Cycling towards cleaner cities? Evidence from New York City's bike share program

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Air pollution in cities

Air pollution is the presence in the atmosphere of substances harmful to human health.

- Significant associated health and economic costs
  - → Yearly death toll between 3 and 9 million worldwide (Lelieveld et al., 2015; Vohra et al., 2021)
  - → Increases morbidity (Guarnieri and Balmes, 2014; Rajagopalan and Brook, 2012; Ibald-Mulli et al., 2001)
  - → Decreases cognitive performance and productivity (Lavy, Ebenstein, and Roth, 2014; Hanna and Oliva, 2015; Shehab and Pope, 2019)
- Urban populations more exposed to air pollution (Strosnider et al., 2017)

Manhattan, ©Lerone Pieters

How do cities deal with air pollution

A large share of urban air pollution comes from ground transport (Transportation Research Board, 2002) and cities have responded with mitigation strategies

- Reducing individual vehicle traffic and congestion
  - $\rightarrow$ low emission zones, congestion pricing, urban tolls
- Encouraging the use of less polluting transport modes
  - $\rightarrow$ increasing access to and supply of public transport
  - $\rightarrow$ incentivizing the use of active transport, e.g. cycling and walking

Cycling as a transport policy

- Cycling has potential to decrease air pollution if it induces modal shifts, i.e. substitution out of polluting modes of transport
- Limited evidence on the effectiveness of cycling policies
  - → Hard to measure bicycle use
  - → Difficult identification problem

Cycling as a transport policy

- Cycling has potential to decrease air pollution if it induces modal shifts, i.e. substitution out of polluting modes of transport

- Limited evidence on the effectiveness of cycling policies
  - $\rightarrow$ Hard to measure bicycle use
  - $\rightarrow$ Difficult identification problem

- Bicycle-share is a good measure of cycling policies because
  - $\rightarrow$ **measurement** usage is precisely measurable
  - $\rightarrow$ **identification** cycling intervention is well-defined in time and space

Research question

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Does bicycle-share reduce local air pollution?

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Does bicycle-share reduce local air pollution?

Hypothesis

The arrival of bicycle share decreases the local cost of cycling relative to other transport modes

→ A share of trips made with polluting vehicles are substituted for bicycle-share

→ Air pollutants associated with polluting vehicles decrease in the areas served by bicycle share

This paper

Exploits the gradual roll-out of bicycle-share in New York City from 2013 to 2019 to compare local air pollution concentrations in bicycle-share-treated areas with control areas using a staggered difference-in-differences strategy.

Work in progress Examines short taxi trips as a potential mechanism for air pollution decrease.

Future work Examines the evidence on health outcomes using geocoded health survey responses, estimates health benefits associated with pollution reduction.

Preview of results

- Reduction in air pollutants associated with road traffic in areas where bicycle-share was implemented:
  - → 2% reduction in nitric oxide compared to pre-treatment mean
  - → 1.7% reduction in black carbon

- Significant reduction in short yellow taxi trips in areas served by bike share

Contributions

Urban air pollution and congestion

Previously Estimated the impact of transport policies on air pollution: Gendron-Carrier et al. (2018), Basagaña et al. (2018), Levy et al. (2018), Cheng (2020), Lelieveld et al. (2015), Pimpin et al. (2018), De Borger et al. (2013), Kheirbek et al. (2016)

→ **Contribution** Analyzing a large-scale cycling policy.

Bicycle literature, a.k.a. "Bikenomics"

Previously Most studies investigating the impact of bike share on pollution and traffic assumed substitution rates and car emissions, ran simulations. Causal paper on bicycle-share and congestion in Washington DC: Hamilton and Wichman (2018). Other causal bicycle infrastructure studies: Daniele et al. (2022), Klingen and van Ommeren (2020)

→ **Contribution** Estimate the causal impact of bicycle-share on air pollution.

Data

Bicycle-share in NYC

- Bicycle-share in NYC started in 2013, expanded over the years
  - → **2013** 338 stations, 23k daily trips on average, 96k yearly subscribers
  - → **2019** 1,166 stations, 51k daily trips on average, 167k yearly subscribers
- Privately run (Lyft), publicly regulated (NYC Department of Transportation)
- How it works
  - → bicycles available at stations 24/7
  - → several membership plans ($185 yearly, discounts available)
  - → first 45 minutes free

▸ Citi Bike Station

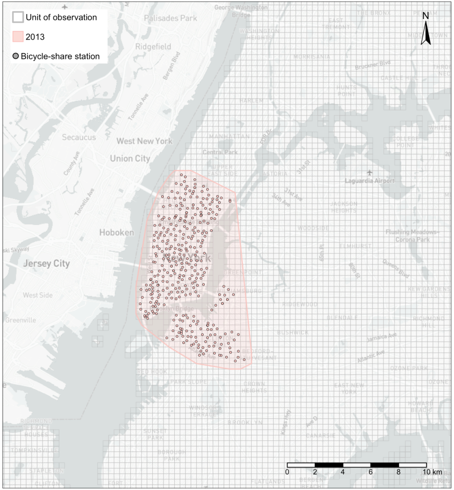
Data · Bicycle-share

Universe of bicycle-share trips publicly available

- +100 million trips from 2013 to 2019
- Origin-destination station, date and time of pickup and drop-off, subscribers' demographics

→ Construct bicyle-share-treated areas ▸ Stations ▸ Routes ▸ All

Bicycle-share service area · yearly growth



Data · Air pollution i

NYC Community Air Survey (NYCCAS), 2009–2019

- Yearly annual averages of six air pollutants for 300-by-300 meters cells
  - → Seasonal data obtained for a subset of years (2009, 2010, 2014, 2016, 2018, 2019)
- Four pollutants of interest: associated with road traffic + measured close to emission source
- Nitric oxide (NO) and nitrous dioxide (NO_2)
  - → Common marker of vehicular traffic
  - → 30% of emissions attributed to on-road traffic
  - → NO marker of fresh combustion emissions: steeper gradient near busy roadways

Data · Air pollution ii

- Particulate matter (PM 2.5) and black carbon (BC)
  - → Significant proportions of PM 2.5 from outside the city, but local variation likely due to local emissions
  - → Traffic may account for up 36–39% of PM 2.5 emissions in high-traffic locations
  - → BC makes up only a small proportion of overall PM 2.5 (4–11% in US cities), but up to 75% of PM 2.5 from diesel exhaust (Matte et al., 2013)

▸ NYCCAS details ▸ NO concentrations 2013

Estimation strategy

Two-Way Fixed Effects

Staggered difference-in-differences: comparing cells treated by bicycle-share with untreated ones, before and after the treatment. Standard Two-Way Fixed Effects (TWFE):

$$Y_{ct} = \beta Treat_{ct} + year_t + cell_c + \boldsymbol{C}_{ct} + \varepsilon_{ct}, \tag{1}$$

for cell c at year t, with $\boldsymbol{C}$ a vector of control variables.

Two-Way Fixed Effects

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for cell c at year t, with $\boldsymbol{C}$ a vector of control variables.

- Y_{ct}: a pollutant's concentration
- $Treat_{ct}$: one of the treatment definition
- $year_t + cell_c$: year and cell fixed effects
- $\boldsymbol{C}_{ct}$: median income, population and proportion of college graduates

Standard errors are clustered at the community district level (neighborhood).

Estimation parameters

- Panel dataset
  - → **units** grid cells (9,171)
  - → **time** years (10, 2010–2019)
  - → **treatment** cell treated by bike-share: station within 300m, within convex hull, crossed by traffic footprint
- Parallel trends conditioned on covariates (pre-treatment value, for each cell)
  - → population
  - → fraction of bachelor graduates
  - → household income
  - → meters of bicycle lanes
  - → distance to coast
  - → land use, building height

Results

ATT · Black carbon, binary treatments

	BC					
	(1)	(2)	(3)	(4)	(5)	(6)
Station	-0.0605***	-0.0571***				
	(0.0194)	(0.0189)				
Convex polygon			-0.0586***	-0.0557***		
			(0.0173)	(0.0168)		
Car route					-0.0567***	-0.0544***
					(0.0151)	(0.0146)
Controls		✓		✓		✓
Cell	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Mean out. pre-treat.	1.004	1.006	1.004	1.006	1.004	1.006
Perc. of mean out. pre-treat.	-6.026	-5.674	-5.832	-5.538	-5.650	-5.401
Observations	96,700	95,678	96,700	95,678	96,700	95,678
R^2	0.925	0.925	0.925	0.925	0.926	0.926
Within R^2	0.037	0.039	0.037	0.039	0.038	0.041

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

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

- Bicycle-share reduced black carbon concentration by 5.3% with respect to mean concentration pre-treatment

ATT · PM 2.5, binary treatments

	PM					
	(1)	(2)	(3)	(4)	(5)	(6)
Station	-0.1695**	-0.1419**				
	(0.0660)	(0.0704)				
Convex polygon			-0.1234*	-0.0924		
			(0.0692)	(0.0733)		
Car route					-0.0818	-0.0518
					(0.0671)	(0.0711)
Controls		✓		✓		✓
Cell	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Mean out. pre-treat.	9.387	9.397	9.387	9.397	9.387	9.397
Perc. of mean out. pre-treat.	-1.806	-1.511	-1.314	-0.983	-0.871	-0.551
Observations	96,700	95,678	96,700	95,678	96,700	95,678
R^2	0.979	0.980	0.979	0.979	0.979	0.979
Within R^2	0.046	0.057	0.037	0.052	0.026	0.040

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

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Year	✓	✓	✓	✓	✓	✓
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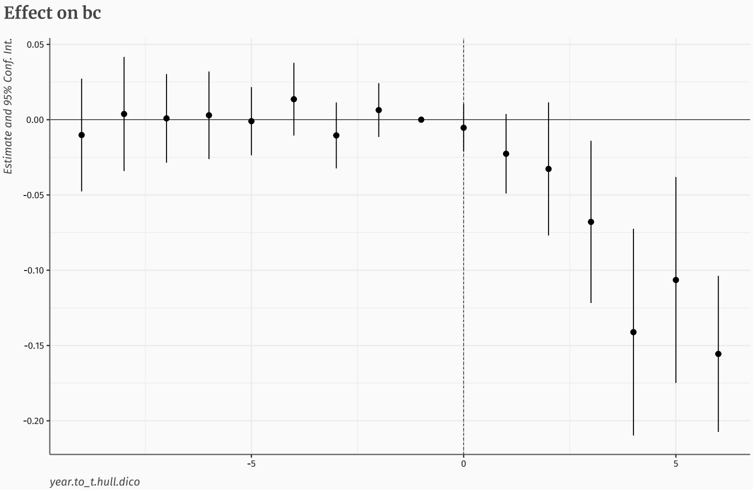
Observations	96,700	95,678	96,700	95,678	96,700	95,678
R^2	0.979	0.980	0.979	0.979	0.979	0.979
Within R^2	0.046	0.057	0.037	0.052	0.026	0.040

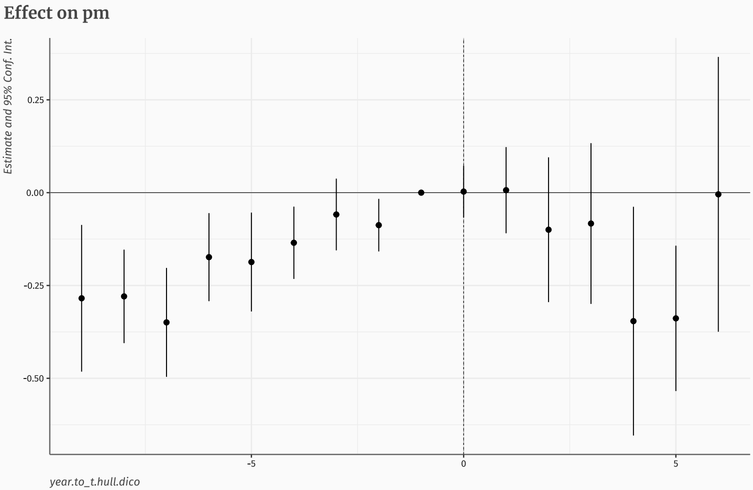
Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

- Bicycle-share reduced PM 2.5 concentration by 0.9% (insignificant) with respect to mean concentration pre-treatment

Event study · Black carbon



Event study · PM



ATT · Nitric Oxide, binary treatments

	NO					
	(1)	(2)	(3)	(4)	(5)	(6)
Station	-3.4934***	-3.2624***				
	(1.0064)	(1.0450)				
Convex polygon			-2.6243***	-2.3084**		
			(0.9449)	(0.9945)		
Car route					-2.3026***	-1.9849**
					(0.8387)	(0.8968)
Controls		✓		✓		✓
Cell	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Mean out. pre-treat.	20.242	20.277	20.242	20.277	20.242	20.277
Perc. of mean out. pre-treat.	-17.258	-16.089	-12.965	-11.385	-11.375	-9.789
Observations	96,700	95,678	96,700	95,678	96,700	95,678
R^2	0.920	0.921	0.916	0.917	0.913	0.914
Within R^2	0.183	0.191	0.140	0.152	0.105	0.119

Clustered (Community district) standard-errors in parentheses

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R^2	0.920	0.921	0.916	0.917	0.913	0.914
Within R^2	0.183	0.191	0.140	0.152	0.105	0.119

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

- Bicycle-share reduced nitric oxide concentration by 11.4% with respect to mean concentration pre-treatment

ATT · Nitric Dioxide, binary treatments

	NO2					
	(1)	(2)	(3)	(4)	(5)	(6)
Station	-1.2417***	-1.0697***				
	(0.2898)	(0.3075)				
Convex polygon			-0.9401***	-0.7589**		
			(0.3062)	(0.3254)		
Car route					-0.8558***	-0.6770**
					(0.2701)	(0.2891)
Controls		✓		✓		✓
Cell	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Mean out. pre-treat.	19.850	19.911	19.850	19.911	19.850	19.911
Perc. of mean out. pre-treat.	-6.256	-5.372	-4.736	-3.811	-4.311	-3.400
Observations	96,700	95,678	96,700	95,678	96,700	95,678
R^2	0.980	0.981	0.980	0.980	0.980	0.980
Within R^2	0.152	0.172	0.116	0.143	0.126	0.150

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

ATT · Nitric Dioxide, binary treatments

	NO2					
	(1)	(2)	(3)	(4)	(5)	(6)
Station	-1.2417***	-1.0697***				
	(0.2898)	(0.3075)				
Convex polygon			-0.9401***	-0.7589**		
			(0.3062)	(0.3254)		
Car route					-0.8558***	-0.6770**
					(0.2701)	(0.2891)
Controls		✓		✓		✓
Cell	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Mean out. pre-treat.	19.850	19.911	19.850	19.911	19.850	19.911
Perc. of mean out. pre-treat.	-6.256	-5.372	-4.736	-3.811	-4.311	-3.400
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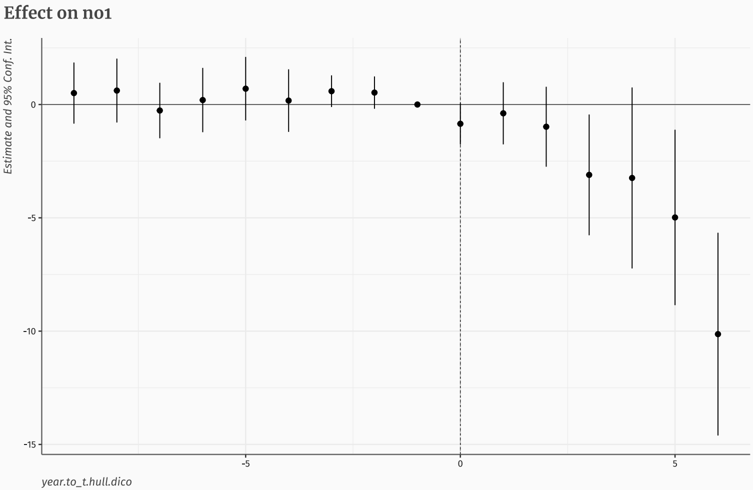
Within R^2	0.152	0.172	0.116	0.143	0.126	0.150

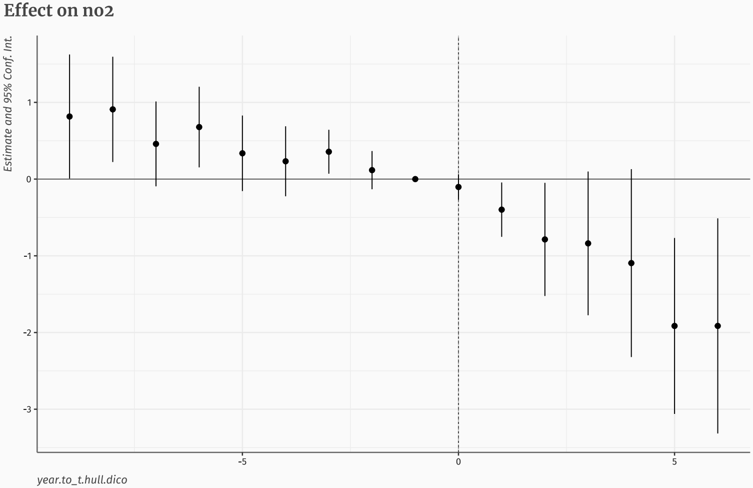
Clustered (Community district) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

- Bicycle-share reduced nitric dioxide concentration by 3.8% with respect to mean concentration pre-treatment

Event study · Nitric Oxide



Event study · Nitric Dioxide



Robustness checks

- Done
  - → Alternative treatment definitions ▸ Stations ▸ Traffic footprint
  - → "Not-yet-treated" as control group ▸ Tables and plots
  - → Seasonal estimations
  - → New DiD method robust to variation in treatment timing and heterogenous treatment effects (Callaway and Sant'Anna, 2021) ▸ Tables and plots
  - → Effects on O_3 and SO_3 ▸ Tables and plots
- Not yet done/ideas
  - → Restrict control group
  - → Exclude boroughs/areas
  - → Spatial spillovers

Mechanism

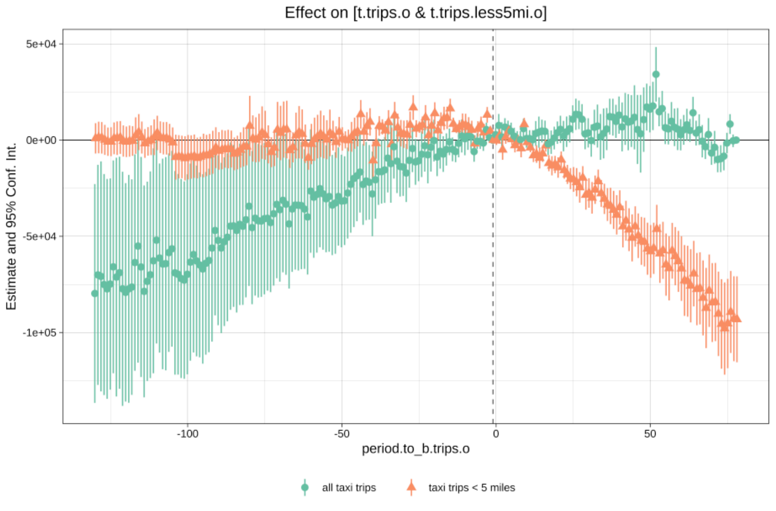
Goal

Is there evidence that commuters switch to cycling after bike share is introduced?

$\rightarrow$ do short taxi trips reduce in areas where bike share is implemented?

- Taxi & Limousine Commission Trip Record Data
  - $\rightarrow$ Universe of taxi trips in NYC, 2009–2019: 2.5 billion trips
  - $\rightarrow$ Spatial resolution: origin/destination taxi zones (263) ▸ Map
  - $\rightarrow$ Use trip distance to identify taxi trips likely to be substituted by bike share (< 5 miles)

Mechanism · results



Thank you

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Air pollution and morbidity

- chronic diseases: respiratory, diabetes, cardiovascular (Guarnieri and Balmes, 2014; Rajagopalan and Brook, 2012; Ibald-Mulli et al., 2001)
- reduced size and weight of newborns (Currie and Walker, 2011; Schembari et al., 2015)
- worsening of mental health (Chen, Oliva, and Zhang, 2018)
- decreasing labor supply (Hanna and Oliva, 2015; Aragón, Miranda, and Oliva, 2017)

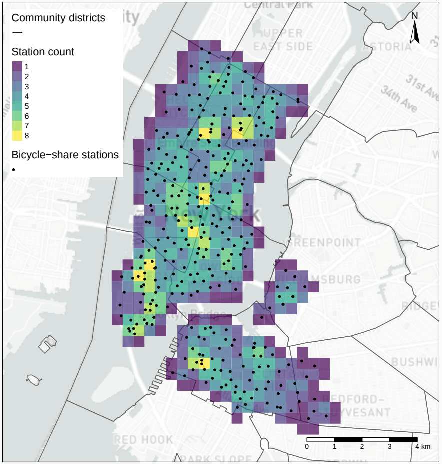
Back

Citi Bike Station

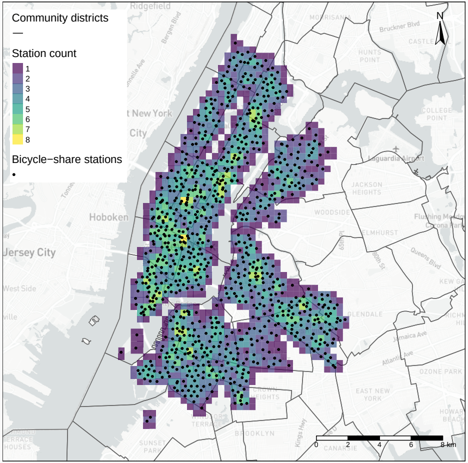
Back

Stations within 300 meters

2013



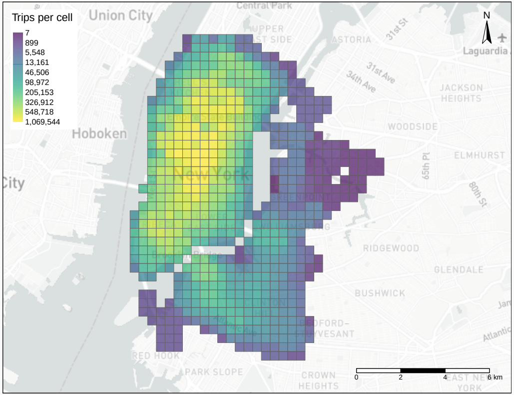
2019



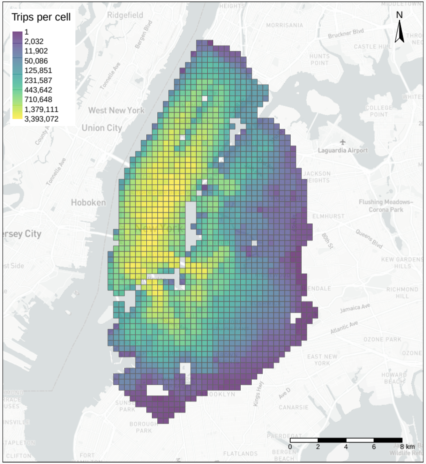
Back

Traffic "footprint"

2013



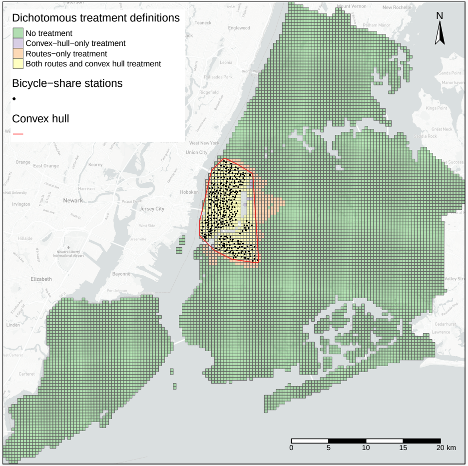
2019



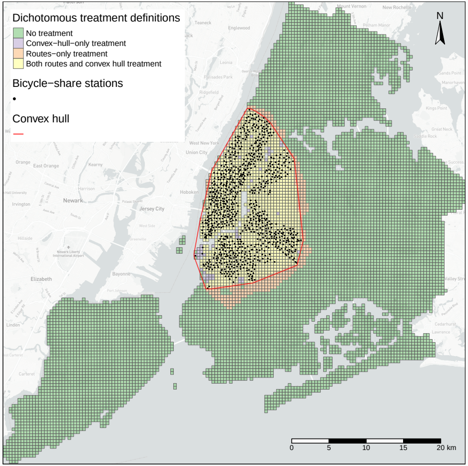
▸ Back

All treatment definitions

2013



2019



Back

NYCCAS details

Concentrations of PM 2.5, black carbon, nitrogen oxides (NO and NO^2), sulfur dioxide (SO^2) and ozone (O^3)

- 150 measurement stations: 120 randomly placed, 30 at purposeful sites
- Overlays a grid over the city made up of square cells 300m wide
- For each cell, estimates the annual average concentration of pollutant using a land-use regression (LUR) model

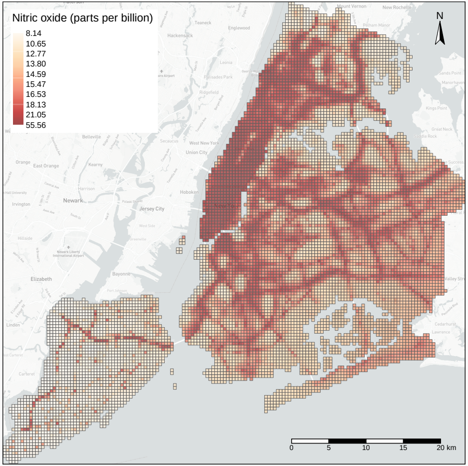
Land-use regression (LUR) model:

$$\begin{aligned} Concentration_{it} = {} & \beta_0 + \beta_1 RefStation_{it} + \beta_2 Source1_i \\ & + \beta_3 Source2_i + \beta_3 Source1_i \times SiteCharac_{it} + \varepsilon_{it} \end{aligned}$$

▸ Back

Mapping air pollution · nitric oxide (NO) 2013

2013



Back

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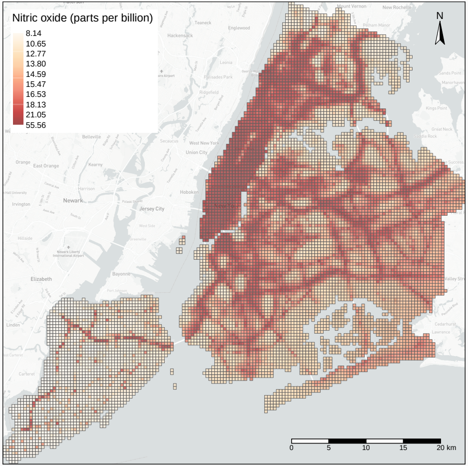
Back

Mapping air pollution · nitric oxide (NO) 2013

2013



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ATT · Black carbon & PM 2.5

	BC		PM 2.5	
	Uncondit. PT	Condit. PT	Uncondit. PT	Condit. PT
Service area ATT	−0.044	−0.023	−0.098	−0.008
	(0.002)	(0.003)	(0.008)	(0.010)
Mean pre-treat.	1.015	1.015	9.433	9.433
Mean pre-treat., treated	1.324	1.324	10.785	10.785
ATT in % of mean pre-treat. treated	3.30	1.72	0.91	0.08
SD	0.287	0.287	1.492	1.492
N (cells)	9171	9171	9171	9171
Years	10	10	10	10

Uncondit. PT: unconditional parallel trends; *Condit. PT*: parallel trends conditional on a set of covariates. Standard-errors in parentheses, clustered at unit level.

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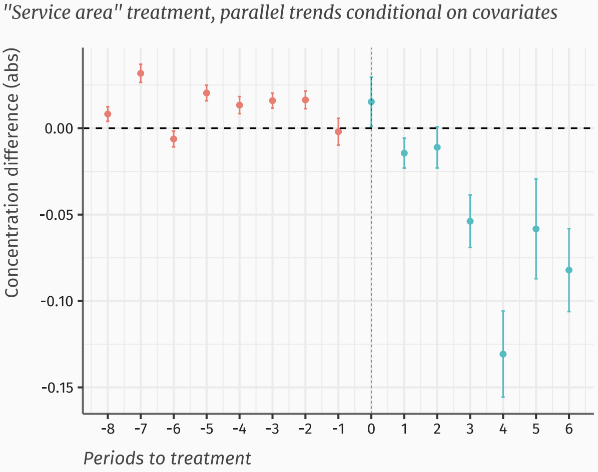
- Bicycle-share reduced black carbon concentration by 1.72% with respect to mean concentration in treated areas pre-treatment

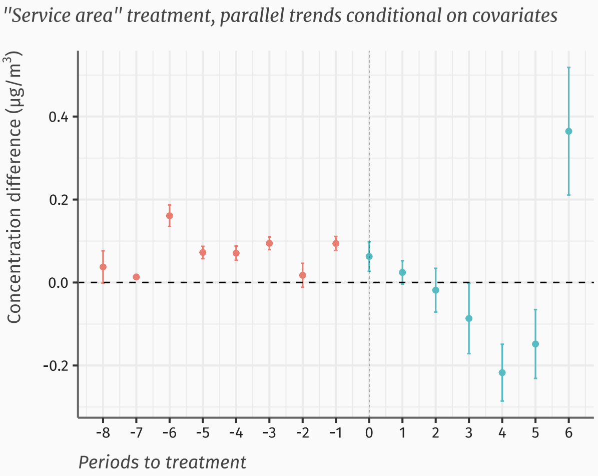
Dynamic effects · Black carbon



- Parallel trends pre-treatment: treated cells display higher concentrations pre-treatment.
- Negative and persistent treatment effects post-treatment.

▸ Back robustness

Dynamic effects · PM



- Slightly higher concentrations pre-treatment in treated cells.
- Negative treatment trend post-treatment, but major outlier period (6).

▸ Back robustness

ATT · NO & NO2

	NO		NO2	
	Uncondit. PT	Condit. PT	Uncondit. PT	Condit. PT
Service area ATT	−1.678	−0.582	−0.538	−0.231
	(0.130)	(0.170)	(0.035)	(0.038)
Mean pre-treat.	20.322	20.322	19.950	19.950
Mean pre-treat., treated	28.646	28.646	26.622	26.622
ATT in % of mean pre-treat. treated	5.86	2.03	2.02	0.87
SD	6.875	6.875	4.961	4.961
N (cells)	9171	9171	9171	9171
Years	10	10	10	10

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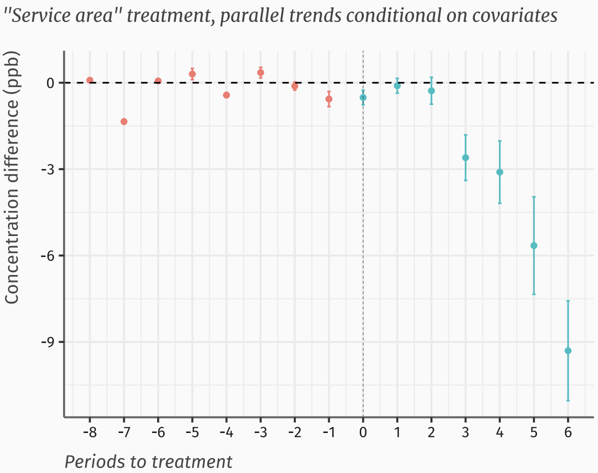
Uncondit. PT: unconditional parallel trends; *Condit. PT*: parallel trends conditional on a set of covariates. Standard-errors in parentheses, clustered at unit level.

- Bicycle-share reduced NO concentration by 2.03% with respect to mean concentration in treated areas pre-treatment

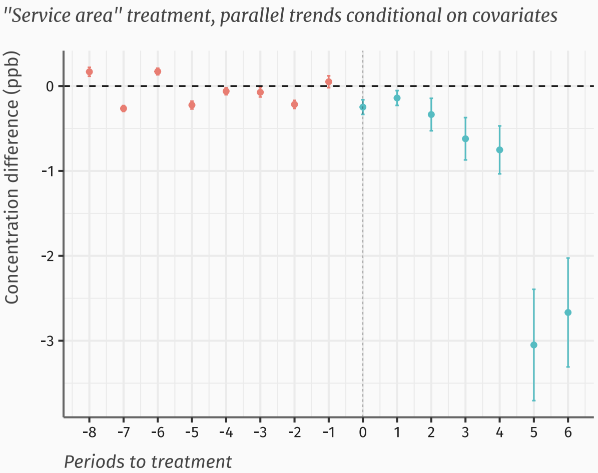
Dynamic effects · NO



- Parallel trends pre-treatment look better, but not perfect.
- Negative and persistent treatment effects post-treatment.

Back robustness

Dynamic effects · NO2



- Parallel trends pre-treatment look better, but not perfect.
- Negative and persistent treatment effects post-treatment.

▸ Back robustness

ATT · O3 & SO2 · Placebo

	O3		SO2	
	Condit. PT	Condit. PT	Uncondit. PT	Condit. PT
On-car-route ATT	0.401	0.393	−0.617	−0.146
	(0.029)	(0.045)	(0.022)	(0.057)
Mean pre-treat.	34.047	34.047	2.759	2.759
Mean pre-treat., treated	30.914	30.914	4.173	4.173
ATT in % of mean pre-treat. treated	1.30	1.27	14.79	3.49
SD	3.229	3.229	1.604	1.604
N (cells)	9171	9171	9171	9171
Years	10	10	7	7

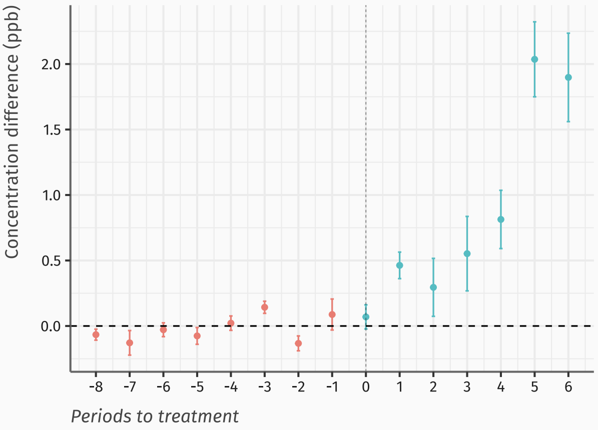
Uncondit. PT: unconditional parallel trends; *Condit. PT*: parallel trends conditional on a set of covariates.

▸ Back robustness

Dynamic effects · O3

▸ Back robustness

"Service area" treatment, parallel trends conditional on covariates



Dynamic effects · SO2

▸ Back robustness

"Service area" treatment, parallel trends conditional on covariates