Can Usage-Based Pricing Reduce Congestion?

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Motivation: traffic congestion is very costly

Traffic jams cost US $87 billion in lost productivity in 2018, and Boston and DC have the nation's worst

PUBLISHED TUE, FEB 12 2019•12:01 AM EST | UPDATED TUE, FEB 12 2019•12:39 PM EST

Phil LeBeau
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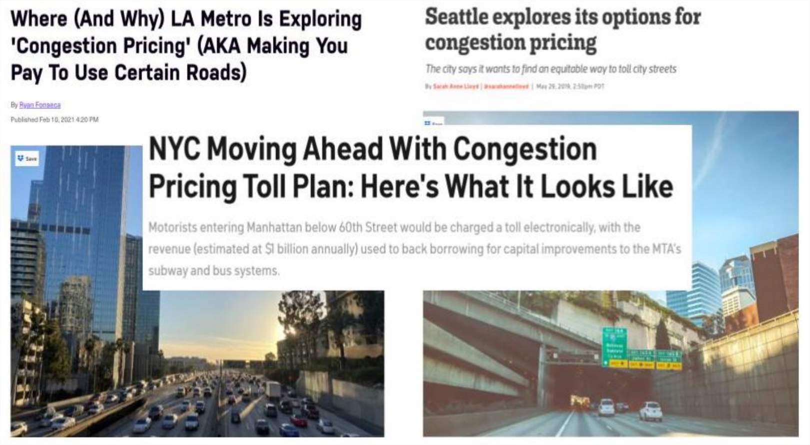
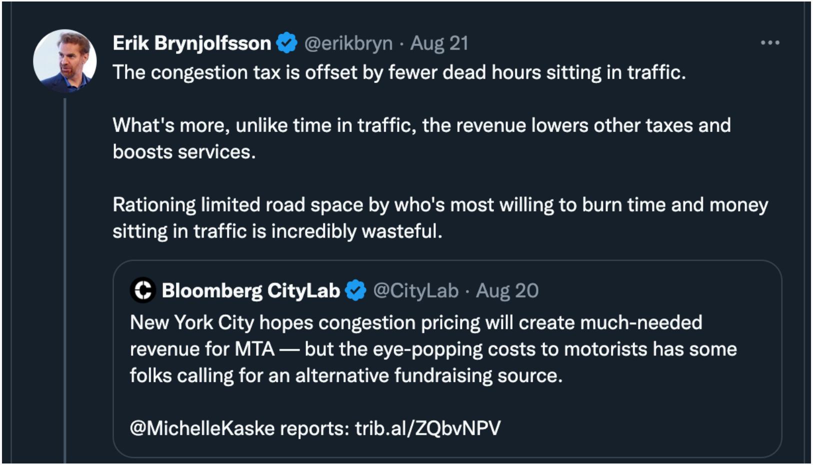
Motivation: Gov'ts are adopting congestion pricing policies



Motivation: Congestion pricing seems like a good idea


Erik Brynjolfsson @erikbryn · Aug 21

The congestion tax is offset by fewer dead hours sitting in traffic.

What's more, unlike time in traffic, the revenue lowers other taxes and boosts services.

Rationing limited road space by who's most willing to burn time and money sitting in traffic is incredibly wasteful.

Bloomberg CityLab @CityLab · Aug 20

New York City hopes congestion pricing will create much-needed revenue for MTA — but the eye-popping costs to motorists has some folks calling for an alternative fundraising source.

@MichelleKaske reports: trib.al/ZQbvNPV

Motivation: But it raises distributional concerns

Alex Imas
@alexoimas

Replying to @erikbryn

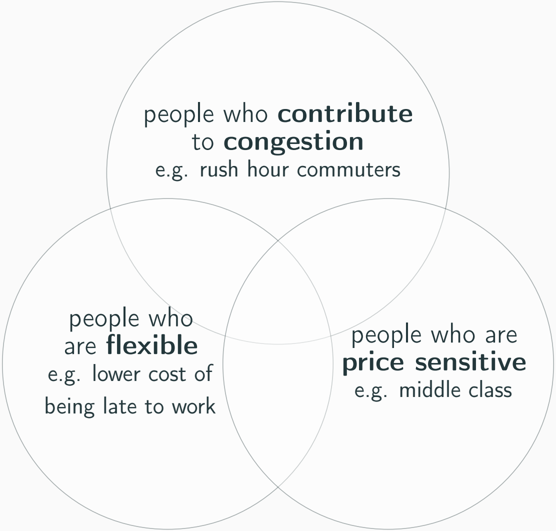
I'm sorry if I'm missing something, but isn't this tax pretty regressive? Low income people who have been priced out of city will have to choose to pay this high tax or "time tax" of stringing together commute on increasingly unreliable MTA. Should at least be means tested, no?

Motivation: Does congestion pricing even work?

- Zone-based prices may backfire
  - ⇒ Travel time in London nearly back to pre-charging levels (TfL)
  - ⇒ Fixed entry fees would encourage idling in NYC (Rosaia, 2020)
- Price elasticities might be too small to shift behavior
  - ⇒ Experimental evidence from Bangalore (Kreindler, 2022)
  - ⇒ Experimental evidence from Australia (Martin and Thornton, 2017)
- Distributional effects may bind
  - Willingness to pay is neither flat nor proportional to income (Bento, Roth & Waxman (2020))
  - Pigouvian tolling would hurt low-income drivers (Hall 2020)

Can Congestion Prices Target the Right People?

▸ Model



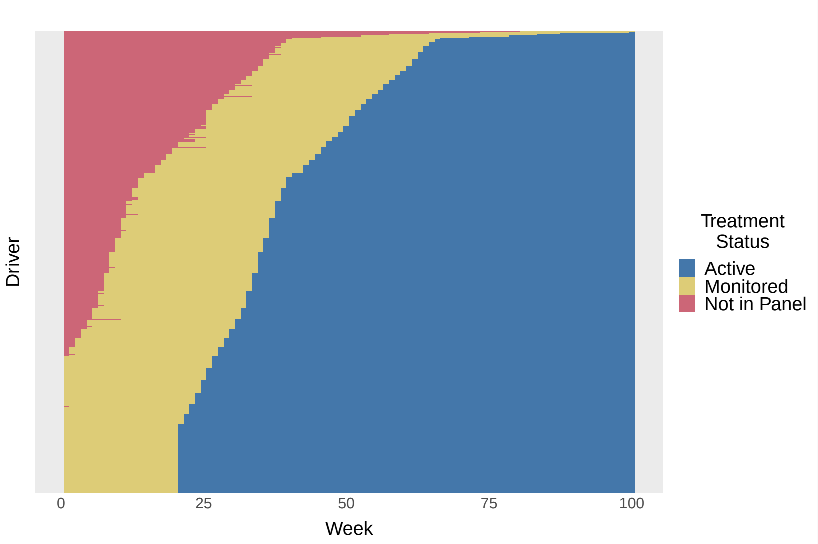
The “Value Road" Pilot

The “Value Road" Pilot

Experimental Design: "Value Road"

- Nationwide pilot run by the Highway Administration
  - ⇒ We are their economics analysis team
- 10k participants recruited across Israel b/w Jan 2020 and June 2021
- Each participant gets a GPS device installed in their car
  - ⇒ "Monitoring" for 6 months w/ no communication
  - ⇒ "Active" for the next 12 months+
    - Invited to download an app w/ usage info
    - Initial budget 4500 NIS (~ $1,300)
    - Subtract per-km fee based on location + time
    - Budget remainder paid out at license-renewal date

Did Prices Change Behavior? Experimental Design



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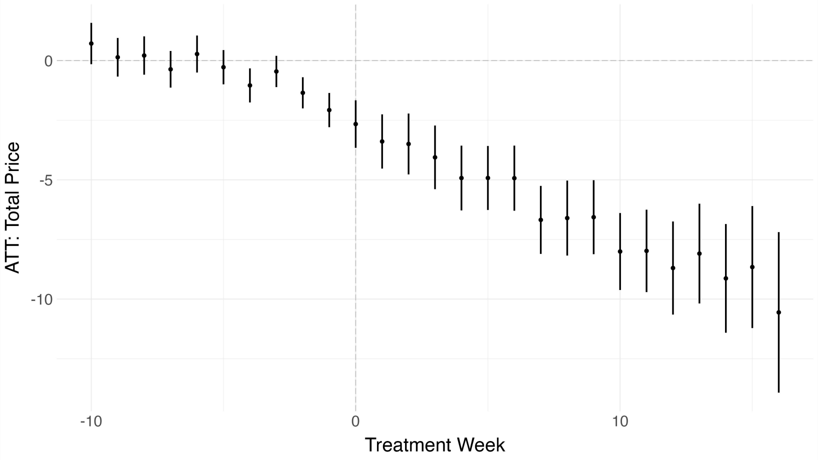
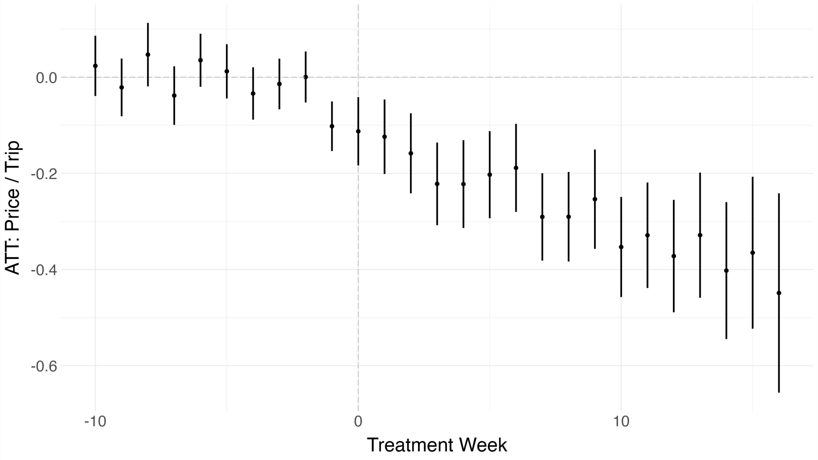
    - Initial budget 4500 NIS (~ $1,300)
    - Subtract per-km fee based on location + time ▸ prices ▸ map
    - Budget remainder paid out at license-renewal date ▸ payment distribution

Did Prices Decrease Congested Driving? ATT on Total Price



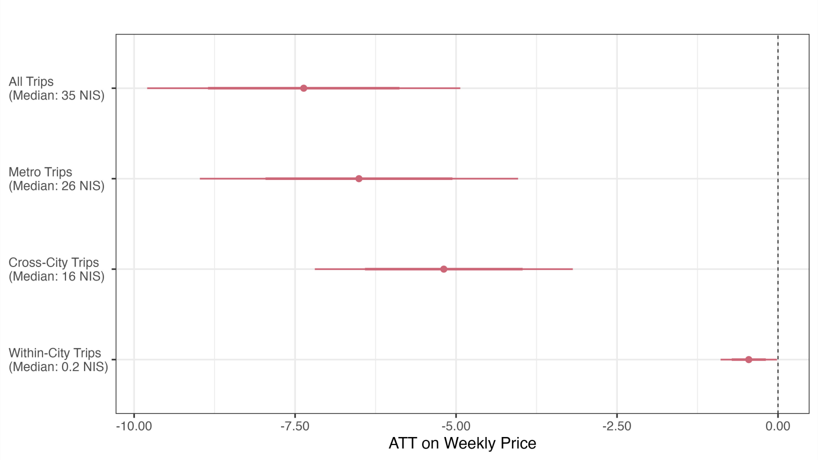
▸ Estimation Details

Did Prices Affect the Intensive Margin? ATT on Price / Trip



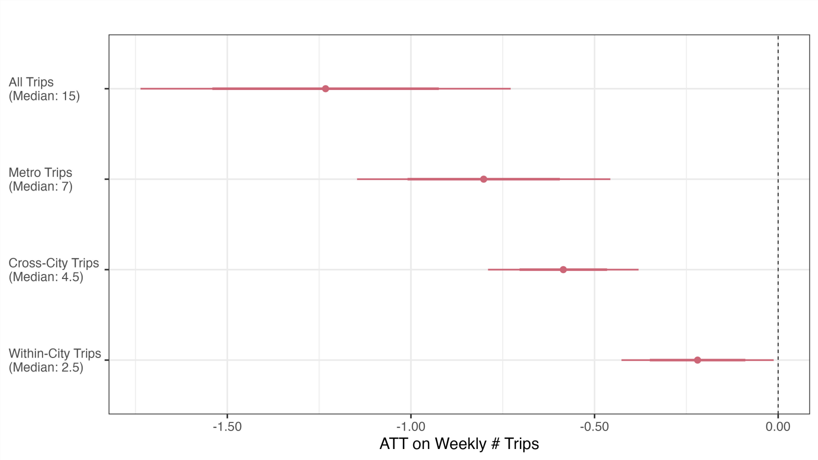
▸ Estimation Details

Would This Affect Traffic? ATT on Total Price Across Trips



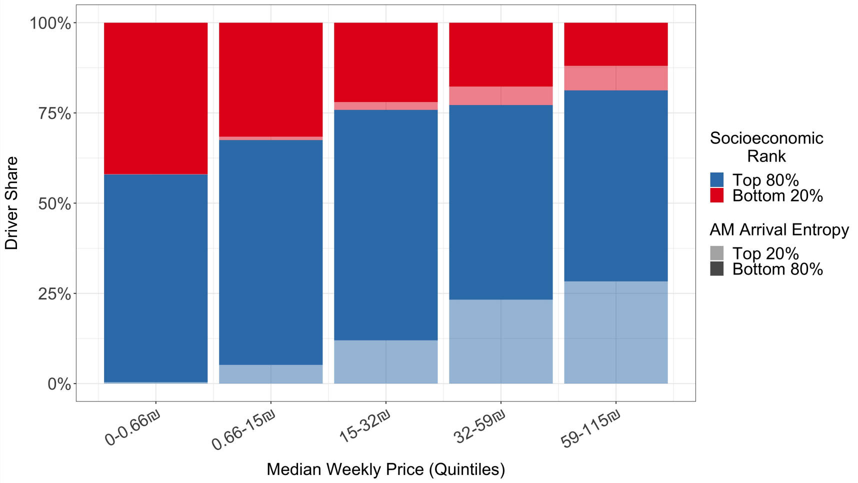
▸ SD Units ▸ Price per Trip ▸ Price per Km

Would This Affect Traffic? ATT on the # of Trips



Who is Affected and How?

Pre-treatment Correlations among "Value Road" Drivers

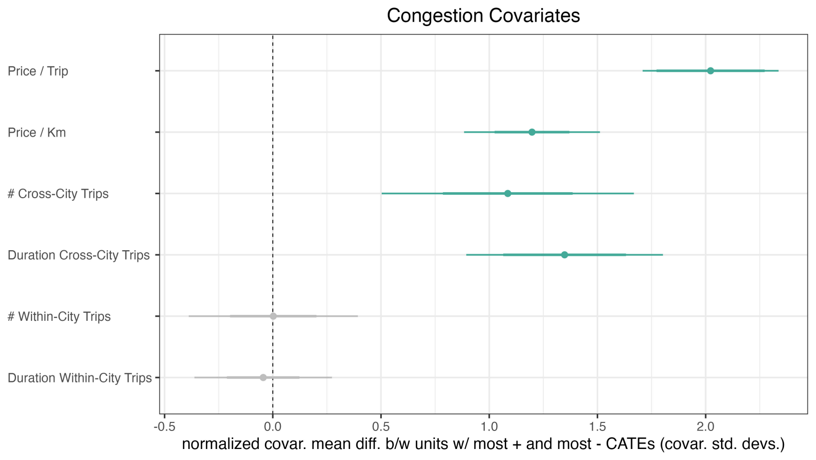


Who Changed their Behavior? Estimation Strategy

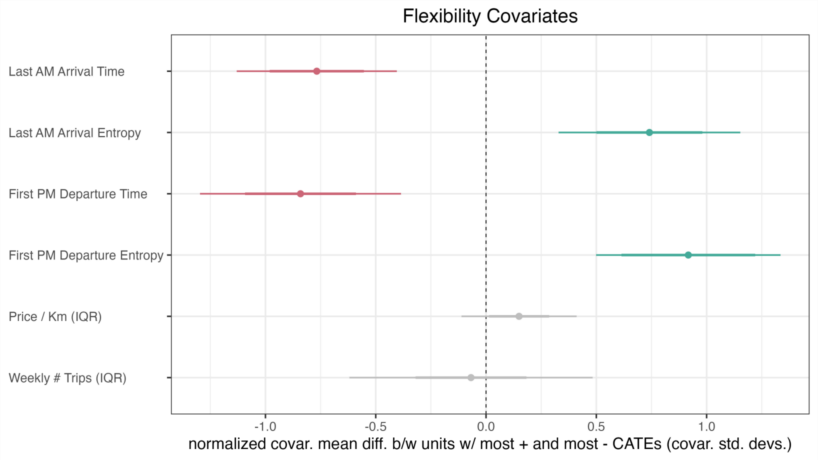
"Sorted Effects Method" (Chernozhukov, Fernández-Val, and Luo, 2018)

1. Impute individual ATTs from control outcome model
2. Project individual ATTs onto driver characteristics
3. Rank predicted individual treatment effects by effect size
4. Compare the average of each characteristic among the top and bottom 20% of the TE distribution
5. Construct confidence intervals corrected for *FWER* per plot via Bayesian Bootstrap
   - $\Rightarrow$ reject zeros using step-down procedure in Romano and Wolf, 2005

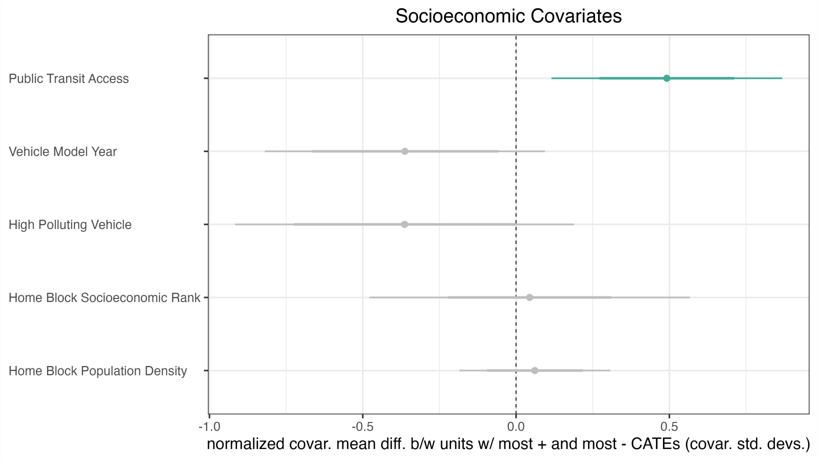
Treatment Effect Heterogeneity: Total Weekly Price



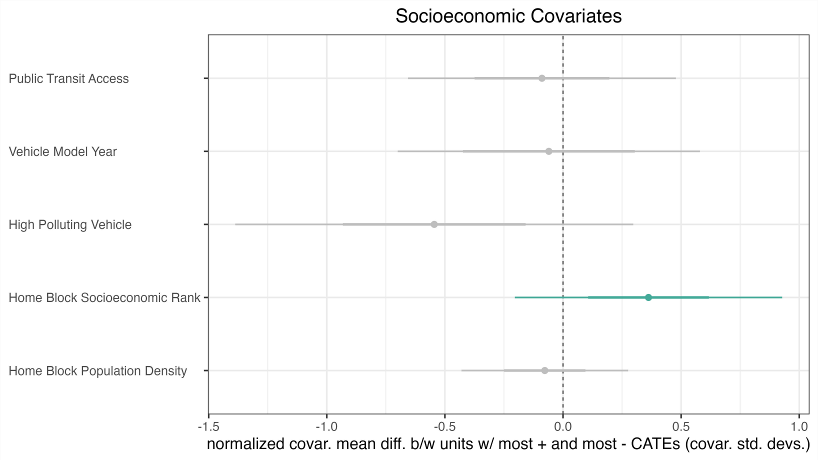
Treatment Effect Heterogeneity: Total Weekly Price



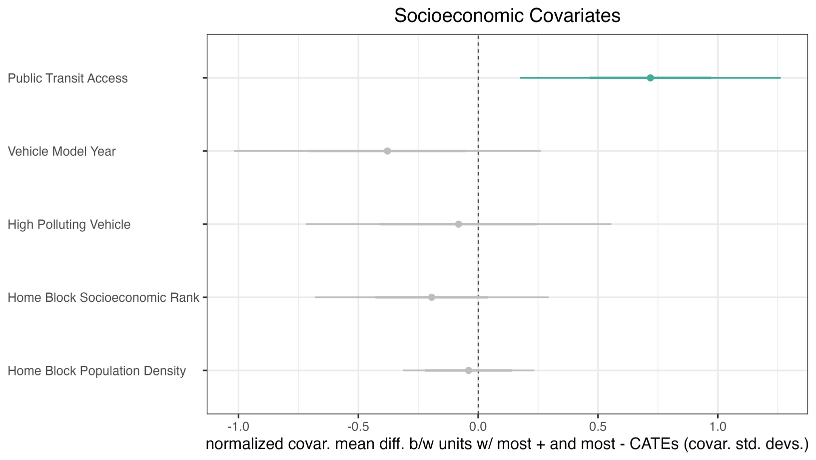
Treatment Effect Heterogeneity: Total Weekly Price



Where is this coming from? TE heterogeneity for # of Trips



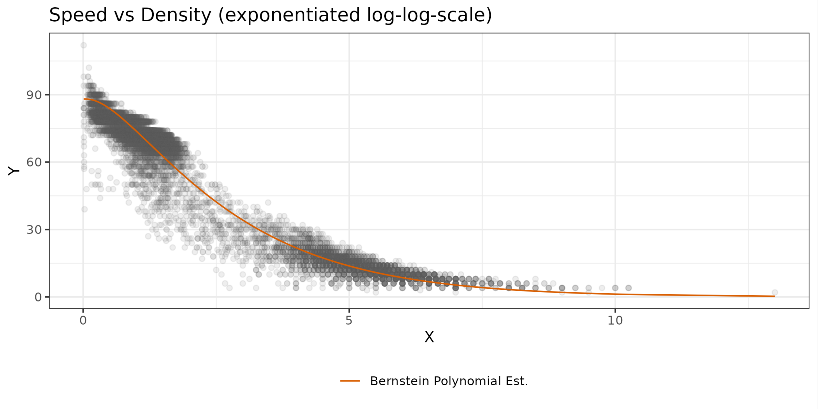
Where is this coming from? TE heterogeneity for Price/Trip



What might this mean for congestion?

Perspective from Ayalon NB to Tel Aviv

▸ Sensor Location



Fitting Speed vs. Density Relationships

- Why is this challenging?
  - Speed and density are simultaneously determined
    - Density $\downarrow \Rightarrow$ speed $\uparrow$, but...
    - Speed $\uparrow \Rightarrow$ density $\uparrow$
  - Staying on the highway is endogenous
- How do we deal with this?
  - Non-parametric IV (NPIV) regression:
    - Classic NPIV model (Newey and Powell, 2003):

      $Y(x) = U \cdot h(x)$ for arbitrary h, but $X \not\perp U$, only $U \perp Z$
    - Estimate $h(x)$ w/ flexible, monotonic approx. in 1st + 2nd stage (Chetverikov and Wilhelm, 2017)
  - IVs: distances^{-1} in speed and time of accidents from sensors (controlling for expected accident prevalence by time-of-day)

    ▸ Sensor Location

What do our ATTs imply for highway speeds?

- **Today:**
  - Take ATT estimates for highway trips in our sample
  - Re-weight ATTs by how nationally-representative each driver is
  - Assume ATTs apply nationally, under ceteris-paribus
  - Impute predicted change in speed under change in trips

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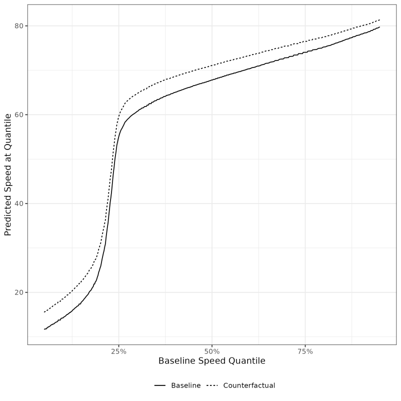
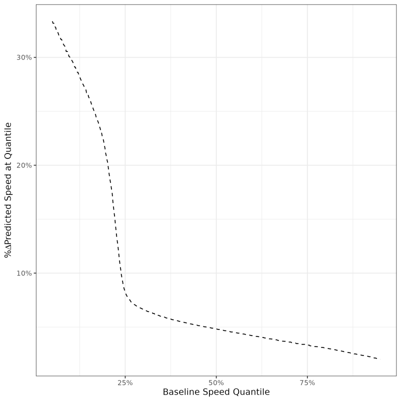
  - Impute predicted change in speed under change in trips
- **In the works:**
  - Estimate demand for travel choice, given price and travel time
  - Predict equilibrium load + speed on each segment of highway
  - Next: Expand from the highway to the whole road network

What do our ATTs imply for highway speeds under ceteris paribus?





Summing Up

- Evidence that usage-based pricing may induce $\downarrow$ in congested driving
- Most affected people tend to be:
  - Heavy commuters
  - More flexible
  - With better public transit options
- Ceteris Paribus Extrapolation Exercise on the Ayalon highway
  - Speed-Density relationship highly nonlinear at the tails
  - $\Rightarrow$ The most congested driving is at the tails
  - $\Rightarrow$ Potentially big gains possible
  - ⚠ This is not taking into account equilibrium effects!
- More to come...

Thank You

Appendix

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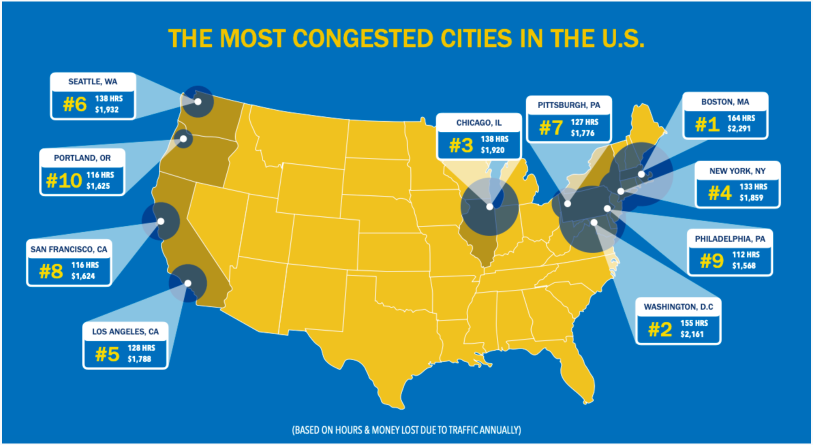
Motivation: traffic congestion is very costly in very many places



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Conceptual Framework: The Vickery Model

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Consider a driver who...

- observes trip characteristics X_d
  - $\Rightarrow$ e.g. the weather, average driving conditions
- decides *whether* to take her trip by car (vs. an outside option)
- decides *what time* t_s to start her trip

Conceptual Framework: The Vickrey Model

Back

$$v(t_s; X_d) = \alpha \cdot \mathbb{E}[\rho(t_s; X_d)] + w_h \cdot t_s + w_\ell \cdot (t_a^* - \mathbb{E}[\tau(t_s; X_d)])$$

where...

- $\mathbb{E}[\rho(t_s; X_d)]$: Expected trip price conditional on starting at t_s
- $\mathbb{E}[\tau(t_s; X_d)]$: Expected time of arrival conditional on starting at t_s
- t_a^* : The driver's ideal time of arrival at her destination
- w_h : Linear value of an additional minute at home
- w_ℓ : Linear value of not being late by an additional minute

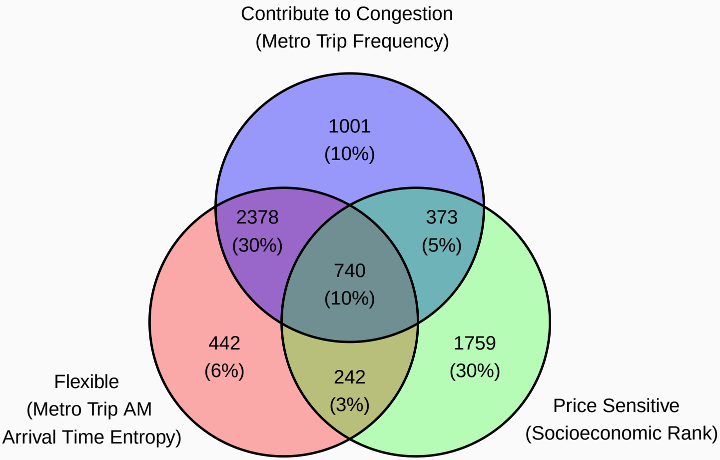
Conceptual Framework: Zooming out from Vickrey

Back

$$v(t_s; X_d) = \alpha \cdot \mathbb{E}[\rho(t_s; X_d)] + w_h \cdot t_s + w_\ell \cdot (t_a^* - \mathbb{E}[\tau(t_s; X_d)])$$

- ‘Congestion" Parameters:
  - $\mathbb{E}[\rho(t_s; X_d)]$: Expected trip price
  - $\mathbb{E}[\tau(t_s; X_d)]$: Expected time of arrival
- “Flexibility" Parameters:
  - w_h : Linear value of an additional minute at home
  - w_ℓ : Linear value of not being late by an additional minute
- “Price sensitivity" Parameters:
  - α : Price coefficient
  - (Not modeled): Budget constraints, income effects, etc.

Mapping the Venn-Diagram to “Value Road": 50-50 Splits



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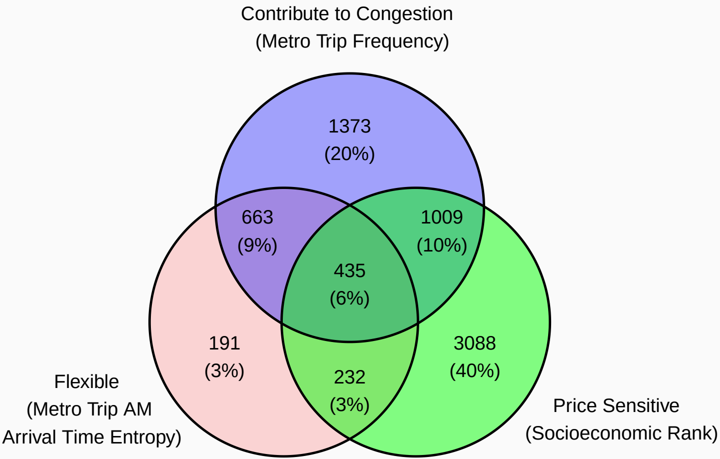
Mapping the Venn-Diagram to “Value Road": 80-20 Splits



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Israeli Driving Statistics

לוח 2- מרחקי נסיעה ממוצעים של נסיעות שנוטרו ב 2007 וב 2018-19 לפי תקופת השבוע
ק"מ

	2007	2018-19	שיעור הגידול
ימי א'-ה	17.6	21.1	20.0%
ימי ו' וערבי חג	16.6	20.5	23.5%
ימי שבת וחג	19.4	23.2	19.6%
ממוצע שבועי	**17.7**	**21.3**	**20.3%**
אורך חציוני (בשבוע)	10.3	12.0	16.5%

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Benchmarking Exercise: US Driving

The average US driver...

- Takes 2.5 trips per day (**12.5 trips** per work week)
- Drives 30 miles per day ($\sim$ **240 km** per work week)
- Spends 1 hour driving per day (**5 hours** per work week)
  - **26 minutes** per 1-way commute nationwide
  - **32 minutes** per 1-way commute in Boston
  - **35 minutes** per 1-way commute in DC

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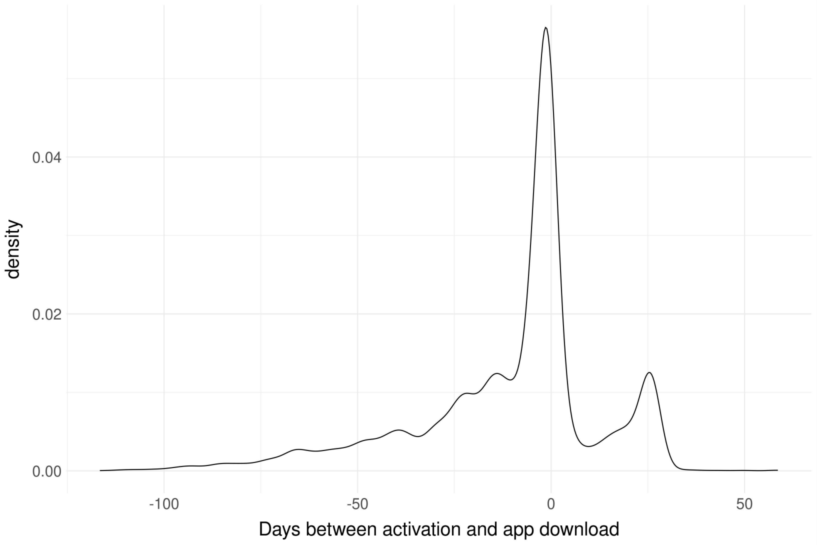
Distribution of App Download Times



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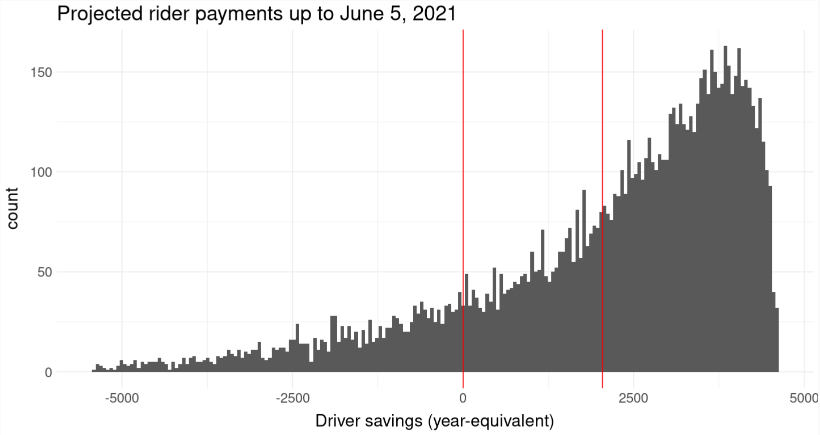
Distribution of Driver Payments



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Pricing Table

	Hours	Metro	Sub-Metro	Periphery
	Weekdays			
Peak	6:45 - 9:30 AM 3:30 - 6:30 PM	1.5	0.3	0
Moderate	9:30 - 3:30 PM 6:30 - 8 PM	0.1	0	0
Low	8PM - 6:45 AM	0	0	0
	Weekends			
	All Hours	0	0	0

Table 1: NIS per Km traveled

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Benchmarking Exercise: Pre-Treatment Driving Behavior

The median driver in our sample...

- Takes **14** trips per week
- Drives **156** Kilometers per week
- Spends **6** hours driving per week
- Pays **32** NIS per week

Benchmarking Exercise: Pre-Treatment Driving Behavior

The median driver in our sample...

- Takes **14** trips per week

  $\Rightarrow$ 65% coming to or from a metro area

- Drives **156** Kilometers per week (11 Km per trip)

  $\Rightarrow$ 113 Km on trips to or from a metro area

- Spends **6** hours driving per week (25 mins per trip)

  $\Rightarrow$ 4 hours on trips to or from a metro area

- Pays **32** NIS per week (2 NIS per trip)

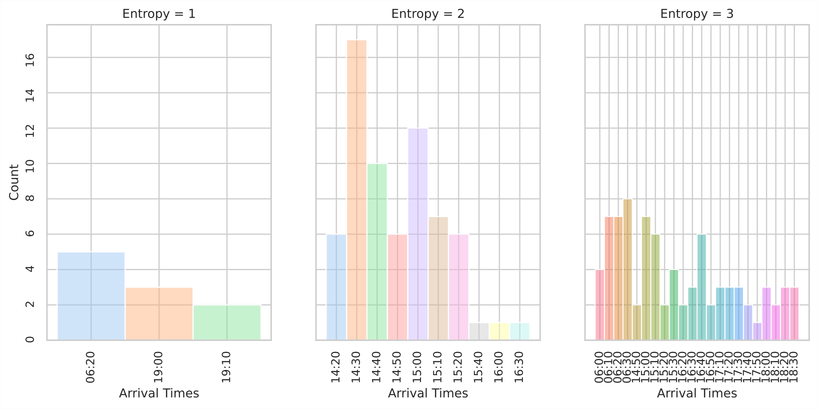
  $\Rightarrow$ 29 NIS on trips to or from a metro area

Benchmarking Exercise: Pre-Treatment Driving Behavior

The median driver in our sample...

- Takes **14** trips per week
  - $\Rightarrow$ 40% during "peak" hours
- Drives **156** Kilometers per week (11 Km per trip)
  - $\Rightarrow$ 57 Km on trips during "peak" hours
- Spends **6** hours driving per week (25 mins per trip)
  - $\Rightarrow$ 3 hours on trips during "peak" hours
- Pays **32** NIS per week (3 NIS per trip)
  - $\Rightarrow$ 29 NIS on trips during "peak" hours

Arrival Time Entropy: Examples I



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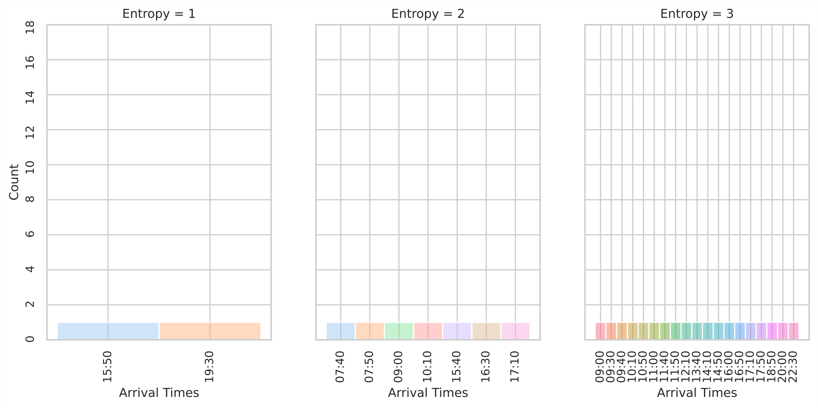
Arrival Time Entropy: Examples II



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Did Prices Change Behavior? Estimation Strategy

- Event study assuming parallel trends on control potential outcomes

$$\iff \mathbb{E}[Y_{i,t}(0) - Y_{i,t-1}(0) \mid C_i] = \beta_t - \beta_{t-1}$$

$$\iff Y_{i,t}(0) = \alpha_i + \beta_t + \varepsilon_{i,t}, \quad \varepsilon_{i,t} := Y_{i,t}(0) - \mathbb{E}[Y_{i,t}(0) \mid \alpha_i]$$

- Estimand is Average Treatment Effect on Treated (ATT):

$$\tau_e = \sum_{c=1}^{T} \sum_{t=1}^{T} \mathbb{1}\{t - c = e\} \mathbb{E}[(Y_{i,t}(c) - Y_{i,t}(0)) \mathbb{1}\{C_i = c\}]$$

- Model-based imputation for unobserved post-treatment control potential outcomes (Borusyak, Jaravel, and Spiess, 2021)

- Confidence intervals corrected for *FWER* per plot via Bayesian Bootstrap (Romano, Shaikh, and Wolf, 2010; Rubin, 1981)
  - $\Rightarrow$ reject zeros using step-down procedure from Romano and Wolf, 2005

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Estimation Formula Notation

- i : individual driver identifier
- t : week of the year identifier (in absolute time)
- c : cohort-identifier (week of activation)
- e : event time relative to activation ($e = t - c$)
- $Y_{i,t}(0)$: potential outcome for driver i in week t under *no* treatment
- $Y_{i,t}(c)$: potential outcome for driver i in week t if they were first treated in week c
- α_i : individual driver fixed effect under the parallel trends imputation model
- β_t : week of the year fixed effect under the parallel trends imputation model

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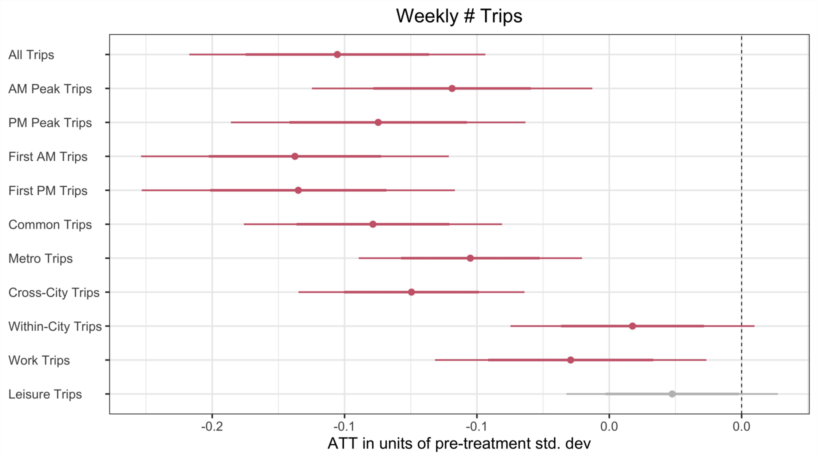
How did Drivers Adjust? ATT on # Trips in SD Units



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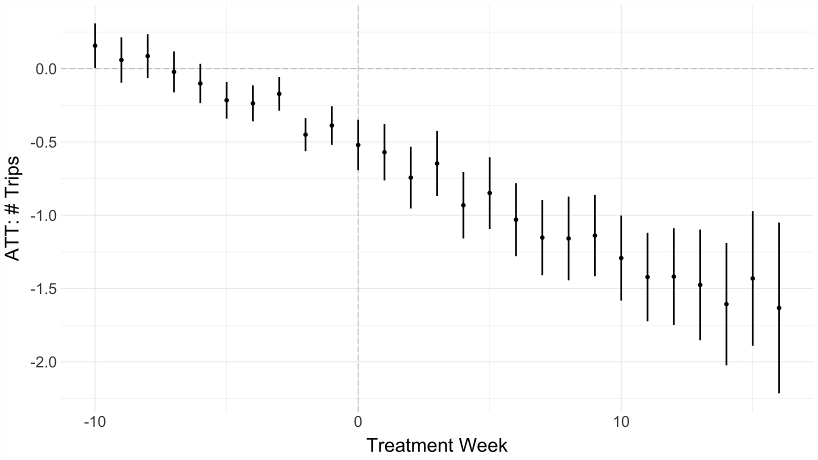
How did Drivers Adjust? ATT on Total # Trips



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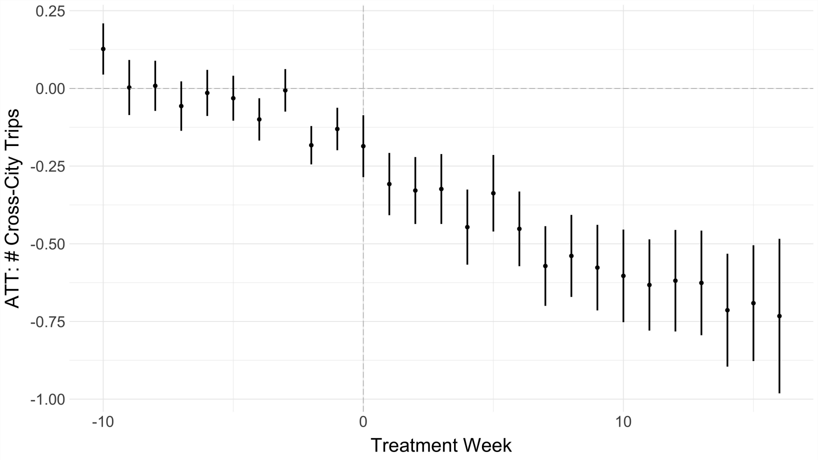
How did Drivers Adjust? ATT on # Cross-City Trips



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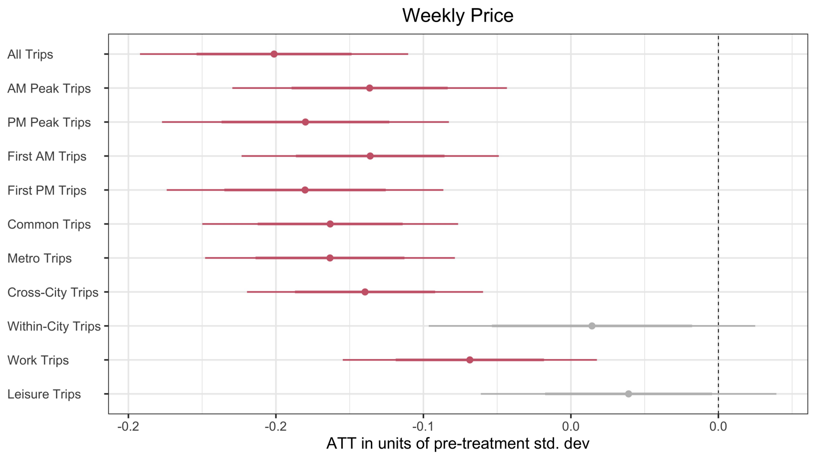
Would This Affect Traffic? ATT on Total Price Across Trips



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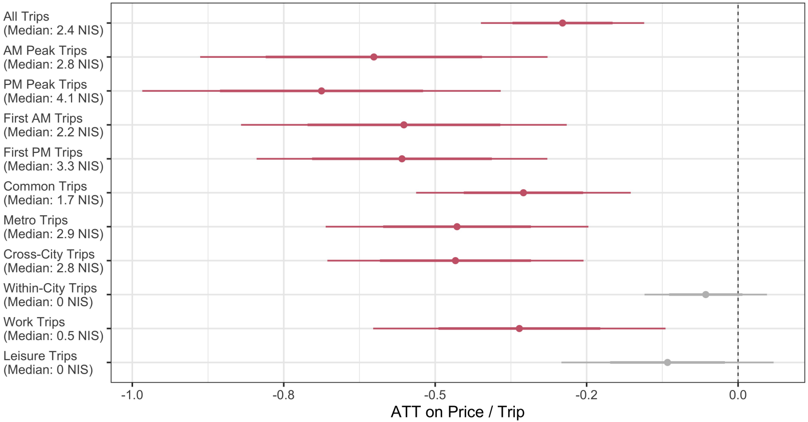
Would This Affect Traffic? ATT on Price per Trip Across Trips



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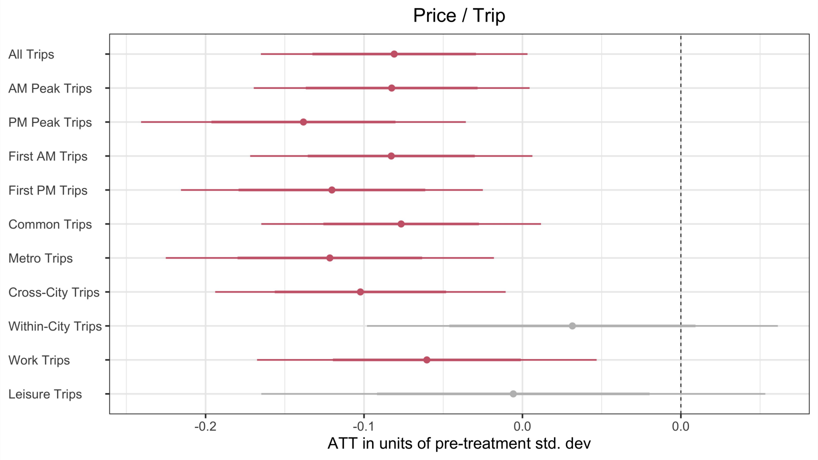
Would This Affect Traffic? ATT on Price per Trip Across Trips



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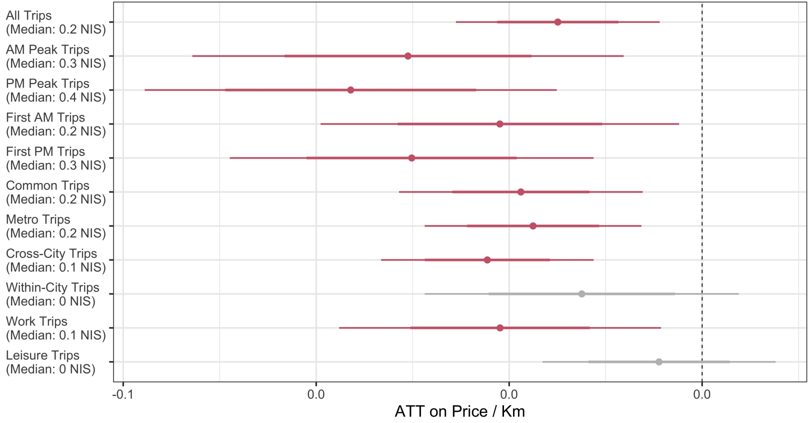
Would This Affect Traffic? ATT on Price per Km Across Trips



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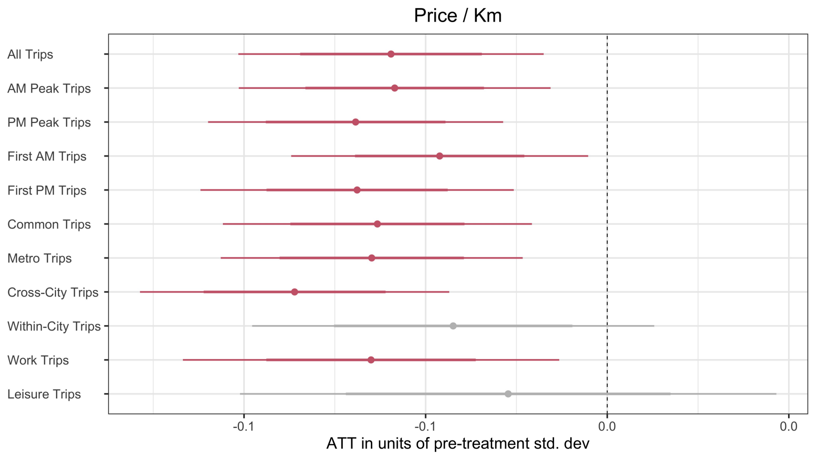
Would This Affect Traffic? ATT on Price per Km Across Trips



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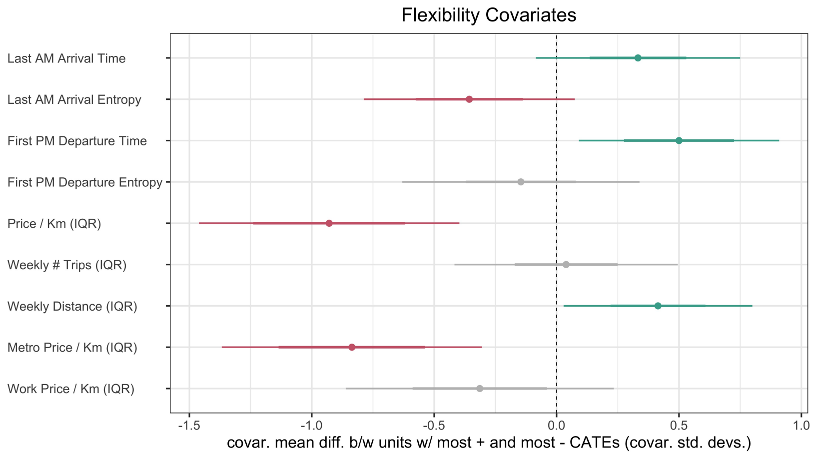
Treatment Effect Heterogeneity: Price per Km



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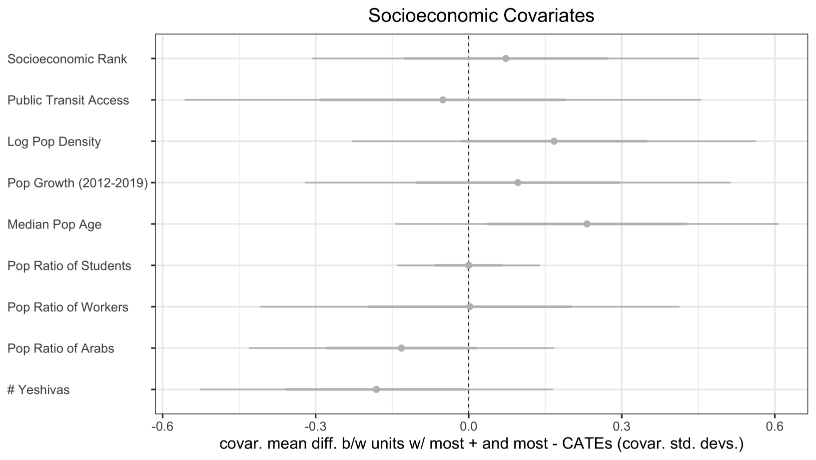
Treatment Effect Heterogeneity: Price per Km



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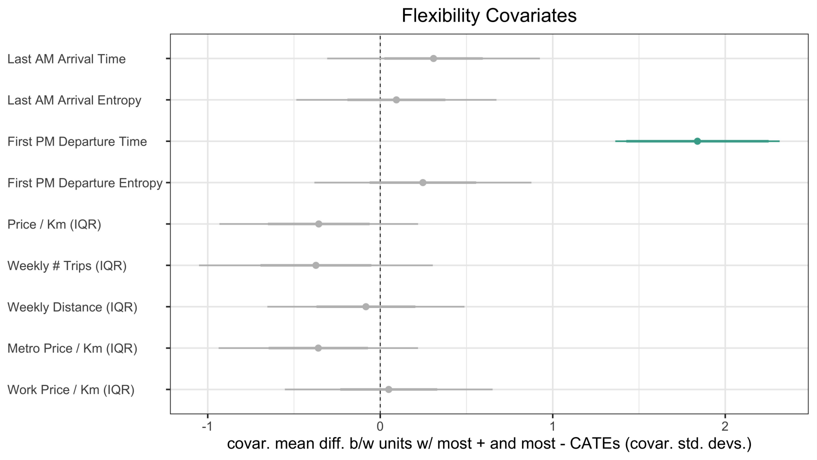
TE Heterogeneity: Time to Peak on Common Trips



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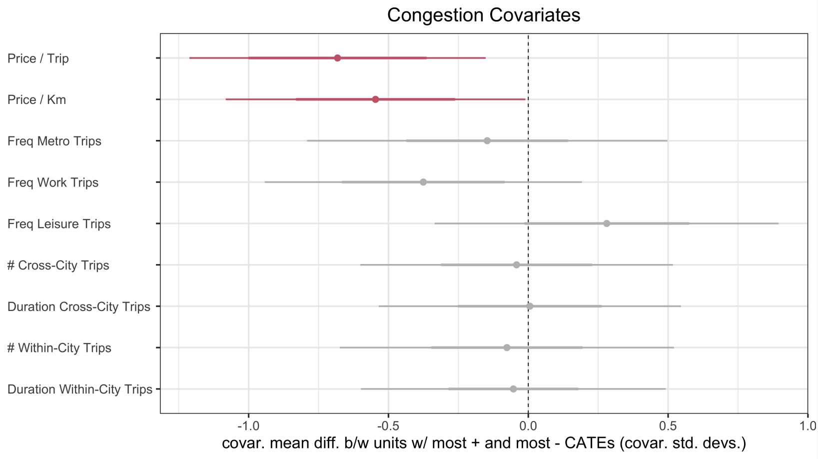
TE Heterogeneity: Time to Peak on Common Trips



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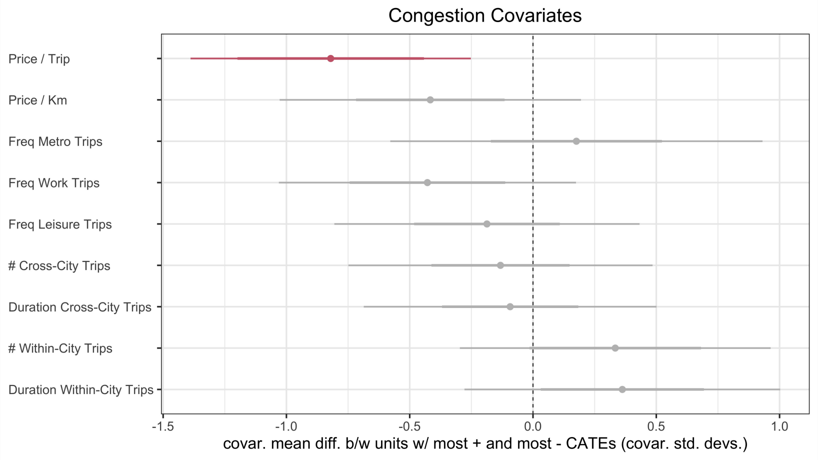
TE Heterogeneity: Time to Peak on Metro



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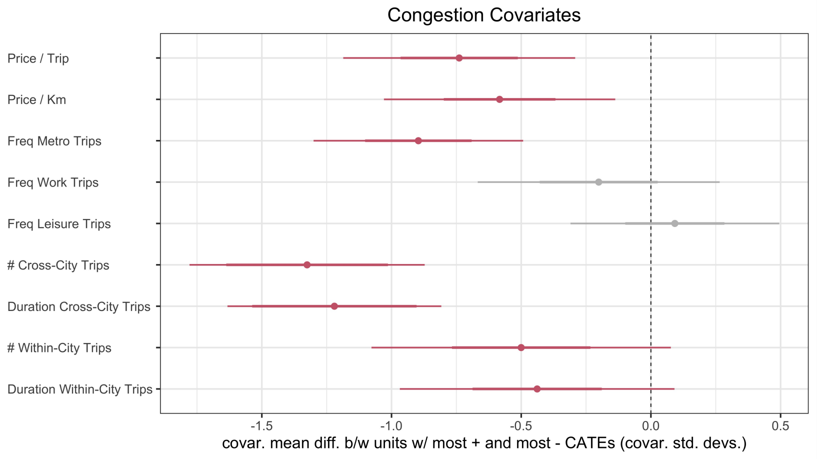
TE Heterogeneity: # Metro Trips



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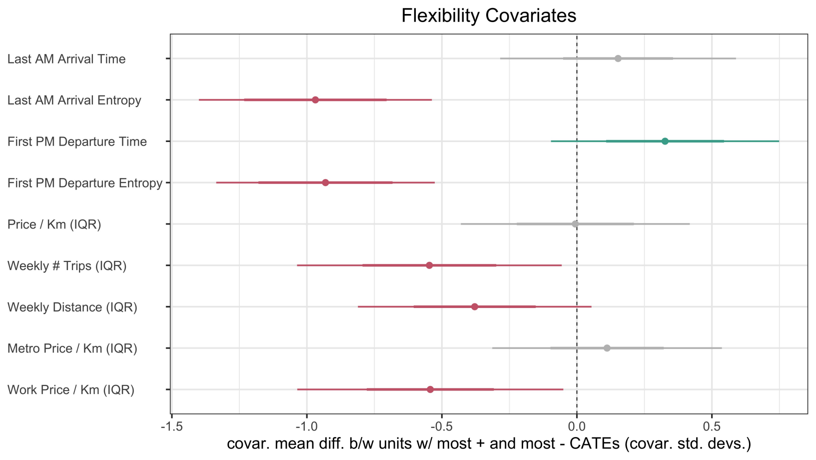
TE Heterogeneity: # Metro Trips



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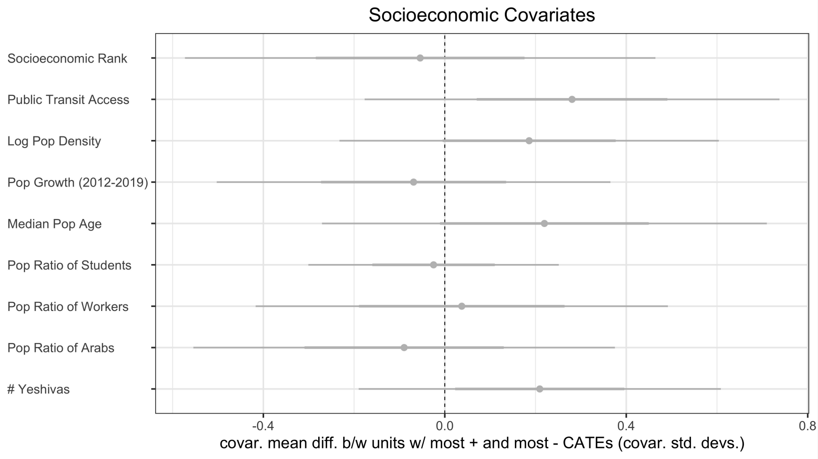
TE Heterogeneity: # Metro Trips



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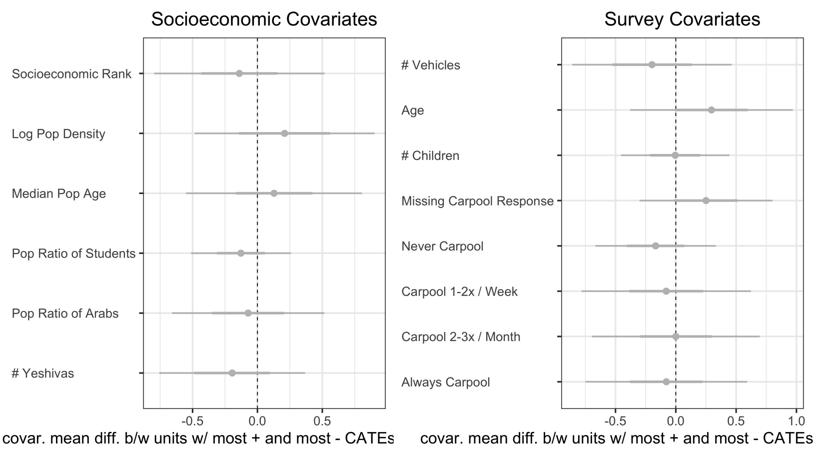
TE Heterogeneity: Home Census Block vs Survey Demos



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Highway Sensor Locations: Zoomed Out

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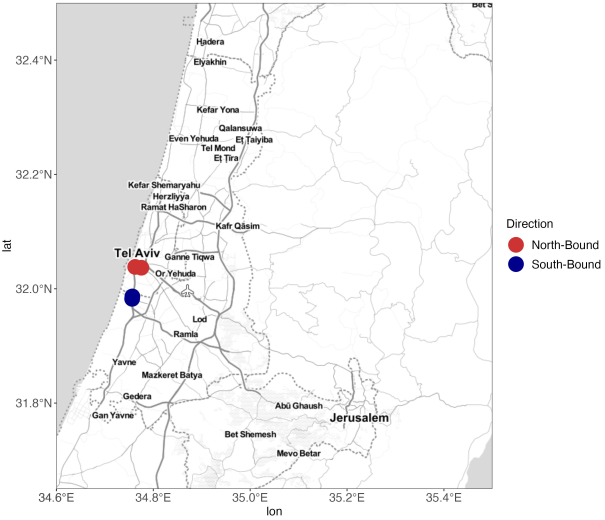

Highway Sensor Locations: Zoomed In

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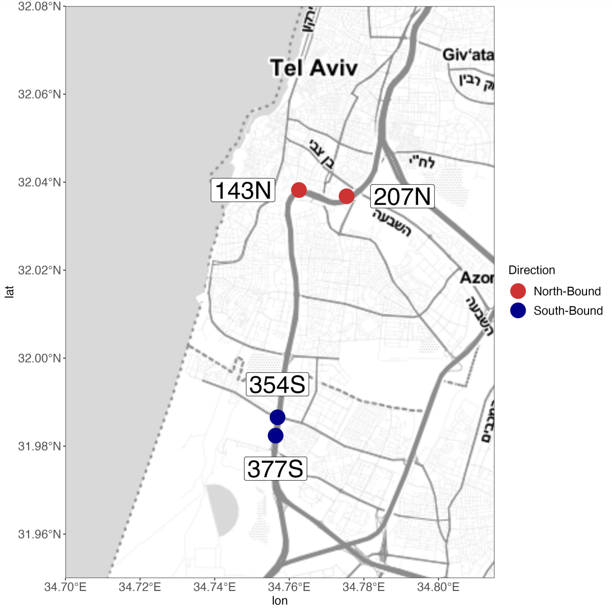

Perspective from Ayalon South from Tel Aviv