# The Distribution of Value of Time: An Analysis from Traffic Congestion and Express Lanes

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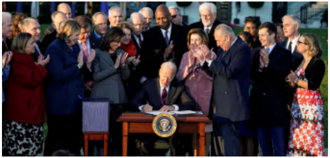
# Why do we care about VOT and commuting?

- Allocation of time to tasks
- Commuting and congestion
- Wage vs residential amenities trade-off
- Infrastructure

$\Rightarrow$ **Need to know VOT distribution**

*Traffic jam in the US.*



*US President Biden signs $1 trillion infrastructure bill.*

# This paper: Express Lanes (ELs) in Minneapolis

- Time savings vs toll trade-off
- Toll changes every 3 minutes
- Identification: tolling function
- "Lexus Lanes"?


*Express Lane on highway I-394 in Minnesota.*

# Analysis in three parts and preview of results

**RDD: travel time savings that EL users exchange for $0.25 toll increase.**

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Median: \$17.42;
75th percentile: \$34.97;
95th percentile: \$166.05.

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Median: $17.42;
75th percentile: $34.97;
95th percentile: $166.05.

**Structural model of when to commute + EL choice:**

Converting the EL into a standard lane increases per-driver welfare by $25.68 per year: 52% of drivers spend less on the EL over a whole year.

# Outline of the paper

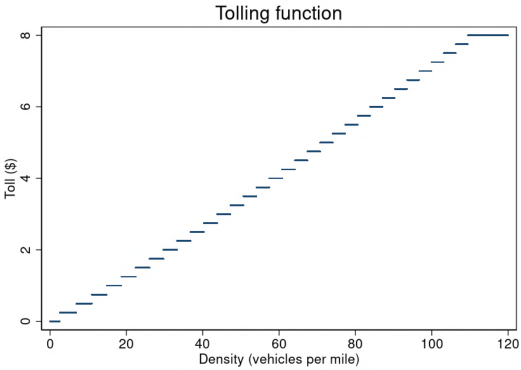
1. Setting and data
2. Step 1: RD analysis of mean VOT among EL drivers
3. Step 2: estimation of VOT distribution among all drivers
4. Step 3: structural model of departure time and EL choice
5. Counterfactuals and distribution of welfare effects

# Outline of the paper

1. **Setting and data**

# Toll function creates 32 cutoffs

Toll changes every 3 minutes as function of traffic density (vehicles per mile) on the EL in the previous 6 minutes: $toll = 0.045 \cdot density^{1.1}$, then rounded to the nearest \$0.25.



# Panel dataset of EL usage and highway traffic

1. **EL panel dataset from MnPASS:**
   - 45,421 distinct EL users, 2017 - 2018, over 3M observations.
   - Includes entry and exit location and time at the seconds level.
   - Identified by transponder tag ID, only observed if on EL.

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   - Includes entry and exit location and time at the seconds level.
   - Identified by transponder tag ID, only observed if on EL.
2. **Highway traffic dataset from Minnesota DOT:**
   - Covers both ELs and free lanes, measurements every 30 seconds.
   - Includes aggregate traffic density (in vehicles per mile), traffic volume (in vehicles per hour) and speed.

Descriptive plots | Map of Minnesota Express Lanes | Facts about commuting in Minnesota and the US

# Outline of the paper

1. Setting and data
2. **Step 1: RD analysis of mean VOT among EL drivers**

# RD identifies reduced-form time saved effect

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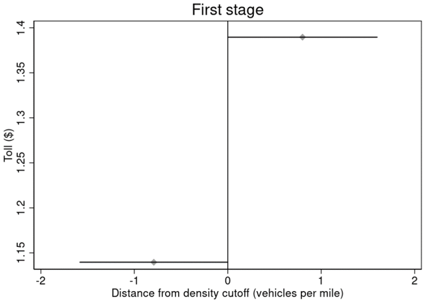
- The RD correctly identifies $\Delta\tau$, the average time saved increase that EL users trade off for a \$0.25 toll increase:

$$\mathbb{E}[\tau^1_{it} - \tau^0_{it} | R = c] = \Delta\tau$$

# RDD results (toll and time saved)



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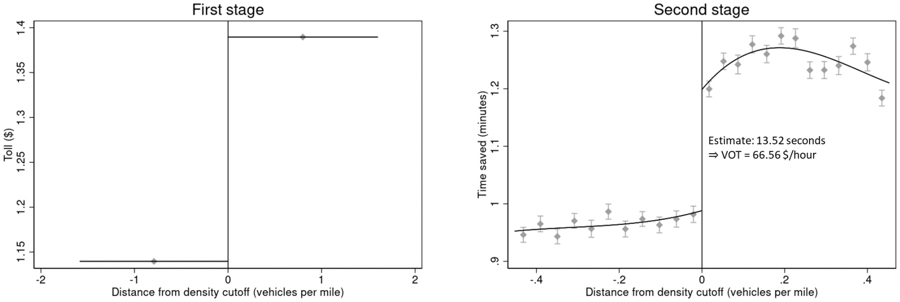
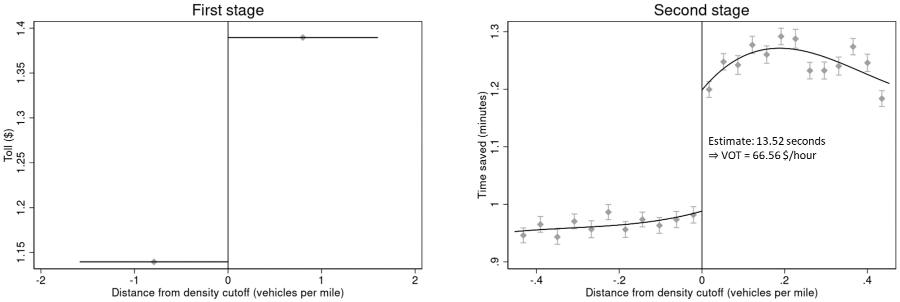


# RDD results (toll and time saved)

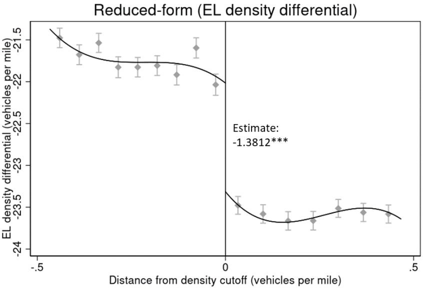
RDD-estimated VOT is $66.56 per hour saved conditional on using the EL.
2.5x the hourly wage in Minnesota in 2018 ($28.52, US BLS).
5x the US government VOT for personal travel ($13.60, US DOT).




RD intuition | RD equations | RD estimate at each cutoff | RD vs hedonic OLS

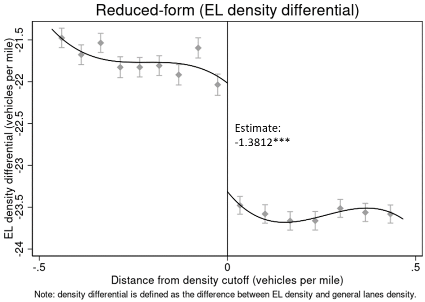
# RDD results (speed and density differentials)

Drivers reallocate to normal lanes.

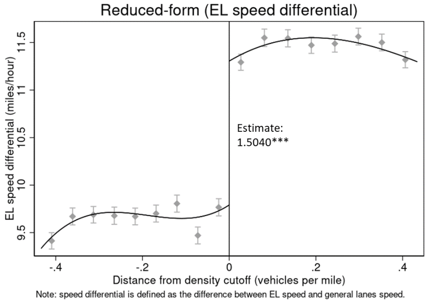


Note: density differential is defined as the difference between EL density and general lanes density.

Drivers reallocate to normal lanes.




EL flows faster.




Heterogeneity in RDD results

# Outline of the paper

1. Setting and data
2. Step 1: RD analysis of mean VOT among EL drivers
3. **Step 2: estimation of VOT distribution among all drivers**

# VOT distribution and EL choice probability

- Aggregate EL choice probability in market $j$ (Fox *et al.* (2011)):

$$s_j^{EL} = \sum_{m=1}^{M} \theta^m s_{j,m}^{EL} = \sum_{m=1}^{M} \theta^m \frac{exp\left(\frac{\delta^{EL} + \beta^{m,VOT} \cdot \tau_j - \pi_j}{s}\right)}{1 + exp\left(\frac{\delta^{EL} + \beta^{m,VOT} \cdot \tau_j - \pi_j}{s}\right)}$$

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- To use exogenous variation at cutoff, focus on $\Delta s_j^{EL} = s_j^{EL,1} - s_j^{EL,0}$.

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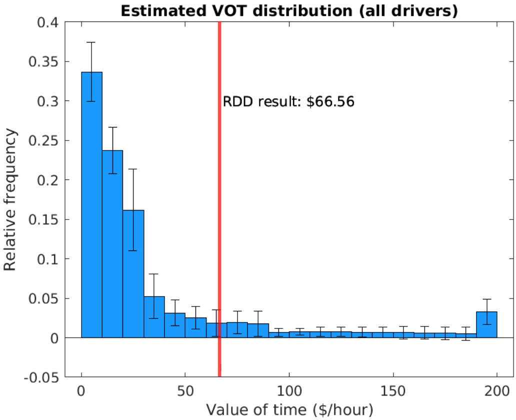
- To use exogenous variation at cutoff, focus on $\Delta s_j^{EL} = s_j^{EL,1} - s_j^{EL,0}$.
- Each market $j$ is a day and cutoff in the sample.
- I estimate:

$$\widehat{\Delta s}_j^{EL} = \sum_m \theta^m \cdot \Delta s_{j,m}^{EL} + \zeta_j$$

Data support for this estimation | More details

# Estimated VOT distribution

Median \$17.42; 75th percentile: \$34.97; 95th percentile: \$166.05.
RDD result \$66.56 is close to the 85th percentile.




Alternative estimation for frequent EL users

# Outline of the paper

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2. Step 1: RD analysis of mean VOT among EL drivers
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4. **Step 3: structural model of departure time and EL choice**

# Model intuition and setup

- People can respond to congestion (and congestion policy) by adjusting what time of day they choose to commute.
- Drivers want to minimize travel time. Heterogeneity: individual VOT.
- In the first stage, drivers choose entry time on the highway. Preference for entry times are population averages.
- In the second stage, conditional on entry time, drivers choose EL or normal lane, in GE framework.

More details Model equations

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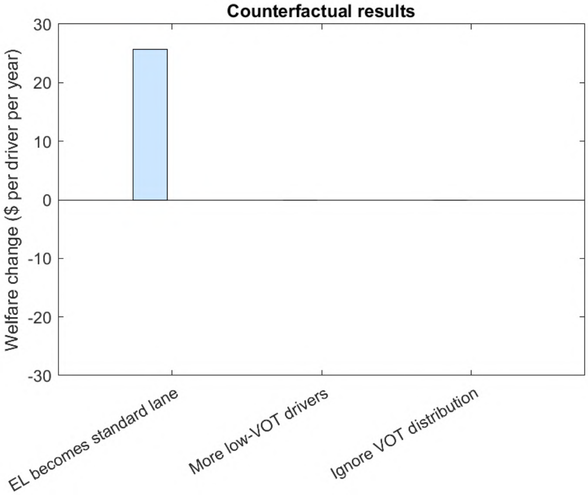
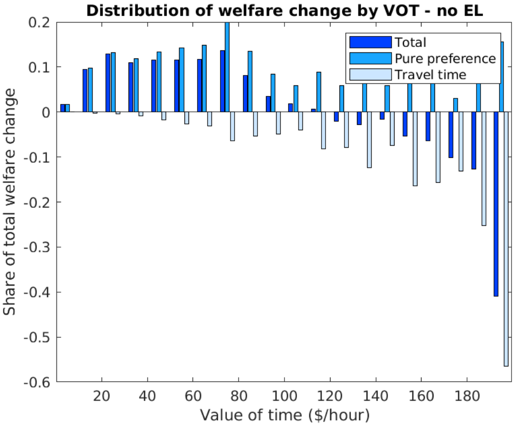
5. **Counterfactuals and distribution of welfare effects**
    1. EL is converted into a standard lane. Graphical intuition
    2. More low-VOT drivers. Graphical intuition
    3. Lower or higher toll.
    4. Ignore VOT heterogeneity. Graphical intuition

# EL converted to free lane: result



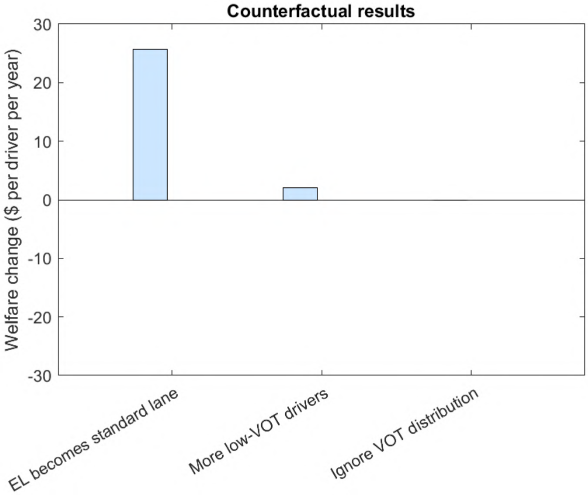
# EL converted to free lane: distribution of effects

Gains are concentrated among low-VOT commuters.



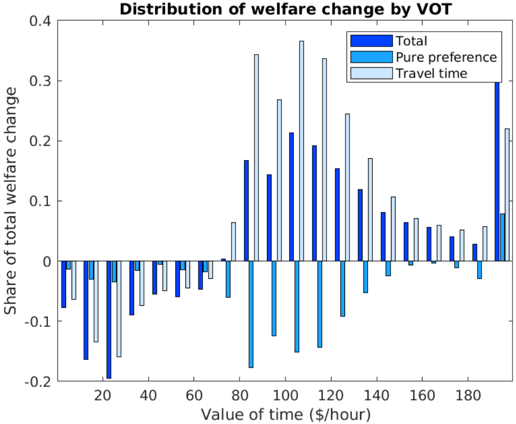

Road-specific distributional effects

# More low-VOT drivers: result



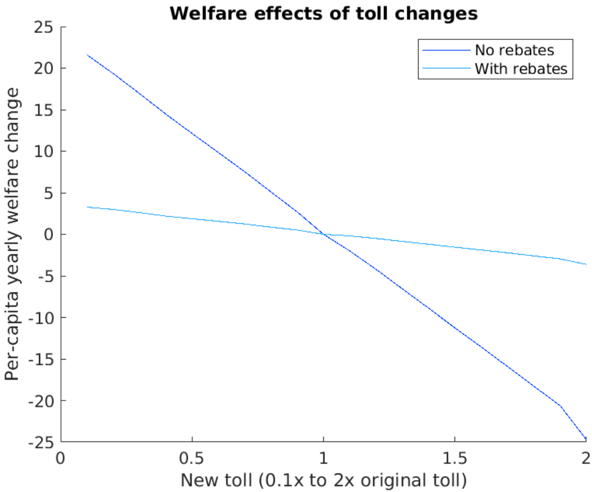
# More low-VOT drivers: distribution of effects

Gains are concentrated among high-VOT commuters.

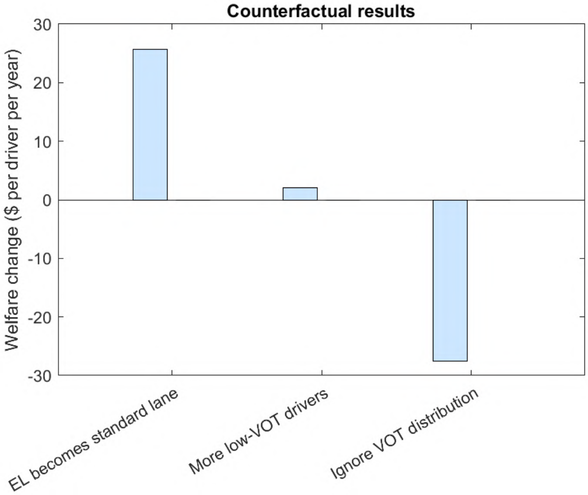



Road-specific distributional effects

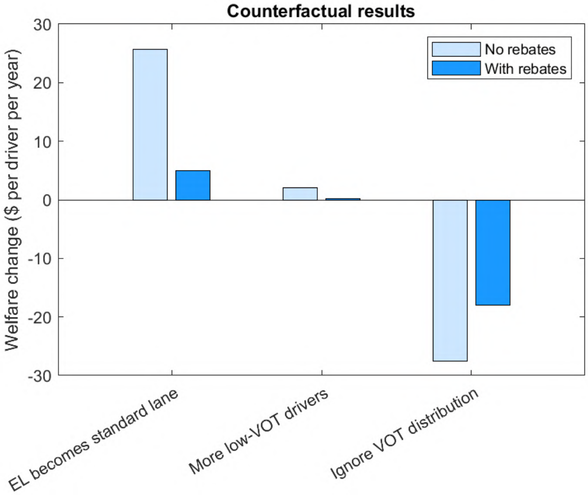
# Changes in toll: 0.1x to 2x original toll



# Ignore VOT heterogeneity: result



# What if we rebated toll revenues to drivers?



# Concluding remarks

- Estimate full VOT distribution of a policy-relevant population using new data: wide heterogeneity in individual VOT.
- The EL maximizes drivers' welfare when the underlying VOT distribution produces a separating equilibrium.
- The VOT distribution is essential to design targeted congestion policy and assess inequality concerns.

Thank you for your attention!

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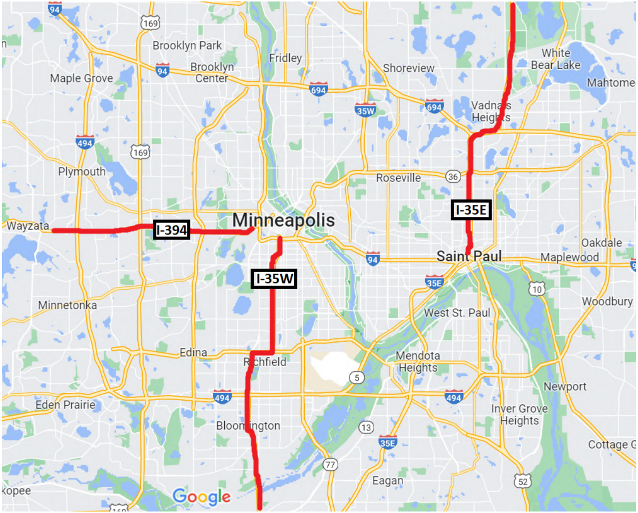
# Contributions of this paper and literature review

1. **Value of time literature:** Deacon and Sonstelie (1985), Chui and McFarland (1987), Small *et al*. (2005), Small *et al*. (2006), Bento *et al*. (2017), Nevo and Wong (2019), Hall (2020), Kreindler (2021), Goldszmidt *et al*. (2021).
   **My contribution: full VOT distribution using new data.**
2. **Welfare effects of congestion policies:** Vickrey (1969), Arnott *et al*. (1993) and (1994), Braid (1996), Small and Verhoef (2007), van den Berg and Verhoef (2011), Hall (2018), Yang *et al*. (2020), Anderson and Davis (2020).
   **My contribution: distributional and welfare effects.**
3. **Distribution of individual valuation of non-transferable good.**

# Map of Express Lanes location

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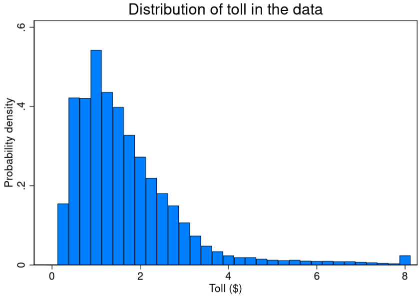
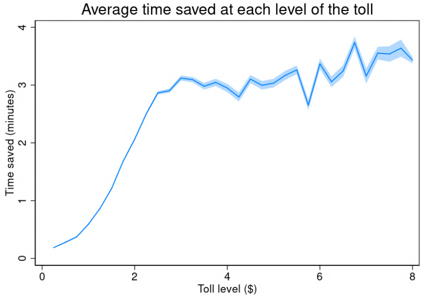
# Toll and time saved observations in the data




(a) Absolute toll levels



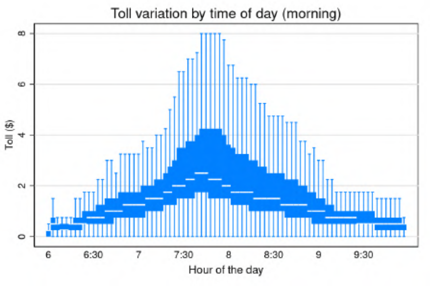

(b) Time saved by toll level

Mean toll: \$1.69
Mean toll per mile: \$0.34

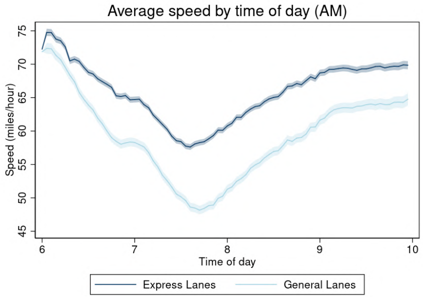
Mean time saved: 1.11 minutes
Max time saved: 24.92 minutes

Distribution of toll paid per mile | Distribution of time saved | Back

# Data: toll is hard to predict and EL goes faster




(a) Toll variation every 3 minutes




(b) Average speeds every 3 minutes

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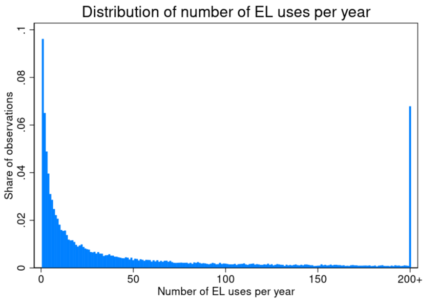
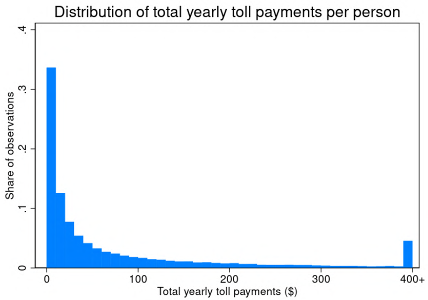
# Data: Lexus Lanes, very few high-frequency users




(a) Yearly number of EL uses per driver




(b) Yearly toll payments per driver

Median: 18
Mean: 52.84
Max: 450

Median: $23.50
Mean: $81.89
Max: $2004.50

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# Facts about commuting in Minnesota and the US

- 75% drove alone to work in 2019 (76% in the US).
- Average one-way commute in 2019: 25.6 minutes (27.6 in the US).
- No significant change in total number of drivers between 2010 and 2018.
- No significant shift to alternative modes between 2010 and 2018.
- Under no plausible congestion level city roads are faster than highways.

Post-COVID commuting trends

Back

# Post-COVID commuting trends in the US

- 68% drove alone to work in 2021 (down from 76% in 2019).
- 19% worked from home in 2021 in metro areas (up from 6% in 2019).
- Carpooling and public transit decreased between 2019 and 2021.
- Congestion was about 20% lower than pre-COVID as of April 2022.

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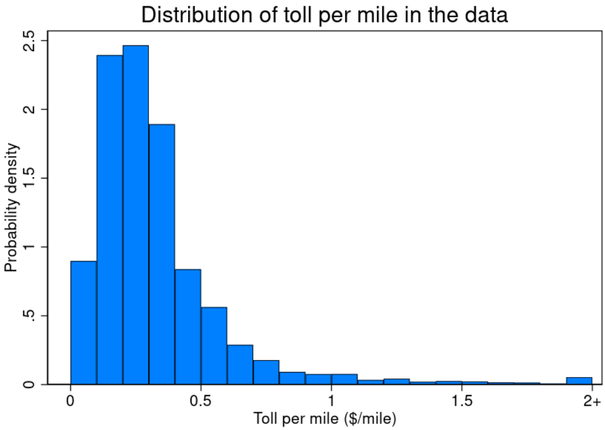
# Distribution of toll paid per mile

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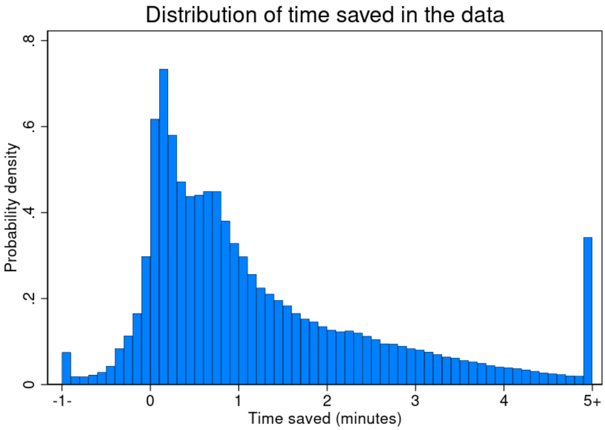
# Distribution of absolute time saved

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# Moving away from hedonic OLS of VOT

- Hedonic regression of EL toll $\pi$ on time saved $\tau$.
- Endogeneity: unobserved driving conditions and individual factors correlated with both toll and time saved (Greenstone (2017)).
- EL discontinuities isolate plausibly exogenous variation in toll.

# Framework for EL demand

- Conditional on commuting, $i$ chooses the EL if utility $u^{EL}$ is positive:

$$u_{it}^{EL} = \delta^{EL} + \beta_i^{VOT} \cdot \mathbb{E}[\boldsymbol{\tau_{it}} | \Psi_{it}] - \boldsymbol{\pi_{it}} + \varepsilon_{it}$$

  where $\delta^{EL}$ is taste for the EL, $\varepsilon_{it}$ is an error term with cdf $G$, $\tau$ is time saved and $\pi$ is toll.

- $\Psi_{it}$ can include surrounding traffic, toll itself, unobservables.

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- $\Psi_{it}$ can include surrounding traffic, toll itself, unobservables.

- The EL choice probability is:

$$P_{it}^{EL} = 1 - G(-\delta^{EL} - \beta_i^{VOT} \cdot \mathbb{E}[\tau_{it} | \Psi_{it}] + \pi_{it})$$

# Assumptions: rational expectation and smoothness

1. **Rational expectation** of time saved is consistent with its realization.

$$\mathbb{E}[\tau_{it}|\Psi_{it}] = \tau_{it} + \nu_{it}, \quad \mathbb{E}[\nu_{it}] = 0$$

   - Implication: can use ex-post measurement of time saved.

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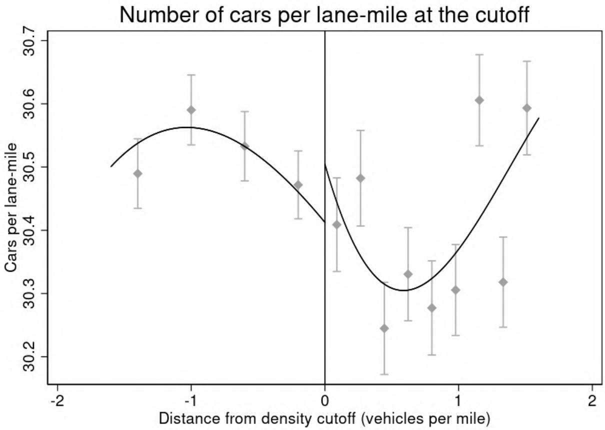
2. **Smoothness:** untreated potential outcome continuous at cutoff.

$$\mathbb{E}[\tau^0_{it}|R = r] \quad \text{is continuous at } r = c, \quad R \text{ running variable}$$

   - Total number of drivers on the road is smooth at the cutoff: drivers reallocate from EL to normal lanes. Check assumption

No selection on observables Back

# No change in total cars on the road at cutoff

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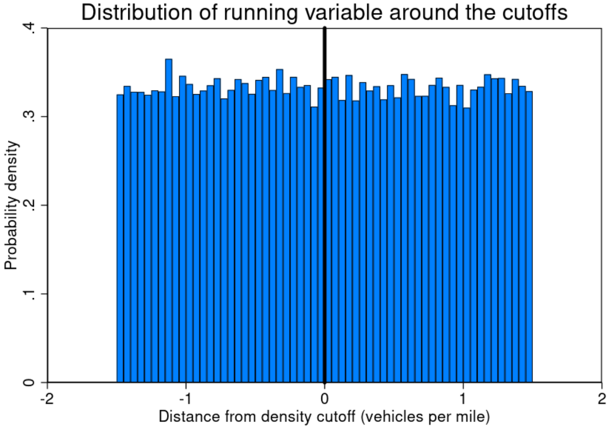
# No selection on observables on EL drivers

EL drivers are not selected on observables on each side of the discontinuity cutoffs:

- No bunching in distribution of running variable [Distribution of running variable]
- No bunching in distribution of entry second [Distribution of entry second]
- Miles traveled on the EL (morning) [Miles (morning)]
- Miles traveled on the EL (afternoon) [Miles (afternoon)]
- Entry time (morning) [Entry time (morning)]
- Entry time (afternoon) [Entry time (afternoon)]

[Back]

# No bunching in distribution of running variable

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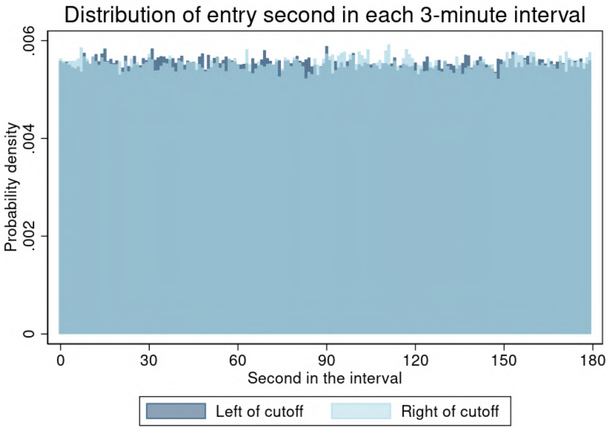
# No bunching in distribution of entry second

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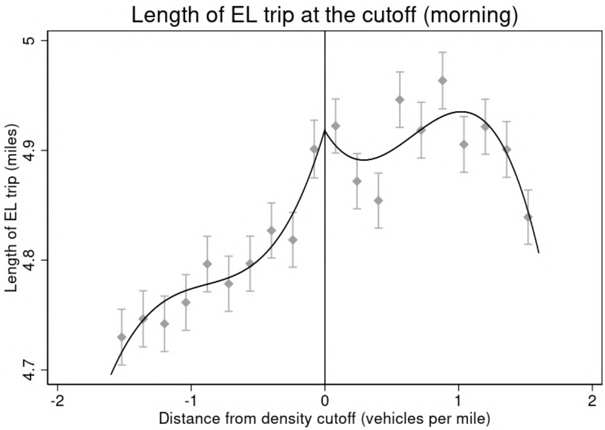
# No selection on observables on EL drivers

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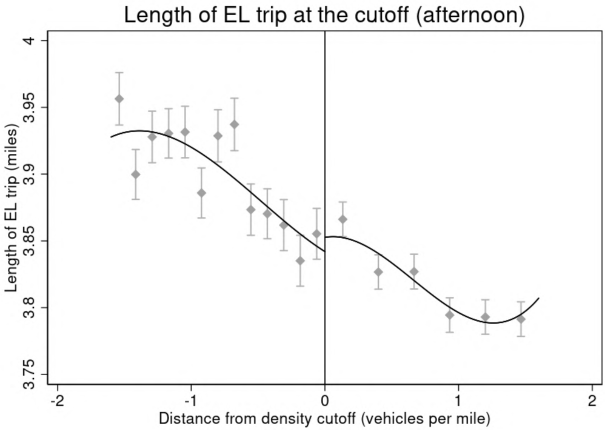


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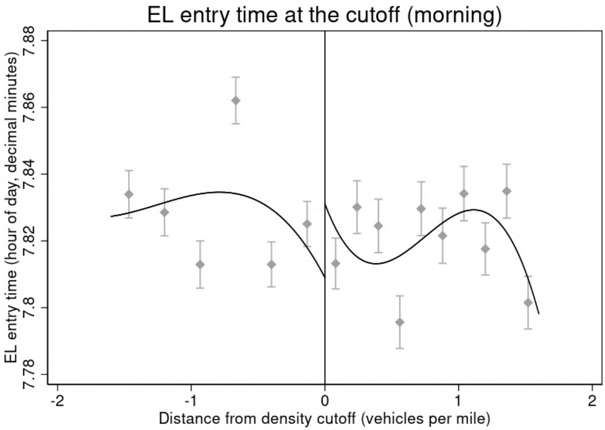


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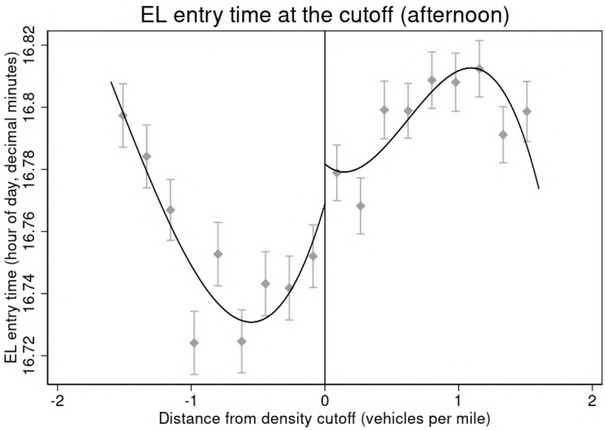


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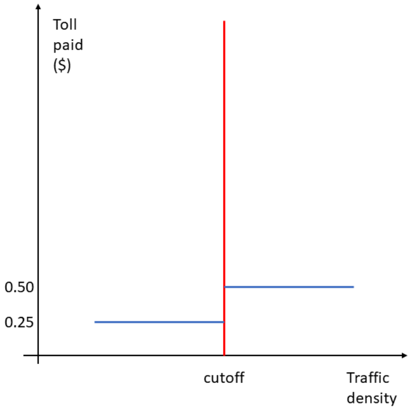
# Intuition for RDD (cutoff 1)



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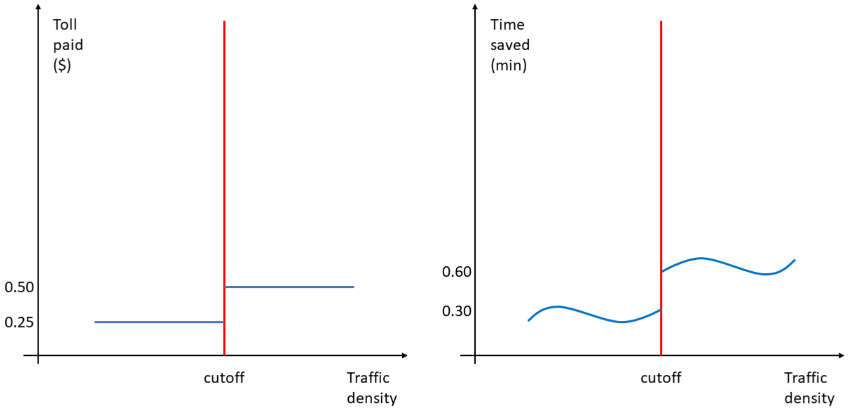
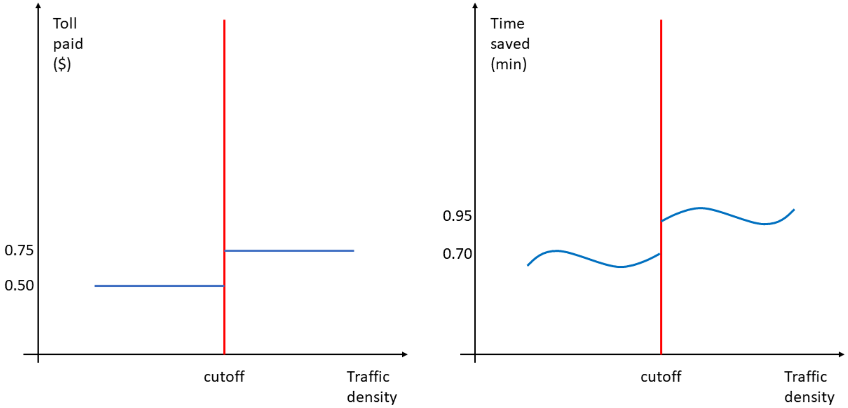
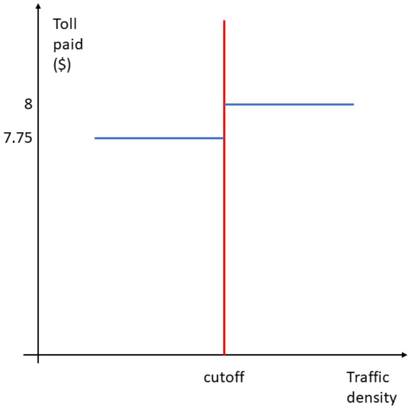
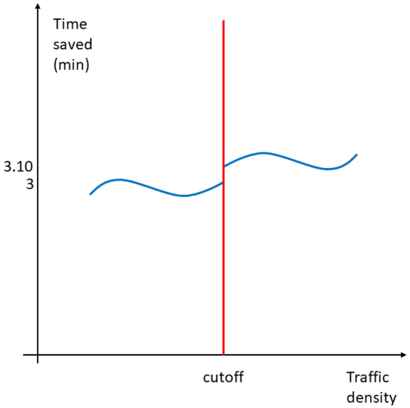


# Intuition for RDD (cutoff 2)



# Intuition for RDD (cutoff 32)

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# Regression equations

- For driver $i$ who uses the EL, at time $t$:

$$\text{FS:}\quad \pi_{it} = \alpha_z^{\pi} + \beta_z^{\pi}\mathbb{1}[d_{it} \geq c_z] + \gamma_z^{\pi} \cdot f(d_{it} - c_z) + \delta_z^{\pi} \cdot \mathbb{1}[d_{it} \geq c_z] \cdot f(d_{it} - c_z) + \eta_{it}$$

$$\text{SS:}\quad \tau_{it} = \alpha^{\tau} + \beta^{\tau}\hat{\pi}_{it} + \gamma_z^{\tau} \cdot f(d_{it} - c_z) + \delta_z^{\tau} \cdot \mathbb{1}[d_{it} \geq c_z] \cdot f(d_{it} - c_z) + \varepsilon_{it}$$

- $\tau_{it}$ is minutes of time saved, $\pi_{it}$ is the toll paid, $d_{it}$ is traffic density, $c_z$ is the cutoff for discontinuity $z$;

# Regression equations

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$$VOT = \frac{1}{\beta^\tau}$$

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$$VOT = \frac{1}{\beta^\tau}$$

- $f(\cdot)$ is a 3rd-degree polynomial (Calonico *et al.* (2017)); standard errors and averaging over all estimates follows Bertanha (2020).

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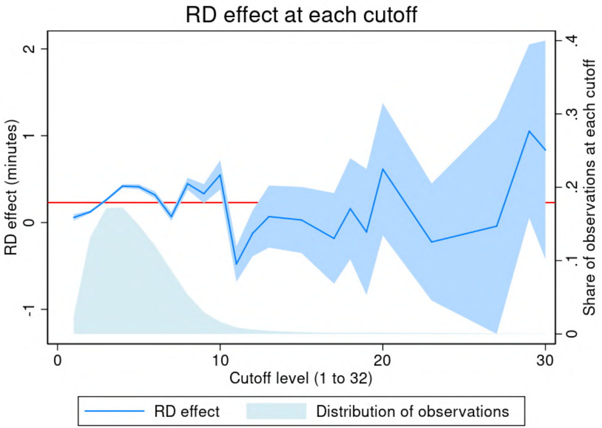
# RD time saved effect at each cutoff

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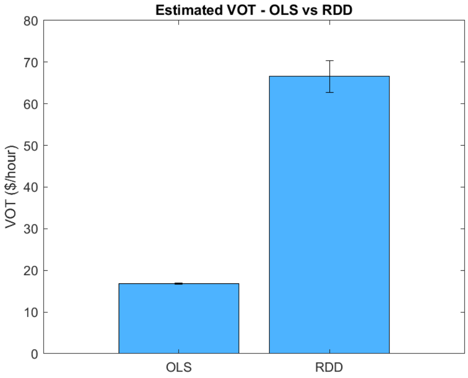
# Comparison between RDD and OLS

Hedonic OLS of toll paid on time saved underestimates VOT.




Regression table Back

# Comparison between RDD and OLS (table)

| *PANEL 1: RDD* | **Dependent: time saved (minutes)** | | | |
|---|---|---|---|---|
| | All roads | I-394 | I-35W | I-35E |
| Estimated RDD effect | 0.225*** | 0.215*** | 0.244*** | 0.254*** |
| | (0.00667) | (0.00741) | (0.0128) | (0.0152) |
| Implied VOT ($/hour) | 66.56 | 69.92 | 61.52 | 59.00 |
| | (1.97) | (2.41) | (3.23) | (3.53) |
| *PANEL 2: OLS* | **Dependent: toll paid ($)** | | | |
| | All roads | I-394 | I-35W | I-35E |
| Time saved (minutes) | 0.281*** | 0.211*** | 0.331*** | 0.143*** |
| | (0.00162) | (0.00121) | (0.00176) | (0.00159) |
| Implied VOT ($/hour) | 16.83 | 12.66 | 19.85 | 8.58 |
| | (0.10) | (0.07) | (0.11) | (0.09) |
| *N* | 1,935,965 | 956,530 | 642,886 | 337,226 |

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

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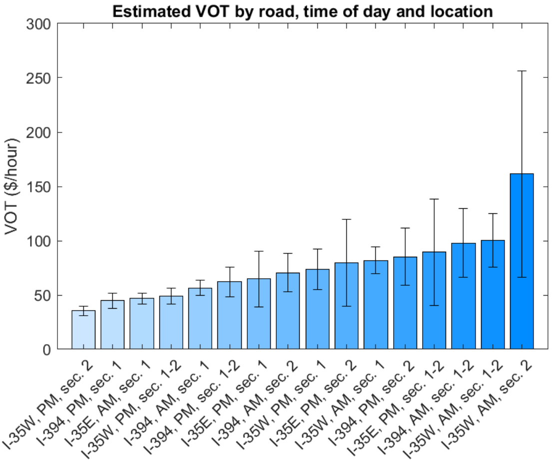
# Results by road and by travel location




Correlation with aggregate economic indicators | Back

# Correlation between VOT results and Census data

| | **Correlation with estimated VOT** |
|---|---|
| Average hourly wage | 0.2324*** |
| Median individual income | 0.1721*** |
| Median household income | 0.3571*** |
| % households >$200k yearly income | 0.3114*** |
| Median owned property value | 0.2172*** |
| % of properties over $1M | 0.1343*** |

Back

# VOT distribution and EL choice probability

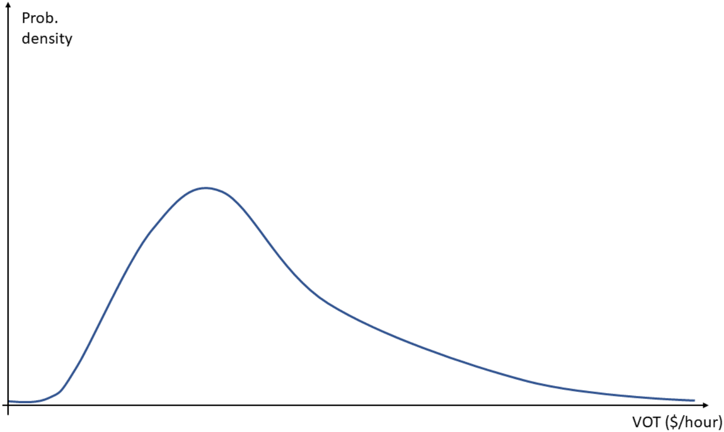
- Outcome of interest: aggregate EL choice probability.
- Conditional on commuting, $i$'s latent EL utility in market $j$ is:

$$u_{ij}^{EL} = \delta^{EL} + \beta_i^{VOT} \cdot \tau_j - \pi_j + \varepsilon_{ij}$$

- Aggregate EL choice probability depends on VOT distribution in the population.

Back

# Intuition: identification of VOT distribution

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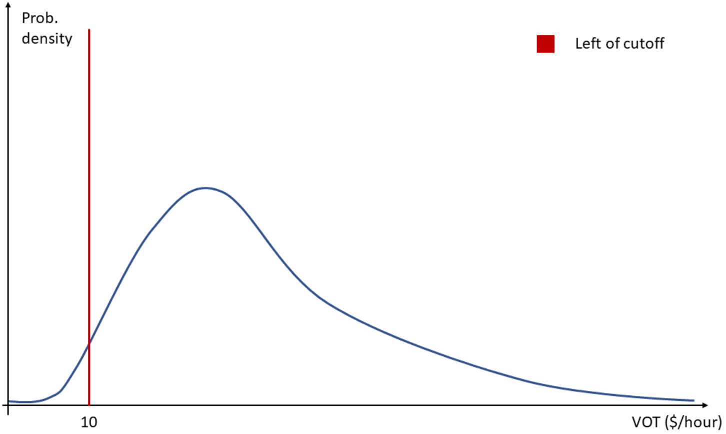
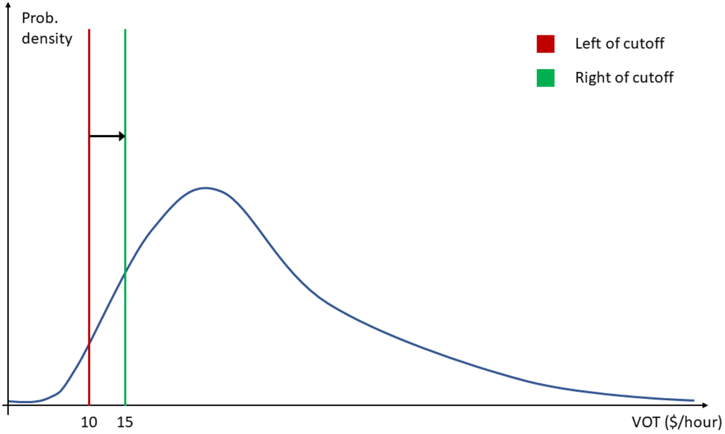
# Intuition: estimation of VOT distribution



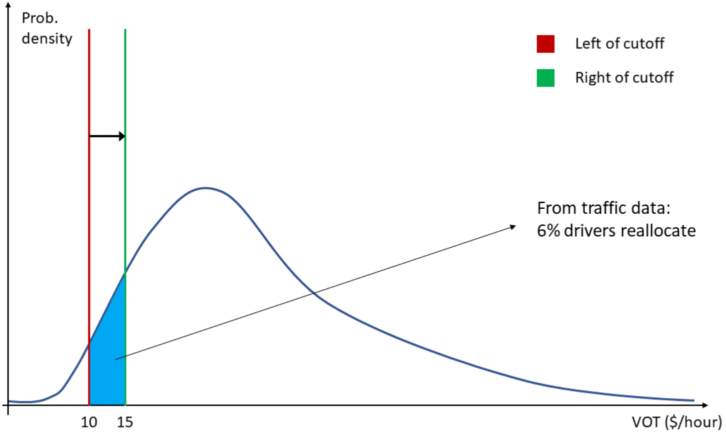

Back

# Intuition: estimation of VOT distribution



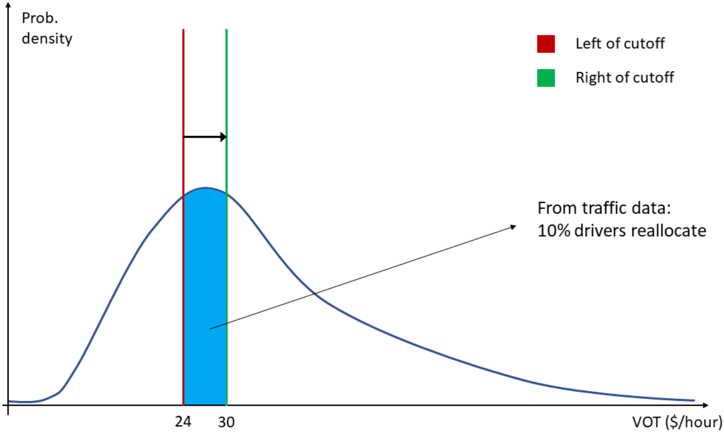

Back

# Intuition: estimation of VOT distribution




Back

# Intuition: estimation of VOT distribution

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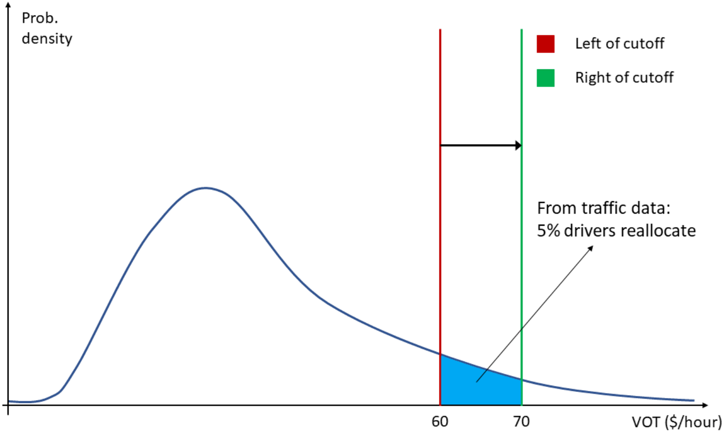
# Intuition: estimation of VOT distribution

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# Specification of aggregate EL choice probability

- Assume $\varepsilon_{it}$ is logistic with scale $s$ and the VOT distribution is approximated by a set of $M$ mass points $\beta_i^{m,VOT}$ with probability $\theta^m$.

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- Aggregate EL choice probability in market $j$ (Fox *et al.* (2011)):

$$s_j^{EL} = \sum_{m=1}^{M} \theta^m s_{j,m}^{EL} = \sum_{m=1}^{M} \theta^m \frac{exp\left(\frac{\delta^{EL}+\beta^{m,VOT}\cdot\tau_j-\pi_j}{s}\right)}{1+exp\left(\frac{\delta^{EL}+\beta^{m,VOT}\cdot\tau_j-\pi_j}{s}\right)}$$

# Specification of aggregate EL choice probability

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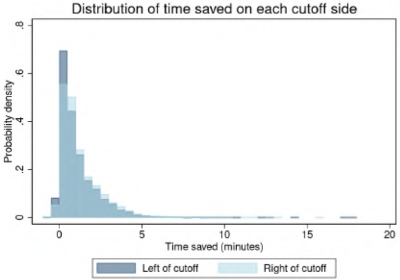
- To use exogenous variation at cutoff, focus on $\Delta s_j^{EL} = s_j^{EL,1} - s_j^{EL,0}$:

$$\Delta s_j^{EL} = \sum_{m=1}^{M} \theta^m \left[ \frac{exp\left(\frac{\delta^{EL}+\beta^{m,VOT}\cdot\tau_j^{\mathbf{1}}-\pi_j^{\mathbf{1}}}{s}\right)}{1+exp\left(\frac{\delta^{EL}+\beta^{m,VOT}\cdot\tau_j^{\mathbf{1}}-\pi_j^{\mathbf{1}}}{s}\right)} - \frac{exp\left(\frac{\delta^{EL}+\beta^{m,VOT}\cdot\tau_j^{\mathbf{0}}-\pi_j^{\mathbf{0}}}{s}\right)}{1+exp\left(\frac{\delta^{EL}+\beta^{m,VOT}\cdot\tau_j^{\mathbf{0}}-\pi_j^{\mathbf{0}}}{s}\right)} \right]$$

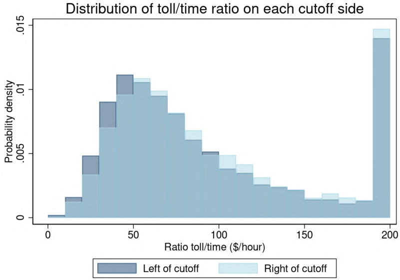
Back

# Assumptions to infer VOT distribution

1. **Independence:** $\mathbb{E}[\theta^m | \tau_j, \pi_j] = \mathbb{E}[\theta^m] \quad \forall j, \quad \forall m$
2. **Relevance:** $\beta^{m,VOT} \in [VOT_j^0, VOT_j^1] \quad \forall m, \quad$ for some $j$




(a) Time saved across subsamples




(b) Ratio toll/time saved across subsamples

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# Implementation of VOT distribution estimation

- Each market $j$ is a day and cutoff in the sample.
- In the data I observe $\widehat{\Delta s}_j^{EL} = \Delta s_j^{EL} + \zeta_j$, with $\mathbb{E}[\zeta_j | \tau, \pi, \beta^{m,VOT}] = 0$. I estimate:
$$\widehat{\Delta s}_j^{EL} = \sum_m \theta^m \cdot \Delta s_{j,m}^{EL} + \zeta_j$$
- Divide VOT space in 20 bins, from \$0 to \$200 per hour saved.

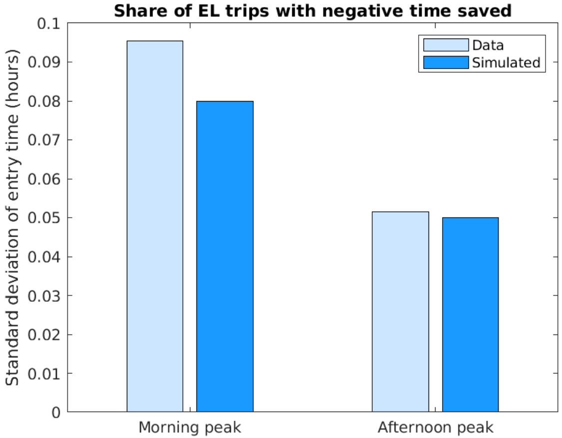
Implementation details Back

# Implementation of VOT estimation

- Estimate the $\hat{\theta}^m$ parameters given a guess for $\delta^{EL}$ and $s$.
- Draw a sample of drivers from VOT distribution given by the $\hat{\theta}^m$.
- Match share of trips with negative time savings and the EL traffic share and iterate to pin down $\delta^{EL}$ and $s$.
- $\delta^{EL}$ is identified as $log(s^{EL}|\tau = 0) - log(1 - s^{EL}|\tau = 0)$ and an open set around $\tau = 0$ is observed.

% trips with negative time saved fit  Back

# % EL trips negative time saved

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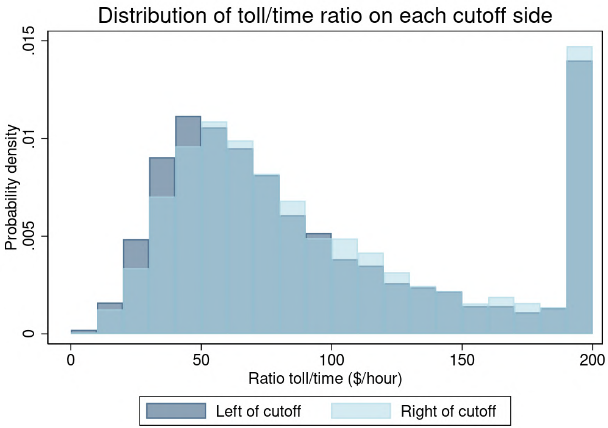
# Data support for VOT distribution estimation

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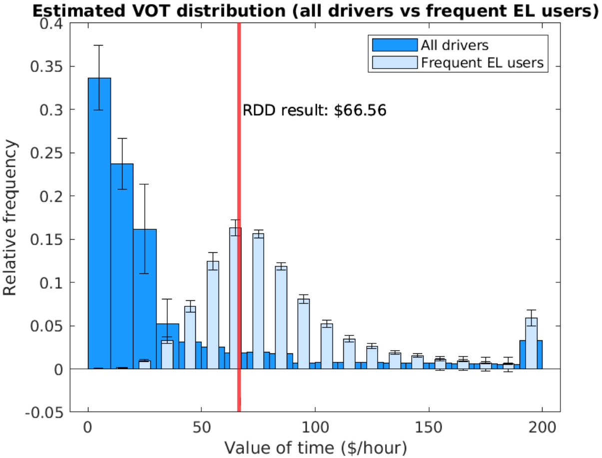
# VOT distribution only for frequent EL users

- Frequent EL user: over 10 uses per year (less than half of the sample). Sample restriction allows to relax assumptions.
- Plug in estimated scale parameter $s$ from general estimation.
- Can estimate $\beta_{i,EL}^{VOT}$ through likelihood, matching each individual's EL usage probability.

Back | Comparison with VOT distribution for all drivers

# Estimated VOT distributions — comparison




Back | Road-specific estimated distributions | Robustness: 20+ yearly uses | Robustness: 50+ yearly uses

# Estimated VOT distributions by road

I-394 (AM)

I-394 (PM)

I-35W (AM)

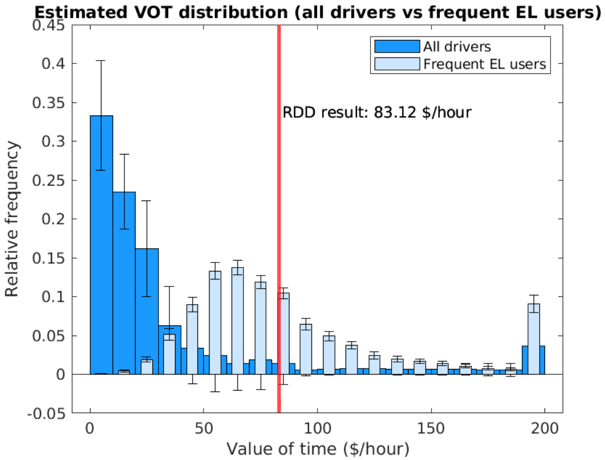
I-35W (PM)

I-35E (AM)

I-35E (PM)

Back

# Estimated VOT distribution

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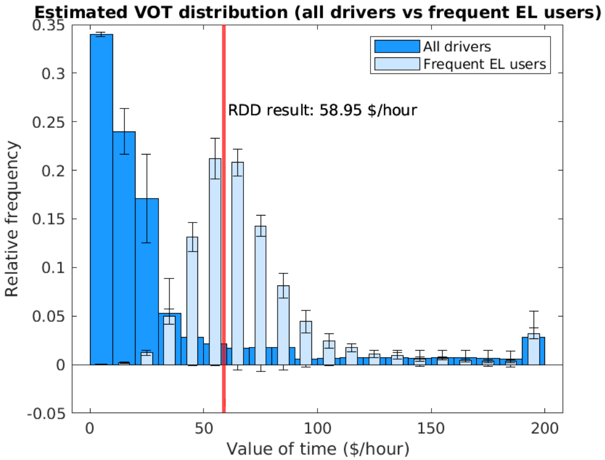
# Estimated VOT distribution

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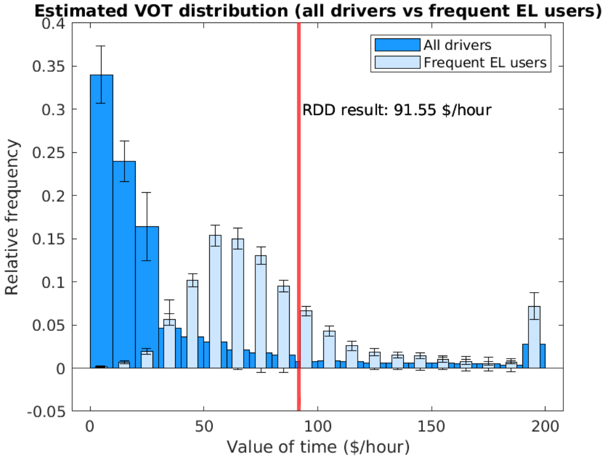
# Estimated VOT distribution

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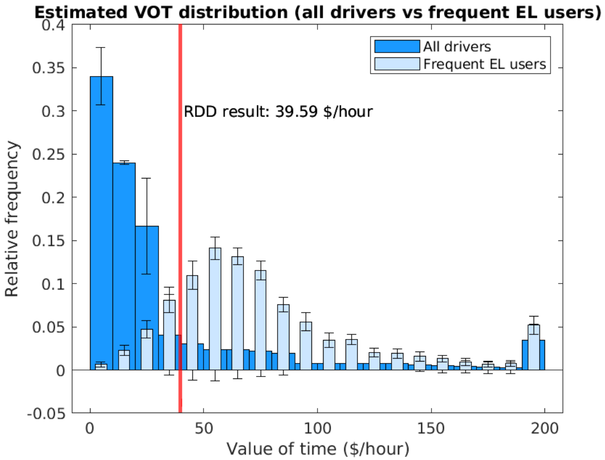
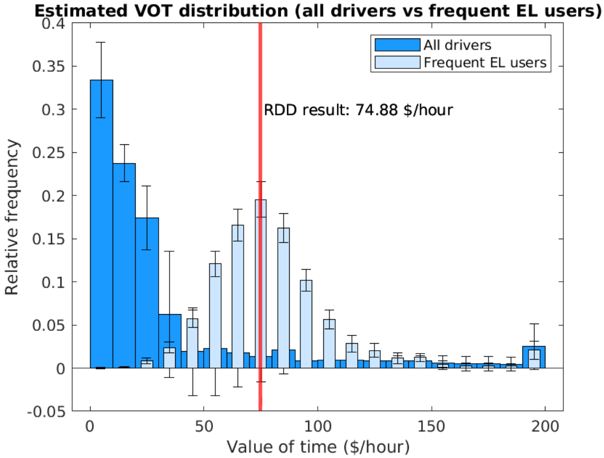
# Estimated VOT distribution



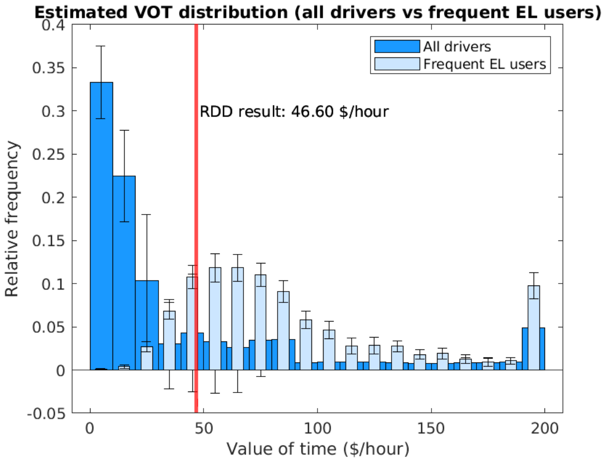

Back

# Estimated VOT distribution




Back

# Estimated VOT distribution

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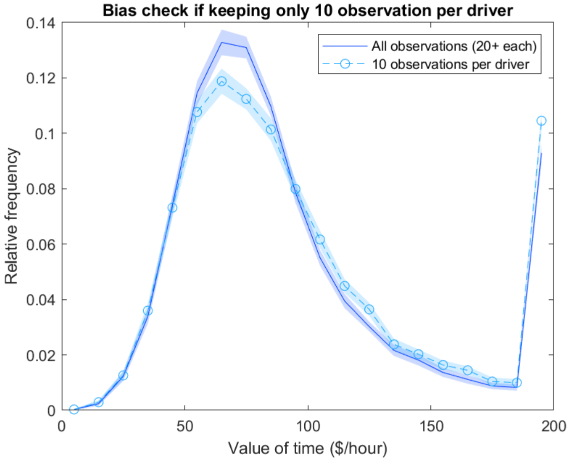
# VOT distribution, frequent users (20+ yearly uses)

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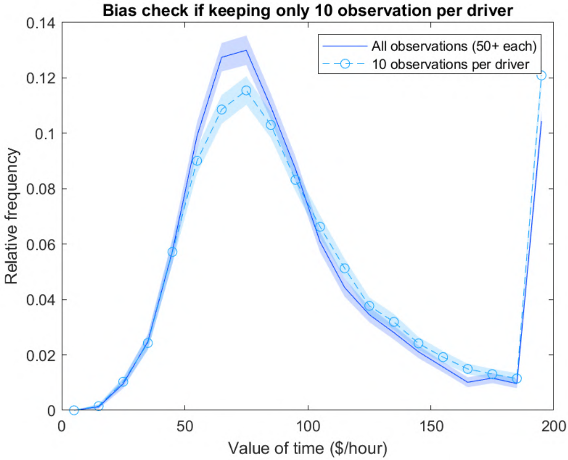
# VOT distribution, frequent users (50+ yearly uses)

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# Key trade-off choice underlying the model

- Pure preference: suppose everyone prefers to commute at 8am.
- Trade-off with commuting time expectation: someone might end up traveling at 7:30am to avoid congestion.
- Including this choice margin is important to fully characterize drivers' response to counterfactuals.

Entry time results (Fridays) Entry time results (holidays) Entry time results (snow days) Back

# Model equations

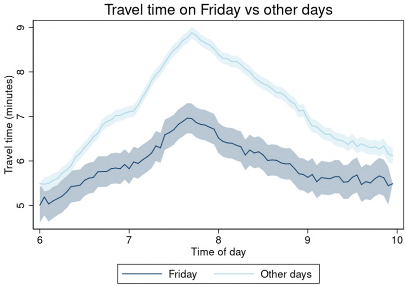
- Stage 1: each driver $i$ chooses, each day $d$ and peak $p$, the departure time $t$ that maximizes expected utility $u(t_{dpi})$ knowing that they might take the Express Lane $EL(t_{dpi})$ or not:

$$u(t_{dpi}) = \beta_{pi} \cdot \boldsymbol{\alpha_{pt}} + max\{EL(t_{dpi}), 0\} + \varepsilon_{dpti}$$
$$EL(t_{dpi}) = \delta^{EL} + \beta_{pi} \cdot \mathbb{E}[\tau_{pt}(t_{dpi})] - \mathbb{E}[\pi_{pt}(t_{dpi})]$$

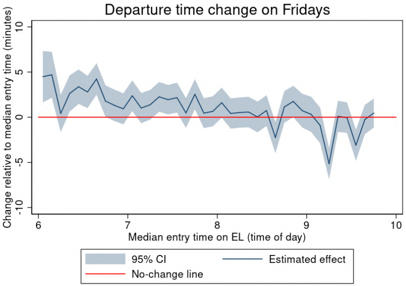
- $\beta_{pi}$ is individual VOT, $\alpha_{pt}$ are entry time FEs, $\tau_{pt}$ is travel time saved, $\pi_{pt}$ is EL toll, $\delta^{EL}$ is taste for the EL. Traffic to travel time relationship
- EL choice in stage 2 replicates the VOT distribution part. Equations

Moments list | Estimation procedure | Moments fit | Untargeted moments | Replication of RD results
Back

# EL entry time results (Fridays)



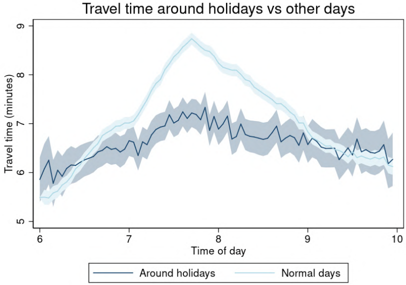

(a) Travel time change



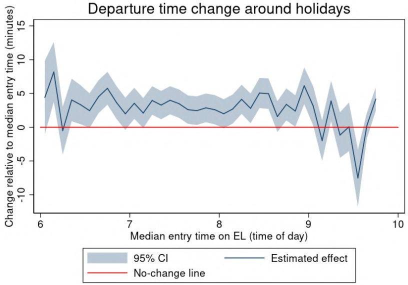

(b) EL entry change relative to median

Back

# EL entry time results (around holidays)




(a) Travel time change




(b) EL entry change relative to median

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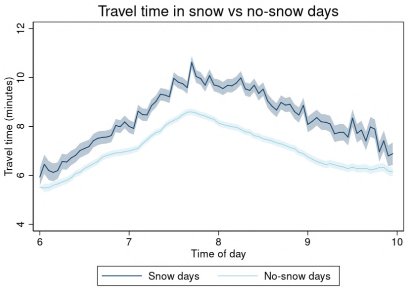
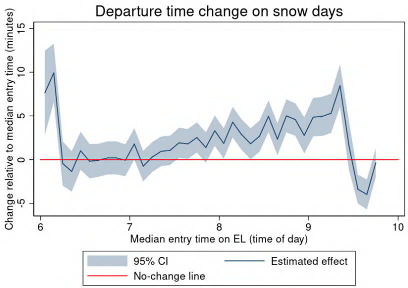
# EL entry time results (snow days)



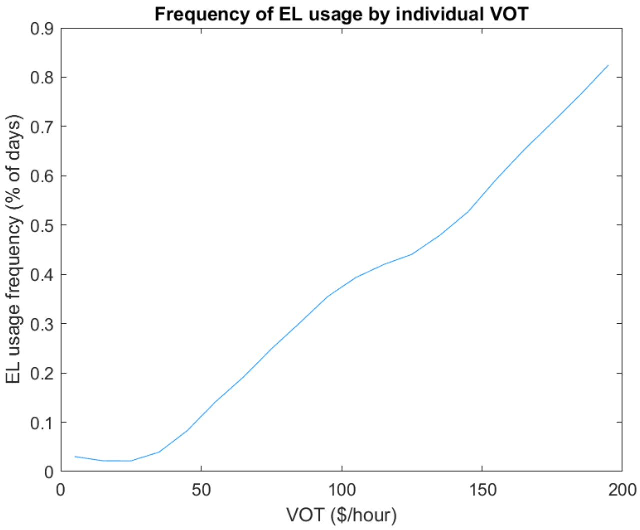

(a) Travel time change




(b) EL entry change relative to median

Back

# Model prediction of EL usage by individual VOT

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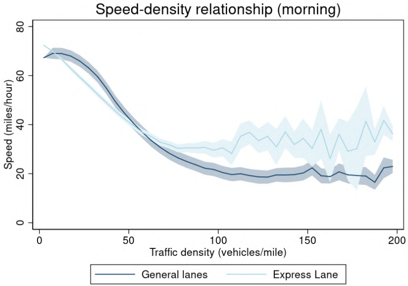
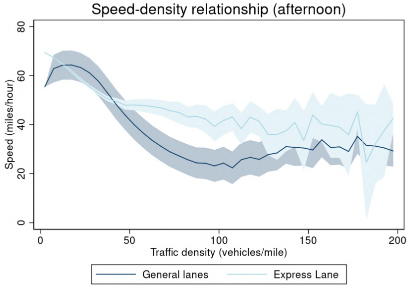
# Speed to traffic density relationship




(a) Morning




(b) Afternoon

Back

# Stage 2: EL choice in general equilibrium

- Each driver $i$ in day $d$ and peak $p$ sees the realization of time savings and toll and chooses the EL if their latent utility $u^{EL}_{dpi}$ is positive:

$$u^{EL}_{dpi} = \delta^{EL} + \beta_{pi} \cdot \tau(t^*_{dpi}) - \pi(t^*_{dpi}) + \eta_{dpi}$$

- Solved sequentially and in general equilibrium: drivers are allocated between EL and GL so that no driver wants to behave differently given what the others are doing.

Back

# 164 moments targeted for 82 parameters

1. Median traffic density in the general lanes every 6 minutes (80 moments).
2. Median traffic density in the ELs every 6 minutes (80 moments).
3. Standard deviation of EL entry time (2 moments).
4. average % change in general lane traffic density at discontinuity cutoffs (2 moments).

Back

# Model estimation procedure

1. Stage 1:
   - Guess departure time shares for each $m$ VOT class.
   - For each $m$ VOT class, find expected value of taking the EL.
   - Compute expected utility of each departure time $t$.
   - After realization of shocks $\varepsilon_{dpti}$, each driver $i$ chooses the optimal $t$ in each day and peak.
   - Aggregate probability of each $t$ needs to be consistent with the initial guess.
2. Stage 2:
   - Given simulated stage 1 choices, find EL traffic equilibrium.
   - Iterate back from stage 1 until moments are matched.

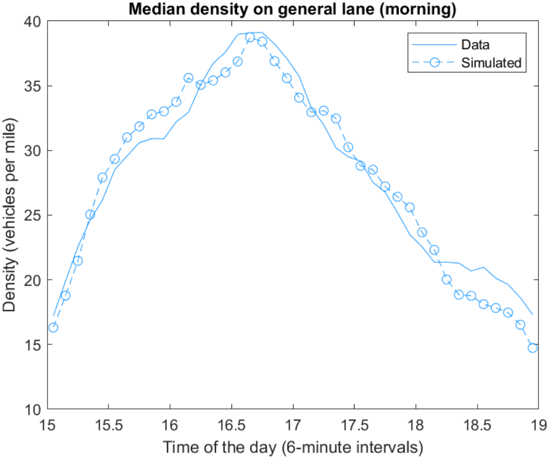
Back

# Targeted moments fit

- Traffic density on standard lane (morning)
- Traffic density on standard lane (afternoon)
- Traffic density on Express lane (morning)
- Traffic density on Express lane (afternoon)
- Standard deviation of EL entry time
- Share of EL trips with negative time saved
- Average % change in standard lane density at cutoff

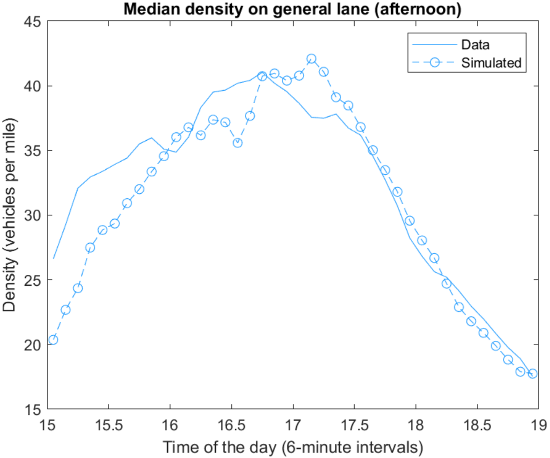
Back

# Moments fit: traffic on standard lane (AM)



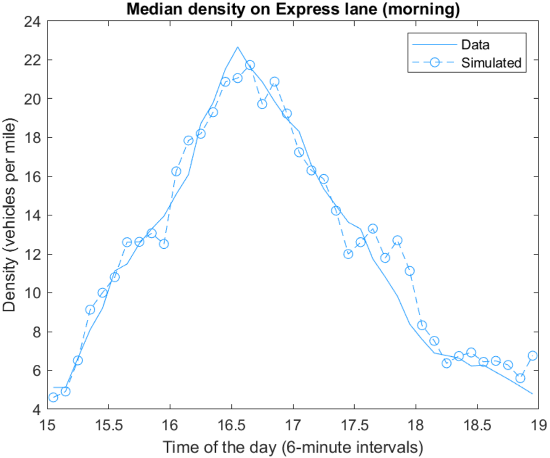

Back to moments list

# Moments fit: traffic on standard lane (PM)




Back to moments list

# Moments fit: traffic on Express lane (AM)

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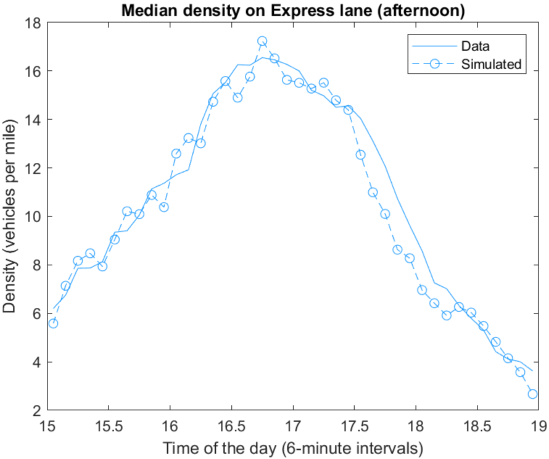
# Moments fit: traffic on Express lane (PM)

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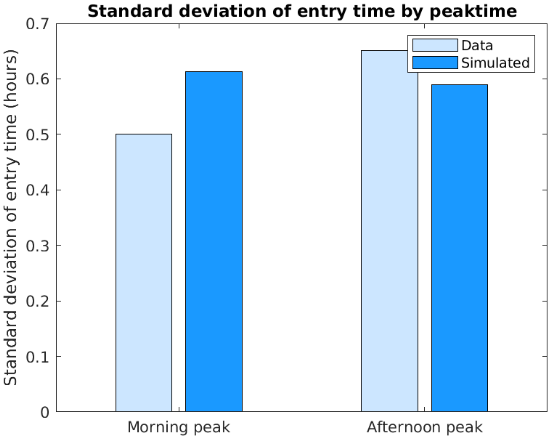
# Moments fit: std of EL entry time

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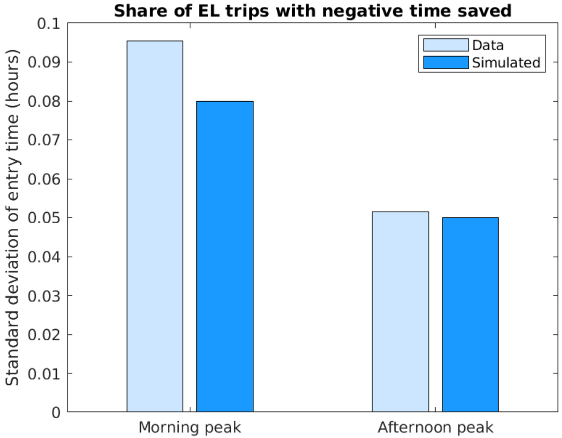
# Moments fit: % EL trips negative time saved

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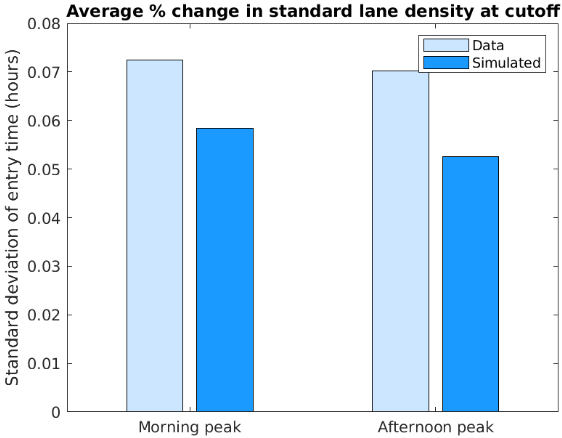
# Moments fit: mean % GL density change at cutoff

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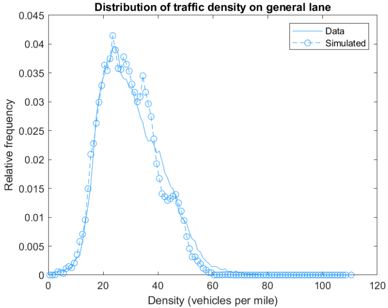
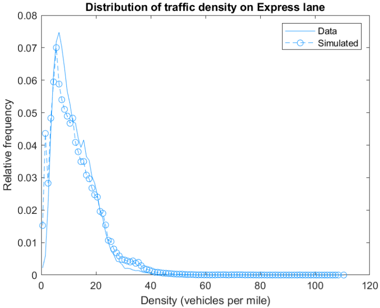
# Untargeted moments fit (1)



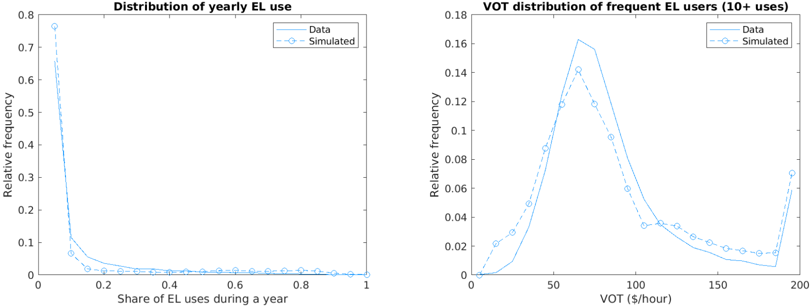

(a) General lanes traffic




(b) EL traffic

Next untargeted moments Back

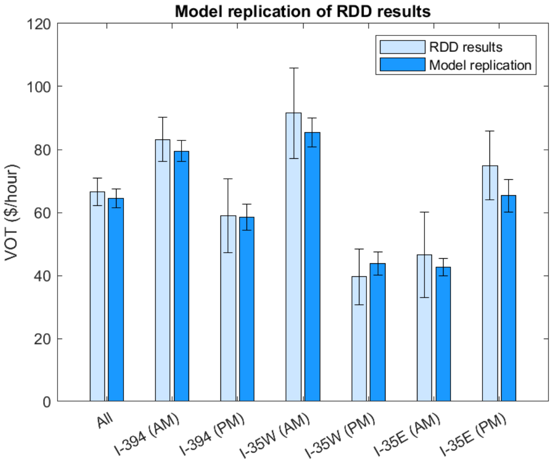
# Untargeted moments fit (2)




(a) EL yearly usage rate (b) VOT of frequent EL users

Previous untargeted moments Back

# VOT model replication of RD results

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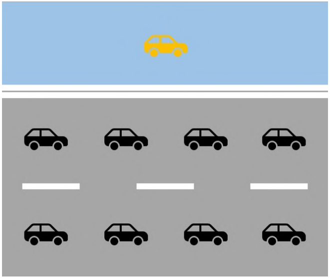
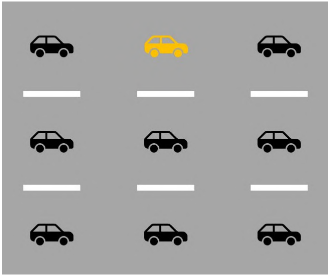
# EL converted to free lane: intuition



*Benchmark with EL*



*3 standard lanes*

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# Distributional effects: EL becomes standard lane


I-394 (AM)

I-394 (PM)

I-35W (AM)

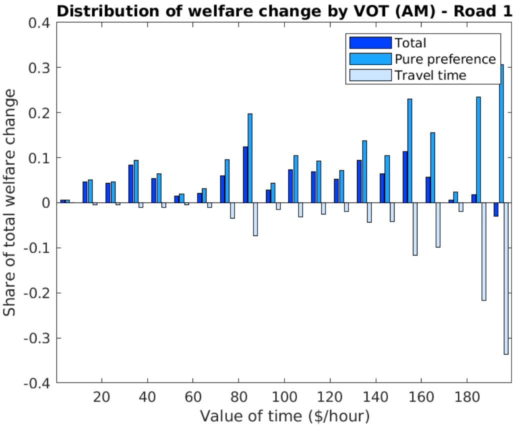
I-35W (PM)

I-35E (AM)

I-35E (PM)

Back

# Distributional effects: EL becomes standard lane




Per-capita welfare change (without rebate): $32.34 per year.
Per-capita welfare change (with rebate): $19.45 per year.

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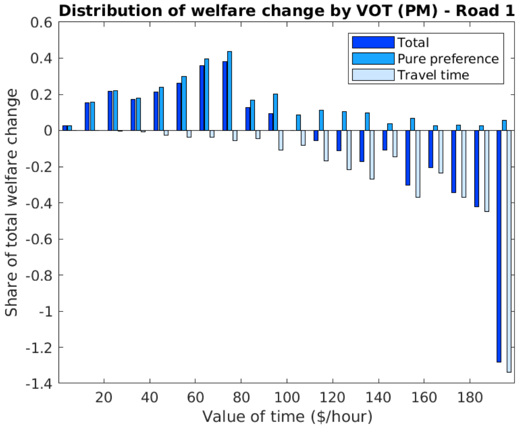
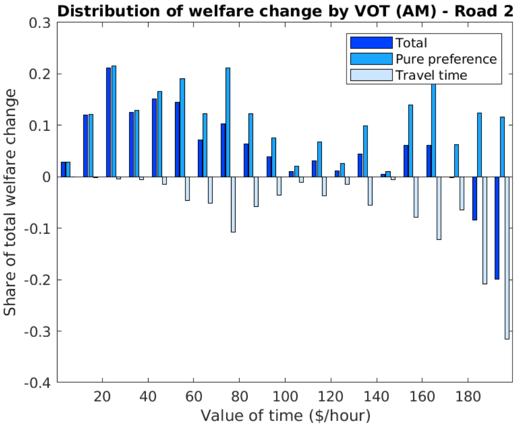
# EL is converted into a general lane




Per-capita welfare change (without rebate): $17.61 per year.
Per-capita welfare change (with rebate): -$11.80 per year. Back

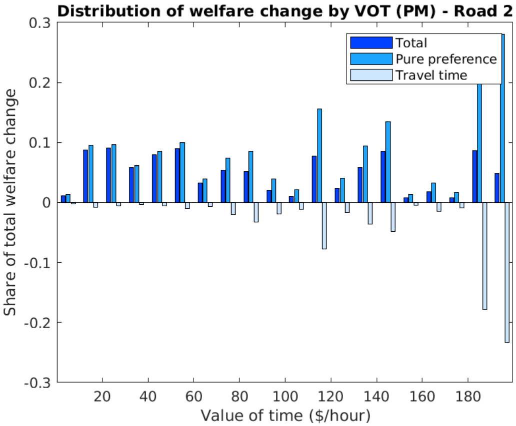
# EL is converted into a general lane




Per-capita welfare change (without rebate): $52.99 per year.
Per-capita welfare change (with rebate): $28.49 per year.

Back

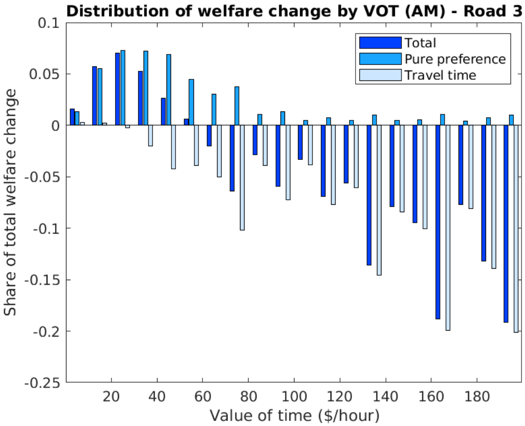
# EL is converted into a general lane




Per-capita welfare change (without rebate): $15.44 per year.
Per-capita welfare change (with rebate): $9.48 per year.

Back

# EL is converted into a general lane

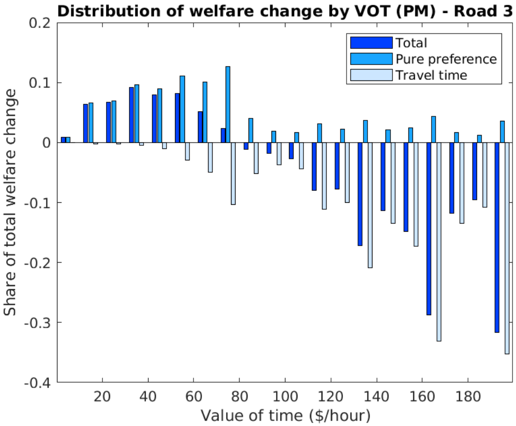



Per-capita welfare change (without rebate): $7.40 per year.

Per-capita welfare change (with rebate): -$28.20 per year.

Back

# EL is converted into a general lane




Per-capita welfare change (without rebate): -$0.28 per year.
Per-capita welfare change (with rebate): -$18.33 per year.

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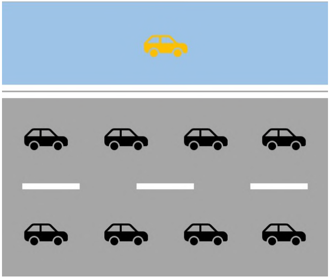
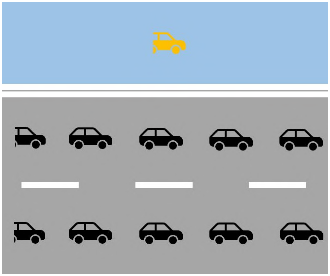
# More low-VOT drivers: intuition



*Benchmark with EL*



*Normal lanes more congested*

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# Distributional effects: more low-VOT drivers

I-394 (AM)

I-394 (PM)

I-35W (AM)

I-35W (PM)

I-35E (AM)

I-35E (PM)

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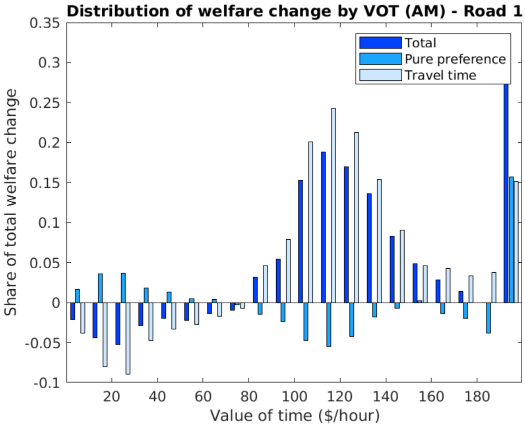
# Distributional effects: more low-VOT drivers




Per-capita welfare change (without rebate): $2.16 per year.
Per-capita welfare change (with rebate): $0.50 per year.

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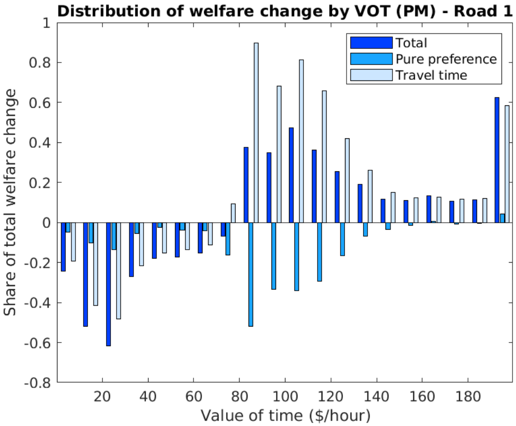
# Change in VOT composition of drivers




Per-capita welfare change (without rebate): $0.96 per year.
Per-capita welfare change (with rebate): -$1.82 per year.

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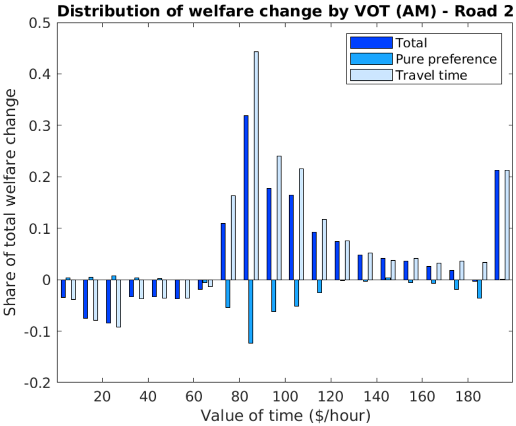
# Change in VOT composition of drivers




Per-capita welfare change (without rebate): $2.39 per year.
Per-capita welfare change (with rebate): $0.28 per year.

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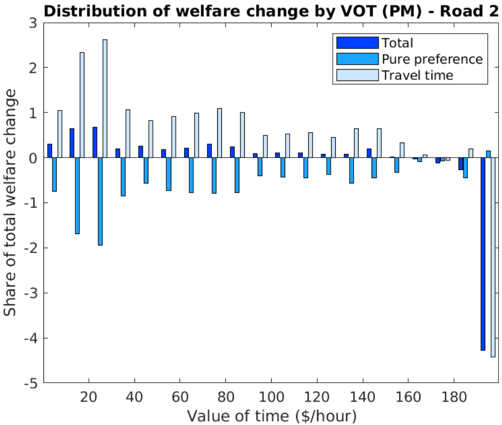
# Change in VOT composition of drivers




Per-capita welfare change (without rebate): $0.34 per year.
Per-capita welfare change (with rebate): -$0.43 per year.

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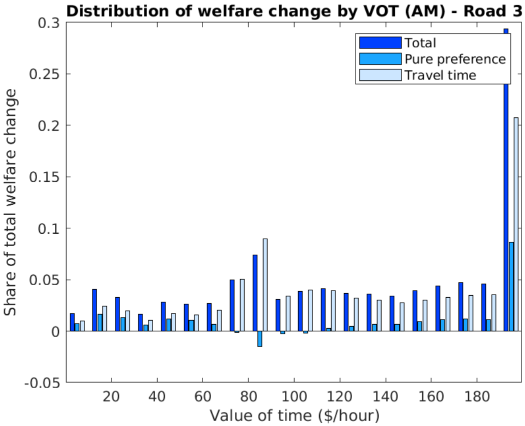
# Change in VOT composition of drivers




Per-capita welfare change (without rebate): $7.83 per year.
Per-capita welfare change (with rebate): $7.39 per year.

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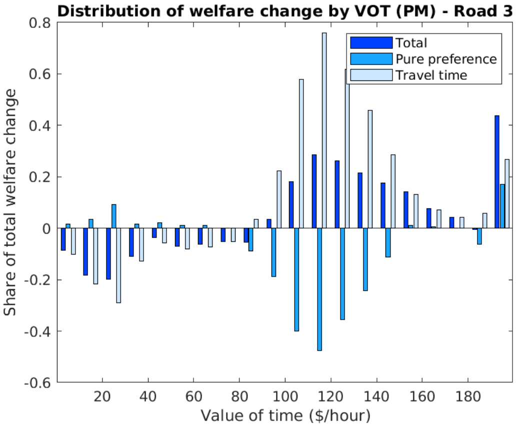
# Change in VOT composition of drivers




Per-capita welfare change (without rebate): $0.93 per year.
Per-capita welfare change (with rebate): -$0.40 per year.

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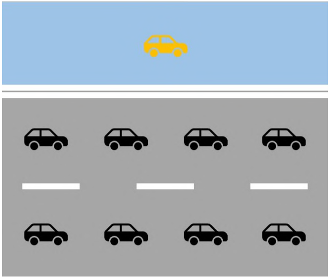
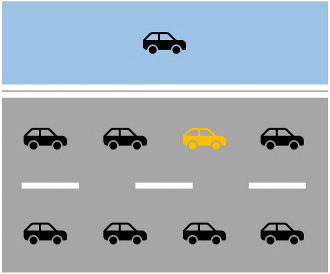
# Ignore VOT heterogeneity: intuition



*Benchmark with EL*



*Random assignment to EL*

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