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

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Why do we care about air pollution?

Air pollution is harmful to human health and the economy

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- Other health impacts: chronic respiratory diseases (asthma, $50 billion/year (Nurmagambetov et al., 2018)), cardiovascular diseases, diabetes, size of newborns, (Guarnieri and Balmes, 2014; Rajagopalan and Brook, 2012; Ibald-Mulli et al., 2001)

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- Decreases cognitive performance, productivity, alteration to decision-making (Lavy, et al., 2014; Hanna and Oliva, 2015; Shehab and Pope, 2019, Aguilar-Gomez et al., 2022)

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Cities and air quality

Air quality is a major issue for cities since they concentrate

- economic activity

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- large human populations $\rightarrow$ harmed by exposure to air pollution

$\rightarrow$ Small reductions in air pollution concentrations for large populations can have substantial positive impacts (Carozzi and Roth, 2023; Strosnider et al., 2017)

The potential of cycling to reduce air pollution

- Road transport is a major source of air pollution
  - → Most road vehicle are powered by internal-combustion engines and emit air pollutants
  - → Transportation emits 30% of local air pollutants in New York City (Matte et al., 2013)

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- Cycling has two features that can address pollution from road transport
  1. It does not emit air pollution
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- Cycling has two features that can address pollution from road transport
  1. It does not emit air pollution
  2. It can replace some road transport trips
- However, it remains unclear if investments in cycling infrastructure...
  - → Induce substitution away from polluting vehicles and towards cycling
  - → Ultimately decrease air pollution

Bike share: widespread, large-scale cycling infrastructure

Bike share has been popular cycling infrastructure intervention in the past 20 years

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→ Causal evidence on their impacts on the environment of cities is scarce

This paper

Research question

Does bike share reduce local air pollution?

This paper

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Does bike share reduce local air pollution?

- This paper estimates the causal impact of bike share on local air pollution concentrations
  - → Exploiting the gradual roll-out of NYC's bike share program since 2013 by using a staggered difference-in-differences strategy
  - → Combining it with ten years of high-resolution, ground-level measures of air pollution

Preview of results

Main results

- In bike share's area of influence:
  - → 13% reduction in nitric oxide (vs pre-treatment mean concentrations)
  - → 5% reduction in black carbon
  - → Back-of-the-envelope social benefits valued to up to $320 million

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Evidence on mechanisms

- Does bike share reduce car traffic? Using taxi trips:
  - → Taxi service is popular and taxi trips are similar to bike share trips → potential substitute
  - → Suggestive evidence of fewer short taxi trips in areas served by bike share

Contribution

Previous literature

- Air quality impacts of other urban transportation interventions: e.g. underground expansion, congestion tolls, electric vehicles (Gendron-Carrier et al., 2018; Green et al., 2020, Basagaña et al., 2018; Levy et al., 2018; De Borger et al., 2013; Kheirbek et al., 2016)
- Scarce causal evidence on the impacts of bike share on air quality (Shr et al., 2022; Wang and Zhou, 2017; Hamilton and Wichman, 2018)

Contribution

Previous literature

- Air quality impacts of other urban transportation interventions: e.g. underground expansion, congestion tolls, electric vehicles (Gendron-Carrier et al., 2018; Green et al., 2020, Basagaña et al., 2018; Levy et al., 2018; De Borger et al., 2013; Kheirbek et al., 2016)

- Scarce causal evidence on the impacts of bike share on air quality (Shr et al., 2022; Wang and Zhou, 2017; Hamilton and Wichman, 2018)

→ First paper to estimate the long-term causal impact of bike share on air quality using high-resolution, ground-level measures of air pollution over ten years.

Data

Air pollution I

- NYC Community Air Survey (NYCCAS), 2009–2019
  - → For 300-by-300 meters cells (units of analysis) ▸ Grid scale illustration
  - → Yearly annual average concentrations of six air pollutants ▸ NYCCAS details
  - → Pollutant selection: associated with road traffic + measured close to emission source

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    - Nitrous dioxide
    - Particulate matter
    - Black carbon

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    - Nitric oxide
    - Nitrous dioxide
    - Particulate matter
    - Black carbon
- 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

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
  - → 35% of PM emissions attributed to traffic in high-traffic locations
  - → BC is a subset of PM 2.5 (4–11% in US cities), but up to 75% of PM 2.5 from diesel exhaust

▸ NO concentrations 2013

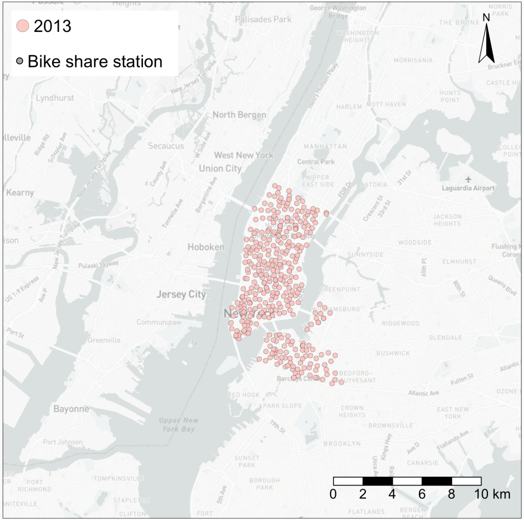
Bike share system in NYC

- Opened in May 2013, gradual expansion
- Fixed docking stations, 24/7
- Stations and bikes
  - → **2013** 332 stations, 6K bikes
  - → **2019** 780 stations, 13K bikes
- Average daily bike share trips
  - → **2013** 22K trips
  - → **2019** 56K trips (+154%)
  - → Most trips by annual subscribers

▸ Bike share usage ▸ Cycling stats ▸ NYC vs Peer Cities

Bike share system roll-out

Bike share system · yearly growth



Conceptual framework

- Bike share reduces the cost of (and improves the accessibility to) cycling in areas where implemented

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→ This change in the relative local attractiveness of cycling *vs* other transport modes leads some individuals to switch to cycling

→ Bike share reduces pollution if bike share trips replace (i.e., substitute away from) motor vehicle trips

  → We expect pollution to reduce where fewer motor vehicles are driven due to bike share

Construction of treatment

- Bike share data: the universe of bike share trips made on the system since opening in May 2013
  - → >100 million trips from 2013 to 2019
  - → variables for each trip: start/end station, time and date, rider demographics

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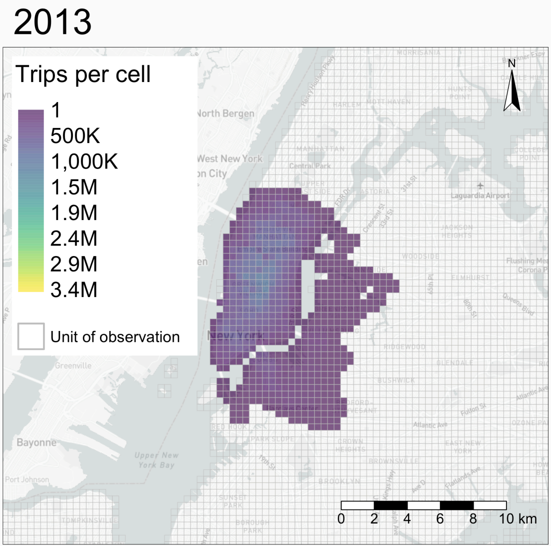
- For each year:
  1. Identify pairs of bike share stations (i.e., at least one trip between the two stations)
  2. Compute optimal car route for each pair stations and add a 300m buffer
  3. Intersect the routes+buffer with the grid map: cells intersected by routes+buffer are considered treated

  → Obtain the spatial extent of bike share's influence on car traffic, i.e., areas where fewer cars are expected to be driven after bike share

Bike share treatment construction

▸ Real routing

Bike share treatment



Estimation strategy and Results

Estimating equation

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

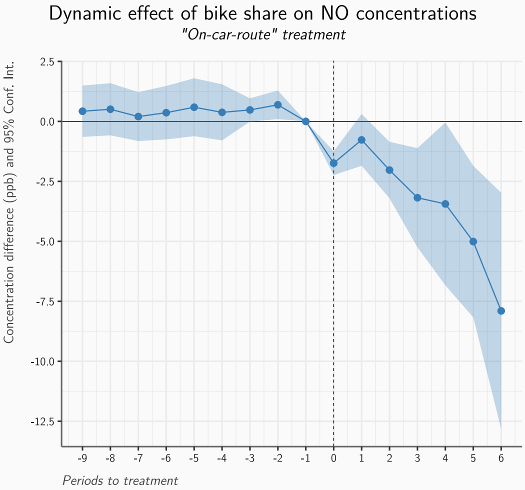
$$Y_{ct} = \beta Treat_{ct} + year_t + cell_c + \mathbf{C}_{ct} + \varepsilon_{ct}, \tag{1}$$

for cell c at year t

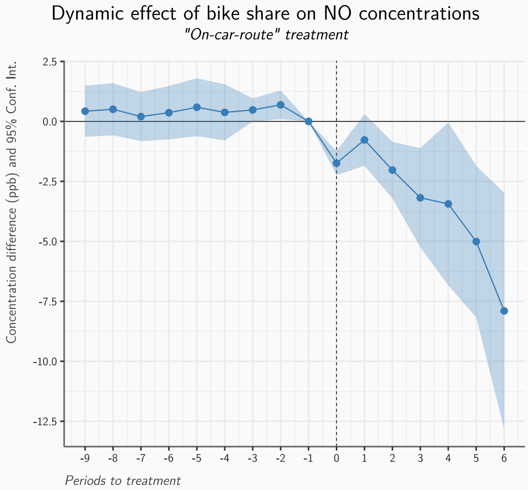
- Y_{ct}: concentration of pollutant y
- $Treat_{ct}$: treated by bike share
- $year_t + cell_c$: year and cell fixed effects
- $\mathbf{C}_{ct_0}$: vector of control variables

Standard errors clustered at the community district level (neighbourhood) ▸ Estimation parameters

Nitric Oxide



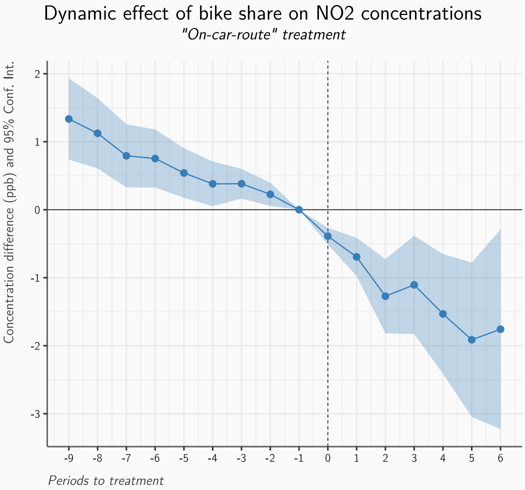
Nitric Oxide



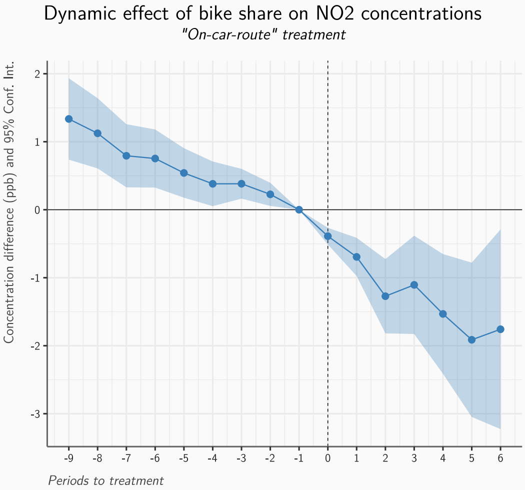
	NO	
	(1)	(2)
On-car-route	-2.5360***	-2.7281***
	(0.8595)	(0.8543)
Baseline controls		✓
Cell FE	✓	✓
Year FE	✓	✓
Mean concentration pre-treat.	20.322	20.353
% mean concentration pre-treat.	-12.479	-13.404
Observations	91,710	90,898
R^2	0.906	0.908
Within R^2	0.049	0.066

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

Nitrous Dioxide



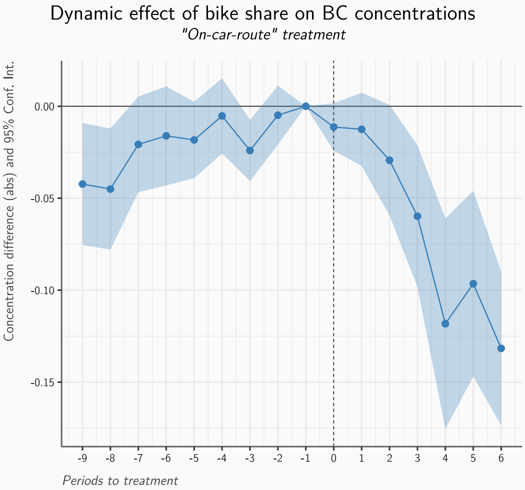
Nitrous Dioxide



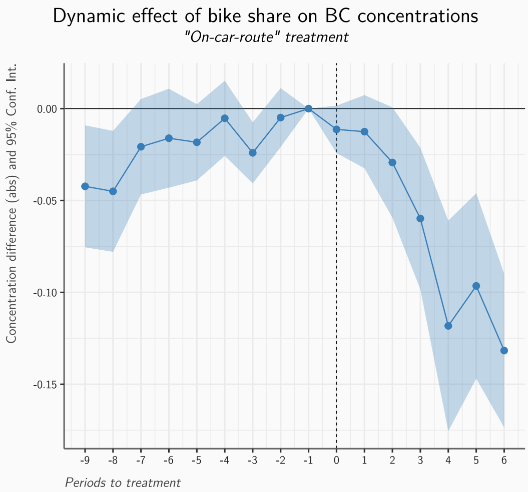
	NO2	
	(1)	(2)
On-car-route	-1.1489***	-1.2554***
	(0.2771)	(0.2759)
Baseline controls		✓
Cell FE	✓	✓
Year FE	✓	✓
Mean concentration pre-treat.	19.950	20.007
% mean concentration pre-treat.	-5.759	-6.275
Observations	91,710	90,898
R^2	0.978	0.979
Within R^2	0.081	0.123

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

Black Carbon



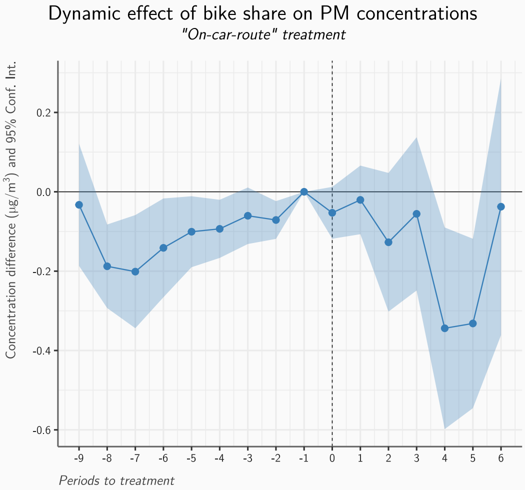
Black Carbon



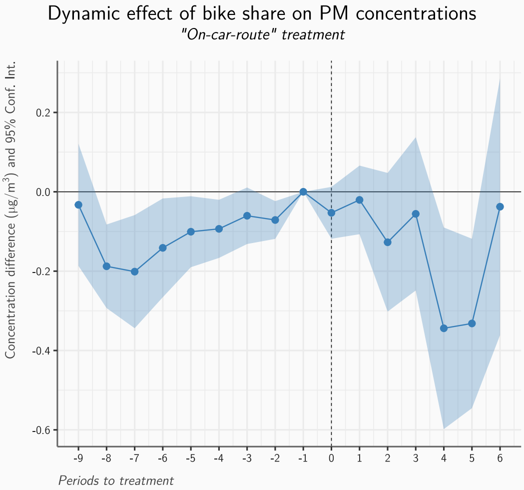
	BC	
	(1)	(2)
On-car-route	-0.0253*	-0.0280**
	(0.0128)	(0.0129)
Baseline controls		✓
Cell FE	✓	✓
Year FE	✓	✓
Mean concentration pre-treat.	1.015	1.017
% mean concentration pre-treat.	-2.494	-2.757
Observations	91,710	90,898
R^2	0.956	0.956
Within R^2	0.006	0.011

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

PM 2.5


Dynamic effect of bike share on PM concentrations
"On-car-route" treatment
Concentration difference (µg/m³) and 95% Conf. Int.
0.2
0.0
-0.2
-0.4
-0.6
-9
-8
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
Periods to treatment

PM 2.5



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

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

Results discussion

- NO and BC concentrations reduce in areas where fewer cars are likely driven due to bike share
  - → By 13.4% and 2.7% compared to pre-bike-share mean concentrations
  - → Results contrast with Shr et al. (2022) who find no effect of bike share on NO concentrations one year after implementation in Taiwan
- Back-of-the-envelope valuation of social benefits from reduction in NO concentrations for the entire post-bike-share period
  - → up to $327 million ▸ Valuation
- Robustness checks
  - → Alternative treatment definitions ▸ Service area ▸ Stations
  - → Intensity of treatment ▸ NO ▸ NO2 ▸ BC ▸ PM
  - → Borusyak, Jaravel and Spiess (2022) estimator robust to variation in treatment timing and heterogenous treatment effects ▸ Plots

Mechanism

Did bike share reduce motor traffic?

- Is there evidence that bike share reduced road traffic, which could explain the decrease in air pollution?
- Taxis serve a similar purpose as bike share: short trips in the city centre
- Is there evidence that taxi trips decrease after the arrival of bike share?

Taxis in NYC

Taxis are a popular transport mode in NYC. In 2014:

	Taxis
Trips	485K trips/day
	55% of trips <3km
	average price $4/km
Passengers	70% ⩽35 years old
	55% male
Traffic	In Midtown, >50% of all vehicles

Source: New York City Taxi and Limousine Commission (2014) and Citi Bike trip data.

▸ Midtown taxi vs bike share

Taxis in NYC

Taxis are a popular transport mode in NYC. In 2014:

	Taxis	Bike share
Trips	485K trips/day	25K trips/day
	55% of trips <3km	>70% of trips <3km
	average price $4/km	
Passengers	70% ⩽35 years old	Median age: 33 years old
	55% male	70% male
Traffic	In Midtown, >50% of all vehicles	

Source: New York City Taxi and Limousine Commission (2014) and Citi Bike trip data.

▸ Midtown taxi vs bike share

Testing the substitution mechanism

- Previous research
  - → Taxis ridership increases when bike share stations go out of service in NYC (Molnar and Ratsimbazafy, 2017)
  - → Taxis are a good approximation of motor traffic in general (Castro et al., 2012; Peng et al., 2016)

Testing the substitution mechanism

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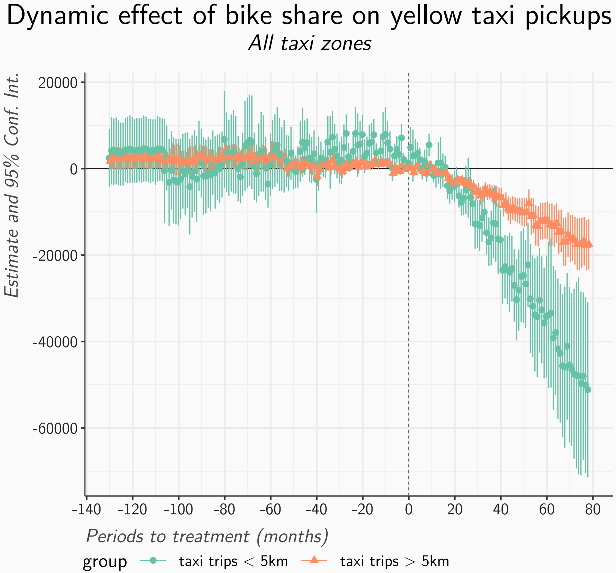
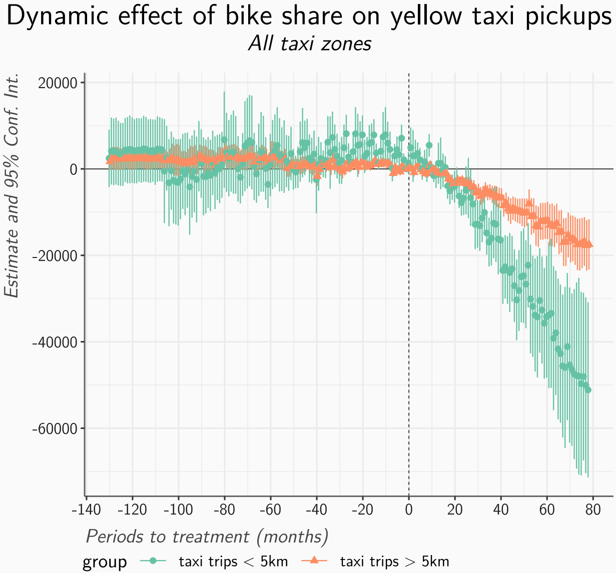
  → Taxis are a good approximation of motor traffic in general (Castro et al., 2012; Peng et al., 2016)

- This paper
  → Use the universe of NYC taxi trips: geolocated, timestamped, measure of distance
  → Identify taxi trips most substitutable by bike share
    - 85% of bike share trips are less than 5km
    → distinguish short (<5km) taxi trips from long (>5km) ones
  → Same identification strategy: does the staggered roll-out of bike share reduce short taxi trips?

Mechanism · results

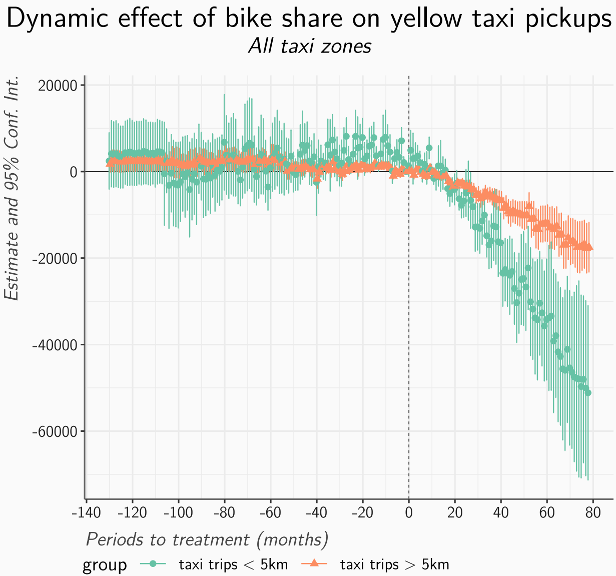


Mechanism · results



Short taxi trips decrease faster than long taxi trips in areas where bike share stations are implemented.

Mechanism · results



Short taxi trips decrease faster than long taxi trips in areas where bike share stations are implemented.

→ Suggestive evidence that bike share substituted some trips away from taxis

Conclusion

This paper

- Estimated the causal impacts of bike share on air quality in NYC from 2013 to 2019
- Found that bike share decreased the concentrations of NO by up to 13.4% and BC by up to 2.7% compared to average concentrations before bike share
  - → Avoided social damages valued at up to $327 million dollars
- Shed light on the substitution mechanism by showing that short taxi trips decreased faster in bike share areas after the arrival of bike share compared to long taxi trips

Thank you

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Research agenda

Low-skilled workers in urban labour markets of developing countries

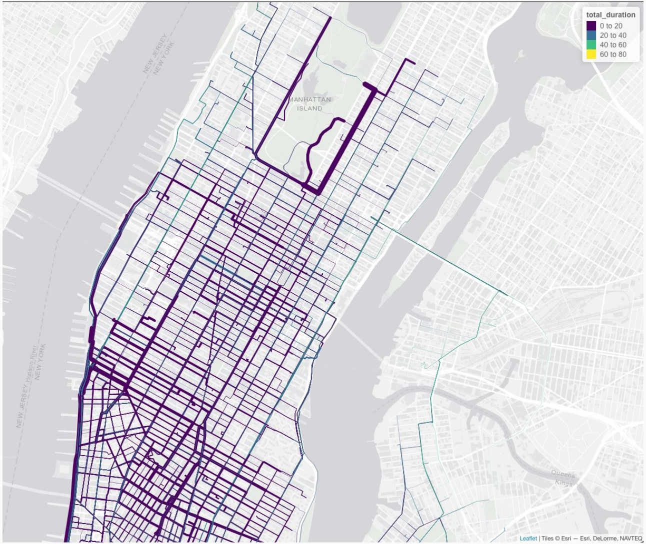
- *Conscientiousness and Labor Market Returns: Evidence from a Field Experiment in Senegal* joint with Mathias Allemand, Martina Kirchberger, Sveta Milusheva, Carol Newman and Brent Roberts
  → Submitted

- *Constructing Africa's Cities: Measuring and Enhancing Construction Worker Welfare in Dakar* joint with Martina Kirchberger, Sveta Milusheva, and Carol Newman
  → Data collection

Impacts of urban transport infrastructure

- *Female Labour Force Participation and Urban Transit: Evidence from the Washington Metro* joint with Maximilian Günnewig-Mönert
  → Preliminary stages

Routing illustration



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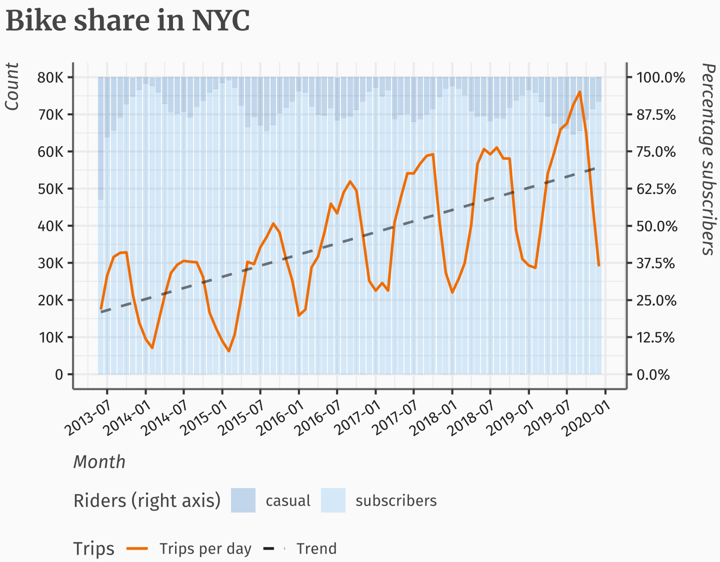
Bike share usage chart



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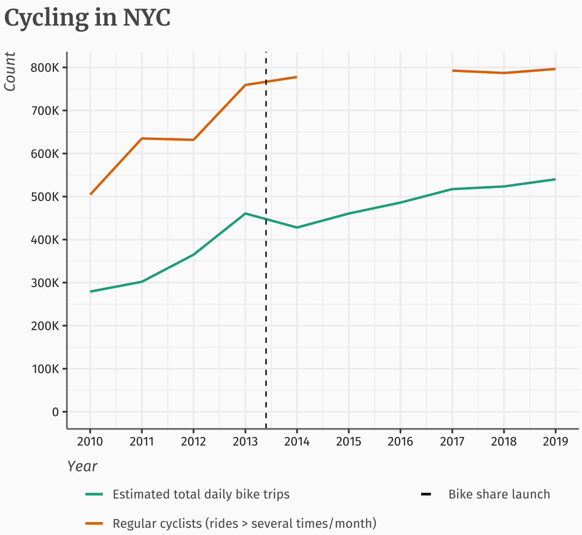
Cycling in NYC

- Daily bike trips estimates
  (NYC DOT Mobility Survey)
  - → **2010** 280K trips
  - → **2019** 520K trips (+85%)
- Rides at least several times a month
  (NYC Community Health Survey)
  - → **2010** 504K cyclists
  - → **2019** 793K cyclists (+57%)



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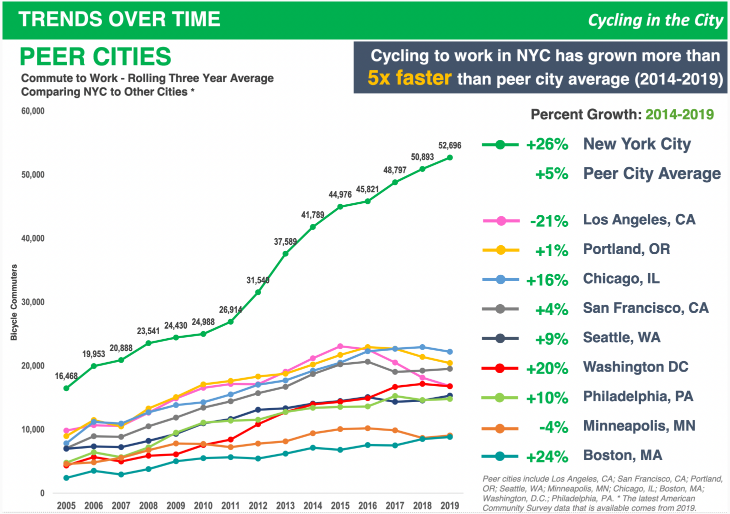
NYC cycling to work *vs* US peer cities



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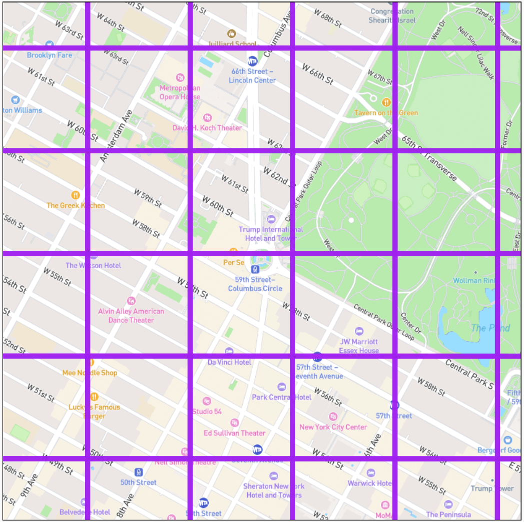
Cycling in the City Report, 2020, NYC DOT

Scale of raster grid · Columbus Circle

Grid scale · 300m×300m



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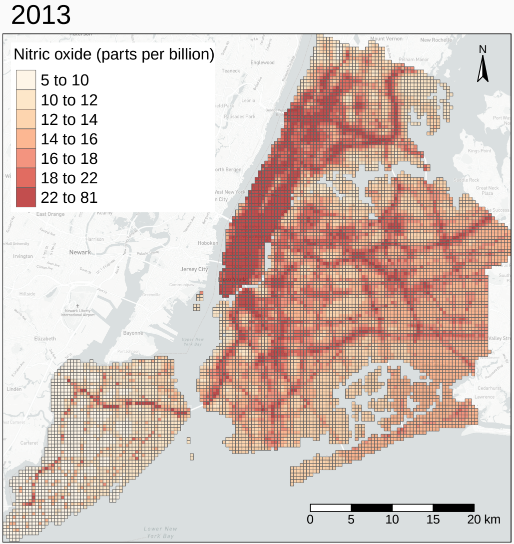
Mapping air pollution · nitric oxide (NO) 2013



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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

Estimation parameters

- Panel dataset
  - → **units** grid cells (9,171)
  - → **time** years (10, 2010–2019)
  - → **treatment** cell treated by bike share: within "traffic footprint" of bike share
- Covariates
  - → population (American Community Survey, ACS)
  - → fraction of college graduates (ACS)
  - → household income (ACS)
  - → meters of bicycle lanes (NYC Department of Transportation)
  - → built surface (NYC Department of City Planning)

Back

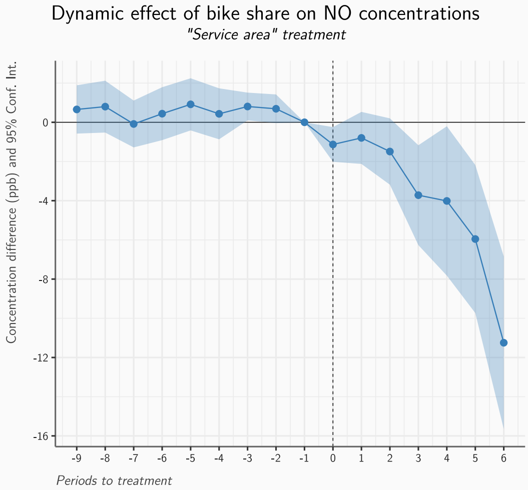
Social benefits valuation

Are the results economically significant?

- Concentration-response function from the epidemiology literature for NO and
  - → mortality
  - → asthma related emergency department (ED) visits and hospitalisations
- Bike share saved up to 33 deaths, 1,122 ED visits and 412 hospitalisations
- Avoided social damages valued at up to \$327 million (\$320M + \$1.2M + \$6.2M)
- Does not take into account other outcome or other pollutants
  - → likely a lower bound

▸ Back

Nitric Oxide · Service area

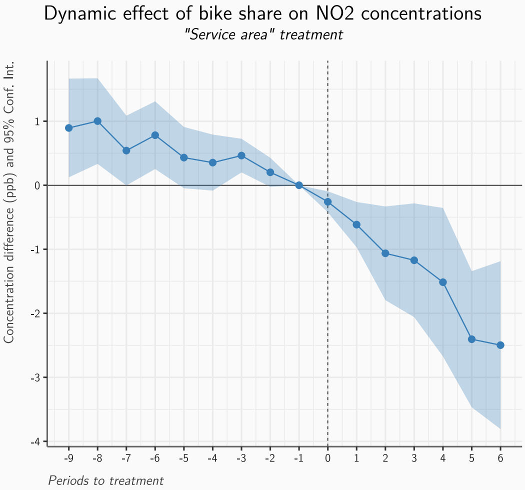


	NO		
	(1)	(2)	(3)
Convex polygon	-2.7534**	-0.1855	-0.3325
	(1.0736)	(0.6438)	(0.5012)
Baseline controls	✓	✓	✓
Cell FE	✓	✓	✓
Year FE	✓	✓	✓
Year-Community district FE		✓	
Year-Borough FE			✓
Mean concentration pre-treat.	20.353	20.353	20.353
% mean concentration pre-treat.	-13.528	-0.911	-1.633
Observations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

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

Back

Nitrogen Dioxide · Service area



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

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

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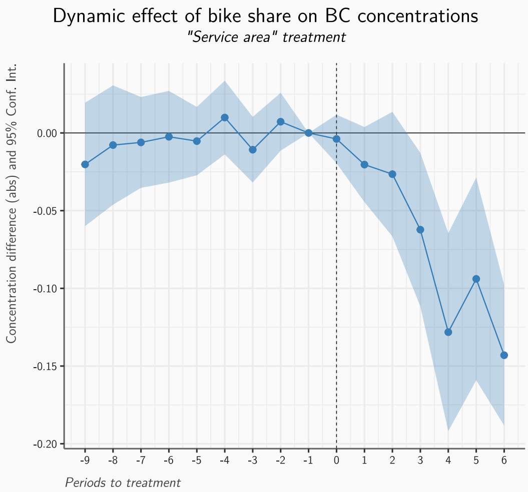
Black carbon · Service area



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

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

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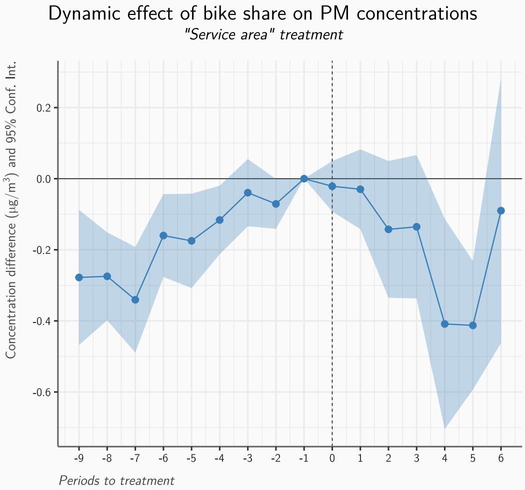
PM 2.5 · Service area



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

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

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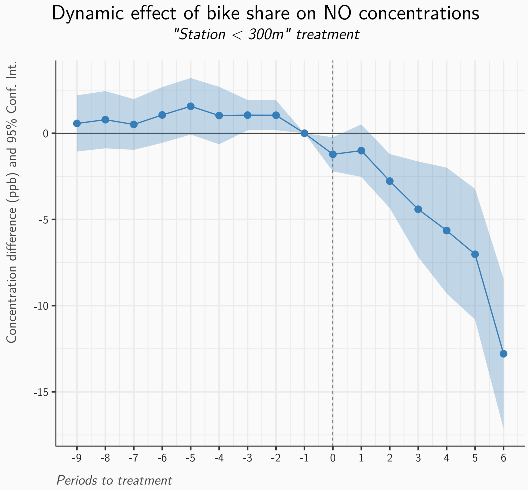
Nitric Oxide · Stations



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

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

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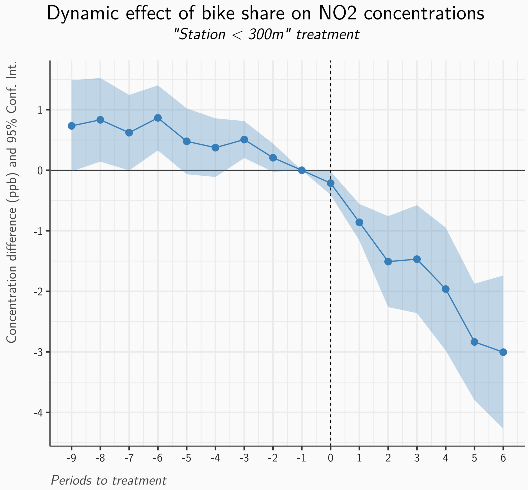
Nitrogen Dioxide · Stations



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

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

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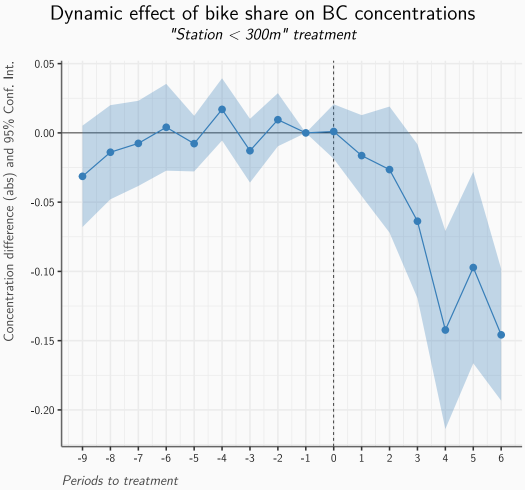
Black carbon · Stations



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

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

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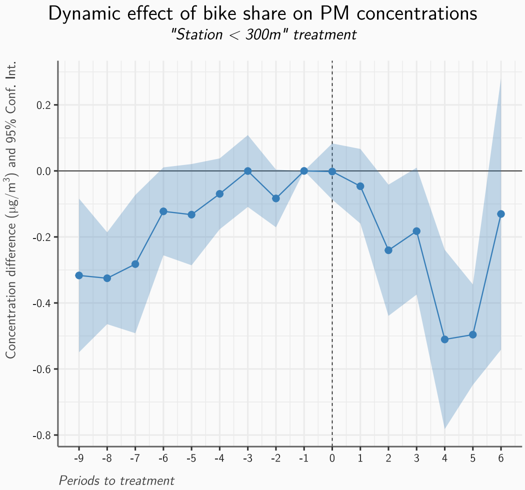
PM 2.5 · Stations



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

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

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ATT · Nitric Oxide

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

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

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ATT · Nitric Dioxide

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

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

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ATT · Black Carbon

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

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

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ATT · PM 2.5

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

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

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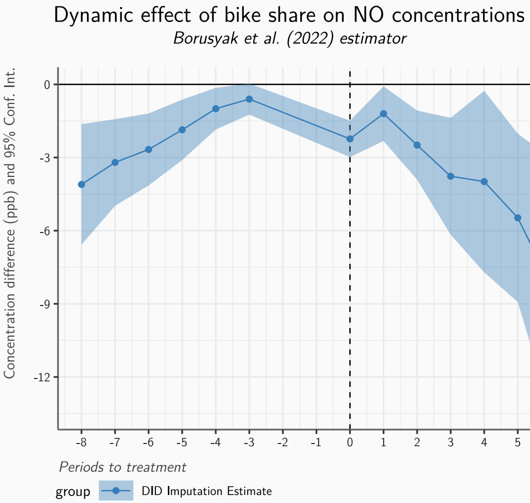
NO · Borusyak, Jaravel & Spiess estimator



Note: "On-car-route" treatment definition

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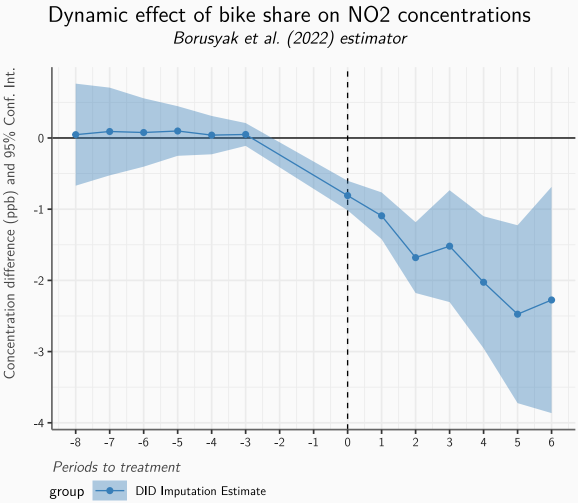
NO2 · Borusyak, Jaravel & Spiess estimator



Note: "On-car-route" treatment definition

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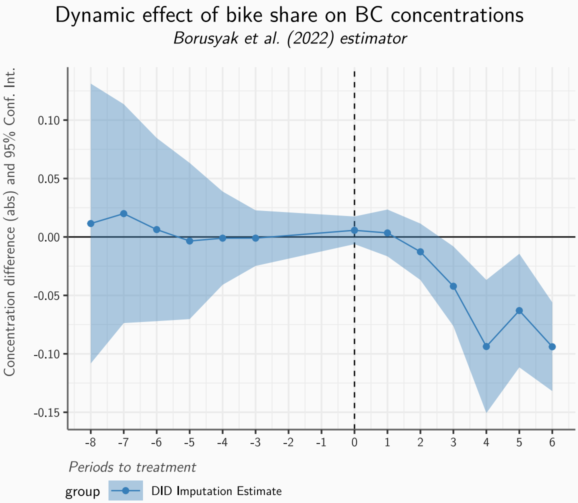
BC · Borusyak, Jaravel & Spiess estimator



Note: "On-car-route" treatment definition

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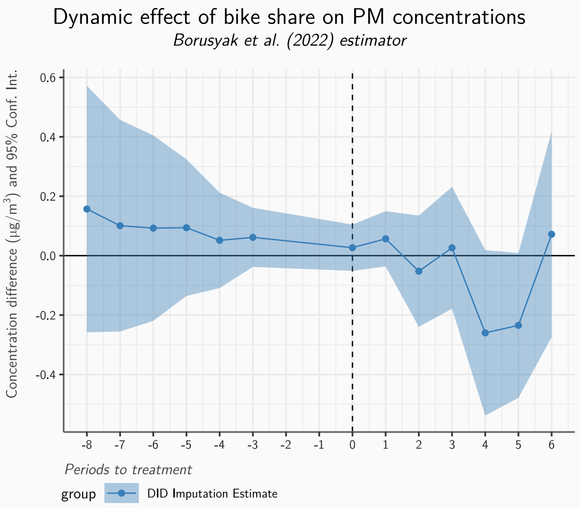
PM · Borusyak, Jaravel & Spiess estimator



Note: "On-car-route" treatment definition

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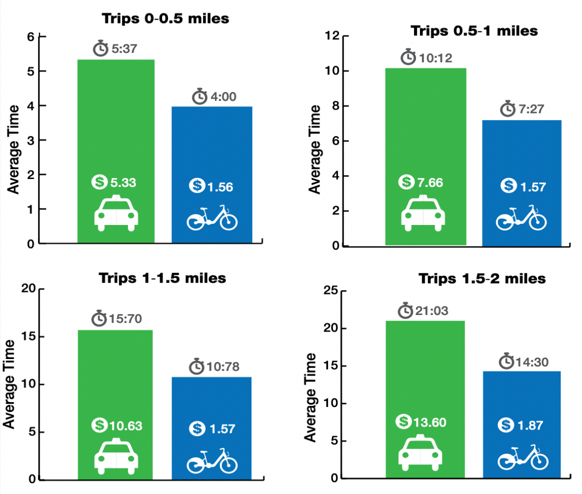

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