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

Vincent Thorne · Trinity College Dublin

PSE Micro-mobility in Cities Workshop

17 October 2022

IRISH RESEARCH COUNCIL
An Chomhairle um Thaighde in Éirinn
www.research.ie

Why do we care about air pollution?

- Air pollution is harmful
  - → In US: 100K–200K excess deaths annually (Tessum et al., 2019; Lelieveld et al., 2019)
  - → Non-lethal medical effects: chronic respiratory diseases (asthma), cardiovascular diseases, diabetes, size of newborns, (Guarnieri and Balmes, 2014; Rajagopalan and Brook, 2012; Ibald-Mulli et al., 2001)
  - → Decreases cognitive performance (test scores, graduation), productivity, alteration to decision-making (Lavy, et al., 2014; Hanna and Oliva, 2015; Shehab and Pope, 2019, Aguilar-Gomez et al., 2022)
  - → Worse in cities: individuals are more exposed (Strosnider et al., 2017)

Manhattan, ©Lerone Pieters

The contribution of road transport to 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 (NYC) (Matte et al., 2013)

The contribution of road transport to 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 (NYC) (Matte et al., 2013)
- Two strategies to reduce the impact of road transport
  - → Make vehicles less polluting
  - → Reduce the number trips made with motor vehicles → substitute trips with less polluting transport modes

The potential of bike share

- Bike share (and other micromobility interventions) has the potential to substitute motor vehicle trips and reduce air pollution
  - → Riding a bike does not pollute...
  - → ... however, new cyclists might be substituting public transport and walking
  - → ... or bike share creates new trips previously not made, inducing no substitution
- The impact of bike share on pollution is uncertain

This paper

Research question

Does bike share reduce local air pollution?

This paper

Research question

Does bike share reduce local air pollution?

- Evaluates the impact of bike share on local air pollution concentrations
  - → Using the gradual roll-out of NYC's bike share program as identification strategy
  - → Combined with ten years of high-resolution, ground-level measures of air pollution
  - → To estimate the causal impact of bike share using a staggered difference-in-differences (DD) analysis

Preview of results

- In areas served by bike share:
  - $\rightarrow$ 5–10% reduction in air pollutants associated with road traffic

Preview of results

- In areas served by bike share:
  - → 5–10% reduction in air pollutants associated with road traffic
- In addition, I use taxi trips to examine substitution from road traffic to bike share
  - → Suggestive evidence of fewer taxi trips in bike share areas

Contribution

Previous literature

- Environmental impact 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)
- Environmental impacts of bike share based on hypothetical substitution rates (Fishman et al., 2014; Kou et al., 2020)

Contribution

Previous literature

- Environmental impact 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)

- Environmental impacts of bike share based on hypothetical substitution rates (Fishman et al., 2014; Kou et al., 2020)

→ First paper to estimate the 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)
- Yearly annual average concentrations of six air pollutants

Air pollution I

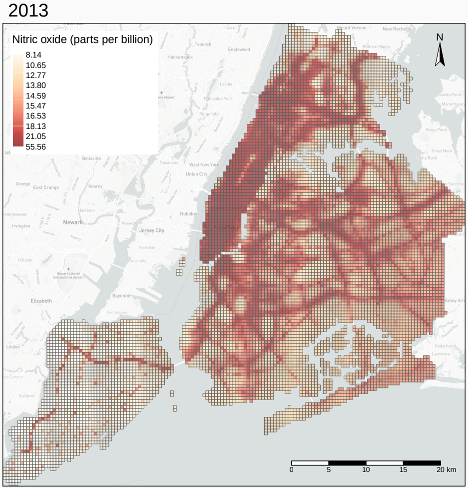
NYC Community Air Survey (NYCCAS), 2009–2019

- For 300-by-300 meters cells (units of analysis)
- Yearly annual average concentrations of six air pollutants
- Pollutant selection: 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

Air pollution II

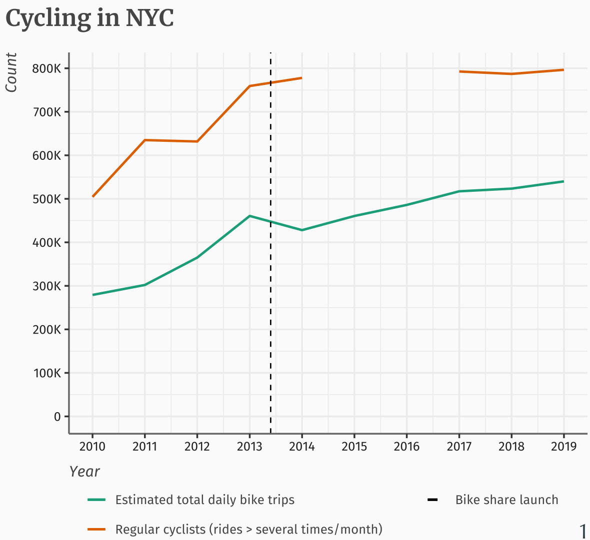
- Particulate matter (PM 2.5) and black carbon (BC)
  - → Significant proportions of PM 2.5 from outside the city, but local variation likely due to local emissions
  - → 35% of PM emissions attributed to traffic in high-traffic locations
  - → BC is a subset of PM 2.5 (4–11% in US cities), but up to 75% of PM 2.5 from diesel exhaust

Mapping air pollution · nitric oxide (NO) 2013



Cycling in NYC

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



NYC Cycling growth compared to peer cities

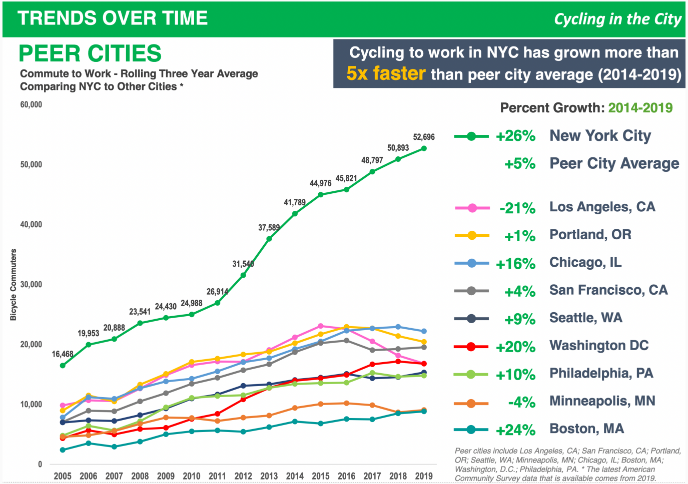


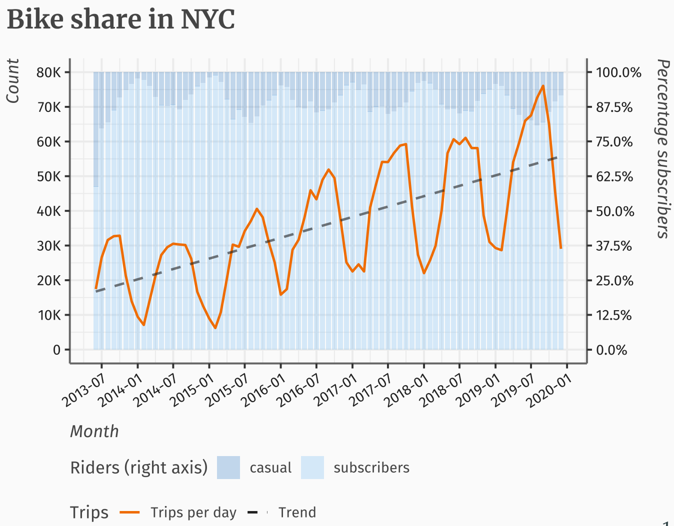
Figure 1: Cycling in the City Report, 2020, NYC DOT

Bike share system in NYC

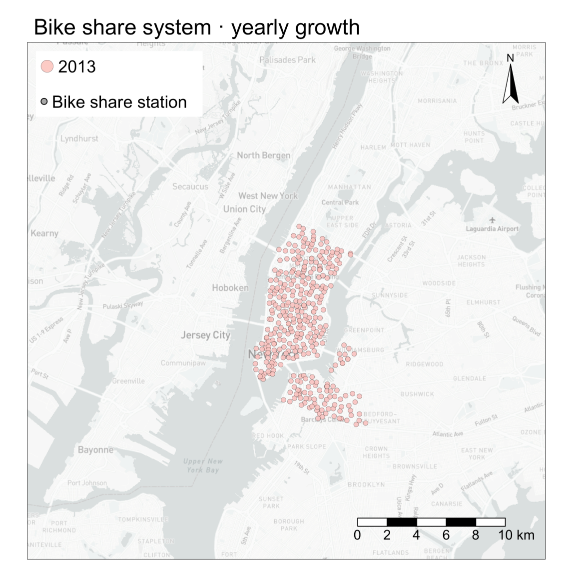
- Opened in May 2013
- Bicycles available at fixed docking stations 24/7
- Membership plans or single-use pricing
- First 45 minutes free

Bike share statistics

- Stations and bikes
  - → **2013** 332 stations, 6,000 bikes
  - → **2019** 780 stations, 13,000 bikes
- Average daily bike share trips
  - → **2013** 22K trips
  - → **2019** 56K trips (+154%)
- Seasonal variation
- Mostly subscribers, especially in winter



Bike share system roll-out



Conceptual framework

- Bike share reduces the price of, and improves the accessibility to, cycling
- This change in the relative attractiveness of cycling vs other transport modes leads some individuals to switch to cycling

Conceptual framework

- Bike share reduces the price of, and improves the accessibility to, cycling
- This change in the relative 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., are substitutes of) trips by motor vehicles
  - → We expect pollution to reduce where motor vehicles are not driven anymore

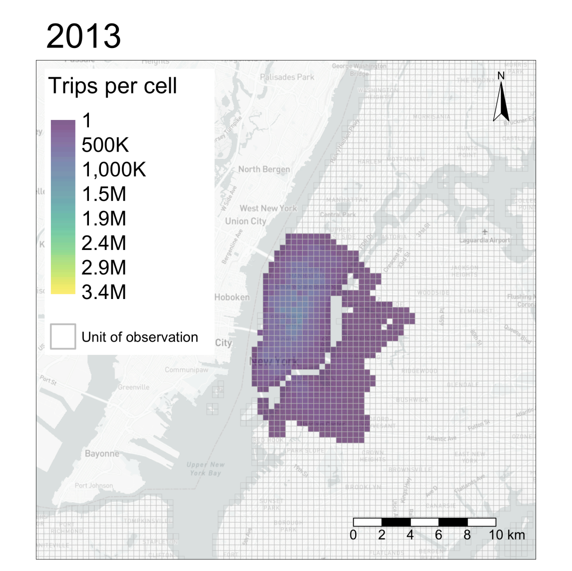
Construction of treatment

- I construct a spatial variable measuring the potential reduction in motor vehicle trips due to bike share
- For each year:
    1. Identify active bike share stations
    2. Compute optimal car route between each pair of stations ▸ Routing
    3. Impute the number of bike share trips on each route
    4. Aggregate at the cell level

Construction of treatment

- I construct a spatial variable measuring the potential reduction in motor vehicle trips due to bike share
- For each year:
  1. Identify active bike share stations
  2. Compute optimal car route between each pair of stations ▸ Routing
  3. Impute the number of bike share trips on each route
  4. Aggregate at the cell level
- Captures the areas where we expect pollution to reduce after bike share

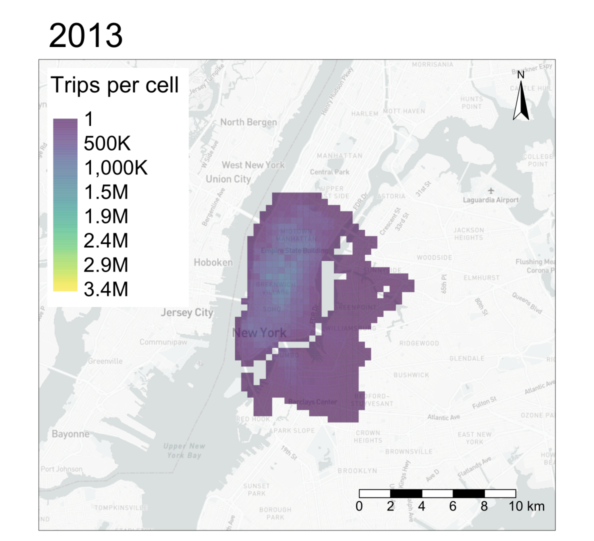
Bike share treatment



Estimation strategy

Identification strategy

- Ideal experiment
  → Randomly place bike share stations across the city
- Reality
  → The location of bike share stations is not random
- Solution
  → Exploit the timing of the staggered roll-out of stations



Estimating equation

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

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

for cell c at year t

- Y_{ct}: a pollutant's concentration
- $Treat_{ct}$: one of the treatment definition
- $year_t + cell_c$: year and cell fixed effects
- $\boldsymbol{C}_{ct}$: vector of control variables

Standard errors clustered at the community district level (neighbourhood).

Estimation parameters

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

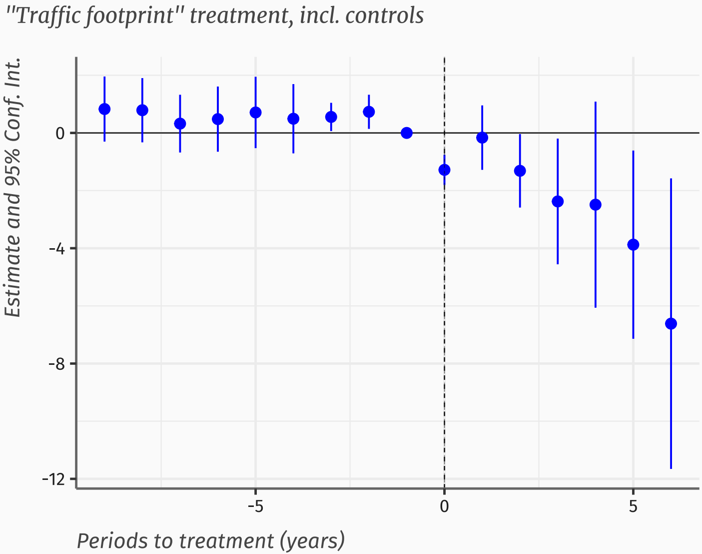
Results

ATT · Nitric Oxide

	NO	
	(1)	(2)
Car route	-2.3026***	-1.9849**
	(0.8387)	(0.8968)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	20.242	20.277
Perc. of mean out. pre-treat.	-11.375	-9.789
Observations	96,700	95,678
R^2	0.913	0.914
Within R^2	0.105	0.119

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

Event study · Nitric Oxide



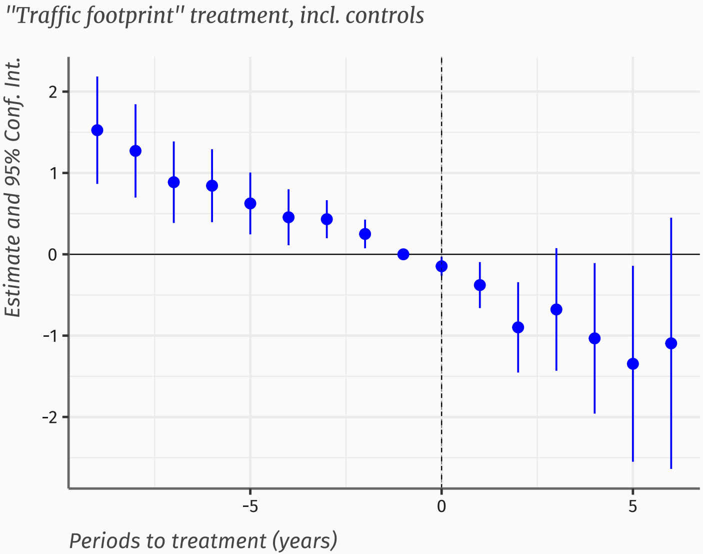
▸ Stations ▸ Convex polygon

ATT · Nitric Dioxide

	NO2	
	(1)	(2)
Car route	-0.8558***	-0.6770**
	(0.2701)	(0.2891)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	19.850	19.911
Perc. of mean out. pre-treat.	-4.311	-3.400
Observations	96,700	95,678
R^2	0.980	0.980
Within R^2	0.126	0.150

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

Event study · Nitric Dioxide



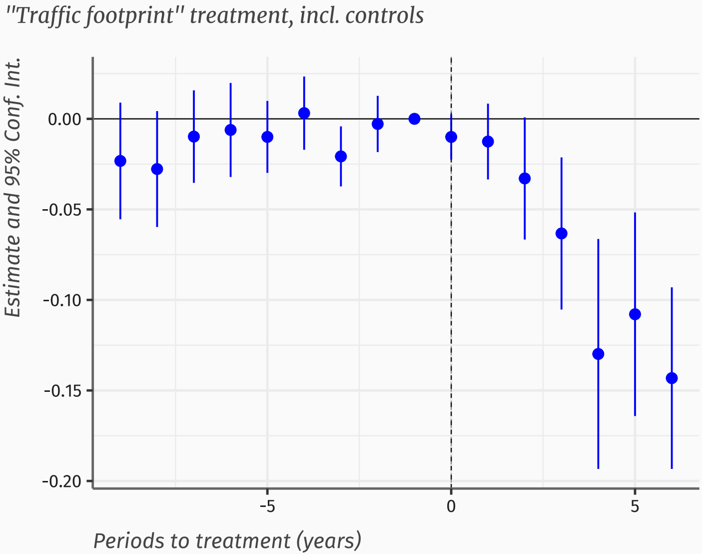
▸ Stations ▸ Convex polygon

ATT · Black carbon

	BC	
	(1)	(2)
Car route	-0.0567***	-0.0544***
	(0.0151)	(0.0146)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	1.004	1.006
Perc. of mean out. pre-treat.	-5.650	-5.401
Observations	96,700	95,678
R^2	0.926	0.926
Within R^2	0.038	0.041

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

Event study · Black carbon



Stations Convex polygon

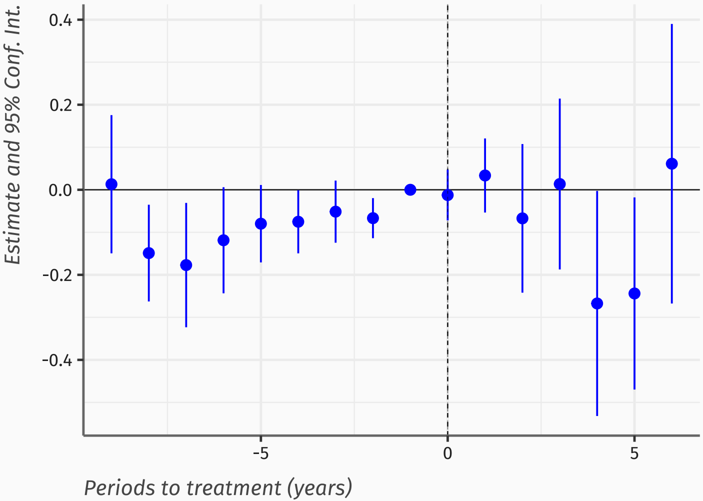
ATT · PM 2.5

	PM	
	(1)	(2)
Car route	-0.0818	-0.0518
	(0.0671)	(0.0711)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	9.387	9.397
Perc. of mean out. pre-treat.	-0.871	-0.551
Observations	96,700	95,678
R^2	0.979	0.979
Within R^2	0.026	0.040

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

Event study · PM

"Traffic footprint" treatment, incl. controls



▸ Stations ▸ Convex polygon

Robustness checks

- Done
  - → Alternative treatment definitions ▸ Stations ▸ Service area
  - → Intensity of treatment ▸ NO ▸ NO2 ▸ BC ▸ PM
  - → New DD estimation robust to variation in treatment timing and heterogenous treatment effects (Callaway & Sant'Anna (CS), 2021) ▸ Plots
  - → "Not-yet-treated" units as control group with CS estimator ▸ Plots
  - → Borusyak, Jaravel and Spiess (2022) estimator ▸ Plots

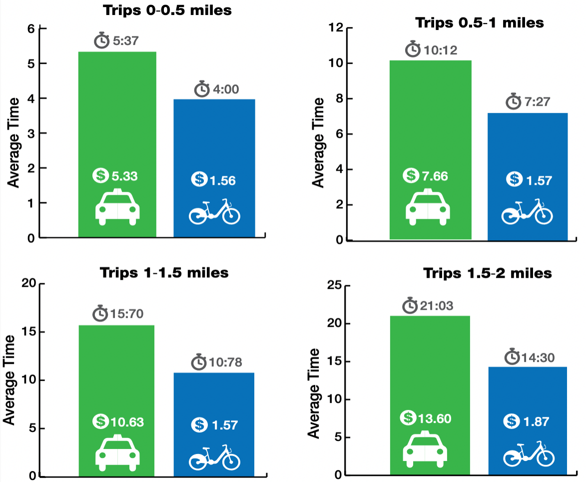
Taxis in NYC

- Taxis are a popular transport mode in NYC. In 2014:
  - → 485K trips/day, 55% of trips $<$ 3km, average price $4/km
  - → 70% of passengers $\leqslant$35 years old, 55% male
  - → In Midtown, >50% of all vehicles are taxis

Taxis in NYC

- Taxis are a popular transport mode in NYC. In 2014:
  - → 485K trips/day, 55% of trips $<$ 3km, average price $4/km
  - → 70% of passengers $\leqslant$35 years old, 55% male
  - → In Midtown, >50% of all vehicles are taxis
- Bike share trips are comparable to many taxi trips
  - → Most trips are less than 3km
  - → Median age is 33 years old, 70% male

NYC 2019 Mobility Report



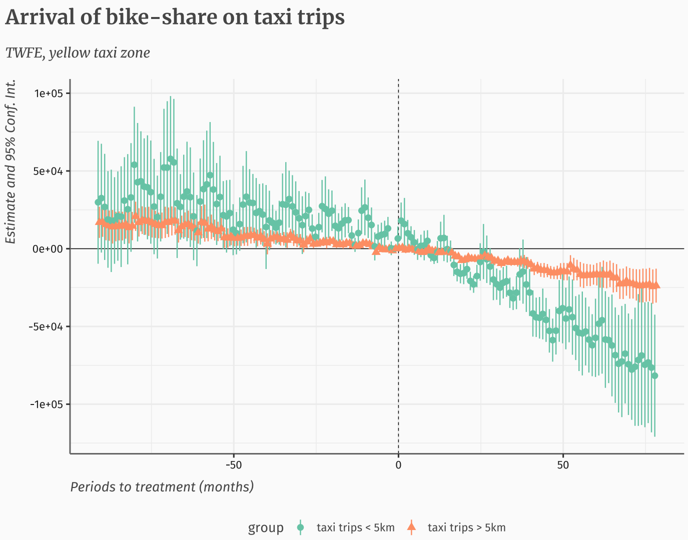
Testing the substitution mechanism

- Previous research
  - → Taxis ridership increases when bike share station 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

- Previous research
  - → Taxis ridership increases when bike share station 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)
- This paper
  - → Use the universe of NYC taxi trips: geolocated, timestamped, measure of distance
  - → Identify most substitutable taxi trips
    - 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



Suggestive evidence that bike share substitutes short taxi trips.

▸ CS estimator

Conclusion

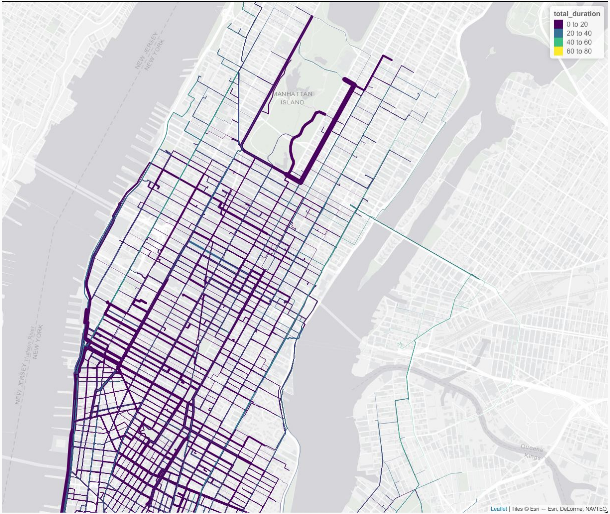
This paper

- Estimated the causal impacts of bike-share on air quality
- Found that bike-share decreased the concentrations of air pollutants by 5 to 10% compared to average concentrations before bike share
- 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

thornev@tcd.ie

Routing illustration



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

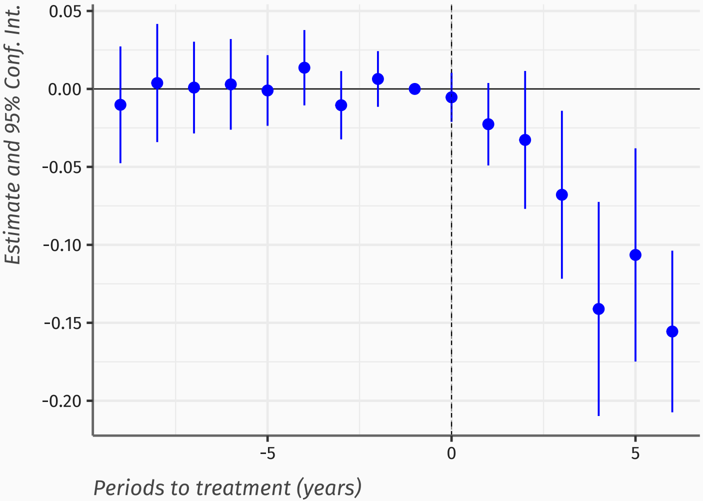
Land-use regression (LUR) model:

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

Back

Event study · Black carbon

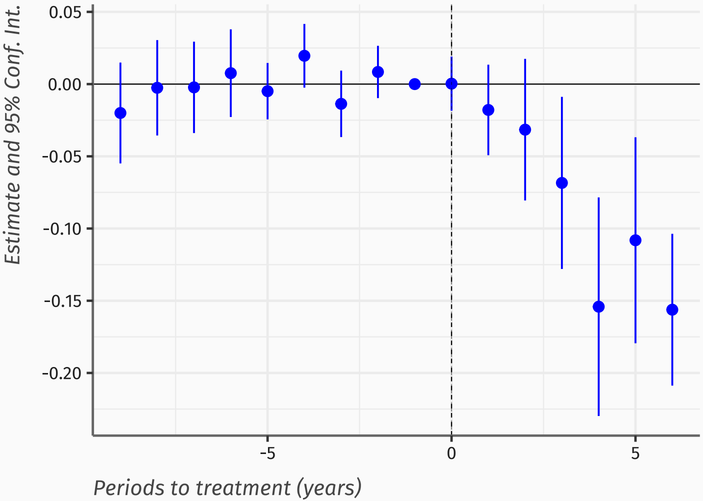
"Convex hull" treatment, incl. controls



Back

Event study · Black carbon

"Stations < 300 m" treatment, incl. controls



▸ Back

ATT · Black Carbon

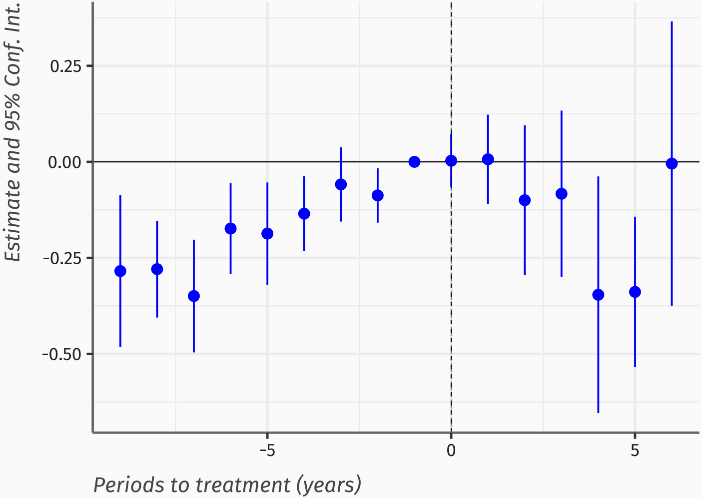
	BC	
	(1)	(2)
Trips (10k)	-0.0567***	-0.0544***
	(0.0151)	(0.0146)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	1.004	1.006
Perc. of mean out. pre-treat.	-5.650	-5.401
Observations	96,700	95,678
R^2	0.926	0.926
Within R^2	0.038	0.041

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

▸ Back

Event study · PM

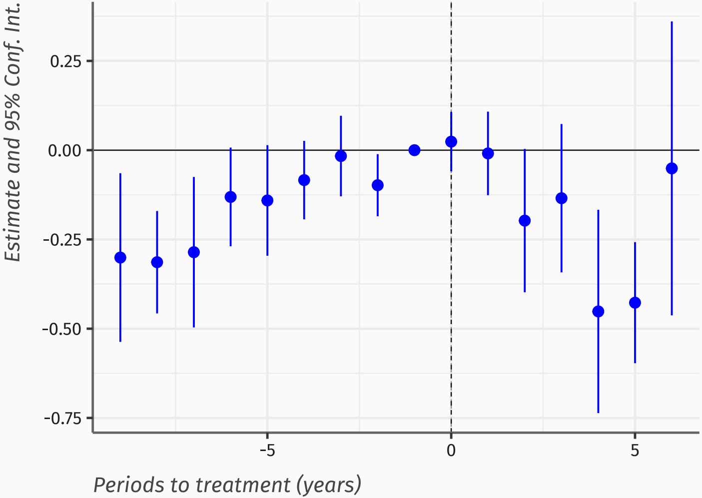
"Convex hull" treatment, incl. controls



▸ Back

Event study · PM

"Stations < 300 m" treatment, incl. controls



▸ Back

ATT · PM

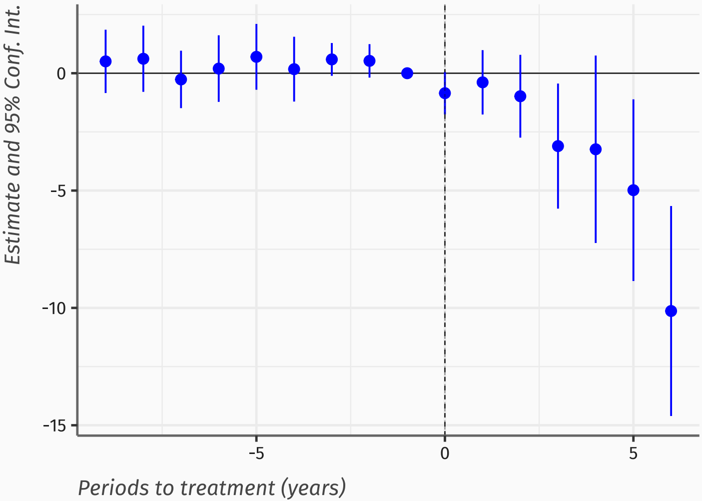
	PM	
	(1)	(2)
Trips (10k)	-0.0818	-0.0518
	(0.0671)	(0.0711)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	9.387	9.397
Perc. of mean out. pre-treat.	-0.871	-0.551
Observations	96,700	95,678
R^2	0.979	0.979
Within R^2	0.026	0.040

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

Back

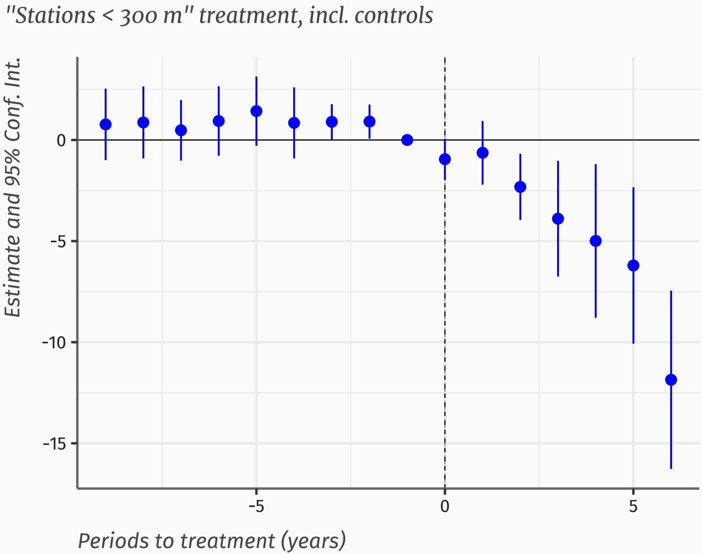
Event study · Nitric oxide

"Convex hull" treatment, incl. controls



▸ Back

Event study · Nitric oxide



▸ Back

ATT · Nitric Oxide

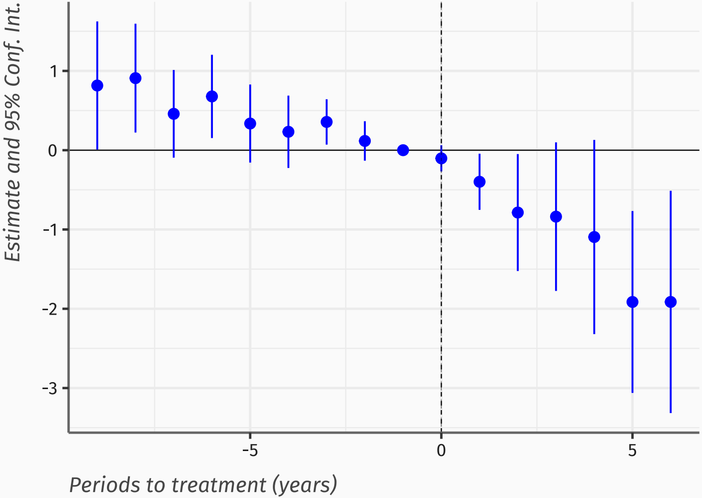
	NO	
	(1)	(2)
Trips (10k)	-2.3026***	-1.9849**
	(0.8387)	(0.8968)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	20.242	20.277
Perc. of mean out. pre-treat.	-11.375	-9.789
Observations	96,700	95,678
R^2	0.913	0.914
Within R^2	0.105	0.119

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

▸ Back

Event study · Nitric dioxide

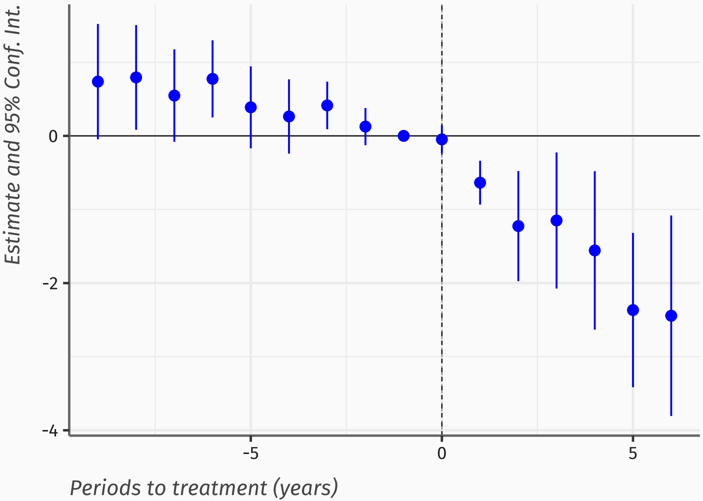
"Convex hull" treatment, incl. controls



Back

Event study · Nitric Dioxide

"Stations < 300 m" treatment, incl. controls



ATT · Nitric Dioxide

	NO2	
	(1)	(2)
Trips (10k)	-0.8558***	-0.6770**
	(0.2701)	(0.2891)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	19.850	19.911
Perc. of mean out. pre-treat.	-4.311	-3.400
Observations	96,700	95,678
R^2	0.980	0.980
Within R^2	0.126	0.150

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

Back

ATT · Nitrous Oxide

	NO	
	(1)	(2)
Station	-3.4934***	-3.2624***
	(1.0064)	(1.0450)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	20.242	20.277
Perc. of mean out. pre-treat.	-17.258	-16.089
Perc. of SD outcome	-51.631	-48.084
Observations	96,700	95,678
R^2	0.920	0.921
Within R^2	0.183	0.191

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

▸ Back

ATT · Nitric Dioxide

	NO2	
	(1)	(2)
Station	-1.2417***	-1.0697***
	(0.2898)	(0.3075)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	19.850	19.911
Perc. of mean out. pre-treat.	-6.256	-5.372
Perc. of SD outcome	-25.267	-21.878
Observations	96,700	95,678
R^2	0.980	0.981
Within R^2	0.152	0.172

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

▸ Back

ATT · Black Carbon

	BC	
	(1)	(2)
Station	-0.0605***	-0.0571***
	(0.0194)	(0.0189)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	1.004	1.006
Perc. of mean out. pre-treat.	-6.026	-5.674
Observations	96,700	95,678
R^2	0.925	0.925
Within R^2	0.037	0.039

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

▸ Back

ATT · PM 2.5

	PM	
	(1)	(2)
Station	-0.1695**	-0.1419**
	(0.0660)	(0.0704)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	9.387	9.397
Perc. of mean out. pre-treat.	-1.806	-1.511
Perc. of SD outcome	-11.433	-9.570
Observations	96,700	95,678
R^2	0.979	0.980
Within R^2	0.046	0.057

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

▸ Back

ATT · Nitrous Oxide

	NO	
	(1)	(2)
Convex polygon	-2.6243***	-2.3084**
	(0.9449)	(0.9945)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	20.242	20.277
Perc. of mean out. pre-treat.	-12.965	-11.385
Perc. of SD outcome	-38.786	-34.024
Observations	96,700	95,678
R^2	0.916	0.917
Within R^2	0.140	0.152

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

Back

ATT · Nitric Dioxide

	NO2	
	(1)	(2)
Convex polygon	-0.9401***	-0.7589**
	(0.3062)	(0.3254)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	19.850	19.911
Perc. of mean out. pre-treat.	-4.736	-3.811
Perc. of SD outcome	-19.130	-15.521
Observations	96,700	95,678
R^2	0.980	0.980
Within R^2	0.116	0.143

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

Back

ATT · Black Carbon

	BC	
	(1)	(2)
Convex polygon	-0.0586***	-0.0557***
	(0.0173)	(0.0168)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	1.004	1.006
Perc. of mean out. pre-treat.	-5.832	-5.538
Observations	96,700	95,678
R^2	0.925	0.925
Within R^2	0.037	0.039

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

▸ Back

ATT · PM 2.5

	PM	
	(1)	(2)
Convex polygon	-0.1234*	-0.0924
	(0.0692)	(0.0733)
Controls		✓
Cell	✓	✓
Year	✓	✓
Mean out. pre-treat.	9.387	9.397
Perc. of mean out. pre-treat.	-1.314	-0.983
Perc. of SD outcome	-8.321	-6.228
Observations	96,700	95,678
R^2	0.979	0.979
Within R^2	0.037	0.052

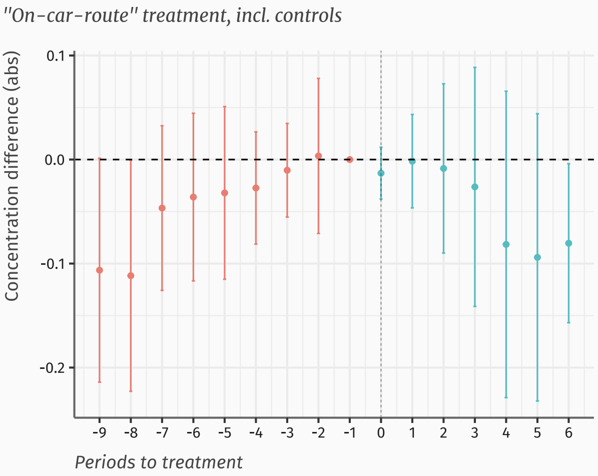
Clustered (Community district) standard-errors in parentheses

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

▸ Back

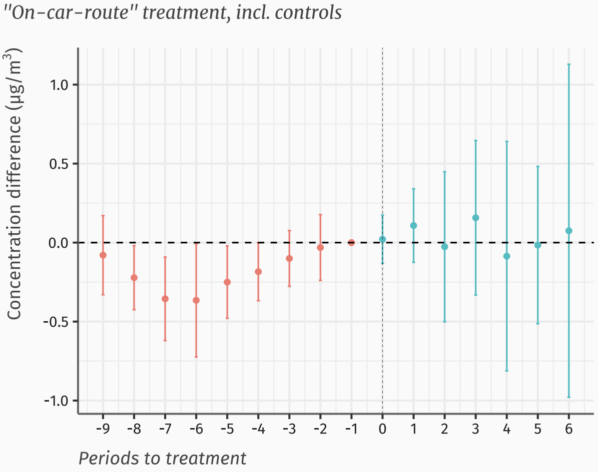
Dynamic effects · Black carbon

Back robustness



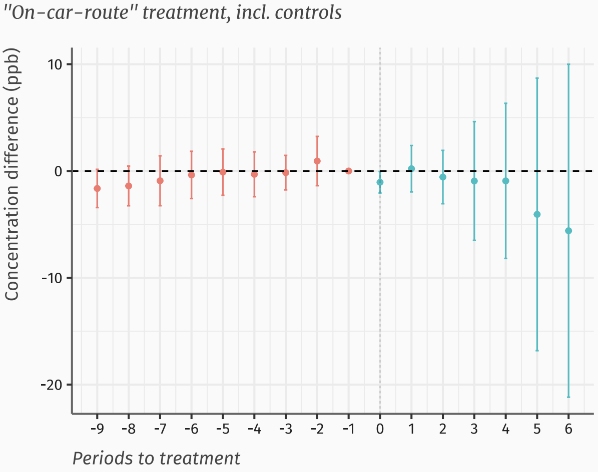
Dynamic effects · PM

Back robustness



Dynamic effects · NO

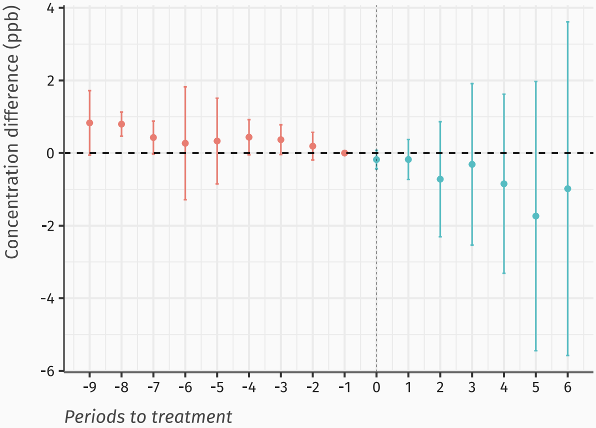
▸ Back robustness



Dynamic effects · NO2

Back robustness

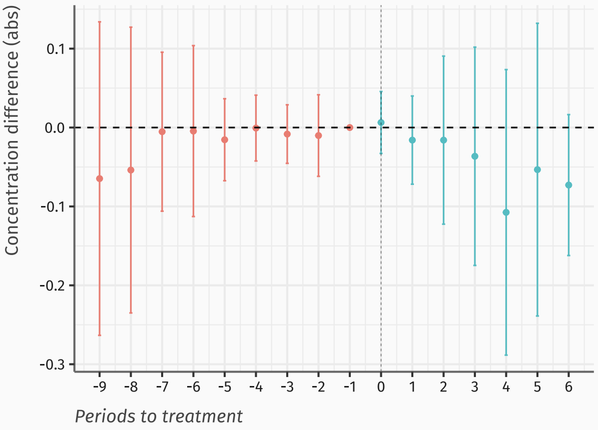
"On-car-route" treatment, incl. controls



Dynamic effects · Black carbon

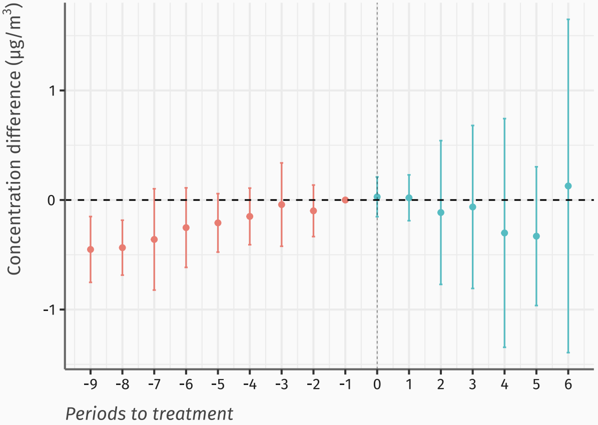
▸ Back robustness

"Station < 300m" treatment, incl. controls



Dynamic effects · PM

"Station < 300m" treatment, incl. controls

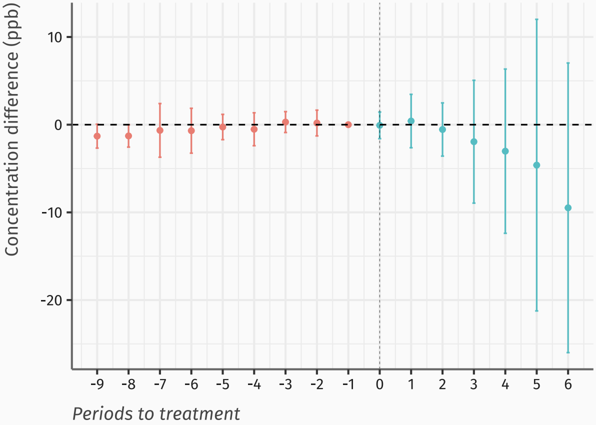


▸ Back robustness

Dynamic effects · NO

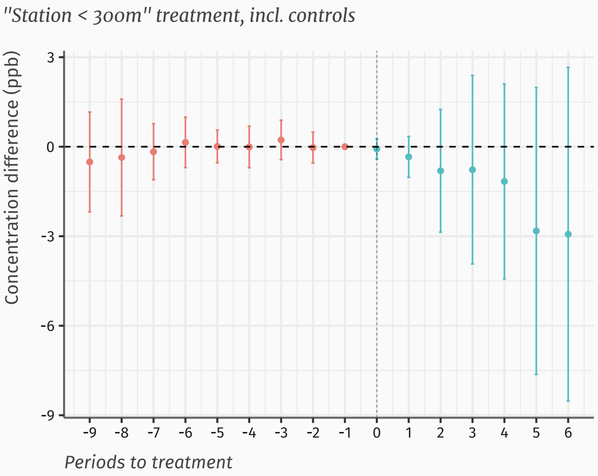
▸ Back robustness

"Station < 300m" treatment, incl. controls

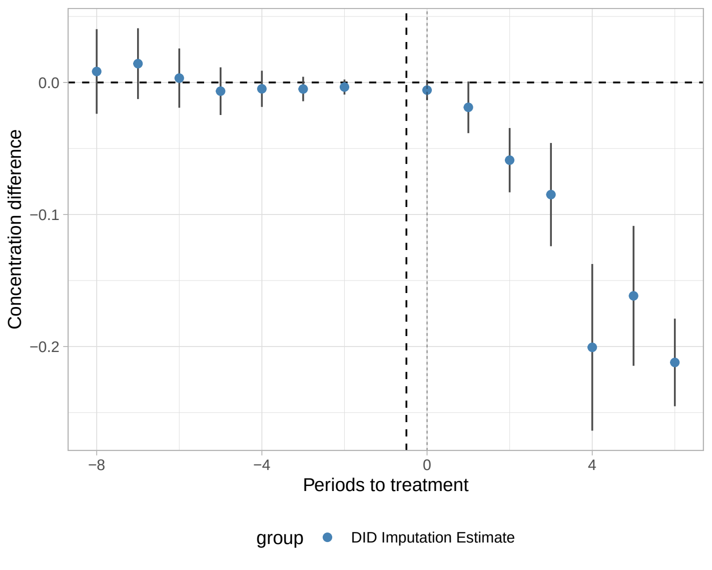


Dynamic effects · NO2

▸ Back robustness

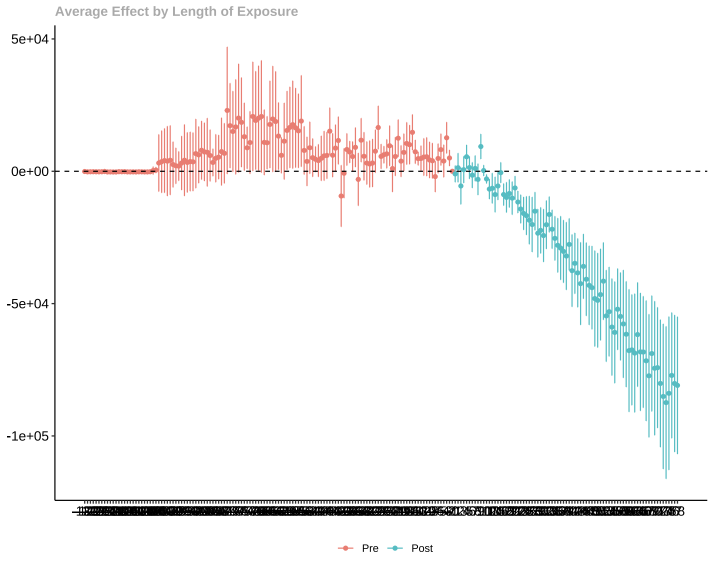


BC · Borusyak, Jaravel, Spiess estimator



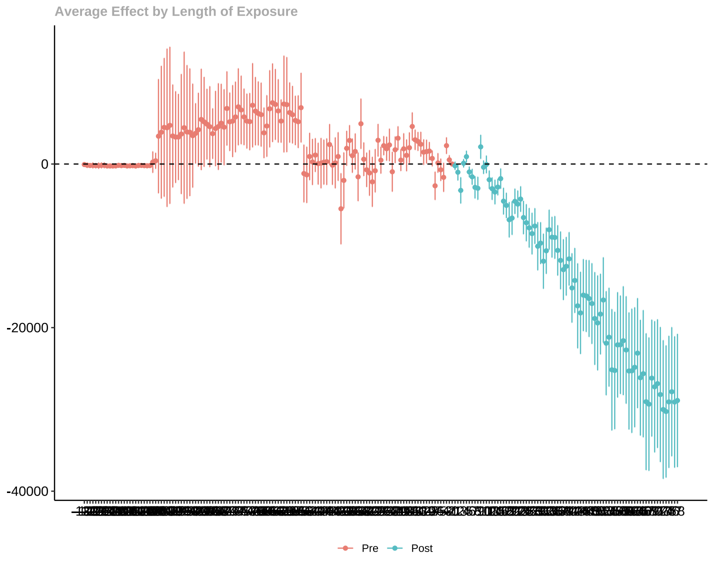
Back

Mechanism · CS estimator, short taxi trips



Back

Mechanism · CS estimator, long taxi trips



Back