Can Apps Save the Planet?

Tech adoption and Urban Mobility

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  - → In the US, 100K–200K excess deaths annually are due to excess air pollution (Tessum et al., 2019; Lelieveld et al., 2019)

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  - → In the US, 100K–200K excess deaths annually are due to excess air pollution (Tessum et al., 2019; Lelieveld et al., 2019)
- Transportation accounts for about 24% of CO_2 emissions, with a significant portion from urban traffic
  - → In cities like New York, road transport can be responsible for up to 50% of CO_2 emissions

Urban transportation and the environment

- Cities are tackling air pollution with several policies (e.g., LEZs, congestion charges).
- Nevertheless, parts of the transportation system remain polluting, create congestion, and are growing in scale: e.g., ride-hailing and taxis

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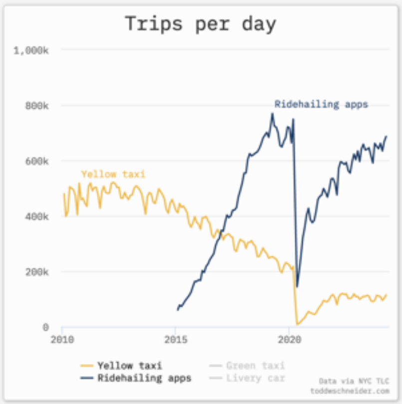

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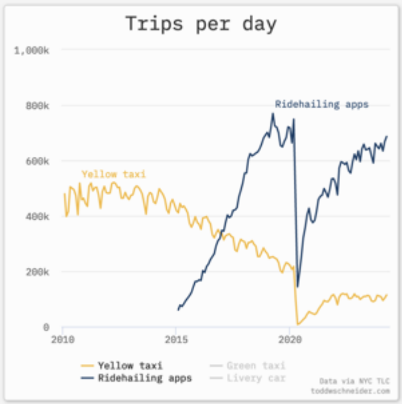

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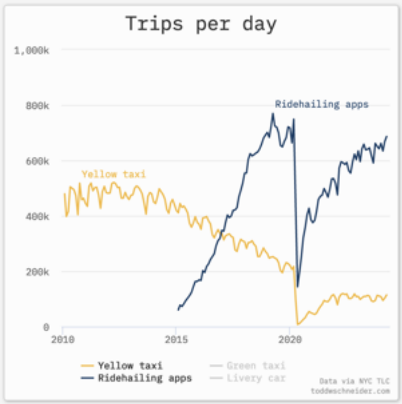

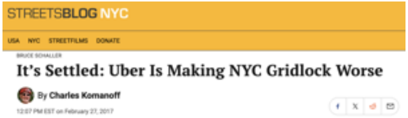

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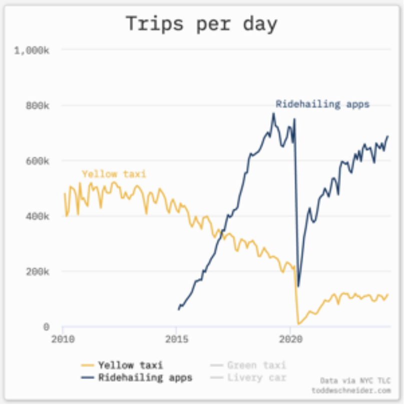
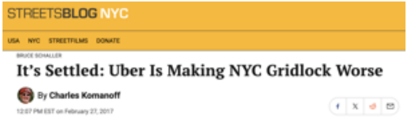



Journal of Urban Economics
Volume 122, March 2021, 103318
The congestion costs of Uber and Lyft
Matthew Tarduno


STREETSBLOG NYC
USA NYC STREETFILMS DONATE
It's Settled: Uber Is Making NYC Gridlock Worse
By Charles Komanoff


The New York Times
Your Uber Car Creates Congestion. Should You Pay a Fee to Ride?

Bicycles as an alternative to motorised traffic

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- However, it may be costly to switch to cycling.

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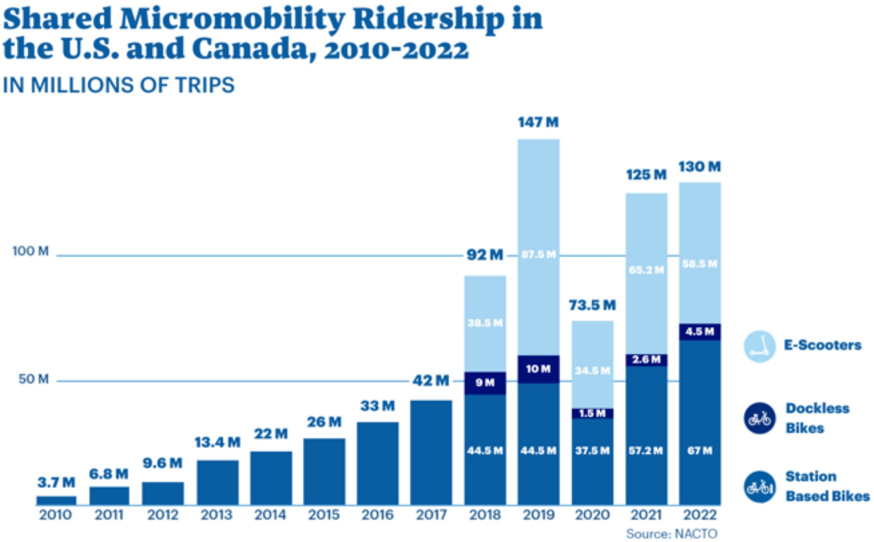
- However, it may be costly to switch to cycling.
- Bike-sharing provides short-term bicycle access in cities.
  - → Over 2,000 programs running around the world
  - → 270 bike share programs in North America
  - → 102 million bike share trips in North America in 2023

Growth of bike-share



What made ride-hailing and bike-share possible?

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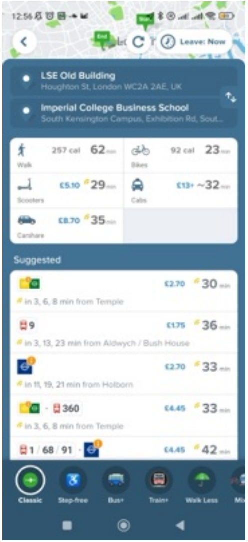
Transportation data and aggregators



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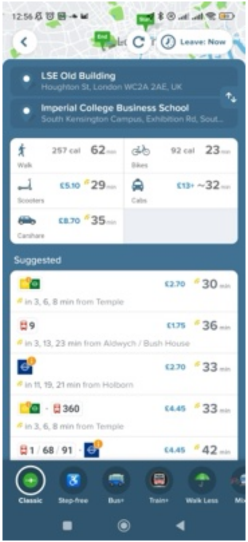

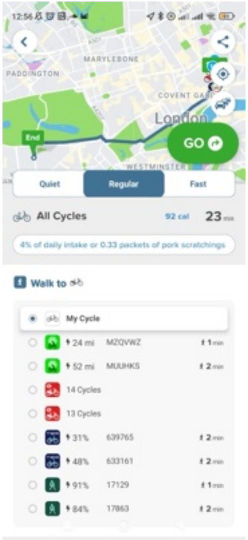

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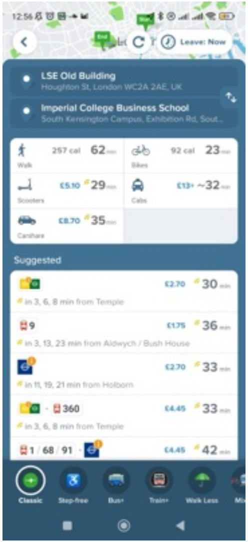
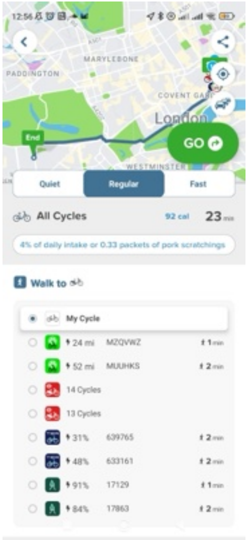
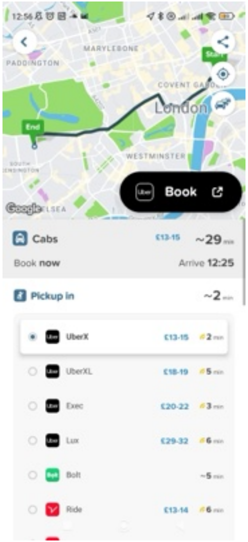
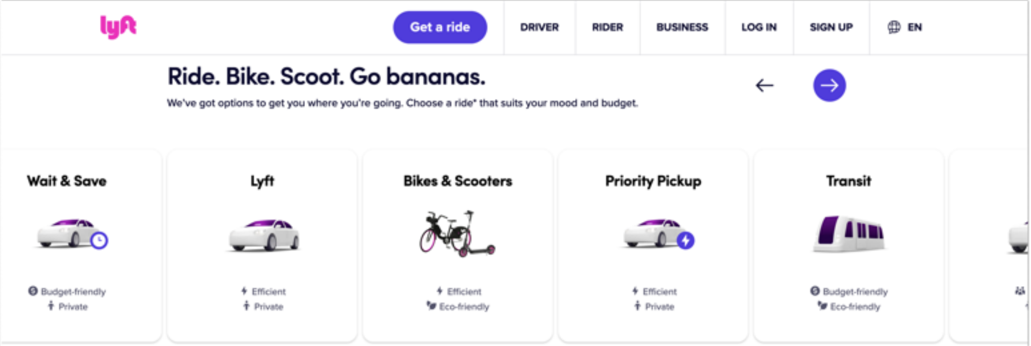






One-stop shop for transportation



Removing information frictions

- Consumers have lot of available information on how to get from A to B, but comparing modes of transport involves a lot of frictions.
  - $\rightarrow$ Apps are still walled gardens and make it harder to compare options and book them.

Removing information frictions

- Consumers have lot of available information on how to get from A to B, but comparing modes of transport involves a lot of frictions.
  - → Apps are still walled gardens and make it harder to compare options and book them.
- What happens when the friction is removed?
- Is removing the information friction good for the environment?

This paper

- We investigate the effect of integrating bike-share information on a ride-hailing app on bike-share ridership in New York City (NYC).

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- Lyft simplified bike-share rental and increased the visibility of the bike-share offering.

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- Lyft simplified bike-share rental and increased the visibility of the bike-share offering.

Research question

How did the integration of bike-share services into the Lyft app influence the adoption behaviour of users?

Are the effects heterogeneous across (1) types of riders, (2) space and (3) time?

How do we answer these questions?

- Difference-in-differences: NYC *vs* Philadelphia + pre *vs* post.
- But are all categories of riders equally likely to respond to the change?

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  - $\rightarrow$ bike-share **subscribers** already familiar with bike-share $\rightarrow$ expected low impact;

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  - $\rightarrow$ bike-share **day users** *less* likely familiar with bike-share $\rightarrow$ expected high impact
    + very low cost to switch to bike-share on the same app

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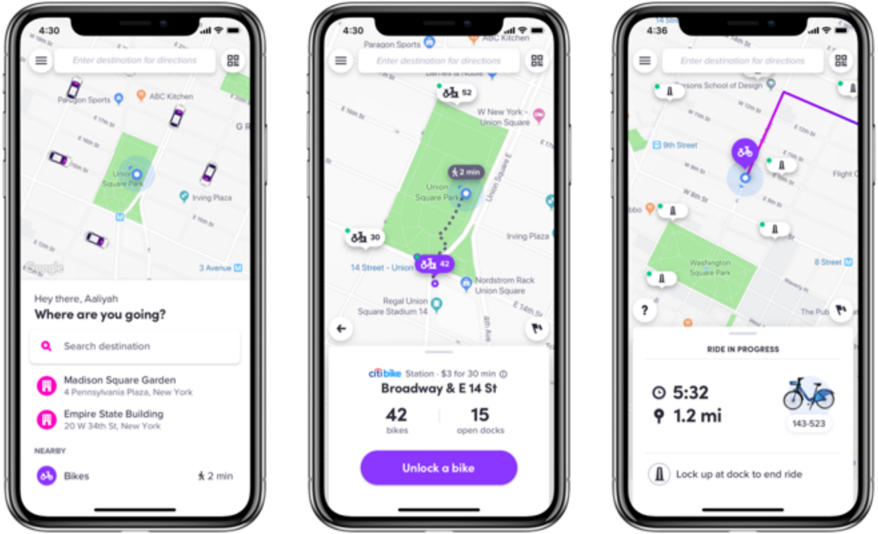
    + very low cost to switch to bike-share on the same app

→ Implement a triple-difference estimation using rider type as the third difference

Treatment

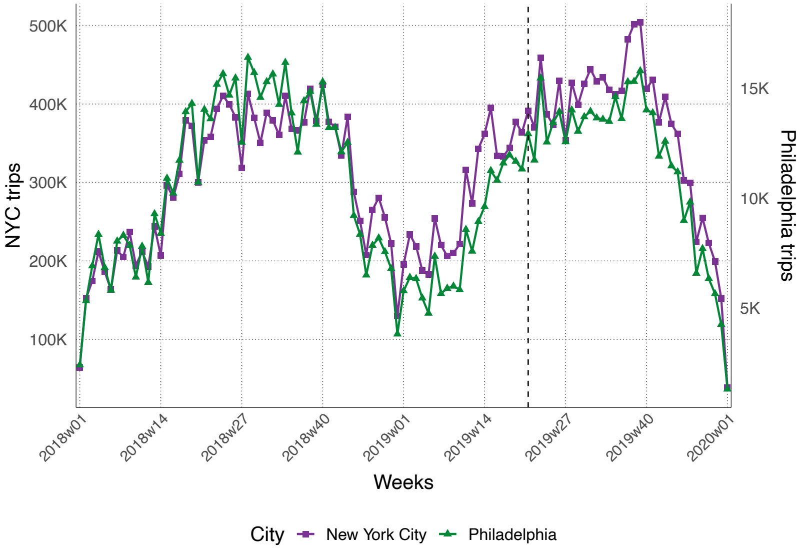

4:30
Enter destination for directions
Paragon Sports
ABC Kitchen
Union Square Park
Irving Plaza
3 Avenue
Hey there, Aaliyah
Where are you going?
Search destination
Madison Square Garden
4 Pennsylvania Plaza, New York
Empire State Building
20 W 34th St, New York
NEARBY
Bikes
2 min
4:30
Paragon Sports
ABC Kitchen
Enter destination for directions
52
W New York - Union Square
2 min
Union Square Park
30
Irving Plaza
14 Street - Union
42
Nordstrom Rack Union Square
Regal Union Square Stadium 14
citibike Station · $3 for 30 min
Broadway & E 14 St
42
bikes
15
open docks
Unlock a bike
4:36
Enter destination for directions
9th Street
Washington Square Park
8 Street
The Pub
RIDE IN PROGRESS
5:32
1.2 mi
143-523
Lock up at dock to end ride

Data

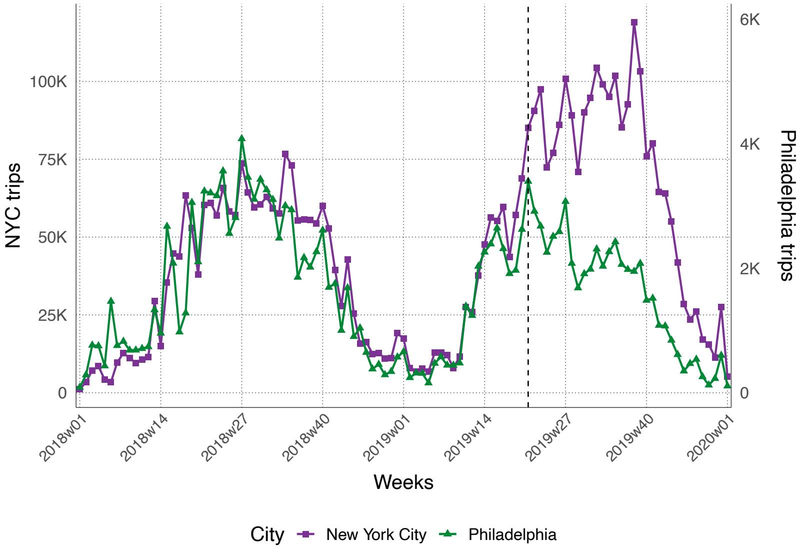
- For each city, we collect the universe of trips made on the bike-share system.
- For the years 2018 and 2019, we use 40 million bike-share trips in NYC and Philadelphia.
- For each trip, we have orgin-destination data, including:
  - → timestamps;
  - → bike-share stations ID (including geographic coordinates);
  - → whether the rider holds a subscription (i.e., at least one month).

▸ Raw data

Raw data trends: Subscribing riders



Raw data trends: Day riders



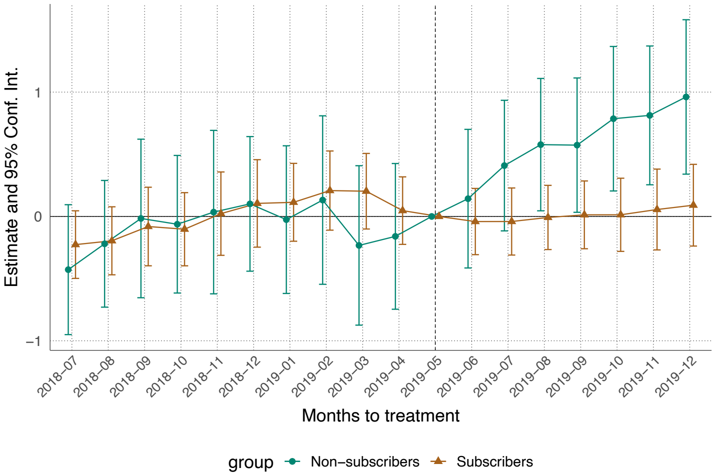
Event study

$$ln(Trips_{itm}) = \alpha + \sum_{\tau=-10}^{-2} \beta_\tau \times Treat_{i\tau} + \sum_{\tau=0}^{7} \beta_\tau \times Treat_{i\tau} + \phi_i + \gamma_m + \varepsilon_{itm}$$

- $Trips_{jtm}$: bike-share trips in city i, date t and year-month m,
- $Treat_{i\tau}$: treatment dummy for city i and relative month to treatment τ,
- $\phi_i + \gamma_m$: city i and month m fixed effects,
- ε_{itm}: error term,
- estimated separately for subscribers and day riders.

Event study

$$ln(Trips_{itm}) = \alpha + \sum_{\tau=-10}^{-2} \beta_\tau \times Treat_{i\tau} + \sum_{\tau=0}^{7} \beta_\tau \times Treat_{i\tau} + \phi_i + \gamma_m + \varepsilon_{itm}$$



Tripe-difference

$$
\begin{aligned}
ln(Trips_{itmr}) = \beta_0 &+ \beta_1 Treat_i + \beta_2 Post_t + \beta_3 RiderType_r \\
&+ \beta_4 Treat_i \times RiderType_r + \beta_5 RiderType_r \times Post_t \\
&+ \beta_6 Treat_i \times Post_t + \beta_7 Treat_i \times RiderType_r \times Post_t \\
&+ \beta_8' X_{it} + \gamma_m + \varepsilon_{itmr}
\end{aligned}
$$

- $Trips_{itmr}$: bike-share trips in city i, date t and month m, by rider type r,
- $Treat_i$: treatment dummy for city i,
- $Post_t$: post period dummy for day t,
- $RiderType_r$: rider type dummy for type r,
- X_{it}: control variables for city i at day t,
- γ_m: month m fixed effects,
- ε_{itmr}: error term.

Tripe-difference

	log(trips)	
	Diff-in-diff	Triple diff
	(1)	
Treated × Post-period	0.1317***	
	(0.0000)	
Treated	3.3640***	
	(0.0000)	
Post-period	-0.0209	
	(0.0179)	
Treated × Post-period × Day rider		
Treated × Day rider		
Post-period × Day rider		
Day rider		
Weather controls		
Month FE (12)	Yes	
Observations	1,460	
Adjusted R^2	0.952	
Within Adjusted R^2	0.950	

Tripe-difference

	log(trips)		
	Diff-in-diff		Triple diff
	(1)	(2)	
Treated × Post-period	0.1317***	0.1233**	
	(0.0000)	(0.0022)	
Treated	3.3640***	3.4577***	
	(0.0000)	(0.0060)	
Post-period	-0.0209	-0.0482	
	(0.0179)	(0.0300)	
Treated × Post-period × Day rider			
Treated × Day rider			
Post-period × Day rider			
Day rider			
Weather controls		Yes	
Month FE (12)	Yes	Yes	
Observations	1,460	1,460	
Adjusted R^2	0.952	0.971	
Within Adjusted R^2	0.950	0.969	

Tripe-difference

	log(trips)		
	Diff-in-diff		Triple diff
	(1)	(2)	(3)
Treated × Post-period	0.1317***	0.1233**	0.0387**
	(0.0000)	(0.0022)	(0.0018)
Treated	3.3640***	3.4577***	3.5424***
	(0.0000)	(0.0060)	(0.0044)
Post-period	-0.0209	-0.0482	-0.1596**
	(0.0179)	(0.0300)	(0.0073)
Treated × Post-period × Day rider			0.7992***
			(0.0000)
Treated × Day rider			-0.2851***
			(0.0000)
Post-period × Day rider			-0.1047***
			(0.0000)
Day rider			-2.2606***
			(0.0000)
Weather controls		Yes	Yes
Month FE (12)	Yes	Yes	Yes
Observations	1,460	1,460	2,920
Adjusted R^2	0.952	0.971	0.935
Within Adjusted R^2	0.950	0.969	0.930

Tripe-difference: interpretation

- $exp(0.799) - 1 = 1.22 \rightarrow$ 122% increase in day rider trips in NYC following the integration of bike-share on the Lyft app.
- Pre-treatment mean weekly trips by day riders 35K $\rightarrow$ treatment lead to +42K weekly trips by day riders in the post-period.
- Robust to including only trips to/from pre-treatment stations.

$\rightarrow$ are these riders displacing Lyft trips?

Heterogeneity: time of travel

	log(trips)
	Non-working day
	(1)
Treated × Post-period × Day riders	0.6360***
	(0.0000)
Treated × Post-period	-0.0062**
	(0.0004)
Treated × Day riders	-0.4047***
	(0.0000)
Post-period × Day riders	0.0602***
	(0.0000)
Treated	3.6535***
	(0.0170)
Post-period	-0.1672**
	(0.0096)
Day riders	-1.5214***
	(0.0000)
Weather controls	Yes
Month FE (12)	Yes
Observations	1,808
Adjusted R^2	0.815
Within Adjusted R^2	0.797

Heterogeneity: time of travel

	log(trips)	
	Non-working day	Working day
	(1)	(2)
Treated × Post-period × Day riders	0.6360***	0.9707***
	(0.0000)	(0.0000)
Treated × Post-period	-0.0062**	0.0526**
	(0.0004)	(0.0021)
Treated × Day riders	-0.4047***	-0.2318***
	(0.0000)	(0.0000)
Post-period × Day riders	0.0602***	-0.2086***
	(0.0000)	(0.0000)
Treated	3.6535***	3.4807***
	(0.0170)	(0.0024)
Post-period	-0.1672**	-0.1608*
	(0.0096)	(0.0212)
Day riders	-1.5214***	-2.8123***
	(0.0000)	(0.0000)
Weather controls	Yes	Yes
Month FE (12)	Yes	Yes
Observations	1,808	4,032
Adjusted R^2	0.815	0.915
Within Adjusted R^2	0.797	0.910

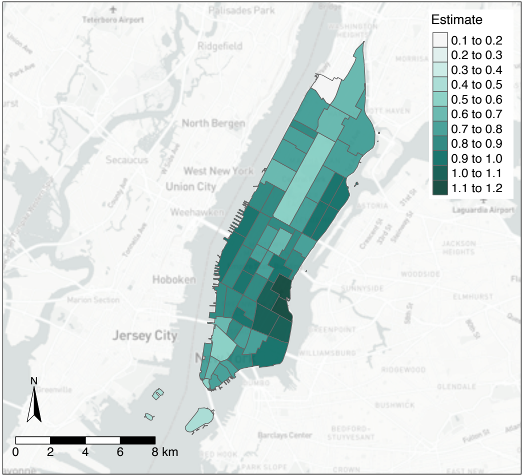
Heterogeneity: time of travel

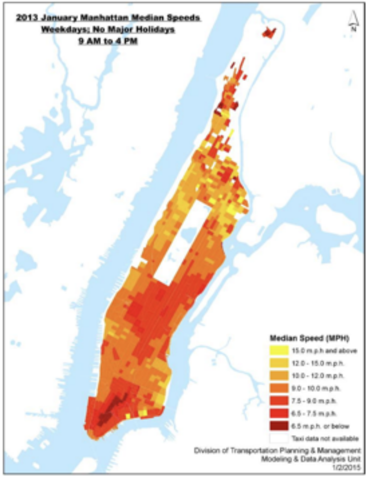
	log(trips)		
	Non-working day	Working day	Outside rush-hour
	(1)	(2)	(3)
Treated × Post-period × Day riders	0.6360***	0.9707***	0.7899***
	(0.0000)	(0.0000)	(0.0000)
Treated × Post-period	-0.0062**	0.0526**	0.0635**
	(0.0004)	(0.0021)	(0.0026)
Treated × Day riders	-0.4047***	-0.2318***	-0.1710***
	(0.0000)	(0.0000)	(0.0000)
Post-period × Day riders	0.0602***	-0.2086***	-0.1395***
	(0.0000)	(0.0000)	(0.0000)
Treated	3.6535***	3.4807***	3.5095***
	(0.0170)	(0.0024)	(0.0016)
Post-period	-0.1672**	-0.1608*	-0.1722**
	(0.0096)	(0.0212)	(0.0028)
Day riders	-1.5214***	-2.8123***	-2.4496***
	(0.0000)	(0.0000)	(0.0000)
Weather controls	Yes	Yes	Yes
Month FE (12)	Yes	Yes	Yes
Observations	1,808	4,032	2,016
Adjusted R^2	0.815	0.915	0.952
Within Adjusted R^2	0.797	0.910	0.949

Heterogeneity: time of travel

	log(trips)			
	Non-working day	Working day	Outside rush-hour	Rush-hour
	(1)	(2)	(3)	(4)
Treated × Post-period × Day riders	0.6360***	0.9707***	0.7899***	1.1515***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Treated × Post-period	-0.0062**	0.0526**	0.0635**	0.0416**
	(0.0004)	(0.0021)	(0.0026)	(0.0015)
Treated × Day riders	-0.4047***	-0.2318***	-0.1710***	-0.2927***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Post-period × Day riders	0.0602***	-0.2086***	-0.1395***	-0.2778***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Treated	3.6535***	3.4807***	3.5095***	3.4519***
	(0.0170)	(0.0024)	(0.0016)	(0.0063)
Post-period	-0.1672**	-0.1608*	-0.1722**	-0.1495
	(0.0096)	(0.0212)	(0.0028)	(0.0397)
Day riders	-1.5214***	-2.8123***	-2.4496***	-3.1749***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Weather controls	Yes	Yes	Yes	Yes
Month FE (12)	Yes	Yes	Yes	Yes
Observations	1,808	4,032	2,016	2,016
Adjusted R^2	0.815	0.915	0.952	0.955
Within Adjusted R^2	0.797	0.910	0.949	0.952

Heterogeneity: space





▸ Whole city

Substitution: event study

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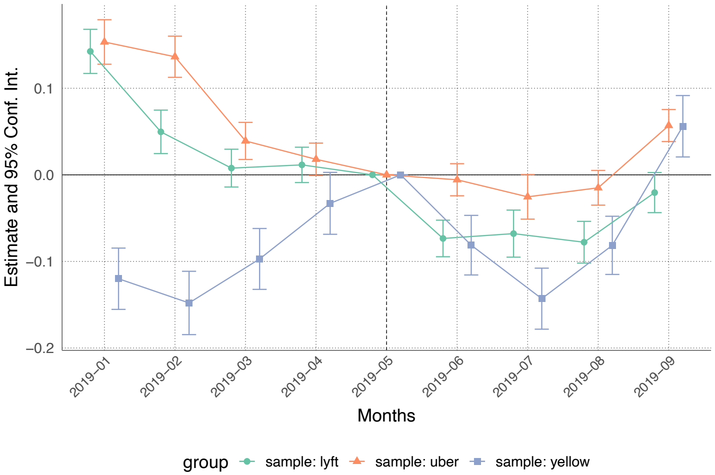

Conclusion

- We study the impact of bike-share information aggregation on a ride-hailing app on bike-share ridership.
- We find that
  - → the integration increased day ridership by 122%,
  - → the increase was concentrated in working days and during rush-hour, consistent with congestion patterns
  - → there is spatial heterogeneity in the impact of integration,
- There is suggestive evidence that the integration reduced ride-hailing traffic
- WIP: environmental damages, value of time, firm's profitability

Thank you

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Raw data illustration

city	start_time	end_time	start_lon	start_lat	end_lon	end_lat	subs
nyc	2018-01-16 20:21:12	2018-01-16 20:36:03	-73.98	40.74	-73.96	40.78	1
nyc	2018-05-24 06:59:50	2018-05-24 07:09:09	-74.01	40.71	-74.01	40.72	1
nyc	2018-07-30 17:57:49	2018-07-30 18:29:52	-73.96	40.72	-73.98	40.73	0
phil	2018-11-01 19:07:00	2018-11-01 19:13:00	-75.18	39.95	-75.18	39.95	1
nyc	2018-12-29 07:15:15	2018-12-29 07:22:48	-73.94	40.80	-73.96	40.81	1
nyc	2019-02-08 16:40:34	2019-02-08 16:44:39	-73.99	40.76	-73.99	40.76	1
nyc	2019-02-28 19:20:31	2019-02-28 19:30:19	-74.00	40.71	-74.01	40.70	1
nyc	2019-10-24 17:19:27	2019-10-24 17:58:56	-73.99	40.74	-73.98	40.68	1

Daily panel illustration

city	date	month	subs	trips	sts_n_month	wind [m/s]	precip [mm]
nyc	2018-01-01	1	0	259	768	7.9	0
nyc	2018-01-01	1	1	5,241	768	7.9	0
phil	2018-01-01	1	0	30	123	4.7	0
phil	2018-01-01	1	1	168	123	4.7	0
nyc	2018-01-02	1	0	318	768	7.0	0
nyc	2018-01-02	1	1	18,500	768	7.0	0
phil	2018-01-02	1	0	9	123	5.9	0
phil	2018-01-02	1	1	640	123	5.9	0

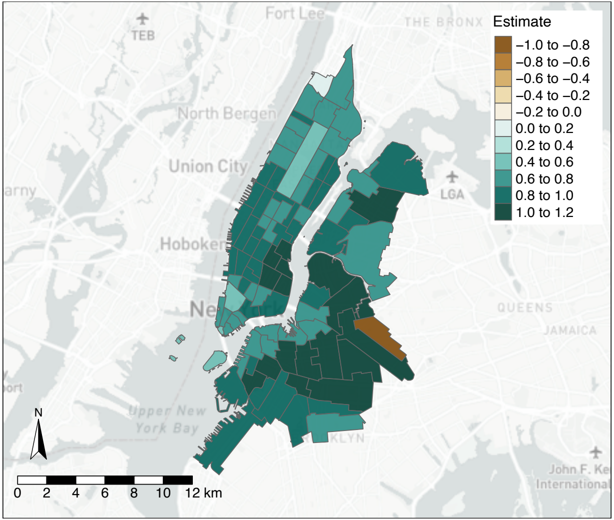
Descriptive statistics: daily

Variable	City	Subs	Mean	Median	SD	Min	Max
Trips (per day)	NYC	0	6,581.64	5,251.5	5,792.55	17.0	39,899.0
		1	45,606.52	45,694.5	17,480.14	1,905.0	82,822.0
		All	52,188.16	53,735.0	20,901.25	1,922.0	98,755.0
	Phil	0	232.97	159.5	230.59	2.0	1,441.0
		1	1,538.94	1,484.0	673.97	108.0	2,917.0
		All	1,771.91	1,829.5	767.01	113.0	3,348.0
Wind [m/s]	NYC	–	5.17	4.7	1.96	1.3	13.4
	Phil	–	4.05	3.8	1.68	0.8	11.9
Precip [mm]	NYC	–	3.81	0.0	8.40	0.0	54.9
	Phil	–	3.79	0.0	9.48	0.0	115.3
Avg temp [°C]	NYC	–	12.56	12.3	9.38	-12.8	31.9
	Phil	–	13.78	14.6	9.84	-11.9	32.4

Descriptive statistics: weekly

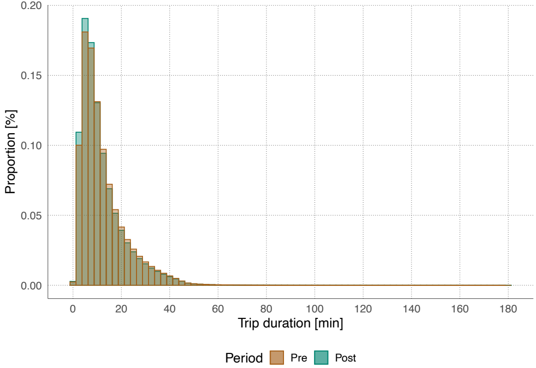
Variable	City	Subs	Mean	Median	SD	Min	Max
Trips (per week)	NYC	0	45,758.06	47,557.0	30,994.61	1,163.0	119,050.0
		1	317,073.93	350,598.0	98,050.34	38,457.0	504,452.0
		All	362,831.99	403,790.0	126,574.74	43,648.0	620,895.0
	Phil	0	1,619.70	1,684.0	1,044.08	88.0	4,079.0
		1	10,699.31	11,599.0	3,691.58	1,304.0	16,405.0
		All	12,319.02	13,577.0	4,588.68	1,413.0	19,866.0
Wind [m/s]	NYC	–	5.17	4.7	1.96	1.3	13.4
	Phil	–	4.05	3.8	1.68	0.8	11.9
Precip [mm]	NYC	–	3.81	0.0	8.40	0.0	54.9
	Phil	–	3.79	0.0	9.48	0.0	115.3
Avg temp [°C]	NYC	–	12.56	12.3	9.38	-12.8	31.9
	Phil	–	13.78	14.6	9.84	-11.9	32.4

Heterogeneity: space



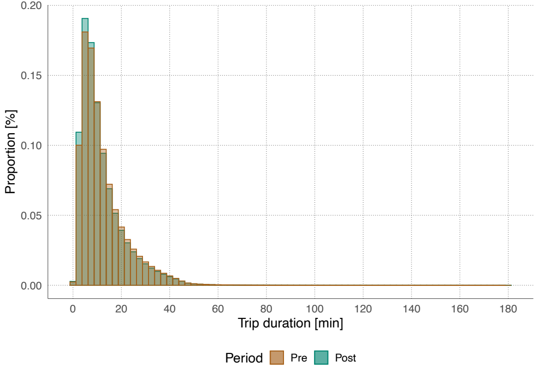
▸ Back

Bike-share usage post-treatment: trip duration

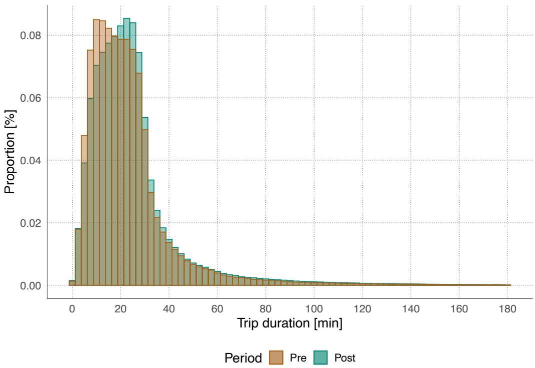


Subscribers

Bike-share usage post-treatment: trip duration



Subscribers



Day riders