The Short-Run Effects of Congestion Pricing in New York City

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Motivation

Economists love congestion pricing, but rare in practice

- Price the externalities of driving (Vickrey, 1963)
- Exists in Singapore, London, Stockholm, Milan, ...

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- $9 for passenger vehicles (5am–9pm)
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Source: New York Times

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"Second-best" congestion pricing

- Subset of roads and times with a $\sim$flat price
- Efficient traffic reduction or just re-shuffling it to unpriced roads?

Source: New York Times

This Project

Research questions

1. Effects inside the Central Business District (CBD)?

2. Spillover effects outside the CBD?

3. Implications for designing congestion pricing programs?

▸ Related literature

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- Data from Google Maps, credit/debit cards, air quality sensors, GPS devices, …
- Estimate treatment effects using data from NYC + control cities
- Evaluate mechanisms & potential effectiveness in other cities

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   $\rightsquigarrow$ Speeds $\uparrow$ 11%. Little-to-no effect on pollution, shop/restaurant visits, or foot traffic
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3. Implications for designing congestion pricing programs?
   - $\rightsquigarrow$ Welfare gains come from diffuse spillovers on unpriced trips
   - $\rightsquigarrow$ Mechanisms: *exposure* to CBD trips & *steepness* of density $\mapsto$ speeds relationship

Approach

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Related literature

Data

- Aggregated + anonymized stats from Google Maps trips (Sept. 2024-June 2025)
  - **Segment-level outcomes**: hourly outcomes at the “road” level
    - traversal speeds
  - **Origin-Destination outcomes**: hourly outcomes at the “trip” level
    - realized trip travel times and speeds
    - estimated fuel consumption

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  - Ambient air quality from PurpleAir sensors
  - Transactions at restaurants and shops from credit/debit cards via MBHS3
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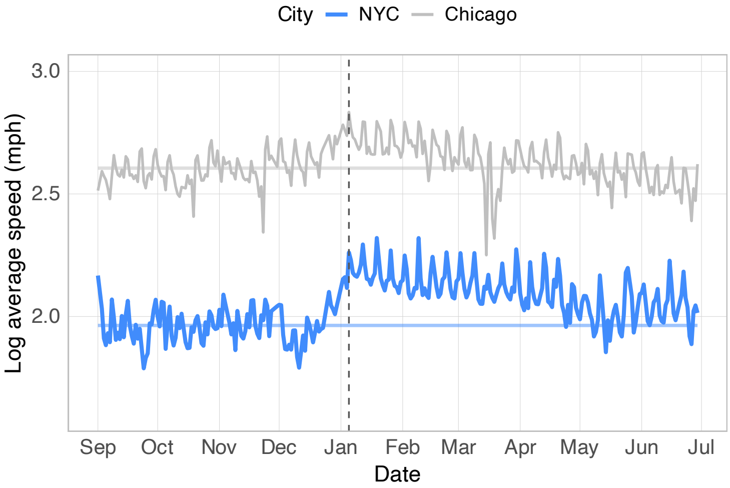
- Coverage: NYC, Philadelphia, Chicago, Boston, Atlanta, and Baltimore metro areas

Data ends in June 2025 – stay tuned for the 1-year update!

What happened inside the CBD?

Methodology: Generalized Synthetic Controls

Key idea: compare log average speeds on CBD segments, NYC vs Chicago



Note: The blue and grey bars are average speeds pre-policy

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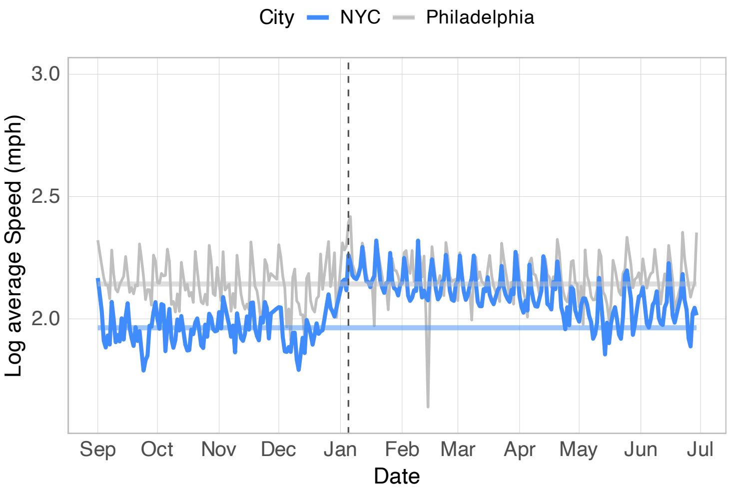

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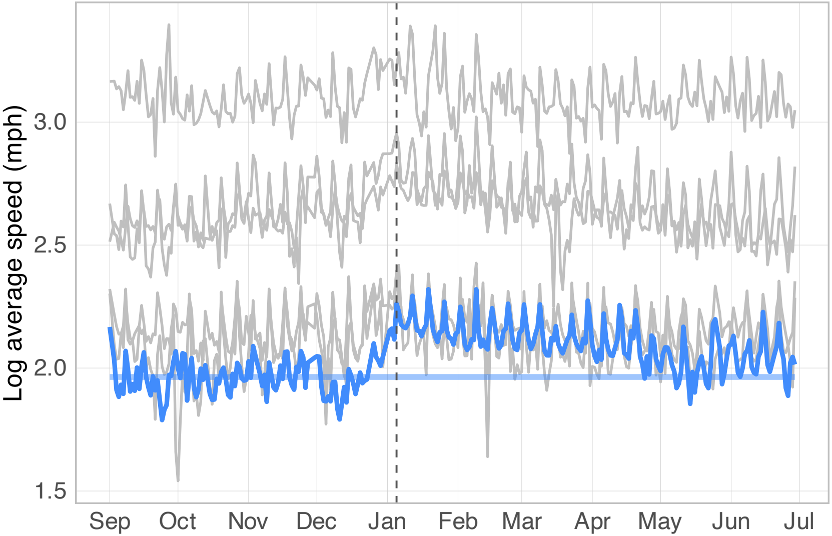
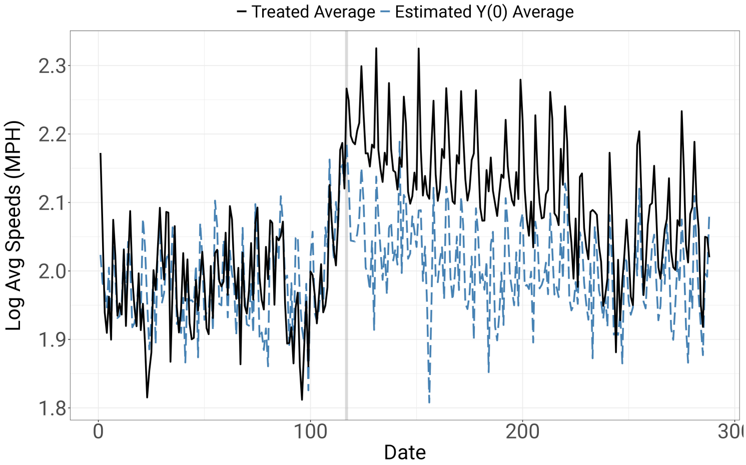


Methodology: Generalized Synthetic Controls

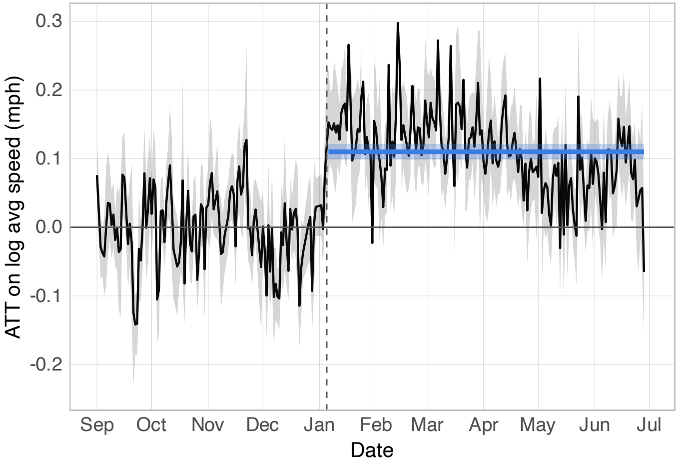
Key idea: combine into 'synthetic control'



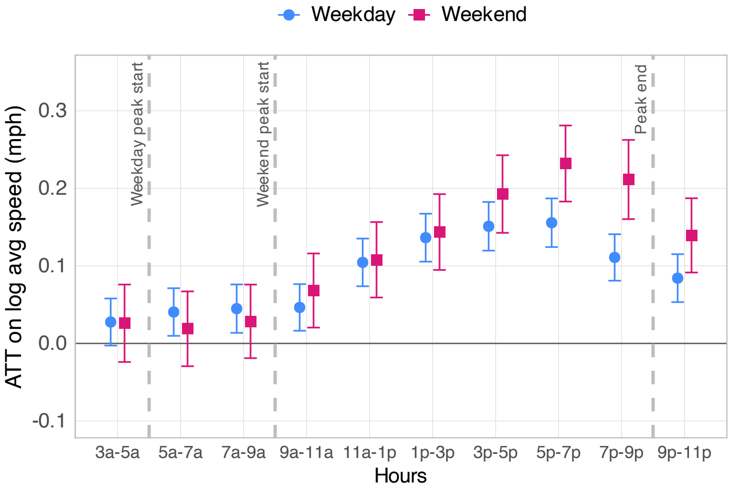
Methodology: Generalized Synthetic Controls

Key idea: difference is the 'average treatment effect' (ATT)

- Average speeds on CBD road segments increased by 11%



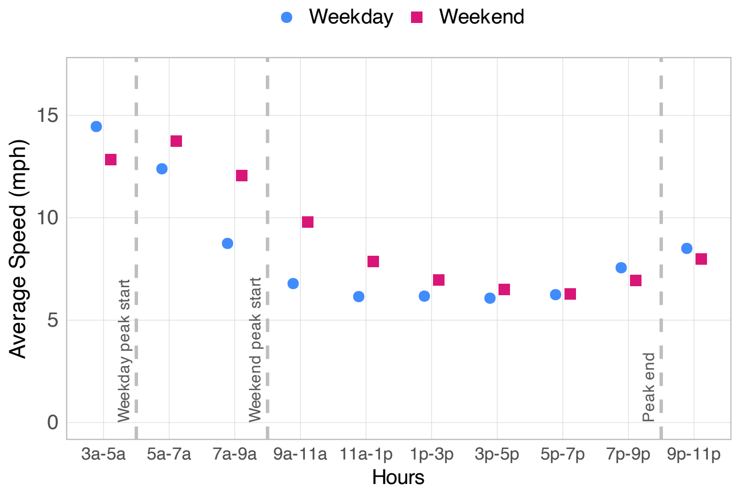
CBD speeds increased the most during the afternoon...



Note: Each ATT is separately estimated using traffic conditions from the other CBDs during the same time of day as synthetic controls. Vertical lines represent 95% confidence intervals, with standard errors clustered by city.

▸ Effects on distribution of speeds

… which is when speeds are usually the slowest



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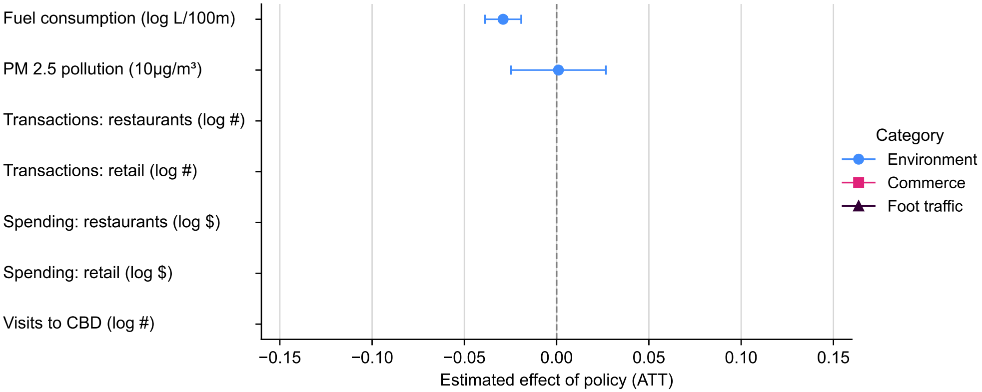
Little-to-no effects on pollution, commerce, or foot traffic



Note: Each point is the estimated ATT using the same five control cities. Fuel consumption is estimated for an average passenger car based on segment characteristics and speed profile. Pollution data from PurpleAir are at day-sensor level, transactions data from MBHS3 are at the zipcode-day level, and foot traffic from Advan are at the tract-day level. Horizontal bars represent 95% confidence intervals, with standard errors clustered by city.

Pollution Transactions Foot traffic

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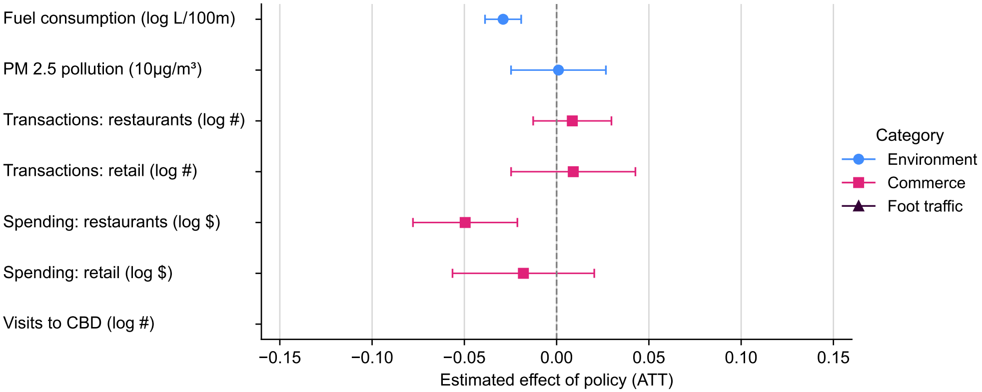

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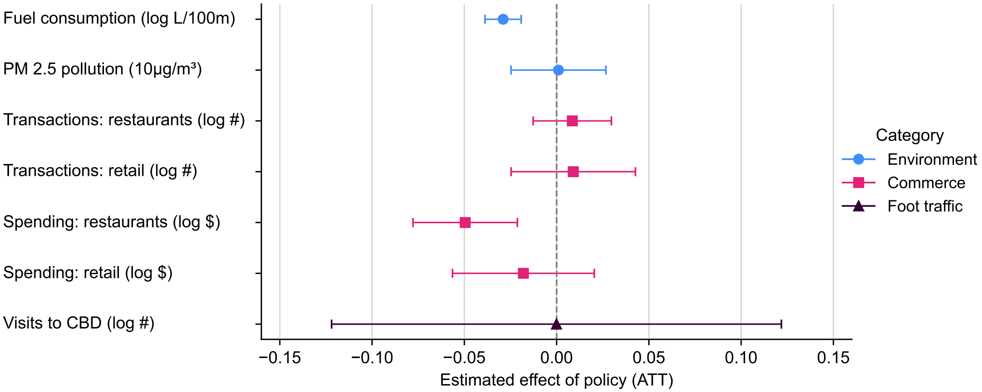

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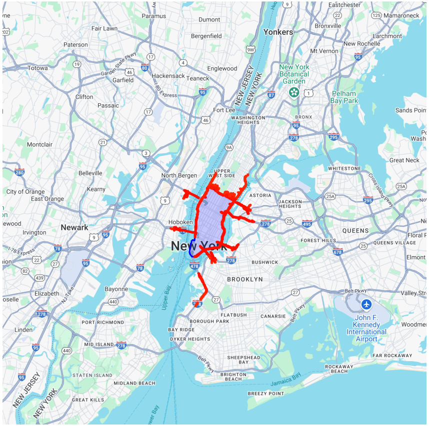
▸ Pollution ▸ Transactions ▸ Foot traffic

What were the spillovers outside the CBD?

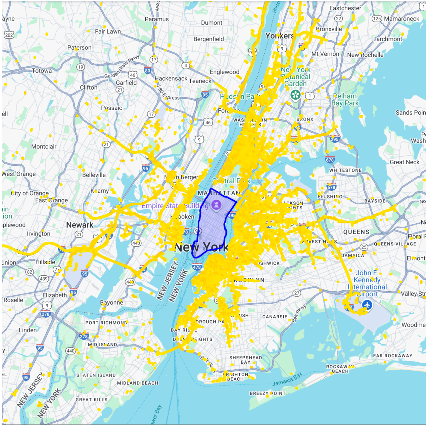
Measure policy exposure using 'co-occurrence'

Road segment co-occurrence: share of traversals that are CBD trips

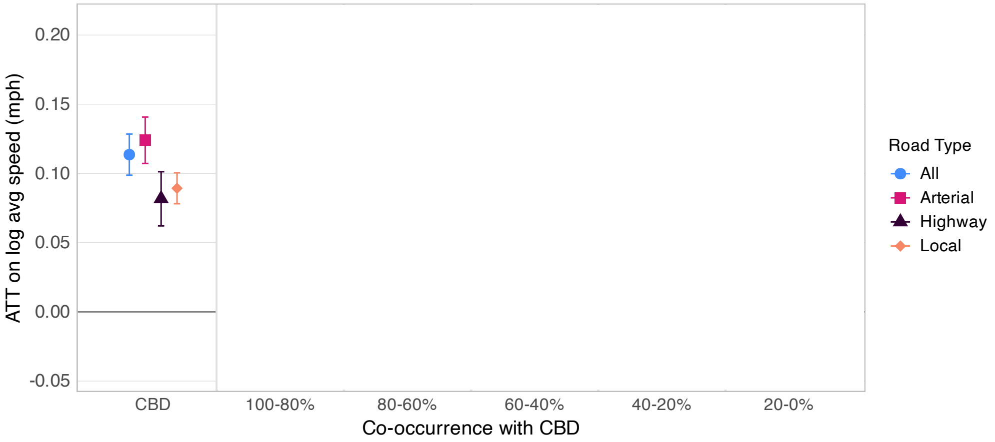
(a) High co-occurrence (80-100%)



(b) Low co-occurrence (10-20%)



More exposed segments → larger effect on speeds



Note: Each point is separately estimated using the average speeds in two-hour bins for segments with the corresponding level of co-occurrence and road segment type for both NYC and the comparison cities. Vertical bars represent 95% confidence intervals, with standard errors clustered by city.

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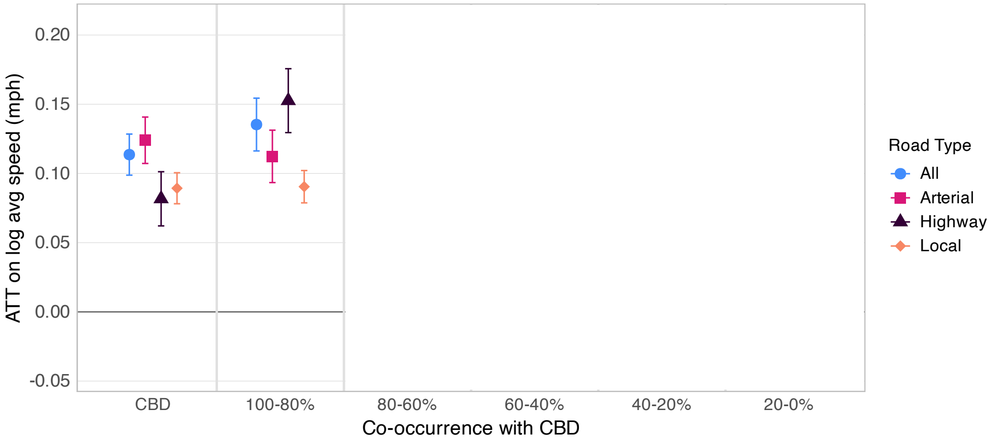

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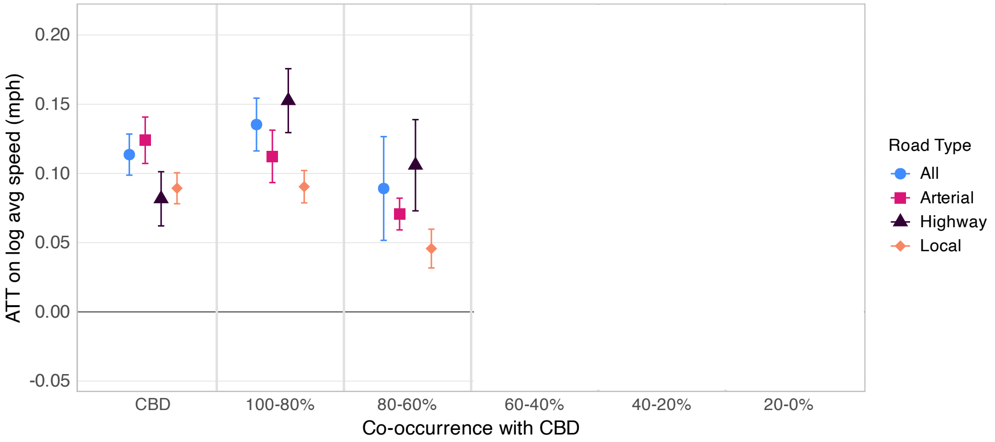

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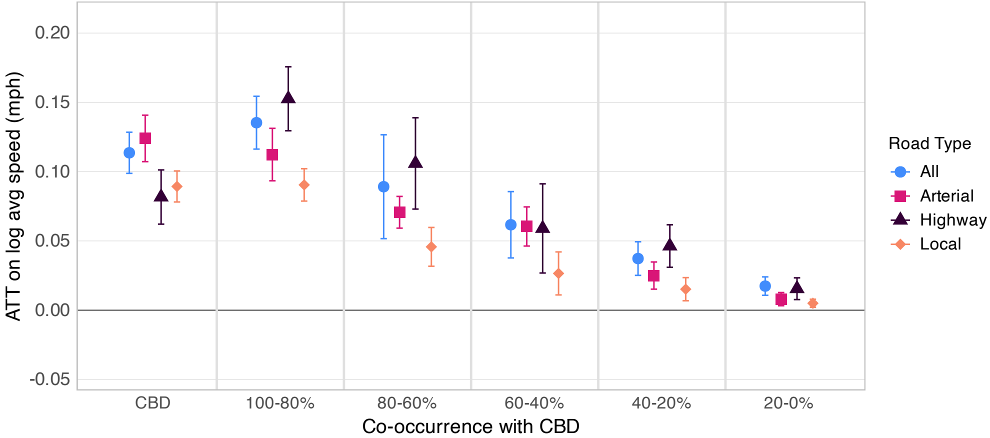

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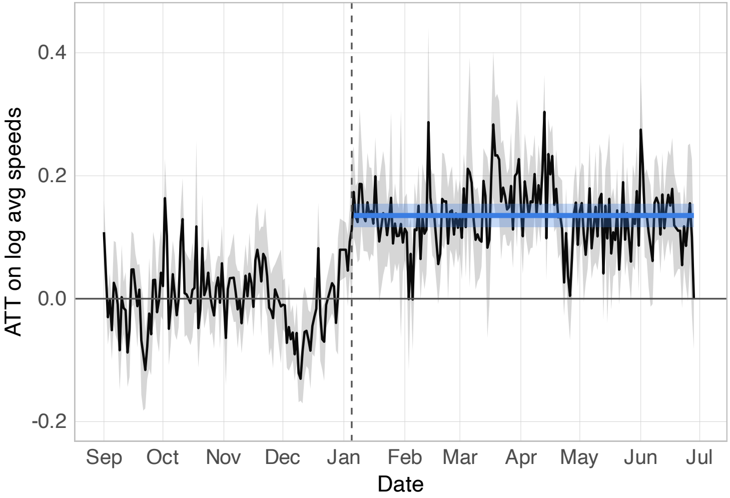
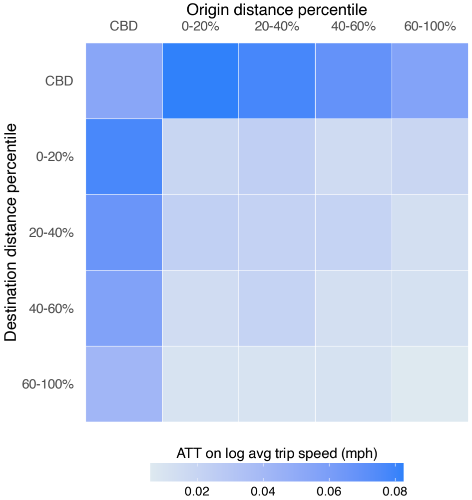
Effects on speeds outside CBD have not attenuated as much

Speeds on 80-100% co-occurrence roads (e.g., Holland Tunnel)



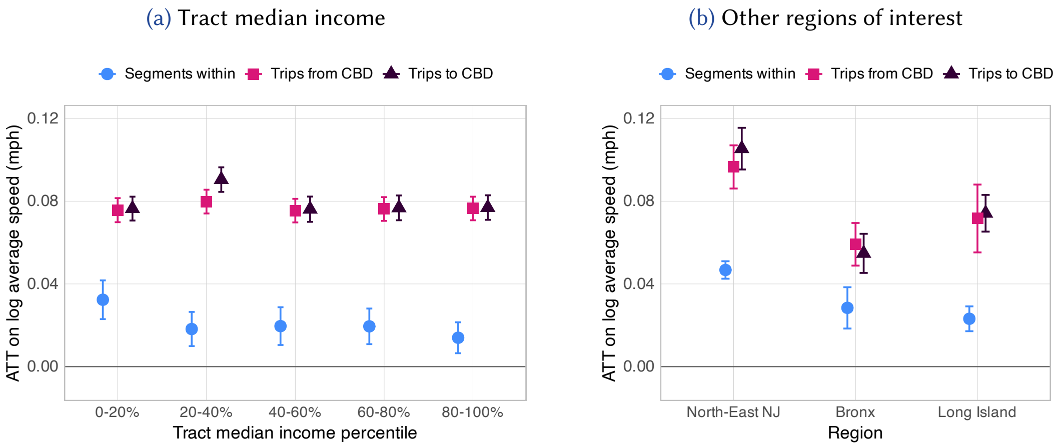
Trips to, from, within, and outside the CBD are all faster

- Divide origin and destinations (ODs) tracts by percentile of distance to CBD ‣ Map
- Estimate separate ATTs on log speeds (mph) for all trips between each OD-pair



Note: Each cell documents the ATT on log trip speeds for trips that originate in the bin indicated in the column labels and end in the bin indicated in the row labels. All results are significant at 5% level, with standard errors clustered by city.

Distributional effects: speeds increased for tracts of all incomes and areas



Note: Speeds are for the road segments within given geography. Trips are subset to those starting (ending) in the geography and going to (from) the CBD. Each point is the estimated ATT using the same five control cities. Vertical lines are 95% confidence intervals, with standard errors clustered by city.

What are the policy implications?

Policy implications

Has congestion pricing ‘worked’ in NYC?

- Revenue up, speeds up. Are drivers better off?

Would it have similar effects in other cities?

- Mechanisms: change in volumes + how volumes affect speeds across network

Evaluating impacts on driver welfare

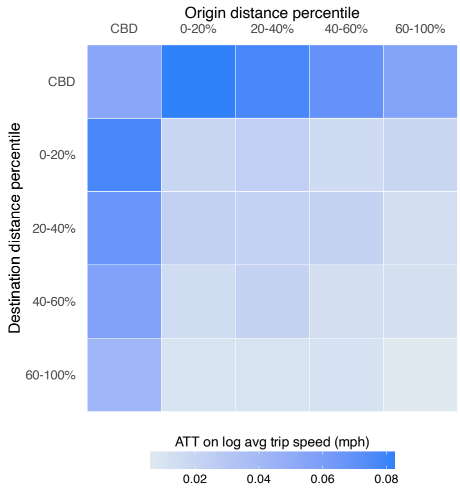
- Simple model: drivers value time driving (t) and price paid (p)
  - For each origin (o) and destination (d), we observe Δp_{od} and can use the ATTs to estimate Δt_{od}
  - Compute change in per-trip welfare as:

$$\Delta W_{od} = \Delta p_{od} + \omega \Delta t_{od}$$

- Challenges: do not observe changes in total volumes or the Value of Travel Time (ω)
  - Assume VOTT of \$40/hour (≈avg hourly wage)
  - Use data on estimated tract-to-tract flows in Q4 2024 from Replica
- In paper: using pre-period flows gives a *lower bound* for the welfare changes

▸ Details

Welfare gains come from *unpriced* trips



Note: Number of trips is the average tract-to-tract passenger car trips from Replica for 2025. Average price is approximated and is below \$9 because of crossing credits for some entries. The welfare estimates are computed for each cell separately and assume a Value of Travel Time (VOTT) of \$40/hour and no revenue recycling. All ATTs are significant at the 95% level with standard errors clustered by city.

▸ Map of bins ▸ Trip counts ▸ OD welfare ▸ Taxi welfare

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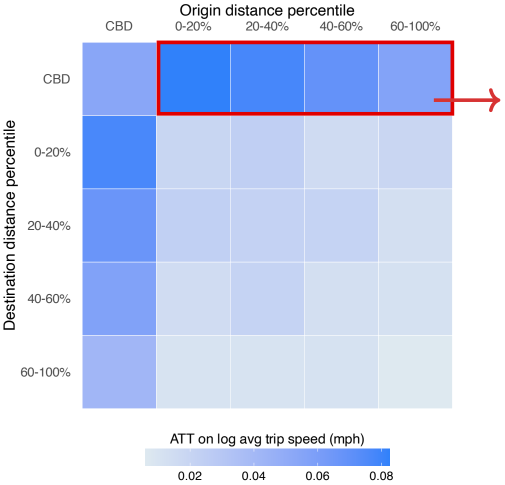

Weekly aggregates
(private autos only)

Priced trips

Number of trips:	1.61 million
Time savings:	83,020 hours
Average price:	$7.9
Driver welfare:	−$9.4 million

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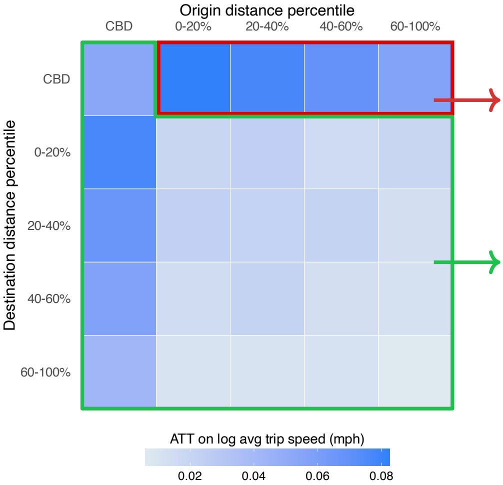

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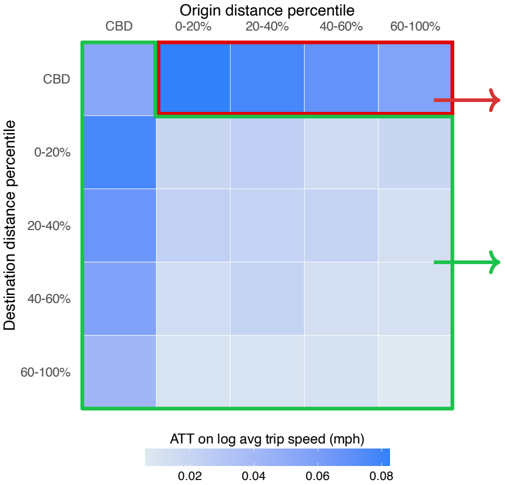

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'Break-even' VOTTs

Average trip to CBD:	\$153/hour
Overall driver welfare:	\$21/hour

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Small environmental benefits via improved fuel economy

Taking stock of per-week effects:

Passenger vehicle drivers	+$12 million
Taxi/FHV passengers	+$1.3 million
Approx revenue	+$14 million

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Environmental benefits?

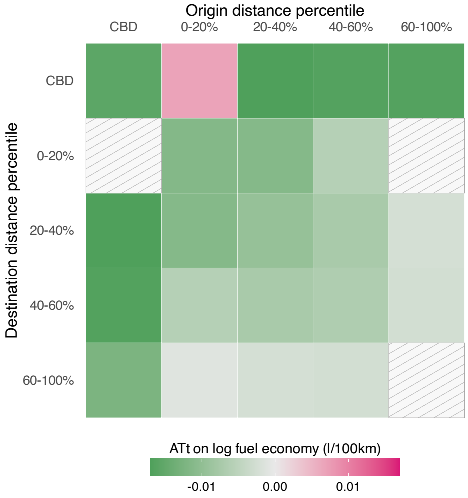
- Compute ATTs on estimated fuel consumption by origin-destination
- Implied savings of:

  74,700 gallons per week (0.28%)

  $\approx$ 653 tonnes of CO_2

  $\approx$ \$120,900 in social cost of CO_2

  (Rennert et al., 2022)



Note: This figure documents the ATT on log fuel economy (l/100km) for trips in each OD pair. Grey hash marks represent estimates that are not significantly different from zero at the 95% level, with standard errors clustered at the city-level.

How well would congesting pricing work in other cities?

Effects of cordon-based congestion pricing depend on:

1. How **prices** affect **volumes**

2. Exposure of other drivers to changes in CBD **volumes**

3. Relationship between **volumes** and **speeds** on different roads

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1. How **prices** affect **volumes**
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2. Exposure of other drivers to changes in CBD **volumes**
   - Closely related to co-occurrence measures
   - Compute average duration-weighted co-occurrence of segments traversed on trips to, from, and outside CBD
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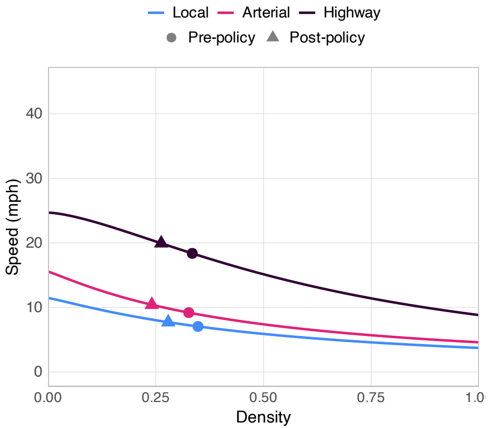
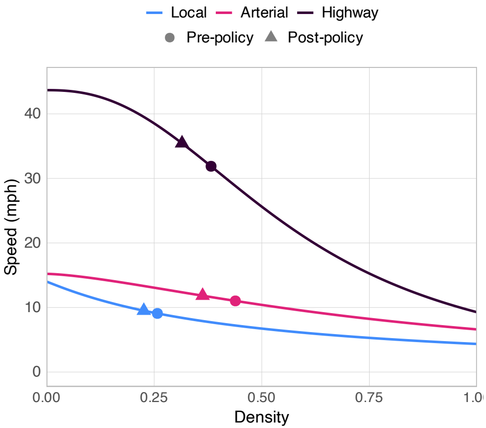
   - Compute average duration-weighted co-occurrence of segments traversed on trips to, from, and outside CBD
3. Relationship between **volumes** and **speeds** on different roads
   - Estimate 'congestion functions' of density $\mapsto$ speed for different roads
     - Vary by road type (e.g., smooth highway vs. bumpy local road)
   - Compute average local elasticity of congestion function for roads traversed

Example congestion functions

(a) CBD roads (NYC)



(b) 80-60% co-occurrence (NYC)



Note: This figure plots estimated congestion functions for roads in NYC. Circles are added to each line based on the raw average speed before the policy's implementation. Triangles are based on the post-period speed, which is computed as the pre-period speed plus the estimated ATT on speeds.

Potential for effects in other cities

City	Avg. exposure ($\bar{e}_l$) To CBD	From CBD	Outside CBD	Avg. elasticity of CF ($\bar{\eta}_l$). To CBD	From CBD	Outside CBD
NYC	57.6%	58.7%	3.0%			
Philadelphia	54.6%	54.9%	3.2%			
Chicago	62.2%	62.7%	7.1%			
Boston	55.4%	55.5%	7.6%			
Atlanta	51.1%	51.8%	7.4%			
Baltimore	49.6%	49.8%	5.3%			

Note: The first three columns document the average exposure to the policy for trips to, from, and outside the CBD, measured as the weighted average co-occurrence of segments traversed with weights corresponding to the average duration on each segment. The latter three columns document the average elasticity of the congestion functions (CF) of roads traversed on each trip type, again weighting by the average duration spent on a given segment type. In each case, we compute averages for each OD pair then aggregate to trip type using pre-period flows as weights.

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Potential for effects in other cities

City	Avg. exposure ($\bar{e}_l$) To CBD	From CBD	Outside CBD	Avg. elasticity of CF ($\bar{\eta}_l$). To CBD	From CBD	Outside CBD
NYC	57.6%	58.7%	3.0%	-0.422	-0.430	-0.270
Philadelphia	54.6%	54.9%	3.2%	-0.254	-0.250	-0.215
Chicago	62.2%	62.7%	7.1%	-0.325	-0.320	-0.170
Boston	55.4%	55.5%	7.6%	-0.387	-0.384	-0.205
Atlanta	51.1%	51.8%	7.4%	-0.336	-0.334	-0.239
Baltimore	49.6%	49.8%	5.3%	-0.255	-0.254	-0.214

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Conclusion

- Policy improved speeds in the CBD roads by 11% over first six months
  - Little-to-no effects on air quality, visits to shops/restaurants, and foot traffic
- Spillovers throughout the metro area
  - Higher co-occurrence with CBD trips $\Longrightarrow$ larger speed increases
  - Welfare gains come from the *unpriced* trips
    - The "losses" are concentrated on CBD-bound trips, the "gains" are diffuse
- Mechanisms: volume response + exposure + congestion functions
  - NYC outside the CBD: low average exposure but steep congestion functions
  - Boston more promising than Philadelphia or Baltimore
- Stay tuned for updated results!

Thank you!

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Related literature

- **Empirical evaluations of congestion pricing programs**

  Existing cordon-based programs in London (2003), Stockholm (2007), and Milan (2008): Leape (2006); Eliasson et al. (2009); Gibson and Carnovale (2015); Green, Heywood and Paniagua (2020); Simeonova et al. (2021); Hierons (2024)

  Other existing/potential policies: Hall (2018); Bento, Roth and Waxman (2020); Kreindler (2024); Cook and Li (2024); Almagro et al. (2024); Barwick et al. (2024); Durrmeyer and Martínez (2024); Ater et al. (2025)

  $\rightsquigarrow$ Causal estimates of effects in NYC on fine-grained outcomes

- **First- and second-best congestion pricing, in theory**

  Vickrey (1963, 1969); Verhoef, Nijkamp and Rietveld (1996); De Palma and Lindsey (2000); Verhoef (2002); Small, Verhoef and Lindsey (2007)

  $\rightsquigarrow$ Spillovers *increase* speeds throughout city

- **Evaluating place-based policies**

  E.g., Glaeser and Gottlieb (2008); Busso, Gregory and Kline (2013); Kline and Moretti (2014); Neumark and Simpson (2015)

  $\rightsquigarrow$ Accounting for diffuse effects outside focal region can flip sign on driver welfare

Back

Pollution data from PurpleAir

We use day-sensor level measures of PM2.5 from PurpleAir. There are 22 outdoor sensors in the NYC CBD. There are few sensors in our control city CBDs, so we use data from 800 sensors throughout the control metro areas when computing ATTs.

We follow EPA's recommended calibration method for PurpleAir data (Barkjohn et al., 2022) to clean the data:

1. Drop records where difference between A and B channels is over $5\mu g/m^3$ or relative difference is over 70%
2. Calibrate adjusted PM2.5 measures using EPA's formula and the relative humidity measurement
3. Aggregate to the day level, dropping any that have fewer than 18 hours of observations
4. Impute missing sensor-date PM2.5 values using a regression with interacted sensor, month, and day of week fixed effects.

Back

Transactions data from MBHS3 (Jan 2024-April 2025)

The data are at the day-zipcode level. Category is defined using 3-digit NAICS. We weight ATTs by the outcome total (transactions or spend) in the pre-period

		All			CBD-only		
City	Category	Count (millions)	Amount (millions $)	Avg. size ($/trans.)	Count (millions)	Amount (millions $)	Avg. size ($/trans.)
NYC	Restaurant	164.7	4613.2	28.0	26.1	941.7	36.0
	Retail	286.1	13247.0	46.3	39.6	2196.0	55.4
PHL	Restaurant	88.5	2291.9	25.9	3.9	125.3	32.1
	Retail	168.6	7549.0	44.8	3.2	115.0	35.5
CHI	Restaurant	114.2	2773.8	24.3	5.8	172.5	29.7
	Retail	148.2	7425.8	50.1	3.7	137.5	37.3
BOS	Restaurant	59.2	1433.1	24.2	0.8	25.6	32.4
	Retail	68.4	3390.8	49.6	0.2	15.9	79.2
BAL	Restaurant	61.7	1066.6	17.3	–	–	–
	Retail	58.4	2644.8	45.3	–	–	–
ATL	Restaurant	141.7	3368.8	23.8	3.6	90.3	25.2
	Retail	190.0	8995.0	47.3	1.2	43.2	37.2
Total	Restaurant	629.9	15547.4	24.7	40.2	1355.6	33.7
	Retail	919.7	43252.4	47.0	47.9	2507.5	52.3

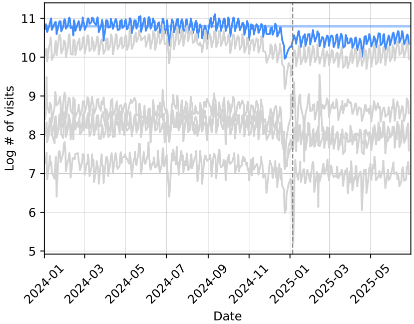
Note: This table documents the aggregate number of transactions and total spending in the MBHS3 data for zipcodes within each of the sample cities. The Baltimore CBD is small and there are no zipcodes whose centroids lie within it.

Back

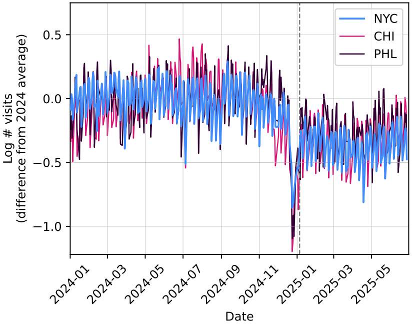
Foot traffic data from Advan Neighborhood Patterns (Jan 2024-June 2025)

We use data at the day-tract level, aggregating foot traffic across all peak hours that day. We weight the ATTs by the number of pre-period stops in a tract

(a) Log average stops per day



(b) Log stops relative to 2024 average



Note: These figures plot daily CBD foot traffic, restricted to weekday peak hours (5am to 9pm). The first panel plots the log total number of visits. The blue horizontal line is the pre-period average for the NYC CBD. The second panel restricts attention to the three largest cities and plots the difference in log trips between a given date and the 2024 average.

Back

Methodology: Generalized Synthetic Controls

- **Challenge:** NYC traffic evolves with many confounders $\Rightarrow$ simple before/after comparisons not causal
- **Approach:** Generalized Synthetic Controls (GSC) (Xu, 2017)
  - Compare NYC to a weighted combination of control cities, fit on pre-policy outcomes.
  - For unit i in time t, model (untreated) outcome as:

$$Y_{it}(0) = \alpha_i + \gamma_t + \boldsymbol{\lambda}_i^\top \mathbf{f}_t + \epsilon_{it}$$

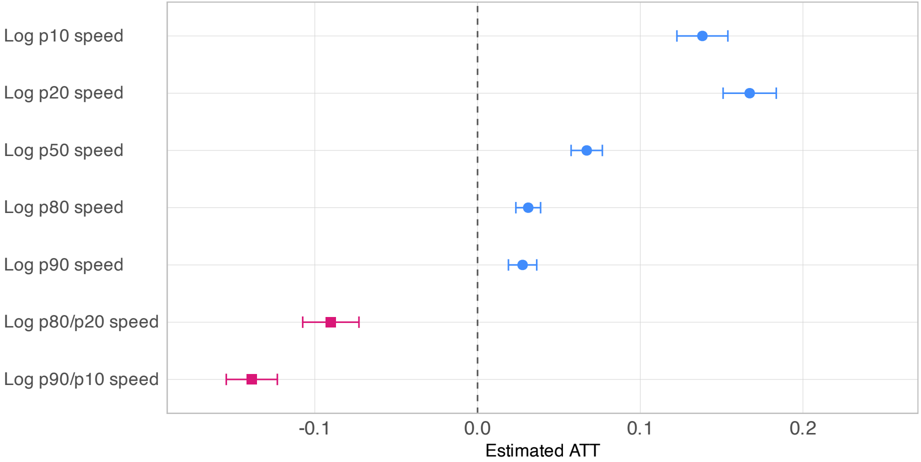
- **Estimation:**
  - Loadings/factors estimated pre-policy; predict counterfactual $\hat{Y}_{it}(0)$ post-policy.
  - Treatment effect:

$$\widehat{\mathrm{ATT}}_t = \frac{1}{|\mathcal{I}^{treated}|} \sum_{i \in \mathcal{I}^{treated}} \left(Y_{it}(1) - \hat{Y}_{it}(0) \right)$$

- Key assumptions: stable factors/loadings and no spillovers to controls

Back

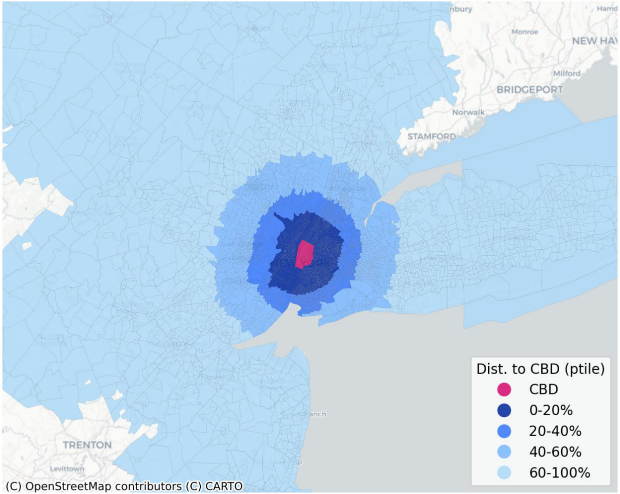
Distribution of speeds compressed → more reliable traffic



Note: Each ATT is separately estimated using traffic conditions from the other CBDs during the same time of day as synthetic controls. The underlying data are an hourly panel of traffic conditions in the CBD. Horizontal lines represent 95% confidence intervals, with standard errors clustered by city.

◂ Back

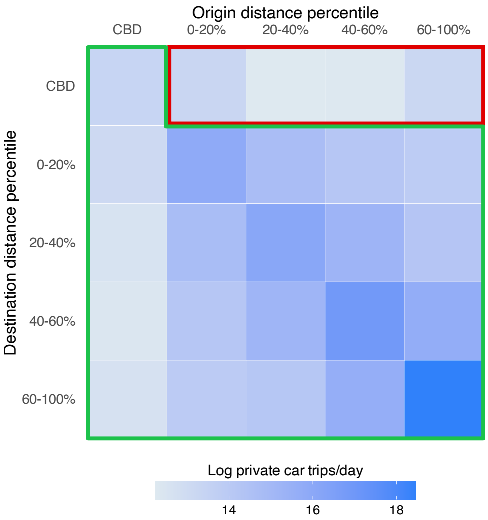
Distance from CBD for NYC metro area



Note: The boundaries are based on the Core Based Statistical Area boundaries. The map is zoomed in slightly to make the CBD more visible; the CBSA extends further in each direction, especially east down Long Island. Distance to CBD is based on the distance between centroid and the closest point of the CBD.

◂ Back ◂ Back

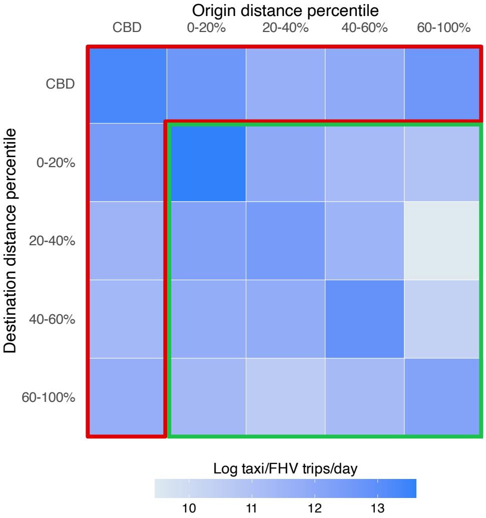
Private auto trips by origin/destination



Note: We compute trips between each OD using a combination of data from Replica and MTA. Replica estimates are used for all trips that do not end in the CBD. For trips to the CBD, we scale the Replica estimates to match the total number of personal auto entries from the MTA. All data are for Jan-June 2025.

Back

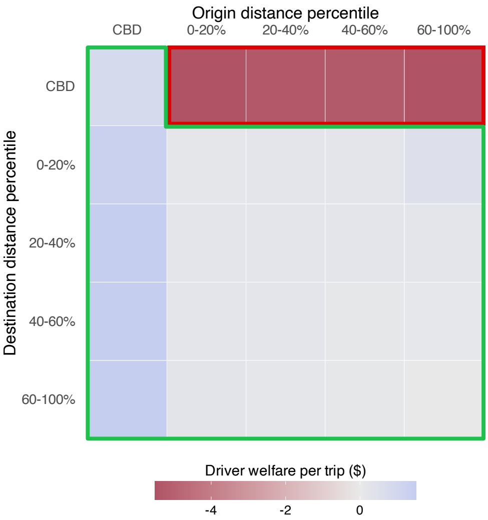
Taxi/FHV trips by origin/destination



Note: We compute trips between each OD using a combination of data from Replica and MTA. Replica estimates are used for all trips that do not end in the CBD. For trips to the CBD, we scale the Replica estimates to match the total number of taxi/FHV from the MTA. All data are for Jan-June 2025.

Back

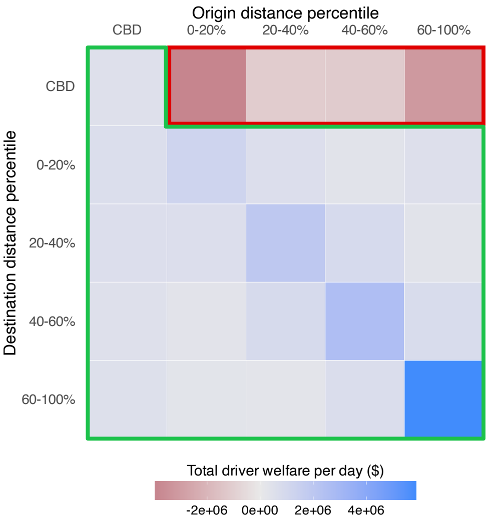
Driver welfare per trip by OD



Note: Grey hashes indicate results that are not statistically different from zero, which are not used for the aggregate effects. The welfare estimates are computed for each cell separately and assume a Value of Travel Time (VOTT) of $40/hour and no revenue recycling.

◂ Back

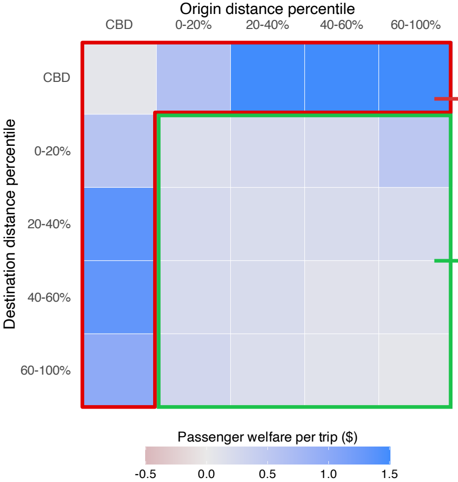
Total driver welfare by OD



Note: Grey hashes indicate results that are not statistically different from zero, which are not used for the aggregate effects. The welfare estimates are computed for each cell separately and assume a Value of Travel Time (VOTT) of $40/hour and no revenue recycling.

◂ Back

Taxi passenger welfare per trip by OD



Weekly aggregates
(taxi passengers only)

Priced trips

Number of trips:	2.09 million
Time savings:	84,440 hours
Average price:	$1
Approx driver welfare:	$1.7 million

Unpriced trips

Number of trips:	2.75 million
Time savings:	12,560 hours
Approx driver welfare:	$0.5 million

'Break-even' VOTTs

Average priced taxi trip:	$19/hour
Overall taxi passenger welfare:	$17/hour

Note: Grey hashes indicate results that are not different from zero at 5% level; these are excluded for aggregate time savings and welfare. Number of trips is the average tract-to-tract passenger car trips from Replica for 2025. Average price is approximated based on $0.75 for taxis and $1.5 for ridesharing. The welfare estimates are computed for each cell separately and assume a Value of Travel Time (VOTT) of $40/hour and no revenue recycling or taxi price changes.

Back

Evaluating impacts on driver welfare

- Drivers value time driving and price paid (the toll)
  - For a trip between origin (o) and destination (d), suppose utility is:

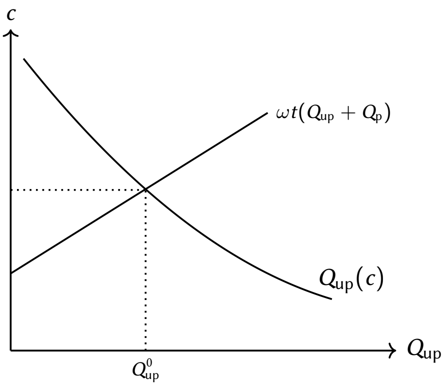
$$u_{od} = \overbrace{\xi_{od}}^{\substack{\text{Baseline}\\ \text{value}}} - \overbrace{p_{od}}^{\text{Price}} - \overbrace{\omega}^{\text{VOTT}} \times \overbrace{t_{od}}^{\text{Travel time}} \tag{1}$$

    where VOTT is the Value of Travel Time (\$/hr).
  - Drivers take trip if u_{od} above outside option $\varepsilon_{i,od}$
- We observe Δp_{od} and can use the ATTs to estimate Δt_{od}, but do not observe volumes or VOTT (ω)
  - Assume VOTT of \$40/hour (≈avg wage)
  - Use data on estimated tract-to-tract flows in Q4 2024 from Replica
- Derive lower bounds for the welfare changes using pre-period flows ▸ Details
  - Similar to 'social savings' in Fogel (1964). No GE effects (Allen and Arkolakis, 2022)

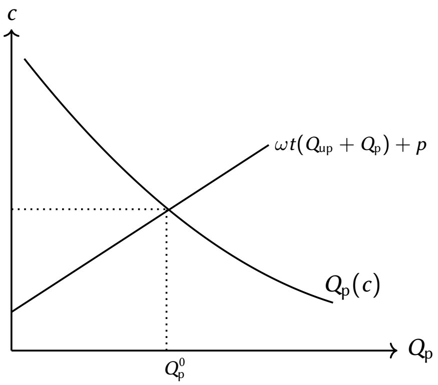
◂ Back

Evaluating impacts on driver welfare

(a) Unpriced trips (Q_{up})



(b) Priced trips (Q_{p})



◂ Back

Evaluating impacts on driver welfare

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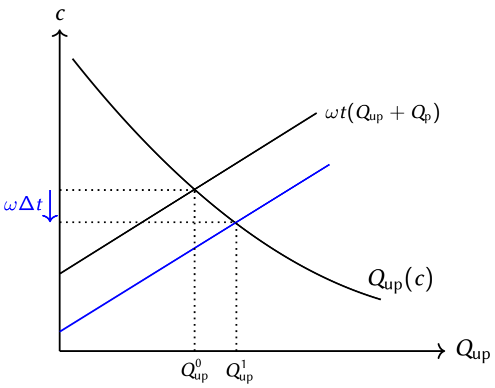
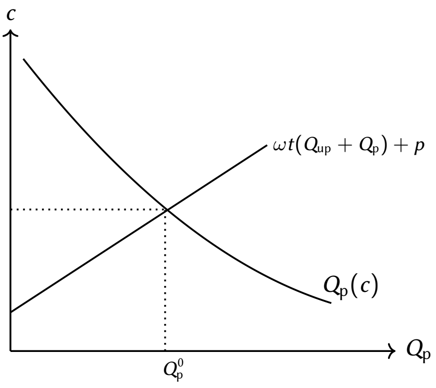


(b) Priced trips (Q_{p})



Back

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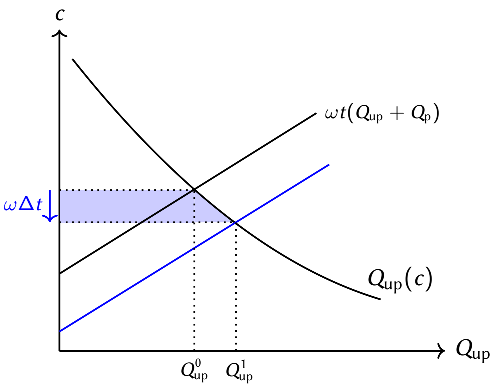
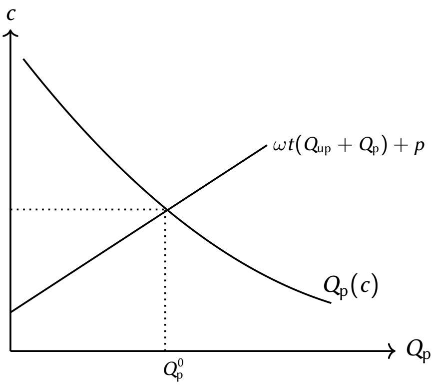


(b) Priced trips (Q_{p})



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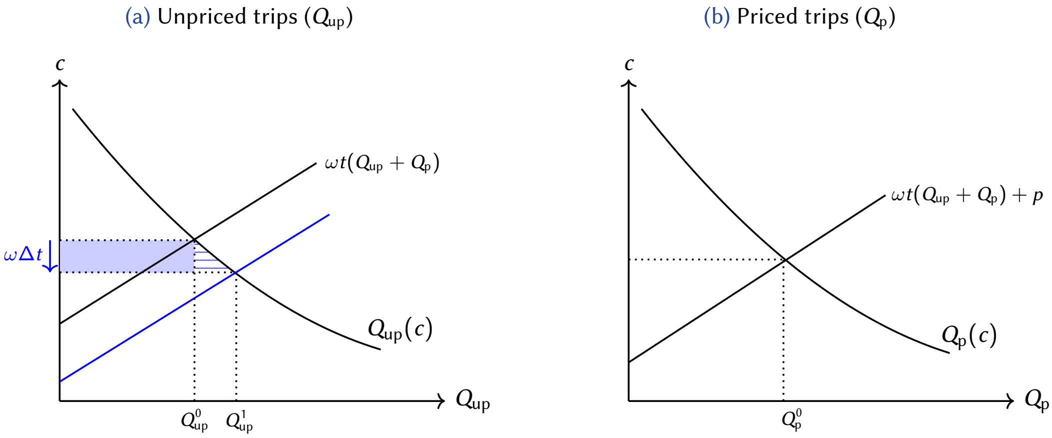
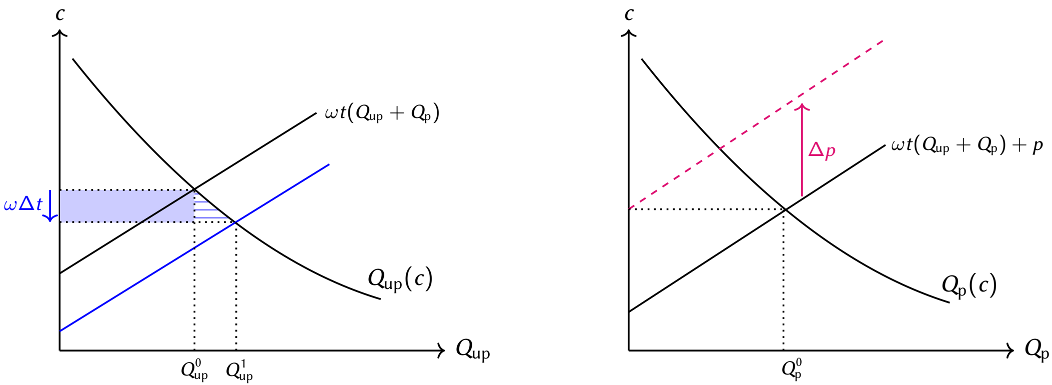
Evaluating impacts on driver welfare



Back

Evaluating impacts on driver welfare

(a) Unpriced trips (Q_{up}) (b) Priced trips (Q_{p})



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Evaluating impacts on driver welfare

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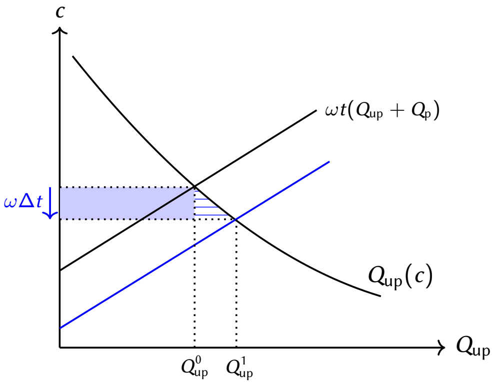
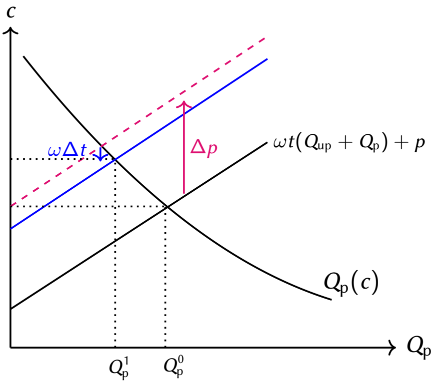


(b) Priced trips (Q_{p})



Back

Evaluating impacts on driver welfare

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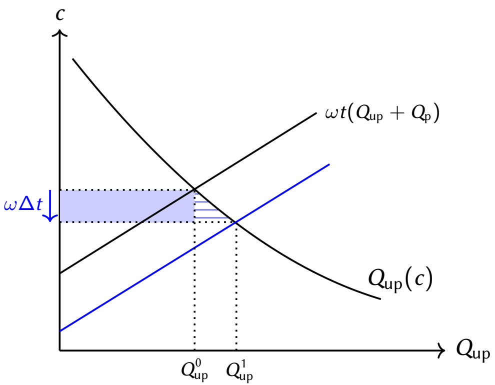
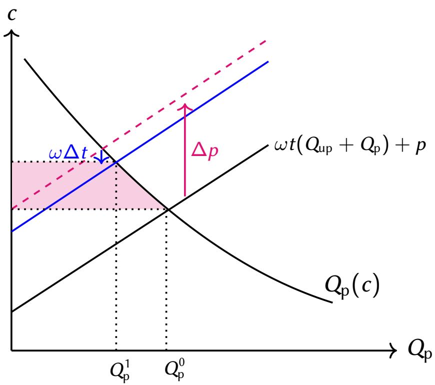


(b) Priced trips (Q_{p})



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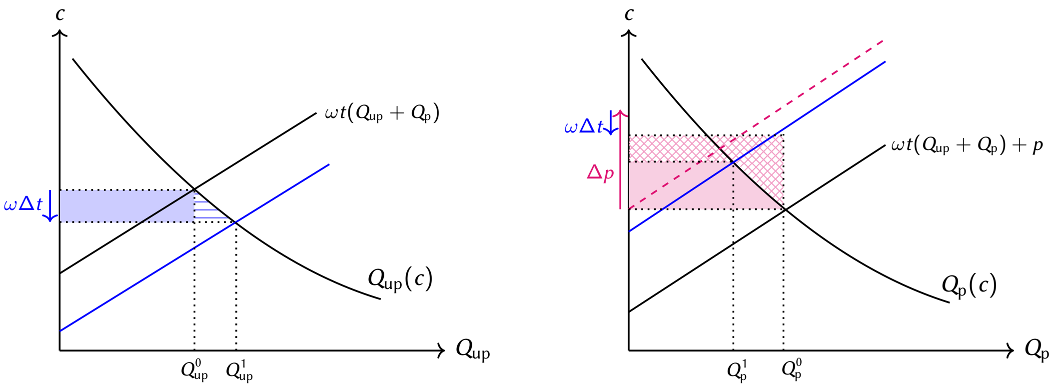
(b) Priced trips (Q_{p})



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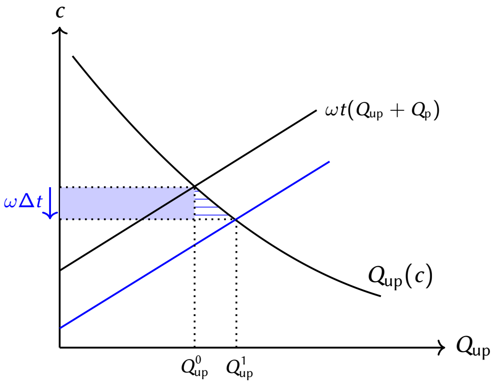
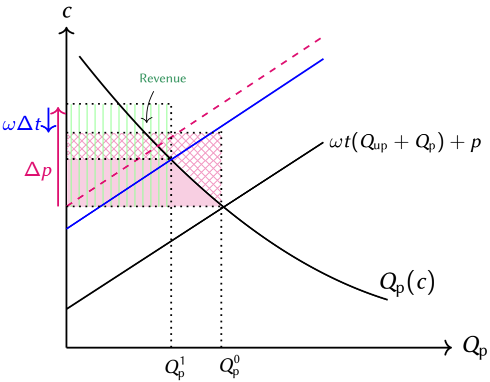


(b) Priced trips (Q_{p})



◂ Back

Average local pre-period elasticity of congestion functions

How *locally elastic* are the roads along different types of trips?

- For a given set of trips, compute *average elasticity* using our estimated congestion functions:

$$\bar{\eta}_{od} = \frac{\sum_c \sum_r \bar{t}^{cr}_{od} \left(v'_{cr}(\rho_{cr}) \frac{\rho_{cr}}{v_{cr}(\rho_{cr})} \right)}{\sum_c \sum_r \bar{t}^{cr}_{od}} \tag{2}$$

  where $v_{cr}(\cdot)$ is the estimated congestion function for co-occurrence c and road type r, ρ_{cr} is the pre-period average density, and $\bar{t}^{cr}_{od}$ is the avg duration that *od* trips spend on *cr* roads.

- Aggregate further to trips to, from, and outside CBD using pre-period flows as weights

◂ Back