on pollution. The coefficient's interpretation, in this case, is the marginal effect of one additional bicycle-trip on pollution measures (to make tables more readable, in the result section I report the effect for ten thousand trips).

The treatment definitions are summarized in table 1. There are three dichotomous (i.e., binary) treatments: stations present, within service area (convex hull) and crossed by car route. Two treatment definitions capture bicycle-share intensity: stations count and car trips per cell. The preferred treatment definition is the routes-dichotomous: it takes into account the area most susceptible to have its pollution decrease and makes use of the raw bicycle-share trip data. However, all definitions are useful to shed light on the issue at hand, and section 5.2 will present the impact of each of them on pollution measures.

4 Data

In this section, I present the data used to run the present analysis. The outcome variable is the average yearly concentration of a range of air pollutants, and is obtained from the NYCCAS from the New York City Department of Health and Mental Hygiene. The main variables of interest are bicycle-share stations' locations, and bicycle-share service area and usage data. Both are sourced from Citi Bike's operator, which releases publicly the universe of trips made on the system. Additional data is obtained from the American Community Survey.

4.1 Pollution data

High-resolution pollution data is hard to come by. Many measurements done by regulatory bodies are made at discrete locations and do not provide a detailed account of pollutants distribution across space. Thankfully, the New York City Department of Health and Mental Hygiene initiated in 2008 a program to tackle the issue of local air pollution variation, the NYCCAS. The survey is built upon numerous measurement locations coupled with statistical inference methods to deliver a high-resolution map of pollutants' concentrations across New York City.

The NYCCAS started in 2008 and monitors concentrations of the following pollutants: PM 2.5, BC, NO, NO_2, O_3 (in summer only), and SO_2 (in winter only). Details on the NYCCAS methods can be found in Matte et al. (2013) and Clougherty et al. (2013), which the following paragraph summarizes.

In order to produce a detailed picture of pollution across the city, the NYCCAS follows a rigorous protocol, using a total of 150 measurement stations surveyed throughout the year. 120 of them are randomly placed across the city's territory, stratified on traffic and building density, i.e., oversampling areas with higher traffic and building density. They then place 30 measuring stations at purposeful sites, i.e., sites with defined characteristics, to ensure good representativity. The NYCCAS team then uses these measures and land use regression to interpolate yearly average concentrations in each and every of the 300 meters (m) by 300m cells that form a grid map overlaid over the city (see figure 2). I use this product to determine the pollutants' concentrations in specific locations across the city and throughout the years. It is worth noting that the NYCCAS is specifically designed to record street-level pollution and enable cross-locations comparisons (Clougherty et al., 2013; Matte et al., 2013).

I select three pollutants for the remaining of the analysis: PM 2.5, BC and NO. These air pollutants are those most likely to emanate from local traffic. Moreover these pollutants, because of their chemical properties, tend to stay localized around their emission source, transforming to other substances with time (Nriagu, 2011). These characteristic make them suitable candidates to measure the impact of bicycle-share. BC in absorbance units (abs), NO in parts per billion (ppb) and PM 2.5 is measured in micrograms per cubic meter ($\mu g/m^3$).

4.2 Bicycle-share data

From the Citi Bike website, I obtain the universe of trips made on the system since its launch in June 2013. The raw data contains the following variables for each trip: start date and time, end date and time, duration, start and end station address, start and end station longitude and latitude coordinates, a dummy if the rider holds a subscription, and if she does, her year of birth and gender. About 100 million such trips were recorded from launch to the end of 2018. These data are the basis of the treatment definitions presented in section 3.2.

For the analysis, we want to keep all the trips made from and to active stations available to the public and that actually resulted in the transport of a person from one location to another. We also want to keep only trips that we are able to map. With these criteria in mind, I cleaned the data in two stages. First, I discarded all the trips of less than 3 minutes, as they are likely "false starts" (e.g., faulty bicycle), as well as round trips (i.e., from station A back to A), as we cannot map through which areas of the city these trips have likely gone through. Secondly, I discard all the trips that have origin or destination station names identified as provisional or for maintenance: we want to keep only the trips actually done by riders to transport themselves, not the artifact trips from the moving and maintenance of bicycles.

4.3 Census data

The American Community Survey (ACS) released by the Census Bureau provides the control variables that might impact both pollution concentration and bicycle-share usage. The ACS is conducted yearly on a sample of the United States' population (about three million respondents every year) and asks socio-economic questions similar to those in the decennial census. Thanks to its yearly frequency, the Census Bureau is able to construct estimates of each variable for different geographic units by combining different years of data: using the last three years of data, the Bureau publishes the ACS-3, and using the last five years, the ACS-5. ACS-5 estimates are available for smaller geographical areas down to the census tract level because not every census tract is surveyed each year.

I use the yearly ACS-5 estimates to proxy population, median household income and educational attainment for census tracts in NYC. I then spatially interpolate these data to cells, under the assumption that these data are homogeneously distributed across the census tracts. In practice, the cell's value for a given measure is the weighted average of the measure for all census tracts it contains, where the weights are the proportional area covered by each census tract within a given cell.

4.4 Data transformations and final dataset

The data presented above are available for different geographic units. I decided to homogenize the spatial variables at the cell-level, where the grid of cells is given by the NYCCAS pollution dataset. The grid is an appropriate level of analysis because it is agnostic to political and administrative divisions within the city, while also retaining stable spatial features (extent, number of neighboring cells, high spatial resolution, etc).

5 Analysis

5.1 Empirical strategy

This subsection describes the empirical strategy employed in the analysis, and discusses the main assumptions necessary for the strategy to be valid.

As described above, the bicycle-share system was gradually rolled-out across different areas of the city. I exploit the staggered nature of the expansion by using a staggered DiD estimation strategy. The staggered DiD effectively compares treated units with control units, before and after the treatment. In the present setting, this translates to comparing grid cells with at least one bicycle-share station (or within the bicycle-share service area) with grid cells without stations (or outside the service area), before and after the arrival of the first bicycle station (or the inclusion in the service area).

5.1.1 Estimation model

The estimation model is a simple two-way fixed effect model, as described in equation 1:

$$Y_{ct} = \beta\, Treatment_{ct-1} + year_t + cell_c + \varepsilon_{ct}, \tag{1}$$

for cell c at year t.

5.1.2 Assumptions

The estimation model laid out in equation 1 rests upon important assumptions regarding the nature of the treatment and the relationship between variables. Specifically, the data should be checked for parallel trends in the outcome variable before treatment, the exogeneity of treatment with respect to the outcome variable, and that no other omitted variables are influencing both the outcome and the treatment. This section explores the most important of these assumptions, parallel trends.

Parallel trends For a DiD strategy to be valid, parallel trends of the outcome variable between treated and control groups before treatment must be established. In the present setting, this means that air pollutants' concentrations should display parallel trends before treatment in both control and to-be-treated cells. In other words, pollution should be following a similar trend between treated and control cells before the arrival of bicycle stations in treated cells.

A well-established approach to check the difference in pre-treatment trends is to plot the full dynamic treatment effects, also known as event study. The event study plots the interaction of treatment status with the periods before and after the treatment. Parallel trends are observed when there is no significant effect of the treatment on the level of the outcome variable before treatment. Equation 2 formalizes the tested relationship and includes two-way fixed effects (i.e., for both time and unit):

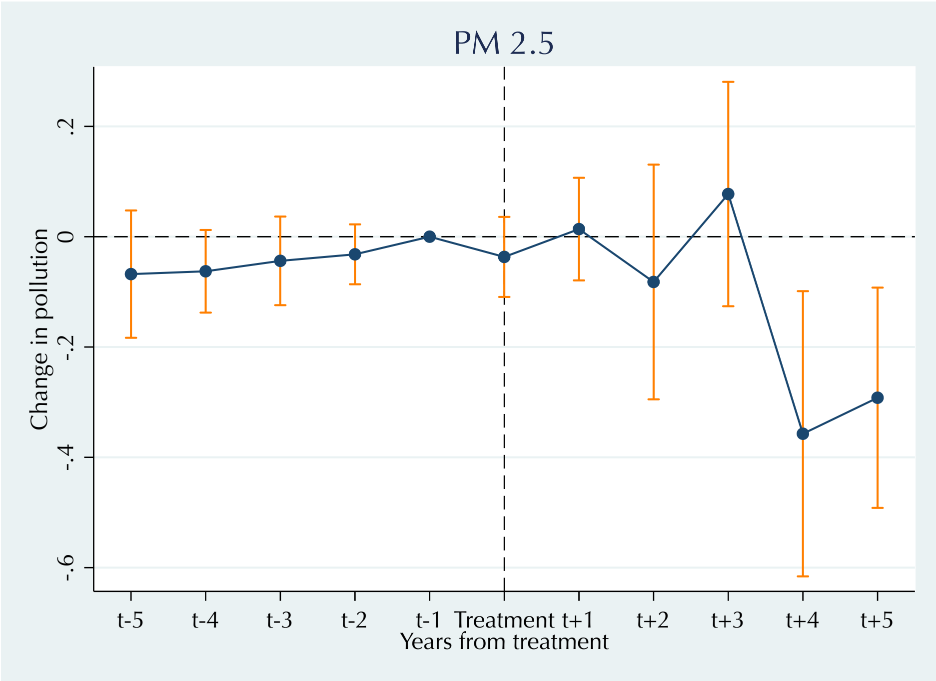

Figure 4: Event study for PM 2.5, route-present treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

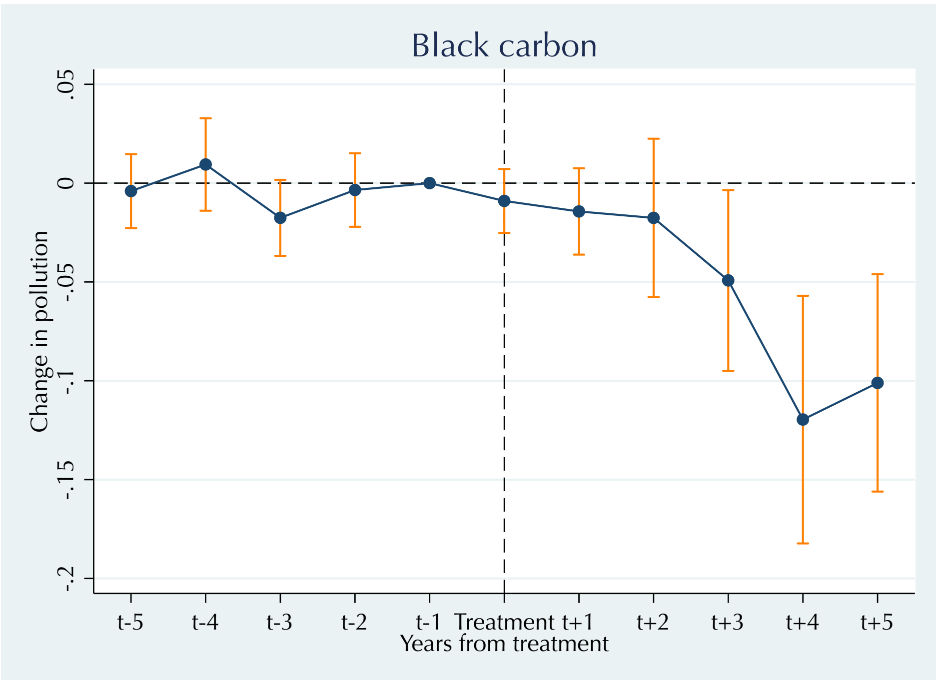

Figure 5: Event study for black carbon, route-present treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

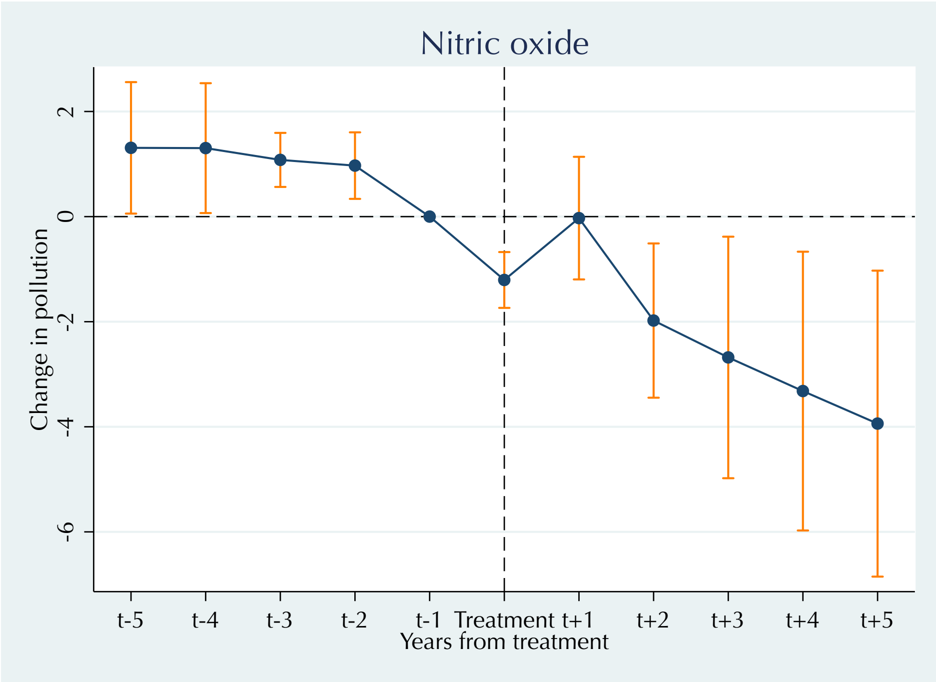

Figure 6: Event study for black carbon, route-present treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

$$Y_{ct} = \sum_{k \neq -1}^{5} \beta_k \, Treatment_c \times RelYear_k + year_t + cell_c + \varepsilon_{ct}. \tag{2}$$

We then run the regression, clustering the standard errors at the community district level, and plot the coefficients β_k alongside their 95 percent confidence intervals. Figures 4 to 6 show the results for PM 2.5, BC and NO when considering the trips-per-cell dichotomous treatment definition, while figures 16 to 18 in appendix B present results for the service-area treatment definition.

For these three pollutants and both treatment definitions, the parallel trends assumption is broadly satisfied. There is an indication of different trends of NO levels in the pre-treatment period under the trips-per-cell dichotomous treatment, but these are absent under the service-area definition, and follow the same patterns, which gives support to the parallel trend assumption.

5.2 Results

This section presents the estimated treatment effects of bicycle-share on pollution measures. The results reported estimate equation 1 for the three air pollutants selected and the five treatment definitions presented in section 3.2. I present the results for each pollutant in turn, first for dichotomous treatment definitions and then intensity of treatment measures.

Table 2: Dependent variable: black carbon, dichotomous treatments

	(1)	(2)	(3)	(4)	(5)	(6)
Station present	-0.0675***	-0.0575***				
	(0.021)	(0.019)				
Service area			-0.0597***	-0.0514***		
			(0.018)	(0.017)		
Car route present					-0.0481***	-0.0382***
					(0.016)	(0.014)
Control mean	.84	.86	.84	.86	.84	.86
Year FE	✓	✓	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
Population		✓		✓		✓
Median income		✓		✓		✓
Bachelor grads		✓		✓		✓
N	77,360	66,583	77,360	66,583	77,360	66,583
R-sq	0.929	0.958	0.930	0.958	0.929	0.957

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors clustered at the community district level.

Table 3: Dependent variable: black carbon, treatment intensities

	(1)	(2)	(3)	(4)	(5)	(6)
Station count	-0.0446***	-0.0372***				
	(0.014)	(0.012)				
Trips per cell			-0.00162***	-0.00143***		
			(0.00030)	(0.00023)		
Trips per cell, IHS					-0.00507***	-0.00423***
					(0.0016)	(0.0014)
Control mean	.84	.86	.84	.86	.84	.86
Year FE	✓	✓	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
Population		✓		✓		✓
Median income		✓		✓		✓
Bachelor grads		✓		✓		✓
N	77,360	66,583	77,360	66,583	77,360	66,583
R-sq	0.929	0.957	0.930	0.958	0.929	0.958

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors clustered at the community district level. For clarity, the coefficient for *Trips per cell* is given for ten thousand trips. *Trips per cell, IHS* is the inverse hyperbolic sine (IHS) transformation of *Trips per cell*, a type of log transformation which preserves zeros (see appendix D for details).

5.2.1 Black carbon

BC appears to be significantly impacted by the roll-out of the bicycle-share in New York City. Starting with table 2 and dichotomous treatments, we observe that the arrival of bicycle-share significantly decreases BC concentrations under all three definitions. When a cell switches from no bicycle-share station to at least one (columns 1 and 2), BC falls by 0.0575 abs, which represents a 6.69 percent decrease from the mean BC concentration in the control cells. Including the cells in the service area (columns 2 and 4), the reduction stays stable at 0.0514 abs (5.98 percent of the control group's mean). We observe a slight decrease when including cells crossed by the car-equivalent routes (columns 5 and 6): 0.0382 abs reduction, 4.44 percent from the mean of the controls.

Table 3 reports the treatment effect coefficients when taking into account the intensity of the bicycle-share intervention. One additional bicycle-share station (columns 1 and 2) decreases BC concentration by an additional 0.0372 abs, or 4.43 percent. Trips per cell also seem to lead to a significant decrease: for each additional 10 thousand car-equivalent trips going through a cell, the concentration of BC decreases by 0.00143 abs. Given that the median number of trips per cell with at least one trip is 45,124 (average: 187,291), the median cell will see a reduction of 0.064 abs, which represents a 2.7 percent reduction from the mean pollution level of the control group.

I then take the inverse hyperbolic sine of trips per cell and report the results in columns 5 and 6. The IHS is a type of log transformation that preserves zero values (abundant in the case of trips-per-cell, as most of the cells are controls with zero trips) while still appreciably linearizing the variable (see MacKinnon and Magee (1990); Bellemare et al. (2013) and appendix D for details). For BC, a one percentage point increase in trips per cell leads to a 0.00423 abs reduction in pollution, 0.5 percent of the controls' mean.

The coefficients reported in table 3 also enable us to look at the effect of bicycle-share at different treatment intensities. Taking the cells at the 80th percentile of trips per cell, the reduction is equivalent to 5.27 percent of the control group's mean. Coefficients for BC are statistically significant across all definitions, which suggests that bicycle-share does have an impact on BC concentration.

5.2.2 Nitric oxide

Dichotomous treatment results (table 4) indicate that bicycle-share has a consequential impact on NO: cells with a station experienced a close-to 20 percent decrease with respect to the control group's mean NO concentration after stations arrived (-3.268 ppb). The decrease when accounting for cells in the service area lowers to 13 percent of the control groups' mean (-2.202 ppb), and is significant at the five percent significance level. For cells located on the car routes, the NO concentration reduces by 10 percent from the controls' mean value. NO reductions are substantive, but lose statistical significance as we progress towards more sophisticated treatment area definitions.

Table 4: Dependent variable: NO, dichotomous treatments

	(1)	(2)	(3)	(4)	(5)	(6)
Station present	-3.760***	-3.268***				
	(1.20)	(1.18)				
Service area			-2.430**	-2.202**		
			(0.97)	(1.02)		
Car route present					-1.992**	-1.777*
					(0.85)	(0.90)
Control mean	16.47	16.65	16.47	16.65	16.47	16.65
Year FE	✓	✓	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
Population		✓		✓		✓
Median income		✓		✓		✓
Bachelor grads		✓		✓		✓
N	77,360	66,583	77,360	66,583	77,360	66,583
R-sq	0.938	0.939	0.937	0.938	0.936	0.938

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors clustered at the community district level.

Table 5: Dependent variable: NO, treatment intensities

	(1)	(2)	(3)	(4)	(5)	(6)
Station count	-2.630***	-2.261***				
	(0.77)	(0.74)				
Trips per cell			-0.121***	-0.113***		
			(0.015)	(0.015)		
Trips per cell, IHS					-0.256***	-0.229**
					(0.087)	(0.088)
Control mean	16.47	16.65	16.47	16.65	16.47	16.65
Year FE	✓	✓	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
Population		✓		✓		✓
Median income		✓		✓		✓
Bachelor grads		✓		✓		✓
N	77,360	66,583	77,360	66,583	77,360	66,583
R-sq	0.938	0.939	0.945	0.946	0.938	0.940

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors clustered at the community district level. For clarity, the coefficient for *Trips per cell* is given for ten thousand trips. *Trips per cell, IHS* is the inverse hyperbolic sine (IHS) transformation of *Trips per cell*, a type of log transformation which preserves zeros (see appendix D for details).

Table 6: Dependent variable: PM 2.5, dichotomous treatments

	(1)	(2)	(3)	(4)	(5)	(6)
Station present	-0.213**	-0.181**				
	(0.086)	(0.087)				
Service area			-0.117	-0.0927		
			(0.078)	(0.085)		
Car route present					-0.0601	-0.0380
					(0.072)	(0.078)
Control mean	8.26	8.33	8.26	8.33	8.26	8.33
Year FE	✓	✓	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
Population		✓		✓		✓
Median income		✓		✓		✓
Bachelor grads		✓		✓		✓
N	77,360	66,583	77,360	66,583	77,360	66,583
R-sq	0.982	0.982	0.982	0.982	0.982	0.982

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors clustered at the community district level.

Looking at treatment intensities (table 5), here again reductions are significant in magnitude: for a cell with the median number of trips, NO falls by 3 percent compared to the control group's mean. The reduction hikes up to 21.8 percent for cells at the 80th percentile of trips per cell. Coefficients for the IHS-transformed treatment are slightly less statistically significant (5 percent level).

5.2.3 Particulate matter < 2.5 microns

The impact of bicycle-share on PM 2.5 appears to be limited. Under the dichotomous treatment definitions (table 6), I find that PM 2.5 significantly decreases in cells where stations were placed (column 1 and 2), but the significance disappears when we include cells from the service area (column 3 and 4) or in dichotomous-routes definitions (column 5 and 6), although they retain the expected negative sign.

In terms of magnitude, the coefficient in column 2 indicates a decrease of $0.181\mu g/m^3$ after a station opened in a given cell, which corresponds to a 2.17 percent decrease with respect to the control group's mean.

When taking into account treatment intensities (table 7), bicycle-share does seem to have an impact on PM 2.5 concentrations: for each additional station opened per cell, PM 2.5 falls by $0.133\mu g/m^3$, the equivalent of 1.60 percent of the control group's mean. Trips per cell also seem to significantly decrease concentrations: for each additional 10 thousand car-equivalent trips going through a cell, the concentration of PM decreases by $0.00709\mu g/m^3$. The cell at the median level of trips will see a reduction of

Table 7: Dependent variable: PM 2.5, treatment intensities

	(1)	(2)	(3)	(4)	(5)	(6)
Station count	-0.154***	-0.133**				
	(0.058)	(0.058)				
Trips per cell			-0.00749***	-0.00709***		
			(0.0016)	(0.0017)		
Trips per cell, IHS					-0.0121*	-0.00977
					(0.0070)	(0.0074)
Control mean	8.26	8.33	8.26	8.33	8.26	8.33
Year FE	✓	✓	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
Population		✓		✓		✓
Median income		✓		✓		✓
Bachelor grads		✓		✓		✓
N	77,360	66,583	77,360	66,583	77,360	66,583
R-sq	0.982	0.982	0.983	0.983	0.982	0.982

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors clustered at the community district level. For clarity, the coefficient for *Trips per cell* is given for ten thousand trips. *Trips per cell, IHS* is the inverse hyperbolic sine (IHS) transformation of *Trips per cell*, a type of log transformation which preserves zeros (see appendix D for details).

$0.319\mu g/m^3$, which represents a 2.7 percent reduction from the mean pollution level of the control group.

The significance of the results fades away with the IHS transformation, with a PM 2.5 reduction of $0.00977\mu g/m^3$(but statistically insignificant) for a one percent increase in bicycle-share trips. On the whole, bicycle-share seems to have a fairly limited if not null impact on PM 2.5 concentrations.

5.2.4 Summary of results

I identify three main take-aways from these results. First, BC seems to be the pollutant most robustly affected by the roll-out of the bicycle-share system. Its coefficients are consistently statistically significant, and reductions are sizable, up to six percent for dichotomous treatments and 5.27 percent at the 80th percentile of trips per cell. Second, NO shows the biggest drops in concentrations, above 10 percent reductions for dichotomous treatments, but these reductions are slightly less statistically robust. Finally, PM 2.5 does not seem systematically impacted by the introduction of the bicycle-share, especially when considering our preferred treatment definitions.

5.3 Robustness checks

Staggered difference-in-differences strategies and more generally difference-in-differences with differential treatment timing have come under intense scrutiny in the past two years. Seminal papers by de Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2018), Callaway and Sant'Anna (2020), Sant'Anna and Zhao (2020), Sun and Abraham (2020) and Athey and Imbens (2021) have shed light on howe traditional two-way fixed effects estimators might be biased when both treatment time and effects vary across cohorts. Appendix C reports in-progress work addressing these issues.

6 Conclusion

This paper set about investigating the impact of the deployment of a bicycle-share system on local pollution concentrations in New York City. It aimed to understand whether the sharp, sudden and well-defined in both time and space decrease in the relative price of cycling in the city would lead to a reduction in pollution through the partial substitution out from cars and taxis towards bicycles.

To answer this question, I used detailed data on the usage of the bicycle-share system and high-resolution measures of pollution. Thanks to the discrete and sudden implementation and expansions of the system, I was able to use a staggered difference-in-difference estimation strategy. Under the important assumption of parallel trends pre-treatment (which I show is broadly satisfied), this strategy yields average treatment effects of the areas treated by the bicycle-share. I defined five such treatment definitions, including measures of the intensity bicycle-share use.

I found that bicycle-share's implementation in New York City has significantly decreased the BC and NO concentrations of treated areas after the arrival of the system. The results are particularly substantial for NO, where treated areas may decrease their concentration of the pollutant by up to 20 percent from the concentration found in the control group. PM 2.5 did not seem to be significantly affected by bicycle-share, however.

6.1 Next steps

The next steps for this paper include few additional key components. First, although parallel trends have been checked, additional tests of the DiD assumptions are necessary, such as checking for the exogeneity of treatment with respect to the outcome variable, omitted variables' bias and running placebo tests. Second, de Chaisemartin and D'Haultfœuille (2020) and Goodman-Bacon (2018) have shown that staggered DiD and two-way fixed effects regressions in general may yield biased estimates under specific circumstances. Checking whether the present analysis suffers from those biases and computing the robust estimator alongside the Goodman-Bacon decomposition will be an unavoidable and important next step. Finally, I will compute the health benefits derived from the bicycle-share intervention. This will greatly improve the paper's significance and relevance to a broader audience.

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Appendices

A Treatment definitions maps

Additional treatment definitions maps for the first year of the bicycle-share (2013) and last year of the sample period (2018).

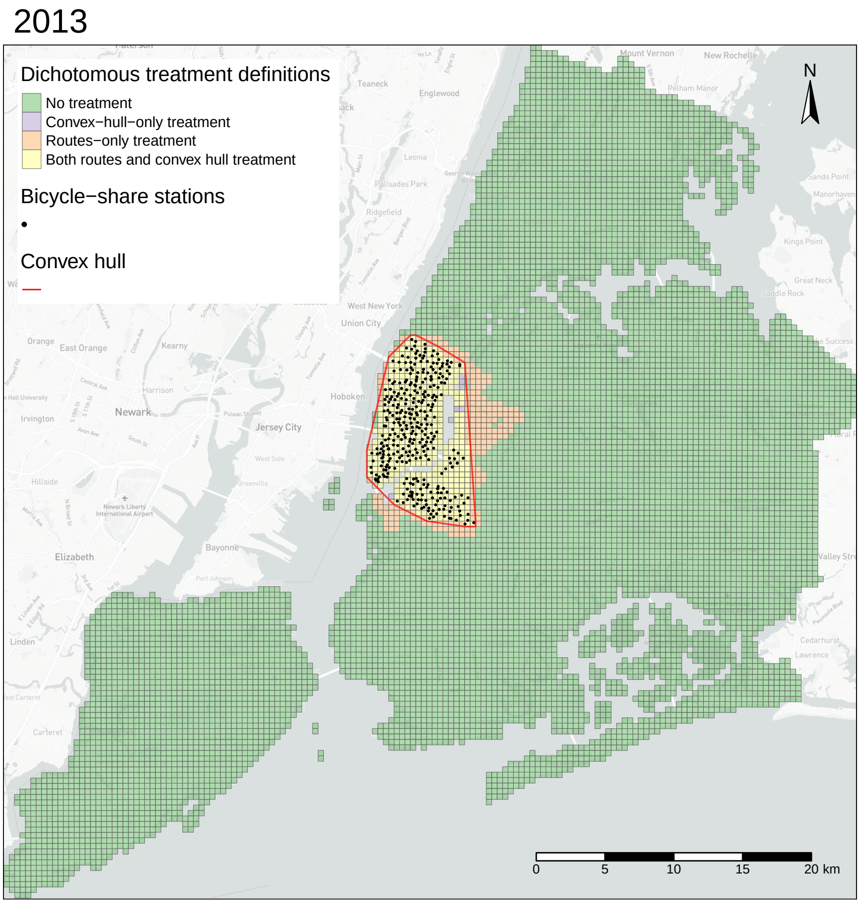

Figure 7: Map of dichotomous treatments in 2013 with stations and the convex hull. Cells are given by the NYCCAS pollution maps and are the units of observation.

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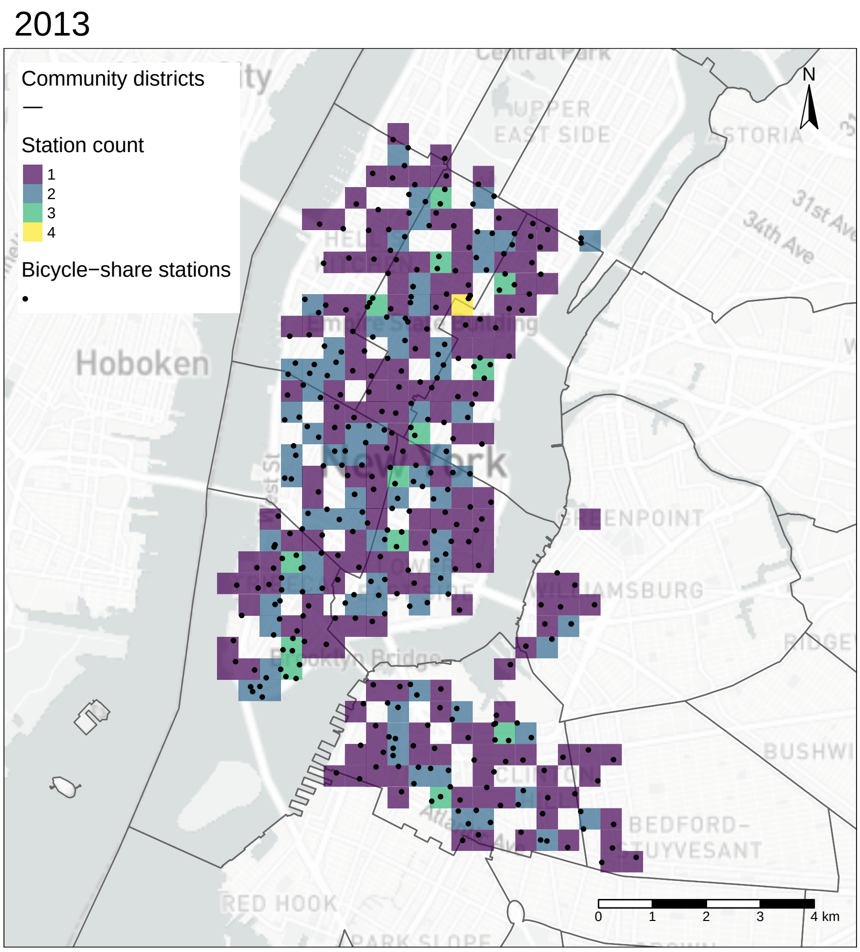

Figure 8: Map of station treatment intensity in 2013 with stations points. Close-up on the treated area. Cells are given by the NYCCAS pollution maps and are the units of observation.

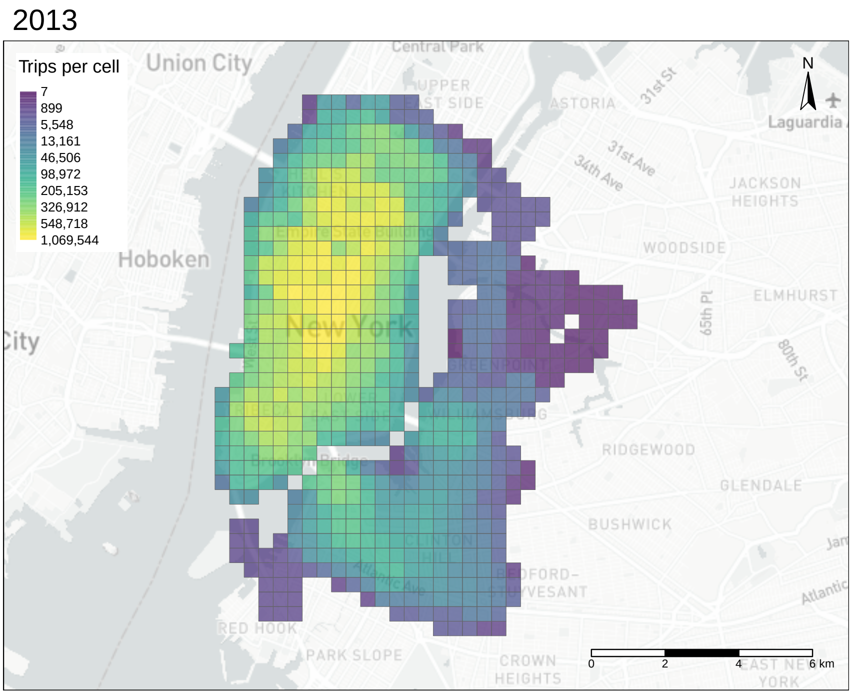

Figure 9: Map of trips-per-cell treatment intensity. Close-up on the treated area. Cells are given by the NYCCAS pollution maps and are the units of observation.

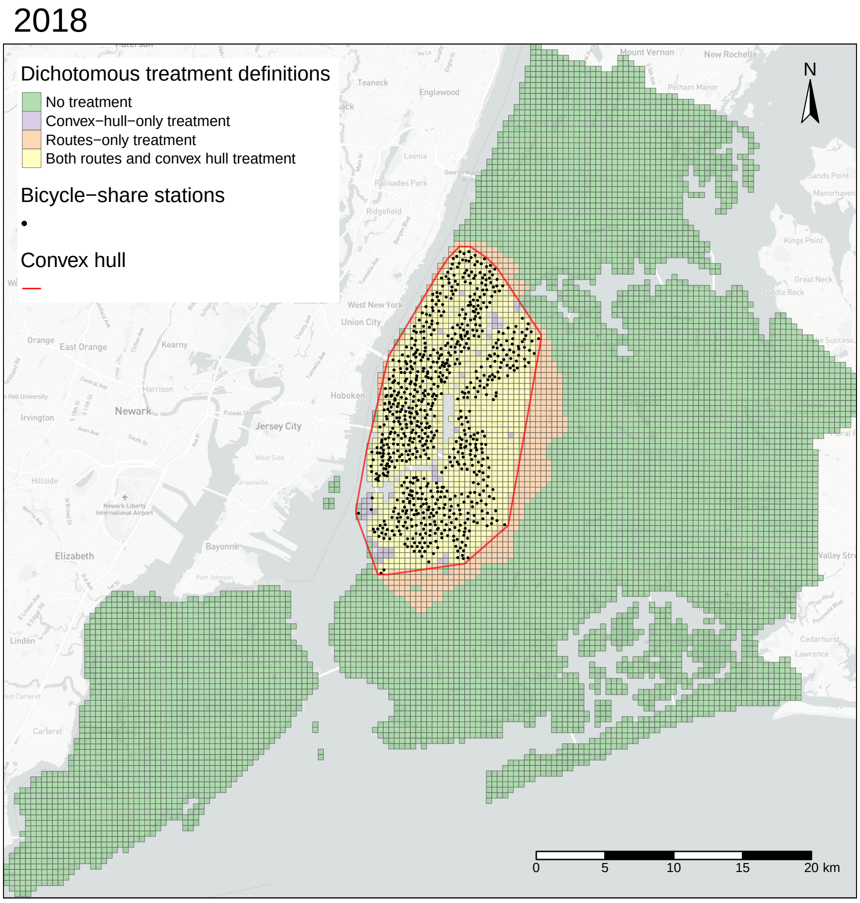

Figure 10: Map of dichotomous treatments in 2018 with stations and the convex hull. Cells are given by the NYCCAS pollution maps and are the units of observation.

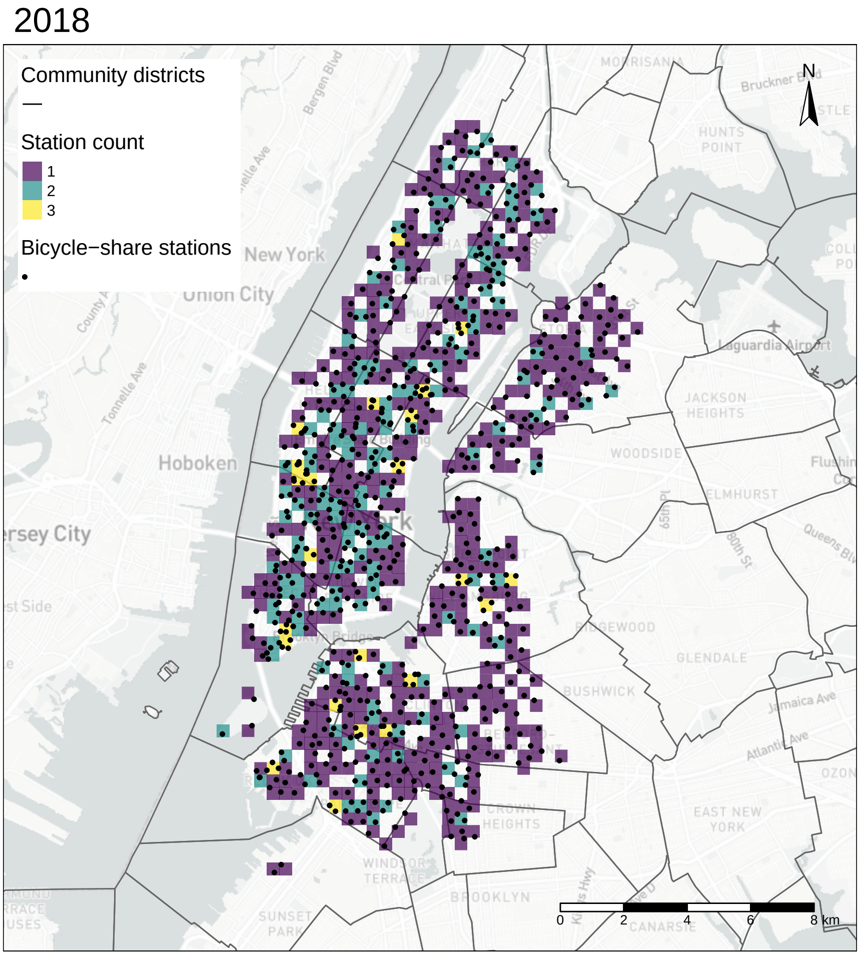

Figure 11: Map of station treatment intensity in 2018 with stations points. Close-up on the treated area. Cells are given by the NYCCAS pollution maps and are the units of observation.

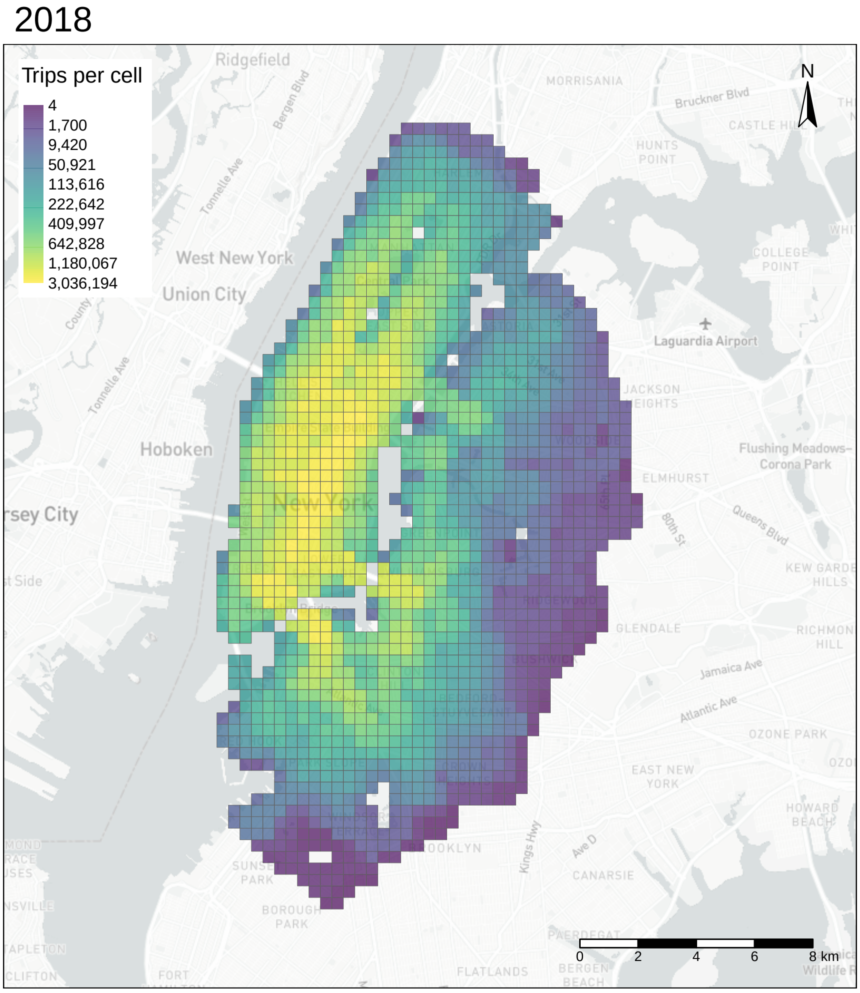

Figure 12: Map of trips-per-cell treatment intensity. Close-up on the treated area. Cells are given by the NYCCAS pollution maps and are the units of observation.

B Event study plots

Additional event study plots are presented here for the other dichotomous treatment definitions: station present, routes dichotomous.

B.1 Station present

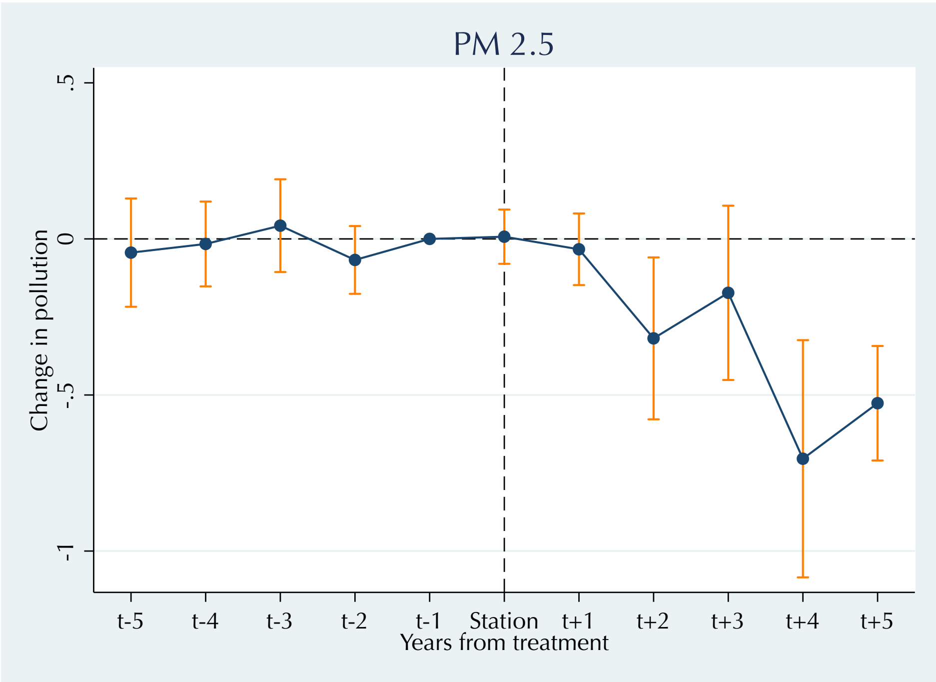

Figure 13: Event study for PM 2.5, station-present treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

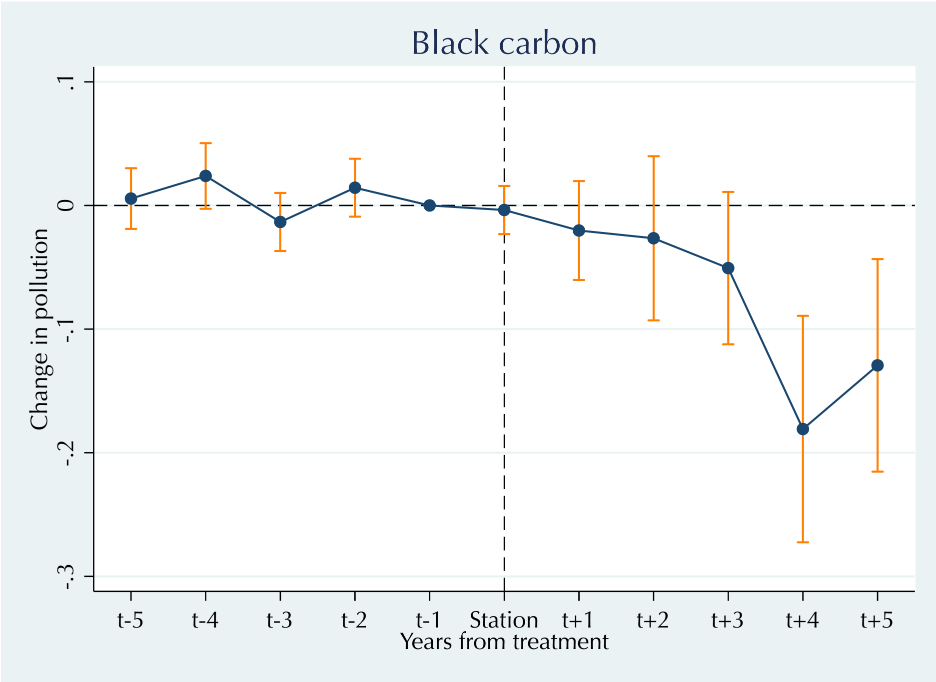

Figure 14: Event study for black carbon, station-present treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

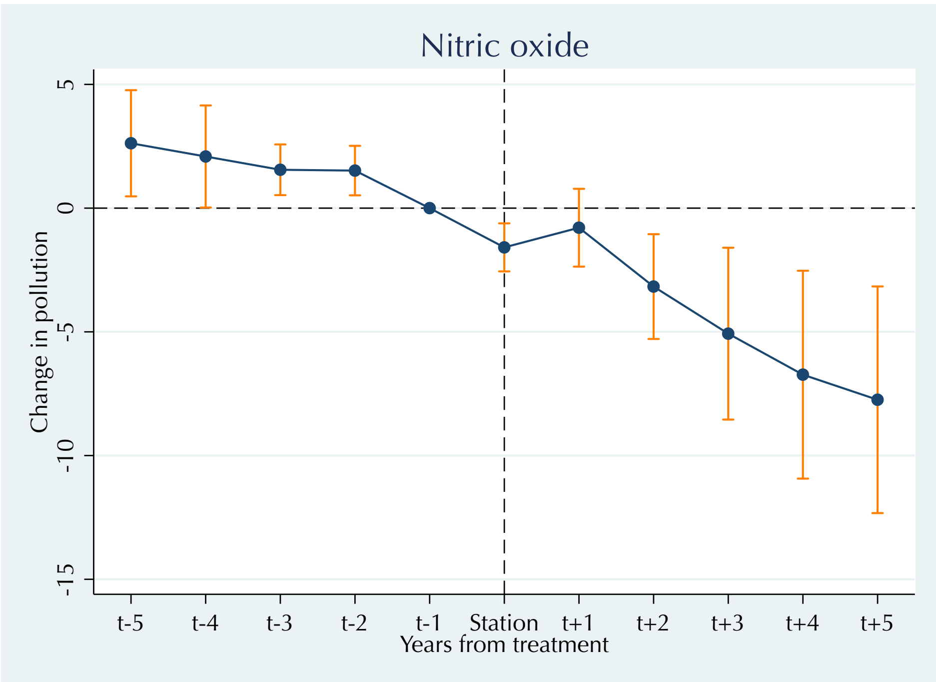

Figure 15: Event study for black carbon, station-present treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

B.2 Convex hull

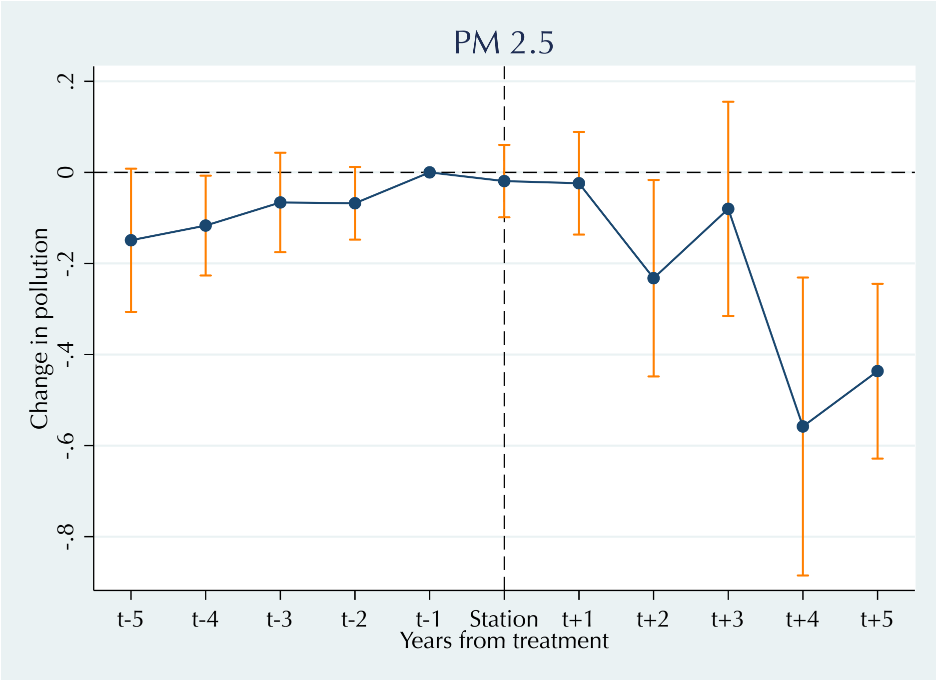

Figure 16: Event study for PM 2.5, service-area treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

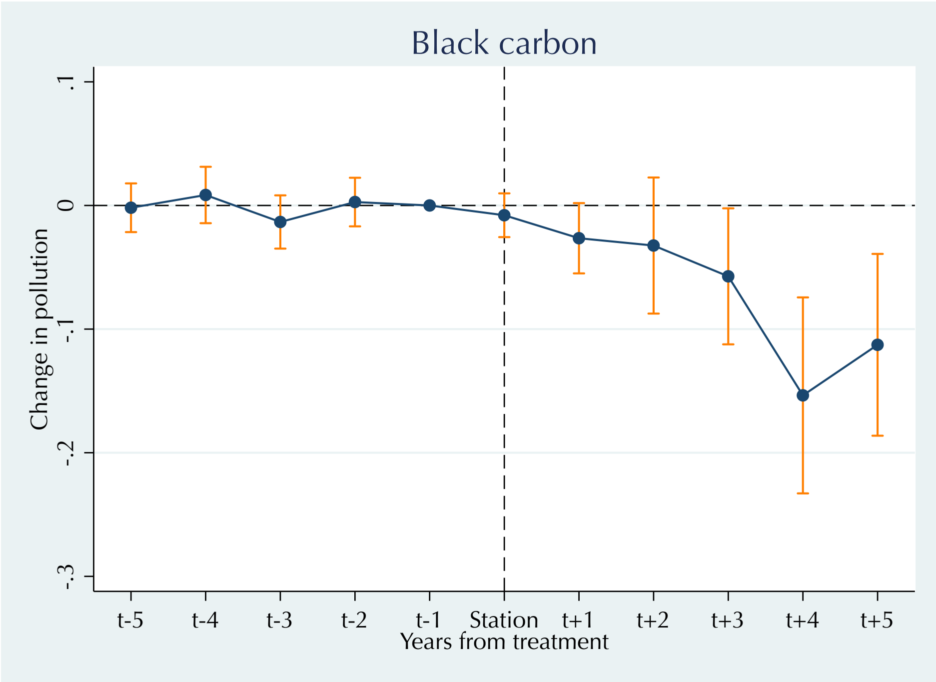

Figure 17: Event study for black carbon, service-area treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

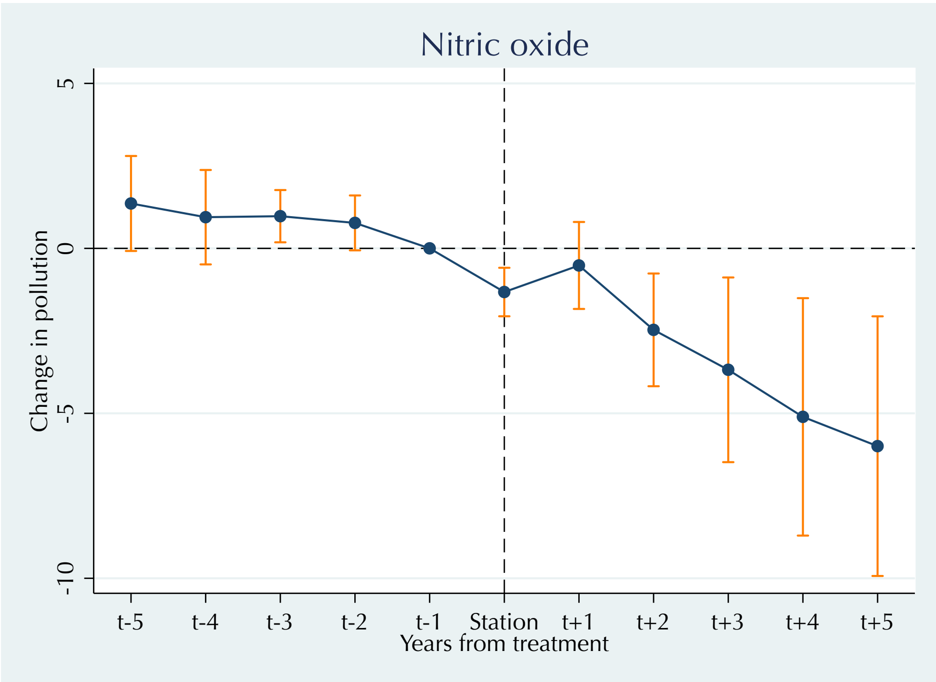

Figure 18: Event study for black carbon, service-area treatment definition. Cell and year fixed effects, standard errors clustered at the community district level.

C Robust staggered difference-in-differences

Difference-in-differences with staggered adoption, variation in treatment timing, multiple time periods and heterogenous treatment effects has been the topic of small revolution in the causal inference community in the past two years. A new strand of the literature has emerged, led by seminal work such as de Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2018), Callaway and Sant'Anna (2020), Sant'Anna and Zhao (2020), Sun and Abraham (2020) and Athey and Imbens (2021).

This appendix reports in-progress work to conform to this new literature and apply the recommended procedures to make difference-in-differences robust to the issues pointed out in these studies.

C.1 Callaway and Sant'Anna (2020) adjustments

Below are the results for the Callaway and Sant'Anna (2020) estimator, yielding robust difference-in-differences for multiple time periods and heterogenous treatment effects. Figures 19 to 21 show the dynamic average treatment effects for the service area treatment definition on the three pollutants of interest.

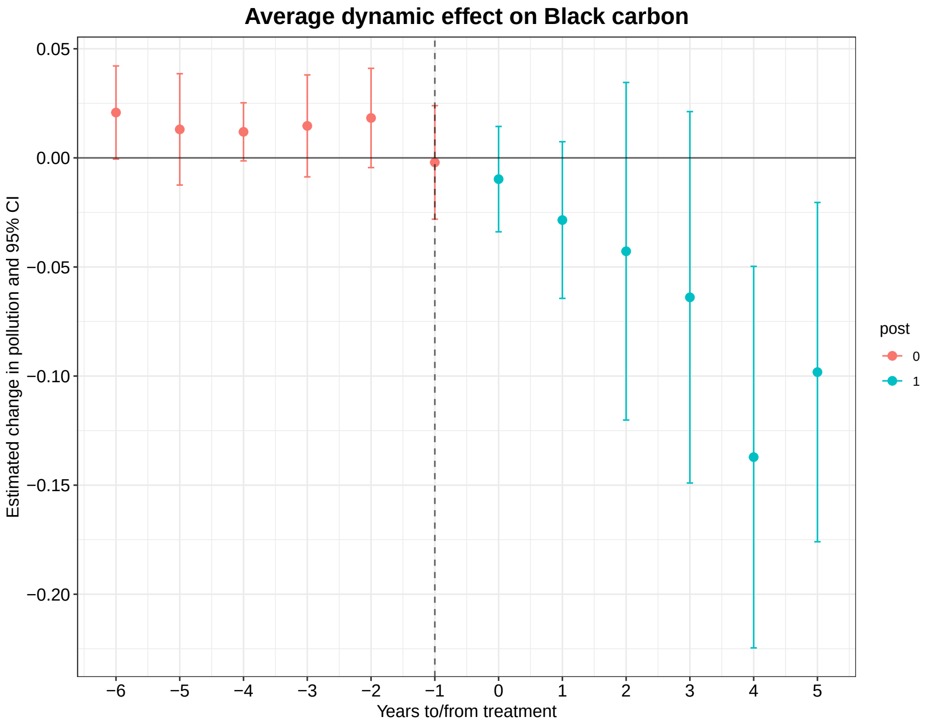

Figure 19: Dynamic average treatment effects of treatment on black carbon, service-area treatment definition. Cell and year fixed effects, standard errors clustered at the community district level. Callaway and Sant'Anna (2020) estimator.

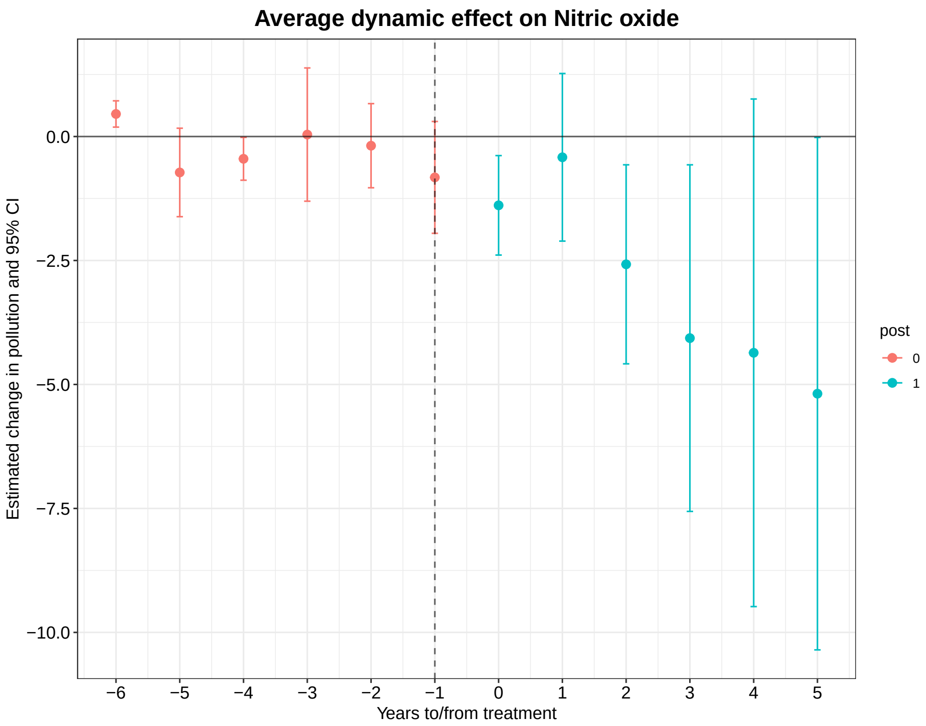

Figure 20: Dynamic average treatment effects of treatment on nitric oxide, service-area treatment definition. Cell and year fixed effects, standard errors clustered at the community district level. Callaway and Sant'Anna (2020) estimator.

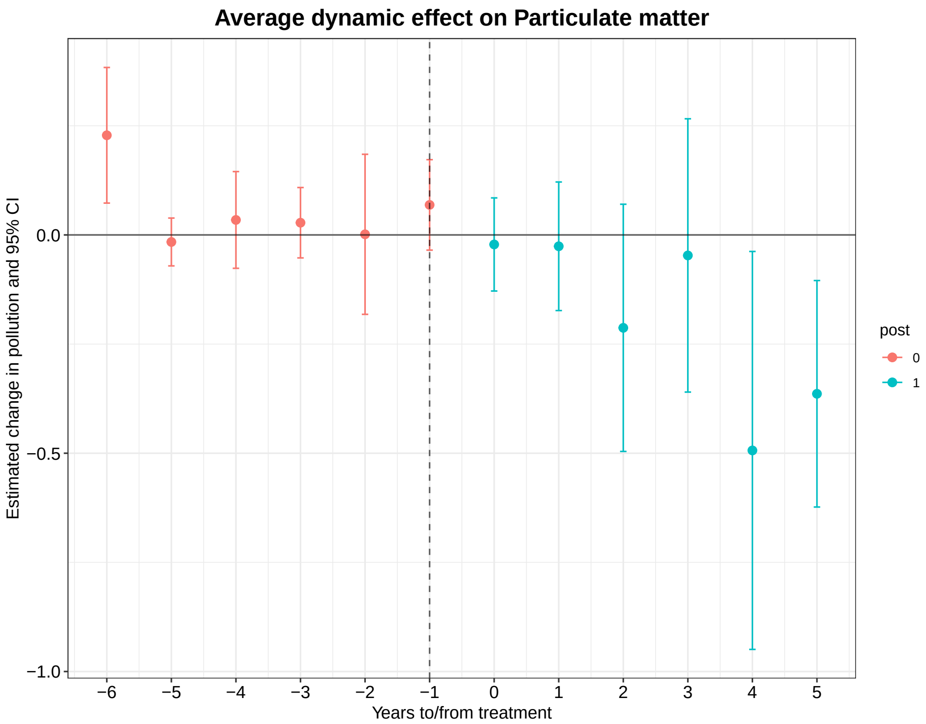

Figure 21: Dynamic average treatment effects of treatment on particulate matter, service-area treatment definition. Cell and year fixed effects, standard errors clustered at the community district level. Callaway and Sant'Anna (2020) estimator.

D Inverse hyperbolic sine

The inverse hyperbolic sine (IHS) is a type of log transformation, particularly suited for variables with a large share of zeros (MacKinnon and Magee, 1990; Bellemare et al., 2013). IHS is computed with the following formula:

$$IHS(x) = ln\left(x + \sqrt{x^2 + 1}\right). \tag{3}$$