Can Usage-Based Pricing Reduce Congestion?

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Traffic jams cost US $87 billion in lost productivity in 2018, and Boston and DC have the nation’s worst
Motivation: Gov’ts are adopting congestion pricing policies

Where (And Why) LA Metro Is Exploring 'Congestion Pricing' (AKA Making You Pay To Use Certain Roads)

By Ryan Poncea
Published Feb 10, 2021 4:20 PM

NYC Moving Ahead With Congestion Pricing Toll Plan: Here's What It Looks Like

Motorists entering Manhattan below 60th Street would be charged a toll electronically, with the revenue (estimated at $1 billion annually) used to back borrowing for capital improvements to the MTA’s subway and bus systems.

Seattle explores its options for congestion pricing

The city says it wants to find an equitable way to toll city streets

By Sarah Anne Lloyd | @sarahannlloyd | May 29, 2019, 2:30pm PDT
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
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?

- People who **contribute** to congestion, e.g. rush hour commuters
- People who are **flexible**, e.g. lower cost of being late to work
- People who are **price sensitive**, e.g. middle class
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
Experimental Design: "Value Road"

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Did Prices Decrease Congested Driving? ATT on Total Price

![Graph showing ATTT: Total Price vs. Treatment Week]
Did Prices Affect the Intensive Margin? ATT on Price / Trip

![Graph showing the relationship between treatment week and ATT price/trip.](image)

**Estimation Details**
Would This Affect Traffic? ATT on Total Price Across Trips

- All Trips (Median: 35 NIS)
- Metro Trips (Median: 26 NIS)
- Cross-City Trips (Median: 16 NIS)
- Within-City Trips (Median: 0.2 NIS)

ATT on Weekly Price

- SD Units
- Price per Trip
- Price per Km
Would This Affect Traffic? ATT on the # of Trips

- All Trips (Median: 15)
- Metro Trips (Median: 7)
- Cross-City Trips (Median: 4.5)
- Within-City Trips (Median: 2.5)

ATT on Weekly # Trips
Who is Affected and How?
Pre-treatment Correlations among “Value Road” Drivers

![Bar chart showing driver share across different median weekly price quintiles, with color-coded sections indicating socioeconomic rank and AM arrival entropy.](image-url)
“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
   ⇒ reject zeros using step-down procedure in Romano and Wolf, 2005
Treatment Effect Heterogeneity: Total Weekly Price

Congestion Covariates

- Price / Trip
- Price / Km
- # Cross-City Trips
- Duration Cross-City Trips
- # Within-City Trips
- Duration Within-City Trips

normalized covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)
Treatment Effect Heterogeneity: Total Weekly Price

Flexibility Covariates

- Last AM Arrival Time
- Last AM Arrival Entropy
- First PM Departure Time
- First PM Departure Entropy
- Price / Km (IQR)
- Weekly # Trips (IQR)

normalized covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)
Treatment Effect Heterogeneity: Total Weekly Price

Socioeconomic Covariates

- Public Transit Access
- Vehicle Model Year
- High Polluting Vehicle
- Home Block Socioeconomic Rank
- Home Block Population Density

normalized covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)
Where is this coming from? TE heterogeneity for # of Trips

Socioeconomic Covariates

- Public Transit Access
- Vehicle Model Year
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Where is this coming from? TE heterogeneity for Price/Trip

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Vehicle Model Year
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Home Block Socioeconomic Rank
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normalized covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)
What might this mean for congestion?
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):
      \[ Y(x) = U \cdot h(x) \text{ for arbitrary } h, \text{ but } X \not\perp U, \text{ only } U \perp Z \]
    - 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)
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

**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
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- Estimate demand for travel choice, given price and travel time
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What do our ATTs imply for highway speeds under ceteris paribus?
Summing Up

• Evidence that usage-based pricing may induce ↓ 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
  ⇒ The most congested driving is at the tails
  ⇒ Potentially big gains possible
  ⚠ This is not taking into account equilibrium effects!

• More to come...
Thank You
Appendix


Motivation: traffic congestion is very costly in very many places.
Consider a driver who...

- observes trip characteristics $X_d$
  - 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

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

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
- \( w_\ell \): Linear value of not being late by an additional minute
\[ v(t_s; X_d) = \alpha \cdot \mathbb{E}[\rho(t_s; X_d)] + w_h \cdot t_s + w_\ell \cdot (t^*_a - \mathbb{E}[\tau(t_s; X_d)]) \]

- **'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
  - \( w_\ell \): Linear value of not being late by an additional minute

- **'Price sensitivity' Parameters:**
  - \( \alpha \): Price coefficient
  - (Not modeled): Budget constraints, income effects, etc.
Mapping the Venn-Diagram to "Value Road": 50-50 Splits

Contribute to Congestion
(Metro Trip Frequency)

Flexible
(Metro Trip AM Arrival Time Entropy)

Price Sensitive
(Socioeconomic Rank)
Mapping the Venn-Diagram to “Value Road": 80-20 Splits

Contribute to Congestion
(Metro Trip Frequency)

Flexible
(Metro Trip AM Arrival Time Entropy)

Price Sensitive
(Socioeconomic Rank)

191 (3%)
663 (9%)
1373 (20%)
232 (3%)
435 (6%)
1009 (10%)
3088 (40%)

Back
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<th>שיעור ה guardar</th>
<th>2018-19</th>
<th>2007</th>
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<td>16.6</td>
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<td>23.2</td>
<td>19.4</td>
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<td>20.3%</td>
<td>21.3</td>
<td>17.7</td>
</tr>
<tr>
<td>16.5%</td>
<td>12.0</td>
<td>10.3</td>
</tr>
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</table>

לוח 2 - מנתחי תכנית משוער של נסיעות伸手יב ב 2007 ו 2018 לפי תקופת השבוש.
The average US driver...

- Takes 2.5 trips per day (12.5 trips per work week)
- Drives 30 miles per day (∼ 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
Distribution of App Download Times

Days between activation and app download

density
Distribution of Driver Payments

Projected rider payments up to June 5, 2021

Driver savings (year-equivalent)

(count)

-5000 -2500 0 2500 5000
## Pricing Table

<table>
<thead>
<tr>
<th>Hours</th>
<th>Metro</th>
<th>Sub-Metro</th>
<th>Periphery</th>
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<tr>
<td><strong>Weekdays</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Peak 6:45 - 9:30 AM</td>
<td>1.5</td>
<td>0.3</td>
<td>0</td>
</tr>
<tr>
<td>3:30 - 6:30 PM</td>
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<tr>
<td>Moderate 9:30 - 3:30 PM</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6:30 - 8 PM</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Low 8PM - 6:45 AM</td>
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<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
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<th>Metro</th>
<th>Sub-Metro</th>
<th>Periphery</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Weekends</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Hours</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**Table 1:** NIS per Km traveled
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
The median driver in our sample...

- Takes 14 trips per week
  \[ \Rightarrow 65\% \text{ coming to or from a metro area} \]

- Drives 156 Kilometers per week (11 Km per trip)
  \[ \Rightarrow 113 \text{ Km on trips to or from a metro area} \]

- Spends 6 hours driving per week (25 mins per trip)
  \[ \Rightarrow 4 \text{ hours on trips to or from a metro area} \]

- Pays 32 NIS per week (2 NIS per trip)
  \[ \Rightarrow 29 \text{ NIS on trips to or from a metro area} \]
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

Entropy = 1

Entropy = 2

Entropy = 3
Arrival Time Entropy: Examples II

Entropy = 1

Entropy = 2

Entropy = 3
Did Prices Change Behavior? Estimation Strategy

• Event study assuming parallel trends on control potential outcomes

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

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

• 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)

\[\Rightarrow \text{reject zeros using step-down procedure from Romano and Wolf, 2005}\]
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 $c$
- $\alpha_i$: individual driver fixed effect under the parallel trends imputation model
- $\beta_t$: week of the year fixed effect under the parallel trends imputation model
How did Drivers Adjust? ATT on # Trips in SD Units

Weekly # Trips

ATT in units of pre-treatment std. dev

All Trips
AM Peak Trips
PM Peak Trips
First AM Trips
First PM Trips
Common Trips
Metro Trips
Cross-City Trips
Within-City Trips
Work Trips
Leisure Trips
How did Drivers Adjust? ATT on # Cross-City Trips
Would This Affect Traffic? ATT on Total Price Across Trips

Weekly Price

ATT in units of pre-treatment std. dev

- All Trips
- AM Peak Trips
- PM Peak Trips
- First AM Trips
- First PM Trips
- Common Trips
- Metro Trips
- Cross-City Trips
- Within-City Trips
- Work Trips
- Leisure Trips
Would This Affect Traffic? ATT on Price per Trip Across Trips
Would This Affect Traffic? ATT on Price per Trip Across Trips

![Graph showing ATT in units of pre-treatment std. dev for different trip types.]
Would This Affect Traffic? ATT on Price per Km Across Trips

- All Trips (Median: 0.2 NIS)
- AM Peak Trips (Median: 0.3 NIS)
- PM Peak Trips (Median: 0.4 NIS)
- First AM Trips (Median: 0.2 NIS)
- First PM Trips (Median: 0.3 NIS)
- Common Trips (Median: 0.2 NIS)
- Metro Trips (Median: 0.2 NIS)
- Cross-City Trips (Median: 0.1 NIS)
- Within-City Trips (Median: 0 NIS)
- Work Trips (Median: 0.1 NIS)
- Leisure Trips (Median: 0 NIS)
Treatment Effect Heterogeneity: Price per Km

Flexibility Covariates

- Last AM Arrival Time
- Last AM Arrival Entropy
- First PM Departure Time
- First PM Departure Entropy
- Price / Km (IQR)
- Weekly # Trips (IQR)
- Weekly Distance (IQR)
- Metro Price / Km (IQR)
- Work Price / Km (IQR)

covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)

Back
Socioeconomic Covariates

- Socioeconomic Rank
- Public Transit Access
- Log Pop Density
- Pop Growth (2012-2019)
- Median Pop Age
- Pop Ratio of Students
- Pop Ratio of Workers
- Pop Ratio of Arabs
- # Yeshivas

covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)
TE Heterogeneity: Time to Peak on Common Trips

Flexibility Covariates

- Last AM Arrival Time
- Last AM Arrival Entropy
- First PM Departure Time
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- Work Price / Km (IQR)

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Back
TE Heterogeneity: Time to Peak on Common Trips

Congestion Covariates

- Price / Trip
- Price / Km
- Freq Metro Trips
- Freq Work Trips
- Freq Leisure Trips
- # Cross-City Trips
- Duration Cross-City Trips
- # Within-City Trips
- Duration Within-City Trips

covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. dev. s)
TE Heterogeneity: Time to Peak on Metro

Congestion Covariates

- Price / Trip
- Price / Km
- Freq Metro Trips
- Freq Work Trips
- Freq Leisure Trips
- # Cross-City Trips
- Duration Cross-City Trips
- # Within-City Trips
- Duration Within-City Trips

covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)
TE Heterogeneity: # Metro Trips

Congestion Covariates

covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)

- Price / Trip
- Price / Km
- Freq Metro Trips
- Freq Work Trips
- Freq Leisure Trips
- # Cross-City Trips
- Duration Cross-City Trips
- # Within-City Trips
- Duration Within-City Trips
TE Heterogeneity: # Metro Trips

Flexibility Covariates

- Last AM Arrival Time
- Last AM Arrival Entropy
- First PM Departure Time
- First PM Departure Entropy
- Price / Km (IQR)
- Weekly # Trips (IQR)
- Weekly Distance (IQR)
- Metro Price / Km (IQR)
- Work Price / Km (IQR)

covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)

Back
TE Heterogeneity: # Metro Trips

Socioeconomic Covariates

- Socioeconomic Rank
- Public Transit Access
- Log Pop Density
- Pop Growth (2012-2019)
- Median Pop Age
- Pop Ratio of Students
- Pop Ratio of Workers
- Pop Ratio of Arabs
- # Yeshivas

covar. mean diff. b/w units w/ most + and most - CATEs (covar. std. devs.)
TE Heterogeneity: Home Census Block vs Survey Demos

Socioeconomic Covariates
- Socioeconomic Rank
- Log Pop Density
- Median Pop Age
- Pop Ratio of Students
- Pop Ratio of Arabs
- # Yeshivas

Survey Covariates
- # Vehicles
- Age
- # Children
- Missing Carpool Response
- Never Carpool
- Carpool 1-2x / Week
- Carpool 2-3x / Month
- Always Carpool

covar. mean diff. b/w units w/ most + and most - CATEs