Bicycle-share: cycling towards cleaner cities?

Evidence from New York

Vincent Thorne

LSE PhD Work-in-Progress · 15 February 2022

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
  - → low emission zones, congestion pricing, urban tolls
- Encouraging the use of less polluting transport modes
  - → increasing access to and supply of public transport
  - → incentivizing the use of active transport, e.g. cycling and walking
- Cycling policies
  - → **Infrastructure** bicycle lanes, bicycle-share, bicycle stands and protected parking
  - → **“Culture”** bicycle festivals, bike-to-work programs, bike schools for children

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

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- Bicycle-share is a good measure of cycling policies because
  - → measurement usage is measurable
  - → identification well-defined in time and space cycling intervention

Research question

Research question

Does bicycle-share reduce air pollution? If yes, do we see improvements in health?

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 the evidence on health outcomes using geocoded health survey responses and explores possible mechanisms using traffic data.

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
- Results robust to staggered treatment timing and heterogenous treatment effects

Contributions

Urban air pollution and congestion

Previously estimate 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** looking at a large-scale cycling policy.

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

Previously most studies assume substitution rates and car emissions, run simulations. Causal paper on bicycle-share and congestion in Washington DC:

Hamilton and Wichman (2018)

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

Roadmap

Data

Estimation strategy

Results

Next steps

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

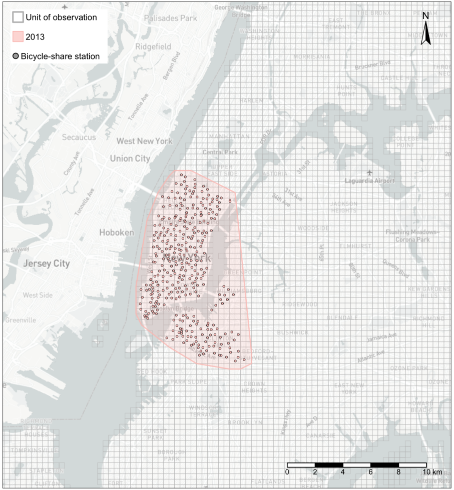
Data · Bicycle-share

Universe of bicycle-share trips publicly available

- +100 million trips from 2013 to 2019
- origin-destination, date and time of pickup and drop-off

→ 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
- 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 to 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

▸ NYCCAS details ▸ NO concentrations 2013

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TWFE Pitfalls

- Two-way fixed effects estimation of difference-in-differences has shown to be biased when
  - → there is variation in treatment timing
  - → treatment effects are heterogenous
- TWFE average treatment effects on the treated (ATT) are a weighted average of individual 2×2 DiD, with weights sensitive to group size and variance
- New DiD literature: Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Goodman-Bacon (2021)

Callaway–Sant’Anna estimator

Properties of Callaway and Sant’Anna (2021)

- unbiased for staggered treatment settings (caveat: no “switch off”)
- allows parallel trends (PT) assumption to hold conditional on covariates
- straightforward aggregation to an overall ATT
- other aggregations to explore heterogeneity of treatment effect

▸ Estimator details

Estimation parameters

- Panel dataset
  - → units grid cells (9,171)
  - → time years (10, 2010–2019)
  - → treatment cell within the bicycle-share service area (convex hull)
- 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
  - → ... to be expanded (land use, building height, ...)

Roadmap

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ATT · Black carbon & PM 2.5

	BC		PM 2.5	
	Condit. PT	Uncondit. 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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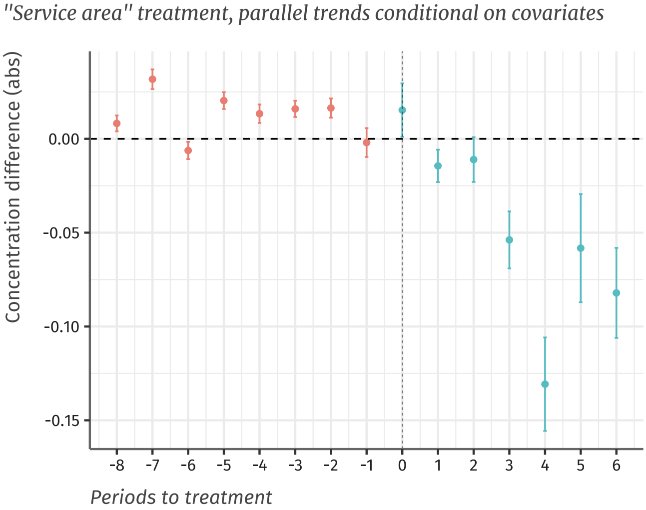
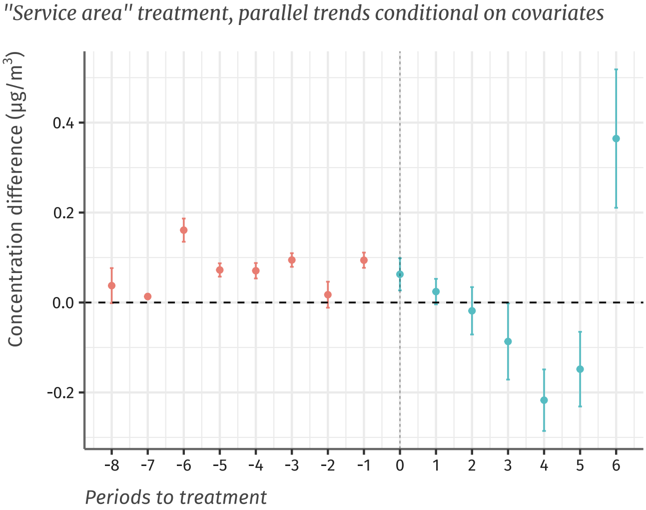
- Bicycle-share reduced black carbon concentration by 1.72% with respect to mean concentration in treated areas pre-treatment

Dynamic effects · Black carbon



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

Dynamic effects · PM



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

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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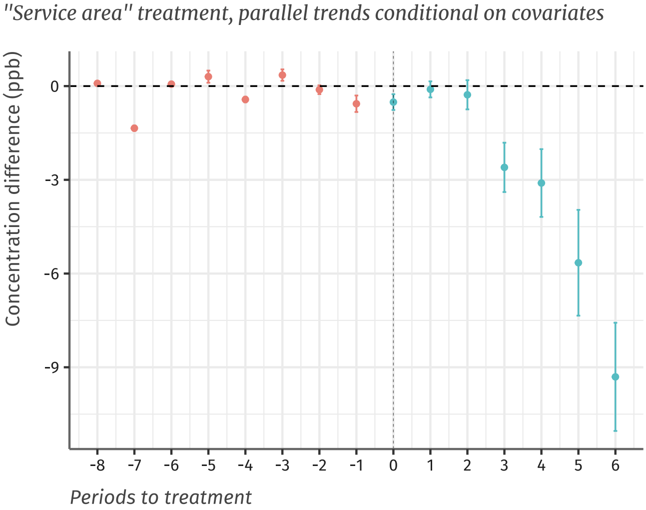
Years	10	10	10	10

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

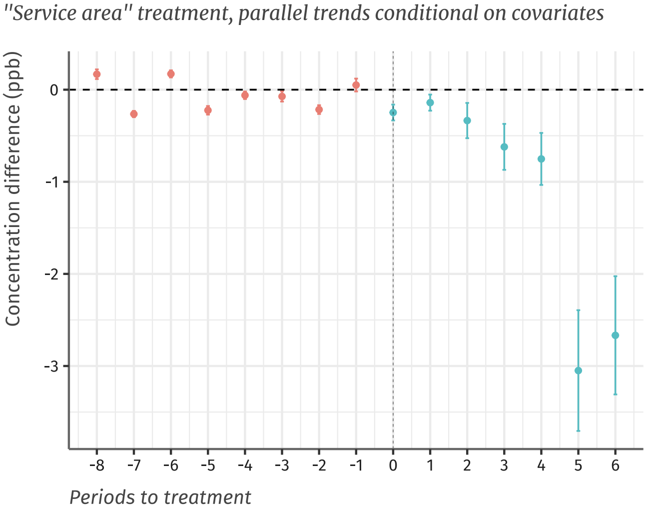
- Bicycle-share reduced NO concentration by 2.03% with respect to mean concentration in treated areas pre-treatment

Dynamic effects · NO



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

Dynamic effects · NO2



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

Robustness checks

- Done
  - → Alternative treatment definitions ▸ Stations ▸ Footprint
  - → "Not-yet-treated" as control group ▸ Tables and plots
  - → Placebo with O_3 and SO_3 ▸ Tables and plots
- Not yet done/ideas
  - → Restrict control group
  - → Exclude boroughs/areas
  - → Spatial spillovers

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Overview

Quantify benefits Is there evidence on improved health outcomes?

Mechanisms Is there evidence that people switch to cycling and traffic decreased?

Health outcomes

Community Health Survey:

- Since 2002, 10,000 yearly respondents, representative of city population
- Spatial resolution: health neighborhood (34) ▸ Map
- Topics of interest
  - → Asthma diagnosis and attacks in past 12 months
  - → High blood pressure diagnosis and medication
  - → Diabetes diagnosis
  - → General health

Mechanisms · Existing evidence

- Hamilton and Wichman (2018) : congestion decreases after the arrival of bicycle-share in Washington DC
  - → upwards of 4% decrease in congestion within neighborhoods
  - → mostly in highly congested areas
- Molnar and Ratsimbazafy (2017) : using outage of Citi Bike stations
  - → show evidence of short-run elasticity between bicycle-share and taxis
  - → estimate 3–4% long-term decline in taxi trips

Mechanisms · Traffic

Taxi data is a well-accepted proxy for traffic in NYC

- Taxi & Limousine Commission Trip Record Data
  - → Universe of taxi trips in NYC since 2009 (caveat: ride-hailing apps)
  - → Spatial resolution: origin/destination taxi zones (263) ▸ Map
- To be validated with traffic counts
- Check whether taxi pickups decrease in bicycle-share areas

Conclusion

- The arrival of bicycle-share significantly decreases concentration of pollutant associated with road traffic
- The results are robust to new difference-in-differences methods and alternative treatment definitions
- Next steps will investigate potential health outcomes and mechanisms

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)

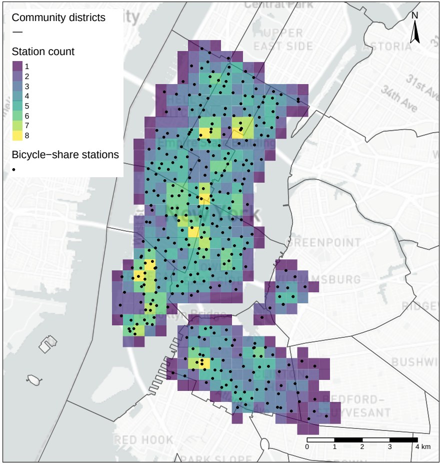
▸ Back

Citi Bike Station

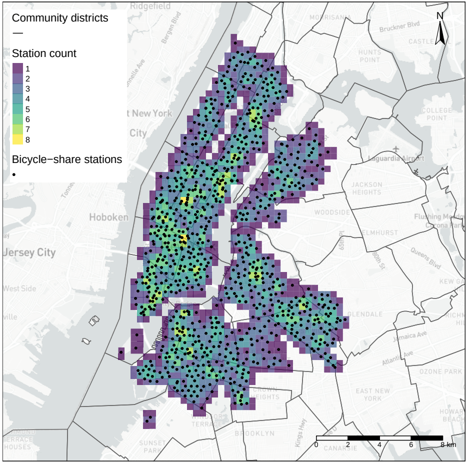
Back

Stations within 300 meters

2013



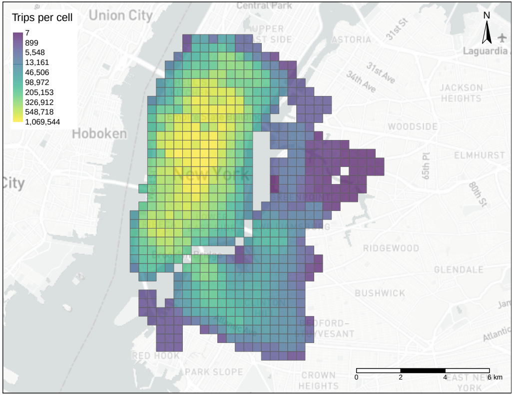
2019



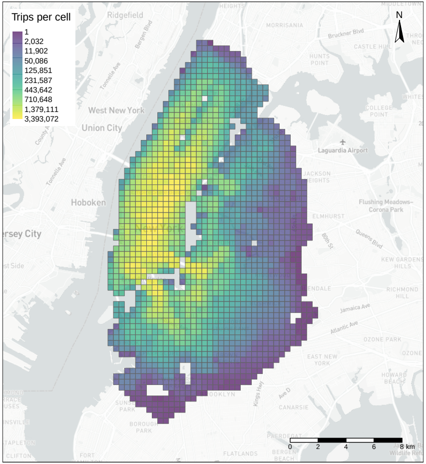
Back

Traffic “footprint”

2013



2019



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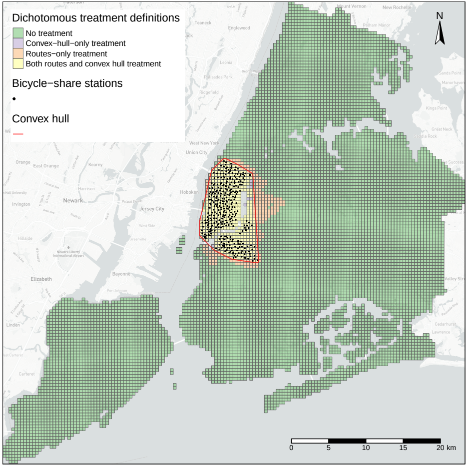
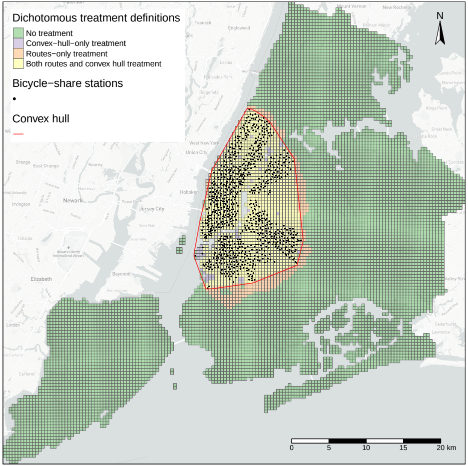
All treatment definitions

2013



2019



▸ Back

NYCCAS details

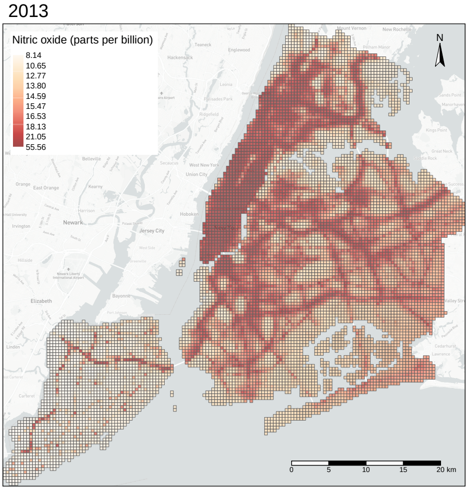
Concentrations of PM 2.5, black carbon, nitrogen oxides (NO and NO^2), sulfur dioxide (SO^2) and ozone (O^3)

- 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:

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

Mapping air pollution · nitric oxide (NO) 2013



▸ Back

Callaway–Sant'Anna estimator

$$ATT(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}(X)C}{1-\hat{p}(X)}}{E\left[\frac{\hat{p}(X)C}{1-\hat{p}(X)}\right]}\right)(Y_t - Y_{g-1})\right] \quad (1)$$

- Computes individual group-time average treatment effect on the treated $ATT(g,t)$ for group (cohort) g at time t
  - $\rightarrow$ group g is a cohort of units treated at the same point in time

- Individual ATTs may be summed using specific weights to produce a single, policy-relevant ATT θ ▸ Weights details

$$\theta = \sum_{g \in \mathcal{G}} \sum_{t=2}^{\mathcal{T}} w(g,t) \cdot ATT(g,t) \quad (2)$$

Callawy–Sant'Anna · Aggregation weights

$$\theta_{sel}(\tilde{g}) = \frac{1}{\mathcal{T} - \tilde{g} + 1} \sum_{t=\tilde{g}}^{\mathcal{T}} ATT(\tilde{g}, t) \tag{3}$$

is the average effect of participating in the treatment among units in group $\tilde{g}$, across all their post-treatment periods.

$$\theta_{sel}^{O} = \sum_{g \in \mathcal{G}} \theta_{sel}(g) P(G = g | G \leq \mathcal{T}) \tag{4}$$

is the average effect of participating in the treatment experienced by all units that ever participated in the treatment.

▸ Back

ATT · Black carbon & PM 2.5 · Stations within 300m

	BC		PM 2.5	
	Uncondit. PT	Condit. PT	Uncondit. PT	Condit. PT
Station ¡ 300m ATT	−0.045	−0.018	−0.128	−0.047
	(0.002)	(0.003)	(0.012)	(0.021)
Mean pre-treat.	1.015	1.015	9.433	9.433
Mean pre-treat., treated	1.345	1.345	10.891	10.891
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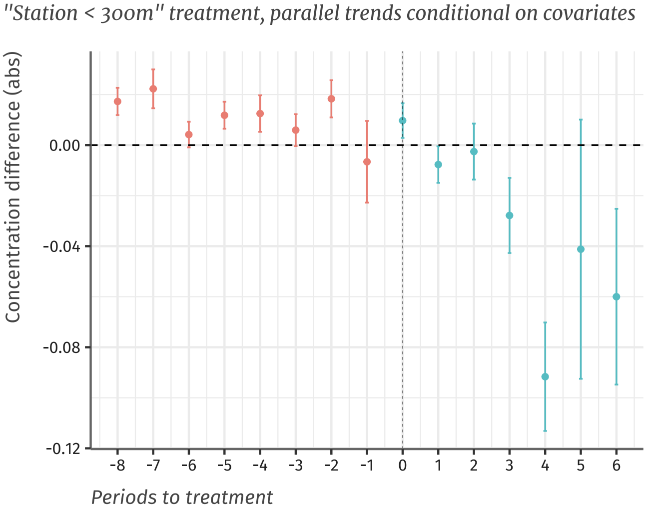
▸ Back robustness

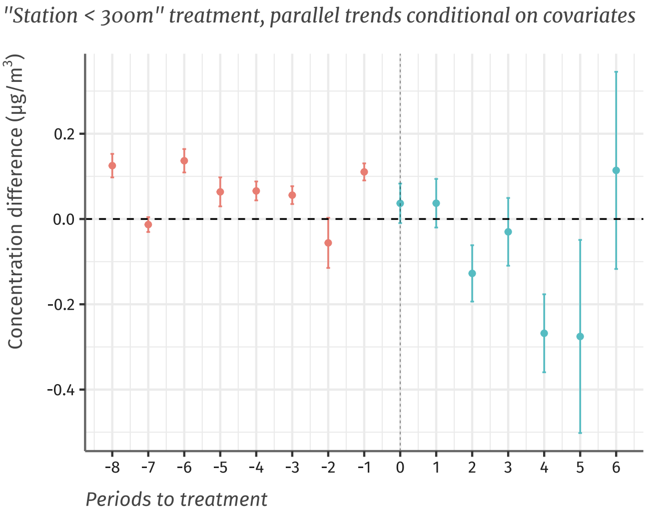
Dynamic effects · Black carbon

▸ Back robustness



Dynamic effects · PM

▸ Back robustness



ATT · NO & NO2 · Stations within 300m

	NO		NO2	
	Uncondit. PT	Condit. PT	Uncondit. PT	Condit. PT
Station ¡ 300m ATT	−2.401	−0.974	−0.807	−0.479
	(0.207)	(0.199)	(0.086)	(0.081)
Mean pre-treat.	20.322	20.322	19.950	19.950
Mean pre-treat., treated	30.459	30.459	27.523	27.523
ATT in % of mean pre-treat. treated	7.88	3.20	2.93	1.74
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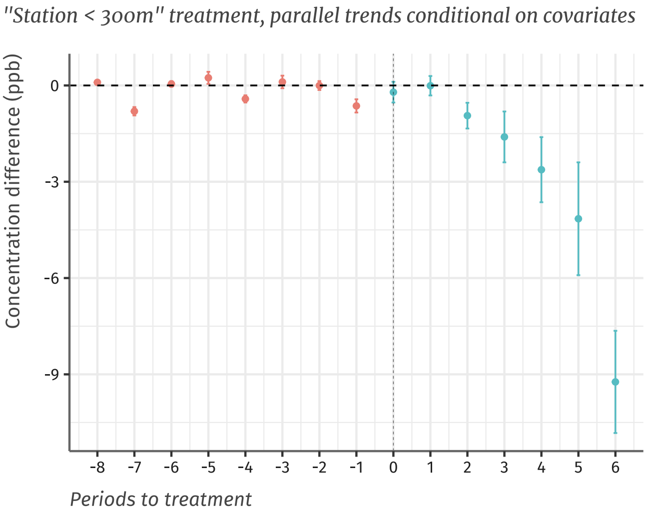
▸ Back robustness

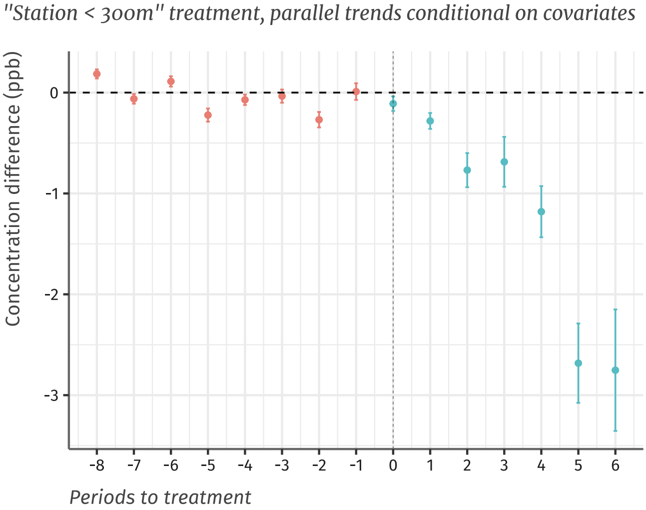
Dynamic effects · NO

▸ Back robustness



Dynamic effects · NO2

Back robustness



ATT · Black carbon & PM 2.5 · Traffic "footprint"

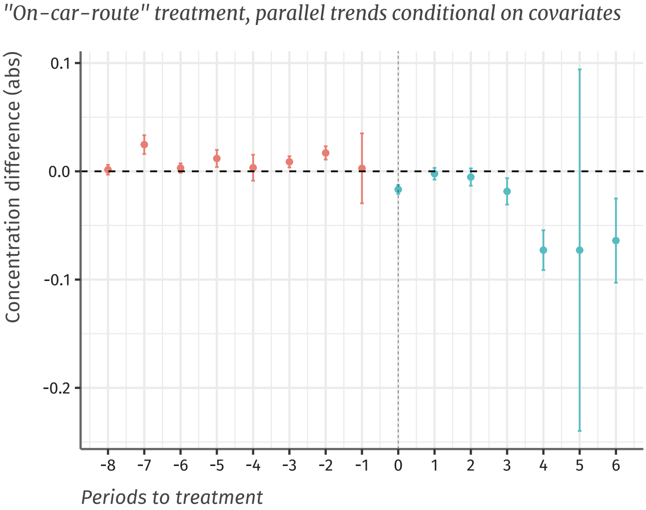
	BC		PM 2.5	
	Uncondit. PT	Condit. PT	Uncondit. PT	Condit. PT
On-car-route ATT	−0.041	−0.025	−0.080	0.012
	(0.002)	(0.004)	(0.008)	(0.010)
Mean pre-treat.	1.015	1.015	9.433	9.433
Mean pre-treat., treated	1.288	1.288	10.632	10.632
ATT in % of mean pre-treat. treated	3.19	1.93	0.75	0.11
SD	0.287	0.287	1.492	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.

▸ Back robustness

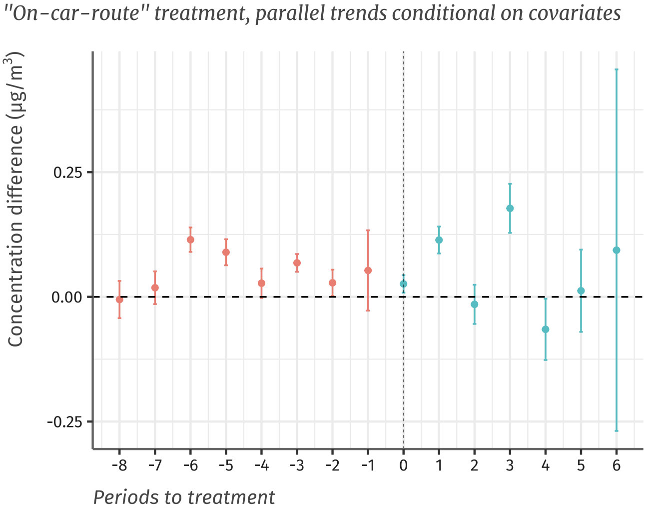
Dynamic effects · Black carbon

▸ Back robustness



Dynamic effects · PM

Back robustness



ATT · NO & NO2 · Traffic "footprint"

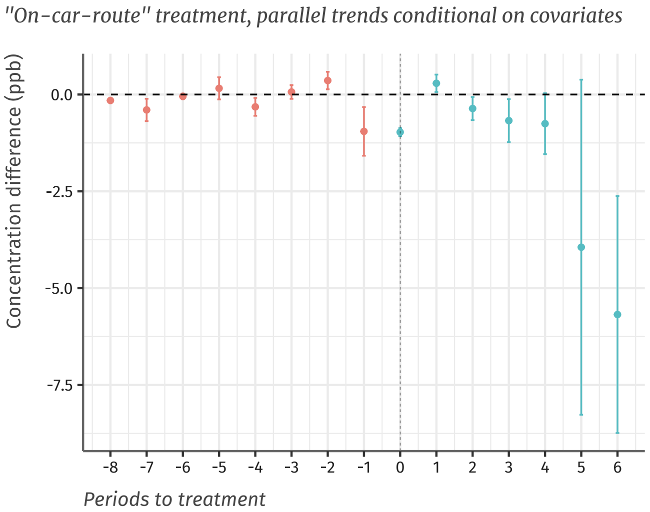
	NO		NO2	
	Uncondit. PT	Condit. PT	Uncondit. PT	Condit. PT
On-car-route ATT	−1.897	−1.017	−0.619	−0.312
	(0.098)	(0.143)	(0.043)	(0.038)
Mean pre-treat.	20.322	20.322	19.950	19.950
Mean pre-treat., treated	27.745	27.745	26.139	26.139
ATT in % of mean pre-treat. treated	6.84	3.67	2.37	1.19
SD	6.875	6.875	4.961	4.961
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.

▸ Back robustness

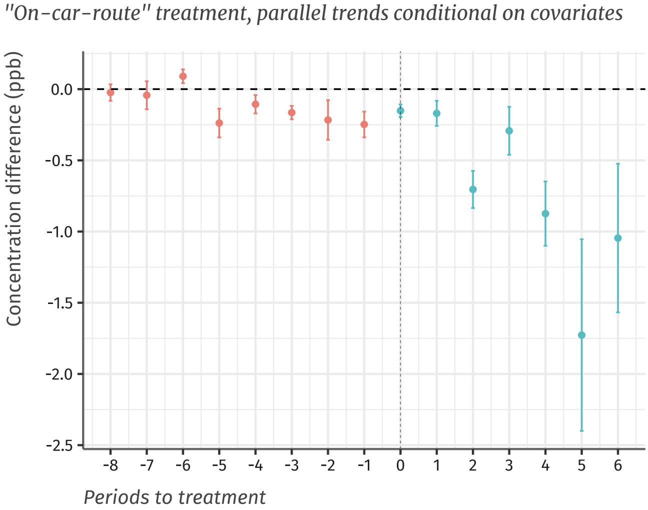
Dynamic effects · NO

▸ Back robustness



Dynamic effects · NO2

Back robustness



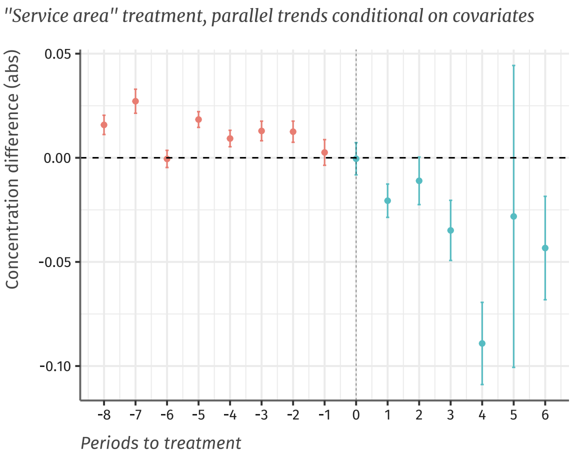
ATT · Black carbon & PM 2.5 · *not-yet-treated* control group

	BC		PM 2.5	
	Incondit. PT	Condit. PT	Uncondit. PT	Condit. PT
Service area ATT	−0.044	−0.023	−0.098	−0.008
	(0.002)	(0.003)	(0.009)	(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.

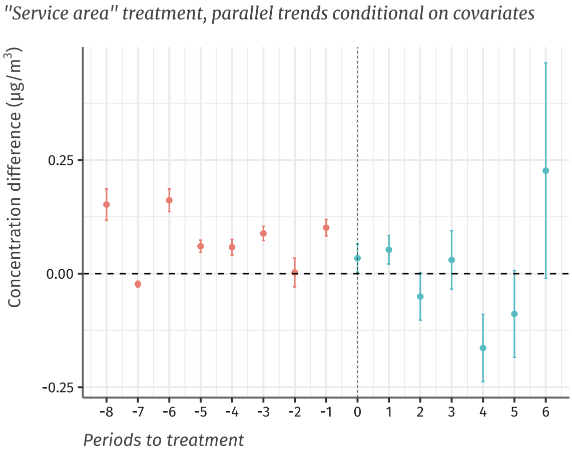
▸ Back robustness

Dynamic effects · Black carbon



▸ Back robustness

Dynamic effects · PM



▸ Back robustness

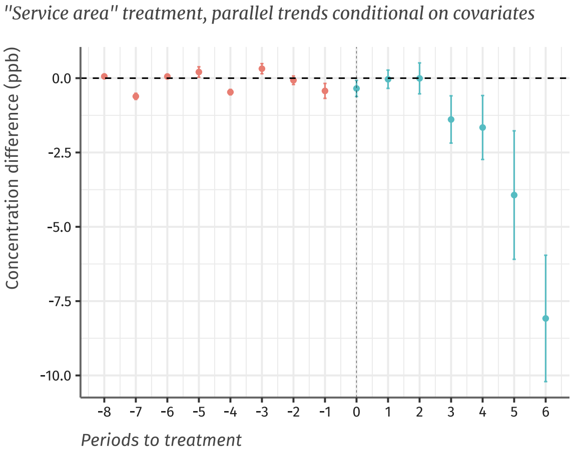
ATT · NO & NO2 · *not-yet-treated* control group

	NO		NO2	
	Uncondit. PT	Condit. PT	Uncondit. PT	Condit. PT
Service area ATT	−1.678	−0.582	−0.538	−0.231
	(0.140)	(0.162)	(0.037)	(0.042)
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

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

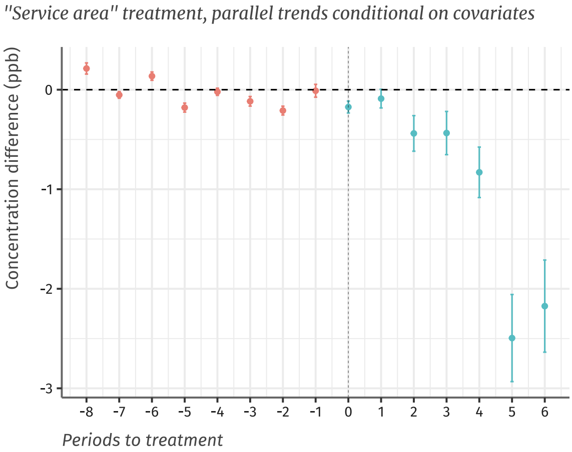
▸ Back robustness

Dynamic effects · NO



▸ Back robustness

Dynamic effects · NO2



▸ Back robustness

ATT · O3 & SO2 · Placebo

	O3		SO2	
	Uncondit. 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

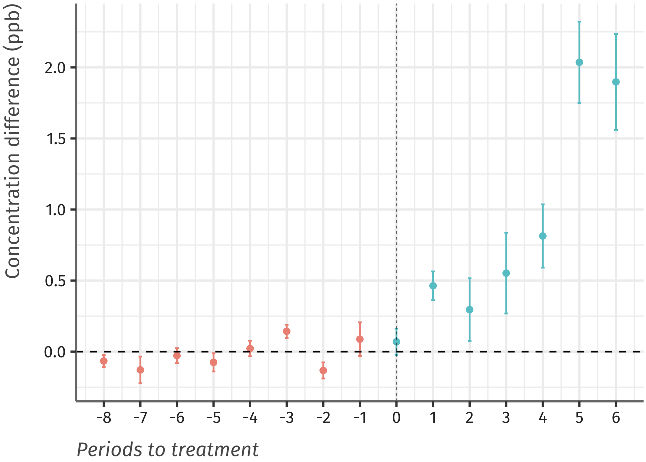
Uncondit. PT: unconditional parallel trends; *Condit. PT*: parallel trends conditional on a set of covariates.

▸ Back robustness

Dynamic effects · O3

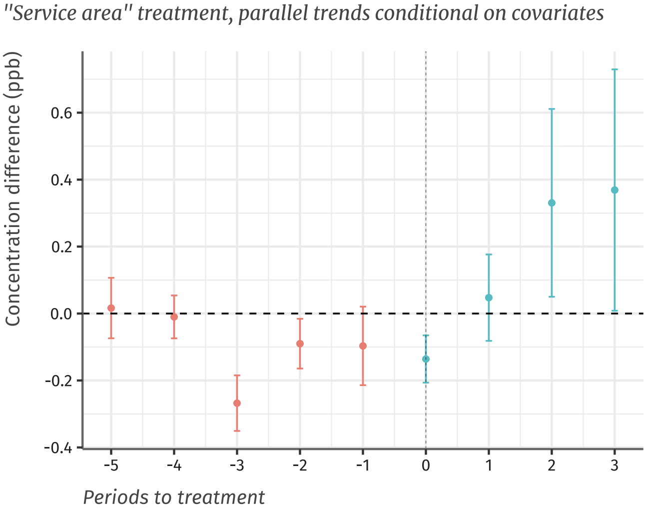
Back robustness

"Service area" treatment, parallel trends conditional on covariates

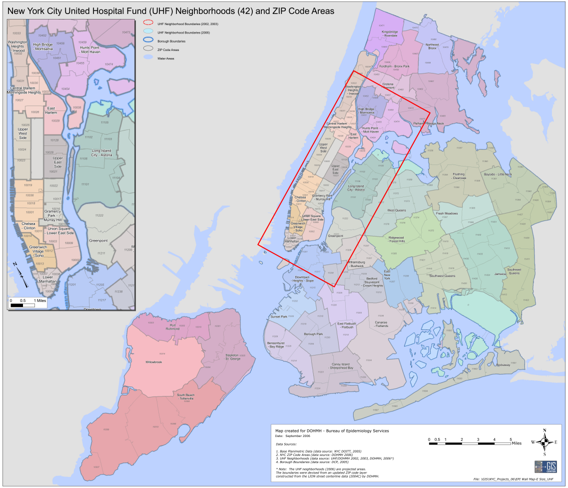


Dynamic effects · SO2

▸ Back robustness

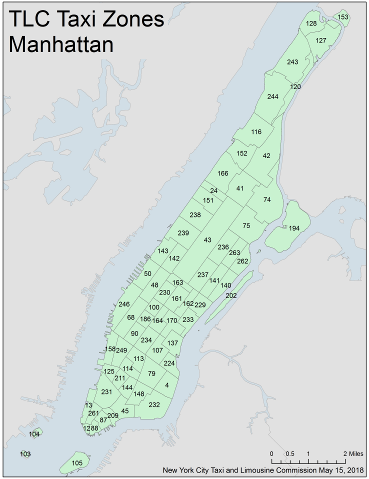


Health neighborhoods



Back

Taxi zones Manhattan



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